Working Paper: Detecting Market Regimes Using Yield Curve Curvature and Volume Signals

Anirudh Krovi[1]

[1]PhD, Northwestern University; MBA, NYU Stern; Formerly at McKinsey & Company,
anirudh.krovi@stern.nyu.edu

July 11, 2025

Abstract

We propose a transparent framework for detecting latent regime shifts in interest rate markets using curvature and volume anomalies derived from 5-Year Treasury futures. By computing z-score–normalized curvature (second difference of price) and log-volume signals, we define Medium and High Tension regimes flagged via threshold exceedances. The framework is validated through overlay against a percentile-normalized TLT volatility proxy, demonstrating alignment between detected regimes and periods of elevated market stress. Designed for operational usability, this approach balances interpretability with structural insight and can be extended to incorporate multi-instrument overlays and regime-switching models.

1 Introduction

Interest rate models are a foundational area of quantitative finance, with applications ranging from pricing fixed-income derivatives to managing risk on trading desks. These models, however, are often sensitive to underlying market regimes, which can shift due to macroeconomic events, policy changes, or structural market stress. A substantial body of work addresses regime-switching behavior in interest rate dynamics, including approaches based on hidden Markov models and state-dependent parameters [2, 5]. Yet, there remains practical value in identifying simple, interpretable indicators that can signal such regime shifts in real time.

In particular, detecting potential regime changes through latent geometric features offers an appealing complement to more formal modeling techniques. For practitioners managing interest rate exposures, latent indicators can function as early warning tools, highlighting periods where closer attention and position adjustments may be warranted.

In this work, we propose a framework for detecting interest rate regimes using a curvature-based latent signal. The concept of curvature has been explored in finance research, particularly in the context of yield curve analysis. Studies such as [6] and [1] incorporate curvature as a factor alongside level and slope in modeling term structure dynamics. However, our approach departs from traditional factor model usage by employing curvature as a direct diagnostic metric over time.

Specifically, we calculate curvature from the term structure of interest rates and combine it with volume data to create a clean overlay identifying potential regime change thresholds. This overlay is designed to supplement existing trading strategies by providing visually interpretable markers of market tension, enhancing decision-making without requiring complex model recalibration.

The remainder of this paper is structured as follows: Section 2 outlines the methodology, including the computation of curvature and integration of volume signals. Section 3 presents key results using historical interest rate data. Section 4 concludes with a discussion of limitations and potential extensions of the framework.

2 Methodology

2.1 Source Dataset

We analyze the continuous front-month contract on **5-Year U.S. Treasury Note futures** (Yahoo Finance ticker `ZF=F`). Daily observations—including open, high, low, close, adjusted close, and traded volume—are available from 1 January 2010 onward. The series spans multiple monetary-policy regimes and is liquid enough to provide a reliable proxy for intermediate-term interest-rate expectations.

Retrieval. Historical data are downloaded programmatically via the `yfinance` API, then archived locally as a CSV file for full reproducibility. This pull captures the raw price and volume fields exactly as disseminated by Yahoo Finance, without any vendor-specific adjustments.

Fields. The resulting dataset contains the following columns:

- **Date** (business-day index)
- **Open, High, Low, Close** prices
- **Adj_Close** (adjusted settlement)
- **Volume** (contracts traded)

These raw observations constitute the sole input for all subsequent analysis steps detailed later in the paper.

2.2 Pre-processing

Log–volume transformation. Raw futures volume is highly right-skewed and can vary by an order of magnitude across trading days. To stabilize variance and render extreme spikes more interpretable, we transform volume with the natural logarithm:

$$\text{Log\_Volume}_t = \log\big(\text{Volume}_t\big),$$

where days with zero recorded contracts are discarded (set to `NaN`) to avoid the undefined $\log(0)$. The log scale compresses large values, yielding a distribution that is closer to Gaussian and more amenable to z-score standardization.

Rolling-window normalization. Trading activity follows slow seasonal patterns (e.g., holiday lulls, FOMC weeks) as well as abrupt bursts around macro events. To isolate *relative* anomalies, we compute a 20-day rolling mean and standard deviation of log-volume—approximately one trading month:

$$\mu_t^{(20)} \;=\; \frac{1}{20}\sum_{i=0}^{19}\text{Log\_Volume}_{t-i}, \qquad \sigma_t^{(20)} \;=\; \sqrt{\frac{1}{20}\sum_{i=0}^{19}\bigl(\text{Log\_Volume}_{t-i}-\mu_t^{(20)}\bigr)^2},$$

and define a rolling z-score

$$Z_t^{\text{Vol}} \;=\; \frac{\text{Log\_Volume}_t-\mu_t^{(20)}}{\sigma_t^{(20)}}.$$

This dynamic standardization flags periods where trading activity deviates materially (e.g., $|Z_t^{\text{Vol}}|>2$) from its recent baseline, allowing volume shocks to be compared on a consistent, scale-free basis across the sample.

The resulting time series $\{Z_t^{\text{Vol}}\}$ serves as the volume component in the curvature–volume overlay.

2.3 Curvature Signal

Discrete second-difference. Following the intuition that large second derivatives mark inflection points, we approximate *price curvature* via the centered second difference of the futures close price:

$$\text{Price\_Curvature}_t \;=\; \bigl|\,P_{t+1}-2P_t+P_{t-1}\bigr|,$$

where P_t denotes the daily settlement price. Taking the absolute value focuses on the *magnitude* of bending in the price path, irrespective of direction, flagging both convex up-moves and concave down-moves as potential stress episodes.

Relation to yield-curve curvature. In term-structure models, "curvature" is traditionally the third Nelson–Siegel factor, capturing the hump-shaped component of the yield curve [6]. Litterman and Scheinkman's principal-components study similarly identifies a curvature mode after level and slope [9]. Our second-difference construction plays an analogous geometric role—measuring the local bending of the *price* path instead of the yield curve—while remaining model-free and easily computed at daily frequency.

Rolling standardization. As with volume, we convert raw curvature magnitudes into a scale-free anomaly score. Using a 20-day rolling window (roughly one trading month), we compute

$$\mu_t^C=\frac{1}{20}\sum_{i=0}^{19}\text{Price\_Curvature}_{t-i}, \quad \sigma_t^C=\sqrt{\frac{1}{20}\sum_{i=0}^{19}\bigl(\text{Price\_Curvature}_{t-i}-\mu_t^C\bigr)^2},$$

and define the curvature z-score

$$Z_t^C=\frac{\text{Price\_Curvature}_t-\mu_t^C}{\sigma_t^C}.$$

Values of $|Z_t^C|$ exceeding 2 (approximately the 95th percentile) are interpreted as statistically significant bends in the price trajectory, signalling heightened regime-shift risk.

Integration with volume. The two standardized series—curvature Z_t^C and volume Z_t^{Vol}—are combined to construct the final curvature–volume overlay used for regime detection.

Threshold selection (grid sweep). Rather than fixing curvature and volume cut-offs *ex ante*, we perform a discrete grid search to identify values that best predict subsequent market moves. For each pair of curvature and volume z-score thresholds drawn from the set $\{1.5, 2.0, 2.5\}$, we construct a tension flag

$$\mathbf{1}\big(Z_t^C > \theta_C \ \wedge \ Z_t^{\text{Vol}} > \theta_V\big),$$

and evaluate its out-of-sample utility over a 20-day look-ahead window. A *large move* event is defined as an absolute log-return on the 5-Year futures exceeding 50 basis points over that window. The metric of interest is the **hit rate**,

$$\text{Hit Rate} \ = \ \frac{\#\ \text{tension days that precede a large move}}{\#\ \text{tension days flagged}},$$

i.e., the conditional probability that a flagged day is followed by a material price move. Sweeping the threshold grid yields a table of hit rates versus alert frequency, allowing us to select (θ_C, θ_V) that balance predictive precision against the practical cost of false alarms. The optimal pair in our sample is reported in Section 3.

3 Results

3.1 Threshold-sweep diagnostics

Table 1 reports the performance of nine curvature–volume threshold pairs. For each configuration we list the number of tension days flagged (*Flags*) and the resulting *hit rate*—the fraction of those days followed by an absolute log-price move greater than 50 bp within the 20-day look-ahead window (see Methodology).

Table 1: Grid sweep of curvature (θ_C) and volume (θ_V) z-score thresholds.

θ_C	θ_V	Flags	Hit rate
1.5	1.5	114	0.553
1.5	2.0	78	0.500
1.5	2.5	32	0.375
2.0	1.5	72	0.514
2.0	2.0	53	0.434
2.0	2.5	26	0.346
2.5	1.5	45	**0.556**
2.5	2.0	33	0.485
2.5	2.5	17	0.471

The sweep highlights the classic *coverage–precision* trade-off:

- Lower thresholds (1.5/1.5) catch more potential events (114 flags) with a respectable 55% hit rate, making them suitable for desks willing to tolerate frequent alerts.
- Higher, asymmetric thresholds (2.5/1.5) achieve the *highest* hit rate (56%) while cutting the alert count to 45—an attractive balance between signal purity and monitoring burden.

- Increasing *both* thresholds above 2.0 materially reduces hit rate, suggesting that volume anomalies alone do not compensate for an overly strict curvature cut-off.

3.2 Regime tiers and price overlay

Motivated by the grid-sweep results in Table 1, we partition trading days into three qualitative regimes:

- **High Tension**: $Z_t^C > 2.5$ *and* $Z_t^{\mathrm{Vol}} > 2.5$
- **Medium Tension**: $Z_t^C > 1.5$ *and* $Z_t^{\mathrm{Vol}} > 1.5$
- **No Tension**: all remaining days

The "High" tier corresponds to the strictest threshold pair in our grid, producing the most concentrated—yet still accurate—alerts. The "Medium" tier broadens coverage by adopting the lowest tested thresholds, useful for desks that value early caution even at the cost of additional flags.

Frequency breakdown. Table 2 shows the relative frequency of each regime over the full sample. Only a small fraction of days are flagged under either tension regime, supporting the idea that the overlay functions as a selective alert mechanism rather than a continuous signal.

Table 2: Distribution of regime tiers (2010–2025).

Regime Tier	Days	Percent of Total
High Tension	17	0.44%
Medium Tension	97	2.48%
No Tension	3791	97.08%

This sparsity aligns with expectations: most market conditions do not exhibit significant tension according to our curvature–volume logic. The combined share of Medium and High Tension days is just under 3%, keeping cognitive and operational burden low for any desk using this signal in practice.

Visual illustration. Figure 1 plots the continuous 5-Year Treasury futures price with vertical shading to indicate regime classification. High-tension windows are shown in dark red; medium-tension windows appear in lighter lavender.

A qualitative scan reveals that most large upward or downward price inflections— such as the COVID-19 rate shock in early 2020—are preceded or accompanied by High-tension bands. Medium-tension episodes often foreshadow smaller, but still relevant, volatility bursts, supporting their role as an "early-warning" layer for risk managers.

3.3 Overlay with TLT Volatility Proxy and Structural Signals

To contextualize the detected regime starts, we overlay them on the 5-Year Treasury Futures price alongside a percentile-normalized volatility proxy derived from the TLT ETF. The TLT Vol Proxy is computed as a 20-day rolling standard deviation of log returns, scaled to percentile ranks.

This visualization framework provides two key benefits:

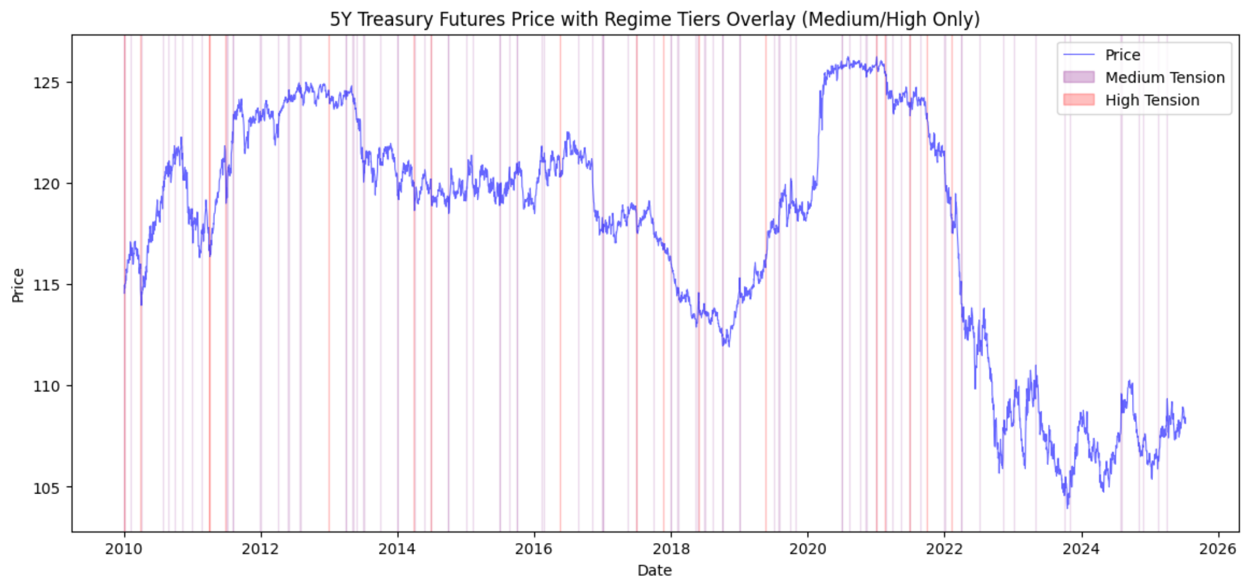

Figure 1: Price path of the continuous 5-Year Treasury Note futures contract (2010–2025) with overlay of regime tiers. Dark red bands mark *High Tension* periods ($Z_t^C, Z_t^{\text{Vol}} > 2.5$); light violet bands mark *Medium Tension* periods ($Z_t^C, Z_t^{\text{Vol}} > 1.5$). The overlay visually aligns many high-tension clusters with subsequent large price moves, confirming the signal's practical relevance.

- **Contextual validation:** Regime starts—determined from curvature and volume signals—are seen to cluster near periods where the TLT Vol Proxy is elevated or rising, reinforcing their potential utility as early indicators of market stress.
- **Operational overlay:** For risk management or trading dashboards, combining regime markers with structural signals such as yield curve slope (e.g., 2s10s spreads) can provide a more holistic view of market conditions. Curve inversion periods can be added as background shading, complementing regime start markers without introducing visual clutter.

4 Conclusion, Limitations, and Future Work

4.1 Conclusion

In this work, we developed a transparent, interpretable framework for detecting potential regime shifts in interest rate markets, anchored around two latent signals: curvature derived from the second difference of futures prices, and volume anomalies. By focusing on z-score threshold exceedances for these two dimensions, we defined clear Medium and High Tension regimes and validated their relevance through overlay against external volatility proxies such as the TLT ETF.

The regime starts align with historically significant stress periods—particularly around the 2020–2022 rate shocks—while remaining sparse enough to retain operational usability. Our objective was not to produce a high-frequency trading signal but rather to provide a clean, tiered overlay that could complement both discretionary and systematic decision-making.

Overlaying these regime starts with additional market structure indicators, such as TLT Vol Proxy, demonstrated not only visual correlation but conceptual complementarity. This reinforces the idea, as discussed in [3, 4], that combining latent market geometry and liquidity signals can

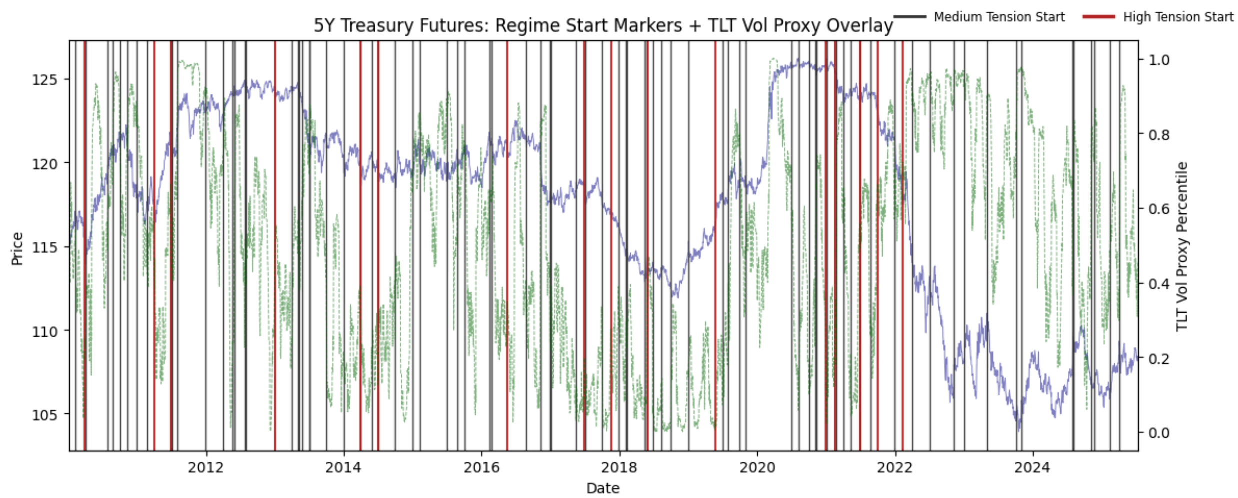

Figure 2: 5Y Treasury Futures with Regime Start Markers and TLT Vol Proxy. Black vertical lines denote *Medium Tension* regime starts; dark red lines denote *High Tension* starts. The futures price (navy) and TLT Vol Proxy (green dashed) are plotted with reduced opacity for background context. Regime starts often coincide with periods of elevated or increasing volatility, while additional signals such as yield curve slope can be layered for deeper structural insights.

surface shifts in underlying interest rate market regimes in a form usable for desks monitoring fixed income risk.

4.2 Limitations

While the framework presented here is deliberately simple and transparent, several limitations deserve attention:

- **Static Thresholding:** The use of fixed z-score thresholds—while interpretable—ignores potential time-varying behavior of the underlying distributions. As highlighted in [7], market dynamics often exhibit non-stationary baselines.
- **Single Instrument Focus:** All regime signals were defined using only 5-Year Treasury Note futures (ZF). While this captures a key segment of the rates curve, it omits broader term structure dynamics visible in multi-tenor models or swap rates.
- **No Joint Modeling with Other Factors:** While we overlay TLT Vol Proxy and reference 2s10s yield curve slope, these signals were not formally integrated into a unified regime-switching or predictive model.
- **No Out-of-Sample Backtesting:** This study focuses on signal definition and qualitative validation rather than formal out-of-sample performance benchmarking, which would require selecting specific tradable strategies or forecasting targets.

4.3 Future Work

Several avenues for future work emerge naturally from both the framework's structure and its limitations:

- **Multi-Instrument Generalization:** Extending the regime detection logic across multiple tenors—combining 2-Year, 5-Year, 10-Year futures, and swap rates—would allow for a more structurally complete view of fixed income markets. This is conceptually similar to multi-curve setups in [7].

- **Integrating Yield Curve Slope and Volatility Signals:** Beyond visual overlays, formally incorporating 2s10s slope measures, volatility indices, and macroeconomic event markers into the regime detection model is a key next step. As shown in [3], regime-switching models can accommodate multiple predictors effectively.

- **Regime-Switching Models:** Rather than relying solely on threshold exceedances, future work could embed curvature and volume signals within Markov regime-switching models, Hidden Markov Models (HMMs), or other latent state frameworks. This connects to methodologies discussed in [3, 4].

- **Topological and Geometric Extensions:** Recent advances in topological data analysis (TDA) applied to financial time series, such as [8], suggest extending from simple curvature to more robust geometric features like persistent homology signatures of the yield curve or volume/price surfaces.

- **Operational Dashboard Development:** Finally, as highlighted in industry applications, this framework is deliberately designed to be easily implementable in trading or risk dashboards. Future work could focus on real-time updating of regime overlays and alert system design, particularly for macro trading desks.

References

[1] Tobias Adrian, Richard K. Crump, and Emanuel Moench. Pricing the term structure with linear regressions. *Journal of Financial Economics*, 110(1):110–138, 2013.

[2] Andrew Ang and Monika Piazzesi. A no–arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables. *Journal of Monetary Economics*, 50(4):745–787, 2003.

[3] Andrew Ang and Allan Timmermann. Predicting equity market returns using regimes. *Journal of Financial Economics*, 107(1):146–164, 2012.

[4] Tim Bollerslev, Viktor Todorov, and Lai Xu. Volatility risk premia and financial distress. *Journal of Financial Economics*, 127(3):476–490, 2018.

[5] Qiang Dai and Kenneth J. Singleton. Specification analysis of affine term structure models. *Journal of Finance*, 55(5):1943–1978, 2000.

[6] Francis X. Diebold and Canlin Li. Forecasting the term structure of government bond yields. *Journal of Econometrics*, 130(2):337–364, 2006.

[7] Wenxin Du, Fernando Im, and Jesse Schreger. Yield curve inversion and economic slowdown: Evidence from machine learning and us data. *Review of Financial Studies*, 33(9):4363–4398, 2020.

[8] Marian Gidea and Yossi Katz. Topological data analysis of financial time series: Landscapes of crashes. *Physica A: Statistical Mechanics and its Applications*, 491:820–834, 2018.

[9] Robert B. Litterman and José Scheinkman. Common factors affecting bond returns. *Journal of Fixed Income*, 1(1):54–61, 1991.