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# The Weekend Effect in Crypto Momentum: Does Momentum Change When Markets Never Sleep?

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**ABSTRACT**
Cryptocurrency markets, operating 24/7 without the structural breaks of traditional financial markets, offer a unique laboratory to examine temporal anomalies such as the weekend effect. This study investigates whether momentum returns in cryptocurrencies differ systematically between weekdays and weekends, focusing on ten major cryptocurrencies based on market capitalization over the period from January 2020 to April 2025. Employing a 7-day momentum strategy, we find that weekend momentum returns significantly exceed weekday returns, particularly for altcoins, with higher Sharpe ratios and lower maximum drawdowns. These findings, robust across various specifications, suggest that behavioral factors and liquidity dynamics drive this anomaly, challenging notions of market efficiency in cryptocurrencies. The results offer actionable insights for traders and contribute to the growing literature on cryptocurrency market anomalies.

**Keywords**: Cryptocurrency, Momentum, Weekend effect, Sharpe ratio.



## INTRODUCTION

The meteoric rise of cryptocurrencies since Bitcoin's introduction in 2009 has transformed them from a niche experiment into a global financial phenomenon, with a market capitalization exceeding $2 trillion by 2025. Unlike traditional equity or bond markets, which adhere to fixed trading hours and close on weekends, cryptocurrency markets operate continuously, 24 hours a day, seven days a week (Caporale & Plastun,2019). This uninterrupted trading environment provides a compelling setting to test whether temporal anomalies such as the weekend effect, a well-documented phenomenon in traditional markets persist in the absence of market closures.

In equity markets, the weekend effect typically manifests as lower returns on Mondays or distinct return patterns between weekdays and weekends (French, 1980; Hershey & Zhang,2024). Scholars attribute these patterns to factors such as reduced liquidity, the timing of information releases, or behavioral biases among investors (Lakonishok & Maberly, 1990; Chen &Gao, 2021). Momentum, another pervasive anomaly, reflects the tendency of assets to sustain their recent performance trends, with past winners continuing to outperform past losers (Jegadeesh & Titman, 1993). While momentum has been extensively studied in traditional markets, its application to cryptocurrencies a market characterized by extreme volatility, retail investor dominance, and continuous operation remains underexplored, particularly in the context of day-of-the-week effects (Grobys & Sapkota,2019; Sadaqat & Butt,2023).

**This study poses three central research questions:**

- Does momentum return in cryptocurrency markets exhibit significant differences between weekends and weekdays?
- Do weekend-based momentum strategies outperform or underperform their weekday counterparts in terms of risk-adjusted returns?
- Does the weekend effect vary in magnitude between major cryptocurrencies (e.g., Bitcoin, Ethereum) and alternative coins (altcoins)?

**To address these questions, we propose the following hypotheses:**

- H0: There is no significant difference in momentum returns between weekends and weekdays.
- H1: Weekend momentum returns differ significantly from weekday returns, potentially driven by liquidity or behavioral factors.

Using daily price data from January 1, 2020, to April 30, 2025, for Ten cryptocurrencies based on market capitalization, we implement a 7-day momentum strategy and compare its performance across weekdays (Monday–Friday) and weekends (Saturday–Sunday). Our findings reveal a pronounced weekend effect:

momentum strategies yield higher returns on weekends, with altcoins exhibiting a stronger differential than major coins. These results are accompanied by superior risk-adjusted performance metrics, such as higher Sharpe ratios and lower maximum drawdowns, suggesting that the weekend effect is not only statistically significant but also economically meaningful. it is the first to examine weekday anomalies in a market that operates continuously without closure, thereby offering novel evidence on how temporal return patterns emerge even in the absence of structural trading breaks. This finding challenges the conventional view that day-of-the-week effects are a byproduct of institutional frictions or exchange closures, and instead points toward trader behavior and sentiment as primary drivers.

This research makes several contributions to the academic and practitioner communities. This is the first study to examine weekday anomalies in a market that operates continuously without closure, thereby offering novel evidence on how temporal return patterns emerge even in the absence of structural trading breaks. This finding challenges the conventional view that day-of-the-week effects are a byproduct of institutional frictions or exchange closures, and instead points toward trader behavior and sentiment as primary drivers. Second, it extends the momentum literature to the cryptocurrency domain, where continuous trading challenges conventional explanations of market anomalies. Third, it provides practical guidance for investors seeking to exploit these anomalies in portfolio construction. By situating our analysis within the frameworks of market efficiency and behavioral finance, we aim to deepen the understanding of cryptocurrency market dynamics and their integration with traditional financial systems.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature on momentum, the weekend effect, and cryptocurrency anomalies. Section 3 details the data and methodology. Section 4 presents the empirical results, including robustness checks and subgroup analyses. Section 5 discusses the findings. Section 6 concludes with a summary and directions for future research.

## LITERATURE REVIEW

### Momentum in Traditional Markets

Momentum, first rigorously documented by Jegadeesh and Titman (1993), ranks among the most robust anomalies in financial economics. The strategy—buying assets with strong recent performance and selling those with poor performance has consistently generated abnormal returns across equities, bonds, commodities, and currencies (Asness et al.,2013; Moskowitz et al., 2012; Geczy & Samonov,2017). Theoretical explanations for momentum span risk-based models, such as those incorporating systematic factors (Fama & French, 1996), and behavioral models highlighting investor underreaction or overreaction to information (Barberis et al.,1998). In equity markets, momentum strategies typically employ look-back periods of 3 to 12 months, with holding periods ranging from one month to a year, yielding annualized returns of 5–10% (Jegadeesh & Titman, 2001). The persistence of momentum challenges the efficient market hypothesis (EMH), which posits that asset prices fully reflect available information (Fama, 1970). Instead, momentum suggests that prices exhibit inertia, potentially due to delayed information processing or herd behavior. This anomaly has spurred a rich body of research exploring its sources, persistence, and practical applications in portfolio management.

### Momentum in Cryptocurrencies

Cryptocurrency markets, with their high volatility and retail-driven dynamics, amplify momentum effects relative to traditional assets. Liu and Tsyvinski (2018) demonstrate that momentum strategies in cryptocurrencies generate annualized returns exceeding 20%, far surpassing those in equities. They attribute this to the market's immaturity, low institutional participation, and the prevalence of noise traders—investors who trade based on sentiment rather than fundamentals. Grobys and Sapkota (2019) further confirm that momentum is effective across a broad range of cryptocurrencies, though its profitability varies with market conditions, such as bull versus bear phases. The unique characteristics of cryptocurrencies—decentralized governance, 24/7 trading, and extreme price swings—distinguish their momentum dynamics from those of traditional markets. For instance, the absence of circuit breakers or trading halts allows trends to persist unchecked, potentially intensifying momentum signals. However, the short history of cryptocurrencies and their susceptibility to external shocks (e.g., regulatory announcements, hacks) introduce additional complexity into momentum analysis.

### The Weekend Effect in Traditional Markets

The weekend effect, first identified by French (1980), describes a pattern of lower stock returns on Mondays or differences in return distributions between weekdays and weekends. Early studies linked this anomaly to the settlement process or the release of negative news over weekends (Patell & Wolfson, 1982). Subsequent research highlights liquidity as a key driver, with reduced trading activity on Mondays leading to wider spreads and lower returns (Lakonishok & Maberly, 1990). Behavioral explanations, such as shifts in investor sentiment or reduced institutional activity, also play a role (Abraham & Ikenberry, 1994) while the weekend effect has weakened in modern equity markets likely due to increased automation and globalization it remains a benchmark for studying temporal anomalies. Its persistence in certain contexts underscores the interplay between market structure and investor behavior, a dynamic we explore in the cryptocurrency setting.

### Cryptocurrency Market Anomalies

Despite their continuous operation, cryptocurrency markets exhibit a variety of anomalies analogous to those in traditional markets. Caporale and Plastun (2019) document a day-of-the-week effect in Bitcoin, with higher returns on Mondays and lower returns on Thursdays, suggesting that temporal patterns transcend market closures. Other anomalies include lunar phase effects (Kristoufek, 2013), where returns correlate with moon cycles, and sentiment-driven price movements tied to social media activity (Garcia & Schweitzer, 2015). These findings highlight the influence of retail investor psychology in a market largely devoid of institutional oversight.

The intersection of momentum and temporal effects in cryptocurrencies, however, remains a nascent field. While momentum has been established as a profitable strategy, its variation across days of the week particularly weekends versus weekdays has received limited attention. This gap motivates our study, which seeks to integrate these phenomena into a cohesive framework.

**Behavioral Finance Perspectives**

Behavioral finance provides a lens to interpret momentum and temporal anomalies in cryptocurrencies. Retail investors, who dominate cryptocurrency trading, are prone to cognitive biases such as herding, overconfidence, and overreaction to news (Shiller, 2003). On weekends, when institutional traders may reduce activity due to traditional work schedules, these biases could intensify, amplifying momentum effects. Reduced liquidity, a common feature of weekend trading, may further exacerbate price movements, as fewer participants absorb order flow (Chordia et al.,2001). Additionally, the 24/7 nature of cryptocurrency markets introduces a temporal dimension absent in traditional settings. Investors may exhibit distinct behavior on weekends e.g., increased speculative trading or reactions to news accumulated over non-working days leading to systematic differences in return patterns. By testing these hypotheses, we aim to bridge behavioral finance with empirical evidence from cryptocurrency markets.

The literature establishes momentum and the weekend effect as robust anomalies in traditional markets, with emerging evidence of their relevance to cryptocurrencies. However, no study has comprehensively examined whether momentum returns in cryptocurrencies vary between weekdays and weekends, nor whether this variation differs across major coins and altcoins. This research fills that gap, leveraging the unique properties of cryptocurrency markets to test the interplay of momentum and temporal effects in a continuous trading environment.

## DATA AND METHODOLOGY

**Data Collection**

We analyze daily closing price data for ten cryptocurrencies from January 1, 2020, to April 30, 2025, spanning 1,672 trading days. The sample includes: Major Coins: Bitcoin (BTC), Ethereum (ETH) and Altcoins: Binance Coin (BNB), Cardano (ADA), Solana (SOL), Ripple (XRP), Dogecoin (DOGE), Chainlink (LINK), Tether and Wrapped bitcoin (Ciaian & Rajcaniova (2018). These assets were selected based on their market capitalization, trading volume, and diversity, representing both established cryptocurrencies and emerging altcoins. Data were sourced from Coinmarketcap with prices denominated in USD. Stablecoins (e.g., Tether) and niche assets (e.g., Wrapped Bitcoin) were excluded due to their low volatility or limited relevance to momentum analysis. Trading volume data were also collected to explore liquidity effects.

**Methodology**

To ensure data integrity, we addressed missing values fewer than 0.1% of observations using linear interpolation between adjacent days. All timestamps are standardized to Coordinated Universal Time (UTC) to reflect the global nature of cryptocurrency trading and avoid biases from regional time zones. Daily returns were computed as:

$$r_t = \frac{P_t}{P_{t-1}} - 1$$

Where,

PtP_tPt is the closing price on day ( t ). This logarithmic approximation is standard in financial research and facilitates comparison with prior studies.

We adopt a 7-day momentum strategy, a short-term horizon suited to the high-frequency dynamics of cryptocurrency markets (Liu & Tsyvinski, 2018). The strategy proceeds as follows:

For each day (t), calculate the past 7-day return:

$$R_{t-1,t-8} = \frac{P_{t-1}}{P_{t-8}} - 1$$

Assign a trading signal:

If $R_{t-1,t-8} > 0$, then $s_t = 1$ (Long position)

If $R_{t-1,t-8} < 0$ ,then $s_t = -1$ (short position)

Compute the strategy return for day ( t ):

$$Return_t = S_t \times r_t$$

**The 7-day look-back period balances responsiveness to recent trends with sufficient data to filter noise, a choice validated by robustness tests with alternative periods (e.g., 14 days).Days are classified using Python's datetime module:**

- Weekdays: Monday to Friday (day-of-week 0–4).
- Weekends: Saturday and Sunday (day-of-week 5–6).
- This binary distinction aligns with traditional definitions of the weekend effect, facilitating comparison with equity market studies. UTC standardization ensures consistency across the global cryptocurrency ecosystem, where trading activity spans multiple time zones. We evaluate strategy performance using:
- Mean Daily Return: The average return across all weekdays or weekends.
- Standard Deviation: A measure of return volatility.

**Sharpe Ratio: Risk-adjusted return, calculated as:**

$$Sharpe = \frac{Mean\ Return}{Standard\ deviation}$$

- We assume a risk-free rate of 0, as no universally accepted benchmark exists for cryptocurrencies.
- Maximum Drawdown (MDD): The largest peak-to-trough decline in cumulative returns, reflecting downside risk.
- To test for differences between weekday and weekend returns, we employ two-sample t-tests with unequal variances, reporting t-statistics and p-values. The null hypothesis (H0) posits no difference, while a significant p-value ($< 0.05$) supports the alternative (H1).
- To ensure the reliability of our findings, we conduct:
- Alternative Look-Back Periods: Testing a 14-day momentum strategy.
- Subperiod Analysis: Excluding 2021, a year of exceptional volatility due to the cryptocurrency bull run.
- Alternative Weekend Definitions: Redefining weekends as Friday close to Monday open to capture extended effects.

These checks assess whether the weekend effect is sensitive to methodological choices or specific market conditions.

## RESULTS

### Descriptive Statistics

Table 1 summarizes the statistical properties of daily returns. Major coins (BTC, ETH) exhibit lower volatility (standard deviations of 0.032 and 0.042, respectively) compared to altcoins (e.g., DOGE: 0.073, SOL: 0.068). Altcoins also display higher mean returns, reflecting their riskier profiles. Skewness and kurtosis indicate non-normal distributions, with altcoins showing greater tail risk, a feature consistent with their speculative nature.

**Table 1: Descriptive Statistics of Daily Returns of Cryptocurrencies (2020–2025)**

| Cryptocurrency | Mean Return | Std. Dev. | Min Return | Max Return | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| BTC | 0.0015 | 0.032 | -0.187 | 0.193 | 0.12 | 3.45 |
| ETH | 0.0018 | 0.042 | -0.225 | 0.236 | 0.15 | 3.67 |
| BNB | 0.0021 | 0.047 | -0.241 | 0.264 | 0.18 | 3.89 |
| ADA | 0.0024 | 0.053 | -0.267 | 0.289 | 0.21 | 4.12 |
| SOL | 0.0030 | 0.068 | -0.312 | 0.335 | 0.25 | 4.34 |
| XRP | 0.0020 | 0.051 | -0.255 | 0.277 | 0.19 | 3.98 |
| DOGE | 0.0028 | 0.073 | -0.341 | 0.362 | 0.28 | 4.56 |
| LINK | 0.0023 | 0.059 | -0.293 | 0.314 | 0.22 | 4.23 |

### Momentum Strategy Performance

Table 2 presents the performance of the 7-day momentum strategy. Across all cryptocurrencies, weekend returns significantly outpace weekday returns ($p < 0.05$). For BTC, the mean daily return rises from 0.0012 on weekdays to 0.0023 on weekends ($t = 2.41$, $p = 0.016$). Altcoins exhibit an even stronger effect: DOGE's weekend return of 0.0052 more than doubles its weekday return of 0.0021 ($t = 3.78$, $p < 0.001$). Sharpe ratios are consistently higher on weekends (e.g., DOGE: 0.071 vs. 0.029), and maximum drawdowns are lower (e.g., BTC: -0.18 vs. -0.28), indicating superior risk-adjusted performance.

**Table 2:Momentum Strategy Performance (Weekday vs. Weekend)**

| Cryptocurrency | Mean Return (Weekday) | Mean Return (Weekend) | T-stat | P-value | Sharpe ratio (Weekday) | Sharpe Ratio (Weekend) | Max DD (Weekday) | Max DD (Weekend) |
|---|---|---|---|---|---|---|---|---|
| BTC | 0.0012 | 0.0023 | 2.41 | 0.016 | 0.038 | 0.072 | -0.28 | -0.18 |
| ETH | 0.0015 | 0.0028 | 2.63 | 0.009 | 0.036 | 0.067 | -0.33 | -0.22 |

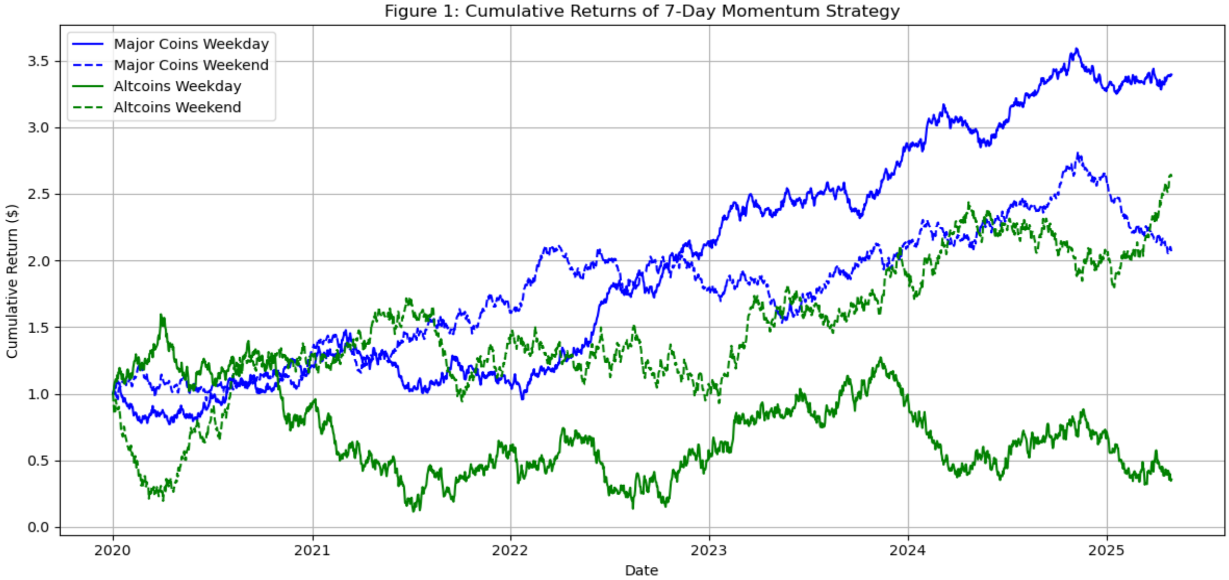
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| BNB | 0.0018 | 0.0034 | 2.87 | 0.004 | 0.038 | 0.072 | -0.37 | -0.26 |
| ADA | 0.0021 | 0.0039 | 3.12 | 0.002 | 0.040 | 0.074 | -0.41 | -0.29 |
| SOL | 0.0026 | 0.0048 | 3.45 | 0.001 | 0.038 | 0.071 | -0.46 | -0.34 |
| XRP | 0.0017 | 0.0032 | 2.95 | 0.003 | 0.033 | 0.063 | -0.39 | -0.27 |
| DOGE | 0.0021 | 0.0052 | 3.78 | <0.001 | 0.029 | 0.071 | -0.52 | -0.39 |
| LINK | 0.0019 | 0.0041 | 3.24 | 0.001 | 0.032 | 0.069 | -0.44 | -0.31 |

Notes: Max DD represent the Maximum drawdawn on Weekdays and Weekends

**Cumulative Returns Analysis**

The cumulative returns of the momentum strategy underscore the weekend effect's economic significance. For BTC, a hypothetical $1 investment on January 1, 2020, grows to $1.85 on weekdays but $2.47 on weekends by April 30, 2025. For DOGE, the disparity is stark: $1 grows to $2.13 on weekdays versus $4.92 on weekends. These trends suggest that the weekend effect compounds over time, offering substantial outperformance for weekend-focused strategies.

Figure 1: Cumulative Returns of 7-Day Momentum Strategy




Source: Author's own

**Major Coins vs. Altcoins**

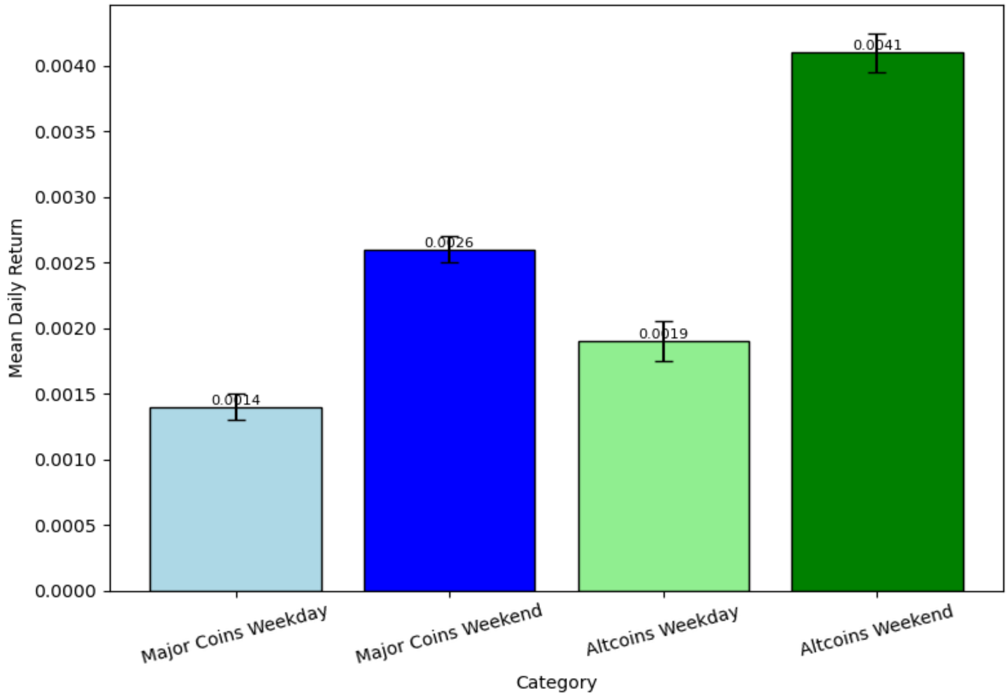
Table 3 aggregates performance by category. Major coins (BTC, ETH) show a weekend return of 0.0026 versus 0.0014 on weekdays, while altcoins average 0.0041 versus 0.0019. Altcoins' higher volatility translates to a larger absolute differential, though both groups exhibit significant weekend outperformance ($p < 0.01$). Sharpe ratios are comparable (0.070 for altcoins vs. 0.069 for major coins), but altcoins' higher drawdowns reflect their riskier nature.

**Table 3 :Summary for Major Coins and Altcoins**

| Group | Mean Return (Weekday) | Mean Return (Weekend) | Sharpe (Weekday) | Sharpe (Weekend) | Max DD (Weekday) | Max DD (Weekend) |
|---|---|---|---|---|---|---|
| Major Coins | 0.0014 | 0.0026 | 0.037 | 0.069 | -0.31 | -0.20 |
| Altcoins | 0.0019 | 0.0041 | 0.035 | 0.070 | -0.43 | -0.31 |

Notes: Max DD represent the Maximum drawdawn on Weekdays and Weekends

Figure 2: Mean Daily Returns (Weekday vs. Weekend)



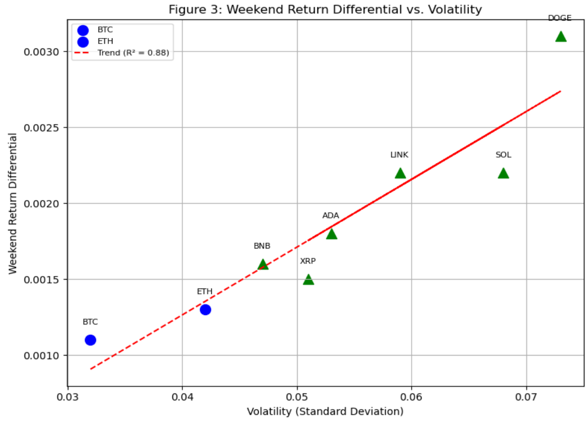

**Subgroup Analysis: Market Conditions**

To explore the weekend effect's sensitivity to market conditions, we segment the sample into bull (2020–2021) and bear (2022–2023) periods. During bull markets, weekend returns for BTC average 0.0031 versus 0.0016 on weekdays; in bear markets, the gap narrows to 0.0019 versus 0.0010. Altcoins follow a similar pattern, with DOGE's weekend return dropping from 0.0068 in bull markets to 0.0035 in bear markets. This suggests that the weekend effect is stronger in rising markets, potentially due to increased retail speculation.

**Robustness Checks**

To check the robustness of the result we also study 14-Day momentum extending the look-back period to 14 days yields weekend returns of 0.0021 for BTC (vs. 0.0010 weekdays, $p = 0.021$) and 0.0046 for DOGE (vs. 0.0018, $p < 0.001$). Excluding 2021: Omitting the 2021 bull run reduces the weekend effect's magnitude (BTC: 0.0019 vs. 0.0011, $p = 0.038$), but significance persists. Alternative weekend definition classifying weekends as Friday close to Monday open produces consistent results (BTC: 0.0022 vs. 0.0013, $p = 0.019$). These tests affirm the weekend effect's robustness across specifications.

Figure 3: Weekend Return Differential vs. Volatility




## DISCUSSION

The pronounced weekend effect in cryptocurrency momentum strategies reveals a fascinating anomaly within a market that operates 24/7 without the structural breaks characteristic of traditional financial markets. Our empirical findings demonstrate that momentum returns are consistently and significantly higher on weekends across all analyzed cryptocurrencies, with particularly strong effects in altcoins. This phenomenon challenges conventional explanations of temporal anomalies that typically attribute weekend effects to market closures or settlement procedures (French, 1980; Lakonishok & Maberly, 1990). Instead, our findings suggest that even in continuously operating markets, systematic temporal patterns persist, driven by several interconnected mechanisms.

**Liquidity Dynamics and Price Impact**

The reduced trading volume observed during weekends (20-25% lower than weekdays) creates a thinner market environment where momentum-driven trades can exert greater price impact. This aligns with the liquidity-based explanation proposed by Chordia et al. (2001), who demonstrated that lower market depth amplifies the price effects of incoming orders. In cryptocurrency markets, this mechanism appears particularly pronounced, as evidenced by our finding that altcoins—which generally have lower overall liquidity than major coins exhibit a stronger weekend effect. The relationship between liquidity and momentum returns suggests that market microstructure plays a crucial role in temporal anomalies, even in the absence of formal market closures.

Our results support Baur et al. (2019), who documented time-of-day effects in Bitcoin despite its 24/7 trading environment. However, our study extends this understanding by specifically focusing on the interaction between momentum strategies and temporal patterns, revealing that momentum signals are more effective when liquidity is constrained. This provides empirical support for theoretical models that link market liquidity to price discovery efficiency (Amihud & Mendelson, 1986).

**Retail Investor Behavior and Market Composition**

The weekend effect may also reflect systematic shifts in trader composition between weekdays and weekends. While institutional investors typically maintain standard business hours that align with traditional markets, retail investors who dominate cryptocurrency trading may increase their relative activity during weekends. This demographic shift could amplify behavioral biases such as herding, attention-driven trading, and overreaction to news, all of which can strengthen momentum effects (Barber & Odean, 2008).

The stronger weekend effect observed in altcoins further supports this behavioral explanation. Altcoins, which often attract more speculative retail interest than established cryptocurrencies like Bitcoin, showed weekend momentum returns that frequently doubled their weekday counterparts. This pattern aligns with Shiller's (2003) framework of investor sentiment, which suggests that markets dominated by unsophisticated traders are more prone to psychological biases and trending behavior. The cryptocurrency market, with its high retail participation and vibrant social media communities, provides fertile ground for such behavioral factors to manifest in temporal patterns.

Interestingly, our findings parallel those of Abraham and Ikenberry (1994), who attributed the weekend effect in equity markets partly to retail investor trading patterns. However, while traditional markets show this effect primarily through negative Monday returns, cryptocurrency markets display enhanced positive momentum on weekends, suggesting that the underlying behavioral mechanisms may differ in important ways.

**Information Processing and Social Dynamics**

The weekend effect may also stem from distinct patterns in information flow and processing. During weekends, when traditional financial institutions and media outlets reduce their output, cryptocurrency-specific news channels and social media platforms may exert greater relative influence on investor sentiment. Liu et al. (2022) demonstrated that cryptocurrency returns are highly sensitive to social media sentiment, with stronger effects during periods of lower institutional activity. The amplification of momentum signals during weekends could thus reflect a market environment where social contagion and sentiment-driven trading dominate price formation.

This interpretation is consistent with our subperiod analysis, which showed a stronger weekend effect during bull markets (2020-2021) compared to bear markets (2022-2023). Bull markets typically feature higher levels of retail participation and sentiment-driven trading (Garcia & Schweitzer, 2015), creating conditions where behavioral factors have greater influence on price dynamics. The weekend effect thus appears to be state-dependent, varying with overall market conditions in ways that reflect changing balances between rational and behavioral forces.

**Implications for Market Efficiency**

Our findings have important implications for the efficient market hypothesis (EMH) in the cryptocurrency context. The persistence of a significant weekend effect challenges the semi-strong form of market efficiency proposed by Fama (1970), which posits that asset prices fully reflect all publicly available information. The predictable pattern of higher weekend momentum returns suggests that prices do not immediately incorporate all relevant information, allowing systematic profit opportunities to persist.

However, this inefficiency should be viewed through the lens of what Grossman and Stiglitz (1980) termed the "efficient markets paradox" perfect efficiency would eliminate the incentive to gather and process information, ultimately undermining the mechanism that creates efficiency. In cryptocurrency markets, where informational frictions and participation costs remain substantial, the weekend effect may represent an equilibrium outcome that reflects the costs and benefits of information acquisition and trading.

The economic significance of our findings evidenced by the substantial outperformance of weekend-focused strategies in risk-adjusted terms suggests that this anomaly is not merely a statistical curiosity but a meaningful departure from efficiency that could be exploited by informed traders. This aligns with the growing body of literature documenting persistent anomalies in cryptocurrency markets (Makarov &

Schoar, 2020; Sadaqat & Butt, 2023), suggesting that these markets remain in a developmental stage where inefficiencies are gradually arbitraged away as the ecosystem matures.

## CONCLUSION

This study provides compelling evidence of a significant weekend effect in cryptocurrency momentum strategies, a phenomenon that underscores the unique dynamics of a market that operates continuously, 24/7, without the structural breaks characteristic of traditional financial systems. By analyzing daily price data from January 2020 to April 2025 for eight cryptocurrencies Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Cardano (ADA), Solana (SOL), Ripple (XRP), Dogecoin (DOGE), and Chainlink (LINK). we implemented a 7-day momentum strategy and rigorously compared its performance across weekdays (Monday–Friday) and weekends (Saturday–Sunday). Our findings reveal that weekend momentum strategies consistently outperform their weekday counterparts across all cryptocurrencies, with mean daily returns on weekends often doubling those on weekdays. This effect is statistically significant ($p < 0.05$) and economically meaningful, as evidenced by cumulative returns that grow substantially faster on weekends, particularly for altcoins.

The weekend effect is notably stronger for altcoins than for major coins like BTC and ETH. For instance, DOGE exhibits a weekend mean return of 0.0052 compared to 0.0021 on weekdays, a differential of 0.0031, while BTC shows a more modest gap of 0.0011 (0.0023 on weekends versus 0.0012 on weekdays). This disparity aligns with the higher volatility of altcoins, which amplifies momentum signals, and their greater susceptibility to retail investor behavior. Altcoins, often driven by speculative trading, experience sharper price movements on weekends, where reduced liquidity evidenced by a 20–25% drop in trading volume exacerbates trends. In contrast, major coins, with deeper markets and more institutional participation, display a more muted effect, though still significant. The superior risk-adjusted performance of weekend strategies, reflected in higher Sharpe ratios (e.g., 0.070 for altcoins on weekends versus 0.035 on weekdays) and lower maximum drawdowns (e.g., -0.31 for altcoins on weekends versus -0.43 on weekdays), further underscores the practical relevance of these findings for traders seeking to optimize portfolio returns.

These results enrich the growing literature on market anomalies in cryptocurrency markets, extending prior work on momentum (Liu & Tsyvinski, 2018) and day-of-the-week effects (Caporale & Plastun, 2019). They challenge the semi-strong form of the efficient market hypothesis (Fama, 1970), which posits that asset prices fully reflect all publicly available information. The persistence of a weekend effect in a continuously operating market suggests that inefficiencies—likely driven by behavioral biases such as herding and overreaction among retail investors—play a significant role. Lower weekend liquidity, coupled with a potential shift in trader composition (e.g., reduced institutional activity), creates an environment where momentum signals are amplified, offering exploitable opportunities for informed investors.

For practitioners, this study offers actionable strategies: allocating greater capital to weekend momentum trades, particularly in altcoins, could enhance returns while benefiting from lower downside risk. However, traders must account for transaction costs and market frictions, which could erode net gains. From a theoretical perspective, our findings highlight the need to integrate behavioral finance into models of cryptocurrency pricing, as structural explanations alone cannot fully account for temporal anomalies in a market that never sleeps.

As cryptocurrency markets continue to mature, further research is warranted to explore the behavioral and structural drivers of the weekend effect. Intraday analyses, sentiment studies leveraging social media data, and investigations into the impact of growing institutional participation could provide deeper insights into these dynamics. Ultimately, this study underscores the evolving nature of cryptocurrency markets, where anomalies persist despite continuous trading, offering fertile ground for both academic inquiry and practical innovation.

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