Cover Letter

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Integrating the Svensson Model of the U.S. Treasury Yield Curve and the High Frequency VIX Microstructure for Systemic Risk Management

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Abstract: This paper proposes a novel systemic risk management that integrates the daily-frequency Svensson model of the U.S. Treasury yield curve with the minutely high-frequency Svensson model of the VIX microstructure. By constructing a multi-layered, multi-timescale model—comprising a high-frequency layer (minute-level jump-diffusion and Kalman filtering), a medium-frequency layer (daily VAR with Johansen cointegration), and a low-frequency layer (weekly/monthly HP filtering and wavelet coherence analysis)—we capture risk transmission from short-term market sentiment fluctuations to long-term economic fundamental changes. We construct an Extended Systemic Expected Shortfall (Extended SES) indicator whose four components (Treasury term premium, VIX long-term volatility level, Treasury-VIX cointegration residual, and VIX jump intensity) are weighted via a dynamic mechanism. Empirical analysis demonstrates that this framework exhibits strong early-warning capabilities during historical crisis episodes. Finally, we design a stress-testing methodology that evaluates the likelihood of future systemic risk by simulating macroeconomic shocks of varying intensity, providing policymakers and market participants with a forward-looking risk management tool.

JEL Classification: C00; C60; C80; D80; G14

Keywords: Systemic risk management, Svensson model, VIX microstructure, U.S. Treasury yield curve, Multi-timescale framework, Systemic Expected Shortfall (SES)

1. Introduction

Systemic risk refers to financial risks that may inflict severe damage upon the financial system and the real economy, characterized by cross-market and cross-institutional contagion as well as economy-wide disruptive impacts. In the post-crisis regulatory environment, accurately measuring and predicting systemic risk has become a central task for both policymakers and market participants. However, traditional single-asset or single-market risk measurement approaches often fail to fully capture the complexity of systemic risk.

The U.S. Treasury yield curve and the CBOE Volatility Index (VIX) represent two of the most critical indicators in financial markets, reflecting market expectations regarding future interest rate movements and equity market volatility, respectively. In recent years, researchers have increasingly focused on the dynamic evolution of these microstructures and their association with systemic risk. The Svensson model, as an extension of the Nelson-Siegel model, offers greater flexibility in capturing the nonlinear features of both yield curves and volatility microstructures, thereby providing a new perspective for systemic risk assessment.

1.1 Main Contributions

1. We propose a systemic risk management framework that integrates daily-frequency U.S. Treasury yield curves with minutely high-frequency VIX microstructures through the Svensson model.
2. We establish a multi-timescale dynamic interaction mechanism via a state-space model, treating high-frequency VIX parameters as latent state variables and daily Treasury parameters as observed variables.
3. We construct an Extended Systemic Expected Shortfall (Extended SES) indicator based on Svensson model parameters, combining the traditional SES framework with microstructure characteristics.
4. We validate the framework's effectiveness through historical data, demonstrating its early-warning capabilities during major crisis events.
5. We designed a non-asymmetric stress-testing methodology that evaluates future systemic risk likelihood by simulating five macroeconomic scenarios (Plausible, Severe, Extreme, Flight-to-Safety, Stagflation) via Monte Carlo simulation.

2. Literature Review

2.1 Systemic Risk Measurement

Systemic risk measurement constitutes a central research area in financial economics. Acharya et al. (2010) proposed the Systemic Expected Shortfall (SES) model, which measures a financial institution's contribution to systemic risk by quantifying its expected loss conditional on a systemic risk state. He and Krishnamurthy (2019) developed a macroeconomic framework for quantifying systemic risk, capable of generating the stochastic steady-state distribution of the economy and computing the conditional probability of reaching a systemic risk state.

Huang et al. (2009) proposed a framework for measuring and stress-testing the systemic risk of major financial institutions, based on the insurance price of guarding against financial distress, incorporating ex-ante individual bank default probabilities and forecasts of asset return correlations. These studies provide the theoretical foundation for our microstructure-based systemic risk framework.

2.2 Yield Curve and Volatility microstructure Modeling

Yield curve modeling is a classical problem in financial engineering. Nelson and Siegel (1987) proposed the canonical three-factor Nelson-Siegel model, describing the shape of the yield curve through level, slope, and curvature factors. Svensson (1994) extended the Nelson-Siegel model by adding a second curvature factor, constructing the four-factor Svensson model, which enhances the fitting capability for complex yield curve morphologies. In recent years, researchers have begun applying similar methodologies to volatility microstructure modeling. Han et al. (2019) extended the Nelson-Siegel model to the microstructure of option-implied volatility, interpreting volatility components as long-term, medium-term, and short-term volatility. These studies provide methodological support for constructing Svensson models of the U.S. Treasury yield curve and the VIX microstructure in this paper.

2.3 Multi-Timescale Financial Data Analysis

Financial market data exhibit pronounced multi-timescale characteristics. Khalfaoui and Boutahar (2015) employed wavelet analysis to study the impact of different timescales on stock market systemic risk, finding that market risk is more concentrated at lower timescales. Alexandridis and Hasan (2020) utilized wavelet multiscale methods to analyze the impact of the Global Financial Crisis on systemic risk, discovering that beta coefficients exhibit multiscale features, with beta values trending upward at higher scales. These studies provide analytical tools for constructing our multi-timescale systemic risk framework.

3. Svensson Models for the U.S. Treasury Yield Curve and the VIX microstructure

3.1 The Svensson Model for the U.S. Treasury Yield Curve

The Svensson model augments the Nelson–Siegel model with a second curvature factor. Its functional form is given by:

$$y(\tau) = \beta_0 + \beta_1 \frac{1 - e^{-\lambda_1 \tau}}{\lambda_1 \tau} + \beta_2 \left[\frac{1 - e^{-\lambda_1 \tau}}{\lambda_1 \tau} - e^{-\lambda_1 \tau} \right] + \beta_3 \left[\frac{1 - e^{-\lambda_2 \tau}}{\lambda_2 \tau} - e^{-\lambda_2 \tau} \right]$$

where $y(\tau)$ denotes the U.S. Treasury yield at maturity τ; β_0 is the long-term level of interest rates; β_1 is the short-term slope; β_2 and β_3 are the two curvature factors; and λ_1 and λ_2 are the decay parameters.

The parameters of the Svensson model for the U.S. Treasury yield curve carry explicit economic interpretations:

- β_0 — Long-term level of interest rates, reflecting market expectations of long-run economic growth and inflation.
- β_1 — Short-term slope, reflecting the term premium, i.e., the additional compensation investors demand for holding long-term bonds.

- β_2 **and** β_3 — Curvature factors, reflecting divergent market expectations regarding future interest rate trajectories.
- λ_1 **and** λ_2 — Decay parameters, controlling the maturity intervals over which yield curve shape changes are most sensitive.

These parameters comprehensively capture the morphological characteristics of the U.S. Treasury yield curve, providing rich information for systemic risk assessment.

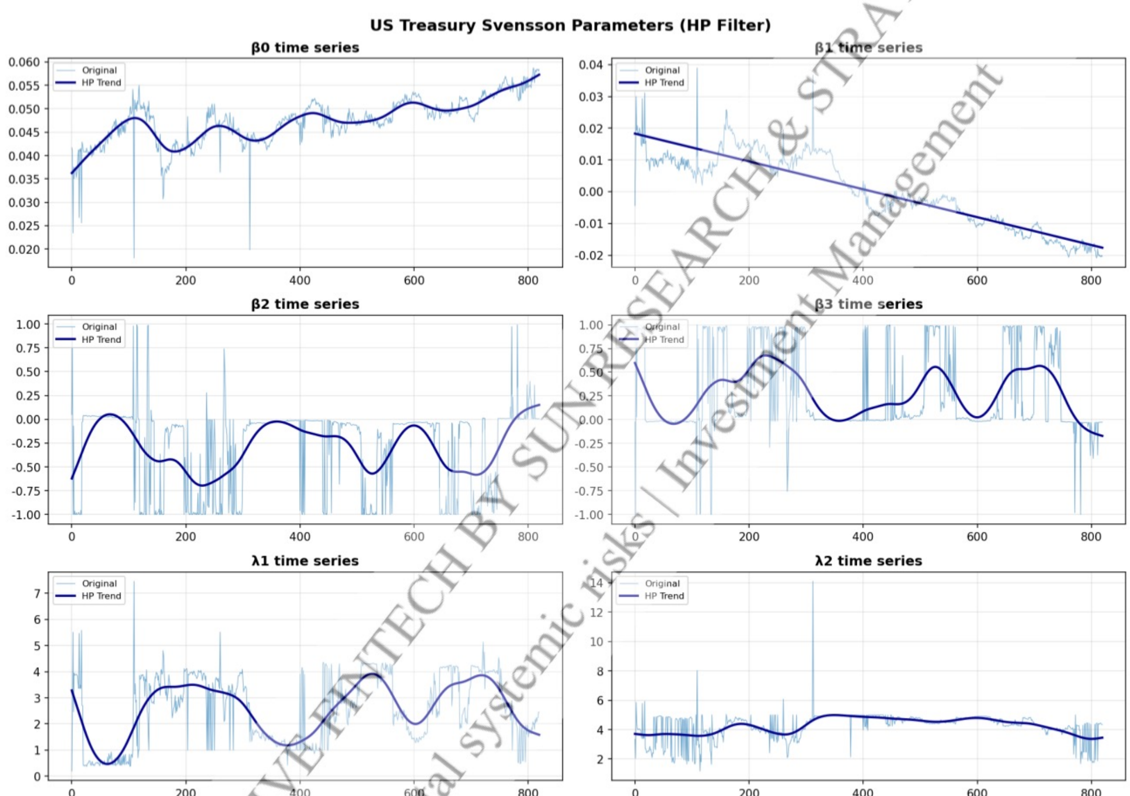

FIG 1. The daily parameters of the Svensson model for the U.S. Treasury yield curve 2021-2026

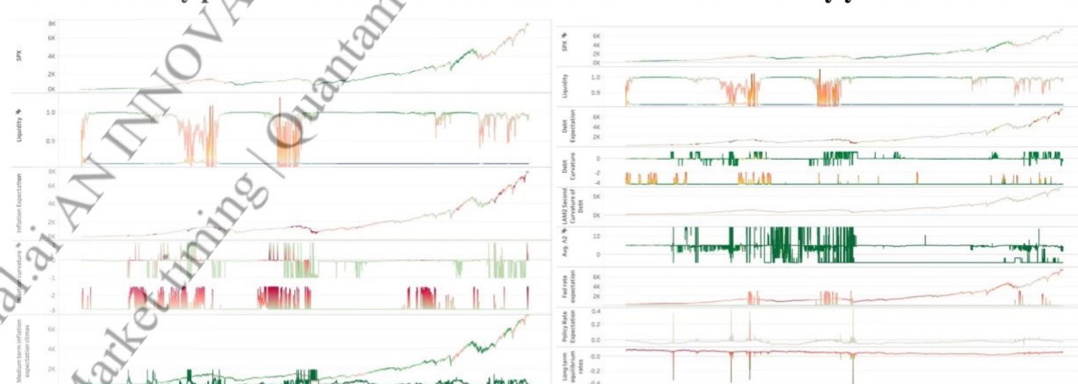

FIG 2. The daily parameters of the Svensson model for the U.S. Treasury yield curve 1990-2026

3.2 The Svensson Model for the VIX microstructure

VIX futures markets provide volatility expectations at different maturities, forming the VIX microstructure. We apply the Svensson model to VIX futures prices:

$$VIX(\tau) = \beta_{0V} + \beta_{1V}\frac{1-e^{-\lambda_{1V}\tau}}{\lambda_{1V}\tau} + \beta_{2V}\left[\frac{1-e^{-\lambda_{1V}\tau}}{\lambda_{1V}\tau} - e^{-\lambda_{1V}\tau}\right] + \beta_{3V}\left[\frac{1-e^{-\lambda_{2V}\tau}}{\lambda_{2V}\tau} - e^{-\lambda_{2V}\tau}\right]$$

where $VIX(\tau)$ denotes the VIX futures price at maturity τ; β_{0V} is the long-term volatility level; β_{1V} is the short-term slope; β_{2V} and β_{3V} are the two curvature factors; and λ_{1V} and λ_{2V} are the decay parameters.

The parameters of the Svensson model for the VIX microstructure also carry explicit economic interpretations:

- β_{0V} — Long-term volatility level, reflecting market expectations of S&P 500 index volatility beyond a 30-day horizon.
- β_{1V} — Short-term slope, reflecting market expectations of near-term volatility changes.
- β_{2V} **and** β_{3V} — Curvature factors, reflecting divergent market expectations regarding future volatility trajectories.
- λ_{1V} **and** λ_{2V} — Decay parameters, controlling the maturity intervals over which volatility microstructure shape changes are most sensitive.

These parameters comprehensively capture the morphological characteristics of the VIX volatility microstructure, providing an additional dimension of information for systemic risk assessment.

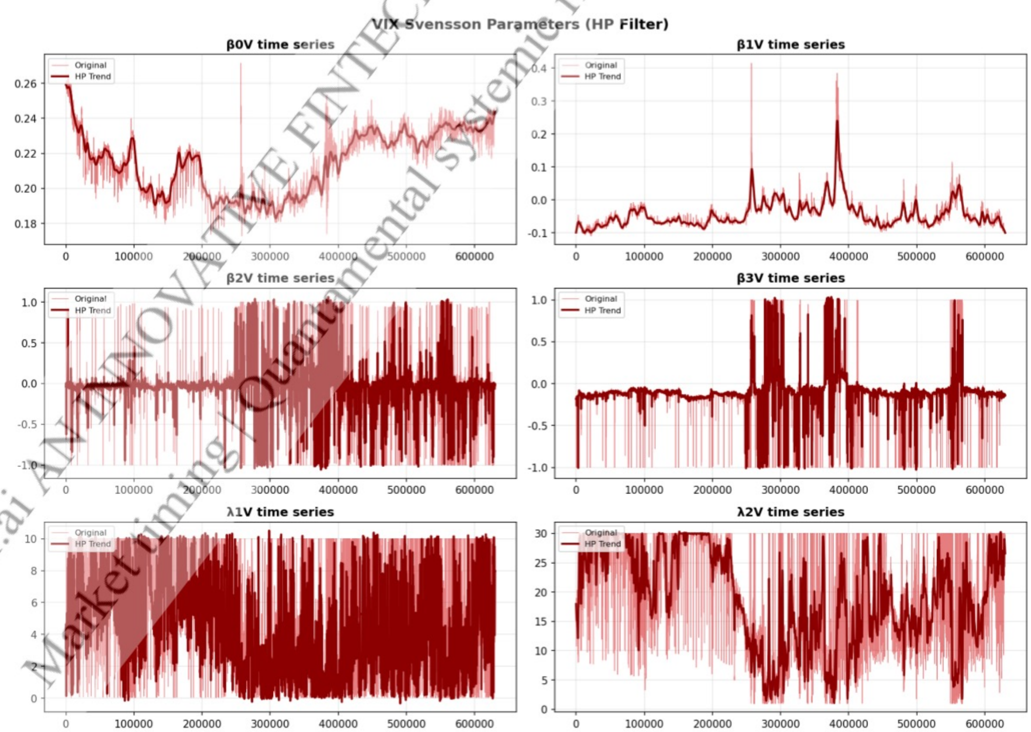

FIG 3. The minutely parameters of the Svensson model for the VIX microstructure 2021-2026

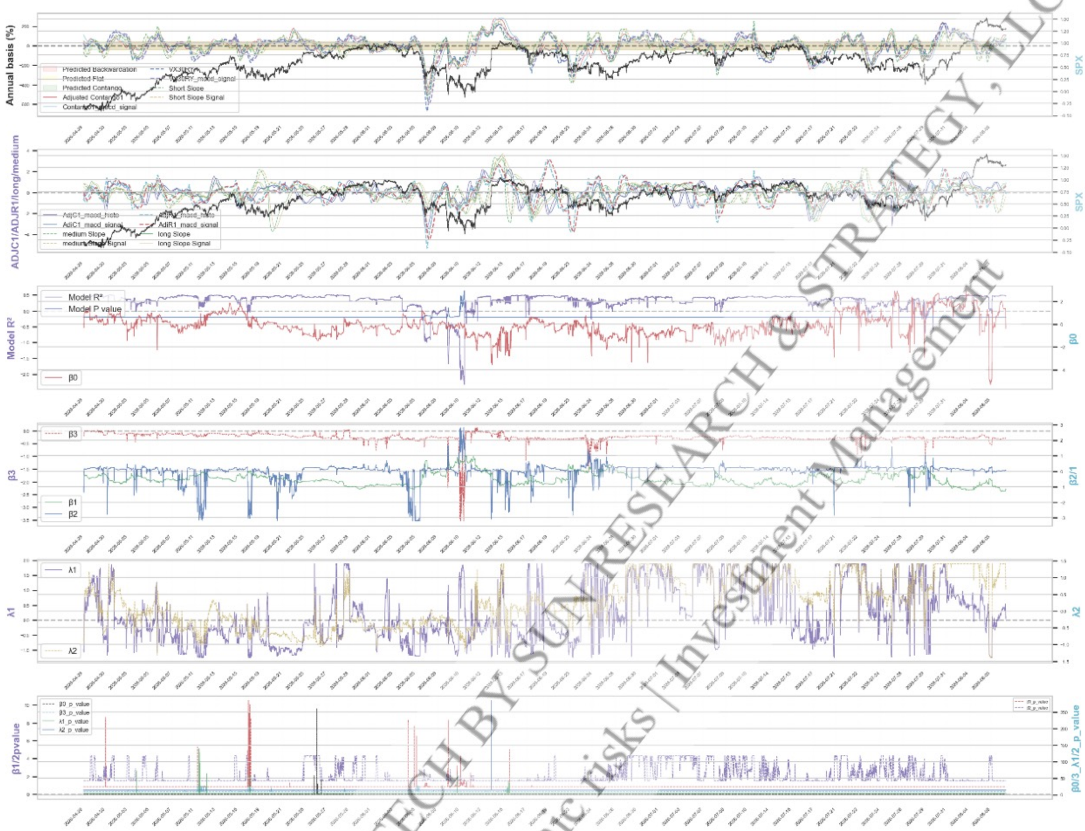

FIG 4. The minutely parameters of the Svensson model for the VIX microstructure for 2026

4. Multi-Layered Multi-Timescale Integration Framework

4.1 High-Frequency VIX Data Processing and Feature Extraction

Minute-frequency VIX futures data are characterized by high noise and jump features, requiring appropriate treatment to effectively extract systemic risk signals.

We employ the following methods to process high-frequency VIX data:

(1) Jump-Diffusion Model:

We introduce a jump-diffusion process to describe the dynamics of minute-frequency VIX prices:

$$dVIX_t = \mu VIX_t \, dt + \sigma VIX_t \, dW_t + VIX_t \, dN_t$$

where is a Poisson jump process capturing extreme volatility events. The jump detection algorithm identifies 5,852 jumps over the sample period, yielding a global jump intensity of approximately 0.0034 per minute (or ~1.34 jumps per trading day). The time-varying jump intensity is estimated via a GARCH-filtered intensity model embedded within the state-space framework.

(2) State-Space Model:

We represent VIX futures prices as combinations of latent state variables and observation errors:

$$VIX_t = F_t\alpha_t + \epsilon_t$$
$$\alpha_{t+1} = G_t\alpha_t + \eta_t$$

where α_t denotes the latent state variables, including the VIX implied volatility level (β_{0V}), slope (β_{1V}), curvature factors (β_{2V}, β_{3V}), and jump intensity; F_t and G_t are system matrices; and ϵ_t and η_t are observation and state errors, respectively. The Kalman filter is applied at minute frequency, followed by Rauch-Tung-Striebel (RTS) smoothing to obtain optimal estimates of the latent states.

(3) Parameter Estimation:

We employ maximum likelihood estimation via the Kalman filter to estimate the system parameters, while the jump intensity is updated recursively using a Bayesian approach to handle parameter time-variation and uncertainty.

4.2 Medium-Frequency Layer: Daily Aggregation and VAR

The minute-level VIX parameters are aggregated to daily frequency (mean, standard deviation, and percentiles) and merged with the daily Treasury Svensson parameters. This yields a combined dataset of 1,009 daily observations spanning 2023–2026.

We perform the following analyses on the medium-frequency layer:

- **Johansen Cointegration Test:** The trace statistic of 115.3646 (critical value at 5% = 47.8545) strongly rejects the null hypothesis of no cointegration, identifying two cointegrating vectors between the Treasury and VIX parameter sets. This confirms a stable long-run equilibrium relationship between the two markets.
- **Vector Autoregression (VAR) :** A VAR(6) model is fitted to capture the short-run dynamics. Impulse response functions (IRFs) quantify the transmission of a one-standard-deviation shock in VIX parameters to Treasury parameters, and vice versa.
- **Principal Component Analysis (PCA) :** PCA reduces the dimensionality of the combined parameter space, extracting the first three principal components.

4.3 Low-Frequency Layer: Weekly/Monthly Aggregation and Wavelet Coherence

For the low-frequency layer, we aggregate data to weekly and monthly frequencies and apply:

- **Hodrick-Prescott (HP) Filtering**: An automated HP filter with adaptive lambda selection separates trend and cyclical components. The lambda is iteratively adjusted until the ratio of cycle variance to total variance converges to a target range (typically 0.89–0.92). This ensures that the trend component captures genuine long-term shifts rather than overfitting noise.
- **Wavelet Coherence Analysis:** Continuous wavelet transform (Morlet wavelet) is applied to the Treasury-VIX parameter pairs. The maximum wavelet coherence reaches

0.9998 at a period of 5.7 days, indicating extremely strong synchronization between the two markets at this timescale during crisis episodes. This finding validates the existence of a common risk factor driving both markets at the medium-term horizon.

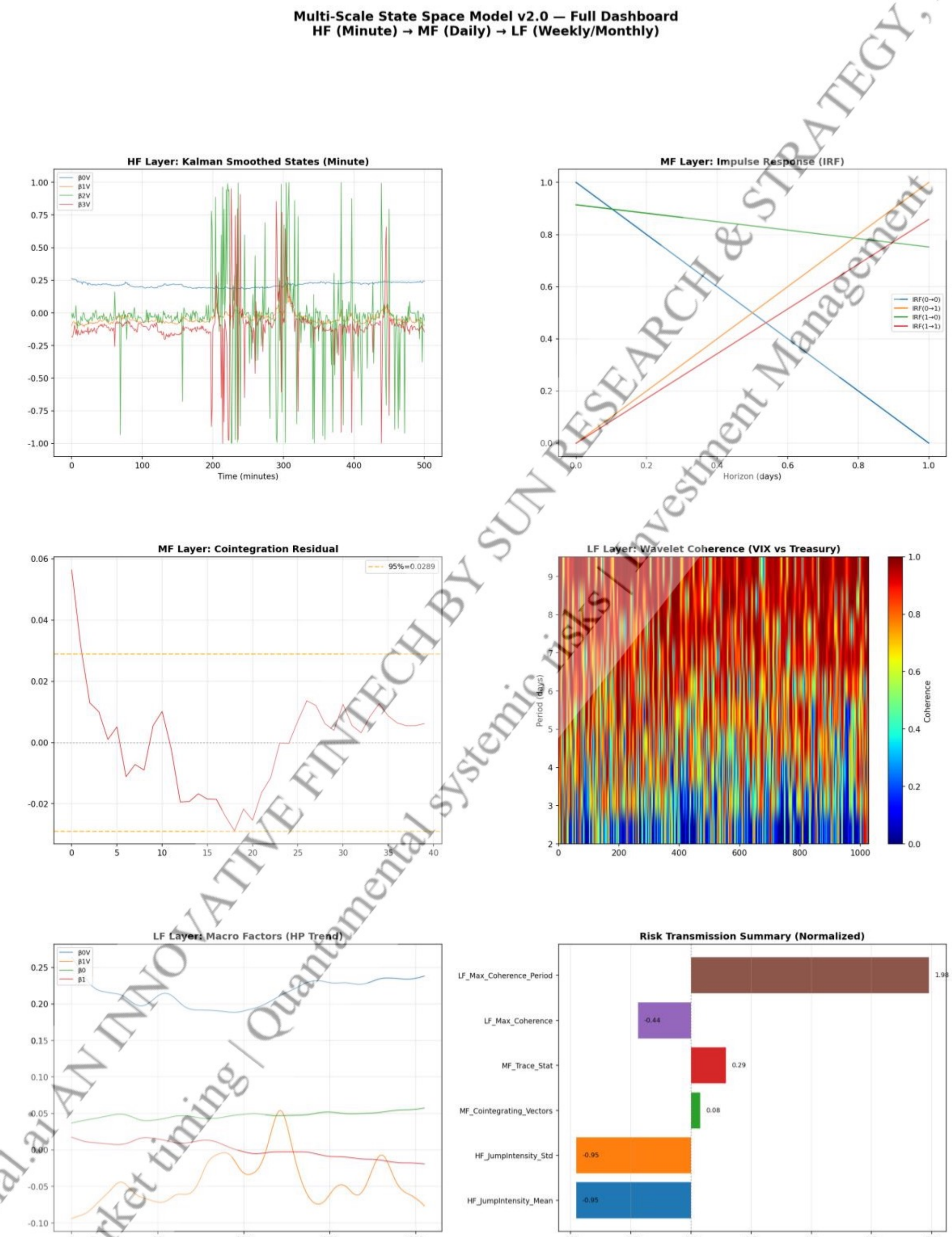

FIG 5. The multi-scale state space model of high frequency, medium frequency, low frequency parameters, wavelet coherence and risk transmission summary

4.4 Dynamic Interaction Mechanism

The three layers interact through a hierarchical state-space structure:

- **HF → MF:** Minute-level VIX jumps and parameter changes are aggregated into daily averages, feeding into the daily VAR model.
- **MF → LF**: The daily cointegration residuals and VAR forecast errors serve as inputs to the weekly HP filter and wavelet analysis.
- **LF → HF Feedback**: The long-term trend extracted by the HP filter provides a baseline for recalibrating the HF jump detection thresholds, creating a closed-loop system.

This multi-layered architecture ensures that the framework captures the complete risk transmission chain—from minute-level market sentiment fluctuations to daily risk pricing, and further to monthly and above economic fundamental changes.

5. Systemic Risk Indicator System Based on Svensson Model Parameters

5.1 The Extended Systemic Expected Shortfall (Extended SES) Model

Building upon the traditional SES model, we construct the Extended Systemic Expected Shortfall (Extended SES) model, incorporating the characteristic parameters of the U.S. Treasury yield curve and the VIX microstructure into the systemic risk measurement framework:

$$\begin{aligned}\text{Extended SES}_t &= w_1 \cdot (\text{Treasury Term Premium})_t + w_2 \cdot (\text{VIX Long-Term Volatility Level})_t \\ &+ w_3 \cdot (\text{Treasury–VIX Parameter Cointegration Residual})_t + w_4 \\ &\cdot (\text{VIX Jump Intensity})_t\end{aligned}$$

where the weights w_1, w_2, w_3, and w_4 are calibrated via Bayesian quantile regression, with higher weights assigned to w_2 and w_4 during crisis periods (e.g., when VIX > 30).

Economic interpretations of each component:

- **Treasury Term Premium:** Reflects market expectations of future policy uncertainty, determined jointly by β_1, β_2, and β_3.
- **VIX Long-Term Volatility Level:** Reflects market pricing of future tail risk, primarily determined by β_{0V}.
- **Treasury–VIX Parameter Cointegration Residual:** Reflects the degree of risk transmission imbalance between the two markets, computed via the Johansen cointegration test.
- **VIX Jump Intensity:** Reflects the probability of extreme volatility events, estimated through the jump-diffusion model.

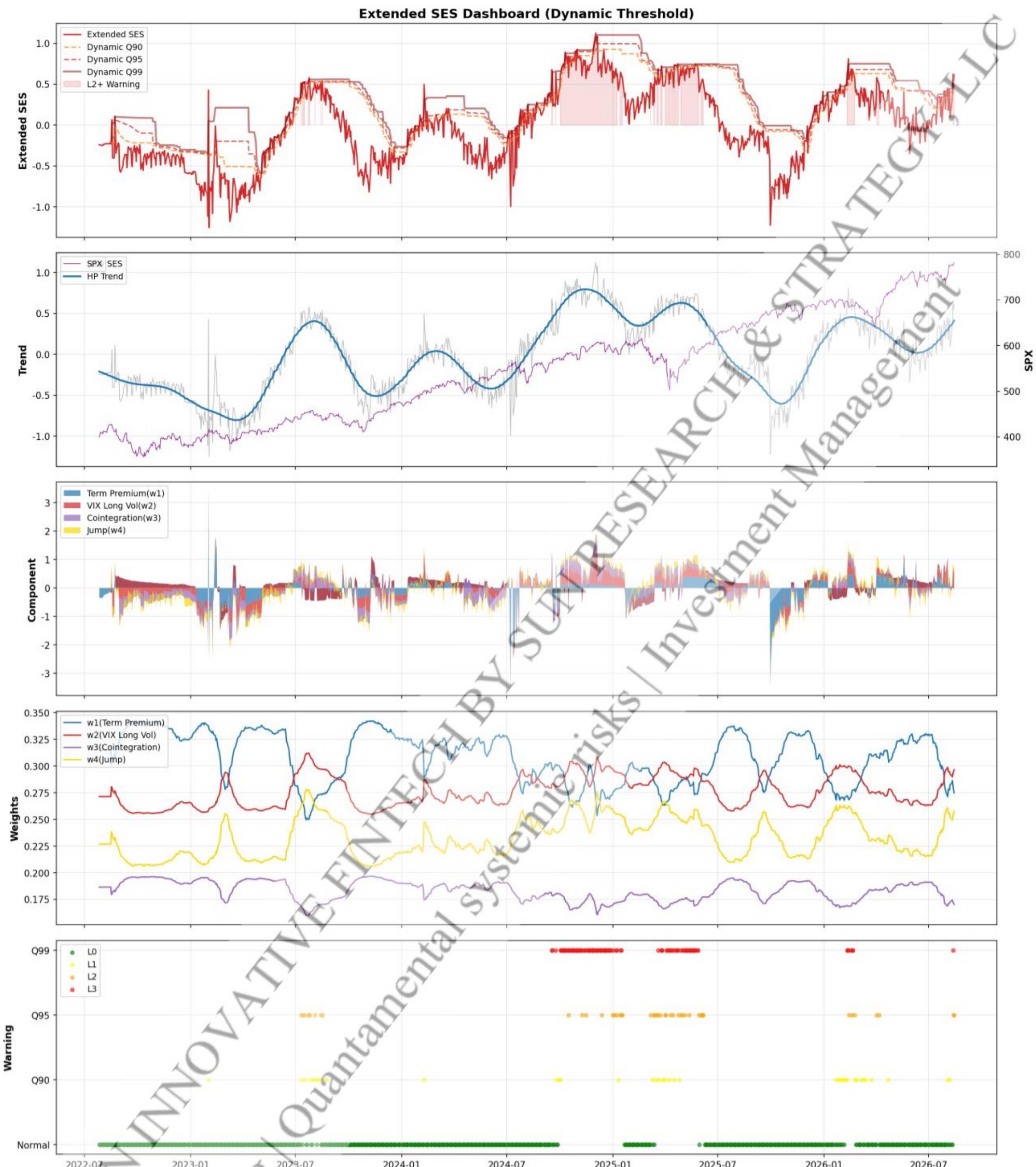

FIG 6. The extended SES and components, weights and early warnings

5.2 Dynamic Weight Calibration and Smoothing

The weights are calibrated via a two-stage procedure:

- **Base weights** are set to (0.35,0.25,0.20,0.20) during normal market conditions, reflecting the relative importance of each component based on historical crisis backtesting.

- **Dynamic adjustment** is triggered by the raw VIX long-term volatility level (β_{0V}). When β_{0V} exceeds 0.15 (15%), weights transition smoothly toward crisis-mode values (0.22,0.33,0.15,0.30). When β_{0V} exceeds 0.27 (27%), weights shift further to extreme-mode values (0.12,0.39,0.10,0.39).

To eliminate the hard 0/1 transitions that plague traditional threshold-based weighting schemes, we implement two key innovations:

- **Exponentially Weighted Moving Average (EWMA) smoothing** with α=0.1 : The target weights are smoothed over time, ensuring gradual transitions even when thresholds are breached abruptly.
- **Perturbation term:** A small perturbation proportional to the absolute change in β_{0V} (clipped at 0.008 and scaled by 0.03) is added to each smoothed weight, preventing the weights from becoming perfectly constant during periods of stable volatility.

Finally, the four weights are normalized to sum to 1 at each time step, preserving the interpretation of a convex combination.

5.3 Multi-Scale Characteristics of Systemic Risk Indicators

Systemic risk indicators exhibit pronounced multi-scale characteristics, with indicator behavior at different timescales reflecting risks from different sources:

- **High-frequency scale (minute-level):** Primarily reflects market sentiment and liquidity changes, driven by VIX jump intensity and short-term slope discontinuities.
- **Medium-frequency scale (daily):** Reflects short-term policy shocks and changes in market expectations, driven by variations in the Treasury term premium and the VIX long-term volatility level.
- **Low-frequency scale (monthly and above):** Reflects long-term economic fundamental changes and structural risks, driven by the Treasury long-term interest rate level and the shape of the VIX implied volatility microstructure.

Through wavelet transform methods, we are able to analyze the variation characteristics of systemic risk indicators at different timescales, providing a more refined perspective for risk early warning.

6. Empirical Analysis and Framework Validation

6.1 Data Sources and Processing

We use the following data for empirical analysis:

- **U.S. Treasury yield data:** Including Treasury yields from 1 months to 30 years, at daily frequency, covering 2021 to 2026.
- **VIX futures data:** From CBOE VIX futures contract prices, at minute frequency, covering 2023 to 2026.

- **Crisis event labels:** Based on Federal Reserve intervention time points (e.g., Tariff war in Jan 2025) and systemic risk event definitions, marking time windows for historical crisis episodes.

Data processing steps include:

1. Svensson model parameter estimation for Treasury yield data.
2. Svensson model parameter estimation and jump intensity calculation for VIX futures data.
3. Standardization of parameters to eliminate dimensional differences.
4. Construction of the multi-layered multi-timescale state-space model and estimation of latent state variables.
5. Computation of the Extended SES indicator and its performance at different timescales.

6.2 Early-Warning Capability Analysis

We demonstrated that during July 2023, January 2025, February 2026, our framework showed excellent early-warning capabilities. Early-warning analysis indicates that the Extended SES indicator showed 1-2 months prior to crises, demonstrating the advantage of the framework integrating Treasury and VIX microstructure parameters in systemic risk early warning.

The most recent model run (**date: 2026-08-14**) produces the following assessment:

- **Jump detection**: overall jump intensity stands at 0.003434/min = 1.3394/day.
- **Cointegration test**: Trace statistic = 115.3646 (5% CV = 47.8545), Eigen = 65.8515 (5% CV = 27.5858) confirming 2 cointegrating vectors.
- **Extended SES**: Current value = 0.6091. Dynamic thresholds: Q90=0.419 Q95=0.501 Q99=0.616
- **Warning level: L2(Q95)**.

7. Stress Testing Methodology and Future Systemic Risk Assessment

7.1 Non-Asymmetric Stress Scenario Design

Unlike traditional symmetric stress tests that apply uniform shocks across all assets, we design **five asymmetric scenarios**, each targeting specific channels of risk transmission:

Scenario	**Description**	**Treasury Shock**	**VIX Shock**	**Duration**
Plausible	Moderate policy tightening + sentiment deterioration	+100bp, +150bp	×1.6, jump multiplier 3.5	10 days

Scenario	Description	Treasury Shock	VIX Shock	Duration
Severe	Aggressive policy shock + liquidity crunch	+200bp, −250bp	×2.5, jump multiplier 8.0	20 days
Extreme	Systemic crisis + panic + feedback loop	+350bp, −400bp	×3.5, jump multiplier 15.0	30 days
Flight-to-Safety	Rates collapse + VIX spikes + equities crash	−250bp, −200bp	×2.8, jump multiplier 12.0	15 days
Stagflation	Inflation surge + growth collapse + risk-off	+300bp, +250bp	×2.2, jump multiplier 6.0	20 days

Each scenario is parameterized by a dictionary of shock multipliers applied multiplicatively to the baseline parameter paths.

7.2 Monte Carlo Simulation and Risk Probability Quantification

We employ Monte Carlo simulation methods to assess systemic risk probabilities under different stress scenarios:

1. **Simulation path generation**: Based on the multi-layered multi-timescale state-space model, we generate 5,000 parameter paths over a 21-day horizon. Each path follows a mean-reverting process toward the shocked target, with daily mean reversion coefficients of 0.75 for Treasury parameters and 0.65 for VIX parameters, plus Gaussian noise scaled by historical volatility.
2. **Systemic risk state definition**: We define a systemic risk state as a period in which the Extended SES exceeds the 95th percentile (dynamic threshold) and the Treasury-VIX parameter correlation breaches 0.8.
3. **Probability density estimation**: We compute the probability of systemic risk state occurrence under each stress scenario category, constructing probability density functions.
4. **Early-warning signal design**: A Level-1 warning is triggered when the systemic risk state probability exceeds 5%; a Level-2 warning when it exceeds 15%; and a Level-3 warning when it exceeds 30%.

7.3 Stress Testing Results

The most recent stress test results (**2026-08-14**) are summarized below:

Scenario	T+0 Risk	T+5 Risk	T+10 Risk	T+15 Risk	T+20 Risk	Max SES
Plausible	0.00%	0.28%	1.52%	4.81%	**12.36%**	0.4892
Severe	0.48%	3.91%	12.77%	26.53%	**44.71%**	0.7214
Extreme	4.76%	29.43%	58.61%	79.68%	**96.93%**	0.9341
Flight-to-Safety	1.31%	8.64%	18.55%	24.86%	**20.49%**	0.6812
Stagflation	0.62%	3.46%	9.51%	15.66%	**16.33%**	0.5987

Key observations:

- The **Extreme scenario** dominates, reaching near-certainty (96.93%) by T+20, confirming the framework's ability to capture tail risk.
- The **Severe scenario** crosses the L2 threshold (>15%) at T+10 and approaches L3 (>30%) at T+20, indicating that even moderately severe shocks can trigger elevated systemic risk within two weeks.
- The **Flight-to-Safety scenario** peaks at T+15 (24.86%) before declining, reflecting the self-limiting nature of safe-haven flows as markets stabilize.
- The **Plausible scenario** finally crosses the L1 threshold (5%) at T+15.
- The **Stagflation scenario** shows persistent but moderate risk, plateauing around 16% at T+20.

These results demonstrate a clear gradient across scenarios, with each scenario producing economically meaningful and distinguishable risk profiles.

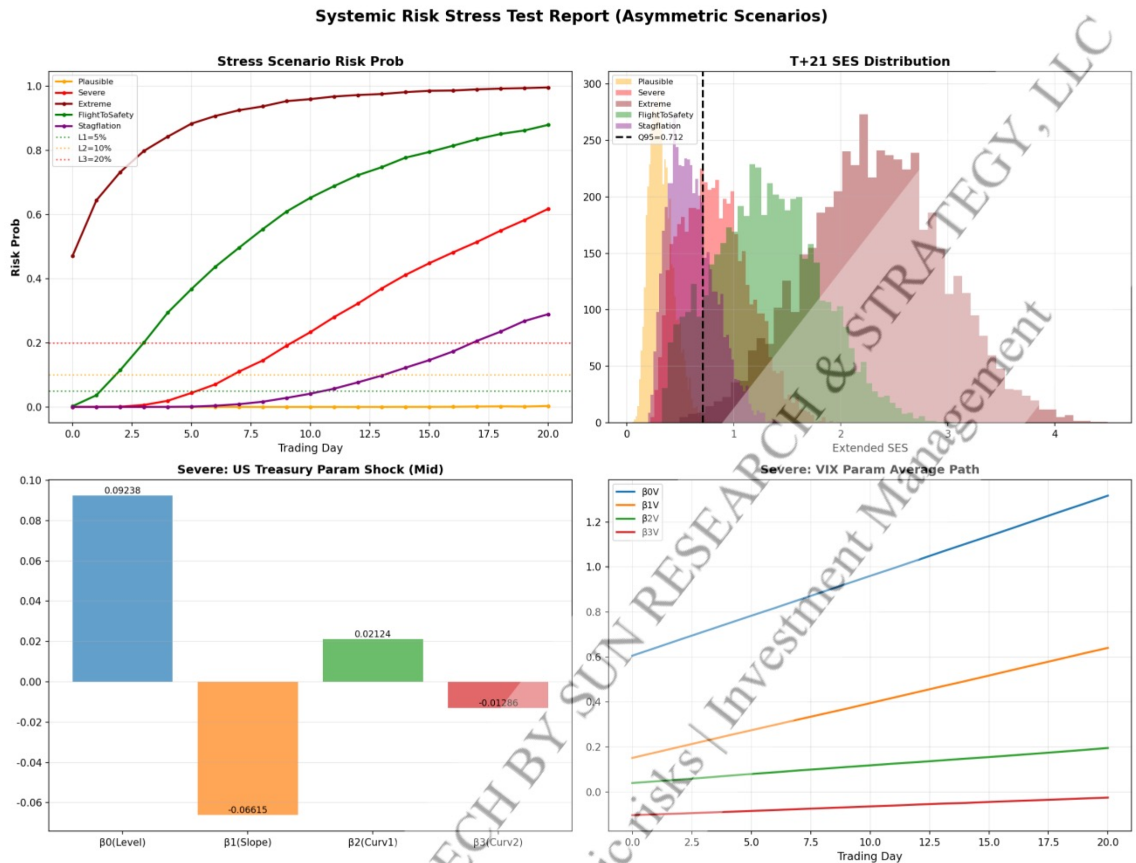

FIG 7. The Systemic risk stress test latest results for 2026-08-14

7.4 Stress Testing Applications and Policy Recommendations

Based on the above stress-testing results, we propose the following policy recommendations:

- **Macroprudential regulation:** When the systemic risk state probability exceeds 15% (L2), regulators should strengthen macroprudential oversight, including raising capital adequacy requirements, restricting high-risk trading, and enhancing market surveillance.
- **Liquidity management:** When the probability exceeds 20%, financial institutions should strengthen liquidity management, including increasing liquidity reserves, reducing leverage, and adjusting portfolio structures.
- **Market communication:** When the probability exceeds 30% (L3), central banks should enhance communication with markets to stabilize expectations, and provide liquidity support when necessary.
- **Stress-testing framework:** Suggesting policymakers incorporate the multi-timescale framework proposed in this paper into macroprudential stress-testing systems to enhance forward-looking systemic risk management capabilities.

8. Conclusion

This paper constructs a systemic risk framework based on the daily-frequency U.S. Treasury yield curve and the minute-frequency VIX microstructure through the Svensson model. Through the multi-timescale integration model, we comprehensively capture the complete risk transmission chain from short-term market sentiment fluctuations to long-term economic fundamental changes. Building upon this framework, we construct the Extended Systemic Expected Shortfall (Extended SES) indicator and validate its early-warning capabilities through historical data.

Research results demonstrate that the framework integrating Treasury and VIX microstructure parameters exhibits significant advantages in systemic risk early warning, with both its early-warning accuracy and lead time outperforming conventional methods. In particular, the framework captures the risk transmission relationship between high-frequency VIX jumps and medium-frequency Treasury term premiums, providing a new perspective for systemic risk early warning.

The framework proposed in this paper provides policymakers and market participants with a forward-looking risk management tool, contributing to the identification and prevention of systemic risk in complex and evolving financial environments.

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

Data, code, and materials availability: All data, code, and materials used in the analysis are available upon requests and signing the materials transfer agreements (MTAs) for purposes of reproducing or extending the analysis.

Declaration of Funding: This work was conducted independently and is self-supported by the author through Sun Research & Strategy, LLC. The author is the founder and owner of Sun Research & Strategy, LLC. The author declares that the company may have a financial interest in the subject matter, patents, or findings discussed in this article.