Theme: Regime-Specific Volatility Forecasting in Bonds, HAR vs Machine Learning with Macro Extensions

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1. Motivation

Volatility forecasting is central to portfolio allocation, risk management, and trading. Kılıç (2025) benchmarked linear HAR models against nonlinear regime-switching HAR variants (THAR, STHAR, MSHAR) and a suite of machine learning (ML) models including XGBoost and LSTMs, using S&P 500 realized volatility. His study showed that simple nonlinear econometric models with regime-switching dynamics consistently outperformed complex ML models, especially in sparse predictor settings. ML approaches only gained ground when macro-financial variables were included .

Our project builds directly on this framework but introduces two key extensions:

1. Asset Class Shift: Instead of equities, we will forecast bond market volatility, proxied by the realized volatility of the iShares 20+ Year Treasury Bond ETF (TLT).

2. Macro-Conditioned Regimes: We will condition forecasts on volatility regimes (tranquil vs stressed), using the MOVE Index (the bond market's "VIX") as the primary regime signal.

This extension is practically relevant because bond volatility plays a critical role in cross-asset allocation, risk parity strategies, and fixed-income VaR models. Equity volatility has been extensively studied; bond volatility forecasting remains underexplored despite its direct influence on macro-sensitive portfolios.

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2. Research Questions

1. Do regime-aware models improve bond volatility forecasts compared to global models?
   - H0: Regime-conditioned HAR and ML models are equal to or worse than global specifications.
   - H1: Regime-conditioned HAR and ML models deliver superior accuracy in stressed and calm bond market states.

2. Do macro-financial drivers provide additional predictive power beyond lagged realized volatility?
    - H0: Macro variables (MOVE, Treasury yields, credit spreads) do not improve accuracy over HAR baselines.
    - H1: Macro variables enhance forecasts by capturing structural shifts in fixed-income volatility.

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3. Methodology

Data

- Target: Daily realized volatility of TLT (constructed from intraday data, or high-frequency approximations if available).
- Regime variable: MOVE Index (bond market implied vol).
- Macro predictors:
    - MOVE (level/change)
    - US 10Y Treasury yield
    - Fed Funds rate
    - High-Yield OAS (credit spread)
    - NFCI (Chicago Fed National Financial Conditions Index)

Sources: Oxford-Man Realized Library (if available for TLT), Bloomberg, FRED.

Baseline Models

1. HAR (linear benchmark):
    - Predictors: 1-day, 5-day, 22-day lagged realized volatility.
2. XGBoost (ML benchmark):

- Predictors: HAR lags, macro-financial variables, regime dummies.
- Training: rolling window, time-series CV, hyperparameter tuning.

3. Optional (time permitting): LSTM
    - Sequence modeling of lagged RV and macro features.

Extensions

- Regime Conditioning: Split into high- and low-vol regimes (threshold on MOVE or realized vol median).
- Macro Augmentation: Add MOVE, yields, credit spreads, NFCI.

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4. Evaluation

- Statistical metrics: MSPE, QLIKE.
- Comparative tests: Diebold–Mariano tests, Model Confidence Set (Hansen et al., 2011).
- Economic metrics:
    - Value-at-Risk backtesting (Kupiec, Christoffersen).
    - Economic utility via volatility targeting portfolios.

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5. Commercial Relevance

- Risk Management: Bond VaR models often underestimate tail risk in crises. Regime-aware forecasts can tighten backtests and reduce regulatory capital charges.
- Asset Allocation: Fixed-income volatility drives risk parity weights and hedging strategies. Better forecasts enhance portfolio resilience.

- Trading & Execution**:** Volatility spikes drive Treasury futures pricing, swaption surfaces, and convexity hedging costs. Knowing when HAR vs ML adds value is critical for desks managing duration and spread risk.

Contribution

Relative to Kılıç (2025) , this project adds new empirical terrain:

- Asset class focus shifts from equity (S&P 500) to bond volatility (TLT).
- MOVE index introduces a natural volatility regime proxy.
- Emphasis on macro-conditioned regimes reflects real-world risk desk practices in fixed income.

This allows us to test whether the findings in equities generalize to bonds, or whether bond volatility, being macro-driven and policy-sensitive, exhibits different dynamics where machine learning adds more value than in equities.