
THE SPECULATIVE PARADOX IN CRYPTOCURRENCY: A DOWNSIDE RISK ANALYSIS FROM THE INDONESIAN INVESTOR'S PERSPECTIVE

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Abstract:

Amidst the rapid growth of cryptocurrency adoption, differentiating between fundamental utility and speculative hype is critical for retail investor protection. This study evaluates the risk-adjusted performance of utility-based versus speculation-based cryptocurrencies over the 2023–2025 period. Employing a quantitative empirical-analytical approach, this study utilizes the Sortino and Calmar Ratios to capture downside risk and maximum drawdown, which are metrics that better address the asymmetric return characteristics of digital assets compared to the conventional Sharpe ratio. The BI 7-Day Reverse Repo Rate is applied as the risk-free benchmark to reflect the domestic opportunity cost for Indonesian investors. Results indicate that Smart Contract Platforms predominantly delivered superior risk-adjusted returns, while AI tokens exhibited broad underperformance reflecting an immature utility phase, and DeFi tokens showed heterogeneous results consistent with a sector consolidation dynamic. Paradoxically, the meme token BONK achieved the highest Calmar Ratio despite an extreme maximum drawdown, supporting Prospect Theory's prediction of lottery-like preferences among retail investors. This study offers Indonesian retail investors, financial educators, and market supervisors a more rigorous and practically applicable framework for cryptocurrency performance assessment, directly supporting the consumer protection objectives established by domestic financial regulation.

Key words: *Calmar Ratio, Cryptocurrency, Indonesian Investor, Performance, Sortino Ratio*

1. Introduction

With the approval of Bitcoin exchange-traded products (ETPs) on January 10, 2024, by the U.S. Securities and Exchange Commission (SEC, 2024), investors can now access Bitcoin exposure with ease comparable to equity investments. The adoption of

cryptocurrency as an investment instrument continues its positive trend through 2025, evolving from niche technology discourse into an integral component of major corporate balance sheets (Chiquitita, 2025). Institutional accumulation of Bitcoin from 2024 to mid-2025 reflects a significant paradigm shift: instruments previously categorized as volatile and experimental have been formally integrated into long-term capital management and financial diversification strategies.

This global trend is also reflected in developing countries, particularly Indonesia. Official data from the Financial Services Authority (OJK) shows a sharp upward trend in the number of cryptocurrency asset investors, from 13.3 million in February 2025 to 19.5 million in November 2025, representing an increase of approximately 46.9% over nine months (see Figure 1). The OJK also reported that cryptocurrency asset transactions through November 2025 reached 449.55 trillion rupiah (OJK, 2025). This trend corroborates prior research indicating that cryptocurrency, initially conceived as a medium of exchange, is increasingly adopted as an investment instrument (Almeida & Gonçalves, 2022; Auer & Tercero-Lucas, 2022), underscoring the urgent need to evaluate the risk-adjusted performance of these digital assets within the domestic market.

However, this growth has triggered escalating speculative activity and significant market risk exposure. Studies and practical reports have documented investor losses attributable to low analytical capability, susceptibility to social media hype, lack of risk management, and psychological biases (BBC, 2024; Hafishina et al., 2023; Hema & García Márquez, 2025; Jayalakshmi et al., 2026; Khan et al., 2024; Phung et al., 2026). More critically, empirical evidence suggests that the majority of retail cryptocurrency investors ultimately incur financial losses (Auer et al., 2023; Chernoff & Jagtiani, 2025). This reality reveals a fundamental challenge: the lack of adequate analytical frameworks and financial literacy to differentiate cryptocurrencies with sound risk-return profiles from those driven primarily by speculation.

This phenomenon underscores the urgency of strengthening consumer protection and financial stability through improved financial literacy. A thorough understanding of risk profiles is essential for loss mitigation and informed decision-making within the volatile cryptocurrency market (Carbó-Valverde et al., 2025; Jones et al., 2024; Rahyuda & Candradewi, 2023). This urgency is further reinforced by OJK regulation through POJK Number 27 of 2024 (POJK, 2024), which mandates supervision, governance, risk management, and consumer protection in digital asset trading, while also emphasizing the importance of consumer literacy in understanding crypto asset performance assessment.

Cryptocurrency assets are highly diverse; there are fundamental differences in function and value proposition between asset types. Generally, industry literature and practice distinguish between two main groups: utility tokens and speculative tokens. Tokens that serve a demonstrable functional purpose within a given blockchain ecosystem are classified as utility tokens, whereas those whose value is driven primarily by market sentiment and speculation are designated as speculative tokens. This distinction affects price behavior, risk, and long-term return prospects (Benedetti & Smith, 2024; Kochergin, 2022; Scharnowski et al., 2023; Umar et al., 2023). Therefore, identifying the underlying drivers of value for each category is essential for a more nuanced understanding of market volatility.

In the context of evaluating cryptocurrency investment performance, metric selection is critical given the unique characteristics of the crypto market, which is subject to extreme volatility and asymmetric return distributions. Conventional metrics such as the Sharpe ratio (Sharpe, 1966), while widely applied in traditional portfolio analysis (Budiartomo & Setiyono, 2023; Laksana et al., 2026; Ruma & Tawe, 2023), treat positive and negative deviations equally in risk calculations, thereby potentially obscuring the true downside risk profile faced by cryptocurrency investors (Bacon, 2023; Sortino & Price, 1994). To address these limitations, this study employs the Sortino Ratio and Calmar Ratio, instruments specifically designed to capture downside deviation and maximum drawdown, respectively, making them more appropriate for the asymmetric nature of cryptocurrency markets.

This study employs the Sortino Ratio as the primary metric for assessing risk-adjusted returns, focusing on downside deviation relative to the minimum acceptable return and thereby more accurately capturing the potential losses most relevant to investors (Ramos-Requena & Bağcı, 2025; Sortino & Price, 1994). The Calmar Ratio is applied complementarily, measuring the efficiency of return generation relative to maximum drawdown during the observation period. The use of the Calmar Ratio is particularly relevant in the cryptocurrency context, given this market's susceptibility to sharp corrections and prolonged bear cycles, where maximum drawdown represents the critical worst-case scenario for investment decision-making (Dichtl et al., 2024; Dombrowski et al., 2023; Young, 1991). By integrating these dual metrics, the research provides a robust evaluation framework that accounts for both downside volatility and extreme capital erosion.

Despite the growing body of research on cryptocurrency in Indonesia, a significant gap remains in the literature. Most existing studies focus on legal and taxation perspectives (Apriliani et al., 2023; Hartono & Budiarsih, 2022; Jakub et al., 2025; Safari et al., 2025; Tambun & Putuhena, 2022), while those addressing investment performance predominantly compare cryptocurrencies against other asset classes such as gold, stocks, or mutual funds using the conventional Sharpe ratio (Budiartomo & Setiyono, 2023; Laksana, 2024; Laksana et al., 2026; Wiliyani & Purnamawati, 2023). To the best of the authors' knowledge, no study in the Indonesian context has specifically compared the risk-adjusted performance of utility-based and speculation-based cryptocurrencies using downside-sensitive metrics. The present study is designed to address this gap and to enhance financial literacy among novice retail cryptocurrency investors, directly supporting the mandates of POJK Number 27 of 2024. The BI 7-Day Reverse Repo Rate is deliberately selected as the domestic risk-free benchmark, representing the primary opportunity cost for Indonesian investors prior to engagement with more complex post-trade variables such as domestic crypto taxation.

This study analyzes the risk-adjusted performance of utility tokens and speculative tokens using the Sortino Ratio and Calmar Ratio, drawing on data covering the 2023 to 2025 period. This three-year window was deliberately selected to capture both a sustained bullish cycle and a significant market correction, thereby encompassing the full spectrum of risk conditions relevant to retail investor decision-making. Asset selection further incorporated market capitalization and asset age as inclusion criteria, given that assets with larger capitalization and longer operational histories are generally less susceptible to sentiment-driven volatility (Lansky, 2020; Pessa et al., 2023). Assets satisfying both criteria are expected to demonstrate more stable risk-adjusted performance relative to lower-ranked

counterparts within their respective categories, providing a theoretically grounded basis for cross-category comparison.

The study makes three primary contributions: (1) providing a practical performance assessment framework for the Indonesian cryptocurrency market by demonstrating how downside-risk metrics, such as the Sortino and Calmar Ratios, offer more relevant insights for retail investors than traditional mean-variance measures; (2) offering empirical evidence that utility-versus-speculative categorization is insufficient to predict risk-adjusted performance; and (3) documenting the speculative paradox as an empirical phenomenon that challenges conventional assumptions about the relationship between fundamentals and valuation in cryptocurrency markets.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methods. Section 4 presents the empirical results. Section 5 discusses the findings in relation to existing literature. Section 6 concludes by summarizing the principal findings and their implications for Indonesian retail investors.

2. Literature review

The literature review is organized into four key pillars. First, Section 2.1 reviews the historical development of Bitcoin and institutional adoption. Section 2.2 analyzes the functional dichotomy between utility and speculative assets. Section 2.3 integrates Prospect Theory as the behavioral foundation for justifying asymmetric risk metrics. This section concludes with Section 2.4, which evaluates the Sortino and Calmar Ratios as the most appropriate measures for assessing performance from a retail investor's perspective.

2.1 Bitcoin and the Evolution of Cryptocurrency

Introduced in 2008 by the pseudonymous Satoshi Nakamoto, Bitcoin is the first decentralized cryptocurrency. It pioneered blockchain technology as a secure, immutable ledger that validates transactions without intermediaries (López-Sorribes et al., 2023; Tommerdahl, 2024; Yi et al., 2022). Bitcoin aims to provide a peer-to-peer digital money system, eliminating the need for third-party financial institutions (Song et al., 2024). This foundational innovation spawned a diverse ecosystem of digital assets with varied functions and risk profiles, which forms the analytical basis of this study.

Driven by demand for efficient transactions and substantial returns, the cryptocurrency market has grown tremendously (Goel & Mittal, 2020; Rao et al., 2025). Institutional participation has been crucial, particularly following the SEC's January 2024 approval of Bitcoin ETPs, which reshaped global market dynamics (Lee & Lee, 2025). This institutional influx influences retail exposure and shapes price behavior across cryptocurrency categories, representing a central dynamic in our performance analysis. Additionally, Bitcoin's price dynamics can be modeled epidemiologically. Aliu (2024) demonstrates that the Susceptible-Infected-Recovered (SIR) model captures the contagion-like spread of speculative sentiment. Furthermore, Aliu (2025) establishes that price narratives diffuse through social networks mirroring epidemic curves. These models provide

a complementary theoretical lens for interpreting price behavior alongside institutional dynamics.

Understanding this evolutionary trajectory is essential as context for distinguishing between the different types of cryptocurrencies that have emerged from this ecosystem—particularly the divergence between tokens with genuine utility functions and those driven primarily by speculative dynamics, which forms the central analytical focus of this study. Taken together, the institutional dynamics, price behavior patterns, and theoretical frameworks reviewed in this section establish the contextual foundation for the comparative performance analysis that follows.

2.2 Classification of Cryptocurrencies: Utility Tokens and Speculative Tokens

The cryptocurrency market is not a homogeneous entity. There is fundamental heterogeneity in the functions and value propositions between categories of crypto assets. The classification that has developed in the literature and industry practice distinguishes cryptocurrencies into two main categories: utility tokens and speculative tokens. Utility tokens are designed with specific functions within a particular blockchain ecosystem, providing users with access to services, paying transaction fees, or participating in decentralized applications (dApps) protocols (Benedetti & Smith, 2024; Kochergin, 2022; Schär, 2021). Prominent examples include Ethereum (ETH), which functions as “gas” for smart contract execution, Binance Coin (BNB) for trading fees on the Binance Exchange, and Chainlink (LINK) for oracle services.

Conversely, speculative tokens tend to lack clear functional use cases or measurable intrinsic value. These assets are primarily traded for profit, with their value largely influenced by market sentiment and speculation rather than underlying economic activity (Scharnowski et al., 2023; Umar et al., 2023). The price appreciation of these types of tokens is primarily driven by market expectations, investor sentiment, narrative strength, and speculative supply-demand mechanisms (Lee et al., 2022; Liu et al., 2025; Wang et al., 2025). This category includes meme coins such as Dogecoin (DOGE) and Shiba Inu (SHIB), as well as various altcoins launched without substantial technological or economic fundamentals (Cordoba Otalora, 2025). The fundamental difference in value proposition has implications for price behavior patterns, risk profiles, and sustainable long-term returns between the two categories.

2.3 Prospect Theory

Understanding why investors disproportionately engage with speculative tokens—despite their inferior fundamental characteristics—requires a behavioral framework. Prospect Theory provides this foundation. Prospect Theory (Kahneman & Tversky, 1979) is a seminal framework in behavioral economics that explains how individuals make decisions under conditions of risk and uncertainty. This theory departs markedly from classical expected utility theory, which assumes that humans are rational decision makers who seek to maximize utility. Prospect Theory effectively explains investor behavior, particularly in contexts involving risk. For example, investors often show risk aversion when considering

potential gains, such as investing in stable stocks, but may take risks when facing potential losses when holding assets that are declining in value (Güler, 2025; Ruggeri et al., 2020). This behavior is crucial in understanding market dynamics and investor choices across various sectors, including finance (Lin et al., 2024; Silva et al., 2023). Ultimately, this psychological asymmetry helps explain why retail investors may hold onto highly speculative digital assets even when faced with significant downside risks.

In the context of this study, Prospect Theory provides the behavioral foundation for justifying downside-oriented performance metrics over symmetric alternatives. Because investors are demonstrably more sensitive to losses than to equivalent gains, the Sortino Ratio—which isolates and penalizes downside risk—is more behaviorally congruent with actual investor preferences than the Sharpe ratio. Equally, maximum drawdown as captured by the Calmar Ratio represents the most psychologically salient risk scenario an investor can face: the worst peak-to-trough loss during the holding period. This framing is particularly acute in cryptocurrency markets, where retail investors are most susceptible to loss-aversion-driven decision errors. Together, the Sortino and Calmar Ratios operationalize the asymmetric loss-gain sensitivity that Prospect Theory predicts, making them the most appropriate instruments for evaluating cryptocurrency performance from a retail investor-centric perspective.

2.4 Cryptocurrency Performance: Sortino Ratio and Calmar Ratio

The Sortino Ratio assesses risk-adjusted returns by focusing on downside deviation relative to the minimum acceptable return (MAR), thereby excluding upside volatility and only calculating negative variations that are relevant to investors concerned about potential losses (Sortino & Price, 1994; Sortino & Van Der Meer, 1991). This approach is more representative in the context of crypto markets, which have asymmetric price movements, as it distinguishes between desirable upside fluctuations and detrimental downside fluctuations, thereby providing a risk-adjusted return measure that is sensitive to extreme losses (Dombrowski et al., 2023; Gerunov, 2022; Gupta & Chaudhary, 2022). By prioritizing the isolation of harmful volatility, this metric ensures that the performance evaluation aligns more closely with the capital protection goals of cautious investors.

Meanwhile, the Calmar Ratio quantifies the efficiency of return generation relative to maximum drawdown—the largest difference between peak and trough during the observation period—using a simple formula of annualized return divided by maximum drawdown (Young, 1991). This metric is particularly relevant in the context of cryptocurrencies given the market's susceptibility to sharp corrections and prolonged bear markets. Maximum drawdown reflects the worst-case scenario that investors may face, which is critical information for prudent investment decision-making (Dichtl et al., 2024; Dombrowski et al., 2023). A higher Calmar Ratio indicates a more favorable risk-return profile, suggesting that the investment generates higher returns for each unit of risk taken.

Combining these two metrics offers a comprehensive perspective: the Sortino Ratio assesses return quality from a downside volatility standpoint, while the Calmar Ratio assesses extended-period stability against peak losses. For comparative categorization, this study adopts an efficiency threshold of 1.0 for both ratios: a value exceeding 1.0 indicates

that excess return adequately compensates for risk taken, while a value below 1.0 indicates that risk exposure outweighs historical return. Although this specific threshold is not universally prescribed in the foundational literature on the Sortino Ratio (Sortino & Price, 1994) or the Calmar Ratio (Young, 1991), it is applied in this study as a practical benchmark that mathematically guarantees at least one equivalent unit of excess return per unit of risk—a prudential standard appropriate for retail investor decision-making. This threshold framework underpins the quadrant-based quality matrix presented in Section 5.4.

3. Methodology

3.1 Data

This study employs a quantitative empirical-analytical approach, analyzing historical market data to evaluate and compare risk-adjusted performance across cryptocurrency categories. Daily closing prices of 20 major cryptocurrency assets were collected from January 1, 2023 to December 31, 2025—a complete three-year observation window that encompasses both a prolonged bullish cycle (2023 through mid-2025) and a significant market correction (second half of 2025). Data were obtained from CoinGecko, a widely recognized platform for transparent and reliable cryptocurrency market data, yielding 1,096 observations per asset (inclusive of both start and end dates) for a total of 21,920 observations. To ensure rigorous performance measurement, the Compound Annual Growth Rate (CAGR) was calculated as the Annualized Geometric Return, utilizing the exact day-count convention of 1,096 days and normalized to a 365-day annual cycle. All calculations were performed using Microsoft Excel.

The Minimum Acceptable Return (MAR) utilized in the downside deviation calculations was dynamically adjusted based on the daily prevailing BI 7-Day Reverse Repo Rate, reflecting the time-varying opportunity cost of capital faced by Indonesian retail investors on each trading day. The annual average BI rate over the 2023 to 2025 observation period was approximately 5.73%, which was applied directly as the annualized risk-free rate (R_f) in the numerator of the Sortino Ratio. The daily equivalent of the prevailing BI rate was separately applied as the dynamic MAR within the downside deviation calculation in the denominator. Consistent with the multi-year, annualized performance evaluation context of this study, the Sortino Ratio is operationalized using the Compound Annual Growth Rate (CAGR) in the numerator rather than sub-period average returns, ensuring that the numerator and denominator are on a comparable annualized basis and facilitating meaningful cross-asset comparison over the three-year observation period. All return series and risk measures were computed using a 365-day annualization framework, consistent with the continuous trading nature of cryptocurrency markets.

The sample was selected through purposive sampling. The taxonomy in this study relies on the CoinGecko sectoral classification to maintain consistency with the analytical tools utilized by retail investors. Specifically, this study groups digital store-of-value assets like Bitcoin together with programmable smart contract platforms under a unified foundational category. This inclusion is theoretically justified because both function as primary Layer-1 base networks that underpin the broader digital asset ecosystem, despite fundamental differences in their native smart contract capabilities.

Furthermore, the assignment of each cryptocurrency to either the utility or speculative group is directly anchored to the value propositions outlined in the literature. Sectors such as Smart Contract Platforms, Decentralized Finance (DeFi), and Artificial Intelligence (AI) were designated as utility assets because their market valuations are theoretically tied to functional use cases, demonstrable network activity, and technological services. Conversely, the Meme token category was classified as speculative because these assets typically lack concrete economic fundamentals, meaning their price action is driven predominantly by community sentiment and social narratives.

Based on this framework, inclusion criteria required the top five cryptocurrency assets by market capitalization within each of these designated classifications. Market capitalization rankings were assessed as of January 2026 at the time of data retrieval from CoinGecko. Finally, the sample encompassed assets that had been actively traded since January 2023 and consistently recorded throughout the observation period, ensuring data reliability for the historical performance analysis.

The rapid growth of the retail investor base in Indonesia directly motivates the choice of a domestic opportunity cost benchmark and the focus on investor protection. As illustrated in Figure 1, the number of registered cryptocurrency investors in Indonesia grew from 13.3 million in February 2025 to 19.5 million in November 2025, representing a 46.9% increase over nine months. This accelerating adoption trajectory underscores the urgency of equipping retail investors with more rigorous risk-adjusted performance tools.

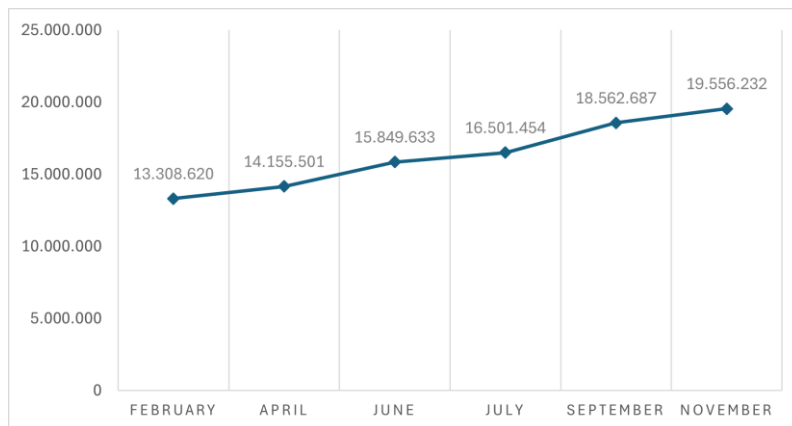


Figure 1. Growth of Indonesian Retail Cryptocurrency Investors 2025

Note. The figure presents monthly cumulative registered cryptocurrency investors in Indonesia from February to November 2025, based on official data published by the Financial Services Authority (OJK, 2025). Over this nine-month window, the investor base expanded from 13.3 million to 19.5 million, representing a 46.9% increase that reflects an accelerating pace of retail adoption. This growth trajectory, combined with reported transaction volumes of 449.55 trillion rupiah, directly motivates the financial literacy and investor protection focus of this study.

To mitigate survivorship bias, this study only includes assets with a minimum of three years of continuous operational history. This requirement is particularly important in the context of speculative cryptocurrency assets such as meme coins, which exhibit high failure rates, with the majority failing within the first year of their launch. Table 1 presents the list of cryptocurrencies that met the inclusion criteria.

Table 1. List of Cryptocurrency Assets 2023-2025

No	Code	Name of Assets	Category
1	BTC	Bitcoin	Smart Contract Platform
2	ETH	Ethereum	Smart Contract Platform
3	BNB	BNB	Smart Contract Platform
4	SOL	Solana	Smart Contract Platform
5	TRX	Tron	Smart Contract Platform
6	STETH	Lido Staked Ether	Decentralized Finance
7	LINK	Chainlink	Decentralized Finance
8	UNI	Uniswap	Decentralized Finance
9	AAVE	Aave	Decentralized Finance
10	CAKE	PancakeSwap	Decentralized Finance
11	NEAR	NEAR Protocol	Artificial Intelligence
12	ICP	Internet Computer	Artificial Intelligence
13	RENDER	Render	Artificial Intelligence
14	FET	Artificial Superintelligence Alliance	Artificial Intelligence
15	GRT	The Graph	Artificial Intelligence
16	DOGE	Dogecoin	Meme
17	SHIB	Shiba Inu	Meme
18	BONK	Bonk	Meme
19	FLOKI	Floki	Meme
20	BABYDOGE	Baby Doge Coin	Meme

Source: coingecko.com, data reprocessed

Note. The table lists 20 cryptocurrencies selected via purposive sampling, with market cap rankings as of January 2026 (CoinGecko). Classification follows CoinGecko taxonomy, grouping Bitcoin with smart contract platforms for consistency with retail tools. Meme tokens are limited to assets with at least three years of trading history to reduce survivorship bias.

Prior to ratio-based performance analysis, descriptive statistics were computed to characterize the distributional properties of daily returns for each asset (Table 2). Positive skewness across all assets indicates return distributions tend toward longer right tails, while excess kurtosis well above zero confirms fat tails—a higher probability of extreme returns than implied by a normal distribution (Gupta & Chaudhary, 2022; Liu & Tsyvinski, 2021). These conditions underscore the importance of downside-risk-oriented evaluation metrics (Gerunov, 2022). Therefore, the empirical evidence of non-normal return distributions justifies the application of more specialized tools that account for tail risk rather than relying on standard mean-variance models.

Table 2. Descriptive Statistics of Daily Returns Cryptocurrency 2023-2025

Assets	Std. Dev	Std. Dev Annualized	Mean Return	Min Return	Max Return	Skewness	Kurtosis
BTC	0.0243	0.4646	0.18%	-8.63%	12.27%	0.5287	2.6957
ETH	0.0331	0.6331	0.14%	-14.66%	21.39%	0.6002	4.6037
BNB	0.0270	0.5158	0.15%	-11.55%	16.51%	0.4326	4.1882
SOL	0.0468	0.8941	0.34%	-20.01%	32.95%	0.8523	4.3108
TRX	0.0353	0.6735	0.20%	-20.90%	88.88%	14.2722	367.5875
STETH	0.0332	0.6343	0.14%	-14.56%	21.26%	0.5882	4.4955
LINK	0.0447	0.8537	0.17%	-20.60%	32.19%	0.6102	4.2627
UNI	0.0526	1.0050	0.14%	-25.33%	53.79%	1.9692	15.9905
AAVE	0.0475	0.9071	0.21%	-18.92%	28.23%	0.5135	3.0903
CAKE	0.0504	0.9628	0.07%	-24.58%	41.65%	1.5165	10.8409
NEAR	0.0525	1.0026	0.15%	-17.12%	36.81%	0.8024	4.5517
ICP	0.0515	0.9840	0.09%	-29.48%	39.16%	1.2147	8.3469
RENDER	0.0598	1.1428	0.28%	-27.17%	36.91%	0.9307	4.5223
FET	0.0648	1.2373	0.27%	-28.78%	56.98%	1.3743	8.2348
GRT	0.0537	1.0258	0.10%	-24.19%	59.61%	1.6958	15.8733
DOGE	0.0458	0.8747	0.16%	-21.92%	27.56%	0.6279	4.2654
SHIB	0.0471	0.9008	0.09%	-18.34%	57.16%	2.6748	26.8277
BONK	0.1163	2.2210	0.89%	-35.35%	168.12%	5.3548	57.8879
FLOKI	0.0791	1.5113	0.42%	-27.41%	68.11%	2.9714	19.8037
BABYDOGE	0.0658	1.2577	0.16%	-21.47%	75.60%	3.4885	34.0420

Source: Authors' calculation

Note. The table presents descriptive statistics of daily returns for each asset over 1,096 days (Jan 2023–Dec 2025). Volatility is shown in daily and annualized terms. Skewness and kurtosis follow the Fisher definition, where positive kurtosis indicates leptokurtosis. TRX shows extreme values due to a one-time price anomaly in Dec 2024 and should be interpreted cautiously.

Within the Smart Contract Platform category, BTC exhibits the most conservative distributional profile (daily standard deviation: 0.0243; annualized: 0.4646), consistent with its position as the largest cryptocurrency by market capitalization. SOL records the highest mean daily return in this group at 0.34%, accompanied by a substantially higher annualized standard deviation of 0.8941. TRX warrants particular interpretive caution: its extreme skewness (14.2722) and kurtosis (367.5875) are attributable to a documented single-day price surge of 88.88% in December 2024, meaning its return distribution departs markedly from normality and its performance metrics must be interpreted in that context.

Within the Decentralized Finance category, AAVE records the highest mean daily return (0.21%) while CAKE records the lowest (0.07%), illustrating the performance heterogeneity that characterizes this sector. STETH exhibits distributional properties closely aligned with ETH across all parameters, which is consistent with its design as a liquid staking derivative whose price closely tracks the underlying asset (Auer et al., 2024). UNI exhibits

the highest skewness in this category (1.9692) and kurtosis of 15.9905, indicating fat-tailed return distributions with vulnerability to sporadic price spikes, as confirmed by a maximum daily return of 53.79%.

The Artificial Intelligence category exhibits the highest volatility among non-meme categories, with all five assets recording annualized standard deviations above 0.98. RENDER records the highest mean daily return in this group (0.28%), while ICP records the lowest (0.09%). Notably, GRT displays the most extreme distributional characteristics within this category, with kurtosis of 15.8733 and skewness of 1.6958, confirming a high frequency of extreme return events and a maximum daily return of 59.61%.

The Meme category displays the most extreme return characteristics across all groups. BONK records the highest mean daily return in the entire sample (0.89%), accompanied by the highest annualized standard deviation (2.2210), skewness of 5.3548, kurtosis of 57.8879, and a maximum daily return of 168.12%, confirming a highly asymmetric distribution with very heavy tails. At the other extreme, DOGE exhibits the distributional profile closest to normality within this category, with skewness of 0.6279 and kurtosis of 4.2654. The remaining three meme assets (FLOKI, BABYDOGE, SHIB) occupy intermediate positions, all exhibiting positive skewness and excess kurtosis consistent with the broad non-normality documented across the full sample.

In aggregate, these distributional characteristics confirm the presence of positive skewness and excess kurtosis across all 20 assets, indicating fat-tailed return distributions with a higher probability of extreme outcomes than implied by a normal distribution. These conditions provide empirical justification for the application of downside-risk-oriented metrics, specifically the Sortino Ratio and the Calmar Ratio, rather than conventional mean-variance frameworks.

3.2 Methods

The performance evaluation follows a sequential seven-step process: (1) calculating daily asset returns; (2) computing the Compound Annual Growth Rate (CAGR) over the 1,096-day observation window; (3) determining the dynamic Minimum Acceptable Return (MAR) from the daily BI 7-Day Reverse Repo Rate; (4) computing annualized downside deviation; (5) measuring Maximum Drawdown (MDD); (6) computing the Sortino Ratio; and (7) computing the Calmar Ratio. The formulas for each step are presented in Table 3.

Table 3. Variable Measurement Formula

Variable	Formula
Return assets	$R = \frac{P_t - P_{t-1}}{P_{t-1}}$
Compound annual growth rate	$CAGR = \left(\frac{EV}{BV} \right)^{\frac{365}{T}} - 1$
Downside deviation	$\sigma_d = \sqrt{\frac{\sum_{t=1}^n \min(R_t - MAR, 0)^2}{n}}$

Variable	Formula
Downside deviation annualized	$\sigma_{d,ann} = \sigma_d \times \sqrt{365}$
Maximum drawdown	$ MDD = \frac{(Trough\ Value - Peak\ Value)}{Peak\ Value}$
Sortino Ratio	$SR = \frac{CAGR - R_f}{\sigma_{d,ann}}$
Calmar Ratio	$CR = \frac{CAGR}{ MDD }$

Source: (Sortino & Price, 1994; Sortino & Van Der Meer, 1991; Young, 1991)

Note. The table outlines a seven-step calculation applied to 20 cryptocurrencies. Returns use daily closing prices, while CAGR is based on prices from Jan 1, 2023 to Dec 31, 2025. Downside deviation includes only returns below the BI rate (MAR). The Sortino Ratio uses CAGR over annualized downside risk, and the Calmar Ratio uses absolute MDD to ensure positive values for assets with positive CAGR.

In operationalizing these formulas, P_t and P_{t-1} denote the daily USD closing prices on trading days t and $t - 1$, respectively. For the first observation date (January 1, 2023), the return is computed using the closing price of December 31, 2022 as the reference price P_{t-1} , thereby establishing a complete and uninterrupted return series of 1,096 daily observations consistent with the stated day-count convention. In the CAGR formula, EV represents the closing price on December 31, 2025; BV represents the closing price on January 1, 2023; and T equals 1,096 days normalized to a 365-day annual cycle. The MAR is operationalized as the daily equivalent of the prevailing BI 7-Day Reverse Repo Rate on each trading day t . In the Sortino Ratio, R_f is the average annual BI rate of 5.73% over the observation period, and $\sigma_{d,ann}$ is the annualized downside deviation. For the Calmar Ratio, $|MDD|$ denotes the absolute value of Maximum Drawdown to ensure consistent evaluation across all assets.

4. Results/findings

Building on the distributional characteristics of the dataset documented in Section 3, this section presents the ratio-based performance evaluation of the 20 cryptocurrency assets using the Sortino and Calmar Ratios. The results are presented in Tables 4 and 5, followed by the inter-category correlation analysis in Table 6.

Table 4. Cryptocurrency Performance Ranking Based on Sortino 2023-2025

No	Code	Category	Downside Deviation Annualized	Sortino Ratio
1	BONK	Meme	96.04%	2.4345
2	BTC	Smart Contract Platform	29.26%	2.3588
3	SOL	Smart Contract Platform	54.33%	2.3261
4	TRX	Smart Contract Platform	31.41%	2.1635

5	BNB	Smart Contract Platform	33.97%	1.3503
6	FLOKI	Meme	78.58%	0.8256
7	STETH	Decentralized Finance	41.43%	0.7296
8	ETH	Smart Contract Platform	41.30%	0.7174
9	AAVE	Decentralized Finance	58.82%	0.6192
10	RENDER	Artificial Intelligence	70.50%	0.5959
11	LINK	Decentralized Finance	55.38%	0.4491
12	FET	Artificial Intelligence	74.16%	0.3407
13	DOGE	Meme	56.75%	0.2610
14	NEAR	Artificial Intelligence	64.61%	0.0076
15	UNI	Decentralized Finance	60.57%	-0.0179
16	SHIB	Meme	53.84%	-0.1867
17	BABYDOGE	Meme	69.38%	-0.2491
18	ICP	Artificial Intelligence	61.63%	-0.2609
19	GRT	Artificial Intelligence	64.15%	-0.3137
20	CAKE	Decentralized Finance	59.67%	-0.3697

Source: Authors' calculation

Note. The Sortino Ratio is calculated as $(CAGR - R_f) / \sigma_{d,ann}$, where the risk-free rate (R_f) is the average annual BI 7-Day Reverse Repo Rate of 5.73% over the 2023–2025 observation period, and $\sigma_{d,ann}$ represents the annualized downside deviation capturing only daily returns falling below the dynamic MAR. Values exceeding 1.0 indicate that excess returns adequately compensate for downside risk, while negative values signal that the asset's CAGR fails to surpass the domestic risk-free benchmark. Assets are ranked in descending order to enable direct cross-category comparison of downside-risk-adjusted performance.

Table 4 presents cryptocurrency performance ranked by the Sortino Ratio, which measures excess return relative to annualized downside deviation. BONK leads the overall ranking with a Sortino Ratio of 2.4345 despite carrying the highest downside deviation of 96.04%, demonstrating that its extreme positive returns were sufficient to compensate for its substantial negative volatility. Among utility tokens, Smart Contract Platforms dominate the top positions, with BTC (2.3588), SOL (2.3261), and TRX (2.1635) occupying ranks two through four. BTC presents the most capital-efficient profile among utility tokens given its comparatively low downside deviation of 29.26%. Assets in the Artificial Intelligence category occupy the lower portion of the overall ranking, with ICP (rank 18; Sortino: -0.2609) and GRT (rank 19; Sortino: -0.3137) placing among the five bottom positions, while NEAR (rank 14; Sortino: 0.0076) recorded the weakest performance within the AI sub-group that remained in positive territory. The lowest position is held by CAKE with a Sortino Ratio of -0.3697 and a downside deviation of 59.67%, indicating that its returns cannot compensate for the downside risk experienced.

Table 5. Cryptocurrency Performance Ranking Based on Calmar 2023-2025

No	Code	Category	CAGR	Max Drawdown	Calmar Ratio
1	BONK	Meme	239.55%	94.78%	2.5275
2	BTC	Smart Contract Platform	74.76%	32.13%	2.3266
3	SOL	Smart Contract Platform	132.11%	59.82%	2.2083
4	TRX	Smart Contract Platform	73.68%	48.96%	1.5051
5	BNB	Smart Contract Platform	51.60%	41.07%	1.2563
6	FLOKI	Meme	70.61%	88.08%	0.8016
7	AAVE	Decentralized Finance	42.15%	67.42%	0.6252
8	STETH	Decentralized Finance	35.95%	63.87%	0.5629
9	ETH	Smart Contract Platform	35.36%	63.85%	0.5537
10	RENDER	Artificial Intelligence	47.73%	90.81%	0.5256
11	LINK	Decentralized Finance	30.60%	62.99%	0.4858
12	FET	Artificial Intelligence	30.99%	94.03%	0.3296
13	DOGE	Meme	20.54%	73.85%	0.2782
14	NEAR	Artificial Intelligence	6.22%	83.82%	0.0742
15	UNI	Decentralized Finance	4.64%	74.54%	0.0623
16	SHIB	Meme	-4.32%	80.66%	-0.0536
17	ICP	Artificial Intelligence	-10.35%	85.36%	-0.1212
18	BABYDOGE	Meme	-11.56%	90.21%	-0.1281
19	GRT	Artificial Intelligence	-14.40%	92.33%	-0.1559
20	CAKE	Decentralized Finance	-16.33%	77.44%	-0.2109

Source: Authors' calculation

Note. The Calmar Ratio is calculated as $CAGR/|MDD|$, where MDD denotes the largest peak-to-trough percentage decline observed within the full January 1, 2023–December 31, 2025 observation window, expressed as an absolute value to preserve the mathematical sign of assets with positive CAGR. A Calmar Ratio exceeding 1.0 indicates that compounded annual returns outpace the severity of the worst historical drawdown, while negative values reflect assets with negative CAGR throughout the observation period. Assets are ranked in descending order, facilitating a direct comparison of drawdown-adjusted performance efficiency across all four cryptocurrency categories.

Table 5 measures asset performance using the Calmar Ratio, which compares CAGR to maximum drawdown as an indicator of extreme risk. BONK once again dominates with a Calmar Ratio of 2.5275, supported by a CAGR of 239.55%, despite experiencing the highest maximum drawdown of 94.78%. BTC ranks second with a Calmar Ratio of 2.3266 (CAGR 74.76%; max drawdown 32.13%), while SOL in third place, though significantly more volatile than BTC, presents a comparatively more moderate profile than BONK with a Calmar Ratio of 2.2083 (CAGR 132.11%; max drawdown 59.82%). This pattern shows that even though BONK and SOL experienced extreme declines, their compound growth was still able to provide adequate compensation. Assets with negative CAGR occupy the bottom five rankings, starting with SHIB with a CAGR of -4.32% and a Calmar Ratio of -0.0536, to CAKE, which recorded the worst performance with a CAGR of -16.33%, maximum

drawdown of 77.44%, and Calmar Ratio of -0.2109 . These findings indicate that these assets not only experienced sharp declines but also failed to generate long-term growth.

Table 6. Correlation Matrix of Equally-Weighted Cryptocurrency Categories 2023-2025

Category	Smart Contract Platform	Decentralized Finance	Artificial Intelligence	Meme
Smart Contract Platform	1.000	0.837	0.778	0.713
Decentralized Finance	0.837	1.000	0.798	0.691
Artificial Intelligence	0.778	0.798	1.000	0.691
Meme	0.713	0.691	0.691	1.000

Source: Authors' calculation

Note. The matrix shows Pearson correlations of daily returns for equally weighted category indices over 1,096 days. All correlations are positive and high, with the strongest between Smart Contract Platforms and DeFi (0.837), indicating strong co-movement and limited diversification benefits across categories.

To assess the efficacy of cross-category diversification, an inter-category correlation analysis was conducted. Daily returns of the assets were aggregated into equally-weighted indices for each of the four categories. As presented in Table 6, the inter-category correlation analysis reveals high positive co-movement across all token categories during the observation period. This pronounced correlation highlights the structural market dynamics where underlying utility functions offer limited decoupling benefits during systemic market shifts.

5. Discussions

5.1 Performance Interpretation

The results summarized in Tables 4 and 5 reveal fundamental differences in risk and return characteristics between utility-based and speculative cryptocurrencies across the 2023 to 2025 observation period. The findings confirm that cryptocurrency investors exhibit asymmetric sensitivity to gains and losses consistent with Prospect Theory, specifically showing risk-seeking behavior in the domain of losses and risk-averse behavior in gains. These results align with Liu and Tsyvinski (2021), who document that cryptocurrency return distributions differ fundamentally from traditional assets, justifying specialized risk metrics beyond conventional mean-variance frameworks. Consequently, this multidimensional analysis provides a granular understanding of how digital assets deviate from conventional financial risk norms.

Utility tokens, specifically those within the Smart Contract Platforms, Decentralized Finance (DeFi), and Artificial Intelligence (AI) sectors, exhibit characteristics aligning with behavioral finance principles by providing more stable risk-adjusted returns. This resilience is supported by studies indicating that cryptocurrencies with strong technological fundamentals better withstand market volatility (Kukacka & Kristoufek, 2023). Within the Smart Contract Platforms sub-group, most assets demonstrate a superior capacity to protect

against downside risk. This is reflected in positive Sortino Ratio values exceeding the 1.0 efficiency threshold across four of the five assets, namely BTC, TRX, BNB, and SOL, indicating that their returns adequately compensate for downside risk. For example, Bitcoin (Calmar Ratio: 2.3266; Sortino Ratio: 2.3588) and Binance Coin (Calmar Ratio: 1.2563; Sortino Ratio: 1.3503) clearly showcase this efficiency.

However, individual performance within this group carries notable nuances. Tron's (TRX) elevated metrics (Calmar Ratio: 1.5051; Sortino Ratio: 2.1635) should be interpreted with caution. Its strong ratios are partly driven by a single extreme positive price event, specifically a maximum daily return of 88.88% and kurtosis of 367.59, which significantly amplified its annualized CAGR rather than reflecting a structurally low-downside profile. This extreme movement coincides with a documented market event in December 2024, where TRX surged following Justin Sun's high-profile investment and heightened media exposure (Chmiel, 2024; Ulmer & Lewis, 2024). Ethereum (ETH) stands as the sole exception in this category with a Sortino Ratio of 0.7174 falling below the efficiency threshold, an outcome underscoring the heterogeneity of risk-adjusted performance even within a single asset sub-category.

Within the Smart Contract Platform category, Solana (SOL) presents a unique outlier showing return characteristics similar to speculative tokens while maintaining strong utility fundamentals, evidenced by a Calmar Ratio of 2.2083 and a CAGR of 132.11% (see Table 5). This phenomenon can be explained through the narrative economics framework (Shiller, 2020), where the narrative of new-generation blockchain technology creates high growth expectations, resulting in volatility that exceeds that of conventional utility tokens. Despite experiencing a maximum drawdown of 59.82%, Solana's Sortino Ratio remains high at 2.3261 (see Table 4), indicating that the excess return generated is sufficient to compensate for its downside risk exposure. This pattern, yielding a favorable risk-adjusted profile that is more acceptable from a risk-averse investor's perspective, is supported by findings from Goel and Mittal (2020) and Rao et al. (2025) that technological innovation in blockchain can drive substantial price appreciation despite high volatility. Solana thus represents a hybrid case where technological utility and speculative momentum converge to create a superior, albeit volatile, investment profile.

The Decentralized Finance sector exhibits significant performance heterogeneity. AAVE leads on Calmar performance (Calmar: 0.6252; Sortino: 0.6192), while STETH leads on Sortino (0.7296) but records a lower Calmar Ratio (0.5629), reflecting distinct risk profiles. In contrast, UNI (Calmar: 0.0623; Sortino: -0.0179) and CAKE (Calmar: -0.2109; Sortino: -0.3697) show substantial underperformance. Prior research highlights that DeFi protocol valuation depends on fundamental metrics such as revenue generation, liquidity, and adoption (Metelski & Sobieraj, 2022), while competitive pressures intensify selection dynamics across protocols (Auer et al., 2024; Shah et al., 2023). This disparity indicates a consolidation phase in which only fundamentally strong protocols are able to sustain their valuation. The negative Sortino Ratios for UNI and CAKE further confirm that downside risk exceeds excess return, resulting in structurally unattractive risk-return profiles.

The AI category yielded weak performance, with RENDER, FET, and NEAR failing to exceed the 1.0 efficiency threshold, while ICP and GRT experienced capital erosion. Extreme drawdowns ranging from 83.82% to 94.03% and high correlations between 0.691

and 0.798 indicate that the market treats AI tokens primarily as speculative instruments rather than assets supported by stable cash flow expectations. Prior studies suggest that such decoupling between technological potential and price behavior is characteristic of immature innovation phases, where valuation is driven more by sentiment than by realized utility (Perez, 2002; Yu, 2022). Most AI-based tokens remain in an early utility stage where ecosystem development has not yet scaled to justify speculative inflows. The strong co-movement with other categories further confirms that price dynamics in this segment are primarily driven by broader market sentiment rather than independent utility fundamentals.

5.2 The Speculative Tokens Paradox: Meme Cryptocurrencies

A central finding of this study is that BONK, a meme token without demonstrable utility, achieved the highest Calmar Ratio (2.5275) and CAGR (239.55%) in the sample, surpassing all utility tokens. This challenges the assumption that utility fundamentals are a prerequisite for risk-adjusted performance. Consistent with Prospect Theory, this reflects how retail investors evaluate lottery-like payoffs and systematically overweight the probability of tail events, sustaining demand for assets with extreme upside potential (Blau et al., 2020; Byun et al., 2020; Huang et al., 2024). However, BONK's 94.78% maximum drawdown confirms a speculative bubble where prices detach from fundamental value (Simsek, 2021). Ultimately, the contrast between BONK and SOL demonstrates that while both exhibit high volatility, only the latter provides a risk-adjusted return profile remaining rational within a long-term framework.

A comparison with other meme tokens such as DOGE (Calmar Ratio: 0.2782), SHIB (Calmar Ratio: -0.0536), and BABYDOGE (Calmar Ratio: -0.1281) reveals substantial performance dispersion within this category (see Table 5). The predominantly low or negative Sortino Ratios indicate that downside risk is generally not compensated by returns. Behavioral finance studies show that retail investors tend to overweight recent winners and underweight base rate probabilities, leading to unstable price dynamics (Blau et al., 2020; Byun et al., 2020; Yadav, 2024). As a result, most meme tokens fail to deliver sustainable risk-adjusted performance despite occasional extreme upside outcomes.

Within the meme token category, FLOKI presents a comparatively less destructive profile (Calmar: 0.8016; Sortino: 0.8256; CAGR: 70.61%), reflecting its hybrid model combining speculative community dynamics with a degree of utility development. However, as noted by Cordoba Otalora (2025) and Simsek (2021), it still fails to cross the efficiency threshold, confirming the broader fragility of the speculative sector despite utility integration attempts. This suggests that even for meme tokens with tangible development efforts, the inherent speculative volatility often remains the dominant factor in their overall risk profile.

The sentiment-driven dynamics observed in the meme token category suggest a contagion-like mechanism similar to the epidemiological price patterns documented for Bitcoin (Aliu, 2024, 2025). Extreme volatility, rapid adoption cycles, and narrative amplification indicate that price movements are strongly influenced by collective investor sentiment rather than fundamental valuation. Only BONK and FLOKI achieved positive risk-adjusted performance, while the majority of meme tokens failed to reach efficiency thresholds, indicating that only a small subset of such assets sustain sufficient momentum

to generate excess returns. This pattern implies that extreme positive outcomes are statistically rare and should not be interpreted as a reliable investment strategy.

5.3 The Effectiveness of Sortino and Calmar Ratios in Cryptocurrency Evaluation

The Sharpe ratio, dominant in prior Indonesian cryptocurrency literature (Budiartomo & Setiyono, 2023; Laksana, 2024; Laksana et al., 2026; Wiliyani & Purnamawati, 2023), treats all volatility as risk, an assumption that may be less appropriate for assets characterized by asymmetric return distributions and extreme tail events (Bacon, 2023; Dombrowski et al., 2023; Gerunov, 2022). The Sortino Ratio addresses this limitation by focusing exclusively on downside deviation, while the Calmar Ratio provides an additional dimension by measuring returns relative to maximum drawdown, which represents the worst-case scenario investors may face (Sortino & Price, 1994; Sortino & Van Der Meer, 1991). This distinction is particularly relevant in cryptocurrency markets, where positive skewness and excess kurtosis are consistently observed across assets, indicating that upside and downside volatility are not distributed symmetrically. Consequently, downside-oriented metrics provide a framework that is more consistent with the asymmetric loss sensitivity emphasized in behavioral finance literature.

The combination of these two metrics allows for a more nuanced categorization of cryptocurrencies. Tokens with high Sortino Ratios and high Calmar Ratios, such as BTC, SOL, TRX, and BNB, may be classified as comparatively risk-efficient assets suited to investors with a long-term investment horizon and tolerance for temporary drawdowns (see Table 4). Meanwhile, tokens recording negative values on both metrics, including ICP, GRT, CAKE, SHIB, and BABYDOGE, demonstrate consistent value destruction and appear comparatively unattractive for long-term portfolio strategies prioritizing downside protection and capital preservation (see Tables 4 and 5).

5.4 The Efficiency Threshold and Quadrant Categorization

To provide a more stringent and meaningful benchmark for Indonesian investors, the quadrant thresholds in Figure 2 are established at an “Alpha Threshold” of 1.0 for both Sortino and Calmar metrics. In financial performance theory, a ratio exceeding 1.0 signifies that the asset’s excess return effectively compensates for the risk taken—specifically, downside deviation in the case of the Sortino Ratio and maximum drawdown in the case of the Calmar Ratio—whereas a ratio below 1.0 indicates that the magnitude of risk exposure outweighs the historical return generated (Sortino & Price, 1994; Sortino & Van Der Meer, 1991; Young, 1991). Thus, this threshold serves as a critical filter for identifying assets that offer a mathematically justifiable reward for the high levels of risk inherent in digital assets.

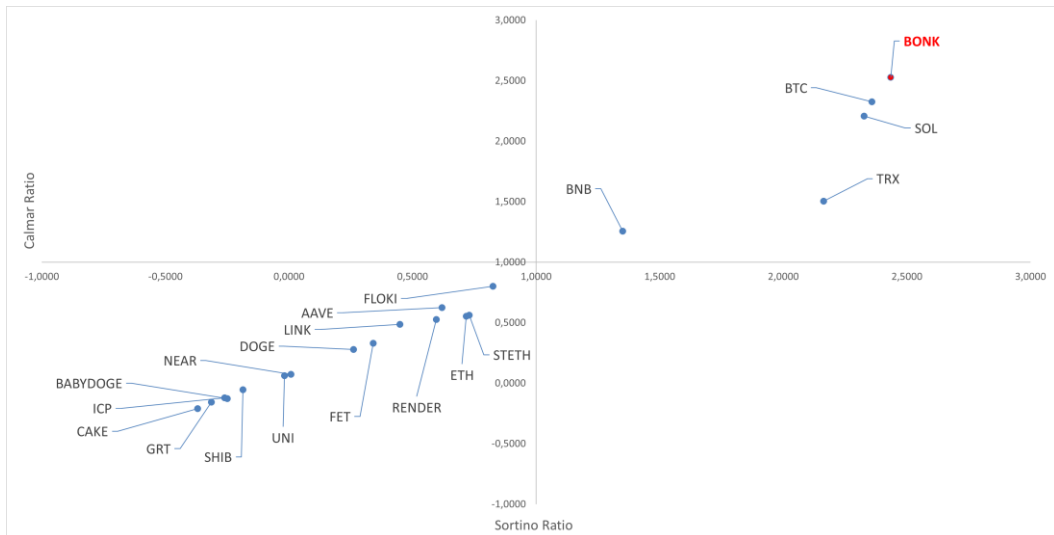


Figure 2. Quadrant Analysis of Risk-Adjusted Quality Matrix (2023-2025)

Note. The figure maps 20 cryptocurrency assets on a risk-adjusted quality matrix defined by the Sortino Ratio (x-axis) and the Calmar Ratio (y-axis), with a threshold of 1.0 on each axis delineating four performance quadrants. Quadrant I (Alpha Leaders) identifies assets delivering excess returns that compensate for both downside deviation and maximum drawdown; Quadrant III (Value Destruction Zone) encompasses assets failing both thresholds, including those with negative ratio values. The vacancy of Quadrants II and IV indicates a structural co-movement between daily downside protection and drawdown resilience in this asset class, while BONK's placement in Quadrant I despite its 94.78% maximum drawdown represents the central empirical manifestation of the speculative paradox examined in this study.

Although classical literature does not prescribe an absolute universally mandated threshold, the 1.0 boundary is applied in this study as a proxy for a rational payoff ratio. A metric exceeding 1.0 mathematically guarantees that for every single unit of downside deviation or peak drawdown endured, the investor is compensated with at least one equivalent unit of excess return—a prudential standard deemed critical for transitional retail investors. Based on this framework and the empirical data presented in Tables 4 and 5, the analyzed assets are categorized into four distinct performance profiles:

- Quadrant I: The Alpha Leaders (Sortino > 1; Calmar > 1). BTC, SOL, TRX, BNB, and BONK represent the gold standard of risk-adjusted performance during 2023-2025. BONK's position here, as a speculative meme token achieving the highest efficiency (Sortino: 2.4345; Calmar: 2.5275), is the central manifestation of the speculative paradox fundamentally challenging the assumption that utility is a prerequisite for superior risk-adjusted returns. Although BONK mathematically delivers the highest risk-adjusted return, its 94.78% maximum drawdown exceeds the risk tolerance of most rational investors. This juxtaposition is precisely what this study terms the Speculative Paradox: extreme mathematical efficiency in recovery metrics coexists with catastrophic capital erosion risk, disqualifying it as a superior asset for capital preservation. BNB joins this quadrant as the fifth alpha leader, demonstrating its compounded growth adequately compensates for downside deviation and maximum drawdown.

- Quadrant II: The Recovery-Without-Protection Zone (Sortino < 1 ; Calmar > 1). No assets from the sample occupied this quadrant during the observation period. This absence indicates that within the cryptocurrency market, it is structurally improbable for an asset to possess the capacity for robust long-term recovery from extreme peak-to-trough losses (Calmar > 1) while simultaneously failing to protect investors from daily negative volatility (Sortino < 1).
- Quadrant III: The Value Destruction Zone (Sortino < 1 ; Calmar < 1). This zone is the most densely populated quadrant, encompassing 15 of the 20 assets in the sample, including all five AI tokens, all five DeFi tokens, four meme tokens, and ETH from the Smart Contract Platform category. While the majority of these assets record low but positive ratios reflecting inadequate but non-destructive risk-adjusted returns, assets with explicitly negative values on both metrics (CAKE, GRT, ICP, SHIB, BABYDOGE) represent the most severe cases of capital erosion. From an investor protection perspective, these assets pose the most significant risk to retail investors and should be excluded from portfolio construction.
- Quadrant IV: High-Yield Fragility (Sortino > 1 ; Calmar < 1). Similarly, no assets occupied this zone. This suggests that crypto assets capable of managing daily downside deviations effectively (Sortino > 1) inherently possess the fundamental resilience required to recover from deep market corrections (Calmar > 1). The absolute vacancy of both Quadrants II and IV empirically confirms a strong, inherent structural co-movement between daily downside protection and historical drawdown resilience in this asset class.

These quadrant classifications carry direct implications for portfolio construction and investor decision-making.

5.5 Implications for Investment Strategy and Portfolio Construction

The findings of this study have significant practical implications for cryptocurrency investment strategies. First, the categorization of utility vs. speculation does not automatically determine risk-adjusted performance. Some utility tokens, particularly in the AI and DeFi categories, show inferior performance compared to certain speculation tokens, challenging the conventional assumption that utility fundamentals are always superior. As highlighted by Metelski and Sobieraj (2022), this indicates the need for more in-depth due diligence beyond categorization labels, focusing on concrete metrics such as adoption rate, network activity, and revenue generation. Relying on broad labels alone is insufficient, making it imperative for investors to employ rigorous data-driven analysis when constructing digital asset portfolios.

Second, for risk-averse investors prioritizing capital preservation, Bitcoin and Binance Coin (BTC, BNB) represent the most defensible core holdings among Smart Contract Platforms. Both assets achieve alpha-generating performance on both metrics, with BTC recording a Sortino Ratio of 2.3588 and Calmar Ratio of 2.3266, and BNB recording a Sortino Ratio of 1.3503 and Calmar Ratio of 1.2563, confirming they adequately compensate for downside deviation and maximum drawdown. Ethereum, while below the efficiency threshold of 1.0, may serve as a lower-volatility supplementary position given its annualized

downside deviation of 41.30%, lower than peers such as AAVE, LINK, and SOL, alongside its documented co-movement with BTC price dynamics (Mungo et al., 2024). TRX presents a complementary profile with the highest Calmar Ratio among utility tokens after BTC and SOL (1.5051), signaling strong return efficiency relative to historical maximum drawdown, though investors should note this is partly influenced by isolated price events.

Third, speculative tokens such as meme cryptocurrencies may serve as satellite positions within a portfolio to enhance upside potential; however, they must be allocated with strict position sizing given the elevated risk of total capital loss. Maximum drawdowns ranging from 74% to 95% across this category indicate that allocations to this sector should never surpass an individual investor's absolute risk tolerance. Given the lack of fundamental utility to drive long-term price recovery, aggressive risk management must prioritize capital preservation and predefined exit strategies rather than continuous capital injection. Therefore, treating these highly volatile assets strictly as restricted satellite positions is essential to maintaining overall portfolio stability while avoiding the catastrophic destruction of core investment capital.

Fourth, cross-category diversification does not automatically mitigate risk in the cryptocurrency market. High positive correlations across both utility and speculative tokens indicate systematic risk that constrains the conventional diversification benefits proposed by Modern Portfolio Theory (Almeida & Gonçalves, 2022; Liu & Tsyvinski, 2021). Elevated maximum drawdowns ranging from approximately 32% to 94% further confirm this systematic risk (see Tables 5 and 6). Consequently, retail investors cannot rely solely on cross-category allocation for risk mitigation and must instead prioritize downside-based risk management frameworks, treating cryptocurrencies as a distinct asset class with unique correlation dynamics requiring a separate allocation strategy.

These findings are directly aligned with the investor protection objectives of POJK Number 27 of 2024, providing market supervisors (OJK) and financial educators more relevant instruments to categorize cryptocurrency assets suitable for retail investors based on actual downside resilience, rather than market capitalization or popularity alone.

5.6 Research Contribution

Building on these investor protection implications, this study makes three practical contributions to the Indonesian cryptocurrency investment landscape. First, by demonstrating that downside-risk metrics yield substantially different performance signals compared to the Sharpe Ratio that dominates prior Indonesian literature (Andaresta & Purwanto, 2023; Budiartomo & Setiyono, 2023; Laksana, 2024; Laksana et al., 2026; Lumbantobing & Sadalia, 2021; Meiyura & Azib, 2020; Wiliyani & Purnamawati, 2023), this study equips retail investors and financial advisors with a more protective evaluation toolkit that prioritizes capital preservation over headline return maximization. Second, the empirical evidence that utility-versus-speculative categorization alone is insufficient to predict performance provides regulators and financial educators with a practical basis for moving beyond broad asset labels toward metric-driven due diligence standards. Third, the documentation of the Speculative Paradox as an empirically observable phenomenon

provides a concrete cautionary reference point for financial literacy programs targeting novice retail investors in Indonesia's rapidly expanding digital asset market.

Practically, this study confirms that Prospect Theory and behavioral finance are essential for understanding cryptocurrency dynamics (Kahneman & Tversky, 1979). Observed differences in risk-taking between utility and speculative tokens highlight how cognitive biases influence market valuation and investor decisions. Furthermore, the risk-adjusted performance of meme tokens reinforces literature regarding lottery-like preferences and the overweighting of tail events (Blau et al., 2020; Byun et al., 2020; Huang et al., 2024). Recognizing these psychological drivers is therefore vital for navigating the irrational price surges typical of speculative digital assets.

Finally, evidence of distinct life cycle phases across categories provides a strategic framework for asset allocation. While Smart Contract Platforms show maturity through moderate volatility, AI and DeFi tokens remain in early developmental stages with higher failure rates. The dynamics of meme tokens also correspond with speculative bubble theory regarding the skewed distribution of winners and losers (Borhan et al., 2017; Zhang & Zheng, 2017). These insights allow investors to better distinguish fundamental maturity from speculative volatility when constructing their portfolios.

5.7 Limitations and Future Research Directions

Several limitations of this study warrant acknowledgment. First, the observation period of 2023 to 2025 represents a relatively short time horizon that captures a specific market cycle, meaning these results may not fully extrapolate to extended long-term periods. Second, the study faces potential selection bias and classification issues, as the boundary between utility and speculative digital assets remains highly fluid and rapidly evolving. Third, the empirical findings are subject to the extreme influence of a few outlier assets. Specifically, the extraordinary metrics of BONK and isolated price events in Tron significantly impact the overall comparative analysis between categories. These constraints underscore the importance of interpreting the reported performance metrics within their specific context.

Despite these limitations, this study points toward several productive directions for future research. Extending the observation window to capture complete market cycles would enable a more robust examination of how risk-return profiles evolve over time. Future work should also expand the analysis by incorporating additional explanatory variables such as adoption rates, network activity, market capitalization, liquidity, and trading volume. Furthermore, exploring the application of complementary tail risk metrics, such as Maximum Drawdown Duration and the Ulcer Index, would further strengthen the practical applicability of the Sortino and Calmar framework. Event study analyses of major market shocks, including regulatory announcements and macroeconomic shifts, could additionally yield insights into the resilience patterns that distinguish different cryptocurrency categories.

6. Conclusions

This study evaluated the risk-adjusted performance of utility-based and speculative cryptocurrencies for Indonesian retail investors using a Sortino and Calmar dual-metric framework. Three principal conclusions emerge. First, Smart Contract Platforms

predominantly delivered the most sustainable risk-adjusted performance across the 2023 to 2025 period, led by Bitcoin (Calmar: 2.3266; Sortino: 2.3588), Solana, and Binance Coin, confirming that assets with strong network fundamentals generate efficient medium-term returns. Tron also recorded high metrics, though influenced by an isolated extreme price event. Second, the DeFi and AI sectors exhibited significant heterogeneity and high inter-category correlations (0.691 to 0.837), demonstrating that the utility label alone does not guarantee superior performance and that cross-category diversification cannot eliminate systematic risk.

Third, the Speculative Paradox was confirmed as BONK achieved the highest Calmar Ratio (2.5275) and CAGR (239.55%) across the entire sample despite a 94.78% maximum drawdown, aligning with Prospect Theory predictions regarding retail investors overweighting extreme-gain probabilities. However, the broader meme token category exhibited extreme return dispersion, with most assets falling below the efficiency threshold.

These conclusions must be interpreted carefully due to potential selection bias, classification challenges, the relatively short time horizon of the study, and the extreme influence of a few outlier assets. As detailed in the limitations section, these factors are critical for understanding the specific context and the generalizability of the empirical outcomes.

The principal contributions of this study are threefold: (1) providing a practical performance assessment framework for the Indonesian cryptocurrency market by demonstrating how downside-risk metrics offer more relevant insights for retail investors than traditional mean-variance measures; (2) offering empirical evidence that utility-versus-speculative categorization alone is insufficient to predict risk-adjusted performance, as demonstrated by the heterogeneous outcomes observed within subcategories; and (3) documenting the speculative paradox as an empirical phenomenon that challenges conventional assumptions about the fundamentals-valuation relationship in cryptocurrency markets. Taken together, these findings provide Indonesian retail investors, financial educators, and market supervisors with a more rigorous and actionable framework for cryptocurrency performance assessment, which directly supports the consumer protection objectives of POJK Number 27 of 2024.

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