Exploring Style Factors in Cryptocurrencies

Individual Research | Blockchain at Emory Review

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Introduction

Research Question Explored

Crypto assets occupy a unique position within the broader investment universe, with many retail investors and professional managers debating their current and future role in this space. In this paper, I utilize the characteristics of cryptocurrencies, such as structural illiquidity, large frictions, and episodic bursts of volatility, to identify return behavior. The return behavior deviates sharply from traditional investments and makes it an ideal setting for studying how liquidity, market depth, and nonlinear risk premia shape asset prices. Despite their increasing institutional relevance, digital assets lack a well-established asset-pricing framework. This gap motivates my central question: ***Can cryptocurrency returns be decomposed into systematic factors, and what do these factors reveal about the role of liquidity in these markets?***

To answer this, I construct a set of factors designed to capture fundamental pricing forces, including Market, Momentum, Value, Short-Term Reversal, Liquidity, Beta, and Residual Volatility. In these markets, investors demand compensation for bearing depth risk, execution risk, and the inability to exit positions during shocks.[1] Cryptocurrency markets amplify these dynamics due to fragmented trading venues and the absence of established centralized liquidity providers. The study develops a factor model, estimates risk premia, evaluates the model's ability to explain cross-sectional returns, and compares results across major assets as well as the benchmarked index. It explores how factor exposures vary meaningfully across assets depending on network structure. The findings contribute to an emerging understanding of crypto as an asset class whose pricing is shaped less by traditional fundamentals and more by liquidity cycles, behavioral flows, and structural risks.

Background and Definition of Factor Models

Over the past three decades, asset-pricing research has documented how cross-sectional variation in expected returns is systematically related to firm characteristics or "factors." These models provide a systematic framework for explaining asset returns by decomposing them into exposures to underlying sources of "risk". This framework started with the Capital Asset Pricing Model (CAPM).[2] The CAPM Model finds the co-movement of an underlying asset and a market proxy. Thereby, it tries to gauge the risk of the asset relative to the market, otherwise known as the market beta. In the decades since, the ideas behind CAPM have evolved as researchers have empirically demonstrated that market beta alone cannot explain persistent return patterns across assets or over time. Fama and French (1992, 1993) identified the Market, Size, and Value factors as persistent drivers of equity

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[1] ***Depth risk** means that crypto markets may not have enough buyers and sellers to handle large trades without moving prices, especially for smaller tokens or during volatile periods. **Execution risk** refers to the possibility that trades are filled at worse prices, with delays, or not at all due to thin liquidity, exchange fragmentation, or network congestion.*

[2] William F. Sharpe, *Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk*, *The Journal of Finance*, vol. 19, no. 3, 1964, pp. 425–442.

returns, later extending to include Momentum. (Carhart, 1997) [3] Subsequent empirical work introduced additional factors, including liquidity (Pastor & Stambaugh, 2003), volatility (Ang et al., 2006), and investment-based factors (Fama & French, 2015). [4] Although these factors were established in equities, many studies explore how factor premia can persist across asset classes. (Asness et al., 2013; Barroso & Santa-Clara, 2015) [5] Their findings suggest that underlying economic mechanisms such as risk compensation, investor behavior, or constraints may be universal. This research collectively formed the foundation of modern multi-factor asset-pricing models. These models reflect the view that returns are shaped not by a single systematic force but by distinct "risk premia" each associated with an economic risk or investor behavioral pattern.

Factor models serve two primary purposes within asset pricing and portfolio construction. First, they provide a framework for risk decomposition, allowing investors and researchers to identify which systematic exposures drive the variation in portfolio returns. By isolating these underlying factors, analysts can better understand the economic risks embedded in an asset or strategy. Second, factor models are used for return generation, forming the theoretical foundation of rule-based "smart beta" strategies that seek to harvest persistent factor premia documented in the literature. These strategies assume that certain characteristics, such as Momentum or Value, offer compensated risk exposure or behavioral anomalies that can be exploited. Together, these two functions position factor models as both explanatory tools for understanding past performance and practical mechanisms for constructing investment strategies. In contrast, the rapidly growing cryptocurrency market remains far less understood within a formal asset-pricing framework.

[3] Eugene F. Fama and Kenneth R. French, "The Cross Section of Expected Stock Returns," *The Journal of Finance*, vol. 47, no. 2, 1992, pp. 427–465; and Eugene F. Fama and Kenneth R. French, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, vol. 33, no. 1, 1993, pp. 3–56.

[4] Ľuboš Pástor and Robert F. Stambaugh, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, vol. 111, no. 3, 2003, pp. 642–685; Andrew Ang, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, "The Cross Section of Volatility and Expected Returns," *The Journal of Finance*, vol. 61, no. 1, 2006, pp. 259–299; and Eugene F. Fama and Kenneth R. French, "A Five Factor Asset Pricing Model," *Journal of Financial Economics*, vol. 116, no. 1, 2015, pp. 1–22.

[5] Clifford S. Asness, Tobias J. Moskowitz, and Lasse H. Pedersen, "Value and Momentum Everywhere," *The Journal of Finance*, vol. 68, no. 3, 2013, pp. 929–985; and Pedro Barroso and Pedro Santa-Clara, "Momentum Has Its Moments," *Journal of Financial Economics*, vol. 116, no. 1, 2015, pp. 111–120.

Data and Sample

Methodology for Investment Universe Construction

When constructing my crypto asset universe, I referenced institutional benchmarks, including the Bitwise Indexes and the Bloomberg Galaxy Crypto Index (BGCI), to identify the largest cryptocurrencies with at least five years of daily trading history. Applying this filter produced a set of twelve underlying assets. The final universe consists of twelve cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), Solana (SOL), Avalanche (AVAX), Cardano (ADA), and Polkadot (DOT), Chainlink (LINK), Binance (BNB), XRP (XRP), Tron (TRX), Dogecoin (DOGE), USD Coin (USDC). Each asset was selected for its economic relevance, trading presence, and data availability.

Defining Factors

Market (MKT)

The **Market factor (MKT)** serves as the baseline measure of aggregate crypto risk. It is constructed as the equal-weighted daily return across all assets in the investment universe, ensuring that no single token dominates the calculation. This factor captures broad sentiment, systematic flows, and ecosystem-wide shifts in risk appetite. In highly correlated frontier markets, such as micro-cap equities or emerging-market credit, the market factor often explains most of the variation in cross-sectional returns. Crypto displays a similar pattern: price movements across major tokens tend to respond to shared liquidity cycles, leverage conditions, and funding availability. The Market factor, therefore, functions as the core reference against which all other factors are interpreted.

$$\frac{1}{n};\ MKT = \Pi_{s=t-1}^{t}(1 + p(A)_s^t) - 1$$

$t = time\ (daily)$
$n = number\ of\ assets$
$p(A) = price\ of\ Asset$

Momentum (MOM)

The **Momentum factor (MOM)** measures the tendency for assets that have recently performed well to continue outperforming. This effect is well documented in equities and commodities but is especially pronounced in frontier markets where information diffusion is slow, and investor sentiment amplifies trends. The signal for Momentum is constructed using each asset's 30-day cumulative return, forming a long–short portfolio that buys the assets with the strongest recent performance and sells those with the weakest. Momentum in digital assets is theoretically supported by delayed reaction to information, speculative trading flows, and the reflexive nature of narrative-driven markets. However, the extreme volatility of crypto raises the possibility that strong Momentum signals may decay quickly or reverse during sharp liquidity shocks.

$$\frac{1}{3}(R_l) - \frac{1}{3}(R_s);\ MOM = \Pi_{s=t-3}^{t}\ (1 + p(A)_s^t) - 1$$

R_l = *the lowest ranked signals representing the long portfolio*
R_s = *the highest ranked signals representing the short portfolio*
t = *time (daily)*
$p(A)$ = *price of Asset*

Value (VAL[6M], VAL[Q])

The **Value factor (VAL[6M], VAL[Q])** is implemented using two complementary approaches to reflect both relative mispricing and structural "quality" within the crypto ecosystem. The first, a 6-month relative value signal (VAL[6M]), identifies assets whose prices have lagged substantially behind their historical levels, functioning as a medium-horizon mean-reversion measure. Assets with large negative 120-day returns are ranked as "cheap," while those with large gains are ranked as "expensive." Because crypto lacks cash flows or book values, this type of price-based valuation serves as a proxy for medium-term dislocations. The second, Value-Quality (VAL[Q]), is not a long–short portfolio but a simple equal-weighted return series of Bitcoin, Ethereum, and USD Coin. These three assets represent the most structurally important and economically grounded tokens in the market—BTC as the monetary premium asset, ETH as the settlement layer for smart contracts, and USDC as stable collateral. This factor acts as a proxy for "fundamental strength" rather than valuation in a traditional sense, recognizing that the highest-quality assets in a frontier market often define its implicit risk-free benchmark.

$$\tfrac{1}{3}(R_l) - \tfrac{1}{3}(R_s); VAL[6M] = -(\Pi_{s=t-120}^{t}(1 + p(A)_s^t) - 1))$$

$$\frac{1}{n}; VAL[Q] = (r(BTC)^t + r(ETH)^t + r(USDC)^t$$

R_l = *the lowest ranked signals representing the long portfolio*
R_s = *the highest ranked signals representing the short portfolio*
$r(BTC)^t = \Pi_{s=t-1}^{t}(1 + p(BTC)_s^t) - 1$; *daily return of Bitcoin*
$r(ETH)^t = \Pi_{s=t-1}^{t}(1 + p(ETH)_s^t) - 1$; *daily return of Etherum*
$r(USDC)^t = \Pi_{s=t-1}^{t}(1 + p(USDC)_s^t) - 1$; *daily return of US Dollar Coin*
t = *time (daily)*
n = *number of assets*
$p(A)$ = *price of Asset*

Short-Term Reversal (STR-1, STR-3)

The **Short-Term Reversal factor (STR-1, STR-3)** captures the well-documented tendency for assets that experience sharp temporary declines to rebound once liquidity pressures subside. This pattern is especially relevant in crypto, where liquidations, funding squeezes, and thin order books can force prices far away from short-term equilibrium. I construct two versions of this signal: STR-1, which measures one-day reversals following abrupt price drops, and STR-3, which captures slightly slower mean reversion over a three-day window.

Both factors are constructed as long–short portfolios, with the long leg holding the worst recent performers and the short leg holding the best performers. In the framework of frontier asset pricing, short-term reversal reflects the market's tendency to overreact under stress and partially unwind once liquidity returns, similar to pricing dynamics observed in distressed credit and small-cap equities.

$$\frac{1}{3}(R_l) - \frac{1}{3}(R_s); STR[1D] = -(\Pi_{s=t-1}^{t}(1 + p(A)_s^t) - 1))$$
$$\frac{1}{3}(R_l) - \frac{1}{3}(R_s); STR[3D] = -(\Pi_{s=t-3}^{t}(1 + p(A)_s^t) - 1))$$

$R_l = the\ lowest\ ranked\ signals\ representing\ the\ long\ portfolio$
$R_s = the\ highest\ ranked\ signals\ representing\ the\ short\ portfolio$
$t = time\ (daily)$
$p(A) = price\ of\ Asset$

Liquidity (LQ)

The **Liquidity factor (LQ),** a central focus of the course and of this paper, isolates the illiquidity premium embedded in crypto markets. This factor ranks assets by trading activity and constructs a long–short portfolio that holds the most illiquid tokens and sells the most liquid ones. In frontier markets, investors demand compensation for holding assets with poor market depth, execution uncertainty, and higher susceptibility to liquidity shocks. Crypto amplifies these frictions because liquidity varies dramatically across tokens and exchanges, market makers withdraw during volatility, and structural fragmentation impedes efficient price discovery. As a result, the liquidity factor serves not only as a return driver but also as a measure of the microstructure environment underlying digital asset markets.

$$\frac{1}{3}(R_l) - \frac{1}{3}(R_s);\ LQ = -(v(A)^t)$$

$R_l = the\ lowest\ ranked\ signals\ representing\ the\ long\ portfolio$
$R_s = the\ highest\ ranked\ signals\ representing\ the\ short\ portfolio$
$t = time\ (daily)$
$n = number\ of\ assets$
$v(A) = Volume\ Traded\ of\ an\ Asset$

Beta (B)

The **Beta factor (B)** measures each asset's sensitivity to market-wide movements, estimated by comparing individual returns to the Market factor over a rolling window. Assets with high beta experience larger swings in response to market sentiment, while low-beta tokens exhibit more muted reactions. In equities, low-beta portfolios have historically outperformed, a pattern linked to leverage constraints and behavioral biases. Applying this idea to crypto provides insight into whether lower-risk tokens earn a premium in a market dominated by high volatility. Beta is constructed as a long–short portfolio that buys lower-beta assets and sells higher-beta assets, capturing any potential "defensive" premium.

$$\frac{1}{3}(R_l) - \frac{1}{3}(R_s); B = \frac{Cov(r(A)_{t-30}^{t}, r(M)_{t-30}^{t})}{Var(r(M)_{t-30}^{t})}$$

$R_l = the\ lowest\ ranked\ signals\ representing\ the\ long\ portfolio$
$R_s = the\ highest\ ranked\ signals\ representing\ the\ short\ portfolio$
$r(A)^t = \Pi_{s=t-1}^{t}(1 + p(A)_s^t) - 1; daily\ return\ of\ Asset$
$r(M)^t = \Pi_{s=t-1}^{t}(1 + p(A)_s^t) - 1; daily\ return\ of\ Market\ Factor$
$t = time\ (daily)$
$n = number\ of\ assets$
$p(A) = price\ of\ Asset$

Residual Volatility (RVOL)

The **Residual Volatility factor (RVOL)** measures the extent to which an asset's price deviates from what would be expected based on its market exposure alone. After estimating each asset's expected return from its Beta and the Market factor, RVOL captures the variance of the remaining idiosyncratic component. Assets with high RVOL are exposed to greater uncertainty, jump risk, and protocol-specific events, where high-volatility frontier assets often underperform due to uncompensated risk. The RVOL factor is constructed as a long–short portfolio that buys low-RVOL assets and sells high-RVOL ones.

$$\frac{1}{3}(R_l) - \frac{1}{3}(R_s); RVOL = \sigma(e)_s = \sqrt{\frac{\Sigma_{i=t-3}^{t}\ (e_i - \mu(e)_s)^2}{30}}$$

$t = time\ (daily)$
$n = number\ of\ assets$
$e = r(A)_t - (B(A)_{t-1} * r(M)_t)$
$\mu(e)_s = \frac{\Sigma_{i=t-3}^{t}\ e_i}{30}$
$p(A) = price\ of\ Asset$

Results

Summary Statistics

The summary statistics reveal the defining characteristics of crypto as a frontier asset class. Across all factors, returns exhibit extremely high volatility, substantial dispersion, and non-normal distributions. The Market, Liquidity, Qualitative Value, and RVOL factors exhibit the highest annualized returns and Sharpe ratios. Market factor performs strongly, reflecting broad growth and the expansion of digital assets over the sample period. Liquidity generates particularly large excess returns, consistent with an illiquidity premium. The VAL[Q] factor also performs well, suggesting that tokens tied to fundamental network strength outperform marginal assets. Momentum and long-horizon reversal signals perform poorly, producing negative annualized returns. This contrasts sharply with equity markets and highlights the unique structure of crypto. While STR displays asymmetric behavior, the 1-day reversal signal delivers a modest premium, suggesting rapid mean reversion following liquidations, while the 3-day signal is negative, indicating that multi-day declines are more often part of larger deleveraging cycles rather than temporary dislocations. Across all factors, skew varies meaningfully across factors, with Momentum showing a strong negative skew and Liquidity showing a positive skew. The results suggest that crypto does exhibit systematic risk premia, but these premia are driven primarily by market structure rather than by traditional valuation anchors or behavioral patterns observed in equities.

	MKT	MOM	VAL[6M]	VAL [Q]	STR-1	STR-3	LQ	B	RVOL
Average Return	0.23%	-0.11%	0.05%	0.11%	0.04%	0.01%	0.28%	0.06%	0.05%
Annualized Return	75.57%	-36.51%	17.14%	32.22%	2.84%	-6.80%	160.38%	14.39%	14.76%
Volatility	0.04	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.01
Sharpe	19.92	-25.19	13.72	14.02	1.42	-3.34	93.14	6.98	11.15
Kurtosis	17.26	15.09	6.99	3.71	519.39	459.49	564.43	289.28	9.36
Skew	0.70	-0.80	0.56	-0.04	-16.44	-14.77	17.93	10.56	1.14

Correlation:

The correlation matrix reveals a few important patterns. Starting with the Market factor, it shows extremely high positive correlation with Beta (0.753), RVOL (0.739), and VAL[Q] (0.910). This is expected given the signal construction of RVOL and Beta. The highest correlation being VAL[Q] also reflects its construction and supports the idea of how foundational major L1 assets are to overall market performance. Liquidity exhibits a negative correlation with Market (–0.337), VAL[Q] (–0.253), and Beta (–0.228) factors. This could suggest that Liquidity, if significant, captures a diverse form of risk. STR shows minimal correlation with the rest of the system, supporting the interpretation that reversal behavior in crypto is driven by individual noise rather than broad market risk.

	MKT	MOM	VAL[6M]	VAL[Q]	STR-1	STR-3	LQ	B	RVOL
MKT	1.000								
MOM	0.152	1.000							
VAL[6M]	0.012	-0.401	1.000						
VAL[Q]	0.910	0.178	-0.081	1.000					
STR-1	-0.026	-0.196	0.134	-0.079	1.000				
STR-3	-0.155	-0.346	0.175	-0.170	0.131	1.000			
LQ	-0.337	-0.251	0.221	-0.253	0.083	0.197	1.000		
B	0.753	-0.047	0.017	0.643	0.056	-0.063	-0.228	1.000	
RVOL	0.739	-0.186	0.287	0.572	0.085	0.008	-0.117	0.736	1.000

Significance/ Risk Premia

The significance tests evaluate whether each factor's return pattern is strong enough to be unlikely due to chance, allowing us to identify which signals reflect genuine market behavior rather than noise. I ran a standard right-tailed t-test with a 95% confidence level. The results show that Market, Liquidity, Qualitative Value, and Momentum (as a negative premium) exhibit statistically meaningful effects, indicating that these factors consistently influence crypto-asset returns. VAL[6M] and RVOL show only borderline significance, while STR and Beta provide little statistical evidence of a persistent premium. Importantly, these findings should be interpreted cautiously because crypto returns are highly volatile, skewed, and fat tailed. They violate the normality assumptions underlying classical significance tests. Overall, the tests highlight a smaller set of potentially robust factors that will be used in isolation in the remainder of this study.

Factor	t-Stat	p-Value (one-tailed)	Significant at 5%?
Market	2.54	0.01	Yes
Momentum	-3.33	0.00	Yes (negative premium)
Value 6M	1.69	0.05	Borderline Yes
Value Q	1.91	0.03	Yes
STR-1 (1-day reversal)	0.77	0.22	No
STR-3 (3-day reversal)	0.2	0.42	No
Liquidity	6.83	0.00	Yes
Beta	1.15	0.13	No
RVOL (Residual Vol.)	1.47	0.07	Borderline Yes

Benchmark Regression Analysis and Factor Decomposition

The Bitwise 10 Large Cap Crypto Index (BTWISE) serves as the benchmark for this study because it represents the institutional standard for diversified exposure to the largest and most established crypto assets. The index is market-cap weighted, rebalanced monthly, and designed to track the economic performance of the dominant large-cap segment of the digital asset market. Because BTWISE adheres to institutional market-hours conventions rather than 24/7 trading, its return series was first cleaned and aligned to a sample beginning on April 7, 2021.

The regression results show that while the factor model explains only a modest share of benchmark performance, the significant coefficients reveal meaningful structure in how the index behaves. The Market factor is small and statistically insignificant, which reflects the fact that BTWISE is driven primarily by Bitcoin and Ethereum rather than the equal-weighted market factor used in this study. Momentum contributes a small but statistically significant positive effect, whereas the VAL[6M] is only borderline significant and does not materially improve explanatory power. In contrast, the VAL[Q] exhibits the strongest loading of all variables. This result is intuitive because BTWISE is heavily influenced by BTC and ETH. Both Liquidity and RVOL are also significant, suggesting that the index performs better in environments where illiquid tokens rally and when lower-volatility, higher-quality assets outperform riskier alternatives. These findings align with the economic intuition behind BTWISE as a large-cap, institutionally oriented benchmark. Although the overall explanatory power is modest ($R^2 \approx 0.18$), the results indicate that BTWISE is most strongly driven by fundamental value rather than traditional risk.

The factor decomposition shows that only a few systematic exposures meaningfully drive BTWISE's expected return. The largest positive contribution comes from the VAL[Q] factor, reflecting the index's heavy concentration in fundamentally strong assets like BTC and ETH. Liquidity and RVOL also add small positive contributions, suggesting that the benchmark benefits when illiquid assets outperform and when large-cap tokens exhibit stable idiosyncratic behavior. By contrast, Momentum and VAL[6M] subtract from returns. Market exposure also contributes slightly negatively. Overall, the decomposition highlights that BTWISE's performance is driven primarily by fundamental strength and liquidity conditions, rather than trend as captured in this study.

I used this analysis as the foundation to compare how the factor model behaves when applied to major individual assets in the next section.

Static Regression Summary

	Factor	Beta	t-Stat	p-Value	Significant?
BTWISE	Market	−0.069	−0.61	0.54	No
	Momentum	0.2280	2.1200	0.03	Yes
	Value 6M	−0.186	−1.70	0.09	Close
	Value Q	1.7600	5.2500	0.00	Yes
	Liquidity	0.1780	3.1200	0.00	Yes
	RVOL	0.4170	2.5400	0.01	Yes
	R^2	0.1770	—	—	—

BTWISE: Factor Decomposition

Factor	Beta	Risk Premium	ER Contribution
Market	-0.07	0.22%	-0.02%
Momentum	0.23	-0.11%	-0.03%
Value 6M	-0.19	0.06%	-0.01%
Value Q	0.73	0.09%	0.07%
Liquidity	0.18	0.28%	0.05%
RVOL	0.42	0.05%	0.02%
Total			**0.08%**

Major Asset Regression Analysis and Factor Decomposition

After evaluating the benchmark, I shifted my analysis toward understanding how the factor model explains returns for the three most economically important Layer-1 blockchains: Bitcoin (BTC), Ethereum (ETH), and Solana (SOL). These assets dominate market structure, liquidity, and investor flows, making them an ideal test for whether traditional factor logic translates to digital assets. The static regressions show that the model provides strong explanatory power for all three assets, with R^2 values of 0.89 for Bitcoin, 0.94 for Ethereum, and 0.65 for Solana. Each chain exhibits a distinct pattern of factor exposures, revealing meaningful differences in risk structure and economic drivers.

Bitcoin's returns are primarily explained by VAL[Q], Liquidity, and RVOL. Its strong loading on VAL[Q] factor reflects its construction and is not surprising. Liquidity contributes positively, consistent with BTC's status as the most widely traded and institutionally adopted token. Importantly, RVOL loads negatively, showing that periods of high idiosyncratic volatility tend to hurt BTC returns. The decomposition confirms that BTC's performance is driven mostly by predictable structural factors rather than speculative components, yielding a modest positive total explained return of 0.16%.

Ethereum shows the strongest overall factor fit, with an R^2 of 0.94, indicating that nearly all of its cross-sectional return variation is captured by the model. Like BTC, its strong loading on VAL[Q] factor reflects its construction. Liquidity again plays a significant role, but with a negative contribution, implying that ETH tends to outperform during higher liquidity phases of the market. Its RVOL exposure is positive, meaning idiosyncratic volatility episodes have historically helped returns. This is likely due to periods of innovation, fee spikes, or speculative surges. ETH's decomposition factor totals 0.11%, reflecting strong alignment.

Solana behaves differently from BTC and ETH, with much larger exposures to Market, Momentum, and RVOL. Its high market beta (0.71) reflects its growth-asset nature, with returns highly sensitive to overall crypto cycles. Momentum loads positively, consistent with SOL's history of strong trend-driven rallies. However, Solana's negative loading on Liquidity indicates that it tends to outperform when liquidity in the broader market is thin; consistent with higher risk-seeking behavior. RVOL contributes the largest share to its explained return, suggesting Solana's performance is driven by idiosyncratic volatility bursts tied to upgrades, outages, or large flows. The total explained return is 0.09%, lower than BTC and ETH.

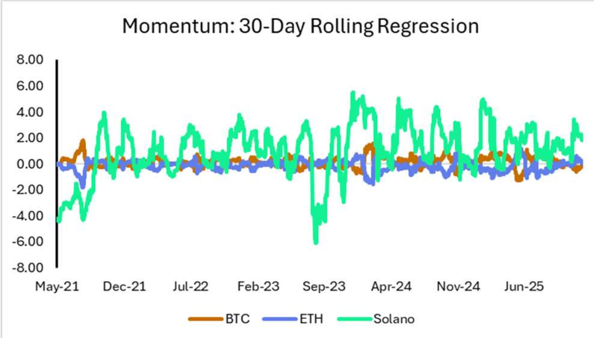
Static Regression Summary

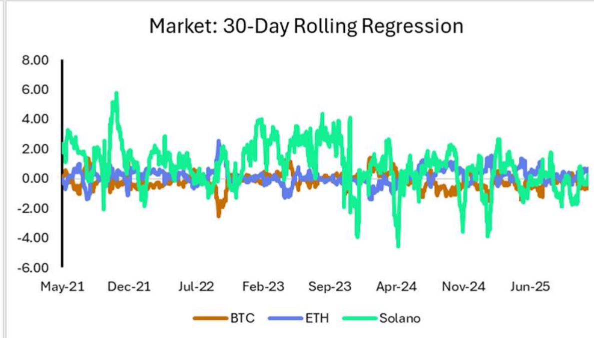
	Factor	Beta	t-Stat	p-Value	Significant?		Factor	Beta	t-Stat	p-Value	Significant?		Factor	Beta	t-Stat	p-Value	Significant?
Bitcoin	Market	0.0545	2.2800	0.02	Yes	Ethereum	Market	−0.0516	−2.14	0.03	Yes	Solana	Market	0.7100	8.7800	0.00	Yes
	Momentum	−0.031	−1.21	0.16	No		Momentum	0.0278	1.2400	0.22	No		Momentum	0.2750	3.6300	0.00	Yes
	Value 6M	0.0476	2.1900	0.04	Yes		Value 6M	−0.0487	−2.15	0.03	Yes		Value 6M	−0.015	−0.20	0.85	No
	Value Q	1.2430	42.4500	0.00	Yes		Value Q	1.7520	59.4500	0.00	Yes		Value Q	0.2680	2.7800	0.01	Yes
	Liquidity	0.1390	5.2500	0.00	Yes		Liquidity	−0.1347	−4.82	0.00	Yes		Liquidity	−0.4516	−4.84	0.00	Yes
	RVOL	−0.1516	−4.30	0.00	Yes		RVOL	0.1503	4.2300	0.00	Yes		RVOL	1.3240	11.1000	0.00	Yes
	R^2	0.8864	—	—	—		R^2	0.9374	—	—	—		R^2	0.6506	—	—	—

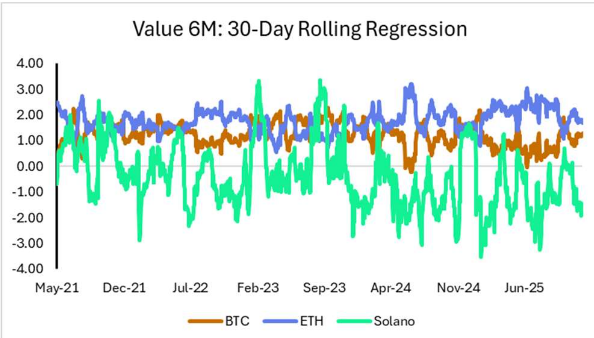
Bitcoin: Factor Decomposition				Etherum: Factor Decomposition				Solano: Factor Decomposition			
Factor	Beta	Risk Premium	ER Contribution	Factor	Beta	Risk Premium	ER Contribution	Factor	Beta	Risk Premium	ER Contribution
Market	0.05	0.22%	0.01%	Market	-0.05	0.22%	-0.01%	Market	0.71	0.22%	0.16%
Momentum	-0.03	-0.11%	0.00%	Momentum	0.03	-0.11%	0.00%	Momentum	0.27	-0.11%	-0.03%
Value 6M	0.05	0.06%	0.00%	Value 6M	-0.05	0.06%	0.00%	Value 6M	-0.01	0.06%	0.00%
Value Q	1.24	0.09%	0.11%	Value Q	1.75	0.09%	0.16%	Value Q	0.27	0.09%	0.02%
Liquidity	0.14	0.28%	0.04%	Liquidity	-0.13	0.28%	-0.04%	Liquidity	-0.45	0.28%	-0.13%
RVOL	-0.15	0.05%	-0.01%	RVOL	0.15	0.05%	0.01%	RVOL	1.32	0.05%	0.06%
Total			**0.16%**	**Total**			**0.11%**	**Total**			**0.09%**

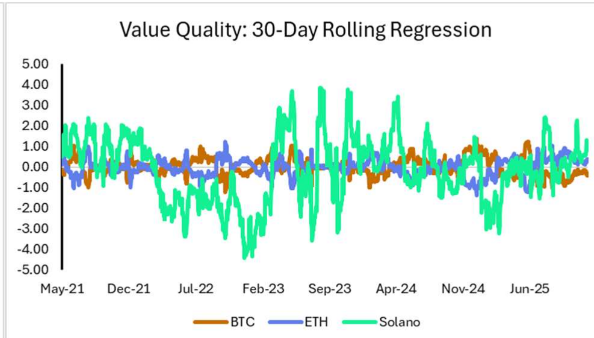
Rolling Regression Analysis of Major Assets

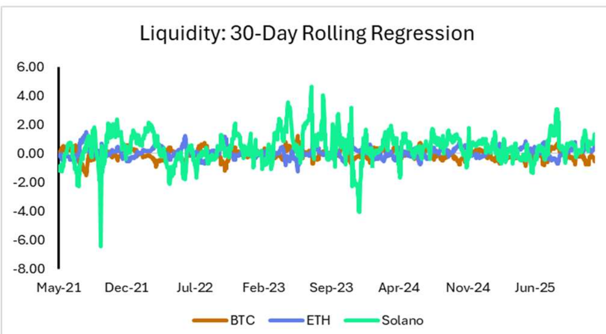
The rolling 30-day regressions illustrate how each asset's factor exposures evolve over time rather than remaining fixed, allowing us to observe how market regimes and liquidity shocks influence exposures dynamically. These charts highlight that factor betas, especially for Solana, can shift rapidly, while Bitcoin and Ethereum generally display more stable, structurally anchored exposures. Together, the rolling windows provide a clearer picture of how risk premia behave in real time and why static regressions alone cannot fully capture crypto's fast-moving market structure.

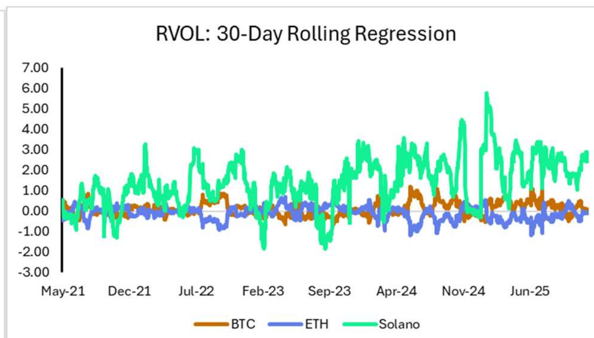

Momentum: 30-Day Rolling Regression
8.00
6.00
4.00
2.00
0.00
-2.00
-4.00
-6.00
-8.00
May-21
Dec-21
Jul-22
Feb-23
Sep-23
Apr-24
Nov-24
Jun-25
BTC
ETH
Solano


Market: 30-Day Rolling Regression
8.00
6.00
4.00
2.00
0.00
-2.00
-4.00
-6.00
May-21
Dec-21
Jul-22
Feb-23
Sep-23
Apr-24
Nov-24
Jun-25
BTC
ETH
Solano


Value 6M: 30-Day Rolling Regression
4.00
3.00
2.00
1.00
0.00
-1.00
-2.00
-3.00
-4.00
May-21
Dec-21
Jul-22
Feb-23
Sep-23
Apr-24
Nov-24
Jun-25
BTC
ETH
Solano


Value Quality: 30-Day Rolling Regression
5.00
4.00
3.00
2.00
1.00
0.00
-1.00
-2.00
-3.00
-4.00
-5.00
May-21
Dec-21
Jul-22
Feb-23
Sep-23
Apr-24
Nov-24
Jun-25
BTC
ETH
Solano


Liquidity: 30-Day Rolling Regression
6.00
4.00
2.00
0.00
-2.00
-4.00
-6.00
-8.00
May-21
Dec-21
Jul-22
Feb-23
Sep-23
Apr-24
Nov-24
Jun-25
BTC
ETH
Solano


RVOL: 30-Day Rolling Regression
7.00
6.00
5.00
4.00
3.00
2.00
1.00
0.00
-1.00
-2.00
-3.00
May-21
Dec-21
Jul-22
Feb-23
Sep-23
Apr-24
Nov-24
Jun-25
BTC
ETH
Solano

Key Insights and Final Thoughts

Discussion

The results show that Liquidity-related factors are the strongest and most consistent drivers of returns in crypto markets. Both Liquidity and RVOL generate large positive premia, indicating that investors are compensated for holding assets with thin markets and fragmented depth. In contrast, traditional equity-style factors such as Momentum perform poorly, suggesting that classical behavioral and valuation mechanisms do not translate cleanly into digital assets. Cross-sectional regressions for BTC, ETH, and SOL further show that each asset's factor exposures reflect its underlying characteristics. Bitcoin behaves like a deep-liquidity benchmark, Ethereum shows mixed structural and market sensitivity, and Solana exhibits high beta and reversal characteristics typical of a more volatile ecosystem. Together, the findings reinforce that crypto risk premia are shaped primarily by liquidity conditions.

Limitations:

This study faces several important limitations that constrain the generalizability of its results. First, the analysis relies solely on price-based data, despite the availability of rich on-chain information (transaction flow, validator behavior, supply dynamics, wallet-level activity) that could materially strengthen factor definitions, especially for Value and Liquidity. Second, the sample window is limited to roughly five years of data, a period that captures only a small subset of crypto market regimes. By extending the window backward or incorporating intraday (minute- or hour-level) pricing data, it would allow for sharper estimation of short-horizon signals. Third, the factor construction itself is necessarily simplified. Future work could refine these factors by incorporating alternative liquidity measures, nonlinear modeling, or hybrid signals that combine market and on-chain fundamentals. Fourth, significance testing is constrained by the non-normal, heavy-tailed nature of crypto returns. More rigorous methods, such as bootstrapping, permutation testing, or Bayesian estimation, would provide stronger statistical validation. Finally, this study does not incorporate key downside-risk metrics, such as maximum drawdown, which are particularly relevant for traders and risk managers operating in highly volatile frontier markets. Incorporating these elements would improve the practical applicability of factor signals and provide a fuller picture of crypto risk premia.

Conclusion

This paper provides an initial attempt to adapt multi-factor asset-pricing frameworks to cryptocurrency markets and to examine whether systematic risk premia exist within a frontier, highly illiquid ecosystem. While several factors exhibited strong in-sample performance, these results should not be interpreted as practical trading signals or robust empirical evidence of persistent premia. The testing period is short, the data is limited, and the crypto market structure changes rapidly, meaning that any conclusions drawn from these factors remain provisional. Moreover, the statistical tests used here highlight how non-normal return distributions, extreme volatility, and structural breaks undermine the reliability of conventional significance testing. Regression results show patterns that appear intuitive, yet none are stable enough to support real-world portfolio construction or risk management. In this sense, the analysis establishes a conceptual foundation rather than definitive empirical insight.

Overall, this work represents a starting point rather than a conclusion. Future research must incorporate longer histories, higher-frequency data, alternative factor definitions, robust methods such as bootstrapping and out-of-sample testing, and deeper integration of on-chain metrics. Only with broader data and more sophisticated statistical tools can we determine whether the factor premia suggested here are meaningful, persistent, and economically interpretable within the unique structure of digital asset markets.

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