

Article

Bitcoin Event Windows and Ecosystem Indicators, 2012–2024: Market, Trust, Protocol, and Institutional Milestones

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Abstract

Bitcoin is often narrated through price cycles, yet major dated events affect different layers of the ecosystem. This study analyzes 21 Bitcoin-related events between 2012 and 2024 using a first-public-information dating rule, a mechanism-based event taxonomy, and daily Coin Metrics data. Price-defined milestones are retained as historical markers but excluded from mechanism-level comparisons. Baseline cumulative abnormal log returns are estimated with a constant-mean model over days -120 to -21 and reported for $[-1,+1]$, $[-3,+3]$, and $[-7,+7]$ windows. The analysis adds standardized CARs, Benjamini–Hochberg multiplicity checks, date-sensitivity tests, estimation-window sensitivity, a market model using a capitalization-weighted Bitcoin-excluded crypto proxy, a crypto-plus-macro model using S&P 500 and broad U.S. dollar-index returns, and non-price ecosystem indicators. In the clean mechanism sample, trust shocks have the most negative median raw CARs (-16.8 , -22.3 , and -21.6 log-return percentage points across the three windows); exact trust-versus-other tests are significant for CAR3 and CAR7 ($p = 0.002$) but not for CAR15 ($p = 0.082$). Standardized tests show the same short-window pattern ($p = 0.009$ and $p = 0.006$). No individual event-level empirical p -value survives a 5% Benjamini–Hochberg correction, and market-model controls attenuate several effects, so the findings are interpreted descriptively rather than causally. On-chain indicators show that trust shocks coincide with elevated exchange flows and spot volume, while active-address and hash-rate measures do not indicate protocol-layer collapse. The study contributes a transparent framework that separates market reaction, service-layer stress, protocol resilience, and institutional significance.

Keywords: Bitcoin; cryptocurrency; event study; abnormal returns; standardized CAR; exchange flows; institutionalization; regulation; trust shocks

JEL Classification: G14; E42; G18



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1. Introduction

Bitcoin began as a proposal for peer-to-peer electronic cash that could transfer value without a trusted central intermediary [1]. Its development subsequently produced a layered ecosystem of miners, nodes, wallets, exchanges, custodians, payment processors, derivatives venues, regulated investment products, public companies, supervisory authorities, and retail users [2,3]. This ecosystem is not reducible to BTC price, even though price remains the most visible measure of attention, liquidity, and market sentiment.

A price-only history is especially incomplete because Bitcoin-related events operate through different mechanisms. A protocol upgrade, a halving, an exchange failure, a

national policy decision, and an exchange-traded product approval do not transmit information through the same channel. Some events mainly affect expected supply, some reveal weaknesses in centralized service providers, some change access to regulated financial markets, and some are selected precisely because the price moved. Treating all of them as a single class of Bitcoin news obscures these differences.

The distinction matters for research and policy. Cryptocurrency returns display distinctive risk factors and are influenced by market-wide conditions [4]. Regulatory announcements can affect valuations, trading activity, and user bases [5], and regulatory changes may spill across jurisdictions [6,7]. Bitcoin can also react to macroeconomic news and to global shocks such as the COVID-19 pandemic [8,9]. These findings imply that a single-event interpretation of a Bitcoin return window should be approached with caution, especially when broad financial-market sentiment moves at the same time.

This study presents an event-based analysis of Bitcoin between 2012 and 2024. It asks three questions. First, how do short-window abnormal returns differ across monetary, technological, trust-shock, and institutional or regulatory milestones once endogenous price-defined milestones are separated from mechanism-level tests? Second, do trust shocks exhibit a more negative pattern after the event date is defined as the first public market-relevant information rather than the later legal filing date? Third, how sensitive are results to volatility standardization, expected-return specifications, multiplicity adjustment, and non-price ecosystem indicators?

The contribution is fourfold. First, the paper makes event dating explicit and documents sensitivity for Mt. Gox, FTX, and the 2024 halving. Second, it separates price-defined historical markers from externally dated mechanism events, thereby reducing a common source of selection bias. Third, it reports raw and standardized CARs, exact permutation tests, Benjamini–Hochberg adjusted event-level inference, constant-mean estimation-window sensitivity, and two market-model specifications. Fourth, it adds active-address, hash-rate, exchange-flow, transaction-count, and spot-volume indicators so that claims about service-layer stress and protocol resilience do not rest on prices alone.

2. Related Work and Conceptual Framework

2.1. Cryptocurrency Event Studies and Market Reaction

Classical event studies compare realized returns around a dated event with an expected-return benchmark [10]. Brown and Warner show that simple models can perform well under some conditions. Still, the same literature also warns that inference is affected by event-induced variance, heteroskedasticity, and cross-sectional or time clustering [11–13]. These concerns are amplified in cryptocurrency markets because trading is continuous, volatility is high, market microstructure changes rapidly, and events often unfold through rumours, leaks, platform statements, official releases, and subsequent legal actions.

Cryptocurrency-specific event studies have examined regulation, attacks, manipulation, macroeconomic news, and external shocks. Auer and Claessens show that regulatory news can move cryptocurrency valuations and activity [5]. Shanaev et al. document economically meaningful reactions to regulatory events [6], while Borri and Shakhnov emphasize cross-border regulatory spillovers [7]. Corbet and co-authors show that macroeconomic news and COVID-19-related disruption can matter for Bitcoin and crypto-market dynamics [8,9]. Griffin and Shams link part of the 2017 crypto-market boom to Tether-related activity [14], and Shanaev et al. demonstrate that security-relevant blockchain events can be studied using event-window methods [15].

This literature motivates the design choices in the present study. The paper does not claim that a short CAR is a sufficient measure of ecosystem importance. Instead, it uses CARs as a market-reaction layer and combines them with classification, sensitivity

tests, and non-price indicators. The novelty therefore lies not in inventing event studies for crypto-assets, but in producing an auditable Bitcoin chronology that distinguishes endogenous price milestones, first-information trust shocks, market-model sensitivity, and ecosystem-layer indicators within one transparent framework.

2.2. Mechanism-Based Interpretation of Bitcoin Events

The protocol layer includes consensus rules, block production, validation, transaction structure, and the issuance schedule. Changes such as Segregated Witness and Taproot were formalized through Bitcoin Improvement Proposals and adopted through network coordination [16,17]. Second-layer systems such as the Lightning Network move repeated transfers away from the base chain while preserving final settlement on it [18], although scalability trade-offs remain central to blockchain economics [19].

The service layer consists of exchanges, brokers, wallets, custodians, stablecoins, payment processors, and analytics providers. This layer makes Bitcoin accessible but reintroduces operational and governance risks. A protocol can keep producing valid blocks even when users lose assets through an exchange failure. Distinguishing protocol resilience from service-layer resilience is therefore essential.

The institutional and regulatory layer includes public companies, regulated investment vehicles, supervisory authorities, tax rules, national policy, and global AML standards. MiCA creates a harmonized European framework for crypto-asset service providers [20], while FATF guidance emphasizes risk-based controls for virtual assets and service providers [21]. Global adoption patterns and the geography of crypto use remain heterogeneous across jurisdictions [22]. Institutional entry can expand access and legitimacy, but it can also increase policy dependence, custody concentration, and exposure to conventional markets.

The framework used in this paper therefore records four outputs: each event's mechanism category, the event-window market reaction, the sensitivity of that reaction to alternative return models, and the behavior of selected on-chain or service-layer indicators. This framework is intentionally modest. It is designed to help interpret selected historical episodes, not to prove a general law of Bitcoin ecosystem formation.

3. Materials and Methods

3.1. Event Selection, Exclusion Rules, and Dating

We constructed the event set from a historical chronology and then restricted it using five inclusion rules. An event required a clearly identifiable calendar date; a plausible mechanism connecting it to Bitcoin's protocol, monetary design, service layer, trust environment, institutional access, or regulation; sufficient daily price history for an estimation window; documentary support from official, scholarly, or established open sources; and non-duplication of substantially identical news. Events were classified before comparing outcomes. Event dates and descriptions were checked against official, scholarly, and established open sources for the Silk Road seizure, Mt. Gox, halvings, corporate treasury disclosures, exchange listings, national policy, ETP approvals, the Terra/UST crisis, FTX, and the 2024 U.S. election reaction [23–39].

The baseline uses a first-public-information dating rule. The event date is the first date on which market-relevant information was publicly available to global participants. For corporate, protocol, regulatory, and policy events, this is normally the official announcement, activation, launch, or decision date. For trust shocks, it is the first public impairment signal rather than a later legal filing. Consequently, Mt. Gox is dated to the withdrawal halt on 7 February 2014, not the bankruptcy filing on 28 February 2014 [24,25], and FTX is dated to the Binance letter of intent and liquidity-crisis disclosure on 8 November 2022, not

the bankruptcy filing on 11 November 2022 [36,37]. The sensitivity table retains the legal filing dates.

The whitepaper publication, genesis, and first commercial transaction are not included in the event-window analysis because reliable market-price data and a pre-event estimation window are unavailable. They remain foundational to the qualitative history. Three price-defined milestones—the first break above USD 1000, the 2017 market peak, and the break below USD 6000—are retained as historical markers but excluded from mechanism-level category comparisons, because the outcome variable selects the event date. We excluded other potentially relevant episodes when they lacked a single non-overlapping Bitcoin-specific date, were primarily altcoin-specific, were already captured by broader trust-shock events, or were better interpreted as global macro shocks rather than Bitcoin events. This selection rule reduces, but does not eliminate, event-selection bias.

The final chronology contains 21 events: four monetary events, two technology events, four trust shocks, eight institutional or regulatory events, and three price-defined historical markers. The fourth halving is dated to 20 April 2024 UTC, when block 840,000 was added to the Bitcoin blockchain [26,27].

3.2. Price Data and Baseline Abnormal Returns

Daily Bitcoin price (USD) observations were obtained from the free Coin Metrics Community Network Data archive [40]. The series was truncated on 31 December 2024. From 31 July 2010 to 31 December 2024, the downloaded Bitcoin series contained no missing calendar dates and no missing PriceUSD observations; therefore, no event window was shortened by deleted price observations. Historical Coin Metrics values may be revised when the public repository is updated, so we report the retrieval date and data path in the references.

For each calendar day t , the continuously compounded return is $r_t = \ln(P_t/P_{t-1})$, where P_t is the Coin Metrics USD price. Bitcoin trades continuously, so we use calendar-day windows throughout. This avoids arbitrary weekday filtering, but it also means that event windows may include weekends and holidays when equity and dollar-index controls are not traded.

The baseline expected return is the arithmetic mean daily log return over event-relative days -120 to -21 . A 20-day gap separates the estimation window from the event window to reduce anticipation contamination. An abnormal return is $AR_t = r_t - \text{mean}(r_{\text{est}})$, and cumulative abnormal returns are summed over $[-1, +1]$ (CAR3), $[-3, +3]$ (CAR7), and $[-7, +7]$ (CAR15). Values are reported as 100 times the log return and should be interpreted as log-return percentage points, not as simple percent changes.

3.3. Inference, Standardization, and Model Sensitivity

For an event-specific rarity measure that does not impose normality, each observed CAR is compared with rolling same-length cumulative deviations inside the estimation window. The two-sided empirical p -value equals one plus the number of absolute rolling sums at least as large as the observed absolute CAR, divided by one plus the number of available rolling sums. Because rolling sums overlap and cryptocurrency returns are serially dependent, these p -values are descriptive local measures. Event-level p -values are also adjusted using the Benjamini–Hochberg procedure [41].

Raw CARs are complemented by standardized CARs. For a window of length L , SCAR equals CAR divided by the estimation-window standard deviation multiplied by the square root of L . This addresses the fact that Bitcoin volatility varies substantially across time; a raw 10-point CAR in 2013 is not directly comparable with a raw 10-point CAR in 2024.

Category-level comparisons focus on medians because the sample is small and heavy-tailed. We compare the trust-shock median with the median of all non-trust events using an exact two-sided permutation test. The clean mechanism sample excludes the three price-defined markers, leaving 18 events for the main category tests. The appendix reports the same logic for the full chronology where appropriate.

Three constant-mean robustness checks are reported as estimation-window sensitivity only: a longer mean window $[-180, -31]$, a shorter mean window $[-90, -11]$, and a median-return benchmark over $[-120, -21]$. These specifications remain members of the same constant-mean family and therefore should not be read as evidence that results are model-invariant.

A separate model-class sensitivity check estimates two event-specific market models over the same estimation window. The first regresses Bitcoin returns on a capitalization-weighted Bitcoin-excluded crypto-market proxy built from available Coin Metrics assets (ETH, XRP, LTC, DOGE, BCH, ADA, XLM, BNB, TRX, LINK, and SOL). The second adds daily S&P 500 returns and daily broad U.S. dollar-index returns [42,43]. The first halving predates sufficient non-BTC market-cap proxy data, so these market-model tables are based on 20 events. Equity and dollar-index levels are forward-filled to the daily calendar grid, producing zero return on non-trading days; this is a practical alignment convention, not a claim that macro markets are active on weekends.

3.4. Non-Price Indicator Construction

To make the ecosystem interpretation less dependent on price, the paper examines selected Coin Metrics variables on the same daily grid: active addresses (AdrActCnt), hash rate (HashRate), exchange inflows (FlowInExNtv), exchange outflows (FlowOutExNtv), transaction count (TxCnt), and reported spot volume in USD. For each event, we compare the average value over days -14 to -1 with the average over days 0 to $+14$. The percentage change is then summarized by category. These indicators are not causal tests; they distinguish service-layer stress from protocol-layer disruption.

All calculations and figures were produced in Python 3.11.8 (Python Software Foundation, Wilmington, DE, USA) using pandas 2.2.2, NumPy 1.26.4, SciPy 1.13.1, Matplotlib 3.8.4, and statsmodels 0.14.2. No physical instruments, devices, chemicals, reagents, commercial cell lines, biological samples, or other laboratory materials were used. The study uses public market and documentary data. It does not involve human participants, personal data, or intervention. It does not provide investment advice. The back matter discloses the use of generative AI during manuscript preparation.

4. Results

4.1. Event Chronology and Full Event-Level Results

Figure 1 places the event chronology on the logarithmic Bitcoin price series. Price-defined markers are visible because they are historically important, but they are not used to estimate mechanism medians. The event distribution also shifts from early monetary and trust episodes to a more institutionally connected environment after 2020. Table 1 lists the event chronology, and Table 2 reports the full baseline event-level CARs.

The first-public-information date rule changes how we interpret the trust-shock category. Mt. Gox and FTX no longer show anomalous positive short-window values because their baseline dates correspond to the first public market-relevant information. The largest negative CAR15 in the full chronology is Mt. Gox (-45.4 log-return percentage points), followed by the China crackdown (-40.0) and the price-defined 2018 break below USD 6000 (-40.4). The largest positive CAR15 remains the price-defined USD 1000 threshold ($+57.5$), which is why we treat price-defined milestones as historical markers rather than

evidence in category tests. Figure 2 displays the CAR15 ranking from the most negative to the most positive event.

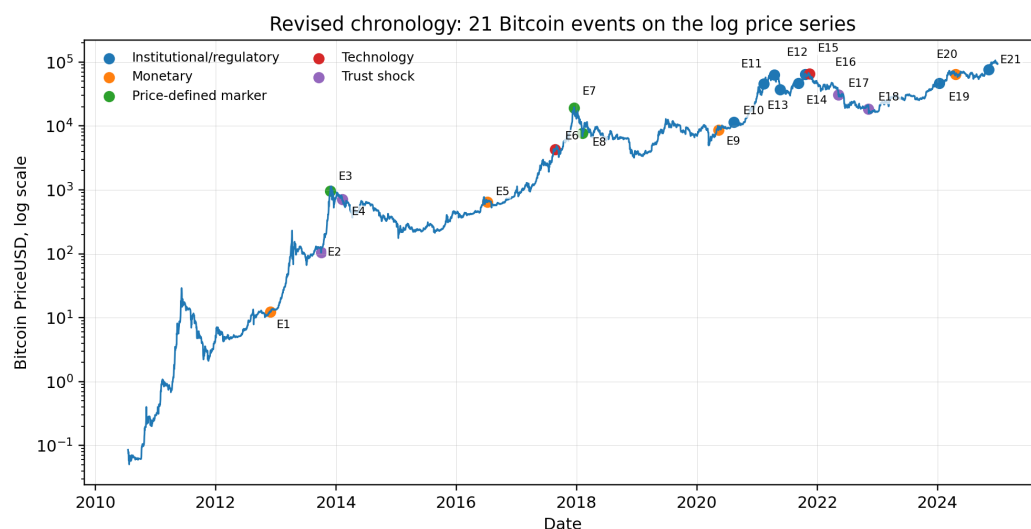


Figure 1. Event chronology on the logarithmic Bitcoin price (USD) series. Event identifiers correspond to Table 1; price-defined markers are retained for historical context but excluded from mechanism-level tests.

Table 1. Event chronology, dating rule, and use in category comparisons.

ID	Date	Event	Category	Included in Mechanism Tests
E1	28 November 2012	First halving	Monetary	Yes
E2	2 October 2013	Silk Road seizure	Trust shock	Yes
E3	27 November 2013	BTC exceeds USD 1000	Price-defined marker	No—historical marker
E4	7 February 2014	Mt. Gox withdrawal halt	Trust shock	Yes
E5	9 July 2016	Second halving	Monetary	Yes
E6	24 August 2017	SegWit activation	Technology	Yes
E7	17 December 2017	2017 market peak	Price-defined marker	No—historical marker
E8	6 February 2018	BTC falls below USD 6000	Price-defined marker	No—historical marker
E9	11 May 2020	Third halving	Monetary	Yes
E10	11 August 2020	MicroStrategy purchase announcement	Institutional/regulatory	Yes
E11	8 February 2021	Tesla purchase disclosure	Institutional/regulatory	Yes
E12	14 April 2021	Coinbase direct listing	Institutional/regulatory	Yes
E13	21 May 2021	China mining/trading crackdown	Institutional/regulatory	Yes
E14	7 September 2021	El Salvador legal-tender launch	Institutional/regulatory	Yes
E15	19 October 2021	First U.S. Bitcoin futures ETF	Institutional/regulatory	Yes
E16	14 November 2021	Taproot activation	Technology	Yes
E17	9 May 2022	Terra/UST crisis	Trust shock	Yes
E18	8 November 2022	FTX liquidity crisis/Binance LOI	Trust shock	Yes
E19	10 January 2024	U.S. spot Bitcoin ETP approvals	Institutional/regulatory	Yes
E20	20 April 2024	Fourth halving	Monetary	Yes
E21	6 November 2024	U.S. election reaction	Institutional/regulatory	Yes

Price-defined markers are retained in the full event table and figures but excluded from mechanism-level category medians and exact tests.

Table 2. Full baseline event-level cumulative abnormal log returns (E1–E21).

ID	Event	Category	CAR3	p3	CAR7	p7	CAR15	p15
E1	First halving	Monetary	2.0	0.606	0.1	1.000	10.1	0.460
E2	Silk Road seizure	Trust shock	−7.1	0.273	−4.6	0.695	1.2	0.966
E3	BTC exceeds USD 1000	Price-defined marker	17.9	0.030	22.1	0.053	57.5	0.011
E4	Mt. Gox withdrawal halt	Trust shock	−20.2	0.121	−29.2	0.242	−45.4	0.356
E5	Second halving	Monetary	−0.3	0.939	−3.9	0.526	−10.8	0.276
E6	SegWit activation	Technology	4.3	0.596	0.7	0.979	−3.4	0.920
E7	2017 market peak	Price-defined marker	4.5	0.505	−6.1	0.589	−19.3	0.218

Table 2. Cont.

ID	Event	Category	CAR3	p3	CAR7	p7	CAR15	p15
E8	BTC falls below USD 6000	Price-defined marker	−10.6	0.333	−7.8	0.716	−40.4	0.161
E9	Third halving	Monetary	−7.8	0.253	−0.8	0.895	11.3	0.575
E10	MicroStrategy purchase announcement	Institutional/regulatory	−1.8	0.646	−0.6	0.895	2.1	0.862
E11	Tesla purchase disclosure	Institutional/regulatory	13.3	0.071	17.2	0.053	19.6	0.115
E12	Coinbase direct listing	Institutional/regulatory	2.4	0.758	−6.0	0.653	−22.3	0.310
E13	China mining/trading crackdown	Institutional/regulatory	−1.5	0.889	−15.3	0.179	−40.0	0.011
E14	El Salvador legal-tender launch	Institutional/regulatory	−10.6	0.212	−8.9	0.389	3.8	0.759
E15	First U.S. Bitcoin futures ETF	Institutional/regulatory	6.8	0.212	−2.2	0.779	3.1	0.851
E16	Taproot activation	Technology	−2.5	0.747	−12.0	0.211	−13.9	0.437
E17	Terra/UST crisis	Trust shock	−13.5	0.040	−22.7	0.011	−24.9	0.011
E18	FTX liquidity crisis/Binance LOI	Trust shock	−28.2	0.010	−21.8	0.011	−18.4	0.034
E19	U.S. spot Bitcoin ETP approvals	Institutional/regulatory	−2.9	0.323	−6.3	0.274	−13.4	0.092
E20	Fourth halving	Monetary	0.9	0.869	0.8	0.916	−12.6	0.287
E21	U.S. election reaction	Institutional/regulatory	10.9	0.040	9.1	0.232	19.1	0.057

CAR values are $100 \times \log$ -return percentage points. Local empirical p -values use rolling same-length estimation-window sums and are not multiplicity-adjusted. Across all 63 event-window p -values, no event-level result remains significant at 5% after Benjamini–Hochberg adjustment; the smallest q -value is 0.121. Trust-shock dates use the first-public-information rule.

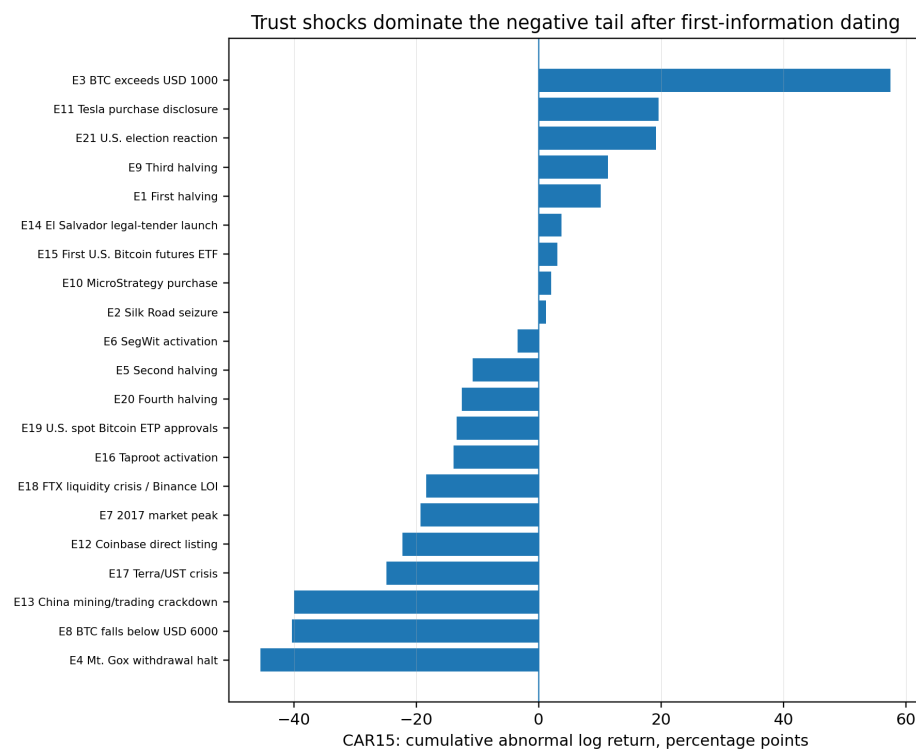


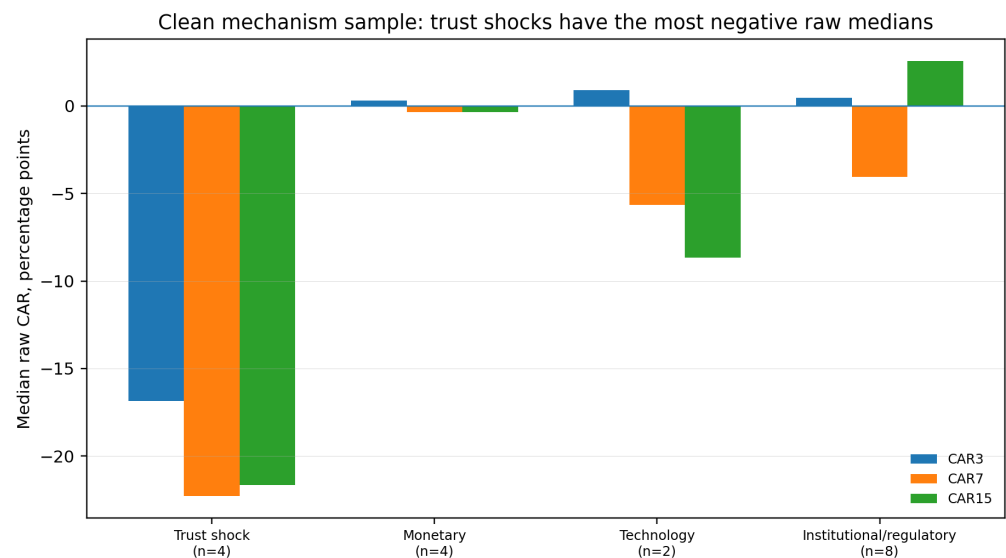
Figure 2. CAR15 values for all 21 events ordered from lowest to highest. The negative tail is dominated by trust shocks after first-information dating, while price-defined milestones appear at both extremes.

4.2. Clean Category Comparisons

Trust shocks have the most negative medians in the clean mechanism sample: -16.8 for CAR3, -22.3 for CAR7, and -21.6 for CAR15. The monetary category moves much closer to zero after removing the three price-defined milestones; its median CAR15 is -0.3 in the clean sample. Institutional and regulatory events remain heterogeneous, with a positive median CAR15 but weak short-window medians. Technology events have negative wider-window medians, but the category includes only SegWit and Taproot. These category-level results are summarized in Table 3 and visualized in Figure 3.

Table 3. Clean mechanism sample: raw and standardized category medians after excluding price-defined markers.

Category	<i>n</i>	Med CAR3	Med CAR7	Med CAR15	Med SCAR3	Med SCAR7	Med SCAR15	CAR15 −/+
Institutional/regulatory	8	0.5	−4.1	2.6	0.05	−0.35	0.20	3/5
Monetary	4	0.3	−0.4	−0.3	0.05	−0.02	−0.30	2/2
Technology	2	0.9	−5.6	−8.7	0.04	−0.62	−0.60	2/0
Trust shock	4	−16.8	−22.3	−21.6	−1.81	−1.89	−1.49	3/1

**Figure 3.** Category-level raw median CARs in the clean mechanism sample. Trust shocks ($n = 4$) are most negative across all three windows; technology contains only two events and should not be interpreted inferentially.

Technology has only two observations; its medians are descriptive only. Standardized CARs divide the raw CAR by estimation-window volatility and the square root of the window length. The associated exact tests are reported in Table 4.

Table 4. Exact trust-shock-versus-other median tests in the clean mechanism sample.

Window	Raw Median Diff.	Raw <i>p</i>	Standardized Diff.	Standardized <i>p</i>	Permutations
CAR3	−17.16	0.0023	−1.87	0.0092	3060
CAR7	−20.79	0.0023	−1.75	0.0059	3060
CAR15	−20.95	0.0817	−1.49	0.0859	3060

The test enumerates all assignments of four events to the trust-shock group among the 18 externally dated mechanism events. The CAR15 *p*-value is larger despite a similar raw difference because the permutation distribution is more dispersed at the 15-day horizon.

The exact tests support a short-window trust-shock pattern. For raw CARs, trust shocks differ from other mechanism events at CAR3 and CAR7 ($p = 0.002$ in both cases), but not at CAR15 ($p = 0.082$). Standardized CARs show the same conclusion for CAR3 and CAR7 ($p = 0.009$ and $p = 0.006$) and remain suggestive but not conventionally significant for CAR15 ($p = 0.086$). The result is therefore strongest in short windows after first-information dating, but it remains a statement about the selected chronology, not a population law for all possible Bitcoin events.

4.3. Date Sensitivity and Estimation-Model Sensitivity

The date-sensitivity check shows why the dating rule matters. When Mt. Gox is dated to the bankruptcy filing, CAR7 is positive (+13.2), although market concern began earlier.

When it is dated to the withdrawal halt, CAR7 is -29.2 , and CAR15 is -45.4 . Similarly, the FTX bankruptcy filing is too late to capture the first market reaction: the 8 November liquidity-crisis date produces a CAR3 of -28.2 , compared with $+6.4$ on the filing date. The fourth halving correction from 19 April to 20 April UTC has a smaller effect but improves date accuracy. Table 5 reports these date-sensitivity checks.

Table 5. Date-sensitivity checks for trust shocks and the fourth halving.

Event/Date Rule	Date	CAR3	CAR7	CAR15
Mt. Gox bankruptcy filing (legal filing date)	28 February 2014	-7.3	13.2	-7.8
Mt. Gox withdrawal halt (first-information date)	7 February 2014	-20.2	-29.2	-45.4
FTX bankruptcy filing (legal filing date)	11 November 2022	6.4	-20.9	-18.5
FTX Binance letter of intent/liquidity crisis (first-information date)	8 November 2022	-28.2	-21.8	-18.4
Fourth halving date used under earlier UTC convention	19 April 2024	4.3	2.1	-16.5
Fourth halving at block 840,000 (revised UTC date)	20 April 2024	0.9	0.8	-12.6

The baseline uses the first public market-relevant information date. Legal filing dates are shown to document sensitivity rather than to optimize statistical significance. Table 6 reports constant-mean estimation-window sensitivity.

Table 6. Constant-mean estimation-window sensitivity: Spearman rank correlation with baseline event ordering.

Alternative Specification	CAR3 rho	CAR7 rho	CAR15 rho
Long mean $[-180, -31]$	0.990	0.968	0.977
Median $[-120, -21]$	0.996	0.962	0.988
Short mean $[-90, -11]$	0.987	0.948	0.962

These specifications differ only in the scalar expected-return estimate and therefore reflect estimation-window sensitivity, not proof of model invariance. Table 7 compares the baseline ranking with market-model CARs.

Table 7. Different model-class sensitivity: rank correlation between baseline constant-mean CARs and market-model CARs.

Model	Window	Spearman rho	<i>n</i>
CryptoProxy	CAR3	0.420	20
CryptoProxy	CAR7	0.180	20
CryptoProxy	CAR15	0.734	20
CryptoProxy + Macro	CAR3	0.450	20
CryptoProxy + Macro	CAR7	0.150	20
CryptoProxy + Macro	CAR15	0.726	20

The market-model sample has 20 events because the first halving lacks sufficient non-BTC market-cap proxy data. Lower short-window correlations show that model choice affects event ordering and should be reported rather than assumed.

Constant-mean estimation-window alternatives preserve the event ordering mechanically well, with correlations from 0.948 to 0.996. By contrast, the different model-class sensitivity checks produce much lower short-window correlations. The Bitcoin-excluded crypto proxy yields correlations of 0.420, 0.180, and 0.734 for CAR3, CAR7, and CAR15; the crypto-plus-macro specification yields 0.450, 0.150, and 0.726. This confirms that the baseline results are best interpreted as transparent descriptive abnormal returns relative to a simple benchmark. Once we include broader crypto co-movement, equity returns, and dollar-index returns, some event-specific magnitudes are attenuated and short-window ordering changes. Table 8 reports category medians under the two market-model specifications.

Table 8. Category medians under market-model expected-return specifications.

Model	Category	<i>n</i>	Med CAR3	Med CAR7	Med CAR15
CryptoProxy	Institutional/regulatory	8	−2.2	−5.2	−2.4
CryptoProxy	Monetary	4	−0.5	−1.2	−6.8
CryptoProxy	Technology	2	3.4	−1.1	−5.4
CryptoProxy	Trust shock	4	−6.3	−5.2	−0.6
CryptoProxy + Macro	Institutional/regulatory	8	−2.1	−4.8	−1.9
CryptoProxy + Macro	Monetary	4	−0.3	−0.7	−7.1
CryptoProxy + Macro	Technology	2	3.7	−1.0	−5.6
CryptoProxy + Macro	Trust shock	4	−8.4	−8.3	−5.4

Market models reduce the magnitude of several trust-shock CARs, particularly at CAR15, indicating that part of the raw reaction co-moved with broader crypto-market and macro-financial conditions. Additional market-model interpretation notes are provided in Appendix A, and excluded-event logic is summarized in Appendix B.

4.4. Non-Price Ecosystem Indicators

The on-chain and service-layer indicators support a layered interpretation. Trust shocks have the largest median increases in exchange inflows (+55.3%), exchange outflows (+58.6%), and reported spot volume (+72.6%). Active addresses also rise modestly (+6.6%), and hash rate does not collapse. This pattern is consistent with service-layer stress, trading reallocation, and heightened liquidity demand rather than a failure of the Bitcoin protocol itself. Table 9 and Figure 4 summarize these non-price indicators by event category.

Table 9. Median post/pre 14-day changes in selected ecosystem indicators by category.

Category	<i>n</i>	Active Addr.	Hash Rate	Exch. Inflows	Exch. Outflows	Tx Count	Spot Vol.
Institutional/regulatory	8	0.4	1.3	3.4	5.7	−1.9	9.1
Monetary	4	−7.3	−3.5	−20.0	−14.8	−3.0	−20.9
Technology	2	−2.5	2.6	−1.4	−8.5	−5.0	−7.3
Trust shock	4	6.6	11.7	55.3	58.6	−1.0	72.6

Values are median percentage changes from the 14-day pre-event average to the 15 days from the event day through day +14. They are descriptive indicators of layer-specific stress, not causal estimates.

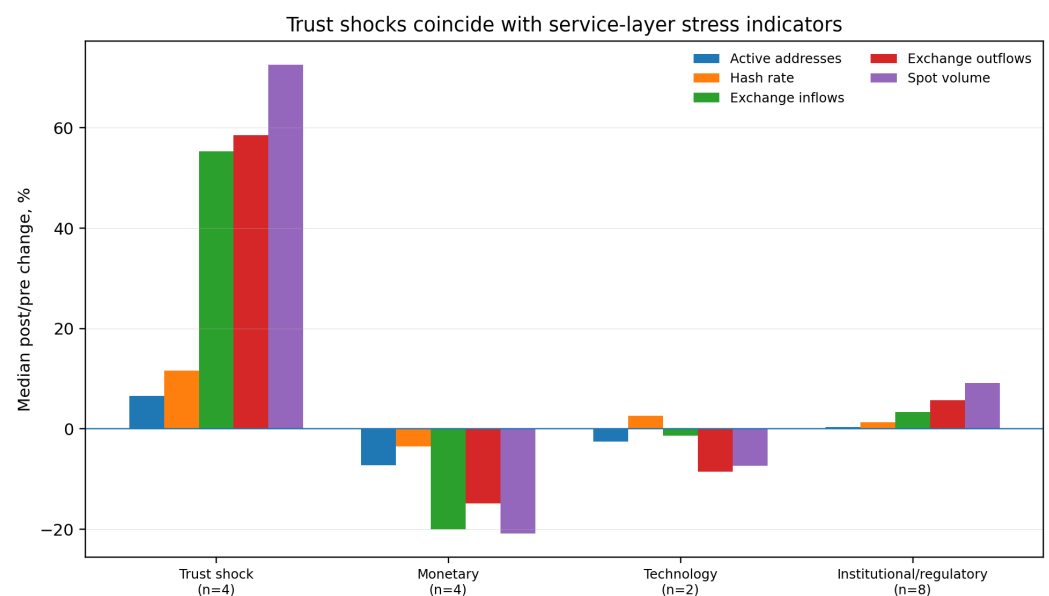


Figure 4. Median post/pre 14-day changes in selected ecosystem indicators. Trust shocks show elevated exchange flows and spot volume, supporting the interpretation that these events stress service and trading layers more directly than the protocol layer.

5. Discussion

5.1. Trust Shocks Are Stronger Under First-Information Dating

The central empirical issue is the first-public-information dating rule. Legal filing dates for Mt. Gox and FTX understate the immediate market reaction because the market had already received the key information. When Mt. Gox is dated to the withdrawal halt and FTX to the liquidity-crisis announcement, the trust-shock category becomes the most negative mechanism in both raw and standardized short windows. This is not a statistical optimization exercise: the same rule is applied uniformly to events where the first market-relevant information can be identified.

The results also clarify what failed. Mt. Gox, Terra/UST, and FTX did not represent equivalent failures of Bitcoin consensus. They revealed weaknesses in exchanges, stablecoin designs, custody arrangements, leverage, liquidity, and governance. The exchange-flow and volume indicators reinforce this interpretation. Trust shocks coincide with movement through service-layer channels, while active-address and hash-rate indicators do not suggest that the base protocol stopped functioning.

5.2. Price-Defined Milestones Are Useful History but Weak Causal Evidence

Separating price-defined milestones addresses a major selection problem. The USD 1000 crossing, the 2017 peak, and the break below USD 6000 are meaningful historical markers, but they are selected because the price moved. Including them in category medians would partly restate the selection rule. After excluding them from mechanism-level tests, monetary events are much less negative at CAR15, and the halving category is better interpreted as a deterministic supply-schedule mechanism rather than a set of surprise announcements.

This distinction is also important for communication. Bitcoin history can still describe price milestones because they shape media attention and retail participation. However, they should not be pooled with externally dated policy, protocol, or trust-shock events when the research question concerns event mechanisms.

5.3. Expected-Return Models Matter

The constant-mean model is transparent and reproducible, but it does not control for crypto-market co-movement, equity sentiment, dollar movements, interest-rate expectations, or geopolitical news. The model-class sensitivity results show that this limitation is not cosmetic. Rank correlations fall sharply in short windows when we introduce a Bitcoin-excluded crypto proxy and macro controls. Therefore, one should read the constant-mean results as a baseline descriptive layer.

This caution matters for events such as Terra/UST and the 2024 U.S. election reaction. The Terra window coincided with broad risk-asset weakness, and the election window coincided with a wider shift in market expectations. The market-model tables do not fully solve concurrent-news contamination, but they show how much interpretation changes when common movement is taken seriously. Future studies should add richer factors such as rates, volatility indices, stablecoin flows, derivative funding rates, and intraday timestamps.

5.4. Technology and Institutionalization Are Not Announcement-Return Concepts Only

SegWit and Taproot do not show a common positive wider-window return, but this does not imply that they were economically irrelevant. Protocol upgrades are discussed publicly, activated only after coordination, and designed to improve functionality over time. Their benefits may appear through later wallet adoption, lower operational risk, second-layer development, or improved transaction design rather than through an immediate price jump.

Institutional and regulatory events are also heterogeneous. Corporate purchases, listings, national policy, futures ETFs, spot ETP approvals, and election-related expectations expand access or change legitimacy in different ways. Some are anticipated, some are ambiguous, and some expose Bitcoin to conventional financial-market narratives. The U.S. spot ETP approval is a useful example: it is structurally important because it expands regulated access, but the local event-window return is not necessarily positive after accounting for anticipation and positioning.

For asset managers and financial institutions, the practical question is therefore not whether a formal institutional event produces a positive CAR on the announcement date. It is whether the event changes custody arrangements, disclosure obligations, suitability assessments, market integrity, operational resilience, and client access. These implications follow from the Bitcoin-specific evidence reported here and are aligned with cryptocurrency regulation and service-provider risk concerns discussed in MiCA, FATF guidance, and cryptocurrency regulation studies [5–7,20,21].

5.5. Implications for Research, Market Surveillance, and Policy

For researchers, the taxonomy provides a replicable way to pre-classify Bitcoin events before measuring returns. The most important design lessons are to state the dating rule, separate price-defined markers, disclose exclusion decisions, report multiple windows, standardize by volatility, and include a different expected-return model class. For market surveillance, combining event-window returns with exchange-flow indicators can help identify whether an episode is primarily a service-layer stress event, a protocol event, or a broad market co-movement event.

For exchanges, custodians, and crypto-asset service providers, the trust-shock pattern underlines the economic value of reserve transparency, segregation of client assets, operational controls, cybersecurity, governance, recovery planning, and clear disclosures. Reporting is not only an administrative burden; it is part of the infrastructure stakeholders use to evaluate risk. For regulators, the evidence supports a layered approach: protocol risk, intermediary risk, market-abuse risk, consumer suitability, and AML compliance require different tools. MiCA and FATF standards address parts of the service-provider and compliance layer, but market resilience depends on implementation quality and understandable disclosure [20,21].

For investors, the findings reinforce a simple but often overlooked point. Bitcoin exposure through centralized platforms, exchange-traded products, or direct self-custody involves different risk channels. Event-window price reactions capture only one of these channels. A mature allocation process should consider custody, counterparty exposure, liquidity, tax treatment, regulatory change, technological risk, and the possibility that broad financial-market conditions may dominate a supposedly Bitcoin-specific event.

5.6. Limitations

The study remains exploratory. The 21-event chronology is purposive rather than exhaustive, and category sizes are small, particularly for technology events. The first-public-information rule improves consistency but cannot remove all ambiguity because some crises develop across several days and time zones. The constant-mean baseline is intentionally simple, while market models remain limited by the quality and availability of an ex-BTC crypto proxy and by daily macro data aligned to a continuously traded asset.

Event windows can contain unrelated news, macroeconomic shocks, monetary-policy expectations, geopolitical events, leverage cycles, and social-media dynamics. Rolling empirical p -values are based on overlapping windows, while the exact permutation tests describe category separation within the selected chronology rather than a population

parameter. Multiple comparisons weaken individual event-level claims, as shown by the Benjamini–Hochberg adjustment. The non-price indicators are also descriptive: exchange flows and volume may reflect many forms of reallocation, not only panic or trust loss.

These limitations justify cautious language. The paper provides a transparent and reproducible description of selected episodes and a framework for future confirmatory studies. Stronger designs could use intraday data, pre-registered event sets, richer factor models, block-bootstrap inference, derivatives data, sentiment measures, and a wider set of protocol and service-layer indicators.

6. Conclusions

Bitcoin's recent history cannot be summarized by price cycles alone. The analysis shows that event interpretation changes materially when dates are assigned by first public information, price-defined markers are separated from mechanism tests, volatility is standardized, and broader market conditions are considered. Trust shocks are the most negative short-window mechanism in the clean sample, and the result is strongest after Mt. Gox and FTX are dated to the first public market-relevant information rather than to later legal filings.

At the same time, the article avoids causal overstatement. No individual event-level p -value survives a 5% Benjamini–Hochberg adjustment, market-model controls change short-window ordering, and several events coincide with broader macro-financial conditions. The most reliable conclusion is therefore layered: trust shocks stress the service and trading infrastructure; price-defined milestones should be treated as historical markers; technology events may matter without immediate announcement returns; and institutional events expand access without guaranteeing positive short-window abnormal returns.

The broader contribution is methodological. A credible history of Bitcoin should distinguish market reaction, service-layer stress, protocol resilience, and institutional significance. The taxonomy, sensitivity checks, and non-price indicators provide one transparent way to make that distinction and a basis for future research on cryptocurrency market events, regulation, and digital-asset infrastructure.

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3.11.8 with pandas 2.2.2, NumPy 1.26.4, SciPy 1.13.1, Matplotlib 3.8.4, and statsmodels 0.14.2, as specified in the Materials and Methods section. The same package can be deposited in Zenodo, OSF, or GitHub if the editorial office requires a persistent DOI.

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Abbreviations

Abbreviation	Meaning
AML	Anti-money laundering
AR	Abnormal return
BH	Benjamini–Hochberg
BIP	Bitcoin Improvement Proposal
CAR	Cumulative abnormal return
ETP/ETF	Exchange-traded product/exchange-traded fund
FATF	Financial Action Task Force
MiCA	Markets in Crypto-Assets Regulation
SCAR	Standardized cumulative abnormal return
USD	United States dollar

Appendix A. Additional Market-Model Category Results

Because the main text contains the full baseline event-level table, this appendix reports only supplementary interpretation notes. The market models show that controlling for broad crypto co-movement and macro-financial proxies reduces some trust-shock magnitudes and changes short-window event ordering. This is why the revised article no longer states that the baseline ordering is robust to the expected-return model; it states only that constant-mean estimation-window changes preserve ordering within the same model family.

Appendix B. Notes on Excluded Events and Selection Bias

The event set is not exhaustive. Examples of excluded episodes include episodes with diffuse timing, events that primarily affected non-Bitcoin tokens without a direct Bitcoin mechanism, and broad macro-financial shocks such as the COVID-19 market panic, where Bitcoin-specific attribution would be weak without a broader cross-asset design. This selection choice increases interpretability but limits generalization. Future research should pre-register a wider event universe and apply block-bootstrap or intraday methods to reduce discretion.

References

1. Nakamoto, S. Bitcoin: A Peer-to-Peer Electronic Cash System. 2008. Available online: <https://bitcoin.org/en/bitcoin-paper> (accessed on 11 August 2026).

2. Narayanan, A.; Bonneau, J.; Felten, E.; Miller, A.; Goldfeder, S. *Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction*; Princeton University Press: Princeton, NJ, USA, 2016. Available online: <https://economics.princeton.edu/books/bitcoin-and-cryptocurrency-technologies-a-comprehensive-introduction/> (accessed on 11 August 2026).

3. Bank for International Settlements. Cryptocurrencies: Looking Beyond the Hype. In *BIS Annual Economic Report 2018*; BIS: Basel, Switzerland, 2018; Chapter V. Available online: <https://www.bis.org/publications/aer-2018/cryptocurrencies-looking-beyond-hype> (accessed on 11 August 2026).
4. Liu, Y.; Tsyvinski, A.; Wu, X. Common Risk Factors in Cryptocurrency. *J. Financ.* **2022**, *77*, 1133–1177. [[CrossRef](#)]
5. Auer, R.; Claessens, S. Regulating Cryptocurrencies: Assessing Market Reactions. *BIS Q. Rev. Sept.* **2018**, 51–65. Available online: https://www.bis.org/publ/qtrpdf/r_qt1809f.htm (accessed on 11 August 2026).
6. Shanaev, S.; Sharma, S.; Ghimire, B.; Shuraeva, A. Taming the Blockchain Beast? Regulatory Implications for the Cryptocurrency Market. *Res. Int. Bus. Financ.* **2020**, *51*, 101080. [[CrossRef](#)]
7. Borri, N.; Shakhnov, K. Regulation Spillovers across Cryptocurrency Markets. *Financ. Res. Lett.* **2020**, *36*, 101333. [[CrossRef](#)]
8. Corbet, S.; Lucey, B.M.; Meegan, A.; Yarovaya, L. The Impact of Macroeconomic News on Bitcoin Returns. *Eur. J. Financ.* **2020**, *26*, 1396–1416. [[CrossRef](#)]
9. Corbet, S.; Larkin, C.; Lucey, B. The Contagion Effects of the COVID-19 Pandemic: Evidence from Gold and Cryptocurrencies. *Financ. Res. Lett.* **2020**, *35*, 101554. [[CrossRef](#)]
10. MacKinlay, A.C. Event Studies in Economics and Finance. *J. Econ. Lit.* **1997**, *35*, 13–39. Available online: <https://www.bu.edu/econ/files/2011/01/MacKinlay-1996-Event-Studies-in-Economics-and-Finance.pdf> (accessed on 11 August 2026).
11. Brown, S.J.; Warner, J.B. Using Daily Stock Returns: The Case of Event Studies. *J. Financ. Econ.* **1985**, *14*, 3–31. [[CrossRef](#)]
12. Boehmer, E.; Musumeci, J.; Poulsen, A.B. Event-Study Methodology under Conditions of Event-Induced Variance. *J. Financ. Econ.* **1991**, *30*, 253–272. [[CrossRef](#)]
13. Kolari, J.W.; Pynnönen, S. Event Study Testing with Cross-Sectional Correlation of Abnormal Returns. *Rev. Financ. Stud.* **2010**, *23*, 3996–4025. [[CrossRef](#)]
14. Griffin, J.M.; Shams, A. Is Bitcoin Really Untethered? *J. Financ.* **2020**, *75*, 1913–1964. [[CrossRef](#)]
15. Shanaev, S.; Sharma, S.; Ghimire, B.; Shuraeva, A. Cryptocurrency Value and 51% Attacks: Evidence from Event Studies. *J. Altern. Investig.* **2019**, *22*, 65–77. [[CrossRef](#)]
16. Wuille, P.; Lombrozo, E.; Lau, J. BIP 141: Segregated Witness (Consensus Layer). 2015. Available online: <https://bips.xyz/141/> (accessed on 11 August 2026).
17. Wuille, P. BIP 341: Taproot—SegWit Version 1 Spending Rules. 2020. Available online: <https://bips.xyz/341/> (accessed on 11 August 2026).
18. Poon, J.; Dryja, T. The Bitcoin Lightning Network: Scalable Off-Chain Instant Payments. 2016. Available online: <https://lightning.network/lightning-network-paper.pdf> (accessed on 11 August 2026).
19. Boissay, F.; Ehlers, T.; Shin, H.S. Blockchain Scalability and the Fragmentation of Crypto. BIS Bulletin 2022, No. 56. Available online: <https://www.bis.org/publ/bisbull56.pdf> (accessed on 11 August 2026).
20. European Parliament and Council. Regulation (EU) 2023/1114 of 31 May 2023 on Markets in Crypto-Assets. *Off. J. Eur. Union* **2023**, *L150*, 40–205. Available online: <https://eur-lex.europa.eu/eli/reg/2023/1114/oj/eng> (accessed on 11 August 2026).
21. Financial Action Task Force. *Updated Guidance for a Risk-Based Approach to Virtual Assets and Virtual Asset Service Providers*; FATF: Paris, France, 2021. Available online: <https://www.fatf-gafi.org/content/dam/fatf-gafi/guidance/Updated-Guidance-VA-VASP.pdf> (accessed on 11 August 2026).
22. Chainalysis. *The 2024 Geography of Crypto Report*; Chainalysis: New York, NY, USA, 2024. Available online: <https://www.chainalysis.com/wp-content/uploads/2024/10/the-2024-geography-of-crypto-report-release.pdf> (accessed on 11 August 2026).
23. Federal Bureau of Investigation. Ross Ulbricht, Alleged Owner and Operator of “Silk Road” Website, Arrested in New York. 2 October 2013. Available online: <https://www.fbi.gov/news/stories/ross-ulbricht-alleged-owner-and-operator-of-silk-road-website-arrested> (accessed on 11 August 2026).
24. Weisenthal, J. Bitcoin Plunges as Major Exchange Mt. Gox Halts All Withdrawals. *Business Insider*. 7 February 2014. Available online: <https://www.businessinsider.com/mtgox-halts-withdrawals-2014-2> (accessed on 11 August 2026).
25. McMillan, R. The Inside Story of Mt. Gox, Bitcoin’s \$460 Million Disaster. *Wired*. 3 March 2014. Available online: <https://www.wired.com/2014/03/bitcoin-exchange/> (accessed on 11 August 2026).
26. The Block. Bitcoin Halving Tracker. Available online: <https://www.theblock.co/trackers/bitcoin-halving> (accessed on 11 August 2026).
27. Nelson, D. Bitcoin Blockchain Has Fourth Halving in 15-Year history. *CoinDesk*. 20 April 2024. Available online: <https://www.coindesk.com/tech/2024/04/20/bitcoin-blockchain-has-fourth-halving-in-15-year-history-in-show-of-monetary-policy-set-by-code> (accessed on 11 August 2026).
28. MicroStrategy Incorporated. MicroStrategy Announces \$250 Million Capital Allocation Strategy, Purchases 21,454 Bitcoins. 11 August 2020. Available online: <https://www.sec.gov/Archives/edgar/data/1050446/000119312520215604/d921849dex991.htm> (accessed on 11 August 2026).

29. Tesla Inc. Annual Report on Form 10-K for the Year Ended 31 December 2020. Filed 8 February 2021. Available online: https://www.sec.gov/Archives/edgar/data/1318605/000156459021004599/tsla-10k_20201231.htm (accessed on 11 August 2026).
30. Coinbase Global Inc. Coinbase Announces Effectiveness of Registration Statement and Anticipated Listing Date on the Nasdaq Global Select Market. 1 April 2021. Available online: <https://investor.coinbase.com/news/news-details/2021/Coinbase-Announces-Effectiveness-of-Registration-Statement-and-Anticipated-Listing-Date-of-its-Class-A-Common-Stock-on-the-Nasdaq-Global-Select-Market/default.aspx> (accessed on 11 August 2026).
31. Reuters. China Vows to Crack Down on Bitcoin Mining, Trading Activities. 21 May 2021. Available online: <https://www.reuters.com/technology/china-says-it-will-crack-down-bitcoin-mining-trading-activities-2021-05-21/> (accessed on 11 August 2026).
32. Banco de España. The Role of Cryptoassets as Legal Tender: The Example of El Salvador. Economic Bulletin 2021, 4/2021. Available online: <https://www.bde.es/f/webbde/SES/Secciones/Publicaciones/Publicaciones/InformesBoletinesRevistas/ArticulosAnaliticos/21/T4/Files/be2104-art35e.pdf> (accessed on 11 August 2026).
33. Alvarez, F.; Argente, D.; Van Patten, D. Are Cryptocurrencies Currencies? Bitcoin as Legal Tender in El Salvador. *Science* **2023**, *382*, eadd2844. [CrossRef]
34. ProShares. ProShares to Launch the First U.S. Bitcoin-Linked ETF on 19 October. 18 October 2021. Available online: <https://www.proshares.com/press-releases/proshares-to-launch-the-first-u.s.-bitcoin-linked-etf-on-october-19> (accessed on 11 August 2026).
35. Reuters. Bitcoin Drops as Wall Street Shares Tumble. 9 May 2022. Available online: <https://www.reuters.com/business/finance/bitcoin-falls-lowest-since-january-line-with-tumbling-stock-markets-2022-05-09/> (accessed on 11 August 2026).
36. Kerber, R.; Soni, A. Behind FTX's Fall, Battling Billionaires and a Failed Bid to Save Crypto. *Reuters*. 10 November 2022. Available online: <https://www.reuters.com/technology/exclusive-behind-ftxs-fall-battling-billionaires-failed-bid-save-crypto-2022-11-10/> (accessed on 11 August 2026).
37. Reuters. Crypto Exchange FTX Files for U.S. Bankruptcy Protection. 11 November 2022. Available online: <https://www.reuters.com/business/ftx-start-us-bankruptcy-proceedings-ceo-exit-2022-11-11/> (accessed on 11 August 2026).
38. U.S. Securities and Exchange Commission. Statement on the Approval of Spot Bitcoin Exchange-Traded Products. 10 January 2024. Available online: <https://www.sec.gov/newsroom/speeches-statements/gensler-statement-spot-bitcoin-011023> (accessed on 11 August 2026).
39. Reuters. Bitcoin Leaps to Record High as Traders Lean toward Trump Victory. 6 November 2024. Available online: <https://www.reuters.com/technology/bitcoin-leaps-record-high-traders-lean-towards-trump-victory-2024-11-06/> (accessed on 11 August 2026).
40. Coin Metrics. Free Coin Metrics Data Archives—Bitcoin Community Network Data. Available online: <https://raw.githubusercontent.com/coinmetrics/data/master/csv/btc.csv> (accessed on 11 August 2026).
41. Benjamini, Y.; Hochberg, Y. Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *J. R. Stat. Soc. Ser. B* **1995**, *57*, 289–300. [CrossRef]
42. FJA05680. S&P 500 Historical Daily Data—SP500.csv. GitHub Repository. Available online: <https://raw.githubusercontent.com/fja05680/dow-sp500-100-years/master/SP500.csv> (accessed on 11 August 2026).
43. Federal Reserve Bank of St. Louis. Trade Weighted U.S. Dollar Index: Broad, Goods and Services (DTWEXBGS). *FRED*. Available online: <https://fred.stlouisfed.org/series/DTWEXBGS> (accessed on 11 August 2026).

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