

Prediction of Gold Price Based on US Dollar Index Using STSR Approach

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ABSTRACT

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Gold is widely recognized as a safe-haven asset, and its price dynamics play a crucial role in global financial markets. However, gold prices exhibit highly volatile and nonlinear behavior, making accurate prediction a challenging task. In addition to the influence of historical gold prices through autoregressive effects, movements in the US Dollar Index (DXY) are known to affect gold price fluctuations through potentially nonlinear relationships. Conventional linear time series models may not adequately capture both the temporal dependence of gold prices and the nonlinear influence of external economic indicators. Therefore, the Semiparametric Time Series Regression (STSR) approach is employed because it combines a parametric autoregressive component with a nonparametric spline component, enabling the model to simultaneously represent linear temporal dependence and nonlinear relationships. This study aims to model and predict gold prices using the STSR approach and evaluate its forecasting performance. The data used in this study consist of daily observations of the GCJ6 gold futures contract and the DXY obtained from Investing.com, covering the period from June 2, 2025 to February 3, 2026, with a total of 140 observations. In the proposed model, the GCJ6 price at the previous period ($GCJ6_{t-1}$) is incorporated as the predictor in the parametric component, while the DXY serves as the predictor in the nonparametric component. The nonparametric function is estimated using a spline estimator with optimal knot selection based on the Generalized Cross Validation (GCV) criterion. Forecasting performance is evaluated using the Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and Mean Absolute Scaled Error (MASE). The proposed STSR model achieved an overall MAPE of 1.478%, an sMAPE of 0.335, and a MASE of 0.618. The overall MAPE below 2% indicates excellent forecasting accuracy, while the low sMAPE and MASE values further confirm the robustness of the proposed model. These findings indicate that the proposed STSR model effectively captures both temporal dependence and nonlinear effects, providing accurate and reliable predictions of gold prices.



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A. INTRODUCTION

The world gold price is a key indicator in global financial markets. Gold is viewed as both a strategic commodity and a financial asset (Makala & Li, 2021). In global financial markets, the world gold price is represented by the GCJ6 gold futures contract. GCJ6 is a global gold futures contract traded on the Commodity Exchange. GCJ6 is used as a proxy for the international gold price because it reflects market prices and market participants' expectations. GCJ6 movements

exhibit complex fluctuations and tend to be influenced by various factors. Over the past ten years, world gold prices have generally shown an upward trend with relatively stable variations. However, in recent periods, extreme price spikes have been identified that deviate from long-term historical patterns. Gold price movements are strongly dependent on values in previous periods (Miranda et al., 2025; Yang, 2019). This dependence on historical data can create an autoregressive pattern in time series data. In addition to internal factors, gold price movements are also influenced by global macroeconomic factors, such as the US dollar exchange rate, as represented by the US Dollar Index (DXY) (Ahmad et al., 2024; Kaewkheaw et al., 2014). However, the relationship between the DXY and GCJ6 is not always linear, but rather nonlinear. This is influenced by financial market conditions and changes in investor behavior.

Methodologically, the relationship between predictor variables and the response is analyzed using a regression approach. An analytical tool for assessing or forecasting the connection between response and predictor variables is regression. Semiparametric, nonparametric, and parametric regression are the three types of regression that are most frequently used. When the relationship model between the predictor and response variables is understood, parametric regression is used (Zhang, 2016). The use of parametric regression requires the fulfillment of several assumptions. Models where the connection between the predictor and response variables is unknown are fitted using nonparametric regression (Caron et al., 2022; Yan, 2018). Since nonparametric regression does not require the same assumptions as parametric regression and yields a smooth curve or function, its application is thought to be more versatile (Eubank, 1999). Both parametric and nonparametric components of regression are present in semiparametric regression, which blends the two types of regression (Ampa et al., 2021; Charles, 2022). Estimating nonparametric functions in nonparametric and semiparametric regression involves smoothing techniques such as kernel (Dewanti et al., 2020; Lestari et al., 2019; Linke et al., 2022; Rahmawati et al., 2021), local linear (Chamidah, Tjahjono, et al., 2018; Chamidah & Rifada, 2016; Cheruiyot, 2020; Darnah et al., 2019), local polynomial (Mansyur & Simamora, 2022; Ulya et al., 2023; Wang et al., 2020), spline (Chamidah, Kurniawan, et al., 2018; Mansyur & Simamora, 2022; Massaid et al., 2019; Ramadan et al., 2019), spline penalized (Chamidah et al., 2022; Hasanah et al., 2021; Mwende et al., 2021), and Fourier series (Anandari et al., 2022; Mardianto et al., 2023; Utami et al., 2023).

Regression analysis, whether parametric, nonparametric, or semiparametric, can be used to analyze cross-sectional data and time series data. Regression analysis, whether parametric, nonparametric, or semiparametric, can be used to analyze cross-sectional data and time series data. Time series data comprises objects generated based on observations at specific intervals, such as daily, weekly, and yearly (Fibriyani & Chamidah, 2020; Zhou et al., 2021). Researchers Xu & Lan (2019) and Yan & Shuangting (2020) have both employed the Autoregressive Integrated Moving Average (ARIMA) model for forecasting in their parametric regression experiments, including time series data. The Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model is an additional tool for forecasting time series data and ARIMA. To be high, the ARIMAX model incorporates exogenous variables deemed to keep a significant influence (Adu et al., 2023). Zheng (2023) also researched using the ARIMAX model to predict the Stock Price Index in Shanghai.

Although ARIMA and ARIMAX have been widely adopted for time series forecasting because of their simplicity and interpretability, these models assume a linear relationship between the

response variable and its predictors. Such an assumption may not be appropriate for financial time series, where external economic indicators often exert nonlinear and time-varying effects. In particular, the influence of the DXY on gold prices is frequently affected by changing market sentiment, macroeconomic uncertainty, and investors' risk preferences, resulting in relationships that cannot be adequately represented by conventional linear models. Consequently, these models may not adequately represent the dynamics of gold price movements.

Previous research has addressed nonparametric regression on time series data. For example, Fibriyani & Chamidah (2021) employed a nonparametric regression using a local polynomial estimator to forecast Indonesian inflation. Research related to modeling based on kernel estimators was carried out by (Chen et al., 2008; Gao & Gijbels, 2008). Meanwhile, Chen et al. (2008) used nonparametric regression research based on a spline estimator for analyzing time series data. Ahmed et al. (2022) utilized semiparametric regression based on a local polynomial estimator to analyze time series data. This research focuses on crop yield prediction and the effects of financial risk factors. semiparametric time series approach using a local polynomial estimator for modeling the case fatality rate of COVID-19 in Indonesia (Fibriyani et al., 2024).

Spline is one of the most widely used smoothing techniques in nonparametric regression because of its flexibility in modeling relationships without requiring a predetermined functional form. Spline regression approximates the relationship using piecewise polynomial functions connected smoothly at predefined knot points. This characteristic enables spline models to effectively capture nonlinear patterns and local variations in the data while maintaining overall smoothness (Alwi et al., 2023). The predictive performance of spline regression depends on the number and locations of the knot points. An excessive number of knots may lead to overfitting, whereas too few knots may result in an oversmoothed model that fails to capture important data characteristics. Therefore, selecting optimal knot points is a crucial step in spline modeling. In this study, the optimal knot configuration is determined using the Generalized Cross Validation (GCV) criterion, which provides a data-driven approach to balancing model complexity and goodness-of-fit without requiring separate validation data (Maharani & Saputro, 2021). The model with the smallest GCV value is considered optimal because it minimizes the expected prediction error while avoiding unnecessary model complexity (Lestari et al., 2018).

From a methodological perspective, this study contributes to the development of semiparametric regression for time series analysis by integrating an autoregressive parametric component with a spline-based nonparametric component within the STSR framework. This integration enables simultaneous modelling of linear temporal dependence and nonlinear effects of exogenous variables while preserving the interpretability of the regression coefficients. Moreover, the use of spline smoothing with optimal knot selection based on the GCV criterion provides a flexible estimation framework that balances model complexity and predictive accuracy. Therefore, the proposed approach extends the application of semiparametric regression to financial time series characterized by mixed linear and nonlinear relationships.

Based on the nonlinear characteristics of gold price movements and the influence of the DXY, this study proposes a spline-based Semiparametric Time Series Regression (STSR) model

for gold price prediction. The proposed model represents temporal dependence through a parametric autoregressive component using the lagged GCJ6 price, while the nonlinear effect of the DXY is modelled using a spline-based nonparametric component. By combining these two components within a unified regression framework, the proposed STSR model is expected to provide more accurate and interpretable predictions than conventional linear time series models while maintaining the flexibility required to capture complex financial market dynamics. This study is expected to be able to provide a model that has a higher accuracy in predicting world gold prices.

B. METHODS

1. Research Design and Data Description

This study employs a quantitative explanatory research design with a time series modelling approach to analyze and predict the movement of international gold prices. The analysis is based on secondary data obtained from the financial database available at www.investing.com. The dataset consists of daily observations of the GCJ6 gold futures contract and the US Dollar Index (DXY) covering the period from 2 June 2025 to 3 February 2026, resulting in a total of 140 observations.

Table 1. Research Variables

Variable	Type	Description
GCJ6	Response	Daily gold futures price
GCJ6 _{t-1}	Parametric Predictor	Previous-period gold futures price
DXY	Nonparametric Predictor	US Dollar Index

In this study, from the Table 1, the GCJ6 variable is treated as the response variable, representing the international gold price. The predictor variables consist of GCJ6 at the previous period (GCJ6_{t-1}) and the US Dollar Index (DXY). The lagged GCJ6 variable is included to capture the autoregressive behavior commonly observed in financial time series, while the DXY is incorporated as an external macroeconomic factor that may influence gold price movements through nonlinear relationships.

The daily frequency is selected because it provides a more detailed representation of short-term fluctuations in gold prices and exchange rate movements compared with weekly or monthly data. Such high-frequency observations are particularly useful for identifying temporal dependence and nonlinear patterns that are essential for semiparametric time series modeling. The data were downloaded in CSV format and processed using statistical software (Rstudio) for time series analysis and spline estimation.

2. Variable Selection and Preliminary Analysis

The variables included in this study were selected based on both theoretical considerations and empirical evidence from previous studies on gold price forecasting. The response variable is the daily closing price of the GCJ6 gold futures contract, which represents the international gold price. Two predictor variables are incorporated into the proposed model: the lagged gold price, denoted as GCJ6_{t-1}, and the US Dollar Index (DXY).

The inclusion of $GCJ6_{t-1}$ is motivated by the autoregressive characteristic commonly observed in financial time series, where the current price is strongly influenced by its immediately preceding value (Miranda et al., 2025; Yang, 2019). Using the first lag provides a parsimonious model while adequately representing temporal dependence in the gold price series. Meanwhile, the DXY is selected because it is one of the primary macroeconomic indicators affecting international gold prices through changes in the strength of the US dollar (Ahmad et al., 2024; Kaewkheaw et al., 2014).

Prior to model estimation, an exploratory data analysis (EDA) was conducted to examine the characteristics of the variables. Time series plots were used to observe overall movement patterns, while scatter plots between GCJ6 and DXY were examined to identify possible nonlinear relationships. In addition, the autocorrelation structure of the GCJ6 series was investigated to confirm the existence of temporal dependence, supporting the inclusion of the autoregressive component in the proposed model.

3. Semiparametric Time Series Regression (STSR)

To accommodate both temporal dependence and nonlinear relationships, this study employs the Semiparametric Time Series Regression (STSR) model. The proposed model combines a parametric autoregressive component and a nonparametric spline component within a unified regression framework. Given STSR model as follows (Ahmed et al., 2022; Fitriyah, Chamidah, & Saifudin, 2025):

$$y_t = \beta_0 + \beta_1 y_{t-1} + f(x_t) + \varepsilon_t \quad (1)$$

where y_t denotes the GCJ6 price at time t , y_{t-1} is the first-order lag of GCJ6, x_t represents the US Dollar Index (DXY), $f(\cdot)$ is an unknown smooth function estimated using spline regression, and ε_t is a random error term satisfying $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = \sigma^2$.

Equation (1) can be expressed in matrix notation as follows:

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\beta} + \mathbf{f}(\mathbf{x}) + \boldsymbol{\varepsilon} \quad (2)$$

Where

$\mathbf{Z} = \begin{bmatrix} 1 & y_0 \\ 1 & y_1 \\ \vdots & \vdots \\ 1 & y_{n-1} \end{bmatrix}$, $\boldsymbol{\beta} = (\beta_0, \beta_1)^T$, $\mathbf{f}(\mathbf{x})$ denotes the vector of spline functions, and $\boldsymbol{\varepsilon}$ is the error vector.

The parametric component models the autoregressive dependence of gold prices, whereas the spline function captures the nonlinear effect of the US Dollar Index. This combination enables the proposed STSR model to simultaneously account for temporal dependence and nonlinear relationships in financial time series.

4. Spline Estimation and Optimal Knot Selection

The unknown smooth function $f(x_t)$ in Eq. (1) is estimated using truncated spline regression. Spline regression approximates nonlinear relationships through piecewise polynomial functions connected at knot points. When the nonparametric component $f(x_t)$ is approximated using the spline estimator with order (p) and knot point (k_i) the function of $f(x_t)$ in Eq. (1) can be represented as (F. Jiang et al., 2018; Liu, 2009; Ramadhan et al., 2024; Xie et al., 2020):

$$f(x_t) = \sum_{j=0}^p \theta_j x_t^j + \sum_{i=1}^n \theta_{p+n} (x_t - k_i)_+^p \quad (3)$$

where,

$$(x_t - k_i)_+^p = \begin{cases} (x_t - k_i)^p; & \text{if } x_t > k_i \\ 0 & ; \text{if } x_t \leq k_i \end{cases}$$

Selecting the optimal knot point has an influence on obtaining the best estimation results. The optimal knot point is determined based on the GCV value, which can be obtained through the following calculation (Chamidah, Lestari, et al., 2025; Siregar et al., 2022):

$$GCV(\lambda) = \frac{MSE(\lambda)}{\left[\frac{1}{n} \text{trace}(\mathbf{I} - \mathbf{H}(\lambda)) \right]^2} \quad (4)$$

where, $\lambda = p, k_1, k_2, \dots, k_n$ is smoothing parameter, p is order spline, k is knot points, and $\mathbf{H}(\lambda)$ is hat matrix with λ parameter.

5. Goodness of Fit Measures

To measure the goodness of fit of the resulting STSR model based on spline estimator, goodness of fit criteria is required. In this study, Mean Absolute Percentage Error (MAPE), Symmetric Absolute Percentage Error (sMAPE), and Mean Absolute Scaled Error (MASE) were used to measure the goodness of fit of the gold price prediction model. The MAPE formula is as follows (Amri, Chamidah, Saifudin, Lestari, et al., 2025; Chamidah, Hasyim, et al., 2025; Utami et al., 2025):

$$\text{MAPE (\%)} = \frac{1}{n} \sum_{t=1}^n \left| \frac{\hat{y}_t - y_t}{y_t} \right| \times 100 \quad (5)$$

with the given MAPE categories in Table 2 (Amri, Chamidah, Saifudin, & Lestari, 2025; Ariesta et al., 2021; Blasco et al., 2013):

Tabel 2. Categorization of MAPE Value

MAPE Category	Category
MAPE > 50%	Inaccurate
20% < MAPE ≤ 50%	Reasonable
10% < MAPE ≤ 20%	Good Prediction
MAPE ≤ 10%	High Accurate Prediction

In addition to the MAPE, this study employs the sMAPE to evaluate the performance of the STSR model based on spline estimator. The sMAPE metric is widely used to assess prediction accuracy, particularly in time series analysis and statistical forecasting. The sMAPE is defined as follows (Hauke et al., 2018; Li et al., 2023):

$$\text{sMAPE } (\%) = \frac{1}{n} \sum_{t=1}^n \frac{2|y_t - \hat{y}_t|}{|y_t| + |\hat{y}_t|} \times 100 \quad (6)$$

The categorization of model accuracy based on sMAPE values is summarized in Table 3:

Tabel 3. Categorization of Model accuracy based on sMAPE

sMAPE Category	Category
sMAPE > 200%	Inaccurate
80% < sMAPE ≤ 200%	Reasonable
40% < sMAPE ≤ 80%	Accurate
sMAPE ≤ 40%	Highly Accurate

Furthermore, to complement the previously mentioned error measures, the MASE is also utilized. This metric is recognized for its scale-free property and greater stability in evaluating forecasting accuracy. The mathematical expression for MASE is given as follows (Hyndman & Koehler, 2006; P. Jiang et al., 2021; Swain et al., 2023):

$$\text{MASE} = \frac{\frac{1}{n} \sum_{t=1}^n |\hat{y}_t - y_t|}{\frac{1}{n} \sum_{t=2}^n |y_t - y_{t-1}|} \quad (7)$$

Category of MASE is presented in Table 4 as follows:

Table 4. Category of MASE Value

MASE Value	Category
MASE < 1	The model performance is better than the baseline model
MASE =1	The performance of the model is the same as the baseline model.
MASE > 1	The model performance is worse than the baseline model.

The MASE metric assesses model accuracy by comparing the average forecast error of the proposed model with that of a simple benchmark model. A MASE value less than one indicates that the proposed model outperforms the benchmark, a value equal to one suggests comparable predictive accuracy, while a value greater than one implies inferior performance.

6. Research Analysis Procedure

The analytical procedure adopted in this study is summarized in Figure 1. The proposed framework consists of sequential stages, beginning with data preparation and exploratory analysis, followed by the construction of the Semiparametric Time Series Regression (STSR) model, parameter estimation, model validation, and performance evaluation.

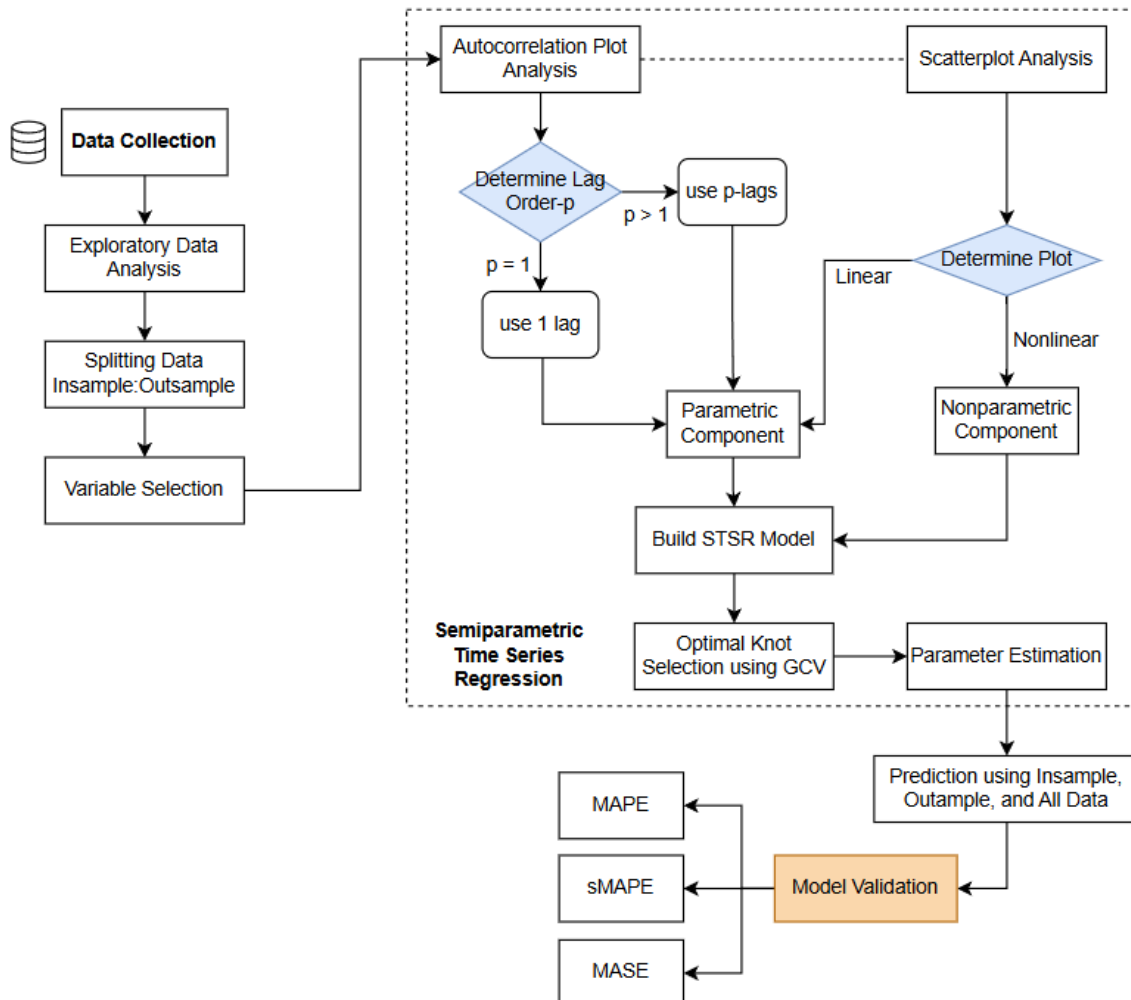


Figure 1. Flowchart of Data Analysis

C. RESULT AND DISCUSSION

Gold is a commodity that plays a crucial role as a safe haven asset and hedge against global uncertainty. Price projections for metal commodities, including gold, have long been a focus for global market players in decision-making (Jin & Xu, 2025). Global gold price movements, in this case the GCJ6 variable, have shown an upward trend over the past 10 years. The GCJ6 trend over the past 10 years is shown in Figure 2.

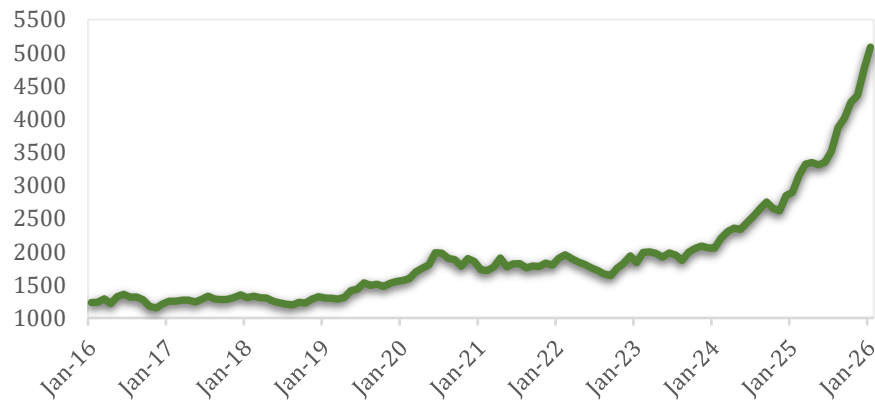


Figure 2. Tren of GCJ6 (last 10 years)

Figure 2 shows that the GCJ6 variable has been trending upward over the past 10 years, with a relatively stable movement until around 2023. However, in recent months, a sharp spike has been observed, with a much steeper curve slope compared to the previous period. This increase indicates a significant price acceleration and indicates global uncertainty and increased gold demand, which have driven extreme price increases in a short period of time. The GCJ6 trend over the past six months is presented in Figure 3.

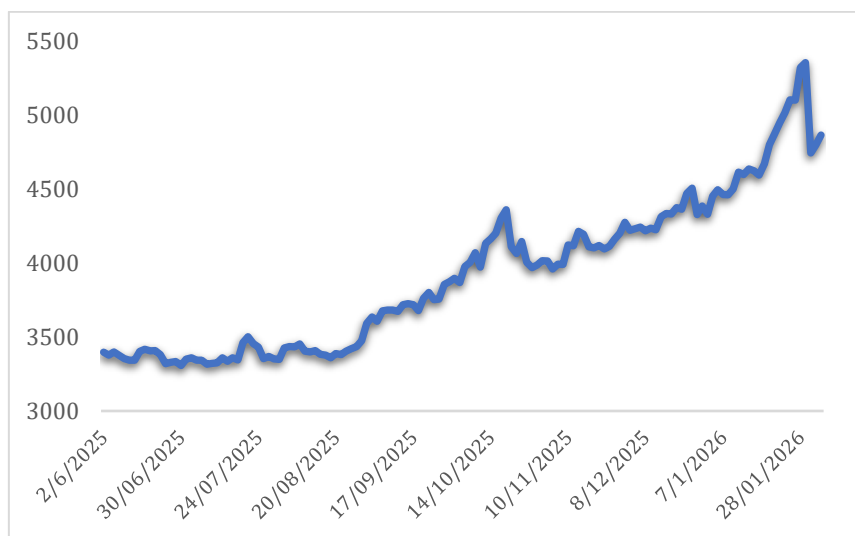


Figure 3. Tren of GCJ6 (last 6 months)

In time series data, the value of a variable is generally influenced by previous data. Gold price movements in previous periods tend to form certain patterns that influence the current price. Apart from that, gold price movements are also influenced by external factors, one of which is the US Dollar Index (DXY) (Zhou & Liang, 2025). This index reflects the strength of the US dollar against other major currencies, often used as a benchmark for global financial markets. Changes can affect gold prices through exchange rate mechanisms, investor expectations, and international capital movements.

This study discusses the prediction of world gold prices (symbol: GCJ6) which is influenced by the US dollar index (DXY) using the Semiparametric Time Series Regression (STSR) approach based on a spline estimator. The data used in this study are daily GCJ6 and DXY data.

The GCJ6 variable acts as a response variable. The previous-period GCJ6 ($GCJ6_{t-1}$) is used as a predictor in the parametric component, while the DXY variable serves as a predictor in the nonparametric component. The data in this study are secondary data sourced from the website www.investing.com. The GCJ6 and DXY data used in this study are daily data for the period June 2, 2025 to February 3, 2026, total 140 data. The proportion of the dataset is divided into two parts, namely 117 data are designated as in-sample data used to construct a nonparametric time series model based on a spline estimator, while 23 data are out-sample data used to test the validity and accuracy of the resulting model predictions. The descriptive statistical analysis of this research data is shown in Table 5.

Table 5. Descriptive Statistic of Variables

Variables	Statistics			
	Min	Max	Mean	Variance
GCJ6	3307.7	5354.8	3920.62	268409.6
DXY	96.22	100.23	98.43	0.761

The relationship between the GCJ6 variable and the previous period's GCJ6 variable shows a linear pattern. Therefore, in this study, the $GCJ6_{t-1}$ variable was selected as the parametric component. The relationship pattern between the $GCJ6_{t-1}$ variable and the GCJ6 variable is shown in Figure 4.

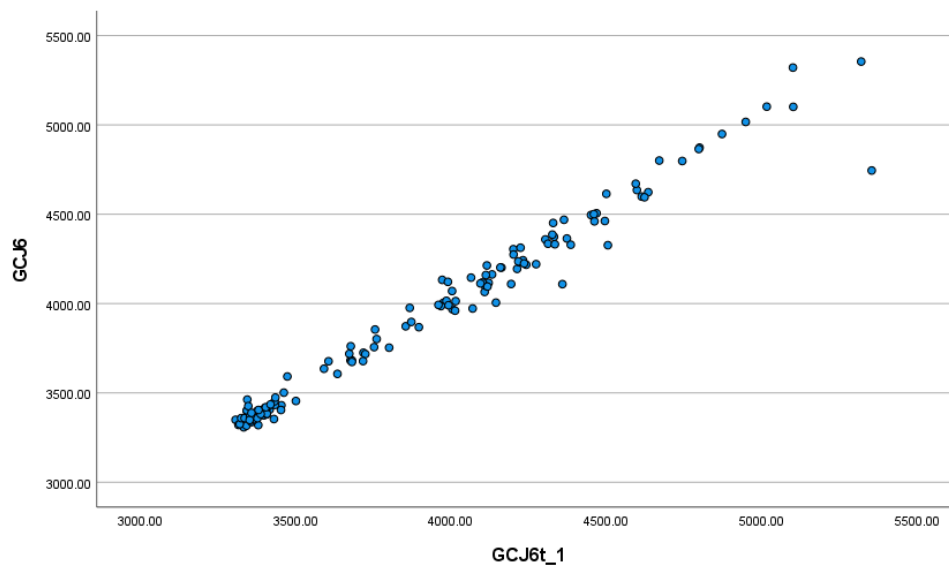


Figure 4. Scatter plot of GCJ6 vs $GCJ6_{t-1}$

In contrast to the relationship pattern of $GCJ6_{t-1}$ with the GCJ6 variable, the relationship pattern between the GCJ6 and DXY variables presented in Figure 5 shows a non-linear pattern, so the DXY variable was chosen as the non-parametric component. This study involved both parametric and non-parametric predictor variables, so data analysis with the STSR approach based on the spline estimator was considered suitable for building a gold price prediction model.

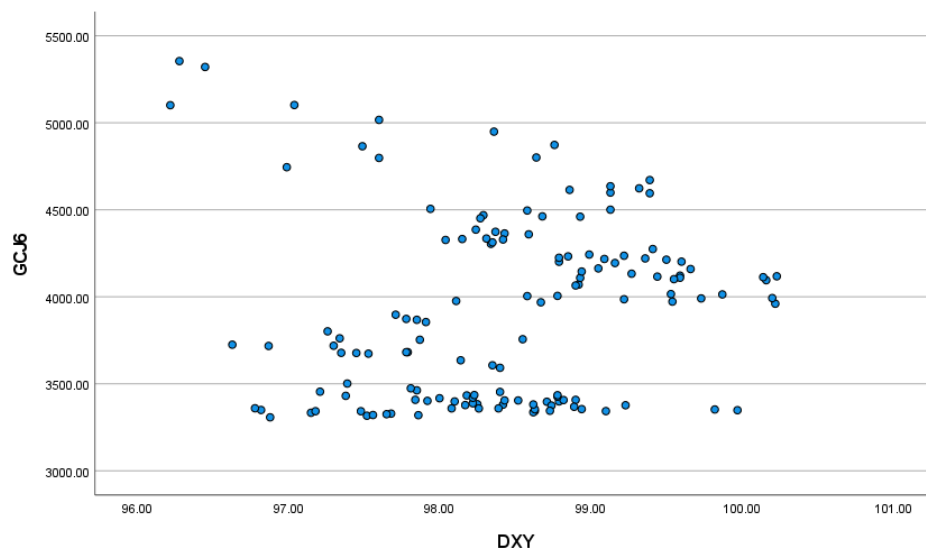


Figure 5. Scatter plot of GCJ6 vs DXY

Model estimation using the STSR approach based on a spline estimator is obtained by selecting the optimal order and knot points based on the GCV value. This study uses order 1 in the STSR model. This choice of order 1 is based on the principle of parsimony, and low-order models are able to produce more stable estimates and avoid the risk of overfitting (Fitriyah et al., 2025). The results of the GCV calculation are presented in Table 6.

Table 6. The Estimation Results are based on STSR Based on Spline Estimator

Knot Points	GCV	MSE
97.86	0.01227	3106.276
98.42	0.01229	3130.693
98.94	0.01230	3133.881
97.86; 98.42	0.01248	3125.769
98.42; 98.94	0.01231	3083.098
97.86; 98.94	0.01241	3107.178
97.86; 98.42; 98.94	0.01253	3082.779

Based on Table 6, the optimal knot point selected based on the smallest GCV value is one knot point, namely 97.86. The STSR model based on the spline estimator that can be built based on the smallest GCV is as follows:

$$y_t = -955.806 + 0.9985y_{t-1} + 9.973x_t - 16.116(x_t - 97.86)_+ \quad (8)$$

Based on equation (8), the relationship between the variable $GCJ6_{t-1}$ and the variable $GCJ6$ has a positive influence. This is explained in equation (9):

$$y_t = -955.806 + 0.9985y_{t-1} + f(x_t) \quad (9)$$

In equation (9), it can be seen that the $GCJ6_{t-1}$ variable positively influences the $GCJ6$ variable. If other variables are held constant and the $GCJ6_{t-1}$ variable increases by one unit, then the

GCJ6 variable will increase by 0.9985. The relationship between the DXY variable and GCJ6 is also explained in equation (10).

$$f(x_t) = \begin{cases} 9.973x_t & ;(x_t \leq 97.86) \\ -1577.12 - 6.143x_t & ;(x_t > 97.86) \end{cases} \quad (10)$$

Based on the nonparametric function estimation results in equation (3), the relationship between the DXY variable and the world gold price (GCJ6) is nonlinear and changes at a threshold point of 97.86. When the DXY value is at or below 97.86, the GCJ6 gold price tends to increase along with the DXY increase, as indicated by a positive coefficient of 9.973. This indicates that at relatively low DXY levels, a strengthening US dollar is followed by an increase in the gold price. Conversely, when the DXY value exceeds 97.86, the relationship between the DXY and GCJ6 changes, where an increase in the DXY is actually followed by a decrease in the GCJ6 gold price, as indicated by a negative coefficient of -6.143. This difference in direction of influence indicates a shift in the pattern of the relationship between the DXY and gold prices at certain DXY levels, confirming that the influence of the DXY on GCJ6 is nonlinear and dependent on the conditions or range of DXY values. The estimation results on the in-sample data obtained based on the STSR based on spline estimator approach are presented in Figure 6.

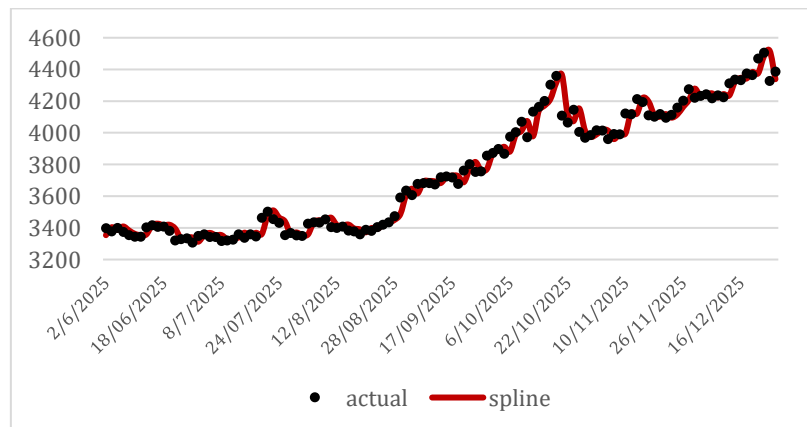


Figure 6. Plot estimation using STSR based on spline estimator (in sample data)

Based on Figure 6, it can be seen that the estimation results of the in-sample data of the GCJ6 variable influenced by the GCJ6_{t-1} and DXY variable using the STSR approach based on the spline estimator produce estimates that are close to the actual value. The estimation results are shown by the red line and the actual value is shown by the black dot. Similar results were also obtained in the estimation of the out-sample data, as depicted in Figure 7.

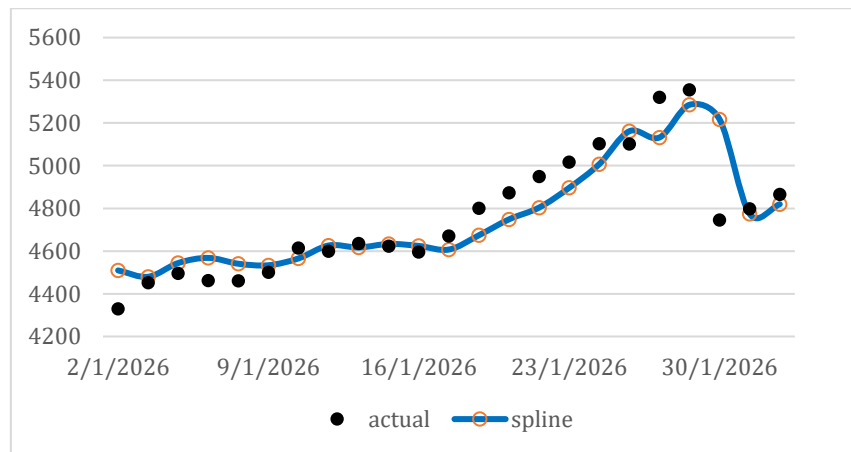


Figure 7. Plot estimation using STSR based on spline estimator (out-sample data)

This study aims to model the gold price prediction (GCJ6) influenced by the $GCJ6_{t-1}$ and DXY variable. Model fit evaluation was performed using MAPE, sMAPE, and MASE values, then compared against the criteria. The results of the three goodness-of-fit criteria are presented in Table 7.

Table 7. Goodness-of-Fit Measures of STSR-Spline Based on MAPE, sMAPE, and MASE

Data	MAPE	sMAPE	MASE
In-sample	1.008%	0.043	0.29
Out-sample	1.948%	0.628	0.947
All-data	1.478%	0.335	0.618

Table 7 shows the forecasting accuracy of the model generated by the STSR-based spline estimator, based on MAPE, sMAPE, and MASE values for in-sample, out-sample, and overall data. The MAPE value generated for the in-sample data is 1.008%, or less than 10%, indicating the model meets the criteria for highly accurate predictions. Similarly, the MAPE value applied to the out-sample data is 1.948%, indicating the model's predictive ability and generalizability. Furthermore, the sMAPE values for both the in-sample, out-sample, and overall data are all less than 10%, indicating the highly accurate model. A MASE value of less than 1 also indicates that the STSR-based spline estimator model has a relatively small forecasting error and a good level of accuracy. From the three measures of goodness of fit, it can be concluded that the proposed model has good and stable forecasting performance, both on in-sample, out-sample, and overall data and is able to produce accurate GCJ6 predictions.

To further evaluate the effectiveness of the proposed STSR-Spline model, its forecasting performance was compared with several widely used forecasting approaches, namely ARIMA, ARIMAX, Random Forest, and Extreme Gradient Boosting (XGBoost). These methods were selected because they represent conventional statistical time series models and modern machine learning approaches that are commonly employed for financial forecasting. All models were evaluated using the same dataset partition and forecasting accuracy measures, including MAPE, sMAPE, and MASE, to ensure a fair and consistent comparison. The comparative results are presented in Table 8.

Table 8. Comparison of Forecasting Performance STSR with Several Methods

Method	MAPE(%)			sMAPE			MASE		
	In-sample	Out-Sample	All Data	In-sample	Out-Sample	All Data	In-sample	Out-Sample	All Data
ARIMA	1.864	7.601	2.806	2.720	8.045	3.595	1.742	9.612	3.035
ARIMAX	2.943	7.625	3.712	2.681	8.036	3.561	2.680	9.594	3.816
Random Forest	0.431	8.957	1.832	0.431	9.474	1.917	0.424	11.167	2.189
XGBoost	0.100	10.539	1.815	0.100	11.247	1.931	0.096	13.112	2.234
STSR-Spline	1.008	1.948	1.478	0.043	0.628	0.335	0.290	0.947	0.618

Table 8 compares the forecasting performance of the proposed STSR-Spline model with conventional statistical models (ARIMA and ARIMAX) and machine learning methods (Random Forest and XGBoost). Although Random Forest and XGBoost achieved the smallest training errors, their testing errors increased substantially, indicating potential overfitting and limited generalization ability. In contrast, the proposed STSR-Spline model produced the lowest out-of-sample and overall forecasting errors across all evaluation metrics, achieving an overall MAPE of 1.478%, sMAPE of 0.335, and MASE of 0.618. These results demonstrate that the spline-based STSR model provides a better balance between model flexibility and predictive stability by simultaneously capturing the autoregressive dependence of gold prices and the nonlinear influence of the DXY. Consequently, the proposed model exhibits superior forecasting performance and stronger generalization capability than both conventional time series models and the evaluated machine learning approaches.

The results of this study indicate that the STSR approach is an appropriate method for modelling global gold price movements (GCJ6). In this study, the predictor variables have both parametric and nonparametric characteristics. The influence of GCJ6 values in the previous period on the current gold price is proven to be positive, confirming the existence of influence in time series data. This finding is in line with the theory and practice of time series modelling, which states that past values have a significant contribution in explaining variable movements in the current period, especially in gold price data that shows patterns of persistence and intertemporal correlation (Bhattacharya, 2025; Hai & Vu, 2025; Huang et al., 2024; Madhika et al., 2023; Naji et al., 2024).

Furthermore, the relationship between the US Dollar Index (DXY) and the GCJ6 gold price exhibits a nonlinear pattern, so this study modelled it using nonparametric components. The spline estimation results indicate a change in the direction of the DXY's influence on gold prices at certain threshold points. At relatively low DXY levels, a strengthening US dollar is followed by an increase in gold prices, while at higher DXY levels, a strengthening US dollar is followed by a decrease in gold prices. This pattern indicates that the relationship between the DXY and gold prices is dependent on the range of DXY values and cannot be adequately explained by the assumption of a single linear relationship. This finding supports the empirical literature stating that the relationship between the US dollar exchange rate and gold prices is dynamic and influenced by specific market conditions (He et al., 2020; Herley et al., 2024).

Theoretically, the relationship between the US dollar and gold prices is often assumed to be negative, with a strengthening US dollar depressing gold prices. However, developments in

global financial markets in recent years have shown that this relationship is increasingly complex and does not always follow traditional patterns. Several studies have suggested that gold no longer functions solely as a physical commodity but also as a strategic financial asset that acts as a hedging instrument and portfolio diversification (Baur & Smales, 2020). In this context, the US dollar is also increasingly viewed as a safe haven asset, so that under certain market conditions, US dollar appreciation can occur simultaneously with rising gold prices (Sebastian et al., 2025).

Furthermore, the sharp surge in gold prices in recent months, as reflected in the six-month chart, reinforces the indication of a shift in the structure of the global gold market. This extreme price increase, unlike previous historical patterns, coincided with the strengthening of the DXY and reflects financial factors in gold price formation. This condition aligns with empirical findings showing that the influence of the US dollar index on gold prices can shift from negative to positive, depending on market dynamics and investor behavior (Basher & Sadorsky, 2016; Baur & Lucey, 2010; Laduni, 2023).

Thus, the results of this study confirm that the combination of parametric components representing the historical dependence of gold prices and nonparametric components capturing nonlinear external influences provides a more flexible and informative modelling framework. The STSR approach based on spline estimators is able to explain the dynamics of the relationship between GCJ6, its historical value, and DXY more comprehensively than purely parametric or nonparametric approaches, and provides an empirical contribution to the study of gold price modeling based on time series data.

D. CONCLUSION AND SUGGESTIONS

This study demonstrates that the Semiparametric Time Series Regression (STSR) approach provides an effective framework for modeling gold price movements by simultaneously accommodating linear temporal dependence and nonlinear relationships with external macroeconomic variables. The proposed model integrates a parametric autoregressive component to capture the influence of previous gold prices and a spline-based nonparametric component to represent the nonlinear effect of the US Dollar Index (DXY). This unified framework enables the model to describe heterogeneous relationship patterns that cannot be adequately represented by conventional linear time series models such as ARIMA or ARIMAX.

From a methodological perspective, this study contributes to the development of semiparametric time series analysis by demonstrating the applicability of spline-based STSR for financial forecasting involving mixed linear and nonlinear structures. Compared with conventional parametric approaches, the proposed model provides greater flexibility in modeling nonlinear exogenous effects while preserving the interpretability of the autoregressive component. This balance between model flexibility and interpretability represents an important advantage of the STSR framework for analyzing complex financial time series. The empirical results further confirm the effectiveness of the proposed approach, yielding low forecasting errors with an overall MAPE of 1.478%, sMAPE of 0.335, and MASE of 0.618, indicating excellent predictive performance for both model fitting and forecasting. These findings suggest that spline-based STSR is a reliable alternative for modelling and predicting gold prices in the presence of nonlinear macroeconomic influences.

Future research may extend the proposed framework by incorporating additional macroeconomic variables, such as interest rates, inflation, stock market indices, exchange rates, crude oil prices, and geopolitical risk indicators, to better explain the dynamics of gold prices. Furthermore, comparative studies between the proposed STSR model and modern forecasting techniques, including Artificial Neural Networks (ANN), Random Forest, Support Vector Regression (SVR), Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), and other deep learning models, are recommended to evaluate the trade-offs between predictive accuracy, model interpretability, and computational efficiency across different financial market conditions.

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