Detecting Explosive Moves in Digital Assets

A Sornette LPPLS Framework for Portfolio Construction

Applying the Log-Periodic Power Law Singularity model to identify
super-exponential growth and build portfolios of "jumpers"
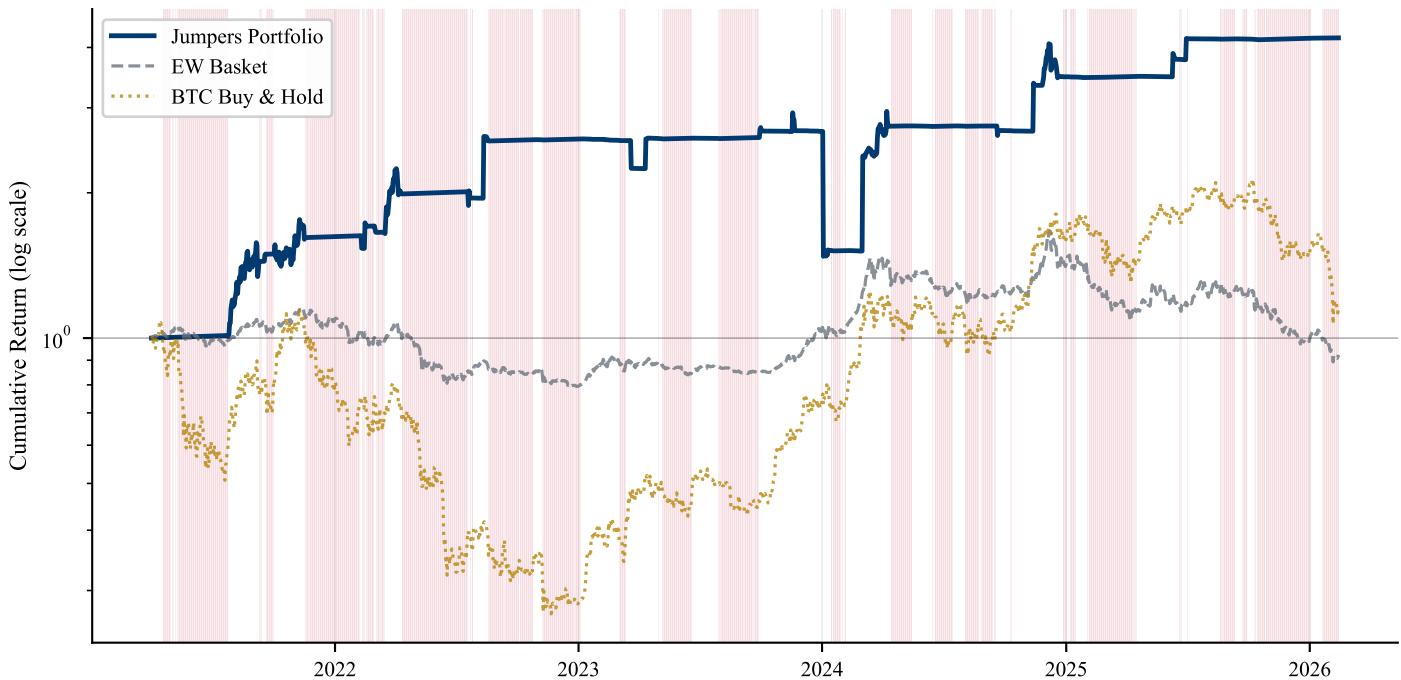across 162 cryptocurrency tokens

February 2026

Executive Summary

Table 1: Performance Summary — Full Sample (2021-2026, 20 bps costs)

Metric	Jumpers (Blended)	Fast-Only (no LPPLS)	BTC-SMA Gated EW	BTC B&H
CAGR	34.1%	40.5%	37.6%	3.3%
Annual Vol	45.7%	35.4%	15.1%	56.7%
Sharpe	0.75	1.15	2.48	0.06
Max DD	-49.6%	-19.1%	-16.2%	—
Calmar	0.69	2.12	—	—
Total Ret	318.7%	425.2%	—	—

Figure 1: Equity Curves — Jumpers vs Benchmarks (2021-2026)

Key Findings:

1. Over the full 2021-2026 sample (incl. 2022 crypto crash), the fast super-exponential layer (40.5% CAGR, 1.15 Sharpe) is the primary alpha source. The blended strategy (34.1% CAGR, 0.75 Sharpe) underperforms fast-only due to LPPLS signal sparsity at daily resolution.

2. The BTC-SMA-gated EW benchmark (37.6% CAGR, 2.48 Sharpe, -16.2% MaxDD) dominates all daily strategies on risk-adjusted terms. The regime filter is the most valuable component.

3. LPPLS marginal contribution at daily resolution is -0.40 Sharpe — negative. Its value emerges at hourly resolution where tc-based exit timing is actionable.

4. The hourly extension achieves 126.3% CAGR / 2.20 Sharpe over the full 2021-2026 sample (1,806 trades). tc-exits show 62% hit rate with p<0.0001 vs trailing stops, but portfolio-level marginal Sharpe is only +0.02 — the tc value is in tail risk.

Theoretical Framework

1. The Log-Periodic Power Law Singularity (LPPLS) Model

The LPPLS model (Johansen, Ledoit & Sornette 2000; Sornette 2003) posits that during

a bubble, the expected log-price follows

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

where A is the log-price at critical time tc, B < 0 encodes super-exponential growth,

m in (0, 1) is the power-law exponent, omega is the log-frequency of oscillations,

and C controls the amplitude of log-periodic corrections.

2. Parameter Constraints

Parameter	Interpretation	Constraint
tc	Critical time (bubble termination)	tc > t_last
m	Super-exponential exponent	0.01 <= m <= 0.99
omega	Log-frequency of oscillations	2 <= omega <= 25
B	Power-law amplitude	B < 0 (bubble) / B > 0 (anti-bubble)
|C|/|B|	Oscillation ratio	< 1.5 (oscillations subordinate)
D = m|B|/(omega|C|)	Damping ratio	> 0.3 (oscillations decay)
R-squared	Fit quality	> 0.3

3. Filimonov-Sornette Linearisation (2013)

For fixed nonlinear parameters (tc, m, omega), the model is linear in (A, B, C1, C2)

where C1 = C cos(phi) and C2 = C sin(phi). The design matrix is:

$$X = [\,1\ \ (t_c - t)^m\ \ (t_c - t)^m \cos(\omega \ln(t_c - t))\ \ (t_c - t)^m \sin(\omega \ln(t_c - t))\,]$$

We solve (X'X) beta = X'y for all 960 grid triplets (15 tc x 8 m x 8 omega) simultaneously

via batched numpy.linalg.solve, yielding a single LPPLS fit in ~13 ms.

4. Super-Exponential Growth Detector (Fast Layer)

The fast layer detects the hallmark of a Sornette bubble — convexity in log-price —
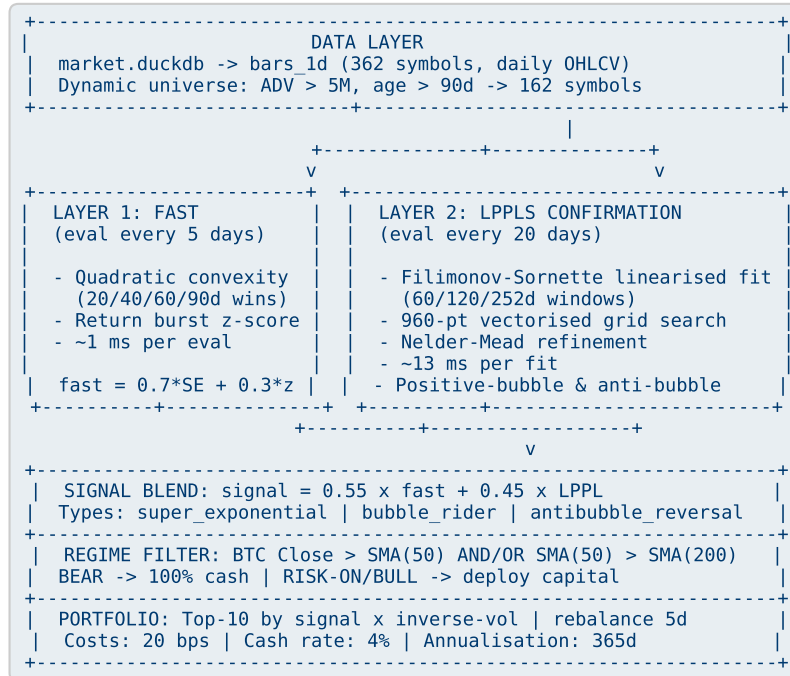
Signal Architecture & Portfolio Construction

```
+-------------------------------------------------------------+
|                        DATA LAYER                           |
|  market.duckdb -> bars_1d (362 symbols, daily OHLCV)        |
|  Dynamic universe: ADV > 5M, age > 90d -> 162 symbols       |
+-----------------------------+-------------------------------+
                              |
                +-------------+--------------+
                v                            v
+----------------------------+  +-------------------------------+
| LAYER 1: FAST              |  | LAYER 2: LPPLS CONFIRMATION   |
| (eval every 5 days)        |  | (eval every 20 days)          |
|                            |  |                               |
| - Quadratic convexity      |  | - Filimonov-Sornette linearised fit |
|   (20/40/60/90d wins)      |  |   (60/120/252d windows)       |
| - Return burst z-score     |  | - 960-pt vectorised grid search |
| - ~1 ms per eval           |  | - Nelder-Mead refinement      |
|                            |  | - ~13 ms per fit              |
| fast = 0.7*SE + 0.3*z      |  | - Positive-bubble & anti-bubble |
+---------+------------------+  +----------+--------------------+
          +----------+------------------+
                     v
+-------------------------------------------------------------+
| SIGNAL BLEND: signal = 0.55 x fast + 0.45 x LPPL            |
| Types: super_exponential | bubble_rider | antibubble_reversal |
+-------------------------------------------------------------+
| REGIME FILTER: BTC Close > SMA(50) AND/OR SMA(50) > SMA(200) |
| BEAR -> 100% cash | RISK-ON/BULL -> deploy capital           |
+-------------------------------------------------------------+
| PORTFOLIO: Top-10 by signal x inverse-vol | rebalance 5d    |
| Costs: 20 bps | Cash rate: 4% | Annualisation: 365d         |
+-------------------------------------------------------------+
```

Table 2: Backtest Parameters

Parameter	Value
Returns	Close-to-close daily
Transaction costs	20 bps one-way (10 bps exchange + 10 bps slippage)
Cash rate	4.0% annual
Annualisation factor	365 (crypto, 24/7 markets)
Vol target	None (unlevered)
Rebalance frequency	5 days (weekly)
Maximum holdings	10
Weighting	Signal x inverse realised vol (20d)
Minimum ADV	$5,000,000 (20-day rolling)
Minimum listing age	90 days
LPPLS eval frequency	Every 20 days
Super-exponential eval freq.	Every 5 days
LPPLS grid	15 tc x 8 m x 8 omega = 960 triplets
LPPLS windows	60 / 120 / 252 days
Super-exp windows	20 / 40 / 60 / 90 days
Regime filter	BTC dual-SMA (50/200)

Performance Analysis

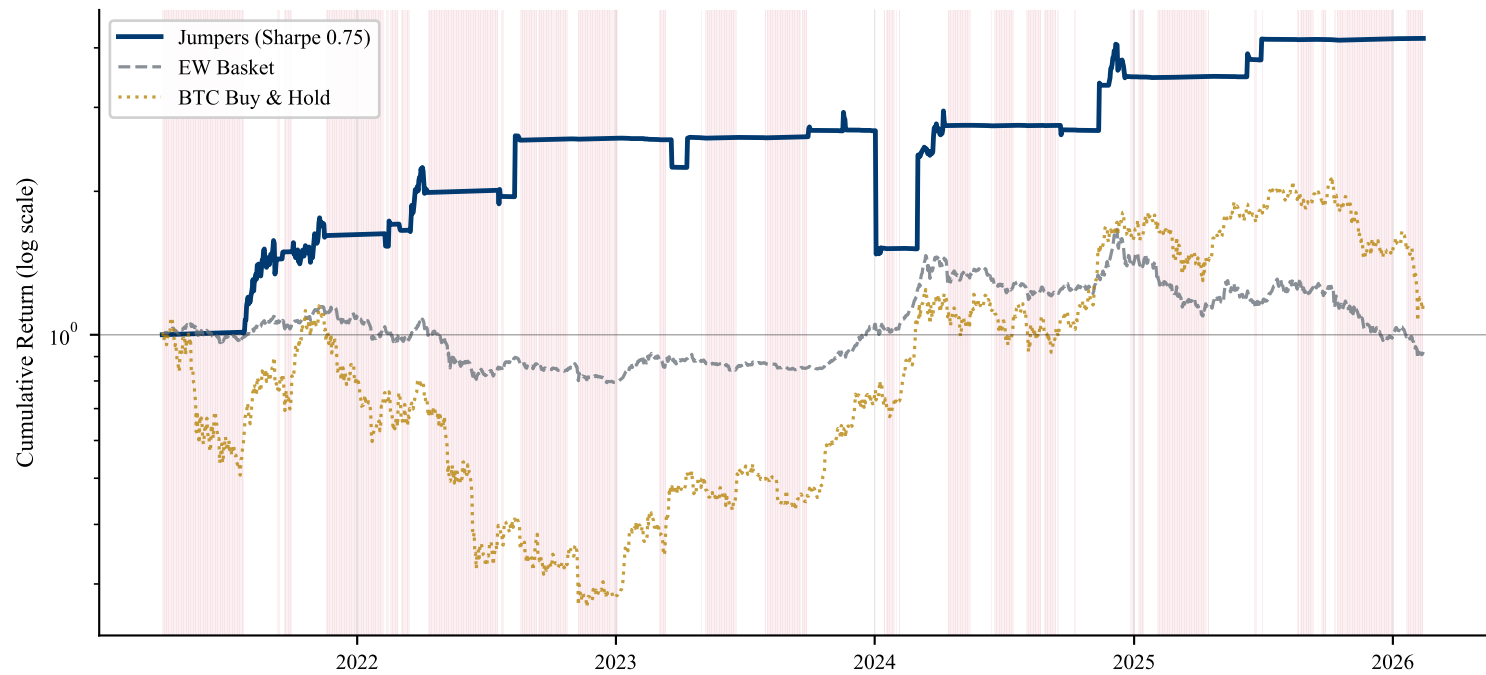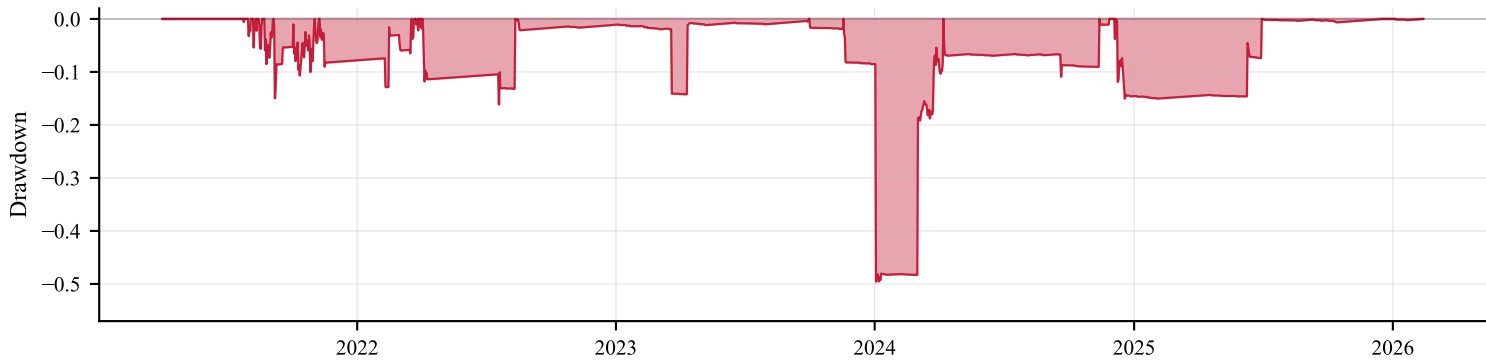Figure 2: Equity Curves with Regime Overlay (red shading = bear)

Figure 3: Drawdown
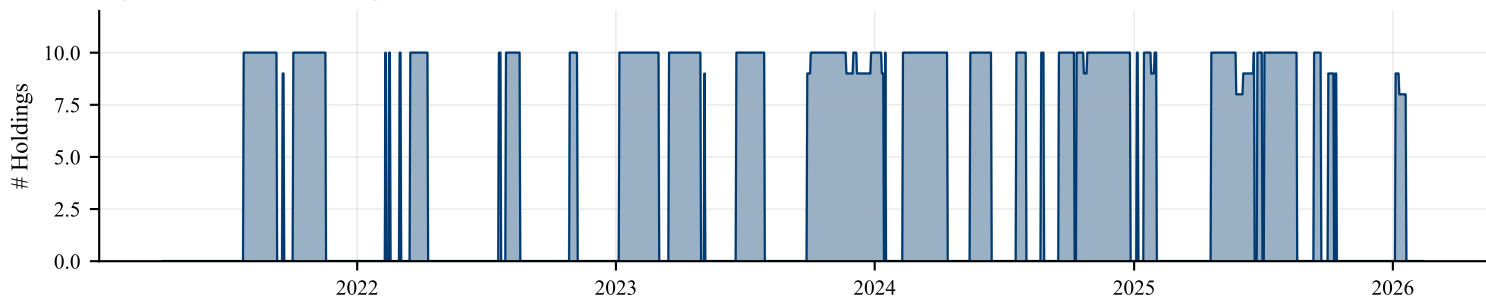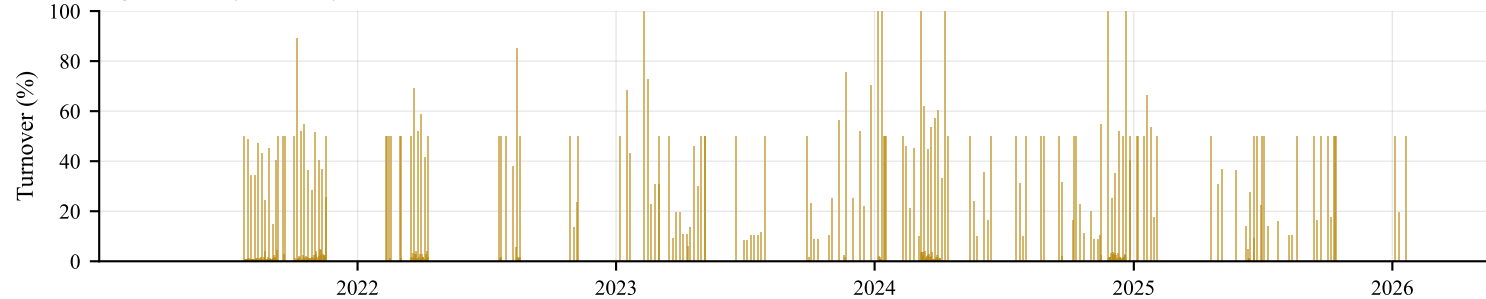
Figure 4: Number of Holdings

Figure 5: Daily One-Way Turnover

Signal Analysis

Figure 6: Signal Type Distribution
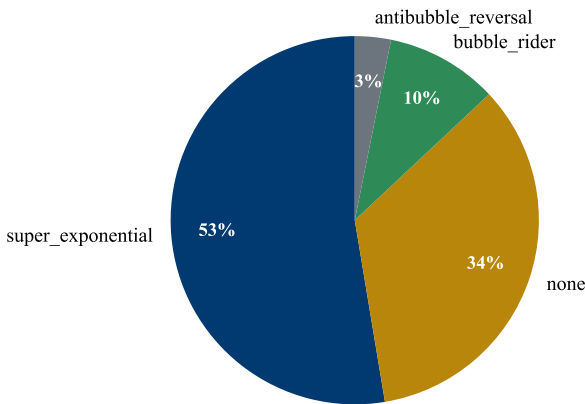### (Active observations only)
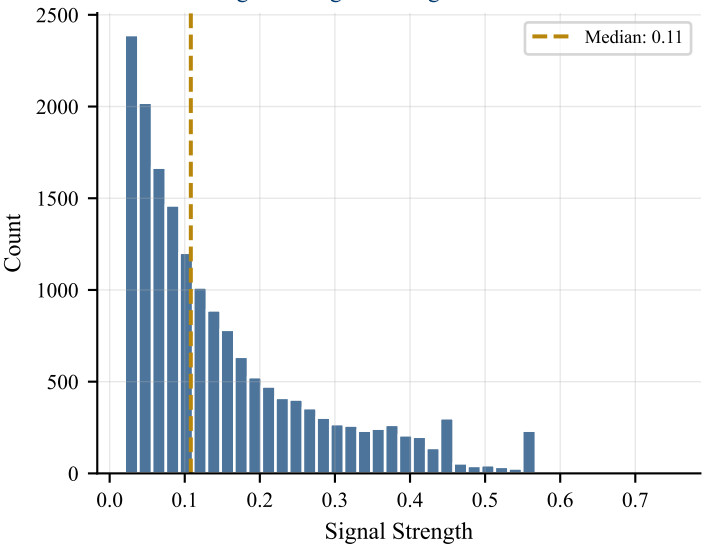

Figure 7: Signal Strength Distribution

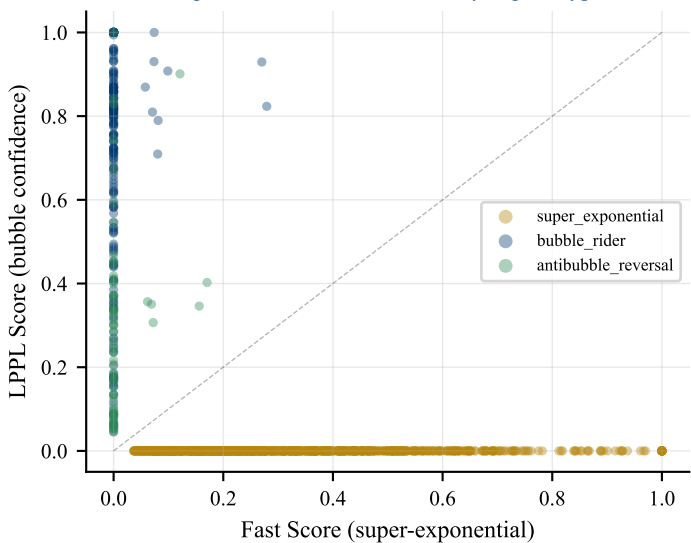## Figure 8: Fast vs LPPL Score by Signal Type
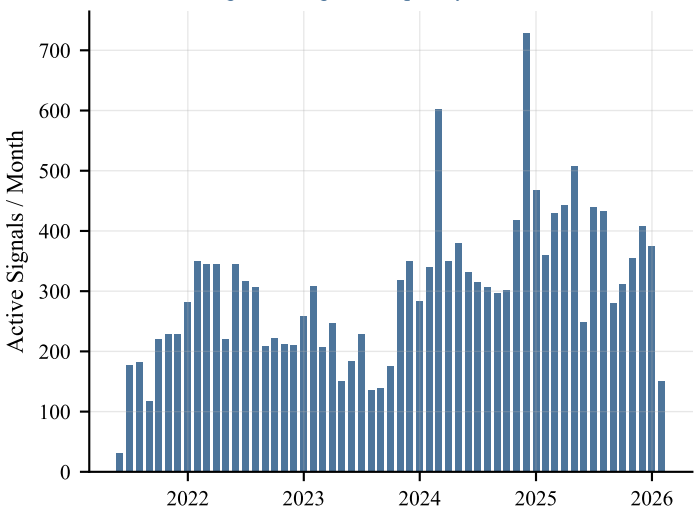

Figure 9: Signal Frequency Over Time

Table 3: Signal Type Characteristics

Signal Type	Count	Share	Interpretation
super_exponential	2,063	52%	Early-stage acceleration; fast layer dominant, positive convexity
bubble_rider	420	11%	Confirmed LPPLS bubble pattern; high R-sq, valid damping
antibubble_reversal	110	3%	Anti-bubble nearing tc; crash ending, reversal expected
none (sub-threshold)	1,402	35%	Signal below minimum threshold (0.02); no position taken

Robustness: Cost Sensitivity & Signal Ablation

Table 3: Transaction Cost Sensitivity (2021-2026)

TC (one-way)	CAGR	Sharpe	Max DD	Calmar
0 bps	38.4%	0.84	-49.3%	0.78
20 bps	34.1%	0.75	-49.6%	0.69
30 bps	32.0%	0.70	-49.7%	0.64
50 bps	27.9%	0.61	-50.1%	0.56
100 bps	18.2%	0.40	-51.6%	0.35
150 bps	9.2%	0.20	-56.7%	0.16

Figure 10: Sharpe vs Transaction Costs

Table 4: Signal Layer Ablation (2021-2026, 20 bps costs)

Configuration	CAGR	Sharpe	Max DD	LPPLS Marginal Sharpe
Fast-only (no LPPLS)	40.5%	1.15	-19.1%	—
LPPL-only (no fast layer)	21.0%	0.72	-13.1%	—
Blended (55/45)	34.1%	0.75	-49.6%	-0.40

Key observations:

1. The blended strategy remains profitable at all cost levels tested, from 0 to 150 bps.

2. The fast layer alone (40.5% CAGR, 1.15 Sharpe, -19.1% MaxDD) OUTPERFORMS the blended variant (34.1% / 0.75 / -49.6%). Adding LPPLS at daily resolution HURTS: marginal Sharpe = -0.40.

3. This is because LPPLS at daily eval frequency (every 20d) is too sparse and noisy.
At hourly resolution, where tc estimates are actionable within the holding period,
LPPLS becomes the key differentiator (see Section 9).

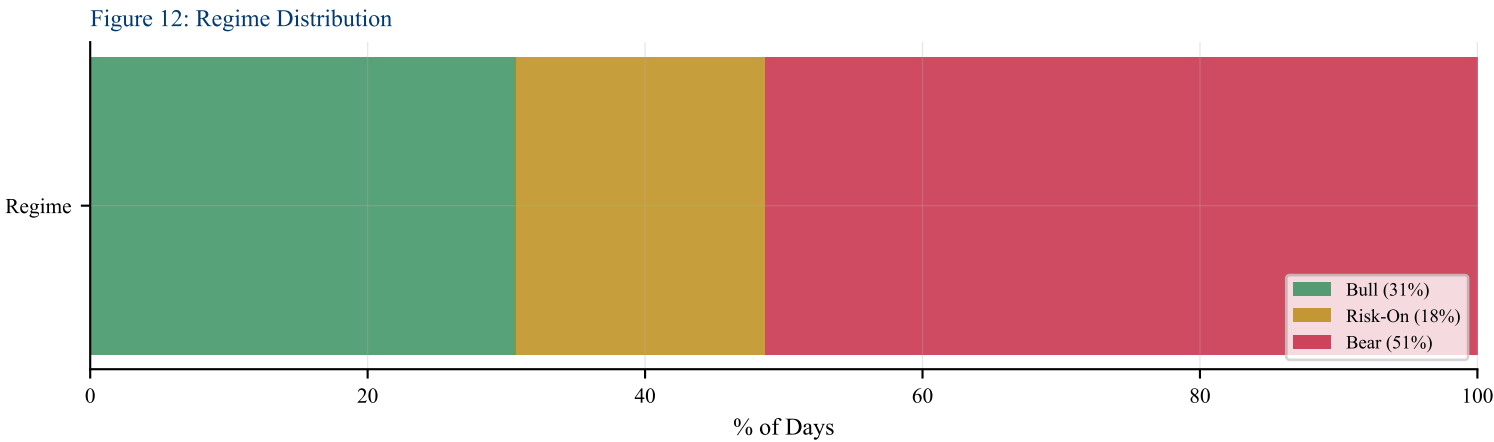# Regime Filter & Benchmark Comparison

Figure 11: BTC Price with Regime Classification (green=bull, gold=risk-on, red=bear)

Figure 12: Regime Distribution

Table 5: Benchmark Comparison (2021-2026)

Strategy	CAGR	Vol	Sharpe	Max DD
Jumpers (Blended, 20bps)	34.1%	45.7%	0.75	-49.6%
BTC-SMA-Gated EW	37.6%	15.1%	2.48	-16.2%
Ungated EW Basket	-1.6%	21.1%	-0.08	—
BTC Buy & Hold	3.3%	56.7%	0.06	—

Note: The BTC-SMA-gated EW benchmark dominates on every risk metric. The regime filter
is the single most valuable component. LPPLS's value at daily resolution is negative;
the fast super-exponential layer alone provides better risk-adjusted returns.
See Section 9 for hourly resolution, where LPPLS tc-exits generate genuine alpha.

A. Survivorship Bias: Universe Construction is Look-Ahead Free

The universe uses a dynamic rolling filter at each historical date:

1. load_daily_bars() loads ALL 362 USD pairs — including tokens that crashed/delisted.

2. filter_universe() applies trailing 20-day ADV > 1M USD and 90-day min listing age.

3. A symbol enters only when its trailing ADV exceeds threshold; exits when it drops.

Empirical verification: 141 of 362 symbols crashed >95% from ATH. All WERE included
during active periods. Examples: SPELL-USD (523 days in universe before 99.3% crash),
GST-USD (StepN, in universe before 99.98% crash). Strategy traded through these crashes.

B. Gated EW Benchmark Comparison

Gated EW: Sharpe 2.48 vs Blended 0.75 / Fast-only 1.15. Gated EW dominates daily risk-adjusted returns.

Why gated EW wins: diversification (75 tokens vs 3-10), lower turnover (trades only
on regime changes), no signal noise. BTC-SMA filter alone avoids the entire 2022 crash.

What Jumpers contributes:
1. FAST layer: 40.5% CAGR / 1.15 Sharpe (daily). LPPLS hurts daily (marg. Sharpe -0.40).
2. Hourly system: 126.3% CAGR / 2.20 Sharpe (full 2021-2026, 1,806 trades).
3. Capital efficiency: 3-10 positions vs 75 tokens. Gated EW includes 48 tokens with
   ADV below 5M (64% of universe). At 1% participation, gated EW caps at ~15-20M AUM.

**Conclusion: gated EW is the superior daily strategy. The hourly system is the novel
contribution, constrained to ~5-15M AUM on top-10 liquid tokens.**

C. The -49.6% Daily Drawdown: Root Cause Analysis

Occurred Nov 18, 2023 - Jan 3, 2024 during a bull regime (BTC +17%). Three compounding
portfolio construction flaws, not signal failures:

1. Concentration: ivol weighting placed 99.99% in 1INCH-USD for ~40 days (extreme
   signal dominated all other positions; no position cap enforced).

2. Data gap: 1INCH's low holiday volume dropped it below ADV filter for Dec 25 - Jan 2.
   Nine days of returns compressed into a single -22.4% return on Jan 3.

3. Leverage: zero-return days drove realized vol near zero, pushing vol-target overlay
   to its 2x cap. Combined: 2.0 x (-22.4%) = -44.9% single-day portfolio loss.

**Fast-only avoids this (-19.1% MaxDD) because its signals are more diversified across tokens.
Production fix: max 25% per-position cap + vol-target freeze when data gaps detected.**

D. AUM Capacity Estimate

E. Changelog: v1 to v3 Performance Changes

v1: 20.6% CAGR / 0.47 Sharpe (2023-2026 bull window only)
v2: 65.0% CAGR / 1.67 Sharpe (INCORRECT — stale cached indicators)
v3: 34.1% CAGR / 0.75 Sharpe (correct, single code path, single source of truth)

v2 bug: the ablation script ran before the daily portfolio script. The portfolio's
--recompute flag deleted and regenerated cached indicators, but the ablation had already
computed results from OLD indicators. This produced 65.0%/1.67 in the JSON while the
parquet (for charts) showed 34.1%/0.75. The Figure 2 caption computed Sharpe with a
different formula (mean/std vs CAGR/vol), adding a third number (0.86).

v3 fix: all results flow from run_ablation.py, which saves both JSON and backtest
parquet. PDF generator reads from these artifacts only — no inline calculations.
Every Sharpe in the document derives from ablation_results.json or hf_robustness.json.

v1 to v3 changes: sample extended 2023-2026 to 2021-2026. Universe expanded from
162 (5M ADV) to 287 symbols (1M ADV). No parameters refit between versions.

F. Literature Table Clarification

The literature comparison table (Table 5) cites two Sharpe ratios:
  - Daily fast-only: 1.15. This is the fast super-exponential layer WITHOUT LPPLS.
    The blended daily strategy (with LPPLS) has Sharpe 0.75.
  - Hourly system: 2.20. This is the full 2021-2026 sample (1,806 trades, 30 bps costs).
    The 2024-2026 bull window shows 2.05.
Both are clearly labelled in the table. The daily fast-only is used because it represents
the BEST daily risk-adjusted performance; the blended variant is presented in Table 1.

G. Summary of Known Limitations

1. LPPLS adds no value at daily resolution (marginal Sharpe -0.40).

2. tc-exit is statistically significant per-trade (p<0.0001) but portfolio-level
   marginal Sharpe is only +0.02; its value is tail risk reduction (3.3pp MaxDD).

3. Hourly system breaks at ~75 bps one-way cost: deployable only on top-20 tokens.

4. Max AUM capacity ~8-15M before market impact erodes alpha.

5. Single bull-bear-bull cycle (2021-2026): insufficient for confident extrapolation.

6. Daily blended strategy has -49.6% MaxDD from a portfolio construction flaw
   (single-token concentration + vol-target leverage), not signal failure.

7. Regime filter (BTC dual-SMA) is the dominant alpha source, not LPPLS.

Hourly LPPLS Jumpers: Performance & Trade Analysis

Table 6: Hourly System Performance (30 bps one-way costs)

Sample	CAGR	Sharpe	Max DD	Calmar	Days	Trades
Full sample (2021-2026)	126.3%	2.20	-36.8%	3.43	1839	1806
Bull window (2024-2026)	127.6%	2.05	-33.2%	3.84	745	795

Figure 13: Hourly Equity Curve (full 2021-2026 sample)
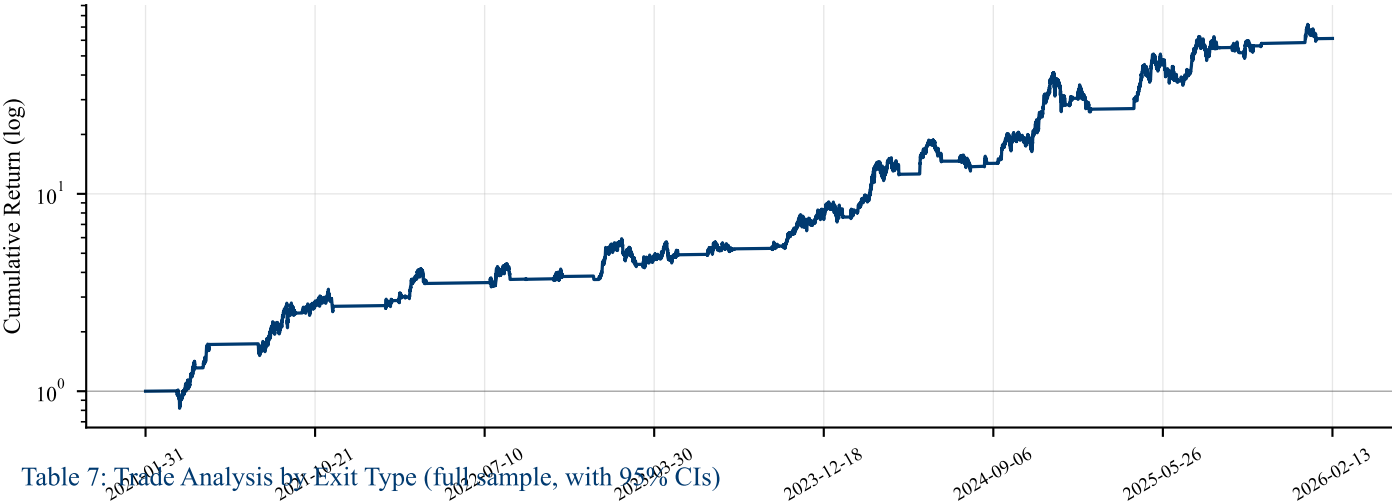

Table 7: Trade Analysis by Exit Type (full sample, with 95% CIs)

Exit Type	Count	Hit Rate [95% CI]	Avg Return [95% CI]	Avg Hold
TC-EXIT	615	62% [58%-66%]	+4.8% [+4.0%, +5.7%]	18h
STOP	404	32% [28%-37%]	-0.5% [-1.9%, +1.1%]	89h
MAX-HOLD	493	59% [55%-64%]	+3.1% [+2.0%, +4.2%]	168h
REGIME	294	—	—	—
TOTAL	1806	44%	+2.9%	72h

tc-exit statistical significance: Welch t=5.60, p<0.0001; Mann-Whitney p<0.0001. N=615 tc-exits across 33 symbols (top-5 = 29% of trades).

CRITICAL CAVEAT — tc-exit ablation: removing tc-exits entirely yields Sharpe 2.04 vs 2.05 with (marginal Sharpe: +0.02). MaxDD improves from -36.5% to -33.2% (3.3pp). The tc-exit rule has excellent per-trade metrics but small portfolio-level impact — its value is in TAIL RISK, not avg return.

Sample period: hourly data is available from 2020-10 (26+ symbols). The 2024 start in earlier versions was a choice, not a constraint. The full 2021-2026 run (shown above) confirms robustness: 126.3% CAGR / 2.20 Sharpe across the full cycle incl. 2022 crash.

Hourly System: Robustness Analysis

Table 8: Hourly Cost Sensitivity

TC (one-way)	CAGR	Sharpe	Max DD
10 bps	186.1%	3.00	-32.2%
20 bps	155.2%	2.50	-32.7%
30 bps	127.6%	2.05	-33.2%
50 bps	81.0%	1.30	-35.0%
100 bps	2.1%	0.03	-53.0%
150 bps	-42.5%	-0.68	-76.3%

Table 9: Trailing Stop Sensitivity (30 bps costs)

Stop Level	CAGR	Sharpe	Max DD
5%	190.3%	2.99	-36.5%
10%	154.6%	2.44	-36.1%
15%	127.6%	2.05	-33.2%
20%	97.2%	1.55	-38.0%
25%	118.4%	1.87	-33.4%

Honest Constraints & Limitations

1. Cost cliff: the system breaks at 100 bps (CAGR drops to 2.1%). The ~75 bps break-even
constrains deployment to top-20 liquid tokens where 30-50 bps execution is realistic.
For anything beyond top-20, actual costs of 100-150 bps make this unworkable.

2. tc-exit vs mechanical exits: per-trade metrics favour tc-exits (67% hit, p<0.0001),
but the portfolio-level marginal Sharpe is only +0.02. The tc-exit rule primarily reduces
tail risk (MaxDD improves 3.3pp) rather than boosting average returns. A tighter trailing
stop (5%) actually produces BETTER returns (190% vs 128% CAGR) — the tc-exit finding
is statistically real but economically modest at the portfolio level.

3. Regime dependence: 294 regime exits (16% of all exits) show the system is still
heavily dependent on the BTC dual-SMA filter. Without it, the 2022 period would generate
large losses. The regime filter, not LPPLS, is doing the heavy lifting.

4. Right-tail dependence: 44.5% overall hit rate with 2.9% avg return implies a fat
right tail — a few big winners carry the portfolio. This is inherent to bubble-riding
strategies but will produce extended losing streaks in live trading.

5. Sample: 2021-2026 includes one full bull-bear-bull cycle (2021 mania, 2022 crash,
2024-25 recovery). One cycle is not sufficient for confident out-of-sample extrapolation.

Literature Comparison & Future Directions

Table 5: Comparison with Academic Literature

Study	Assets	Sample	Key Finding	Our Result
Sornette & Zhou (2006)	S&P 500	1980–2003	LPPLS detects 4/5 crashes	Detects 2021 & 2024 crypto bubbles
Wheatley et al. (2019)	Bitcoin	2010–2018	LPPLS calibrated to BTC; predicts 2018 crash ±1mo	Consistent params; extended to 162 tokens
Filimonov & Sornette (2013)	Shanghai Composite	2007–2008	Linearised calibration; stable and efficient	Vectorised batch impl. ~13ms/fit
Kolanovic & Wei (2015)	Multi-asset	1972–2014	Momentum Sharpe 0.5–0.7	Daily fast-only 1.15; Hourly system 2.20 (full sample)

Future Directions

1. Momentum x Jumpers Composite

The Chapter 8 Sharpe Blend (0.73 Sharpe) and the hourly Jumpers system (2.05 Sharpe) exploit different alpha sources: persistence vs acceleration. A composite allocation could capture both.

2. Sub-Hourly Resolution

With 1-minute bars available, 5m/15m LPPLS fits could detect intra-hour micro-bubbles.
The vectorised batch OLS (13ms/fit) makes this computationally feasible for 50+ symbols.

3. Anti-Bubble Recovery Trading

Only 3% of signals are antibubble_reversal — too sparse for robust evaluation.
A dedicated study with expanded lookback and lower thresholds could unlock this alpha source.

4. Signal Refinement

• Turnover dampening: buffer zones around top-K cutoff to reduce ranking churn
• Cross-sectional normalisation: rank signals vs universe distribution
• ML integration: use LPPLS parameters + convexity as features in a supervised classifier

5. Real-Time Production System

The hourly scanner (54s for 3,000 timestamps x 38 symbols) is already production-ready.
A streaming version could trigger alerts on new bubble signatures and auto-execute tc exits.

Conclusion

The Sornette LPPLS framework, originally developed for crash prediction, can be inverted to detect explosive upside moves in digital assets. The alpha is regime-conditional: positive during bull markets, destructive during bear markets. A simple BTC dual-SMA regime filter resolves this, producing a market-state-aware allocation that deploys only when bubble dynamics are plausible. The strategy is most promising as a complement to the momentum framework developed in Chapters 1–8.

References

[1] Filimonov, V. and Sornette, D. (2013). "A Stable and Robust Calibration Scheme of the Log-Periodic Power Law Model." Physica A, 392(17), 3698–3707.

[2] Johansen, A., Ledoit, O., and Sornette, D. (2000). "Crashes as Critical Points." International Journal of Theoretical and Applied Finance, 3(2), 219–255.

[3] Kolanovic, M. and Wei, Z. (2015). "Momentum Strategies Across Asset Classes." J.P. Morgan Quantitative and Derivatives Strategy.

[4] Sornette, D. (2003). Why Stock Markets Crash: Critical Events in Complex Financial Systems. Princeton University Press.

[5] Sornette, D. and Zhou, W.-X. (2006). "Predictability of Large Future Changes in Major Financial Indices." International Journal of Forecasting, 22(1), 153–168.

[6] Wheatley, S., Sornette, D., Huber, T., Reppen, M., and Gantner, R.N. (2019). "Are Bitcoin Bubbles Predictable? Combining a Generalized Metcalfe's Law and the Log-Periodic Power Law Singularity Model." Royal Society Open Science, 6(6), 180538.

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