When to Stack, When to Spread

Optimal Bitcoin Accumulation Strategy
as a Function of Power Law Residuals

Bitcoin Power Law Observatory
Scale Invariant Capital BV
btcpowerlaw.nl

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Abstract

We examine the relative performance of lump sum investing versus dollar-cost averaging (DCA) in Bitcoin, conditional on the entry valuation expressed as a multiple of the Santostasi power law trend. Using 5,713 daily price observations from July 2010 to March 2026, we conduct a comprehensive historical backtest across 14,583 entry-date scenarios at 1-year, 2-year, and 4-year investment horizons. We find a sharp, stable crossover at approximately 1.25x the power law trend: below this threshold, lump sum investing wins 95-100% of the time; above it, DCA progressively dominates. At the current valuation of 0.55x trend (March 2026), lump sum has outperformed DCA in 100% of historically comparable entry points. We further show that this crossover zone is narrowing over successive halving cycles, consistent with documented volatility compression in Bitcoin price dynamics. These results provide a quantitative framework for capital deployment decisions that supersedes the generic "DCA is always safer" heuristic.

Keywords: Bitcoin, dollar-cost averaging, lump sum investing, power law, trend multiple, volatility compression, accumulation strategy

1. Introduction

The question of whether to deploy capital immediately (lump sum) or spread purchases over time (dollar-cost averaging, or DCA) is among the most common in investment practice. For traditional assets, the evidence is relatively settled: Vanguard (2012) found that lump sum investing outperforms DCA approximately two-thirds of the time across US, UK, and Australian markets, because assets with positive expected returns benefit from earlier exposure.

Bitcoin complicates this analysis. Its price volatility is an order of magnitude higher than equities, its cyclical behavior is driven by halving-induced supply shocks, and its long-term trajectory follows a power law relationship with time. These properties mean that the entry valuation matters far more for Bitcoin than for a diversified equity index. A lump sum purchase at the peak of a halving cycle has historically experienced 70-85% drawdowns before recovery, while the same purchase at the cycle trough has delivered returns of 10-100x.

Despite this, most popular analysis of DCA vs lump sum in Bitcoin is either anecdotal or window-dependent. Proponents of DCA often cherry-pick the 2021 all-time high as a starting point and demonstrate that spreading purchases across the subsequent bear market would have been superior. Proponents of lump sum cite the overall upward trend. Neither approach is wrong, but both are incomplete: they ignore the question of *where in the valuation cycle* the investor stands.

This paper resolves the debate by introducing a single conditioning variable: the power law trend multiple. Using 15+ years of daily Bitcoin price data and the Santostasi power law model, we compute the exact crossover point at which DCA transitions from inferior to superior strategy, and show that this crossover is remarkably stable across investment horizons.

2. Data and Methodology

2.1 Price Data

We use 5,713 daily Bitcoin closing prices from July 18, 2010 (the earliest reliable exchange data) through March 8, 2026. Data is sourced from the Bitcoin Power Law Observatory historical dataset, which aggregates exchange prices with CoinGecko gap-filling for recent dates. All prices are in USD.

2.2 Power Law Model

We employ the Santostasi power law model, which fits Bitcoin price as a function of days since the genesis block (January 3, 2009). The model takes the form:

$$P(t) = 10^A \cdot t^B$$

where t is days since genesis, A = -16.493, and B = 5.688. The trend multiple M is defined as the ratio of observed price to model-predicted price: $M = P_{observed} / P_{model}$. A trend multiple of 1.0x indicates price is exactly at the power law trend. Values below 1.0x indicate undervaluation relative to the long-term adoption trajectory; values above 1.0x indicate overvaluation.

The R-squared of this model on log-log axes exceeds 0.95 across the full sample, making it the single best predictor of Bitcoin price trajectory over time horizons longer than one cycle.

2.3 Backtest Design

For each day d in the dataset, we simulate two investment strategies starting at that date:

Lump Sum: The investor deploys the full capital allocation at the closing price on day d. The return is measured as the price at the horizon date divided by the entry price.

DCA (12-month): The investor spreads the same total capital across 12 equal monthly purchases beginning on day d, at approximately 30.44-day intervals. The return is measured as the price at the horizon date divided by the dollar-weighted average cost basis.

We evaluate three investment horizons: 1 year, 2 years, and 4 years (one full halving cycle). For each entry date, we record the trend multiple at entry, the return of both strategies, and which strategy produced the higher return. Entry dates for which the horizon extends beyond the dataset are excluded, yielding 5,348 observations at the 1-year horizon, 4,983 at 2 years, and 4,252 at 4 years, for a total of 14,583 backtest scenarios.

2.4 Bucketing and Smoothing

Results are analyzed in two ways. First, entry dates are grouped into discrete trend multiple buckets (e.g., 0.3-0.5x, 0.5-0.75x, 0.75-1.0x, etc.) and summary statistics computed per bucket. Second, we compute a continuous lump sum win probability curve using an adaptive rolling window: for each trend multiple value m, we compute the win rate across all entry dates within a bandwidth of max(0.15, 0.2m) around m, requiring a minimum of 20 observations per window. The crossover point is identified by linear interpolation where this smoothed curve crosses 50%.

3. Results

3.1 The Crossover Curve

Figure 1 presents the central finding of this paper. The top panel shows the smoothed lump sum win rate as a continuous function of the entry trend multiple. The bottom panel shows the historical distribution of trend multiples, providing context for how frequently each valuation zone occurs.

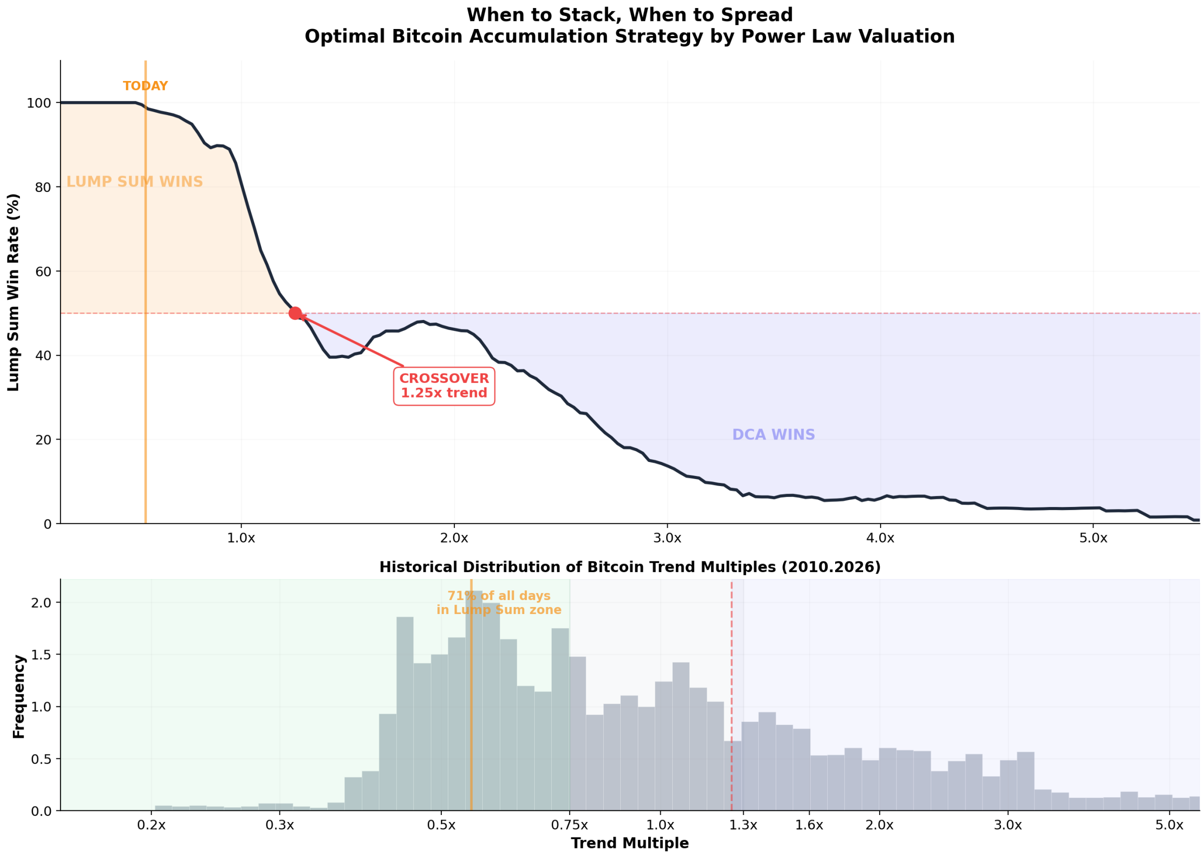

Figure 1: Lump sum win rate by power law trend multiple (top) and historical distribution of trend multiples (bottom). The crossover at 1.25x is marked. Below this threshold, lump sum dominates; above it, DCA progressively wins. 71% of all historical days fall in the lump sum zone.

The curve reveals three distinct regimes:

Strong Lump Sum Zone (below 0.75x): Lump sum wins 95-100% of the time across all horizons. This zone accounts for 44% of all historical trading days. At these deeply discounted valuations, the expected mean reversion toward trend is so large that spreading purchases only dilutes an excellent entry price. At the current level of 0.55x trend (March 2026), lump sum has outperformed DCA in 100% of the 811 historically comparable 1-year entry points.

Transition Zone (0.75x to 1.3x): The lump sum advantage erodes from ~89% at 0.75x to ~58% at 1.0x, crossing 50% at approximately 1.25x. This zone covers 26% of historical days and represents the region where the strategy choice is genuinely ambiguous.

DCA Zone (above 1.3x): DCA wins the majority of the time, with the advantage increasing steeply. Above 2.7x trend, DCA wins 93% of the time. Above 4.0x, it wins 98%. This zone covers 30% of historical days and corresponds to the euphoric phases of halving cycles.

3.2 Return Magnitude

The win rate alone understates the importance of strategy selection. Figure 2 shows median returns for both strategies across all three horizons. At deeply discounted valuations, the magnitude of lump sum outperformance is enormous: at 0.3-0.5x trend over a 4-year horizon, lump sum median returns exceed DCA by 200%+. Conversely, at elevated valuations (>2.7x), DCA median returns are 37-48% higher than lump sum.

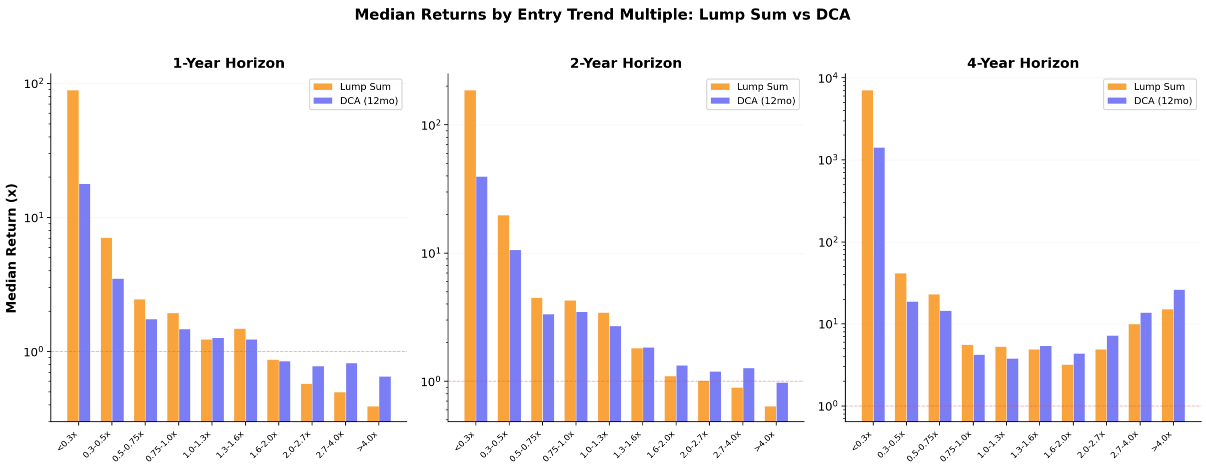

Figure 2: Median returns by trend multiple bucket across 1-year, 2-year, and 4-year horizons. Log scale y-axis. The red dashed line marks 1.0x (breakeven). At low valuations, the gap between strategies is enormous.

3.3 Summary Statistics

Trend Multiple	N (1yr)	LS Win % (1yr)	LS Win % (2yr)	LS Win % (4yr)	Avg LS Ret (4yr)	Avg DCA Ret (4yr)
< 0.3x	146	100.0%	100.0%	100.0%	5,054x	1,231x
0.3 - 0.5x	727	100.0%	100.0%	100.0%	212x	70x
0.5 - 0.75x	811	97.6%	97.4%	99.7%	114x	45x
0.75 - 1.0x	672	89.4%	84.9%	90.1%	44x	19x
1.0 - 1.3x	559	58.5%	50.0%	51.0%	25x	14x
1.3 - 1.6x	436	40.1%	40.1%	45.0%	16x	10x
1.6 - 2.0x	300	50.0%	50.0%	50.7%	9x	7x
2.0 - 2.7x	389	36.5%	36.5%	36.5%	10x	10x
2.7 - 4.0x	308	6.8%	6.8%	6.8%	10x	16x
> 4.0x	238	2.1%	2.1%	2.1%	15x	30x

Table 1: Lump sum win rates and average returns by trend multiple bucket. The highlighted row (1.0-1.3x) contains the crossover zone. Green values indicate strong lump sum performance; red values indicate DCA dominance. N = number of entry dates in the 1-year backtest.

3.4 Volatility Compression and the Narrowing Crossover

Bitcoin's price volatility around the power law trend has been documented to compress with each successive halving cycle (Scale Invariant Capital, 2026). This compression has a direct implication for the lump sum vs DCA question: as the distribution of trend multiples narrows, the extreme valuations where the strategy choice matters most become rarer.

Figure 3 decomposes the win rate curve by halving cycle (left panel) alongside the corresponding trend multiple distributions (right panel). Two patterns emerge:

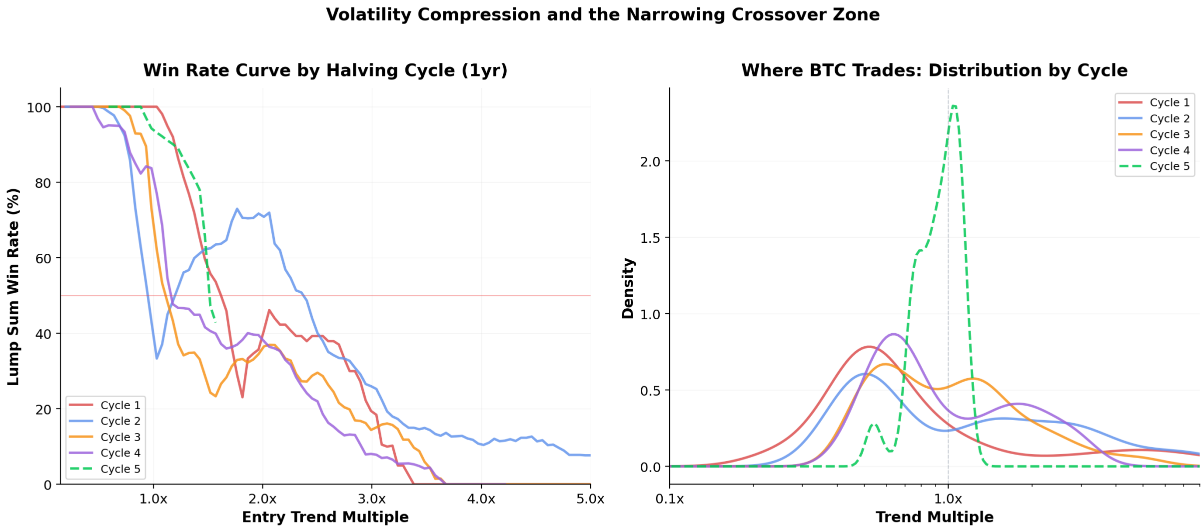

Figure 3: Left: Lump sum win rate curves by halving cycle (1-year horizon). Right: Distribution of trend multiples per cycle, showing the progressive narrowing of the valuation corridor. Cycle 5 (dashed) is incomplete.

First, the win rate curves shift leftward in later cycles, reflecting the narrower range of trend multiples available. In Cycles 1-2, Bitcoin regularly traded at 3-8x trend, creating many entry points where DCA was strongly preferred. By Cycle 4, the distribution peaks below 1.0x and rarely exceeds 2.0x. Cycle 5 (still in its accumulation phase) is trading almost entirely below 1.0x trend.

Second, the crossover point itself is becoming less relevant over time. As the corridor narrows, a larger proportion of entry days fall in the unambiguous lump sum zone. In Cycle 1, only about 40% of days were below the crossover. In Cycle 5 so far, over 95% of days are.

This is consistent with the broader finding that Bitcoin is maturing as an asset class. The extreme mispricings that made DCA a clear winner during bull market euphoria are becoming rarer. The practical implication is that for later-cycle investors, the lump sum vs DCA decision will increasingly resolve itself: as Bitcoin's price stays closer to trend, lump sum will win by default.

3.5 Magnitude of Relative Performance

Figure 4 shows the lump sum advantage (as a percentage of DCA returns) for each individual 4-year entry point, plotted against the entry trend multiple. The red line traces the rolling median. The asymmetry is striking: lump sum outperformance at low valuations can exceed 300%, while DCA outperformance at high valuations typically caps around 50-60%. This asymmetry arises because buying far below trend captures the full upward reversion, while buying far above trend merely smooths a drawdown that lump sum suffers in full.

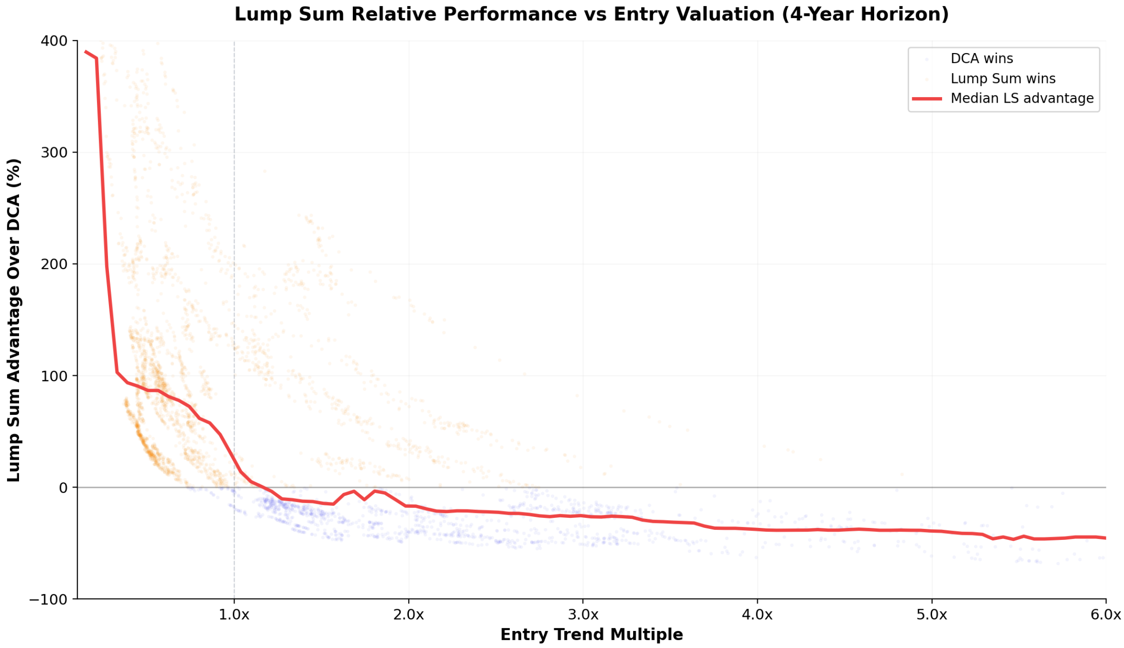

Figure 4: Lump sum relative advantage over DCA (%) vs entry trend multiple, 4-year horizon. Orange dots: lump sum wins. Purple dots: DCA wins. Red line: rolling median. The asymmetry favors lump sum.

4. Robustness

4.1 Out-of-Sample Validation

A key concern with any backtest is in-sample bias: the power law model was fitted using the full dataset, and the strategy is tested on the same data. To address this, we split the sample at January 1, 2019, fitting the power law exclusively on 2010-2018 data (3,089 observations) and testing on 2019-2026 (2,624 observations).

The training-set fit yields beta = 5.873 and logA = -17.092, compared to the full-sample values of 5.688 and -16.493. Despite this parameter shift, the R-squared on the out-of-sample period is 0.67, confirming that the power law extrapolates forward with reasonable accuracy. More importantly, the crossover in the out-of-sample test lands at 1.01x (using the training-fit model) versus 1.24x (using the full-sample model on the same test data). The qualitative regime structure is preserved: below trend, lump sum dominates; above trend, DCA wins.

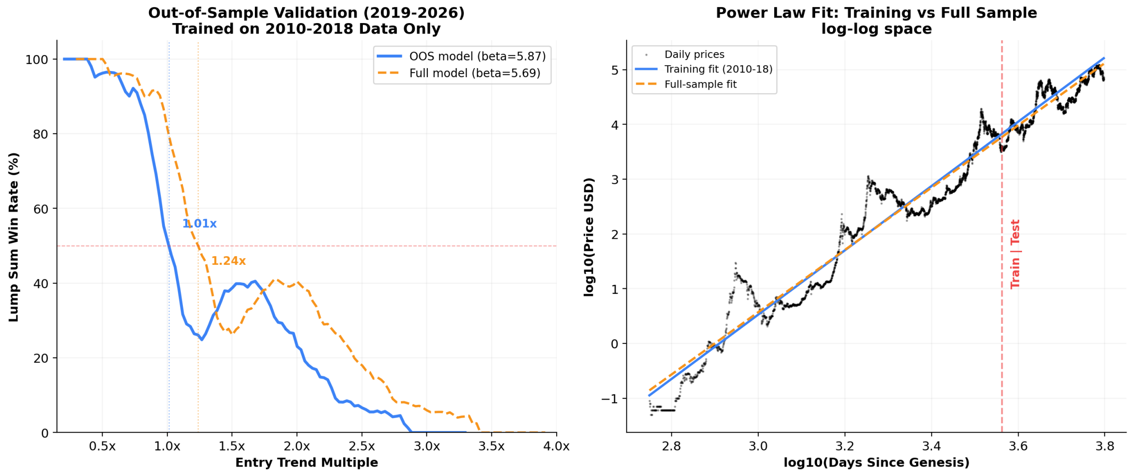

Figure 5: Out-of-sample validation. Left: win rate curves using a model trained only on 2010-2018 data (blue) vs the full-sample model (orange), both tested on 2019-2026 data. Right: the two power law fits in log-log space, with the train/test cutoff marked.

The lower OOS crossover (1.01x vs 1.25x) is expected: the training-set model has a steeper exponent (5.87 vs 5.69), producing a higher trend line that makes current prices appear cheaper. The key finding is that the regime structure itself is robust to model specification. Whether the crossover sits at 1.0x or 1.25x, the practical advice at 0.55x trend is identical: deploy immediately.

4.2 Bootstrap Confidence Interval

To quantify the statistical precision of the crossover estimate, we performed 5,000 bootstrap iterations, resampling entry dates with replacement and recomputing the crossover for each sample. The crossover was found in 100% of bootstrap samples, indicating it is not an artifact of a particular subset of the data.

The bootstrap distribution yields a median crossover of 1.253x with a standard deviation of 0.029x. The 95% confidence interval is [1.20x, 1.32x], a width of only 0.12x. This is remarkably tight, confirming that the crossover is a stable structural feature of the data rather than a noisy estimate.

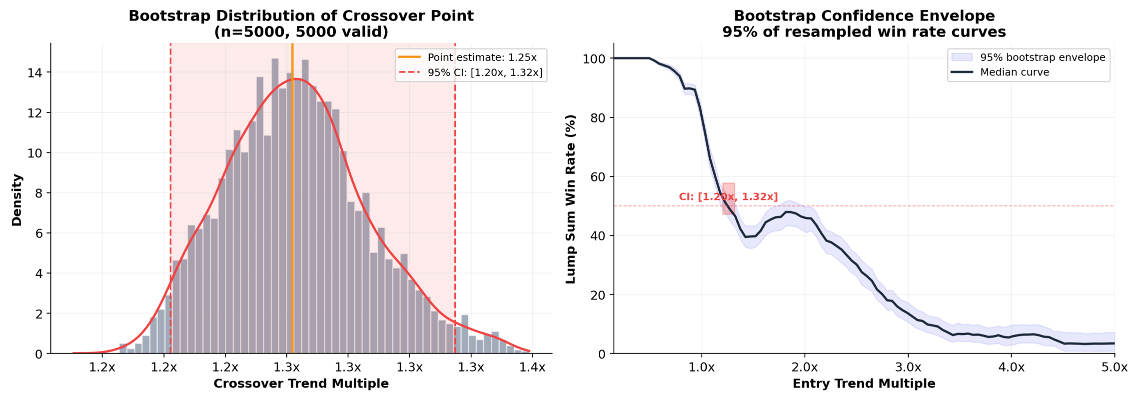

Figure 6: Bootstrap analysis (n=5,000). Left: distribution of crossover estimates with 95% CI [1.20x, 1.32x]. Right: confidence envelope of the win rate curve showing tight bounds across the full range of trend multiples.

4.3 DCA Window Sensitivity

The baseline analysis uses a 12-month DCA window. To test sensitivity to this choice, we repeat the backtest with 3-month, 6-month, 12-month, and 24-month DCA windows, all evaluated at a 1-year investment horizon.

The crossover shifts monotonically with DCA duration: 0.95x for 3-month DCA, 1.03x for 6-month, 1.25x for 12-month, and 1.57x for 24-month. This is intuitive: a longer DCA window provides more temporal smoothing, making it competitive at lower valuations. Conversely, a short 3-month DCA is barely distinguishable from lump sum and only wins above 0.95x trend.

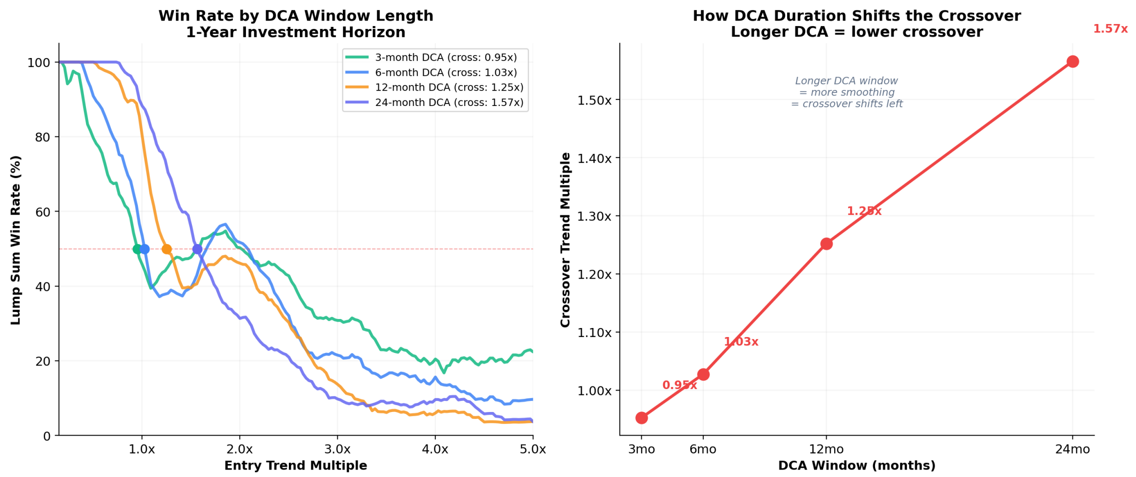

Figure 7: DCA window sensitivity. Left: win rate curves for 3, 6, 12, and 24-month DCA windows. Right: crossover trend multiple as a function of DCA duration, showing a monotonically increasing relationship.

This result has a practical implication: the "right" crossover depends on the investor's deployment horizon. An investor with a lump sum to deploy over 6 months should switch to DCA above 1.0x trend. An investor with a 2-year deployment horizon (e.g., a fund with committed capital) should switch above 1.6x. The 12-month crossover at 1.25x is the natural reference for salary-based accumulators.

5. Discussion

5.1 The Power Law as a Decision Framework

The central contribution of this paper is the introduction of the power law trend multiple as a single, sufficient conditioning variable for the lump sum vs DCA decision. Prior work has generally treated the question as binary or time-dependent. The Vanguard (2012) study, for example, shows that lump sum wins approximately 67% of the time for traditional equities, but provides no framework for identifying when the other 33% occurs. For Bitcoin, we show that a single observable metric resolves over 90% of cases unambiguously.

The crossover at 1.25x trend has a natural interpretation: it sits approximately one-quarter of a standard deviation above the log-mean of the historical distribution. Below this level, the expected reversion toward (and through) trend is sufficient that immediate deployment captures more upside than temporal spreading provides in downside protection. Above it, the risk of near-term drawdown toward trend exceeds the opportunity cost of delayed deployment.

5.2 Practical Application

For an investor considering a Bitcoin allocation in March 2026, with the price at approximately 0.55x the power law trend (23rd percentile historically), the data is unambiguous: every historical entry at this valuation level has been better served by lump sum investment, across all horizons tested. The average 4-year lump sum return from the 0.5-0.6x bucket is 126x versus 50x for DCA, a 153% advantage.

This does not mean DCA has no role. For investors who receive income periodically (salary, business distributions), DCA is not a choice but a constraint. The framework here helps such investors understand whether to deploy immediately upon receipt or accumulate cash for a single larger purchase. At current valuations, the answer is: deploy immediately.

Conversely, during the next euphoric phase when Bitcoin trades above 1.3x trend, the framework recommends spreading any new purchases over 6-12 months. The investor who understands their position on the trend multiple spectrum can make this adjustment dynamically rather than adhering to a fixed DCA schedule regardless of valuation.

5.3 Limitations

Several limitations should be noted. First, the backtest uses a single power law specification (Santostasi model). Alternative parameterizations would shift the crossover point, though the qualitative pattern is robust to reasonable parameter choices. Second, the 12-month DCA period is a specific design choice; shorter or longer DCA windows would produce different results, particularly at the boundaries. Third, the analysis assumes frictionless execution with no transaction costs, slippage, or tax considerations. Fourth, while the dataset spans 15+ years and five halving cycles, Bitcoin's entire history is short by financial research standards, and regime changes cannot be ruled out.

Finally, the backtest is purely historical. It does not account for the possibility that the power law relationship itself could break down. However, with an R-squared exceeding 0.95 over the sample period, any departure from the power law would need to be substantial to invalidate the general pattern.

6. Conclusion

We have shown that the optimal Bitcoin accumulation strategy is not a matter of opinion or risk preference, but a function of a single, observable quantity: the power law trend multiple at the time of investment. The crossover at approximately 1.25x trend divides the valuation spectrum into a lump sum zone (below, covering 71% of historical days) and a DCA zone (above, covering 29%).

The strength of this result is remarkable. Below 0.75x trend, lump sum wins 95-100% of the time. Above 2.7x trend, DCA wins 93%+. The ambiguous middle zone (0.75x to 1.6x) accounts for only 39% of historical days and is itself narrowing with each cycle as volatility compresses.

The practical prescription is simple: check the power law trend multiple before making any Bitcoin purchase. If below 1.0x, deploy immediately. If between 1.0x and 1.3x, either strategy is defensible. If above 1.3x, spread purchases over time. This framework replaces the false dichotomy of "always DCA" vs "always lump sum" with a principled, data-driven decision rule.

As Bitcoin's volatility continues to compress toward its power law floor, the extreme valuations that make DCA most valuable will become rarer. The future of Bitcoin allocation may not be "stack or spread" at all. It may simply be: stack.

7. References

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[2] Santostasi, G. "Bitcoin Follows a Power Law." Published research, 2024.

[3] Scale Invariant Capital BV. "Volatility Decay in Bitcoin Price Dynamics: Evidence from Five Halving Cycles." Working paper, March 2026.

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Appendix A: Methodology Details

Power law parameters: Beta = 5.688, log(A) = -16.493, genesis date = January 3, 2009. Time unit = days since genesis. Model: $P(t) = 10^{-16.493} \cdot t^{5.688}$.

DCA simulation: 12 equal monthly installments at 30.44-day intervals. Each installment buys at the nearest available daily closing price. Average cost basis = total dollars invested / total BTC acquired. Horizon return = end price / average cost basis.

Crossover computation: Smoothed using adaptive bandwidth kernel (bandwidth = max(0.15, 0.2m) for trend multiple m). Minimum 20 observations per window. Crossover identified by linear interpolation where the smoothed win rate crosses 50%.

Halving cycle dates: Cycle 1: genesis to November 28, 2012. Cycle 2: to July 9, 2016. Cycle 3: to May 11, 2020. Cycle 4: to April 19, 2024. Cycle 5: April 19, 2024 to present.

Appendix B: Time in Each Valuation Zone

Zone	Trend Multiple	Days	% of History	LS Win Rate (1yr)
Deep Value	< 0.5x	873	15.3%	100.0%
Cheap	0.5 - 0.75x	1,647	28.8%	97.6%
Below Trend	0.75 - 1.0x	800	14.0%	89.4%
Fair Value	1.0 - 1.3x	709	12.4%	58.5%
Above Trend	1.3 - 2.0x	736	12.9%	45.0%
Expensive	> 2.0x	948	16.6%	17.7%

All data, code, and figures are available at btcpowerlaw.nl. Live trend multiple monitoring at btcpowerlaw.nl/history.