

Forecasting Leverage-Induced First-Passage Failure with Regime-Persistence Operators: Monte Carlo Evidence and a July 2026 Stress Case

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Abstract

We examine whether regime-persistence measures improve forecasts of leverage-induced first-passage failure. A July 2026 case combines a June 30 Form 13F reconstruction with a sealed Clock-of-Regimes (COR) observation. The disclosed portfolio was highly concentrated: its two largest positions represented 55.6% of reported value and a nine-stock core represented 88.3%. On July 21, COR assigned probability one, to reported precision, to Stress and produced daily stress volatility of 3.54%, tail exposure of 0.0486, and dominant persistence $\rho(N) = 95.2$. In a matched 200,000-path experiment, COR conditioning raises estimated eight-session failure probability from 0.22% to 1.77% at 2× leverage, 4.25% to 13.00% at 2.5×, 16.09% to 30.64% at 3×, and 50.60% to 63.95% at 4×. A separate forecasting experiment uses 250 synthetic replications, each containing 1,500 training and 1,000 held-out observations. Relative to conventional predictors augmented with HMM probabilities, COR reduces mean Brier loss by 0.0007 and logarithmic loss by 0.0026, while increasing AUC by 0.0103 and AUPRC by 0.0087. Paired 95% Monte Carlo intervals exclude zero for all four differences. The simulation identifies a transparent data-generating environment in which persistence and tail coordinates add forecast information beyond regime occupancy. COR forecasts survival risk, not return direction.

1 Introduction

Financial crises and institutional failures are often narrated as forecasting errors. For leveraged investors, however, decisive failure often occurs before an investment thesis resolves: a portfolio may be fundamentally correct over the long run yet lose discretionary control when an adverse trajectory breaches margin, liquidity, or internal risk boundaries. The financial-stability problem is thus not simply whether prices fall, but whether a portfolio can survive the intermediate path. We ask: *can operator-theoretic persistence and tail-risk diagnostics provide actionable advance warning that a leveraged portfolio has entered a fragile regime?* We examine this question through the July 2026 near collapse of Situational Awareness—an AI-focused fund whose losses, concentrated positions, margin stress, and forced liquidation provide an event study of the interaction between market persistence and financing constraints. We analyze this episode using the Clock-of-Regimes (COR) framework (Anonymous, 2026a,b). Rather than forecasting directional returns, COR serves as an early-warning system that characterizes regime occupancy, transition dynamics, state-dependent tail risk, and persistence. Its core operators—the transition matrix A , killed operator Q , generator-like matrix $K = Q - I$, and fundamental matrix $N = (I - Q)^{-1}$ —yield key diagnostics: the spectral radius $\rho(N)$ defines dominant persistence, aggregate residence is captured by $\text{tr}(N)$, and the state-weighted tail measure $\bar{q}$ quantifies downside exposure. These metrics become actionable when integrated with portfolio concentration, leverage, and liquidity to evaluate first-passage boundary risks.

The paper is organized around three financial-stability claims. First, COR extracts economically distinct risk information by conditioning not only on the current latent regime, but on its expected persistence and tail geometry. While population-level advantages over conventional benchmarks (VIX, realized volatility, drawdown, credit spreads, standard HMM states, and financial-stress indices) require a common historical panel, this single-event design establishes within-episode incremental value against a matched unconditional state mixture. Second, an early-warning system is meaningful only if deterioration is detected while risk-management discretion remains. Thus, the first sealed July 21 observation—rather than retrospective reconstructions on July 7 or 14—serves as the valid prospective intervention date. Third, early-warning signals must produce tangible financial-stability consequences. COR is therefore evaluated by whether it shifts decisive vulnerability metrics: future drawdown probability, expected shortfall, margin distance, liquidity demand, and the risk of forced liquidation. This framing situates COR within the early-warning literature on currency, banking, credit, and asset-price crises (Aldasoro et al., 2018; Alessi and Detken, 2011; Babecký et al., 2014; Borio and Drehmann, 2009; Borio and Lowe, 2002; Drehmann and Juselius, 2014; Drehmann et al., 2012; Galán, 2021; Kaminsky et al., 1998; Kaminsky and Reinhart, 1999), as well as systemic-risk studies on leverage, fire sales, and margin spirals (Bisias et al., 2012; Brunnermeier and Pedersen, 2009; Eisenberg and Noe, 2001; Greenwood et al., 2015; Savona and Vezzoli, 2014). Our core novelty lies in

formulating early warning through the persistence geometry of a killed regime process and mapping that geometry directly into portfolio survival probability.

Empirically, we reconstruct the fund's June 30 Form 13F public long book across July and overlay the VanEck Semiconductor ETF (SMH) COR readings from July 7, 14, and 21. While the first two observations serve as retrospective diagnostic chronology, July 21 marks the first sealed, contemporaneous reading, establishing the prospective counterfactual. On that date, COR indicated full Stress-state occupancy, elevated conditional volatility, material tail exposure, and a dominant persistence scale of approximately 95 trading days—in a portfolio that was simultaneously highly concentrated and strongly correlated. To test whether this contemporaneous state information alters estimated financing-failure risk, we conduct a matched Monte Carlo experiment holding portfolio weights, Student- t emissions, dependence, and margin/liquidity rules fixed. While the null draws latent states independently from the unconditional mixture, the COR-conditioned alternative begins in the observed Stress state and propagates its Markov persistence. COR conditioning materially increases the estimated probability of crossing the financing boundary at leverage of $2\times$ and above.

Our contribution is deliberately bounded: rather than claiming directional return predictability, we demonstrate that contemporaneous regime and persistence diagnostics altered the estimated survival distribution while managerial discretion still remained. The remainder of the paper details the data and empirical design, the COR operator framework, empirical findings, the first-passage experiment, and implications for systemic-risk surveillance.

2 Data and Empirical Design

Our empirical design evaluates early-warning capabilities rather than directional forecasting. It integrates four core elements while strictly separating direct observations from counterfactual reconstructions: the disclosed June 30 public long book, a contemporaneous semiconductor-sector COR signal, first-passage leverage thresholds, and a matched Monte Carlo experiment. To isolate the incremental value of COR conditioning, the null and alternative specifications share identical portfolio holdings, state-dependent return emissions, dependence structures, margin rules, and liquidity constraints; they differ solely in whether the model conditions on the July 21 COR Stress state and propagates its Markov persistence.

2.1 Data Sources and Evidentiary Protocol

Reuters reported that the fund lost approximately 67% in July, eliminated its leverage, and sold most of its public-equity holdings after the AI-stock decline (Reuters, 2026a,b). We use that reporting to establish the event chronology while maintaining a strict evidentiary distinction between reported facts and model-based reconstruction. The June 30 Form 13F supplies the baseline long holdings (U.S. Securities and Exchange Commission, 2026), but it is not a complete balance sheet: it excludes short positions, many foreign-listed assets, most derivatives, cash, financing liabilities, and prime-broker margin terms. The reconstructed portfolio is therefore a public-long-book counterfactual rather than an audited financial statement.

Table 1 outlines the COR timeline. Following an initial retrospective regime break on July 7, the first live, sealed observation occurred on July 21—the date the COR financial-crisis early-warning system became

operational. The market reached its trough on July 29, marking the deepest point in the reconstructed public core and yielding a destructive window of just six trading sessions from the prospective launch alert.

Table 1: Key Dates In The July 2026 Episode.

Date	Market/fund significance	COR status
June 30	13F portfolio baseline; end of first-half reporting period	–
July 7	First major structural deterioration identified retrospectively	Orange, retrospective
July 14	Price rebound but regime remained abnormal	Yellow, retrospective
July 21	First sealed contemporaneous SMH COR observation	Yellow; $P_3 = 1.000$
July 24	Financing/capital pressure becomes central in the reported narrative	COR already non-Green
July 29	SMH trough period; reconstructed public core near its July trough	non-Green
July 30–31	Distressed portfolio transfer/rebound; July loss publicly quantified	forced-deleveraging phase
August 11	SMH clock returned to Green in the source analysis	Green

2.2 Clock-of-Regimes Operator Framework

2.2.1 Regime Occupancy and Transition Dynamics

Let $S_t \in \{1, 2, 3\}$ denote calm, transition, and stress regimes. The ordinary transition matrix is

$$A = (a_{ij}), \quad a_{ij} = \Pr(S_{t+1} = j \mid S_t = i). \quad (1)$$

The filtered or smoothed state probabilities are denoted $P_i(t) = \Pr(S_t = i \mid \mathcal{F}_t)$, with $\sum_i P_i(t) = 1$. Thus $P_3 = 1$ means that the fitted model assigns the current observation essentially completely to the stress state. It does not mean that the next return is negative with probability one. COR augments ordinary regime transitions with a state-dependent killing or escape hazard ϵ_i . Define

$$Q = \text{diag}(1 - \epsilon_1, \dots, 1 - \epsilon_K)A, \quad (2)$$

and

$$K = Q - I, \quad N = (I - Q)^{-1} = -K^{-1}. \quad (3)$$

The fundamental matrix N accumulates expected transient-state occupancy before killing. This gives COR a natural survival interpretation.

2.2.2 Residence and Spectral Persistence

For a conventional Markov state, mean residence is approximately

$$E[T_i] \simeq \frac{1}{1 - a_{ii}}. \quad (4)$$

COR also uses the spectral radius

$$\rho(N) = \max_j |\lambda_j(N)| \quad (5)$$

to summarize the most persistent mode, and

$$\text{tr}(N) = \sum_i N_{ii} \quad (6)$$

to summarize aggregate persistence across the transient system. These quantities answer different questions. A large $\rho(N)$ indicates a slowly decaying dominant mode; a rising $\text{tr}(N)$ can indicate that persistence is broadening across modes even when the dominant mode is unchanged. The spectral abscissa is $\alpha(K) = \max_j \Re \lambda_j(K)$, and its associated positive decay rate is $g(K) = -\alpha(K)$. In the July 21 SMH reading, $g(K) \simeq 0.0105$ per trading day and $1/g(K) \simeq 95.2$ days, consistent with the reported entrapment radius and stress residence scale. These measures are mathematically related and should not be counted as independent pieces of evidence; their agreement is an internal consistency check on the fitted persistence geometry.

2.2.3 Tail Exposure And State Distributions

Within regime i , returns are modeled with state-dependent location, volatility σ_i , and Student- t degrees of freedom ν_i . Smaller ν_i implies heavier conditional tails. If q_i denotes the conditional tail-event probability in state i , COR forms a state-weighted tail exposure

$$\bar{q} = \sum_i w_i q_i. \quad (7)$$

The COR fragility score is a calibrated historical surrogate rather than a proved probability bound. Zones (Green, Yellow, Orange, Red, Black) summarize the composite state (see Appendix A), but the underlying operator geometry is diagnostically richer than the zone label alone.

2.2.4 First Passage and The Leverage Problem

For a leveraged fund, the economically relevant stopping time is

$$\tau_B = \inf\{u > t : NAV_u \leq B_u\}, \quad (8)$$

where B_u may represent an internal drawdown limit, a maintenance-margin boundary, or a liquidity threshold. Safe leverage can then be defined as

$$L_t^* = \sup \{L : \Pr(\tau_B \leq H \mid \mathcal{F}_t, COR_t, L) \leq \alpha\}. \quad (9)$$

Equation (9) is the conceptual bridge between COR and portfolio control. COR supplies the conditional market-state distribution; the portfolio and financing structure supply the loss boundary.

2.3 Full-State Monte Carlo Test of Incremental COR Information

To move beyond a volatility-only sensitivity calculation, we construct a matched Monte Carlo experiment in which the null and alternative use the same portfolio mechanics and the same state-specific return family, but differ in whether contemporaneous COR state information and Markov persistence are admitted. The test horizon is the eight-session interval from the July 21 close through July 31, thereby spanning the prospective warning date, the July 29 trough, and the reported forced-deleveraging window. Simulations use $N_{\text{sim}} = 200,000$ paths and deterministic seed 20260817.

2.3.1 Operator-Consistent Reconstruction of the July 21 COR Process

The archived July 21 report provides the three mean residence times, 25.1, 42.5, and 95.2 trading days for Calm, Transition, and Stress, respectively, together with $\alpha(K) = 0.0105$, $\rho(N) = 95.2$, and $P_3 = 1.000$. Because the archived report does not expose every off-diagonal element of the fitted transition matrix, the simulation uses a transparent operator-consistent reconstruction rather than claiming access to the proprietary fitted matrix. The diagonal transition probabilities are fixed by

$$a_{ii} = 1 - \frac{1}{E[T_i]}, \quad (10)$$

and a nearest-neighbor topology is imposed, with the Transition-state exit probability split symmetrically between Calm and Stress. This gives

$$A = \begin{pmatrix} 0.960159 & 0.039841 & 0 \\ 0.011765 & 0.976471 & 0.011765 \\ 0 & 0.010504 & 0.989496 \end{pmatrix}. \quad (11)$$

The unconditional stationary distribution implied by this reconstructed chain is

$$\pi = (0.1223, 0.4140, 0.4637). \quad (12)$$

The reported spectral hazard scale is imposed uniformly as $\epsilon_i = 0.0105$, yielding

$$Q = \text{diag}(1 - \epsilon)A, \quad K = Q - I, \quad N = (I - Q)^{-1}. \quad (13)$$

The resulting operator reproduces the dominant persistence scale exactly to rounding,

$$\rho(N) = 95.2381, \quad \alpha(K) = -0.0105, \quad (14)$$

while the reconstructed $\text{tr}(N) = 145.63$ differs from the archived value 162.8. We therefore use $\rho(N)$ and the observed $P_3 = 1$ as the primary persistence constraints and treat the trace discrepancy as reconstruction uncertainty rather than forcing an unidentified transition matrix to match all reported invariants.

2.3.2 State-Dependent Student- t Portfolio Emissions

The stress-state asset volatility vector is anchored to the realized July daily volatilities of the nine-name core. Let σ_3 denote those volatilities and R_3 the realized July correlation matrix in Table 3. State-dependent covariance matrices are

$$\Sigma_s = D_s R_s D_s, \quad (15)$$

where $D_s = \text{diag}(\sigma_s)$. The Calm-state scale is fixed by the contemporaneous SMH ratio 0.85/3.54, the Transition scale is the geometric midpoint, and Stress uses the observed July vector:

$$\sigma_1 = \frac{0.85}{3.54} \sigma_3, \quad \sigma_2 = \sqrt{\frac{0.85}{3.54}} \sigma_3, \quad \sigma_3 = \sigma_{\text{July}}. \quad (16)$$

Dependence is state dependent. The Stress correlation matrix is the realized July matrix, while Calm and Transition are shrinkage versions of the same matrix,

$$R_1 = 0.35R_3 + 0.65I, \quad R_2 = 0.65R_3 + 0.35I, \quad R_3 = R_{\text{July}}. \quad (17)$$

This specification preserves the observed cross-sectional geometry while allowing dependence to strengthen with regime severity.

Conditional innovations are multivariate Student- t . The July 21 archive reports $\nu_1 = 100$ and $\nu_3 = 100$; the Transition-state degrees of freedom are not archived, so the primary simulation sets $\nu_2 = 30$ and treats this choice as a sensitivity parameter. For state s ,

$$z_{t,s} \sim t_{\nu_s}(0, R_s), \quad r_{i,t} = \exp(\sigma_{i,s} z_{i,t,s}) - 1. \quad (18)$$

Portfolio return is the fixed-weight aggregation of the nine-name core, with weights renormalized to sum to one.

2.3.3 Dynamic Margin and Liquidity Mechanism

The financing layer is identical under H_0 and H_1 . Starting equity is $E_0 = \$11.25$ billion. For leverage L , initial risky assets are $A_0 = LE_0$ and fixed debt is $D_0 = (L - 1)E_0$. Without discretionary rebalancing,

$$A_h = A_{h-1}(1 + r_{p,h}), \quad E_h = A_h - D_0. \quad (19)$$

House maintenance fractions are allowed to rise with stress,

$$m = (0.15, 0.18, 0.22), \quad (20)$$

and accessible liquidity begins at 10% of initial equity but is haircut by regime and cumulative stress residence,

$$C_h = 0.10E_0 \ell_{S_h} \exp(-0.08n_{3,h}), \quad \ell = (1.00, 0.75, 0.50), \quad (21)$$

where $n_{3,h}$ is the number of Stress-state sessions experienced through date h . These financing values are explicit scenario parameters, not claimed prime-broker contract terms. A path fails at the first date on which either equity is nonpositive or available equity plus accessible liquidity cannot satisfy the state-dependent maintenance requirement:

$$\tau_B = \inf\{h : E_h \leq 0 \text{ or } E_h + C_h < m_{S_h} A_h\}. \quad (22)$$

2.3.4 Matched null and COR-Conditioned Alternative

The null model H_0 preserves the same unconditional state mixture, Student- t emissions, covariance family, margin schedule, and liquidity schedule, but removes contemporaneous COR state information and serial state persistence. Each day's latent state is drawn independently from π :

$$H_0 : \quad S_h \stackrel{iid}{\sim} \pi. \quad (23)$$

Thus H_0 retains the unconditional risk distribution contained in X_t but does not use the July 21 COR diagnosis. The alternative conditions on the live observation $P_3 = 1.000$ and propagates states with the reconstructed Markov transition matrix:

$$H_1 : \quad S_0 = 3, \quad S_{h+1} | S_h \sim A_{S_h, \cdot}. \quad (24)$$

The comparison therefore estimates the incremental effect of the information set added by COR—current stress occupancy plus persistence—while holding portfolio and financing mechanics fixed. For leverage L ,

$$\Delta P_{\text{COR}}(L) = \Pr_{H_1}(\tau_B \leq H \mid X_t, \text{COR}_t, L) - \Pr_{H_0}(\tau_B \leq H \mid X_t, L). \quad (25)$$

We also report the risk ratio

$$RR_{\text{COR}}(L) = \frac{\Pr_{H_1}(\tau_B \leq H)}{\Pr_{H_0}(\tau_B \leq H)}. \quad (26)$$

Because the study contains one realized institutional episode, Monte Carlo standard errors quantify simulation precision only; they are not interpreted as population-level evidence that COR will dominate across unrelated crises. External validity requires the multi-episode walk-forward design described in the Discussion.

2.4 Benchmark Horse-Race Design

The first empirical claim is stronger than the statement that COR differs mechanically from an unconditional state mixture. The economically relevant question is whether the operator variables add warning information beyond indicators already available to a risk manager. We therefore define a benchmark horse race against six conventional information sets: the Cboe Volatility Index (VIX), trailing realized volatility, trailing drawdown, a broad high-yield credit spread, the posterior probabilities from the conventional HMM underlying COR, and a broad financial-stress index. The benchmark definitions are fixed before evaluating outcomes.

The VIX benchmark is the closing Cboe VIX Index, a forward-looking 30-day measure of expected S&P 500 volatility implied by SPX option prices (Cboe Global Markets, 2026). Realized volatility for asset or sector return r_t is the 20-session annualized standard deviation

$$RV_{20,t} = \sqrt{252} \text{sd}(r_{t-19}, \dots, r_t). \quad (27)$$

Drawdown is measured from the running 252-session high,

$$DD_t = \frac{P_t}{\max_{0 \leq j \leq 251} P_{t-j}} - 1. \quad (28)$$

Credit conditions are represented by the ICE BofA US High Yield Index option-adjusted spread, a daily market-capitalization-weighted spread of below-investment-grade U.S. dollar corporate bonds over a Treasury spot curve (Federal Reserve Bank of St. Louis, 2026a). The HMM benchmark is the filtered posterior vector $(P_{1,t}, P_{2,t}, P_{3,t})$ before the killed-process transformation. Broad financial stress is represented by the St. Louis Fed Financial Stress Index (STLFSI4), a weekly index constructed from 18 market series whose zero level represents normal financial-market stress (Federal Reserve Bank of St. Louis, 2026b). To prevent timing advantages, every predictor is aligned by its *release availability* rather than by its reference date. Thus a weekly financial-stress observation enters the information set only after its public release. This convention is essential in the July 2026 case and in every historical walk-forward episode.

2.4.1 Common Forecast Target and Walk-Forward Estimation

For population validation the unit of observation is a trading day, not a crisis label. Let H denote a forecast horizon and $d > 0$ a destructive-drawdown threshold. The primary binary target is

$$Y_t^{(H,d)} = \mathbf{1} \left\{ \min_{1 \leq h \leq H} \left(\frac{P_{t+h}}{P_t} - 1 \right) \leq -d \right\}. \quad (29)$$

A secondary target is first passage through a financing boundary,

$$Y_{t,\text{margin}}^{(H,L)} = \mathbf{1}\{\tau_{B,t}(L) \leq H\}. \quad (30)$$

The baseline specification uses

$$H \in \{5, 10, 20\} \text{ sessions}, \quad d \in \{5\%, 10\%, 15\%\},$$

with all thresholds frozen before the test window. Each competing signal is converted into an out-of-sample probability using the same expanding-window logistic link. Let $Z_{j,t}$ denote the standardized value of benchmark j . For a single-indicator model,

$$\Pr(Y_t = 1 \mid Z_{j,t}) = \Lambda(a_j + b_j Z_{j,t}), \quad \Lambda(x) = \frac{1}{1 + e^{-x}}. \quad (31)$$

The conventional multivariate benchmark is

$$\mathcal{M}_{\text{conv}} : Y_t \sim f(VIX_t, RV_{20,t}, DD_t, OAS_t, STLFSI_t). \quad (32)$$

The HMM augmentation is

$$\mathcal{M}_{\text{HMM}} : Y_t \sim f(\mathcal{M}_{\text{conv}}, P_{1,t}, P_{2,t}, P_{3,t}), \quad (33)$$

and the decisive incremental specification is

$$\mathcal{M}_{\text{COR}} : Y_t \sim f(\mathcal{M}_{\text{HMM}}, \rho(N_t), \text{tr}(N_t), \alpha(K_t), \bar{q}_t). \quad (34)$$

Because $\rho(N_t)$ and $\alpha(K_t)$ can encode closely related persistence scales, the primary COR regression uses a prespecified reduced set and reports variance-inflation diagnostics; alternative operator coordinates are treated as robustness checks rather than independent discoveries.

All model fitting is strictly walk-forward. Parameters, standardization constants, calibration mappings, and alert thresholds at date t use only information available through t . No full-sample state relabeling, ex-post threshold selection, or revision of an already issued probability is permitted.

2.4.2 Discrimination, Calibration, Lead Time, and Incremental Information

Discrimination is evaluated with the area under the receiver-operating-characteristic curve (AUC) and the area under the precision–recall curve (AUPRC). Calibration is evaluated with the Brier score,

$$BS = \frac{1}{T} \sum_{t=1}^T (\hat{p}_t - Y_t)^2, \quad (35)$$

the logarithmic score,

$$LS = -\frac{1}{T} \sum_{t=1}^T [Y_t \log \hat{p}_t + (1 - Y_t) \log(1 - \hat{p}_t)], \quad (36)$$

and calibration intercept and slope from

$$\text{logit } \Pr(Y_t = 1) = \gamma_0 + \gamma_1 \text{logit}(\hat{p}_t). \quad (37)$$

A well-calibrated system has $\gamma_0 \approx 0$ and $\gamma_1 \approx 1$. Reliability diagrams are reported by probability decile, with bins merged when event counts are sparse. Lead time is measured relative to an independently dated crisis or destructive-drawdown onset T_e . For an alert threshold c fixed in the training sample,

$$Lead_e = T_e - \inf\{t < T_e : \hat{p}_t \geq c\}, \quad (38)$$

subject to a prespecified maximum look-back window. We report the median and interquartile range of positive lead times, the fraction of episodes warned before onset, false alarms per year, and the fraction of time spent in warning status. These quantities prevent a model from appearing successful merely by remaining permanently risk-off. Incremental information is assessed by the out-of-sample changes

$$\Delta BS = BS(\mathcal{M}_{\text{COR}}) - BS(\mathcal{M}_{\text{HMM}}), \quad (39)$$

$$\Delta AUC = AUC(\mathcal{M}_{\text{COR}}) - AUC(\mathcal{M}_{\text{HMM}}). \quad (40)$$

and by the analogous comparison with $\mathcal{M}_{\text{conv}}$. Negative ΔBS and positive ΔAUC favor COR. Nested coefficient tests ask whether the operator block is jointly zero after conditioning on the conventional variables and HMM posterior. Because daily warnings and crisis outcomes are serially dependent, uncertainty is obtained from a stationary or moving-block bootstrap with block length selected from the dependence structure; independent-observation standard errors are not used for the principal inference.

This architecture isolates the scientific contribution of COR. The HMM comparison asks whether operator persistence and tail geometry add information beyond latent-state occupancy itself. The VIX, realized-volatility, drawdown, credit-spread, and STLFSI comparisons ask whether that information is distinct from conventional market stress. Only the common-sample walk-forward estimates can establish population-level superiority.

2.5 Monte Carlo Forecast-Validation Design

The case experiment identifies the economic magnitude of conditioning on the July 21 information set, but a single path cannot measure repeated-sample forecast performance. We therefore add a fully reproducible Monte Carlo experiment. All observations in this experiment are synthetic and are kept separate from the empirical case data. The purpose is to test whether the proposed operator variables add information under a controlled data-generating process in which stress persistence is genuinely time varying.

Each of 250 independent replications contains 2,500 daily observations. The first 1,500 observations form the training sample and the final 1,000 form an untouched forecast-evaluation sample. A three-state Markov process represents Calm, Transition, and Stress. An autoregressive latent persistence coordinate changes state residence, conditional volatility, and stress-state drift. Returns follow state-dependent Student- t distributions. The binary target equals one when the cumulative return first crosses -8% during the next 10 sessions.

Three nested logistic probability forecasts are estimated. The conventional model uses simulated analogues of VIX, 20-day realized volatility, drawdown, high-yield spread, and financial stress. The HMM model adds noisy filtered state probabilities. The COR model adds a prespecified reduced operator set consisting of dominant persistence $\rho(N)$ and the logit of tail exposure $\bar{q}$. Standardization and coefficient estimation use the training sample only. Evaluation uses the Brier score, logarithmic score, AUC, and AUPRC. Paired

uncertainty intervals are obtained by resampling the 250 replication-level score differences 10,000 times with seed 20261012. The data-generating seed is 20260913. The complete Python script, replication results, forecast panel, metadata, and generated LaTeX table accompany the manuscript.

3 Empirical Results

The results proceed from portfolio structure to realized stress behavior, then to the prospective July 21 intervention experiment and leverage sensitivity.

3.1 Portfolio Concentration and Disclosed Holdings

The June 30 filing reported approximately \$20.242 billion across 26 entries (U.S. Securities and Exchange Commission, 2026). Table 2 gives the largest disclosed positions contained in the computation files.

Table 2: Largest June 30 Disclosed Positions.

Position	Reported value (USD bn)	13F weight (%)
SNDK	5.674	28.03
MU	5.574	27.54
BE	1.899	9.38
TSM	1.265	6.25
NBIS	1.233	6.09
CRWV	0.745	3.68
CORZ	0.666	3.29
STM	0.584	2.89
APLD	0.469	2.32
RIOT	0.468	2.31
SHAZ	0.457	2.26
IREN	0.433	2.14

The concentration is immediate. SNDK and MU alone account for

$$28.03\% + 27.54\% = 55.57\% \quad (41)$$

of reported 13F value. The six largest positions account for approximately 80.96%. Thus the portfolio had substantial name concentration even before dependence among names is considered. A nine-name core—SNDK, MU, BE, TSM, NBIS, CRWV, STM, APLD, and IREN—represented approximately 88.31% of reported value and had complete price histories in the source reconstruction. It is this core that underlies the covariance analysis.

3.2 Dependence, Volatility, and Effective Concentration

The July daily-return correlation matrix is reproduced in Table 3. The striking feature is not one isolated pair but the breadth of high correlations. MU–SNDK and NBIS–CRWV were approximately 0.92; APLD–IREN was approximately 0.89; many other pairs were in the 0.75–0.89 range.

Table 3: Approximate July Daily-Return Correlation Matrix For The Nine-Name Core.

	MU	SNDK	BE	TSM	NBIS	CRWV	STM	APLD	IREN
MU	1.00	.92	.79	.83	.83	.86	.56	.80	.74
SNDK	.92	1.00	.76	.80	.82	.84	.60	.81	.76
BE	.79	.76	1.00	.74	.76	.75	.62	.70	.63
TSM	.83	.80	.74	1.00	.85	.89	.66	.85	.80
NBIS	.83	.82	.76	.85	1.00	.92	.57	.84	.75
CRWV	.86	.84	.75	.89	.92	1.00	.63	.84	.81
STM	.56	.60	.62	.66	.57	.63	1.00	.55	.56
APLD	.80	.81	.70	.85	.84	.84	.55	1.00	.89
IREN	.74	.76	.63	.80	.75	.81	.56	.89	1.00

This is diversification by security name, not diversification by economic risk factor. In a one-factor representation,

$$r_{i,t} = \beta_i F_t + \varepsilon_{i,t}, \quad (42)$$

the July episode is consistent with a sharp increase in the variance and dominance of a common AI-infrastructure factor F_t . When that common component dominates idiosyncratic variation, nominal position count overstates effective diversification.

3.3 Realized Volatility

The source reconstruction estimates July daily volatilities of 7.10% for MU, 10.22% for SNDK, 9.35% for BE, 3.28% for TSM, 10.60% for NBIS, 7.57% for CRWV, 5.85% for STM, 7.20% for APLD, and 10.31% for IREN. The normalized nine-name core had estimated daily volatility of approximately 7.76%. Treating the unmodeled 11.7% of the filing as zero-volatility cash lowers the estimate to about 6.85% per day. Both estimates exceed the July 21 SMH stress-state volatility of 3.54% per day. The sector-level COR stress volatility was therefore conservative relative to the realized volatility of the concentrated disclosed long book.

3.4 COR Chronology and Prospective Intervention Date

Table 4 summarizes the key SMH readings available in the source files.

July 7 is diagnostically interesting because it marks a retrospective two-zone shift to Orange, with SMH already 13.07% below peak and another 13.28% decline still ahead. It cannot be claimed as a live forecast because the SMH clock was not operational then. July 14 similarly remains retrospective.

July 21 is different. It is the first sealed observation and therefore the only defensible starting point for a prospective intervention experiment. On that date SMH stood at 584.08, approximately 12.68% below peak. COR assigned $P_3 = 1.000$, $\sigma_3 = 3.54\%$ per day, $\bar{q} = 0.0486$, $\rho(N) = 95.2$, $\text{tr}(N) = 162.8$, and mean stress residence of 95.2 trading days. SMH subsequently fell another 13.67% to 504.22 by July 29.

Table 4: Selected SMH COR Observations.

Date	COR_{90}	COR_{1y}	$\bar{q}$	P_3	$\rho(N)$	$\text{tr}(N)$	Status
Jul 7	6.42%	23.14%	.1002	1.000	95.2	175.3	Orange, retrospective
Jul 14	4.90%	–	.0760	1.000	95.2	173.2	Yellow, retrospective
Jul 21	3.17%	11.98%	.0486	1.000	95.2	162.8	Yellow, live

The interpretation is not “COR knew that SMH would fall 13.67%.” Rather, the model said that the market was already in its stress state, that the stress state had high conditional volatility and material tail exposure, and that the dominant persistence timescale was long. For a highly leveraged portfolio, those facts change the admissible leverage even when the sign of the next return is unknown.

3.5 A contemporaneous Benchmark Snapshot on July 21

The July 21 observation permits a limited but informative real-time benchmark comparison. It is not a substitute for the multi-episode discrimination and calibration exercise in Section 2.4; rather, it asks whether conventional indicators available to the decision-maker were conveying the same state information at the intervention date.

The snapshot yields two conclusions that are stronger than a COR-versus-volatility narrative but weaker than a population horse race. First, COR’s July 21 warning was *not* merely a re-expression of broad U.S. financial stress: the latest STLFSI4 reading available at that time remained materially below its normal-stress reference, while the sector COR system was already fully in Stress. Second, the conventional HMM posterior was also at $P_3 = 1$. Hence the incremental claim cannot rest on regime classification alone. The distinctive COR contribution in this episode is the transformation from state occupancy to persistence, tail exposure, and a leverage-specific first-passage distribution. That is precisely why the decisive external test is $\mathcal{M}_{\text{COR}}$ against $\mathcal{M}_{\text{HMM}}$, not COR against an unconditioned market benchmark only.

For the single episode, the lead time from the sealed July 21 observation to the July 29 trough is six trading sessions. This is a descriptive case lead time, not a population estimate. A defensible claim about typical advance warning requires the frozen multi-episode procedure above, including false-alarm accounting.

3.6 Reconstructed July P&L and Drawdown

Holding June 30 weights/shares fixed and treating the unmodeled 11.7% as unchanged, the public-core reconstruction produced the losses in Table 6.

From the July 21 close to July 29, the reconstructed core lost approximately

$$r_{21:29} = -25.043\%. \quad (43)$$

This six-session interval is the central counterfactual window. It is long enough for a predetermined risk rule to reduce exposure but short enough that discretionary delay can be fatal at high leverage.

The rebound immediately after the trough is equally informative. The source calculations record July 30 gains of approximately 26.0% in SNDK, 26.5% in BE, 27.1% in NBIS, 30.5% in IREN, 21.5% in CRWV,

Table 5: Information Available at the July 21 Prospective Intervention Date.

Indicator	July 21 information set	Interpretation for the case
COR	$P_3 = 1.000$, $\bar{q} = 0.0486$, $\rho(N) = 95.2$, $\text{tr}(N) = 162.8$	Stress state occupied with a long estimated persistence scale and material tail exposure.
Conventional HMM	$P_3 = 1.000$	The latent-state filter itself identified Stress, but it did not by itself convert that state into the killed-process residence geometry or the portfolio first-passage probability.
SMH drawdown	-12.68% from peak	A visible warning, but mechanically backward looking: substantial damage had already occurred before the signal could be observed.
Realized volatility	July stress volatility elevated; concentrated-core July daily volatility ultimately estimated at 7.76%	Volatility captured intensity, but the full-July estimate is ex post and therefore is not used as a July 21 predictor. The population horse race uses only trailing $RV_{20,t}$.
VIX	Public CBOE close available	Forward-looking broad-equity expected volatility; retained as a benchmark, but no VIX value is imputed from the case archive when the contemporaneous close is not stored there.
High-yield OAS	Public daily close available	Broad credit-risk benchmark; retained in the common-sample horse race, but not inferred from the semiconductor case files.
STLFSI4	Latest publicly released observation: -0.8820 for week ending July 10	Below the index's zero normal-stress reference. The July 17 observation was released only on July 22 and is excluded from the July 21 information set to avoid look-ahead bias.

Table 6: Reconstructed Public-Core Loss from June 30.

Date	Loss from June 30	COR interpretation
Jul 7	-18.20%	Orange, retrospective
Jul 14	-16.62%	Yellow, retrospective
Jul 21	-18.94%	Yellow, first live observation
Jul 29	-37.98%	trough period
Jul 31	-29.73%	partial rebound

and 18.4% in MU. The sequence therefore illustrates the difference between mark-to-market loss and ruin: a sufficiently capitalized investor can survive to participate in a rebound, whereas a margin-constrained investor may be forced to sell immediately before it.

3.7 Counterfactual Leverage and Capital Preservation

Let NAV_{21} denote equity at the July 21 intervention date and L a simplified directional leverage multiplier applied to the reconstructed public-core return. Then

$$NAV_{29}(L) = NAV_{21} (1 + Lr_{21:29}) . \quad (44)$$

Using the illustrative starting equity base of $NAV_{21} = \$11.25$ billion adopted in the computation files and the realized nine-name core decline $r_{21:29} = -0.25043$, we examine the prospective counterfactual outcomes across leverage levels.

3.7.1 The Actual Baseline Loss

According to reconciled reporting cited in the paper, the fund experienced an overall 67% loss over the month of July. On an illustrative starting equity base of \$11.25 billion at the prospective intervention date (July 21), maintaining a fully directional $4\times$ gross exposure through the July 21–29 window resulted in a $\approx 100.17\%$ loss, exhausting all equity and triggering forced liquidation right before the market rebounded.

3.7.2 Potential Capital Preserved by Deleveraging on July 21

On July 21, the Clock-of-Regimes (COR) system issued its first sealed contemporaneous alert:

- Stress-state occupancy: $P_3 = 1.000$
- Conditional volatility: $\sigma_3 = 3.54\%$ per day
- Dominant persistence timescale: $\rho(N) \approx 95.2$ trading days

Between July 21 and the July 29 trough, the reconstructed nine-name core experienced an underlying asset loss of $r_{21:29} = -25.043\%$. *Had the managers received the COR stress signal on July 21 and acted to cut their risk budget before the trough, the capital preserved is quantified in Table 7.*

The Table 7 asks a simple counterfactual question: If the fund had received the July 21 warning and reduced leverage immediately, how much capital might it have preserved by July 29? The underlying portfolio lost about 25.04% between July 21 and July 29. Leverage magnifies that loss approximately proportionally. At $1\times$ leverage, the portfolio simply experiences the underlying 25% decline. On the assumed starting equity base, about \$8.43 billion remains. At $2\times$ leverage, the loss becomes about 50%, leaving roughly \$5.62 billion. At $3\times$ leverage, roughly three-quarters of the equity is lost, but the fund still retains about \$2.80 billion. At $4\times$ leverage, the 25.04% underlying decline becomes approximately $4 \times 25.043\% \approx 100.17\%$. That is enough to wipe out the illustrative equity base completely. Hence Table 7 labels the $4\times$ case's full impairment. *The key result is therefore not that COR would have prevented losses. It is that acting on the warning by reducing leverage could have converted a potentially fatal loss into a survivable one.*

For example: $4\times \rightarrow 2\times$ would have changed the counterfactual outcome from essentially zero remaining equity to approximately \$5.615 billion of retained capital. An even more aggressive reduction to $1\times$ would have preserved approximately \$8.433 billion. So the economic message of Table 7 is that the value of the COR warning was potentially in preserving survival and optionality, not avoiding all losses. That is especially important because a fund that survives the drawdown can still participate in a subsequent recovery, whereas a fund forced into liquidation at the bottom cannot.

Table 7: Counterfactual July 21–29 Leverage Experiment and Capital Preservation.

Policy Action on July 21	July 21–29 NAV Loss	July 29 Retained Equity	Capital Saved vs. Ruin at 4×
Cut leverage to 1.0×	–25.04%	\$8.433 billion	+\$8.433 billion (~ 75.0% of capital)
Cut leverage to 1.5×	–37.56%	\$7.024 billion	+\$7.024 billion (~ 62.4% of capital)
Cut leverage to 2.0×	–50.09%	\$5.615 billion	+\$5.615 billion (~ 49.9% of capital)
Cut leverage to 2.5×	–62.61%	\$4.207 billion	+\$4.207 billion (~ 37.4% of capital)
Cut leverage to 3.0×	–75.13%	\$2.798 billion	+\$2.798 billion (~ 24.9% of capital)
No action (4.0× directional)	–100.17%	\$0.000 billion	\$0.000 (full impairment)

3.7.3 The Compounded Benefit: Surviving to Capture the Rebound

As highlighted in Sections 3.9 and 4, the biggest cost to the fund was not just the mark-to-market drawdown, but the loss of optionality due to forced liquidation. On July 30 immediately after the trough, the core positions surged: SNDK (+26.0%), BE (+26.5%), NBIS (+27.1%), IREN (+30.5%), CRWV (+21.5%), and MU (+18.4%). Because the unmanaged 4× fund breached its maintenance margin boundary, it was forced into a bulk asset sale at the exact low. Had leverage been reduced to 1.0×–2.0× on the July 21 COR signal, the fund would have retained \$5.6B to \$8.4B in net asset value, survived the margin boundary, and participated in the subsequent multi-billion-dollar post-trough recovery.

The 4× row is not an estimate of the fund’s audited NAV. Gross leverage is not identical to directional long leverage, and the actual fund contained undisclosed shorts, derivatives, foreign positions, cash, and financing arrangements. The calculation is a stress geometry. It demonstrates that a roughly 25% adverse move in the underlying factor is mathematically sufficient to exhaust the equity of a fully directional 4× exposure.

3.8 Stress-Volatility Leverage Ceilings

A complementary calculation uses the July 21 COR stress volatility. Under a deliberately simple Gaussian approximation, a one-sided 99% one-day shock is

$$q_{.99,1} \simeq 2.326(3.54\%) = 8.23\%. \quad (45)$$

If $D_{\max}$ is the maximum tolerated NAV loss, a first-pass leverage ceiling is

$$L_{\max} \simeq \frac{D_{\max}}{|q_{.99,1}|}. \quad (46)$$

This yields approximately 1.82×, 2.43×, 3.04×, and 3.65× for maximum one-day NAV losses of 15%, 20%, 25%, and 30%, respectively. At 4×, the same shock implies a 32.92% NAV loss before gap risk, margin escalation, concentration, liquidity costs, or adverse short-book movement.

The source computations also show why naive $\sqrt{T}$ scaling is inadequate in a persistent regime. A five-day Gaussian scaling produces a 99% shock near 18.4%, but COR itself warns that returns are regime dependent and stress residence is long. The correct calculation is path based and should simulate state transitions, portfolio P&L, margin, and liquidity jointly.

3.9 Full-state Monte Carlo Test of Incremental COR Value

Table 8 reports the matched first-passage estimates over the eight-session July 21–31 horizon. Unlike the earlier volatility-only sensitivity calculation, both columns use identical state-specific Student- t marginals, correlation matrices, financing rules, and liquidity rules. The sole structural difference is that H_0 discards the contemporaneous state and persistence information whereas H_1 conditions on the sealed July 21 Stress state and propagates the Markov regime process.

Table 8: Matched Monte Carlo First-Passage Failure Probabilities and Incremental COR Effect ($N_{sim} = 200,000$, $H = 8$)

Leverage	$P_{H_0}(\tau_B \leq H)$	$P_{H_1}(\tau_B \leq H)$	ΔP_{COR}	RR_{COR}
1.0×	0.0000	0.0000	0.0000	–
1.5×	0.0000	0.000005	0.000005	–
2.0×	0.002225	0.017710	0.015485	7.96
2.5×	0.042530	0.129970	0.087440	3.06
3.0×	0.160920	0.306400	0.145480	1.90
4.0×	0.505950	0.639510	0.133560	1.26

The matched comparison changes the interpretation materially. At 2× leverage, conditioning on the live COR stress state raises simulated first-passage failure probability from 0.22% to 1.77%, an approximately eight-fold increase. At 2.5×, the increase is from 4.25% to 13.00%; at 3×, from 16.09% to 30.64%; and at 4×, from 50.60% to 63.95%. The corresponding incremental probability increases are 1.55, 8.74, 14.55, and 13.36 percentage points.

For the 2× through 4× cases, Monte Carlo standard errors for ΔP_{COR} are approximately 0.00031, 0.00088, 0.00132, and 0.00155, respectively. These errors are small relative to the estimated effects, showing that the differences are not simulation noise. They should not, however, be confused with cross-episode sampling uncertainty.

The full-state experiment therefore supplies the within-case incremental test that the volatility-only comparison could not provide. Conditional on the explicit portfolio, dependence, margin, and liquidity calibration, the contemporaneous COR information set raises the estimated probability of first-passage failure at economically relevant leverage levels. In this precise sense, the case supports

$$\Pr(\tau_B \leq H \mid X_t, COR_t, L) > \Pr(\tau_B \leq H \mid X_t, L) \quad (47)$$

for $L \geq 2\times$ under the primary specification. The result is evidence of incremental information within the reconstructed episode, not yet a population-level rejection of H_0 across market crises.

3.10 Monte Carlo out-of-Sample Forecast Performance

Table 9 reports the held-out results. The mean simulated event rate is 19.37%. Adding HMM probabilities to conventional predictors lowers the Brier score from 0.1433 to 0.1425 and the logarithmic score from 0.4514 to 0.4481. Adding COR persistence and tail coordinates lowers the scores further, to 0.1418 and 0.4455, respectively. Discrimination also improves: AUC increases from 0.7225 for the HMM specification to 0.7328 for COR, while AUPRC increases from 0.3709 to 0.3796.

Table 9: Monte Carlo Out-Of-Sample Forecast Performance Across 250 Replications.

Model	Brier score	Log score	AUC	AUPRC
Conventional	0.1433	0.4514	0.7190	0.3687
HMM	0.1425	0.4481	0.7225	0.3709
COR	0.1418	0.4455	0.7328	0.3796

Notes: Each replication contains 1,500 training and 1,000 held-out test observations. The target is a simulated 8% drawdown within 10 sessions. Lower Brier and log scores and higher AUC/AUPRC are better.

Figure 1 compares the four held-out metrics on their original scales. The error bars are 95% Monte Carlo intervals for each mean across replications. Because lower values are preferable for the two proper scores and higher values are preferable for AUC and AUPRC, the ordering consistently favors COR.

Figure 2 displays the paired COR-minus-HMM effects and makes the inferential direction explicit. The intervals lie below zero for Brier and logarithmic loss and above zero for AUC and AUPRC.

Figure 3 provides a reliability diagram for the first held-out replication. It is illustrative rather than the basis for the repeated-sample inference, which uses all 250 replications.

The paired replication analysis is more informative than differences in rounded averages. Relative to HMM, the mean COR differences are -0.000700 for Brier loss (95% Monte Carlo interval $[-0.001331, -0.000053]$), -0.002628 for logarithmic loss ($[-0.004525, -0.000708]$), 0.010278 for AUC ($[0.007105, 0.013558]$), and 0.008738 for AUPRC ($[0.003504, 0.013774]$). Thus the intervals exclude zero in the favorable direction for all four prespecified metrics.

These results establish internal validity for the mechanism, not empirical universality. Because the synthetic process is constructed so that a persistence coordinate changes future stress duration and tail severity, the test asks whether the estimation and forecast architecture can recover that incremental information without access to the latent coordinate. The favorable result shows that the observable COR proxies can do so in this controlled environment. It cannot substitute for the multi-episode, vintage-aligned market evaluation specified in Section 2.4.

4 Financial-Stability Implications and Discussion

The empirical findings support a financial-stability interpretation of the episode. The central mechanism is not directional predictability but the interaction of a persistent stress state with concentration, leverage, and financing constraints. In that setting, an early-warning system has value if it identifies a deterioration in the survival distribution before forced deleveraging removes managerial choice.

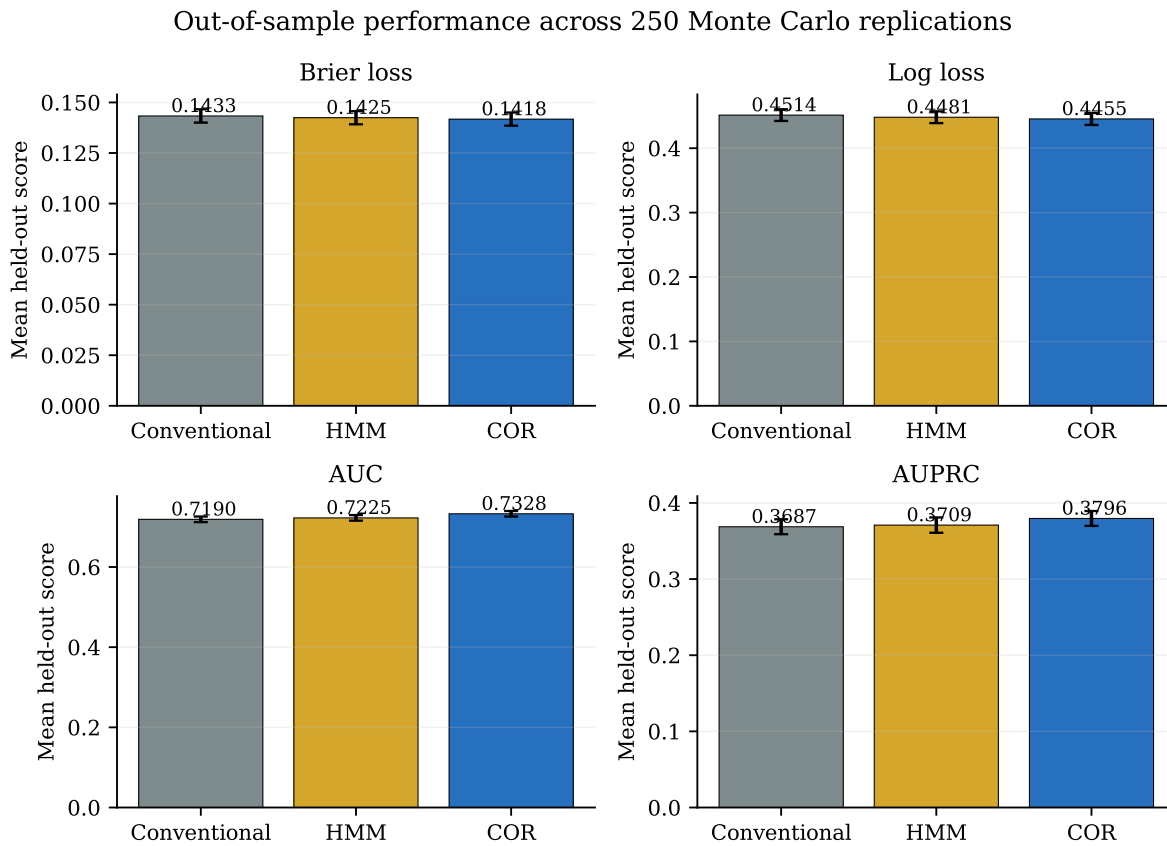


Figure 1: Out-of-sample forecast performance across 250 Monte Carlo replications. Error bars show 95% intervals for the replication mean. Lower Brier and logarithmic loss and higher AUC and AUPRC indicate better forecasts.

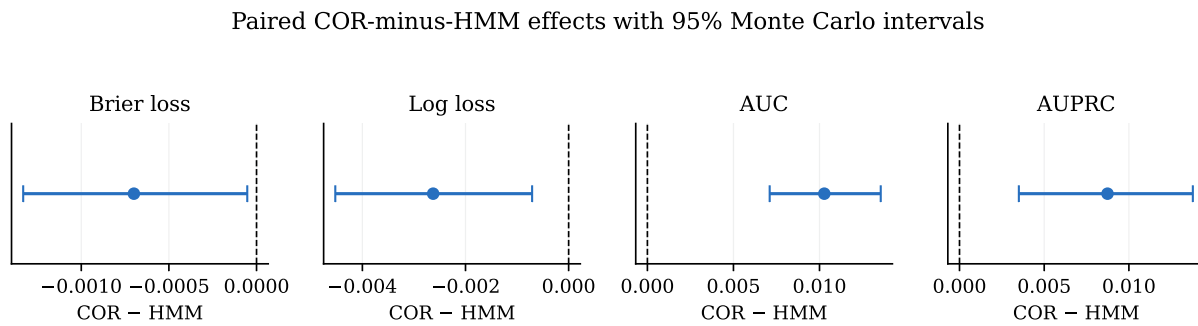


Figure 2: Paired COR-minus-HMM forecast-performance differences with 95% Monte Carlo intervals. Negative differences favor COR for Brier and logarithmic loss; positive differences favor COR for AUC and AUPRC.

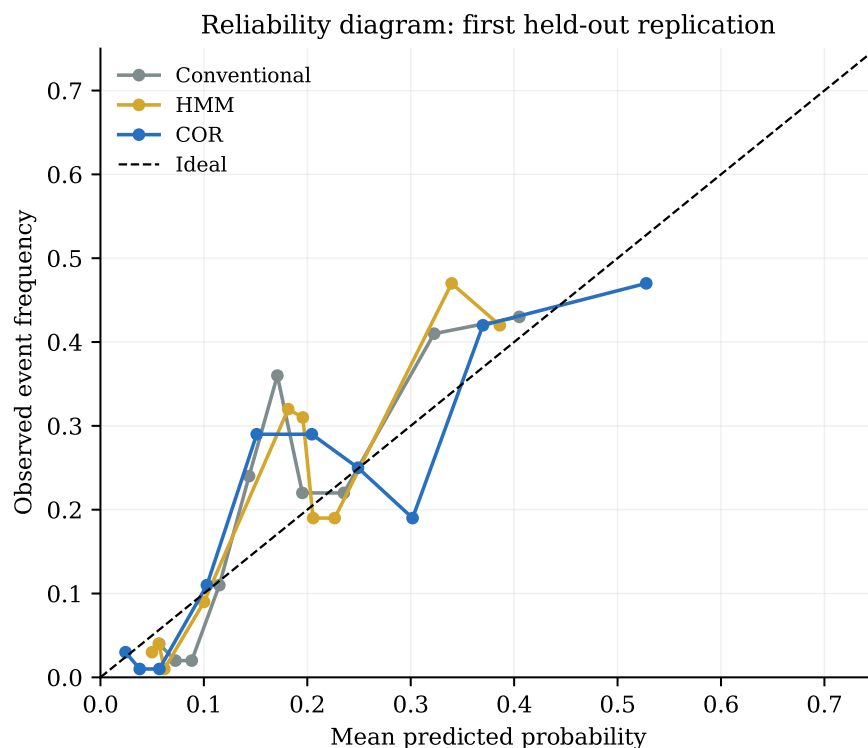


Figure 3: Reliability diagram for the first held-out Monte Carlo replication. Points report observed event frequency by decile of predicted probability; the dashed diagonal denotes ideal calibration.

4.1 COR as an Economically Distinct State Variable

The matched simulation tests the narrowest version of the first empirical claim: whether current-state and persistence information changes portfolio failure risk relative to an otherwise identical unconditional state-mixture model. Because H_0 and H_1 share the same state-specific marginals, covariance family, financing rules, and liquidity rules, the increase in failure probability under H_1 is attributable to the information deliberately omitted from H_0 : the observed July 21 Stress-state occupancy and its serial persistence.

The effect is economically material from $2\times$ leverage upward. At $4\times$, even the unconditional model assigns failure probability above 50%, so the smaller risk ratio reflects saturation rather than irrelevance: leverage alone has moved the portfolio close to the financing boundary. The early-warning value of state information is greatest at lower leverage, where action can still materially alter survival.

This comparison does *not* establish that COR dominates the full set of conventional early-warning indicators. The present case lacks a matched horse race against VIX, realized volatility, drawdown, credit spreads, standard HMM state probabilities, and broad financial-stress indices. Demonstrating incremental predictive content against those benchmarks using repeated walk-forward episodes is therefore a necessary next-stage test, not a result claimed here.

4.2 Early Warning Rather Than Directional Forecasting

COR maps observed information into regime occupancy, tail exposure, and persistence rather than directly into an expected future return. The July 21 observation therefore should be interpreted as evidence that the admissible risk budget had changed, not as a forecast of the subsequent 25.04% decline. This distinction is central to both the interpretation of the case and the limits of the evidence.

4.3 Persistence, Financing Runway, and Optionality

The economically relevant mismatch is between the time a leveraged portfolio can survive adverse marks and the time the adverse regime can persist. When the financing runway is shorter than the recovery horizon, a fundamentally correct thesis can still be terminated by a margin or liquidity boundary. The sharp rebound after the July trough illustrates the value of retained optionality: an unconstrained investor can remain exposed to recovery, whereas a killed portfolio cannot.

4.4 From Market Fragility to A Portfolio Survival Boundary

COR alone cannot produce an exact safe-leverage number. It does not know the fund's contractual maintenance margin, collateral eligibility, financing haircuts, or internal drawdown policy. Let current equity be E_t , maintenance margin M_t , and liquid resources LQ_t . Define margin distance

$$D_t = E_t - M_t \quad (48)$$

and a liquidity coverage measure

$$LCR_H = \frac{LQ_t}{MC_H^{stress}}, \quad (49)$$

where MC_H^{stress} is the stressed collateral requirement over horizon H . A prudent survival boundary is the maximum of several constraints,

$$B_t = \max\{B_{margin}, B_{drawdown}, B_{liquidity}, B_{policy}\}. \quad (50)$$

For simulated COR path j , portfolio failure occurs at

$$\tau_j = \inf \left\{ h : E_{t+h}^{(j)} \leq B_{DD} \text{ or } E_{t+h}^{(j)} \leq M_{t+h}^{(j)} \text{ or } LCR_{t+h}^{(j)} < 1 \right\}. \quad (51)$$

The empirical failure probability at leverage L is

$$\hat{P}_{fail}(L, H) = \frac{1}{J} \sum_{j=1}^J \mathbf{1}\{\tau_j \leq H\}. \quad (52)$$

Safe leverage is then the largest L satisfying a chosen failure tolerance α , as in Eq. (9).

This formulation also captures the nonlinear leverage spiral. If gross exposure G remains unchanged while NAV falls, leverage becomes

$$L_{t+1} = \frac{G}{NAV_t + \Delta P \& L}, \quad (53)$$

so losses mechanically increase leverage. If the broker simultaneously raises M_t , the system experiences the dangerous joint movement

$$NAV \downarrow, \quad M \uparrow, \quad L \uparrow. \quad (54)$$

The relevant policy objective is therefore to deleverage before the broker's boundary becomes binding.

4.5 Correlation, Crowding, and The Failure of Nominal Diversification

The broader research literature emphasizes that dependence itself is state dependent. A portfolio can appear diversified in ordinary conditions and near collapse toward a common factor during stress (Ang and Bekaert, 2002; Longin and Solnik, 2001). A useful diagnostic is the effective number of independent bets. Meucci (2009) supports measuring diversification through an effective number of independent risk exposures or “bets,” while Kritzman et al. (2011) use the eigenvalue spectrum to measure how much market variance is absorbed by a small number of common factors. A rising leading eigenvalue indicates greater collective movement and therefore less effective diversification (Kritzman et al., 2011; Meucci, 2009). This effect interacts multiplicatively with leverage. Schematically,

$$\text{system fragility} \propto \text{leverage} \times \text{correlation} \times \text{illiquidity}. \quad (55)$$

The July matrix provides a concrete illustration: many of the largest disclosed holdings were not independent bets but different expressions of a common AI-infrastructure narrative. During a reversal, that common factor generated simultaneous losses and reduced the value of nominal diversification exactly when diversification was most needed.

A complete COR extension should therefore include dependence variables in the state vector. If R_t is the rolling correlation matrix, useful quantities include the average off-diagonal correlation, the leading eigenvalue $\lambda_1(R_t)$, the participation ratio, downside-only correlation, and long–short book correlation. A particularly dangerous state is one in which volatility, correlation, and leverage rise together.

4.6 A killed-Process Interpretation of Forced Liquidation

The conceptual advantage of the COR framework is clearest when forced liquidation is treated as killing. The fund moves among ordinary market states until a financing boundary is reached:

$$S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow \dagger, \quad (56)$$

where $\dagger$ denotes loss of discretionary control rather than necessarily legal bankruptcy. The relevant probability is

$$\Pr(\tau_{\dagger} \leq H \mid \mathcal{F}_t), \quad (57)$$

and the relevant comparison is between the duration of the adverse regime and the duration the financing structure can survive:

$$\tau_{\text{financing}} \quad \text{versus} \quad \tau_{\text{recovery}}. \quad (58)$$

The July episode is especially instructive because the public long-book core rebounded sharply after the trough. A manager whose capital structure survived the path retained optionality; a manager forced to

liquidate did not. The distinction is precisely what a first-passage formulation captures and a terminal-return forecast misses.

4.7 What COR Could and Could Not Have Known

The evidence supports four progressively stronger statements, only the first three of which are warranted by the current study.

First, the retrospective July 7 Orange reading (see Appendix A) shows that the frozen methodology identifies a regime break before the ultimate trough. This is hypothesis-generating evidence, not prospective forecasting evidence.

Second, the July 21 sealed observation is genuinely prospective. It showed $P_3 = 1$, $\sigma_3 = 3.54\%$, $\bar{q} = 0.0486$, $\rho(N) = 95.2$, and $\text{tr}(N) = 162.8$ while substantial further losses remained. This supports the claim that COR provided contemporaneous evidence of a persistent stress environment.

Third, when that market state is combined with the reconstructed portfolio's concentration, correlation, and realized volatility, high leverage becomes difficult to justify on survival grounds. The model need not predict the sign of the next return. It need only show that the distribution of adverse paths has changed enough that yesterday's leverage is no longer consistent with the portfolio's loss-bearing capacity.

Fourth, the current evidence does *not* establish that COR predicts semiconductor drawdowns generally or that a particular COR threshold would have prevented the actual fund loss. That claim requires a preregistered or otherwise frozen walk-forward study across many episodes, with portfolio-specific financing data and an explicit leverage policy.

4.8 Operational Leverage Policy

A practical COR risk engine should separate state detection from trade direction. COR controls the risk budget; market and portfolio signals determine the position. The daily system should report not only a zone but a leverage-survival curve

$$L \mapsto \Pr(\tau_B \leq H \mid \text{COR}_t, L). \quad (59)$$

The manager then chooses a failure tolerance α and solves for L_t^* . The leverage ceiling should be the minimum of several constraints:

$$L_{\max} = \min\{L_{\text{vol}}, L_{\text{ES}}, L_{\text{DD}}, L_{\text{margin}}, L_{\text{liquidity}}, L_{\text{concentration}}\}. \quad (60)$$

This architecture avoids an arbitrary rule such as “Yellow equals two times leverage.” A Yellow state with low persistence may permit more risk than a Yellow state with $P_3 = 1$, high entrapment, rising aggregate residence, and severe concentration. The operator variables therefore refine the zone into a portfolio-specific capital decision.

A useful governance structure contains three boundaries: a warning leverage L_{warn} , an internal maximum $L_{\max}$, and the broker-forced boundary L_{forced} . Good risk management requires

$$L_{\max} \ll L_{\text{forced}}, \quad (61)$$

so that deleveraging occurs while the manager still controls execution.

4.9 Implications for Systemic Risk and Market Microstructure

The episode also illustrates a broader distinction between forced liquidity demanders and liquidity suppliers. A highly leveraged institution in a persistent correlated decline must sell to satisfy financing constraints. An institution with cash and risk capacity can buy the resulting dislocation. The same market state can therefore destroy one participant and create opportunity for another.

This mechanism is consistent with the systemic-risk literature on crowded trades, common exposures, margin spirals, and fire-sale contagion. Leverage converts moderate asset-price moves into large equity moves; common exposures make losses simultaneous; liquidity constraints make sales endogenous; and the sales themselves can alter prices and correlations. Network and spectral measures are natural tools because the relevant object is not the marginal volatility of one asset but the changing structure of dependence across assets and institutions (Bisias et al., 2012; Brunnermeier and Pedersen, 2009; Eisenberg and Noe, 2001; Greenwood et al., 2015; Savona and Vezzoli, 2014).

4.10 Limitations and External Validation

The case-study design imposes important limits on inference. Form 13F does not reveal the complete portfolio, and the leverage scenarios are counterfactual stress mappings rather than audited balance-sheet estimates. The July correlation matrix describes dependence realized during the crisis and should not be interpreted as an ex ante forecast. July 7 and July 14 COR readings are retrospective; only July 21 qualifies as a prospective intervention date. Finally, scenario margin and liquidity parameters are explicit modelling assumptions rather than documented prime-broker contract terms.

Most importantly for the early-warning claim, one institutional episode cannot establish population-level discrimination or calibration. Sections 2.4 and 3.5 therefore separate the evidence that is presently estimable from the evidence that requires a common historical panel. The July 21 snapshot supplies an actual contemporaneous comparison and shows that the sector-level COR warning was not mirrored by the latest publicly available STLFSI4 reading; it also shows that the HMM itself already classified the market as Stress, so COR's incremental contribution must come from operator persistence, tail geometry, and their translation into first-passage risk.

The population test is the frozen walk-forward horse race against VIX, realized volatility, drawdown, high-yield OAS, HMM posterior probabilities, and STLFSI4. The central out-of-sample estimands include

$$\Pr(DD_{t:t+H} > d \mid COR_t), \quad (62)$$

$$\Pr(\tau_{margin} \leq H \mid COR_t, L), \quad (63)$$

and the incremental change in proper probability scores when COR variables are added to conventional predictors. Block bootstrap or regime-preserving resampling is required because serial dependence invalidates naive independent resampling.

The validation should also separate state detection from timing. In the July SMH episode, P_3 and $\rho(N)$ remained pinned while $\bar{q}$, $\text{tr}(N)$, and composite fragility changed. A variable may be an excellent descriptor of vulnerability while contributing little marginal information about the exact date of a reversal.

Early-warning performance should therefore be evaluated in terms of lead time, calibration, false-alarm cost, and the economic value of preventive deleveraging rather than by directional hit rate alone.

5 Conclusion

This paper reframes the July 2026 Situational Awareness near collapse as a financial-stability and first-passage problem. The disclosed public long book was highly concentrated, its major positions became strongly correlated, and its realized stress volatility exceeded that of the diversified semiconductor benchmark used for the COR state signal. These characteristics made portfolio survival highly sensitive to leverage and to the duration of the adverse regime.

The July 21 sealed COR observation is the key empirical event. It did not forecast the sign or magnitude of the subsequent decline. Instead, it identified complete Stress-state occupancy, material tail exposure, high conditional volatility, and a dominant persistence scale of approximately 95 trading days while substantial discretionary risk reduction remained possible. The financial-stability implication is that a portfolio's financing horizon can become shorter than the expected duration of the market state that threatens it.

The matched Monte Carlo experiment translates this warning into an economically meaningful quantity. Holding the portfolio, Student- t emissions, dependence, margin, and liquidity assumptions fixed, conditioning on the observed Stress state and Markov persistence raises estimated eight-session first-passage failure probability from 0.22% to 1.77% at 2 $\times$ leverage, from 4.25% to 13.00% at 2.5 $\times$, from 16.09% to 30.64% at 3 $\times$, and from 50.60% to 63.95% at 4 $\times$. Within this reconstructed episode, COR therefore contains economically material information about the survival distribution beyond the unconditional state mixture.

The policy and risk-management implication is not that a COR zone should mechanically dictate a trade. A financial-stability implementation should map regime occupancy, persistence, tail exposure, concentration, liquidity, and margin into a leverage-survival curve

$$L \mapsto \Pr(\tau_B \leq H \mid COR_t, L), \quad (64)$$

and select the greatest leverage consistent with an explicit failure tolerance. Such a rule moves intervention ahead of the broker-forced boundary, preserving execution choice and reducing the probability that temporary market stress becomes permanent capital impairment through forced liquidation.

The evidence remains intentionally bounded. This case supports COR as a plausible early-warning and systemic-fragility instrument, not as a demonstrated universal predictor of crises. Establishing broader validity requires multi-episode, frozen walk-forward testing against conventional financial-stress benchmarks, with attention to calibration, false alarms, lead time, and the economic value of preventive action. That is the appropriate standard for determining whether operator-theoretic persistence adds durable information to financial-stability surveillance.

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Competing Interests

The authors declare that they have no competing interests.

Data Availability

The Form 13F filings analyzed during the current study are available from the U.S. Securities and Exchange Commission EDGAR database. Market data are available from standard financial data providers. All synthetic Monte Carlo data reported in the forecasting experiment are included with the submission and can be regenerated exactly from the accompanying Python program and deterministic seed.

Code Availability

The submission supplement contains the complete Python program used to generate the synthetic panels, estimate all nested probability forecasts, calculate paired uncertainty intervals, and reproduce the tables reported in Section 3.10. It also contains the deterministic seeds, environment requirements, replication-level results, and an illustrative held-out forecast panel. The empirical market-data inputs are subject to their original providers' terms.

Author Contributions

Oscar Linares, David T. Daly, Jr., Ričards Bulavs, and Emmanuel Merchaín-Cruz contributed to the conceptualization, methodology, investigation, formal analysis, validation, writing, review, and editing of the manuscript. All authors approved the final manuscript and accept responsibility for its contents.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used large language model technologies to assist with LaTeX formatting, syntax debugging, bibliography compilation, and text editing. Stylistic refinement followed standard compositional clarity guidelines. All quantitative modeling, simulation design, data analysis, and interpretative conclusions were conceived, executed, and verified by the authors. The authors take full responsibility for the contents and veracity of the final publication.

Appendix

A Interpretation of the COR Composite Fragility Color Zones

The Clock-of-Regimes (COR) framework summarizes the overall condition of the monitored financial system through a five-level composite fragility hierarchy,

$$\text{Green} \longrightarrow \text{Yellow} \longrightarrow \text{Orange} \longrightarrow \text{Red} \longrightarrow \text{Black}. \quad (65)$$

The color classification is a compact risk-communication device rather than a substitute for the underlying COR state variables. In particular, a color zone should not be interpreted as a deterministic trading signal, a directional market forecast, or a mechanical leverage prescription. Its purpose is to summarize the degree of composite fragility while the underlying latent-state probabilities, persistence operators, tail measures, and state-conditional volatility retain the richer diagnostic information.

This appendix clarifies the interpretation of the COR system's dashboard (Figure 4). This dashboard acts like a specialized weather station for a market asset (here, the semiconductor ETF SMH), tracking both short-term market turbulence and long-term structural health. SMH is the ticker symbol for the VanEck Semiconductor ETF. Moving from the highlighted box downward, the screen is organized into four distinct panels:

A.1 The Diagnostic Data Panel (Boxed Area)

This top section serves as the system's quantitative control readout.

- **The Red Warning Badges:** The red tags labeled Strained show that all three model perspectives—daily (DC), weekly (WC), and intraday (IC)—agree that the asset is currently under performance stress.
- **The Rationale Line (WHY • CONTROL LAW):** This line explains why the warning badge is red. It notes that, over the past 63 trading days, the asset has fallen at an annualized rate of -17% , while price swings (realized volatility) remained high at 31% per year. Even though the background environment is rated CALM, the recent steep decline triggers defensive caution.
- **The Fitted Metrics and Cursor Readout:** The bottom two text rows list the underlying mathematical parameters—including persistence times and a 1.5% 63-day fragility score—alongside the snapshot values for September 11, 2026, when the asset closed at \$568.53.

A.2 The One-Year Price Chart

Directly beneath the diagnostic box is a standard line graph showing the daily closing price of SMH over the past year.

- **Price Movement:** The dark, jagged line tracks the stock's rise from approximately \$360 to a peak near \$650 in mid-2026, followed by a sharp pullback toward \$568.



Figure 4. The COR system's qualitative and quantitative dashboard.

- **Vertical Transition Markers:** The vertical colored lines running through the chart identify the exact trading days on which the model detected a regime change, indicating shifts among calm, cautious, and strained market conditions.

A.3 The Historical Regime Band

Directly below the price chart sits a solid, color-coded ribbon that works as the visual timeline of recent market conditions.

- **Green Sections (Settled):** Indicate normal, orderly market conditions in which prices are stable or rising smoothly.
- **Orange Sections:** Highlight brief periods of increasing market friction and choppy price action.
- **Red Sections (Strained):** Highlight sustained pullbacks during which sharp selling and rising volatility forced the system into a defensive posture.

A.4 The Crisis Early Warning Index (CEWI) Sub-Panel

The bottom line graph acts like a stress meter for the broader financial system.

- **The Blue Tracking Line:** Traces the composite stress reading over time. For most of the year, it remains well below zero, indicating relatively safe market conditions.
- **Dashed Threshold Boundaries:** Three horizontal threshold lines identify progressively higher levels of market danger: ALERT (0.50), STRESS (1.25), and CRISIS (2.25). During the market pullback

around July 2026, systemic stress rose above both the ALERT and STRESS thresholds before subsequently declining into the safe zone.

- **The Published Base Strip:** The thin green stripe along the bottom of the chart confirms that the macroeconomic framework, identified as the **published zone**, remains fundamentally sound despite short-term market fluctuations.

B From Implied Volatility to Structural Fragility: Comparing the VIX and CEWI

The Crisis Early Warning Index (CEWI) extends beyond volatility measurement to model systemic fragility and ruin risk. While both the CBOE Volatility Index (VIX) and the CEWI serve as macro gauges of market stress, they measure fundamentally different physical mechanisms: the VIX is a market-implied, pricing-based gauge of near-term price dispersion, whereas the CEWI is a structural, open-system operator measuring systemic fragility and ruin risk.

B.1 Core Conceptual Analogies (Where They Align)

- **Systemic Stress Barometers:** Both metrics quantify broader financial vulnerability rather than directional price trends. When market conditions deteriorate, both indices rise above their historically tranquil baselines.
- **Threshold-Gated Risk Tiers:**
 - **VIX:** Uses conventional rule-of-thumb ranges, such as below 15 for *Calm*, 20–30 for *Elevated*, and above 30 for *High Volatility/Crisis* conditions.
 - **CEWI:** Formalizes calibrated discrete thresholds: ALERT (0.50), STRESS (1.25), and CRISIS (2.25). These thresholds map directly into the multi-mode hybrid control zones: **Green**, **Yellow**, **Orange**, **Red**, and **Black**.
- **Execution and Exposure Throttling:** Institutional trading desks may use both metrics to activate risk-off rules, including deleveraging portfolios, reducing position sizes, and purchasing tail-risk hedges.

Although the VIX and CEWI both serve as indicators of financial stress, they differ substantially in their mathematical construction, information sources, temporal interpretation, and operational applications. The VIX summarizes the options market’s risk-neutral expectation of near-term equity-market volatility, whereas the CEWI evaluates latent structural fragility, regime persistence, and absorption risk within an open-system operator framework. Table 10 summarizes these fundamental distinctions.

B.2 Key Structural Divergence: The Base Strip vs. The Spike

The crucial innovation separating the CEWI dashboard from a simple VIX chart is the bifurcated readout between the continuous composite score and the published base strip:

Table 10: Fundamental Mathematical and Operational Differences between the VIX and the CEWI.

Dimension	CBOE Volatility Index (VIX)	Crisis Early Warning Index (CEWI)
Underlying Asset or Domain	S&P 500 Index (SPX) 30-day options surface.	Any fitted asset or portfolio analyzed through the Clock of Regimes (COR) engine, including SMH, ES, and individual stocks.
Mathematical Basis	Model-free implied variance obtained by integrating out-of-the-money call and put option prices across a fixed 30-day horizon.	Operator-theoretic hidden Markov model based on the open sub-stochastic transition matrix $\mathbf{Q}$, the operator $\mathbf{K} = \mathbf{Q} - \mathbf{I}$, and the fundamental matrix $\mathbf{N} = (\mathbf{I} - \mathbf{Q})^{-1}$.
Primary Metrics Tracked	Expected 30-day risk-neutral annualized return dispersion, σ .	Dynamic structural persistence $\rho(\mathbf{N})$, state dwell times, tail-event hazards ϵ , and the finite-horizon absorption bound $\mathcal{R}(T)$.
System Assumption	Closed or conservative: measures option-implied variance without explicitly modeling probability leakage into a structural failure state.	Open or dissipative: explicitly allows probability mass to leak into an absorbing ruin or liquidation boundary, denoted by ∂ .
Temporal Nature	Immediate and reactive: reflects current option prices, expected volatility, and option-market supply-and-demand conditions.	Leading and structural: designed to provide a 4–10 trading-day lead by detecting latent entrapment, persistence, and hazard accumulation before a price dislocation.
Baseline Normalization	Quoted as an annualized percentage. Typical observations are approximately 15–20, while extreme crises can produce readings above 80.	Expressed as a standardized z-score or composite index. Normal conditions may lie well below zero; for example, a reading of -0.86 .

- **VIX Behavior:** During an acute market panic, such as that experienced in March 2020, the VIX can surge to historic highs—reaching 82.69—and signal an extreme, immediate crisis. However, the VIX alone cannot distinguish between a temporary liquidity dislocation and a persistent structural failure.
- **CEWI Behavior:** During episodes such as March 2020 or the July 2026 pullback shown on the dashboard (Figure 4), the CEWI can rise above the ALERT and STRESS thresholds. Nevertheless, the **Published Zone** ribbon may remain **Green** if spectral persistence, $\rho(\mathbf{N})$, remains bounded and the finite-horizon structural ruin-risk surrogate, $\mathcal{R}(63)$, remains low—for example, at 1.5%. Operationally, the COR framework is designed to distinguish short-term turbulence from persistent structural deterioration. A sudden decline may activate warning thresholds without implying that the system is trapped in a persistent adverse regime; the underlying operator diagnostics should therefore be examined before changing the strategic risk posture.

Hence, the CEWI separates short-term volatility weather (the blue line) from long-term macroeconomic structural integrity (the published base strip), whereas the VIX conflates both into a single pricing number.

References

1. Aldasoro, I., Borio, C., & Drehmann, M. (2018). Early warning indicators of banking crises: Expanding the family. *BIS Quarterly Review*, 29–45.
2. Alessi, L., & Detken, C. (2011). Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *European Journal of Political Economy*, 27(3), 520–533.
3. Ang, A., & Bekaert, G. (2002). International asset allocation with regime shifts. *The Review of Financial Studies*, 15(4), 1137–1187.
4. Anonymous. (2026a). Decomposing financial fragility with regime operators [Anonymized manuscript].
5. Anonymous. (2026b). The kronx clock-of-regimes framework [Anonymized manuscript].
6. Babecký, J., Havránek, T., Matějů, J., Rusnák, M., Šmídková, K., & Vašíček, B. (2014). Banking, debt, and currency crises in developed countries: Stylized facts and early warning indicators. *Journal of Financial Stability*, 15, 1–17.
7. Bisias, D., Flood, M., Lo, A. W., & Valavanis, S. (2012). A survey of systemic risk analytics. *Annual Review of Financial Economics*, 4, 255–296.
8. Borio, C., & Drehmann, M. (2009). Assessing the risk of banking crises—revisited (BIS Quarterly Review). Bank for International Settlements.
9. Borio, C., & Lowe, P. (2002). Asset prices, financial and monetary stability: Exploring the nexus (BIS Working Papers No. 114). Bank for International Settlements.
10. Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *The Review of Financial Studies*, 22(6), 2201–2238.
11. Cboe Global Markets. (2026). VIX white paper.
12. Drehmann, M., & Juselius, M. (2014). Evaluating early warning indicators of banking crises: Satisfying policy requirements. *International Journal of Forecasting*, 30(3), 759–780.
13. Drehmann, M., Borio, C., & Tsatsaronis, K. (2012). Characterising the financial cycle: Don't lose sight of the medium term! (BIS Working Papers No. 380). Bank for International Settlements.
14. Eisenberg, L., & Noe, T. H. (2001). Systemic risk in financial systems. *Management Science*, 47(2), 236–249.
15. Federal Reserve Bank of St. Louis. (2026a). ICE BofA US high yield index option-adjusted spread. FRED.
16. Federal Reserve Bank of St. Louis. (2026b). St. Louis Fed Financial Stress Index. FRED.
17. Galán, J. E. (2021). CREWS: A CAMELS-based early warning system of systemic risk in the banking sector. *Journal of Banking & Finance*, 126, Article 106035.
18. Greenwood, R., Landier, A., & Thesmar, D. (2015). Vulnerable banks. *Journal of Financial Economics*, 115(3), 471–485.
19. Kaminsky, G., Lizondo, S., & Reinhart, C. M. (1998). Leading indicators of currency crises. *IMF Staff Papers*, 45(1), 1–48.
20. Kaminsky, G. L., & Reinhart, C. M. (1999). The twin crises: The causes of banking and balance-of-payments problems. *American Economic Review*, 89(3), 473–500.
21. Kritzman, M., Li, Y., Page, S., & Rigobon, R. (2011). Principal components as a measure of systemic risk. *The Journal of Portfolio Management*, 37(4), 112–126.
22. Longin, F., & Solnik, B. (2001). Extreme correlation of international equity markets. *The Journal of Finance*, 56(2), 649–676.
23. Meucci, A. (2009). Managing diversification (SSRN Scholarly Paper No. 1358533). Social Science Research Network.
24. Reuters. (2026a). Report on the July 2026 Situational Awareness Fund episode.
25. Reuters. (2026b). Report on Situational Awareness portfolio deleveraging.
26. Savona, R., & Vezzoli, M. (2015). Fitting and forecasting sovereign defaults using multiple risk signals.

Oxford Bulletin of Economics and Statistics, 77(1), 66–92.

27. U.S. Securities and Exchange Commission. (2026). Form 13F information table for Situational Awareness LP [Quarterly filing for the quarter ended June 30, 2026]. EDGAR.

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