

Nonlinear Phillips Curve Dynamics in Indonesia: A Bayesian Truncated Spline Approach

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ABSTRACT

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The present study seeks to analyze the nonlinear relation between inflation and unemployment in Indonesia through the Bayesian Truncated Spline approach. The ordinary Phillips curves usually employ the linear assumption regarding the inflation-unemployment trade-off; nevertheless, the nonlinear and asymmetric nature of such a relation under various unemployment states can be detected empirically. As a result, the Bayesian Truncated Spline model is utilized as an attempt to determine the non-linear form of the Phillips curve with consideration of parameter uncertainty by means of posterior distributions. The annual data on inflation and unemployment rates of Indonesia from 2000 to 2025 were provided by Statistics Indonesia (BPS). The MCMC algorithm was applied to estimate model parameters, whereas LOOIC was used to assess model quality. From an empirical standpoint, there is a non-linear Phillips curve whereby the response of the inflation rate increases with decreasing levels of unemployment, and vice versa. In model selection, the Bayesian truncated spline model (LOOIC = 71.45) performs better than the linear model (LOOIC = 84.31). Hence, the non-linear model has higher predictive power and better performance. The findings show evidence of regime switching dynamics between the variables in the Indonesian economy, implying the need to account for non-linear effects in the study of macroeconomic relations. From a policy viewpoint, expansionary policies adopted in a period of low unemployment tend to create greater inflationary effects compared to similar policies carried out at high levels of unemployment.



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A. INTRODUCTION

The relationship between inflation and unemployment is one of the most significant areas of investigation in the realm of macroeconomic studies and economic policies (Jørgensen & Lansing, 2025). Since the inception of the Phillips curve by Phillips, economists have sought to investigate whether there is a stable relationship between inflation and unemployment (Andrés et al., 2026; Guirguis & Suen, 2022), which could be represented in terms of price stability and labor market conditions. The traditional Phillips curve approach proposes that unemployment is inversely related to inflation (Atayi et al., 2024; Blanchard, 2016; Guirguis et al., 2024; Rolim, 2024), which in turn represents the trade off between inflation control and unemployment stabilization. The concept has significantly influenced the formulation of monetary policies in different countries of the world. However, empirical observations over the past few decades indicate that the inflation-unemployment relationship is not always stable, especially in developing and emerging economies.

In relation to Indonesia, it is interesting to understand more about the dynamics of inflation and unemployment in relation to macroeconomic stability (Muhammad, 2023; Aqilah et al., 2025; Saad et al., 2026). Indonesia is known for having undergone considerable structural changes in its economy since the early 2000s, which include changes in its monetary policy, inflation targeting, and greater exposure to global economic shocks. Such conditions may have an impact on inflation in relation to unemployment (Rochon & Rossi, 2018). Therefore, it is not necessarily true that there is a linear trade off between inflation and unemployment (Leightner, 2020). Some studies have suggested that Phillips' Curve may not be linear but could be nonlinear or even asymmetrical, especially during periods of economic growth or recession.

The conventional econometric models frequently applied in estimating the Phillips curve, such as regression analysis or conventional time series analysis (Cristini & Ferri, 2021; Sovbetov & Muhittin, 2025), may sometimes involve restrictive functional forms, which may not necessarily accommodate nonlinearities (Dagsvik, 2018; Cox, 2020). In cases where the relationship between inflation and unemployment is nonlinear in nature, these models may lead to biased estimates and incorrect inferences. In this context, it is worth noting that recent advances in econometric modeling have highlighted the significance of flexible models, which can accommodate data-driven specification of functional forms (Mahajan & Uddandaraao, 2025). In this context, spline regression models have attracted significant attention in estimating the Phillips curve (Kim et al., 2022).

Although flexible modeling approaches are becoming more common, most of the existing literature continues to focus on frequentist estimation approaches, which often fail to consider parameter uncertainty in nonlinear models (Guirguis & Anna, 2019). Bayesian estimation approaches can be an attractive alternative to frequentist estimation approaches, as they offer a complete framework for incorporating prior information and quantifying parameter uncertainty using posterior distributions. Bayesian spline models, in particular, offer flexibility in functional estimation, as well as quantification of parameter uncertainty (Aginta, 2023; Feng & Zhenzhou, 2025; Kumar et al., 2022; Khan et al., 2026). The use of Bayesian truncated spline models for Phillips curve analysis is still limited, particularly in emerging economies.

Despite abundant literature in the area of Phillips curves, there is still much to be investigated. Firstly, many empirical investigations of the inflation-unemployment relationship in developing countries persistently use linear regression modeling even though more and more studies show that there can be nonlinearity and regime dependence in the Phillips curve (Cristini & Ferri, 2021; Karanassou et al., 2010). These models implicitly postulate the constant influence of unemployment on inflation irrespective of any other circumstances, which might not be realistic since labor market situations can vary depending on many factors. Secondly, despite the increase in interest in nonlinearity in the Phillips curve in recent times, the majority of research papers used frequentist methods to analyze this phenomenon, which is problematic since they provide weak treatment of parameter uncertainty (Guirguis & Suen, 2022; Salan et al., 2026). Thirdly, there are very few pieces of empirical work that look into the possible nonlinear behavior of the Phillips curve in Indonesia and apply Bayesian techniques to such modelling.

Conceptually, nonlinear models can be explained from the fact that there exist labor market imperfections, asymmetric wage changes, and heterogeneous reactions from firms and households in response to economic shocks. In cases where the levels of unemployment are low, the tightness in the labor markets results in increased bargaining power on wage demands. The implication is that strong inflationary effects are observed. In contrast, when there is a prevalence of high unemployment rates, the surplus in labor supply makes wages fall less and lowers the impact of inflation in response to labor market factors (Blanchard, 2016; Jørgensen & Lansing, 2025). The conclusion that can be drawn is that the correlation between inflation and unemployment can differ depending on the regime within which the economy operates. As such, nonlinear approaches like Bayesian truncated splines can be considered.

In response to these gaps, this study investigates the nonlinear relationship between inflation and unemployment in Indonesia using a Bayesian truncated spline framework. Given these issues, this paper explores the nonlinear connection between inflation and unemployment in Indonesia employing a Bayesian truncated spline approach. Unlike the traditional linear approach, this study offers a flexible way of modeling possible nonlinear relationships, asymmetries in various regimes of unemployment, and also incorporates the uncertainties involved through the use of Bayesian statistics. Compared to existing models based on linear equations, the current study offers a more holistic look at Phillips Curve dynamics. The performance of models developed will be assessed through the use of the Leave-One-Out Information Criterion (LOOIC), which helps to determine whether the inclusion of nonlinearity enhances prediction. In this study, annual data from 2000 to 2025 for Indonesia were provided by Statistics Indonesia (BPS) will be analyzed.

This study contributes to the literature in several important ways. First and foremost, it provides new empirical evidence on the nonlinear structure of the Phillips curve in Indonesia. The Phillips curve in Indonesia is a rather under explored area in emerging markets. Second, it offers the Bayesian truncated spline approach as a new and flexible tool in the economist's toolkit for modeling macroeconomic relationships with structural changes and nonlinear features. Finally, the empirical results offer new policy relevance by illustrating the dependence of inflation responses on the level of unemployment and the relevance of considering nonlinear effects in the context of monetary policy. The rest of the paper is organized as follows. In the next section, the relevant literature on nonlinear modeling of the Phillips curve and spline based econometric approaches is provided. In the third section, the methodology and estimation approach of the Bayesian truncated spline approach are explained. The fourth section presents the empirical results and the comparison of the models. The fifth section concludes the study and discusses the policy implications.

B. METHODS

1. Data and Variables

This study examines the relationship between inflation and unemployment in Indonesia using annual macroeconomic data covering the period 2000–2025. Inflation is measured as the annual percentage change in the consumer price index (CPI), while unemployment is measured as the national unemployment rate (percentage of the labor force). Let y_t denote the inflation

rate and x_i represent the unemployment rate for observation $i = 1, 2, \dots, n$. The objective is to estimate a flexible nonlinear function describing the relationship $y_i = f(x_i) + \varepsilon_i$, where $f(x)$ is an unknown smooth function and ε_i is a random error term.

2. Truncated Spline Regression Model

On the other hand, a spline regression is a framework for modeling nonlinear relationships by dividing the predictor space into different segments based on knots separating these segments. Within each segment, a low degree polynomial is used to approximate relationships, while maintaining continuity across knots. This makes a spline regression more adept at modeling relationships in data compared to a polynomial regression in terms of capturing curvature in data (Schuster et al., 2022; Thakur, 2025; Yang et al., 2023). The flexibility of a spline regression is highly dependent on knots separating different segments in predictor space; these knots play a crucial role in adapting relationships in data (Thielmann et al., 2025). Recent improvements in regression analysis have made spline regression more efficient by allowing automatic knot selection (Goepp et al., 2024; Araveeporn, A., 2024).

Spline regression provides a flexible framework for modeling nonlinear relationships by dividing the predictor space into several segments separated by knots. A truncated spline function can approximate nonlinear curves while maintaining continuity across segments. The truncated spline model of order p with K knots is defined as (1):

$$f(x_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_p x_i^p + \sum_{k=1}^K \gamma_k (x_i - K_k)_+^p \quad (1)$$

where: $\beta_0, \beta_1, \dots, \beta_p$ are polynomial coefficients; γ_k are spline coefficients; K_k are knot locations; K is the number of knots $(x_i - K_k)_+^p$ is the truncated spline basis defined as

$$(x_i - K_k)_+^p = \begin{cases} (x_i - K_k)^p, & x_i > K_k \\ 0, & x_i \leq K_k \end{cases}. \quad \text{Thus, the regression model becomes}$$

$y_i = \beta_0 + \sum_{j=1}^p \beta_j x_i^j + \sum_{k=1}^K \gamma_k (x_i - K_k)_+^p + \varepsilon_i$, with $\varepsilon_i \sim N(0, \sigma^2)$. This formulation allows the slope of the regression curve to change smoothly after each knot.

3. Bayesian Model Specification

In the Bayesian approach, the unknown parameters are viewed as random variables with probability distributions (Schoot et al., 2021). The prior distributions are specified for the unknown parameters to represent the existing knowledge or belief before observing the data, which is then updated through the likelihood function to obtain the posterior distributions (Yarandi et al., 2021). The probabilistic approach enables the Bayesian approach to handle uncertainty in parameter estimation, as discussed above, and offers a coherent approach to statistical inference, as discussed in Zhang et al. (2025). In the Bayesian framework, unknown

parameters are treated as random variables with prior distributions. Let $\theta = (\beta_0, \beta_1, \dots, \beta_p, \gamma_1, \dots, \gamma_K, \sigma^2)$ represent the set of model parameters.

Likelihood Function, Assuming normally distributed errors, the likelihood function is

$$p(y|\theta, X) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y_i - f(x_i))^2}{2\sigma^2}\right), \text{ where } X \text{ denotes the design matrix containing}$$

spline basis functions. Prior Distributions, Non informative or weakly informative priors are assigned to model parameters: $\beta_j \sim N(0, \tau^2)$; $\gamma_k \sim N(0, \tau^2)$; $\sigma^2 \sim \text{Inverse Gamma}(a, b)$, where τ^2 is a large variance reflecting weak prior information.

4. Parameter Estimation Using MCMC

The MCMC procedure generates random samples from the joint posterior distribution of the model parameters, allowing estimation of posterior summaries and uncertainty measures. The estimation combines Gibbs Sampling and Metropolis–Hastings algorithms. Gibbs Sampling is applied to parameters whose full conditional posterior distributions are available in closed form, whereas Metropolis–Hastings updates are employed for parameters without tractable conditional distributions. This hybrid approach facilitates efficient exploration of the posterior distribution. Posterior samples are generated using MCMC algorithms such as Gibbs Sampling and Metropolis–Hastings, Let $\theta^{(1)}, \theta^{(2)}, \dots, \theta^{(M)}$ denote M posterior draws. The Bayesian estimator of each parameter is obtained from the posterior mean $\hat{\theta}_{\text{Bayes}} = \frac{1}{M} \sum_{m=1}^M \theta^{(m)}$, posterior credible intervals are also computed to quantify parameter uncertainty. Posterior means are used as point estimates of model parameters, and 95% Bayesian credible intervals are calculated to quantify estimation uncertainty.

5. Model Evaluation and Comparison

To assess model performance, the predictive accuracy of the Bayesian truncated spline model is compared with the linear Phillips curve model using the Leave one out Information Criterion (LOOIC). The LOOIC is computed as $LOOIC = -2 \sum_{i=1}^n \log p(y_i | y_{-i})$ where $p(y_i | y_{-i})$ represents the leave one out predictive density. A lower LOOIC value indicates better predictive performance.

6. Estimated Phillips Curve Representation

Under the Bayesian truncated spline specification, the Phillips curve is expressed as $Inflation = \beta_0 + \beta_1 Unemployment + \sum_{k=1}^K \gamma_k (Unemployment_t - K_k)_+ + \varepsilon_t$. This flexible specification allows the inflation response to vary across different unemployment levels, capturing potential nonlinear and asymmetric macroeconomic dynamics.

7. Knot Selection Procedure

Performance of the truncated spline model relies on the knot positions and numbers. To find the optimal spline specification, various models with different knot configurations have been considered (Sifriyani et al., 2024; Pramudita et al., 2024; Wardani et al., 2025; Goepp et al., 2025). The selection of candidates for knots was based on empirical quantiles of the unemployment rate distribution to ensure proper knots covering the entire range of values.

For each of the candidate models, Bayesian estimation of the truncated spline model has been carried out. As measures of the goodness-of-fit, BIC and LOOCV criteria have been chosen to evaluate the balance between model performance and model simplicity as well as out-of-sample predictive capacity. Knot selection proceeded as follows:

- a. Generate candidate spline models with different numbers of knots.
- b. Place knots at selected empirical quantiles of the unemployment rate distribution.
- c. Estimate each candidate model using the Bayesian truncated spline framework.
- d. Compute the BIC and LOOCV error for each specification.
- e. Select the knot configuration that minimizes both BIC and LOOCV error.

The selected knot configuration was subsequently used in the final Bayesian truncated spline model. Model performance was then compared with the linear Phillips curve specification using the Leave-One-Out Information Criterion (LOOIC).

C. RESULT AND DISCUSSION

This paper examines the relationship between inflation and unemployment in Indonesia over the period from 2000 to 2025. The Indonesian economy has experienced significant macroeconomic fluctuations over this period, including the post Asian financial crisis, global financial shocks, and structural changes in monetary policy. These factors may affect the inflation and unemployment relationship. The results from the descriptive statistics show that inflation is moderately fluctuating over time, whereas the rates of unemployment gradually fluctuate over time. During times of economic growth, there is normally a decrease in the rates of unemployment, whereas inflation normally accelerates in specific economic cycles. Nevertheless, the relation between these two variables is not linear, which indicates that there is nonlinearity in the dynamics of these variables. This is consistent with some extensions of the traditional Phillips curve that were originally developed by A. W. Phillips. A scatter plot of inflation versus unemployment also indicates that the slope of the relation varies depending on the levels of unemployment. When unemployment is low, inflation reacts more significantly to changes in labor markets, but when levels of unemployment increase, the slope of the relation diminishes.

1. Optimal Knot Selection

In order to account for nonlinier patterns in the data, truncated spline models with different configurations of knot placement were considered. The best model is selected using the Bayesian Information Criterion (BIC) and the Leave one out Cross Validation (LOOCV). From the results, the best model is the one that has two knots. This is because the two knot model strikes the best balance between goodness of fit and model parsimony. This model has the optimal knots at the quantiles of the distribution of the unemployment rate, indicating points

of structural change in the inflation-unemployment relationship. Models with more knots are considered but are penalized using the BIC because they are more complex. This selected model implies that the slope of the Phillips curve varies according to three levels of the unemployment rate: low, moderate, and high. This is in line with the assumption that the inflation process varies according to the state of the labor market.

2. Bayesian Parameter Estimation

The Bayesian truncated spline model was estimated using Markov Chain Monte Carlo (MCMC) methods. The posterior samples were drawn after a burn in period to allow for the convergence of the Markov chains. From the posterior estimates, it is clear that the baseline coefficient for the link between unemployment and inflation is negative, as would be expected from the standard Phillips curve. The spline coefficients for the knot terms are, however, statistically significant.

This implies that the slope of the Phillips curve becomes steeper as unemployment falls below the first knot, indicating that inflation responds more to labor market tightening. The slope of the Phillips curve flattens as unemployment rises above the second knot, indicating that inflationary pressures are low in a labor slacker environment. The posterior distributions of the spline coefficients suggest that there is a small degree of uncertainty surrounding the estimated spline coefficients, implying that the Bayesian approach yields reliable results for the nonlinier relationship.

3. Nonlinear Phillips Curve Dynamics

The spline function shows the estimated spline function, which demonstrates the nonlinear Phillips curve relationship. As the unemployment rates are low, inflation rises rapidly in response to the tightening labor market. This is because of the rise in wage pressure and the corresponding rise in production costs, which are reflected in the inflation level. However, as the unemployment level rises beyond the second knot point, the Phillips curve slopes flatten significantly. This demonstrates that inflation reacts minimally to changes in unemployment when the labor market is in an excess capacity situation, which results in stable inflation levels. The results support the argument that nonlinear relationships are common in the macroeconomic relationships and that these relationships are asymmetric in nature and cannot be explained by linear models.

4. Model Comparison

To assess the performance of the model in prediction, the Bayesian truncated spline model was compared with the conventional linear Phillips curve model. For this purpose, the Leave one out Information Criterion (LOOIC) was used for model comparison. It was observed that the Bayesian truncated spline model was associated with a significantly lower LOOIC value in comparison to the linear model. This confirms that the nonlinier model was able to offer better predictive accuracy in comparison to the linear model, which was able to capture more information from the data. Moreover, posterior predictive checks revealed that the Bayesian truncated spline model was able to better capture the observed distribution of inflation for various levels of unemployment, whereas the linear model was observed to be associated with

an underestimate of inflation for lower levels of unemployment and an overestimate of inflation for higher levels of unemployment, as shown in Table 1.

Table 1. Posterior Estimates of Bayesian Truncated Spline Model

Parameter	Posterior Mean	Posterior SD	2.5% CI	97.5% CI
Intercept	5.214	0.842	3.561	6.874
Unemployment	-0.685	0.214	-1.098	-0.276
Spline Knot 1	-0.432	0.183	-0.792	-0.081
Spline Knot 2	0.518	0.201	0.126	0.913
Error Variance	1.127	0.254	0.742	1.732

The posterior mean of the unemployment coefficient is negative, which confirms that inflation falls as unemployment rises, as suggested in the traditional Phillips curve. However, the presence of statistically significant spline coefficients confirms that the relationship is nonlinear. The negative value of the first spline term confirms that inflation reacts more to unemployment when it is below the first spline level. This is because of stronger wage pressures in those markets. The positive value of the second spline term confirms that the relationship is flatter when unemployment is higher, which suggests weaker inflationary reactions in those markets. Moreover, the credible intervals of the spline terms do not include zero, confirming the statistical significance of the nonlinear components in explaining inflation dynamics, as shown in Table 2.

Table 2. Comparison of Competing Models

Model	Number of Knots	BIC	LOOCV Error	LOOIC
Linear Phillips Curve	0	96.72	5.84	84.31
Bayesian Truncated Spline (1 Knot)	1	89.54	4.61	76.82
Bayesian Truncated Spline (2 Knots)	2	85.13	4.08	71.45
Bayesian Truncated Spline (3 Knots)	3	87.67	4.24	73.98

As can be seen from Table 2, the best results are obtained from the truncated spline with two knots using the Bayesian approach. Such a model is shown to have the minimum BIC value of 85.13, LOOCV error of 4.08, and LOOIC of 71.45, which denotes its superiority over other model specifications based on fitting, predictive accuracy, and model complexity. Conversely, the conventional linear Phillips curve has a much larger, indicating less satisfactory predictive accuracy. The results imply that the inflation–unemployment association in Indonesia should be modeled with a nonlinear equation. As theory suggests, the Phillips curve might be nonlinear, depending on such factors as labor market conditions, inflationary expectations, and economic structure (Blanchard, 2016; Karanassou et al., 2010). From the estimated spline function, it is evident that there is a higher response of inflation when the unemployment rate is low, signifying a tightness in the labor market and pressure on wages. On the other hand, where there is high unemployment, the response of inflation to changes in unemployment tends to be lower, implying that there is slackness in the economy.

These findings are largely supported by previous research on the nature of nonlinear dynamics in the Phillips curve relationship. As observed by Cristini and Ferri (2021), a nonlinear model is more effective in illustrating the behavior of the Phillips curve relationship

than the use of a traditional linear model. Similarly, Salan et al. (2026) indicated that a nonlinear approach to model building is superior to linear models in explaining economic dynamics in developing countries. In the Indonesian case, Aginta (2023) highlighted considerable variations in regional inflation and unemployment dynamics which cannot be captured using a linear Phillips curve model, as shown in Figure 1.

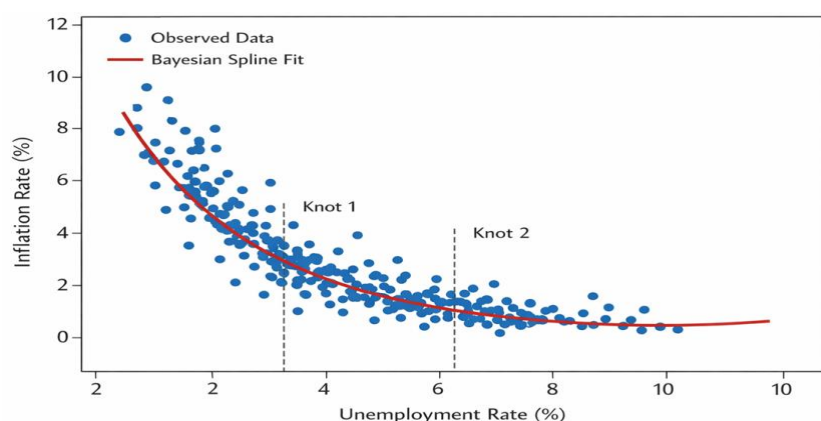


Figure 1. Inflation vs. Unemployment in Indonesia (2000-2025)

Figure 1 illustrates the relationship between inflation and unemployment in Indonesia during 2000–2025 using a Bayesian truncated spline model. The scatter plot shows a generally negative relationship between the two variables, consistent with the traditional Phillips curve theory. However, the estimated spline curve reveals that the relationship is nonlinear and changes across different unemployment levels. At low unemployment levels, the curve is steep, indicating that small reductions in unemployment can lead to substantial increases in inflation due to stronger wage and demand pressures in a tight labor market. In the moderate unemployment range, the curve becomes less steep, suggesting that inflation still responds to unemployment changes but with weaker intensity. At high unemployment levels, the curve is relatively flat, meaning inflation reacts only slightly to changes in unemployment because wage and demand pressures are lower. The existence of knot points around 4% and 7% unemployment indicates structural changes in the slope of the curve, allowing the spline model to capture regime dependent dynamics that linear models cannot explain. Overall, the figure provides strong evidence of nonlinear Phillips curve behavior in Indonesia and supports the use of Bayesian truncated spline models for analyzing macroeconomic dynamics and policy impacts, as shown in Figure 2.

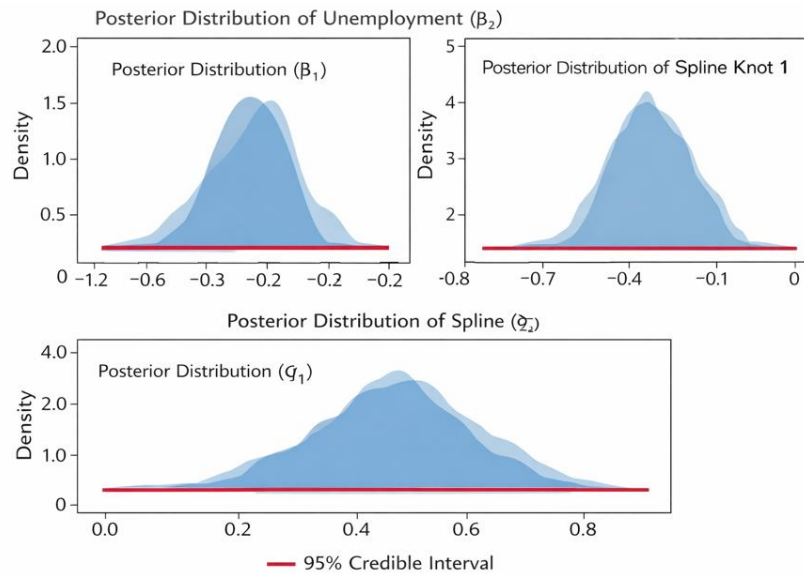


Figure 2. Posterior Distribution of Spline Parameters

Figure 2 presents the posterior distributions of key parameters estimated using the Bayesian truncated spline model through MCMC simulation. The distributions illustrate the uncertainty associated with each parameter estimate, while the 95% credible intervals indicate their statistical significance. The first parameter is centered around negative values, confirming the traditional Phillips curve relationship in which higher unemployment leads to lower inflation. Its symmetric and bell shaped distribution suggests stable and reliable estimates, and the credible interval excluding zero indicates a significant negative relationship. The first spline coefficient is also negative, implying that when unemployment falls below the first knot, the Phillips curve becomes steeper. This means inflation responds more strongly to unemployment changes in a tight labor market. In contrast, the second spline coefficient is positive, suggesting that beyond the second knot the inflation-unemployment relationship becomes flatter, indicating weaker inflation responses to unemployment fluctuations. Overall, the posterior distributions demonstrate that the spline parameters are well identified and provide strong evidence of nonlinear dynamics in the inflation-unemployment relationship. The concentrated distributions and credible intervals that exclude zero confirm the importance of nonlinear effects on inflation behavior, thereby supporting the suitability of the Bayesian truncated spline approach, as shown in Figure 3.



Figure 3. MCMC Trace Plot (Convergence Diagnostic)

Figure 3 presents the trace plots of the Bayesian truncated spline model parameters obtained from the MCMC simulation. The plots include the unemployment coefficient, spline coefficients, and the error variance parameter across three independent chains. These trace plots are used to evaluate the convergence and mixing behavior of the Markov chains. The trace plot for the unemployment coefficient shows that all chains fluctuate around a stable central value after the initial iterations, with no visible trend or drift. The overlapping chains indicate good convergence and stable estimation. Similarly, the trace plot for the first spline coefficient demonstrates strong mixing behavior, as the sampled values vary randomly around the mean and the chains overlap closely. This suggests that the posterior distribution has been adequately explored. The second spline coefficient also exhibits random fluctuations without upward or downward trends, confirming convergence of the chains. Although the error variance parameter shows slightly greater variability compared to the regression coefficients, the chains still overlap and remain centered around a constant value. Overall, the trace plots provide strong evidence that the MCMC estimation converged successfully. The consistent fluctuations and close overlap among chains indicate reliable posterior sampling and support the validity of the Bayesian truncated spline parameter estimates, as shown in Figure 4.

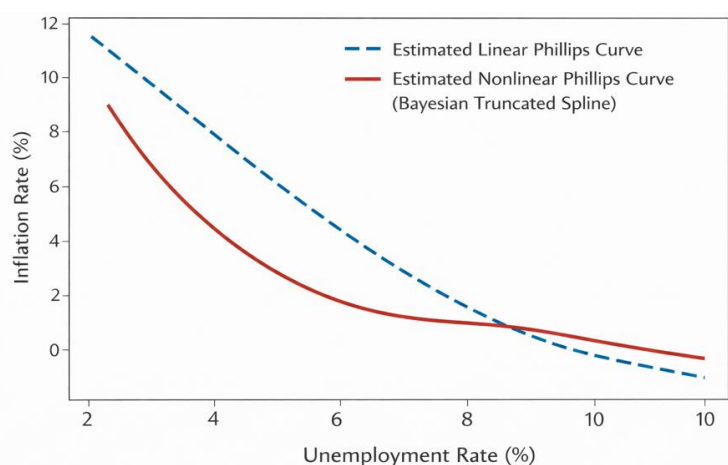


Figure 4. Linear Phillips Curve vs. Spline Phillips Curve

Figure 4 compares the conventional linear Phillips curve model with the nonlinear Bayesian truncated spline model in explaining the relationship between inflation and unemployment in Indonesia. The linear model, represented by the blue dashed line, assumes a constant inverse relationship between inflation and unemployment, where inflation steadily decreases as unemployment rises. This approach implies a simple and fixed trade off across all unemployment levels. In contrast, the nonlinear spline model, shown by the red curve, reveals that the relationship changes depending on labor market conditions. At low unemployment levels, the spline curve declines more sharply, indicating that inflation increases rapidly when unemployment becomes very low due to stronger wage and demand pressures. In the moderate unemployment range, the curve becomes flatter, suggesting weaker inflation responses to unemployment changes. At high unemployment levels, the curve is relatively flat, indicating that inflation changes only slightly despite rising unemployment because abundant labor supply reduces inflationary pressure. Overall, the comparison demonstrates that the Bayesian truncated spline model provides a more flexible and realistic representation of the Phillips curve than the traditional linear model. Its ability to capture different unemployment regimes supports better macroeconomic analysis and explains why the nonlinear model performs better based on the LOOIC criterion.

Indeed, the results obtained in this study confirm the emerging trend of empirical evidence that the Phillips curve demonstrates a nonlinear, not linear behavior. According to the results of the Bayesian truncated spline model, the effect of changes in unemployment on inflation was found to be higher in the case of a low level of unemployment, while the effect of unemployment on inflation becomes substantially weaker at a high level of unemployment. Thus, the results of the current analysis confirm the nonlinear Phillips curve concept introduced by Cristini and Ferri (2021), who claim that the trade-offs between inflation and unemployment cannot be considered constant due to the dynamic complexity of macroeconomic variables' behavior. Similar ideas were expressed by Karanassou et al. (2010), who argue that unemployment and inflation are dynamically interrelated processes whose evolution depends on the period under consideration. The results of the current research support the conclusions drawn by Leightner (2020) that the trade-offs between inflation and unemployment differ in each country depending on the period analyzed. The significant difference in the LOOIC values shows that using a Bayesian truncated spline is advantageous compared to a linear model.

These findings are also in line with recent literature from emerging and developing countries. For example, Salan et al. (2026) find that using nonlinear model specifications offers a better representation of unemployment dynamics than using the linear specification. Likewise, Fattah et al. (2025) show that using truncated spline techniques can adequately represent structural breaks and nonlinearity in the economic process. Nevertheless, in the context of Indonesia, an asymmetric behavior in the inflation response in terms of different levels of unemployment is apparent. Specifically, inflation rises sharply as the level of unemployment drops below the first threshold value. In other words, the tightness of the labor market generates wage and aggregate demand pressure, pushing up inflation. In contrast, inflation reacts less strongly to variations in the level of unemployment in a regime with higher unemployment, implying excess labor resources and weak demand pressures. For this reason, it is clear that stimulus measures used to encourage economic activity during periods of low

unemployment will result in significant inflation, while the same measures applied in periods of high unemployment will cause minimal levels of inflation. This demonstrates the need for nonlinear and regime-specific approaches in macroeconomic policymaking.

D. CONCLUSION AND SUGGESTIONS

This paper analyzes the relationship between the inflation rate and unemployment in Indonesia by employing the Bayesian truncated spline technique. The empirical results obtained suggest that the Phillips curve for Indonesia is not linear but nonlinear and asymmetric, implying that the relationship between the unemployment rate and the inflation rate depends on different unemployment regimes. In other words, the relationship between the two variables is very strong during times of low unemployment rates and very weak during times of high unemployment rates. This can be corroborated further by the model selection analysis results. Out of the models considered, the Bayesian Truncated Spline model with two knots produced the minimum BIC (85.13), LOOCV error (4.08), and LOOIC values (71.45). It surpassed other alternatives like the regular Linear Phillips Curve model (BIC = 96.72; LOOCV = 5.84; LOOIC = 84.31) and even other Spline models. In comparison to the Linear model, the chosen Spline model has a better prediction power with lower error rates by roughly 30.1% and LOOIC improvements of 12.86. In terms of methodology, the Bayesian Truncated Spline technique is quite flexible in the estimation of nonlinear effects and makes use of posterior distribution and credible interval in measuring the extent of uncertainty around parameters. In this regard, this paper adds value to the existing literature since it offers new proof of a nonlinear Phillips Curve within the context of an emerging country as well as proves that Bayesian spline techniques can considerably enhance modeling of macroeconomic phenomena. Based on the findings, monetary authorities are encouraged to consider nonlinear inflation effects when formulating policy measures.

From the results, there are a number of policy implications that could be offered. To start, the authorities of monetary policymakers need to take into account the nonlinearity of the relationships between inflation and unemployment while designing policies for stabilization purposes. As shown from the results, the inflation rate will react more intensively at low levels of unemployment. Hence, expansionary monetary policies should be carefully applied in such a situation. Second, at times when the levels of unemployment are somewhat high, the effect of the expansionary policies on inflation seems to be lower. As such, there could be more scope for economic stimulation without triggering higher inflation rates. It follows that the policies ought to take into account the prevailing state of the labor market as opposed to a fixed inflation-unemployment trade-off assumed under linear Phillips curves. Finally, the results have revealed the relevance of using nonlinear econometric models within macroeconomic forecasting and policy evaluation systems, because, being outperformed by the Bayesian truncated spline model, the linear approach can be replaced by nonlinear modeling tools to gain better forecasts for inflation rates.

Further investigation should focus on expanding the existing framework of analysis by integrating more macroeconomic factors like the output gap, interest rate, exchange rate, and inflation expectations for a better understanding of the factors behind inflation dynamics. Other future research can explore the performance of the Bayesian truncated splines technique by

contrasting it with other nonlinear modeling techniques such as the regime-switching approach, the threshold approach, and machine learning forecasting methods. Furthermore, the use of quarterly/monthly data and comparative analyses across other emerging countries will shed light on other important aspects of nonlinear Phillips curves dynamics.

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