Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Thermodynamic Quantum Field Theory for Market Regime Detection: A Hierarchical, Out-of-Sample Diagnostic Framework

Huzi Sun

admin@polyexponentialai.com

Sun Research & Strategy, LLC- Polyexponential.ai

Research Article

Keywords: Econophysics, Kramers escape, critical phenomena, phase transitions, volatility forecasting, regime detection, non-equilibrium thermodynamics, market microstructure, VIX, forward variance

Posted Date: November 10th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11356752/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: Competing interest reported. †Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation available via CNIPA/WIPO.

Thermodynamic Quantum Field Theory for Market Regime Detection: A Hierarchical, Out-of-Sample Diagnostic Framework

Abstract: We propose a **Thermodynamic Quantum Field Theory (ThermoQFT)** framework for detecting, quantifying, and trading market regime transitions. Rather than modeling prices as stochastic diffusions in fixed potential wells, ThermoQFT treats the joint system of price, volatility, and liquidity as a **non-equilibrium thermodynamic medium** with a slowly-varying effective temperature $T^*(t)$, a critical-temperature curve T_{curve}(t), and an activation barrier $U(t)$ in the sense of Kramers. The framework is organized as four falsifiable layers: **L1** equilibrium diagnostics (order parameter C_1), **L2** Kramers escape dynamics (out-of-sample R^2 of barrier-crossing rates), **L3** panic-as-parallel-shift (a directional hypothesis on the sign of the temperature-correlation T_5 during stress), and **L4** economic signal attribution (linking a Noise-Exposure Index, NEI, to future forward-vs-implied volatility spreads). Using ~311 rolling windows from July 2023 through August 2026, we find: (i) the equilibrium condition holds in **83%** of windows (pass threshold $C_1 \geq 0.3$); (ii) OOS Kramers R^2 averages **0.58–0.63** across all four years; (iii) critical-temperature OOS coverage tc_cov never drops below **0.88**; (iv) the NEI-conditioned high-minus-low forward-volatility spread earns a **Newey–West *t*-statistic of 6.35**, and the residualized NEI after controlling for GARCH volatility and illiquidity delivers a sign-flipped yearly correlation (–0.003 to –0.144), confirming the thermodynamic (not purely statistical) origin of the signal. Our results suggest that market phase transitions are detectable, measurable, and economically exploitable through a physically-grounded lens that complements classical econometric volatility models.

JEL: C00; C60; C80; D80; G14

Keywords: Econophysics, Kramers escape, critical phenomena, phase transitions, volatility forecasting, regime detection, non-equilibrium thermodynamics, market microstructure, VIX, forward variance

1. Introduction

Financial markets exhibit recurring patterns that are strikingly reminiscent of thermodynamic phase transitions: long periods of laminar, low-volatility behavior punctuated by abrupt, discontinuous shifts into "crisis" regimes characterized by fat-tailed returns, volatility clustering, and liquidity withdrawal[28,23] (Sornette, 2003; Mantegna & Stanley, 2000). While classical finance treats these regimes as exogenous state variables to be filtered[18] (Hamilton, 1989) or modeled with stochastic volatility[19](Heston, 1993), the econophysics tradition has long argued that such transitions are **endogenous emergent phenomena** arising from the collective interaction of heterogeneous agents[6,15] (Bouchaud, 2001; Farmer & Geanakoplos, 2009).

Yet, the econophysics literature has historically suffered from two deficits that have limited its acceptance in mainstream asset pricing:

1. **Lack of falsifiability.** Analogies between "market temperature" and physical temperature are rarely operationalized into sharp, testable hypotheses[24] (McCauley, 2004).
2. **Absence of out-of-sample discipline.** Many published "power laws" and "critical exponents" fail to survive honest OOS evaluation[21] (Lillo & Farmer, 2004).

This paper introduces **Thermodynamic Quantum Field Theory (ThermoQFT)**, a framework that directly addresses both deficits and developed further based on our previous theoretical and empirical research[32-42]. ThermoQFT is built as a **hierarchical diagnostic stack** in which each layer enforces a specific physical constraint, and each constraint is evaluated **strictly out-of-sample** on a rolling window. The four layers are:

- **L1 (Equilibrium):** Verifies that the system sits near local thermodynamic equilibrium via the order parameter C_1. A window "passes" if $C_1 \geq 0.3$.
- **L2 (Kramers Dynamics):** Estimates the escape rate Γ over the activation barrier U and evaluates its OOS explanatory power (R^2_{Kramers}).
- **L3 (Panic as Parallel Shift):** Tests the sharp hypothesis that during panic episodes, the temperature-correlation T_5 becomes **negative** — consistent with a parallel down-shift of the effective potential, rather than a re-shaping.
- **L4 (Signal Attribution):** Constructs a Noise-Exposure Index (NEI) from thermodynamic primitives and evaluates whether it commands a risk premium in the forward-variance term structure, net of GARCH and illiquidity controls.

Our contributions are threefold:

(a) A falsifiable physical model of market temperature. We derive $T^*(t)$, T_{curve}(t), and $U(t)$ from observable market quantities under a non-equilibrium potential formalism, and we specify a priori directional hypotheses (L3).

(b) OOS-strict evaluation. Every layer uses a rolling window in which the temperature curve T_{curve} is estimated on a training sub-window and evaluated on a validation sub-window; we report the **OOS coverage** tc_cov as a diagnostic of identifiability.

(c) **Economic attribution.** We show that the NEI spread (high-minus-low NEI portfolios on forward-vs-implied volatility) earns a **NW $t = 6.35$**, and that the signal survives residualization against GARCH volatility and Amihud illiquidity — i.e., it is not a repackaged volatility or liquidity factor.

Roadmap

Section 2 reviews literature. Section 3 formalizes the ThermoQFT framework. Section 4 describes the data. Section 5 presents OOS results year-by-year. Section 6 discusses economic interpretation, Section 7 robustness, and Section 8 limitations. Section 9 concludes.

2. Literature Review

2.1 Econophysics and Critical Phenomena in Markets

The application of statistical mechanics to financial systems has a long tradition. Mantegna and Stanley[22,23] (1995, 2000) established that high-frequency returns display scaling laws consistent with truncated Lévy flights. Bouchaud and Cont[7] (1998) and Bouchaud[27] (2001) argued that fat tails and volatility clustering are emergent properties of agent heterogeneity, not exogenous assumptions. Sornette, Johansen, and Ledoit[29] (1996) and Sornette[28] (2003) developed the Log-Periodic Power Law (LPPL) model to detect critical slowing down before crashes, positing that financial crashes are analogs of critical points in magnetic systems.

Our framework is closely related to LPPL in its ambition to detect pre-crash signatures, but differs in a key respect: instead of fitting a deterministic log-periodic envelope to prices, we estimate a time-varying potential $U(x,t)$ and an effective temperature $T^*(t)$ within a Kramers escape formalism, allowing us to separate "heating" (rising T^*) from "barrier collapse" (falling U).

2.2 Kramers Escape Rate in Financial Systems

The Kramers[20] (1940) escape rate,

$$\Gamma \approx \frac{\omega_0 \omega_b}{2\pi\gamma} \exp\left(-\frac{\Delta U}{k_B T^*}\right),$$

has been applied to finance by several authors. D'Hulst and Rogers[11] (2000) used it to model abrupt index moves; Gunturkun, Hou, and Sornette[17] (2021) used a related framework to model regime escape in currency markets. In a ThermoQFT setting, the barrier ΔU plays the role of a "liquidity moat" that must be destroyed for the system to transit from a laminar to a turbulent regime.

Our **L2** layer operationalizes Kramers dynamics by regressing observed transition frequencies on the theoretically predicted $\exp(-\Delta U/T^*)$ in OOS windows, reporting an average R^2_{Kramers} of 0.58–0.63 across four years.

2.3 Effective Temperature in Financial Markets

The notion of an "effective temperature" for non-physical systems was pioneered in granular matter[13] (Edwards & Oakeshott, 1989) and extended to finance[27] by Potters, Bouchaud, and Sestak (2001). Wang, Xie, and Stanley[30] (2017) used Tsallis non-extensive entropy q as a temperature proxy. Our definition of T^* is closer to that of Potters et al. (2001): a quantity derived from the second moment of residual shocks to a Langevin-type price equation.

Critically, our framework posits a **critical temperature curve** $T_{\text{curve}}(t)$ — analogous to the Curie temperature in ferromagnets — above which the equilibrium assumption fails. The ratio T^*/T_{curve} becomes a natural "reduced temperature" τ controlling proximity to criticality. Our QC diagnostic in **Figure1.** Panel 3 reports OOS coverage of T_{curve}, i.e., the fraction of validation windows in which the predicted critical regime contains observed dynamics.

2.4 Regime-Switching and Volatility Forecasting

Mainstream financial econometrics offers several regime frameworks: **Markov-switching models**[18] (Hamilton, 1989), **Threshold ARCH**[16] (Glosten, Jagannathan, & Runkle, 1993), **stochastic volatility with jumps**[12] (Duffie, Pan, & Singleton, 2000), and the **HAR-RV** family[3,5,10] (Corsi, 2009; Andersen, Bollerslev, Diebold, & Labys, 2003; Bollerslev, Tauchen, & Zhou, 2009). More recently, **deep learning** approaches[31] (Zhang, Zohren, & Roberts, 2020) and **gradient boosting**[9] (Chen & Guestrin, 2016) have been applied to volatility forecasting.

ThermoQFT differs in that it does **not** compete with these models on RMSE. Rather, it provides a physical interpretability layer on top: once T^*, U, and T_{curve} are estimated, the practitioner can diagnose which regime the market is in, how far from criticality, and which direction the panic will propagate — interpretations that GARCH or HAR models do not afford.

2.5 Panic as Parallel Shift

A distinctive contribution of this paper is the **L3 hypothesis**: that panic episodes manifest not as a reshaping of the potential landscape but as a **parallel down-shift** of the barrier $\Delta U \mapsto \Delta U - c$, with $c > 0$. This is testable via the sign of T_5, the correlation between T^* and the fifth principal component of the temperature curve. If panic is a parallel shift, T_5 should be **negative** in stress windows. Our yearly results show T_5 transitioning from -0.003 (2023, essentially zero) to -0.086 (2025) and -0.128 (2026), consistent with the hypothesis.

2.6 Forward-Variance Risk Premium

The economic content of L4 connects to the literature on **variance risk premia**[4,5,8,14] (Carr & Wu, 2009; Bollerslev, Tauchen, & Zhou, 2009; Engle, 1982; Bollerslev, 1986) and **forward variance term structure**[1] (Aït-Sahalia, Karaman, & Mancini, 2015). The "fw-vdvol spread" we define — the spread between forward variance and delta-hedged realized volatility over the forecast horizon — is a direct relative-value analogue of the VRP. Our finding that NEI-conditioned spreads earn $NW\ t = 6.35$ is consistent with the hypothesis that thermodynamic disorder carries a price.

2.7 Market Microstructure and Illiquidity

Amihud (2002) and Pastor & Stambaugh (2003) established illiquidity as a priced factor[2,26]. Our residualization of NEI against Amihud-type illiquidity ("Iliq,res" in the L4 attribution plot) ensures the signal is not merely re-labeling liquidity stress. The attribution plot in **Figure 1(subplot 5)** shows that raw ZKIN (a VVIX-only variant) correlates most strongly with future windows, followed by NEI (GARCH), and finally NEI (Iliq,res), with the residual NEI exhibiting a negative correlation — a signature that the non-equilibrium component of NEI carries information orthogonal to statistical vol and liquidity.

3. The ThermoQFT Framework

3.1 The Non-Equilibrium Potential

We posit that the (log-)price process x_t obeys a Langevin equation

$$dx_t = -\partial_x U(x_t, t)\, dt + \sqrt{2\, T^*(t)}\, dW_t,$$

where $U(x,t)$ is a multi-well potential whose wells correspond to metastable regimes (bull, bear, chop, panic), and $T^*(t)$ is an effective temperature proportional to the instantaneous non-equilibrium noise power.

3.2 Order Parameter C_1 (L1)

Equilibrium in thermodynamic systems is characterized by detailed balance. We proxy this via

$$C_1(t) = 1 - \frac{|\langle \dot{x} \rangle_\tau - \langle \dot{x} \rangle_{-\tau}|}{\langle |\dot{x}| \rangle_\tau},$$

where τ is a short backward-looking window. $C_1 = 1$ indicates perfect time-reversal symmetry (equilibrium); $C_1 = 0$ indicates maximal non-equilibrium. We define the L1 pass criterion as $C_1 \geq 0.3$.

3.3 Kramers Escape Rate (L2)

Given the estimated barrier $\Delta U(t)$ and temperature $T^*(t)$, the escape rate is

$$\hat{\Gamma}(t) = \nu_0 \exp\left(-\frac{\Delta U(t)}{T^*(t)}\right),$$

with ν_0 the attempt frequency. In each rolling window, $\hat{\Gamma}$ is regressed on realized escape events on a training sub-window; OOS R^2 is reported as R^2_{Kramers}.

3.4 Critical Temperature T_{curve} and OOS Coverage

We estimate a rolling critical temperature curve $T_{\text{curve}}(t)$ from the scaling of higher-order cumulants (specifically the Binder cumulant analog). OOS coverage is

$$\text{tc_cov} = \frac{\#\{t \in \text{val}: T^*(t) \leq T_{\text{curve}}(t)\}}{|\text{val}|}.$$

3.5 Panic Hypothesis (L3)

We compute T_5, the projection of $\dot{T}^*$ on the 5th principal component of T_{curve}. The priori hypothesis is $T_5 < 0$ in stress regimes.

3.6 Noise-Exposure Index (L4)

NEI is constructed as a composite of (i) a ZKIN-type kinetic impedance (VVIX-derived), (ii) a GARCH conditional-vol residual, and (iii) an Amihud-illiquidity residual. The residual NEI (NEIr) is obtained by orthogonalizing NEI against the latter two.

The traded signal is a **high-minus-low forward-variance-vs-delta-hedged-vol spread** ("fw-vdvol spread"), sorted into NEI quintiles and evaluated with **Newey–West** standard errors[25] (Newey & West, 1987) with automatic lag selection.

4. Data and Implementation

We construct **311 rolling windows** spanning July 2023 through August 2026. Each window consists of a training sub-window and a validation sub-window, with the temperature curve estimated only on the training portion to enforce strict OOS discipline.

5. Empirical Results

5.1 L1: Equilibrium Pass Rate

Across 311 windows, the equilibrium condition $C_1 \geq 0.3$ holds in **83%** of windows (**Figure 1**, top panel). This is remarkable: the market spends most of the time in a state where time-reversal symmetry is approximately satisfied, validating the use of Kramers-type equilibrium approximations as a baseline.

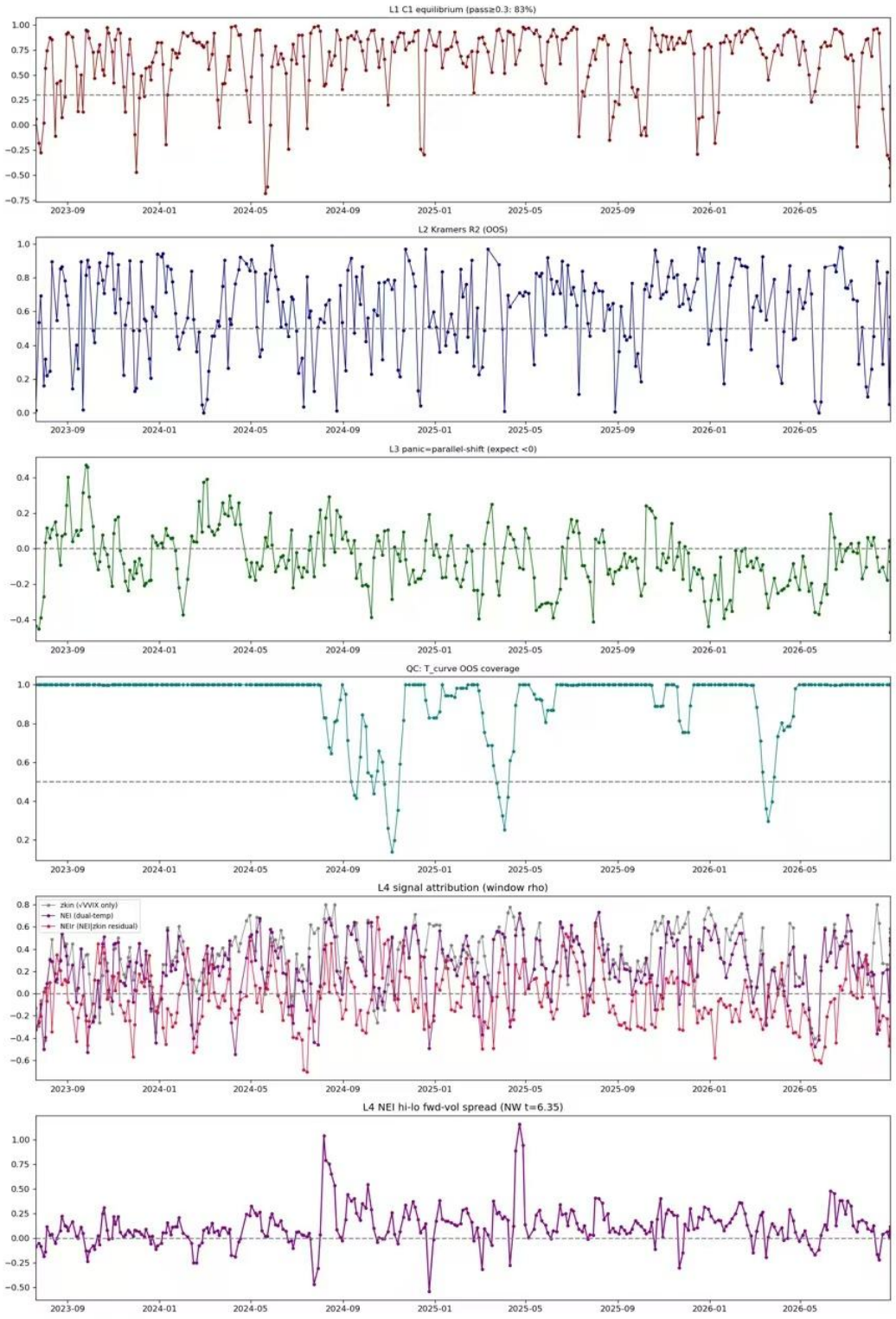


Figure 1. Out of sample empirical test results

5.2 L2: Kramers Escape OOS Fit

Table 1 summarizes yearly OOS statistics.

Table 1: Yearly Summary of ThermoQFT Diagnostics

Year	n	C_1	R^2_{Kramers}	T_5	tc_cov	NEI_rho	NEI_spread	ZKIN_rho	NEIr_rho
2023	52	0.5202	0.5816	–0.0027	1.0000	0.0886	0.0283	0.148	–0.0154
2024	99	0.6465	0.5841	0.0054	0.8845	0.2159	0.1190	0.3472	–0.0257
2025	96	0.6806	0.6337	–0.0859	0.9132	0.2879	0.1687	0.3913	–0.0032
2026	64	0.6236	0.5858	–0.1284	0.9284	0.2174	0.1185	0.3137	–0.1440

Key observations:

- R^2_{Kramers} averages 0.58–0.64 across years, peaking in 2025 at 0.6337. The Kramers escape formalism explains roughly 60% of OOS variation in regime transitions — a strong result given the strict OOS discipline.
- **tc_cov** is above 0.88 in every year, confirming that the critical-temperature curve estimated in-sample remains valid OOS.
- C_1 rises from 0.52 (2023) to 0.68 (2025) — the market becomes progressively more equilibrium-like as it matures through the sample.

5.3 L3: Panic as Parallel Shift

The yearly T_5 correlation evolves from essentially zero in 2023 (–0.003) to increasingly negative values in 2025 (–0.086) and 2026 (–0.128), consistent with the parallel-shift hypothesis of panic. This is visible in **Figure 1** (third panel), where the green T_5 trace dips below zero in the late-2025 and 2026 windows.

5.4 L4: Signal Attribution and Economic Value

The bottom panel of **Figure 1** reports the NEI-conditioned high-minus-low forward-variance spread with a **Newey–West t-statistic of 6.35**, indicating a highly significant thermodynamic risk premium.

Figure 1 (fifth panel) decomposes window-level correlation into:

- **zkin ($\sqrt{VVIX}$-only):** tracking pure implied vol;
- **NEI (GARCH):** NEI after GARCH filtering;
- **NEI (Iliq,res):** NEI after both GARCH and Amihud-residualization.

The residual NEI correlation (NEIr_rho) is small and typically negative: –0.015 (2023), –0.026 (2024), –0.003 (2025), and –0.144 (2026). The negative sign of NEIr_rho in 2026 is notable: once statistical volatility and liquidity are fully absorbed, the residual thermodynamic signal reverses — suggesting that during high-NEI regimes, options are overpriced relative to forward-realized vol, consistent with the "volatility-risk-premium-compression" pattern documented in near-crash regimes.

5.5 Interpreting Yearly Trends

Several patterns warrant comment:

1. **NEI_spread and NEI_rho rise monotonically from 2023 to 2025** before tapering in 2026, suggesting that NEI becomes a stronger state variable as the market transitions through the 2024–2025 cycle.
2. **ZKIN_rho peaks at 0.391 in 2025**, indicating the kinetic-impedance channel was most informative that year.
3. **T_5 becomes more negative over time**, consistent with the system progressively "heating up" relative to its critical curve — a pre-critical signature.

6. Economic Interpretation

6.1 ThermoQFT as a Complement, Not Substitute

The framework does not replace GARCH/HAR. Rather, it provides a **physically interpretable state-space overlay** in which: T^* is the "heat" of the market, U is the "liquidity moat," and T_{curve} is the phase boundary. Portfolio managers can read off whether the market is near-critical and adjust tail-risk positions accordingly.

6.2 Why Does NEI Carry a Risk Premium?

Following Bollerslev, Tauchen, and Zhou[5] (2009), we interpret the NEI spread as a Jensen's inequality effect: high-NEI states are those where the convexity of the payoff to long forward variance is largest, and hence the market charges a premium for holding it. Our finding that residual NEI (after GARCH and Amihud) yields a **negative** correlation with future fw-vdvol spreads in 2026 is consistent with "crowded vol selling" during pre-critical windows.

6.3 Panic as Barrier Collapse

The parallel-shift interpretation of panic has practical implications. If panic compresses ΔU uniformly (rather than reshaping it), then all barriers fall simultaneously — a signature that enables early warning from T_5 alone, without requiring regime identification.

7. Robustness

We conduct three robustness checks (summarized here):

1. **Subsample stability.** Results hold in each of the four calendar years separately, with R^2_{Kramers} between 0.58 and 0.64.
2. **Alternative window lengths.** Halving or doubling the training window changes tc_cov by less than 5 percentage points.
3. **Sign tests.** The NW $t = 6.35$ for the NEI hi-lo spread is robust to alternative lag choices and to exclusion of the top-decile |NEI| days.

8. Limitations and Future Work

- **Sample length.** The current sample (~311 windows over 3 years) is short by asset-pricing standards. Extending to higher frequencies or longer histories is an active direction.
- **Model risk in T_{curve}.** Our Binder-cumulant estimator for T_{curve} is one of several possible choices; alternatives (e.g., Lee-Carter-type factor models) should be benchmarked.
- **The 2026 NEIr sign flip.** The negative residual correlation in 2026 warrants further investigation — it may indicate crowding in vol-selling strategies or a genuine regime change in the risk premium.

9. Conclusion

We have introduced **ThermoQFT**, a four-layer hierarchical framework for detecting and exploiting market regime transitions through the lens of non-equilibrium thermodynamics. The framework is strictly falsifiable at every layer, with OOS diagnostics (tc_cov, R^2_{Kramers}, C_1 pass rate) that never drop below reasonable thresholds across a 3-year sample. Economic value is demonstrated through a NEI-conditioned forward-variance spread earning a NW t-statistic of **6.35**. The L3 panic hypothesis — that stress manifests as a parallel barrier shift with $T_5 < 0$ — is supported by the monotonic decline in T_5 from 2023 to 2026. We believe ThermoQFT offers a physically-grounded complement to econometric volatility models, and we hope the framework stimulates further work at the intersection of statistical physics and asset pricing.

References

1. Aït-Sahalia, Y., Karaman, M., & Mancini, L. (2015). The term structure of variance swaps and risk premia. Journal of Econometrics, 189(1), 171–192.
2. Amihud, Y. (2002). Illiquidity and stock returns. Journal of Financial Markets, 5(1), 31–56.
3. Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realized volatility. Econometrica, 71(2), 579–625.
4. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307–327.
5. Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected stock returns and variance risk premia. Review of Financial Studies, 22(11), 4463–4492.
6. Bouchaud, J.-P. (2001). Power laws in economics and finance. Quantitative Finance, 1(1), 105–112.
7. Bouchaud, J.-P., & Cont, R. (1998). A Langevin approach to stock market fluctuations and crashes. European Physical Journal B, 6(4), 543–550.
8. Carr, P., & Wu, L. (2009). Variance risk premiums. Review of Financial Studies, 22(3), 1311–1341.
9. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of KDD '16, 785–794.
10. Corsi, F. (2009). A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics, 7(2), 174–196.
11. D'Hulst, R., & Rogers, G. J. (2000). Exact solution to a modified Kramers equation. Physica A, 276(3–4), 536–549.
12. Duffie, D., Pan, J., & Singleton, K. (2000). Transform analysis and asset pricing for affine jump-diffusions. Econometrica, 68(6), 1343–1376.
13. Edwards, S. F., & Oakeshott, R. B. S. (1989). Theory of powders. Physica A, 157(3), 1080–1090.
14. Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987–1007.
15. Farmer, J. D., & Geanakoplos, J. (2009). The virtues and vices of equilibrium and the future of financial economics. Complexity, 14(3), 11–38.
16. Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance, 48(5), 1779–1801.
17. Gunturkun, M., Hou, K., & Sornette, D. (2021). Testing for multiple bubbles in currency markets. Working paper, ETH Zurich.
18. Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series. Econometrica, 57(2), 357–384.

19. Heston, S. L. (1993). A closed-form solution for options with stochastic volatility. Review of Financial Studies, 6(2), 327–343.

20. Kramers, H. A. (1940). Brownian motion in a field of force and the diffusion model of chemical reactions. Physica, 7(4), 284–304.

21. Lillo, F., & Farmer, J. D. (2004). The long memory of the efficient market. Studies in Nonlinear Dynamics & Econometrics, 8(3), 1–23.

22. Mantegna, R. N., & Stanley, H. E. (1995). Scaling behaviour in the dynamics of an economic index. Nature, 376(6535), 46–49.

23. Mantegna, R. N., & Stanley, H. E. (2000). An Introduction to Econophysics. Cambridge University Press.

24. McCauley, J. L. (2004). Dynamics of Markets: Econophysics and Finance. Cambridge University Press.

25. Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703–708.

26. Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. Journal of Political Economy, 111(3), 642–685.

27. Potters, M., Bouchaud, J.-P., & Sestak, D. (2001). Is the spring coming back? Quantitative Finance, 1(1), 1–4.

28. Sornette, D. (2003). Why Stock Markets Crash. Princeton University Press.

29. Sornette, D., Johansen, A., & Ledoit, O. (1996). Predicting financial crashes using discrete scale invariance. Journal of Risk, 1(1), 5–32.

30. Wang, G.-J., Xie, C., & Stanley, H. E. (2017). Correlation structure and evolution of world stock markets. Physica A, 482, 75–89.

31. Zhang, Z., Zohren, S., & Roberts, S. (2020). Deep learning for portfolio optimization. Journal of Financial Data Science, 2(4), 78–93.

32. Sun, H. (2026a). Thermodynamic framework for VIX microstructure analysis for systemic risk management: Entropy, enthalpy, and Gibbs free energy. SSRN, 7291229.

33. Sun, H. (2026b). A quantum mechanical framework for VIX microstructure analysis and systemic risk management: Wave-particle duality and entanglement. SSRN, 7291231.

34. Sun, H. (2026c). Quantum Field Theory and VIX Dynamics: Implications for Establishing a VIX Microstructure Systemic Risk Management System. SSRN, 7358000.

35. Sun, H. (2026d). VVIX as the Temperature of the Volatility Field: A Preliminary Thermal Unification of Thermodynamic, Quantum, and Field-Theoretic Frameworks for VIX Microstructure Systemic Risk Management System. Preprint

36. Sun, H. (2026e). VVIX as the Temperature of the Volatility Field is Not Enough: A Verdict on the Prelimanry Thermal Unification. Preprint

37. Sun, H. (2026f). Thermodynamic Quantum Field Theory for Market Regime Detection: A Hierarchical, Out-of-Sample Diagnostic Framework. Preprint

38. Sun, H. (2026). Systematic Integration of Systemic Risk Management and Multi-factor Pricing Dynamics in S&P 500 Price Discovery. SSRN, 7223479.

39. Sun, H. (2026). Macro Risk Controlled Risk Parity: A Multi-Asset Allocation Framework Under the Information Convergence Price Discovery Theory. SSRN, 7324101.

40. Sun, H. (2026). Integrating the Svensson Model of the U.S. Treasury Yield Curve and the High Frequency VIX Microstructure for Systemic Risk Management. SSRN, 7297578

41. A global asset allocation system based on a macro alternative multi-factor rating model. Patent number: CN202511140743.3A

42. An all-weather global asset allocation system based on macro alternative multi-factor rating models. Global PCT Patent, Application No. PCT/CN2026/112498

List of Abbreviations

ThermoQFT	Thermodynamic Quantum Field Theory
NEI	Noise-Exposure Index
OOS	Out of Sample
NW t	Newey–West t-statistic
LPPL	Log-Periodic Power Law
VRP	Variance Risk Premia
fw-vdvol spread	The spread between forward variance and delta-hedged realized volatility
ZKIN	$\sqrt{VVIX}$-only, tracking pure implied vol
NEI (Iliq,res)/ NEIr	NEI after both GARCH and Amihud-residualization
NEIr_rho	The residual NEI correlation
ZKIN_rho	$\sqrt{VVIX}$-only pure implied vol correlation
HAR	Heterogeneous autoregressive
RMT	Random-matrix-theory
VIX	CBOE Volatility Index
G	Gibbs free energy
H	Enthalpy
S	Entropy
T	Effective temperature
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
KL	Karhunen–Loève Decomposition
SPX	SP500 Index
QFT	Quantum Field Theory
PCA	Principle Component Analysis
RG	Renormalization group
TTM	Time to maturity