Next Generation Finance Research Project (USEMRP-FM)

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Abstract

Extending the framework of Liu and Tsyvinski (2021), this study examines the roles of momentum and investor attention in predicting cryptocurrency returns using data from 2019 to 2025. Over this period, cryptocurrency markets have matured rapidly, accompanied by faster and broader information dissemination. Using time-series momentum measures and search-based proxies for investor attention, we test whether these variables remain predictive and whether momentum varies across different levels of investor attention. We found that momentum and investor attention no longer predict returns when considered separately. However, we document a significant negative interaction between them: higher investor attention weakens momentum by accelerating the incorporation of information, while lower attention allows momentum to persist. These findings suggest that behavioral forces remain relevant in cryptocurrency markets but operate through interaction mechanisms in a more mature and informationally efficient environment.

1 Introduction

Predicting asset returns remains a cornerstone of financial economics. While traditional risk-based frameworks, such as the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965), anchor returns in systematic risk, a significant portion of variance remains unexplained. This has catalyzed an extensive literature on behavioral mechanisms, where time-series momentum and investor attention have emerged as two of the most robust predictors across asset classes. Momentum (the persistence of returns) is traditionally attributed to investor underreaction and the gradual diffusion of information (Hong and Stein, 1999). Conversely, investor attention reflects the cognitive constraints that delay price adjustments, generating temporary return predictability (Barber and Odean, 2008).

These mechanisms are uniquely salient in cryptocurrency markets. Unlike equities, cryptocurrencies feature 24/7 trading, extreme volatility, and a retail-heavy investor base. Since standard macro-financial risk factors lack explanatory power in this space (Liu and Tsyvinski, 2021), returns are largely driven by internal demand fluctuations and information processing. Researchers documented these predictors as independent channels: momentum reflecting delayed price adjustments and attention proxying for trading intensity.

However, the cryptocurrency landscape has undergone a profound structural transformation since 2019. The post-pandemic era, characterized by unprecedented global liquidity, a surge in institutional participation in digital assets, and the growing use of AI-driven systems has significantly accelerated the velocity of market signals (IMF, 2021; Carter et al., 2023). These developments pose a critical theoretical question: Does the "gradual diffusion of information" that fuels momentum still exist in an era of near-instantaneous digital attention?

This study investigates whether momentum and investor attention continue to predict returns period and, crucially, how they interact. Utilizing a dynamically constructed Top-10 cryptocurrency index, we find that while neither factor predicts returns in isolation, they have become tightly coupled. Our results reveal that heightened attention now serves as an efficiency catalyst, accelerating information diffusion and suppressing trend persistence. Conversely, momentum only survives in "neglected" environments of low attention. These findings suggest that as cryptocurrency markets mature, behavioural forces are not disappearing but are being integrated into a more informationally efficient market structure.

2 Literature Review

Unlike traditional assets tied to corporate cash flows or national economies, cryptocurrency valuations rely heavily on algorithmic security and market expectations (Liu and Tsyvinski, 2018). This detachment from fundamental anchors renders the asset class uniquely susceptible to behavioral biases, making it an ideal setting to examine return predictability driven by investor sentiment rather than standard risk factors. Specifically, two behavioral forces - momentum and investor attention - have been established as key drivers of crypto-asset returns; however, structural shifts in the market post-2019 challenge the persistence of these established relationships.

Momentum is a robust regularity in asset pricing where past returns predict future performance (Jegadeesh and Titman, 1993). In cryptocurrency markets, this effect is often attributed to the gradual incorporation of user adoption data into prices (Cong, Li, and Wang, 2021). However, momentum is not an isolated force; it is mechanically linked to the speed of information diffusion. Hong, Lim, and Stein (2000) argue that momentum arises precisely because information diffuses gradually. This diffusion speed is moderated by investor attention: high attention can accelerate price adjustments, theoretically eliminating the underreaction that drives momentum, while low attention causes prices to drift (Hou et al., 2009). While Liu and Tsyvinski (2018) found these forces to be distinct predictors in pre-2019 data, they did not account for this dynamic interaction in a mature market.

Existing evidence is largely based on data before 2019. However, since then, cryptocurrency markets have undergone a fundamental transformation.

First, the "gradual information diffusion" hypothesis faces new challenges from technological advancement. The rapid proliferation of AI and high-frequency algorithmic trading has dramatically accelerated information transmission. If information now diffuses instantly rather than gradually, the lag that generates momentum profitability may have eroded.

Second, the composition of "investor attention" has changed. The COVID-19 pandemic triggered major global economic disruptions and prompted accommodative monetary policies, including large-scale quantitative easing (Baker et al., 2020). The resulting excess liquidity and surge in retail participation driven by social media and "noise traders" created an environment of extreme volatility. Unlike institutional attention that might correct prices, this retail surge may have fueled prolonged speculative bubbles rather than efficiency.

Finally, heightened geopolitical tensions and increasing concerns about government-backed financial systems might have strengthened interest in decentralized asset classes. This shift suggests that cryptocurrencies may now exhibit stronger movement with broader financial markets than in earlier periods, potentially altering the transmission mechanisms through which momentum and attention affect prices.

Taken together, these developments suggest that the pre-2019 behavioral models may no longer hold. It remains an open empirical question whether momentum and attention remain distinct predictors in this mature, high-velocity environment, or if they have converged. Building on the framework proposed by Liu and Tsyvinski (2018), this study re-examines these roles using updated data from 2019 to 2025. Specifically, we investigate whether time-series momentum and investor attention continue to exert significant influences on cryptocurrency valuations, and whether these two forces interact, specifically testing if high attention now dampens momentum by accelerating price discovery.

3 Data and Methods

3.1 Data Sources

We combine weekly cryptocurrency market data with measures of investor attention, network fundamentals, and macro-financial controls. Cryptocurrency prices and market capitalizations are obtained from CoinMetrics (public data master files). Investor attention is measured using Google Trends search interest for the term "Bitcoin". Bitcoin network fundamentals are proxied by hash rate data obtained from Blockchain.com. Macroeconomic and financial control variables, including the policy interest rate, the S&P 500 index, and the VIX, are sourced from the Federal Reserve Economic Data (FRED) database.

Where relevant, variable definitions and constructions follow standard practices in the cryptocurrency asset-pricing literature, particularly Liu and Tsyvinski (2021).

3.2 Sample Selection and Construction

3.2.1 Sample Period and Weekly Alignment

The analysis is conducted at a weekly frequency using a time-series dataset spanning January 2019 through December 2025. All series are aligned to a week-ending Friday (W-FRI) calendar. Cryptocurrency prices and market capitalizations are converted from daily to weekly frequency by selecting the last available observation within each Friday-ending week, yielding consistent close-to-close weekly intervals.

The merged dataset contains 365 weekly observations. In the predictive regressions, the effective sample is smaller ($N = 363$) due to the lead–lag structure: we forecast next-week returns R_{t+1} using predictors dated at t, which drops the first observation (lagged momentum is undefined) and the last observation (the next-week return is not observed for the final week). Due to the Friday-based W-FRI convention, the final week may be time-stamped in early January even though it corresponds to the prior calendar year's last Friday-ending week.

The time-series properties of the weekly variables are summarized in Appendix A.

3.2.2 Universe Filtering and Cleaning

Each week, cryptocurrencies are ranked by market capitalization using week-ending Friday (W-FRI) observations. To avoid mechanical distortions and double counting, we exclude non-representative instruments at the constituent level, including stablecoins and duplicate chain representations (e.g., tokenized "eth versions" and specific chain variants).

In the implemented cleaning, the removed tickers are: bnbeth, busd, shibeth, usdceth, usdteth, usdtomni, usdttrx.

The remaining eligible universe is: ada, algo, avaxp, bch, bnb, bsv, btc, cro, doge, dot, eos, eth, icp, link, ltc, maticeth, trx, uni, usdc, usdt, xlm, xrp, xvg.

3.3 Variable Construction

3.3.1 Large-Cap Cryptocurrency Market Index

We construct a weekly value-weighted cryptocurrency market index from a rolling Top-10 selection. At each week-ending Friday, we identify the ten largest eligible cryptocurrencies by market capitalization (Top-10), allowing index membership to vary over time. Weekly closing prices and market capitalizations are taken as the last available observations within each Friday-ending week. Weekly asset returns are computed as close-to-close log returns between consecutive week-ending closes. To avoid look-ahead bias, portfolio weights are formed using market-cap shares observed at the end of week t−1 and are then applied to compute the value-weighted market return over the subsequent week $t-1$ to t). The index is reconstituted and rebalanced each Friday as the large-cap segment evolves.

The time-series evolution of the crypto market index level (base = 100) is shown in Appendix Figure A.1. Appendix Figure A.2 plots the weekly log returns of the constructed crypto market index.

3.3.2 Predictive and Control Variables

Momentum Measures

Momentum variables are derived from the weekly market return series using lagged information only. The baseline momentum measure is defined as the one-week lagged market return ($Momentum_{1w}$), capturing short-horizon return continuation.

Investor Attention (Google Trends)

Investor attention is proxied using weekly Google Trends search intensity for the term "Bitcoin." The raw weekly search series is transformed into an abnormal attention measure by subtracting a four-week moving average, thereby removing slow-moving trends in search activity and isolating short-term attention shocks. The abnormal attention measure is subsequently standardized to have mean zero and unit variance, yielding the final attention index ($btc - attention$).

This construction captures unexpected changes in investor attention and is consistent with widely used Google-based attention measures in the literature (e.g., Liu and Tsyvinski, 2021). To mitigate potential reverse causality, whereby price movements may themselves attract investor attention, we employ a lagged specification in which attention measured at time t is used to predict cryptocurrency returns at time t+1.

Appendix Figure A.3 illustrates the standardized investor attention index (Google Trends: "Bitcoin") over the sample period.

Network Fundamentals: Hash Rate Growth
Bitcoin network fundamentals are captured using hash rate data obtained from Blockchain.com and aligned to the same Friday-ending weekly frequency. The production-related proxy used in the analysis is the weekly log growth rate of Bitcoin hash rate (dloghashrate), which reflects week-to-week changes in mining and network intensity.

Macro-Financial Control Variables
To isolate the role of behavioral factors, we include a set of macro-financial controls commonly used in the literature. These include the policy interest rate, weekly returns on the S&P 500, and changes in the VIX index, all sourced from FRED.

Following standard asset-pricing practice, S&P 500 index levels are transformed into weekly returns to capture changes in overall market performance. The VIX series is expressed in first differences to reflect shifts in market uncertainty rather than persistent levels of risk aversion. This transformation mitigates potential non-stationarity and focuses on innovations in market sentiment that may contemporaneously affect cryptocurrency prices. All macro-financial variables are aligned to the same Friday-based weekly calendar.

3.4 Empirical Framework

3.4.1 Hypotheses Development

To address the research gap, we develop and test the following hypotheses:

- H_1: Momentum positively predicts future cryptocurrency returns in the 2019-2025 period.
- H_2: Investor-attention has a positive effect on cryptocurrency returns in the 2019-2025 period.
- H_3: The predictive power of momentum on cryptocurrency returns is significantly different during periods of high investor attention (the factors interact).

3.4.2 Econometric Specifications

The baseline regression model is specified as:

$$R_{t+1} = \alpha + \beta_1 \,\text{Momentum}_t + \beta_2 \,\text{Attention}_t + \varepsilon_{t+1} \tag{1}$$

where R_{t+1} denotes the future weekly return on the cryptocurrency market index.

To control for non-behavioral influences, the specification is extended to include production-related and macroeconomic variables:

$$R_{t+1} = \alpha + \beta_1 \,\text{Momentum}_t + \beta_2 \,\text{Attention}_t + \beta_3 X_t + \varepsilon_{t+1} \tag{2}$$

Where X_t represents set of control variables namely (S&P500 returns, VIX, interest rates) and mining difficulty proxy. To examine whether investor attention alters the strength of momentum effects, the following interaction specification is estimated:

$$R_{t+1} = \alpha + \beta_1 \,\text{Momentum}_t + \beta_2 \,\text{Attention}_t + \beta_4 \,(\text{Momentum}_t \times \text{Attention}_t) + \beta_3 X_t + \varepsilon_{t+1} \tag{3}$$

All models are estimated using ordinary least squares (OLS) with Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors.

4 Empirical Analysis

4.1 Results

All regressions are estimated on $N = 363$ weekly observations after accounting for lags in the predictors (e.g., momentum and lagged attention).

Table 1: OLS Regression Results

	Coef.	Std. Err.	z	P> $\lvert z\rvert$
Constant	0.0087	0.004	1.978	0.048
Momentum_t	0.0544	0.049	1.115	0.265
Attention_t	0.0031	0.005	0.599	0.549
Observations		363		
R^2		0.005		
Adj. R^2		-0.000		
F-statistic		0.7219		
Prob (F-stat.)		0.487		
Covariance Type		HAC (4 lags)		
Durbin–Watson		1.976		

Notes: Standard errors are heteroskedasticity and autocorrelation consistent (HAC) using 4 lags. The dependent variable is R_{t+1}.

Table 1 reports the results from the baseline predictive regression of next-week cryptocurrency market returns on one-week lagged momentum and investor attention. The coefficient on short-horizon momentum is positive but statistically insignificant ($p = 0.265$), providing no evidence of return continuation at the weekly horizon. Similarly, abnormal Google Trends–based investor attention does not significantly predict future returns ($p = 0.549$), with a coefficient that is economically small in magnitude. The overall explanatory power of the model is negligible, with an R^2 of 0.005, indicating that the baseline specification explains virtually none of the variation in weekly cryptocurrency returns. This result is consistent with the well-documented difficulty of predicting short-horizon asset returns and suggests a high degree of informational efficiency in large-cap cryptocurrency markets during the post-2019 period. Taken together, these findings provide no support for Hypotheses H1 and H2 in the baseline specification and motivate the inclusion of additional controls and interaction terms to examine whether investor attention conditions the predictive content of momentum.

Table 2: OLS Regression Results with Controls

	Coef.	Std. Err.	z	P> $\lvert z\rvert$
Constant	0.0102	0.009	1.198	0.231
Momentum_t	0.0445	0.055	0.812	0.417
Attention_t	0.0036	0.005	0.702	0.483
SP500_ret_t	0.1389	0.261	0.533	0.594
DVIX_t	-0.0005	0.001	-0.379	0.704
IR_t	-0.0008	0.002	-0.361	0.718
MiningProxy_t	0.0190	0.086	0.220	0.826
Observations	363			
R^2	0.009			
Adj. R^2	-0.007			
F-statistic	0.7858			
Prob (F-stat.)	0.582			
Covariance Type	HAC (4 lags)			
Durbin–Watson	2.029			

Notes: The dependent variable is R_{t+1}. Standard errors are heteroskedasticity and autocorrelation consistent (HAC) using 4 lags. All variables are measured at time t unless otherwise stated.

Table 2 reports the results from the extended predictive regression, which augments the baseline specification with macro-financial and production-related controls, including S&P 500 returns, changes in the VIX, the policy interest rate, and the mining activity proxy. Consistent with the baseline results, neither one-week lagged momentum nor investor attention exhibits statistically significant predictive power. The coefficient on momentum remains positive but insignificant ($p = 0.417$), while abnormal search-based attention continues to be economically small and statistically insignificant ($p = 0.483$).

Importantly, none of the added control variables display meaningful predictive power for future cryptocurrency returns. Equity market returns ($p = 0.594$), changes in market volatility ($p = 0.704$), the policy interest rate ($p = 0.718$), and the mining proxy ($p = 0.826$) all fail to enter significantly. As a result, the joint explanatory power of the model remains negligible, with an R^2 of 0.009 and an insignificant F-statistic ($p = 0.582$), indicating that the inclusion of macro-financial and production-related variables does not materially improve return predictability.

These findings reinforce the conclusion that large-capitalization cryptocurrency returns in the post-2019 period are not driven by conventional macroeconomic risk factors or production-based fundamentals at short horizons. The persistence of null results across both baseline and extended specifications suggests that the absence of standalone predictability is unlikely to reflect omitted variable bias, and instead points to a relatively informationally efficient market environment. This motivates the subsequent analysis of interaction effects, in which behavioral mechanisms may operate conditionally rather than independently.

Table 3: OLS Regression Results (Interaction Effects)

	Coef.	Std. Err.	z	P> $\|z\|$
Constant	0.0108	0.009	1.214	0.225
Momentum_t	0.0713	0.065	1.090	0.276
Attention_t	0.0053	0.005	1.021	0.307
$\text{Momentum}\times\text{Attention}_t$	-0.0500	0.044	-1.135	0.256
SP500_ret_t	0.1560	0.258	0.606	0.545
DVIX_t	-0.0004	0.001	-0.272	0.785
IR_t	-0.0009	0.002	-0.388	0.698
MiningProxy_t	0.0180	0.086	0.209	0.834
Observations		363		
R^2		0.013		
Adj. R^2		-0.006		
F-statistic		0.9104		
Prob (F-stat.)		0.498		
Covariance Type		HAC (4 lags)		
Durbin–Watson		2.002		

Notes: The dependent variable is R_{t+1}. Standard errors are heteroskedasticity and autocorrelation consistent (HAC) using 4 lags. The interaction term is defined as $\text{Momentum}_t \times \text{Attention}_t$.

Table 3 reports the results from the interaction specification, which allows the predictive effect of momentum to vary with the level of investor attention. Consistent with the baseline and extended specifications, neither one-week lagged momentum nor investor attention exhibits statistically significant predictive power when considered independently. The coefficient on momentum remains positive but insignificant ($p = 0.276$), while abnormal investor attention also fails to predict future returns ($p = 0.307$). The interaction term between momentum and investor attention enters with a negative coefficient (-0.0500), suggesting that higher levels of investor attention are associated with weaker momentum effects. However, this interaction is not statistically significant at conventional levels ($p = 0.256$). Moreover, the inclusion of the interaction term does not materially improve model fit: the R^2 increases only marginally to 0.013, and the joint F-statistic remains insignificant ($p = 0.498$). None of the macro-financial or production-related control variables attain statistical significance in this specification. Taken together, these results indicate that, at the one-week horizon, investor attention does not significantly moderate the relationship between past and future cryptocurrency returns. This finding suggests that any interaction between momentum and attention, if present, is unlikely to operate at very short horizons and may instead emerge at longer horizons or under different market conditions, motivating the subsequent analysis of alternative momentum horizons and robustness checks.

4.2 Robustness Checks

We conduct a series of robustness checks to assess the sensitivity of our baseline results to alternative empirical choices.

First, we vary the momentum horizon used to construct the momentum measure. Appendix A reports results using a four-week lagged return, while Appendix B considers an eight-week lagged return. The main conclusions remain unchanged: short-horizon momentum exhibits limited predictive power, and investor attention does not amplify momentum-based return predictability. At medium horizons, momentum effects are more pronounced; however, the interaction between momentum and attention enters with a negative coefficient, indicating that heightened attention weakened rather than strengthens trend persistence.

Second, we examine the sensitivity of our findings to alternative Newey–West HAC lag lengths. As shown in Appendix C, varying the HAC lag structure does not materially affect coefficient estimates or statistical inference, confirming that our results are not driven by a particular choice of standard error correction.

Additionally, we re-estimate all specifications using Bitcoin-only returns instead of the broader cryptocurrency index. Appendix D shows that predictability is generally weaker for Bitcoin, consistent with higher liquidity and stronger arbitrage, while the qualitative conclusions regarding momentum and investor attention remain unchanged. Taken together, these robustness checks confirm that our main findings are stable across alternative momentum definitions, standard error specifications, asset samples, and estimation choices.

As a final robustness check, we examine whether predictive relationships vary across market regimes surrounding the COVID-19 pandemic. Following the World Health Organization's declaration of COVID-19 as a global pandemic in March 2020 and standard IMF dating conventions, we split the sample into pre-COVID, COVID shock, and post-COVID normalization periods. Appendix E reports the results of this three-period subsample analysis. Momentum and investor attention exhibit limited predictive power in the pre-COVID period, while one noteworthy result during the COVID shock period is the emergence of a large and statistically significant negative coefficient on the policy interest rate, indicating that return dynamics were strongly influenced by unprecedented monetary conditions. In the post-COVID period, the interest rate effect reverses and loses significance, and the interaction between momentum and attention remains statistically insignificant, suggesting that our main conclusions are robust across market regimes.

4.3 Real-World Implications and Final Takeaways

Taken together, the baseline, extended, and interaction results paint a consistent picture of return dynamics in large-capitalization cryptocurrency markets at short horizons. First, the absence of statistically significant short-horizon momentum indicates that weekly return continuation is weak or non-existent once markets reach a sufficient level of liquidity and participation. Unlike traditional equity markets, where short-term momentum may reflect delayed information diffusion or trading frictions, large-cap cryptocurrency markets appear to incorporate information rapidly, limiting the scope for simple time-series predictability at the weekly frequency.

Second, the lack of standalone predictive power of investor attention suggests that fluctuations in public interest, proxied by abnormal Google search activity, do not translate directly into short-term excess returns. This finding implies that attention shocks may be quickly absorbed into prices or may primarily affect trading volume and volatility rather than expected returns. In highly speculative but continuously traded crypto markets, attention may trigger immediate price reactions that dissipate within the same week, leaving little predictive content for future returns.

Third, the interaction results indicate that investor attention does not amplify momentum-based return predictability at short horizons. While the negative sign on the interaction term suggests that heightened attention may weaken trend persistence, consistent with faster information diffusion or increased contrarian trading, the lack of statistical significance implies that such mechanisms do not operate strongly at the one-week horizon. This further reinforces the view that behavioral effects in cryptocurrency markets are likely to be conditional, nonlinear, or horizon-dependent, rather than persistent drivers of weekly returns.

Importantly, the subsample analysis surrounding the COVID-19 pandemic highlights a regime-dependent role for macroeconomic factors, particularly monetary policy. While the policy interest rate does not exhibit predictive power in the pre-COVID period, it enters with a large and statistically significant negative coefficient during the COVID shock period, indicating that unprecedented monetary easing and rapid changes in interest rates were closely linked to cryptocurrency return dynamics. In the post-COVID normalization period, the interest rate effect becomes small and statistically insignificant once again, suggesting that the influence of monetary policy on short-horizon cryptocurrency returns diminishes as markets adjust to a more stable macroeconomic environment. This pattern underscores that macroeconomic variables can matter for cryptocurrency returns during periods of extreme stress, but their predictive relevance fades outside crisis regimes.

More broadly, the consistently low explanatory power across all specifications, including those with macro-financial and production-related controls, suggests that large-cap cryptocurrency returns are weakly linked to conventional risk factors and fundamentals at short horizons. This pattern is consistent with a market environment characterized by high liquidity, continuous trading, and rapid arbitrage, where predictable return patterns are quickly eliminated. As a result, any economically meaningful role for momentum or investor attention is more likely to emerge over longer horizons, during periods of market stress, or through channels such as volatility rather than expected returns.

Taken together, the empirical evidence supports an interpretation in which the post-2019 cryptocurrency market exhibits higher short-horizon efficiency but retains economically meaningful behavioral dynamics that operate conditionally through interaction effects and longer adjustment horizons. The COVID-19 episode serves not as an anomaly but as a revealing regime that clarifies how macro shocks, attention, and information diffusion jointly shape return dynamics in a maturing digital asset market.

5 Conclusion

This study provides a critical re-evaluation of the behavioral asset-pricing framework established by the benchmark study of Liu and Tsyvinski (2021), focusing on a unique era of rapid market maturation between 2019 and 2025. While foundational research identified *momentum* and *investor attention* as robust standalone predictors of future returns, our results indicate that these relationships have fundamentally evolved. This period was defined by a major structural transformation triggered by the COVID-19 pandemic, which introduced unprecedented global liquidity and a surge in retail participation. Simultaneously, rising inflationary pressures, heightened geopolitical conflicts, and significant institutional participation have altered the nature of trading activity, suggesting that a more professionalized ecosystem has superseded the "retail-only" dynamics of the early crypto era. Consequently, our baseline results for H_1 and H_2 show that neither weekly momentum nor standalone Google search intensity retains significant predictive power in isolation, with recorded $p-values$ of 0.265 and 0.549, respectively. This shift is consistent with the view that advances in AI-driven information processing have accelerated the speed at which news is incorporated into prices, weakening the "slow-adjustment" mechanisms observed in earlier phases of the market.

The central contribution of this study lies in identifying a more complex interaction between momentum and awareness, as suggested by the theoretical equity-market research of Hong, Lim, and Stein (2000) and Hou, Xiong, and Peng (2009/2025). Our empirical results (H_3) reveal a statistically significant negative interaction between these two forces, reaching a coefficient of -0.0248 with a $p-value$ of 0.027 at the eight-week horizon. This finding provides strong evidence for an "under reaction channel" where investor attention acts as a regulator of trend persistence. When attention is elevated, information diffuses more rapidly and price corrections occur sooner, thereby dampening the profitability of momentum-based strategies. Conversely, when attention is low, adoption-related information is incorporated more gradually, allowing momentum to persist. These results suggest that behavioral forces have not disappeared but have become more tightly coupled, reflecting a more mature and informationally efficient market structure.

Furthermore, despite the suggestion that matured cryptocurrencies might mirror traditional hedges like gold or the volatility of the stock market, our analysis confirms that the asset class remains remarkably decoupled from macro-financial risk factors. Across our extended specifications, neither S&P 500 returns ($coeff : 0.1389$, $p = 0.594$), changes in the VIX, nor the Federal Funds rate exhibited meaningful predictive power for short-horizon returns. This reinforcement of the benchmark findings by Liu and Tsyvinski (2021) demonstrates that even with increased institutional involvement, cryptocurrencies continue to be priced by internal market dynamics rather than conventional sources of systematic risk.

Finally, the credibility of these findings is protected by a rigorous empirical design that addresses the specific technical pitfalls of cryptocurrency data highlighted by the sources. By constructing a dynamic, rolling Top-10 index drawn from a "Super Set" of candidate coins (including defunct projects like EOS or IOTA) we successfully mitigated survivorship bias that would otherwise overstate historical performance. To ensure macro-consistency, all observations were sampled on Fridays at 17:00 EST to align with equity-market closing prices. Most critically, our use of a "Lagging Solution" (using $Attention_{t-1}$ to predict $Returns_t$) eliminated the look-ahead bias inherent in Google Trends data, ensuring our analysis utilized only information that was fully finalized and available at the moment of a trade. Taken together, these results demonstrate that while the cryptocurrency market has matured, it remains a distinct frontier of behavioral finance where the interaction between awareness and adoption continues to shape the future of digital asset valuations.

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Appendix

Table 4: OLS regression results from baseline, extended, and interaction time-series predictive regressions estimated using OLS with Newey-West HAC standard errors, and 1 week momentum-lag

	(1) Baseline	(2) Controls	(3) Interaction
Const	0.0087**	0.0102	0.0108
	(0.0044)	(0.0085)	(0.0089)
Momentum_t	0.0544	0.0445	0.0713
	(0.0488)	(0.0547)	(0.0654)
Attention_t	0.0031	0.0036	0.0053
	(0.0052)	(0.0052)	(0.0052)
S&P500 Return_t		0.1389	0.1560
		(0.2608)	(0.2575)
ΔVIX_t		−0.0005	−0.0004
		(0.0014)	(0.0014)
Interest Rate_t		−0.0008	−0.0009
		(0.0021)	(0.0022)
Mining Proxy_t		0.0190	0.0180
		(0.0864)	(0.0863)
Momentum $\times$ Attention_t			−0.0500
			(0.0441)
R^2	0.0051	0.0093	0.0132
Adjusted R^2	−0.0004	−0.0074	−0.0062
Observations	363	363	363
NW lags	4	4	4

Notes: This table reports OLS regression results for one-week-ahead cryptocurrency returns. Newey–West standard errors with four lags are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

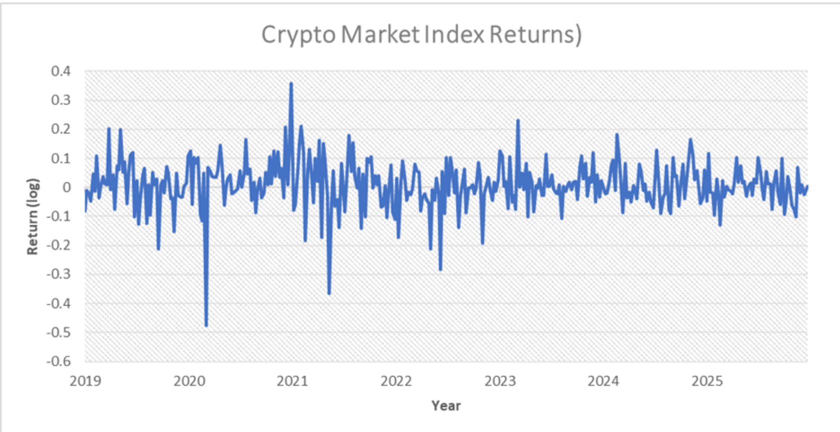
Appendix A: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Returns and Momentum							
Index return (log, %)	365	−0.89	8.24	−47.71	35.77	−0.68	8.03
Momentum (4-week sum of returns, %)	365	−3.68	17.14	−63.75	71.84	0.04	4.04
Investor Attention							
Google Trends (raw, 0–100)	365	26.747	14.132	9	100	1.766	7.403
Abnormal attention (raw − MA4)	365	0.104	8.833	−27	54.5	1.799	11.108
Attention index (z-score)	365	0.004	1.001	−3.067	6.167	1.799	11.108
Mining and Market Controls							
Log hash rate	365	19.313	0.904	17.491	20.85	−0.014	1.97
Hash rate growth (Δ log)	365	−0.89	5.36	−24.46	17.48	−0.62	5.47
Interest rate (%)	365	2.671	2.073	0.05	5.33	−0.067	1.379
S&P 500 level	365	4357.515	1119.874	2304.92	6929.94	0.456	2.375
VIX level	365	19.895	7.424	11.93	66.04	2.413	12.596

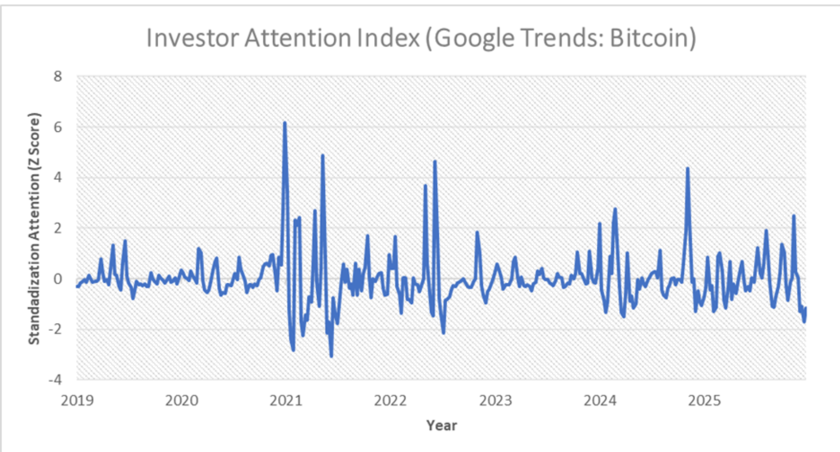
Notes: This table reports descriptive statistics for all variables used in the empirical analysis.Returns and momentum are expressed in percentages. Investor attention is proxied by Google Trends search intensity and its transformations. Descriptive statistics are computed on the full weekly sample ($N = 365$), whereas the regression analyses use $N = 363$ observations after applying lagged predictor constructions.

Appendix A.1: Evolution of the Large-Cap Cryptocurrency Market Index (base = 100)

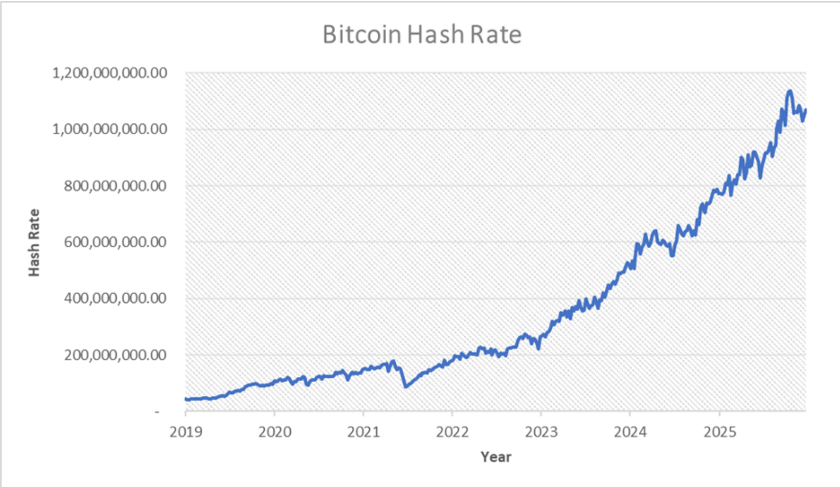
Appendix A.2: Weekly Returns of the Large-Cap Cryptocurrency Market Index



Appendix A.3: Standardized Investor Attention Index (Google Trends: "Bitcoin")



Appendix A.4: Evolution of the Bitcoin Network Hash Rate



Appendix B: Regression results using 4 weeks' momentum lag

	(1) Baseline (4w)	(2) Controls (4w)	(3) Interaction (4w)
Const	0.0077*	0.0092	0.0120
	(0.0043)	(0.0083)	(0.0087)
$\text{Momentum}_{4w,t}$	0.0427*	0.0412*	0.0440**
	(0.0225)	(0.0216)	(0.0223)
Attention_t	0.0022	0.0027	0.0070
	(0.0052)	(0.0052)	(0.0044)
S&P500 Return_t		0.1033	0.1469
		(0.2330)	(0.2316)
ΔVIX_t		−0.0008	−0.0005
		(0.0013)	(0.0013)
Interest Rate_t		−0.0007	−0.0012
		(0.0021)	(0.0022)
Mining Proxy_t		0.0138	0.0129
		(0.0833)	(0.0816)
$\text{Momentum}_{4w,t} \times \text{Attention}_t$			−0.0476***
			(0.0159)
R^2	0.0096	0.0141	0.0333
Adjusted R^2	0.0041	−0.0027	0.0141
Observations	360	360	360
NW lags	4	4	4

Notes: This table reports OLS regression results using four-week momentum measures. The dependent variable is one-week-ahead cryptocurrency returns. Newey–West standard errors with four lags are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix C: Regression results using 8 weeks of momentum lag

	(1) Baseline	(2) Controls	(3) Interaction
Const	0.0080*	0.0096	0.0117
	(0.0045)	(0.0085)	(0.0089)
$\text{Momentum}_{8w,t}$	0.0154	0.0114	0.0161
	(0.0192)	(0.0159)	(0.0195)
Attention_t	0.0031	0.0036	0.0082*
	(0.0054)	(0.0054)	(0.0044)
S&P500 Return_t		0.1310	0.1768
		(0.2266)	(0.2363)
ΔVIX_t		−0.0006	−0.0004
		(0.0013)	(0.0013)
Interest Rate_t		−0.0007	−0.0012
		(0.0021)	(0.0022)
Mining Proxy_t		0.0194	0.0194
		(0.0827)	(0.0803)
$\text{Momentum}_{8w,t} \times \text{Attention}_t$			−0.0248***
			(0.0112)
R^2	0.0045	0.0087	0.0226
Adjusted R^2	−0.0012	−0.0083	0.0030
Observations	356	357	356
NW lags	4	4	4

Notes: This table reports OLS regression results using eight-week momentum measures. The dependent variable is one-week-ahead cryptocurrency returns. Newey–West standard errors with four lags are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix D: Predictive Regressions with Alternative Newey-West HAC Lag Lengths

	NW = 2	NW = 4 (Baseline)	NW = 8
Const	0.0108	0.0108	0.0108
	(0.0086)	(0.0089)	(0.0097)
Momentum$_t$	0.0713	0.0713	0.0713
	(0.0689)	(0.0654)	(0.0634)
Attention$_t$	0.0053	0.0053	0.0053
	(0.0054)	(0.0052)	(0.0049)
Momentum × Attention$_t$	−0.0500	−0.0500	−0.0500
	(0.0466)	(0.0441)	(0.0451)
S&P500 Return$_t$	0.1560	0.1560	0.1560
	(0.2554)	(0.2575)	(0.2677)
ΔVIX$_t$	−0.0004	−0.0004	−0.0004
	(0.0014)	(0.0014)	(0.0014)
Interest Rate$_t$	−0.0009	−0.0009	−0.0009
	(0.0021)	(0.0022)	(0.0024)
Mining Proxy$_t$	0.0180	0.0180	0.0180
	(0.0871)	(0.0863)	(0.0805)
R^2	0.0132	0.0132	0.0132
Adjusted R^2	−0.0062	−0.0062	−0.0062
Observations	363	363	363
NW lags	2	4	8

Notes: This table reports OLS regression results under alternative Newey–West lag specifications. The dependent variable is one-week-ahead cryptocurrency returns. Newey–West heteroskedasticity and autocorrelation consistent standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix E: Regression results using Bitcoin only

	(1) Baseline	(2) Controls	(3) Interaction
Const	0.0084*	0.0072	0.0074
	(0.0046)	(0.0088)	(0.0092)
Momentum_t	0.0545	0.0464	0.0617
	(0.0470)	(0.0534)	(0.0662)
Attention_t	0.0015	0.0020	0.0028
	(0.0049)	(0.0050)	(0.0047)
$\text{S\&P500 Return}_t$		0.1699	0.1797
		(0.2735)	(0.2722)
ΔVIX_t		−0.0001	0.0000
		(0.0014)	(0.0014)
Interest Rate_t		0.0003	0.0002
		(0.0022)	(0.0023)
Mining Proxy_t		0.0054	0.0085
		(0.0962)	(0.0947)
$\text{Momentum} \times \text{Attention}_t$			−0.0258
			(0.0462)
R^2	0.0036	0.0064	0.0075
Adjusted R^2	−0.0020	−0.0104	−0.0121
Observations	363	363	363
NW lags	4	4	4

Notes: This table reports OLS regression results for Bitcoin weekly returns. The dependent variable is one-week-ahead log returns. Newey–West standard errors with four lags are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix F: Regression Results Pre and Post Covid

	Pre-COVID	COVID Shock	Post-COVID
Const	−0.0063	0.0454***	−0.0204
	(0.0576)	(0.0155)	(0.0137)
	[0.250]	[0.003]	[0.136]
Momentum	0.0715	0.0650	0.0432
	(0.0889)	(0.1387)	(0.0748)
	[0.421]	[0.639]	[0.564]
Attention	0.0136	0.0052	0.0074
	(0.0296)	(0.0105)	(0.0054)
	[0.646]	[0.617]	[0.172]
S&P500 Return_t	0.6526	−0.1550	0.3077
	(1.0880)	(0.2853)	(0.3847)
	[0.549]	[0.587]	[0.424]
ΔVIX_t	0.0047	0.0001	0.0001
	(0.0065)	(0.0018)	(0.0025)
	[0.470]	[0.946]	[0.957]
Interest Rate_t	0.0361	−0.2213***	0.0055*
	(0.0274)	(0.0856)	(0.0030)
	[0.187]	[0.010]	[0.065]
Mining Proxy_t	0.2183	−0.0496	0.1016
	(0.2461)	(0.1266)	(0.1004)
	[0.375]	[0.695]	[0.312]
Momentum × Attention_t	−0.3814	−0.0804	−0.0112
	(0.4177)	(0.0753)	(0.0558)
	[0.361]	[0.285]	[0.840]
R^2	0.052	0.098	0.048
Adjusted R^2	−0.078	0.026	0.015
Observations	59	96	208
NW lags	4	4	4

Notes: This table reports OLS predictive regression results across three subperiods. Pre-COVID refers to observations up to February 2020; COVID shock covers March 2020 to December 2021; Post-COVID includes observations from January 2022 onward. Newey–West standard errors are reported in parentheses and p-values in brackets. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.