

Spot Bitcoin ETF Flows and Bitcoin Returns: Timestamp Alignment and Asymmetric Feedback

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Abstract

This study examines whether U.S. spot Bitcoin ETF flows predict Bitcoin returns after correcting the timestamp mismatch between U.S. ETF trading sessions and Bitcoin's 24/7 market. Using daily spot Bitcoin ETF flows and Bitcoin prices measured at 16:00 New York time, we construct a true NYSE/Nasdaq trading-calendar sample covering the cash-creation regime from 11 January 2024 to 28 July 2025 (386 trading sessions), followed by a post-change subsample after in-kind creations and redemptions were permitted. Timing matters. Pairing day- t flows with the day- t UTC daily return (the daily-close convention) yields 4.89 percentage points per USD 1 billion of net inflow (adjusted $R^2 = 0.228$) because the UTC day contains the ETF session itself. Aligning the return window to the 24 hours after the session close reduces the coefficient to 1.67 (HAC $p = 0.007$, adjusted $R^2 = 0.036$), and a window that starts after the flow is public shows no positive association. The reverse channel is significant under every convention — a prior 24-hour Bitcoin return ending before the ETF trading day predicts same-day flows (HAC $p < 0.001$). In an information-consistent VAR, lagged returns predict flows, whereas lagged flows predict returns only marginally. The flow-to-return coefficient does not differ significantly between the cash-creation and in-kind regimes. Engle–Granger tests do reject no cointegration, and Johansen rank inference is not robust across deterministic terms. Timestamp alignment and information timing, rather than a universal flow-to-price coefficient, shape inference about Bitcoin ETF flow-return feedback.

Keywords: Bitcoin; cryptocurrency; exchange-traded fund; fund flows; return predictability; Granger causality; cointegration

1. Introduction

U.S. spot Bitcoin ETFs make institutional demand observable through daily creation and redemption flows after the SEC's January 2024 approvals and the later 2025 shift that permitted in-kind creations and redemptions for crypto ETPs (Securities and Exchange Commission, 2024, 2025). Earlier work shows that regulated crypto ETPs can affect legitimacy, liquidity and price discovery (Liu & Yang, 2024), that pre-ETF Bitcoin price discovery was shaped by unregulated venues (Alexander & Heck, 2020), and that spot Bitcoin ETF flows are closely associated with Bitcoin price formation (Mazur & Polyzos, 2025). Recent studies have further documented price-to-flow feedback (Oefe, 2025), long-run cointegration evidence between ETF assets and Bitcoin prices (Guliyev & Ahmadova, 2025), bidirectional flow-return predictability (Lim, 2026), and intraday price-discovery channels (Kia et al., 2026).

Against this literature, this paper separates four often-conflated mechanisms. First, it distinguishes high trend fit in levels from formal cointegration evidence. Second, it uses a 16:00 New York Bitcoin timestamp to match the U.S. ETF trading session to Bitcoin's 24/7 market and shows, by re-estimating the same regression under alternative conventions, how much of the apparent flow-to-return effect is contemporaneous with the session. Third, it separates the 24 hours in which a flow is executed and published from windows that start after the flow is public, and it separates immediate predictive regressions from an information-consistent VAR. Fourth, it shows that conclusions depend on timestamp alignment, information timing and dynamic specification rather than on the existence of a single universal flow-to-price coefficient.

2. Data and empirical design

The main sample covers the cash-creation regime from 11 January 2024 through 28 July 2025, ending immediately before the U.S. shift that permitted in-kind creations and redemptions for crypto ETPs. The sample contains 386 NYSE/Nasdaq trading sessions. Full exchange holidays are removed rather than set to zero flow. Early-close sessions remain in the sample and are timestamped at 16:00 New York for comparability, and SPY/TLT controls are lagged returns computed only on exchange-session prices. Daily net flows come from Farside Investors (n.d.). Bitcoin prices at 16:00 New York are the closes of Binance BTCUSDT one-hour spot candles whose close timestamps correspond to 16:00 in the America/New_York time zone (Binance, n.d.). SPY and TLT prices are Yahoo Finance daily data obtained through the yfinance package and retained only on U.S. exchange trading sessions (Yahoo Finance, n.d.). A post-change check covers 29 July–31 December 2025, with 109 trading sessions.

The main flow-to-return outcome is the constant 24-hour Bitcoin log return from 16:00 New York on ETF trading day t to 16:00 New York on the following calendar day. A Friday ETF flow is therefore paired with the Saturday 16:00 close, not the Monday close. The reverse-direction test uses the Bitcoin return ending at 16:00 New York on $t-1$, so the return is known before ETF trading day t . The return from 16:00($t-1$) to 16:00(t) is reported only as a contemporaneous association because it includes the ETF trading session.

Predictive regressions use HC3 and Newey–West HAC standard errors and five-day moving-block bootstrap intervals (Newey & West, 1987). The flow-to-return regression controls for the contemporaneously observed 16:00($t-1$)–16:00(t) Bitcoin return, lagged ETF flow, lagged Bitcoin return, and lagged SPY and TLT returns. Cointegration is examined with Engle–Granger residual-based tests and Johansen rank tests (Engle & Granger, 1987; Johansen, 1991), using MacKinnon cointegration p -values for the residual-based tests (MacKinnon, 1994). Stationary VAR/VARX models are kept distinct from Toda–Yamamoto modified Wald tests in augmented levels (Toda & Yamamoto, 1995). Generalised impulse responses follow Pesaran and Shin (1998).

To make the timing argument explicit, we re-estimate the flow-to-return regression under four alternative conventions: (i) the day- t UTC daily return (00:00 to 00:00 UTC), which contains the ETF session, (ii) the UTC daily return of the next trading session, which pairs Friday flows with Monday, (iii) the 16:00 New York close-to-close return between consecutive sessions, which spans 72 hours over weekends, and (iv) the baseline horizon with full holidays retained as zero-flow rows. Ex-ante variants start the return window only after the flow is public — they pair flow($t-1$) with the 24-hour return from 16:00(t) and flow(t) with the 24-hour return from 16:00($t+1$). The clean reverse-direction return ending at 16:00($t-1$) requires the calendar to close two days before a session. Because the price panel stores 16:00 New York closes for sessions and the calendar days adjacent to them, this return is unavailable for the ten sessions that follow a holiday-extended weekend in the cash-creation sample and for one such session in the post-change sample. A pooled regression with a regime interaction tests the equality of coefficients across the two subsamples.

3. Results

Table 1 summarises the corrected timing results. ETF flow remains positively related to the following 24-hour Bitcoin return. A USD 1 billion net inflow is associated with a 1.67 percentage point higher next-day return in the cash-creation sample (HAC $p = 0.007$), equivalent to about 0.56 percentage points for a one-standard-deviation flow of USD 0.335 billion. The effect is economically visible but has modest explanatory power (adjusted $R^2 = 0.036$), consistent with a noisy short-run predictive relationship rather than a stable pricing law.

Sample/direction	N	Coefficient	HAC p	Block 95% CI	Adj. R ²
Cash: Flow→next 24h BTC return	385	1.670	0.007	[0.600, 2.975]	0.036
Cash: Clean prior BTC return→flow	375	0.031	<0.001	[0.018, 0.046]	0.365

Cash: Same-day BTC return→flow	385	0.039	<0.001	[0.029, 0.050]	0.435
Post-change: Flow→next 24h BTC return	108	1.046	0.122	[-0.488, 2.429]	0.008
Post-change: Clean prior BTC return→flow	108	0.046	0.007	[0.018, 0.086]	0.279

Table 1. Corrected flow-return regressions using true exchange trading sessions and 16:00 New York Bitcoin timestamps.

The clean reverse channel is more robust. A prior 24-hour Bitcoin return ending before the ETF day predicts ETF flow on day t with HAC $p < 0.001$. The same-day 16:00($t-1$)–16:00(t) return is even more strongly associated with flow, but we report it as contemporaneous because it includes the ETF trading session. On the common 375-session sample, the standardised effect of the prior return on flow (0.27, incremental adjusted R^2 0.052) exceeds that of flow on the next 24-hour return (0.21, 0.019). At the same time, most of the reverse regression's fit reflects flow persistence (flow($t-1$) alone yields an adjusted R^2 of 0.310). The asymmetry is therefore one of robustness and incremental fit rather than of magnitude. In the shorter post-change subsample, the flow-to-return coefficient is 1.046 (HAC $p = 0.122$), and a pooled regression with a regime interaction does not reject equality with the cash-creation estimate (difference -0.12 , HAC $p = 0.851$). The reverse coefficient is likewise unchanged (difference 0.013, $p = 0.438$, supplementary sections S10 and S11).

Table 2 shows that the flow-to-return coefficient depends on the timing convention. Under the UTC daily-close convention, the coefficient is 4.89 (HAC $p < 0.001$) with an adjusted R^2 of 0.228, almost three times the aligned estimate, because the UTC day includes the session during which flows are executed. Pairing Friday flows with the next session's UTC return gives 0.93 ($p = 0.145$), and the 16:00 close-to-close return between sessions gives 1.89 ($p = 0.012$). Retaining holidays as zero-flow rows leaves the baseline unchanged (1.66, $p = 0.004$). Ex-ante variants show no positive predictability. Lagged flow alone predicts a lower next-day return (-1.00 , $p = 0.037$), and day- t flow is unrelated to the return from 16:00($t+1$) to 16:00($t+2$) (-0.46 , $p = 0.442$). Within the baseline model, flow(t) and flow($t-1$) enter with opposite signs (1.67 and -1.72 , both $p < 0.01$). The association is thus with the flow innovation and reverses thereafter, a pattern consistent with temporary price pressure around execution and publication rather than with information that predicts returns. The reverse channel is positive and significant under every convention, with coefficients between 0.027 and 0.033 in Table 2 and up to 0.043 for the contemporaneous variants in supplementary section S8 (all $p < 0.001$).

Design	N	Coefficient	HAC p	Adj. R^2
Flow(t) → 16:00(t) to 16:00($t+1$), aligned baseline	385	1.670	0.007	0.036
Flow(t) → day- t UTC daily return (00:00–00:00 UTC)	385	4.892	<0.001	0.228
Flow(t) → UTC daily return of next session (Fri → Mon)	385	0.931	0.145	0.008
Flow(t) → 16:00 close-to-close, next session (Fri → Mon)	384	1.889	0.012	0.023
Flow(t) → 16:00(t) to 16:00($t+1$), holidays as zero-flow rows	385	1.661	0.004	0.034
Flow($t-1$) → 16:00(t) to 16:00($t+1$), ex ante	385	-1.002	0.037	0.015
Flow(t) → 16:00($t+1$) to 16:00($t+2$), ex ante	375	-0.457	0.442	-0.002
Prior 24h return ending 16:00($t-1$) → flow(t), aligned	375	0.031	<0.001	0.365
UTC daily return ($t-1$) → flow(t)	385	0.033	<0.001	0.374

Return ending at the close of session $t-1 \rightarrow \text{flow}(t)$	384	0.027	<0.001	0.368
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Table 2. Flow-return regressions under alternative timing conventions and ex-ante windows (cash-creation sample). OLS with the Table 1 controls adapted to each convention and Newey–West HAC(5) p-values. Coefficients are in percentage points per USD 1 billion in flow-to-return rows and in USD billions per percentage point in return-to-flow rows. Full specifications are in supplementary sections S8 and S9.

The dynamic models refine this interpretation. We specify the stationary VAR in information-consistent order, $y_t = (r_t, f_t)$, where r_t is the 16:00($t-1$)–16:00(t) return, known when the session closes, and f_t is the standardised flow reported after the close. BIC selects one lag, and results are similar for one to five lags. The contemporaneous residual correlation of 0.46 absorbs the same-day association. Block-exclusion (Granger causality) tests show that lagged returns predict flows at every lag order (HAC $p < 0.001$), whereas lagged flows predict returns only marginally (HAC p between 0.03 and 0.09, supplementary section S12). A VAR that instead pairs the day- t flow with the following 24-hour return, reported in supplementary section S5, tests predictability beyond the first 24 hours and does not reject flow-to-return exclusion (HAC $p = 0.132$ at two lags, rising to 0.591 at four). Its return-to-flow result partly reflects the same-day association. By contrast, the Toda–Yamamoto augmented levels tests reject both block exogeneity directions, with the price-to-flow direction again stronger.

Long-run evidence remains specification-sensitive. Engle–Granger residual-based tests using MacKinnon cointegration p-values do reject no cointegration for cumulative USD flows ($p = 0.235$ with a constant and $p = 0.388$ with a trend) or for BTC-equivalent cumulative net creations ($p = 0.430$ and $p = 0.742$). Johansen trace tests with a constant do not reject a zero rank for either measure at any lag length, and maximum-eigenvalue tests reject it only marginally for USD flows at one and three lags. Without a deterministic term, both tests reject at all lags. With a linear trend, the BTC-equivalent measure rejects both $r = 0$ and $r \leq 1$, implying full rank. This contradicts the unit-root evidence and indicates that the trend specification is unreliable here. Because both log price and cumulative flows drift, the specification with a constant is the natural benchmark, and rank inference is not treated as robust evidence of a long-run equilibrium (supplementary sections S3 and S13).

Figure 1 reports generalised impulse responses from the VAR that pairs the day- t flow with the following 24-hour return. A one-standard-deviation flow shock, approximately USD 0.335 billion, is associated with a return response of 0.343% on impact, which restates the within-window association of Table 1 and reflects contemporaneous residual correlation rather than lagged predictability. It is followed by negative responses (−0.21% at one step), and the cumulative log-price response is statistically indistinguishable from zero at the 10-step horizon. The 10-step FEVD attributes 2.83% of return forecast-error variance to flow shocks and 26.45% of flow variance to return shocks. In the information-consistent VAR, by contrast, the same-day co-movement (1.37% on impact) does not reverse (supplementary section S14) — co-movement during the session behaves like information. In contrast, the association after the close is temporary.

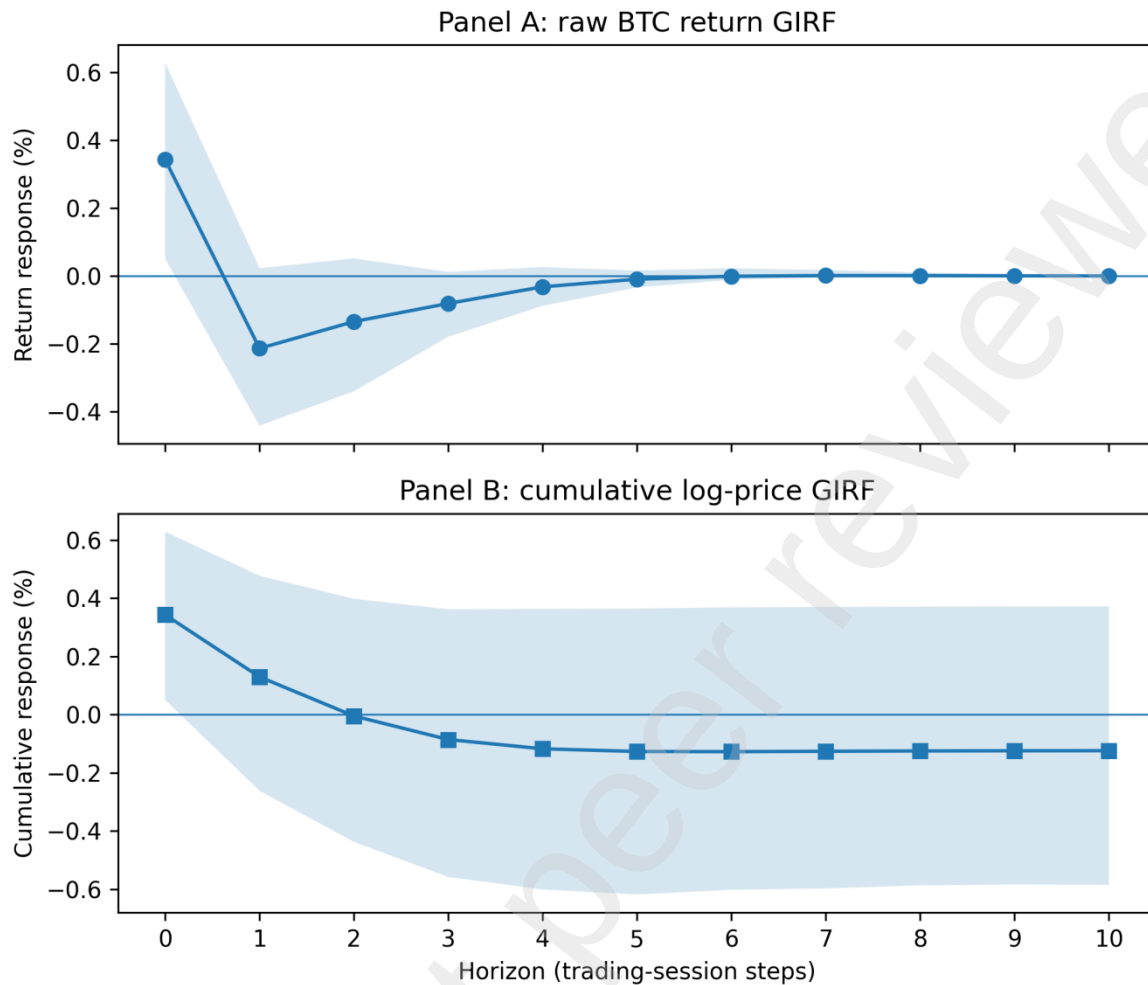


Figure 1. Generalised impulse responses to a one-standard-deviation ETF-flow shock (USD 0.335 billion) in the VAR that pairs the day- t flow with the following 24-hour return. Panel A reports the raw BTC return GIRF and Panel B the cumulative log-price GIRF. Shaded areas are 95% residual-bootstrap confidence intervals. Horizons are trading-session steps.

4. Discussion and conclusion

The corrected estimates support a narrower contribution than a claim that ETF flows drive Bitcoin prices. Under the UTC daily-close convention, the flow regression attains an adjusted R^2 of 0.228 and a coefficient almost three times the aligned estimate. Under aligned timing, the association is modest, confined to the 24 hours in which the flow is executed and published, followed by a reversal, and no longer positive once the flow is public. By contrast, price-to-flow feedback is significant under every timing convention, in the clean pre-day regression, in the contemporaneous association and in the information-consistent VAR.

The main implication is methodological. In Bitcoin ETF research, calendar construction and information timing are part of identification. Pairing day- t flows with the day- t UTC close, setting closed exchange days to zero flow or pairing Friday ETF flow with Monday's Bitcoin close changes the economic object being measured. The UTC daily-close convention changes it most, and pairing Friday flows with Monday's UTC return removes significance. In contrast, the 16:00 close-to-close pairing and zero-flow holidays leave the estimate close to the baseline even though the measured object differs. Similarly, high R^2 in levels does not establish a stable long-run equilibrium when residual-based cointegration tests and Johansen rank inference disagree across deterministic assumptions.

This study is limited by the short post-ETF sample and by reliance on daily ETF flows rather than intraday creation and redemption timestamps. Daily flows are published only after the ETF trading session closes, so the aligned flow-to-return regression describes the association between reported flows and the subsequent 24-hour return rather than a signal available at 16:00. Under cash creations, part of this association may reflect issuers' execution of Bitcoin purchases after the session. The evidence should therefore be read as associational and consistent with feedback, not as structural causality. Future work should combine intraday ETF quotes, exchange-level Bitcoin order-book data and authorised-participant activity to distinguish flow anticipation, execution effects and price discovery. For now, the evidence indicates asymmetric feedback. Bitcoin returns are a robust predictor of ETF flows. In contrast, ETF flows are at most a marginal predictor of subsequent Bitcoin returns, and this conclusion depends critically on timestamp alignment and information timing.

Declaration statements

Data availability: ETF flow data are publicly available from Farside Investors, hourly Bitcoin prices from Binance Public Data, and SPY and TLT prices from Yahoo Finance. The cleaned trading-session panel, derived variables, output tables, figure data, and reproduction script are provided in the accompanying data-and-code package.

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