Kaiko Factor Model

Beyond Homogeneity:

A Taxonomic Approach to Digital Asset Factor Models

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Contents

Abstract **2**

Introduction **3**

1. Literature Review **5**

2. Data **6**

- 2.1 Data Source 6
- 2.2 Kaiko Investable Universe 6

3. Factors **9**

- 3.1 Market 9
- 3.2 Size 11
- 3.3 Low Volatility 12
- 3.4 Momentum 12

4. Factor Model **16**

- 4.1 Time-series regression model 16
- 4.2 Asset Taxonomy 17
- 4.3 Cross-Sectional Regression Model 17

5. Results **19**

- 5.1 Overview 19
- 5.2 Analysis of Crypto-Native Assets 24
- 5.3 Analysis of Meme Coins 27
- 5.4 Outlier Analysis: Real-World Asset 29

6. Conclusion **31**

- 6.1 Summary of Findings 31
- 6.2 Implication for Institutional Investors 32
- 6.3 Limitations and Avenues for Future Research 33

7. Reference **35**

8. Appendix **37**

- 8.1 Asset Classification Details 37
- 8.2 Time-series Regression Results (72 assets) 39
- 8.3 Walk-Forward validation of out-of-sample test 41

Abstract

Digital asset markets have evolved into a legitimate asset class exceeding $3 trillion in market capitalization, yet existing research treats digital assets as homogeneous despite fundamental differences in their economic characteristics and value drivers. This study examines whether traditional factor investing principles can be effectively applied to digital assets and how factor model performance varies across economically distinct digital asset categories. Using institutional-grade Kaiko Market Data covering 72 digital assets, we employ a four-factor model encompassing market, size, momentum, and low-volatility factors through time-series and cross-sectional regression analyses following the Fama-MacBeth methodology. We classify assets into two distinct categories based on their fundamental value propositions: utility-driven Crypto-Native assets and sentiment-driven Meme coins. Our results reveal striking heterogeneity in factor model effectiveness. Crypto-Native assets demonstrate substantial explanatory power (median $R^2 = 0.524$), while meme coins show limited systematic structure (median $R^2 = 0.367$). Walk-forward validation with 5-year history confirms model robustness, achieving a median out-of-sample R-squared of 0.5994 with an RMSE of 0.0278, demonstrating substantial predictive capability under realistic market conditions. Critically, cross-sectional analysis identifies momentum as the sole systematically priced risk factor for Crypto-Native assets ($t = 2.24$, $p < 0.05$), whereas meme coins exhibit no systematic risk pricing across any factors, with returns driven by idiosyncratic, narrative-based dynamics. These findings establish that digital asset markets have matured sufficiently to support systematic factor investing, but require category-specific implementation strategies rather than uniform approaches. This research transforms digital asset investment from pure speculation to evidence-based systematic investing, providing the quantitative foundation necessary for institutional adoption in this evolving asset class.

Introduction

This research employs proprietary Kaiko methodologies, indices, and data sources. The analysis was conducted by the author in their professional capacity at Kaiko, building upon the company's established frameworks for digital asset analysis and factor construction.

The digital asset market has undergone a remarkable transformation over the past fifteen years, evolving from a niche technological experiment into a legitimate asset class with hundreds of liquid tokens and a peak global market capitalization exceeding $3 trillion. The maturation of digital asset in 2025 represents a watershed moment, with 73% of institutional investors now holding digital assets beyond Bitcoin and Ethereum (EY-Parthenon & Coinbase, 2025) showing a dramatic surge from just 29% of institutional exposure in 2023 (PWC, 2024). This rapid expansion and increasing complexity have created a need for rigorous quantitative frameworks. Such frameworks can help investors navigate extraordinary volatility and investment strategy beyond traditional Bitcoin-centric approaches.

The application of factor investing principles to digital asset markets represents a natural evolution in digital asset research. Traditional finance has long recognized that asset returns are driven by multiple systematic risk factors rather than a single market premium. The seminal work of Fama and French (1993), which extended the Capital Asset Pricing Model (CAPM) to include size and value factors, fundamentally reshaped our understanding of equity risk premia. Subsequent research expanded this framework to encompass various investment factors with models for explaining cross-sectional return variations. Early attempts to adapt these principles to digital assets have shown promise demonstrating that market, size, and momentum factors can explain significant portions of digital asset return variations, suggesting that digital assets, despite their unique characteristics, are subject to identifiable systematic risk drivers. (Liu & Tsyvinski, 2018)

However, a critical limitation in existing digital asset research is the tendency to treat this diverse ecosystem as a homogeneous asset class. This approach overlooks the market's complexity, the differences in its purpose, technological foundations, and value drivers across digital assets. For example, Ethereum (ETH) derives its value from network effects, transaction fees, and its role as a computational infrastructure for decentralized application. In contrast, Dogecoin (DOGE) derives its value primarily from social media sentiment and cultural trend, with minimal technological utility. Applying uniform factor models to such fundamentally different assets raises serious questions about model validity and economic interpretation.

This study addresses these limitations by proposing and empirically validating a novel taxonomic approach to digital asset factor analysis. Rather than assuming homogeneous factor exposures across all digital assets, we classify digital assets into two economically distinct categories: Crypto-Native assets with protocols and applications integral to the digital economy, and Meme coins driven primarily by social sentiment. We then examine how a four-factor model, consisting of market, size, momentum, and low-volatility factors, performs across these distinct categories.

The principal contributions of this research are threefold. First, and most critically, we conduct our analysis using institutional-grade investable portfolios constructed from clean, validated price data rather than hypothetical constructs, ensuring the practical applicability and statistical integrity of our findings. This methodological rigor addresses a key limitation in existing digital asset factor research, which often relies on theoretical portfolios that may not reflect real-world trading constraints or data quality issues. Second, we develop a theoretically grounded taxonomy for digital asset classification that moves beyond superficial categorizations to capture fundamental economic differences across Crypto-Native, and Meme coin categories. Third, we provide the first systematic empirical analysis of factor model performance across these distinct digital asset categories using investable strategies, revealing significant heterogeneity in risk exposures and offering actionable insights for portfolio construction and risk management in digital asset markets.

The remainder of this paper unfolds across six sections. Section 2 synthesizes the relevant literature spanning factor investing in traditional finance and its emerging applications in digital asset markets. Section 3 details our comprehensive data sources and price construction methodology. Section 4 establishes our four-factor framework, defining market, size, momentum, and low-volatility factors within the digital asset context. Section 5 presents our taxonomic classification system and empirical modeling approach. Section 6 delivers our core empirical findings, examining systematic differences in factor sensitivities across Crypto-Native, and Meme coin categories. Section 7 concludes with economic interpretations of our results promising avenues for future research in this rapidly evolving field.

1. Literature Review

The field of asset pricing has evolved significantly from the foundational Capital Asset Pricing Model (CAPM), which posited that an asset's expected return is a function of its sensitivity to a single systematic risk factor: the market portfolio (Fama & French, 1993). While elegant, the CAPM's empirical shortcomings led to the development of multi-factor models that better explain the cross-section of stock returns. The most influential of these is the Fama-French three-factor model, which augmented the market factor with two additional risk premia: size (*SMB, or Small Minus Big*) and value (*HML, or High minus Low*). The size factor captures the historical tendency of small-capitalization stocks to outperform large-capitalization stocks, while the value factor accounts for the outperformance of stocks with high book-to-market ratios (value stocks) over those with low ratios (growth stocks). This model explained over 90% of diversified portfolio returns, a substantial improvement over the CAPM.

Subsequently, Fama and French expanded their framework into a five-factor model, incorporating profitability (*RMW*, or Robust Minus Weak) and investment (*CMA*, or Conservative Minus Aggressive) (Fama & French, 2015). This extension was motivated by the dividend discount model, which implies that, all else equal, companies with higher profitability and more conservative investment policies should have higher expected returns. These factors, particularly RMW, are often referred to as "quality" factors. Despite the expanded model's success, it has faced criticism for omitting other well-documented anomalies, most notably momentum and low volatility. The momentum factor, where past winners tend to continue winning, and the low-volatility anomaly, where less volatile stocks have historically provided higher risk-adjusted returns, are considered critical gaps by many researchers, leading to the proposal of six-factor models that incorporate them.

The emergence of digital assets as a distinct asset class has presented a new frontier for asset pricing theory. Characterized by high volatility, novel technologies, and unique value drivers, the crypto market challenges the direct application of traditional financial models. Nevertheless, a growing body of academic and practitioner research has sought to adapt factor investing principles to this nascent space. An early and influential study by Liu and Tsyvinski (2018) found that three factors with a digital asset market factor, a size factor, and a momentum factor could explain a significant portion of the cross-sectional returns of digital assets. This foundational work established that, despite their unique characteristics, digital assets are not entirely alienated from the systematic risk drivers observed in other markets. While recent studies by MSCI (2021) and CF Benchmarks (2024) have explored multi-factor models for digital assets, these approaches treat them as a homogeneous asset class.

2. Data

2.1 Data Source

Asset price data were obtained from Kaiko Reference Rates calculated at 4pm London Time that provide standardized USD-denominated pricing benchmarks for digital assets. Kaiko Reference Rates employ a systematic, rules-based methodology designed to enhance pricing transparency and market integrity in digital asset markets. The rates are constructed exclusively from USD-denominated transactions on centralized exchanges, ensuring that price discovery reflects actual trading activity rather than indicative quotes or over-the-counter transactions. The sample period is from January 1, 2020 to June 30, 2025.

2.1.1 Methodology of Kaiko Reference Rate

All centralized exchanges are thoroughly evaluated, and only those that meet rigorous reliability and transparency standards are included in the hard-vetted exchange list. This list is reviewed on a quarterly basis, with exchanges categorized into two tiers based on their compliance with predefined vetting criteria. Reference Rates incorporate data from exchanges that meet fundamental eligibility criteria, absent from any sanction list, providing a broader yet systematically screened dataset.Full methodology details are available on the Kaiko website. The key characteristics of Kaiko Reference Rates are as follows:

- **Liquidity optimization**: From the curated exchange list, an optimization process selects the most relevant exchanges to maximize liquidity and offer accurate price discovery.
- **Robust Aggregation Method**: A Volume-Weighted Median (VWM) combined with a Time-Weighted Average Price (TWAP) methodology is applied to derive fair and representative prices based on executed transactions from the selected exchanges.
- **Quarterly Review**: The exchange constituents and calculation window of the Reference Rates are reviewed quarterly to ensure alignment with prevailing market conditions.

2.2 Kaiko Investable Universe

The Kaiko Digital Asset Universe consists of thousands of digital assets, each with unique characteristics and risks profiles. It goes through a multi-tier vetting process to assess asset quality and ensure suitability for index inclusion. Digital assets classified as Asset-Referenced Tokens (ARTs) or Electronic Money Tokens (EMTs), as defined by the European Banking Authority (EBA), are excluded from it. Kaiko Digital Asset Universe covers more than +2,300 spot digital assets currently traded on approximately 70 exchanges.

2.1.2 KAIKO BENCHMARK UNIVERSE

The Kaiko Benchmark Universe comprises digital assets from the broader Kaiko Digital Asset Universe that satisfy four fundamental screening criteria:

- **Asset Type Exclusion**: Assets whose value derives from underlying securities or assets are excluded from the universe. This filter removes stablecoins, tokenized equities, tokenized exchange-traded funds (ETFs), and leveraged or inverse digital asset products, ensuring the universe contains only native digital assets with independent price discovery mechanisms.
- **Centralized Exchange Coverage**: Assets trading exclusively on decentralized platforms are excluded to ensure consistent data quality and market accessibility. This requirement limits the universe to assets with established centralized exchange presence, facilitating reliable price formation and institutional access.
- **Data Availability**: Assets lacking essential tokenomics data are excluded from consideration. Required metrics include total supply, circulating supply, and other fundamental parameters necessary for comprehensive market analysis and valuation.
- **Trading History**: Assets with insufficient trading history are excluded, specifically those with less than 90 days of continuous trading data on at least one Kaiko-covered centralized exchange. This criterion ensures adequate historical data for robust statistical analysis.

2.1.3 KAIKO INVESTABLE UNIVERSE

The Kaiko Investable Universe represents a subset of the Benchmark Universe that meets additional liquidity and tradability requirements:

- **Multi-Exchange Tradability**: Assets must maintain active trading on at least two exchanges that have undergone a rigorous vetting process. This requirement ensures diversified market access and reduces single-venue dependency risk.
- **Liquidity Thresholds**: Assets must satisfy dual liquidity and size criteria to ensure meaningful market participation:
    - Volume Requirement: The asset's 90-day rolling average daily trading volume ($ADTV_{90}$) must represent at least 0.01% of the total market $ADTV_{90}$ across soft-vetted exchanges.
    - Market Capitalization Requirement: The asset's 90-day rolling average daily circulating market capitalization ($ADCMC_{90}$) must constitute at least 0.01% of the total market $ADCMC_{90}$.

These screening procedures ensure that the final investable universe contains only liquid, accessible, and data-complete digital assets suitable for institutional-grade analysis and investment consideration. As of 30 August 2025, 72 assets that are the components of Kaiko Investable Universe are used for this study.

3. Factors

We propose four factors, market, size, low volatility, and momentum factors. These concepts derive from traditional finance models with the metric of market capitalization, volatility and the momentum dynamic. The performance and risk metrics are on Table 1. We designed this framework to maintain simplicity and avoid complexity. Future research will incorporate digital asset-specific metrics to expand our analytical scope.

Table 1. Risk and Return Profile of the factors

	Gross Rate of Return*				Kaiko Realized Volatility**				Return-to-Risk Ratio***			
Factor	1m	3m	1y	3y	1m	3m	1y	3y	1m	3m	1y	3y
Market	-3.22	15.7	15.4	653.1	52.5	58.9	58.7	69.7	-0.1	-0.3	0.3	9.4
Size	-12.3	-4.2	20.3	122.7	61.5	64.9	71.3	66.4	-0.2	-0.1	0.3	1.9
LowVol	-7.3	4.81	42.8	235.8	54.0	56.7	63.6	59.1	-0.1	0.1	0.7	4.0
Momentum	-4.8	15.1	40.7	406.8	68.0	90.0	85.9	83.7	-0.1	0.2	0.5	4.9

* Gross Rate of Return = (index level (today) / index level (historical point) - 1) * 100

** Kaiko Realized Volatility is a proprietary statistical measure that calculates the dispersion of returns for a specific asset over a defined time period considering potential autocorrelation of the underlying asset. As digital assets often exhibit autocorrelation in their log returns, Kaiko Realized Volatility provides a more accurate assessment of risk and volatility.

*** Return-to-Risk Ratio: Gross Rate of Return / Kaiko Realized Volatility

3.1 Market

The performance of the market factor is measured using the return of the Kaiko Investable Market Index that provides comprehensive and segmented coverage of the digital asset market, representing the full investable universe of digital assets.

$$R_{MKT,\,t} = R_{Kaiko\ Investable\ Market\ Index,\,t}$$

The coefficient of market factor in the factor model is interpreted as the digital asset market beta, analogous to the market factor in traditional asset pricing models. It measures the sensitivity of an individual asset's returns to the returns of the overall digital asset market portfolio. A coefficient greater than 1 indicates that the asset is more volatile than the market, while a coefficient less than

1 suggests lower volatility. The market factor is consistently found to be the most significant driver of digital asset returns, capturing the systemic risk inherent in the asset class as a whole.

3.1.1 UNIVERSE DEFINITION AND ASSET SELECTION OF KAIKO INVESTABLE MARKET INDICES

The investment universe is the Kaiko Investable Universe. Asset selection is conducted through a market capitalization-based screening process. Rebalancing is conducted on a quarterly basis.

3.1.2 WEIGHTING SCHEME OF KAIKO INVESTABLE MARKET INDICES

The Kaiko Investable Market Indices methodology applies a dual-weighting framework that incorporates both circulating market capitalization and liquidity to enhance the representativeness and investability of the index. While market capitalization provides a measure of an asset's relative size within the market, liquidity ensures that the index constituents are sufficiently tradable to support replication and efficient execution.

3.1.2.1 Circulating Market Capitalization Weight

Circulating Market Capitalization Weights are calculated as the 90-day Average Daily Circulating Market Capitalization for each underlying component in the index composition over the 90-day Total Circulating Market Capitalization of the index at time t.

$$w(CircMktCap)_t^i = \frac{(Average\ Daily\ Circulating\ Market\ Cap_{90})_t^i}{\sum_{k=1}^{n}(Average\ Daily\ Circulating\ Market\ Cap_{90})_t^k}$$

3.1.2.2 Liquidity weight

Liquidity Weights are calculated as the 90-days Average Daily Trading Volume or each underlying component in the index composition over the 90-days Total Average Daily Trading Volume of the index at time t.

$$w(ADTV)_t^i = \frac{(Average\ Daily\ Trading\ Volume_{90})_t^i}{\sum_{k=1}^{n}(Average\ Daily\ Trading\ Volume_{90})_t^k}$$

3.1.2.3 Composite Weighting

Final weights are determined through an equally-weighted combination of circulating market capitalization (50%) and liquidity weights (50%). The methodology incorporates a concentration limit whereby individual asset weights are capped at 30% to mitigate single-asset risk and enhance diversification.

$$Weight_i = \frac{1}{2}w(CircMktCap)_t^i + \frac{1}{2}w(ADTV)_t^i$$

3.2 Size

The size factor identifies the systematic risk premium, so-called altcoin premium, associated with investing in alternative digital assets beyond Bitcoin's market-leading position. It measures the excess compensation that market participants require when allocating capital to smaller, less established digital assets compared to the dominant digital asset. This phenomenon mirrors the size effect in traditional finance, where investors historically earn higher returns from smaller-capitalization stocks to compensate for their increased risk and reduced liquidity relative to large-cap equities.

The size factor is constructed as the return differential between the Kaiko Size Factor Index and the Kaiko Bitcoin Reference Rate. This methodology represents a digital asset-specific adaptation of the Fama-French Small Minus Big (SMB) factor, where Bitcoin serves as the large-cap benchmark due to its market dominance and established role in digital asset markets.

$$SMB_{crypto,\, t} = R_{Kaiko\ Size\ Factor\ Index,\, t} - R_{Kaiko\ Bitcoin\ Reference\ Rate,\, t}$$

A statistically significant positive coefficient on this factor indicates a size premium effect, whereby the asset outperforms during periods when smaller altcoins outperform Bitcoin. This relationship provides empirical evidence for systematic risk premiums associated with non-dominant digital assets, suggesting investors require additional compensation for holding assets beyond the market leader.

3.1.3 Universe Definition and Asset Selection of Kaiko Size Factor Indices

The investment universe is defined as the subset of digital assets within the Kaiko Investable Universe that satisfy predetermined data quality and liquidity thresholds. Asset selection is conducted through a market capitalization-based screening process that identifies the ten largest assets by market value, explicitly excluding Bitcoin from consideration. Rebalancing is conducted on a quarterly basis.

3.1.4 Weighting Scheme of Kaiko Size Factor Indices

The Size factor score for each constituent is calculated as the inverse of its market capitalization. Final weights are determined by normalizing individual factor scores relative to the aggregate where the summation encompasses all ten index components.

$$Factor\ Score_{Size,\, i} = \frac{1}{Market\ Cap_i}$$

$$Weight_i = \frac{Factor\ Score_{Size,\, i}}{\Sigma(Factor\ Score_{Size,\, i})}$$

3.3 Low Volatility

The Low Volatility Factor is constructed to evaluate the performance of assets with minimal price volatility within the digital asset market. This factor aims to optimize risk-adjusted returns by prioritizing portfolio stability over absolute return maximization, embodying a defensive investment strategy that demonstrates particular efficacy during periods of heightened market uncertainty and stress.

The performance of the low Volatility factor is quantified through the price dynamics of the Kaiko Low Volatility Factor Index, which employs the proprietary Kaiko Realized Volatility Methodology. This methodology incorporates the unique autocorrelation properties inherent in digital asset markets when measuring asset price volatility, providing a more accurate representation of risk characteristics specific to the digital asset ecosystem compared to traditional volatility measures designed for conventional financial markets.

$$LowVol_{crypto,\,t} = R_{Kaiko\ lowVol\ Factor\ Index,\,t}$$

3.1.5 Universe Definition and Asset Selection

The investment universe is defined as the subset of digital assets within the Kaiko Investable Universe. Asset selection is conducted through an inverse volatility ranking based on Kaiko Realized Volatility metrics, which systematically identifies the ten digital assets demonstrating the lowest historical price volatility over the measurement period. Rebalancing is conducted on a quarterly basis.

3.1.6 Weighting Scheme

The lowVol factor score for each constituent is calculated as the inverse of its Kaiko Realized Volatility. Final weights are determined by normalizing individual factor scores relative to the aggregate where the summation encompasses all ten index components.

$$Factor\ Score_{lowVol,\,i} = \frac{1}{Kaiko\ Realized\ Volatility_i}$$

$$Weight_i = \frac{Factor\ Score_{lowVol,\,i}}{\Sigma(Factor\ Score_{lowVol,\,i})}$$

3.4 Momentum

Digital assets demonstrating strong recent performance exhibit momentum effects, continuing to outperform in subsequent periods. This creates identifiable patterns of persistent performance across time horizons. The underlying mechanism operates through investor behavior. Positive price movements attract increased capital inflows, which subsequently reinforce upward price trajectories. This feedback loop reflects the behavioral aspects of digital asset markets, where sentiment plays a significant role in price formation. It is cyclical reinforcement mechanisms within market psychology, where initial performance gains generate investor interest that perpetuates the original trend through sustained capital allocation.

The performance of the momentum factor is quantified through the price dynamics of the Kaiko Momentum Factor Index. In order to produce a momentum-tilted portfolio that accurately depicts market dynamics, the momentum factor uses RSI-based asset selection and weighting. Rebalancing is conducted on a monthly basis.

$$MOM_{crypto,\,t} = R_{Kaiko\ Momentum\ Factor\ Index,\,t}$$

3.1.7 UNIVERSE DEFINITION AND ASSET SELECTION OF KAIKO MOMENTUM FACTOR INDEX

The investment universe is constrained to assets within the Kaiko Investable Universe. From this universe, asset selection employs a momentum-ranking methodology that identifies the five top digital assets exhibiting the strongest recent price trends as measured by the Relative Strength Index (RSI). This concentrated approach balances the exploitation of momentum signals with adequate diversification to mitigate asset-specific risks.

3.1.8 WEIGHTING SCHEME OF KAIKO MOMENTUM FACTOR INDEX

3.4.2.1 Theoretical Background

The methodology builds upon the seminal work of Jegadeesh, N., & Titman, S. (1993), who demonstrated that assets exhibiting superior performance over intermediate horizons tend to continue outperforming in subsequent periods. The index construction process systematically identifies and weights assets based on their recent price momentum, providing a rules-based approach to capturing momentum anomalies in digital asset markets.

The momentum signal is operationalized through the Relative Strength Index, originally developed by J. Welles Wilder Jr. (1978) in his foundational work New Concepts in Technical Trading Systems. The RSI represents a bounded momentum oscillator that addresses key limitations of traditional momentum measures by constraining output values to [0, 100], eliminating extreme outliers that can distort cross-sectional comparisons. The indicator standardizes momentum measurement across assets with different price levels and volatilities while incorporating exponential smoothing to enhance signal-to-noise ratios by filtering short-term price fluctuations. These theoretical properties make RSI particularly well-suited for momentum factor construction in digital asset markets, where high volatility and diverse asset characteristics necessitate robust normalization methodologies.

3.4.2.2 Relative Strength Index (RSI) Calculation

The RSI methodology begins with asymmetric decomposition of daily price movements, recognizing that upward and downward price movements may exhibit different statistical properties and investor behavioral responses:

$$\Delta_{i,t} = P_{i,t} - P_{i,t-1}$$

$$G_{i,t} = max(\Delta_{i,t}, 0)$$

$$L_{i,t} = max(-\Delta_{i,t}, 0)$$

where $P_{i,t}$ denotes the closing price of $asset_i$ on day t. This asymmetric decomposition allows for separate modeling of upward and downward price movements, recognizing that these may exhibit different statistical properties and market implications.

The gain and loss series are smoothed using Wilder's exponential smoothing methodology, which employs a smoothing parameter $\alpha = \frac{1}{n}$ where n denotes the lookback period.

$$AvgGain_{i,t} = \alpha G_{i,t} + (1 - \alpha)AvgGain_{i,t-1}$$

$$AvgLoss_{i,t} = \alpha G_{i,t} + (1 - \alpha)AvgLoss_{i,t-1}$$

This smoothing approach provides exponential memory decay where recent observations receive higher weights with influence declining exponentially for older observations, stability through reduction of outlier impacts, and computational efficiency via recursive formulation that enables efficient real-time calculation.

The relative strength ratio $RS_{i,t}$ quantifies the relationship between average gains and losses and the RSI applies a logistic transformation to bound the indicator:

$$RS_{i,t} = \frac{AvgGain_{i,t}}{AvgLoss_{i,t}}$$

$$RSI_{i,t} = 100 - \frac{100}{1+RS_{i,t}}$$

This transformation exhibits monotonicity such that RSI is strictly increasing in RS, boundedness where RSI ∈ [0, 100] regardless of RS magnitude, and symmetry around RSI = 50 corresponding to RS = 1.

3.4.2.3 Methodological Considerations

The Kaiko Momentum Factor Index employs a 8-week lookback period, chosen to balance signal responsiveness with statistical stability. This parameter selection aligns with empirical research on optimal momentum measurement horizons, which suggests that intermediate-term lookback periods of 4-8 weeks provide superior momentum signal quality relative to shorter or longer alternatives.

To minimize initialization bias, RSI calculations incorporate a warm-up period that is 3 times of the lookback period. During this period, initial average gain and loss values are seeded with the first observation, while subsequent values employ the exponential smoothing recursion. The warm-up ensures that initialization effects contribute less than 5% to final RSI values due to the recursion.

The RSI-based momentum measure provides advantages over simple return-based metrics by incorporating the relative strength of price movements, keeping all scores within a fixed range to make cross-asset comparison straightforward, and providing superior signal-to-noise characteristics through its inherent smoothing properties.

3.4.2.4 Momentum Score & Weight

To facilitate portfolio weighting, RSI values are transformed through a multi-step standardization process.

First, RSI values are converted to z-scores using the cross-sectional mean and standard deviation of RSI values across all constituents.

$$Z - score_i = \frac{RSI_{i,t} - Mean\ of\ RSIs}{Standard\ Deviation\ of\ RSIs}$$

To ensure non-negative weights suitable for portfolio construction, z-scores are linearly rescaled to the interval [0.01, 1.00] through an affine transformation.

$$Factor\ Score_{Momentum,\, i} = 0.01 + (1 - 0.01)\frac{Z{-}score_i - Min(Z{-}Score)}{Max(Z{-}Score) - Min(Z{-}Score)}$$

Finally, these adjusted scores are normalized, yielding proportional weights for index construction.

$$Weight_i = \frac{Factor\ Score_{Momentum,\, i}}{\Sigma(Factor\ Score_{Momentum,\, i})}$$

4. Factor Model

4.1 Time-series regression model

We implement a time-series multi-factor regression framework using the digital asset-specific factors identified in our analysis. The empirical model employed in this study follows a four-factor specification adapted for digital asset markets. The regression equation for each digital asset $asset_i$ takes the following form:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,MKT}(R_{MKT,t} - R_{f,t}) + \beta_{i,Size}(SMB_{crypto,t}) + \beta_{i,MOM}(MOM_{crypto,t}) + \beta_{i,LowVol}(LowVol_{crypto,t}) + \epsilon_{i,t}$$

where:

- $R_{i,t} - R_{f,t}$ represents the excess return of digital asset $asset_i$ over the risk-free rate in period t
- α_i captures the asset's abnormal return after controlling for systematic risk factors (Jensen, 1968)
- $\beta_{i,MKT}$, $\beta_{i,Size}$, $\beta_{i,MOM}$, and $\beta_{i,LowVol}$ represent the factor loadings measuring the sensitivity of $asset_i$ to the market, size, momentum, and low-volatility factors, respectively
- $R_{MKT,t}$ denotes the digital asset market factor return with Kaiko Investable Market Index
- $SMB_{crypto,t}$ represents the digital asset-specific size factor measured by Kaiko Size Factor Index
- $MOM_{crypto,t}$ captures the momentum factor in digital asset markets measured by Kaiko Momentum Factor Index
- $LowVol_{crypto,t}$ represents the low-volatility factor measured by Kaiko lowVol Factor Index
- $\epsilon_{i,t}$ is the idiosyncratic error term assumed to be independently and identically distributed

The risk-free rate ($R_{f,t}$) is assumed to be zero in our analysis, as the digital asset ecosystem currently lacks a widely accepted risk-free digital asset equivalent to traditional government bonds or treasury bills. The factor loadings (β coefficients) quantify each asset's exposure to systematic risk factors and serve as the primary focus of our empirical analysis. These coefficients are estimated using ordinary least squares regression and provide the basis for our comparative analysis across asset categories.

4.2 Asset Taxonomy

A key insight of this research is that digital assets cannot be analyzed as a homogeneous group. The 72 assets in our dataset exhibit fundamentally different price drivers, necessitating separate analysis by asset type. We classify digital assets into two primary categories that capture the fundamental economic drivers: Crypto-Native assets with protocols integral to the digital economy and Meme coins which are sentiment-driven assets.

We also analyze PAX gold (PAXG) as a distinct case study that illustrates the constraints of applying crypto-native factor models to tokenized traditional assets. While PAXG is included in the Kaiko Investable Universe, it requires separate treatment due to its unique characteristics as a tokenized commodity. The complete asset classification with detailed justifications is provided in Appendix 8.1.

4.1.1 CRYPTO-NATIVE ASSET

Crypto-Native assets are digital assets whose value stems from their role in the blockchain ecosystem. Their prices are driven by network adoption, utility, and technological developments. This category includes:

- **Layer-1 & Layer-2 Protocols**: Base blockchain networks and their scaling solutions that provide the infrastructure for the ecosystem.
- **DeFi Protocols**: Applications offering financial services like lending and trading.
- **Infrastructure & Oracle Services**: Projects providing essential blockchain services and data connectivity.

4.1.2 MEME COINS

Meme coins derive value from social media trends and community sentiment rather than utility or technology. Their prices are driven by speculation, viral marketing, and hype cycles. Examples include Doge, Shiba-Inu, Pepe, Bonk, and Popcat.

4.3 Cross-Sectional Regression Model

To empirically validate the proposed asset pricing model, this study employs the two-stage regression procedure developed by Fama and MacBeth (1973), which represents the standard methodology for determining whether proposed risk factors command statistically significant risk premiums in asset markets. The primary objective is to ascertain whether the identified factors are systematically priced within the digital asset universe and whether these premiums exhibit variation across the defined asset categories of Crypto-Native, and Meme coins.

4.1.3 Factor Loading Estimation

The initial stage involves estimating factor exposures for each individual asset through time-series regression analysis. For every asset i in the sample, excess returns are regressed against the proposed risk factors according to the 4.1. Time-series Regression Model. The resulting regression coefficients $\hat{\beta}_{i,f}$ quantify each $asset_i$ sensitivity to the corresponding risk factors f, yielding a unique risk profile for every constituent in the sample.

4.1.4 Risk Premium Determination

The second stage utilizes the estimated factor loadings to determine risk premiums through cross-sectional regression analysis. For each time period t, excess returns across all assets serve as dependent variables, with first-stage estimated betas functioning as independent variables:

$$R_{i,t} - R_{f,t} = \gamma_i + \gamma_{MKT,t}\hat{\beta}_{i,MKT} + \gamma_{Size,t}\hat{\beta}_{i,Size} + \gamma_{MOM,t}\hat{\beta}_{i,MOM} + \gamma_{lowVol,t}\hat{\beta}_{i,lowVol} + u_{i,t}$$

The coefficient $\gamma_{f,t}$ represents the estimated risk premium for a factor f at time t. This regression is performed across all time periods, generating a time series of risk premium estimates for each factor.

4.1.5 Statistical Inference and Validation

The final analytical stage examines the time series properties of estimated risk premiums. For each factor f, the mean premium $\underline{\gamma}_f$ is calculated by averaging coefficients across all time periods, with statistical significance assessed through t-tests using standard errors derived from the time series of gamma coefficients. A statistically significant and positive mean premium provides empirical evidence that factor exposure has been systematically rewarded by the market, thereby validating the factor as a priced risk determinant.

This rigorous methodology enables empirical validation of the proposed factor model while investigating different risk pricing across distinct digital asset classifications, contributing to a more nuanced understanding of digital asset market structure and cross-sectional return determinants.

5. Results

5.1 Overview

5.1.1 TIME-SERIES REGRESSION RESULTS SUMMARY

To synthesize the findings from the individual category analyses, Table 2 presents a comparative summary of the factor exposures. This table provides a clear, quantitative overview of the systematic differences in risk profiles across the two asset classes, representing the central empirical result of this paper. Crypto-Native assets are defined by their high market beta and high model explanatory power. Meme coins fall in between in terms of market beta but have low R-squared values overall, with momentum emerging as a key distinguishing factor.

Table 2: Factor Exposures by Asset Category

Factor/Metric	Crypto-Native (62 assets)	Meme (9 assets)
Median Adj. R-Squared	0.524	0.367
Market		
Median Coefficient	0.745	1.195
Median T-Statistic	5.81	4.777
% Significant ($p < 0.05$)	53 (85%)	8 (89%)
Size		
Median Coefficient	0.191	0.03
Median T-Statistic	2.04	0.08
% Significant ($p < 0.05$)	34 (55%)	1 (11%)
Momentum		
Median Coefficient	0.087	0.173
Median T-Statistic	1.37	1.35
% Significant ($p < 0.05$)	23 (37%)	4 (44%)
Low Volatility		
Median Coefficient	0.330	0.102
Median T-Statistic	2.07	0.387
% Significant ($p < 0.05$)	34 (55%)	2 (22%)

Given the non-normal distribution of residuals, t-statistics were recalculated using Newey-West hetero- skedasticity and autocorrelation consistent (HAC) standard errors. Financial time series data often exhibit such deviation from normality due to volatility clustering, heavy tails, and asymmetric return distributions, first systematically documented by Fama (1965) and later formalized in Cont's (2001) comprehensive review of stylized facts in financial markets.

5.1.1.1 Representative Time-series Regression Results

Table 3 presents detailed regression results for representative assets from each category. Bitcoin (BTC) and Ethereum (ETH) represent Crypto-Native assets, and Dogecoin (DOGE) and Pepe(PEPE) represent Meme coins. Complete results for all 72 assets are provided in Appendix 8.2.

Table 3: Representative Time-series Regression Results

Asset	Observations	Intercept (α)	Low Volatility	Size	Momentum	Market	R^2	Adjusted R^2
btc	2023	0.000	0.157***	-0.443***	-0.006	0.803***	0.926	0.926
eth	2023	0.001	-0.04	-0.028	-0.070***	1.169***	0.886	0.886
xrp	2023	0.001	0.114	0.367***	-0.06	0.869***	0.533	0.532
sol	1756	0.003*	-0.445***	0.191*	0.144*	1.275***	0.462	0.460
ada	2023	0.001	0.098	0.411***	0.065	0.787***	0.635	0.634
paxg	2011	0.000	0.080***	-0.023*	-0.011	-0.021	0.028	0.026
doge	2023	0.003	-0.162	0.009	0.165*	1.018***	0.182	0.180
pepe	760	0.002	0.102	-0.363	0.493*	1.294***	0.506	0.503

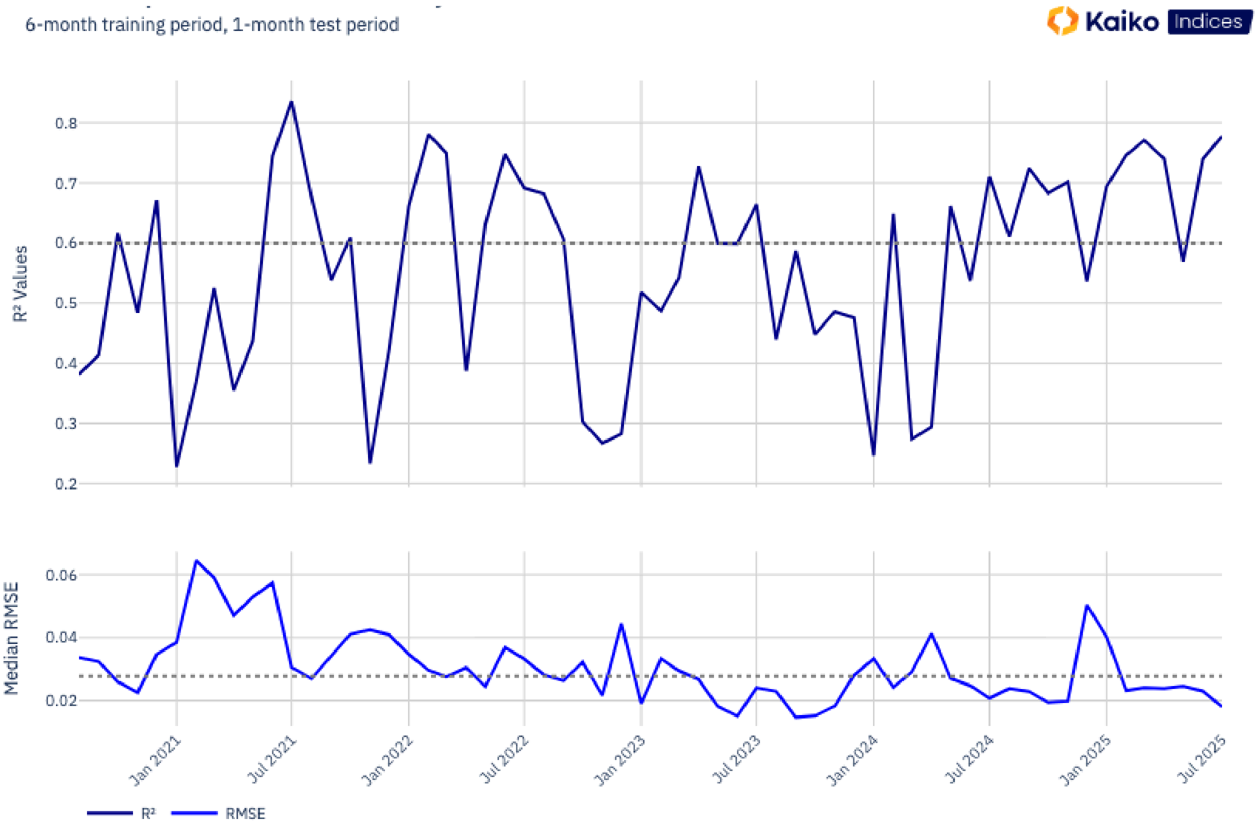
The representative results demonstrate clear categorical patterns with important methodological considerations. Bitcoin and Ethereum demonstrate exceptionally high R-squared values of 0.926 and 0.886, respectively. This strong explanatory powers of Bitcoin stem partly from Kaiko factor construction methodology, in which Bitcoin serves as the large-cap benchmark for calculating the size factor, which is defined as small-cap minus large-cap returns. This methodological choice creates an inherent mechanical relationship that naturally enhances the model's explanatory power for this largest market asset. Consistent with Bitcoin's role as the large-cap benchmark, it exhibits a strongly negative size coefficient of -0.443, confirming the expected inverse relationship between asset size and the size factor.

Beyond these methodological effects, the results reveal economically meaningful patterns. Crypto-Native assets show strong market correlations with heterogeneous secondary factor exposures reflecting their diverse roles within the digital economy. Meme coins exhibit amplified market sensitivity with notable momentum characteristics. On the other hand, we also run the analysis on PAXG which is a Real-World Asset token pegged to gold. It shows that PAXG has negligible crypto factor exposures which indicates its classification outside the Crypto-Native framework.

5.1.1.2 Walk-forward validation

Walk-forward validation represents a robust backtesting framework specifically designed for time-series forecasting models. The methodology operates by systematically partitioning historical data into sequential training and testing periods, where each model iteration learns from a historical window and validates performance on the subsequent out-of-sample period. As the process advances, both training and testing windows roll forward chronologically, maintaining strict temporal boundaries that prevent any look-ahead bias. This approach authentically replicates live trading conditions by ensuring predictions rely exclusively on information available at each point in time, providing a more realistic assessment of model performance than traditional cross-validation methods that ignore temporal dependencies.

[Graph 1: Median R-Squared of Walk-Forward Analysis]



6-month training period, 1-month test period

Beginning in January 2020, we used 6-month training windows with 1-month forward validation periods, rolling monthly to assess model performance systematically. The factor model demonstrated robust predictive capability with a median R-squared across the entire period of 0.5990 and a Root Mean Square Error (RMSE) of 0.0278, indicating the model explains 59.9% of individual asset performance variance while maintaining a 2.78% error boundary. These results suggest substantial explanatory power, indicating that the factor model captures meaningful relationships while providing reasonable prediction accuracy under realistic market conditions.

Complete walk-forward validation results and detailed statistical analysis are available in Appendix 8.3.

5.1.1.3 Statistical check on classification

To validate the differentiated factor exposures across our proposed digital asset categories, we conducted t-tests on the regression coefficients from our four-factor model. This statistical approach assesses whether observed differences in factor sensitivities between Crypto-Native and Meme coin categories are statistically significant.

Table 4: t-test results

Factor	Crypto Native			Meme			Result	
	Mean(μ)	**Std (σ)**	**n**	**Mean(μ)**	**Std(σ)**	**n**	**t-stat**	**Cohen's *d***
Market	0.616	0.701	62	1.990	2.542	9	-3.538 ***	-1.262
Low Volatility	0.425	0.435	62	0.251	0.514	9	1.098	0.392
Momentum	0.110	0.246	62	0.377	0.446	9	-2.699 **	-0.963
Size	0.229	0.369	62	-0.096	0.487	9	2.370 *	0.846

Notes: Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The t-tests provide a support for our theoretical framework, revealing statistically significant differences in factor sensitivities across asset categories. Cohen's *d* (Cohen, 1988) measures effect size by calculating the standardized difference between two group means, computed as the mean difference divided by the pooled standard deviation. Effect sizes are interpreted as small ($d = 0.2$), medium ($d = 0.5$), or large ($d = 0.8$), indicating practical significance by showing how many standard deviations separate the groups.

Market factor coefficients differed significantly between categories, with Meme coins ($\mu = 1.990$, $\sigma = 2.542$, n = 9) exhibiting substantially higher market sensitivity than Crypto-Native assets ($\mu = 0.616$, $\sigma = 0.701$, n = 62). This large effect size ($t(69) = -3.538^{***}$, $d = 1.262$) provides strong quantitative evidence that Meme coins operate as amplified market instruments, systematically magnifying both positive and negative digital asset market movements by approximately 70% relative to their Crypto-Native counterparts.

Momentum factor analysis corroborated these categorical distinctions, with Meme coins ($\mu = 0.377$, $\sigma = 0.446$) exhibiting significantly stronger trend-following behavior than Crypto-Native assets ($\mu = 0.110$, $\sigma = 0.246$). This statistically significant difference ($t(69) = -2.699^{**}$, $d = 0.963$) empirically validates the theoretical proposition that Meme coins are driven by social contagion effects and sentiment cascades, displaying momentum coefficients more than triple those of fundamental-driven assets.

Size factor loadings revealed a significant difference between categories, with Crypto-Native assets (μ = 0.229, σ = 0.369) showing positive size sensitivity while Meme coins (μ = -0.096, σ = 0.487) exhibited negative loadings ($t(69)$ = 2.370, d = 0.846). This large effect size suggests that Meme coins may actually benefit from association with larger, more established projects rather than exhibiting traditional small-cap premiums, potentially reflecting their reliance on mainstream visibility and social media reach.

Low volatility factor analysis showed no significant difference ($t(69)$ = 1.098, d = 0.392) between Crypto-Native assets (μ = 0.425, σ = 0.435) and Meme coins (μ = 0.251, σ = 0.514). It suggests that low volatility preferences operate similarly across both asset types.

These results provide robust statistical validation of our categorization framework's ability to capture economically meaningful differences in digital asset risk-return characteristics. The significant differences in market (d = 1.262), momentum (d = 0.963), and size (d = 0.846) factors, all demonstrating large effect sizes, confirm that our taxonomic approach identifies genuine structural differences rather than spurious statistical artifacts. The consistent pattern of large effect sizes across three of four factors establishes a strong empirical foundation for category-specific portfolio construction and risk management strategies in digital asset markets.

5.1.2 Cross-Sectional Regression Results Summary

Although the time-series regressions presented in Section 5.1.1 successfully measured how sensitive each asset is to various risk factors, they fell short of determining whether these factors consistently earn a risk premium over time. To assess whether these factors are truly priced in the market, we performed the cross-sectional regression test developed by Fama and MacBeth (1973). It shows the validity of our categorical framework by examining whether investors receive statistically significant compensation for bearing each unit of factor risk.

The Fama-MacBeth analysis presented in Table 5 reveals significant heterogeneity in risk pricing across digital asset categories. While the pooled sample of 72 assets exhibits high risk premiums for momentum (t = 3.18) and market factors (t = 2.00), Meme coins exhibit no significant risk pricing across any factor, indicating their returns are predominantly driven by idiosyncratic, narrative-based dynamics that operate outside traditional systematic risk frameworks.

Table 5. Fama-MacBeth T-Statistics for Factor Daily Risk Premia (RP)

Factor/Metric	Kaiko Investable Universe (72 assets)		Crypto-Native (62 assets)		Meme (9 assets)	
	avg. RP (%)	t-stat	avg. RP (%)	t-stat	avg. RP (%)	t-stat
Constant	0.03	0.40	0.02	0.10	-0.08	-0.10
Market	0.21	2.00*	0.20	0.94	0.34	0.42
Low Volatility	0.06	0.59	0.01	0.45	0.35	0.75
Momentum	0.76	3.18**	0.60	2.24*	0.49	0.92
Size	0.03	0.33	0.06	0.68	-0.03	-0.09

Notes: Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

5.2 Analysis of Crypto-Native Assets

5.1.3 TIME-SERIES REGRESSION RESULTS

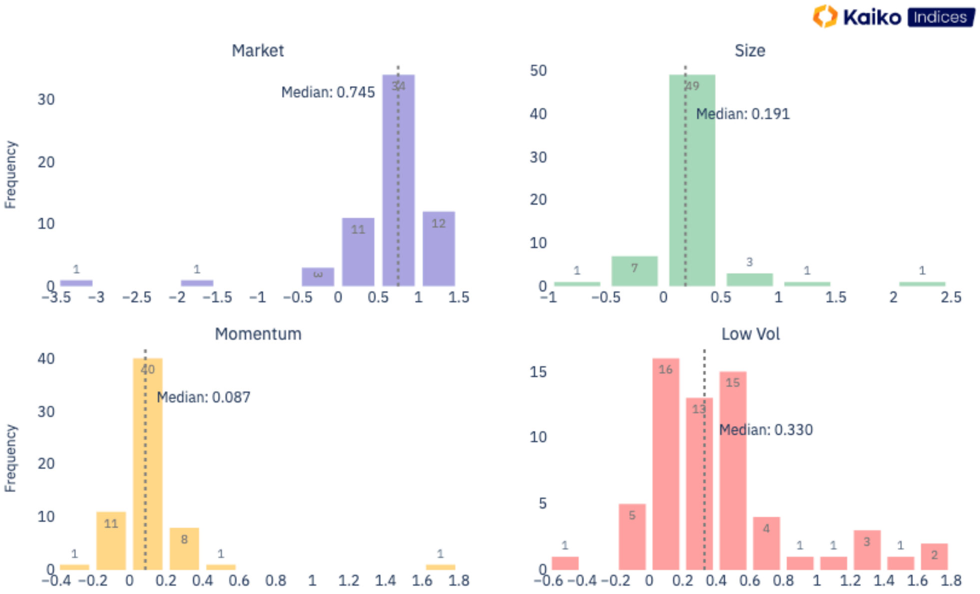
6.2.1.1 Model Performance and Explanatory Power

The regression analysis for Crypto-Native assets, which constitute most observations in our sample, provides strong evidence for their role as the structural foundation of digital asset markets. The four-factor model demonstrates substantial explanatory power across this category, achieving a median adjusted R-squared of 0.54. This finding indicates that systematic risk factors, specifically market exposure, size effects, momentum patterns, and volatility characteristics typically explain approximately 54% of the cross-sectional variation in returns for these foundational protocols and applications.

The heterogeneity in model performance across Crypto-Native assets provides insight into market maturation processes. Established protocols with clear utility propositions and substantial network effects tend to exhibit higher R-squared values, while newer or more specialized protocols show greater idiosyncratic variation. This pattern suggests that as the digital asset market matures, systematic risk factors become increasingly important relative to asset-specific developments.

6.2.1.2 Factor-wise analysis

Graph 2: Factor Coefficient Distribution - Crypto-Native



Our analysis reveals that the market factor ($\beta_{i, MKT}$) serves as the primary determinant of returns within the Crypto-Native category. The median market coefficient is 0.745, with statistical significance observed across 85% of assets in this classification. The magnitude of associated t-statistics provides robust evidence for the systematic relationship between individual asset returns and broad market movements. This finding supports the theoretical framework that Crypto-Native assets function as primary conduits for a systemic risk of digital assets. The prevalence of market betas approaching or exceeding unity confirms the sensitivity of these assets to ecosystem-wide capital flows and their role as fundamental building blocks of the blockchain economy.

The size factor ($\beta_{i,Size}$) exhibits statistical significance for approximately 50% of Crypto-Native assets, with a median coefficient of 0.191. This positive loading provides empirical evidence for the existence of a size premium within digital asset markets, analogous to the small-cap premium documented in traditional equity markets. We view the "altcoin premium" as extra compensation that investors demand for taking on the higher risks of investing in smaller, established protocols compared to Bitcoin. This factor effectively captures the higher-growth, higher-risk profile characteristic of protocols in their maturation phase, consistent with theoretical predictions regarding the risk-return trade-off in emerging technology sectors.

While momentum factor ($\beta_{i, MOM}$) significance is not uniformly distributed across the Crypto-Native category, notable exceptions provide insight into narrative-driven investment dynamics. Fetch.ai

(FET) exemplifies this phenomenon, exhibiting a statistically significant momentum coefficient with a t-statistic of 4.60. We attribute this momentum sensitivity to FET's association with the artificial intelligence narrative. The asset's trend-following characteristics suggest that exposure to dominant technological themes can induce momentum effects even within the Crypto-Native category, creating risk profiles that partially overlap with more speculative asset classifications.

Contrary to conventional expectations for high-volatility digital asset assets, several established Crypto-Native tokens exhibit significant positive low-volatility factor loadings ($\beta_{i,LowVol}$), including LayerZero (0.746**), Worldcoin (1.323**), and Hedera (0.651**). These utility-focused protocols outperform when markets favor established infrastructure over speculation. For institutional investors, these represent more mature protocols with reduced systematic risk exposure toward the assets that have transitioned from speculation to utility-driven value creation.

5.1.4 CROSS-SECTIONAL REGRESSION

For Crypto-Native assets, the cross-sectional regression results demonstrate a surprising disconnection between factor exposure and risk pricing. While these assets exhibit high market sensitivity in the time-series analysis (Section 5.2), the market factor fails to command a significant risk premium ($t = 0.87$, $p > 0.10$). Instead, momentum emerges as the sole systematically priced risk factor ($t = 2.23$, $p < 0.05$), suggesting that investors in this category are primarily compensated for bearing trend-following risk rather than broad market exposure.

5.1.5 IMPLICATIONS FOR INSTITUTIONAL INVESTORS

The empirical results demonstrate that Crypto-Native assets exhibit complex risk structures that reflect their evolution from speculative instruments to foundational infrastructure components. The combination of dominant market exposure with heterogeneous responses to size, momentum, and volatility factors indicates the emergence of distinct sub-segments within the broader Crypto-Native classification.

For institutional investors and portfolio managers, these findings demand a fundamental shift from treating crypto-native assets as homogeneous Bitcoin alternatives to adopting sophisticated factor-based portfolio construction. The pronounced momentum risk premiums create clear opportunities for systematic trend-following strategies to generate positive risk-adjusted returns, while low-volatility effects enable defensive positioning during market stress. Rather than generic crypto allocation, investors should strategically leverage specific factor exposures: deploying low-volatility assets for portfolio defense and high-momentum assets for tactical alpha generation.

The coexistence of high market betas with varied secondary factor exposures also suggests that correlation-based risk management approaches may be insufficient for digital asset portfolios. Traditional risk management techniques that rely primarily on correlation matrices may miss important factor-based sources of systematic risk that operate independently of market-wide movements.

5.3 Analysis of Meme Coins

5.1.6 TIME-SERIES REGRESSION RESULTS

5.3.1.1 Model Performance and Explanatory Power

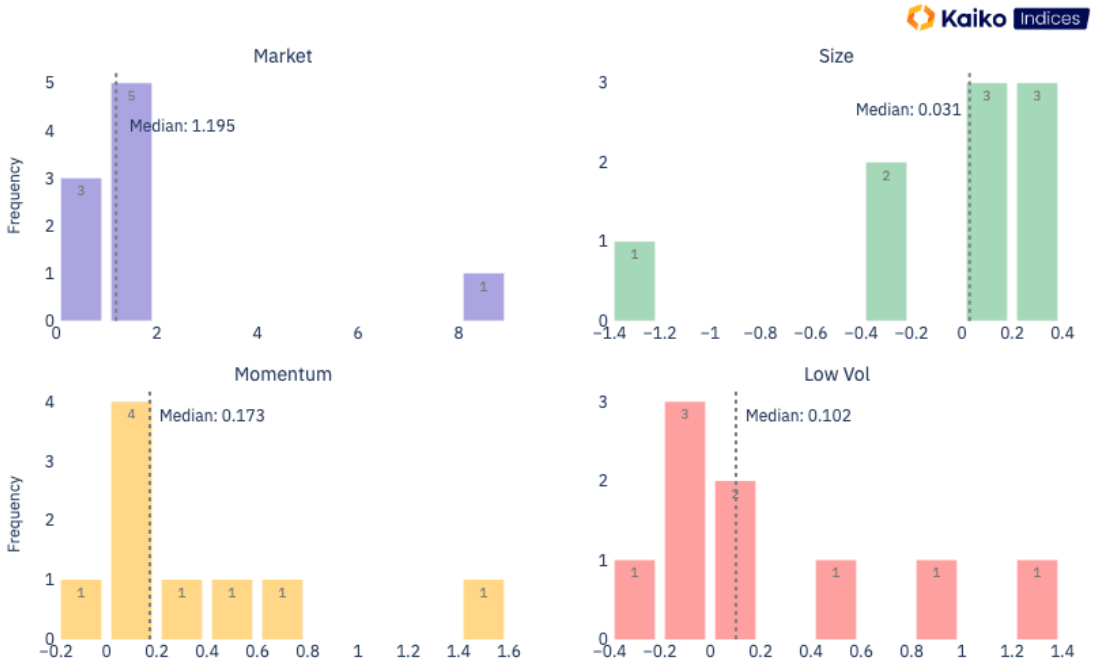
The regression analysis for the Meme coin category reveals a risk profile that fundamentally diverges from a Crypto-Native providing quantitative confirmation of their unique position as speculative, sentiment-driven instruments.

The four-factor model demonstrates notably limited explanatory power for this asset class, with an average adjusted R-squared of approximately 0.367. It indicates that more than 60% of daily return variance for typical Meme coins remains idiosyncratic, driven by factors beyond the scope of traditional asset pricing models. This substantial unexplained variance component aligns with the fundamental nature of Meme coins, whose valuations are heavily influenced by external factors including social media trends, community engagement dynamics, and broader cultural trends rather than underlying economic fundamentals.

5.3.1.2 Factor-wise analysis

The systematic component of Meme coin returns exhibits distinct characteristics that differentiate this category from other crypto assets. Most notably, Meme coins demonstrate pronounced sensitivity to the market factor, with a median beta coefficient of 1.195 across the category. This elevated market sensitivity indicates that Meme coins function as high-leverage instruments relative to the broader digital asset market, systematically amplifying both positive and negative market-wide movements. During periods of crypto market expansion, Meme coins tend to deliver outsized returns, while market contractions result in correspondingly severe underperformance. This high-beta characteristic establishes Meme coins as leveraged plays on overall crypto market sentiment rather than independent investment vehicles.

Graph 3: Factor Coefficient Distribution - Meme



Equally significant is the category's meaningful exposure to momentum factors, which provides empirical evidence of the trend-following behavior inherent to these assets. The positive and often statistically significant momentum loadings capture the self-reinforcing dynamics characteristic of social contagion effects, where rising prices attract additional speculative interest, creating feedback loops that further amplify price movements. This momentum sensitivity reflects the underlying social and psychological mechanisms that drive Meme coin valuations, distinguishing them from assets whose returns are primarily determined by fundamental economic factors.

Conversely, the analysis reveals a conspicuous absence of exposure to factors typically associated with fundamental value or portfolio stability. The size factor demonstrates minimal statistical significance, suggesting that Meme coin returns are not consistently driven by small-cap risk premiums that characterize traditional equity markets. Furthermore, the category exhibits negative, though largely insignificant, correlation with low-volatility factors, confirming that these assets represent the antithesis of defensive investments within the digital asset ecosystem. This factor structure reinforces the classification of Meme coins as pure risk-seeking instruments that cannot serve stabilizing functions in diversified portfolios.

5.1.7 CROSS-SECTIONAL REGRESSION RESULT

The most remarkable discovery concerns Meme coins, where no risk factors command statistically significant premia. All t-statistics remain low, suggesting that average factor returns are indistinguishable from zero. This provides compelling quantitative evidence that Meme coin performance operates outside traditional systematic risk frameworks. Their returns appear predominantly idiosyncratic, driven by narrative dynamics, sentiment shifts, and speculative force that lie beyond the scope of conventional factor models. This empirically validates their characterization as highly speculative instruments whose risk profiles defy explanation through established financial theory.

5.1.8 IMPLICATIONS

The regression results establish Meme coins as a distinct and unique asset category characterized by amplified market exposure, momentum-driven price dynamics, and substantial idiosyncratic risk components that operate outside traditional financial frameworks. Their return generation process combines systematic leverage to broader digital asset market movements with highly unpredictable, narrative-based speculative drivers.

This combination creates a unique risk-return profile that requires specialized analytical approaches and risk management frameworks. Traditional portfolio theory, which relies on systematic risk factors and diversification benefits, may be inadequate for understanding and managing Meme coin investments. Instead, successful Meme coin investing may require skills more commonly associated with cultural analysis, social media monitoring, and trend identification.

For institutional investors, the findings suggest that Meme coins should be treated as a separate asset class requiring distinct allocation and risk management approaches. Their amplified market sensitivity and lack of systematic risk pricing make them unsuitable for core portfolio positions but potentially valuable as tactical allocation opportunities for investors with high risk tolerance and specialized expertise in sentiment-driven markets.

The momentum characteristics of Meme coins also suggest potential opportunities for systematic trading strategies based on trend-following and sentiment analysis. However, the high idiosyncratic risk component means that such strategies would require careful risk management and position sizing to avoid excessive losses during periods when narrative-driven factors work against established positions.

5.4 Outlier Analysis: Real-World Asset

The regression analysis of Pax Gold (PAXG) provides an interesting implication of our taxonomic approach by demonstrating how tokenized traditional assets behave outside digital asset factor frameworks. While the four-factor model achieves statistical significance (F-statistic p-value =

0.0016), the economic explanatory power remains substantially limited, as evidenced by an adjusted R-squared of only 0.026.

This finding indicates that the systematic risk factors commonly associated with digital asset markets collectively explain merely 2.6% of PAXG's daily return variation. The substantial unexplained variance (97.4%) suggests that price dynamics of PAX gold are predominantly driven by idiosyncratic factors external to the digital asset ecosystem, most notably the price movements of its underlying collateral asset, physical gold.

An examination of individual factor coefficients provides additional evidence of PAXG's fundamental disconnection from digital asset market dynamics. The loadings on primary Crypto-Native factors exhibit both statistical insignificance and economic negligibility: market beta ($\beta_{PAXG, MKT}$ = -0.019, $p > 0.05$), size effect ($\beta_{PAXG, SIZE}$ = -0.020, $p > 0.05$), and momentum ($\beta_{PAXG, MOM}$ = -0.011, $p > 0.05$). These results empirically demonstrate PAXG's isolation from systematic risk factors that characterize the broader digital asset universe, including market-wide movements, altcoin size premiums, and trend-following behaviors.

The most noteworthy result emerges from the low-volatility factor loading ($\beta_{PAXG, LowVol}$ = 0.0079, $p = 0.000887$), which, while statistically significant, reveals a relationship that is economically modest in magnitude. This coefficient indicates that a one-unit increase in the low-volatility factor corresponds to only a 0.79 percentage point increase in PAXG returns.

The PAXG results serve as a powerful natural experiment that validates the necessity of our taxonomic approach. By including an asset that is technologically implemented on blockchain infrastructure but economically anchored to traditional markets, we can empirically demonstrate that technological implementation alone does not determine factor exposure patterns.

6. Conclusion

6.1 Summary of Findings

This paper has conducted a comprehensive empirical analysis of factor model applicability in digital asset markets, demonstrating that the effectiveness of systematic risk factors is fundamentally contingent on the economic characteristics and value drivers of different digital assets. Through rigorous analysis of 72 digital assets using a four-factor model encompassing market, size, momentum, and low-volatility factors, this study provides robust empirical evidence that factor investing principles require substantial adaptation when applied to the heterogeneous digital asset ecosystem. Our analysis yields four principal findings that collectively advance understanding of factor model performance and systematic risk pricing in digital asset markets.

First, we establish that factor model effectiveness varies dramatically across asset types within the digital asset universe. Traditional factor approaches achieve substantial explanatory power for utility-driven Crypto-Native assets (median adjusted $R^2 = 0.524$) but demonstrate limited effectiveness for sentiment-driven Meme coins (median adjusted $R^2 = 0.367$). This variation in model performance indicates that factor investing strategies cannot be uniformly applied across all digital asset categories without significant loss of explanatory power and practical utility.

Second, systematic risk pricing mechanisms operate differently across digital asset categories, challenging assumptions about universal factor premium existence. Cross-sectional analysis reveals that momentum represents the sole systematically priced risk factor for Crypto-Native assets ($t = 2.24$, $p < 0.05$), indicating that investors are compensated for bearing trend-following risk associated with technological narratives and adoption cycles. Conversely, Meme coins exhibit complete absence of systematic risk pricing across all factors examined, with returns appearing predominantly driven by idiosyncratic forces that operate outside of the traditional factor model. This fundamental asymmetry in risk pricing suggests that factor investing strategies require category-specific implementation approaches.

Third, market sensitivity patterns reveal systematic differences in factor exposures that have profound implications for portfolio construction and risk management. Meme coins demonstrate amplified market sensitivity (median $\beta = 1.195$) compared to Crypto-Native assets (median $\beta = 0.745$), representing 60% higher systematic risk exposure. Statistical validation through two-sample t-tests confirms these differences are economically meaningful (Cohen's $d = 1.47$ for market factors), indicating that factor-based portfolio construction must account for category-specific risk characteristics rather than assuming homogeneous exposures.

Fourth, the analysis of PAX Gold provides a methodological implication that factor model applicability depends on fundamental economic drivers rather than technological implementation. Pax Gold (PAXG) demonstrates near-complete disconnection from digital asset systematic risk factors ($R^2 = 0.026$, market $\beta = -0.019$), despite its blockchain-based implementation. This finding confirms that factor model selection should be based on economic substance rather than technological infrastructure, with important implications for the growing tokenized asset and securities.

These findings collectively establish that successful factor investing in digital asset markets requires recognition of fundamental heterogeneity in systematic risk relationships. The differential effectiveness of factor models across asset categories indicates that portfolio construction, risk management, and performance attribution strategies must be tailored to the specific economic characteristics of different digital asset segments rather than applying uniform factor approaches across the entire digital asset universe.

6.2 Implication for Institutional Investors

The empirical findings of this research carry profound implications for institutional investors, asset managers, portfolio strategists, and financial advisors navigating the increasingly complex digital asset landscape. As digital assets transition from speculative instruments to legitimate portfolio components, the application of rigorous factor modeling becomes essential for systematic risk management, performance attribution, and strategic allocation decisions.

For institutional investors, this research demonstrates that digital asset markets have reached sufficient maturity to support systematic factor investing approaches. The substantial explanatory power achieved by our four-factor model (median adjusted R^2 ranging from 0.367 to 0.524 across different asset types) indicates that systematic risk factors now drive a significant portion of digital asset returns, moving beyond the purely speculative dynamics that characterized early digital asset markets.

Portfolio Construction

The systematic measurement of factor exposures provides portfolio managers with quantitative tools for risk assessment that extend far beyond simple correlation analysis. Understanding that certain assets exhibit amplified market sensitivity ($\beta = 1.195$) while others demonstrate momentum characteristics enables precise risk budgeting and exposure management across systematic risk dimensions. The identification of momentum as a systematically priced risk factor ($t = 2.24$, $p < 0.05$) provides empirical evidence that certain systematic strategies can generate consistent risk-adjusted returns in digital asset markets. This finding transforms digital asset investment from pure speculation to evidence-based systematic investing, enabling institutional adoption of quantitative approaches with measurable risk-return characteristics.

Risk management

This research demonstrates that successful digital asset investment increasingly depends on systematic analytical approaches rather than speculative trading strategies. Factor models provide institutional investors with evidence-based frameworks for generating consistent risk-adjusted returns while maintaining professional investment standards and compliance. As digital asset markets continue to mature, factor-based investment approaches will become increasingly essential for institutional participation and long-term investment success in digital asset markets.

6.3 Limitations and Avenues for Future Research

6.1.1 FACTOR MODEL COMPLETENESS

The four-factor model employed in this study, while providing meaningful insights, exhibits clear limitations in explanatory power, particularly for Meme coins with median adjusted R-squared values of only 0.367. This suggests that substantial systematic risk factors remain unidentified. The significant unexplained variance (approximately 60% for Meme coins) indicates that our current factor framework captures only a fraction of the systematic risk structure in digital asset markets.

For the future study, we will explore whether additional factors such as value, quality, and growth with blockchain-related metrics as how traditional finance defines factors gets challenged when applied to digital asset markets. Book-to-market ratios are meaningless for protocol tokens, and traditional valuation metrics often fail to capture the unique value propositions of decentralized networks, such as network fundamentals (active addresses, transaction volumes, developer activity), protocol economics (token velocity, staking ratios, fee generation), governance metrics (proposal participation, voting concentration), and technical indicators (hash rates for PoW, validator counts for PoS). Additionally, we will employ a sectoral approach, such as layer 2 and computing, to identify digital-asset-specific risk patterns across different blockchain ecosystems and the role in the digital asset framework. It will enable more targeted risk assessment tailored to the unique characteristics of various digital asset sectors.

6.1.2 MARKET REGIME ANALYSIS

Our analysis assumes temporal stability of factor loadings, which may not hold across different market cycles or structural breaks in the digital asset ecosystem. The rapid evolution of the crypto market including regulatory changes, technological advance, and institutional adoption may cause factor sensitivities to shift over time. Future research should incorporate time-varying factor models or regime-switching frameworks to account for structural instability.

6.1.3 RISK-FREE RATE ASSUMPTION

The assumption of a zero risk-free rate, while pragmatic given the current digital asset ecosystem, may bias our factor premium estimates. As the digital asset space matures and risk-free instruments emerge within the digital asset ecosystem such as staking yields from established proof-of-stake networks, future models should incorporate appropriate risk-free benchmarks.

7. Reference

Barrera, D. R., & Minovitsky, S. (2021). *Could Factors Have Explained Cryptocurrency Risk?* MSCI Research & Insights. https://www.msci.com/research-and-insights/blog-post/could-factors-have-explained-cryptocurrency-risk

Charles, A. (2024, October 10). *6th Annual Global Crypto Hedge Fund Report*. PwC. Retrieved September 3, 2025, from https://www.pwc.com/gx/en/industries/financial-services/crypto-services/sixth-annual-global-crypto-hedge-fund-report.html

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). LAWRENCE ERLBAUM ASSOCIATES.

Cont, R. (2001). Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues. *QUANTITATIVE FINANCE*, *1*(1), 223-236. http://rama.cont.perso.math.cnrs.fr/pdf/empirical.pdf

EY Pantheon & Coinbase. (2025). *2025 Institutional Investor Digital Assets Survey*. https://www.ey.com/content/dam/ey-unified-site/ey-com/en-us/insights/financial-services/documents/ey-growing-enthusiasm-propels-digital-assets-into-the-mainstream.pdf

Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, *38*(1), 34-105. https://www.jstor.org/stable/2350752

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56. https://www.bauer.uh.edu/rsusmel/phd/Fama-French_JFE93.pdf

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

Isac, C., & Erdosi, T. (2024). *A Factor Model for Digital Assets*. CF Benchmark. https://docs.cfbenchmarks.com/A-Factor-Model-for-Digital-Assets.pdf

Jagadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, *48*(1), 65-91. https://www.jstor.org/stable/2328882

Jensen, M. C. (1968). The Performance of Mutual Funds in the Period 1945–1964. *The Journal of Finance*, *23*(2), 389-416. https://doi.org/10.1111/j.1540-6261.1968.tb00815.x

Liu, Y., & Tsyvinski, A. (2018). Risks and Returns of Cryptocurrency. Available at SSRN: https://ssrn.com/abstract=3226952

Wilder, J. W. (1978). *New Concepts in Technical Trading Systems*. Trend Research.

8. Appendix

8.1 Asset Classification Details

Asset	Asset Name	Category	Description
aave	Aave	Crypto Native	A decentralized liquidity protocol where users can participate as suppliers or borrowers
ada	Cardano	Crypto Native	A public, proof-of-stake Layer-1 blockchain platform.
akt	Akash Network	Crypto Native	A decentralized cloud computing marketplace built on the Cosmos SDK.
algo	Algorand	Crypto Native	A proof-of-stake Layer-1 blockchain and digital asset.
apt	Aethir	Crypto Native	A decentralized cloud computing platform providing decentralized GPU infrastructure
arb	Aptos	Crypto Native	A Layer-1 blockchain using the Move language, focused on scalability and security.
ath	Arbitrum	Crypto Native	An Ethereum Layer-2 scaling solution using optimistic rollups.
atom	Cosmos	Crypto Native	A protocol for creating an "internet of blockchains" enabling interoperability.
avax	Avalanche	Crypto Native	A Layer-1 blockchain platform known for speed and scalability, rivaling Ethereum.
axs	Axie Infinity	Crypto Native	Governance token for a Pokémon-style NFT game
bch	Bitcoin Cash	Crypto Native	A hard fork of Bitcoin, designed for faster and cheaper payments.
bonk	Bonk	Meme	A Solana-based "dog coin" created as a community-driven response to VC dominance.
btc	Bitcoin	Crypto Native	The very first digital asset, a decentralized store of value and payment system.
crv	Curve DAO Token	Crypto Native	The governance token for Curve.fi, a DeFi exchange for stablecoins and ERC-20 tokens.
doge	Dogecoin	Meme	The original Meme coin, created as a joke based on the "doge" internet meme.
dot	Polkadot	Crypto Native	A nominated proof-of-stake blockchain platform enabling cross-chain communication.
egld	MultiversX	Crypto Native	The native token for the MultiversX (formerly Elrond) distributed blockchain network.
eigen	EigenLayer	Crypto Native	A protocol on Ethereum introducing "restaking" to extend crypto-economic security.
ena	Ethena	Crypto Native	A synthetic dollar protocol whose governance token (ENA)
ens	Ethereum Name Service	Crypto Native	A decentralized naming protocol on Ethereum for human-readable addresses.
eos	EOS.IO	Crypto Native	A blockchain platform for the development of decentralized applications (dApps).
etc	Ethereum Classic	Crypto Native	The original Ethereum blockchain, maintaining the pre-DAO-fork history.
eth	Ethereum	Crypto Native	A decentralized, open-source blockchain with smart contract functionality
fartcoin	FartCoin	Meme	A digital asset with a name clearly designed for virality
fet	Fetch.ai	Crypto Native	A decentralized machine learning platform for applications like trading and optimization.
fil	Filecoin	Crypto Native	A decentralized storage network that allows users to rent unused hard drive space.
floki	Floki	Meme	A community-driven digital asset inspired by Elon Musk's Shiba Inu dog, Floki.
gala	Gala	Crypto Native	The utility token for the Gala Games ecosystem, a blockchain gaming platform.
grass	Grass	Crypto Native	A token for a project that lets you monetize an unused internet bandwidth.

Asset	Asset Name	Category	Description
grt	The Graph	Crypto Native	A decentralized protocol for indexing and querying data from blockchains.
hbar	Hedera	Crypto Native	The native token of the Hedera public network, used for fees and securing the network.
icp	Internet Computer	Crypto Native	A public blockchain network designed to extend the internet with cloud computing.
inj	Injective	Crypto Native	A specialized Layer-1 protocol for building exchange, DeFi, and Web3 applications.
jasmy	JasmyCoin	Crypto Native	An ERC-20 token for the Jasmy platform, focusing on data sovereignty and IoT.
ksm	Kusama	Crypto Native	A pre-production "canary network" for Polkadot, used for testing new features.
ldo	Lido DAO	Crypto Native	The governance token for Lido, a liquid staking solution for PoS blockchains.
link	Chainlink	Crypto Native	A decentralized oracle network that connects smart contracts with off-chain data.
ltc	Litecoin	Crypto Native	An early peer-to-peer digital asset, inspired by Bitcoin but with faster block times.
mana	Decentraland	Crypto Native	The digital asset for Decentraland, a 3D virtual world platform on Ethereum.
mkr	Maker	Crypto Native	The governance token for the MakerDAO protocol, which issues the DAI stablecoin.
morpho	Morpho DAO	Crypto Native	A decentralized finance (DeFi) protocol that acts as a lending optimizer
near	NEAR Protocol	Crypto Native	A dApp platform and Ethereum competitor focused on developer and user-friendliness.
om	MANTRA	Crypto Native	A security-focused Layer-1 blockchain designed specifically for the tokenization of RWAs.
ondo	Ondo	Crypto Native	The governance token for Ondo Finance, a DeFi protocol of tokenization
op	Optimism	Crypto Native	An Ethereum Layer-2 scaling solution using optimistic rollups to reduce fees and latency.
paxg	Pax Gold	-	An asset-backed token where one token represents one troy ounce of a gold bar.
pendle	Pendle	Crypto Native	A DeFi protocol that enables the tokenization and trading of future yield.
pepe	Pepe	Meme	A Meme coin inspired by the "Pepe the Frog" internet meme, built on Ethereum.
pol	Polygon	Crypto Native	A Layer-2 scaling platform for Ethereum, aiming to create a multi-chain system.
popcat	Popcat	Meme	A memecoin inspired by the viral internet meme of a cat making a "pop" sound.
pyth	Pyth Network	Crypto Native	A decentralized oracle platform providing high-fidelity, real-time financial data.
qnt	Quant	Crypto Native	The token for the Quant Network's Overledger, designed for blockchain interoperability.
render	Render Token	Crypto Native	The token for a decentralized GPU rendering network on Ethereum.
sand	The Sandbox	Crypto Native	The native token of The Sandbox, a virtual world for monetizing gaming experiences.
sei	Sei blockchain	Crypto Native	A Layer 1 blockchain built to be the absolute fastest environment for on-chain trading
shib	Shiba Inu	Meme	An Ethereum-based token positioned as a "Dogecoin killer."
sol	Solana	Crypto Native	A high-performance Layer-1 blockchain known for its speed and low transaction costs.
stx	Stacks	Crypto Native	A network that enables smart contracts and decentralized applications on Bitcoin.
sui	Sui	Crypto Native	A permissionless Layer-1 smart contract platform using the Move programming language.
trump	Official Trump	Meme	A memecoin inspired by the unofficial Maga (TRUMP) meme coin
trx	TRON	Crypto Native	A decentralized, proof-of-stake blockchain with smart contract functionality.
uni	Uniswap	Crypto Native	The governance token for the Uniswap decentralized exchange (DEX) protocol.
vet	VeChain	Crypto Native	A L1 smart contract platform focused on supply chain and data management.
virtual	Virtual Protocol	Crypto native	A decentralized protocol enabling the autonomous AI agents on blockchain
w	Wormhole	Crypto Native	An interoperability protocol that allows communication between blockchain networks.
wif	Dogwifhat	Meme	A Solana-based Meme coin featuring a Shiba Inu dog wearing a hat.
wld	Worldcoin	Crypto Native	The identity verification project by scanning people's irises
xlm	Stellar	Crypto Native	A decentralized payment network for cross-border transactions.
xrp	XRP	Crypto Native	The native token of the XRP Ledger, designed for fast and cost-efficient global payments.

Asset	Asset Name	Category	Description
xtz	Tezos	Crypto Native	A Layer-1 blockchain with on-chain governance and smart contract functionality.
zec	Zcash	Crypto Native	A privacy-focused digital asset using zk-SNARKs to enable shielded transactions.
zro	LayerZero	Crypto Native	An interoperability protocol designed to connect different blockchains.

8.2 Time-series Regression Results (72 assets)

Asset	Observations	Intercept (α)	Low Volatility	Size	Momentum	Market	R^2	Adjusted R^2
aave	1670	0.001	-0.074	0.268***	0.052	1.161***	0.593	0.592
ada	2023	0.001	0.098	0.411***	0.065	0.787***	0.635	0.634
akt	1140	0.001	0.19	0.032	0.087	0.850***	0.267	0.265
algo	2023	0.000	0.407**	0.312***	0.129**	0.500***	0.530	0.529
apt	942	0.000	0.248	0.201	0.139*	0.876***	0.446	0.444
arb	760	-0.002*	0.397	0.335***	0.018	0.899***	0.644	0.642
ath	293	-0.003	0.670**	-0.188	0.104	0.320	0.337	0.328
atom	2023	0.000	0.282**	0.341***	0.061	0.657***	0.557	0.556
avax	1669	0.001	0.087	0.365***	0.102	0.950***	0.550	0.549
axs	1488	0.001	0.310*	0.193*	0.144**	0.728***	0.422	0.420
bch	2023	-0.001	0.560***	-0.023	0.007	0.554***	0.643	0.642
bonk	486	0.002	-0.252	0.219	0.173	1.568***	0.513	0.509
btc	2023	0.000	0.157***	-0.443***	-0.006	0.803***	0.926	0.926
crv	1664	0.001	0.166	0.349***	0.124*	0.889***	0.537	0.536
doge	2023	0.003	-0.162	0.009	0.165*	1.018***	0.182	0.180
dot	1761	-0.001	0.397**	0.189*	0.089**	0.634***	0.697	0.696
egld	1670	0.000	0.287**	0.166*	0.138***	0.654***	0.509	0.507
eigen	207	-0.001	1.389***	0.683**	0.171	-0.111	0.670	0.664
ena	365	0.000	0.501	0.011	0.148	1.014**	0.484	0.478
ens	1305	0.001	-0.022	0.242*	0.126*	1.081***	0.491	0.489
eos	2023	-0.001*	0.421***	0.254***	0.014	0.598***	0.668	0.668
etc	2023	0.000	0.481***	0.177**	0.183	0.423*	0.505	0.504
eth	2023	0.001	-0.04	-0.028	-0.070***	1.169***	0.886	0.886
fartcoin	25	0.002	1.254*	-1.243	1.424***	8.687***	0.260	0.112
fet	1760	0.001	0.198	0.086	0.281***	0.716***	0.451	0.449
fil	1670	-0.001	0.492**	0.148	0.163**	0.391**	0.502	0.501

Asset	Observations	Intercept (α)	Low Volatility	Size	Momentum	Market	R^2	Adjusted R^2
floki	540	0.004	0.405	0.031	0.333	0.956**	0.263	0.258
gala	1306	-0.001	0.172	0.379*	0.243***	0.890***	0.553	0.552
grass	171	0.000	0.951**	0.529	-0.070	0.029	0.169	0.149
grt	1579	-0.001	0.107	0.168*	0.161**	0.957***	0.621	0.620
hbar	2020	0.002	0.651**	0.054	0.098	0.324	0.322	0.320
icp	1488	-0.001	0.183	0.207*	0.087	0.852***	0.521	0.519
inj	1480	0.001	0.025	0.158*	0.342***	0.794***	0.438	0.436
jasmy	1305	0.000	0.269	0.119	0.234***	0.762***	0.417	0.415
ksm	1670	-0.001	0.424*	0.205**	0.078	0.622***	0.509	0.508
ldo	1214	0.000	0.204	0.101	0.044	1.308***	0.481	0.479
link	2023	0.001	-0.036	0.423***	-0.004	1.074***	0.677	0.677
ltc	2023	-0.001	0.507***	-0.026	0.024	0.585***	0.714	0.714
mana	1815	0.002	0.513**	0.078	0.222***	0.473***	0.382	0.380
mkr	1886	0.001	0.124	0.108	0.205	0.711***	0.436	0.434
morpho	206	0.001	1.556***	0.391	-0.023	-0.240	0.495	0.484
near	1486	0.001	0.178	0.184*	0.135**	0.958***	0.503	0.501
om	25	-0.008*	1.652***	2.386***	0.587***	-3.429**	0.719	0.663
ondo	389	0.000	0.215	0.116	0.003	1.094***	0.535	0.530
op	1033	-0.001	0.167	0.190	0.154**	1.090***	0.566	0.564
paxg	2011	0.000	0.080***	-0.023*	-0.011	-0.021	0.028	0.026
pendle	296	0.000	0.656**	-0.122	0.059	0.798***	0.573	0.568
pepe	760	0.002	0.102	-0.363	0.493*	1.294***	0.506	0.503
pol	319	-0.002*	1.157***	0.428***	-0.113*	0.076	0.776	0.773
popcat	388	0.002	0.15	-0.212	0.132	1.824***	0.374	0.367
pyth	460	-0.004*	0.515*	0.152	0.006	0.884***	0.605	0.601
qnt	1397	0.000	0.529***	0.123	0.101	0.376**	0.452	0.451
render	486	-0.001	0.353	0.107	0.025	1.113***	0.641	0.638
sand	1488	0.001	0.208	0.233**	0.255***	0.653***	0.450	0.449
sei	669	0.001	0.027	0.138	0.056	1.288***	0.369	0.365
shib	1488	0.002	-0.012	0.390**	0.043	0.917***	0.344	0.343
sol	1756	0.003*	-0.445***	0.191*	0.144*	1.275***	0.462	0.460
stx	1577	0.001	0.278*	-0.183**	0.205**	0.792***	0.397	0.396
sui	760	0.002	-0.12	0.350**	0.001	1.191***	0.361	0.358
trump	178	-0.004	0.899**	0.216	-0.012	0.448	0.439	0.426
trx	2023	0.001	1.250***	0.547	-0.129	-0.281	0.453	0.452
uni	1670	0.001	0.119	0.203**	0.062	0.949***	0.554	0.553
vet	1979	0.000	0.498***	0.216**	0.08	0.613***	0.622	0.621

Asset	Observations	Intercept (α)	Low Volatility	Size	Momentum	Market	R^2	Adjusted R^2
virtual	25	-0.007*	1.642**	1.049	1.735***	-1.751	0.607	0.528
w	373	-0.003	0.576*	0.315*	-0.008	0.714**	0.450	0.444
wif	508	0.004	-0.123	0.089	0.638**	1.195**	0.388	0.384
wld	216	0.000	1.323**	-0.700	-0.350	0.970	0.340	0.328
xlm	2023	0.001	0.581**	0.405***	-0.040	0.483**	0.562	0.561
xrp	2023	0.001	0.114	0.367***	-0.060	0.869***	0.533	0.532
xtz	2023	-0.001	0.349**	0.322***	0.005	0.661***	0.620	0.619
zec	2023	-0.001	0.541***	0.077	0.088*	0.448***	0.558	0.558
zro	298	-0.002	0.746**	0.144	-0.095	0.700**	0.465	0.458

8.3 Walk-Forward validation of out-of-sample test

Overall Performance Summary:

- Number of Windows: 60
- Median R-squared: 0.5994
- Median Root Mean Squared Error (RMSE): 0.0278
- Median Mean Absolute Error (MAE): 0.0200
- Date Range: 2020-01-01 to 2025-07-01
- Model Type: newey_west

Table: Full result of Walk-Forward Validation

Training Period		Testing Period		RMSE	MAE	R2	assets
Start Date	End date	Start date	End date				
2020-01-01	2020-07-01	2020-07-01	2020-08-01	0.0337	0.0236	0.3817	19
2020-02-01	2020-08-01	2020-08-01	2020-09-01	0.0324	0.0207	0.4138	19
2020-03-01	2020-09-01	2020-09-01	2020-10-01	0.0259	0.0190	0.6164	19
2020-04-01	2020-10-01	2020-10-01	2020-11-01	0.0226	0.0156	0.4844	20
2020-05-01	2020-11-01	2020-11-01	2020-12-01	0.0346	0.0266	0.6713	20
2020-06-01	2020-12-01	2020-12-01	2021-01-01	0.0385	0.0271	0.2277	22
2020-07-01	2021-01-01	2021-01-01	2021-02-01	0.0645	0.0491	0.3702	22
2020-08-01	2021-02-01	2021-02-01	2021-03-01	0.0590	0.0422	0.5251	22
2020-09-01	2021-03-01	2021-03-01	2021-04-01	0.0471	0.0357	0.3549	30
2020-10-01	2021-04-01	2021-04-01	2021-05-01	0.0529	0.0434	0.4377	30

Training Period		Testing Period		RMSE	MAE	R2	assets
Start Date	End date	Start date	End date				
2020-11-01	2021-05-01	2021-05-01	2021-06-01	0.0574	0.0446	0.7447	30
2020-12-01	2021-06-01	2021-06-01	2021-07-01	0.0305	0.0230	0.8360	32
2021-01-01	2021-07-01	2021-07-01	2021-08-01	0.0270	0.0194	0.6766	32
2021-02-01	2021-08-01	2021-08-01	2021-09-01	0.0340	0.0247	0.5382	32
2021-03-01	2021-09-01	2021-09-01	2021-10-01	0.0411	0.0291	0.6090	38
2021-04-01	2021-10-01	2021-10-01	2021-11-01	0.0425	0.0329	0.2333	38
2021-05-01	2021-11-01	2021-11-01	2021-12-01	0.0409	0.0283	0.4232	38
2021-06-01	2021-12-01	2021-12-01	2022-01-01	0.0347	0.0254	0.6613	39
2021-07-01	2022-01-01	2022-01-01	2022-02-01	0.0296	0.0234	0.7804	39
2021-08-01	2022-02-01	2022-02-01	2022-03-01	0.0275	0.0212	0.7497	39
2021-09-01	2022-03-01	2022-03-01	2022-04-01	0.0304	0.0232	0.3873	42
2021-10-01	2022-04-01	2022-04-01	2022-05-01	0.0245	0.0185	0.6306	42
2021-11-01	2022-05-01	2022-05-01	2022-06-01	0.0368	0.0259	0.7475	42
2021-12-01	2022-06-01	2022-06-01	2022-07-01	0.0332	0.0237	0.6063	44
2022-01-01	2022-07-01	2022-07-01	2022-08-01	0.0282	0.0195	0.6819	44
2022-02-01	2022-08-01	2022-08-01	2022-09-01	0.0263	0.0194	0.6063	44
2022-03-01	2022-09-01	2022-09-01	2022-10-01	0.0322	0.0252	0.3028	44
2022-04-01	2022-10-01	2022-10-01	2022-11-01	0.0216	0.0149	0.4686	44
2022-05-01	2022-11-01	2022-11-01	2022-12-01	0.0445	0.0268	0.5238	44
2022-06-01	2022-12-01	2022-12-01	2023-01-01	0.0192	0.0142	0.7273	45
2022-07-01	2023-01-01	2023-01-01	2023-02-01	0.0333	0.0268	0.5960	45
2022-08-01	2023-02-01	2023-02-01	2023-03-01	0.0295	0.0142	0.5944	45
2022-09-01	2023-03-01	2023-03-01	2023-04-01	0.0267	0.0181	0.7278	46
2022-10-01	2023-04-01	2023-04-01	2023-05-01	0.0182	0.0138	0.5998	46
2022-11-01	2023-05-01	2023-05-01	2023-06-01	0.0151	0.0112	0.5990	46
2022-12-01	2023-06-01	2023-06-01	2023-07-01	0.0240	0.0177	0.6642	46
2023-01-01	2023-07-01	2023-07-01	2023-08-01	0.0229	0.0166	0.4393	46
2023-02-01	2023-08-01	2023-08-01	2023-09-01	0.0147	0.0116	0.5870	46
2023-03-01	2023-09-01	2023-09-01	2023-10-01	0.0152	0.0114	0.4479	48
2023-04-01	2023-10-01	2023-10-01	2023-11-01	0.0183	0.0132	0.4860	48
2023-05-01	2023-11-01	2023-11-01	2023-12-01	0.0281	0.0213	0.4762	48
2023-06-01	2023-12-01	2023-12-01	2024-01-01	0.0333	0.0251	0.2464	48
2023-07-01	2024-01-01	2024-01-01	2024-02-01	0.0242	0.0192	0.6490	49
2023-08-01	2024-02-01	2024-02-01	2024-03-01	0.0292	0.0206	0.2742	49
2023-09-01	2024-03-01	2024-03-01	2024-04-01	0.0413	0.0310	0.2943	49
2023-10-01	2024-04-01	2024-04-01	2024-05-01	0.0270	0.0194	0.6613	49

Training Period		Testing Period		RMSE	MAE	R2	assets
Start Date	End date	Start date	End date				
2023-11-01	2024-05-01	2024-05-01	2024-06-01	0.0247	0.0173	0.5375	49
2023-12-01	2024-06-01	2024-06-01	2024-07-01	0.0208	0.0155	0.7098	49
2024-01-01	2024-07-01	2024-07-01	2024-08-01	0.0238	0.0180	0.6106	49
2024-02-01	2024-08-01	2024-08-01	2024-09-01	0.0229	0.0163	0.7244	49
2024-03-01	2024-09-01	2024-09-01	2024-10-01	0.0194	0.0156	0.6829	49
2024-04-01	2024-10-01	2024-10-01	2024-11-01	0.0198	0.0153	0.7017	49
2024-05-01	2024-11-01	2024-11-01	2024-12-01	0.0503	0.0336	0.5365	49
2024-06-01	2024-12-01	2024-12-01	2025-01-01	0.0402	0.0280	0.6941	49
2024-07-01	2025-01-01	2025-01-01	2025-02-01	0.0232	0.0179	0.7464	49
2024-08-01	2025-02-01	2025-02-01	2025-03-01	0.0241	0.0188	0.7708	49
2024-09-01	2025-03-01	2025-03-01	2025-04-01	0.0239	0.0180	0.7405	49
2024-10-01	2025-04-01	2025-04-01	2025-05-01	0.0245	0.0194	0.5691	49
2024-11-01	2025-05-01	2025-05-01	2025-06-01	0.0230	0.0165	0.7399	49
2024-12-01	2025-06-01	2025-06-01	2025-07-01	0.0180	0.0132	0.7771	49

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