Risk without Reward? The Introduction of Bitcoin Spot ETFs

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Abstract

Our study examines to what extent the introduction of Bitcoin spot exchange-traded funds (ETFs) affected Bitcoin's properties, including market dynamics, volatility, returns, return distribution, and tracking errors. Using block bootstrap simulations, OLS regression, EGARCH modeling, and non-parametric tests, we find that Bitcoin ETFs increase volatility and downside risk while leaving average returns unchanged. Return distribution shifts, including reduced skewness and kurtosis, suggest partial normalization, typically linked to greater liquidity and market participation. However, unlike traditional ETFs, Bitcoin ETFs introduce fail-to-deliver (FTD) occurrences, previously absent in Bitcoin markets, which mitigate extreme price movements through delayed settlement. Tracking error analysis confirms that spot ETFs more accurately track Bitcoin's price than futures-based ETFs. These findings offer critical insights into Bitcoin ETFs' market effects, particularly regarding stability and investor behavior.

Keywords: *Bitcoin, ETFs, volatility, market dynamics, FTDs*

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Introduction

The launch of a traditional stock ETF typically meets well-established expectations based on decades of market behavior. Financial theory and empirical evidence indicate that these ETFs generally improve market stability and efficiency (Ben-David et al., 2017; Ben-David et al., 2018; Laborda et al., 2024). In contrast,

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the introduction of Bitcoin (BTC) spot ETFs in early 2024 presents a unique challenge. Bitcoin differs significantly from traditional stocks due to its high volatility, minimal regulation, and fundamentally distinct characteristics (Katsiampa, 2017; Corbet et al., 2018). Operating on a decentralized, peer-to-peer network, Bitcoin's price is influenced by factors such as speculation (Ciaian et al., 2018; Makarov and Schoar, 2020), regulatory changes (Auer and Claessens, 2018), and macroeconomic trends that are distinct from those affecting traditional stock markets (Bouri et al., 2017; Albrecht and Kočenda, 2026).

The introduction of the Bitcoin spot ETF raises several critical questions for academic discussion. Primarily, has the launch of these ETFs made Bitcoin a less risky asset? The question is rooted in the expectation that ETFs generally stabilize prices and reduce volatility across various asset classes (Todorov, 2021). By enhancing liquidity and increasing market participation, especially from institutional investors, Bitcoin spot ETFs could potentially lower volatility. Theoretically, greater liquidity enables more market participants to absorb price fluctuations, thereby mitigating extreme price movements. Research on ETFs in other markets, such as commodities and stock indices, supports this hypothesis, showing that ETFs can indeed moderate volatility (Todorov, 2024). However, the application of this expectation to Bitcoin is not straightforward. Rather than a uniform reduction in risk, the introduction of spot Bitcoin ETFs may alter the way in which volatility is generated and transmitted. In particular, increased institutional participation and improved market access can change the speed and intensity with which new information is incorporated into prices, without necessarily affecting average return levels or long-run risk persistence (Ben-David et al., 2018).

From an economic perspective, Bitcoin's market structure suggests that ETF-driven effects may operate differently than in traditional asset classes. Bitcoin pricing remains largely driven by expectations, sentiment, and heterogeneous beliefs among market participants (Albrecht et al., 2025). The entry of ETFs lowers frictions for institutional capital, but at the same time introduces higher trading intensity and tighter integration with global financial markets. Rather than smoothing price dynamics, this combination can amplify the immediate impact of news, as a broader and more sophisticated investor base reacts more quickly and in a more coordinated manner (Converse et al., 2023). In such an environment, liquidity provision does not necessarily dampen fluctuations but may instead facilitate rapid reallocation of positions, leading to stronger short-term price adjustments (Pastorek and Albrecht, 2026). Consequently, the key effect of ETFs in the Bitcoin market may lie not in reducing overall risk, but in altering the mechanism of volatility formation.

Recent empirical evidence is broadly consistent with this interpretation. Early post-ETF studies show that Bitcoin's integration with traditional financial markets has strengthened, with correlations to equity markets increasing, suggesting tighter transmission of macroeconomic and financial shocks. At the same time, research on ETF flows indicates that capital movements into spot Bitcoin ETFs have become a dominant driver of price formation, amplifying the role of demand shocks and investor positioning in short-run dynamics. Complementary findings point to improved price discovery and liquidity, but also higher sensitivity to market-wide information and cross-market linkages. This emerging body of evidence nevertheless leaves several important dimensions of the ETF effect insufficiently explored. In particular, existing studies tend to focus either on aggregate measures of volatility (Shalvardjiev, 2026) or on market integration (Hong et al., 2025) and price discovery (Wu, 2025), without clearly distinguishing between changes in unconditional volatility and shifts in the underlying dynamics of volatility formation. As a result, it remains unclear whether the observed changes reflect a broad increase in risk or rather a more subtle transformation in how Bitcoin responds to new information and external shocks. Moreover, relatively little attention has been devoted to disentangling short-run reactions from longer-run volatility persistence, or to assessing whether Bitcoin's post-ETF behavior differs systematically from comparable cryptocurrencies that were not subject to a similar institutional shock. Addressing these dimensions is essential for a more precise understanding of how ETF-driven financialization reshapes the risk profile of Bitcoin beyond conventional volatility metrics.

From an economic perspective, this shift is important because it implies that the introduction of ETFs transforms Bitcoin from a relatively segmented asset into one more deeply embedded within the global financial system. As a result, volatility becomes increasingly driven by information flow, capital allocation, and cross-asset interactions rather than purely crypto-native dynamics. This has direct implications for portfolio construction, as Bitcoin may offer different diversification properties than in the pre-ETF period, with stronger co-movement during periods of market stress. Moreover, the altered sensitivity to shocks from the persistence perspective affects risk management, pricing of derivatives, and the effectiveness of hedging strategies, as volatility may react more quickly to new information without necessarily becoming more persistent. These considerations highlight that ETF-driven financialization is less about reducing risk and more about reshaping its structure and transmission across markets. To the best of our knowledge, these aspects have not been thoroughly investigated yet.

To address this, we first examine whether the introduction of spot Bitcoin ETFs is associated with changes in average returns and unconditional daily volatility.

Drawing on ordinary least squares, we test for shifts in mean returns and simple volatility measures proxied by absolute returns, thereby establishing a transparent pre/post benchmark. The results indicate no significant change in average returns and no evidence of a systematic increase in baseline daily volatility, suggesting that any ETF-related effects are not captured by first-order moments. We then extend the analysis using a Difference-in-Differences framework, comparing Bitcoin's post-ETF evolution with a control group of major cryptocurrencies. This approach allows us to isolate ETF-specific effects from broader crypto-market dynamics. The findings point to an increase in Bitcoin's relative daily volatility compared to other cryptocurrencies, but primarily in terms of absolute return fluctuations rather than extreme movements, indicating stronger day-to-day reactions rather than amplified tail risk.

To further explore the underlying mechanism, we employ an EGARCH model to capture time-varying volatility and its response to new shocks. This framework distinguishes between volatility persistence and short-run sensitivity to information. The results suggest that while volatility persistence remains largely unchanged, the sensitivity of conditional volatility to new shocks increases in the post-ETF period, consistent with faster and more pronounced absorption of information. Finally, we complement this high-frequency perspective with block bootstrap simulations of 30-day cumulative returns to assess implications for short-term investor risk. Despite the stronger short-run volatility response, downside risk measures such as Value at Risk (VaR) and Conditional Value at Risk (CVaR) do not deteriorate, indicating that increased responsiveness to shocks does not translate into worse short-horizon tail risk.

Taken together, these results suggest that spot Bitcoin ETFs do not materially alter average returns or overall risk levels, but instead reshape the dynamics through which volatility is generated, leading to stronger short-run reactions to information without increasing persistent risk.

1. Literature Review

The introduction of exchange-traded funds has been widely studied in traditional financial markets, where their effects are typically analyzed through the lenses of liquidity provision, market efficiency, and price discovery. A large body of empirical literature shows that ETFs tend to lower transaction costs, broaden investor participation, and facilitate arbitrage, thereby contributing to improved market efficiency (Ben David et al., 2017; Glosten et al., 2021). At the same time, their impact on volatility remains ambiguous. While some studies document a stabilizing role through enhanced liquidity and diversification (Todorov, 2024), others highlight that ETFs can increase short-term volatility by accelerating information transmission and amplifying trading activity (Ben David et al., 2018). From an economic perspective, ETFs act as a transmission mechanism that links underlying assets with broader capital markets, enabling faster price adjustment to new information and altering the balance between noise trading and informed trading.

The economic transmission channels associated with ETF introduction can be grouped into several key mechanisms. First, improved liquidity reduces trading frictions and allows market participants to enter and exit positions more easily, which in theory should dampen price fluctuations (Liebi, 2020). Second, arbitrage mechanisms between the ETF and the underlying asset enforce price alignment, potentially reducing mispricing and volatility. Third, increased participation by institutional investors introduces more sophisticated trading strategies, which may enhance price discovery but also increase the speed of reaction to news (Shalvardjiev, 2026). Finally, ETFs facilitate cross-market integration by linking the underlying asset to global portfolios, making it more sensitive to macroeconomic conditions and broader financial cycles (Converse et al., 2023). The net effect of these channels is therefore theoretically ambiguous, as stabilizing forces related to liquidity coexist with destabilizing forces related to faster and more coordinated trading.

In the context of cryptocurrencies, these mechanisms may operate differently due to the unique structural characteristics of the market. Bitcoin, unlike traditional assets, lacks fundamental valuation anchors and is largely driven by expectations, sentiment, and speculative demand (Ciaian et al., 2018; Corbet et al., 2018). As a result, the introduction of ETFs may not just simply add liquidity, but it fundamentally alters the composition of market participants and the process of price formation. Recent studies emphasize that the approval of spot Bitcoin ETFs represents a major step in the financialization of the crypto market, leading to increased participation by institutional investors and closer integration with traditional financial systems (Hong et al., 2025). Empirical evidence shows that Bitcoin's correlation with equity markets increased significantly after the ETF introduction, indicating stronger co-movement with global risk factors. This suggests that ETF-driven access reduces segmentation and exposes Bitcoin to the same macroeconomic shocks that affect other risk assets (Converse et al., 2023).

Another strand of literature highlights the role of capital flows through ETFs as a key driver of Bitcoin price dynamics (Wu, 2025). Using flow-based analysis, recent research finds that inflows into Bitcoin ETFs became a dominant determinant of price levels, with strong predictive power for short-term price movements (Pastorek and Albrecht, 2026). From an economic standpoint, this implies that demand shocks originating from portfolio reallocation can have a direct and immediate impact on the underlying asset. Unlike in traditional markets, where ETFs reflect underlying fundamentals, Bitcoin ETFs may actively shape price dynamics due to the absence of intrinsic valuation anchors. The mechanism reinforces the idea that ETF introduction can increase the sensitivity of prices to investor behavior rather than stabilizing them (Converse et al., 2023). Further evidence suggests that ETFs may improve certain dimensions of market quality while simultaneously introducing new sources of risk (Hong et al., 2025). Studies document improvements in price discovery and market accessibility following ETF introduction, reflecting enhanced transparency and trading efficiency (Babalos et al., 2025). However, the same studies also highlight increased sensitivity to market-wide information and cross-market linkages, which can amplify the transmission of shocks across asset classes. Complementary analyses of volatility dynamics indicate that while long-term volatility may exhibit signs of gradual stabilization, short-term fluctuations remain pronounced and may even intensify due to higher trading intensity and faster reaction to information (Shalvardjiev, 2026). Such a dual effect reflects a transition from a segmented and predominantly retail-driven market to a more integrated and institutionally influenced system.

From the perspective of investors, these structural changes have several important implications. First, increased integration with traditional markets reduces the diversification benefits of Bitcoin, as its returns become more correlated with equities and other risk assets (Hung et al., 2025). Second, stronger short-term reactions to information imply that downside risk may materialize more quickly, even if long-run risk levels remain unchanged (Babalos et al., 2025). Third, the growing importance of ETF flows shifts the focus from fundamental analysis to flow-driven dynamics, where capital allocation decisions by large investors play a central role (Stejskalová, 2023; Mohamad, 2025). Finally, the enhanced speed of information absorption affects trading strategies, as opportunities for arbitrage and excess returns may diminish in more efficient and integrated markets (Converse et al., 2023).

Despite the growing body of evidence, several important questions remain unresolved. Existing studies tend to focus on aggregate measures of volatility or on correlations with other asset classes, without clearly distinguishing between different dimensions of volatility dynamics. In particular, limited attention has been devoted to separating unconditional volatility from conditional responses to new information. Similarly, the extent to which ETF-related effects are specific to Bitcoin or reflect broader developments in cryptocurrency markets remains insufficiently explored. A more nuanced understanding of these mechanisms requires an empirical framework that jointly considers average returns, relative volatility dynamics, and the underlying process through which volatility responds to new shocks.

2. Data and Methods

2.1. Data

To assess the Bitcoin ETF's impact on Bitcoin's risk-return profile, we employ a multi-method approach, combining block bootstrap, OLS regression, EGARCH modelling, Difference-in-Differences, and a non-parametric Mann-Whitney U test. Such a suite of approaches enables us to capture potential shifts in returns, volatility clustering, and distributional changes, offering a comprehensive view of the ETF's effect on Bitcoin's risk dynamics. We employ daily data from Bloomberg covering the period from the beginning of January 2021 to April 2026. Returns are computed as simple daily returns, defined as the percentage change in prices from one trading day to the next. The data covers a recent and comparable pre-ETF period, ensuring that the analysis captures Bitcoin's behavior under similar market conditions immediately preceding the introduction of spot ETFs.

Additionally, we incorporate daily data on settlement failures, specifically fails-to-deliver (FTD) reports from the U.S. Securities and Exchange Commission (SEC) for Bitcoin spot ETFs. These ETFs include ARKB, BITB, BRRR, BTC, BTCO, BTCW, EZBC, FBTC, GBTC, HODL, and IBIT. The regulatory filings document instances where ETF shares were not successfully delivered at settlement. While FTDs have been studied in traditional equity markets as indicators of market inefficiencies and short-selling constraints (Pastorek et al., 2023), their emergence in Bitcoin spot ETFs represents a novel development in cryptocurrency markets. The inclusion of FTD data enables a structured examination of potential liquidity constraints and market structure effects arising from these settlement failures.[1]

2.2. Risk and Distribution Analysis

We employ a block bootstrap technique to simulate Bitcoin return distributions in the pre- and post-ETF periods. The procedure samples overlapping blocks of daily returns rather than individual observations, allowing short-term time-series dependence and volatility clustering in Bitcoin returns to be partially preserved. For each period, we generate 5,000 resampled return paths and compute cumulative returns over a 30-day investment horizon. Cumulative returns in the bootstrap exercise are computed as compounded simple returns over the simulated 30-day horizon. In addition to the full post-ETF period, we also distinguish between the first year after the introduction of spot Bitcoin ETFs and the subsequent post-ETF period, which allows us to assess whether the distributional effects are concentrated in the initial adjustment phase or persist over time (see Figure A1).

[1] The data will be available upon reasonable request.

The simulated distributions are used to estimate key risk and distributional metrics. Value at Risk (VaR) and Conditional Value at Risk (CVaR) at the 5% level capture downside tail risk, while mean and median summarize the central tendency of simulated cumulative returns. Skewness and kurtosis describe distributional asymmetry and tail characteristics. The approach provides an investor-horizon perspective on whether changes in daily volatility dynamics translate into materially different short-term downside risk.

Then, we apply the Mann-Whitney U test to assess whether Bitcoin returns differ systematically between the pre- and post-ETF periods. The rank-based non-parametric test evaluates whether observations from one period tend to be larger or smaller than observations from the other period, without requiring normally distributed returns. It therefore provides an additional distributional check beyond the comparison of average returns, which is particularly relevant for Bitcoin given the non-normal and heavy-tailed nature of cryptocurrency returns.

2.3. Volatility and Return Analysis

To examine whether the introduction of spot Bitcoin ETFs is associated with changes in average returns and unconditional volatility, we estimate a set of OLS regressions based on daily Bitcoin returns. The baseline specification uses a post-ETF dummy variable, $Period_t$, which equals one from 11 January 2024 onward and zero before this date. We extend the sample from January 2021 to April 2026, which allows us to compare a longer pre-ETF period with the post-ETF period. The baseline return model is specified as follows:

$$R_t = \beta_0 + \beta_1 Period_t + \varepsilon_t \tag{1}$$

where R_t denotes the daily Bitcoin return. The intercept β_0 captures the average return in the pre-ETF period, while β_1 measures the difference in average returns between the post-ETF and pre-ETF periods. We then extend the return model by including market-wide controls:

$$R_t = \beta_0 + \beta_1 Period_t + \beta_2 SP500_t + \beta_3 VIX_t + \varepsilon_t \tag{2}$$

where $SP500_t$ denotes daily S&P 500 returns and VIX_t captures the level of broader financial market uncertainty. The specification controls for general market conditions that may affect Bitcoin returns independently of the ETF launch. Finally, we estimate an event-adjusted specification:

$$R_t = \beta_0 + \beta_1 Period_t + \beta_2 SP500_t + \beta_3 VIX_t + \gamma' Events_t + \varepsilon_t \tag{3}$$

where $Events_t$ includes dummy variables for FOMC announcement windows, major crypto-regulatory events, and the Bitcoin halving window. These controls are included to reduce the risk that the estimated post-ETF coefficient reflects other major events occurring during the post-ETF period rather than the ETF introduction itself. To examine changes in volatility, we use the absolute value of daily Bitcoin returns as a simple non-parametric proxy for daily volatility. The baseline volatility model is:

$$|R_t| = \alpha_0 + \alpha_1 Period_t + u_t \tag{4}$$

Here, α_0 captures the average absolute return in the pre-ETF period, while α_1 measures the change in average absolute returns after the introduction of spot Bitcoin ETFs. The controlled volatility specification is:

$$|R_t| = \alpha_0 + \alpha_1 Period_t + \alpha_2 \, |SP500_t| + \alpha_3 VIX_t + u_t \tag{5}$$

where $|SP500_t|$ controls for equity market volatility and VIX_t captures broader market uncertainty. The event-adjusted volatility model is then written as:

$$|R_t| = \alpha_0 + \alpha_1 Period_t + \alpha_2 \, |SP500_t| + \alpha_3 VIX_t + \delta' Events_t + u_t \tag{6}$$

All OLS specifications are estimated with heteroskedasticity and autocorrelation consistent standard errors. The purpose of these models is not to establish causal identification on their own, but to provide a transparent pre/post benchmark and to test whether the main post-ETF coefficient is sensitive to the inclusion of market controls and event-window variables. The corresponding implementation uses S&P 500 returns, VIX, FOMC windows, crypto-regulatory windows, and the Bitcoin halving window as controls. The event-window controls are constructed from publicly available official sources, where available. FOMC announcement windows are based on the scheduled meeting dates and policy statement dates reported by the Board of Governors of the Federal Reserve System. The Bitcoin halving window is centered around the April 2024 halving date. Crypto-regulatory windows are constructed around major regulatory and policy events, including SEC-related announcements and the phased implementation of the EU Markets in Crypto-Assets Regulation. These variables are included to verify that the estimated post-ETF coefficient is not mechanically driven by well-known macroeconomic or regulatory event windows.

To capture time-varying volatility and volatility clustering, we employ separate Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models for the pre- and post-ETF periods. The EGARCH(1,1) specification is suitable because it models the logarithm of conditional variance and captures the dynamic response of volatility to new shocks, as well as volatility persistence in financial returns (Yildirim and Bekun, 2023):

$$\ln\left(\sigma_t^2\right) = \omega + \beta \ln\left(\sigma_{t-1}^2\right) + \alpha \frac{\left|\varepsilon_{t-1}\right|}{\sigma_{t-1}} \tag{7}$$

where ω is the constant term in the variance equation, σ_t^2 denotes the conditional variance at time t, and ε_t is the residual innovation. The parameter α_1 captures the sensitivity of conditional volatility to the magnitude of new standardized shocks, while β_1 measures the persistence of volatility through the lagged conditional variance.

By comparing the estimated coefficients, specifically ω, α_1, and β_1, across the pre-ETF and post-ETF periods, we examine whether the introduction of spot Bitcoin ETFs is associated with changes in Bitcoin's volatility dynamics. In particular, α_1 allows us to assess whether volatility reacts more strongly to new shocks after the ETF launch, while β_1 indicates whether volatility shocks become more persistent over time. Such a distinction enables us to separate short-run shock sensitivity from longer-run volatility persistence.

2.4. Difference-in-Differences Approach

To strengthen the identification strategy and to address the limitations of a simple pre- and post-ETF comparison, we additionally employ a Difference-in-Differences approach. The specification compares the evolution of Bitcoin returns and volatility after the introduction of spot Bitcoin ETFs with a control group of alternative cryptocurrencies that did not experience a comparable spot ETF event during the main sample window. The control group consists of Litecoin, Ripple, Solana, Cardano, Dogecoin, and Bitcoin Cash.[2]

For each cryptocurrency i and day t, we construct daily returns, absolute returns, and squared returns. Daily returns capture average return effects, absolute returns proxy for daily volatility, and squared returns provide an additional measure of larger return fluctuations. The treatment indicator BTC_i equals one for Bitcoin and zero for the control cryptocurrencies. The post-treatment indicator $Post_t$ equals one from 11 January 2024 onward, corresponding to the first trading day of spot Bitcoin ETFs. The interaction term $BTC_i \times Post_t$ is the main Difference-in-Differences variable of interest. The baseline DiD specification is estimated as:

[2] Ethereum is excluded from the main Bitcoin control group because it later experienced its own spot ETF event.

$$Y_{i,t} = \alpha + \beta_1 \left(BTC_i \times Post_t \right) + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{8}$$

where $Y_{i,t}$ denotes alternatively daily returns, absolute returns, or squared returns. The term μ_i represents cryptocurrency fixed effects, which absorb time-invariant differences across assets, while λ_t represents daily fixed effects, which absorb market-wide shocks common to all cryptocurrencies on a given day. The coefficient β_1 captures whether Bitcoin changed differently after the ETF launch relative to the control group. In this specification, market-wide daily shocks are absorbed directly by daily fixed effects. As an additional specification, we estimate DiD models with asset fixed effects, month fixed effects, and market controls:

$$Y_{i,t} = \alpha + \beta_1 \left(BTC_i \times Post_t \right) + \beta_2 Market_t + \beta_3 VIX_t + \mu_i + \tau_m + \varepsilon_{i,t} \tag{9}$$

For the return model, $Market_t$ is measured by S&P 500 daily returns. For the volatility models, it is measured by absolute S&P 500 returns. The VIX level is included to control for broader financial market uncertainty. Month fixed effects, τ_m, capture lower-frequency time variation while allowing the inclusion of these market controls. The DiD framework, therefore, complements the OLS and EGARCH analyses. While the OLS models provide a direct Bitcoin pre/post benchmark and the EGARCH models examine conditional volatility dynamics, the DiD approach tests whether Bitcoin's post-ETF behaviour differs from a broader set of comparable cryptocurrencies. This distinction is important because it helps separate ETF-specific changes in Bitcoin from broader crypto-market movements occurring over the same period.

2.5. Fail-to-Deliver Occurrences and Market Stability

To analyze the role of fail-to-deliver (FTD) occurrences in Bitcoin ETFs, we examine daily FTD quantities alongside Bitcoin price and trading volume data. FTD quantities are log-transformed using $\log\left(1 + FTD\right)$ to reduce skewness and limit the influence of extreme observations. Where applicable, FTD data are aligned with the trading activity that led to settlement failures by accounting for the standard settlement lag. We compute daily Bitcoin returns and 30-day rolling volatility. Significant price movements are defined as days when the absolute daily Bitcoin return exceeds 2 %. The threshold provides a transparent classification of large daily price movements and is used to compare FTD levels on high-movement and normal trading days. In addition, high-volatility and high-volume periods are identified using percentile-based thresholds. The main specification uses the top 20% of observations, while additional robustness checks use the top 10 % and top 30% thresholds (as in Mancini, 2009; IMF, 2024).

To test whether FTD occurrences are associated with specific market conditions, we conduct independent two-sample Welch *t*-tests. First, log-transformed FTD quantities on significant price movement days are compared with normal trading days. Second, log-transformed FTD quantities in high-volatility periods are compared with those in lower-volatility periods. To further assess whether FTD occurrences are driven by trading demand or volatility conditions, we estimate the following OLS regression model:

$$\begin{aligned} \log\left(1+FTD_t\right) &= \beta_0 + \beta_1 HighVolume_t + \beta_2 HighVolatility_t + \\ &+ \beta_3\left(HighVolume_t \times HighVolatility_t\right) + \varepsilon_t \end{aligned} \tag{10}$$

Here, $HighVolume_t$ indicates whether Bitcoin trading volume belongs to the selected upper percentile of the sample, while $HighVolatility_t$ indicates whether 30-day rolling volatility belongs to the corresponding upper percentile. The interaction term captures whether FTD activity increases disproportionately when high trading volume and high volatility occur simultaneously. The model is estimated with HC3 robust standard errors.

2.6. Identification of the Tracking Error

Additionally, we use daily ETF and Bitcoin price data to evaluate the tracking accuracy of Bitcoin ETFs. The dataset includes Bitcoin prices and two categories of Bitcoin ETFs: spot-based ETFs and futures-based ETFs. Since spot Bitcoin ETFs became available only after their January 2024 approval, the tracking error comparison is conducted over the common post-approval period for which both spot and futures ETF return data are available, ending in April 2026.

We calculate the tracking error for each ETF as the 30-day rolling standard deviation of the daily return differential between the ETF and Bitcoin. Tracking errors are first computed separately for individual spot Bitcoin ETFs to assess the extent of replication differences across funds (we follow the approach of Frino and Gallagher (2001)). We then compute average tracking errors for spot and futures-based ETFs and compare both groups over the common post-approval period. Lower tracking error indicates closer replication of Bitcoin returns, while higher tracking error reflects larger deviations from the underlying Bitcoin price dynamics.

3. Results

In this section, we present the empirical results on how the introduction of spot Bitcoin ETFs affected Bitcoin's risk–return profile, with particular emphasis on the underlying dynamics of volatility formation rather than its unconditional level.

Building on the multi-method framework outlined in they previous section, we systematically evaluate (i) changes in average returns and baseline volatility, (ii) shifts in relative volatility compared to other cryptocurrencies, and (iii) the evolution of conditional volatility responses to new information. In addition, we examine distributional properties of returns, the emergence of fail-to-deliver (FTD) occurrences as a novel market feature, and the tracking performance of spot versus futures-based ETFs. Taken together, these results provide a comprehensive assessment of whether ETF-driven financialization alters the level of risk or primarily transforms the mechanism through which market shocks are transmitted and absorbed.

3.1. Risk-Return Properties

Table 1 reports distributional characteristics of simulated 30-day cumulative Bitcoin returns before and after the introduction of spot ETFs. The results indicate no meaningful change in average returns, as both the mean and median remain broadly stable across periods. At the same time, downside risk measures (VaR and CVaR) do not deteriorate and, if anything, suggest a mild improvement, implying that the ETF introduction is not associated with a systematic increase in short-horizon tail risk. In contrast, higher-moment statistics point to a gradual normalization of the return distribution, with a decline in skewness and kurtosis, particularly in the later post-ETF subsample. Taken together, these findings do not support a simple interpretation in which ETFs increase overall risk. Instead, they suggest that while the unconditional distribution of returns becomes more regular and less driven by extreme outcomes, any ETF-related effects are more likely to operate through changes in the dynamics of volatility (such as the speed and intensity of responses to new information) rather than through shifts in average performance or tail risk at the investor horizon.

T a b l e 1

Distribution Metrics for Bitcoin Returns Pre- and Post-ETF

Metrics	Pre-ETF distribution	Post-ETF full period	Post-ETF first year	Post-ETF after first year
Mean	0.0300	0.0300	0.0800	–0.0100
Median	0.0100	0.0200	0.0600	–0.0100
VaR 5%	–0.2600	–0.1800	–0.1600	–0.1900
CVaR 5%	–0.3200	–0.2300	–0.2100	–0.2400
Skewness	0.5600	0.5200	0.6500	0.1000
Kurtosis	3.8300	3.7200	3.9500	3.2500

Note: The table reports distributional metrics from block-bootstrap simulations of 30-day cumulative Bitcoin returns. The extended pre-ETF distribution, based on the pre-introduction period starting in January 2021, is compared with three post-ETF samples: the full post-ETF period, the first year after the introduction of spot Bitcoin ETFs, and the period after the first post-ETF year. The simulations use a six-day block size and 5,000 resampled return series. VaR and CVaR are reported at the 5% level and capture downside tail risk. Mean, median, skewness, and kurtosis describe the central tendency, asymmetry, and tail characteristics of the simulated return distributions.

Source: Bloomberg and authors' calculations.

Supplementary bootstrap simulations presented in Appendix Figure A1 indicate that the overall shape of the return distribution remains broadly comparable across periods, supporting the view that ETF effects do not materially alter investor horizon risk.

Table 2 reports OLS estimates for Bitcoin returns (Panel A) and volatility (Panel B) before and after the introduction of spot Bitcoin ETFs and provides a clear benchmark assessment of first-order changes in its risk-return profile. The results consistently indicate that the ETF introduction is not associated with statistically significant changes in average daily returns, as the period indicator remains insignificant across all specifications, including models with market controls and additional event adjustments. At the same time, Bitcoin returns exhibit a strong positive relationship with equity market returns, suggesting that broader market conditions play a more important role than the ETF introduction itself. In this sense, the evidence in Table 2 does not support a simple narrative in which ETFs alter expected returns or generate excess performance, but rather points to the continued dominance of macro and cross-market factors in shaping Bitcoin returns.

In contrast, the volatility results in Table 2 show that the period indicator is negative and statistically significant when volatility is proxied by absolute returns, implying that average daily volatility does not increase following the ETF introduction and may even decline. It is consistent with evidence from commodity ETF markets, where the introduction of ETF structures enhanced liquidity and price efficiency, leading to a moderation of observed volatility (Todorov, 2024). The finding remains robust across specifications that control for equity market volatility, market uncertainty, and major events (Table 2), reinforcing the interpretation that baseline daily fluctuations did not intensify in the post-ETF environment. Moreover, the significance of equity market volatility and, to a lesser extent, broader uncertainty measures highlights that Bitcoin volatility is closely linked to the wider risk environment. The findings are consistent with recent evidence showing that Bitcoin has become more integrated with traditional financial markets, with correlations to major equity indices strengthening after ETF introduction and institutional adoption, implying that macroeconomic shocks and equity market conditions now more directly transmit into Bitcoin volatility (Wu, 2025). Importantly, these results suggest that the ETF introduction did not lead to a straightforward increase in risk. Instead, they serve as a crucial benchmark indicating that any changes associated with ETFs are more likely to reflect shifts in the underlying dynamics of volatility formation rather than simple increases in its level, a distinction that motivates the subsequent focus on conditional volatility models.

T a b l e 2

Regression Results for Bitcoin Returns and Volatility Pre- and Post-ETF Periods

Panel A: Bitcoin Returns

Variable	Returns Base	Returns Controls	Returns Controls + Events
Constant	0.0013 (0.0015)	0.0043 (0.0037)	0.0043 (0.0038)
Period dummy	0.0000 (0.0019)	–0.0009 (0.0017)	–0.0009 (0.0018)
S&P 500 returns		1.2868*** (0.1211)	1.2861*** (0.1211)
VIX level		–0.0002 (0.0002)	–0.0002 (0.0002)
Fed window			0.0005 (0.0024)
Regulatory window			–0.0007 (0.0036)
Halving window			–0.0047 (0.0064)
Observations R-squared Adjusted R-squared	1336 0.0000 –0.0007	1336 0.1411 0.1392	1336 0.1413 0.1374

Panel B: Bitcoin Volatility, Measured by Absolute Returns

Variable	Volatility Base	Volatility Controls	Volatility Controls + Events
Constant	0.0283*** (0.0013)	0.0174*** (0.0036)	0.0180*** (0.0036)
Period dummy	–0.0058*** (0.0017)	–0.0041** (0.0016)	–0.0041** (0.0016)
Absolute S&P 500 returns		0.4760*** (0.1581)	0.4854*** (0.1585)
VIX level		0.0003* (0.0002)	0.0003* (0.0002)
Fed window			–0.0034 (0.0022)
Regulatory window			–0.0024 (0.0025)
Halving window			0.0016 (0.0046)
Observations R-squared Adjusted R-squared	1336 0.0120 0.0112	1336 0.0424 0.0402	1336 0.0440 0.0397

Note: The table reports OLS estimates for Bitcoin returns and volatility before and after the introduction of spot Bitcoin ETFs. The period dummy equals one for observations from 11 January 2024 onward and zero otherwise. Volatility is measured as the absolute value of daily Bitcoin returns. Control specifications include S&P 500 returns or absolute S&P 500 returns, the VIX level, and event-window controls for FOMC meetings, major crypto-regulatory events, and the Bitcoin halving. Heteroskedasticity and autocorrelation consistent standard errors are reported in parentheses. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Source: Bloomberg and authors' calculations.

Following the previous results, we employ the EGARCH[3] models to account for the persistence of volatility and sensitivity of previous shocks. Table 3 reports

[3] We employ EGARCH due to its advantages in modeling the asymmetric effects (Yildirim and Bekun, 2023).

the EGARCH estimates for the pre- and post-ETF periods and provides a deeper view of volatility dynamics beyond the unconditional measures discussed earlier. The results do not support a change in volatility persistence. The persistence parameter remains high and statistically significant in both periods, indicating that volatility clustering is a structural feature of the Bitcoin market rather than a consequence of ETF introduction. The finding is consistent with prior research showing that cryptocurrencies exhibit strong and persistent volatility patterns driven by market structure and trading behavior (Katsiampa, 2017). As a result, the evidence in Table 3 suggests that the ETF introduction did not create or amplify long-term volatility persistence, but rather operates through a different transmission channel.

The key contribution of Table 3 lies in the behavior of the parameter capturing the sensitivity of conditional volatility to new shocks. While this parameter is not statistically meaningful in the pre-ETF period, it becomes both larger and significant after the ETF introduction, indicating that volatility reacts more strongly to new information. In economic terms, this means that unexpected market movements are more rapidly incorporated into volatility expectations, reflecting a shift toward faster information absorption. The interpretation aligns with recent studies documenting that ETF-driven institutional participation increases the speed of price adjustment and strengthens the role of information flows in crypto markets (Cheah, 2025). Together with the OLS findings, the results point to a coherent narrative in which spot Bitcoin ETFs do not raise average returns or baseline volatility, but instead reshape the mechanism of volatility formation, leading to stronger short-run responses to new shocks without altering their persistent nature.

Table 3

EGARCH Model Parameter Estimates for Pre- and Post-ETF Periods

Metric	Parameter	Estimate	Std. Error	t-stat	p-value	Observations
EGARCH Pre-ETF	μ	0.1851	0.1580	1.1680	0.2430	759
	ω	0.1047	0.2070	0.5060	0.6130	759
	α_1	0.1258	0.2200	0.5710	0.5680	759
	β_1	0.9648	0.0689	14.0100	$<0.0100^{***}$	759
EGARCH Post-ETF	μ	0.1905	0.1120	1.6980	0.0900^{*}	577
	ω	0.2072	0.0881	2.3530	0.0190^{**}	577
	α_1	0.2647	0.0843	3.1410	$<0.0100^{***}$	577
	β_1	0.9118	0.0386	23.6490	$<0.0100^{***}$	577

Note: The table presents estimated parameters from the EGARCH(1,1) model fitted separately for the pre-ETF and post-ETF Bitcoin return series. Returns are expressed in percentage points. The pre-ETF period covers observations before 11 January 2024, while the post-ETF period covers observations from 11 January 2024 onward. The parameter μ denotes the constant mean return, ω captures the constant component of the conditional variance equation, α_1 measures the sensitivity of volatility to new shocks, and β_1 captures volatility persistence. Robust standard errors are reported. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Source: Bloomberg and authors' calculations.

Table 4 provides a non-parametric benchmark by comparing the distribution of Bitcoin returns before and after the introduction of spot ETFs. The Mann-Whitney U test indicates that there is no statistically significant shift in the central tendency of returns across the two periods. In economic terms, this finding reinforces the earlier evidence that the ETF introduction is not associated with a change in typical daily performance. Rather, it suggests that any post-ETF adjustments in Bitcoin's behaviour are not captured by shifts in median returns but may instead operate through other dimensions of the return distribution, such as dispersion or higher moments.

Table 4

Non-Parametric Tests for Distributional Differences

Test	Statistic	p-Value	Observations	Interpretation
Mann-Whitney U test	220655	0.8096	Pre-ETF: 759, Post-ETF: 577	No statistically significant difference in return distributions / ranks

Note: The table reports a non-parametric Mann-Whitney U test comparing Bitcoin return distributions before and after the introduction of spot Bitcoin ETFs.

Source: Bloomberg and authors' calculations.

To identify ETF-specific effects beyond a simple pre/post comparison, Table 5 presents the Difference-in-Differences (DiD) estimates, comparing Bitcoin with a control group of major cryptocurrencies that did not experience a comparable ETF event. The control group includes Litecoin, Ripple, Solana, Cardano, Dogecoin, and Bitcoin Cash, while Ethereum is appropriately excluded due to its own ETF-related developments. The framework directly addresses concerns regarding identification, as it isolates Bitcoin-specific changes from broader market-wide dynamics affecting the cryptocurrency space.

The DiD results show that the interaction term for Bitcoin in the return specifications is not statistically significant across both model variants, including the specification with daily fixed effects and the specification augmented with market controls and month fixed effects. It implies that, relative to comparable cryptocurrencies, Bitcoin did not experience a statistically distinguishable change in average daily returns following the introduction of spot ETFs. From an economic perspective, this finding is important because it confirms that ETF-driven financialization does not translate into excess returns or improved performance, but rather leaves expected returns broadly unchanged. In contrast, the results for absolute returns, used as a proxy for daily volatility, reveal a positive and statistically significant DiD effect across both specifications (Table 5). Such a result indicates that, after the ETF introduction, Bitcoin exhibits higher day-to-day return magnitudes relative to the control group of cryptocurrencies. In other words, while the overall level of unconditional volatility does not increase in a simple pre/post sense (as shown in earlier OLS results in Table 2), Bitcoin's relative short-term volatility rises when benchmarked against comparable assets. It constitutes the central finding of the paper, suggesting that the ETF introduction is associated with stronger short-run price adjustments, consistent with increased market participation, higher trading intensity, and faster incorporation of information.

T a b l e 5

Difference-in-Differences Estimates for Bitcoin Spot ETF Effects

Variable	**Return**	**Abs. Return**	**Squared Return**	**Return**	**Abs. Return**	**Squared Return**
Model	Asset FE + Daily FE	Asset FE + Daily FE	Asset FE + Daily FE	Controls + Asset FE + Month FE	Controls + Asset FE + Month FE	Controls + Asset FE + Month FE
DID BTC	0.0022 (0.0014)	0.0028** (0.0013)	0.0031 (0.0026)	0.0022 (0.0022)	0.0037** (0.0017)	0.0043 (0.0028)
S&P 500 returns				1.6500*** (0.0863)		
Absolute S&P 500 returns					0.8002*** (0.0702)	0.0572 (0.0790)
VIX level				0.0003 (0.0004)	0.0009** (0.0003)	0.0012 (0.0012)
Asset fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Daily fixed effects	Yes	Yes	Yes	No	No	No
Month fixed effects	No	No	No	Yes	Yes	Yes
Market controls	No	No	No	Yes	Yes	Yes
Observations	13,769	13,769	13,769	9,464	9,464	9,464
R-squared	0.4805	0.3836	0.1459	0.0948	0.1105	0.0110

Note: The table reports difference-in-differences estimates for Bitcoin around the introduction of spot Bitcoin ETFs. The dependent variables are daily returns, absolute daily returns, and squared daily returns. DID BTC equals one for Bitcoin observations after 11 January 2024 and zero otherwise. The control group consists of Litecoin, Ripple, Solana, Cardano, Dogecoin, and Bitcoin Cash. Ethereum is excluded from the Bitcoin control group because it later experienced its own spot ETF event. Columns 1 – 3 include asset and daily fixed effects. Columns 4 – 6 include asset and month fixed effects together with S&P 500 returns or absolute S&P 500 returns and the VIX level. Robust standard errors are reported in parentheses. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Source: Bloomberg and authors' calculations.

At the same time, the DiD estimates for squared returns are not statistically significant. Such a distinction is crucial for interpretation. While absolute returns capture the average size of daily fluctuations, squared returns place greater weight on extreme observations and are commonly interpreted as a proxy for tail risk or large volatility spikes. The absence of a significant effect in squared returns, therefore, indicates that the ETF introduction is not associated with a robust increase in extreme daily movements or tail risk relative to other cryptocurrencies. Taken together, the DiD results point to a nuanced conclusion. Spot Bitcoin ETFs are not associated with changes in average returns, but they are linked to an increase in short-term daily volatility relative to comparable cryptocurrencies. Importantly, this effect is visible in measures of typical daily fluctuations (absolute returns), but not in measures capturing extreme movements (squared returns). As such, the evidence supports an interpretation in which ETF introduction amplifies the frequency and magnitude of routine daily price adjustments, rather than generating a systematic rise in extreme risk. This is consistent with the broader narrative that ETF-driven financialization reshapes the mechanism of volatility formation (leading to more responsive and reactive price dynamics) without necessarily increasing tail risk or altering expected returns (Ben-David et al., 2018).

3.2. Existence of Fail-to-Deliveries

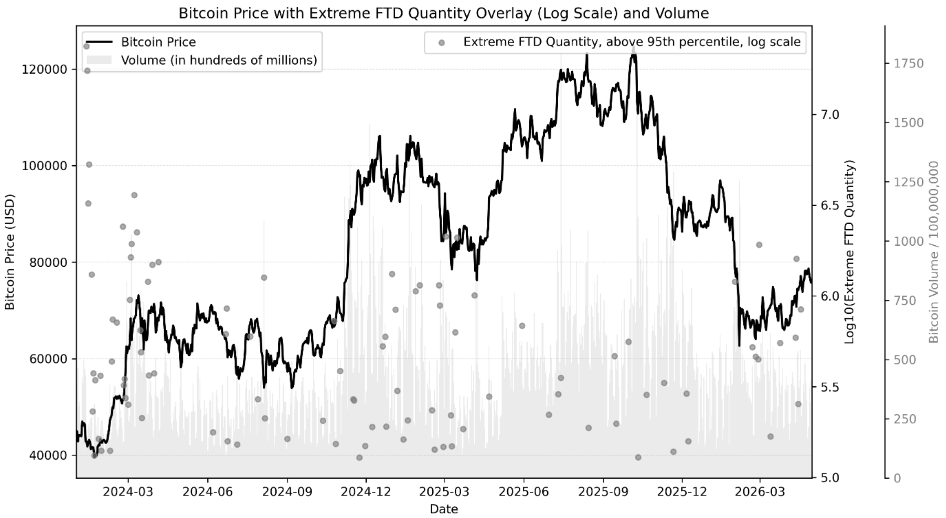
Figure 1 provides a visual representation of the relationship between Bitcoin price dynamics, trading activity, and fail-to-deliver occurrences in the post-ETF period. A key pattern that emerges from the figure is the clustering of elevated fail-to-deliver observations during periods of intensified market activity. In particular, spikes in failed deliveries tend to coincide with phases of strong price movements and increased trading volume, especially during upward trends and periods of heightened market adjustments. The visual evidence is further explored in Table 6, which identifies trading volume as the crucial driver of settlement failures. At the same time, the figure suggests that failures to deliver are not uniformly distributed across all volatile periods. Episodes of moderate or declining prices with lower trading intensity are associated with relatively fewer fail-to-deliver observations. Such a finding indicates that volatility alone does not systematically generate settlement frictions, reinforcing the earlier finding that failed delivery dynamics are more closely linked to transactional demand than to price variability in isolation.

An additional insight from the figure relates to the timing and clustering of failed delivery events. The presence of concentrated clusters rather than isolated spikes suggests that settlement pressures persist over short horizons, particularly during sustained periods of elevated market activity. The pattern is consistent with the idea that failure to deliver occurrences reflects temporary imbalances between trading demand and settlement capacity, which may take several days to resolve. Economically, the figure supports the interpretation that failures to deliver occurrences arise primarily in environments characterized by strong trading demand, and that their incidence increases further when such demand coincides with periods of heightened market movements (Fleming and Garbade, 2005). At the same time, the absence of systematic failure to deliver spikes during all volatile episodes suggests that these mechanisms are not purely driven by uncertainty, but rather by the interaction between trading intensity and market adjustment dynamics.

We further explore this mechanism in Table 6. Here, we study the determinants of failure to deliver occurrences in Bitcoin spot ETFs across three threshold definitions based on the top 10 percent, 20 percent, and 30 percent of trading volume and volatility. The main conclusion remains unchanged. Fail-to-deliver occurrences are primarily associated with high trading volume, as the coefficient on the high-volume variable remains positive and statistically significant across all three thresholds. Although slightly lower than in the original specification, the effect remains economically strong and stable, indicating that the result is robust to alternative definitions of high trading activity. In contrast, the high volatility variable remains statistically insignificant in all specifications, suggesting that elevated volatility alone does not explain variation in fail-to-deliver occurrences. Market turbulence without corresponding trading intensity does not appear to generate settlement frictions.

F i g u r e 1

Bitcoin Price with Extreme FTD Quantity Overlay (Log Scale) and Volume



Note: The figure presents Bitcoin's daily closing price alongside high fail-to-deliver (FTD) quantities and trading volume from January 2024 to April 2026. The black line represents the Bitcoin price, while the grey bars indicate trading volume, scaled in hundreds of millions and shown on a secondary axis. The grey dots denote high FTD observations, displayed in log scale, and defined as aggregate daily FTD quantities exceeding the 80th percentile of the empirical FTD distribution for the analysed period. FTD observations are shifted backward according to the prevailing settlement cycle, using two business days before the transition to T+1 settlement and one business day thereafter. This adjustment is intended to approximately align reported settlement-date FTD observations with the trading conditions that likely preceded them, while recognizing that reported FTD quantities represent settlement-date balances rather than newly generated trade-date failures.

Source: Bloomberg, U.S. Securities and Exchange Commission, and author's construction.

The key change is observed in the interaction between high volume and high volatility (see Table 6). While previously negative and insignificant, the interaction is now positive across all threshold definitions and becomes statistically significant at the 20 percent threshold and marginally significant at the 30 percent threshold, while remaining insignificant at the most extreme 10 percent level. The pattern suggests that the amplification effect is strongest in broader periods of elevated market activity rather than in the most extreme tail observations. Overall, the results reinforce that trading volume is the primary driver of fail-to-deliver occurrences, while volatility plays a conditional role by strengthening this effect when combined with high trading activity. It supports the interpretation that failures to deliver arise mainly from demand driven pressure, with the strongest effects appearing in periods that combine elevated trading intensity with increased market volatility.

T a b l e 6

OLS Regression Results for FTDs

Variable	**Top 10% threshold**	**Top 20% threshold**	**Top 30% threshold**
Intercept	4.9039*** (0.3070)	4.5598*** (0.3440)	4.3712*** (0.4050)
High Volume	2.9640*** (0.7450)	2.8397*** (0.6410)	2.5306*** (0.6340)
High Volatility	1.5717 (1.0250)	0.7944 (0.7850)	0.3969 (0.7070)
High Volume × High Volatility	2.1248 (1.9050)	3.7533*** (1.2850)	2.2187* (1.3060)
Observations	348	348	348
R-squared	0.0380	0.0770	0.0750
Adjusted R-squared	0.0300	0.0690	0.0670

Note: This table presents Ordinary Least Squares (OLS) regression results for log-transformed fail-to-deliver (FTD) quantities. The dependent variable is the natural logarithm of one plus aggregate daily FTD quantities. High Volume and High Volatility are dummy variables equal to one when Bitcoin trading volume and 30-day rolling volatility exceed the respective empirical thresholds. The Top 10%, Top 20%, and Top 30% specifications define high-volume and high-volatility periods as observations in the upper 10%, 20%, and 30% of their respective empirical distributions. The interaction term captures days characterized by both high trading volume and high volatility. Robust standard errors computed using the HC3 estimator are reported in parentheses. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Source: Bloomberg, U.S. Securities and Exchange Commission, and author's calculations.

3.3. Tracking Error Analysis

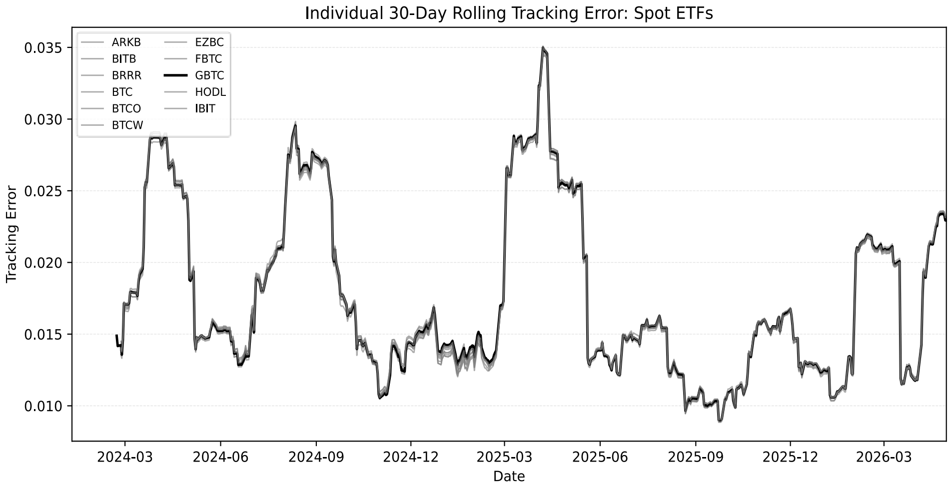
Consequently, we examine the tracking errors between Bitcoin spot ETFs and Bitcoin futures-based ETFs (Figures 2 and 3). The results reveal significant differences, with spot ETFs consistently exhibiting lower tracking errors (Figure 3). Spot ETFs, which replicate the underlying Bitcoin price through direct asset holdings, achieve average 30-day rolling tracking errors below 0.03. It indicates a high degree of alignment with Bitcoin's spot price. The finding is consistent with prior research on ETF tracking fidelity, which shows that direct asset-holding structures generally have reduced tracking errors, especially in highly volatile asset classes

(Elton et al., 2002; Cremers et al., 2013). The low tracking error observed here suggests that Bitcoin spot ETFs are effective at minimizing tracking deviations despite the inherent volatility and liquidity constraints associated with Bitcoin.

In contrast, futures-based ETFs show higher average tracking errors, frequently exceeding those of spot ETFs by 0.01 to 0.02 (see Figure 3), particularly during periods of elevated volatility. The average difference in tracking error (Futures ETFs – Spot ETFs) represents a value close to 0.004. Such divergence is likely attributable to structural features of futures markets, including rolling and term structure effects, which influence price dynamics and may complicate replication (Milonas and Henker, 2001). It aligns with broader evidence from commodities and other asset classes where futures-based ETFs often experience larger tracking discrepancies relative to spot ETFs (Chang et al., 2013), reflecting inefficiencies introduced by derivative exposures.

F i g u r e 2

Individual 30-Day Rolling Tracking Error of Bitcoin Spot ETFs Compared to Bitcoin Spot Price



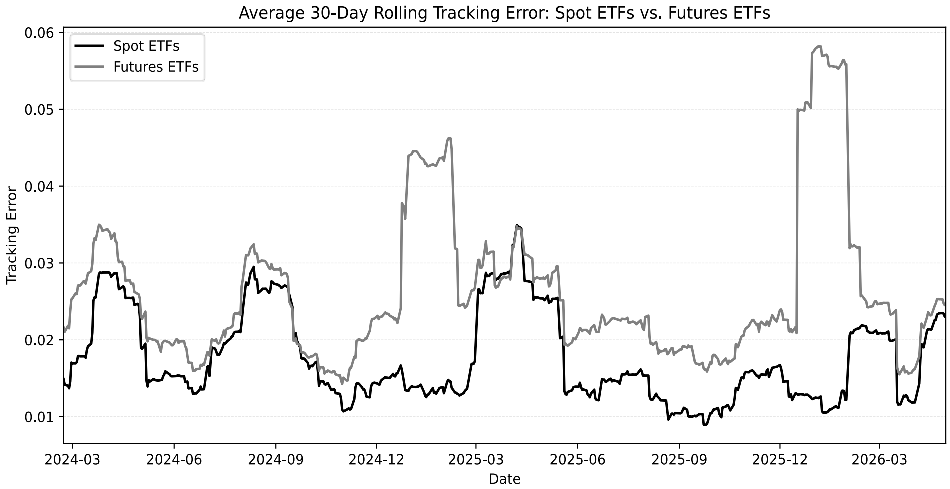
Note: The figure illustrates the 30-day rolling tracking error for individual Bitcoin spot ETFs relative to Bitcoin from January 2024 to April 2026. Tracking error is computed as the rolling standard deviation of the daily return differential between each ETF and Bitcoin. Higher values indicate larger deviations between ETF returns and Bitcoin returns, suggesting weaker short-term replication accuracy, while lower values indicate closer tracking of Bitcoin price movements.

Source: Bloomberg and authors' calculations.

The results suggest that while both ETF types provide investors with Bitcoin exposure, spot ETFs offer a more precise representation of Bitcoin's underlying price dynamics. The lower tracking error associated with spot ETFs underscores the advantage of direct asset holdings in achieving tracking accuracy.

F i g u r e 3

Average 30-Day Rolling Tracking Error: Bitcoin Spot ETFs vs. Bitcoin Futures ETFs



Note: The figure compares the average 30-day rolling tracking error of Bitcoin spot ETFs and Bitcoin futures-based ETFs from January 2024 to April 2026. Tracking error is calculated as the rolling standard deviation of the daily return differential between each ETF and Bitcoin. The plotted series represent the cross-sectional average tracking error within each ETF group. Lower values indicate closer tracking of Bitcoin returns, while higher values reflect larger deviations from Bitcoin price movements.

Source: Bloomberg and authors' calculations.

To conclude the empirical analysis, it is important to relate the observed tracking error differences to underlying fund characteristics and market frictions. While spot Bitcoin ETFs exhibit consistently low tracking errors, this outcome should be interpreted in light of their structural features. In particular, the direct holding of the underlying asset eliminates the need for contract rolling, which is a key source of deviation in futures-based ETFs. Futures ETFs are inherently exposed to roll costs, contango and backwardation effects, which can generate systematic tracking discrepancies even in the absence of operational inefficiencies. Additionally, heterogeneity across individual ETFs plays a nontrivial role. Differences in management fees, replication strategies, and liquidity provision can contribute to variation in tracking performance within both spot and futures ETF categories. For example, funds with higher fees or less efficient execution mechanisms may exhibit slightly larger deviations from the benchmark.

Therefore, the observed superiority of spot ETFs in tracking accuracy should not be viewed solely as a reflection of market efficiency, but rather as a consequence of structural design advantages and lower exposure to derivative related frictions.

Conclusion

Our study examines how the introduction of spot Bitcoin exchange-traded funds has affected the risk-return profile of Bitcoin, with a particular focus on the underlying mechanisms of volatility formation. Using a comprehensive empirical framework that combines regression analysis, conditional volatility modelling, distributional methods, and a difference in differences design, the evidence provides a consistent and nuanced picture of ETF-driven market transformation. The results show that the introduction of spot Bitcoin ETFs does not materially alter average returns. Across all specifications, expected returns remain statistically unchanged, both in simple pre and post comparisons and in relative terms when benchmarked against other cryptocurrencies. The finding is reinforced by non-parametric evidence, indicating that the central tendency of returns remains stable despite the structural change in market access and participation. In this sense, ETF-driven financialization does not generate excess performance, nor does it improve the fundamental risk-return trade-off from an average return perspective.

Similarly, unconditional measures of volatility do not indicate a systematic increase in overall risk. Baseline daily volatility, as captured by absolute returns, remains stable or slightly lower following the ETF introduction. Distributional evidence at the investor horizon further confirms that downside tail risk does not deteriorate. At the same time, higher moment statistics suggest a gradual normalization of the return distribution, consistent with a more mature and liquid market environment. Taken together, these findings exclude a simple narrative in which ETFs either increase or reduce risk in aggregate terms. The main contribution of the study lies in uncovering how ETFs reshape the dynamics through which volatility is generated. Conditional volatility modelling shows that the persistence of volatility remains largely unchanged, indicating that long-run risk characteristics continue to be driven by structural features of the Bitcoin market. In contrast, the sensitivity of volatility to new shocks increases significantly in the post-ETF period, implying that market reactions to new information become stronger and more immediate, reflecting faster information incorporation and more coordinated trading behaviour. The difference in differences analysis complements this result by showing that Bitcoin exhibits higher relative daily volatility compared to other cryptocurrencies after the ETF introduction. Importantly, this effect is concentrated in typical day-to-day fluctuations rather than extreme movements, as it is present in absolute returns but not in squared returns. The combined evidence therefore supports a consistent interpretation in which ETF introduction amplifies the responsiveness of prices to information without increasing the frequency of extreme outcomes.

Additional insights emerge from the analysis of failed delivery occurrences, which represent a novel feature in the Bitcoin market environment. The results indicate that these settlement frictions are primarily driven by trading demand and become more pronounced during periods of elevated market activity. Rather than reflecting pure inefficiency, they appear to be linked to temporary imbalances arising from intensified trading, suggesting a new channel through which market structure interacts with price dynamics. Finally, the tracking error analysis shows that spot Bitcoin ETFs replicate the underlying asset with high precision and significantly outperform futures-based ETFs in terms of tracking accuracy. It confirms that direct exposure through spot structures provides a closer link to underlying price dynamics, even in a highly volatile asset class.

Overall, the evidence suggests that the introduction of spot Bitcoin ETFs does not change the level of risk or returns in a traditional sense, but fundamentally transforms the mechanism through which risk is transmitted. Bitcoin becomes more integrated with the broader financial system, more sensitive to information flows, and more responsive to capital allocation decisions. These findings have important implications for portfolio management and risk assessment, as they indicate that the role of Bitcoin shifts from a segmented and predominantly speculative asset toward one that is increasingly embedded in global financial dynamics. Future research should further explore the long-term consequences of this transition, particularly in relation to market integration, cross-asset linkages, and the evolving nature of volatility transmission.

References

ALBRECHT, P. – KOČENDA, E. (2026): Event-Driven Changes in Return Connectedness among Cryptocurrencies. Financial Innovation, *12*, No. 1 pp. 1 – 37. DOI: 10.1186/s40854-025-00808-6.

ALBRECHT, P. – PASTOREK, D. – MAŇOUŠEK, D. (2025): Riding the Waves of Crypto Sentiment: Examining the Dynamics between Returns and Sentiment in the Cryptocurrency Market. Czech Journal of Economics and Finance, *75*, No. 2, pp. 98 – 127. DOI: 10.32065/CJEF.2025.02.01.

AUER, R. – CLAESSENS, S. (2018): Regulating Cryptocurrencies: Assessing Market Reactions. BIS Quarterly Review, September, pp. 51 – 65. Available at: <https://www.bis.org/publ/qtrpdf/r_qt1809f.htm>.

BABALOS, V. – BOURI, E. – GUPTA, R. (2025): Does the Introduction of U.S. Spot Bitcoin ETFs Affect Spot Returns and Volatility of Major Cryptocurrencies? The Quarterly Review of Economics and Finance, *102*, No. C, 102006. DOI: 10.1016/j.qref.2025.102006.

BEN-DAVID, I. – FRANZONI, F. A. – MOUSSAWI, R. (2017): Exchange-Traded Funds. Annual Review of Financial Economics, *9*, No. 1, pp. 169 – 189. DOI: 10.1146/annurev-financial-110716-032538.

BEN-DAVID, I. – FRANZONI, F. – MOUSSAWI, R. (2018): Do ETFs Increase Volatility? The Journal of Finance, *73*, No. 6, pp. 2471 – 2535. DOI: 10.1111/jofi.12727.

BOURI, E. – MOLNÁR, P. – AZZI, G. – ROUBAUD, D. – HAGFORS, L. I. (2017): On the Hedge and Safe Haven Properties of Bitcoin: Is It Really More than a Diversifier? Finance Research Letters, *20*, No. C, pp. 192 – 198. DOI: 10.1016/j.frl.2016.09.025.

CIAIAN, P. – KANCS, D'A. – RAJCANIOVA, M. (2018): The Price of Bitcoin: GARCH Evidence from High-Frequency Data. Applied Economics, *50*, No. 60, pp. 6590 – 6610.

CHANG, E. C. – SANDNES, M. – CHIAO, C. (2013): How Closely Do Commodity ETF Returns Track the Underlying Commodity Futures' Returns? Journal of Asset Management, *14*, No. 1, pp. 18 – 29.

CHEAH, J. E. T. – DAO, T. – DO, H. – MISHRA, T. (2025): Speed of Adjustment in Digital Assets in a Decentralized Financial World. Journal of Futures Markets, *46*, No. 2, pp. 320 – 333. DOI: 10.1002/fut.70055.

CONVERSE, N. – LEVY-YEYATI, E. – WILLIAMS, T. (2023): How ETFs Amplify the Global Financial Cycle in Emerging Markets. Review of Financial Studies, *36*, No. 9, pp. 3423 – 3462. DOI: 10.1093/rfs/hhad014.

CORBET, S. – LUCEY, B. – YAROVAYA, L. (2018): Datestamping the Bitcoin and Ethereum Bubbles. Finance Research Letters, *26*, September, pp. 81 – 88. DOI: 10.1016/j.frl.2017.12.006.

CREMERS, M. – PETAJISTO, A. – ZITZEWITZ, E. (2013): Should Benchmark Indices Have Alpha? Revisiting Performance Evaluation. Critical Finance Review, *2*, No. 1, pp. 1 – 48. DOI: 10.1561/104.00000007.

ELTON, E. J. – GRUBER, M. J. – COMER, G. – LI, K. (2002): Spiders: Where are the Bugs? Journal of Business, *75*, No. 3, pp. 453 – 472.

FLEMING, M. J. – GARBADE, K. D. (2005): Explaining Settlement Fails. Current Issues in Economics and Finance, *11*, No. 9, pp. 1 – 7.

FRINO, A. – GALLAGHER, D. R. (2001): Tracking S–P 500 Index Funds. Journal of Portfolio Management, *28*, No. 1, pp. 44 – 55. DOI: 10.3905/jpm.2001.319822.

GLOSTEN, L. R. – NALLAREDDY, S. – ZOU, Y. (2021): ETF Activity and Informational Efficiency of Underlying Securities. Management Science, *67*, No. 1, pp. 22 – 47. DOI: 10.1287/mnsc.2019.3427.

HONG, Y. – FENG, H. – WANG, Y. – LI, B. (2025): The Impact of Bitcoin ETF Approval on Bitcoin's Hedging Properties Against Traditional Assets. arXiv. DOI: 10.48550/arXiv.2512.12815.

IMF (2024): Identifying Idiosyncratic Jumps in Stock Returns. In: Global Financial Stability Report: Advances in Artificial Intelligence: Implications for Capital Market Activities. (Annex 3.1). Washington, DC: International Monetary Fund.

KATSIAMPA, P. (2017): Volatility Estimation for Bitcoin: A Comparison of GARCH models. Economics Letters, *158*, No. C, pp. 3 – 6. DOI: 10.1016/j.econlet.2017.06.023.

LABORDA, J. – LABORDA, R. – DE LA CRUZ, J. (2024): Can ETFs Affect U.S. Financial Stability? A Quantile Cointegration Analysis. Financial Innovation, *10*, No. 1, pp. 1 – 24. DOI: 10.1186/s40854-023-00591-2.

MAKAROV, I. – SCHOAR, A. (2020): Trading and Arbitrage in Cryptocurrency Markets. Journal of Financial Economics, *135*, No. 2, pp. 293 – 319. DOI: 10.1016/j.jfineco.2019.07.001.

MANCINI, C. (2009): Non-Parametric Threshold Estimation for Models with Stochastic Diffusion Coefficient and Jumps. Scandinavian Journal of Statistics, *36*, No. 2, pp. 270 – 296. DOI: 10.1111/j.1467-9469.2008.00622.x.

MILONAS, N. T. – HENKER, T. (2001): Price Spread and Convenience Yield Behaviour in the International Oil Market. Applied Financial Economics, *11*, No. 1, pp. 23 – 36. DOI: 10.1080/09603100150210237.

MOHAMAD, A. (2025): Do Bitcoin ETFs Lead Price Discovery Following Their Introduction in the Bitcoin Market? Comput Econ., *66*, No. 1, pp. 947 – 969. DOI: 10.1007/s10614-025-10998-x.

PASTOREK, D. – DRÁBEK, M. – ALBRECHT, P. (2023): Confirmation of T+35 Failures-to-Deliver Cycles: Evidence from GameStop Corp. Czech Journal of Economics and Finance, *73*, No. 1, pp. 56 – 80. DOI: 10.32065/CJEF.2023.01.03.

PASTOREK, D. – ALBRECHT, P. (2026): ETF Settlement Clocks in Cryptocurrency Markets. [MENDELU Working Papers in Business and Economics, No. 109/2026.] Brno: Mendel University in Brno.

SHALVARDJIEV, D. (2026): How Bitcoin Spot ETFs Affect Spot Prices. Economic Studies, No. 2, pp. 175 – 196.

STEJSKALOVÁ, J. (2023): Behavioral Attention and Stock Returns: Evidence from Automobile Companies. Ekonomický časopis/Journal of Economics, *71*, No. 3, pp. 202 – 221. DOI: 10.31577/ekoncas.2023.03.02.

TODOROV, K. (2021): Launch of the First US Bitcoin ETF: Mechanics, Impact, and Risks. BIS Quarterly Review. Available at: <https://www.bis.org/publ/qtrpdf/r_qt2112t.htm>.

TODOROV, K. (2024): When Passive Funds Affect Prices: Evidence from Volatility and Commodity ETFs. Review of Finance, *28*, No. 3, pp. 831 – 863.

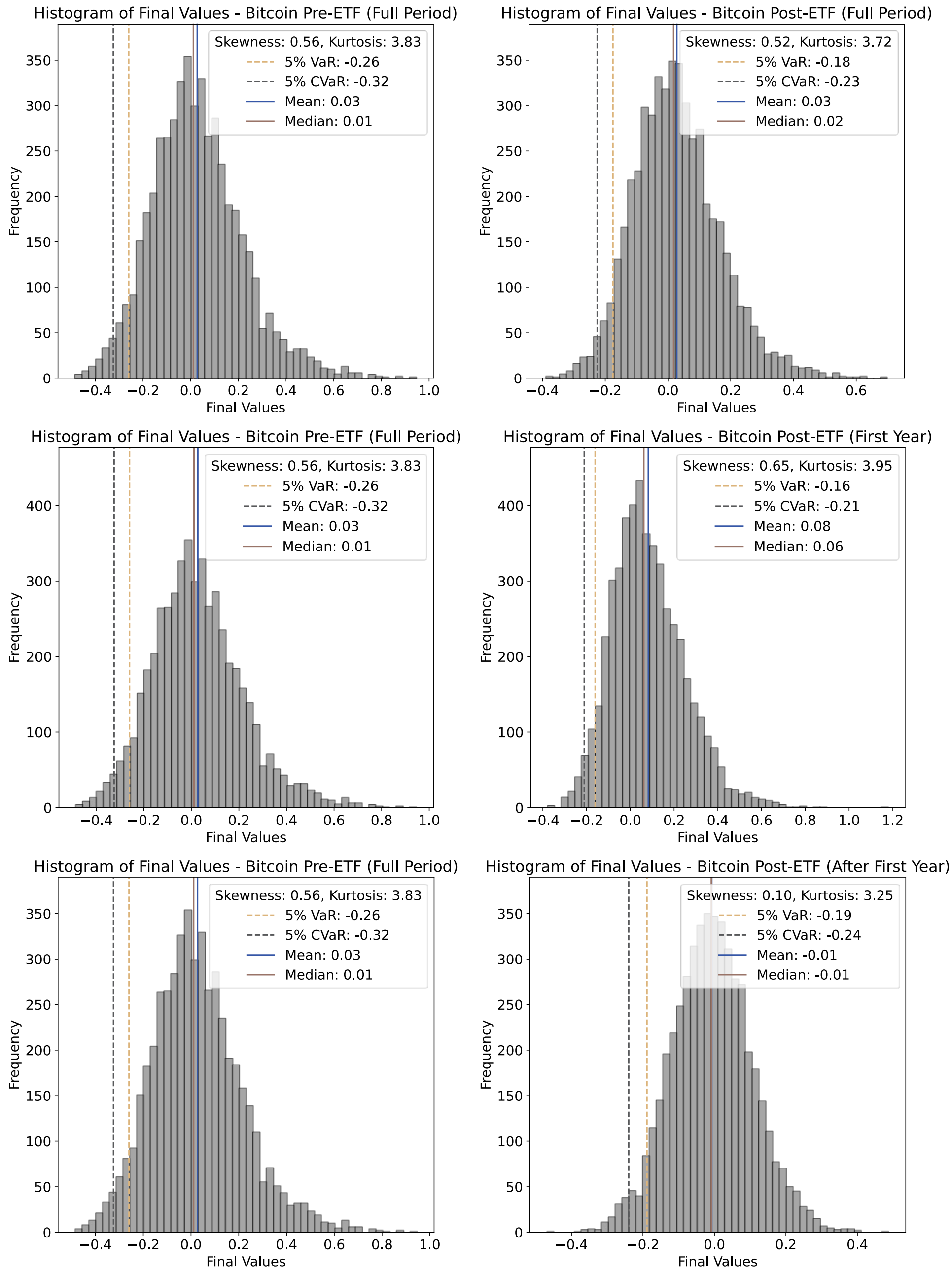
WU, D. (2025): Institutional Adoption and Correlation Dynamics: Bitcoin's Evolving Role in Financial Markets. arXiv. DOI: 10.48550/arXiv.2501.09911.

YILDIRIM, H. – BEKUN, F. V. (2023): Predicting Volatility of Bitcoin Returns with ARCH, GARCH and EGARCH Models. Future Business Journal, *9*, No. 1, pp. 1 – 8. DOI: 10.1186/s43093-023-00255-8.

Appendix

Figure A1

Distribution of Final Values for Bitcoin Pre- and Post-ETF Periods



Note: The figure presents histograms of simulated 30-day cumulative Bitcoin returns based on the block bootstrap analysis. In each row, the left-hand panel shows the extended pre-ETF benchmark distribution, based on Bitcoin returns from the pre-introduction period starting in January 2021. The right-hand panels show three post-ETF samples in the following order: the full post-ETF period, the first year after the introduction of spot Bitcoin ETFs, and the period after the first post-ETF year. The simulated distributions are obtained using a block bootstrap procedure with a six-day block size and 5,000 resampled return series, allowing short-term dependence in Bitcoin returns to be partially preserved. Final values represent cumulative returns over a 30-day investment horizon. The 5% Value at Risk (VaR) and the corresponding 5% Conditional Value at Risk (CVaR) capture downside tail risk. Mean, median, skewness, and kurtosis summarize the central tendency, asymmetry, and tail characteristics of the simulated return distributions.

Source: Bloomberg and authors' calculations.