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Bitcoin's Weekend Effect: Returns, Volatility, and Volume (2014–2024)

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Abstract: Using daily BTC-USD data from September 19, 2014 to January 21, 2024, this paper re-examines whether weekends differ from weekdays for Bitcoin along three margins: average returns, close-to-close volatility, and trading activity. We implement Welch mean comparisons and HAC-robust OLS with month fixed effects (bandwidths 5, 7, and 14). In the full sample and across subsamples (2016–2019; 2020–2023; early 2024), we find no detectable weekend–weekday gap in average returns, while volatility and trading activity are lower on weekends. The patterns are robust to using squared returns as a volatility proxy. The joint evidence is consistent with liquidity and attention mechanisms—quieter weekends rather than compensating return premia. Replication files reproduce all tables and figures.

Keywords: Bitcoin; Weekend effect; Day-of-the-week; Volatility; Trading volume; HAC; Cryptocurrency

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1. Introduction

1.1. Background and motivation

Calendar anomalies—such as day-of-the-week or weekend effects—have long attracted empirical scrutiny in both traditional assets and cryptocurrencies [1–3]. Unlike equities that cease trading overnight and over weekends, Bitcoin (BTC) operates in a 24/7 environment. Continuous trading weakens exchange-hours explanations but sharpens alternative channels linked to liquidity, investor attention, and information arrival. A priori, weekends could feature lower participation and thinner order books as institutions scale down activity, with fewer macro or firm-level announcements to process; these forces can compress trading intensity and realized volatility without requiring a weekend return premium [1–4]. At the same time, round-the-clock access and globally distributed retail participation could, in principle, generate distinct weekend dynamics. The net weekend–weekday contrast is therefore an empirical question.

1.2. Related literature and gap

Early studies on cryptocurrencies documented mixed day-of-the-week patterns in returns and activity, with evidence often sensitive to sample windows, modelling choices, and market regimes [1–3]. Post-2020, structural features around participation and volatility changed markedly for BTC, motivating updates that extend the window and re-examine simple, policy-relevant outcomes [4]. Beyond mean returns, a practical angle for risk management is how active and how volatile weekends are relative to weekdays. Microstructure research links order-flow, depth, and spreads to realized volatility and execution costs; for crypto markets, weekend shifts in activity and depth have been discussed alongside attention proxies such as Google Trends [5,6]. A compact, replication-ready reassessment that foregrounds returns, close-to-close volatility, and trading activity over a long horizon remains valuable.

1.3. Research questions and contributions

This paper asks whether BTC's weekend days differ from weekdays along three margins: (1) average close-to-close returns; (2) a volatility proxy based on absolute returns; and (3) trading activity measured by volume. Our contributions are threefold. (1) Scope: We assemble a decade-long daily sample (2014–2024), covering multiple market regimes, and study both the full sample and three subsamples (2016–2019; 2020–2023; early-2024). (2) Transparency: We use Welch mean comparisons and ordinary least squares (OLS) with Newey–West HAC errors and month fixed effects; replication files reproduce every table and figure. (3) Focus on activity: Rather than chasing unstable mean-return premia, we foreground volatility/activity contrasts that directly inform execution and timing decisions [1–4,6].

1.4. Preview of methods and data

We compute close-to-close log returns (in basis points, bp) from publicly available BTC-USD daily data. Weekends are coded for Saturday/Sunday. We first compare weekend and weekday means via Welch's unequal-variance t-tests. We then estimate a parsimonious regression, $Y\_t = \alpha + \beta \cdot Weekend\_t + Month\ FE + \varepsilon\_t$, where Y_t alternates between return (bp), |return| (bp), and ln(1+Volume). Standard errors are HAC-robust (bandwidth 7) with sensitivity checks at 5 and 14. For robustness, we replace absolute returns with squared returns [1–4].

1.5. Key findings and implications (preview)

We find no detectable weekend–weekday gap in average returns, whereas both absolute returns and trading activity are lower on weekends. These patterns hold across subsamples and HAC bandwidths. Interpreted through microstructure and attention lenses, BTC's weekends look quieter rather than risk-compensated: lower participation and fewer salient information releases plausibly dampen volatility and volume without creating an excess weekend return premium [1–4,6]. For practitioners, execution of large, time-sensitive orders may be favored on weekdays with deeper liquidity, while small non-urgent flows may exploit quieter weekends if spreads are acceptable.

2. Materials and methods

2.1. Data and sample

Data provenance and provider conventions: We use publicly accessible BTC-USD daily data exported from Yahoo Finance under the provider's native day boundary and aggregation. Prices and volumes are standardized to the fields Date, Open, High, Low, Close, Volume. We keep close-to-close intervals as provided, noting that alternative time-zone alignments (e.g., UTC re-aggregation) are immaterial for our weekend–weekday contrast by construction (See **Notes**).

We use daily BTC-USD data exported from Yahoo Finance. The sample spans 2014-09-19 to 2024-01-21 (inclusive). We keep the provider's native day boundary and standardize fields (Date, Open, High, Low, Close, Volume) prior to analysis.

2.2. Variables and measurement

Variable construction: Close-to-close log returns are converted to basis points (bp = 10^{-4}). Our main volatility proxy is |return| in bp; robustness uses squared returns in bp^2. Trading activity is proxied by RawVolume; regressions use ln(1+Volume) to limit skew. Weekend is an indicator for Saturday/Sunday. Subsamples are P1 = 2016–2019, P2 = 2020–2023, P3 = January-2024.

Return (bp): close-to-close log return reported in basis points (bp). Volatility proxy (bp): |return| (bp) as the main proxy; squared returns (bp^2) for robustness. Trading activity: RawVolume; regressions use ln(1+Volume). Weekend = 1 for Saturday/Sunday. Subsamples: P1 = 2016–2019; P2 = 2020–2023; P3 = 2024 (January).

2.3. Empirical design

Estimation details: Welch tests use unequal variances with two-sided p-values. For OLS, we include month fixed effects to absorb seasonality and report HAC (Newey–West) errors with a default bandwidth of 7 and sensitivity at 5 and 14. Coefficients are shown with standard errors, *P*-values, and *t*-based 95% confidence intervals.

Cleaning rules and reproducibility: We sort by date, drop rows with missing Date/Close/Volume, compute returns via first differences of log prices, and retain observations with non-missing outcomes and covariates. All steps are scripted; replication files include the cleaned CSV and code that regenerates all tables and figures.

We contrast weekend and weekday means using Welch's *t*-tests and estimate OLS with Newey–West HAC errors (bandwidth 7; sensitivity 5 and 14) and month fixed effects. Coefficients are reported with standard errors, *P*-values, and 95% confidence intervals.

2.4. Ethics and reproducibility

Public, non-identifiable market data; replication files reproduce all tables and figures.

3. Results

3.1. Descriptive patterns

Descriptive statistics (**Table 1**) suggest lower weekend activity and tighter |return| distributions; average returns look similar.

Table 1. Descriptive statistics by weekend indicator

Group	Variable	N	Mean	SD	Median	P25	P75
Weekday	Return (bp)	2436	15.17	400.18	15.23	-143.62	184.49
Weekend	Return (bp)	975	9.13	290.95	11.23	-87.94	129.37
Weekday	|Return| (bp)	2436	262.63	302.29	162.9	64.9	344.42
Weekend	|Return| (bp)	975	190.44	220.07	112.29	38.96	256.05
Weekday	ln(1+Volume)	2436	21.94	2.75	23.31	19.06	24.09
Weekend	ln(1+Volume)	975	21.69	2.76	22.94	18.75	23.82

Notes: Weekend = Saturday/Sunday. Return in bp; |return| in bp; volume in log units.

3.2. Mean comparisons (Welch tests)

See **Table 2** and **Figures 1** to **3** below.

Table 2. Weekend vs. weekday: Mean differences (Welch tests)

Outcome	*n* (Wd)	*n* (W)	Mean (Weekday)	Mean (Weekend)	Diff (W – Wd)	*t*	*P*
Return (bp)	2436	975	15.17	9.13	-6.04	-0.49	0.625
|Return| (bp)	2436	975	262.63	190.44	-72.18	-7.73	0.0
In(1+Volume)	2436	975	21.94	21.69	-0.24	-2.34	0.019

Notes: Welch two-sample tests with unequal variances; two-sided *P*-values.

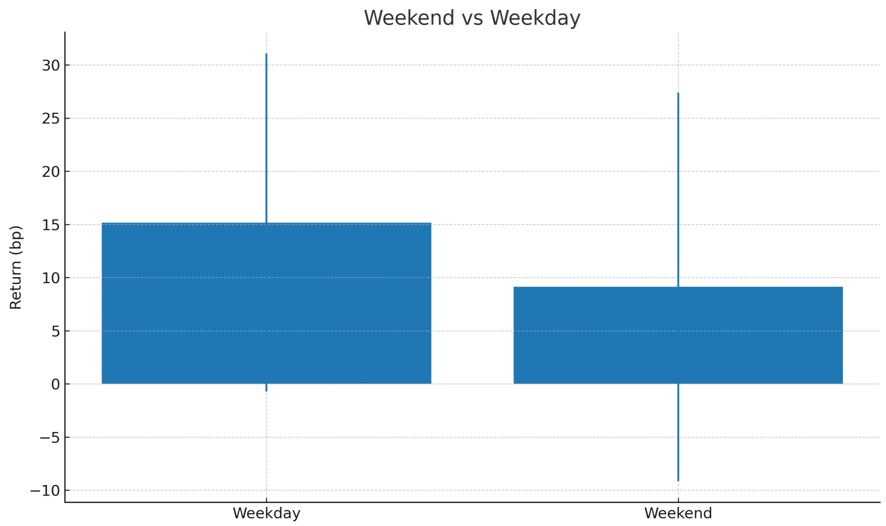

Figure 1. Mean daily Return (bp): Weekend vs. weekday (95% CI)

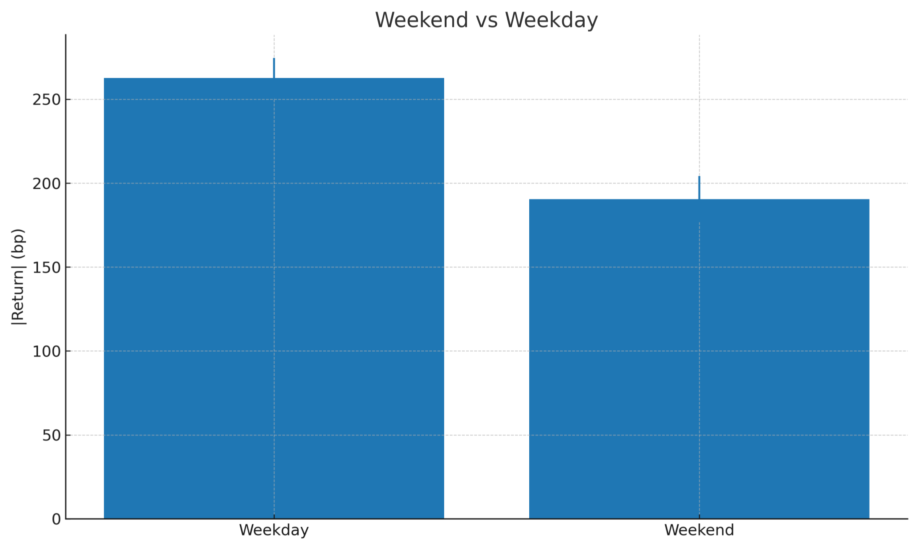

Figure 2. Mean |Return| (bp): Weekend vs. weekday (95% CI)

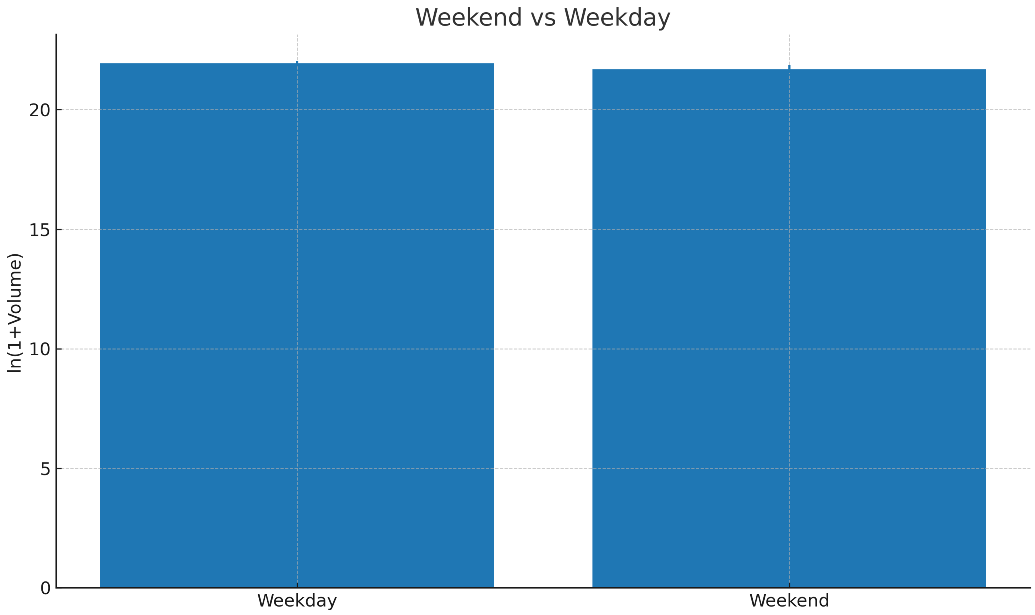

Figure 3. Mean ln(1+Volume): Weekend vs. weekday (95% CI)

3.3. Baseline HAC-OLS (full and subsamples)

See **Table 3** and **Figures 4** to **6** below.

Table 3. Weekend effect (β on Weekend) — OLS with HAC(7)

Outcome	Subsample	β	SE	95% CI lo	95% CI hi	*P*	*n*
Return (bp)	full	-6.38	11.62	-29.14	16.39	0.583	3411
|Return| (bp)	full	-71.8	8.72	-88.88	-54.72	0.0	3411
In(1+Volume)	full	-0.24	0.04	-0.32	-0.17	0.0	3411
Return (bp)	P1	9.59	19.78	-29.17	48.35	0.628	1461
|Return| (bp)	P1	-58.77	14.75	-87.67	-29.87	0.0	1461
In(1+Volume)	P1	-0.17	0.05	-0.26	-0.08	0.0	1461
Return (bp)	P2	-12.11	15.28	-42.05	17.84	0.428	1461
|Return| (bp)	P2	-104.63	10.88	-125.96	-83.3	0.0	1461
In(1+Volume)	P2	-0.3	0.02	-0.33	-0.26	0.0	1461
Return (bp)	P3	-69.35	50.72	-168.76	30.06	0.172	20
|Return| (bp)	P3	-210.28	49.51	-307.32	-113.25	0.0	20
In(1+Volume)	P3	-0.66	0.1	-0.85	-0.47	0.0	20

Notes: OLS with month fixed effects; Newey–West HAC standard errors (bandwidth = 7).

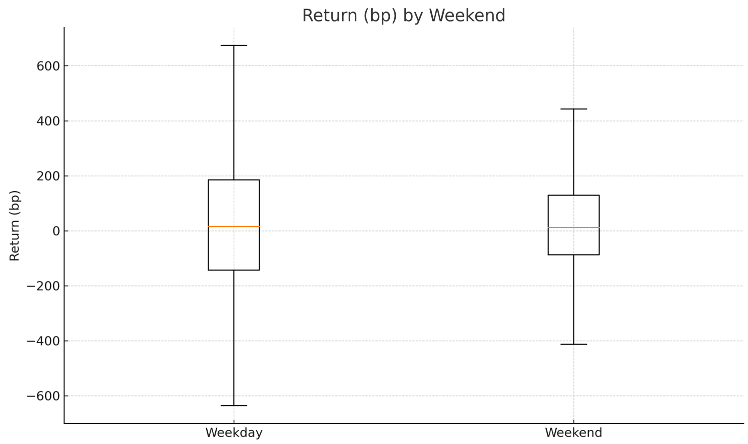

Figure 4. Return (bp): Boxplot by weekend indicator

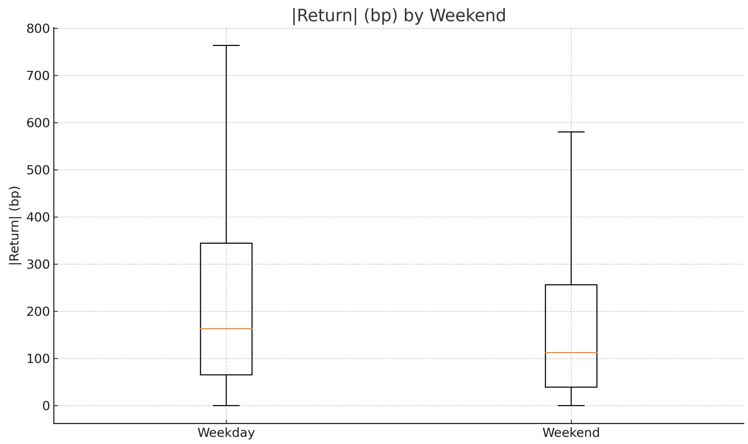

Figure 5. |Return| (bp): Boxplot by weekend indicator

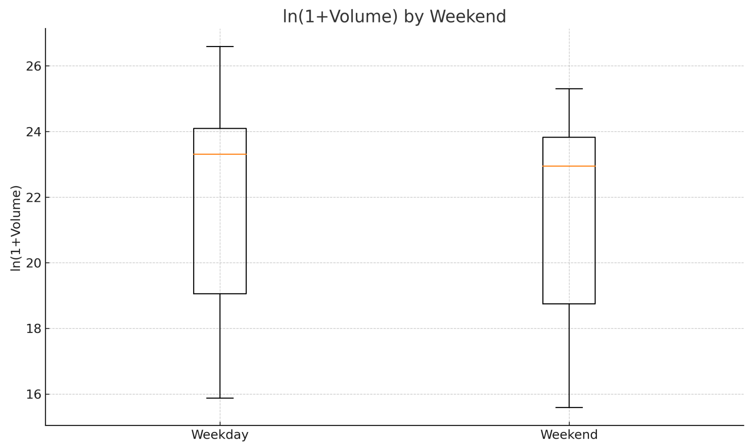

Figure 6. ln(1+Volume): Boxplot by weekend indicator

4. Discussion

4.1. Mechanisms: Liquidity, attention, and information flow

Interpreting weekend quietness: Lower |return| and volume on weekends suggest thinner participation and slower information diffusion, consistent with attention-based mechanisms and microstructure links between depth, order-flow, and realized volatility [1–4,6]. In a 24/7 market, the absence of exchange closures does not preclude weekend-specific frictions: staffing, market-making intensity, and news cadence can still vary meaningfully across the week [5,6].

Our evidence—no weekend premium in average returns but lower weekend |return| and trading activity—aligns with a combination of liquidity, investor attention, and information-arrival channels. Liquidity: thinner order books and fewer liquidity providers can compress trading intensity and slow price discovery on weekends [5]. Investor attention: participation plausibly declines on weekends due to competing activities and reduced institutional coverage, lowering order arrivals and realized volatility [6]. Information flow: macro and firm announcements cluster on weekdays, leaving fewer salient signals on weekends; with less news to process, both activity and volatility decrease without requiring a return premium [1–4].

4.2. Relation to prior studies

Prior work on day-of-the-week or weekend anomalies in Bitcoin and broader crypto markets reports mixed return patterns, often sensitive to sample windows and model choices [1–4]. Our results update the window through 2024-01 and emphasize activity/volatility rather than return premia, consistent with research linking trading intensity and volatility clustering.

4.3. Practical implications

For risk management, the weekend pattern highlights timing risk rather than mean-return differences: liquidity-demanding trades may face lower depth and slower price discovery. For execution, concentrating larger flows on weekdays may reduce slippage; conversely, weekend execution might suit small, non-urgent orders if spreads are acceptable.

4.4. Limitations and future work

Our inference is intentionally simple and transparent. We rely on daily close-to-close measures and provider-native day boundaries; intraday depth/spread data and alternative time-zone aggregations are promising extensions. While BTC is the most liquid cryptoasset, examining cross-asset heterogeneity (e.g., large-cap altcoins) could test whether weekend patterns scale with liquidity.

Limitations include provider-native day boundaries and volume definitions, reliance on daily close-to-close measures, and the BTC-only focus. Extensions include intraday depth/spread analysis, on-chain and attention proxies, multi-asset tests, and updating the sample beyond 2024-01.

HAC bandwidths 5 and 14, and squared-return volatility proxies, deliver the same qualitative takeaway: no weekend return premium; lower weekend volatility/activity. These checks mitigate concerns about short-run serial correlation and the form of the volatility proxy.

5. Conclusion

We document no detectable weekend–weekday gap in average returns for Bitcoin, alongside lower weekend volatility and trading activity. These patterns persist across subsamples and remain robust under squared-return volatility and alternative HAC bandwidths. The joint evidence favors liquidity/attention mechanisms—quieter weekends rather than compensating return premia.

Notes

(1) We adopt the data provider's native day boundary and timestamp convention for BTC-USD without re-aggregating to an alternative timezone (e.g., UTC). Our inference focuses on close-to-close differences between weekends and weekdays; results are robust to reasonable boundary variations. Replication files reproduce all tables and figures.

(2) We treat Volume as provided natively in the downloaded CSV for BTC-USD (provider-native aggregation). Since our main analyses use ln(1+Volume) and focus on weekend–weekday contrasts rather than levels, conclusions are unlikely to hinge on minor provider conventions.

Disclosure statement

The author declares no conflict of interest.

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