What Drives Cryptocurrency Returns: A Returns-Based Style Analysis

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Abstract

This paper applies returns-based style analysis (RBSA) to 27 major cryptocurrencies. Our analysis focuses on four key factors: market risk, monetary policy, currency fluctuations, and crypto-specific dynamics. Our empirical results show that although traditional financial factors, such as equity market performance, interest rates, and exchange rates, do influence cryptocurrency returns, crypto-related factors have the most significant impact. Bitcoin and Ethereum exhibit strong sensitivity to market risk, underscoring their integration with traditional financial markets. In contrast, altcoin returns are predominantly driven by crypto-specific dynamics. Financial tokens demonstrate greater responsiveness to interest rate shifts, while meme coins are largely influenced by speculative trading and investor sentiment. These findings highlight the dominant role of cryptocurrency-specific factors in driving returns while maintaining linkages to traditional financial markets. The results provide valuable insights for portfolio managers, policymakers, and investors managing the changing crypto market.

***Keywords**: Cryptocurrencies; Bitcoin; Returns-based style analysis; Machine learning; Gradient boosting*

***JEL classifications**: G10; G11; G12; C61*

1. Introduction

As cryptocurrencies continue to grow in popularity and achieve mainstream acceptance, their increasing impact on the financial system makes it increasingly important for economists, policymakers, and investors to understand what drives their prices. Academic interest in this topic has also grown significantly and the respective empirical evidence shows that cryptocurrency prices are influenced by factors like market-specific trends, economic conditions, stock performance, commodity prices, investor sentiment, and uncertainty (Nagl, 2024).

Researchers have used various methods to identify the factors driving cryptocurrency returns. In this paper, we take a different approach by applying returns-based style analysis (RBSA) - a traditional tool for analyzing mutual fund returns - to the study of cryptocurrencies. To the best of our knowledge, RBSA has not yet been employed in the context of cryptocurrency markets. This innovative application provides new insights into the factors influencing cryptocurrency performance. In our empirical analysis, we focus on four key factors to explain cryptocurrency returns: the general risk premium factor, the interest rate factor, the dollar factor, and the crypto-specific factor[1].

To capture the general risk premium factor, which reflects changes in investor risk appetite, we use S&P 500 returns. The interest rate factor, which captures the effects of monetary policy shocks on cryptocurrencies, is captured by the two-year Treasury yields, which effectively reflect market expectations of short- to medium-term interest rate movements and monetary policy shifts. Schilling and Uhlig (2019) note that cryptocurrency returns are sensitive to macroeconomic risks, particularly those arising from monetary policy decisions. The dollar factor, which captures the impact of currency fluctuations on cryptocurrency markets, is proxied by the daily returns of the U.S. Dollar Index (DXY), which measures the performance of the dollar against a basket of major global currencies and usually serves as an indicator of broader currency trends. According to Schilling and Uhlig (2019) and Athey et al. (2016), the coexistence and competition between fiat currencies and cryptocurrencies play a significant role in forming the latter price dynamics. Finally, the crypto-specific factor is measured using changes in the market capitalization of stable coins, which are regarded as safe assets within the broader digital asset ecosystem (see, e.g., Baur and Hoang, 2021; Grobys et al., 2021; Lyons and Viswanath-Natraj, 2023). This factor helps differentiate between shifts driven by crypto adoption and those driven by risk sentiment within the crypto market. Specifically, a crypto risk sentiment shock occurs when investors move from volatile cryptocurrencies to safer stable coins, leading to an increase in stablecoin market capitalization.

Our paper also contributes to the strand of literature that attempts to understand and address the limitations of RBSA and finds ways of improving the method's accuracy and stability (see Rekenthaler et al., 2006 and DeRoon et al., 2004 for a relevant discussion). By using a Gradient Boosting Regressor (GBR) model, we address key limitations of traditional returns-based style analysis, providing a more reliable assessment of cryptocurrencies' exposure to individual factors. Gradient boosting, a powerful machine learning algorithm for regression and classification tasks (Friedman, 2001), enhances predictive accuracy by combining multiple weak learners, typically decision trees. Its effectiveness in delivering robust predictive models has been widely recognized (Chen & Guestrin, 2016). Additionally, traditional style analysis struggles to distinguish between significant and insignificant style weights, complicating risk interpretation. While Lobosco and DiBartolomeo (1997) introduced a two-step method for calculating confidence intervals, our approach improves upon this by using bootstrapped

[1] These factors were selected after evaluating a range of alternatives (e.g., the VIX), which ultimately did not provide additional explanatory power.

confidence intervals, offering deeper insights into the stability and significance of style factor exposures.

Our empirical findings show that, while traditional financial factors like general market risks, interest rates, and the US dollar have varying degrees of influence on cryptocurrency returns, crypto-specific factors have the strongest impact. Specifically, the average risk factor sensitivity of 0.3463 highlights the significant role of broader market risks, while the relatively low sensitivity to interest rates (0.1027) suggests limited exposure to macroeconomic rate changes. Moderate sensitivity to the US dollar (0.1984) reflects its continued importance in crypto transactions despite the global nature of the market. However, the highest average sensitivity of 0.3526 to crypto-specific factors underscores the dominant influence of technological advancements, regulatory developments, and ecosystem growth in shaping cryptocurrency performance.

The rest of the paper is organized as follows: the next section reviews the relevant empirical literature. Section 3 analyzes the data and methodology employed, while section 4 presents and discusses the empirical results. Section 5 includes the concluding remarks.

2. Relevant Literature

2.1 Predictability of cryptocurrency returns

The predictability of cryptocurrency returns has been extensively explored in recent years, with researchers focusing on identifying key drivers and determining how these factors fit into prediction models. Some studies highlight the importance of cryptocurrency-specific information; for example, Jia et al. (2021) show that higher moments of intraday cryptocurrency returns can predict future returns, with extreme positive returns playing a key role in this predictability. Their findings suggest that cryptocurrency investors prefer lottery-like payoffs and are less worried about potential crashes. Liebi (2022) examines the existence of a value premium in crypto asset returns and investigates whether cryptocurrency prices reflect fundamentals, finding that while cryptocurrency with high ratios of active addresses to network value (value crypto assets) yield higher returns than those with low ratios (growth crypto assets), empirical evidence reveals the influence of non-fundamental factors despite theoretical models suggesting a positive relationship between network size and value. Similarly, Liu et al. (2020) identify three cryptocurrency risk factors: market return, size (market capitalization), and momentum, showing these factors explain the average cryptocurrency returns well. Separately, Liu et al. (2022) investigate common risk factors in cryptocurrency returns, identifying 24 characteristics related to size, momentum, volume, and volatility that can predict returns, drawing on established return predictors from the stock market.

Additionally, macroeconomic factors, stock market data, and commodities are important for predicting cryptocurrency returns. Liu et al. (2023) find that indicators such as the unemployment rate, inflation, and industrial production growth are strong predictors, while assets such as the equities, gold, and bonds are less effective. On the other hand, Liu & Tsyvinski (2021) study the exposure of cryptocurrency returns to precious metals (gold, platinum, and silver) and macroeconomic factors, but conclude that cryptocurrency returns can be predicted by factors specific to cryptocurrency markets, such as network effects, momentum, and investor attention.

Finally, there are studies that show the significance of investor behavior and sentiment; see Almeida and Gonçalves (2023) for a comprehensive relevant discussion. Generally, existing empirical evidence shows that cryptocurrency returns are influenced by several factors, such as cryptocurrencies fundamentals, financial assets, macroeconomic indicators, investors and market sentiment. Pečiulis et al. (2024) provide a systematic literature review of cryptocurrency forecasting, examining the relevant trends, and research themes.

2.2 Methods for identifying cryptocurrency return drivers

To identify the factors influencing cryptocurrency returns and their links to traditional financial assets, researchers have used methods like time-series analysis, factor models, and machine learning (ML). Many studies use machine learning to forecast cryptocurrency returns, with varying success and a focus on different factors. Akyildirim et al. (2021) analyze the predictability of returns for twelve liquid cryptocurrencies using ML algorithms, such as support vector machines, logistic regression, artificial neural networks, and random forests; their results show that the algorithms consistently achieved over 50% accuracy, suggesting predictability of price trends in the cryptocurrency markets. Basher & Sadorsky (2022) review the literature on Bitcoin price forecasting, noting that machine learning methods generally have higher predictive accuracy than parametric regression approaches. Cakici et al. (2024) investigate cross-sectional return predictability in cryptocurrency markets using a range of ML models and find that machine learning techniques can be successfully applied to predict returns. However, they show that the benefits from model complexity were limited, with simpler models outperforming more complex ones. Their findings also indicate that cryptocurrency returns are mainly determined by simple characteristics like market price, past alpha, momentum, and illiquidity.

Goodell et al. (2023) suggest that many existing studies of forecasting cryptocurrency prices suffer from a lack of explanatory power and propose a new explainable AI framework that can improve forecasting performance and interpretability. Similarly, Liu et al. (2021) use a deep learning method named to predict Bitcoin prices and show that it performs better than traditional machine learning methods. Furthermore, Liu et al. (2023) employ machine learning models to predict returns for a large set of 3703 cryptocurrencies over a long period and show that the eXtreme Gradient Boosting model performs well, and can capture nonlinear relationships between features and returns, outperforming OLS. Finally, Nagl (2024) uses machine learning models (XGBoost and Lasso) to investigate the intricacies of cryptocurrency returns.

2.3 Return-Based Style Analysis

In conclusion, our paper also contributes to the body of literature that focuses on understanding and addressing the limitations of Return-Based Style Analysis (RBSA) while exploring ways to enhance its accuracy and stability. Since Sharpe's (1992) seminal work introducing the traditional RBSA model, which uses regression analysis to assess a portfolio's exposure to different asset classes, numerous studies have applied RBSA, offering insights into its applications, shortcoming, and potential improvements. Indicatively, Agarwal and Naik (2000) develop a generalized style analysis by relaxing the constraints of traditional RBSA, allowing for negative style weights and weights that do not sum to 100%, making the method more suitable for hedge funds that take short positions. Lobosco and DiBartolomeo (1997) focus on the issue of statistical significance of style weights in RBSA by proposing a method for approximating confidence intervals for style weights, allowing for the identification of significant risk exposures, while DiBartolomeo and Witkowski (1997) apply an iterative application of Sharpe's method of style analysis to the classification of equity mutual funds. Swinkels and Van Der Sluis (2006) address the assumption of constant investment styles over time in traditional RBSA by using a Kalman filter to explicitly model time-varying exposures of mutual funds, which leads to more efficient use of data. Mason et al (2014) combine RBSA with characteristics-based style analysis to create a more comprehensive model and find that membership of style groups significantly explains the cross-sectional performance of mutual funds. Finally, Vistocco (2024) investigates the use of quantile regression to draw inferences on style coefficients, particularly in the presence of outliers.

3. Data and Methodology

Our dataset initially consists of the fifty largest cryptocurrencies by market capitalization, based on data from Yahoo Finance as of October 2024. After applying a screening process - selecting only cryptocurrencies with a first trading day before March 2021 and excluding stablecoins - we refine our sample to 27 cryptocurrencies. Table 1 presents their respective market capitalizations. Bitcoin is the largest by a significant margin, with a market capitalization of approximately 1.5 trillion USD. It is followed, at a considerable distance, by Ethereum, with Binance Coin and Solana ranking next. The sample period spans from March 2021 to October 2024.

< Insert Table 1 about here >

Predicting cryptocurrency returns relies on identifying key drivers and how they fit into the prediction model. We focus on the most common drivers from different categories. In particular, we analyze the daily return series of four key assets: the S&P 500 Index, two-year Treasury zero-coupon bonds, the U.S. Dollar Index (DXY), and the total market capitalization of all stablecoins. Data for stablecoins is sourced from DefiLlama, while the S&P 500, DXY, and two-year interest rates are obtained from Yahoo Finance.

Our empirical methodology is based on Sharpe's approach to analyzing mutual funds, which is called returns-based style analysis (RBSA). In simple terms, RBSA involves performing a constrained regression of mutual fund returns against relevant style indices (Sharpe, 1992). In particular, RBSA utilizes a multivariate linear regression framework where the dependent variable represents the historical returns of the portfolio under evaluation, and the independent variables correspond to the historical returns of asset class factors. This method, known as Sharpe's style regression, can be written as:

$$R' = F' \times \beta' + \varepsilon'$$

in which, R' denotes a (T × 1) vector of the portfolio's returns over T time periods, F' is a (T × N) matrix containing the historical returns of N selected factors, β' is a (N × 1) vector capturing the factor exposures, and ε' represents a (T × 1) vector of residual errors. The factors are subject to two constraints: their values must sum up to one, and they must remain non-negative. To identify the optimal set of exposures that minimize the residual (or tracking) variance, a quadratic programming algorithm is applied, ensuring adherence to these constraints.

In our analysis however, we use the Gradient Boosting Regressor (GBR) model to enhance prediction accuracy and minimize errors within the returns-based style analysis. GBR works well for regression tasks because it combines several simple models, usually decision trees, to create a stronger one (see Friedman, 2001 for details). GBR is a good fit for studying the effects on cryptocurrencies returns, as it can handle non-linear relationships and moderate potential multicollinearity issues. Because of its outstanding prediction performance in financial datasets and its capacity to manage non-linear interactions, GBR was chosen above other machine learning models including Random Forest, Neural Networks, and XGBoost. In contrast to Random Forest, which averages several decision trees, GBR constructs trees in a sequential manner to fix earlier mistakes and improve accuracy. Although comparable, XGBoost is computationally demanding and might not offer significant advantages for this dataset.

The pseudo-code for the GBR algorithm, adapted from Friedman (2001), is as follows:

Input: training set $\{(x_i, y_i)\}_{i=1}^{n}$, differentiable loss function $L(y, F(x))$ and number of iterations M

Output: trained GBR model $F_m(x)$

Steps:

Step 1. Initialize model with a constant value:

$$F_0(x) = arg\min_{\gamma}\sum_{i=1}^{n} L(y_i, \gamma)$$

Step 2. For m = 1 to M repeat the following:

2.1 Compute the pseudo-residuals: $r_{im} = -\left[\frac{\vartheta L(y_i, F(x_i))}{\vartheta F(x_i)}\right]_{F(x)=F_{m-1}(x)}$, for i = 1,2, ..., n

2.2 Fit a base learner $h_m(x)$ to pseudo-residuals: train $h_m(x)$ on the training set $\{(x_i, r_{im})\}_{i=1}^{n}$

2.3 Compute multiplier ρ_m by solving the following one-dimensional optimization problem: $r_{im} = arg\min_{\rho}\sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + \rho h_m(x_i)$

2.4 Update the model: $F_m(x) = F_{m-1}(x) + \gamma_m \ where \ \gamma_m = \ \rho_m h_m(x)$

Step 3. Get the final model: $F_m(x)$

We employ the squared error as the loss function: $L(y, F) = \frac{1}{2}(y - F)^2$

The corresponding pseudo-residual (anti-gradient) is calculated as:

$$r_{im} = -\left[\frac{\vartheta L(y_i, F(x_i))}{\vartheta F(x_i)}\right]_{F(x)=F_{m-1}(x)} = y_i - F_{m-1}(x_i)$$

The optimal value of γ_m is determined using the mean squared error with Friedman's improvement score: $\gamma_m = \underset{i=1,2,\ldots,N}{\text{mean}}\left\{\frac{y_i - F_{m-1}(x_i)}{h_m(x_i)}\right\}$

Weights are assigned as: $w_i = |h_m(x_i)|$

All computations are executed using Python's Scikit-learn library (Pedregosa et al., 2011).

A separate Gradient Boosting Regressor (GBR) model was trained for each cryptocurrency, using the returns of four factors as input features. The training process consisted of the following steps:

- Model Initialization: Each GBR model was initialized with 100 decision trees, and a fixed random state was set to ensure reproducibility of the results.
- Model Training: The models were trained on the returns of individual cryptocurrencies, with the four factor returns serving as input features. The GBR algorithm minimizes prediction errors through gradient descent in a stage-wise process, where each new tree corrects the residuals left by the previous trees.
- Feature Importance Extraction: Once training was complete, feature importance scores were extracted from each model. These scores measure the impact of each factor on predicting cryptocurrency returns.

Additionally, we apply bootstrapped confidence intervals to assess the stability and significance of each factor's contribution to cryptocurrency returns. By creating numerous bootstrap samples, these intervals help evaluate the variability and reliability of the estimated factor exposures. They provide a range within which each factor's contribution to cryptocurrency returns is likely to fall, offering a specified level of confidence in the results.

4. Empirical Results

The returns-based style analysis results, presented in Table 2 and illustrated in Figure 1, provide insights into the sensitivity of the 27 cryptocurrencies under review to four key factors: market risk, interest rates, the US dollar, and crypto-specific influences.

< Insert Table 2 and Figure 1 about here >

When analyzing the average factor sensitivities across all cryptocurrencies under review (illustrated in Figure 2) interesting trends emerge. The average risk factor sensitivity stands at 0.3463, highlighting the significant influence of general market risks on the crypto asset class as a whole. The average interest rates factor sensitivity is relatively low at 0.1027, showing that most cryptocurrencies are less affected by changes in macroeconomic interest rates. The average dollar factor sensitivity is 0.1984, demonstrating moderate exposure to changes in the US dollar. This is because, while cryptocurrencies are traded in many currencies, most cryptocurrency transactions and valuations are still primarily anchored to the US dollar despite the international scope of the crypto ecosystem. The average crypto factor sensitivity is the highest among the four, at 0.3526, reinforcing the idea that crypto-specific developments, such as technological innovations, regulatory shifts, and ecosystem growth, play a dominant role in driving the returns of these digital assets. This suggests that while traditional financial factors still influence cryptocurrencies, their unique ecosystem dynamics remain the most critical drivers of performance.

< Insert Figure 2 about here >

When examining the factor sensitivities of specific cryptocurrencies, Bitcoin and tokens backed by Bitcoin (such as Wrapped Bitcoin and Bitcoin BEP2) exhibit the highest sensitivity to the risk factor, with coefficients around 0.44, suggesting their strong correlation with broad market movements and traditional financial risks. In contrast, tokens like UNUS SED LEO and OKB display much lower risk factor sensitivities, suggesting a degree of separation from general market volatility. Crypto-specific factors have the most substantial impact on the returns of altcoins, such as TRON and Dogecoin, suggesting that these crypto-assets are heavily influenced by developments within the cryptocurrency ecosystem. In contrast, Bitcoin-related assets, such as Wrapped Bitcoin, exhibit lower crypto factor sensitivities, reflecting a degree of diversification from purely crypto-centric events. Regarding the interest rate factor, UNUS SED LEO stands out with a coefficient of 0.3142, significantly higher than most other cryptocurrencies. This finding suggests that the particular token is more affected by shifts in interest rates, likely due to its financial service-related use. On the other hand, cryptocurrencies such as Polkadot and Cardano show minimal sensitivity to interest rate changes, suggesting that they do not perform as traditional financial instruments. Finally, the dollar factor sensitivity is highest for Solana, Ripple, and Uniswap, indicating that the returns of these cryptocurrencies are more influenced by fluctuations in the value of the US dollar. On the contrary, TRON and Dogecoin show relatively low sensitivity to the dollar factor, highlighting their detachment from traditional currency movements, perhaps due to their speculative nature.

The R-squared values reported in Table 2, which represent the proportion of return variance explained by the four factors, vary significantly across cryptocurrencies under review. For TRON, Ethereum Classic, and OKB we find the highest R-squared values (at around 60%), indicating that the specific factors effectively capture the majority of the return variability of these cryptos. In contrast, for NEAR Protocol and Fetch.ai we find the lowest R-squared values (approximately 45%), suggesting the returns of these cryptocurrencies are mainly driven by idiosyncratic factors. Generally, the average R-squared value of 53.33% suggests that just over half of the return variability of the cryptocurrencies under examination can be explained by these four factors. This indicates a moderate explanatory power, highlighting the relevance of both traditional financial factors and crypto-specific dynamics, while also pointing to the presence of other unique, idiosyncratic influences that contribute to the performance of these assets. According to these data, speculative trading and ecosystem-specific events are the main drivers of some cryptocurrencies, such as meme coins and altcoins, whereas other cryptocurrencies, like Bitcoin and Ethereum, show high correlations with macroeconomic issues. Investors must take asset-specific risk exposures into account when building bitcoin portfolios, which have important ramifications.

Overall, the analysis highlights the diverse risk profiles and factor sensitivities of different cryptocurrencies. Bitcoin, Ethereum and their related tokens are heavily influenced by market risk, while altcoins like TRON and Dogecoin are more affected by crypto-specific factors. Financial service tokens such as UNUS SED LEO exhibit higher sensitivity to interest rates, reflecting their exposure to macroeconomic conditions. The variation in R-squared values further underscores the heterogeneous nature of the crypto market, where some assets are tightly linked to macroeconomic and crypto-specific factors, while others are driven by distinct, project-specific dynamics.

< Insert Figure 3 about here >

Bootstrapped confidence intervals are presented in Table 2, with their graphical representations shown in Figure 3. These 95% confidence intervals offer valuable insights into the stability and reliability of the estimated factor contributions for each cryptocurrency, indicating the range within which the true contribution of each factor is likely to fall with a high degree of confidence. Smaller intervals indicate greater confidence in the consistency of the estimated factor contributions, whereas larger intervals reflect higher uncertainty or fluctuations in the estimates. Cryptocurrencies such as Bitcoin, Ethereum, and their related tokens exhibit relatively narrow confidence intervals for the risk factor (e.g., Bitcoin's range from 0.3049 to 0.4669 and Ethereum's from 0.3089 to 0.4688), indicating strong stability and a high degree of confidence in the robustness of their risk sensitivity estimates. This suggests that the contribution of market risk to their returns is consistent and less prone to variability over time. Conversely, altcoins display wider confidence intervals, particularly concerning the crypto-specific factor. For instance, TRON's crypto factor ranges from 0.3282 to 0.7389, and Dogecoin's from 0.3064 to 0.6572, indicating greater uncertainty in the exact magnitude of their sensitivity to crypto market dynamics. This variability may stem from their reliance on market sentiment, speculative trading behavior, and ecosystem-specific developments, which are inherently more volatile. In the case of financial tokens (like UNUS SED LEO), the interest rate factor shows a particularly wide confidence interval (0.1062 to 0.5176), reflecting significant uncertainty in estimating how macroeconomic interest rate changes influence its returns. Meanwhile, meme and speculative coins, such as Dogecoin and Stacks, demonstrate both high upper bounds and wide intervals for the crypto factor, underscoring the speculative and sentiment-driven nature of their price movements.

Generally, narrower confidence intervals for major cryptocurrencies indicate more reliable factor estimates, likely reflecting their stable market behavior and close integration with traditional financial systems. In contrast, wider intervals seen in altcoins and speculative assets indicate greater sensitivity to unexpected events, higher volatility, and unpredictable market conditions. These findings emphasize the importance of considering both point estimates and the associated confidence intervals when evaluating the factor exposures of cryptocurrencies, as they provide a clearer picture of both the magnitude and reliability of these relationships.

The methodology employed aims to identify the fixed exposures that best explain the returns of cryptocurrencies over the specified period, resulting in an average style analysis. However, to capture the time-varying nature of crypto market dynamics, we also apply a rolling style analysis. Specifically, we estimate the GBR algorithm using a fixed number of historical return observations for the four largest cryptocurrencies by market capitalization: Bitcoin, Ethereum, Binance Coin, and Solana. Given the availability of daily data spanning a four-year period (March 2021 to October 2024), we implement a rolling estimation window of 30 observations.

< Insert Figures 5-8 about here >

The rolling estimation style analysis results for Bitcoin, Ethereum, Binance Coin, and Solana, presented in Figures 5 through 8, offer valuable insights into the time-varying behavior of factor exposures for these leading cryptocurrencies over the period from March 2021 to October 2024. For Bitcoin (illustrated in Figure 5), the factor exposures exhibit relatively stable patterns, particularly in relation to market risk, which consistently shows strong influence over time. This stability aligns with Bitcoin's established role as a mature asset within the crypto ecosystem and its strong correlation with broader financial markets. While there are fluctuations, they tend to be moderate, indicating that Bitcoin's sensitivity to external factors remains fairly consistent despite market volatility. In contrast, Ethereum (illustrated in Figure 6), the second largest cryptocurrency, exhibits greater variability across the identified factors than Bitcoin, particularly with respect to the crypto-specific factor, reflecting the dynamic nature of the Ethereum ecosystem. Binance Coin (illustrated in Figure 7) exhibits even greater fluctuations in factor exposures, particularly regarding interest rates and crypto-specific factors, which maybe the result of its close association with the activity of the Binance exchange. Finally, Solana (illustrated in Figure 8) demonstrates the highest degree of volatility in its factor exposures among the four cryptocurrencies under review. This heightened variability most likely indicates the relative immaturity of Solana's ecosystem compared to more established crypto assets, such as Bitcoin and Ethereum.

In conclusion, the rolling analysis shows that factor sensitivities vary and change over time across major cryptocurrencies. Bitcoin has relatively stable exposures, reflecting its role as a digital store of value, while Ethereum, Binance Coin, and Solana are more dynamic due to their evolving ecosystems and technology. Our empirical findings highlight the need to consider changing factor exposures when analyzing cryptocurrency performance, as static models may miss important shifts caused by market events and ecosystem developments.

5. Conclusion

In this paper, we analyze cryptocurrency returns by applying a returns-based style analysis (RBSA) using four factors: the conventional risk premium factor (proxied by S&P 500 returns), the monetary policy factor (proxied by two-year interest rates), the currency factor (proxied by U.S. Dollar Index returns), and the crypto-specific factor (proxied by the market capitalization of stablecoins). Furthermore, the application of the Gradient Boosting Regressor model enhances the traditional RBSA by improving the accuracy and stability of factor exposure estimates.

Our empirical results show that Bitcoin, Ethereum, and their related tokens exhibit strong sensitivity to market risk, highlighting their close connection to traditional financial markets, while demonstrating moderate sensitivity to other factors, such as interest rates, the US dollar, and crypto-specific influences. In contrast, altcoins display high exposure to crypto-specific factors indicating that their returns are heavily influenced by developments within the cryptocurrency ecosystem. Financial tokens, often linked to DeFi platforms or exchange-based services, demonstrate higher sensitivity to interest rates, likely due to their dependence on conditions that affect lending and borrowing within decentralized finance. Meme and speculative coins, such as Dogecoin, exhibit a different dynamic, characterized by high sensitivity to crypto-specific factors but low sensitivity to interest rates, suggesting that their performance is largely driven by speculative trading behavior and investor sentiment rather than traditional economic indicators.

Additionally, the rolling style analysis further shows the time-varying nature of factor sensitivities, with Bitcoin maintaining relatively stable exposures, while Ethereum, Binance Coin, and Solana show more dynamic shifts in response to crypto ecosystem developments and macroeconomic changes. These findings emphasize the importance of considering both static and time-varying models when analyzing cryptocurrency returns in order to capture the full spectrum of factors influencing performance.

In conclusion, our study contributes to the growing literature on cryptocurrency return drivers by offering a comprehensive analysis of both traditional financial and crypto-specific factors. It also demonstrates the value of integrating machine learning techniques with traditional empirical models to enhance predictive accuracy and provide robust insights into the evolving dynamics of cryptocurrency markets. Future research could expand on this work by incorporating additional fundamental factors, such as inflation expectations or liquidity. Additionally, investigating the efficacy of different machine learning techniques, such as reinforcement learning and deep learning, may improve prediction accuracy. Finally, further insightful information could be obtained by researching how regulatory changes and developments in decentralized finance affect cryptocurrencies returns.

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Table 1. Market Capitalization of Selected Cryptocurrencies

Cryptocurrency Name	Symbol	Market Cap ($)
Bitcoin	BTC	1.424T
Ethereum	ETH	316.642B
Binance Coin	BNB	85.700B
Solana	SOL	81.830B
Ripple	XRP	29.493B
Staked Ether	STETH	25.713B
Dogecoin	DOGE	25.107B
TRON	TRX	14.693B
Cardano	ADA	12.594B
Wrapped Bitcoin	WBTC	10.582B
Avalanche	AVAX	10.476B
Wrapped Ether	WETH	8.898B
Chainlink	LINK	7.605B
Bitcoin Cash	BCH	7.398B
Polkadot	DOT	6.156B
UNUS SED LEO	LEO	5.603B
Litecoin	LTC	5.355B
NEAR Protocol	NEAR	5.113B
Uniswap	UNI7083	4.735B
Bitcoin BEP2	BTCB	4.7B
Fetch.ai	FET	3.225B
Monero	XMR	2.956B
Ethereum Classic	ETC	2.873B
Stellar	XLM	2.776B
Stacks	STX4847	2.583B
OKB	OKB	2.341B
Aave	AAVE	2.246B

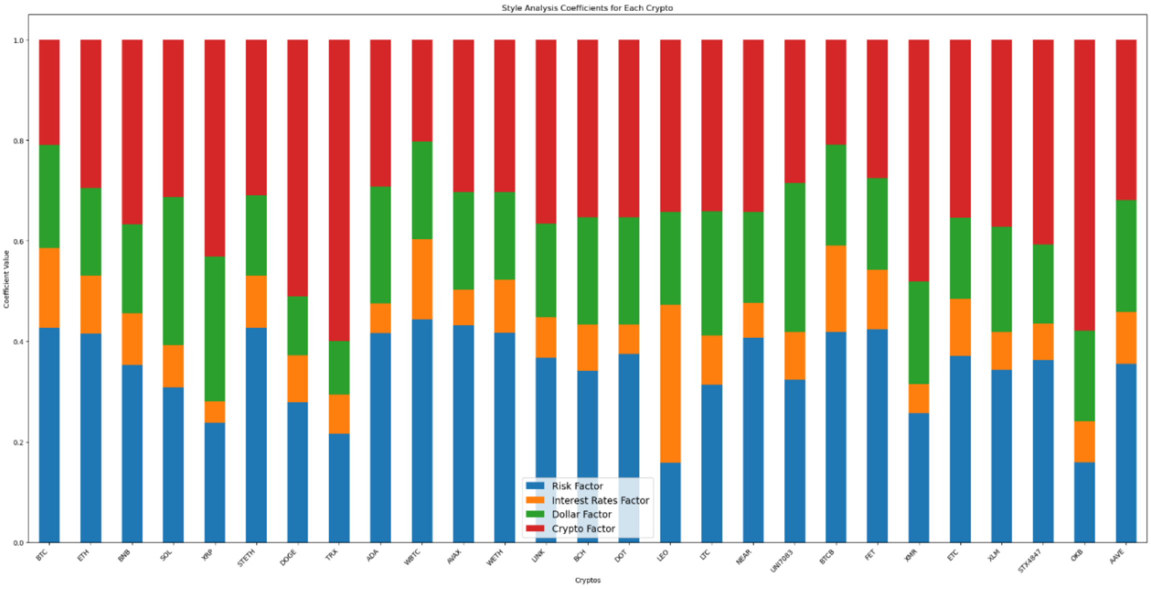
Notes: This table includes the market capitalization in US dollars (as of October 31, 2024) of the 27 cryptocurrencies used in the empirical analysis.

Table 2. Style Analysis results

	Risk factor			Interest Rates factor			Dollar factor			Crypto factor			R^2
	Lower Bound	*Mean*	*Upper Bound*	*Lower Bound*	*Mean*	*Upper Bound*	*Lower Bound*	*Mean*	*Upper Bound*	*Lower Bound*	*Mean*	*Upper Bound*	
Bitcoin	0.3049	**0.4275**	0.4669	0.0782	**0.1579**	0.2660	0.1455	**0.2046**	0.2690	0.1903	**0.2100**	0.3265	52%
Ethereum	0.3089	**0.4156**	0.4688	0.0720	**0.1146**	0.2024	0.1288	**0.1746**	0.2575	0.2101	**0.2951**	0.3926	56%
Binance Coin	0.2381	**0.3533**	0.4148	0.0555	**0.1027**	0.1585	0.1269	**0.1764**	0.2712	0.2933	**0.3676**	0.4760	53%
Solana	0.2592	**0.3075**	0.4083	0.0549	**0.0849**	0.1359	0.1954	**0.2947**	0.3591	0.2335	**0.3129**	0.4053	47%
Ripple	0.1546	**0.2376**	0.3950	0.0402	**0.0433**	0.1694	0.1140	**0.2885**	0.5113	0.2093	**0.4307**	0.6386	59%
Staked Ether	0.2871	**0.4270**	0.4788	0.0604	**0.1037**	0.1981	0.1264	**0.1590**	0.2725	0.2063	**0.3102**	0.3854	54%
Dogecoin	0.1722	**0.2780**	0.4065	0.0503	**0.0943**	0.1632	0.0785	**0.1169**	0.2748	0.3064	**0.5108**	0.6572	60%
TRON	0.1184	**0.2167**	0.3447	0.0465	**0.0770**	0.2078	0.0579	**0.1065**	0.2476	0.3282	**0.5998**	0.7389	61%
Cardano	0.3182	**0.4166**	0.4630	0.0516	**0.0591**	0.1308	0.1575	**0.2316**	0.3110	0.2034	**0.2927**	0.3977	50%
Wrapped Bitcoin	0.3015	**0.4434**	0.4753	0.0812	**0.1600**	0.2658	0.1398	**0.1937**	0.2711	0.1873	**0.2030**	0.3317	52%
Avalanche	0.2874	**0.4321**	0.4570	0.0477	**0.0709**	0.1405	0.1324	**0.1943**	0.2716	0.2616	**0.3027**	0.4313	49%
Wrapped Ether	0.3104	**0.4174**	0.4695	0.0743	**0.1052**	0.2048	0.1275	**0.1747**	0.2640	0.2041	**0.3027**	0.3988	55%
Chainlink	0.2531	**0.3674**	0.4267	0.0565	**0.0805**	0.1527	0.1548	**0.1859**	0.3460	0.2364	**0.3663**	0.4379	50%
Bitcoin Cash	0.2104	**0.3410**	0.4626	0.0621	**0.0920**	0.1925	0.1270	**0.2138**	0.3790	0.2171	**0.3532**	0.4413	51%
Polkadot	0.2851	**0.3749**	0.4349	0.0487	**0.0581**	0.1360	0.1279	**0.2139**	0.2617	0.2847	**0.3531**	0.4507	51%
UNUS SED LEO	0.1070	**0.1578**	0.3352	0.1062	**0.3142**	0.5176	0.1050	**0.1851**	0.3258	0.1835	**0.3429**	0.4950	55%
Litecoin	0.2420	**0.3138**	0.3968	0.0690	**0.0976**	0.1667	0.1483	**0.2471**	0.2975	0.2792	**0.3414**	0.4353	54%
NEAR Protocol	0.2841	**0.4076**	0.4556	0.0539	**0.0684**	0.1241	0.1408	**0.1812**	0.2813	0.2447	**0.3428**	0.4204	45%
Uniswap	0.2577	**0.3233**	0.4340	0.0602	**0.0949**	0.1718	0.1374	**0.2967**	0.3877	0.2091	**0.2851**	0.3864	51%
Bitcoin BEP2	0.3041	**0.4183**	0.4694	0.0869	**0.1718**	0.2750	0.1458	**0.2016**	0.2775	0.1859	**0.2084**	0.3368	51%
Fetch.ai	0.2546	**0.4244**	0.4295	0.0792	**0.1178**	0.1908	0.1578	**0.1822**	0.3174	0.2134	**0.2756**	0.3755	45%
Monero	0.1941	**0.2563**	0.3976	0.0488	**0.0586**	0.1517	0.1294	**0.2041**	0.3301	0.2990	**0.4809**	0.5676	55%
Ethereum Classic	0.2065	**0.3708**	0.4205	0.0488	**0.1137**	0.2093	0.1173	**0.1614**	0.4080	0.2363	**0.3541**	0.4643	61%
Stellar	0.1793	**0.3435**	0.4261	0.0534	**0.0750**	0.1579	0.1292	**0.2097**	0.5062	0.1858	**0.3718**	0.4694	54%
Stacks	0.1773	**0.3634**	0.5831	0.0368	**0.0716**	0.2025	0.0841	**0.1571**	0.3041	0.1869	**0.4079**	0.6854	57%
OKB	0.1103	**0.1591**	0.2911	0.0420	**0.0823**	0.1598	0.1186	**0.1801**	0.3788	0.3430	**0.5785**	0.6673	61%
Aave	0.2638	**0.3549**	0.4174	0.0734	**0.1041**	0.1731	0.1456	**0.2219**	0.2916	0.2361	**0.3190**	0.4128	52%

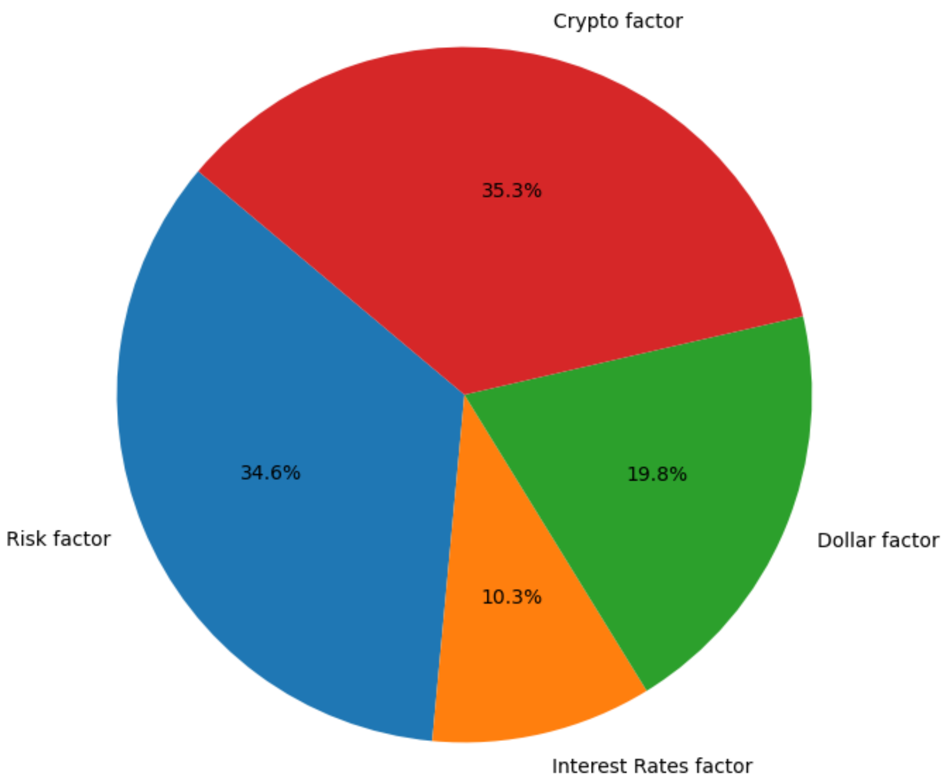
Notes: This table displays the results of the style analysis for each cryptocurrency. The confidence intervals are derived from bootstrapped feature importances, with the lower bound representing the 2.5th percentile and the upper bound representing the 97.5th percentile. The R-squared value reflects the proportion of return variance explained by the four factors (risk, interest rates, the dollar and crypto). The analysis covers the sample period from March 2021 to October 2024.

Figure 1. Graphical Representation of Style Analysis Coefficients for Each Cryptocurrency



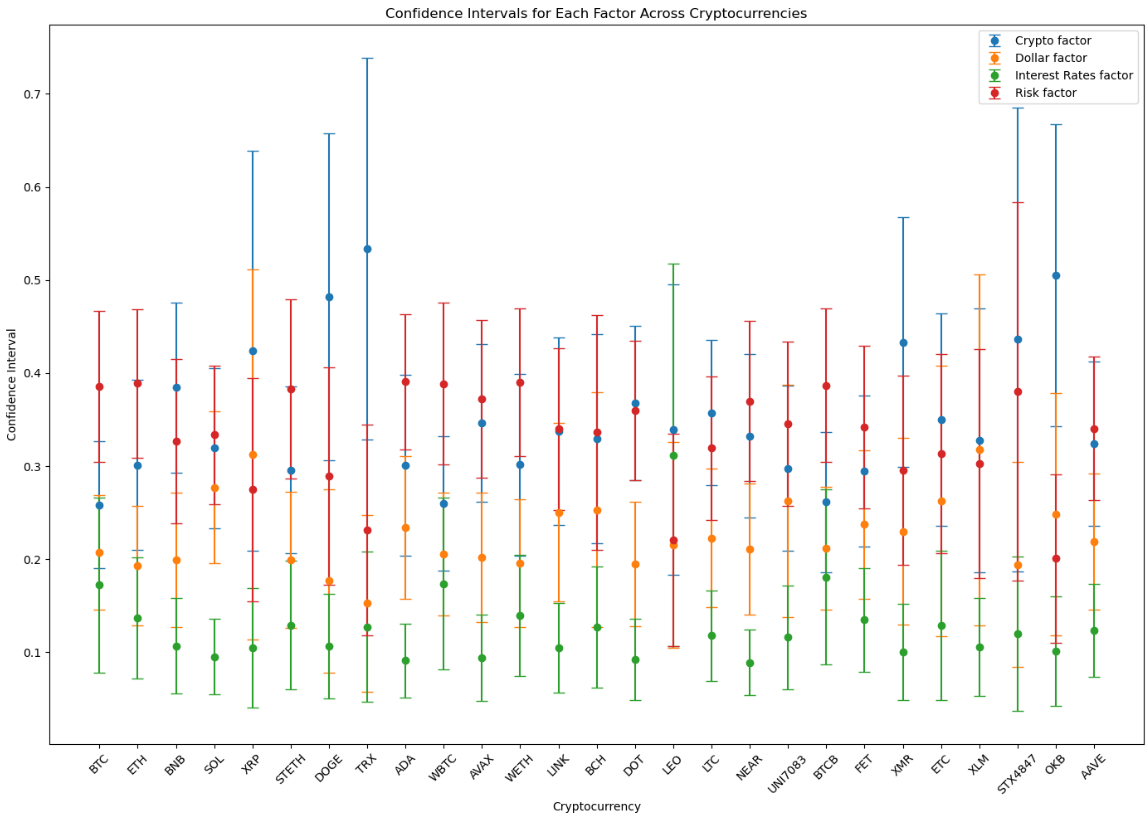
Notes: This figure graphically illustrates the style analysis coefficients for each of the four factors across all cryptocurrencies.

Figure 2. Average Contribution of Each Factor



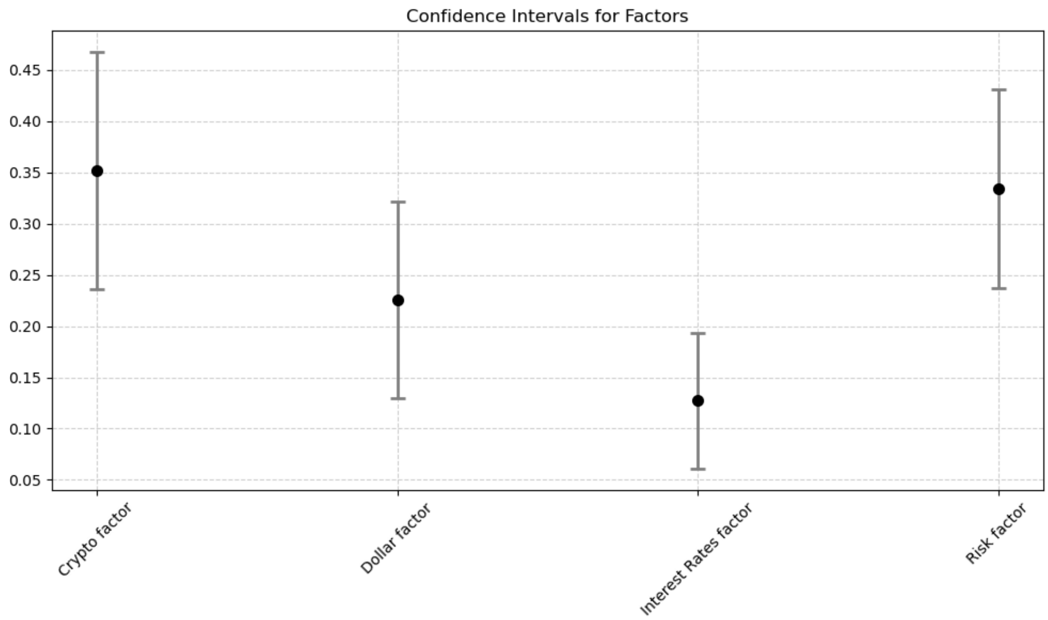
Notes: This figure displays the average coefficients of the four factors across all 27 cryptocurrencies analyzed, illustrating their varying levels of exposure to market risk, interest rates, currency fluctuations, and crypto-specific influences.

Figure 3. Graphical Representation of Confidence Intervals for Each Cryptocurrency



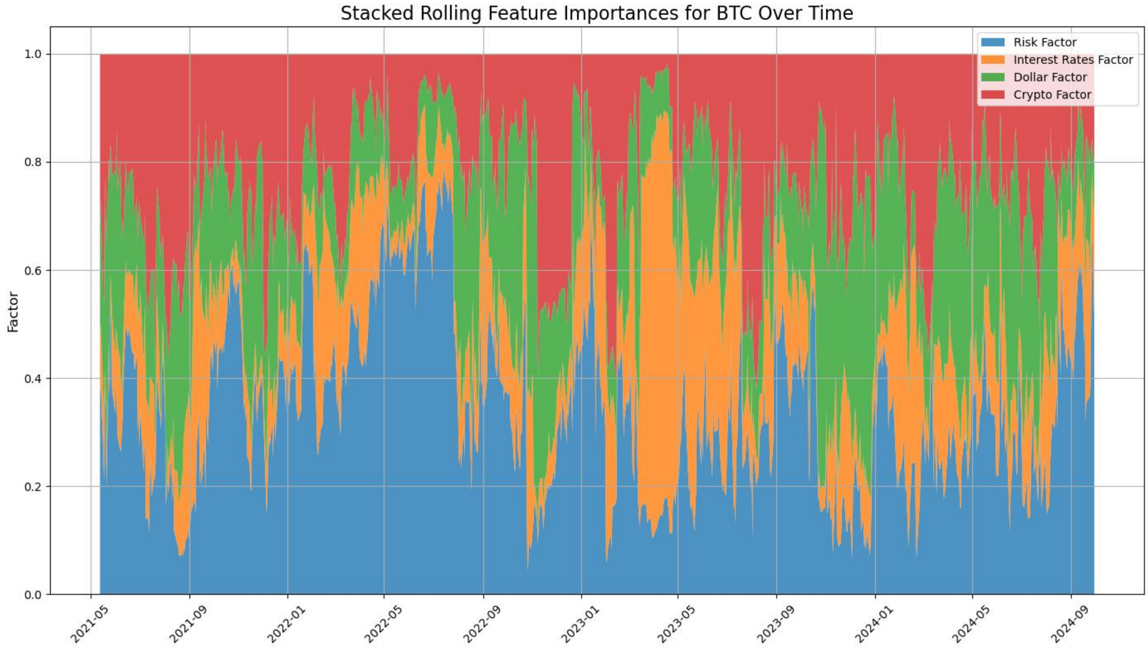
Notes: This figure graphically presents the confidence intervals for each of the four factors across all cryptocurrencies. The lower bound represents the 2.5th percentile, and the upper bound represents the 97.5th percentile of the bootstrapped feature importances.

Figure 4. Average Confidence Interval Ranges



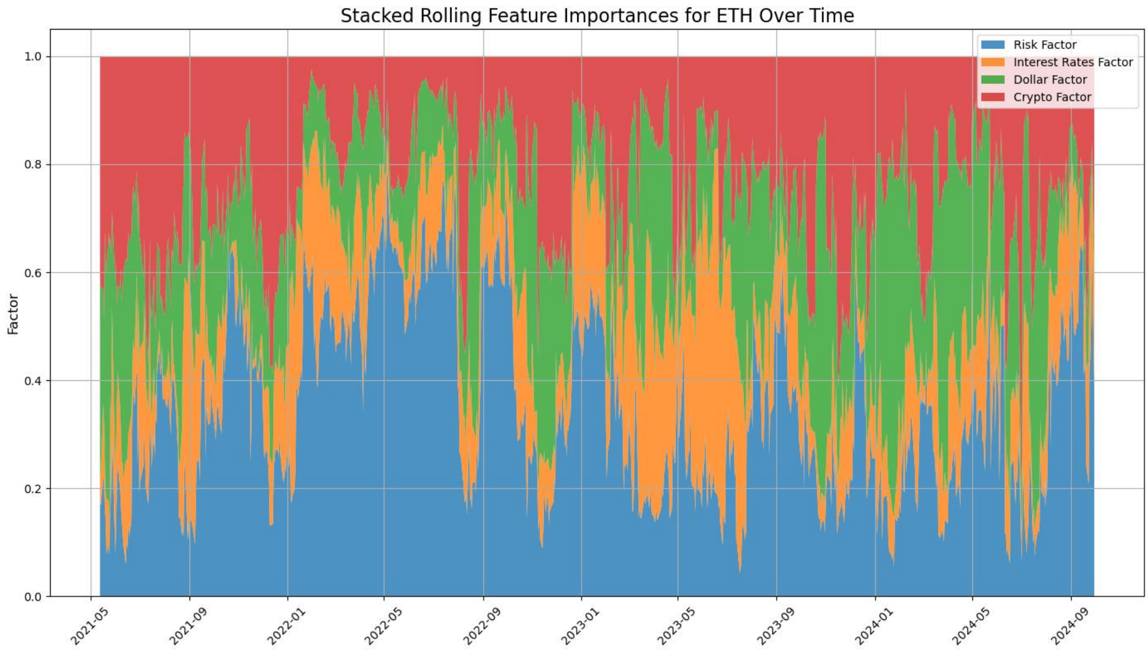
Notes: This figure graphically presents the average confidence interval coefficients for each of the four factors across all 27 cryptocurrencies under review. The confidence intervals for each factor are determined using the bootstrapped feature importances aggregated from all iterations.

Figure 5. Rolling estimation Style Analysis results for Bitcoin (BTC)



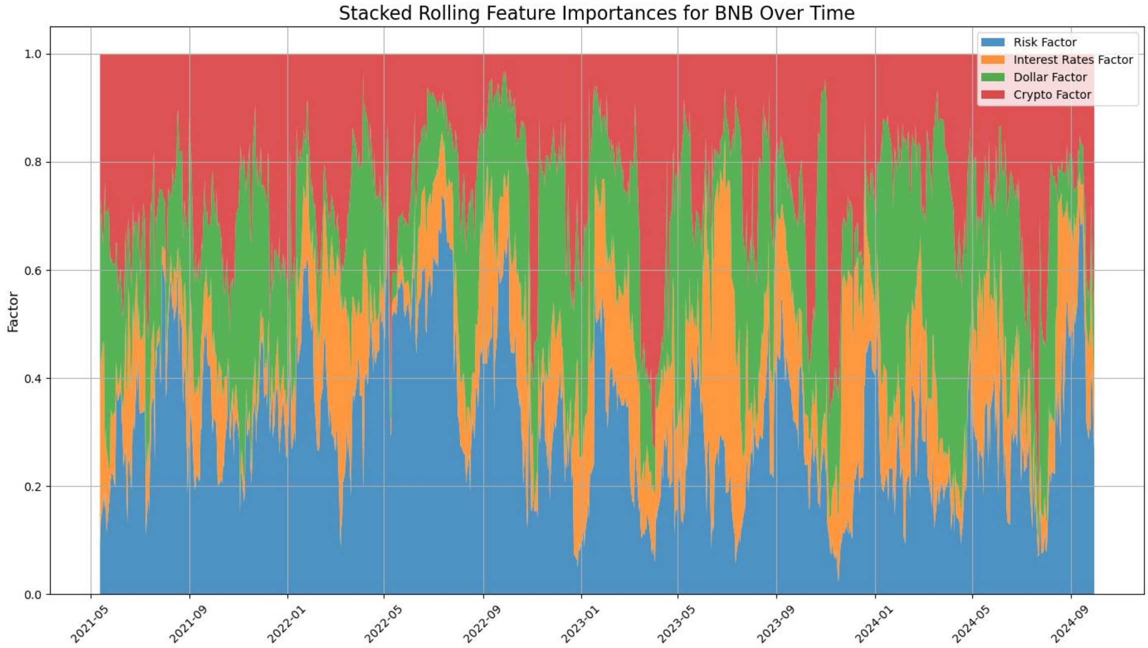
Notes: This figure plots the style analysis results for Bitcoin for the period March 2021 – October 2024 using a rolling estimation window of 30 observations.

Figure 6. Rolling estimation Style Analysis results for Ethereum (ETH)



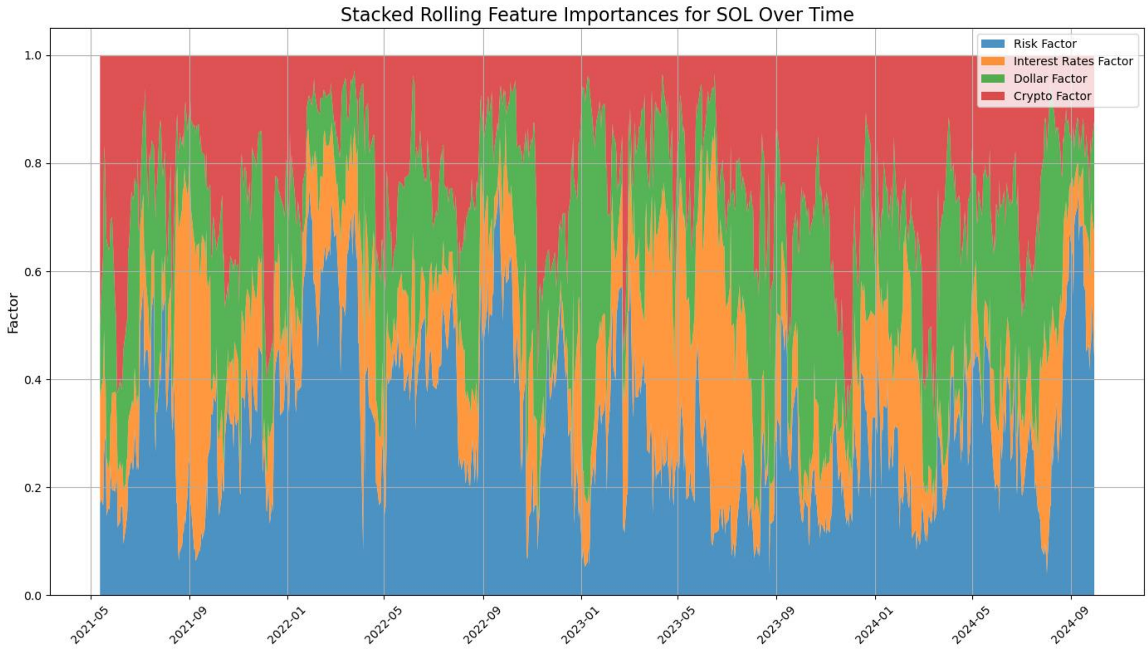
Notes: This figure plots the style analysis results for Ethereum for the period March 2021 – October 2024 using a rolling estimation window of 30 observations.

Figure 7. Rolling estimation Style Analysis results for Binance Coin (BNB)



Notes: This figure plots the style analysis results for Binance Coin for the period March 2021 – October 2024 using a rolling estimation window of 30 observations.

Figure 8. Rolling estimation Style Analysis results for Solana (SOL)



Notes: This figure plots the style analysis results for Solana for the period March 2021 – October 2024 using a rolling estimation window of 30 observations.