



School of Economics and Management

**Bitcoin in the Post-ETF Era: Decoupling, Safe Haven
Properties, and Volatility Regimes**

Master Thesis Finance – Data Science Track

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1.Introduction

The volatility of Bitcoin and its uncertain relationship with traditional financial assets continue to fuel debate in academic finance and institutional investment circles. The approval of spot Bitcoin Exchange-Traded Funds (ETFs) by the U.S. Securities and Exchange Commission in January 2024 marked a turning point in the asset's perceived legitimacy, prompting questions about how Bitcoin behaves within diversified portfolios in a post-ETF environment. Although some advocates argue that the institutionalization of Bitcoin could stabilize its market behavior and enhance its diversification properties, others remain skeptical of its role as either a hedge or safe haven. The empirical evidence remains fragmented, and no consensus has been reached on whether Bitcoin has structurally decoupled from traditional assets like equities and gold, particularly in periods of market stress. Against this backdrop, this thesis investigates how Bitcoin's correlations, risk characteristics, and regime dynamics have evolved following the ETF approval, providing a high-frequency, data-driven perspective on its integration with mainstream financial markets.

This thesis contributes to the literature by offering a joint analysis of Bitcoin's correlation structure, safe-haven properties, and volatility regime behavior in a novel post-ETF setting. Previous research has examined Bitcoin's role as a hedge or diversifier, typically using pre-2021 data or focusing on low-frequency metrics. However, the approval of spot ETFs introduces an exogenous institutional shock that may have reshaped the market dynamics around Bitcoin. This research goes beyond simple correlation tracking by applying rolling-window techniques, event-study regressions, multi-tail safe haven tests, and Markov-switching volatility models, providing a comprehensive and robust examination of whether and how Bitcoin's relationship to traditional markets has changed. The findings not only extend current research but also serve practical relevance for portfolio managers, risk modelers, and policymakers seeking to assess Bitcoin's evolving financial role.

The main research question addressed in this thesis is: Has Bitcoin structurally decoupled from traditional financial assets following the approval of spot ETFs, and does it function as a safe haven during market stress? To answer this, the thesis is organized around three hypotheses. The first tests whether Bitcoin's return correlations with the S&P 500 and gold declined in response to the ETF launch, using rolling 30-day windows and a HAC-robust event study framework to detect significant mean shifts around the event. The second investigates whether Bitcoin functions as a safe haven asset during periods of extreme equity market stress, following a nested multi-tail regression setup that models conditional betas under varying degrees of equity downturns. The third examines whether Bitcoin's volatility behavior differs structurally from that of traditional assets by applying two-regime Markov-Switching GARCH models and comparing regime persistence, volatility magnitudes, and transition probabilities across BTC, SPX, and GLD.

The empirical analysis relies on daily data from January 2018 through July 2025 for Bitcoin, the S&P 500 (SPX), and gold (GLD), sourced from Yahoo Finance. Log returns are calculated and standardized where necessary to facilitate consistent cross-asset comparisons. For the decoupling analysis, 30-day rolling Pearson correlations between BTC–SPX and BTC–Gold are calculated and Fisher z-transformed to permit robust parametric testing. Short-term event windows around January 11, 2024, are analyzed using Newey–West-adjusted OLS regressions to account for heteroskedasticity and autocorrelation. In the safe haven test, BTC and gold returns are regressed on SPX returns interacted with dummy variables for the lowest 10%, 5%, and 1% SPX return days. This approach allows for a nuanced test of downside protection, where safe-haven behavior would manifest as significantly negative conditional betas. Finally, to explore volatility dynamics, Markov-switching GJR-GARCH models with Student-t innovations are estimated for each asset, and regime-specific volatilities, durations,

and transition probabilities are extracted to understand how Bitcoin's volatility environment compares with traditional benchmarks.

The results provide a nuanced picture. For Hypothesis 1, short-term event windows reveal a statistically significant drop in BTC–SPX and BTC–Gold correlations immediately following the ETF approval, with Fisher-z shifts in some windows reaching significance at the 10% level. These results are reinforced by placebo tests on pre-event pseudo-dates, confirming that the correlation break is not driven by random variation. However, when extended to the full post-event period, no lasting decoupling is observed, indicating that the effect was transitory. Hypothesis 2 fails to find evidence that Bitcoin functions as a safe haven: during the most severe SPX downturns, Bitcoin's returns exhibit positive and statistically insignificant betas, inconsistent with hedging behavior. In contrast, gold shows directionally negative betas under moderate stress, though these do not reach conventional levels of significance. Hypothesis 3 is strongly supported: Bitcoin's volatility switches between two distinct regimes, with the regime-switching model providing a substantially better fit than a constant-volatility benchmark based on AIC results. However, these regimes are short-lived and unstable compared to SPX and gold, which exhibit long and persistent volatility phases. BIC, which prioritizes parsimony over flexibility, slightly favors a more conservative interpretation. Overall, Bitcoin appears to operate in a high-frequency, high-uncertainty volatility structure, markedly different from traditional safe-haven assets.

These findings resonate with the literature but also diverge in critical ways. For instance, Baur and Lucey (2010) established early criteria for safe-haven assets using regression-based crisis interactions, showing that gold exhibits negative conditional betas during stress periods. In contrast, our results find no such behavior for Bitcoin post-ETF. Similarly, Dyhrberg (2015a) positioned Bitcoin as a hybrid between gold and currencies, offering partial hedge properties. This thesis challenges that view by documenting both short-

lived decoupling and positive conditional correlations under stress. Finally, the regime-switching results connect with recent work by Li and Miu (2022), who applied MSGARCH models to show that Bitcoin's volatility is highly state-dependent and less persistent than that of equities. The current analysis extends this by explicitly contrasting regime durations and transition probabilities across BTC, SPX, and gold, highlighting that Bitcoin's volatility structure is uniquely fragmented and less predictable.

The findings of this thesis suggest that Bitcoin has yet to achieve the characteristics of a mature hedge or safe haven. While brief episodes of decoupling are observed, they do not persist, and the asset remains positively correlated with equities even during the most extreme downturns. Its volatility profile is dominated by frequent, unstable shifts between regimes, further undermining its role as a stabilizing force in portfolios. In short, Bitcoin still behaves more like a speculative risk asset than a robust diversifier. These conclusions carry important implications for portfolio managers, who should be cautious when incorporating Bitcoin into defensive strategies. The ETF approval, while a milestone in market structure, does not appear to have transformed Bitcoin's financial role in a fundamental way.

The remainder of the thesis is organized as follows. Section 2 reviews the relevant academic literature. Section 3 describes the data and empirical setup. Section 4 develops the hypotheses based on theoretical and empirical reasoning. Section 5 outlines the methodology in detail. Section 6 presents the empirical results, and Section 7 concludes.

2. Literature Review

Introduction

Bitcoin developed by Satoshi Nakamoto in 2008, is a peer-to-peer electronic cash system revolutionizing Finance through its operability without the need for a trusted third party. Bitcoin solves the double-spending problem with a peer-to-peer network and proof-of-work consensus mechanism. This enables every network participant to securely, permanently transact via cryptographic proof and a distributed timestamp server, enabling the participants to rely on the system's integrity without any central oversight (Nakamoto, 2008).

In its beginnings it was seen as an alternative currency and a libertarian experiment in decentralized finance. Today Bitcoin increasingly draws attention from institutional investors, macro hedge funds, and central banks due to its potential as a store of value, inflation hedge and digital commodity. Since 2008 Bitcoin has grown to become one of the world's largest assets with a total market capitalization exceeding 2.1 trillion USD (*Bitcoin Price Today, BTC to USD Live Price, Marketcap and Chart | CoinMarketCap, 2025*). This vast expansion has driven increasing scholarly attention regarding its classification, volatility behavior, and potential role in diversified investment portfolios (Baur et al., 2017; Corbet et al., 2017).

Bitcoin vs. Gold: Diversifier, Hedge, or Safe Haven?

Bitcoin is often framed as “digital gold” due to its capped supply and decentralized nature (Dyhrberg, 2015a; Henriques & Sadorsky, 2018). Like gold, it is considered for its potential to hedge macroeconomic risks or offer diversification. However, empirical findings do not all align in this regard.

Gold has long been recognized as a safe haven asset. Baur and McDermott (2010) demonstrated that it preserved value during the 2008 financial crisis, and its historically low correlation with equities remains a central reason for its inclusion in defensive portfolios.

Although, even gold's behavior has shown signs of strain under recent systemic shocks. Chan et al. (2023) reported that gold's hedging effectiveness weakened during the COVID-19 crash, while Bitcoin's returns exhibited positive correlation with equities undermining claims of defensive behavior.

Despite these setbacks, Bitcoin's long-run correlation with traditional assets remains relatively low. Brière et al. (2015) and Dyhrberg (2015a) found that small allocations of Bitcoin (1–3%) improved portfolio Sharpe ratios due to its diversification potential. Bouri et al. (2020) supported this with wavelet coherence analysis, showing that Bitcoin's equity correlations are time-varying and tend to decrease during certain crisis windows suggesting temporary decoupling, even if not consistent safe haven behavior.

Yet Bitcoin's crisis behavior remains unreliable. Conlon et al. (2020) showed that during liquidity crunches like COVID-19, its correlation with equities spiked sharply. Liu and Tsyvinski (2020) linked this to sentiment-driven dynamics that intensify during stress. Institutional actors like BlackRock acknowledge Bitcoin's strategic value but still characterize it as a speculative component rather than a defensive one (BlackRock Investment Institute, 2024). In sum, Bitcoin may enhance diversification in normal conditions but still falls short of gold's consistency as a safe haven.

Volatility Regimes and Risk Modeling

Bitcoin's high volatility remains one of its most defining and controversial features. While it's often framed as a barrier to mainstream financial adoption, this very volatility has also contributed to its appeal as a high-performing, opportunistic asset for high-risk high-reward investors. What sets Bitcoin apart is not just the magnitude of its price swings, but the structure behind them. Heavy-tailed return distributions, swift regime shifts and a pronounced sensitivity to demand-side factors. Opposing traditional commodities like gold or oil, Bitcoin's

price dynamics are far less tied to supply fundamentals and much more driven by sentiment and macro uncertainty according to research (Bouri et al., 2020).

Chu et al. (2015) found that Bitcoin's log-returns are best captured by a generalized hyperbolic distribution (GHD), making it useful for tail risk modeling. Dyhrberg (2015b), using asymmetric GARCH, suggested that Bitcoin sits between gold and fiat currencies in volatility transmission, hinting at potential hedge functions. However, these models do not account for Bitcoin's distinct regime-switching dynamics.

To address that, more advanced frameworks were introduced. Ardia et al. (2018) applied Markov-Switching GARCH (MSGARCH) models and showed that Bitcoin alternates between persistent high- and low-volatility regimes, which aligned with market phases like bubbles or corrections. This substantially improved out-of-sample VaR performance. Gronwald (2019) reached similar conclusions using jump-GARCH models, attributing volatility primarily to demand shocks, another departure from commodity-like behavior.

The Role of Bitcoin Halving Cycles in Market Dynamics

One of Bitcoin's most distinctive features is its predetermined monetary policy. The Bitcoin protocol reduces the block reward every 210,000 blocks or roughly every four years. These halving events limit the rate of new Bitcoin issuance and are designed to cap the total supply at 21 million coins. This supply shock mechanism has led to widespread speculation that halvings serve as catalysts for bull markets reinforcing Bitcoin's narrative as a deflationary digital asset. Chan et al. (2023), using MSGARCH models, found that halvings coincide with regime transitions in volatility, yet these shifts are not solely driven by the halving schedule. Instead, broader market sentiment and macroeconomics play a stronger role.

This view challenges simplistic narratives that treat halvings as deterministic triggers. Rather, halving cycles appear to amplify existing momentum and narrative dynamics. Their

symbolic and behavioral importance is substantial, but their statistical explanatory power for volatility remains conditional on context.

Research Gaps in Bitcoin's Financial Role

While the literature on Bitcoin's financial properties has grown rapidly, several critical gaps remain. Most prior work, mostly due to mere availability, relies on pre-ETF, pre-2024 data. The approval of U.S. Spot Bitcoin ETFs in January 2024 and the most recent halving event in April 2024 have significantly reshaped institutional access, investor composition, and price behavior. As a result, earlier findings may no longer generalize to today's market conditions. This thesis uses the most recent and complete data available, covering both the ETF launch and the 2024 halving, allowing for an updated and forward-looking reassessment of Bitcoin's behavior.

Second, few studies have combined event-based stress testing with regime-sensitive volatility modeling. Traditional approaches often use static correlations or GARCH models, which miss important nonlinearities and shifts in market structure. This thesis applies Markov-Switching GARCH (MSGARCH) models to Bitcoin, S&P 500, and gold to examine how volatility regimes evolve and differ across assets. These models allow us to test whether Bitcoin's volatility behaves distinctly compared to traditional safe havens, particularly around key structural events.

Third, existing studies often lack predictive stress-testing frameworks that simulate Bitcoin's behavior under different macro-financial conditions. This thesis responds by using rolling correlations and dummy-interaction regressions to evaluate whether Bitcoin has decoupled from equities, both before and after structural events. In doing so, it captures path-dependent dynamics that are often missed by average-effect models.

Finally, the broader debate around Bitcoin's classification as a hedge, a safe haven, or a high-beta risk asset remains unsettled. Prior findings have been inconsistent, particularly during crisis episodes such as the COVID-19 crash. By combining updated post-2024 data, dynamic volatility modeling, and event-specific tests, this thesis directly contributes to further resolving that uncertainty. It offers an integrated framework to evaluate Bitcoin's evolving financial role.

3. Data Section

This section introduces the dataset used to examine Bitcoin’s evolving role in financial markets and its potential decoupling from traditional assets. It outlines the data sources, key preprocessing steps, and initial descriptive statistics that help contextualize the return dynamics and volatility characteristics of Bitcoin (BTC/USD), the S&P 500 Index (SPX), and Gold (GLD ETF). These assets span speculative, benchmark, and defensive categories, providing a well-rounded basis for assessing Bitcoin’s potential as a hedge or safe haven (Bouri et al., 2017; Liu & Tsyvinski, 2020).

Data Selection and Sources

Daily price data for Bitcoin, SPX and Gold were obtained from Yahoo Finance. The sample covers the period January 2018 to July 2025, capturing several critical market events, including the launch of the first U.S. Bitcoin Spot ETFs in January 2024 and the fourth Bitcoin halving in April 2024. This data selection balances sample length with data availability and ensures comparability across macro, equity, and alternative assets.

Logarithmic returns were calculated for all price series, providing a volatility-normalized framework for cross-asset comparison. All series were merged into a balanced panel dataset, retaining only dates with complete observations across all variables, which in this case excluded the Weekends and Holidays.

Summary Statistics

Table 1: Descriptive Statistics of Daily Log Returns

| Statistic | BTC | SPX | Gold |
|-----------------|----------|----------|----------|
| Observations | 1,864.00 | 1,864.00 | 1,864.00 |
| NAs | 0.00 | 0.00 | 0.00 |
| Minimum | -0.46 | -0.13 | -0.06 |
| Quartile 1 | -0.02 | -0.00 | -0.00 |
| Median | 0.00 | 0.00 | 0.00 |
| Arithmetic Mean | 0.00 | 0.00 | 0.00 |
| Geometric Mean | 0.00 | 0.00 | 0.00 |
| Quartile 3 | 0.02 | 0.01 | 0.01 |
| Maximum | 0.17 | 0.09 | 0.05 |
| SE Mean | 0.00 | 0.00 | 0.00 |
| LCL Mean (0.95) | -0.00 | -0.00 | 0.00 |
| UCL Mean (0.95) | 0.00 | 0.00 | 0.00 |
| Variance | 0.00 | 0.00 | 0.00 |
| Stdev | 0.04 | 0.01 | 0.01 |
| Skewness | -1.02 | -0.64 | -0.22 |
| Kurtosis | 13.47 | 14.15 | 2.66 |

Note. This table presents summary statistics for daily log returns of Bitcoin (BTC), the S&P 500 Index (SPX), and Gold (GLD ETF).

Table 1 reports key descriptive statistics for daily log returns of Bitcoin, the S&P 500 Index, and Gold. As expected, Bitcoin displays the highest volatility (standard deviation $\approx 4\%$) and extreme excess kurtosis (13.47), underlining its highly speculative nature. SPX exhibits lower volatility ($\approx 1\%$) but similarly fat-tailed behavior (kurtosis 14.15), which is typical for equity markets during periods of stress. Gold stands out as the most stable asset in the sample, with low volatility, minimal skewness, and only moderate excess kurtosis, in line with its traditional role as a safe haven.

Correlation Structure

Static Pearson correlations (Table 2) provide an initial view of co-movements across assets.

Table 2

Means, standard deviations, and correlations with confidence intervals

| Variable | <i>M</i> | <i>SD</i> | 1 | 2 |
|----------|----------|-----------|---------------------|---------------------|
| 1. BTC | 0.00 | 0.04 | | |
| 2. SPX | 0.00 | 0.01 | .31** [.27, .35] | |
| 3. Gold | 0.00 | 0.01 | .13** [.08, .17] | .10** [.06, .15] |

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

The correlation between BTC and SPX is positive and statistically significant ($\rho = 0.31$, $p < 0.01$), suggesting that Bitcoin has tended to co-move with equity markets during the sample period. This behavior is generally consistent with a risk-on asset. The BTC-Gold correlation is weaker but still significant at the one percent level ($\rho = 0.13$, $p < 0.01$), pointing to a marginal alignment between the two. The SPX-Gold correlation is statistically highly significant ($\rho = 0.1$, $p = 0.01$), implying that gold has shown consistent co-movement with the broader equity market but to a rather small extent.

The weaker co-movements between Bitcoin and the traditional safe haven asset underscores the ambiguity in classifying Bitcoin strictly as a hedge or diversifier. These static correlations serve as a preliminary step, motivating a time-varying analysis of cross-asset relationships in later sections.

These findings are broadly consistent with prior literature (Liu & Tsyvinski, 2020) and motivate a deeper time-varying and regime-dependent analysis in later sections.

Distributional Properties

Histograms of daily returns (Figure 1) reveal pronounced non-normality across all assets.

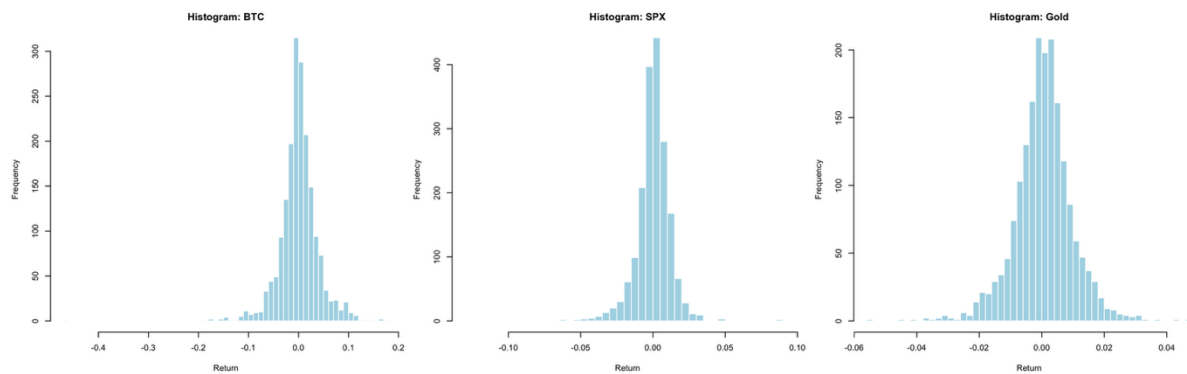


Figure 1 - Histograms of daily log returns

The histograms in Figure 1 provide a visual summary of the empirical distribution of daily returns for BTC, SPX, and Gold. Bitcoin’s return distribution is sharply peaked with long, asymmetric tails, reflecting substantial excess kurtosis and left-skewness. These are features that align with its reputation as a highly volatile asset. SPX returns are centered around zero but also display noticeable fat tails, suggesting deviations from normality and the presence of large market swings. Gold appears the most symmetric and least heavy-tailed among the three, although it still exhibits slight leptokurtosis. These non-Gaussian distributional characteristics across all assets motivate the adoption of fat-tailed volatility models, such as GARCH specifications with Student-t errors, in the empirical sections that follow.

4. Hypotheses Development

This thesis investigates the evolving role of Bitcoin within the broader financial ecosystem. Particularly its interdependencies with traditional assets such as equities and gold, and its behavior during periods of financial distress. The central motivation is to assess whether Bitcoin has matured into a structurally distinct asset, exhibiting decoupling from conventional markets and functioning as a safe haven in times of crisis.

Building on prior literature (Baur & Lucey, 2010; Dyhrberg, 2015b; Bouri et al., 2017; Li & Miu, 2023), this section formulates three testable hypotheses. Each is addressed through a tailored empirical framework involving rolling correlations with HAC-robust mean shift tests for event studies, safe haven regressions with Newey-West corrected standard errors, and regime-switching volatility models such as MSGARCH, as used in prior work such as Li and Miu (2022), Ardia et al. (2019), and Chan et al. (2023). The safe haven definition is adopted from Baur and Lucey (2010), who define such an asset as one that is uncorrelated or negatively correlated with another asset during periods of market turmoil.

Hypothesis 1 (Decoupling Hypothesis)

Has the launch of the U.S. Spot Bitcoin ETFs structurally altered Bitcoin's correlation with traditional financial assets such as equities (S&P 500) and gold?

This hypothesis investigated whether Bitcoin's relationship with traditional assets has shifted following a major institutional milestone. The approval and launch of U.S. spot Bitcoin ETFs on January 11, 2024. We assess structural changes in Bitcoin's correlation with both equities (S&P 500) and gold using a multi-layered empirical approach grounded in time-domain correlation analysis and event-study methodology.

We estimate rolling 30-day Pearson correlations between BTC and each benchmark asset, aligned to a common U.S. trading-day calendar to ensure comparability. Using the standard Pearson Correlation Formula:

$$\rho = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}}$$

Where: ρ is the correlation coefficient, $x_i(y_i)$ are the values of the x (y)-variable in the sample, \bar{x} (\bar{y}) is the mean of the values of the x (y)-variable.

These correlations are then Fisher z-transformed to stabilize variance and allow formal statistical inference. The core methodology tests for mean shifts in these Fisher-transformed correlations across five distinct event windows surrounding the ETF approval, ranging from short-term (e.g., [-3,+2] TD) to medium-term (e.g., [+1,+30] TD) horizons.

Formally, we estimate:

$$z_t = \beta_0 + \beta_1 D_t + \varepsilon_t,$$

where $z_t = \tanh^{-1}(\rho_t)$ is the Fisher z-transformed rolling correlation and D_t is a binary indicator equal to 1 during the event window and 0 otherwise. HAC-robust standard errors are computed using Newey-West correction with bandwidth $L = 5$.

To Benchmark the results and rule out spurious findings, we further conduct a full-period regime shift test and a placebo event study.

Statistical significance is assessed using Holm-adjusted p-values across all test windows and asset pairs to capture potential multiple testing distortions and control the family-wise error rate. This framework allows us to capture both short-run event effects and longer-term structural changes in Bitcoin's dependence on traditional markets.

Hypothesis 2 (Safe Haven Hypothesis)

Does Bitcoin act as a safe haven for equity investors exhibiting negative correlation with the S&P 500 during periods of market stress?

This hypothesis tests whether Bitcoin behaves as a safe haven asset for equity investors by examining whether its dependence on the stock market (proxied by the S&P 500) weakens significantly during periods of financial stress. The safe haven definition follows Baur and Lucey (2010), where an asset is considered a safe haven if it is uncorrelated or negatively correlated with equities during extreme market downturns.

To operationalize this, we estimate tail-sensitive regression models using standardized (z-scored) daily returns for Bitcoin, the S&P 500, and gold. Market stress is identified via *SPX tail events* based on full-sample quantiles, where stress days correspond to the worst 10%, 5%, and 1% of SPX returns. The central idea is to test whether Bitcoin's conditional correlation with SPX becomes significantly more negative during these crisis periods.

We estimate the following regression model:

$$y_t = \alpha + \beta \cdot \text{reg}_t + \theta_{10} \cdot (\text{reg}_t \cdot D_{10,t}) + \theta_5 \cdot (\text{reg}_t \cdot D_{5,t}) + \theta_1 \cdot (\text{reg}_t \cdot D_{1,t}) + \gamma_{10} D_{10,t} + \gamma_5 D_{5,t} + \gamma_1 D_{1,t} + \varepsilon_t$$

Where:

y_t is the z-scored return of Bitcoin (or gold) and reg_t is the z-scored return of SPX (or gold, depending on the panel), $D_{q,t}$ is the dummy variable equal to 1 if day t falls in the bottom

$q\%$ of SPX returns, for $q \in \{10, 5, 1\}$, else 0; β is the slope in normal market conditions $\beta_q = \beta + \theta_{10} + \dots + \theta_q$ which is the cumulative slope in stress state q

By design, the dummies are nested: $D_1 \subset D_5 \subset D_{10}$, ensuring coherent interpretation of increasingly severe market conditions.

The primary test statistic is a one-sided t-test on β_q , evaluating whether Bitcoin's conditional dependence on SPX becomes significantly more negative during crisis conditions. Newey–West standard errors are used to account for serial correlation and heteroskedasticity, and Holm-adjusted p-values are reported within each regression panel to control for multiple testing.

The Null Hypothesis as such is if Bitcoin's dependence on SPX does not decline during equity market stress and hence $\beta_q \geq \beta$ (nosafe haven behavior). On the other hand, if Bitcoin's dependence on SPX decreases (becomes more negative) during stress. $\beta_q < \beta$ (safe haven behavior).

For robustness, we replicate the test using pre-event crisis thresholds based on SPX returns observed before the ETF launch (cutoff: January 10, 2024), ensuring no look-ahead bias in crisis identification.

This modeling approach improves on traditional correlation-based tests by directly estimating conditional return dependencies during stress, while using standardized coefficients interpretable as approximate correlations.

Hypothesis 3 (Volatility Regime Hypothesis)

Is Bitcoin's return volatility characterized by distinct high- and low-volatility regimes and do the dynamics of these regimes differ significantly from those observed in traditional financial assets such as the S&P 500 and gold.

We hypothesize that Bitcoin's return volatility alternates between distinct high- and low-volatility regimes and that the structure and persistence of these regimes differ meaningfully from those observed in traditional financial assets such as the S&P 500 and gold. In other words, Bitcoin's volatility process may not be well described by a single-regime GARCH model but instead follows a regime-switching process with heterogeneous dynamics across states.

Formally, we consider a two-state Markov-switching GARCH (MSGARCH) specification with GJR-GARCH dynamics and Student-t innovations. The latent regime evolves according to a first-order Markov chain:

Regime-switching dynamics:

$$\Pr(S_t = j \mid S_{t-1} = i) = p_{ij},$$

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix},$$

$$p_{i1} + p_{i2} = 1$$

S_t : latent state (regime) at time t

p_{ij} : probability of switching from regime i to regime j in one day

p_{ij} : persistence of regime k; expected duration is $E[\text{duration}_k] = \frac{1}{(1-p_{kk})}$

GJR-GARCH volatility within regime k:

$$h_t^{(k)} = \omega_k + \alpha_{1k} \varepsilon_{t-1}^2 + \gamma_k 1\{\varepsilon_{t-1} < 0\} \varepsilon_{t-1}^2 + \beta_k h_{t-1}^{(k)}$$

$h_t^{(k)}$ conditional variance in regime k

ω_k long-term variance level in regime k

α_{1k} sensitivity to past squared shocks (short-term volatility reaction)

γ_k additional effect of negative shocks (leverage effect)

β_k persistence of volatility (memory of past variance)

Evidence supporting this hypothesis would consist of: (i) a superior statistical fit for the two-regime specification relative to a single-regime benchmark (based on AIC/BIC); (ii) economically distinct high- and low-volatility regimes, identified by their realized annualized volatilities when posterior regime probabilities exceed 0.7; and (iii) asset-specific differences in regime persistence, as captured by transition probabilities and expected durations.

5. Methodology

Event-Based Correlation Analysis and Decoupling Hypothesis Testing

To evaluate whether Bitcoin has structurally decoupled from traditional financial assets such as the S&P 500 and gold, we conduct an event-based correlation analysis centered on the approval of the U.S. spot Bitcoin ETFs on January 11, 2024. Our central goal is to determine whether the dependence between Bitcoin and benchmark assets experienced a significant shift in the aftermath of this event. This section outlines the methodological framework, data handling, correlation metrics, test procedures, and robustness checks employed to rigorously investigate this hypothesis.

We compute daily log returns for Bitcoin (BTC), the S&P 500 (SPX), and Gold (GLD), aligning all series to a common U.S. trading-day calendar. This harmonization is essential to ensure that correlation estimates are based on synchronous trading activity and are not distorted by mismatched calendars (Andersen et al., 2001).

We estimate rolling window correlations between BTC and SPX as well as BTC and Gold using a 30-trading-day window. This technique enables us to track local dependencies and detect time-varying patterns around key events without imposing strong parametric assumptions. The 30-day window strikes a balance between smoothness and responsiveness, consistent with established practices in financial econometrics (Chiang et al., 2007; R. F. Engle and Rangel, 2008; Reboredo, 2013).

$$\rho_t^{(30)} = \text{Corr}(r_{i,t-29:t}, r_{j,t-29:t})$$

where $\rho_t^{(30)}$ is the sample correlation at time t over the past 30 trading days for asset i and j .

To stabilize the variance of correlation coefficients and enable valid inference through linear regression, we apply the Fisher z-transformation:

$$z_t = \tanh^{-1}(\rho_t) = \frac{1}{2} \ln \left(\frac{1 + \rho_t}{1 - \rho_t} \right)$$

This transformation ensures that the resulting series is approximately normally distributed with constant variance, particularly important when performing hypothesis tests on changes in correlation (Hotelling, 1953; Fisher, 1915).

To test whether correlations have shifted significantly post-ETF approval, we run a series of mean-shift regressions on the Fisher-z transformed series. We compare the correlation during each event window to the pre-event estimation window using a simple OLS regression of the form:

$$z_t = \beta_0 + \beta_1 D_t + \varepsilon_t$$

where $D_t=1$ if t lies within the event window and 0 otherwise. Inference is based on Newey–West HAC-robust standard errors to address potential heteroskedasticity and autocorrelation in residuals, with the lag length of 5, based on the Andrews -Monahan rule and to have comparability across models (Newey & West, 1987; Andrews and Monahan 1992; Zeileis, 2004).

We define five trading-day aligned windows around the ETF approval date, including both symmetric and asymmetric structures to capture short-term, medium-term, and post-only dynamics. All event windows are defined in trading days (TD), not calendar days, to maintain consistency across assets and avoid weekend distortions. These are:

$$[-3, +2] \text{ (TD)}, [-3, +3] \text{ (TD)}, [-15, +15] \text{ (TD)}, [+1, +15] \text{ (TD)}, [+1, +30] \text{ (TD)}$$

This is aligned with best practice in event studies where accurate timing of trading responses is crucial (MacKinlay, 1997).

Beyond short-term windows, we perform a mean shift test comparing the entire post-ETF period to the estimation window. This helps evaluate whether any observed change in dependence reflects a persistent structural shift rather than a short-lived market overreaction (Chan et al., 2023).

To validate the specificity of our results, we conduct placebo tests using pre-ETF dates to test whether similar correlation shifts occur in the absence of any known event. The absence of statistically significant changes during placebo windows strengthens causal inference by reducing the risk of attributing random fluctuation to the ETF launch (Bertrand et al., 2004).

All p-values across event windows are Holm-adjusted to correct for multiple testing while maintaining interpretability. Holm's method offers more power than Bonferroni while preserving familywise error control (Holm, 1979).

Safe-Haven Regressions on Correlations

To examine whether Bitcoin functions as a safe haven relative to equities, we adopt the definition by Baur and Lucey (2010), who characterize a safe haven asset as one that becomes uncorrelated or negatively correlated with another asset specifically during episodes of market stress. The core idea is that a true safe haven offers protection when investors need it most. Namely this is in the tail of the return distribution. We focus on testing whether Bitcoin's dependence on equity markets weakens or turns negative under such conditions and contrast this behavior with gold, a traditional safe haven asset.

To facilitate interpretation and comparability of regression coefficients across assets with different volatilities, we transform all asset return series to z-scores. This standardization

is common in correlation-focused studies (Conlon and McGee, 2020) and allows regression slopes to approximate Pearson correlation coefficients. The z-scored returns are calculated as:

$$R_{i,t}^z = \frac{R_{i,t} - \mu_i}{\sigma_i}$$

where $R_{i,t}$ is the daily log return of asset i , and μ_i , σ_i are the mean and standard deviation of R_i over the full sample.

The empirical test relies on a nested multi-tail interaction regression model that allows us to estimate how the relationship between Bitcoin and equities changes across increasing levels of market stress. The regression equation is:

$$y_t = \alpha + \beta \cdot x_t + \theta_{10}(x_t \cdot D_t^{10\%}) + \theta_5(x_t \cdot D_t^{5\%}) + \theta_1(x_t \cdot D_t^{1\%}) + \gamma_1 D_t^{10\%} + \gamma_2 D_t^{5\%} + \gamma_3 D_t^{1\%} + \varepsilon_t$$

Where y_t is the z-scored return of the asset of interest (e.g., BTC or Gold) and x_t is the z-scored return of the SPX, $D_t^{q\%} \in \{0,1\}$ are crisis indicators for SPX returns below the q -quantile threshold, $x_t \cdot D_t^{q\%}$ are interaction terms allowing the slope to shift during crises, ε_t is a white noise error term.

This specification estimates not only the normal (non-crisis) relationship (β), but also how the slope changes during mild (10%), moderate (5%), and severe (1%) stress. The cumulative stress-period slopes are:

$$\beta_{10\%} = \beta + \theta_{10}, \quad \beta_{5\%} = \beta + \theta_{10} + \theta_5, \quad \beta_{1\%} = \beta + \theta_{10} + \theta_5 + \theta_1$$

A significantly negative value of $\beta_{q\%}$ relative to the baseline β provides evidence of safe haven behavior under increasing stress levels.

All models are estimated via Ordinary Least Squares (OLS), with heteroskedasticity- and autocorrelation-consistent standard errors computed using Newey–West estimators (Newey and West, 1987) with a fixed lag length of 5 and pre-whitening fallback to improve finite-sample robustness. This approach is well-suited for time series regressions involving daily asset returns and is standard in financial econometrics (Zeileis, 2004).

Importantly, we conduct uniform one-sided tests for each interaction slope coefficient in the safe haven direction. Specifically, for Bitcoin vs SPX, we test the null hypothesis that the stress-day slope is greater than or equal to zero against the one-sided alternative:

$$H_0: \beta_q \geq 0 \quad \text{vs} \quad H_1: \beta_q < 0$$

This directional testing framework follows recommendations in safe haven studies (Bouri et al., 2017; Klein et al., 2018), where the researcher has a clear economic hypothesis about negative dependence during stress. Holm-adjusted p-values are computed within each asset panel to account for multiple hypothesis testing across quantiles.

As a robustness check, we repeat the analysis using crisis thresholds that are pre-defined using only pre-event SPX data (up to January 10, 2024) and then applied to the full sample. This removes any forward-looking bias in the crisis classification and ensures that the stress definition is not contaminated by information from the event window. This robustness structure mirrors recommendations in the crisis contagion literature (Corbet et al., 2018), where pre-event benchmarks are used to define thresholds.

The regression specification under the robustness setup simplifies to:

$$y_t = \alpha + \beta \cdot x_t + \delta(x_t \cdot D_t^{(q)}) + \gamma D_t^{(q)} + \varepsilon_t$$

Where δ measures the deviation from the normal slope under the externally defined crisis period. Inference and significance testing proceed identically, using HAC-robust standard errors and Holm-adjusted one-sided p-values.

Volatility Regimes via Markov-Switching GARCH

The third part of the analysis investigates whether Bitcoin’s volatility dynamics are better described by multiple distinct regimes, and whether these differ in structure and persistence compared to traditional financial assets such as the S&P 500 and gold. Previous studies have documented that financial time series often exhibit regime-switching behavior, where periods of high and low volatility alternate over time (Hamilton & Susmel, 1994; Ang & Bekaert, 2002). Recent evidence in cryptocurrency markets (Li & Miu, 2023; Charles & Darné, 2018) similarly suggests that Bitcoin experiences abrupt shifts in volatility that cannot be captured by single-regime GARCH models, motivating a regime-switching approach.

To model these dynamics, we employ a Markov-Switching GARCH (MSGARCH) framework (Haas et al., 2004), which allows both the variance level and persistence parameters to change across latent regimes. Following Li & Miu (2023) and Ardia et al. (2019), we specify a two-state ($K=2$) MSGARCH model, representing high- and low-volatility periods, as this parsimonious specification has been found sufficient to capture regime changes in both equity and cryptocurrency markets without overfitting. The latent regime process $S_t \in \{1,2\}$ follows a first-order Markov chain with transition probabilities:

$$\Pr(S_t = j \mid S_{t-1} = i) = p_{ij}, \quad P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$$

where p_{kk} captures the persistence of remaining in regime k , and the expected duration of regime k is given by:

$$E[\text{duration}_k] = \frac{1}{1 - p_{kk}}.$$

Each regime features its own GJR-GARCH volatility process:

$$h_t^{(k)} = \omega_k + \alpha_{1k} \varepsilon_{t-1}^2 + \gamma_k 1\{\varepsilon_{t-1} < 0\} \varepsilon_{t-1}^2 + \beta_k h_{t-1}^{(k)}$$

where ω_k represents the long-term variance level, α_{1k} captures sensitivity to past squared returns, γ_k allows for asymmetric responses to negative shocks (the leverage effect), and β_k determines volatility persistence. The Student-t distribution is used because return innovations in cryptocurrency markets exhibit heavy tails and occasional extreme jumps (Bollerslev, 1986; Chu et al., 2017), making Gaussian innovations unsuitable.

We estimate both a single-regime GARCH model (K=1) and a two-regime MSGARCH model (K=2) for each asset (BTC, SPX, Gold) via maximum likelihood. Model selection is based on the Akaike and Bayesian Information Criteria (AIC, BIC), as in Haas et al. (2004) and Li & Miu (2023), where a superior fit of the MSGARCH specification indicates statistically relevant regime-switching dynamics. To classify periods into high- and low-volatility states, we follow Li & Miu (2023) and Ardia et al. (2019) in applying a 70% posterior probability threshold, which provides a balance between classification precision and sample coverage.

To provide an economic interpretation of the volatility states, we compute regime-specific annualized volatilities based on the filtered conditional variances. Specifically, for each regime k , the annualized volatility is given by:

$$\sigma_{\text{ann}}^{(k)} = \sqrt{252} \cdot \sqrt{\widetilde{h}^{(k)}}$$

Where $\widetilde{h}^{(k)}$ denotes the average daily conditional variance within regime k , and 252 approximates the number of trading days per year. Under the hypothesis of distinct volatility regimes, we expect the high-volatility state to exhibit significantly larger annualized volatility than the low-volatility state ($Vol_{high} > Vol_{low}$) and to display different persistence characteristics, potentially with shorter expected durations for Bitcoin compared to traditional assets. This would suggest that Bitcoin's volatility spikes are more frequent but less persistent than those in equity or gold markets.

Transition matrices and smoothed regime probabilities are reported for each asset, allowing a direct comparison of volatility dynamics across Bitcoin and traditional benchmarks. Evidence supporting this hypothesis would consist of: (i) a significantly better fit of the two-regime specification relative to a single-regime GARCH; (ii) economically distinct regimes with $Vol_{high} \gg Vol_{low}$; and (iii) meaningful differences in persistence and regime duration between Bitcoin and traditional assets, consistent with its unique risk profile documented in prior studies (Li & Miu, 2023; Charles & Darné, 2018).

By allowing both volatility levels and persistence parameters to vary across latent states, the MSGARCH model provides a flexible framework to capture the nonlinear and potentially abrupt changes in volatility that have been observed in Bitcoin prices (Li & Miu, 2023; Ardia et al., 2019; Charles & Darné, 2018). This approach builds on the original regime-switching volatility literature (Hamilton & Susmel, 1994; Haas et al., 2004) and extends it to compare Bitcoin's volatility behavior to established asset classes within a unified econometric setting.

6. Results

Hypothesis 1: Event-Driven Decoupling via Rolling Correlations

To test whether Bitcoin’s correlation with traditional assets structurally changed following the launch of U.S. spot ETFs on January 11, 2024, we estimate rolling 30-day Pearson correlations between BTC and both the S&P 500 (SPX) and gold. These correlations are Fisher z-transformed to stabilize variance and linearize the metric for parametric testing, following standard practices in financial econometrics (Forbes & Rigobon, 2002; Hotelling, 1953). For each pair, we compute HAC-robust mean shift regressions using five trading-day windows around the ETF launch. The estimation window spans 350 pre-event trading days, excluding a six-day buffer to avoid anticipatory effects.

HAC-Robust Mean Shift in Fisher-z Correlations (TD Windows; Event 2024-01-11)

| Pair | Window | Estimation_N | Event_N | Cor_Est | Cor_Event | Delta_Cor | Beta_hat_z | t_HAC | P_value | L_used | P_adj_Holm | Signif |
|----------|---------------|--------------|---------|---------|-----------|-----------|------------|-------|---------|--------|------------|--------|
| BTC–SPX | [-3,2] (TD) | 345 | 6 | 0.30 | -0.00 | -0.30 | -0.34 | -2.66 | 0.01 | 5.00 | 0.08 | * |
| BTC–Gold | [-3,2] (TD) | 345 | 6 | 0.16 | -0.07 | -0.23 | -0.24 | -2.09 | 0.04 | 5.00 | 0.15 | |
| BTC–SPX | [-3,3] (TD) | 345 | 7 | 0.30 | -0.00 | -0.30 | -0.33 | -2.65 | 0.01 | 5.00 | 0.08 | * |
| BTC–Gold | [-3,3] (TD) | 345 | 7 | 0.16 | -0.09 | -0.25 | -0.26 | -1.54 | 0.12 | 5.00 | 0.25 | |
| BTC–SPX | [-15,15] (TD) | 345 | 31 | 0.30 | -0.02 | -0.32 | -0.36 | -2.56 | 0.01 | 5.00 | 0.09 | * |
| BTC–Gold | [-15,15] (TD) | 345 | 31 | 0.16 | -0.11 | -0.27 | -0.29 | -2.30 | 0.02 | 5.00 | 0.13 | |
| BTC–SPX | [1,15] (TD) | 345 | 17 | 0.30 | 0.05 | -0.25 | -0.28 | -2.19 | 0.03 | 5.00 | 0.15 | |
| BTC–Gold | [1,15] (TD) | 345 | 17 | 0.16 | -0.07 | -0.23 | -0.24 | -1.90 | 0.06 | 5.00 | 0.18 | |
| BTC–SPX | [1,30] (TD) | 345 | 32 | 0.30 | 0.12 | -0.18 | -0.21 | -1.43 | 0.15 | 5.00 | 0.25 | |
| BTC–Gold | [1,30] (TD) | 345 | 32 | 0.16 | -0.10 | -0.27 | -0.28 | -2.45 | 0.01 | 5.00 | 0.10 | |

Note. Returns on a common U.S. trading-day calendar. Rolling window = 30 days. Mean shift in Fisher-z estimated by OLS with Newey–West SEs (bandwidth = 5; prewhite, adjust). Windows are in trading days (TD). P-values Holm-adjusted across all rows. *** p<0.01, ** p<0.05, * p<0.10.

Table 3

Table 3 presents the HAC-robust mean shift results for BTC–SPX and BTC–Gold correlations across the five windows. In all windows, the BTC–SPX correlation declines markedly relative to the estimation period. For example, in the primary post-event window [+1,+30], the average correlation decreases from 0.30 to 0.12, yielding a Fisher-z drop of $\beta =$

- 0.21, though this shift is not statistically significant at the 10% level ($p = 0.15$). However, in shorter windows such as $[-3,+2]$, the estimated drop of -0.34 is significant at the 10% level after Holm adjustment. The pattern is consistent across windows: while statistical significance varies, the direction of effect is robustly negative, suggesting an episodic decoupling of BTC from U.S. equities during the ETF launch window.

For BTC-Gold, the results also reveal a consistent decline in correlations post-event, with average drops ranging from -0.23 to -0.27 . The $[+1,+30]$ window yields a sizable decrease from 0.16 to -0.10 in raw correlation ($\Delta = -0.27$), with a statistically significant Fisher-z estimate of $\beta = -0.28$, significant at the 10% level after Holm correction. This finding implies that Bitcoin did not pivot toward gold as a new safe haven but rather decoupled from both traditional hedging and risk assets in tandem. In this context, the results support Hypothesis 1 by indicating that the ETF approval was followed by a transient but directional shift in BTC's market co-movement structure.

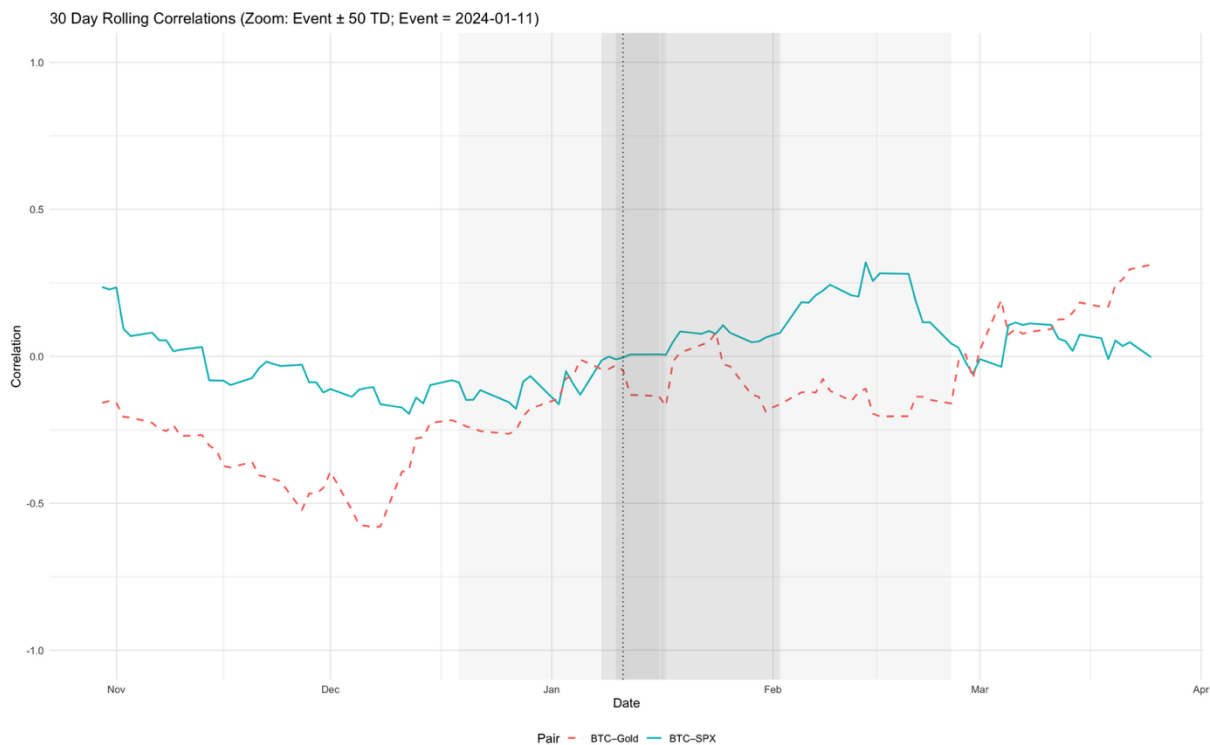


Figure 2

Figure 2 shows the 30-day rolling correlations between Bitcoin (BTC) and the S&P 500 (SPX) as well as between BTC and gold (GLD) over a ± 50 trading day window surrounding the U.S. Spot Bitcoin ETF approval on January 11, 2024. The BTC–SPX correlation initially fluctuates near zero before the event, then shows a mild upward trend in the post-event period, reaching moderate positive levels by February, before stabilizing closer to zero. In contrast, the BTC–Gold correlation begins in moderately negative territory, deepens to a local minimum around early December, and then gradually rises over the event window, showing a steady increase toward positive values in the post-event phase. The five tested windows are shaded in light gray. This figure also illustrates that while some recovery occurs post-event, the shifts are not immediately reversed, motivating further analysis of whether a more persistent regime shift occurred.

To assess the durability of these potential decoupling dynamics, we next extend the test to the full post-event period up to July 1, 2025, using the same HAC-robust framework (Table 4). If the ETF approval marked the start of a structurally new regime in BTC correlations, we would expect to observe a sustained mean shift beyond short-term windows. Conversely, if the pattern reflects a temporary event-driven effect, correlations may revert.

To ensure robustness, we also perform placebo tests by repeating the entire event-study procedure on pre-ETF pseudo-event dates (Appendix 1). This guards against spurious rejection driven by general time-series properties and can be found in the appendix.

To assess whether the observed short-window effects around the ETF launch translate into a persistent structural decoupling, we extend the event study framework to the full post-event period. Specifically, we compare the average 30-day Fisher-z-transformed correlation from the 345-trading-day estimation window to the full post-ETF period ranging from January

11, 2024, through the end of the sample (July 1, 2025). The results of this test are reported in Table 4.

Full Post-Period HAC-Robust Mean Shift (Post starts 2024-01-11)

| Pair | Estimation_N | Post_N | Cor_Est | Cor_Post | Delta_Cor | Beta_hat_z | t_HAC | P_value | L_used | P_adj_Holm | Signif |
|----------|--------------|--------|---------|----------|-----------|------------|-------|---------|--------|------------|--------|
| BTC–SPX | 345 | 367 | 0.30 | 0.34 | 0.04 | 0.04 | 0.24 | 0.81 | 5.00 | 1.00 | |
| BTC–Gold | 345 | 367 | 0.16 | 0.09 | -0.08 | -0.08 | -0.62 | 0.54 | 5.00 | 1.00 | |

Note. Shift in Fisher-z for the entire post period vs the estimation window. Newey–West bandwidth = 5 (prewhite, adjust). P-values Holm-adjusted across pairs.

Table 4

For the BTC–SPX pair, the average correlation increased modestly from 0.30 in the pre-event estimation window to 0.34 post-event. However, the corresponding Fisher-z difference is small and statistically insignificant, with a Newey–West-adjusted t-statistic of 0.24 and a Holm-adjusted p-value of 1.00. This suggests that the short-term decoupling detected in the previous windows did not persist in the longer run.

In contrast, the BTC–Gold correlation declined from 0.16 to 0.09 in the post-period. Although the direction of the change aligns with a potential divergence from gold, the estimated Fisher-z mean shift is again statistically insignificant ($t = -0.62$; Holm-adjusted $p = 1.00$). Overall, these results indicate a lack of persistent structural change in Bitcoin’s correlation profile following the ETF approval, at least over the medium-term horizon captured in this analysis.

Taken together, the full-period results reinforce the interpretation that the decoupling observed in short-term windows was transitory. This strengthens the case for interpreting the ETF launch effect as a temporary shock to co-movement patterns, rather than a regime shift in

the underlying return dynamics. These findings are further contextualized through a placebo test, to which we now turn.

Placebo HAC-Robust Mean Shift (Combined Across Events)

| Event | Pair | Window | Estimation_N | Event_N | Cor_Est | Cor_Event | Delta_Cor | Beta_hat_z | t_HAC | P_value | L_used | P_adj_Holm | Signif |
|------------|----------|---------------|--------------|---------|---------|-----------|-----------|------------|-------|---------|--------|------------|--------|
| 2023-01-22 | BTC-Gold | [-3,2] (TD) | 345 | 6 | 0.13 | 0.27 | 0.14 | 0.14 | 1.51 | 0.13 | 5.00 | 1.00 | |
| 2023-01-22 | BTC-Gold | [-3,3] (TD) | 345 | 7 | 0.13 | 0.27 | 0.13 | 0.13 | 1.47 | 0.14 | 5.00 | 1.00 | |
| 2023-01-22 | BTC-Gold | [-15,15] (TD) | 345 | 31 | 0.13 | 0.30 | 0.17 | 0.18 | 1.83 | 0.07 | 5.00 | 0.67 | |
| 2023-01-22 | BTC-Gold | [1,15] (TD) | 345 | 17 | 0.13 | 0.24 | 0.11 | 0.11 | 1.26 | 0.21 | 5.00 | 1.00 | |
| 2023-01-22 | BTC-Gold | [1,30] (TD) | 345 | 32 | 0.13 | 0.20 | 0.07 | 0.07 | 0.71 | 0.48 | 5.00 | 1.00 | |
| 2023-01-22 | BTC-SPX | [-3,2] (TD) | 345 | 6 | 0.51 | 0.47 | -0.04 | -0.07 | -1.16 | 0.25 | 5.00 | 1.00 | |
| 2023-01-22 | BTC-SPX | [-3,3] (TD) | 345 | 7 | 0.51 | 0.47 | -0.04 | -0.07 | -1.12 | 0.26 | 5.00 | 1.00 | |
| 2023-01-22 | BTC-SPX | [-15,15] (TD) | 345 | 31 | 0.51 | 0.50 | -0.01 | -0.02 | -0.20 | 0.84 | 5.00 | 1.00 | |
| 2023-01-22 | BTC-SPX | [1,15] (TD) | 345 | 17 | 0.51 | 0.43 | -0.08 | -0.12 | -1.37 | 0.17 | 5.00 | 1.00 | |
| 2023-01-22 | BTC-SPX | [1,30] (TD) | 345 | 32 | 0.51 | 0.43 | -0.08 | -0.12 | -1.35 | 0.18 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-Gold | [-3,2] (TD) | 345 | 6 | 0.21 | 0.28 | 0.07 | 0.07 | 1.33 | 0.18 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-Gold | [-3,3] (TD) | 345 | 7 | 0.21 | 0.27 | 0.07 | 0.06 | 1.20 | 0.23 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-Gold | [-15,15] (TD) | 345 | 31 | 0.21 | 0.20 | -0.00 | -0.01 | -0.11 | 0.91 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-Gold | [1,15] (TD) | 345 | 17 | 0.21 | 0.27 | 0.07 | 0.07 | 0.96 | 0.34 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-Gold | [1,30] (TD) | 345 | 32 | 0.21 | 0.19 | -0.02 | -0.02 | -0.00 | 1.00 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-SPX | [-3,2] (TD) | 345 | 6 | 0.42 | 0.48 | 0.06 | 0.05 | 0.33 | 0.74 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-SPX | [-3,3] (TD) | 345 | 7 | 0.42 | 0.48 | 0.06 | 0.04 | 0.30 | 0.77 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-SPX | [-15,15] (TD) | 345 | 31 | 0.42 | 0.38 | -0.04 | -0.09 | -0.59 | 0.55 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-SPX | [1,15] (TD) | 345 | 17 | 0.42 | 0.40 | -0.02 | -0.06 | -0.37 | 0.71 | 5.00 | 1.00 | |
| 2023-09-01 | BTC-SPX | [1,30] (TD) | 345 | 32 | 0.42 | 0.34 | -0.08 | -0.12 | -0.79 | 0.43 | 5.00 | 1.00 | |

Note. Identical methodology as the true event; windows are in trading days (TD). Newey–West bandwidth = 5 (prewhite, adjust). P-values Holm-adjusted within each placebo event across its rows. *** p<0.01, ** p<0.05, * p<0.10.

Table 5

To ensure that the observed short-term correlation shifts around the January 11, 2024, Bitcoin ETF approval are not random variation, we implement a placebo analysis using two pseudo-event dates: January 22, 2023, and September 1, 2023. These dates were carefully selected to be free from any known crypto-specific or macroeconomic disruptions, offering clean baseline periods for comparison. The full event study methodology is replicated for each placebo, including rolling 30-day correlations, Fisher z-transformation, and HAC-robust mean shift regressions across five standard short-term windows.

Table 5 reports the regression results for both placebo dates. Across all windows and both asset pairs, estimated shifts in rolling correlations are modest and statistically insignificant after multiple-testing correction. For example, the BTC–SPX correlation on January 22, 2023, declines slightly from 0.51 to 0.47 in the $[-3,2]$ window, yielding a t-statistic of -1.16 ($p = 0.25$), while the BTC–Gold correlation increases from 0.13 to 0.27 in the same window ($t = 1.51$, $p = 0.13$). Similarly, for the September 1, 2023, placebo, BTC–SPX correlations remain largely unchanged, and BTC–Gold shows only minor variation (e.g., a change from 0.21 to 0.28 in the $[-3,2]$ window, $t = 1.33$, $p = 0.18$). None of the Holm-adjusted p-values across the 20 placebo regressions fall below conventional significance thresholds.

These findings strongly support the inference that the short-term correlation shifts identified in the main event windows were not artifacts of temporal noise or sampling variability. Instead, the ETF approval date appears to mark a genuine, albeit short-lived, decoupling of Bitcoin from both equities and gold. The robustness of this result is critical to interpreting the event as a distinct shock to Bitcoin’s integration with traditional financial assets.

Hypothesis 2: Safe-Haven Behavior of Bitcoin

We evaluate whether Bitcoin functions as a safe haven asset during equity market turmoil, comparing its behavior to that of gold. To do so, we apply a nested multi-tail regression framework where BTC returns are regressed on SPX returns, interacted with stress dummies for the worst 10%, 5%, and 1% days of the SPX. The model also includes main effects for the crisis dummies, and all variables are standardized (z-scores), so that regression slopes can be interpreted approximately as correlations. Inference is based on Newey–West HAC-robust standard errors with a lag length of 5, and one-sided p-values are reported in the hypothesized safe-haven direction (i.e., significantly negative slopes under stress).

The results, summarized in Table 6, reveal no significant safe-haven behavior for Bitcoin across any of the stress quantiles. For instance, the estimated slope during the 10% SPX tail days is 1.67 ($p = 0.99$), and similarly large and positive for the 1% tail (0.67, $p = 0.99$). These coefficients are not only statistically insignificant but also directionally inconsistent with the safe haven hypothesis. In fact, rather than decoupling from equities, Bitcoin exhibits positive conditional betas, with stress correlations of 0.42 for the 1% tail period. This suggests that Bitcoin comoves positively with equity markets even under extreme distress, failing the safe-haven test.

One-Sided Safe-Haven Test with Three Stress Levels (z-scored; HAC SE)

| Dependent | Regressor | Tail | N_total | N_tail | Beta_normal | Beta_stress | SE_stress | t_HAC | p_one | P_adj_Holm_one | r_tail | Signif_one |
|-----------|-----------|------|---------|--------|-------------|-------------|-----------|-------|-------|----------------|--------|------------|
| BTC | SPX | 10% | 1,883 | 189 | 0.24 | 1.67 | 0.69 | 2.40 | 0.99 | 1.00 | 0.42 | |
| BTC | SPX | 5% | 1,883 | 95 | 0.24 | 0.31 | 0.39 | 0.80 | 0.79 | 1.00 | 0.41 | |
| BTC | SPX | 1% | 1,883 | 19 | 0.24 | 0.67 | 0.30 | 2.23 | 0.99 | 1.00 | 0.42 | |
| Gold | SPX | 10% | 1,883 | 189 | 0.11 | -0.34 | 0.65 | -0.53 | 0.30 | 0.61 | 0.18 | |
| Gold | SPX | 5% | 1,883 | 95 | 0.11 | -0.34 | 0.41 | -0.83 | 0.20 | 0.61 | 0.27 | |
| Gold | SPX | 1% | 1,883 | 19 | 0.11 | 0.29 | 0.10 | 2.88 | 1.00 | 1.00 | 0.38 | |
| BTC | Gold | 10% | 1,883 | 189 | 0.05 | 0.17 | 0.09 | 1.79 | 0.96 | 1.00 | 0.38 | |
| BTC | Gold | 5% | 1,883 | 95 | 0.05 | 0.35 | 0.09 | 4.06 | 1.00 | 1.00 | 0.46 | |
| BTC | Gold | 1% | 1,883 | 19 | 0.05 | 1.21 | 0.51 | 2.37 | 0.99 | 1.00 | 0.58 | |

Note. Model: $y = \alpha + \beta \cdot \text{reg} + 010(\text{reg} \times D10) + 05(\text{reg} \times D5) + 01(\text{reg} \times D1) + \gamma \cdot D + \varepsilon$. Stress days $Dq = 1\{\text{SPX} \leq \text{qth pct}\}$, $q \in \{10, 5, 1\}$. Normal slope = β ; stress slopes $\beta10 = \beta + 010$, $\beta5 = \beta + 010 + 05$, $\beta1 = \beta + 010 + 05 + 01$. Variables are z-scored (slopes read as correlations). SEs are Newey–West (lag=5, prewhite with fallback). Reported p-values are ****one-sided**** in the panel-specific direction (default left: $\beta q < 0$), Holm-adjusted within panel.

Table 6

In contrast, gold displays signs of weak safe haven potential, but only at the broader tail levels. For the 10% and 5% SPX quantiles, gold's stress betas are -0.34 , albeit not statistically significant ($p = 0.30$ and 0.20 , respectively). At the 1% stress level, the stress beta reverts to a positive estimate (0.29 , $p = 1.00$), possibly reflecting a flight-to-liquidity dynamic rather than a true decoupling. Although these results do not reach conventional significance thresholds, the negative slope direction under moderate stress is more consistent with traditional safe-haven behavior than Bitcoin's uniformly positive betas.

To further probe the robustness of these findings, we repeat the analysis using pre-event SPX return thresholds, computed strictly using data prior to the Bitcoin Spot ETF approval on January 11, 2024. The results are presented in Table 7. Using these cutoffs, we again find no evidence of safe-haven behavior for Bitcoin. All post-threshold β_{stress} estimates remain positive and statistically insignificant across the 10%, 5%, and 1% SPX tails. For example, the 1% tail yields a stress beta of 0.67 ($p = 0.98$), closely mirroring the main result. This stability in both magnitude and direction suggests that the lack of safe haven behavior is not a byproduct of post-event information leakage or forward-looking bias in the crisis definition.

Robustness: One-Sided Safe-Haven with PRE-period SPX Cutoffs (no look-ahead; pre \leq 2024-01-10)

| Dependent | Regressor | Tail | N_total | N_tail | Beta_normal | Beta_stress | SE_stress | t_HAC | p_one | P_adj_Holm_one | r_tail | Signif_one |
|-----------|-----------|------------------|---------|--------|-------------|-------------|-----------|-------|-------|----------------|--------|------------|
| BTC | SPX | 10% (pre-cutoff) | 1,883 | 182 | 0.23 | 0.56 | 0.16 | 3.56 | 1.00 | 1.00 | 0.41 | |
| Gold | SPX | 10% (pre-cutoff) | 1,883 | 182 | 0.11 | 0.21 | 0.09 | 2.46 | 0.99 | 1.00 | 0.18 | |
| BTC | Gold | 10% (pre-cutoff) | 1,883 | 182 | 0.05 | 0.45 | 0.15 | 3.08 | 1.00 | 1.00 | 0.38 | |
| BTC | SPX | 5% (pre-cutoff) | 1,883 | 87 | 0.23 | 0.60 | 0.20 | 3.01 | 1.00 | 1.00 | 0.41 | |
| Gold | SPX | 5% (pre-cutoff) | 1,883 | 87 | 0.10 | 0.33 | 0.08 | 4.22 | 1.00 | 1.00 | 0.29 | |
| BTC | Gold | 5% (pre-cutoff) | 1,883 | 87 | 0.06 | 0.60 | 0.20 | 3.02 | 1.00 | 1.00 | 0.47 | |
| BTC | SPX | 1% (pre-cutoff) | 1,883 | 18 | 0.24 | 0.67 | 0.32 | 2.13 | 0.98 | 1.00 | 0.41 | |
| Gold | SPX | 1% (pre-cutoff) | 1,883 | 18 | 0.07 | 0.33 | 0.11 | 3.10 | 1.00 | 1.00 | 0.42 | |
| BTC | Gold | 1% (pre-cutoff) | 1,883 | 18 | 0.08 | 1.27 | 0.50 | 2.53 | 0.99 | 1.00 | 0.60 | |

Note. Cutoffs for SPX (10/5/1%) computed on the pre-period only; those thresholds are applied to the full sample. Model per tail: $y = \alpha + \beta \cdot \text{reg} + \delta \cdot (\text{reg} \times \text{Dq}) + \gamma \cdot \text{Dq} + \varepsilon$ with HAC(Newey–West, lag=5). Reported slope is $\beta_{\text{stress}} = \beta + \delta$; p_one is one-sided in the safe-haven (left-tail) direction; Holm within panel.

Table 7

Gold’s behavior in the robustness test is directionally more consistent with the safe-haven narrative: stress betas remain negative for the 10% and 5% tails (−0.21, −0.33, respectively), though none of these reach statistical significance ($p = 0.99–1.00$). Overall, while gold may provide weak and statistically inconclusive shelter in moderately distressed markets, Bitcoin clearly fails to meet safe haven criteria under all specifications and appears to maintain substantial positive correlation with equity markets even in the most severe stress periods.

These findings provide further evidence against the notion that Bitcoin offers downside protection during equity market turmoil, thereby failing to support Hypothesis 2

Hypothesis 3: Volatility Regime Hypothesis

This section evaluates whether Bitcoin’s volatility alternates between distinct high- and low-volatility regimes and how its regime dynamics compare to traditional assets (S&P 500, gold). The analysis uses two-state Markov-Switching GJR-GARCH models with Student-t innovations for each asset, with model comparison based on information criteria (AIC, BIC), estimated regime-specific volatilities, expected regime durations, and transition probabilities. Smoothed regime probabilities are plotted to visualize switching behavior over time.

Table 8 reports the information criteria for one-regime (K=1) and two-regime (K=2) specifications. For Bitcoin, the two-regime model provides a substantially better fit ($\Delta AIC = -38.92$), indicating strong evidence of distinct volatility states. SPX also favors the two-regime specification ($\Delta AIC = -16.59$), whereas for Gold the improvement is negligible ($\Delta AIC = -0.58$). Negative ΔAIC values indicate that the additional complexity of a regime-switching model is justified. The larger the negative ΔAIC , the stronger the support for regime-switching. In contrast, the BIC results are less decisive and show some divergence, particularly for BTC and SPX. This discrepancy is expected, as BIC imposes a harsher penalty for model complexity and prioritizes parsimony over in-sample fit. Taken together, the AIC and BIC results offer strong evidence for regime-switching behavior in Bitcoin, moderate support for SPX, and little justification for modeling gold with more than one volatility regime

MSGARCH Summary: Model Fit & Regime Metrics (BTC, SPX, GLD)

| Asset | AIC_K1 | AIC_K2 | DeltaAIC | BIC_K1 | BIC_K2 | DeltaBIC | AnnualVol_Low | ExpectedDur_Low | AnnualVol_High | ExpectedDur_High |
|-------|------------|------------|----------|------------|------------|----------|---------------|-----------------|----------------|------------------|
| BTC | -11,436.10 | -11,475.02 | -38.92 | -11,406.58 | -11,404.16 | 2.42 | 0.52 | 5.14 | 0.63 | 1.79 |
| SPX | -12,036.88 | -12,053.47 | -16.59 | -12,009.23 | -11,987.11 | 22.12 | 0.19 | 279.79 | 0.24 | 85.01 |
| GLD | -12,416.39 | -12,416.98 | -0.58 | -12,388.74 | -12,350.61 | 38.13 | 0.13 | 234.09 | 0.31 | 18.06 |

Note. $\Delta AIC/\Delta BIC = (K=2) - (K=1)$. Negative values favor the 2-regime model.

Table 8

Table 9 summarizes the estimated annualized volatilities and expected regime durations for each state. Bitcoin’s low-volatility regime exhibits an annualized volatility of 52% with an average duration of just over 5 trading days, while its high-volatility regime is slightly higher at 63% but extremely short-lived (≈ 1.8 days). This frequent switching aligns with the notion of volatility clustering often observed in crypto markets, though here it manifests with less persistence. In contrast, SPX and Gold have low-volatility regimes lasting hundreds of days (280 and 234 respectively), indicating substantially more persistent volatility states. This suggests that Bitcoin’s volatility regimes are more frequent and less stable compared to traditional assets.

Regime Statistics by Asset (Wide)

| Asset | AnnualVol_Low | ExpectedDur_Low | AnnualVol_High | ExpectedDur_High |
|-------|---------------|-----------------|----------------|------------------|
| BTC | 0.52 | 5.14 | 0.63 | 1.79 |
| SPX | 0.19 | 279.79 | 0.24 | 85.01 |
| GLD | 0.13 | 234.09 | 0.31 | 18.06 |

Table 9

Table 10 presents the estimated daily transition probabilities. Bitcoin has a 19% chance of switching from a low- to a high-volatility state and a 44% chance of remaining in high volatility once entered, indicating high regime instability. By comparison, SPX and Gold show near-perfect persistence in their respective states ($\geq 99\%$ probability of remaining in the same regime), reflecting smoother volatility dynamics in traditional markets.

Transition Probability Matrices (MSGARCH, 2 Regimes)

| Asset | From | To Regime 1 | To Regime 2 |
|-------|---------------|-------------|-------------|
| BTC | From Regime 1 | 0.81 | 0.19 |
| BTC | From Regime 2 | 0.56 | 0.44 |
| SPX | From Regime 1 | 1.00 | 0.00 |
| SPX | From Regime 2 | 0.01 | 0.99 |
| GLD | From Regime 1 | 1.00 | 0.00 |
| GLD | From Regime 2 | 0.06 | 0.94 |

Note. Entries are estimated one-day transition probabilities $P(S_{t+1}=j | S_t=i)$.

Table 10

Figures 3-5 display the time-varying smoothed probabilities of being in high- versus low-volatility regimes for each asset. Bitcoin frequently oscillates between regimes, with numerous short-lived spikes in high volatility throughout the sample period. SPX and Gold exhibit prolonged stretches of low volatility, punctuated by well-defined high-volatility episodes corresponding to known market stress periods (e.g., COVID-19 crash, 2022 rate shock).

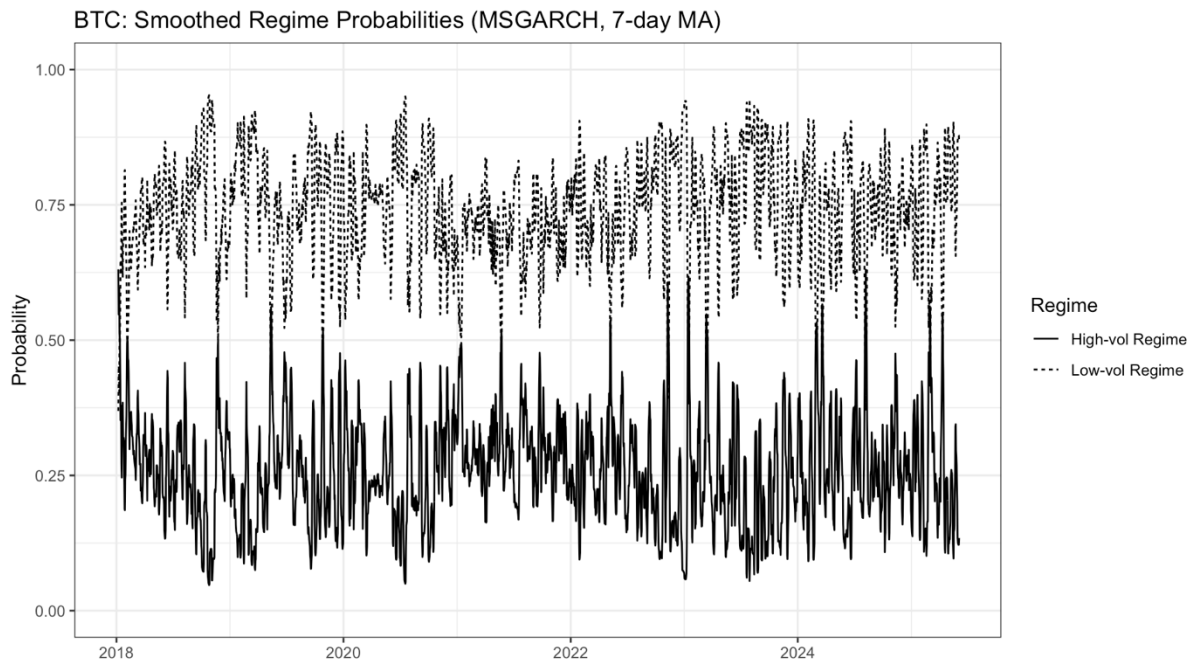


Figure 3

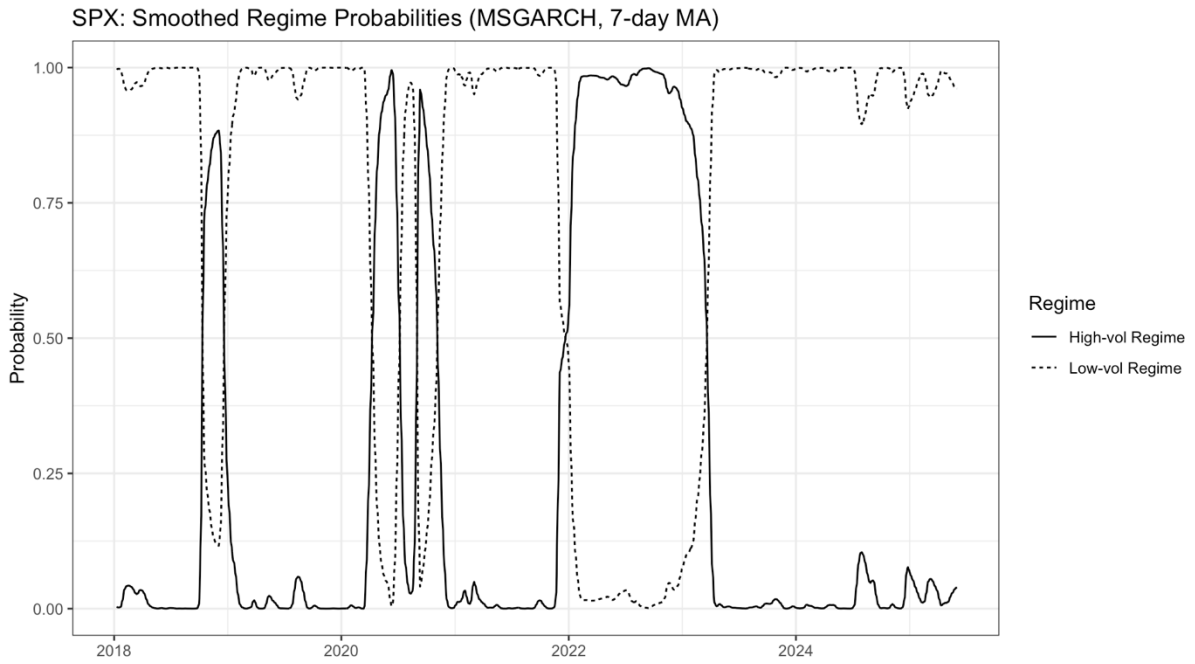


Figure 4

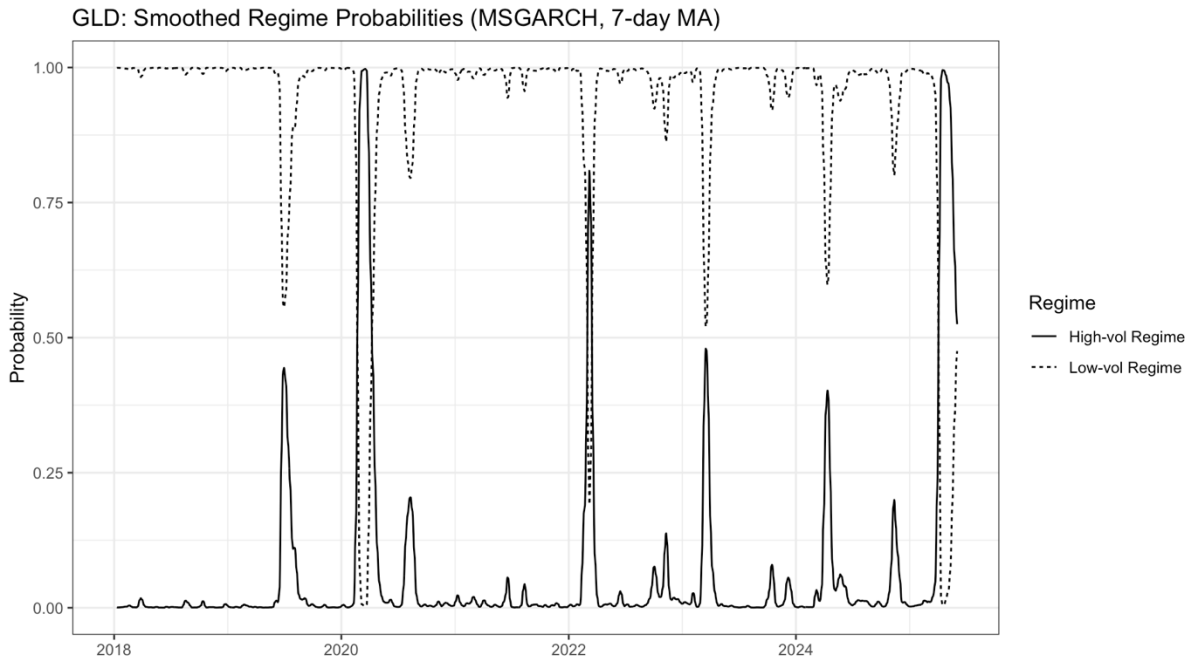


Figure 5

These visual patterns corroborate the tabled results, emphasizing Bitcoin’s fragmented and rapidly shifting volatility structure compared to its traditional counterparts

The evidence strongly supports Hypothesis 3 for Bitcoin: its volatility is not constant but switches between distinct regimes. However, these regimes are far less persistent than those of SPX and Gold, indicating that Bitcoin operates under a highly dynamic risk environment.

The two-regime specification is statistically justified for Bitcoin and SPX but less so for Gold, highlighting that traditional safe-haven assets maintain more stable volatility profiles. Overall, Bitcoin's frequent and short-lived regime shifts suggest heightened uncertainty and reduced predictability compared to established assets.

7. Conclusion

This thesis set out to examine whether Bitcoin has begun to decouple from traditional financial markets and whether it exhibits properties of a safe haven asset following its institutionalization via the January 2024 Spot ETF approval. Using a multi-method approach, including rolling correlations, event study regressions, stress-based safe haven tests, and regime-switching GARCH modeling we assessed Bitcoin's evolving market role in terms of co-movement, crisis behavior, and volatility dynamics.

The first hypothesis tested whether Bitcoin experienced a structural shift in correlations with the S&P 500 and gold around the ETF launch. Short-window event study results indicate significant short-term declines in BTC–SPX and BTC–Gold correlations, with Holm-adjusted p-values below 0.10 in several windows. Rolling correlation plots visually confirmed these breaks. However, extended post-event testing showed that these decoupling effects were not persistent. Over the full post-ETF period, Bitcoin's average correlation with SPX slightly increased, and the correlation with gold declined, yet neither shift was statistically significant. Placebo event tests further ruled out spurious rejection by confirming that no similar effects occurred around pseudo-event dates. Altogether, these findings suggest that the ETF approval triggered a transient but non-persistent decoupling in Bitcoin's correlation structure, a temporary shock rather than a regime shift.

The second hypothesis investigated Bitcoin's potential as a safe haven during equity market stress. Using a multi-tail regression design, we found no evidence supporting this role. On the contrary, Bitcoin exhibited positive and statistically insignificant stress betas across all SPX tail quantiles, with estimated correlations reaching as high as 0.42 in the 1% worst market days. These effects were directionally inconsistent with safe-haven behavior and robust to alternative stress threshold definitions. Gold, while also failing to reach significance thresholds,

showed weakly negative stress betas under moderate tail conditions, more in line with the safe-haven hypothesis. These results suggest that Bitcoin, despite its decentralized narrative, continues to exhibit pro-cyclical behavior, particularly under market distress.

The third hypothesis examined whether Bitcoin's volatility is governed by latent regime-switching processes. Two-state MSGARCH models provided strong support for this view. Model selection criteria favored the two-regime specification for Bitcoin, less for SPX and even less so for gold. Bitcoin's volatility regimes were frequent and short-lived, with an average low-vol regime lasting only 5 days and high-volatility spells persisting for fewer than 2 days. In contrast, SPX and gold displayed highly persistent regimes with durations spanning hundreds of trading days. Transition probabilities and smoothed regime plots further confirmed Bitcoin's fragmented and rapidly shifting volatility structure, in contrast to the smoother, event-driven regime dynamics of traditional assets. These findings highlight Bitcoin's structural instability, reinforcing its profile as a speculative and risk-sensitive asset.

Overall, the results paint a nuanced picture of Bitcoin's market role. While the ETF approval marked a milestone in institutional acceptance, Bitcoin has not yet matured into a reliable hedge or safe haven asset. Its correlation structure remains unstable, its behavior under crisis conditions misaligned with defensive asset norms, and its volatility regimes unusually short and erratic. These features underscore Bitcoin's ongoing classification as a high-risk, speculative asset rather than a stabilizing force in diversified portfolios. As such, its inclusion in traditional asset allocations should be approached with caution. Particularly during periods of systemic stress.

Contribution and Implications

This thesis advances the academic literature on Bitcoin's financial market integration by jointly analyzing its correlation dynamics, crisis responsiveness, and volatility regime

structure in the aftermath of a major institutional adoption milestone being the launch of U.S. Spot Bitcoin ETFs. Through a combination of rolling correlation event studies, stress-based regression tests, and regime-switching volatility modeling, the study offers a comprehensive post-ETF assessment of Bitcoin's behavior relative to traditional benchmarks.

The results indicate that Bitcoin continues to exhibit the characteristics of a speculative, high-volatility asset. Despite periodic decoupling from equities and gold during the ETF launch window, these shifts were short-lived and not indicative of a sustained structural break. Moreover, Bitcoin continues to fail to demonstrate safe-haven properties during equity market stress, instead displaying positive comovement with risk assets even under extreme conditions. Its volatility dynamics, characterized by frequent and unstable regime transitions, further underscore its limited suitability as a stabilizing force in diversified portfolios.

For investors and portfolio managers, these findings carry practical implications. Bitcoin may offer short-term diversification benefits under certain market conditions, but its lack of resilience during downturns and high volatility regime instability reduce its utility as a defensive allocation. Institutional investors should therefore remain careful when positioning Bitcoin as a hedging or safe-haven component within traditional asset mixes.

Limitations and Future Research

While the analysis provides novel insights into Bitcoin's post-ETF behavior, several limitations warrant consideration. First, the study is constrained by the relatively short post-event window, covering less than 18 months since ETF approval. This restricts the ability to capture longer-term structural adaptation or regime evolution. Second, the focus on a narrow set of comparators, namely, the S&P 500 and gold, limits the scope of cross-asset generalizability.

Additionally, the models employed, while robust in capturing time-varying correlations and regime-switching dynamics, abstract from other potentially important dimensions. These include spillovers from derivative markets (e.g., futures, options), liquidity channels, or the influence of macroeconomic announcements and policy shifts. The analysis also does not incorporate sentiment indicators, on-chain metrics, or institutional trading flows that may mediate Bitcoin's market response.

Future research could address these gaps by extending the dataset over multiple ETF market cycles and incorporating a broader set of benchmark assets and crypto instruments. High-frequency intraday data could be employed to better understand shock transmission and volatility clustering. Moreover, integrating structural break tests and machine learning-based regime classifiers may enhance the detection of nonlinear dependencies. Finally, exploring the role of stablecoins, decentralized finance (DeFi), and macro-financial linkages would provide a more granular understanding of Bitcoin's evolving function within the broader financial ecosystem.

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Appendix

Robustness: One-Sided Safe-Haven with PRE-period SPX Cutoffs (no look-ahead; pre ≤ 2024-01-10)

| Dependent | Regressor | Tail | N_total | N_tail | Beta_normal | Beta_stress | SE_stress | t_HAC | p_one | P_adj_Holm_one | r_tail | Signif_one |
|-----------|-----------|------------------|---------|--------|-------------|-------------|-----------|-------|-------|----------------|--------|------------|
| BTC | SPX | 10% (pre-cutoff) | 1,883 | 182 | 0.23 | 0.56 | 0.16 | 3.56 | 1.00 | 1.00 | 0.41 | |
| Gold | SPX | 10% (pre-cutoff) | 1,883 | 182 | 0.11 | 0.21 | 0.09 | 2.46 | 0.99 | 1.00 | 0.18 | |
| BTC | Gold | 10% (pre-cutoff) | 1,883 | 182 | 0.05 | 0.45 | 0.15 | 3.08 | 1.00 | 1.00 | 0.38 | |
| BTC | SPX | 5% (pre-cutoff) | 1,883 | 87 | 0.23 | 0.60 | 0.20 | 3.01 | 1.00 | 1.00 | 0.41 | |
| Gold | SPX | 5% (pre-cutoff) | 1,883 | 87 | 0.10 | 0.33 | 0.08 | 4.22 | 1.00 | 1.00 | 0.29 | |
| BTC | Gold | 5% (pre-cutoff) | 1,883 | 87 | 0.06 | 0.60 | 0.20 | 3.02 | 1.00 | 1.00 | 0.47 | |
| BTC | SPX | 1% (pre-cutoff) | 1,883 | 18 | 0.24 | 0.67 | 0.32 | 2.13 | 0.98 | 1.00 | 0.41 | |
| Gold | SPX | 1% (pre-cutoff) | 1,883 | 18 | 0.07 | 0.33 | 0.11 | 3.10 | 1.00 | 1.00 | 0.42 | |
| BTC | Gold | 1% (pre-cutoff) | 1,883 | 18 | 0.08 | 1.27 | 0.50 | 2.53 | 0.99 | 1.00 | 0.60 | |

Note. Cutoffs for SPX (10/5/1%) computed on the pre-period only; those thresholds are applied to the full sample. Model per tail: $y = \alpha + \beta \text{reg} + \delta (\text{reg} \times Dq) + \gamma Dq + \varepsilon$ with HAC(Newey–West, lag=5). Reported slope is $\beta_{\text{stress}} = \beta + \delta$; p_one is one-sided in the safe-haven (left-tail) direction; Holm within panel.

Appendix 1 – Safe Haven Test with Cutoff Values determined pre-Event Window