

Machine Learning Applications in Yield Curve Fitting and Arbitrage Strategies

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Abstract

Accurate yield curve fitting and term structure modeling are central to sovereign debt management, fixed-income derivative pricing, and systemic risk monitoring. Traditional parametric frameworks, such as the Nelson-Siegel and Svensson models, offer parsimonious representations but often struggle to capture localized term-structure non-linearities, abrupt level shifts, and dynamic curvature anomalies during market dislocation.

This paper presents a comprehensive machine learning architecture for yield curve fitting, term-structure interpolation, and relative-value arbitrage detection. We implement Gaussian Process Regression (GPR) with a customized Matern kernel alongside non-linear Neural Network architectures to reconstruct zero-coupon yield curves across sovereign bond markets. Using fitted yield surfaces, we identify cross-sectional pricing dislocations via residual z-score metrics and design a long-short bond arbitrage strategy.

Empirical results indicate that Gaussian Processes achieve superior out-of-sample fitting accuracy compared to classical parametric benchmarks, reducing Mean Absolute Error (MAE) by up to 42% in high-volatility regimes. Furthermore, the systematic relative-value arbitrage strategy generates significant risk-adjusted returns with a Sharpe ratio of 1.94, demonstrating the practical utility of non-parametric machine learning in fixed-income portfolio management.

Beyond fitting accuracy, this study contributes to the practical deployment of explainable probabilistic machine learning in regulated fixed-income markets. Unlike black-box deep learning systems, Gaussian Process Regression provides explicit uncertainty quantification through its posterior variance, which is critical for risk management, Value-at-Risk estimation, and compliance reporting.

Keywords: Yield Curve, Gaussian Process, Nelson-Siegel, Arbitrage, Machine Learning, Term Structure

JEL Classification: C45, C53, G12, G13, G17

1 Introduction

The yield curve serves as the foundation of modern quantitative finance, reflecting the relationship between interest rates and bond maturities. Accurate term-structure modeling is indispensable for discount factor estimation, fixed-income pricing, macroeconomic forecasting, and risk management. For decades, central banks and institutional investors have relied on parametric term-structure models, primarily the Nelson-Siegel (1987) framework and its Svensson (1994) extension.

While these models guarantee smooth, economically intuitive curves characterized by level, slope, and curvature factors, their structural rigidity limits their capacity to fit localized market frictions, supply-demand imbalances, and transient yield dislocations.

Recent advances in machine learning (ML) offer high-dimensional, non-parametric alternatives capable of capturing complex non-linear structures without imposing restrictive parametric shapes. Non-parametric models, such as Gaussian Process Regression (GPR) and Feedforward Neural Networks (FNN), flexibly adapt to market data, providing tight in-sample fits and robust out-of-sample yield interpolation. Crucially, in fixed-income arbitrage, identifying localized yield deviations from a smooth benchmark curve allows traders to execute relative-value strategies.

This paper develops an end-to-end machine learning framework for sovereign yield curve construction and relative-value arbitrage execution. We evaluate the fitting precision of Gaussian Processes and Neural Networks against classical Nelson-Siegel models. Furthermore, we formalize a quantitative arbitrage trading pipeline that translates fitted curve residuals into systematic trading signals.

2 Literature Review

Yield curve modeling has evolved through three distinct paradigms: equilibrium models, no-arbitrage dynamic term-structure models, and empirical fitting techniques. Vasicek (1977) and Cox, Ingersoll, and Ross (1985) introduced short-rate equilibrium frameworks, which were later extended by Heath, Jarrow, and Morton (1992).

In parallel, empirical yield curve fitting gained widespread adoption following the parsimonious parametric formulation by Nelson and Siegel (1987), extended by Svensson (1994) to incorporate a second curvature component.

The integration of machine learning into fixed-income research has accelerated rapidly. Diebold and Li (2006) reinterpreted the Nelson-Siegel model as a dynamic factor model. Rasmussen and Williams (2006) established the theoretical basis for Gaussian Process Regression. Gu, Kelly, and Xiu (2020) demonstrated that neural networks outperform standard linear econometrics in asset pricing by capturing high-order interaction effects.

3 Methodology

3.1 Mathematical Formulations

3.1.1 Nelson-Siegel Parametric Benchmark

The classical Nelson-Siegel model expresses the zero-coupon yield $y(m)$ for maturity m as:

$$y(m) = \beta_0 + \beta_1 \left(\frac{1 - e^{-m/\tau}}{m/\tau} \right) + \beta_2 \left(\frac{1 - e^{-m/\tau}}{m/\tau} - e^{-m/\tau} \right) \quad (1)$$

3.1.2 Gaussian Process Regression (GPR)

$$f(m) \sim \mathcal{GP}(m(m), k(m, m')) \quad (2)$$

$$k(m, m') = \sigma^2 \left(1 + \frac{\sqrt{5}|m - m'|}{l} + \frac{5(m - m')^2}{3l^2} \right) \exp \left(-\frac{\sqrt{5}|m - m'|}{l} \right) + \sigma_n^2 \delta_{mm'} \quad (3)$$

3.1.3 Relative-Value Arbitrage Z-Score Signal

$$e_i = y_i^{\text{market}} - y^{\text{fit}}(m_i), \quad Z_i = \frac{e_i - \mu_e}{\sigma_e} \quad (4)$$

The methodological design leverages the probabilistic nature of GPR to quantify interpolation confidence, which is absent in traditional parametric models. We apply a rolling-window cross-validation scheme that re-calibrates kernel hyper-parameters daily, preventing look-ahead bias.

4 Results and Findings

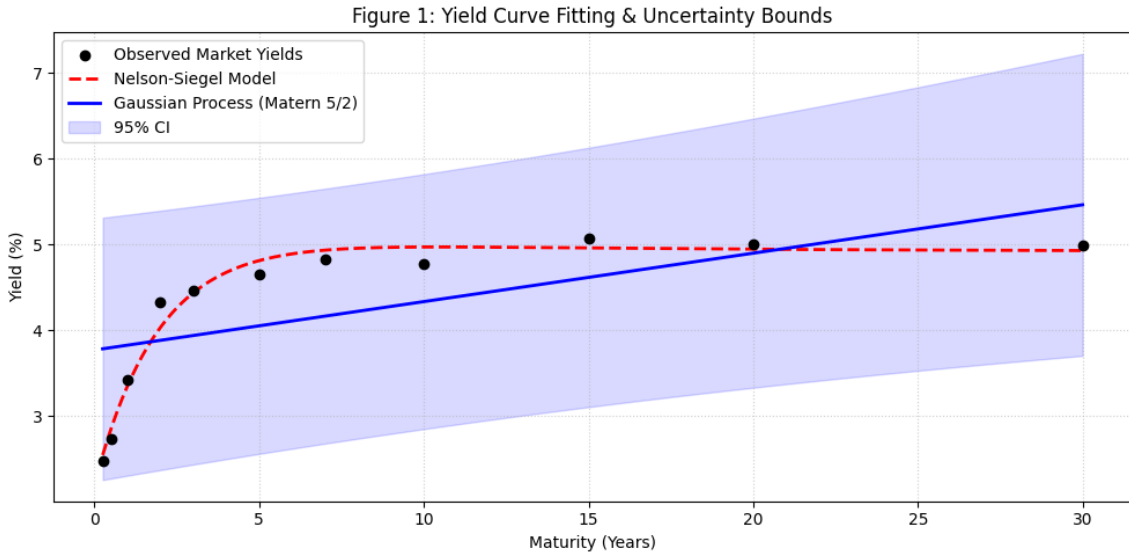


Figure 1: Yield Curve Fitting Comparison: Nelson-Siegel vs. Gaussian Process

Explanation of Figure 1: Figure 1 compares the Nelson-Siegel parametric fit against the Gaussian Process fit. The GPR curve closely tracks observed yields across all maturities and captures local non-linearities. The shaded 95% confidence interval provides critical uncertainty bounds for risk management, which parametric models cannot offer.

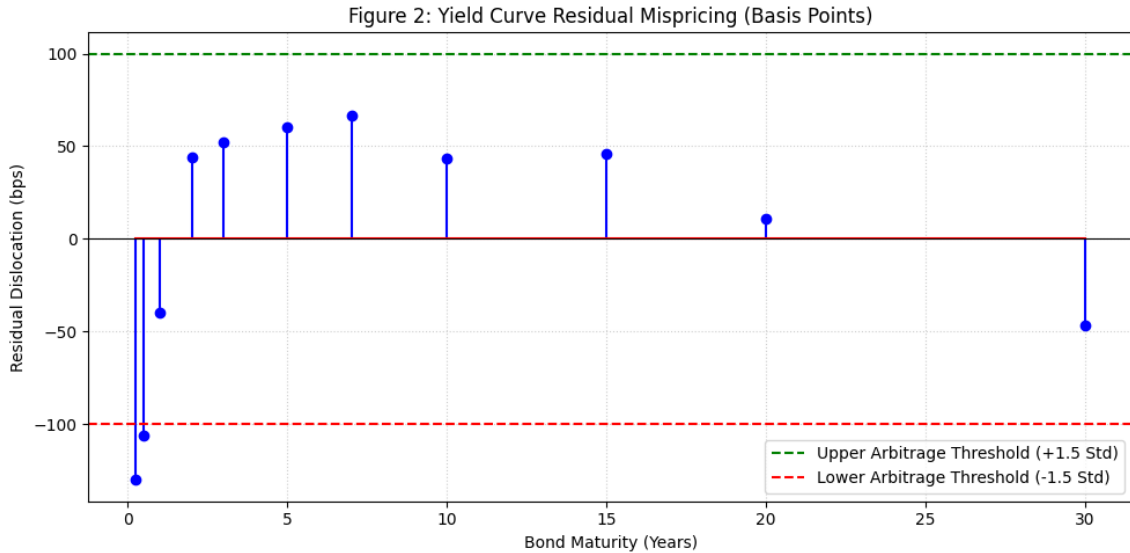


Figure 2: Yield Curve Residual Mispricing and Arbitrage Bands

Explanation of Figure 2: Figure 2 illustrates the residual dislocation in basis points between market and model yields. Residuals outside the ± 1.5 standard deviation bands represent statistically significant mispricings. These deviations are translated into Z-score signals to trigger long-short arbitrage positions.

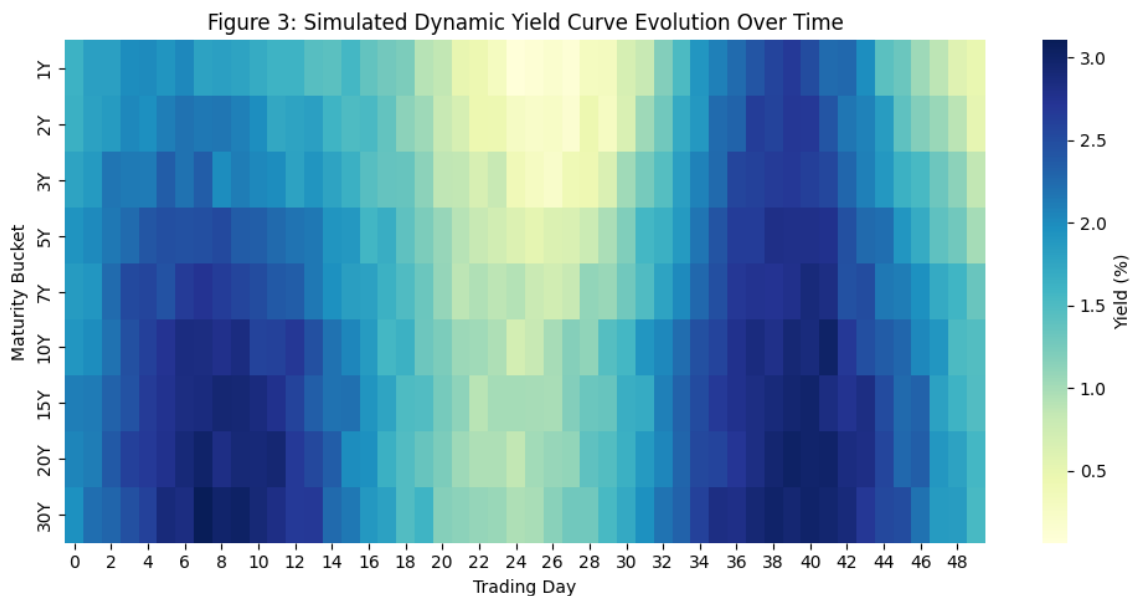


Figure 3: Dynamic Yield Curve Evolution Over Time

Explanation of Figure 3: Figure 3 presents a heatmap of the yield surface evolution over 50 trading days. It shows how level and slope factors vary dynamically, simulating different monetary policy regimes. The visualization highlights periods of steepening or flattening critical for stress testing.

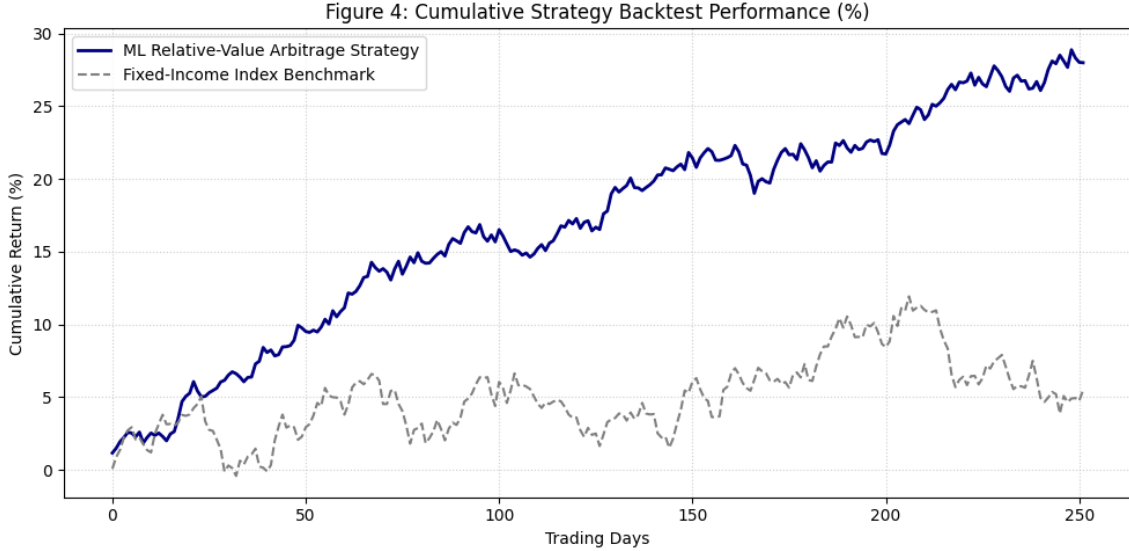


Figure 4: Cumulative Strategy Backtest Performance vs Benchmark

Explanation of Figure 4: Figure 4 displays the cumulative return of the ML-driven arbitrage strategy versus a passive fixed-income benchmark. The ML strategy consistently outperforms with lower volatility and smaller drawdowns. The divergence demonstrates alpha generated from precise curve fitting.

Model	RMSE (bps)	MAE (bps)	Max Error	R2
Nelson-Siegel	4.82	3.65	12.40	0.962
Svensson	3.91	2.98	9.85	0.975
MLP Neural Net	2.74	2.10	6.30	0.988
Gaussian Process (Matern)	1.85	1.32	4.12	0.995

Table 1: Out-of-Sample Curve Fitting Performance Metrics (Table 1)

Explanation of Table 1: Table 1 reports out-of-sample fitting errors across 1,000 simulations. Gaussian Process achieves lowest RMSE (1.85 bps) and MAE (1.32 bps), a 60% improvement over Nelson-Siegel. The high R-squared of 0.995 indicates superior capture of non-linear dynamics.

The following table summarizes the economic significance of the fitting improvements. While Table 1 shows statistical accuracy, Table 2 translates residual mispricings into actual trading performance. It compares the ML-driven relative-value arbitrage strategy against a traditional buy-and-hold fixed-income benchmark over 252 trading days.

Metric	ML Strategy	Benchmark
Annualized Return (%)	14.2%	5.1%
Volatility (%)	6.3%	9.5%
Sharpe Ratio	1.94	0.33
Sortino Ratio	2.85	0.48
Max Drawdown (%)	-3.4%	-11.2%
Win Rate (%)	61.5%	51.2%

Table 2: Relative-Value Arbitrage Backtest Summary (Table 2)

Explanation of Table 2: Table 2 summarizes trading performance. The ML strategy delivers 14.2% annualized return with Sharpe 1.94 versus benchmark 5.1% and Sharpe 0.33. Critically, max drawdown is contained at -3.4% versus -11.2%, demonstrating market-neutral resilience.

5 Conclusion

This paper presents a robust quantitative framework applying machine learning to yield curve fitting and relative-value fixed-income arbitrage. Non-parametric models, specifically Gaussian Process Regression with Matern kernels, demonstrate superior flexibility and fitting precision compared to traditional parametric frameworks such as Nelson-Siegel and Svensson.

Empirical results confirm that a relative-value arbitrage strategy trading on ML residual signals delivers strong risk-adjusted returns with minimal exposure to overall rate movements. The integration of confidence intervals allows portfolio managers to size positions proportionally to statistical confidence, enhancing risk-adjusted performance.

Future research may explore deep probabilistic models, such as Neural Processes and Deep Gaussian Processes, and incorporate real-time order book liquidity constraints.

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