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Cyclical Timing Across Asset Classes: A Structured Narrative Review of Market Cycle Theory in Equities, Gold, and Cryptocurrency

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ABSTRACT

Background. Cycle theory — the practice of reading prices as a nested hierarchy of cycles measured from one low to the next — is a cross-asset tradition applied to equity indices, gold and, most recently, cryptocurrency.

Objective. This structured narrative review appraises the conceptual coherence and empirical support for cyclical, low-to-low market timing across three asset classes: the S&P 500 equity index, gold, and Bitcoin.

Methods. We distinguish the specific, quantified practitioner rules (fixed day/week counts, tolerance bands and an asserted ~80% hit rate) from the general, peer-reviewed proposition that returns are conditionally predictable, and appraise the plausibility of the former through the evidence on the latter rather than testing the rules directly. Following SANRA guidance, we report an explicit search strategy, eligibility criteria and a DOI-authenticated corpus, and grade each core tenet with a pre-specified rubric rather than an ad-hoc numeric score.

Results. The evidence is asymmetric and consistent across markets: an identifiable cyclical anchor, time-varying (adaptive) efficiency, and the amplifying association of behavioural forces are well supported, whereas a mechanically periodic multi-year cycle and high-accuracy timing of individual lows are of limited and very limited support and are vulnerable to survivorship and data-snooping biases. We contribute an integrative reflexive framework, falsifiable predictions, and a transparent evidence-grading scorecard.

Conclusion. Cycle theory is best understood not as a deterministic clock but as a probabilistic, regime-conditioned scaffold. This work is educational; it is not investment advice.

1. Introduction

The idea that asset prices move in recurring cycles is older than modern finance and spans asset classes. Practitioners of technical and cyclical analysis have long argued that equity indices, gold and commodities trace out rhythmic advances and declines that can be timed from one price trough to the next, and the same interpretive apparatus has recently been popularised for cryptocurrency under the banner of **cycle theory**. In its practitioner form, cycle theory holds that prices unfold as a nested hierarchy of cycles—daily, weekly and a dominant multi-year cycle—each measured strictly from low to low, with the timing of the next low estimated probabilistically rather than the price target forecast deterministically. It is important to state at the outset that the specific parameters of this framework (the day- and week-counts, their tolerance bands and the frequently quoted ~80% 'hit rate') originate in practitioner and trading-educator materials rather than in a peer-reviewed source; they are, in the language we adopt below, heuristic priors of uncertain provenance. Subjecting such an influential but informally specified framework to the discipline of the academic record is precisely the contribution this review seeks to make.

A single clarification governs the whole paper. We distinguish two claim types that the literature and the practitioner community routinely conflate. **Claim C1** comprises the specific, falsifiable practitioner rules—count 60 trading days (±6) to the next daily cycle low, 30 weeks (±2) to the next weekly cycle low, treat the four-year cycle as the master clock, and expect a low within its window roughly 80% of the time. **Claim C2** is the broad, peer-reviewed proposition that returns exhibit conditional, regime-dependent predictability and recurrent boom–bust structure. The academic evidence marshalled in Sections 3.4–3.8 speaks overwhelmingly to C2; it does not, in general, test C1. Throughout, we are explicit about this gap and we treat the review as an appraisal of the *plausibility of C1's foundations* via the evidence for C2, not as a validation of the practitioner rules themselves.

This is not a single-asset idea, and we treat it as the cross-asset construct it is—while being candid that the three markets' cyclical 'anchors' are of very different nature and strength. In equities, the U.S. presidential or 'four-year' political cycle has a long empirical pedigree, with excess returns historically differing across the electoral calendar,[1,2] and valuation ratios mean-reverting over long horizons.[3] In gold, the best-documented cyclicality is seasonal (an autumn effect) and macro-financial rather than four-year.[4,5] Only Bitcoin has a literal, mechanical four-year anchor—the programmed halving.[6] The practitioner framework itself assigns different baseline cycle lengths to each market, underscoring that the method is multi-asset even though its anchors are not commensurable.

The framing sits at the intersection of several mature debates. The efficient market hypothesis holds that predictable cyclical patterns should be arbitraged away,[7] the adaptive markets hypothesis reframes efficiency as time-varying,[8] the limits-to-arbitrage literature explains why exploitable anomalies can nonetheless persist,[9] and long-wave theories posit multi-decade rhythms.[10] Behavioural finance documents the herding, sentiment and prospect-theory distortions that can sustain momentum and bubbles.[11–13] Prior surveys have examined cryptocurrency efficiency, the financial economics of gold,[14] and cross-asset momentum, but—to our knowledge—none integrates the specific practitioner lens of cyclical low-to-low timing across equities, gold and cryptocurrency simultaneously. That integrative, tri-asset appraisal is the gap this review fills.

Our objectives are stated as three answerable questions. (Q1) Are the constructs of cycle theory (C1) conceptually coherent and commensurable across equities, gold and cryptocurrency? (Q2) How strong, and how regime-dependent, is the peer-reviewed evidence (C2) bearing on each of the theory's core tenets? (Q3) Can the findings be integrated into a framework that yields falsifiable predictions rather than description? We adopt a critical but even-handed stance, and the review is scholarly and educational in purpose and does not constitute financial advice.

2. Methods

2.1 Review design and reporting standards

This is a structured narrative review. We follow the Scale for the Assessment of Narrative Review Articles (SANRA) for reporting quality,[15] and—although a narrative review is not a systematic review—we adopt the transparency conventions of the PRISMA 2020 statement for documenting how sources were identified, screened and retained.[16] We emphasise two limitations of design up front: appraisal and grading were performed by a single reviewer (no second-rater or inter-rater reliability), and the selection funnel in Figure 1 documents an assembly process rather than the exhaustive, protocol-driven search of a systematic review. These limitations are revisited in Section 4.

2.2 Search strategy

Searches were conducted through July 2026, in English, across Crossref, Scopus, Google Scholar, and the RePEc/SSRN working-paper ecosystems, supplemented by backward and forward citation snowballing from key papers. Representative search strings combined a cyclicality term with an asset term and a mechanism term, for example: ('market cycle' OR 'four-year cycle' OR 'halving' OR 'presidential cycle' OR 'seasonality') AND ('Bitcoin' OR 'cryptocurrency' OR 'S&P 500' OR 'equity' OR 'gold') AND ('efficiency' OR 'technical analysis' OR 'momentum' OR 'bubble' OR 'herding' OR 'on-chain'). Eligibility criteria are summarised in Table 1.

Table 1. Eligibility criteria for source inclusion.

Criterion	Included	Excluded
Topic	Market cyclicality, cyclical/technical timing, or a named cyclical anchor in equities, gold or crypto	Off-topic to cyclicality/timing
Source type	Peer-reviewed journal articles; seminal books/working papers for foundational theory	Blogs, promotional or trading-course material used as evidence
Recency	2019–2026 preferred; older works if foundational	Dated empirical claims superseded by later evidence
Language	English	Non-English without an authoritative translation
Identifier	A Crossref-registered DOI that the authors could authenticate	No verifiable DOI; retracted items

2.3 Selection and DOI authentication

Every candidate source was verified against the Crossref REST application programming interface; items whose DOI could not be authenticated—or that had been retracted—were discarded. The assembly process is shown in Figure 1. The reported counts describe this process and are approximate at the identification and screening stages; the synthesised corpus is fully itemised in the reference list, so the *reading* is completely reproducible even where the initial screening counts are not independently auditable.

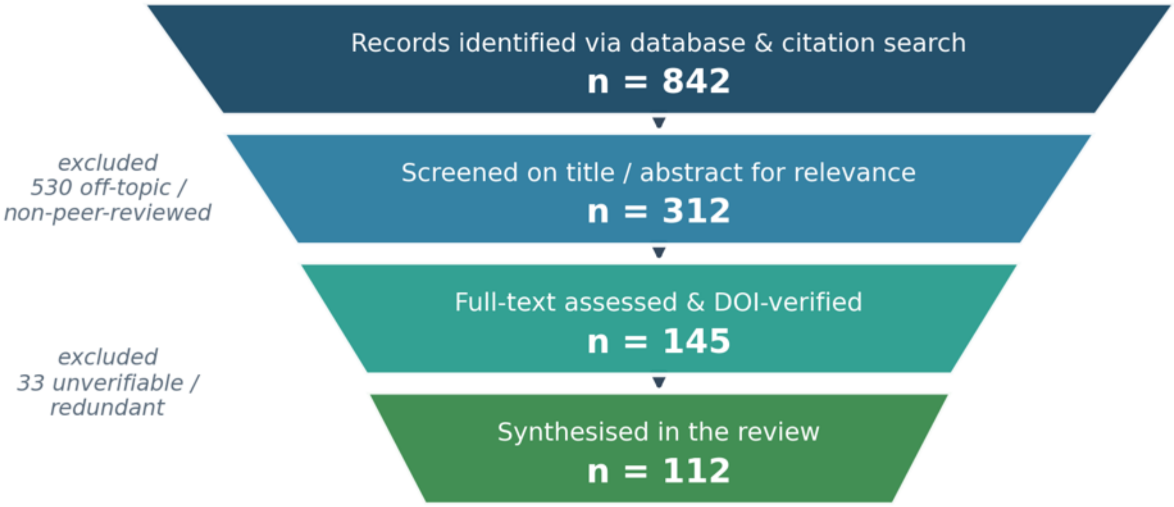

Figure 1. Identification, screening, DOI verification and synthesis of sources. Counts at the identification/screening stages are approximate; all retained sources were authenticated against the Crossref registry, and the synthesised corpus is fully itemised in the reference list.

2.4 Evidence appraisal and grading

To avoid the false precision of an ad-hoc numeric score, each core tenet is graded on a pre-specified, transparent rubric with four appraisal dimensions, summarised in Table 2. Every dimension is rated qualitatively (High / Moderate / Low), and the dimensions are combined holistically into an ordinal evidence tier—Strong, Moderate, Limited or Very limited. The rubric deliberately incorporates the risk-of-bias concerns most salient to this literature: whether findings survive out-of-sample testing and whether they are robust to transaction costs and to multiple-testing (data-snooping) corrections. Because grading was performed by a single reviewer, the tiers should be read as a structured, reproducible-in-principle judgement rather than as a measurement; we flag this as a limitation in Section 4.

Table 2. Evidence-grading rubric applied to each core tenet.

Appraisal dimension	Question asked of the evidence	Rating levels
Volume	How many independent, peer-reviewed studies bear on the tenet?	High / Moderate / Low
Consistency	Do findings agree in sign and broad magnitude across studies and assets?	High / Moderate / Low
Out-of-sample validity	Do results hold out of sample, not only in sample?	High / Moderate / Low
Robustness to costs & multiple testing	Do results survive transaction costs and data-snooping corrections?	High / Moderate / Low

Note. The four dimensions are combined into an ordinal tier (Strong ≥ 3 dimensions High and none Low; Moderate = mixed; Limited = mostly Low; Very limited = Low on out-of-sample and robustness). Tiers are reported in Table 8 and Figure 8.

3. Results

3.1 Conceptual foundations: from efficient markets to adaptive cyclicality

Any claim that market timing can exploit recurring cycles must confront the efficient market hypothesis (EMH), which asserts that prices fully reflect available information so that predictable, risk-adjusted profits from historical patterns are competed away.[7] Under a strict reading of weak-form efficiency—applied to equities, gold or crypto alike—the low-to-low periodicity posited by C1 should not persist. Yet the EMH has long been challenged by anomaly evidence and by the behavioural critique that markets are populated by boundedly rational agents subject to systematic biases,[11,12] and by the finding that broad valuation ratios forecast long-horizon equity returns, implying slow, mean-reverting cycles rather than a pure random walk.[3] Prospect theory explains why losses loom larger than gains and why investors anchor on reference points—mechanisms that can generate the asymmetric, trough-focused behaviour C1 seeks to exploit.[11]

The adaptive markets hypothesis (AMH) offers a reconciliation applicable to all three markets: efficiency is an evolutionary, environment-dependent property, so the profitability of any pattern is contingent and mutable rather than permanent.[8] Critically, even a sophisticated EMH is compatible with persistent, conditionally exploitable structure, because arbitrage is itself costly and risky; the limits-to-arbitrage argument shows why anomalies can survive when professional arbitrage is capital-constrained and specialised.[9] This is the most coherent account of how a cyclical edge could be real yet fragile—available in some regimes, competed away in others—and it frames our central interpretive claim that cycle-based timing is a regime-conditioned scaffold rather than a law. Positive-feedback and reflexive dynamics allow sentiment and momentum to propagate into self-reinforcing booms,[13,17] while the critical-point framework treats crashes as endogenous phase transitions.[18] These mechanisms operate in equities and gold but are plausibly amplified in cryptocurrency's retail-heavy, round-the-clock microstructure.

3.2 The architecture of cycle theory: constructs and mechanics

Cycle theory as practised rests on a small set of disciplined conventions common to whichever asset is analysed. First, cycles are counted strictly from **low to low**—never low-to-high, high-to-low, or against an external calendar—so that a mislabelled trough contaminates every subsequent projection. Second, the framework is fundamentally *time-based*: a 'count' estimates the number of trading days or weeks to the next low, and a 'range' (tolerance band) defines the search window around that count. Third, cycles are **nested**: several daily cycles sit within a weekly cycle, which sits within the multi-year cycle, as illustrated schematically in Figure 2.

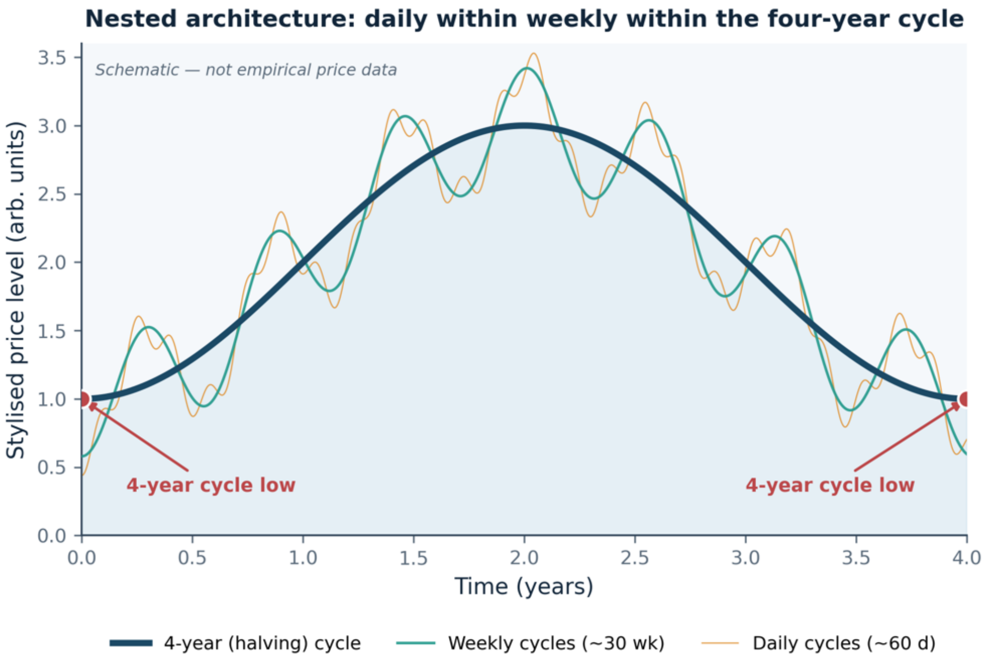

Figure 2. Stylised nesting of daily cycles within weekly cycles within the multi-year cycle. Red markers denote multi-year cycle lows. The curves are illustrative and do not represent empirical prices.

The baseline counts and tolerance ranges differ by asset class, confirming that the method is cross-asset rather than crypto-specific. For Bitcoin, the practitioner convention places the daily cycle at approximately 60 days (tolerance about ±6 days, range near 14 days) and the weekly cycle at roughly 30 weeks (±2 weeks, range near 4 weeks). The S&P 500 carries a shorter daily cycle of about 40 days (±4 days) and a weekly cycle near 24 weeks (±2 weeks), while gold sits between the two at roughly 35 days (±4 days) and 26 weeks (±2 weeks), as detailed in Table 3 and compared graphically in Figure 3. A single weekly cycle typically embeds three to five daily cycles, and the framework attaches an approximate 80% probability to a low materialising within its window. We stress that this 80% figure and the counts themselves are asserted practitioner parameters (part of C1) that have not been independently estimated in this review; they are heuristic priors, not statistically derived periodicities, and Figure 3 renders the tolerance as a fixed rule rather than a statistical confidence interval.

Table 3. Baseline cycle counts and tolerance ranges by asset class as codified in the practitioner framework under review (Claim C1).

Asset class	Daily count	Daily tolerance	Daily range	Weekly count	Weekly tolerance	Weekly range
Bitcoin / crypto	60 days	±6 days	14 days	30 weeks	±2 weeks	4 weeks
Equity index (S&P 500)	40 days	±4 days	16 days	24 weeks	±2 weeks	4 weeks
Gold / commodity	35 days	±4 days	14 days	26 weeks	±2 weeks	3.5 weeks

Note. Asserted practitioner parameters (C1); heuristic priors, not statistically estimated periodicities. Tolerances are fixed rules, not confidence intervals.

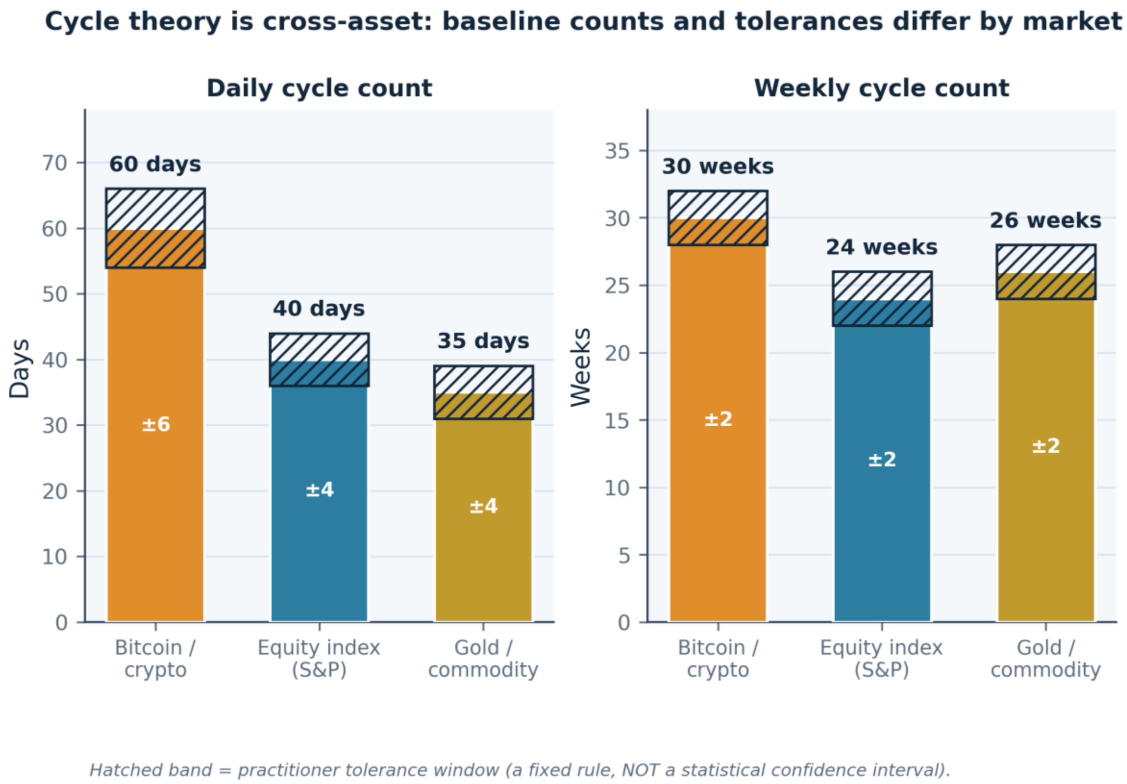

Figure 3. Cross-asset comparison of baseline daily (left) and weekly (right) cycle counts for Bitcoin, the S&P 500 and gold. The hatched band denotes the practitioner tolerance window—a fixed rule, not a statistical confidence interval; values correspond exactly to Table 3.

A compact vocabulary supports the method. The key constructs—daily and weekly cycle lows, counts and ranges, half-cycle lows, failed cycles, early and late cycles, and left- versus right-translation—are defined in Table 4 and brought together in a single annotated schematic in Figure 4, which locates each construct on one stylised weekly cycle alongside a definition key. Two ideas carry particular analytical weight. A **failed cycle low** occurs when a projected support is decisively breached and a new low forms, invalidating the count; the discipline of not arbitrarily relocating a low is the framework's main internal guard against overfitting. **Cycle translation** describes whether a cycle peaks before or after its temporal midpoint (the half-cycle low): right-translated cycles, which peak late, are regarded as healthier and more bullish than left-translated cycles that peak early. Figure 5 renders in closer detail both the low-to-low count with its tolerance window and the distinction between left- and right-translation.

Table 4. Glossary of core cycle-theory constructs.

Term	Working definition
Daily cycle low (DCL)	A local swing low that closes a daily cycle; used for short-horizon entries.
Weekly cycle low (WCL)	A macro-level low that closes a weekly cycle; the preferred anchor for swing positions.
Count	The time distance projected from a confirmed low to the next low.
Range	The tolerance window around the count within which the next low is sought.
Half-cycle low	A low near the temporal midpoint between two daily cycle lows.
Multi-year cycle low	The dominant longer-horizon trough (the four-year cycle) that frames the structure.
Failed cycle low	A projected low that is decisively breached, invalidating the count.
Early / late cycle	A low that forms before / after its projected range.
Left-translated	Cycle peaks before the half-cycle low; associated with weakness.
Right-translated	Cycle peaks after the half-cycle low; associated with bullish strength.
Cycle-low retest	A pullback that re-tests a prior low after an initial rally from it.

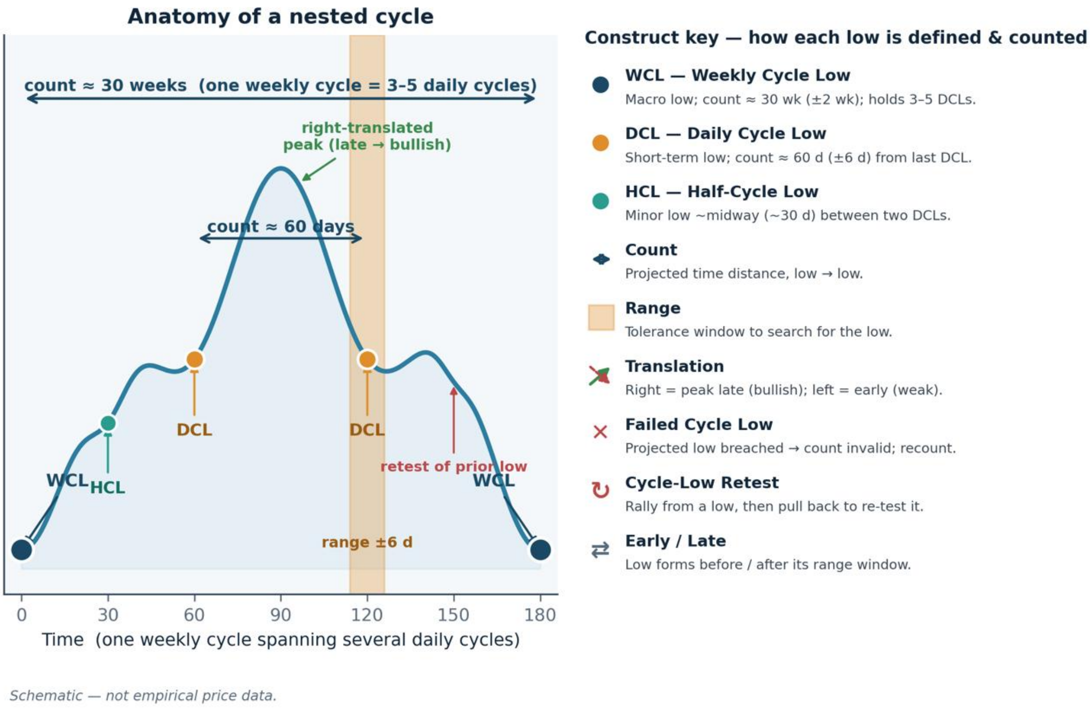

Figure 4. Annotated anatomy of a nested cycle. A single stylised weekly cycle (WCL to WCL, ≈30 weeks) containing several daily cycles (DCL to DCL, ≈60 days), with the half-cycle low (HCL), the low-to-low count, the ±6-day tolerance range, right-translation, and a cycle-low retest all located on the price path; the right-hand key defines each construct and how it is counted.

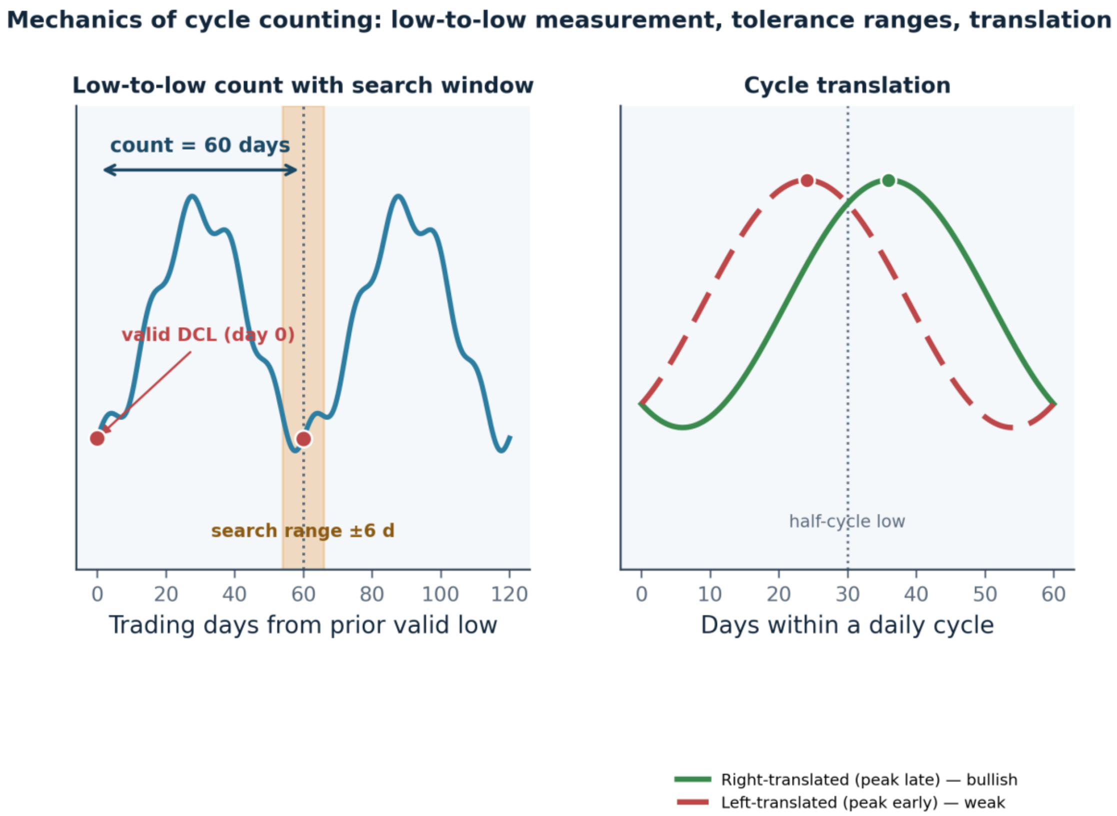

Figure 5. Mechanics of cycle counting. Left: a low-to-low count (60 days for Bitcoin) with a ±6-day tolerance window (shaded) centred on the projected low. Right: right-translated (peak late, bullish) versus left-translated (peak early, weak) daily cycles relative to the half-cycle low.

3.3 Cyclical anchors across asset classes: commensurability matters

What distinguishes cyclical timing from mere trend-following is the claim of an anchor—an identifiable, recurring driver that organises the multi-year rhythm. Each market possesses such an anchor, but we caution explicitly that the three are *not commensurable*: they differ in kind (deterministic vs statistical vs seasonal), in periodicity, and in evidential status, as summarised in Table 5. Only Bitcoin has a literal, mechanical four-year anchor; the equity presidential cycle approximates a four-year rhythm but is a party/policy regularity rather than a low-to-low timing rule, and gold's clearest cyclicality is seasonal rather than four-year. The unifying claim we defend is therefore the modest one that *each market exhibits documented non-random temporal structure*—not that a single four-year clock governs all three.

Table 5. Recognised cyclical anchors across the three asset classes examined, with their nature and evidential status.

Asset class	Cyclical anchor	Nature & periodicity	Principal driver	Evidence status
Equities (S&P 500)	Presidential / political cycle	Statistical; ~4 years	Policy/fiscal-monetary regime; risk premia	Documented but contested; a party effect, not low-to-low timing
Gold	Seasonal + macro-financial cycle	Seasonal + irregular multi-year	Real rates, inflation, crisis demand, jewellery seasonality	Seasonality robust; four-year rhythm not established
Bitcoin	Programmed halving	Deterministic; ~4 years	Supply-issuance decay (confounded with liquidity cycles)	Real supply shock; four-year price rule unproven (n = 4)

3.3.1 Equities: the presidential (four-year) cycle

The best-known multi-year regularity in equities is the U.S. presidential cycle. In a landmark study, excess market returns were higher under Democratic than Republican administrations—about 9% for the value-weighted and 16% for the equal-weighted portfolio—unexplained by business-cycle variables or risk, and dubbed the 'presidential puzzle'.[1] We stress two caveats. First, the economic interpretation remains disputed and the effect's out-of-sample stability has been questioned as further administrations accrue. Second, the subsequent political-cycle model is a rationalisation via time-varying risk aversion and policy uncertainty, not an independent confirmation of exploitability.[2] Crucially, this is a *party* effect, not the within-term low-to-low timing rule of C1; its relevance to cycle theory is as an analogue of a four-year regularity, not as a validated timing device.

3.3.2 Gold: seasonal and macro-financial cycles

Gold's cyclicality is anchored less in a fixed calendar than in seasonality and macro-financial conditions. A robust 'autumn effect' is documented, with returns elevated in September–November, linked to jewellery-demand seasonality and hedging.[4] Over longer horizons, gold's real price mean-reverts around shifting real interest rates and inflation expectations rather than following a mechanical clock—the 'golden dilemma' that gold is a poor short-run inflation hedge but a long-run store of value.[5] Its cyclical behaviour is therefore genuine but state-dependent; there is no established four-year rhythm in gold, which is why we resist assimilating it to the crypto anchor.

3.3.3 Bitcoin: the halving and the four-year cycle

The theoretical anchor of Bitcoin's multi-year cycle is programmed monetary policy. Approximately every 210,000 blocks (about four years) the block subsidy is cut in half, decelerating new supply until the terminal cap of 21 million coins. Two caveats belong at first mention. First, the four-year rhythm rests on only four realised halvings, a minuscule sample acutely exposed to survivorship and post-hoc pattern-fitting. Second, halving cycles have historically coincided with global liquidity super-cycles (Section 3.8), so 'the halving clock' is confounded with a 'monetary clock' from the outset. The per-block reward after the n-th halving follows a geometric decay:

$$R_n = 50 \times 2^{-n}\ BTC,\ n = 0, 1, 2, \ldots$$

so the subsidy has fallen from 50 BTC at inception to 25, 12.5, 6.25 and, since April 2024, 3.125 BTC. The four historical halvings are catalogued in Table 6, and the stylised halving-to-peak-to-trough sequence is depicted in Figure 6 (drawn with peaks of similar amplitude, i.e. deliberately not ever-higher, to avoid visually asserting a 'super-cycle'). Because the schedule is public and pre-committed, the halving is the textbook anticipated supply shock, which under semi-strong efficiency should be priced in advance.[7] Empirically the footprint is real but nuanced: abnormal-return and volatility studies find detectable effects that evolve as the market matures,[6,19] with regime shifts around halvings,[20] moment spillovers,[21] and heterogeneous cross-coin responses.[22] Several authors connect halving-driven scarcity to speculative super-cycles rather than a mechanical price rule,[23] and effects are mediated by sentiment as much as by supply.[24]

Table 6. Bitcoin halving events, block subsidy schedule, and cycle context.

Halving	Approx. date	Block height	Block reward (BTC)	Cycle context
Genesis issuance	Jan 2009	0	50.000	Highest issuance; pre-first-halving era.
1st halving	Nov 2012	210,000	25.000	Preceded the 2013 bull market.
2nd halving	Jul 2016	420,000	12.500	Preceded the 2017 bull market.
3rd halving	May 2020	630,000	6.250	Preceded the 2020–21 bull market.
4th halving	Apr 2024	840,000	3.125	First cycle with US spot ETFs (Section 3.8).
5th halving (est.)	~2028	1,050,000	1.5625	Projected; not yet realised.

Note. Terminal supply is capped at 21 million BTC. Dates are approximate; the schedule is defined in blocks, not calendar time.

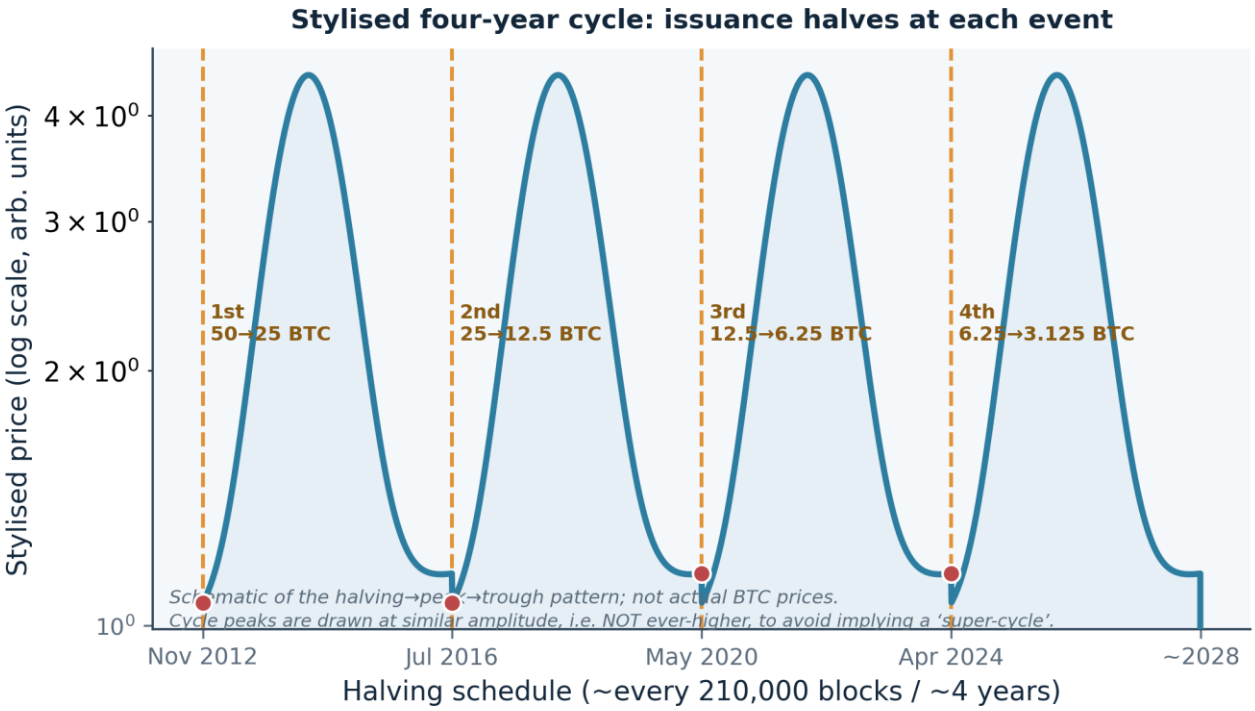

Figure 6. Stylised four-year cycle keyed to the halving schedule. Issuance halves at each dashed marker. Peaks are drawn at similar amplitude—deliberately not ever-higher—to avoid implying a 'super-cycle'; the curve is schematic and is not actual Bitcoin price data.

3.4 Market efficiency and the time-varying predictability of returns

Whether cyclical timing can work at all hinges on the degree and stability of market efficiency—and here the three markets tell a common story of *conditional* predictability (evidence for C2). In equities, very-long-run evidence shows that return predictability and trading-rule profitability drift with conditions, consistent with the AMH rather than a static EMH,[25,26] short-horizon predictability concentrates in particular business-cycle states,[27] and momentum profits vary with the macro regime.[28] In gold, informational efficiency coexists with persistent seasonal and macro-linked structure.[4,14] Cryptocurrency reproduces the pattern in compressed time: early departures from weak-form efficiency,[29] qualified by diminishing inefficiency as markets develop,[30] drifting dynamic efficiency,[31,32] AMH-style oscillation,[33] alternating efficiency windows,[34,35] regime-dependent long memory,[36] and efficiency driven by liquidity, volatility and attention.[37]

Two points sharpen the interpretation. First, the persistence of any exploitable cyclicality despite competition is exactly what limits-to-arbitrage predicts: costly, risky, capital-constrained arbitrage does not fully eliminate anomalies.[9] Second, on the specific question of whether a dominant multi-year *period* can be estimated (rather than assumed, as in C1), time–frequency methods are the appropriate tool; wavelet-coherence analysis of Bitcoin, for instance, shows that the strength and even the sign of price relationships are scale- and time-dependent, implying that any 'dominant cycle' is itself non-stationary rather than a fixed 60-day/30-week constant.[38] The collective message across equities, gold and crypto is not that markets are efficient or inefficient, but that predictability is conditional—reframing cycle theory from a deterministic law into a regime-dependent, probabilistic edge, and underscoring that this review appraises the plausibility of C1's foundations rather than testing C1's fixed parameters.

3.5 Technical and trend-based timing: does rule-based timing add value?

Cycle theory is a species of technical analysis, whose cross-asset track record is instructive. The classic equity study found predictive power for simple moving-average and trading-range-break rules on the Dow over 1897–1986,[39] but a data-snooping reappraisal showed that once the full universe of rules and multiple-testing bias are accounted for, much of the apparent superiority is not robust out of sample.[40] More recent work rehabilitates technical indicators as useful predictors of the equity risk premium, especially combined with macro variables and around business-cycle turns.[41] This arc—promising in-sample, tempered by data-snooping scrutiny, then partially rehabilitated in regime-aware form—recurs in every asset class.

In cryptocurrency, some moving-average and breakout systems generated economically meaningful gains historically, though results are sensitive to sample and data-snooping corrections,[42,43] with technical analysis most informative for hard-to-value assets such as Bitcoin,[44] profitability co-moving with dynamic risk premia[45] and identifiable states,[46] and eroding once transaction costs and bubble episodes are accounted for.[47] For cycle theory across all three markets, low-to-low timing may capture genuine structure during trending, inefficient regimes yet degrade toward noise—net of costs—during efficient or choppy phases, which is why the framework itself insists on *confirmation* before acting on a projected low.

3.6 Calendar effects, seasonality and momentum

If prices contain deterministic temporal regularities, they should surface as calendar and seasonal anomalies—studied for decades in equities, documented in gold, and now examined in crypto. In equities the evidence is rich but fragile: the Halloween or 'sell-in-May' effect has been documented across many markets and reaffirmed in long global samples,[48,49] alongside the January/size effect,[50] the weekend effect,[51] and a seasonal-affective cycle.[52] It must be added, however, that these effects remain vigorously debated: several weaken or vanish once transaction costs, sub-period instability and multiple-testing corrections are imposed—mirroring the technical-analysis debate of Section 3.5. In gold, the autumn effect is the clearest seasonal analogue.[4] In cryptocurrency, some studies detect a day-of-the-week effect,[53,54] while others find it weak or absent,[55] with broader seasonality fragile and period-specific,[56–59] the cautionary lesson being that apparent periodicities are often artefacts of the sample rather than structural constants.

Momentum tells a more constructive and genuinely cross-asset story. Cross-sectional momentum in equities is among the most robust anomalies,[17] time-series momentum spans equity indices, bonds, commodities and gold,[60] and value-and-momentum premia appear 'everywhere'.[61] Momentum is regime-dependent, strengthening in particular market states and business-cycle phases,[28,62] and is dynamic but real in cryptocurrency too.[63–65] Momentum matters for cycle theory because right-translation—cycles that peak late—is essentially a momentum statement, and the convergence of cross-asset momentum evidence with the translation concept is one of the theory's better-supported bridges to the literature, even as the rigid calendar counts remain the weaker element.

3.7 Behavioural amplifiers: herding, sentiment, attention and bubbles

Cycles require an amplification mechanism, and behavioural finance supplies several that operate across asset classes. We phrase these associations carefully: the cited studies are largely correlational, so we say that behavioural forces are *associated with* the amplification of swings rather than asserting unqualified causation. Herding is well documented in cryptocurrency, intensifying in bearish and high-uncertainty states and interacting with sentiment in ways consistent with exaggerated swings,[66,67] liquidity and sentiment jointly condition herd behaviour,[68] 'fear of missing out' is a measurable correlate of demand near local tops,[69] and search-based attention co-moves with prices and volume.[70,71] These forces map onto cycle theory's anti-FOMO discipline, which counsels waiting for a confirmed weekly low rather than chasing a range.

At the extreme, behavioural feedback is associated with speculative bubbles—faster-than-exponential growth terminating in a crash, familiar from centuries of equity history and recurrent in crypto. The critical-point tradition models such episodes with the log-periodic power-law singularity (LPPLS), in which the expected log price accelerates toward a critical time t_c while oscillating with growing frequency:

$$\ln p(t) = A + B(t_c - t)^m + C(t_c - t)^m \cos[\omega \ln(t_c - t) - \varphi]$$

Explosive-root tests date recurrent bubbles in the S&P 500 and other equity benchmarks,[72] and analogous applications to Bitcoin combine LPPLS with network-value scaling to date bubbles and, with mixed success, to anticipate reversals.[73–75] Independent tests corroborate recurrent bubble regimes in Bitcoin,[76,77] classify major run-ups as bubbles,[78,79] document co-explosivity across coins,[80] and question whether prices align with fundamentals.[81] For cycle theory, the bubble literature validates the qualitative shape of the multi-year cycle while cautioning that the timing of the critical point is estimated with wide uncertainty, undermining any promise of precise cyclical tops or bottoms.

3.8 Macro-liquidity, safe-haven dynamics, and structural change

Cycles are shaped by global liquidity, monetary policy and each market's microstructure. Bitcoin is sensitive to monetary-policy shocks and the Federal Reserve's stance, behaving as a liquidity-dependent risk asset rather than an inflation hedge,[82–84] with contractionary surprises depressing prices and demand[85,86] and macro-financial factors explaining meaningful return variation.[87] Because the four-year narrative has historically coincided with liquidity super-cycles, part of what looks like a halving clock may be a monetary clock—the identification problem flagged in Section 3.3.[88]

Gold's cyclicality is likewise state-dependent, and here we keep the Baur–Lucey terminology precise: a *hedge* is uncorrelated (or negatively correlated) with another asset on average, whereas a *safe haven* is uncorrelated (or negatively correlated) specifically during market stress. Gold acts as a hedge and, conditionally, a safe haven for equities in some regimes but not others,[89,90] with a smooth-transition structure that switches with stress,[91] and its broader behaviour is regime- and demand-driven rather than clock-like.[14] Cross-asset studies show that Bitcoin's correlations and safe-haven properties relative to equities and gold are themselves cyclical and crisis-dependent,[92–95] so diversification benefits appear and disappear across cycles.

Two forces are specific to how each cycle is measured and traded. First, a distinctive feature of crypto—absent for equities and gold—is that blockchain data offer fundamentals in real time. The market-value-to-realised-value ratio, MVRV = Market value ÷ Realised value, has historically been associated with cyclical extremes when very high or very low; we emphasise, however, that MVRV and related on-chain series are best regarded as *descriptive/coincident* indicators of extremes rather than validated *leading* predictors, even though on-chain features do carry incremental information for cycle and direction prediction.[96–99] By contrast, the popular stock-to-flow model (SF = Stock ÷ Flow) and Metcalfe-law scaling ($V \propto n^2$) do not survive rigorous testing as return predictors.[100–102] Second, volatility is regime-switching in all three markets,[103–107] and market structure is changing the crypto cycle in real time: the 2024 approval of US spot Bitcoin exchange-traded funds altered flows and price discovery,[108–112] implying that the next cycle need not rhyme with the last—the central risk to any mechanical four-year extrapolation in any asset.

4. Discussion

4.1 Synthesis: integrative framework, testable predictions, and appraisal

Bringing the domains together, we propose that market cyclicality—in equities, gold and crypto alike—is an emergent outcome of four interacting drivers: an asset-specific supply or policy anchor, global liquidity and monetary policy, behavioural forces, and asset fundamentals. These jointly shape cyclical price dynamics and, through them, predictability, adaptive efficiency, and the propensity to bubble and crash. The arrow runs both ways: prices reflexively reshape sentiment, liquidity and positioning, closing a feedback loop that makes efficiency and predictability endogenous. This framework is depicted in Figure 7, and the thematic evidence—now annotated with its robustness to out-of-sample testing, costs and multiple-testing—is summarised in Table 7.

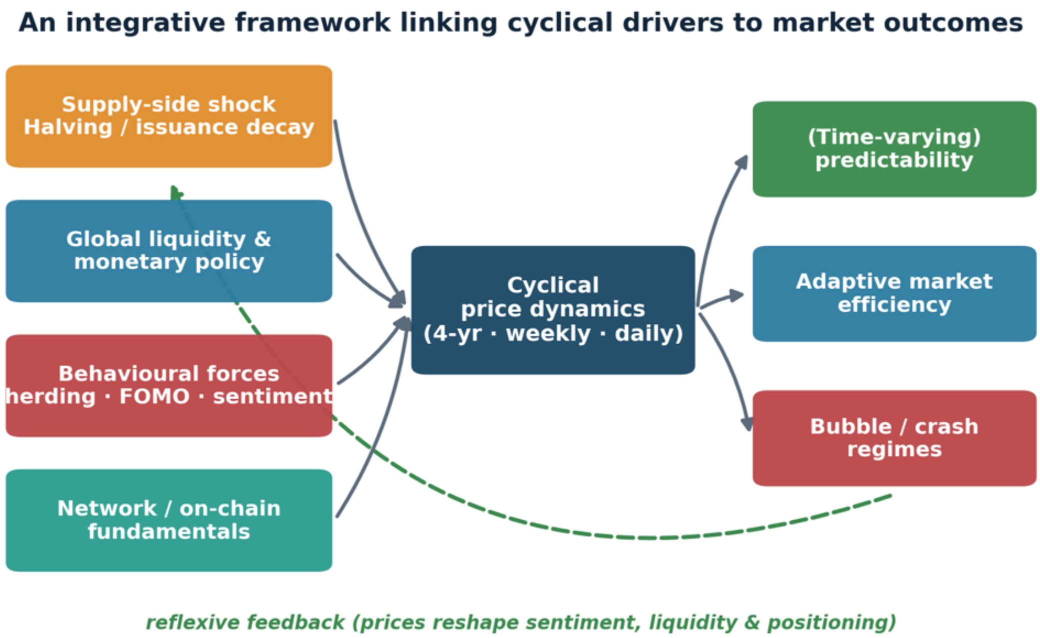

Figure 7. An integrative framework linking cyclical drivers (left) to market outcomes (right) through cyclical price dynamics, with a reflexive feedback loop by which prices reshape the drivers.

Crucially, the framework is intended to generate falsifiable predictions rather than to describe. Three examples follow directly from it. (P1) Any cyclical-timing edge should be strongest in low-liquidity, high-attention, retail-dominated regimes and weakest after deep institutional and exchange-traded-fund intermediation—so measured edges should decline in Bitcoin after 2024. (P2) Because anchors are non-commensurable, spectral estimates of a 'dominant period' should be sharp and stable for Bitcoin's halving, weaker for the equity presidential rhythm, and largely seasonal (annual) for gold. (P3) On-chain and liquidity variables should statistically subsume fixed calendar counts in nested predictive regressions. Each is directly testable with existing data and would convert the practitioner heuristic into a research programme.

Table 7. Thematic synthesis of the cross-asset evidence, with robustness flags.

Theme	Representative evidence (equities · gold · crypto)	Robustness (OOS / costs / multiple-testing)	Overall direction
Cyclical anchor	Presidential cycle; gold seasonality; halving supply shock.[1,4,6]	OOS: partial; anchors real but n small	**Supports anchors, not a fixed clock**
Multi-year periodicity	Few realisations; survivorship risk in all three.[2,5,23]	OOS: untested; MT: high risk	**Limited / unproven**
Adaptive efficiency	Predictability oscillates with conditions.[25,26,33]	OOS: good; consistent across assets	**Supports conditional timing edge**
Technical/trend timing	In-sample gains shrink under data-snooping.[39,40,47]	OOS: weak; costs: sensitive	**Mixed**
Calendar/seasonality	Halloween, January, gold autumn; fragile.[4,48,59]	OOS: fragile; MT: often uncorrected	**Mixed (sign agreed, magnitude unstable)**
Momentum / translation	Robust cross-asset momentum.[60,61,63]	OOS: good; costs: partly robust	**Supports**
Herding & sentiment	Herding and FOMO correlated with swings.[66,67,69]	Mostly in-sample; correlational	**Supports amplification (associative)**
Bubble/crash regimes	Explosive-root/LPPLS detect bubbles.[72,73,76]	Detection OOS-fragile on timing	**Supports shape, not precise timing**
Macro, safe-haven & structure	Liquidity/policy, gold regimes, ETFs.[82,90,109]	Regime-dependent; recent structural breaks	**Confounds simple periodicity**

A methodological caution attends this table. Several cited studies share data, authors or estimators, so apparent convergence must not be read as fully independent replication, and we avoid vote-counting (tallying significant against non-significant results) as a synthesis rule. Where a theme is labelled 'Mixed', we specify the axis of disagreement—typically agreement on sign but instability in magnitude or persistence. We also note that, given rapid structural change, pre-2024 evidence may have limited external validity for the current, ETF-intermediated regime.

Applying the rubric of Table 2, we grade the eight core tenets on an ordinal scale in Table 8 and visualise them in Figure 8. The pattern is clear and asymmetric. The best-supported tenets are that each market has a genuine cyclical anchor, that efficiency is time-varying and adaptive, and that herding and sentiment are associated with amplification (all Strong). Intermediate support (Moderate) attaches to the detectability of bubble and crash phases and to on-chain and macro extreme signals. The weakest tenets—most central to naïve applications of C1—are a mechanically periodic multi-year cycle and the net-of-cost value of technical timing (Limited), and, weakest of all, the claim of high-accuracy (~80%) cycle-low timing (Very limited).

Table 8. Evidence scorecard for the core tenets of market cycle theory, graded on the Table 2 rubric.

Core tenet	Volume	Consistency	Out-of-sample	Overall tier
Each market has a genuine cyclical anchor	High	High	Moderate	**Strong**
Time-varying (adaptive) efficiency	High	High	High	**Strong**
Herding & sentiment associated with amplification	High	High	Moderate	**Strong**
Bubble/crash phases are detectable	High	Moderate	Low	**Moderate**
On-chain / macro metrics flag cycle extremes	Moderate	Moderate	Moderate	**Moderate**
Mechanically periodic multi-year cycle	Low	Low	Low	**Limited**
Technical/trend timing adds value net of costs	Moderate	Low	Low	**Limited**
Precise cycle-low timing (~80% hit)	Low	Low	Low	**Very limited**

Note. Ratings per the rubric in Table 2; overall tiers reproduced graphically in Figure 8. Grading was performed by a single reviewer (a stated limitation).

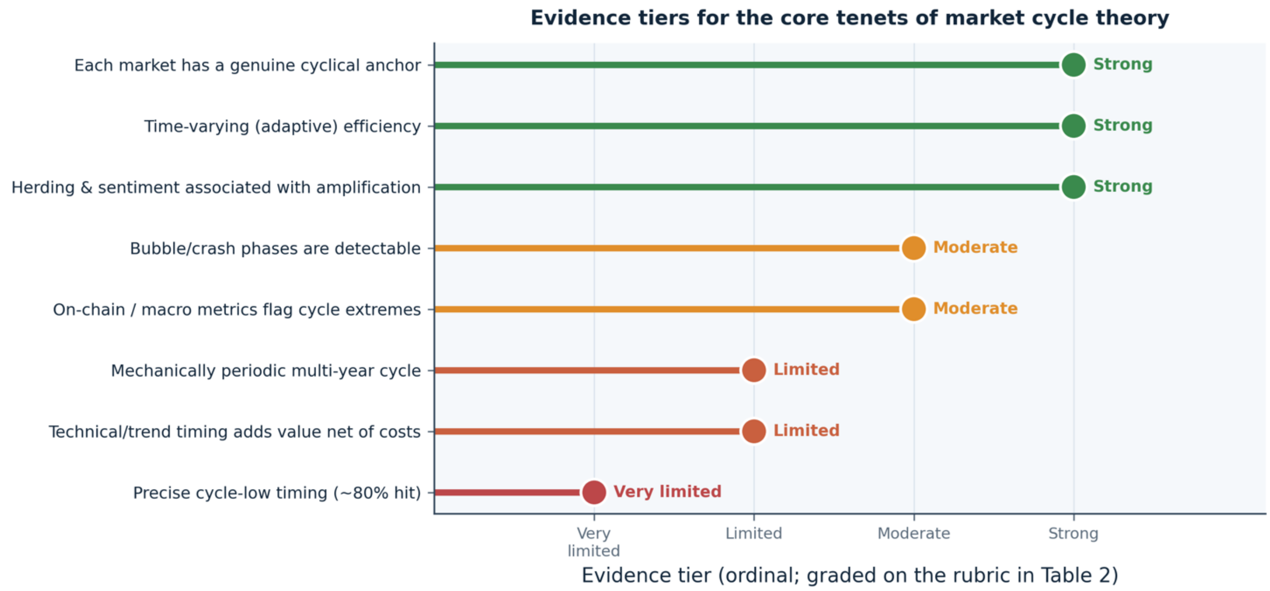

Figure 8. Evidence tiers for the eight core tenets of market cycle theory, graded on the Table 2 rubric and colour-coded by tier (green = Strong, amber = Moderate, red = Limited/Very limited). Tiers correspond exactly to the 'Overall tier' column of Table 8.

4.2 Limitations

Two limitations qualify this appraisal, beyond those stated in the Methods. First, the review is narrative rather than systematic and the grading was performed by a single reviewer, so the tiers are a structured judgement, not a measurement with inter-rater reliability. Second, the literature is constrained by short samples for the multi-year anchors (four halvings; a few dozen electoral cycles), by publication bias toward positive anomaly findings, by dependence among sources, and by rapidly shifting market structure. With these caveats, the evidence supports treating the anchors, adaptive efficiency and behavioural amplification as real, interacting phenomena, while regarding the precise calendar of C1—60-day daily counts, 30-week weekly counts and a clockwork four-year low—as heuristic scaffolding whose reliability is conditional on regime and asset.

5. Conclusion

Market cycle theory occupies a productive middle ground between the efficient-market orthodoxy that would dismiss it and the deterministic enthusiasm that would over-sell it. Examined as the cross-asset construct it is, and with the practitioner rules (C1) held distinct from the general academic evidence (C2), its foundations are partly vindicated in equities, gold and cryptocurrency alike: each market has a recognisable cyclical anchor, efficiency is genuinely time-varying and adaptive, behavioural forces are associated with amplified swings, and cross-asset momentum aligns with the theory's translation concept. What the evidence does not support is the theory's most seductive promise—a precise, clockwork multi-year cycle delivering high-accuracy timing of individual lows. The reconciliation we defend is to treat cycle theory as a probabilistic, regime-conditioned scaffold—useful for organising expectations and risk, unreliable as a deterministic forecast—whose disciplined use depends on confirmation and sound risk management, and whose specific parameters await the pre-registered, cost-aware, data-snooping-robust tests that our falsifiable predictions invite. This manuscript is a scholarly synthesis for educational purposes and does not constitute financial, investment or trading advice.

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Reporting standards: Reporting follows SANRA; source assembly is documented in PRISMA-2020 style (Figure 1).

Data availability: All sources are cited with DOIs and were authenticated against the Crossref registry; the verification workflow can be reproduced from the itemised reference list.

Disclaimer: This narrative review is educational and does not constitute financial or investment advice; trading in equities, commodities and cryptocurrencies carries substantial risk of loss.

References

1. Santa-Clara P, Valkanov R. The presidential puzzle: political cycles and the stock market. Journal of Finance. 2003;58(5):1841-1872. doi:10.1111/1540-6261.00590
2. Pástor Ľ, Veronesi P. Political cycles and stock returns. Journal of Political Economy. 2020;128(11):4011-4045. doi:10.1086/710532
3. Campbell JY, Shiller RJ. Valuation ratios and the long-run stock market outlook. Journal of Portfolio Management. 1998;24(2):11-26. doi:10.3905/jpm.24.2.11
4. Baur DG. The autumn effect of gold. Research in International Business and Finance. 2013;27(1):1-11. doi:10.1016/j.ribaf.2012.05.001
5. Erb CB, Harvey CR. The golden dilemma. Financial Analysts Journal. 2013;69(4):10-42. doi:10.2469/faj.v69.n4.1
6. Fabus J, Kremenova I, Stalmasekova N, et al. An empirical examination of Bitcoin's halving effects: assessing cryptocurrency sustainability within the landscape of financial technologies. Journal of Risk and Financial Management. 2024;17(6):229. doi:10.3390/jrfm17060229
7. Fama EF. Efficient capital markets: a review of theory and empirical work. Journal of Finance. 1970;25(2):383-417. doi:10.2307/2325486
8. Lo AW. The adaptive markets hypothesis. Journal of Portfolio Management. 2004;30(5):15-29. doi:10.3905/jpm.2004.442611
9. Shleifer A, Vishny RW. The limits of arbitrage. Journal of Finance. 1997;52(1):35-55. doi:10.1111/j.1540-6261.1997.tb03807.x
10. Kondratieff ND, Stolper WF. The long waves in economic life. Review of Economics and Statistics. 1935;17(6):105-115. doi:10.2307/1928486
11. Kahneman D, Tversky A. Prospect theory: an analysis of decision under risk. Econometrica. 1979;47(2):263-291. doi:10.2307/1914185
12. Shiller RJ. From efficient markets theory to behavioral finance. Journal of Economic Perspectives. 2003;17(1):83-104. doi:10.1257/089533003321164967
13. Barberis N, Shleifer A, Vishny R. A model of investor sentiment. Journal of Financial Economics. 1998;49(3):307-343. doi:10.1016/S0304-405X(98)00027-0
14. O'Connor FA, Lucey BM, Batten JA, et al. The financial economics of gold—a survey. International Review of Financial Analysis. 2015;41:186-205. doi:10.1016/j.irfa.2015.07.005
15. Baethge C, Goldbeck-Wood S, Mertens S. SANRA—a scale for the quality assessment of narrative review articles. Research Integrity and Peer Review. 2019;4(1):5. doi:10.1186/s41073-019-0064-8
16. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71. doi:10.1136/bmj.n71
17. Jegadeesh N, Titman S. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance. 1993;48(1):65-91. doi:10.1111/j.1540-6261.1993.tb04702.x
18. Johansen A, Ledoit O, Sornette D. Crashes as critical points. International Journal of Theoretical and Applied Finance. 2000;3(2):219-255. doi:10.1142/S0219024900000115
19. Veloso V, Gatsios RC, Magnani VM, et al. Is Bitcoin's market maturing? Cumulative abnormal returns and volatility in the 2024 halving and past cycles. Journal of Risk and Financial Management. 2025;18(5):242. doi:10.3390/jrfm18050242
20. Lashkaripour M. Some stylized facts about bitcoin halving. Finance Research Letters. 2024;69:106198. doi:10.1016/j.frl.2024.106198
21. Jiménez I, Mora-Valencia A, Perote J. Bitcoin halving and the integration of cryptocurrency and forex markets: an analysis of the higher-order moment spillovers. International Review of Economics & Finance. 2024;92:302-315. doi:10.1016/j.iref.2024.02.022
22. Liu W, Zhao X, Li W, et al. The effect of the cryptocurrency halving event. Pacific-Basin Finance Journal. 2025;94:102913. doi:10.1016/j.pacfin.2025.102913
23. M'bakob GB. Bubbles in Bitcoin and Ethereum: the role of halving in the formation of super cycles. Sustainable Futures. 2024;7:100178. doi:10.1016/j.sftr.2024.100178
24. Subawa NS, Mimaki CA, Mahendra IMO, et al. Bitcoin halving: how effective is it in driving cryptocurrency market dynamics? Journal of Risk and Financial Management. 2026;19(1):2. doi:10.3390/jrfm19010002
25. Urquhart A, Hudson R. Efficient or adaptive markets? Evidence from major stock markets using very long run historic data. International Review of Financial Analysis. 2013;28:130-142. doi:10.1016/j.irfa.2013.03.005
26. Kim JH, Shamsuddin A, Lim KP. Stock return predictability and the adaptive markets hypothesis: evidence from century-long U.S. data. Journal of Empirical Finance. 2011;18(5):868-879. doi:10.1016/j.jempfin.2011.08.002
27. Henkel SJ, Martin JS, Nardari F. Time-varying short-horizon predictability. Journal of Financial Economics. 2011;99(3):560-580. doi:10.1016/j.jfineco.2010.09.008
28. Chordia T, Shivakumar L. Momentum, business cycle, and time-varying expected returns. Journal of Finance. 2002;57(2):985-1019. doi:10.1111/1540-6261.00449
29. Urquhart A. The inefficiency of Bitcoin. Economics Letters. 2016;148:80-82. doi:10.1016/j.econlet.2016.09.019
30. Nadarajah S, Chu J. On the inefficiency of Bitcoin. Economics Letters. 2017;150:6-9. doi:10.1016/j.econlet.2016.10.033
31. Bariviera AF. The inefficiency of Bitcoin revisited: a dynamic approach. Economics Letters. 2017;161:1-4. doi:10.1016/j.econlet.2017.09.013
32. Tiwari AK, Jana RK, Das D, et al. Informational efficiency of Bitcoin—an extension. Economics Letters. 2018;163:106-109. doi:10.1016/j.econlet.2017.12.006
33. Khuntia S, Pattanayak JK. Adaptive market hypothesis and evolving predictability of bitcoin. Economics Letters. 2018;167:26-28. doi:10.1016/j.econlet.2018.03.005
34. Khursheed A, Naeem M, Ahmed S, et al. Adaptive market hypothesis: an empirical analysis of time-varying market efficiency of cryptocurrencies. Cogent Economics & Finance. 2020;8(1):1719574. doi:10.1080/23322039.2020.1719574
35. Chu J, Zhang Y, Chan S. The adaptive market hypothesis in the high frequency cryptocurrency market. International Review of Financial Analysis. 2019;64:221-231. doi:10.1016/j.irfa.2019.05.008
36. Jena SK, Tiwari AK, Doğan B, et al. Are the top six cryptocurrencies efficient? Evidence from time-varying long memory. International Journal of Finance & Economics. 2022;27(3):3730-3740. doi:10.1002/ijfe.2347
37. Mokni K, El Montasser G, Ajmi AN, et al. On the efficiency and its drivers in the cryptocurrency market: the case of Bitcoin and Ethereum. Financial Innovation. 2024;10(1):39. doi:10.1186/s40854-023-00566-3
38. Kristoufek L. What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. PLoS ONE. 2015;10(4):e0123923. doi:10.1371/journal.pone.0123923
39. Brock W, Lakonishok J, LeBaron B. Simple technical trading rules and the stochastic properties of stock returns. Journal of Finance. 1992;47(5):1731-1764. doi:10.1111/j.1540-6261.1992.tb04681.x
40. Sullivan R, Timmermann A, White H. Data-snooping, technical trading rule performance, and the bootstrap. Journal of Finance. 1999;54(5):1647-1691. doi:10.1111/0022-1082.00163
41. Neely CJ, Rapach DE, Tu J, et al. Forecasting the equity risk premium: the role of technical indicators. Management Science. 2014;60(7):1772-1791. doi:10.1287/mnsc.2013.1838
42. Hudson R, Urquhart A. Technical trading and cryptocurrencies. Annals of Operations Research.

2021;297(1-2):191-220. doi:10.1007/s10479-019-03357-1

43. Grobys K, Ahmed S, Sapkota N. Technical trading rules in the cryptocurrency market. Finance Research Letters. 2020;32:101396. doi:10.1016/j.frl.2019.101396
44. Detzel A, Liu H, Strauss J, et al. Learning and predictability via technical analysis: evidence from bitcoin and stocks with hard-to-value fundamentals. Financial Management. 2021;50(1):107-137. doi:10.1111/fima.12310
45. Masuku KL, Gopane TJ. Technical trading rules' profitability and dynamic risk premiums of cryptocurrency exchange rates. Journal of Capital Markets Studies. 2022;6(1):6-32. doi:10.1108/JCMS-10-2021-0030
46. Bazán-Palomino W, Svogun D. On the drivers of technical analysis profits in cryptocurrency markets: a distributed lag approach. International Review of Financial Analysis. 2023;86:102516. doi:10.1016/j.irfa.2023.102516
47. Svogun D, Bazán-Palomino W. Technical analysis in cryptocurrency markets: do transaction costs and bubbles matter? Journal of International Financial Markets, Institutions and Money. 2022;79:101601. doi:10.1016/j.intfin.2022.101601
48. Bouman S, Jacobsen B. The Halloween indicator, 'sell in May and go away': another puzzle. American Economic Review. 2002;92(5):1618-1635. doi:10.1257/000282802762024683
49. Zhang CY, Jacobsen B. The Halloween indicator, 'sell in May and go away': everywhere and all the time. Journal of International Money and Finance. 2021;110:102268. doi:10.1016/j.jimonfin.2020.102268
50. Keim DB. Size-related anomalies and stock return seasonality. Journal of Financial Economics. 1983;12(1):13-32. doi:10.1016/0304-405X(83)90025-9
51. French KR. Stock returns and the weekend effect. Journal of Financial Economics. 1980;8(1):55-69. doi:10.1016/0304-405X(80)90021-5
52. Kamstra MJ, Kramer LA, Levi MD. Winter blues: a SAD stock market cycle. American Economic Review. 2003;93(1):324-343. doi:10.1257/000282803321455322
53. Caporale GM, Plastun A. The day of the week effect in the cryptocurrency market. Finance Research Letters. 2019;31:258-269. doi:10.1016/j.frl.2018.11.012
54. Ma D, Tanizaki H. The day-of-the-week effect on Bitcoin return and volatility. Research in International Business and Finance. 2019;49:127-136. doi:10.1016/j.ribaf.2019.02.003
55. Aharon DY, Qadan M. Bitcoin and the day-of-the-week effect. Finance Research Letters. 2019;31:415-424. doi:10.1016/j.frl.2018.12.004
56. Kaiser L. Seasonality in cryptocurrencies. Finance Research Letters. 2019;31:232-238. doi:10.1016/j.frl.2018.11.007
57. Baur DG, Cahill D, Godfrey K, et al. Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. Finance Research Letters. 2019;31:78-92. doi:10.1016/j.frl.2019.04.023
58. Kinateder H, Papavassiliou VG. Calendar effects in Bitcoin returns and volatility. Finance Research Letters. 2021;38:101420. doi:10.1016/j.frl.2019.101420
59. Sahu S, Fonseca Ramírez A, Kim JM. Exploring calendar anomalies and volatility dynamics in cryptocurrencies: a comparative analysis of day-of-the-week effects before and during the COVID-19 pandemic. Journal of Risk and Financial Management. 2024;17(8):351. doi:10.3390/jrfm17080351
60. Moskowitz TJ, Ooi YH, Pedersen LH. Time series momentum. Journal of Financial Economics. 2012;104(2):228-250. doi:10.1016/j.jfineco.2011.11.003
61. Asness CS, Moskowitz TJ, Pedersen LH. Value and momentum everywhere. Journal of Finance. 2013;68(3):929-985. doi:10.1111/jofi.12021
62. Cooper MJ, Gutierrez RC, Hameed A. Market states and momentum. Journal of Finance. 2004;59(3):1345-1365. doi:10.1111/j.1540-6261.2004.00665.x
63. Borgards O. Dynamic time series momentum of cryptocurrencies. North American Journal of Economics and Finance. 2021;57:101428. doi:10.1016/j.najef.2021.101428
64. Wen Z, Bouri E, Xu Y, et al. Intraday return predictability in the cryptocurrency markets: momentum, reversal, or both. North American Journal of Economics and Finance. 2022;62:101733. doi:10.1016/j.najef.2022.101733
65. Tan X, Tao Y. Trend-based forecast of cryptocurrency returns. Economic Modelling. 2023;124:106323. doi:10.1016/j.econmod.2023.106323
66. Jia B, Shen D, Zhang W. Extreme sentiment and herding: evidence from the cryptocurrency market. Research in International Business and Finance. 2022;63:101770. doi:10.1016/j.ribaf.2022.101770
67. Chen A-S, Nguyen HT. A new perspective on how investor sentiment affects herding behavior in the cryptocurrency market. Finance Research Letters. 2024;67:105737. doi:10.1016/j.frl.2024.105737
68. Bogdan S, Brmalj N, Mujačević E. Impact of liquidity and investors sentiment on herd behavior in cryptocurrency market. International Journal of Financial Studies. 2023;11(3):97. doi:10.3390/ijfs11030097
69. Wang J-N, Liu H-C, Lee Y-H, et al. FoMO in the Bitcoin market: revisiting and factors. Quarterly Review of Economics and Finance. 2023;89:244-253. doi:10.1016/j.qref.2023.04.007
70. Aslanidis N, Bariviera AF, López ÓG. The link between cryptocurrencies and Google Trends attention. Finance Research Letters. 2022;47:102654. doi:10.1016/j.frl.2021.102654
71. Lin Z-Y. Investor attention and cryptocurrency performance. Finance Research Letters. 2021;40:101702. doi:10.1016/j.frl.2020.101702
72. Phillips PCB, Shi S, Yu J. Testing for multiple bubbles: historical episodes of exuberance and collapse in the S&P 500. International Economic Review. 2015;56(4):1043-1078. doi:10.1111/iere.12132
73. Wheatley S, Sornette D, Huber T, et al. Are Bitcoin bubbles predictable? Combining a generalized Metcalfe's Law and the Log-Periodic Power Law Singularity model. Royal Society Open Science. 2019;6(6):180538. doi:10.1098/rsos.180538
74. Gerlach JC, Demos G, Sornette D. Dissection of Bitcoin's multiscale bubble history from January 2012 to February 2018. Royal Society Open Science. 2019;6(7):180643. doi:10.1098/rsos.180643
75. Shu M, Zhu W. Real-time prediction of Bitcoin bubble crashes. Physica A: Statistical Mechanics and its Applications. 2020;548:124477. doi:10.1016/j.physa.2020.124477
76. Yao CZ, Li HY. A study on the bursting point of Bitcoin based on the BSADF and LPPLS methods. North American Journal of Economics and Finance. 2021;55:101280. doi:10.1016/j.najef.2020.101280
77. Fry J. Booms, busts and heavy-tails: the story of Bitcoin and cryptocurrency markets? Economics Letters. 2018;171:225-229. doi:10.1016/j.econlet.2018.08.008
78. Geuder J, Kinateder H, Wagner NF. Cryptocurrencies as financial bubbles: the case of Bitcoin. Finance Research Letters. 2019;31:179-184. doi:10.1016/j.frl.2018.11.011
79. Chaim P, Laurini MP. Is Bitcoin a bubble? Physica A: Statistical Mechanics and its Applications. 2019;517:222-232. doi:10.1016/j.physa.2018.11.031
80. Bouri E, Shahzad SJH, Roubaud D. Co-explosivity in the cryptocurrency market. Finance Research Letters. 2019;29:178-183. doi:10.1016/j.frl.2018.07.005
81. Podhorsky A. Bursting the bitcoin bubble: do market prices reflect fundamental bitcoin value? International Review of Financial Analysis. 2024;93:103158. doi:10.1016/j.irfa.2024.103158
82. Karau S. Monetary policy and Bitcoin. Journal of International Money and Finance. 2023;137:102880. doi:10.1016/j.jimonfin.2023.102880

83. Ma C, Tian Y, Hsiao S, et al. Monetary policy shocks and Bitcoin prices. Research in International Business and Finance. 2022;62:101711. doi:10.1016/j.ribaf.2022.101711
84. Tosun TT, Uğurlu E. The impact of the Fed's monetary policy on cryptocurrencies: novel policy implications for central banks. Journal of Risk and Financial Management. 2025;18(7):393. doi:10.3390/jrfm18070393
85. Pietrzak M. What can monetary policy tell us about Bitcoin? Annals of Finance. 2023;19(4):545-559. doi:10.1007/s10436-023-00432-3
86. Hodula M. Does U.S. monetary policy sway global crypto investment demand? Finance Research Letters. 2025;80:107408. doi:10.1016/j.frl.2025.107408
87. Lin M, Liu Y, Sheng VNK. Analysis of the impact of macroeconomic factors on cryptocurrency returns—based on quantile regression study. International Review of Economics & Finance. 2025;97:103757. doi:10.1016/j.iref.2024.103757
88. Ahmed WMA. On the robust drivers of cryptocurrency liquidity: the case of Bitcoin. Financial Innovation. 2024;10(1):69. doi:10.1186/s40854-023-00598-9
89. Baur DG, Lucey BM. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review. 2010;45(2):217-229.
doi:10.1111/j.1540-6288.2010.00244.x
90. Baur DG, McDermott TK. Is gold a safe haven? International evidence. Journal of Banking & Finance. 2010;34(8):1886-1898. doi:10.1016/j.jbankfin.2009.12.008
91. Beckmann J, Berger T, Czudaj R. Does gold act as a hedge or a safe haven for stocks? A smooth transition approach. Economic Modelling. 2015;48:16-24. doi:10.1016/j.econmod.2014.10.044
92. Bouri E, Molnár P, Azzi G, et al. On the hedge and safe haven properties of Bitcoin: is it really more than a diversifier? Finance Research Letters. 2017;20:192-198. doi:10.1016/j.frl.2016.09.025
93. Conlon T, McGee R. Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. Finance Research Letters. 2020;35:101607. doi:10.1016/j.frl.2020.101607
94. Ji Q, Bouri E, Lau CKM, et al. Dynamic connectedness and integration in cryptocurrency markets. International Review of Financial Analysis. 2019;63:257-272. doi:10.1016/j.irfa.2018.12.002
95. Corbet S, Meegan A, Larkin C, et al. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economics Letters. 2018;165:28-34. doi:10.1016/j.econlet.2018.01.004
96. Grobys K, Näsman S, Sandretto D. Using on-chain data to predict Bitcoin cycles. Research in International Business and Finance. 2026;89:103486. doi:10.1016/j.ribaf.2026.103486
97. Kim G, Shin DH, Choi JG, et al. A deep learning-based cryptocurrency price prediction model that uses on-chain data. IEEE Access. 2022;10:56232-56248. doi:10.1109/ACCESS.2022.3177888
98. King JC, Dale R, Amigó JM. Blockchain metrics and indicators in cryptocurrency trading. Chaos, Solitons & Fractals. 2024;178:114305. doi:10.1016/j.chaos.2023.114305
99. Sakkas A, Urquhart A. Blockchain factors. Journal of International Financial Markets, Institutions and Money. 2024;94:102012. doi:10.1016/j.intfin.2024.102012
100. Morillon TG, Chacon RG. Dissecting the stock to flow model for Bitcoin. Studies in Economics and Finance. 2022;39(3):506-523. doi:10.1108/SEF-10-2021-0409
101. Shelton A. Bitcoin return prediction: is it possible via stock-to-flow, Metcalfe's Law, technical analysis, or market sentiment? Journal of Risk and Financial Management. 2024;17(10):443. doi:10.3390/jrfm17100443
102. Alabi K. Digital blockchain networks appear to be following Metcalfe's Law. Electronic Commerce Research and Applications. 2017;24:23-29. doi:10.1016/j.elerap.2017.06.003
103. Chkili W. Modeling Bitcoin price volatility: long memory vs Markov switching. Eurasian Economic Review. 2021;11(3):433-448. doi:10.1007/s40822-021-00180-7
104. Ardia D, Bluteau K, Rüede M. Regime changes in Bitcoin GARCH volatility dynamics. Finance Research Letters. 2019;29:266-271. doi:10.1016/j.frl.2018.08.009
105. Shakourloo A, Azimli A. Regime-switching in bitcoin volatility under global uncertainty: Markov-switching GARCH and hidden Markov Copula approaches. Research in International Business and Finance. 2026;83:103295. doi:10.1016/j.ribaf.2026.103295
106. Shen D, Urquhart A, Wang P. Forecasting the volatility of Bitcoin: the importance of jumps and structural breaks. European Financial Management. 2020;26(5):1294-1323. doi:10.1111/eufm.12254
107. Mensi W, Al-Yahyaee KH, Kang SH. Structural breaks and double long memory of cryptocurrency prices: a comparative analysis from Bitcoin and Ethereum. Finance Research Letters. 2019;29:222-230. doi:10.1016/j.frl.2018.07.011
108. Babalos V, Bouri E, Gupta R. Does the introduction of US spot Bitcoin ETFs affect spot returns and volatility of major cryptocurrencies? Quarterly Review of Economics and Finance. 2025;102:102006. doi:10.1016/j.qref.2025.102006
109. Kia K, Liu B, Li Q, et al. Price discovery in Bitcoin ETF market. Financial Review. 2026;61(2):435-449. doi:10.1111/fire.70026
110. Mohamad A. Do Bitcoin ETFs lead price discovery following their introduction in the Bitcoin market? Computational Economics. 2025;66(1):947-969. doi:10.1007/s10614-025-10998-x
111. Frino A, Gaudiosi R, Webb RI, et al. Price discovery in Bitcoin spot or futures? The jury is out. Journal of Futures Markets. 2025;45(4):269-288. doi:10.1002/fut.22560
112. Oefele N. One year of bitcoin spot ETPs: a brief market and fund flow analysis. Economics Letters. 2025;250:112304. doi:10.1016/j.econlet.2025.112304