

BITCOIN'S REACTION TO U.S.
FOMC AND CPI ANNOUNCEMENTS

by

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A thesis submitted in partial fulfillment of the
requirements for the degree of

MA in Business and Financial Economics

Kyiv School of Economics

2025

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ACKNOWLEDGMENTS

I would like to thank my thesis advisor, Professor Olesia Verchenko, for the time she devoted to our conversations and for her guidance in writing this thesis.

I would also like to thank the friends I made while studying at KSE. They inspired and supported me throughout my time there.

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LIST OF ABBREVIATIONS

BTC Bitcoin

CPI Consumer Price Index

FOMC Federal Open Market Committee

CAR Cumulative Abnormal Return

USDT Tether USD

USDC USD Coin

GDP Gross domestic product

ETF Exchange Traded Fund

OHLC Open-High-Low-Close

RS Rogers–Satchell

PK Parkinson

CHAPTER 1

INTRODUCTION

The cryptocurrency market often reacts strongly when U.S. macroeconomic announcements are released or when the Federal Reserve announces its policy decisions. Examples include monthly inflation data (CPI) and the eight scheduled FOMC rate meetings each year. Market participants routinely observe rapid price moves around these events.

Despite the growing importance of cryptocurrencies and huge size of the cryptocurrency market, few academic studies have systematically measured the reaction of bitcoin to planned macroeconomic announcements. This paper aims to fill this gap by measuring exactly how large these volatility spikes typically are and, more importantly, how long the increased uncertainty lasts after a major release.

We focus on the 2020-2025 period. These years include the initial shock from the COVID-19 pandemic, record-high inflation levels in 2022 and fastest cycle of interest rate increases in the United States in more than forty years. Given this context, analyzing this particular time period offers an opportunity to understand Bitcoin's behavior under different macroeconomic and policy conditions.

Studying Bitcoin's reaction to chosen events also gives insights about whether the cryptocurrency market behaves similarly to traditional financial markets or not. Traditional assets such as stocks, bonds and foreign exchange rates have long been known to systematically respond to economic data releases as shown by Kim, McKenzie and Faff (2004). If Bitcoin shows similar reactions, it could mean that crypto market is becoming more integrated with the traditional financial system. Alternatively, if Bitcoin reacts in a

different way: perhaps stronger, shorter or even in opposite directions, this could show differences between cryptocurrencies and traditional markets.

From a personal perspective, understanding these dynamics is not just an academic exercise, but a practical need. Practically, clearer short-horizon volatility expectations help traders and risk managers anticipate swings, size positions, set stop-losses, and choose leverage and hedges more effectively. A clearer understanding of the timing and magnitude of market reactions will allow for more effective risk management, including making better-informed decisions about leverage, hedging and when to enter and exit positions.

In addition, studying these reactions helps to expand knowledge that is useful to many stakeholders. More accurate volatility expectations help traders and risk managers make decisions about position sizes, stop-loss levels and risk control strategies before major economic releases. This knowledge also makes it easier for exchanges and market makers to improve their liquidity planning and margin setting processes, helping to prevent potential failures caused by sudden spikes in trading volumes or extreme price fluctuations. Researchers and policymakers might gain useful insights into how effectively and quickly crypto markets incorporate publicly available macroeconomic information, a topic that is important to the continuing debate on market efficiency, financial stability and appropriate regulatory structures.

To answer the research question, this study uses a daily event-study approach with a market model benchmark against the S&P 500 to compute CAR, and changes in volatility using Rogers–Satchell and Parkinson volatility measures.

CHAPTER 2

INDUSTRY OVERVIEW AND RELATED STUDIES

2.1 Brief overview of the Bitcoin industry

Bitcoin was introduced in January 2009, and a year earlier, in 2008, Satoshi Nakamoto's white paper was published and the open-source Bitcoin network was launched. At its core, Bitcoin is a peer-to-peer electronic-cash system that records ownership on a public, append-only ledger known as the blockchain (Nakamoto, 2008). Transactions are grouped into blocks, miners compete to add each block by solving a proof-of-work puzzle, thereby securing the network and earning newly created Bitcoins plus transaction fees. The protocol issues a fixed reward that halves roughly every four years, limiting total supply at 21 million coins – a design feature intended to mimic the shortage of digital money. Because no central authority can alter this monetary rule, Bitcoin is often described as programmable hard money.

Bitcoin's development can be sketched in three main stages. From its launch in 2009 until the mid-2010s it was traded almost entirely by retail users on lightly regulated online platforms and peer-to-peer networks. The second stage began in 2017, when large, conventional exchanges started listing cash-settled Bitcoin futures and options. Those listings gave hedge funds, private companies and corporates a regulated hedge and marked Bitcoin's first real bridge to traditional capital markets. The third, still ongoing stage is characterized by rapid institutionalization. Since 2020 asset managers, pension funds and publicly listed companies have built dedicated crypto teams. Global custodians provide insured cold-storage solutions and scores of exchange-traded products offer Bitcoin exposure through the world's major stock exchanges. As a result, Bitcoin's turnover is now spread across a multi-layered market structure: order-book spot exchanges, futures, options and exchange-traded funds.

Liquidity has deepened alongside this institutionalization. Average daily spot volume across the ten largest exchanges: Binance, Coinbase, Kraken and others, regularly exceeds ten billion U.S. dollar equivalents, while open interest in listed derivatives has climbed above thirty billion on peak days. Market depth is no longer dominated by a handful of retail exchanges – instead, algorithmic liquidity providers and high-frequency trading firms arbitrage prices across exchanges, narrowing spreads and speeding the incorporation of new information.

The main part of spot Bitcoin today is quoted against dollar-linked stablecoins instead of the fiat USD. In 2024 the combined market value of USDT and USDC exceeded \$150 billion and BTC-USDT pairs on major platforms regularly exceeded the volume of BTC-USD pairs by four times. In this way, supply of stablecoins acts as a shadow supply of dollars in the crypto market: when monetary conditions in the U.S. tighten, demand for stablecoins can decline, reducing Bitcoin liquidity, when conditions soften, new stablecoin supply often follows bull cycles. This stablecoin channel provides an additional way through which U.S. policy decisions affect Bitcoin price dynamics.

The market around Bitcoin has grown far beyond simple spot trading. Regulated futures were the first big step: since their launch in late 2017, open interest on the Chicago Mercantile Exchange has climbed to about 6 billion USD and volume in Binance’s perpetual-swap contracts is even higher. Options activity on platforms such as Deribit now competes with options on mid-cap stocks. These derivatives let traders hedge or take leverage and research shows that prices on the Chicago Mercantile Exchange often move ahead of spot markets, making regulated futures an important guide for price discovery. Access expanded again on 10 January 2024, when the U.S. Securities and Exchange Commission approved eleven spot-Bitcoin exchange-traded funds, leading products from BlackRock and Fidelity drew more than 10 billion USD in their first month. ETFs allow anyone with a brokerage account to own Bitcoin, so they are expected to deepen liquidity and link the asset more closely to mainstream finance.

Changes on the technical side have been just as large. After China banned industrial mining in 2021, most of the network's computing power shifted to the United States and Kazakhstan. U.S. now hosts roughly 40 percent of global hash-rate. Because many U.S. miners are listed companies, they publish energy-mix data and buy renewable power when possible, adding transparency to a long-debated environmental issue. Finally, holder base has become diverse. Long-term "Whale" wallets move coins rarely, while high frequency trading firms arbitrage tiny price gaps across exchanges around the clock. Each group reacts differently to economic news, which helps explain why Bitcoin sometimes behaves like a tech stock, sometimes like a commodity and sometimes doesn't react at all.

Regulation remains fragmented and country dependent, but there is a clear global trend toward bringing Bitcoin within existing financial market frameworks. Most major economies now apply anti-money-laundering and know-your-customer rules to crypto asset brokers. Derivatives markets operate under commodity and securities laws. Insurance as well as audit standards have emerged for custodians. Although the details of the policy differ from country to country, but general direction is towards gradual integration rather than a complete ban.

2.2 Related studies review

Ma et al. (2022) provide the most detailed daily-frequency test of Federal Reserve surprises to date. Using Fed funds futures pricing to isolate the unexpected portion of every FOMC decision between 2018 and 2021, they estimate the effect on Bitcoin's close-to-close returns. Policy tightening reliably pushes Bitcoin lower by about 0.25% on the day of the meeting. The authors also show that the impact is state dependent: it is strongest during bull-market phases when leverage and speculative flows are elevated. In short, once institutional money and regulated futures arrive, Bitcoin began to trade much like other high-beta assets that reprice when the Fed shifts the discount rate forecast.

Pyo and Lee (2020), working with an earlier sample of 2010-2018. Their event-study and GARCH tests show that broad U.S. macro releases (inflation, payrolls, growth) sometimes interrupt Bitcoin's typical drift, but FOMC days themselves do not generate significant abnormal returns. That result suggested an early-period "macro disconnect," consistent with a retail-dominated market that paid little attention to central-bank signals.

Corbet et al. (2020) examine the relationship between macroeconomic news announcements and Bitcoin returns, extending previous research on traditional financial assets to the digital asset market. Their findings indicate that positive news surrounding unemployment rates and durable goods leads to a decrease in Bitcoin returns, while negative news for these indicators correlates with an increase in Bitcoin returns. News related to GDP and CPI, however, does show no statistically significant relationship with Bitcoin returns. This suggests that Bitcoin may act as a safe-haven asset during times of economic negativity and that the cryptocurrency market is maturing, showing unique interactions with macroeconomic news. The authors note the high volatility of Bitcoin compared to traditional financial markets, explaining this by the relative novelty of the market, its speculative nature, and lower liquidity.

Kim, McKenzie, and Faff (2004) investigate the impact of scheduled government macroeconomic news announcements on the risk and return of three major U.S. financial markets: bond, stock, and foreign exchange. They find that these markets do not primarily react to the release of information itself, but rather to the "news" content, defined as the deviation between actual and expected announcement numbers. Specifically, unexpected balance of trade news had the greatest impact on mean returns in the foreign exchange market. In the bond market, news related to the internal economy (excluding CPI) was significant, while for the U.S. stock market, consumer and producer price information proved important. They observed that financial market volatility increased in response to some announcements and decreased for others, a phenomenon partly explained by differential "policy feedback" effects. This study highlights the importance of a

comprehensive approach when studying macroeconomic news in different financial markets in order to distinguish the type of news to which each market reacts.

An industry perspective from S&P Global (2023) connects the two academic findings. Reviewing 2020–2022, this analysis documents a clear negative correlation between Bitcoin and U.S. real-rate expectations: as the Fed moved from emergency easing to rapid tightening, Bitcoin fell in tandem with valued technology shares. The report's simple regressions show that rising interest rate expectations and a stronger dollar explain a significant portion of Bitcoin's decline in 2022, supporting the view that cryptocurrencies are now behaving as risky assets sensitive to liquidity cycles.

Taken together, these studies paint a solid but still incomplete picture. Early evidence (2010–2018) points to limited or mixed reactions and even safe-haven-type patterns in some news dimensions, whereas post-2018 work using policy-surprise measures detects a measurable, directionally intuitive effect of Fed decisions on Bitcoin returns. Cross-market research shows that assets react to the surprise component rather than the release itself, and industry analysis for 2020–2022 confirms stronger macro sensitivity as crypto moved closer to high-beta equities during the tightening cycle. This paper contributes to the literature by offering a single, coherent daily design that jointly examines CPI releases and scheduled FOMC meetings across 2020–2025, a period spanning COVID-19, high inflation and the fastest tightening cycle in decades. Unlike most prior studies that focus on one event type or earlier subperiods, we analyze both series in one dataset, and report results by the direction of the change (hike/cut, CPI up/down) as well as “no-change” events. This design allows us to quantify not only the immediate price impact but also how long elevated volatility persists after announcements.

CHAPTER 3 METHODOLOGY

3.1 Research question and hypotheses

This study examines whether Bitcoin reacts to scheduled United States announcements. We focus on two announcement types that regularly attract market attention: monthly CPI releases and Federal Reserve FOMC policy announcements. We compare the behavior of Bitcoin around an announcement day with its typical behavior outside of such days. The goal is to isolate the short-term reaction, which is likely related to new public information coming in at a known time.

The analysis considers two outcomes. The first outcome is daily return, which captures the immediate price response to news. The second outcome is daily volatility, which reflects changes in uncertainty and trading intensity that often follow important announcements. An event day gives a clean time marker for when information becomes public. By aligning many events on a common event-time scale and then averaging them, we can estimate whether there is a systematic pattern rather than just random post-announcement movements.

Macroeconomic announcements can move Bitcoin because they change the relative attractiveness of safe assets and investors' risk appetite. On FOMC days, when the policy rate is raised, U.S. Treasuries become more attractive, the U.S. dollar often strengthens, and liquidity for risky assets tightens, so Bitcoin return can move down. When the rate is cut, the opposite forces may support Bitcoin. On CPI days, lower inflation is read as less pressure for future rate hikes and a more stable macro outlook, so investors may take more risk, higher inflation points to tighter policy ahead and can reduce demand for risky assets.

To test this, we formulate two hypotheses:

- H1: Bitcoin’s volatility increases on days when FOMC decisions are announced and CPI data are released.
- H2: Bitcoin’s cumulative abnormal return differs from zero on days when FOMC decisions are announced and CPI data are released.

3.2 Events and sample construction

An event is defined at the daily frequency as a calendar day on which either a CPI release or an FOMC policy announcement occurs. If the both announcements fall on the same calendar day, we exclude that day from the event sample so that each event is uniquely linked to a single source of information. We then store metadata for each event, including its positional index in the daily panel. We work with calendar time t and event time τ .

For each saved event we build an event-time grid $\tau \in \{-2, -1, 0, +1, +2\}$ where $\tau = 0$ is the announcement day. The grid is constructed by index around t_0 . A given $(event, \tau)$ observation is kept only if the corresponding calendar date exists in the merged daily panel. Since measures require information from the pre-event window $[t_0 - 20, t_0 - 3]$, we also require that this full window is available in the data. This guarantees that all data necessary for basic indicators and further modeling are available for each event.

Return-based abnormal measure that relies on the market factor is computed only on days when the S&P 500 is open. If the S&P 500 is closed on a given τ -day, the corresponding return-based abnormal measure is treated as missing for that $(event, \tau)$, while volatility-based measures remain available, if required Open-High-Low-Close (OHLC) data exist.

3.3 Market Model

For each event at calendar date t_0 we estimate a single-factor market model on the pre-event window $[t_0 - 20, t_0 - 3]$. The dependent variable is Bitcoin’s daily log return r_t^{BTC} . The regressor is the S&P 500 daily log return r_t^{SPX} . The specification is

$$r_t^{BTC} = \alpha_i + \beta_i r_t^{SPX} + \varepsilon_t, \quad t \in E(t_0) \quad (3.1)$$

where i indexes the event and $E(t_0)$ is the set of SPX trading days in $[t_0 - 20, t_0 - 3]$ for which both r_t^{BTC} and r_t^{SPX} are observed. The model is estimated by OLS separately for each event. We save the estimated coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$, the coefficient of determination R_i^2 , and the sample size $n_i^{est} = |E(t_0)|$.

To guarantee minimum data quality, an event passes the model-estimation filter only if $n_i^{est} \geq 10$. Events that fail this pre-event market model filter are excluded from the analysis sample used for both return- and volatility-based measures to keep a common set of events. The model-estimation stage uses only information that is available prior to the announcement day.

The fitted parameters are later used to form the event-time expected return on day $t = t_0 + \tau$ as $\hat{r}_t^{exp} = \hat{\alpha}_i + \hat{\beta}_i r_t^{SPX}$. Bitcoin’s abnormal return for a given (i, τ) is then defined as $AR_{i,\tau} = r_t^{BTC} - \hat{r}_t^{exp}$ and is computed only on SPX-open days, as per the SPX-day rule in Section 3.2. Volatility-based measures do not depend on this model and are defined in the next subsection.

3.4 Volatility measures and baselines

We use two high–low–open–close proxies of daily variance that are standard to the literature (Oprisor et al. (2024), Vivek et al. (2025)). The Rogers–Satchell variance for day t (Rogers and Satchell, 1991) is

$$RS_t = \ln\left(\frac{H_t}{C_t}\right) \ln\left(\frac{H_t}{O_t}\right) + \ln\left(\frac{L_t}{C_t}\right) \ln\left(\frac{L_t}{O_t}\right) \quad (3.2)$$

and the Parkinson variance (Parkinson, 1980) is

$$P_t = \frac{\left(\ln\left(\frac{H_t}{L_t}\right)\right)^2}{4\ln 2} \quad (3.3)$$

Here O_t, H_t, L_t, C_t are Bitcoin's open, high, low and close on day t . For each proxy we report daily volatility as $\sigma_t^{RS} = \sqrt{\max\{RS_t, 0\}}$ and $\sigma_t^P = \sqrt{\max\{P_t, 0\}}$, where $\max\{x, 0\}$ denotes zero-truncation of the scalar $\{x\}$. This prevents taking a square root of tiny negative values caused by floating-point rounding or rare OHLC inconsistencies, in clean data $RS_t, P_t \geq 0$ and the truncation has no effect.

For each event i with announcement date t_0 we construct a pre-event volatility baseline on the window $[t_0 - 20, t_0 - 3]$. The baseline is defined separately for the two proxies as the simple average of daily volatilities in that window: $\sigma_t^{RS,pre} = \text{mean}(\sigma_t^{RS} : t_0 - 20 \leq t \leq t_0 - 3)$ and $\sigma_t^{P,pre} = \text{mean}(\sigma_t^P : t_0 - 20 \leq t \leq t_0 - 3)$. To reduce the influence of outliers when building the baseline, we winsorize the pre-event daily volatilities at the 1st and 99th percentiles before averaging. We require 18 valid days in $[t_0 - 20, t_0 - 3]$, if any OHLC inputs are missing or non-finite, the event does not receive a baseline and its observations are dropped at this stage. This rule matches the pre-event window used elsewhere in the analysis and avoids look-ahead.

Abnormal volatility on an event-time day τ is defined as the difference between the day- $t_0 + \tau$ volatility and the event's pre-event baseline. We compute it in percentage points of daily volatility, separately for each proxy:

$$AVOL_{i,\tau}^{RS} = (\sigma_{t_0+\tau}^{RS} - \sigma_i^{RS,pre}) * 100 \quad (3.4)$$

$$AVOL_{i,\tau}^P = (\sigma_{t_0+\tau}^P - \sigma_i^{P,pre}) * 100 \quad (3.5)$$

These measures are well defined whenever the required OHLC data exist on day $t_0 + \tau$. They do not depend on whether the S&P 500 is open.

3.5 Aggregation, windows, and inference

All reactions are aggregated across events in an equal-weighted way. At the day level, we align observations by event time τ and compute the cross-sectional mean of each measure over the set of events that have a valid value at that τ . For returns we report the mean of the within event cumulative abnormal return ($CAR_{i,\tau}$), which is the cumulative sum of abnormal returns from the start of the event grid up to day τ . This object can be read as the conventional cross-sectional average cumulative abnormal return at day τ . For volatility we report the cross-sectional mean of abnormal volatility $AVOL_{i,\tau}$ separately for the Rogers–Satchell and Parkinson proxies.

To summarize reactions over short windows, we form event-level statistics and then average them across events. For returns, the event-level window statistic is the sum of abnormal returns within the window, an event affects a window if it contains at least one valid abnormal-return day in that window. For volatility, the event-level window statistic is the simple average of daily abnormal volatility within the window, an event contributes only if all daily values in the window are finite. We use two symmetric windows that exclude the announcement day, a pre-window $[-2, -1]$ and a post-window $[+1, +2]$. The announcement day $\tau = 0$ is reported in the day-by-day.

Statistical inference is based on cross-sectional t-tests of the mean. For a given cell (event type and day or window), let x_i denote the event-level statistic and n the number of contributing events. Compute the sample mean \bar{x} , the sample standard deviation s , and the t-statistic $t = \bar{x}/(\frac{s}{\sqrt{n}})$ with $n - 1$ degrees of freedom. We report two-sided p-values. This choice is conservative with respect to the directional hypotheses. Units are kept consistent with construction: CAR is reported in daily log-return units and abnormal volatility is reported in percentage points of daily volatility. For readability, we also display a reference annualized scale for abnormal volatility by multiplying the daily mean by $\sqrt{365}$. This rescaling is for interpretation only and does not affect testing.

3.6 Limitations

This design has several limitations that impact interpretation. First, all return-based abnormal measures depend on days when the S&P 500 is open, if the index is closed, the corresponding observations are missing. This rule protects the market-model logic but mechanically reduces sample size and power and it can impact selection if event-time days fall on U.S. holidays or weekends. Second, the event-time grid is short, restricted to -2 through $+2$. This focuses attention on the immediate reaction, but may miss earlier leaks of information or slower adjustments after the announcement. The end of the day also compresses intraday dynamics, while the CPI and FOMC are published at specific times in the US that do not coincide with daily OHLC bars. Third, volatility proxies use daily high–low–open–close information and are only approximations of true volatility, Rogers–Satchell and Parkinson have different sensitivities to microstructure noise and to how exchanges form daily OHLC candles for Bitcoin (we use UTC-based days). The design provides non-negativity and averages pre-event daily volatilities after winsorization at the 1st and 99th percentiles. Fourth, events are allowed to occur close in calendar time, so windows for different events may overlap. The analysis treats each event independently, which is typical in event studies, but can leave residual dependence across observations. Also, scheduled announcements are used as clean timing markers, yet other news can

coincide with the same dates and data sources may contain minor inconsistencies in OHLC values or time-zone mapping. These issues do not invalidate the design but suggest that results should be read as average short-run reactions under the stated assumptions rather than as structural causal effects.

CHAPTER 4 DATA

4.1 Data

Bitcoin historical data come from Yahoo Finance and the S&P 500 historical data come from Stooq, both sources offer daily open, high, low, close and volume series in U.S. dollar. Using OHLC rather than close-only data is advantageous because the high-low range supplies a richer volatility proxy: if a macro shock produces an intraday spike that partially reverses before midnight, the closing price alone would understate the disturbance, whereas the range captures it.

Macroeconomic announcement information is collected from publicly available calendar: Investing.com, which lists the release date and the consensus (median) market forecast for every CPI and FOMC. After each release, the same calendar publishes the actual figure, permitting a straightforward calculation of the surprise component. Official data (for example, CPI from the Bureau of Labor Statistics and FOMC statements from the Federal Reserve) are cross-checked for accuracy but do not provide consensus forecasts.

The study period spans 1 January 2020 through 31 May 2025, delivering sixty-five inflation prints and forty-four FOMC decision days. Two dates on which CPI and FOMC coincided are excluded to keep each event tied to a single information source. Bitcoin trades continuously, yet daily bars are timestamped at 00:00 UTC on Yahoo Finance. U.S. announcements occur within the same UTC calendar day covered by the bar, all series are merged by calendar date.

Two limitations arise from daily frequency. Firstly, any price reaction shorter than a day, an intraday spike and full reversal, can be muted in the close-to-close return, although the high-low range reduces this risk. Secondly, by linking a whole day to a single

announcement, there is a risk of noise from other news and averaging across many events and using a narrow event window reduces this problem.

4.2 Data description

Table 1. Descriptive statistics for daily open, high, low, close prices

Variable	Count	Min	Max	Mean	Median
Open	1,978	5,002.58	111,679.36	40,682.71	35,881.46
High	1,978	5,331.83	111,970.17	41,551.55	37,241.01
Low	1,978	4,106.98	109,285.07	39,778.52	34,746.78
Close	1,978	4,970.79	111,673.28	40,729.78	35,954.35

As shown in Table 1, the closing price of Bitcoin ranged from a minimum of \$4,971 to a maximum of \$111,673, with a mean of \$40,730 and a median of \$35,954. Open, high and low prices display similar ranges and central trends, showing day-to-day volatility of Bitcoin. The daily high–low range, which is informative about volatility (in the analysis we use the Rogers–Satchell and Parkinson proxies), averaged \$1,773 per day with a maximum single-day change of \$12,865. The median high–low range is \$1,306, which shows that most trading days have price fluctuations in the range of one to two thousand dollars.

Overall, these descriptive statistics highlight both high average price level and volatility that have characterized Bitcoin market during the sample period.

Table 2. Event pipeline

Event type	Events	Overlaps	After removal	MM (n<10)	Final events
CPI	65	2	63	1	62
FOMC	44	2	42	0	42

As described in Table 2, the investigated period contains sixty-five CPI dates and forty-four FOMC dates over the sample. Two calendar overlaps, when CPI and FOMC fell on the same day, are excluded so that each event is related to a single source of information. After removing these overlaps, the sample includes sixty-three CPI and forty-two FOMC days, we then apply the pre-event market-model quality check that requires at least ten SPX-open observations in the $[t_0 - 20, t_0 - 3]$ window. One CPI date fails this filter, while all FOMC dates pass. The final sample includes sixty-two CPI and forty-two FOMC events or one hundred and four events in total. After all checks, we dropped five events. Groups by direction used in Section 5.2 are summarized in Appendix Table 10.

Table 3. Descriptive statistics: daily returns of Bitcoin and S&P 500

Metric	Count	Min	Max	Mean	Median
BTC simple return (daily)	1,977	-37.17%	18.75%	0.19%	0.06%
BTC log return (daily)	1,977	-46.47%	17.18%	0.14%	0.06%
S&P 500 Simple return (daily)	1,359	-11.98%	9.52%	0.05%	0.09%
S&P 500 Log return (daily)	1,359	-12.77%	9.09%	0.04%	0.09%

Table 3 contains descriptive statistics for daily returns of Bitcoin and S&P 500 during the investigated period. There are 1,977 observations because the first calendar day misses a lagged close, and 1,359 S&P 500 observations reflecting the U.S. trading-day calendar. Central tendency is small: the mean is 0.19% for simple returns and 0.14% for log returns, while the median is 0.06% in both cases, indicating that a typical day shows only a modest price change. The range is wide, with periodic large moves: from -37.17% to $+18.75\%$ for simple returns and from -46.47% to $+17.18\%$ for log returns. For the S&P 500, the mean is lower 0.05% for simple and 0.04% for log with a 0.09% median for both, and the range is much narrower from -11.98% to $+9.52\%$ for simple and from -12.77% to $+9.09\%$ for log, showing that the index is less volatile than Bitcoin. The log transformation leaves the center nearly unchanged, but slightly compresses large positives and makes big negatives more noticeable, which is expected. In what follows we work with daily log returns for consistency with the modeling framework in Chapter 3.

Figure 1. BTC vs SPX daily log returns, scatter plot

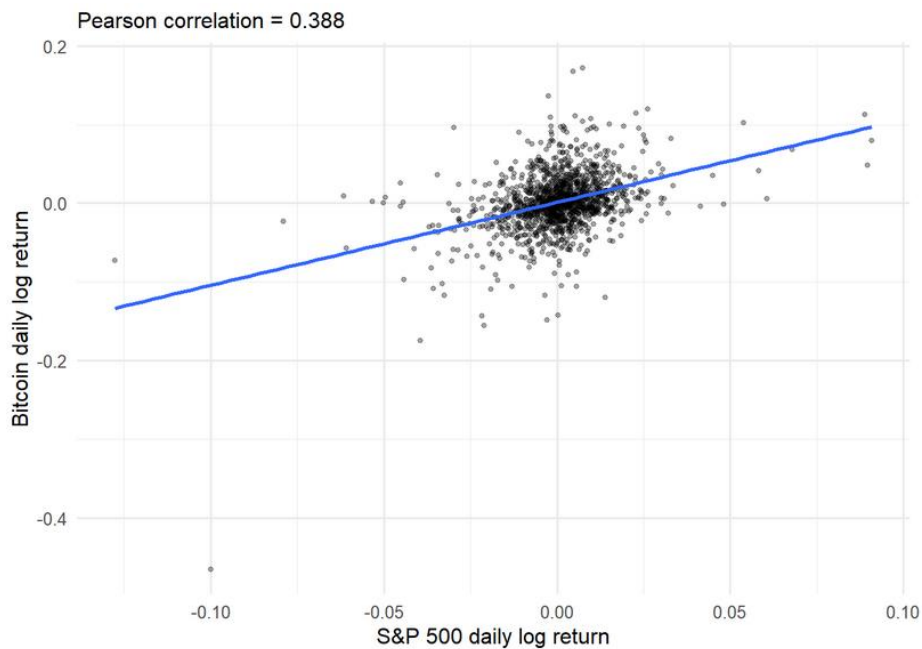


Figure 1 plots Bitcoin’s daily log return against the S&P 500 daily log return for all days with both series available. The cloud of points is concentrated near zero with a clear upward tilt, and the fitted OLS line has a positive slope. The Pearson correlation is about 0.39, which is moderate: Bitcoin tends to rise when the S&P 500 rises, but the dispersion around the line is large, indicating a substantial idiosyncratic component. A few outliers reflect days with very large moves in one or both markets.

Figure 2. Distributions of daily volatility (σ , RS and Parkinson)

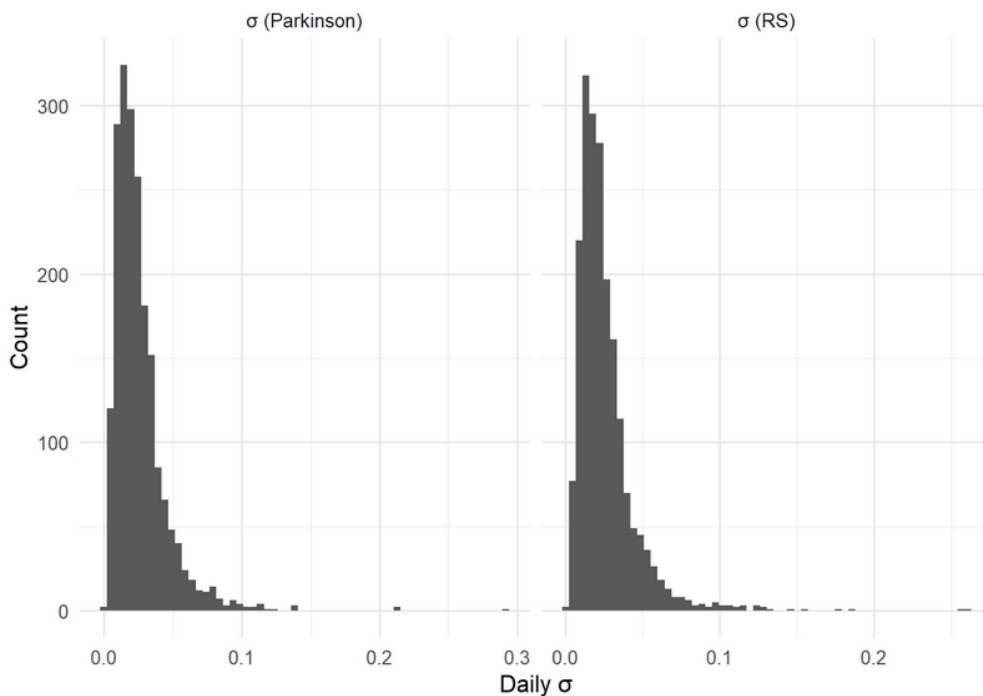


Figure 2 shows the distribution of Bitcoin’s daily volatility measured by the Parkinson proxy on the left and by the Rogers–Satchell proxy on the right. Both distributions are non-negative and strongly right-skewed: most days have low σ , while a small number of days exhibit very high σ , so the mean exceeds the median. The two proxies produce very similar shapes, indicating that they capture the same volatility pattern. The RS proxy has a slightly

longer right tail, which is reasonable because it uses both the high–low range and the open–close positions and can react more on days with a large intraday move and a shift between open and close.

CHAPTER 5

RESULTS

The final sample contains sixty-two CPI events and forty-two FOMC events after removing overlap days and applying the pre-event market-model filter. Results are reported for two outcomes: cumulative abnormal return (CAR), measured as log returns (natural logs) and abnormal volatility (AVOL), defined as the change in daily volatility σ relative to the event's pre-event baseline, expressed in percentage points (p.p.). Volatility is shown using two proxies: Rogers–Satchell (RS) and Parkinson (PK).

5.1 Event-study results for each day of the event window

Table 4. CPI event-study results for each day of the event window

Day	Measure	N	Mean	Mean (ann.)	t-test	p	
-2	AVOL (PK)	62	0.70	13.28	2.49	0.015	*
-1	AVOL (PK)	62	0.53	10.19	2.34	0.023	*
0	AVOL (PK)	62	0.81	15.52	3.68	<0.001	***
1	AVOL (PK)	62	0.68	13.05	1.43	0.157	
2	AVOL (PK)	62	0.40	7.71	1.18	0.244	
-2	AVOL (RS)	62	0.60	11.52	2.04	0.046	*
-1	AVOL (RS)	62	0.44	8.34	2.39	0.020	*
0	AVOL (RS)	62	0.81	15.40	3.98	<0.001	***
1	AVOL (RS)	62	0.41	7.84	1.68	0.098	
2	AVOL (RS)	62	0.47	9.06	1.12	0.269	
-2	CAR	45	0.0029		0.44	0.664	
-1	CAR	62	-0.0006		-0.08	0.937	
0	CAR	61	0.003		0.35	0.726	
1	CAR	58	-0.0012		-0.10	0.923	
2	CAR	43	0.0045		0.31	0.759	

As presented in Table 4, abnormal volatility rises already two days before the CPI release and peaks on the announcement day. Using the Parkinson proxy, AVOL averages 0.70 p.p. on $\tau = -2$ ($p=0.015$), 0.53 p.p. on $\tau = -1$ ($p=0.023$), and 0.81 p.p. on $\tau = 0$ ($p<0.001$), which corresponds to about 15 p.p. in annualized terms. The Rogers–Satchell proxy shows the same pattern and similar results: 0.60 p.p. on $\tau = -2$ ($p=0.046$), 0.44 p.p. on $\tau = -1$ ($p=0.020$), and 0.81 p.p. on $\tau = 0$ ($p<0.001$). After the release, AVOL becomes statistically insignificant on $\tau = +1$ and $\tau = +2$ for Parkinson, and only marginally significant for RS on $\tau = +1$ ($p=0.098$). Cumulative abnormal returns are insignificant on all days in the event window, the lower N reflects the SPX-day rule from Section 3.2.

Table 5. FOMC event-study results for each day of the event window

Day	Measure	N	Mean	Mean (ann.)	t-test	p	
-2	AVOL (PK)	42	1.26	24.06	2.39	0.022	*
-1	AVOL (PK)	42	0.21	3.95	0.89	0.381	
0	AVOL (PK)	42	1.03	19.65	4.09	<0.001	***
1	AVOL (PK)	42	0.60	11.51	2.20	0.034	*
2	AVOL (PK)	42	0.34	6.52	1.54	0.130	
-2	AVOL (RS)	42	1.23	23.41	1.93	0.061	
-1	AVOL (RS)	42	0.24	4.59	1.21	0.235	
0	AVOL (RS)	42	0.93	17.85	3.02	0.004	**
1	AVOL (RS)	42	0.70	13.42	2.14	0.039	*
2	AVOL (RS)	42	0.53	10.07	2.06	0.046	*
-2	CAR	41	-0.0109		-1.59	0.120	
-1	CAR	40	-0.0049		-0.54	0.595	
0	CAR	40	0.0113		1.11	0.272	
1	CAR	42	0.0101		0.78	0.437	
2	CAR	40	0.0090		0.55	0.584	

As presented in Table 5, on the FOMC announcement days the volatility response is strong and extends beyond the announcement day. With the Parkinson proxy, abnormal volatility is already high 1.26 p.p. on $\tau = -2$ ($p=0.022$), 1.03 p.p. on $\tau = 0$ ($p<0.001$), and remains positive 0.6 p.p. on $\tau = +1$ ($p=0.034$). The Rogers–Satchell proxy shows similar results: significant 0.93 p.p. on $\tau = 0$ ($p=0.004$), significant 0.70 p.p. on $\tau = +1$ ($p=0.039$) and 0.53 p.p. $\tau = +2$ ($p=0.046$), with a borderline rise on $\tau = -2$ ($p=0.061$) and no effect on $\tau = -1$. Cumulative abnormal returns are insignificant on all days in the event window, the lower N reflects the SPX-day rule from Section 3.2.

5.2 Event-study results aggregated over the event window

Table 6. CPI event-study results window average

Window	Measure	N	Mean	Mean (ann.)	t-test	p	
[-2,-1]	CAR	62	-0.0006		-0.08	0.937	
[-2,-1]	AVOL (RS)	62	0.52	9.93	2.59	0.012	*
[-2,-1]	AVOL (PK)	62	0.61	11.74	2.89	0.005	**
[1,2]	CAR	58	-0.0030		-0.43	0.672	
[1,2]	AVOL (RS)	62	0.44	8.45	1.45	0.153	
[1,2]	AVOL (PK)	62	0.54	10.38	1.37	0.176	

As presented in Table 6, the two-day pre-event window [-2,-1] shows a clear volatility build-up: AVOL equals 0.52 p.p. with RS ($p=0.012$) and 0.61 p.p. with Parkinson ($p=0.005$), about 10–12 p.p. in annualized terms. In the post-event window [1,2] volatility remains positive but is smaller and not statistically significant (0.44–0.54 p.p., $p=0.153$ –0.176). CARs are near zero and insignificant in both windows (pre: -0.0006 , $p=0.937$, post: -0.0030 , $p=0.672$), the lower N reflects the SPX-day rule from Section 3.2.

Table 7. FOMC event-study results window average

Window	Measure	N	Mean	Mean (ann.)	t-test	p	
[-2,-1]	CAR	42	-0.0064		-0.72	0.473	
[-2,-1]	AVOL (RS)	42	0.73	14.00	1.99	0.053	
[-2,-1]	AVOL (PK)	42	0.73	14.01	2.22	0.032	*
[1,2]	CAR	42	0.0013		0.15	0.884	
[1,2]	AVOL (RS)	42	0.61	11.74	2.75	0.009	**
[1,2]	AVOL (PK)	42	0.47	9.02	2.58	0.014	*

As presented in Table 7, for FOMC, the two-day pre-event window [-2,-1] shows a significant rise in volatility and no price drift. AVOL is 0.73 p.p. with the Parkinson proxy ($p=0.032$) and very close with RS 0.73 p.p. ($p=0.053$, borderline). In the post-event window [1,2] the volatility increase remains and is statistically significant: 0.61 p.p. with RS ($p=0.009$) and 0.47 p.p. with Parkinson ($p=0.014$). CARs are small and insignificant in both windows (-0.0064 pre, 0.0013 post).

Therefore, according to the results presented in Tables 5-7, inflation and policy rate announcements result in Bitcoin's positive abnormal volatility within the chosen event window, but are not associated with significant abnormal returns. A possible reason for the absence of significant results for CAR could be that Bitcoin price has opposite reactions to positive and negative announcements. While these reactions could be individually significant, pooling all announcements together might lead to zero average CAR. To investigate whether this is indeed the case, we split all CPI and FOMC announcements into sub-samples by their direction and present the results for each of them in Tables 8 and 9.

Table 8. CPI event-study results by YoY inflation direction window average

Group	Window	Measure	N	Mean	Mean (ann.)	t-test	p	
CPI YoY ↑	[-2,-1]	AVOL (PK)	30	0.54	10.37	2.29	0.030	*
CPI YoY ↑	[-2,-1]	AVOL (RS)	30	0.49	9.32	1.59	0.122	
CPI YoY ↑	[-2,-1]	CAR	30	0.0104		0.92	0.364	
CPI YoY ↑	[1,2]	AVOL (PK)	30	-0.1	-2.52	-0.81	0.423	
CPI YoY ↑	[1,2]	AVOL (RS)	30	-0.05	-0.93	-0.28	0.782	
CPI YoY ↑	[1,2]	CAR	27	-0.0018		-0.35	0.731	
Unchanged	[-2,-1]	AVOL (PK)	4	-0.27	-5.20	-0.86	0.451	
Unchanged	[-2,-1]	AVOL (RS)	4	-0.43	-8.18	-1.32	0.279	
Unchanged	[-2,-1]	CAR	4	-0.0306		-2.07	0.130	
Unchanged	[1,2]	AVOL (PK)	4	-0.32	-6.02	-1.35	0.271	
Unchanged	[1,2]	AVOL (RS)	4	-0.63	-11.94	-3.14	0.052	
Unchanged	[1,2]	CAR	4	-0.0034		-0.43	0.697	
CPI YoY ↓	[-2,-1]	AVOL (PK)	28	0.82	15.62	2.08	0.047	*
CPI YoY ↓	[-2,-1]	AVOL (RS)	28	0.69	13.17	2.36	0.026	*
CPI YoY ↓	[-2,-1]	CAR	28	-0.0081		-0.67	0.507	
CPI YoY ↓	[1,2]	AVOL (PK)	28	1.39	26.55	1.65	0.110	
CPI YoY ↓	[1,2]	AVOL (RS)	28	1.12	21.41	1.77	0.087	
CPI YoY ↓	[1,2]	CAR	27	-0.0042		-0.29	0.774	

As presented in Table 8, for CPI announcements split by the YoY direction, the volatility response is strongest when inflation falls. In the pre-announcement window [-2,-1], AVOL is 0.82 p.p. with the Parkinson proxy ($p=0.047$) and 0.69 p.p. with the RS proxy ($p=0.026$) for “CPI YoY ↓”, while post-window [1,2] effects are weaker and only borderline with RS (1.12 p.p., $p=0.087$). When inflation rises (“CPI YoY ↑”), there is a smaller but significant

pre-window increase with the Parkinson proxy (0.54 p.p., $p=0.030$). RS is not significant and there is no post-window effect. The “unchanged” group has only four events, so estimates are imprecise. The only near-signal is a negative RS effect in [1,2] (-0.63 p.p., $p\approx 0.052$). Across all groups and windows, CARs are insignificant. See Appendix Table 11 for day-by-day estimates.

Table 9. FOMC event-study results by policy-rate move window average

Group	Window	Measure	N	Mean	Mean (ann.)	t-test	p
Hike (rate ↑)	[-2,-1]	AVOL (PK)	11	0.53	10.17	0.92	0.378
Hike (rate ↑)	[-2,-1]	AVOL (RS)	11	0.40	7.69	0.90	0.388
Hike (rate ↑)	[-2,-1]	CAR	11	-0.0336		-2.56	0.029 *
Hike (rate ↑)	[1,2]	AVOL (PK)	11	0.31	5.86	0.82	0.429
Hike (rate ↑)	[1,2]	AVOL (RS)	11	0.26	5.05	0.92	0.378
Hike (rate ↑)	[1,2]	CAR	11	-0.0067		-0.47	0.645
Unchanged	[-2,-1]	AVOL (PK)	26	0.48	9.13	1.50	0.145
Unchanged	[-2,-1]	AVOL (RS)	26	0.46	8.73	1.45	0.160
Unchanged	[-2,-1]	CAR	26	0.0012		0.10	0.922
Unchanged	[1,2]	AVOL (PK)	26	0.49	9.35	2.31	0.030 *
Unchanged	[1,2]	AVOL (RS)	26	0.59	11.36	2.37	0.026 *
Unchanged	[1,2]	CAR	26	0.0025		0.21	0.835
Cut (rate ↓)	[-2,-1]	AVOL (PK)	5	2.50	47.79	1.36	0.247
Cut (rate ↓)	[-2,-1]	AVOL (RS)	5	2.89	55.30	1.18	0.303
Cut (rate ↓)	[-2,-1]	CAR	5	0.014		1.60	0.185
Cut (rate ↓)	[1,2]	AVOL (PK)	5	0.75	14.29	0.94	0.400
Cut (rate ↓)	[1,2]	AVOL (RS)	5	1.49	28.47	1.20	0.297
Cut (rate ↓)	[1,2]	CAR	5	0.0126		0.47	0.665

As presented in Table 9, for FOMC announcements split by the rate move, the volatility response is concentrated in “unchanged” meetings. In the post-announcement window [1,2], AVOL is 0.49 p.p. with the Parkinson proxy ($p=0.030$) and 0.59 p.p. with the RS proxy ($p=0.026$), while the pre-window $[-2, -1]$ is not significant for either proxy. When the rate is hiked, both proxies are small and insignificant in both windows. The only clear signal is a negative pre-window return drift: CAR in $[-2, -1]$ is -0.0336 in log returns ($\approx -3.36\%$ simple) ($t=-2.56, p=0.029$). For rate cuts the sample is very small ($N=5$), and neither AVOL nor CAR is significant in any window. See Appendix Table 12 for day-by-day estimates.

5.3 Summary of results

Bitcoin’s volatility rises around U.S. macro announcements, while returns show no consistent drift. For CPI, volatility builds up before the release and peaks on the announcement day: about 0.5–0.7 p.p. on $\tau = -2 \dots -1$ and about 0.8 p.p. on $\tau = 0$ (Tables 4 and 6). After the release the effect fades and is not different from zero on $\tau = +1 \dots +2$ (Tables 4 and 6). For FOMC, the day-0 spike is 1.0 p.p. and volatility stays elevated on $\tau = +1 \dots +2$ at roughly 0.5–0.6 p.p. (Tables 5 and 7).

Cross-section results follow the same pattern. For CPI, the largest response is when YoY inflation falls: the pre-window $[-2, -1]$ is about 0.7–0.8 p.p., while it is smaller (about 0.5 p.p.) when inflation rises, the “unchanged” CPI group is too small for precise estimates (Table 8, Appendix Table 11). For FOMC, the post-window effect is mainly in “unchanged” meetings at about 0.5–0.6 p.p. in [1, 2], hikes and cuts show insignificant in the two-day windows (Table 9, Appendix Table 12). Returns are close to zero throughout, the only pattern is a small negative drift before rate hikes in $[-2, -1]$ of about -3.3% in logs (Table 9).

Overall, H1 is supported: volatility increases around CPI and FOMC, with a sharp one-day CPI spike and a more persistent FOMC effect. For returns, H2 is generally not supported:

across specifications the average CAR does not differ significantly from zero on announcement days, and pre- or post-window CARs are also mostly insignificant. The only noticeable exceptions are a small negative CAR in $[-2, -1]$ before rate hikes and a few significant day-level FOMC results, however, these are based on small subsamples don't change the overall conclusion

CHAPTER 6 CONCLUSIONS AND RECOMMENDATIONS

The patterns documented in the thesis point to a simple message for practice: plan in advance for announcement days, manage risk first, and avoid relying on one-way bets. Scheduled news changes market expectations, so positions get rebalanced, day-level ranges tend to widen, and trading can become one-sided for a while. These effects matter even when the final price move is small. Our evidence is based on daily data, not intraday data, so the guidance below focuses on day-level ranges rather than intraday timing.

For spot trading, preparation is more useful than prediction. Use an event calendar, expect wider day-level ranges, and tighten risk controls around the release window. Smaller position sizes, more careful execution, and temporary pauses near the announcement time help to avoid forced decisions in fast markets. After the meeting or release, let positions scale back up only when price action and depth look normal again.

For options, strategies that profit from bigger ranges are usually safer than one-way bets. Entering before the announcement and exiting in steps can balance gains from the move with the possibility that realized volatility falls after the event. Position sizing should reflect that the main risk depends on the path the price takes: large ranges can occur without a clear direction. This guidance shows a repeated pattern of higher daily ranges around the announcements, not a forecast about the news itself.

For market makers, exchanges, and brokers, it is reasonable to widen spreads and raise initial margin and liquidation buffers around scheduled announcements. The goal is to protect inventories and clients against sudden gaps and temporary order-book imbalances. In FOMC weeks, keeping some of these controls until the next day is consistent with the more persistent response in our results.

For treasuries, miners, and large corporate conversions, avoid bunching large transfers around the announcement window. Execution risk and slippage rise when spreads widen

and depth is thin. Plan outside the immediate window especially when YoY CPI later falls, because the pre-announcement window is more sensitive in that subgroup.

For portfolio and risk management, short-horizon limits should reflect the event pattern. Value-at-Risk and Expected Shortfall inputs can be increased on CPI days ($\tau = 0$) and through FOMC $\tau = 0 \dots + 2$, and risk budgets can be shifted away from strategies that are highly sensitive to sudden changes in day-level range. Signals that occasionally appear before specific meeting outcomes are not strong or consistent enough to justify systematic directional exposure.

Overall, the practical rule is simple: on announcement days, prioritize risk discipline over forecasts, let position size and leverage do most of the work, and give markets time (especially after FOMC) to absorb the information before returning to normal.

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APPENDIX

Table 10. Event count by direction

Event	-1 (down)	0 (unchanged)	1 (up)
FOMC	5	26	11
CPI	28	4	31

Table 11. CPI event-study results by YoY inflation direction for each day of the event window

Group	Day	Measure	N	Mean	Mean (ann.)	t-test	p	
CPI YoY ↑	-2	AVOL (PK)	30	0.79	15.11	1.90	0.068	
CPI YoY ↑	-1	AVOL (PK)	30	0.29	5.62	1.27	0.213	
CPI YoY ↑	0	AVOL (PK)	30	0.60	11.46	2.06	0.048	*
CPI YoY ↑	1	AVOL (PK)	30	-0.20	-3.78	-0.88	0.385	
CPI YoY ↑	2	AVOL (PK)	30	-0.07	-1.26	-0.26	0.800	
CPI YoY ↑	-2	AVOL (RS)	30	0.80	15.28	1.60	0.120	
CPI YoY ↑	-1	AVOL (RS)	30	0.18	3.36	0.77	0.449	
CPI YoY ↑	0	AVOL (RS)	30	0.53	10.26	2.15	0.040	*
CPI YoY ↑	1	AVOL (RS)	30	-0.11	-2.04	-0.46	0.650	
CPI YoY ↑	2	AVOL (RS)	30	0.010	0.17	0.04	0.971	
CPI YoY ↑	-2	CAR	24	0.0107		1.08	0.292	
CPI YoY ↑	-1	CAR	30	0.0104		0.92	0.364	
CPI YoY ↑	0	CAR	30	0.0110		0.91	0.373	
CPI YoY ↑	1	CAR	27	0.0134		0.90	0.374	

CPI YoY ↑	2	CAR	21	0.0133		0.72	0.478	
Unchanged	-2	AVOL (PK)	4	0.05	1.04	0.11	0.916	
Unchanged	-1	AVOL (PK)	4	-0.60	-11.44	-1.26	0.297	
Unchanged	0	AVOL (PK)	4	-0.40	-7.61	-0.53	0.633	
Unchanged	1	AVOL (PK)	4	-0.29	-5.55	-0.98	0.399	
Unchanged	2	AVOL (PK)	4	-0.34	-6.49	-0.65	0.563	
Unchanged	-2	AVOL (RS)	4	-0.43	-8.16	-1.13	0.340	
Unchanged	-1	AVOL (RS)	4	-0.43	-8.20	-0.87	0.449	
Unchanged	0	AVOL (RS)	4	0.23	4.47	0.25	0.821	
Unchanged	1	AVOL (RS)	4	0.11	2.02	0.35	0.751	
Unchanged	2	AVOL (RS)	4	-1.37	-26.08	-6.28	0.008	**
Unchanged	-2	CAR	4	-0.0108		-0.64	0.566	
Unchanged	-1	CAR	4	-0.0306		-2.07	0.130	
Unchanged	0	CAR	4	-0.0481		-2.59	0.081	
Unchanged	1	CAR	4	-0.0637		-2.42	0.094	
Unchanged	2	CAR	1	-0.0347		NA	NA	
CPI YoY ↓	-2	AVOL (PK)	28	0.68	13.07	1.60	0.121	
CPI YoY ↓	-1	AVOL (PK)	28	0.95	18.18	2.25	0.033	*
CPI YoY ↓	0	AVOL (PK)	28	1.21	23.17	3.47	0.002	**
CPI YoY ↓	1	AVOL (PK)	28	1.77	33.75	1.77	0.088	
CPI YoY ↓	2	AVOL (PK)	28	1.01	19.36	1.46	0.156	
CPI YoY ↓	-2	AVOL (RS)	28	0.54	10.31	1.43	0.164	
CPI YoY ↓	-1	AVOL (RS)	28	0.84	16.03	2.80	0.009	**
CPI YoY ↓	0	AVOL (RS)	28	1.19	22.68	3.55	0.001	***
CPI YoY ↓	1	AVOL (RS)	28	1.01	19.24	2.20	0.037	*
CPI YoY ↓	2	AVOL (RS)	28	1.23	23.59	1.40	0.174	
CPI YoY ↓	-2	CAR	17	-0.0049		-0.49	0.629	
CPI YoY ↓	-1	CAR	28	-0.0081		-0.67	0.507	
CPI YoY ↓	0	CAR	27	0.0016		0.13	0.900	

CPI YoY ↓	1	CAR	27	-0.0067	-0.30	0.769
CPI YoY ↓	2	CAR	21	-0.0024	-0.10	0.920

Table 12. FOMC event-study results by policy-rate move for each day of the event window

Group	Day	Measure	N	Mean	Mean (ann.)	t-test	p
Hike (rate ↑)	-2	AVOL (PK)	11	1.18	22.61	1.47	0.172
Hike (rate ↑)	-1	AVOL (PK)	11	-0.12	-2.28	-0.29	0.779
Hike (rate ↑)	0	AVOL (PK)	11	1.17	22.33	2.88	0.016 *
Hike (rate ↑)	1	AVOL (PK)	11	0.61	11.65	0.95	0.363
Hike (rate ↑)	2	AVOL (PK)	11	0.00	0.06	0.01	0.992
Hike (rate ↑)	-2	AVOL (RS)	11	0.61	11.65	1.16	0.272
Hike (rate ↑)	-1	AVOL (RS)	11	0.20	3.73	0.39	0.702
Hike (rate ↑)	0	AVOL (RS)	11	1.50	28.62	2.00	0.074
Hike (rate ↑)	1	AVOL (RS)	11	0.28	5.36	0.72	0.487
Hike (rate ↑)	2	AVOL (RS)	11	0.25	4.74	0.82	0.430
Hike (rate ↑)	-2	CAR	11	-0.0289		-2.06	0.066
Hike (rate ↑)	-1	CAR	11	-0.0336		-2.56	0.029 *
Hike (rate ↑)	0	CAR	11	-0.0254		-2.09	0.063
Hike (rate ↑)	1	CAR	11	-0.0317		-1.50	0.165
Hike (rate ↑)	2	CAR	11	-0.0322		-1.42	0.185
Unchanged	-2	AVOL (PK)	26	0.85	16.32	1.86	0.075
Unchanged	-1	AVOL (PK)	26	0.10	1.94	0.36	0.725
Unchanged	0	AVOL (PK)	26	0.99	18.95	2.84	0.009 **
Unchanged	1	AVOL (PK)	26	0.48	9.08	1.76	0.090
Unchanged	2	AVOL (PK)	26	0.50	9.62	1.55	0.134

Unchanged	-2	AVOL (RS)	26	0.78	14.82	1.59	0.124	
Unchanged	-1	AVOL (RS)	26	0.14	2.63	0.59	0.561	
Unchanged	0	AVOL (RS)	26	0.63	11.97	2.20	0.037	*
Unchanged	1	AVOL (RS)	26	0.61	11.15	1.71	0.099	
Unchanged	2	AVOL (RS)	26	0.58	11.14	1.57	0.129	
Unchanged	-2	CAR	26	-0.0032		-0.36	0.722	
Unchanged	-1	CAR	25	0.0034		0.26	0.795	
Unchanged	0	CAR	25	0.0218		1.56	0.131	
Unchanged	1	CAR	26	0.0197		1.13	0.270	
Unchanged	2	CAR	25	0.0196		0.84	0.408	
Cut (rate ↓)	-2	AVOL (PK)	5	3.53	67.49	1.02	0.367	
Cut (rate ↓)	-1	AVOL (PK)	5	1.47	28.09	1.86	0.136	
Cut (rate ↓)	0	AVOL (PK)	5	0.91	17.41	1.22	0.290	
Cut (rate ↓)	1	AVOL (PK)	5	1.25	23.86	0.95	0.396	
Cut (rate ↓)	2	AVOL (PK)	5	0.24	4.66	0.57	0.597	
Cut (rate ↓)	-2	AVOL (RS)	5	4.92	93.93	1.06	0.350	
Cut (rate ↓)	-1	AVOL (RS)	5	0.87	16.67	2.06	0.108	
Cut (rate ↓)	0	AVOL (RS)	5	1.30	24.74	0.88	0.430	
Cut (rate ↓)	1	AVOL (RS)	5	2.13	40.74	1.10	0.335	
Cut (rate ↓)	2	AVOL (RS)	5	0.85	16.19	1.12	0.327	
Cut (rate ↓)	-2	CAR	4	-0.0115		-2.61	0.080	
Cut (rate ↓)	-1	CAR	4	0.0222		6.16	0.009	**
Cut (rate ↓)	0	CAR	4	0.0465		2.57	0.082	
Cut (rate ↓)	1	CAR	5	0.0521		2.75	0.051	
Cut (rate ↓)	2	CAR	4	0.0558		4.19	0.025	*

Table 13. CPI daily volatility

Metric	Count	Min	Max	Mean	Median	Mean(ann.)
σ_{pre} (PK)	62	0.62	5.89	2.47	2.33	47.26
σ_{pre} (RS)	62	0.67	6.31	2.45	2.29	46.90

Table 14. FOMC daily volatility

Metric	Count	Min	Max	Mean	Median	Mean(ann.)
σ_{pre} (PK)	42	0.95	6.25	2.55	2.29	48.69
σ_{pre} (RS)	42	0.97	6.79	2.50	2.26	47.73