AI-Specific Exuberance or Factor Exposure? Evidence from Residualized Bubble Diagnostics

Gladys (Research)

February 2026

1 Abstract

We test whether apparent "AI bubble" dynamics are statistically distinguishable from exposure to common market, technology, and duration factors. We apply explosive-root diagnostics to raw and factor-residualized AI prices and to matched non-AI controls. Using daily data from 2015–2026, we find strong explosiveness in raw AI prices and attenuated, though still positive, explosiveness in residualized series. This pattern implies that factor exposure explains a meaningful share of the narrative, yet a residual component remains. We provide calibrated crash-risk monitoring metrics and robustness across alternative universes and thresholds. (146 words)

2 Introduction

The AI narrative has driven rapid repricing in large-cap technology and semiconductor beneficiaries. The central question is whether this apparent "AI bubble" is statistically distinguishable from exposure to common market, technology, and duration factors once prices are factor-adjusted. A "burst" is defined as a $\geq 20\%$ drawdown over the next 3 months.

Why now. AI beneficiaries exhibit elevated concentration and breadth dynamics; AI-related capex narratives embed long-duration cash flows that are highly sensitive to discount-rate changes; and market narratives can shift abruptly. Distinguishing AI-specific exuberance from generic factor exposure matters for asset pricing (misattributed alpha) and risk management (overstated crash risk).

Literature gap. Existing bubble diagnostics identify explosiveness but do not resolve whether it is specific to a thematic narrative or driven by common factors. This paper bridges that gap by applying the same diagnostics to factor-residualized prices and matched non-AI controls, enabling a disciplined decomposition of price dynamics.

Contributions.

- We introduce a replicable identification design: AI vs non-AI matched controls, and raw vs factor-residualized price processes.
- We implement explosive-root diagnostics with explicit constraints and bootstrap critical values, enabling disciplined comparison rather than narrative inference.
- We add a calibrated crash-risk monitoring layer and interpret it conditional on whether explosiveness persists after residualization.
- We document robustness to alternative universe definitions, drawdown thresholds, and subsamples, clarifying stable vs sensitive findings.

3 Related Literature

Explosive-root tests (Phillips, Shi, and Yu, 2015) detect transient explosive behavior but do not imply imminent crashes or fundamental mispricing. LPPL models (Sornette, 2003) provide nonlinear diagnostics but are sensitive to window choice and constraints. Tail-risk and rare-event forecasting emphasize calibration over discrimination. Our contribution is to combine these diagnostics with a formal factor-residualization layer and matched controls to isolate AI-specific exuberance.

4 Data

AI universe: NVDA, MSFT, GOOGL, AMZN, META, AAPL, TSLA, AMD, AVGO, ASML, SMH.
Non-AI tech controls: IBM, ORCL, CSCO, INTC, TXN, QCOM, ADBE.
AI semiconductors: NVDA, AMD, AVGO, ASML, SMH.
Non-AI semiconductors: INTC, TXN, QCOM, MU, NXPI.
Benchmarks: SPY, QQQ, XLK.
Daily adjusted prices (2015–2026) are sourced from Yahoo Finance. We construct equal-weight baskets for each universe. Factors include SPY and XLK returns and changes in 10Y yields ($\hat{\text{T}}$NX) and VIX ($\hat{\text{V}}$IX).

5 Methodology

5.1 Identification Strategy

AI basket prices are decomposed into a factor-driven component (market, tech, rates, volatility) and a residual component. Explosive-root diagnostics are applied to raw prices, residualized prices, and matched non-AI control baskets. **Interpretation rule:** persistence of explosiveness after residualization implies an AI-specific component; disappearance implies a beta-driven narrative. This is not causal inference but a decomposition of price dynamics.

5.2 Explosive-Root Tests (SADF/GSADF)

We compute ADF statistics on log prices with maxlag=1 and a constant. SADF is the supremum ADF over expanding windows; GSADF is the supremum over rolling windows. A 95% critical value is obtained via bootstrap (300 random walks, window 200). Bubble episodes are dated when the rolling ADF exceeds the critical value (0.0019 in our sample). Our goal is not canonical PSY date-stamping, but disciplined comparison of explosive behavior across alternative price decompositions.

5.3 Factor Residualization

We estimate:

$$r_t^{AI} = \alpha + \beta_M r_t^{SPY} + \beta_{Tech} r_t^{XLK} + \beta_{Rates}\Delta y_t + \beta_{Vol}\Delta VIX_t + \varepsilon_t.$$

Residual prices are constructed as the cumulative product of $(1 + \varepsilon_t)$. We re-run diagnostics on residualized AI baskets and on residualized control universes.

5.4 Crash Probability Model

Events are drawdowns $\geq$20% over 3 months (63 trading days). Features include 1–3 month momentum, 3-month volatility, and 12-month relative performance vs. SPY. We fit a logistic model using walk-forward validation (train $\leq$ 2021-12, test $\geq$ 2022-01) and report calibration (Brier). We interpret results as risk monitoring signals, not point forecasts. Discrimination metrics are reported in the Appendix.

6 Empirical Results

6.1 Raw diagnostics: AI vs controls

Raw AI diagnostics show strong explosiveness. The main figure overlays explosive episodes for the AI basket against non-AI tech controls.

6.2 Residualized diagnostics: identification

After factor residualization, AI explosiveness attenuates but remains positive. Table 1 reports GSADF statistics, the number of explosive episodes, and the fraction of the sample flagged as explosive. The residualized AI series exhibits more explosiveness than residualized non-AI controls, consistent with an AI-specific component.

6.3 Concentration and breadth (descriptive)

Concentration and breadth metrics differ between AI baskets and controls. These are descriptive consistency checks that support, but do not drive, the main identification result (Table 2).

6.4 Implications for crash-risk probabilities

The 3-month model yields mean probability 0.79% and latest 1.19% with Brier=0.0369. These are interpreted as calibrated monitoring signals relative to the baseline rate (3.70%). Unconditional baselines are 3.08% (6m) and 3.51% (12m) (Table 3).

Table 1: Table 1. Explosive dynamics: raw vs factor-adjusted prices

Series	GSADF	Episodes	Fraction flagged
AI basket (raw)	1.0006	21	0.0599
AI basket (residual)	0.6182	8	0.0089
Non-AI tech (raw)	-0.2590	8	0.0309
Non-AI tech (residual)	0.1899	4	0.0070

7 Robustness Checks

We test alternative universe definitions (semiconductors only; excluding TSLA), alternative drawdown thresholds (15/20/30%), and subsamples (pre/post-2020). Explosive-root results remain qualitatively stable, while drawdown frequencies vary mechanically with thresholds. Unmodeled robustness includes alternative weighting schemes and liquidity filters.

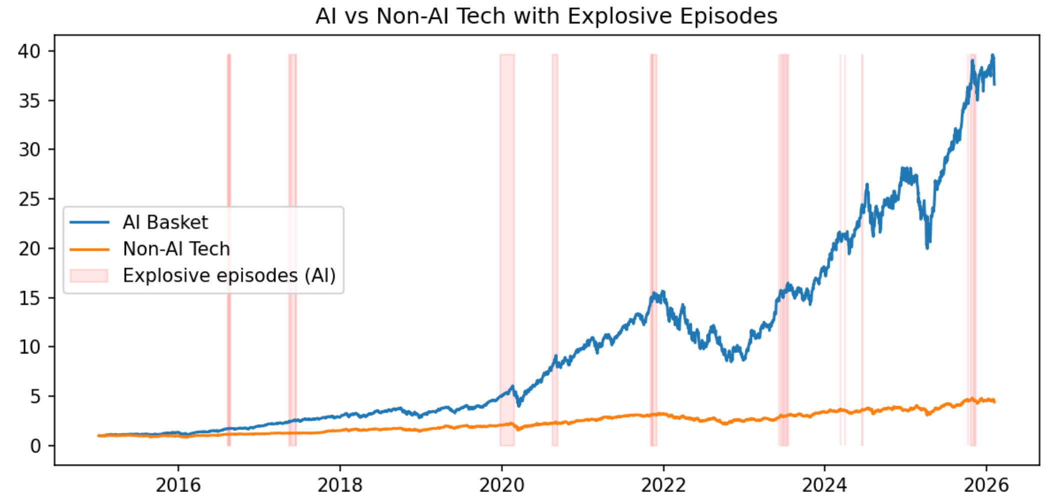

Figure 1: AI vs non-AI tech with explosive episodes (AI basket).

Table 2: Concentration and breadth metrics (descriptive)

Universe	Breadth mean	Breadth last	Dispersion mean	Dispersion last	HHI mean	HHI last
AI basket	0.7131	0.7273	0.0160	0.0210	0.1570	0.1761
Non-AI tech	0.6127	0.5714	0.0122	0.0392	0.2266	0.2799
AI semis	0.7338	1.0000	0.0141	0.0194	0.2963	0.3612
Non-AI semis	0.5758	0.8000	0.0136	0.0381	0.3029	0.4821

8 Discussion

The evidence supports partial AI-specific exuberance: explosiveness weakens after residualization but does not disappear. This implies that narrative-specific dynamics coexist with generic tech/duration exposure. **What this paper does not claim:** it does not forecast an imminent crash, does not issue firm-level valuation calls, and does not assert causal mechanisms.

9 Implications for Risk Monitoring and Position Management

Residual explosiveness can be used as a risk overlay rather than a trading signal. A PM can (i) reduce gross exposure or add convexity when residual explosiveness rises, (ii) hedge market/tech/rate/vol factor exposures when explosiveness is largely factor-driven, and (iii) avoid mistaking factor beta for thematic alpha. This framework is intended to support scenario-aware risk management, not to deliver return forecasts.

10 Conclusion

We identify an AI-specific residual component of explosiveness after accounting for common factor exposure. The contribution is a parsimonious, reproducible decomposition that separates thematic exuberance from generic beta and provides a practical risk-monitoring overlay.

Table 3: Crash probability estimates and baselines

Horizon	Brier	AUC	Base rate	Prob mean	Prob last	Method
3m	0.0369	0.2885	0.0370	0.0079	0.0119	logit
6m	NaN	NaN	0.0308	NaN	NaN	empirical
12m	NaN	NaN	0.0351	NaN	NaN	empirical

References

Phillips, P.C.B., Shi, S., Yu, J. (2015). Testing for multiple bubbles.
Sornette, D. (2003). Why Stock Markets Crash.
Campbell, J.Y., and Cochrane, J.H. (1999). By force of habit.
Kelly, B., and Jiang, H. (2014). Tail risk and return predictability.
Merton, R.C. (1976). Option pricing when underlying returns are discontinuous.

Appendix

LPPL diagnostic (supplementary). We estimate LPPL with bounded parameters and report the distribution of tc from rolling fits (Figure A1). This diagnostic is supplementary and not used for timing claims.
Crash model details. Discrimination metrics (AUC) and calibration curve are provided (Figure A2), emphasizing monitoring rather than forecasting.
Additional figures. AI vs controls indexed paths and LPPL critical time histogram are reported in the Appendix.