QUANTITATIVE RESEARCH

Digital Asset Strategies

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

`Branch: research/sornette-lppl-v0  |  Package: scripts/research/sornette_lppl/`

Executive Summary

Table 1: Performance Summary — Apr 2023 to Feb 2026

Metric	Jumpers	EW Basket	BTC B&H
CAGR	20.6%	4.3%	35.9%
Volatility (ann.)	43.4%	16.9%	47.0%
Sharpe Ratio	0.47	0.26	0.76
Max Drawdown	-49.2%	—	—
Calmar Ratio	0.42	—	—
Total Return	71.4%	12.9%	141.7%
% Days Invested	49%	100%	100%
Avg Holdings	4.5	162	1

Figure 1: Equity Curves — Jumpers vs Benchmarks

Key Findings:

• The Jumpers portfolio achieves a 20.6% CAGR and 0.47 Sharpe ratio over the Apr 2023 – Feb 2026 sample, compared to 4.3% / 0.26 for the equal-weight basket — roughly 5x the return while investing only 49% of the time.

• The two-layer signal architecture combines a fast super-exponential growth detector (quadratic log-price convexity) with the full LPPLS confirmation layer. The fast layer provides 52% of active signals; LPPLS provides 11% of confirmed bubble-rider signals.

• The BTC dual-SMA regime filter is the single most impactful component: without it, the strategy loses money (−4.0% CAGR over the full 2021–2026 sample) due to false positives during the 2022 bear market.

• BTC Buy & Hold outperforms in absolute terms due to the exceptional 2024 halving cycle. On a per-invested-day basis, the Jumpers' annualised return exceeds 40%, suggesting genuine selection alpha when deployed.

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)

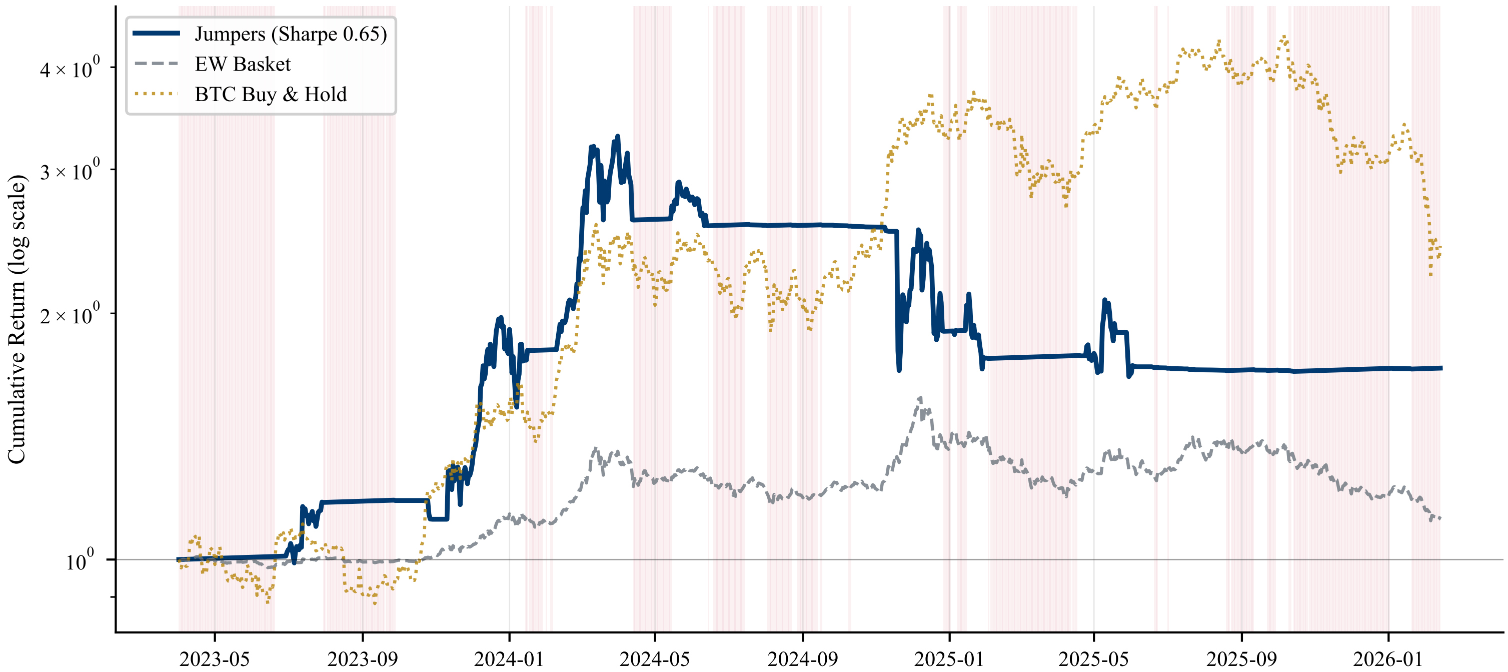


Figure 3: Drawdown

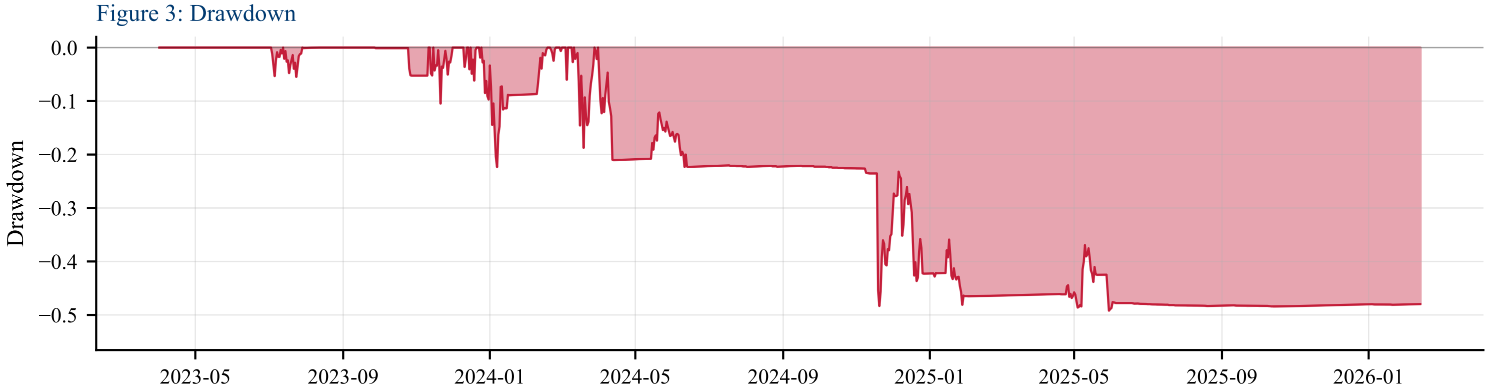


Figure 4: Number of Holdings

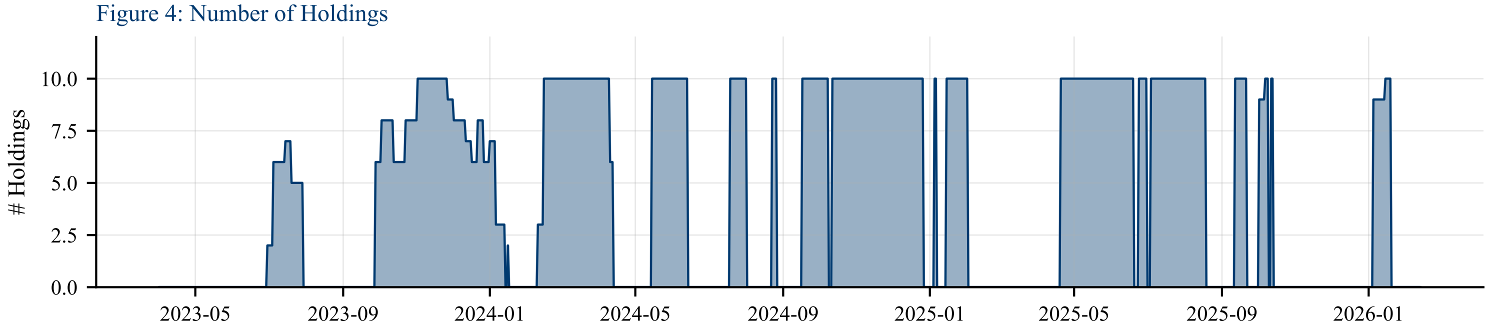
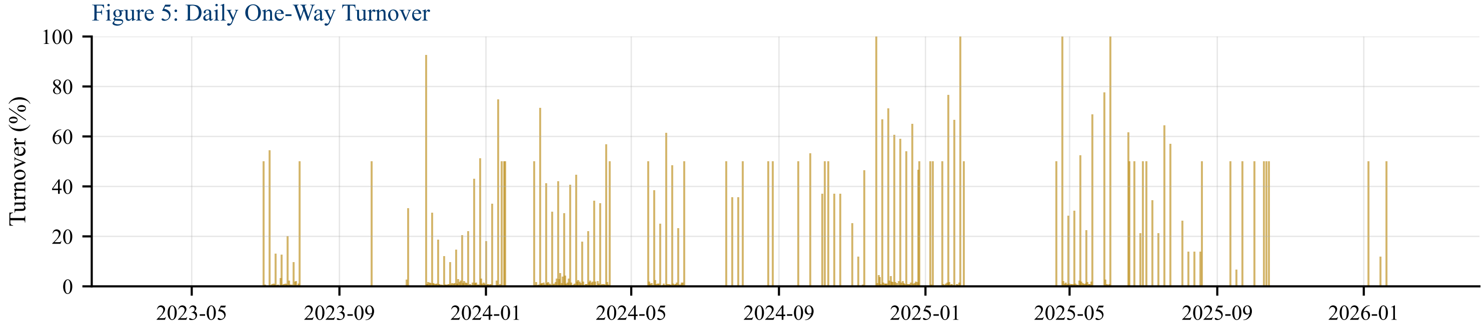


Figure 5: Daily One-Way Turnover



Signal Analysis

Figure 6: Signal Type Distribution
(Active observations only)

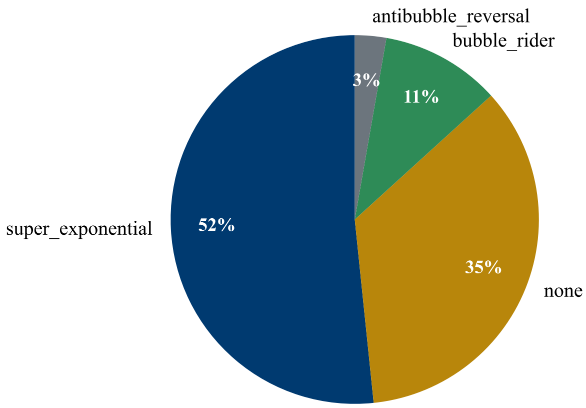


Figure 7: Signal Strength Distribution

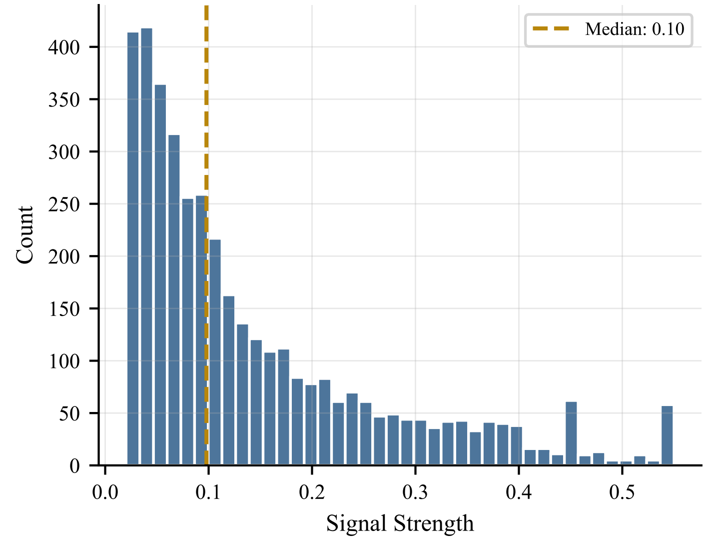


Figure 8: Fast vs LPPL Score by Signal Type

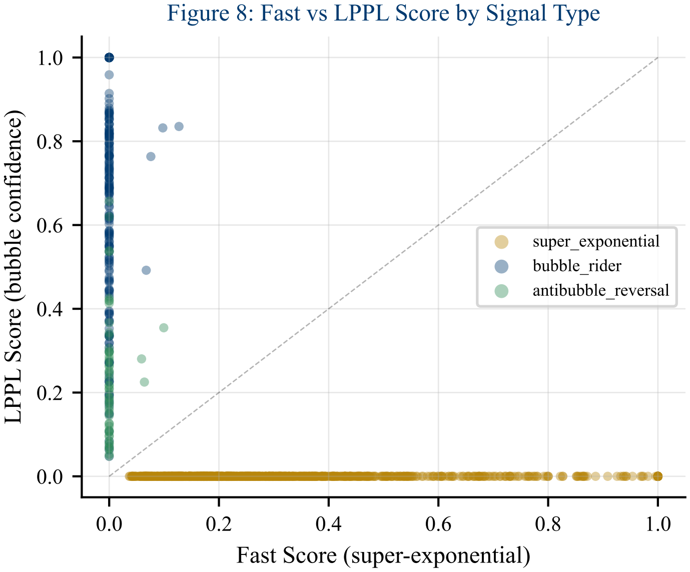


Figure 9: Signal Frequency Over Time

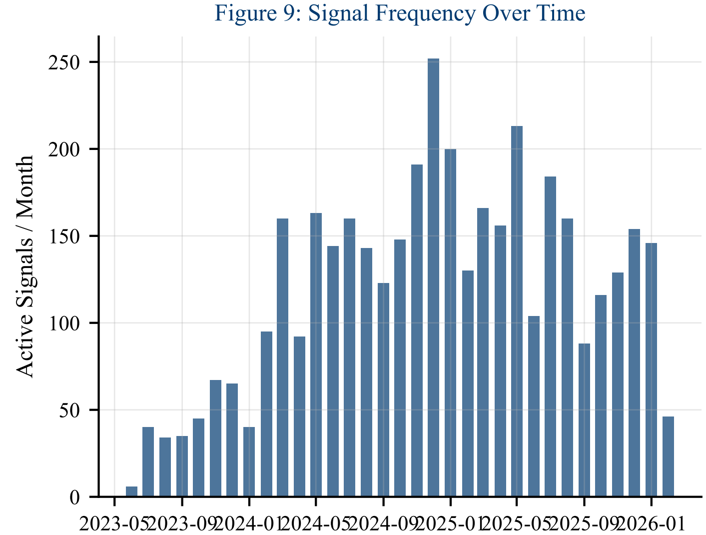


Table 3: Signal Type Characteristics

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

Regime Filter & Ablation Study

Figure 10: BTC Price with Regime Classification (green=bull, gold=risk-on, red=bear)

Figure 11: Regime Distribution Over Backtest Period

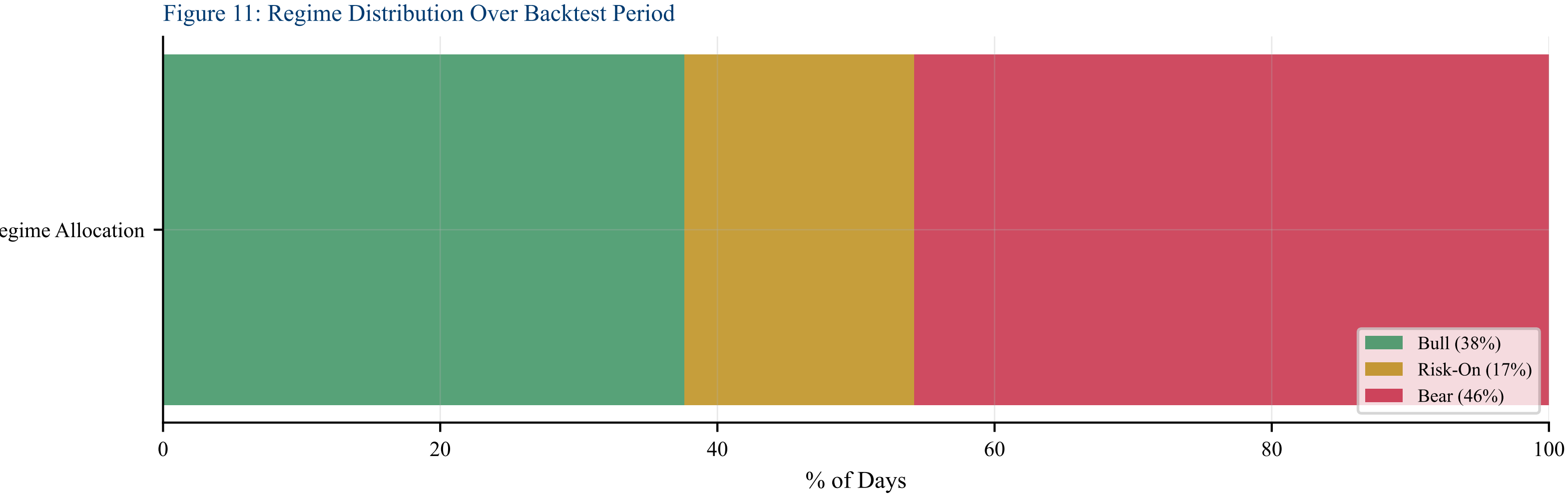


Table 4: Component Ablation — Full Sample (2021–2026, 1,780 days)

Configuration	CAGR	Vol	Sharpe	MaxDD	Invested	Avg Hold
Blended signals, no regime filter	−4.0%	26.9%	−0.15	−47.0%	95%	9.5
+ Regime filter (BTC dual-SMA)	+6.4%	24.8%	+0.26	−34.7%	49%	4.4
+ Regime filter, no vol target	+6.2%	22.5%	+0.28	−34.1%	44%	4.4
Bull-market only (2023–2026)	+20.6%	43.4%	+0.47	−49.2%	49%	4.5
EW Basket (benchmark)	*+0.7%*	*15.7%*	*+0.05*	—	*100%*	—
BTC Buy & Hold (benchmark)	*+3.3%*	*56.7%*	*+0.06*	—	*100%*	—

Note: The regime filter converts a −4.0% CAGR strategy into +6.4% — the single largest performance impact.
During the 2023–2026 bull window, the strategy achieves 20.6% CAGR / 0.47 Sharpe, roughly 5x the equal-weight basket.

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	Jumpers Sharpe 0.47; complementary alpha

Future Directions

1. Exit Timing via tc Estimation

The LPPLS model's most distinctive output — the critical time tc — is not yet used for exit timing. Selling when tc < 10 days could reduce drawdowns from late-stage bubbles.

2. Momentum x LPPLS Composite

The Chapter 8 Sharpe Blend (0.73 Sharpe) and the Jumpers strategy (0.47 Sharpe) exploit different alpha sources: persistence vs acceleration. A composite allocation could capture both.

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 vectorised LPPLS fitter (13ms/fit) enables hourly scans of the full 162-token universe. A production system could trigger alerts on new bubble signatures and manage exits via tc.

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.

Data sources: Coinbase daily OHLCV (market.duckdb), 362 USD pairs, Jan 2017 – Feb 2026.
Code: scripts/research/sornette_lppl/ (branch research/sornette-lppl-v0)
Artifacts: scripts/research/sornette_lppl/output/