JTAM (Jurnal Teori dan Aplikasi Matematika)
http://journal.ummat.ac.id/index.php/jtam
p-ISSN 2597-7512 | e-ISSN 2614-1175
Vol. 10, No. 1, January 2026, pp. 1-14

Modelling Consumer Price Index Effect on 10-year US Treasury Bond Yields using Least Square Spline Approach

Julia Widiyanti[1], Safira Salsabila[1], Dwika Maya Harsanti[1], Dita Amelia[1*], Marisa Rifada[1]
[1]Department of Mathematics, Universitas Airlangga, Indonesia
dita.amelia@fst.unair.ac.id

Article History:
Received : 07-07-2025
Revised : 15-08-2025
Accepted : 15-08-2025
Online : 01-01-2026

Keywords:
Least Square Spline;
Consumer Price Index;
US 10-year Treasury Bond;
Nonparametric Model;
Inflation.

ABSTRACT

Inflation measured by the Consumer Price Index (CPI) is a critical indicator in the government bond market that directly affects the yields of long-term securities such as the 10-year US Treasury Bond. This study is an explanatory quantitative study that aims to examine the complex dynamics of this relationship using the nonparametric least square spline method. The analysis uses monthly CPI data from FRED and 10-year US Treasury bond yield data from Investing.com for the period 2013-2025. This method divides the data into simple polynomial segments that are smoothly connected at transition points (knots), enabling the modelling of nonlinear patterns without assuming an initial curve shape. The analysis results indicate that a first-degree polynomial spline model (piecewise linear) with three knots successfully represents the bond yield response to inflation shocks with R^2 = 86.48%. Model segmentation identified four regimes: (1) Post-crisis recovery phase, with a negative relationship driven by Fed monetary stimulus suppresing yields despite initial inflation emergence; (2) Policy normalization phase, with a positive relationship aligned with monetary tightening in response to moderate inflation; (3) During the COVID-19 pandemic, a negative relationship due to a surge in demand for safe-haven bonds despite rising inflation; (4) Post-pandemic, the relationship turned positive again following the Fed's aggressive monetary tightening in response to high global inflation. These findings highlight the urgency of regime-based monitoring for investors and policymakers, while contributing concretely to SDG 8 (decent work and economic growth) through the facilitation of appropriate interest rate policies for sustainable macroeconomic stability, and supporting SDG 9 (industry, innovation, and infrastructure) through the identification of inflation patterns that strengthen shock-resistant infrastructure investment planning and financial innovation during turbulent economic transitions.

Crossref
https://doi.org/10.31764/jtam.v10i1.33020

A. INTRODUCTION

Inflation has become a critical global economic challenge. In the United States, inflation peaked at 9.1% in June 2022, the highest level in four decades, before falling to 3.3% in May 2024 (Azam & Khan, 2022). This volatility significantly disrupts macroeconomic stability and reduces purchasing power, particularly affecting long-term investment assets such as 10-year US Treasury Bonds. This extreme volatility increases uncertainty in global financial markets while underscoring the urgency of a comprehensive understanding of inflation transmission mechanisms.

The Consumer Price Index (CPI) is universally recognized as the primary indicator of inflation. As a measure of changes in the prices of essential commodities (housing, transportation, food), this index shows the main contributors to post-pandemic inflation (Ghodke, 2023). Meanwhile, the 10-year US Treasury Bond yields have served as a safe haven against stock market losses (Chang et al., 2022). The yield on US Treasury Bond fluctuated during the COVID-19 crisis, reach 4.5% in 2023 following the implementation of monetary tightening policies (Laumer & Schaffer, 2025), reflecting market confidence in the stability of the US economy and long-term inflation projections (Bekaert & Ermolovv, 2023).

Theoretically, an increase in CPI leading to higher nominal bond yields as investors demand higher returns to compensate for the decline in the purchasing power of future interest payments (Hetzel, 2017). However, in practice, this pattern is distorted by exogenous factors such as Quantitative Easing program (2013-2015), which suppressed yields despite stable inflation (Belke et al., 2017). Geopolitical shocks and global commodity supply instability further exacerbate this asymmetric distortion, creating nonlinear dynamics that require specialized modelling approaches (Suryavanshi, 2023).

This study models the nonlinear dynamics of CPI and 10-year US Treasury Bond yields using the Least Square Spline framework, which statistically the response curve into polynomial segments at optimized knot points (Utami et al., 2020). This approach captures structural breaks and relationship changes between variables, with error minimization per segment ensuring local precision (Mankowski & Moshkov, 2021), while the optimization of knot locations minimizes global approximation error through adaptive segmentation (Mohr et al., 2023). The spline's capacity to handle nonstationarity and avoid overfitting stems from its segment-based error minimization mechanism, which enhances parametric flexibility (Bantis et al., 2020).

Previous empirical research has validated the effectiveness of the spline approach in financial econometric modelling. Shelevytsky et al. (2020) demonstrated the superiority of the spline approach in estimating yield curves, achieving 98.7% accuracy on European Government Bond data and outperforming conventional parametric methods. Karčiauskas (2023) findings further validate the ability of the spline method to capture the nonlinearity of the relationship between inflation and bonds during the 2022 geopolitical crisis, with the spline model able to detect structural shifts that were not detected by linear regression identification. Although this empirical evidence confirms the superiority of splines in certain contexts, their application specifically for modelling the nonlinear relationship between Consumer Price Index (CPI) and the yield on 10-year US Treasury Bonds within the Least Square Spline remain relatively limited.

Based on empirical and methodological urgency in previous literature, this study aims to examine the complex dynamics of this relationship using the nonparametric least square spline method. The results of this analysis are expected to serve as the basis for formulating inflation risk mitigation strategies and adaptive monetary policies that support the achievement of SDG 8 (Decent Work and Economic Growth) through strengthening financial market stability. Additionaly, mapping inflation trends will support SDG 9 (Industry, Innovation, and Infrastructure), particularly in investment planning during turbulent economic transitions.

B. METHODS

1. Research Design and Data Source

This study employs secondary data from reputable and official databases, covering monthly time-series observations from January 2013 to March 2025. The dataset consists of the Consumer Price Index (CPI) obtained from the Federal Reserve Economic Data (FRED), developed and maintained by the Research Division of the Federal Reserve Bank of St. Louis, and the 10-year U.S. Treasury Bond Yields sourced from Investing.com, a global financial market platform established in 2007. The dependent variable (Y) is the 10-year Treasury Bond Yield, while the independent variable (X) is the CPI. The Least Squares Spline method was chosen because, after examining the scatterplot, the relationship between the two variables appeared does not follow a specific pattern, more flexible in following the shape of the data. Least Squares Spline is capable of producing smooth yet easily interpretable curves, as well as reducing the risk of overfitting through the adjustment of the number of knots and smoothing penalties. Thus, this method balances flexibility in capturing non-linear patterns and model readability, making it suitable for modelling the relationship between the two variables. The following Research Variables are shown in Table 1.

Table 1. Research Variables

Variable	Variable Description	Unit	Measurement Scale	Variable Type
Y	10-year US Treasury Bond Yields	Percent	Interval	Continuous
X	Consumer Price Index (CPI)	Index	Ratio	Continuous

2. Least Square Spline Formulation

One of the most popular approaches for determining the parameters of a regression model is the least squares method. The goal of the least squares principle for estimating parameters is to reduce the model's error so that the regression model can adequately describe the data (Marchelina et al., 2023). In greater detail, when the model is constructed using k knot points and a polynomial of order p, it can be formulated as follows:

$$g(x) = \sum_{j=0}^{p+k} \beta_j \varphi_j(x) \quad (1)$$

where $\boldsymbol{\beta} = \left(\beta_0, \beta_1, \dots, \beta_{p+k}\right)^T$ is the parameter vector that can be calculated in the following form:

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X^T X})^{-1} \boldsymbol{X^T} \quad (2)$$

where $\boldsymbol{X}$ is a matrix design with elements:

$$\boldsymbol{X} = \begin{pmatrix} 1 & x_1^1 & x_1^2 & \cdots & x_1^p & (x_1 - \tau_1)_+^p & \cdots & (x_1 - \tau_k)_+^p \\ 1 & x_2^1 & x_2^2 & \cdots & x_2^p & (x_2 - \tau_1)_+^p & \cdots & (x_2 - \tau_k)_+^p \\ \vdots & \vdots & \vdots & & & \vdots & & \\ 1 & x_n^1 & x_n^2 & \cdots & x_n^p & (x_n - \tau_1)_+^p & \cdots & (x_n - \tau_k)_+^p \end{pmatrix} \quad (3)$$

while φ_j may be described as follows:

$$\varphi_j = \begin{cases} x^j, & for\ 0 \le j \le p \\ (x-\tau_{j-p})_+^p, & for\ p+1 \le j \le p+k \end{cases} \tag{4}$$

with

$$(x-\tau_{j-p})_+^p = \begin{cases} (x-\tau_{j-p})^p & for\ x \ge \tau_{j-p} \\ 0, & for\ x < \tau_{j-p} \end{cases} \tag{5}$$

3. Model Validation Framework

a. Goodness of Fit Measures

In this study, the author applied two metrics, namely MSE and the coefficient of determination (R^2). he expected value of the model, expressed as the mean square error, can be measured using MSE. In addition, MSE can also be used to assess the accuracy of predictions between different forecasting methods. On the other hand, the coefficient of determination (R^2) serves to measure how much variation can be explained by the model. MSE is expected to have the lowest possible value, while the coefficient of determination (R^2) will be better if its value is close to 1 (Maharani & Saputro, 2021). The formula for MSE is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

while the coefficient of determination (R^2) formula is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{7}$$

b. Knot Selection Procedure

A knot point is defined as a meeting point or intersection where a change in data behavior occurs (Sifriyani et al., 2023). The best nonparametric regression model depends on the optimal knot point. The selection of the optimal node point in the Least Square Spline estimator can use the Generalized Cross Validation (GCV) method. The GCV function for the nonparametric spline regression model is as follows:

$$GCV = \frac{MSE}{\left(\frac{1}{n}tr[\boldsymbol{I}-\boldsymbol{H}]\right)^2} \tag{8}$$

where

$$\boldsymbol{H} = \boldsymbol{X}(\boldsymbol{X^T X})^{-1}\boldsymbol{X^T} \tag{9}$$

4. Statistical Validation

a. Parameter Significance Testing

Model parameter testing was conducted to evaluate whether the model of independent variables had a significant effect on the response variable. The following are the hypotheses used based on the nonparametric spline regression model.

$H_0: \beta_1 = \beta_2 = \cdots = \beta_j = 0$

H_1: There is at least one $\beta_j \neq 0,\ j = 1,2,\dots,n$

The test statistic used in this test is the F test statistic, which has the following formula.

$$F = \frac{MS_{regression}}{MS_{residual}} = \frac{\frac{\sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2}{j}}{\frac{\sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2}{n-j-1}} \tag{10}$$

Reject H_0 if F > $F_{\alpha;j;\,n-j-1}$ or $p - value < \alpha$.

Then, partial testing serves to identify whether the parameters individually have a significant influence on the response variable. The hypothesis used is as follows.

$H_0: \beta_j = 0$

$H_1:\ \beta_j \neq 0, \qquad j = 1,2,\dots,n$

The test statistics used in this test are as follows (Suhada et al., 2023).

$$t = \frac{\hat{\beta}_j}{\sqrt{SE(\hat{\beta}_j)}} \tag{11}$$

Reject H_0 if $|t| > t_{\frac{\alpha}{2};\,(n-j-1)}$ or $p\ -\ value\ <\ \alpha$.

b. Residual Diagnostics

Identical assumption testing is used to evaluate the uniformity of residual variance. This test uses the Glejser test (Sutopo & Slamet, 2017). The hypothesis used is as follows:

$H_0: \sigma_1^2 = \sigma_2^2\ = \cdots = \sigma_n^2 = \sigma^2$

H_1: There is at least one $\sigma_i^2 \neq \sigma^2,\ i = 1,2,\dots,n$

with the test statistics used as follows:

$$F = \frac{\frac{\left[\sum_{i=1}^{n}(|\hat{\varepsilon}_i|-|\bar{\varepsilon}|)^2\right]}{j-1}}{\frac{\left[\sum_{i=1}^{n}(|\hat{\varepsilon}_i|-|\bar{\varepsilon}|)^2\right]}{n-j}} \tag{13}$$

Reject H_0 if F > $F_{\alpha;j-1;\,n-j}$ or $p - value < \alpha$.

Then, the independent assumption test is used to determine the presence or absence of correlation between residuals and this test can use several ways, one of which is to do the Durbin-Watson test with the following hypothesis.

$H_0: \rho = 0$ (independent residuals)
$H_1: \rho \neq 0$ (dependent residuals)

The test statistics used in this test are as follows:

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \tag{14}$$

The decision rules in this test are as follows, if:
1) 0 < d < dL or (4 - dL) < d < 4, then reject H_0.
2) dU < d < (4 - dU), then fail to reject H_0.
3) dL ≤ d ≤ dU or (4 - dU) ≤ d < (4 - dL), then there is no decision to reject H_0 or fail to reject H_0.

The hypothesis used is as follows. Furthermore, testing the normal distribution assumption is an assumption test used to detect whether the residual data has followed a normal distribution. According Kurniawati & Budiantara (2019), this test can use the Kolmogorov-Smirnov test. The hypothesis used is as follows.
H_0: $F_0(x) = F(x)$ (residuals follow a normal distribution)
H_1: $F_0(x) \neq F(x)$ (residuals do not follow a normal distribution)

The test statistics used are as follows:

$$D = Sup|F_n(\varepsilon) - F_0(\varepsilon)| \tag{15}$$

Reject H_0 if $D > D_\alpha$ or $p - value < \alpha$.

5. Step of Analysis

Research Procedure for Modelling the Relationship between the Consumer Price Index (CPI) and 10-Year U.S. Treasury Bond Yields.

a. Preliminary Description of Variables
   1) Examine the concentration and spread of each variable (10-year Treasury yields and CPI) by calculating their mean, standard deviation, and range.
   2) Create a scatter plot showing the relationship between the dependent variable (10-year Treasury yield) and the independent variable (CPI) to visually assess the pattern or trend.

b. Nonparametric Regression Modelling Using the Least Squares Spline Estimator:
   1) Determine possible knot point combinations based on the visual patterns from the scatter plots.
   2) Identify the optimal knot point configuration by selecting the one with the smallest Generalized Cross Validation (GCV) value, as stated in equation (9).
   3) Estimate model parameters using the optimal knot points.
   4) Compute the coefficient of determination (R^2) to assess model fit.

5) Testing the significance of model parameters simultaneously with F test statistics in equation (11) and partially with t test statistics in equation (12).
6) Verify model assumptions of identical, independent, and normally distributed residuals (IIDN).
7) Formulate the final best-fit model equation.

c. Model Interpretation.
   a. Plot and compare the fitted values from the model against the actual observed data.
   b. Interpret the model's meaning and implications by analyzing the estimated parameter values.
   c. Draw conclusions and suggestions.

C. RESULT AND DISCUSSION

1. Descriptive Patterns and Nonlinear Pattern Identification

Based on data obtained from Fred and Investing.com. An overview of the Consumer Price Index (CPI) data and 10-year US Treasury Bond Yields on monthly data from January 2013 to March 2025 is obtained in Table 2 as follows.

Table 2. Descriptive Statistics

Variable	N	Mean	StDev	Minimum	Maximum
Consumer Price Index (CPI)	147	262.79764	27.895484	231.679	319.775
10-year US Treasury Bond Yields	147	2.49864	1.014877	0.533	4.926

Based on 147 observations, the Consumer Price Index (CPI) recorded an average value of 262.80 with a standard deviation of 27.90, indicating relatively low variation. The lowest CPI, 231.679, occurred in January 2013 during the early phase of economic recovery following the 2008–2009 Global Financial Crisis, while the highest value, 319.775, was recorded in February 2025. In comparison, the 10-year US Treasury Bond Yield averaged 2.49864 percent with a standard deviation of 1.014877 percent, also reflecting low volatility, reaching its minimum of 0.533 percent in July 2020 and peaking at 4.926 percent in October 2023, as shown in Figure 1.

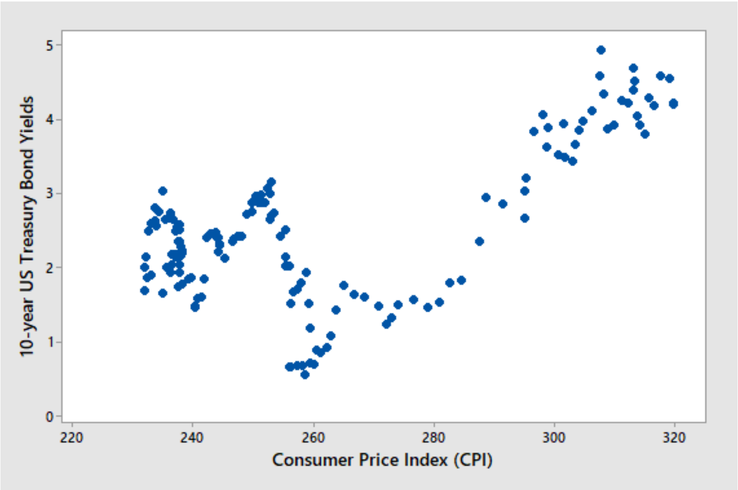

Figure 1. Scatterplot Data

From the scatter plot shown in Figure 1, the distribution of data points between the Consumer Price Index (CPI) and the 10-year U.S. Treasury Bond Yields does not exhibit a clear functional pattern. This suggests that a nonparametric regression approach, specifically the least squares spline estimator, is appropriate for modeling the relationship, as the data indicate changes in behavior across certain intervals.

2. Optimal Least Square Spline and Model Validation

The nonparametric regression model using the least squares spline estimator incorporates smoothing parameters, which include the placement of knot points and the selection of the polynomial degree. Knot points represent the location of the transition where changes in data behavior patterns occur. The selection of the best model is based on the minimum Generalized Cross Validation (GCV), Mean Squared Error (MSE) values, and the maximum coefficient of determination (R^2). The determination of the optimal knot points (1, 2, or 3 knots) is performed automatically by the program based on the optimization criteria of these three metrics. A small GCV value indicates the optimal selection of knot points, while a low MSE reflects minimal model error. On the other hand, a high R^2 indicates the model's ability to explain data variation. In this study, a first-order polynomial was used. The computational process and model selection were performed using R software. The result of the nonparametric least square spline regession analysis yielded model performance as shown by GCV, MSE, and R^2 in Table 3.

Table 3. Model Calculation with Least square Spline Estimator

Number of Knot	Knot Point	GCV	MSE	R^2
1	271.962	0.2810	0.2697	0.7364
2	252.772 258.352	0.1664	0.1574	0.8461
3	240.545 252.182 258.352	0.1483	0.1383	0.8648

Based on the optimization criteria in Table 3, the model with 3 knot points was selected as the optimal model. This model was then tested for parameter significance and residual assumptions to ensure its validity.

3. Statistical Validation

a. Parameter Significance Tests

After the optimal model was identified using the GCV, MSE, and R^2 criteria in Table 3 (model with 3 knots), parameter significance testing was performed to validate the model's feasibility. The fisrt stage was simultaneous significance testing (overall F-test), which aimed to test whether the model as a whole was significant in explaining data variation. The F-test results are presented in Table 4.

Table 4. Overall F-test

Source	DF	SS	MS	F	p-value
Regression	4	130.0393	32.5098	226.9922	<0.001
Residual Error	142	20.3372	0.1432		
Total	146	150.3765			

Based on Table 4, it is known that the p-value is <0.001 and the F is 226.9922, by comparing the p-value to α (0.05) and the F to $F_{0.05;4;142}$ which is 2.4354, the decision is to reject H_0. This indicates that at least one predictor has a significant effect on the 10-year US Treasury Bond yields. The next step is a partial significance test (partial t-test) to confirm the individual contribution of each coefficient. This test is performed on the five model coefficient (intercept β_0 and four spline coefficient β_1 to β_4). The t-test results are presented in Table 5 below:

Table 5. Partial t-Test

Source	Estimate	Std. Error	t	p-value	Decision
β_0	15.0921	4.6590	3.2393	0.0015	Significant
β_1	-0.0546	0.0197	-2.7748	0.0063	Significant
β_2	0.1438	0.0296	4.8495	<0.001	Significant
β_3	-0.4421	0.0327	-13.5221	<0.001	Significant
β_4	0.4159	0.0237	17.5356	<0.001	Significant

Based on Table 5, it is known that all p-values are less than the α (0.05) and all absolute t are greater than $t_{0.025;4;142}$ which is 1.9768, resulting in a decision to reject H_0. This means that all the predictor variables constructed have a significant effect on the 10-year US Treasury Bond yields.

b. Residual Diagnostic

1) Test for Homoscedasticity of Residuals

The homogeneity assumption test serves to assess whether residual variance maintains consistency or if heteroscedasticity issues are absent. The Glejser test methodology is employed to detect heteroscedasticity symptoms. This testing procedure involves creating a regression model between predictor variables and the absolute residual values, as shown in Table 6.

Table 6. Glejser Test

F Statistic	F Critical *Value* (α = 0.05)	*P value*
2.150	2.67	0.063

Since the p-value (0.063) exceeds the significance threshold of 0.05 and the calculated F-statistic (2.150) is lower than the critical F-value (2.67), there is insufficient evidence to reject the null hypothesis. This indicates that the residuals satisfy the homoscedasticity assumption, meaning the error variance remains constant across all values of the independent variables.

2) Test for Independence of Residuals
Independence assumption examination serves to verify the absence of serial correlation among residual values. The independence assumption assessment is conducted through the Durbin-Watson testing procedure, with findings displayed in the Table 7.

Table 7. Durbin-Watson Test

d	$d_{L(0,05)}$	$d_{U(0,05)}$	$4-d_{U(0,05)}$	$4-d_{L(0,05)}$
1.806	1.675	1.786	2.213	2.325

Given that the Durbin-Watson statistic (d = 1.806) falls within the range of $d_{U(0.05)}$ (1.786) and $4-d_{U(0.05)}$ (2.213), specifically $d_{U(0.05)} < d < 4-d_{U(0.05)}$, we can confidently conclude that there is no positive or negative autocorrelation among the residuals. This indicates that the residuals are independent.

3) Test for Normality of Residuals
Following the fulfillment of independence and identical assumptions, one additional requirement must be satisfied by the residuals: the normality distribution assumption. The Kolmogorov-Smirnov test represents one method available for assessing data normality, as shown in Table 8.

Table 8. Kolmogorov-Smirnov Test

D statistic	*Critical D value*	*P value*
0.035	11201.420	0.993

With a P value of 0.993, which is greater than the chosen significance level of 0.05, we fail to reject the null hypothesis. This outcome suggests that the residuals are normally distributed.

4. Final Model and Segment Interpretation

Based on the test results, the final model of the first-order nonparametric spline regression model with 3 knot points was obtained:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x + \hat{\beta}_2 (x-\tau_1)_+ + \hat{\beta}_3 (x-\tau_2)_+ + \hat{\beta}_4 (x-\tau_3)_+$$
$$\hat{y} = 15.0921 - 0.0546x + 0.1438 (x-240.545)_+ - 0.4421 (x-252.182)_+$$
$$+0.4159 (x-258.352)$$

Based on the calculation of the estimated model value for each segment, the model estimate in the form of a starcase function can be written as follows:

$$\hat{y} = \begin{cases} 15.0921 - 0.0546x, & x < 240.545 \\ -19.4983 + 0.0892x, & 240.545 \leq x < 252.182 \\ 91.9914 - 0.3531x, & 252.182 \leq x < 258.352 \\ -15.4572 + 0.0628x, & x > 258.352 \end{cases}$$

After the final model was formed, residual assumption testing was conducted to ensure that there were no violations of classical assumptions in the model. To further understand the movement pattern of 10-year US Treasury Bond post-COVID-19 pandemic, Figure 2 illustrates the dynamic trend analyzed using the spline regression approach. This figure shows important inflection points in the relationship between inflation and bond yields over the period January 2013 to March 2025.

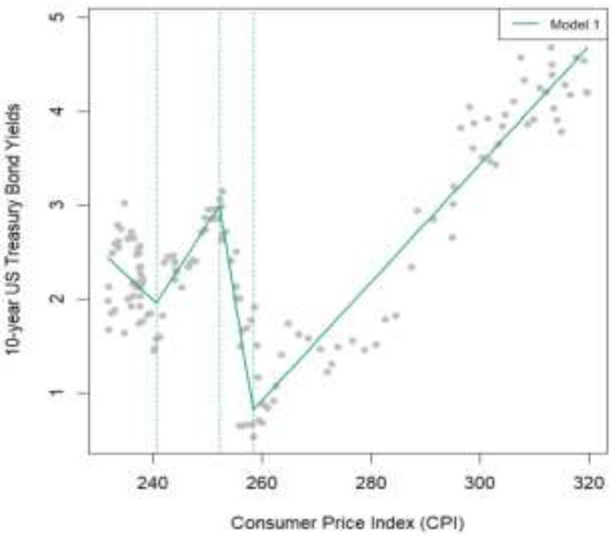

Figure 2. Value Plot Estimates and Observations

In general, the increase in CPI is the main driver of changes in bond yields in the observation period. The higher the CPI, the higher the market's inflation expectation, so investors demand inflation risk compensation through higher bond yields. However, this relationship is non-linear, as shown by the spline model divided into the following four segments:

a. Segment I (x < 240.545):
In this period, CPI is still at a low level, especially during the early post-crisis economic recovery (around 2013-2015). The model shows that every increase in CPI by 1 unit is followed by a decrease in yield by 0.0546. This reflects the condition when the Fed's monetary stimulus kept the yield low even though inflation started to increase slowly.

b. Segment II (240.545 ≤ x < 252.182):
In this interval, there is a shift in behavior. Every 1 unit increase in CPI causes an increase in yield by 0.0892. This period correlates with the normalization phase of the Fed's monetary policy (around 2016-2018), where an increase in inflation began to be responded to by an increase in the benchmark interest rate, so that bond yields also rose.

c. Segment III (252.182 ≤ x < 258.352):
In this range, there is an opposite relationship, where every increase in CPI by 1 unit is followed by a decrease in yield by 0.3531. This illustrates a transition period like the beginning of the COVID-19 pandemic (2020), where even though inflation is increasing due to supply disruptions, investors still seek safe haven in bonds, causing high demand and falling yields.

d. Segment IV ($x \geq 258.352$):
   At CPI above 258.352 (post-pandemic period, 2021-2025), the model again shows a positive relationship, where every 1 unit increase in CPI is followed by a 0.0628 increase in yield. This is consistent with the period of global high inflation, when aggressive monetary tightening by the Fed triggered a rise in bond yields.

Thus, the spline model shows that the effect of CPI on yield is not constant over time, but depends on the macroeconomic context. An increase in yield tends to follow an increase in CPI, but in some periods, other factors such as monetary intervention or market turmoil can temporarily reverse this relationship. The results of this study are consistent with the findings of (Krivobokova et al., 2006), who applied penalized spline regression to estimate the term structure of interest rates with high flexibility and accuracy. Although their research focused on modelling pure yield curves, while this study emphasizes the nonlinear relationship between inflation (CPI) and long-term bond yields, both approaches highlight the importance of using flexible, data-driven models to capture regime shifts and structural changes in financial markets. Therefore, this study supports existing literature on spline-based methods while offering additional insights into macro-financial interactions influenced by inflationary dynamics.

D. CONCLUSION AND SUGGESTIONS

This study demonstrates the success of modelling the nonlinear dynamics of the relationship between the Consumer Price Index (CPI) and the 10-year US Treasury yield using the least square spline approach, identifying three critical CPI points (≈ 240, 252, and 258) as structural transition thresholds for market response. From an economic perspective, this model explains 86.48% of yield variability and reveals four critical policy regimes: a negative response during the post-crisis stimulus period, a positive relationship during the normalization phase, a negative correlation during the pandemic, and a return to a positive response in the post-pandemic period. These findings serve as an early warning system for investors and the Fed when inflation reaches critical thresholds (≈ 240–258), where inflationary pressures trigger significant reactions in global markets. Therefore, the model significantly contributes to decent work and economic growth (SDG 8) through early detection of inflation risks and supports planning for industry, innovation, and infrastructure (SDG 9) in turbulent economic conditions.

For further research, it is recommended to integrate additional macroeconomic variables such as the Fed interest rate and GDP growth to strengthen the accuracy of predictions through multivariate variables. High-degree polynomial analysis is also needed to capture the complexity of the CPI-yield relationship that may have been overlooked, while expanding the historical data range to include the 2008 crisis period to test the model's robustness across various economic cycles. Implementing these recommendations will enrich inflation-resistant infrastructure financing strategies and the development of sustainable bond instruments during market turbulence.

ACKNOWLEDGEMENT

The authors would like to acknowledge the Undergraduate Statistics Program, Faculty of Science and Technology, Universitas Airlangga for providing a supportive environment that enabled the completion of this work. The computational process in this research was facilitated by the use of open-source analytical tools, which allowed for efficient model development and evaluation.

REFERENCES

Azam, M., & Khan, S. (2022). Threshold effects in the relationship between inflation and economic growth: Further empirical evidence from the developed and developing world. *International Journal of Finance and Economics*, *27*(4), 4224–4243. DOI: https://doi.org/10.1002/ijfe.2368

Bantis, L. E., Tsimikas, J. V., & Georgiou, S. D. (2020). Survival estimation through the cumulative hazard with monotone natural cubic spline using convex optimization-the HCNS approach. *Computer Methods and Programs in Biomedicine*, 190, Article 105357. https://doi.org/10.1016/j.cmpb.2020.105357

Bekaert, G., & Ermolov, A. (2023). International Yield Comovements. *Journal of Finance and Quantitative Analysis*, *58*(1), 250–288. https://doi.org/10.1017/S0022109022000515

Belke, A., Gros, D., & Osowski, T. (2017). The effectiveness of the Fed's quantitative easing policy: New evidence based on international interest rate differentials. *Journal of International Money and Finance*, *73*, 335–349. https://doi.org/10.1016/j.jimonfin.2017.02.011

Chamidah, N., & Lestari, B. (2022). *Analisis Regresi Nonparametrik dengan Perangkat Lunak R* (Z. Abadi, A. Riyanto, & R. Wahyudi, Eds.; pp. 91–103). Airlangga University Press.

Chang, M. S., Ju, P., Liu, Y., & Hsueh, S. C. (2022). Determining hedges and safe havens for stocks using interval analysis. *North American Journal of Economics and Finance*, 61, 286 – 293. https://doi.org/10.1016/j.najef.2022.101671

Ghodke, M., & Giri, P. (2023). Consumer Price Index (CPI) – Types & Sources*. Indian Journal of Community Health*, 35(4), 520–525. https://doi.org/10.47203/IJCH.2023.V35I04.020

Hetzel, R. L. (2017). *Indexed bonds as an aid to economic policy*. In Handbook of Debt Management (pp. 781–792). Taylor and Francis.

Laumer, S., & Schaffer, M. (20hetzelbelke25). Monetary policy transmission under supply chain pressure. *European Economic Review*, *172*, 410 – 420. https://doi.org/10.1016/j.euroecorev.2024.104949

Karčiauskas, K. (2023). Quadratic-Attraction Subdivision. *Computer Graphics Forum*, *42*(5), 644—657. https://doi.org/10.1111/cgf.14900

Krivobokova, T., Kauermann, G., & Archontakis, F. (2006). Estimating the term structure of interest rates using penalized splines. *Statistical Papers, 47*(3), 443–457. https://doi.org/10.1007/s00362-006-0297-8

Maharani, M., & Saputro, D. R. S. (2021). Generalized Cross Validation (GCV) in Smoothing Spline Nonparametric Regression Models. *Journal of Phsics:Conference Series*, *1808*(1). https://doi.org/10.1088/1742-6596/1808/1/012053

Mankowski, M., & Moshkov, M. (2021). Segmented Least Squares. In *Studies in Systems, Decision and Control* (Vol. 331, pp. 147–156). Springer Science and Business Media Deutschland GmbH.

Marchelina, R., Bakar, N., & Asfa'ani, E. (2023). Karakteristik Solusi Kuadrat Terkecil. *MAp (Mathematics and Applications) Journal*, *5*(2), 127–136. https://doi.org/10.15548/map.v5i2.7045

Mohr, R., Coblenz, M., & Kirst., Peter. (2023). Globally optimal univariate spline approximations. *Computational Optimization and Application*, 85(2), 409 – 439. DOI: https://doi.org/10.1007/s10589-023-00462-7

Rogan, K. J. (2025). Fictions of the market: The shelter component of the consumer price index in theory and practice. *Journal Human Geography (United Kingdom)*. *33*(1), 1–???. https://doi.org/10.1177/19427786251316868

Shelevytsky, I., Shelevytska, V., Semenva, K., & Bykov, I. (2020). Regression Spline-Model in Machine Learning for Signal Prediction and Parameterization. *Advances in Interlligent Systems and Computing*, 158–174. https://doi.org/10.1007/978-3-030-26474-1_12

Sifriyani, Sari, A. R. M., Dani, A. T. R., & Jalaluddin, S. (2023). Bi-Response Truncated Spline Nonparametric Regression With Optimal Knot Point Selection Using Generalized Cross-Validation in Diabetes Mellitus Patient'S Blood Sugar Levels. *Communications in Mathematical Biology and Neuroscience*, *2023*, 1–18. https://doi.org/10.28919/cmbn/7903

Suhada, A., Syafriandi, Vionanda, D., & Fitri, F. (2023). Modeling Open Unemployment Rate in West Sumatera Province Using Truncated Spline Regression. *UNP Journal of Statistics and Data Science*, *1*(1), 39–44. https://doi.org/10.24036/ujsds/vol1-iss1/3

Suryavanshi, S. (2023). A study of Fisher Effect in India. *Journal Indian Economic Review*, *58*, 485–503. DOI: https://doi.org/10.1007/s41775-023-00180-1

Sutopo, E., & Slamet, A. (2017). *Inferential Statistics*. Andi Publisher.

Utami, T. W., Haris, M. A., Prahutama, A., & Purnomo, E. A. (2020). Optimal knot selection in spline regression using unbiased risk and generalized cross validation methods. In D. Nurhadiyanto, Sutopo, B. R. Setiadi, & H. Pratiwi (Eds.), *Journal of Physics: Conference Series* (pp. 12–49). Institute of Physics Publishing. https://doi.org/10.1088/1742-6596/1446/1/012049