International Journal of Academic and Applied Research (IJAAR)
ISSN: 2643-9603
Vol. 10 Issue 10, October - 2026, Pages: 154-162

Modeling Inflation and Interest Rates in BRICS Countries Using Nonparametric Biresponse Truncated Spline Regression on Panel Data

Suliyanto[1], Dita Amelia [1], Ailsa Shafa Salsabila[1], Refa Berliana Putri[1]

[1]Department of Mathematics, Faculty of Science and Technology, Universitas Airlangga, Surabaya, Indonesia
suliyanto@fst.unair.ac.id, dita.amelia@fst.unair.ac.id, ailsa.afa.salsabila-2023@fst.unair.ac.id, refa.berliana.putri-2023@fst.unair.ac.id

Abstract: *BRICS is a group of emerging economies that plays a significant role in the global economy. However, its integration with the global economic system makes its member countries vulnerable to various shocks, including the COVID-19 pandemic, the Russia–Ukraine geopolitical conflict, and public debt dynamics, all of which may affect macroeconomic stability, particularly inflation and interest rates. This study aims to investigate the influence of geopolitical and economic factors on inflation and interest rates in BRICS countries to provide insights for formulating policies that support macroeconomic stability. The study employs a nonparametric biresponse truncated spline regression approach using panel data from five BRICS countries covering the period 2016–2025. The result indicates that the best model is a first-order truncated spline with two knot points for each of the first three predictors and three knot points for the fourth, achieving the minimum Generalized Cross Validation (GCV) value and a coefficient of determination* R^2 *of 99.60043%. Furthermore, the model demonstrates that geopolitical and economic factors can simultaneously capture the nonlinear relationships with inflation and interest rates, thereby providing a more comprehensive representation of the response variables. Therefore, truncated spline biresponse nonparametric regression can serve as an alternative approach for modeling inflation and interest rates in BRICS countries and provide insights to support the formulation of more adaptive economic policies in response to global dynamics.*

Keywords—BRICS; Inflation; Interest Rates; Nonparametric Biresponse Truncated Spline Regression; Panel Data

1. INTRODUCTION

BRICS is an international political organization established with the aim of providing developing countries with the opportunity to play a greater role in the global economy. As it has evolved, BRICS has become a forum for cooperation in addressing various global issues and promoting a more balanced world economic order that is not dominated by Western countries [1], [2]. BRICS accounts for approximately 40% of the world's population, 25% of global gross domestic product (GDP), 18% of world trade, and global foreign exchange reserves totaling around US$4 trillion. However, this close integration with the global economy also makes BRICS countries vulnerable to various global economic shocks.

In recent years, the global economy has faced various challenges, such as the COVID-19 pandemic [3]. Geopolitical tensions stemming from the Russia–Ukraine conflict [4], public debt Dynamics [5], and various other factors. These events have increased economic uncertainty and put pressure on economic stability in various countries, including the BRICS nations.

These pressures can be examined through inflation and interest rates as macroeconomic indicators that are subject to fluctuations. The relationship between inflation and interest rates is explained by the Fisher Effect theory, which states that changes in inflation expectations will be followed by changes in nominal interest rates [6]. The interconnection between inflation and interest rates indicates that both indicators play a crucial role in maintaining macroeconomic stability. Therefore, understanding the dynamics of inflation and interest rates is a crucial aspect to consider when assessing the economic conditions of BRICS countries.

Several previous studies have identified various factors that influence inflation and interest rates. [7] state that public debt and global geopolitical risks are strongly associated with significant increases in inflation. Furthermore, a study by [8] indicates that exchange rates have a long-term relationship with inflation. Additionally, [9] note in their research that economic growth, as indicated by GDP growth, has a significant impact on inflationary pressures of a country.

In addition to affecting inflation, various studies have also shown that economic and external factors can influence interest rates as a monetary policy instrument. [10] note in their study that geopolitical conditions can influence central banks' decisions to adjust interest rate and liquidity policies. Furthermore, [11] discuss the relationship between exchange rates and interest rates in their study. In the long run, exchange rates and interest rates exhibit a strong, stable, yet asymmetric relationship. Furthermore, [12] conducted a study on the effect of GDP growth on interest rates in the world's largest economies. The results show that GDP growth and interest rates are positively correlated, meaning that GDP growth is followed by an increase in interest rates.

Based on these various studies, it can be concluded that economic factors such as gross domestic product (GDP) growth, the nominal effective exchange rate (NEER), and government debt are correlated with inflation and interest rate dynamics. Furthermore, developments in the global landscape

indicate that non-economic factors, such as geopolitical risk, also have the potential to affect a country's macroeconomic stability. Therefore, this study uses GDP, NEER, government debt, and the Geopolitical Risk Index (GPR Index) as predictor variables to model inflation and interest rates in BRICS countries.

Although various studies have examined the factors influencing inflation and interest rates, most focus on a single response variable and do not consider the relationship between the two simultaneously. Among the few studies employing a biresponse nonparametric approach, [13] used nonparametric biresponse truncated spline regression to model inflation and the IHSG in Indonesia, but relied on single-entity time-series data and did not include interest rates or non-economicpredictors. [14] applied a similar biresponse truncated spline approach across 34 Indonesian provinces, yet their data were purely cross-sectional (a single year, 2021) , and the authors themselves noted that extending the method to longitudinal data remained an open direction for future work. A genuine panel data application only appeared very recently in [15], who modeled three Indonesian banks and explicitly described their work as the first of its kind—evidence thatpanel-based extensions of biresponse truncated spline regression remain uncommon in the literature.

Beyond this methodological gap, the relationship between macroeconomic indicators and their determinants is often complex and does not always follow a specific parametric pattern, and this complexity is further compounded when observed across multiple countries due to heterogeneous economic conditions and differing global dynamics. This study therefore addresses these combined gaps by applying nonparametric truncated spline regression to biresponse panel data to model inflation and interest rates simultaneously across BRICS countries—extending prior work beyond single-response, single-entity, or cross-sectional settings, while leveraging both cross-country and cross-period information to better capture cross-country heterogeneity.

Beyond the biresponse panel-data approach itself, this study also broadens the predictor set by combining economic and geopolitical factors—Gross Domestic Product (GDP), the Nominal Effective Exchange Rate (NEER), government debt, and the Geopolitical Risk Index (GPR Index). The inclusion of the GPR Index is particularly noteworthy, as it captures uncertainty stemming from conflicts, political tensions, and other global geopolitical events that may affect economic stability. The observation period, spanning 2016 to 2025, further covers major global disruptions such as the COVID-19 pandemic and the Russia–Ukraine conflict, allowing the study to capture how economic and geopolitical factors relate to inflation and interest rates under conditions of heightened global uncertainty. The resulting findings are expected to support the formulation of economic policies that are more adaptive to global shocks and to contribute to the Sustainable Development Goals (SDGs), particularly Goal 8 (Decent Work and Economic Growth) and Goal 16 (Peace, Justice, and Strong Institutions).

2. METHODS

2.1 Data Type and Source

The data used in this study are secondary data from various sources. Data on inflation, interest rates, and the government debt-to-GDP ratio were obtained from the Trading Economics website, Geopolitical Risk Index data was obtained from the Economic Policy Uncertainty website, Nominal Effective Exchange Rate (NEER) data was obtained from the Bank for International Settlements (BIS) website, and Gross Domestic Product (GDP) growth data was obtained from the Worldometer website.The research variables used in this study include response variables and predictor variables on a ratio scale, as presented in Table 1 below.

Table 1. Research Variables

Variable	Operational Definition	Unit
Inflation (Y_1)	The general and continuous rate of price increases in a country	Percent (%)
Interest Rate (Y_2)	The benchmark interest rate set by a country's commercial banks	Percent (%)
Geopolitical Risk Index ($X_!$)	A global geopolitical risk index based on the frequency of discussions regarding conflicts, international tensions, and military threats	Index
Nominal Effective Exchange Rate (X_2)	The nominal effective exchange rate of a country's cur rency against the currencies of its trading partners, cal culated using a volume-weighted average based on trade volume	Index

Variable	Operational Definition	Unit
Percentage of Government Debt (X_3)	Debt issued or guaranteed by a country's government	Percent (%)
Gross Domestic Product (X_4)	The total value of goods and services produced by a country during a specific period, usually one year	Percent (%)

2.2 Research Steps

Thestagesofanalysisusedinthisstudycorrespondtothefollowingresearchsteps.

1. Describe the characteristics of the data using the mean, standard deviation, maximum value, minimum value, and range.
2. Detect multicollinearity using the VIF value. If the VIF value is greater than 10, it can be concluded that multicollinearity exists in a predictor variable [16]. The VIF value is calculated as follows

$$VIF_j = \frac{1}{1 - R_j^2}, j = 1,2, \dots, k \quad (1)$$

Where R_j^2 is the coefficient of determination for the regression of predictor variable X_j on the other predictor variables.

3. Create a scatter plot to identify whether there is a pattern of relationship between the response variable and the predictor variables.
4. Conduct a Pearson correlation test between the response variables using the following formula

$$r_{12} = \frac{\sum_{i=1}^{N}\sum_{t}^{T} y_{1it}y_{2it} - (\bar{y}_1..)(\bar{y}_2..)}{\sqrt{(\sum_{i=1}^{N}\sum_{t}^{T} y_{1it}^2 - \bar{y}_{1it}^2..)(\sum_{i=1}^{N}\sum_{t}^{T} y_{2it}^2 - \bar{y}_{1it}^2..)}} \quad (2)$$

where

r_{12} is the Pearson correlation coefficient between the response variables Y_1 and Y_2
n is the number of samples or observations.
y_{1it} is the value of the first response variable for the i-th and individual at the t-th time period.
y_{2it} is the value of the second response variable for the i-th and individual at the t-th time period.
$\bar{y}_1..$ $\bar{y}_2..$ are the mean value of the first and second response variables, respectively.

5. Determine the optimal combination of polynomial order and number of knot points for each predictor variable.
6. Constructing the weighting matrix **V**

The weighting matrix **V** is constructed based on the covariance matrix of the errors of the two response variables. The weighting matrix **V** is expressed as follows.

$$\boldsymbol{V} = \boldsymbol{D} \otimes \boldsymbol{I}_T = \begin{pmatrix} \boldsymbol{D}_{(1)} & \boldsymbol{D}_{(12)} \\ \boldsymbol{D}_{(21)} & \boldsymbol{D}_{(2)} \end{pmatrix} \otimes \boldsymbol{I}_T \quad (3)$$

where

$\boldsymbol{D}_{(1)} = \text{diag}\left(\sigma_{1(1)}^2, \sigma_{2(1)}^2, \dots, \sigma_{N(1)}^2\right)$, with $var\left(\varepsilon_{it}^{(1)}\right) = \sigma_{i(1)}^2$ denoting the error variance of response 1 for the i-th individual
$\boldsymbol{D}_{(2)} = \text{diag}\left(\sigma_{1(2)}^2, \sigma_{2(2)}^2, \dots, \sigma_{N(2)}^2\right)$, with $var\left(\varepsilon_{it}^{(2)}\right) = \sigma_{i(2)}^2$ denoting the error variance of response 2 for the i-th individual
$\boldsymbol{D}_{(12)} = \text{diag}\left(\sigma_{1(12)}^2, \sigma_{2(12)}^2, \dots, \sigma_{N(12)}^2\right)$, with $cov\left(\varepsilon_i^{(1)}, \varepsilon_i^{(2)}\right) = \sigma_{i(12)}^2$ denoting the error covariance of response 1 and response 2 fot the i-th individual
The error structure in the nonparametric, two-response, truncated spline panel regression model is adjusted for the dimensions of country and time in the research data. Temporal dependence in the residuals is assumed not to exist, so that the residuals for a given country in a specific period are not correlated with the residuals from the previous period. Cross-sectional dependence is also assumed not to exist, so that the residuals from different countries in the same period are considered uncorrelated with one another. Furthermore, the model structure accommodates heteroscedasticity a cross-countries, characterized by the fact that the variances of the error terms for response 1and response 2 differ for each country.

7. Determine the optimal knot points by minimizing the GCV and MSE, as expressed below

$$GCV(\tau) = \frac{MSE(\tau)}{\left[\frac{1}{qNT} tr\left(\boldsymbol{I} - \boldsymbol{A}(\tau)\right)\right]^2} \quad (4)$$

where

$$MSE(\tau) = \frac{1}{qNT}\sum_{m=1}^{q}\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{mit} - \hat{y}_{mit})^2 \quad (5)$$

International Journal of Academic and Applied Research (IJAAR)
ISSN: 2643-9603
Vo 10 Issue 7, July – 2026, Pages: 1-1

and $\boldsymbol{A}(\tau)$ is the smoother (hat matrix) associated with the selected knot configuration, obtained from the relationship $\boldsymbol{y} =. \boldsymbol{A}(\tau)\boldsymbol{y}$

$$\boldsymbol{A}(\tau) = \boldsymbol{X}_\tau(\boldsymbol{X}_\tau^T\boldsymbol{V}^{-1}\boldsymbol{X}_\tau)^{-1}\boldsymbol{X}_\tau^T\boldsymbol{V}^{-1} \quad (6)$$

Knot points were selected using an equally-spaced grid search, while the number of knots was determined using an exhaustive search of all possible combinations, with the combination yielding the minimum GCV selected as the final model structure.

8. Calculate the coefficient of determination (R^2) for the response variable.
9. Estimate the best model parameters based on a combination of the optimal number of knots and the highest R^2 value obtained according to the following calculation [14].

$$R^2 = \frac{\sum_{m=1}^{q}\sum_{i=1}^{N}\sum_{t=1}^{T}(\hat{y}_{mit} - \bar{y}_{m\cdot\cdot})^2}{\sum_{m=1}^{q}\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{mit} - \bar{y}_{m\cdot\cdot})^2} \quad (7)$$

where
y_{mit} is the observed value of the m-th response variable for the i-th cross-sectional unit at the t-th time period.
$\hat{y}_{mit}$ is the estimated value of the m-th response variable for the i-th cross-sectional unit at the t-th time period.
$\bar{y}_{m\cdot\cdot}$ is the overall mean of the m-th response variable.

10. Estimate the best truncated biresponse spline model for each response variable using panel data. In general, a truncated biresponse spline model is expressed as follows.

$$\begin{aligned} y_{it}^{(1)} &= f_1(x_{1it}) + f_1(x_{2it}) + \cdots + f_1(x_{pit}) + \varepsilon_{1it} \\ y_{it}^{(2)} &= f_2(x_{1it}) + f_2(x_{2it}) + \cdots + f_2(x_{pit}) + \varepsilon_{2it} \\ &\vdots \\ y_{it}^{(q)} &= f_q(x_{1it}) + f_q(x_{2it}) + \cdots + f_q(x_{pit}) + \varepsilon_{qit} \end{aligned} \quad (8)$$

11. Interpreting the truncated biresponse spline nonparametric regression model for panel data.

3. Result and Discussion

3.1 Descriptive Statistics

Descriptive analysis of the research data was conducted to obtain an overview of the characteristics of the variables used. The results of the descriptive statistics are presented in Table 2 below.

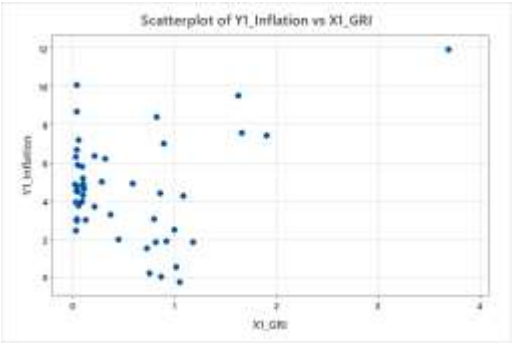
Table 2. Descriptive Statistics

Variable	Mean	St Dev	Min	Median	Max
Y_1	4.612	2.58136	-0.23	4.535	11.92
Y_2	7.1812	3.98157	2	6.5	21
$X_!$	0.5118	0.67705	0.02	0.17	3.69
X_2	105.787	10.5758	86.585	104.986	140.055
X_3	61.4554	25.5571	12.1	71.19	99.2
X_4	3.0964	3.61757	-6.17	3.065	9.69

Based on the results in Table 3, the inflation variable (Y_1) indicates differences in inflation rates among BRICS member countries during the study period. The interest rate variable (Y_2) also shows significant differences among countries, reflecting the diversity of monetary policies implemented. The Geopolitical Risk Index variable (X_1) reflects fluctuations in geopolitical risk experienced by BRICS countries, while the nominal effective exchange rate variable (X_2) reflects differences in effective exchange rates among countries. In addition, the percentage of government debt (X_3) and Gross Domestic Product (GDP) growth (X_4) show considerable variation, reflecting differences in fiscal conditions and economic growth among BRICS member countries during the 2016–2025 period.

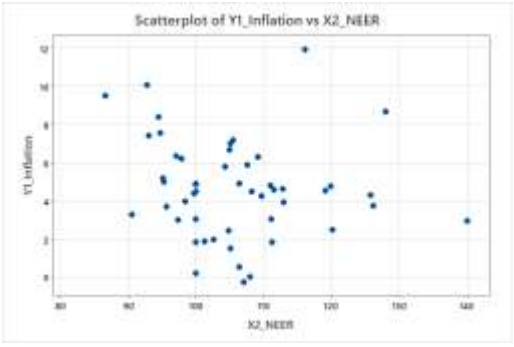
3.2 Scatterplot of Predictor Variables and Response Variables

To visualize the distribution of each predictor variable with respect to the first response variable, scatterplots are presented in Fig. 1.

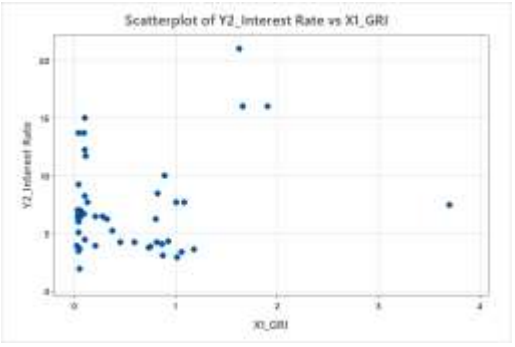


(a) Relationships between X_1 and Y_1

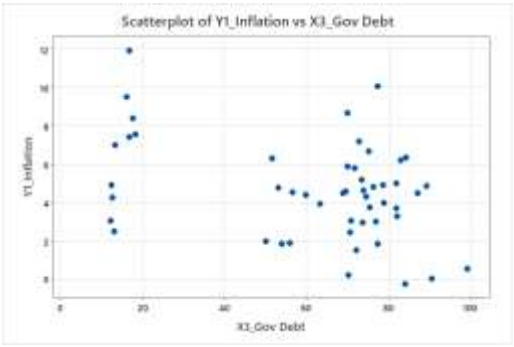
International Journal of Academic and Applied Research (IJAAR)
ISSN: 2643-9603
Vo 10 Issue 7, July – 2026, Pages: 1-1



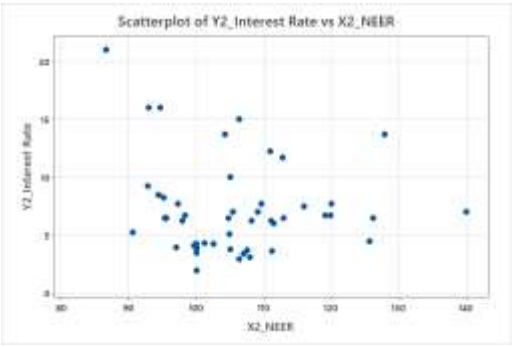
(b) Relationships between X_2 and Y_1



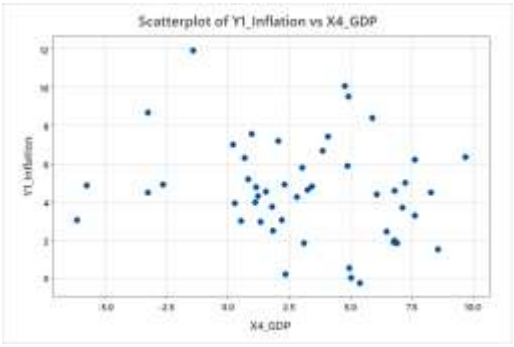
(a) Relationships between X_1 and Y_2



(c) Relationships between X_3 and Y_1



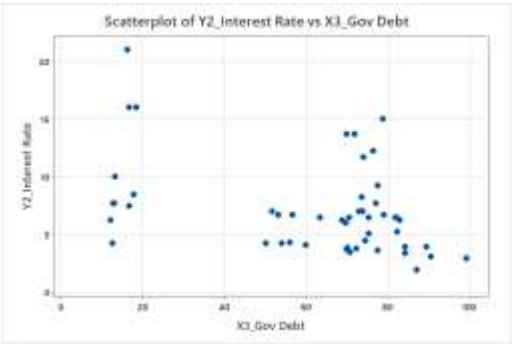
(b) Relationships between X_2 and Y_2



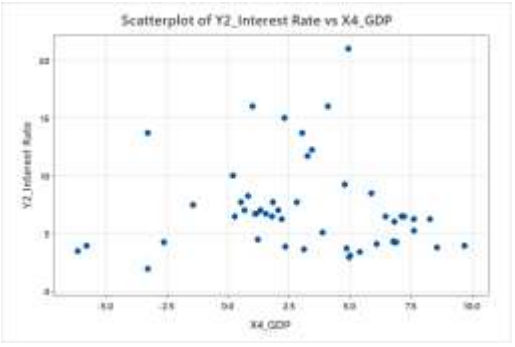
(d) Relationships between X_4 and Y_1

Fig. 1. *Scatterplots illustrating the relationships between (a) X_1 and Y_1, (b) X_2 and Y_1, (c) X_3 and Y_1, and (d) X_4 and Y_1.*

As shown in Fig. 1, the relationships between the predictor variables and the first response variable do not exhibit any distinct functional pattern and appear to be randomly scattered. This indicates that the truncated spline nonparametric regression approach for panel data is appropriate for modeling the relationship. Furthermore, to examine the distribution of each predictor variable with respect to the second response variable, the corresponding scatterplots are presented in Fig. 2.



(c) Relationships between X_3 and Y_2



(d) Relationships between X_4 and Y_2

Fig. 2. *Scatterplots illustrating the relationships between (a) X_1 and Y_2, (b) X_2 and Y_2, (c) X_3 and Y_2, and (d) X_4 and Y_2.*

International Journal of Academic and Applied Research (IJAAR)
ISSN: 2643-9603
Vo 10 Issue 7, July – 2026, Pages: 1-1

As shown in Fig. 2, the relationships between the predictor variables and the second response variable do not exhibit any distinct functional pattern and appear to be randomly scattered. These findings suggest that the truncated spline nonparametric regression approach for panel data is suitable for modeling the relationship between the predictor variables and the second response variable.

3.3 Pearson's Correlation Test

Before constructing the truncated spline biresponse nonparametric regression model for panel data, the relationship between the response variables was first examined using the Pearson correlation test. The results are presented in Table 3.

Table 3. Results of the Pearson Correlation Test

	Correlation Coefficient	P-Value
Y1 and Y2	0.574	0.000

To examine the linear relationship between inflation (Y1) and interest rates (Y2), the Pearson correlation test was performed. The analysis yielded a Pearson correlation coefficient (r) of 0.574 with a statistically significant (p-value) of 0.000.

3.4 Best Model Selection

The optimal model was selected by identifying the combination of polynomial order and knot locations for each predictor variable that yielded the minimum Generalized Cross Validation (GCV) and Mean Squared Error (MSE) values. The selection process was performed iteratively by considering polynomial orders up to the third order and a maximum of three knot locations to maintain model parsimony. To illustrate the model selection process, the GCV values obtained from all evaluated combinations of polynomial orders and knot locations are presented in Fig. 3.

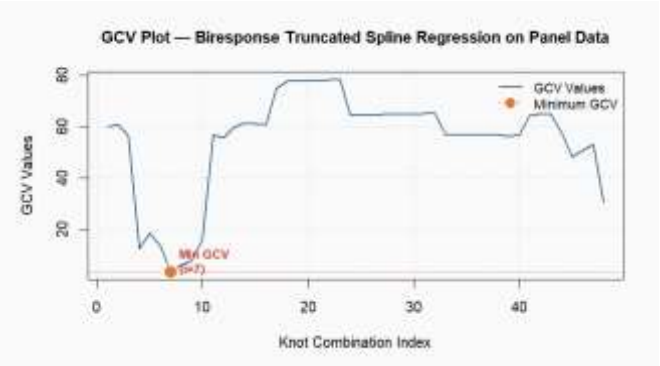


Fig. 3. *Generalized Cross Validation (GCV) values for all evaluated combinations of polynomial orders.*

As shown in Figure 3, the minimum GCV value of 3.521478 was achieved by the seventh model combination. The optimal polynomial order and number of knots for each predictor variable were determined globally through the GCV minimization process, resulting in a first-order polynomial with two knots for X1, X2, and X3, and three knots for X4, applied consistently across all five countries. However, the specific knot locations were estimated separately for each country, as presented in Table 4, allowing the model to capture heterogeneous relationships between the predictors and the response variables across BRICS countries. This indicates that the GCV-based selection process did not merely favor the most complex model configuration, but instead selected a relatively simpler one, suggesting that the explanatory power of the resulting model does not stem from excessive flexibility. The corresponding polynomial orders and optimal knot locations for each predictor variable a cross the five countries a represented in Table 4 below.

Table 4. Optimal Polynomial Order and Knot Points

Country	Polynomial Order				Optimal Knot Points Country			
	X_1	X_2	X_3	X_4	X_1	X_2	X_3	X_4
Brazil	1	1	1	1	0.067	110.787	76.354	-0.983
					0.09	126.547	82.054	1.027
								3.037
China	1	1	1	1	0.728	104.05	68.743	4.117
					0.971	107.91	85.143	5.672
								7.227
India	1	1	1	1	0.153	98.508	76.568	-1.36
					0.27	105.48	83.391	2.508
								6.375
Russia	1	1	1	1	1.771	99.344	14.462	-0.216
					2.804	110.508	16.529	1.914
								4.044
South Africa	1	1	1	1	0.068	104.573	62	-3.019
					0.101	112.844	71.1	-0.261

International Journal of Academic and Applied Research (IJAAR)
ISSN: 2643-9603
Vo 10 Issue 7, July – 2026, Pages: 1-1

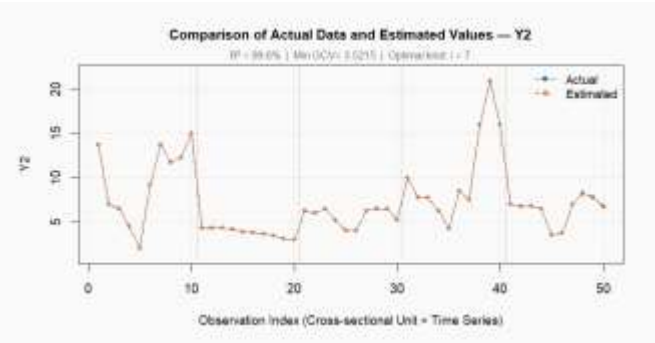
Country	Polynomial Order				Optimal Knot Points Country			
	X_1	X_2	X_3	X_4	X_1	X_2	X_3	X_4
								2.496

After determining the optimal combination of spline polynomial order and knot points, the next step is to estimate the parameters of the truncated spline nonparametric regression model for the panel data. Each of the five regions observed over a ten-year period has its own set of parameters corresponding to the spline polynomial order and knot points described in Table 5.

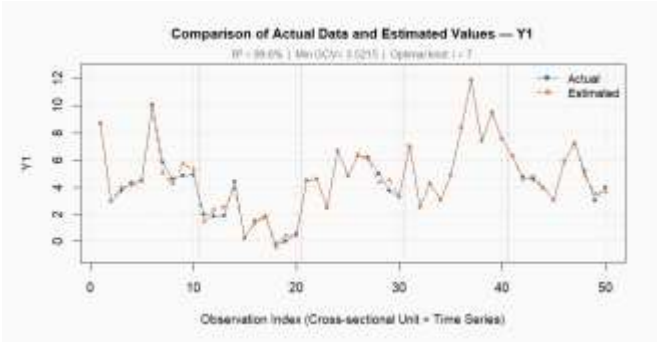
Table 5. Estimated Parameter Results for Russia

Parameters for Response-1		Parameters for Response-2	
α_{1410}	-0.005	α_{2410}	1.506
α_{1411}	0.946	α_{2411}	0.908
β_{111}	0.237	β_{121}	-4.390
β_{211}	0.235	β_{221}	-1.179
⋮	⋮	⋮	⋮
β_{314}	1.260	β_{324}	1.556

The model achieved an R^2 value of 99.60043%, indicating that 99.60043% of the variability in the two response variables is explained by the four predictor variables included in the model, while the remaining 0.39957% is attributable to factors not accounted for by the model. To further assess the model's performance visually, a comparison between the actual and estimated values is presented in Fig. 4.



(a) Response variable Y_1



(b) Response variable Y_2

Fig. 4. *Comparison between the actual and estimated values for (a) response variable Y1 and (b) response variable Y2.*

As shown in Figure 4, the estimated values closely follow the pattern of the actual data for both response variables. The close agreement between the actual and estimated values across nearly all observations indicates that the proposed truncated spline biresponse nonparametric regression model for panel data provides highly accurate estimates.

Next, the obtained model will be interpreted. The interpretation is conducted for each predictor variable, assuming the other predictor variables are constant. Given the large number of observation regions and parameters, this study will only illustrate the model for Russia as the country with the highest inflation rate and interest rate in 2025. Based on the parameter estimation results, the following truncated spline nonparametric regression model was obtained from the panel data for Russia:

$$\begin{aligned}\hat{y}_{4,t}^{(1)} = {} & -0.005 + 0.946x_{14t} + 0.237(x_{14t} - 1.771)_+ + 0.235(x_{14t} - 2.804)_+ - 0.165x_{24t} \\ & + 0.323(x_{24t} - 99.344)_+ - 0.417(x_{24t} - 110.508)_+ + 1.695x_{34t} - 1.888(x_{34t} - 14.462)_+ \\ & - 0.107(x_{34t} - 16.529)_+ + 0.123x_{44t} - 1.717(x_{44t} + 0.216)_+ + 1.736(x_{44t} - 1.914)_+ \\ & + 1.260(x_{44t} - 14.044)_+ \end{aligned} \quad (9)$$

$$\begin{aligned}\hat{y}_{4,t}^{(2)} = {} & 1.506 + 0.908x_{14t}4.390(x_{14t} - 1.771)_+ - 1.179(x_{14t} - 2.804)_+ - 0.8505x_{24t} + 1.130(x_{24t} - 99.344)_+ \\ & - 0.870(x_{24t} - 110.508)_+ + 6.444x_{34t} - 7.257(x_{34t} - 14.462)_+ - 1.998(x_{34t} - 16.529)_+ \\ & - 0.761x_{44t} + 2.623(x_{44t} + 0.216)_+ - 5.280(x_{44t} - 1.914)_+ + 1.556(x_{44t} - 14.044)_+ \end{aligned}$$

Based on Eq.(9),the prediction from the truncated biresponse spline nonparametric regression model for panel data for Russia in 2025 is obtained if $x_1 = 1.66$, $x_2 = 94.683$, $x_3 = 18.3$, and $x_4 = 0.98$, withcut-off $x_{1,4t} < 1.771$, $x_{2,4t} < 99.344$, , and $-0.216 < x_{4,4t} < 1.914$, the estimated model is given as follows.

$$\begin{aligned}\hat{y}_{4,t}^{(1)} &= -0.005 + 0.946x_{14t} - 0.165x_{24t} + 1.695x_{34t} - 1.888(x_{34t} - 14.462) - 0.107(x_{34t} - 16.529) + 0.123x_{44t} \\ &\quad - 1.717(x_{44t} + 0.216), \\ \hat{y}_{4,t}^{(2)} &= 1.506 + 0.908x_{14t} - 0.850x_{24t} + 6.444x_{34t} - 7.257(x_{34t} - 14.462) - 1.998(x_{34t} - 16.529) - 0.761x_{44t} \\ &\quad + 2.623(x_{44t} + 0.216)\end{aligned} \tag{10}$$

Based on Eq. (10), this can be interpreted as follows:

If the geopolitical risk index in Russia increases by 1 unit, assuming all other predictor variables remain constant, the average inflation rate is expected to increase by 0.946%. Furthermore, under the same assumption, a 1 unit increase in the geopolitical risk index is expected to increase the average interest rate by 0.908%.

If Russia's nominal effective exchange rate increases by 1 unit, assuming all other predictor variables remain constant, the average inflation rate is expected to decrease by 0.165%. Furthermore, under the same assumption, a 1-unit increase in the nominal effective exchange rate is expected to decrease the average interest rate by 0.850%.

If Russia's government debt increases by 1%, assuming all other predictor variables remain constant, the average inflation rate is expected to increase by 2.052%. Furthermore, under the same assumption, a 1% increase in government debt is expected to increase the average interest rate by 5.715%.

If Russia's GDP growth increases by 1%, assuming all other predictor variables remain constant, the average inflation rate is expected to increase by 0.068%. Furthermore, under the same assumption, a 1% increase in GDP growth is expected to decrease the average interest rate by 1.714%.

Based on Eq. (10), the inflation and interest rates in Russia for 2025 can be predicted by substituting, , $x_3 = 18.3$, and $x_4 = 0.98$ into the estimated model, as follows:

$$\begin{aligned}\hat{y}_{410}^{(1)} &= -0.005 + 0.946(1.66) - 0.165(94.683) + 1.695(18.3) - 1.888(18.3 - 14.462) - 0.107(18.3 - 16.529) \\ &\quad + 0.123(0.98) - 1.717(0.98 + 0.216) \\ &= 7.593 \\ \hat{y}_{410}^{(2)} &= 1.506 + 0.908(1.66) - 0.850(94.683) + 6.444(18.3) - 7.257(18.3 - 14.462) - 1.998(18.3 - 16.529) \\ &\quad - 0.761x_{44t} + 2.623(18.3 + 0.216) \\ &= 11.458\end{aligned} \tag{11}$$

Therefore, when the geopolitical risk index, nominal effective exchange rate, government debt, and GDP growth in Russia in 2025 are 1.66, 94.683, 18.3%, and 0.98%, respectively, the predicted average inflation rate is 7.593%, while the predicted average interest rate is 11.458%.

4. CONCLUSION

This study aimed to identify the influence of economic and geopolitical factors on inflation and interest rates in BRICS countries using nonparametric biresponse truncated spline regression on panel data. The modeling results show that this approach is able to capture the variation in inflation and interest rates very well, with the relationships between the Geopolitical Risk Index (GPR Index), the Nominal Effective Exchange Rate (NEER), government debt, and GDP growth and both response variables being nonlinear, with the direction of influence differing across variables, as illustrated in the case of Russia. These findings confirm that relationships among macroeconomic indicators do not always follow a specific parametric pattern, making the nonparametric approach a relevant alternative for modeling them.

The main contribution of this study lies in extending biresponse truncated spline regression to a cross-country panel data context, which has not been widely explored in previous studies that were generally limited to single time-series or purely cross-sectional data. In addition, incorporating geopolitical factors through the Geopolitical Risk Index (GPR Index) alongside conventional economic variables enriches the understanding of the determinants of inflation and interest rates, particularly during a period marked by global shocks such as the COVID-19 pandemic and the Russia–Ukraine conflict. The findings of this study are expected to serve as a basis for policymakers in BRICS countries in formulating economic policies that are more adaptive to global economic and geopolitical dynamics, as well as supporting the achievement of the Sustainable Development Goals (SDGs), particularly Goal 8 (Decent Work and Economic Growth) and Goal 16 (Peace, Justice, and Strong Institutions).

This study has several limitations. The cross-sectional units are limited to five BRICS countries observed over the 2016–2025 period as the time-series unit, and the spline order used is restricted to first order, with the number of knot points tested

limited to a maximum of three knots for each predictor variable. Future research is recommended to extend the scope to other countries that play a significant role and contribution in the global economy, as well as to consider incorporating additional predictor variables beyond those used in this study.

5. ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Statistics Study Program, Department of Mathematics, Faculty of Science and Technology, Universitas Airlangga, for the support, facilities, and opportunities provided throughout the research process. The valuable support has greatly contributed to the completion of this research and the preparation of this article. The authors also extend their appreciation to the data providers for their valuable contribution and for providing the data required to support this research. Their assistance has been essential in facilitating the analysis and achieving the objectives of this study.

6. REFERENCES

[1] N. I. Alfiyah, V. Andrianingsih, D. N. L. Asih, and M. B. Ainun, "Upaya BRICS dalam Mengimbangi Dominasi Dolar AS," *J. MISSY (Management Bus. Strateg.*, vol. 5, no. 2, pp. 75–81, 2024.

[2] M. W. Nurifqi, F. M. Lubis, and P. Marsingga, "Pengaruh Organisasi Brazil, Rusia, India, China dan Afrika Selatan (BRICS) dalam Kerja sama Ekonomi Global," *Innov. J. Soc. Sci. Res.*, vol. 4, no. 3, pp. 18448–18460, 2024.

[3] G. Desalegn, A. Tangl, and M. Fekete-Farkas, "From Short-Term Risk to Long-Term Strategic Challenges: Reviewing the Consequences of Geopolitics and COVID-19 on Economic Performance †," *Sustain.*, vol. 14, no. 21, p. 14455, 2022, doi: 10.3390/su142114455.

[4] S. A. Džogović and Z. Šabotić, "Geopolitical Tensions and their Impact on the International Economy: A Case Study of the Russian-Ukrainian Conflict," *J. Econ. Coop. Dev.*, vol. 45, no. 3, pp. 31–63, 2024.

[5] N. Patel and A. P. Alva, *Public Debt Dynamics and the Impact of Fiscal Policy*, no. 087. International Monetary Fund, 2024. doi: 10.5089/9798229014137.069.ch01.

[6] I. Fisher, *The Theory of Interest*. The Macmillan Company, 1930. doi: 10.1057/9781137026149_20.

[7] D. Caldara, S. Conlisk, M. Iacoviello, and M. Penn, "Do geopolitical risks raise or lower inflation?," *J. Int. Econ.*, vol. 159, p. 104188, 2026, doi: https://doi.org/10.1016/j.jinteco.2025.104188.

[8] S. Obradović, "Exchange Rate and Inflation Dynamics: Asymmetric Effects in a NARDL Framework," *Financ. Mark. Institutions Risks*, vol. 9, no. 1, pp. 30–42, 2025, doi: 10.61093/fmir.9(1).30-42.2025.

[9] X. Ujkani and A. Gara, "Determinants of the Inflation Rate: Evidence From Panel Data," *ECONOMICS*, vol. 11, no. 2, pp. 169–182, 2023, doi: 10.2478/eoik-2023-0054.

[10] E. Salachas, G. P. Kouretas, and N. T. Laopodis, "Understanding central bank responses to geopolitical risks: Evidence from the Fed and ECB," *J. Financ. Stab.*, vol. 80, p. 101452, 2025, doi: https://doi.org/10.1016/j.jfs.2025.101452.

[11] H. Karamelikli and M. S. Karimi, "Asymmetric Relationship Between Interest Rates and Exchange Rates: Evidence from Turkey," *Int. J. Financ. Econ.*, vol. 27, no. 1, pp. 1269–1279, 2020, doi: https://doi.org/10.1002%2Fijfe.2213.

[12] K.-S. Lee and R. A. Werner, "Reconsidering Monetary Policy: An Empirical Examination of the Relationship Between Interest Rates and Nominal GDP Growth in the U.S., U.K., Germany and Japan," *Ecol. Econ.*, vol. 146, pp. 26–34, 2018, doi: https://doi.org/10.1016/j.ecolecon.2017.08.013.

[13] R. D. Rahmawati, Suparti, and A. Prahutama, "Pemodelan Inflasi dan Indeks Harga Saham Gabungan Menggunakan Regresi Nonparametrik Birespon Spline Truncated dengan Pembobot Invers Matriks Variansi-KOvariansi Error Respon," *Statistika*, vol. 7, no. 1, pp. 29–38, 2019.

[14] A. P. Anisar, Sifriyanti, and A. T. R. Dani, "Estimation Of A Bi-Response Truncated Spline Nonparametric Regression Model On Life Expectancy And Prevalence Of Underweight Children In Indonesia," *BAREKENG J. Math. Its Appl.*, vol. 17, no. 4, pp. 2011–2022, 2023, doi: https://doi.org/10.30598/barekengvol17iss4pp2011-2022.

[15] R. Pahlepi, I. Sriliana, W. Agwil, and C. R. Oktarina, "Biresponse Spline Truncated Nonparametric Regression Modeling for Longitudinal Data on Monthly Stock Prices of Three Private Banks in Indonesia," *Barekeng*, vol. 19, no. 4, pp. 2467–2480, 2025, doi: 10.30598/barekengvol19iss4pp2467-2480.

[16] E. Supriyadi, S. Mariani, and Sugiman, "Perbandingan Metode Partial Least Square (PLS) DAN," vol. 6, no. 2, pp. 117–128, 2017.