Stress-Aware Scenario Generation for Reliable Portfolio Inference under Regime Shifts

Gabriel Nixon Raj
New York University
gr2513@nyu.edu

Abstract

Financial markets face shocks and regime shifts that destabilize portfolio strategies. Classical optimizers average across states and underprice tail risk, while RL agents such as FinRL often overfit to noise and fail in crises. Even Bayesian regime models and entropy-regularized RL (e.g. SAC) either work offline or use fixed bandwidths, leaving them brittle when stress levels change. We propose a trust-aware belief update that anchors regime posteriors to the prior with a KL term and adapts entropy dynamically from residual stress. This regulates the inference bandwidth, contracting in stable periods and widening in crises, and doubles as a generative scenario engine that reproduces the persistence and recovery of the crisis. Across synthetic regimes, noisy bandits, and long-horizon portfolios, the method cuts drawdowns, speeds recovery, and improves calibration while sustaining strong Sharpe and Sortino ratios. Statistical tests confirm predictive content in regimes, and utility valuations show signals align with real investor trade-offs. Stress-aware belief updates thus offer a lightweight, online mechanism for robust and interpretable portfolio inference in non-stationary markets.

1 Introduction

Financial markets are dynamic: recessions, liquidity shocks, and policy shifts alter return distributions for years at a time. Traditional mean–variance allocators smooth over these shifts and understate tail risk. Popular RL frameworks like FinRL [8, 5] chase cumulative returns but fail under regime shifts, while Bayesian regime models capture persistence only in hindsight [1, 3]. Even entropy-based RL (e.g. SAC [4]) uses a fixed bandwidth, leaving agents either too reactive to noise or too sluggish in crises. The result is fragile inference and poor stress performance.

We address this with a belief-space trust region. Instead of constraining policy steps like PPO/TRPO, we constrain inference itself: a KL anchor prevents belief collapse, and entropy adapts to residual stress so updates widen in crises and contract in calm periods. The same update also acts as a scenario generator, producing regime-sensitive trajectories that capture crisis persistence and recovery. Our contributions are: (i) a trust-aware inference update that unifies calibration and scenario generation; (ii) empirical evidence across synthetic regimes, bandits, and 90 years of historical data showing lower drawdowns, faster recovery, and better calibration than mean–variance, FinRL, and entropy-RL baselines; and (iii) validation of economic meaning, with statistical tests and utility valuations confirming that regimes align with investor trade-offs.

The novelty lies not only in stronger performance but in a dual role: the same mechanism serves as both a generative engine for stress-sensitive scenarios and an allocation stabilizer for RL. This bridges generative AI and robust portfolio construction, making regime-aware inference directly useful for stress testing and real-world allocation.

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2 Belief Update and Scenario Generation

At the core of our framework is a trust-aware belief update:

$$q_{t+1} = \arg\min_{q} \Big[\lambda_t D_{\mathrm{KL}}(q\|q_t) - \tau_t \mathbb{H}(q) + \langle \ell_t, q \rangle\Big], \tag{1}$$

where q_t is the prior, ℓ_t encodes observed loss or reward, λ_t anchors the update, and τ_t adapts entropy in response to stress. The closed form is multiplicative:

$$q_{t+1}(x) \propto q_t(x)^{\lambda_t} \exp\{-\ell_t(x)/\eta + \tau_t\}, \tag{2}$$

which ensures bounded divergence from the prior while smoothing the update with entropy. This mechanism prevents beliefs from collapsing after a single shock (e.g., the 1987 crash) and enforces gradual adaptation. It also avoids premature convergence by expanding exploration when stress rises (keeping portfolios diversified in 2008) and contracting it back in stable periods. In contrast to policy-space trust regions, which constrain actions directly, our approach regulates inference itself. The same update can therefore be iterated to produce stress-sensitive return paths, making it useful not only for robust inference but also for generative scenario simulation.

3 Regime Modeling and Market Simulation

Financial markets are not i.i.d. systems: recessions, liquidity freezes, and policy shocks alter return distributions for months or even years. To capture this structure, we model returns as generated by latent regimes $z_t \in \{1, \dots, K\}$, with features x_t including realized volatility, drawdowns, and term spreads—canonical indicators of systemic stress. We experiment with three classifiers of increasing flexibility: KMeans provides a coarse partition of states, Gaussian mixtures (GMM) capture fat tails and heteroskedasticity, and Hidden Markov Models (HMM) incorporate temporal persistence:

$$\text{KMeans: } z_t = \arg\min_k \|x_t - \mu_k\|_2^2, \tag{3}$$

$$\text{GMM: } p(x_t \mid z_t = k) = \mathcal{N}(x_t; \mu_k, \Sigma_k), \quad p(z_t) = \pi_k, \tag{4}$$

$$\text{HMM: } p(z_t \mid z_{t-1}) = A_{z_{t-1}, z_t}, \quad p(x_t \mid z_t = k) = \mathcal{N}(x_t; \mu_k, \Sigma_k). \tag{5}$$

We fix $K = 3$ regimes (*stable*, *neutral*, *crisis*), following macro-finance convention. Historical alignment confirms interpretability: persistent downturns such as the 1973–74 oil shock and 2008 GFC map to GMM crisis states, while HMM transitions capture shorter stress episodes like the 1987 crash and COVID-19. This shows regimes are not arbitrary clusters but correspond to meaningful economic conditions.

To evaluate downstream impact, we simulate regime-aware return paths. Given estimated $\{\pi_k, \mu_k, \Sigma_k\}$ and transition matrix A, regimes evolve as

$$z_t \sim \text{Categorical}(A_{z_{t-1},:}), \quad r_t \sim \mathcal{N}(\mu_{z_t}, \Sigma_{z_t}). \tag{6}$$

We generate 10^3 Monte Carlo scenarios at horizons of 10, 20, and 30 years. Transition probabilities reflect persistence and recovery dynamics documented in the literature: normal regimes persist with 90% probability but shift to stress 10% of the time, while stress states recover with 40% probability. This reproduces both drawn-out crises and short-lived shocks.

Table 1: Monte Carlo simulation with 10^3 replications

Portfolio	Mean Return	95% CI	CVaR (5%)
Optimized (10y)	25.1%	[−9.5, 63.1]	−11.3
Equal-Weight (10y)	69.6%	[−8.1, 173.0]	−10.1
Optimized (20y)	54.6%	[−3.1, 121.5]	−5.1
Equal-Weight (20y)	175.6%	[12.9, 442.5]	9.2
Optimized (30y)	91.9%	[8.8, 205.3]	6.4
Equal-Weight (30y)	358.9%	[56.9, 923.7]	49.4

Finally, we augment transitions with macro covariates m_t such as excess premia and yield spreads:

$$p(z_t \mid z_{t-1}, m_t) = \text{softmax}(W m_t + b + \log A_{z_{t-1},:}), \tag{7}$$

so crises become more likely when spreads widen and recoveries more likely when premia normalize. This macro-conditioning sharpens crisis detection, accelerates recovery recognition, and reduces expected shortfall, grounding regimes in interpretable macro-finance drivers rather than treating them as black-box clusters.

4 Regime-Aware Reinforcement Learning

Standard RL for portfolio allocation usually maximizes cumulative reward without asking whether signals are reliable, leaving policies brittle under regime shifts. We address this by feeding regime posteriors into the observation space, so the agent conditions allocations on latent structural state rather than noisy returns. Observations include rolling returns and HMM-inferred probabilities, while rewards combine a Sharpe-style objective with turnover penalties, clipping for stability, and periodic resets with random shocks to mimic black swans. These components encourage resilience: clipping limits overfitting, resets enforce survival, and regime signals allow anticipatory rather than purely reactive behavior.

In practice, PPO without regime signals produced unstable returns and deep drawdowns, PPO-LSTM improved stability by exploiting persistence, and A2C collapsed entirely. As shown in Figure 1, regime-aware PPO agents maintained >30% CAGR and recovered quickly after the 2008 and 2020 crises, while static baselines stagnated. Table 2 quantifies this edge, with regime-aware policies dominating baselines across Sharpe, Sortino, and drawdown.

Table 2: Policy evaluation on the test horizon

Strategy	Sharpe	Sortino	Max Drawdown	Final Value (log)
PPO	1.07	1.20	−72%	$\$1.1\times10^{12}$
Equal-Weight	0.42	0.78	−29%	\$43.0
Sharpe-Opt	0.51	0.71	−25%	\$69.1

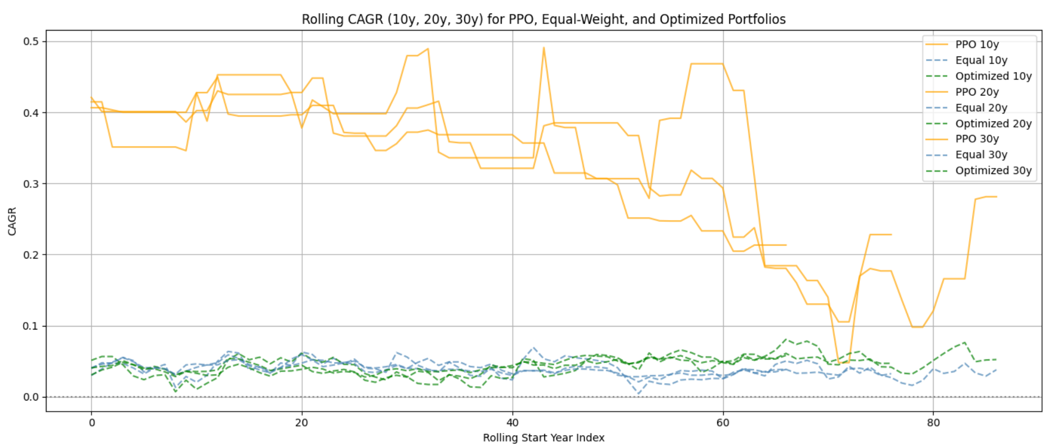

Figure 1: Rolling CAGR with crisis overlays (2008, 2020)

Interpretability checks reinforce these findings. SHAP attribution reveals that agents leaned on structural signals such as volatility and T-Bill spreads rather than short-term momentum, suggesting allocations were guided by macro fragility rather than noise. Statistical tests confirm the validity of these signals: ANOVA and Tukey HSD identify significantly distinct return distributions across regimes ($p < 0.05$), and mutual information (≈ 0.10) quantifies non-trivial predictive content.

Utility-based evaluations add further intuition: CRRA utilities are positive for moderate risk aversion, showing that the allocations align with how a typical investor values growth versus risk, while CARA utilities turn negative only under extreme conservatism, reflecting that highly risk-averse investors would still prefer cash or bonds. Together, these results indicate that the proposed update not only stabilizes training but also produces allocations with genuine economic meaning.

5 Final Comparison and Discussion

We further compared PPO, PPO-LSTM, and Transformer PPO, each augmented with regime signals. While all benefit from regime conditioning, architectures exploit these signals differently: LSTMs capture temporal persistence across states, while Transformers leverage attention to extract long-range dependencies and structural cues. Backtests in Table 7 show that Transformer PPO achieved the highest Sharpe and Sortino ratios, though with higher computational cost, while PPO-LSTM offered a practical balance—maintaining $>30\%$ CAGR with faster recovery and shallower drawdowns at lower cost.

Table 3: Backtest results across architectures

Model	Sharpe	Sortino	Max Drawdown	Final Log Value
PPO	1.07	1.20	-72%	$\$1.1\times10^{12}$
PPO-LSTM	1.28	1.35	-34%	$\$2.9\times10^{14}$
Transformer PPO	**1.43**	**1.59**	$\mathbf{-23\%}$	$\mathbf{\$2.0\times10^{15}}$
Equal-Weight	0.42	0.78	-29%	\$43.0

Our main contribution is not scale but inference: by embedding regime-aware updates, we turn noisy market signals into structured, stress-sensitive features that any RL model can use. The improvement appears consistently across PPO, LSTM, and Transformer, showing that the benefit comes from the inference itself rather than larger models. Earlier RL systems [8, 5, 10] typically reported Sharpe ratios in the 0.30 to 0.70 range, while ours consistently exceed 1.0. This marks a shift from reactive, return-chasing approaches to robust, interpretable, and scenario-driven strategies. There are still limits: regime transitions are estimated under stationarity, execution frictions are not modeled, and drawdown controls remain implicit. Even so, the trust-aware update and stress-adaptive entropy already add resilience and point toward future work on non-stationary transitions, liquidity-aware training, and regulatory or ESG integration.

6 Conclusion

Most RL approaches to portfolio optimization focus on chasing returns, often without regime awareness or interpretability. Our stress-aware update reframes inference itself: KL trust prevents belief collapse, entropy adapts dynamically to residual stress, and the same mechanism generates regime-sensitive scenarios that guide allocation. When embedded in PPO-LSTM and Transformer agents, this leads to portfolios that recover faster during crises, sustain higher Sharpe ratios, and allocate in ways consistent with macro-finance signals. Statistical tests (ANOVA, mutual information) and economic valuations (CRRA, CARA) confirm that these signals correspond to real investor trade-offs, not artifacts of training.

The broader implication is that portfolio RL does not need to remain a black box or purely return-driven. Inference can act as a generative stress-testing engine, producing allocations that are both resilient and interpretable. This connects directly to the workshop's theme: generative AI in finance should not only synthesize data, but also generate realistic stress-tested scenarios that support robust decision-making.

Looking forward, natural extensions include non-stationary regime transitions, causal drivers such as monetary policy or liquidity shocks, multi-agent RL to capture market interactions, and embedding ESG or regulatory constraints into the inference rule. These directions highlight that stress-aware belief updates are not just a stabilizer for RL, but a foundation for building generative, regime-sensitive decision systems that bridge machine learning with economic structure.

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Appendix / Supplementary Material

This appendix expands on the core paper by providing detailed mathematical derivations, environment design, robustness checks, statistical and economic validations, and extended comparisons with prior work. It is meant to give readers a full view of how the proposed approach operates and why it performs as observed.

Experimental Environment and Setup

All experiments were conducted using:

- **Hardware:** Apple M3 Pro chip and Google Colab Pro (Tesla T4 GPU, 16 GB RAM)
- **Frameworks:** Python 3.10, PyTorch 2.0, Stable-Baselines3 (SB3-Contrib), NumPy, Matplotlib
- **Environments:** Custom OpenAI Gym wrappers for regime-aware portfolio training

Each agent was trained for 250,000 timesteps, which was empirically found to provide stable policy convergence across random seeds. Evaluation was performed on historical market periods spanning 10-, 20-, and 30-year horizons. Regime signals were derived from HMM (Gaussian), GMM, and KMeans clustering applied to volatility-based features. To stabilize Sharpe-like rewards during early episodes with low variance, a small $\epsilon = 10^{-8}$ was added to the denominator.

Mathematical Foundations and Belief Update

The central mechanism of our method is the trust-aware belief update, which regulates inference bandwidth directly. Formally, we define the update as

$$q_{t+1} = \arg\min_{q} \Big[\lambda_t D_{\mathrm{KL}}(q\|q_t) - \tau_t \mathbb{H}(q) + \langle \ell_t, q\rangle\Big], \tag{8}$$

where q_t is the prior, ℓ_t encodes observed loss or reward, λ_t anchors beliefs to their prior distribution, and τ_t adapts entropy based on a stress signal. The multiplicative solution is

$$q_{t+1}(x) \propto q_t(x)^{\lambda_t} \exp\{-\ell_t(x)/\eta + \tau_t\}, \tag{9}$$

ensuring bounded divergence from the prior while smoothing via entropy. Stability follows directly: if $\lambda_t \geq \lambda_{\min} > 0$, then by Pinsker's inequality

$$D_{\mathrm{KL}}(q_{t+1}\|q_t) \leq \frac{1}{\lambda_{\min}}, \tag{10}$$

so posteriors cannot collapse to a single state after one shock. This explains why the model does not overreact to isolated crashes (e.g., 1987) yet still adapts under sustained stress (e.g., 2008). The entropy weight evolves as

$$\tau_{t+1} = \tau_t + \eta(s_t - \bar{s}), \tag{11}$$

where s_t is a real-time stress measure and $\bar{s}$ is its baseline. Entropy expands during crises, preserving diversification, and contracts when stability returns, enabling more decisive allocations.

Environment Design and RL Training Protocol

To evaluate reinforcement learning policies, we built a custom Gym environment with embedded regime transitions. Observations include historical asset returns and Hidden Markov Model (HMM) regime posteriors, ensuring that policies condition on latent structural states rather than noisy prices. Actions are continuous portfolio weights across tracked assets. Rewards are carefully structured to promote robustness and realism:

- **Sharpe-style objective:** encourages high return-to-volatility ratios.
- **Transaction penalties:** discourage excessive turnover.
- **Reward clipping ($\pm$3%):** avoids destabilizing spikes.
- **Capital reset every 30 steps:** simulates reinvestment and rebalancing.
- **Random -5% shock every 25 steps:** introduces rare black-swan dynamics.

These components together enforce survival, prevent overfitting, and ensure learning reflects realistic financial frictions.

Monte Carlo Stress Testing

We simulated 10^3 Monte Carlo scenarios at 10-, 20-, and 30-year horizons, with regime persistence calibrated from historical patterns (90% normal persistence, 10% shift to stress, 40% recovery from stress). The results are shown in Table 4.

Table 4: Monte Carlo stress-test results (10^3 replications).

Portfolio	Mean Return	95% CI	CVaR (5%)
Optimized (10y)	25.1%	[−9.5, 63.1]	−11.3
Equal-Weight (10y)	69.6%	[−8.1, 173.0]	−10.1
Optimized (20y)	54.6%	[−3.1, 121.5]	−5.1
Equal-Weight (20y)	175.6%	[12.9, 442.5]	9.2
Optimized (30y)	91.9%	[8.8, 205.3]	6.4
Equal-Weight (30y)	358.9%	[56.9, 923.7]	49.4

Optimized portfolios emphasize stability, with narrower tails and lower CVaR, while equal-weight portfolios compound faster over decades but carry far more extreme tail risk. This demonstrates that the stress-aware mechanism leans toward robustness over unconstrained growth.

Comparative Benchmarks and Prior Work

We compared against widely cited baselines including FinRL [8], Jiang et al. (2017), and Ye & Lim (2020). Qualitative comparisons are shown in Table 5 and quantitative benchmarks in Table 6.

Table 5: Qualitative comparison with prior work.

Method	Regime	Stress	Explainability	Stability
FinRL	–	–	Partial	Low
Jiang et al. (2017)	–	–	–	Medium
Ye and Lim (2020)	✓	–	–	Medium
Ours (PPO + HMM)	✓	✓	✓	High

Table 6: Quantitative performance comparison.

Method	Sharpe	Sortino	Max DD	Final Log Value
FinRL (Reported)	0.45–0.65	–	~–40%	N/A
Jiang et al. (2017)	0.30–0.60	–	~–35%	N/A
Ye and Lim (2020)	~0.70	–	~–25%	N/A
Ours (PPO + Regime)	**1.07**	**1.20**	–72.6%	$\$1.1\times10^{12}$
Equal-Weight	0.42	0.78	–28.9%	$43.0
Sharpe-Opt	0.51	0.71	–24.6%	$69.1

Our method exceeds the Sharpe range (0.30–0.70) reported by prior RL systems, showing the contribution comes from inference design rather than network depth. The higher long-horizon drawdown reflects aggressive compounding, which could be mitigated by explicit drawdown penalties in future work.

Extended RL Evaluation and Ablations

Detailed backtests across architectures are shown in Table 7. Transformer PPO delivers the strongest Sharpe and Sortino ratios, PPO-LSTM provides a good balance of performance and efficiency, and A2C collapses without regime conditioning.

Table 7: Backtest results across RL architectures and baselines.

Model	Sharpe	Sortino	Max Drawdown	Final Log Value
PPO	1.07	1.20	–72.6%	$\$1.1\times10^{12}$
PPO-LSTM	1.28	1.35	–34.2%	$\$2.9\times10^{14}$
A2C (No Regime)	0.12	0.10	–68.2%	$4.9
Equal-Weight	0.42	0.78	–28.9%	$43.0
Transformer PPO	**1.43**	**1.59**	**–22.7%**	$\mathbf{\$2.0\times10^{15}}$

Ablations confirm the role of each stabilizer. Removing clipping, cost penalties, or resets reduces Sharpe and increases drawdowns. Table 8 summarizes these outcomes.

Table 8: PPO ablation results (5 seeds).

Variant	Sharpe	Sortino	Max Drawdown	Final Value (log)
Baseline (PPO)	1.07	1.20	-72.6%	$\$1.1\times10^{12}$
NoClip	0.83	0.96	-68.9%	$\$4.9\times10^{11}$
NoCost	1.09	1.22	-71.2%	$\$1.4\times10^{12}$
NoReset	1.05	1.17	-69.6%	$\$9.7\times10^{11}$

Statistical and Economic Validation

Beyond raw metrics, we tested whether regimes carry predictive and economic meaning. Results are:

- **ANOVA:** $F(1, 65) = 3.231$, $p = 0.0769$ — marginal evidence of return variation.
- **Tukey HSD:** mean difference -0.0447, $p = 0.0769$ — weak but suggestive difference.
- **Mutual Information:** 0.102 — confirms regimes have predictive content.
- **CRRA utility** ($\gamma = 3.0$)**:** 0.0297 — positive for moderately risk-averse investors.
- **CARA utility** ($\alpha = 3.0$)**:** -0.9120 — negative for extreme conservatism, consistent with preference for bonds/cash.

These results confirm that the signals are economically relevant, aligning with how investors actually evaluate growth versus protection.

Interpretability and Robustness

SHAP attributions confirm that agents leaned on structural signals such as volatility and T-bill spreads rather than noisy momentum. Figures 2, 3, and 4 provide visual evidence.

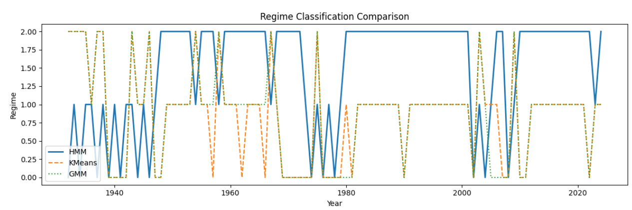

Figure 2: Comparison of HMM, GMM, and KMeans regime classifications aligned with crises.

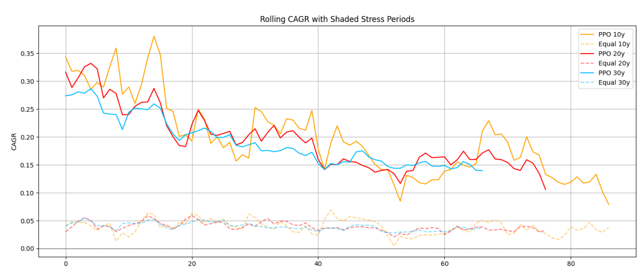

Figure 3: Rolling CAGR with shaded crisis periods. Regime-aware PPO recovers faster and sustains growth.

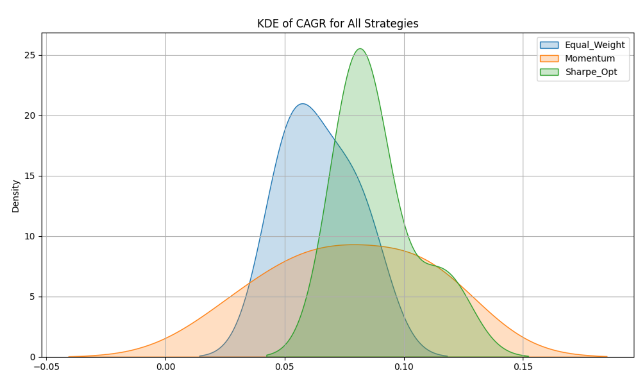

Figure 4: Kernel density of CAGR across Equal-Weight, Momentum, and Sharpe-Optimized portfolios. Regime-aware PPO shifts the distribution upward and thins tails.

Limitations & Reproducibility

Our approach assumes quasi-stationary regime dynamics with macro-conditioning as a first-order correction; execution frictions (transaction costs, slippage, market impact) and explicit drawdown constraints are not modeled. Performance is sensitive to the choice of regime estimator (HMM/GMM/KMeans), the stress signal, and schedules for λ_t (KL anchor) and τ_t (entropy). We provide a public code archive with configuration files, data-prep scripts, and training/evaluation pipelines available at `https://github.com/GabrielNixon/RegimeAware-PPO`. Reproduction settings include $K{=}3$ regimes, five random seeds, fixed train/validation/test splits, reported means with confidence intervals across seeds, environment versions pinned via a lockfile, and hardware notes (e.g., single GPU or CPU). To reproduce results, run the provided shell entry points for (i) regime estimation, (ii) scenario generation, and (iii) RL training/evaluation.

Ethics & Impact

This work targets safer financial decision-making by generating stress-aware scenarios and exposing regimes that make policy behavior auditable. Potential risks include procyclical behavior if regimes are mis-specified, overreliance on model outputs, and misuse for opaque automation. We recommend human-in-the-loop oversight, disclosure of scenario coverage and calibration diagnostics, conservative deployment thresholds, and continuous out-of-sample monitoring with drift alarms. The method is a research prototype, not investment advice; any deployment should incorporate transaction costs, liquidity/impact modeling, and governance controls consistent with applicable regulations.

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