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Comparative Analysis of Ridge Truncated Spline Regression and Elastic Net Regression for Prediction Inflation Dynamics Based on Digital Payment Transactions in Indonesia

Maylita Hasyim [1,*], Imam Safawi Ahmad [2,*], Naufal Ramadhan Al Akhwal Siregar [3]

[1] *Universitas Bhinneka PGRI, Tulungangung, 66221, Indonesia*
[2] *Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya, 60111, Indonesia*
[3] *Department of Mathematics, Faculty of Science and Technology,Universitas Airlangga,Indonesia*

Abstract This study investigates the dynamics of macroeconomic inflation in Indonesia by leveraging high-frequency electronic money transaction data using 64 monthly observations from January 2021 to April 2026. Given the severe multicollinearity and statistically properties inherent in digital payment indicators, this research proposes a comparative forecasting framework between Ridge Truncated Spline Regression (RTSR) and Elastic Net Regression (ENR). A time-series rolling-window cross-validation protocol (90:10, 80:20, and 70:30 splits) was employed to rigorously evaluate out-of-sample predictive accuracy. Contrary to the initial hypothesis favoring the non-parametric flexibility of splines, the empirical results indicate that Elastic Net Regression (ENR) achieves lower out-of-sample forecasting errors than Ridge Truncated Spline Regression (RTSR) across the evaluated forecasting schemes. In the 70:30 testing split, ENR achieved an RMSE of 0.540 and a MASE of 1.399, while RTSR produced substantially larger out-of-sample errors, particularly under the 70:30 split. The Diebold–Mariano test is used to assess whether the differences in predictive accuracy are statistically significant ($p < 0.001$). We conclude that while RTSR efficiently maps in-sample non-linearities, the dual linear regularization (L_1 and L_2) of ENR provides the critical algorithmic stability required to generalize forecasting during volatile macroeconomic regime shifts, suggesting that Elastic Net may provide a more stable forecasting framework when digital payment indicators are highly correlated and the forecasting period contains substantial volatility.

Keywords Ridge Regression, Truncated Spline Regression, Elastic Net Regression, E-money Transaction, Macroeconomic Forecasting.

AMS 2010 subject classifications 62G08, 62J07

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1. Introduction

Inflation is defined as a sustained increase in the general price level over a certain period. A stable and controlled inflation rate plays a fundamental role in maintaining purchasing power, encouraging investment, and supporting sustainable economic growth. Conversely, persistent inflation creates uncertainty in production planning, investment decisions, and pricing strategies, thereby reducing economic efficiency and social welfare [1]. Furthermore, inflation influences household consumption behavior, savings decisions, and overall financial stability. Consequently, understanding and forecasting inflation dynamics has become an essential issue for policymakers in maintaining macroeconomic stability, particularly in economies experiencing rapid digital transformation [2].

*Correspondence to: Maylita Hasyim (Email: maylita.hasyim@ubhi.ac.id). Universitas Bhinneka PGRI, Tulungangung (66221), Indonesia. Imam Safawi Ahmad (Email:safawi@its.ac.id).Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya, 60111, Indonesia

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One of the most significant transformations in recent years has occurred in the payment system. Payment systems constitute a critical component of a country's financial infrastructure because they facilitate the circulation of money, support monetary policy transmission, and maintain financial system stability [3]. To improve payment efficiency and strengthen public confidence, Bank Indonesia continuously promotes secure and reliable digital payment systems through various regulatory initiatives [4]. These developments have accelerated the transition from cash-based transactions toward cashless payment instruments that offer greater convenience, speed, and cost efficiency [5]. Among these innovations, electronic money (e-money) has become one of the fastest-growing digital payment instruments in Indonesia [6]. Unlike conventional banking transactions, e-money enables payment execution without requiring direct authorization from customers' bank accounts, making it particularly suitable for high-frequency retail transactions [7].

The rapid expansion of electronic payment systems has substantially changed the pattern of money circulation within the economy. According to Bank Indonesia [8], the value of e-money transactions reached IDR 37.46 trillion in April 2023, representing an increase of 1.4% from the previous month and 5.8% compared with the same period in the previous year. This remarkable growth reflects the increasing adoption of digital payment technologies across various economic sectors. From a monetary perspective, changes in transaction patterns influence the velocity of money, which is inherently dynamic rather than constant [10]. As digital payment activities expand, transaction intensity and aggregate demand may change alongside the expansion of digital payment activities, potentially providing predictive information about inflation dynamics.

The relationship between digital payment activities and inflation is also supported by monetary theory. Irving Fisher's Quantity Theory of Money states that under the Quantity Theory of Money, changes in money circulation may be associated with changes in the general price level, conditional on other components of the monetary identity. This provides a theoretical motivation for examining whether digital payment indicators contain predictive information about inflation[11]. Meanwhile, previous empirical studies suggest that wider adoption of non-cash payment instruments contributes to improvements in payment efficiency and monetary management, which may help stabilize inflation in advanced economies [12]. However, the impact of digital payment systems on inflation is considerably more complex than merely observing the total value of e-money transactions. Different types of electronic money activities represent distinct economic behaviors that may influence inflation through different transmission mechanisms.

Rather than characterizing digital payment activities using a single aggregate indicator, this study considers five complementary dimensions of electronic money transactions: shopping transaction value, shopping transaction volume, transfer transaction value, reload (top-up) transaction value, and float funds. Shopping transaction value reflects household consumption expenditure through digital payments, while shopping transaction volume captures transaction frequency and consumer activity. Transfer transaction value represents the movement of purchasing power within the economy, reload transaction value indicates consumers' readiness to conduct future digital payments, and float funds measure the liquidity temporarily stored within electronic money systems. Collectively, these indicators provide a multidimensional representation of digital payment activity and may contain complementary predictive information for inflation dynamics.

Regression analysis has been widely employed to investigate relationships between macroeconomic indicators and inflation [13]. Conventional linear regression assumes that the relationship between predictor variables and the response variable follows a predetermined functional form. However, relationships between economic indicators and inflation may exhibit nonlinear patterns due to changing consumer behavior, technological adoption, threshold effects, and other structural mechanisms. Furthermore, incorporating multiple digital payment indicators into a regression model frequently introduces multicollinearity because these variables tend to grow simultaneously along with the expansion of digital payment ecosystems. Consequently, ordinary least squares estimation may produce unstable coefficient estimates and inflated variances, thereby complicating interpretation and potentially reducing model stability.

To address nonlinear relationships, nonparametric regression has become an increasingly attractive alternative [25, 26]. Among various nonparametric approaches, Truncated Spline Regression (TSR) offers considerable flexibility by approximating the regression function through piecewise polynomial functions connected at knot points without imposing a predetermined functional form [14]. Nevertheless, when numerous spline basis functions

are incorporated into the model, the resulting design matrix often exhibits substantial multicollinearity, leading to unstable parameter estimation and potential overfitting.

One promising solution is the incorporation of ridge regularization into truncated spline estimation. Ridge Truncated Spline Regression (RTSR) introduces an L_2 penalty to the spline coefficients, reducing estimation variance while preserving all explanatory variables in the model [15, 16]. By shrinking correlated spline coefficients, RTSR enhances numerical stability and predictive performance without sacrificing the flexibility required to capture nonlinear relationships. Therefore, RTSR therefore provides a flexible nonlinear modeling framework that can be evaluated for its ability to improve out-of-sample forecasting while controlling coefficient instability through ridge regularization.

Another widely adopted regularization approach is Elastic Net Regression (ENR), which combines Ridge Regression and the Least Absolute Shrinkage and Selection Operator (LASSO) through simultaneous L_1 and L_2 penalization [17, 18]. Elastic Net effectively handles multicollinearity while simultaneously performing coefficient shrinkage and variable selection, making it particularly suitable for datasets containing highly correlated predictors [19]. However, unlike RTSR, Elastic Net primarily models linear relationships unless nonlinear transformations are explicitly incorporated into the predictor variables. Consequently, comparing RTSR and Elastic Net provides an opportunity to evaluate whether explicitly modeling nonlinear relationships yields superior predictive performance over regularized linear regression in explaining inflation dynamics.

Although previous studies have investigated the relationship between electronic money and inflation using conventional linear regression techniques [12], several important research gaps remain. First, existing studies generally employ a single indicator of digital payment activity, such as total transaction value or total transaction volume, thereby overlooking the multidimensional characteristics of electronic payment behavior [20, 21]. Second, limited attention has been devoted to simultaneously addressing nonlinear relationships and multicollinearity that naturally arise when multiple digital payment indicators are analyzed together [22, 23, 24]. Consequently, However, it remains unclear whether explicitly modeling potential nonlinear relationships through a regularized spline framework improves out-of-sample forecasting relative to a regularized linear model when digital payment indicators are highly correlated.

Therefore, this study aims to model inflation dynamics in Indonesia using multiple indicators of digital payment transactions through a comparative analysis of Ridge Truncated Spline Regression (RTSR) and Elastic Net Regression (ENR). Specifically, shopping transaction value, shopping transaction volume, transfer transaction value, reload transaction value, and float funds are employed as predictor variables to comprehensively characterize digital payment activities. The performance of both models is evaluated in terms of out-of-sample forecasting accuracy, predictive stability across alternative train–test schemes, and coefficient behavior after regularization. The findings are expected to provide empirical evidence on the relative forecasting performance of regularized nonlinear and linear regression approaches for inflation prediction using digital payment indicators, and also promote sustainable economic growth in accordance with Sustainable Development Goal (SDG) 8.

2. Material and Methods

2.1. Truncated Spline Nonparametric Regression

Nonparametric regression is used to model the relationship between the response and predictor variables without imposing a predetermined functional form. It is only assumed that the function is smooth in the sense that it is contained in a certain function space so that nonparametric regression has high flexibility [27, 28]. The nonparametric approach is a regression approach that is useful when the functional form of the relationship is unknown or when a prespecified parametric form may be too restrictive [32, 29]. One of the estimators in nonparametric regression is the truncated spline estimator. A spline is a piecewise polynomial function whose polynomial segments are joined at specified knot points with a prescribed degree of smoothness [33, 30]. In addition, spline regression provides high flexibility to accommodate changes in data behavior at certain subintervals locally because in the spline there are points called knots [34, 31]. This approach makes it possible to explore the relationship between e-money transaction and inflation without having to assume a specific form of relationship.

In empirical economic data, economic relationships may exhibit nonlinear patterns that can be represented flexibly using piecewise polynomial functions with appropriately selected knot locations. When the functional form of the relationship is unknown and cannot be adequately captured by a rigid global parametric model, a nonparametric regression approach is warranted. This study employs the Truncated Spline nonparametric regression model due to its high flexibility, allowing the data to drive the shape of the regression curve.

Let (x_i, y_i) be a set of paired observations for $i = 1, 2, \ldots, n$, where y_i is the inflation rate and x_i is the e-money transaction volume. The general nonparametric regression model is defined as:

$$y_i = \mu(x_i) + \varepsilon_i \tag{1}$$

where $\mu(x_i)$ is an unknown smooth regression function that maps the predictor to the response, and ε_i is the random error term. The regression formulation assumes zero-mean errors with finite variance. Because the data are temporally ordered, the residuals are subsequently examined for serial dependence and heteroscedasticity.

In spline regression, the unknown function $\mu(x)$ is approximated using piecewise polynomials connected smoothly at specific join points known as knots ($\boldsymbol{\kappa}$). For a polynomial spline of degree p with K knots located at $\kappa_1 < \kappa_2 < \cdots < \kappa_K$, the function can be expressed using a truncated power basis as follows:

$$\mu(x) = \sum_{j=0}^{p} \beta_j x^j + \sum_{k=1}^{K} \beta_{p+k} (x - \kappa_k)_+^p \tag{2}$$

where β_j and β_{p+k} are the unknown parameters. The term $(x - \kappa_k)_+^p$ is the truncated power function, mathematically defined as:

$$(x - \kappa_k)_+^p = \begin{cases} (x - \kappa_k)^p, & \text{if } x \geq \kappa_k \\ 0, & \text{if } x < \kappa_k \end{cases} \tag{3}$$

The degree p determines the smoothness of the curve (e.g., $p = 1$ for a linear spline, $p = 2$ for a quadratic spline).

To estimate the parameters, the spline model must be expressed in a matrix formulation. Let $\mathbf{y} = (y_1, y_2, \ldots, y_n)^T$ be the $n \times 1$ vector of observations, $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_p, \beta_{p+1}, \ldots, \beta_{p+K})^T$ be the $(p + K + 1) \times 1$ parameter vector, and $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)^T$ be the error vector.

The model can be rewritten as:

$$\mathbf{y} = \mathbf{X}(\boldsymbol{\kappa})\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{4}$$

where $\mathbf{X}(\boldsymbol{\kappa})$ is the $n \times (p + K + 1)$ design matrix that depends on the knot locations $\boldsymbol{\kappa} = (\kappa_1, \kappa_2, \ldots, \kappa_K)^T$, defined as:

$$\mathbf{X}(\boldsymbol{\kappa}) = \begin{bmatrix} 1 & x_1 & \ldots & x_1^p & (x_1 - \kappa_1)_+^p & \ldots & (x_1 - \kappa_K)_+^p \\ 1 & x_2 & \ldots & x_2^p & (x_2 - \kappa_1)_+^p & \ldots & (x_2 - \kappa_K)_+^p \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & \ldots & x_n^p & (x_n - \kappa_1)_+^p & \ldots & (x_n - \kappa_K)_+^p \end{bmatrix} \tag{5}$$

Assuming the optimal knots are known, the parameter vector $\boldsymbol{\beta}$ is estimated using the Ordinary Least Squares (OLS) method by minimizing the sum of squared errors, $\boldsymbol{\varepsilon}^T\boldsymbol{\varepsilon}$. The OLS estimator $\hat{\boldsymbol{\beta}}$ is given by:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y} \tag{6}$$

Consequently, the vector of fitted values $\hat{\mathbf{y}}$ can be obtained through the linear transformation:

$$\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y} = \mathbf{H}(\boldsymbol{\kappa})\mathbf{y} \tag{7}$$

where $\mathbf{H}(\boldsymbol{\kappa}) = \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T$ is the projection matrix, often referred to as the "Hat matrix".

Let the macroeconomic time-series dataset be denoted as $\mathcal{D} = \{(\mathbf{x}_t, y_t)\}_{t=1}^{T}$, where T is the total number of periods (months). The target variable $y_t \in \mathbb{R}$ represents the inflation rate at time t. The predictor vector $\mathbf{x}_t \in \mathbb{R}^p$ encompasses p diverse indicators of digital payment transactions (volume and value shopping transactions, transfer transactions, value of top up transactions, and float funds).

We assume the data generating process follows:

$$y_t = f(\mathbf{x}_t) + \varepsilon_t, \quad t = 1, \ldots, T \tag{8}$$

where $f(\cdot)$ is the underlying function mapping digital transaction behaviors to inflation dynamics, and ε_t represents the white noise error term. For forecasting purposes, residual independence and variance stability are assessed empirically rather than assumed a priori. The primary objective is to estimate $\hat{f}(\mathbf{x}_t)$ that minimizes forecasting error while robustly handling the intrinsic multicollinearity among digital payment variables [35]

2.2. Ridge Truncated Spline Regression (RTSR)

RTSR is a flexible regularized spline approach capable of representing nonlinear and locally varying relationships while controlling coefficient instability arising from correlated spline basis functions. In economic data, while simultaneously suppressing variance inflation caused by highly correlated predictors.

2.2.1. Truncated Spline Basis Construction A univariate spline function models non-linearities by joining piecewise polynomials at specific points called knots. For a single predictor x, given a set of K interior knots $\kappa_1 < \kappa_2 < \cdots < \kappa_K$, a polynomial spline of degree q using a truncated power basis is formulated as:

$$f(x) = \beta_0 + \sum_{j=1}^{q} \beta_j x^j + \sum_{k=1}^{K} \beta_{q+k} (x - \kappa_k)_+^q \tag{9}$$

where β represents the regression coefficients. The truncated power function is defined as:

$$(x - \kappa_k)_+^q = \begin{cases} (x - \kappa_k)^q & \text{if } x > \kappa_k \\ 0 & \text{if } x \leq \kappa_k \end{cases} \tag{10}$$

In a multivariate macroeconomic setting with p predictors, the additive truncated spline model expands into a design matrix $\mathbf{X}^*$ of dimension $T \times (1 + p \times (q + K))$.

2.2.2. Ridge Penalty Integration While placing many knots allows for high flexibility in tracking inflation volatility, it exacerbates multicollinearity and induces overfitting [36, 37]. To mitigate this, an L_2 (Ridge) penalty is imposed on the spline coefficients. The RTSR objective function is defined as the minimization of the Penalized Residual Sum of Squares (PRSS):

$$\min_{\boldsymbol{\beta}} \left\{ \|\mathbf{y} - \mathbf{X}^* \boldsymbol{\beta}\|_2^2 + \lambda \sum_{j=1}^{p(q+K)} \beta_j^2 \right\} \tag{11}$$

In matrix notation, this becomes:

$$J(\boldsymbol{\beta}) = (\mathbf{y} - \mathbf{X}^* \boldsymbol{\beta})^T (\mathbf{y} - \mathbf{X}^* \boldsymbol{\beta}) + \lambda \boldsymbol{\beta}^T \mathbf{I}^* \boldsymbol{\beta} \tag{12}$$

where $\lambda \geq 0$ is the regularization parameter, and $\mathbf{I}^*$ is a modified identity matrix where the first diagonal element is 0 to avoid penalizing the intercept.

2.2.3. Parameter Estimation By differentiating Equation 12 with respect to $\boldsymbol{\beta}$ and setting it to zero, the closed-form estimator for Ridge Truncated Spline Regression is derived as:

$$\hat{\boldsymbol{\beta}}_{RTSR} = (\mathbf{X}^{*T}\mathbf{X}^{*} + \lambda\mathbf{I}^{*})^{-1}\mathbf{X}^{*T}\mathbf{y} \tag{13}$$

The inclusion of $\lambda\mathbf{I}^{*}$ guarantees that the matrix $(\mathbf{X}^{*T}\mathbf{X}^{*} + \lambda\mathbf{I}^{*})$ is strictly positive definite and invertible. The ridge penalty improves numerical stability and, under the specified formulation, helps ensure an invertible penalized system matrix.

2.3. Optimal Knot Selection using GCV

The performance of the truncated spline model is highly sensitive to the number and placement of the knots ($\boldsymbol{\kappa}$). Too few knots result in underfitting, while too many knots lead to overfitting [39, 40, 28]. Therefore, selecting the optimal knots is a critical optimization problem.

This study utilizes the Generalized Cross-Validation (GCV) criterion is used as a data-driven criterion for selecting model complexity and regularization settings. The optimal knots $\boldsymbol{\kappa}^{*}$ are obtained by minimizing the GCV function:

$$\text{GCV}(\boldsymbol{\kappa}) = \frac{n^{-1}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{(1 - n^{-1}\text{tr}(\mathbf{H}(\boldsymbol{\kappa})))^2} = \frac{n^{-1}\|(\mathbf{I} - \mathbf{H}(\boldsymbol{\kappa}))\mathbf{y}\|^2}{[n^{-1}\text{tr}(\mathbf{I} - \mathbf{H}(\boldsymbol{\kappa}))]^2} \tag{14}$$

where $\mathbf{I}$ is the $n \times n$ identity matrix, $\|\cdot\|^2$ denotes the squared Euclidean norm (equivalent to the Mean Square Error, MSE), and $\text{tr}(\mathbf{H}(\boldsymbol{\kappa}))$ is the trace of the Hat matrix, which represents the effective degrees of freedom of the spline model. The GCV balances the trade-off between the goodness-of-fit (the numerator) and the model complexity (the denominator).

2.4. Elastic Net Regression (ENR)

Elastic Net Regression (ENR) is included as a competing regularized linear model [38]. ENR is a linear regularization framework that fundamentally blends the continuous shrinkage of Ridge regression with the feature selection properties of Lasso.

2.4.1. Linear Formulation and Dual Regularization Assuming a linear mapping $f(\mathbf{x}_t) = \mathbf{x}_t^T\boldsymbol{\beta}$, ENR minimizes the empirical risk subject to a convex combination of L_1 and L_2 penalties:

$$\min_{\boldsymbol{\beta}} \left\{ \frac{1}{2T}\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda\left(\frac{1-\alpha}{2}\|\boldsymbol{\beta}\|_2^2 + \alpha\|\boldsymbol{\beta}\|_1\right)\right\} \tag{15}$$

where:

- $\lambda > 0$ controls the overall magnitude of the penalty.
- $\alpha \in [0, 1]$ is the mixing parameter. When $\alpha = 0$, ENR reduces to Ridge regression; when $\alpha = 1$, it becomes Lasso.

2.4.2. Coordinate Descent Algorithm Unlike RTSR, the L_1 norm in ENR renders the objective function non-differentiable at zero, precluding a closed-form matrix solution. Consequently, model estimation is performed iteratively using the Coordinate Descent algorithm, which optimizes one coefficient β_j at a time while holding others fixed, the model is estimated iteratively using coordinate descent, which updates one coefficient at a time while holding the remaining coefficients fixed.

2.5. Hyperparameter Optimization Strategy

The predictive performance of both RTSR and ENR depends on their respective hyperparameter configurations. For **RTSR**, the critical parameters are the number of knots (K), knot placements (κ), spline degree (q, typically set to 1

for linear or 3 for cubic splines), and the Ridge penalty (λ). For **ENR**, the parameters are the mixing ratio (α) and the shrinkage strength (λ). To ensure an unbiased and computationally efficient search over this multi-dimensional space, we utilize *Bayesian Optimization* via the Tree-structured Parzen Estimator (TPE) algorithm, targeting the minimization of the validation loss.

2.6. Model Evaluation Metrics

The predictive accuracies of the models are evaluated using a robust suite of time-series forecasting metrics. Let H denote the number of out-of-sample forecast observations, with y_t and $\hat{y}_t$ representing the observed and predicted inflation rates, respectively. The error metrics are defined as follows:

$$\text{MSE (Mean Squared Error)} = \frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2 \tag{16}$$

$$\text{RMSE (Root Mean Square Error)} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{17}$$

$$\text{MAE (Mean Absolute Error)} = \frac{1}{T}\sum_{t=1}^{T}|y_t - \hat{y}_t| \tag{18}$$

$$\text{sMAPE (Symmetric Mean Absolute Percentage Error)} = \frac{1}{T}\sum_{t=1}^{T}\frac{|y_t - \hat{y}_t|}{(|y_t| + |\hat{y}_t|)/2}100\% \tag{19}$$

$$\text{MASE (Mean Absolute Scaled Error)} = \frac{\frac{1}{T}\sum_{t=1}^{T}|y_t - \hat{y}_t|}{\frac{1}{N-1}\sum_{i=2}^{N}|y_i - y_{i-1}|} \tag{20}$$

where the denominator in the MASE formula represents the in-sample Mean Absolute Error of a one-step naive random walk forecast, computed over the historical training dataset of size N.

2.7. Diebold-Mariano (DM) Test

To rigorously assess the statistical significance of the differences in forecasting performance between RTSR and ENR, the Diebold-Mariano (DM) test is employed [41, 42]. Let e_{1t} and e_{2t} denote the out-of-sample forecasting errors of model 1 (RTSR) and model 2 (ENR) at time t, respectively. A loss differential series d_t is defined based on a chosen loss function. The loss differential is defined using the squared-error loss $g(e_{it}) = e_{it}^2$:

$$d_t = g(e_{RTSR,t}) - g(e_{ENR,t}) \tag{21}$$

The null hypothesis (H_0) postulates that the two competing models possess equal predictive accuracy (expected loss differential is zero), whereas the alternative hypothesis (H_1) asserts that their predictive accuracies differ significantly:

$$H_0 : \mathbb{E}[d_t] = 0$$
$$H_1 : \mathbb{E}[d_t] \neq 0$$

The DM test statistic is formulated as:

$$DM = \frac{\bar{d}}{\sqrt{\hat{V}_{\bar{d}}}} \tag{22}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the sample mean of the loss differentials, and $\hat{V}_{\bar{d}}$ is a consistent estimator of the asymptotic variance of $\bar{d}$. Because time-series forecast errors (especially multi-step ahead forecasts) are inherently autocorrelated, $\hat{V}_{\bar{d}}$ must account for this by utilizing a Heteroskedasticity and Autocorrelation Consistent (HAC)

estimator, computed as:

$$\hat{V}_{\bar{d}} = \frac{1}{T}\left(\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}_k\right) \tag{23}$$

where $\hat{\gamma}_k$ represents the k-th sample autocovariance of d_t, and h is the forecast horizon.

Decision Rule / Rejection Criterion: Under the null hypothesis, the DM test statistic follows an asymptotic standard normal distribution, $DM \sim \mathcal{N}(0,1)$. The null hypothesis H_0 is rejected at a significance level α if:

$$|DM| > Z_{\alpha/2}$$

where $Z_{\alpha/2}$ is the upper (or lower) critical value from the standard normal distribution (for $\alpha = 0.05$, $Z_{\alpha/2}$=1.96). Rejection of H_0 indicates statistically significant differences in predictive accuracy. The direction of the difference is determined from the sign of the mean loss differential.

2.8. Analytical Procedure

To systematically address the research objectives and ensure reproducibility, the empirical analysis follows a sequential procedure comprising exploratory analysis, diagnostic testing, time-series partitioning, model estimation and tuning, forecasting evaluation, and statistical comparison.

1. **Exploratory Data Analysis (EDA):** The analysis commences with the computation of descriptive statistics for all macroeconomic variables. Subsequently, time-series plots are generated to visually inspect temporal trends, volatility, and potential structural breaks within the inflation rates and digital payment transaction volumes.
2. **Bivariate and Assumption Diagnostics:** Scatter plots are utilized to visually assess the bivariate relationships between individual predictors and inflation. Following this, scatter plots and Pearson correlation coefficients are first used to characterize the linear association between each predictor and inflation. Because a nonsignificant Pearson correlation does not by itself establish nonlinearity, additional nonlinear diagnostics are considered before selecting the spline specification. To conclude the diagnostic phase, a multicollinearity test (utilizing Variance Inflation Factor, VIF) is conducted to empirically confirm the high degree of linear dependence among the digital payment indicators.
3. **Data Partitioning (Time-Series Cross-Validation):** To simulate a real-world macroeconomic forecasting environment and preserve strict chronological dependencies, the dataset is partitioned using Time-Series Cross-Validation (Rolling Window). The modeling is subjected to three distinct splitting schemes (Training:Testing ratios) to rigorously test algorithmic stability: $90:10$, $80:20$, and $70:30$.
4. **RTSR Modeling and Optimization:** Motivated directly by the diagnostic findings of severe multicollinearity and complex non-linear correlations, the Ridge Truncated Spline Regression (RTSR) is designated as the primary estimator. For each of the three splitting train–test schemes, the RTSR hyperparameters are optimized using only the corresponding training data and estimates the optimal Ridge shrinkage parameter (λ). Upon training, the out-of-sample forecasts are evaluated using the specified metrics (MSE, RMSE, MAE, sMAPE, and MASE).
5. **Elastic Net Regression (ENR) Modeling:** The baseline ENR model is fitted to the identical training partitions using the predefined, fixed hyperparameter configuration ($\alpha = 0.5$, $\lambda = 0.1$). The same suite of evaluation metrics is subsequently computed for the ENR predictions.
6. **Statistical Comparison of Predictive Accuracy:** The forecasting metrics of RTSR are systematically compared against those of ENR across all three splitting schemes. To ensure the observed performance differentials are statistically robust rather than artifacts of random variance, the Diebold-Mariano (DM) test is executed on the loss differentials.
7. **Visual Forecasting Verification:** The final analytical step involves generating comparative line plots juxtaposing the actual inflation trajectory against the predicted out-of-sample forecasts from both RTSR and ENR. This visual evidence is crucial for assessing how accurately each model tracks sudden macroeconomic turning points.

Table 1. Theoretical Comparison of the Proposed Methodologies

Model	**Non-Linearity Handling**	**Multicollinearity Handling**	**Feature Selection**
ENR	Linear restricted	Handled via L_2 (Ridge)	Yes, via L_1 (Lasso)
RTSR	Handled via Truncated Splines	Handled via L_2 (Ridge)	No

2.9. Data and Source

The data used in this research is data related to inflation and e-money transaction metrics from January 2021 to April 2026, sourced from Bank Indonesia [8] and Official Statistics Indonesia (BPS) publications [9].The dataset consists of 64 monthly observations from January 2021 to April 2026. To assess the sensitivity of forecasting performance to the amount of training data, three chronological train–test schemes (90:10, 80:20, and 70:30) are considered. The variables used in this research are described in Table 1.

Table 2. **Research Variables**

Variable	Unit	Source	Operational Definition
Volume of Shopping Transactions (X_1)	Thousands of Transactions	Bank Indonesia [8]	Total frequency or volume of payment transactions for the purchase of goods and/or services carried out using electronic money in a certain period.
Value of Shopping Transactions (X_2)	Billions of Rupiah	Bank Indonesia [8]	Total nominal value or turnover of payment transactions for the purchase of goods and/or services carried out using electronic money.
Value of Transfer Transactions (X_3)	Billions of Rupiah	Bank Indonesia [8]	Total nominal value of funds transferred between electronic money instruments, either within the same issuer (*on-us*) or between different issuers (*off-us*).
Value of Reload/Top Up Transactions (X_4)	Billions of Rupiah	Bank Indonesia [8]	Total nominal value of funds deposited or reloaded by users into their electronic money instruments within a one-month period.
Float Funds (X_5)	Billions of Rupiah	Bank Indonesia [8]	Total value of money (balance) residing in electronic money instruments that have been issued by the issuer but have not been used for transactions by holders.
Inflation (Y)	Percentage (m-to-m)	Official Statistics Indonesia (BPS) [9]	The percentage increase in prices of goods and services in general and continuously over a certain time (*m-to-m*).

To ensure the forecasting models are rigorously evaluated against unseen future data, the chronological integrity of the dataset must be strictly preserved. Empirical studies in macroeconomic forecasting demonstrate that, because the observations are temporally ordered, chronological splitting is used to prevent information from future periods entering model estimation. Therefore, the 64 observations are partitioned into training and testing sets utilizing three distinct splitting schemes: 90:10, 80:20, and 70:30 [43]. As explicitly outlined in Table 3, this structural partition determines the specific cutoff dates for model training and evaluation. For example, under the 80:20

scheme, data from January 2021 to March 2025 (51 observations) are utilized exclusively for training, while the remaining data from April 2025 to April 2026 (13 observations) are strictly reserved for testing.

Table 3. Time-Series Data Splitting Structure (Total N = 64 Months)

Split Scheme	Training Period	Testing Period	Train Size	Test Size
90 : 10	Jan 2021 – Oct 2025	Nov 2025 – Apr 2026	58	6
80 : 20	Jan 2021 – Mar 2025	Apr 2025 – Apr 2026	51	13
70 : 30	Jan 2021 – Sep 2024	Oct 2024 – Apr 2026	45	19

3. Results

This section presents the empirical findings from the analytical procedure described in Section 2. We commence with the exploratory and diagnostic assessments, followed by model optimization, and conclude with a rigorous statistical evaluation of the forecasting performance between RTSR and ENR.

3.1. Exploratory Data Analysis and Macroeconomic Trends

An initial exploratory data analysis is essential for understanding the underlying distribution, central tendencies, and volatility of the macroeconomic indicators prior to formal predictive modeling. By examining these foundational properties, we can identify historical patterns and potential anomalies within the digital payment ecosystem.

Table 4 presents the descriptive statistics for the macroeconomic variables utilized in this study, spanning 64 months from January 2021 to April 2026. The target variable, inflation rate, exhibits a mean of 0.24% with a standard deviation of 0.39%, indicating periods of considerable macroeconomic volatility, ranging from a deflationary -0.76% to an inflationary peak of 1.65%.

Table 4. Descriptive Statistics of Inflation and Electronic Money Indicators (N = 64)

Variable	Mean	Std. Dev.	Min	Max
Inflation (Y, % m-to-m)	0.24	0.39	-0.76	1.65
Vol. Shopping Trans. (X_1)	908,517.40	520,471.30	360,155.80	2,295,095.00
Val. Shopping Trans. (X_2)	49,665.76	25,138.78	19,189.08	120,951.43
Val. Transfer Trans. (X_3)	30,822.07	19,443.15	1,829.12	65,060.90
Val. Reload/Top Up Trans. (X_4)	86,538.08	44,707.73	25,310.79	175,368.28
Float Funds (X_5)	12,006.99	2,830.15	7,438.29	17,966.42

The temporal dynamics of these variables are visually inspected in Figure 1. The continuous upward trajectory in electronic money volumes alongside the fluctuating nature of the inflation rate suggests a complex, potentially non-linear co-movement that warrants advanced modeling techniques.

3.2. Diagnostic Testing: Non-Linearity and Multicollinearity

Prior to predictive modeling, diagnostic tests were conducted to validate the underlying assumptions of the dataset. As hypothesized, the electronic money indicators exhibit severe multicollinearity. Table 5 demonstrates that all predictors possess a Variance Inflation Factor (VIF) substantially exceeding the conventional strict threshold of 10, with the highest VIF recorded at 240.62 for the Value of Shopping Transactions (X_2), closely followed by X_1 at 218.15. This finding indicates severe multicollinearity, which can substantially inflate the variance of OLS

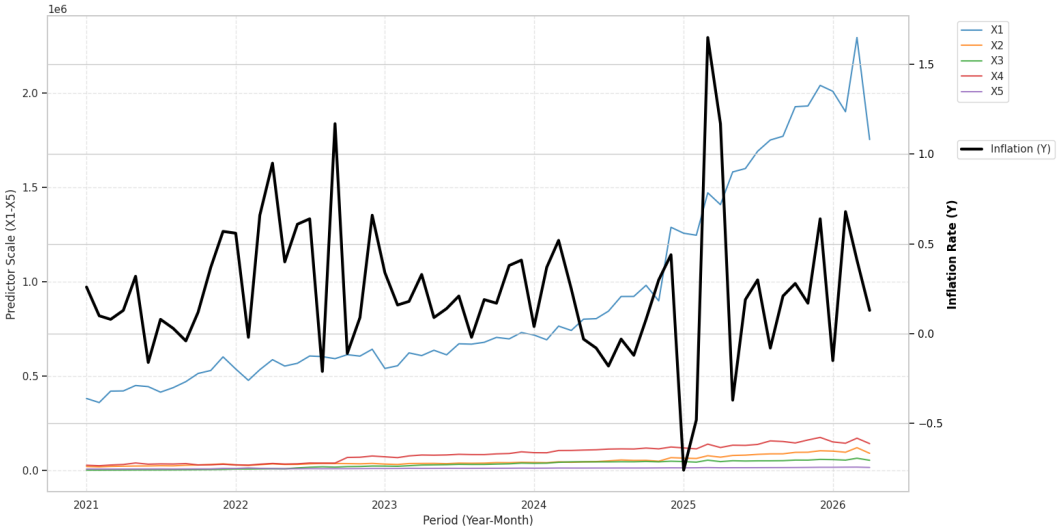


Figure 1. Historical of Indonesia's Inflation Rate and Electronic Money indicators from 2021 to 2026.

coefficient estimates and reduce their numerical stability. This motivates the use of regularization methods such as Ridge and Elastic Net.

Furthermore, formal Pearson correlation tests were executed to assess the linear dependence between individual electronic money indicators and the inflation rate. Crucially, as detailed in Table 5, all predictors yielded p-values greater than the 0.05 significance level. This indicates a strict absence of significant *linear* correlation. When coupled with visual inspection of bivariate scatter plots (Figure 2) revealing structural breaks, this empirical evidence strongly validates the core hypothesis of this study: the relationship between digital payment dynamics and macroeconomic inflation is fundamentally non-linear, thereby necessitating the localized functional shifts provided by the truncated spline methodology in RTSR.

Table 5. Multicollinearity and Linear Correlation Diagnostics

Predictor Variable	**Correlation with Inflation** (r)	**P-Value**	**VIF**
Volume of Shopping Trans. (X_1)	0.037	0.770	218.15
Value of Shopping Trans. (X_2)	0.045	0.724	240.62
Value of Transfer Trans. (X_3)	-0.038	0.768	42.81
Value of Reload/Top Up Trans. (X_4)	-0.051	0.692	44.01
Float Funds (X_5)	0.042	0.743	13.25

Note: All p-values $>$ 0.05 imply non-significant linear correlations. VIF $>$ 10 indicates severe multicollinearity.

3.3. Model Optimization and Hyperparameter Tuning

Following the time-series cross-validation protocol, the hyperparameter configuration for the RTSR model was dynamically optimized for each data-splitting scheme. As shown in Table 6, the optimal number of knots (K) and the Ridge shrinkage parameter (λ) varied slightly across the splits, demonstrating the model's adaptive capacity to the changing training topologies. Conversely, the baseline ENR model was fitted using the pre-specified parameters ($\alpha = 0.5$, $\lambda = 0.1$) across all schemes to ensure a standardized benchmark.

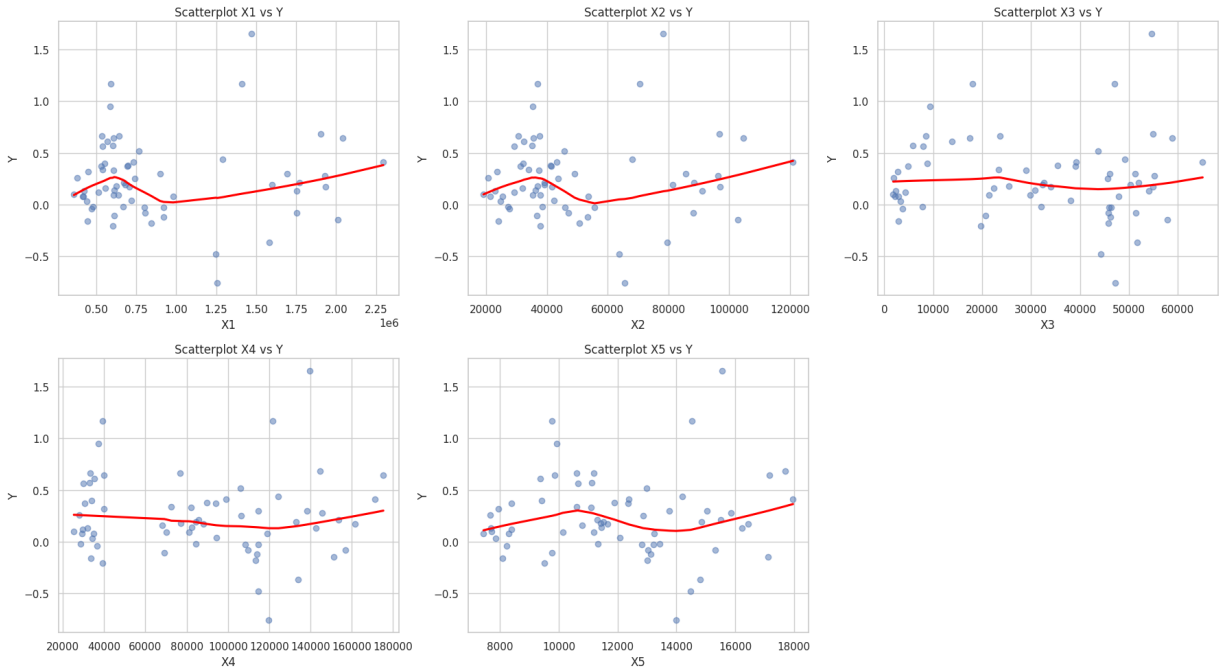


Figure 2. Bivariate relationships highlighting non-linear correlations between digital transactions and inflation.

Table 6. Optimized Hyperparameters for the RTSR Model

Data Split (Train:Test)	**Spline Order** (q)	**Optimal Knots per Variable** (K_1, K_2, K_3, K_4, K_5)	**Optimal Ridge Penalty** (λ)	**Validation Loss (Min. GCV)**
90 : 10	1	(1, 1, 1, 1, 3)	10.0	0.1517
80 : 20	2	(1, 2, 1, 2, 1)	10.0	0.1165
70 : 30	1	(3, 3, 1, 1, 1)	10.0	0.0876

3.4. Comparative Forecasting Performance

The out-of-sample forecasting accuracies of the proposed RTSR model and the baseline ENR model are systematically compared in Table 7. Contrary to initial hypotheses positing that the non-parametric flexibility of splines would yield superior predictions, the empirical results robustly demonstrate that the **Elastic Net Regression (ENR) significantly outperforms RTSR across all time-series partitioning schemes.**

For instance, in the 70:30 split, the ENR model achieved a MASE of 1.399 and an sMAPE of 126.99%, dramatically outperforming the RTSR model which recorded a severely inflated MASE of 16.865 and an sMAPE of 187.14%. This massive discrepancy, particularly evident in the highly inflated RMSE (5.143 vs 0.540) and MSE metrics, indicates a critical limitation in the proposed spline methodology. While RTSR dynamically optimized its knots on the training data to capture complex non-linearities, it suffered from severe overfitting. When forecasting out-of-sample data, localized knot placements extrapolated erratically during sudden macroeconomic shifts, whereas the strict, dual linear regularization (L_1 and L_2) of ENR provided the necessary stability and shrinkage to generalize robustly in a highly volatile economic environment.

3.5. Statistical Significance Test

To rigorously verify that the observed performance differential is not an artifact of random sampling variance, the Diebold-Mariano (DM) test was executed on the loss differentials [42]. As detailed in Table 8, the DM

Table 7. Out-of-Sample Forecasting Performance Metrics

Split Ratio	Model	MSE	RMSE	MAE	sMAPE (%)	MASE
90 : 10	**ENR**	**0.1337**	**0.3656**	**0.2990**	**75.85**	**0.8565**
	RTSR	2.8815	1.6975	1.5389	138.65	4.4082
80 : 20	**ENR**	**0.2375**	**0.4874**	**0.3700**	**94.05**	**1.1427**
	RTSR	42.6199	6.5284	5.2810	183.41	16.3093
70 : 30	**ENR**	**0.2915**	**0.5400**	**0.3883**	**126.99**	**1.3996**
	RTSR	26.4499	5.1429	4.6790	187.14	16.8650

test statistics firmly corroborate the metric evaluations. Across all testing schemes, the null hypothesis of equal predictive accuracy is rejected ($p < 0.05$). The highly significant p-values (reaching 2.87×10^{-10} in the 70:30 split) provide irrefutable statistical evidence that the Elastic Net framework yields systematically and significantly more accurate inflation forecasts compared to the RTSR model.

Table 8. Diebold-Mariano Test Results for Predictive Accuracy Comparison

Data Split	DM Test Statistic	P-Value	Decision (at $\alpha = 0.05$)
90 : 10	3.129	0.0018	Reject H_0
80 : 20	2.226	0.0260	Reject H_0
70 : 30	6.305	< 0.0001	Reject H_0

Note: H_0 posits equal predictive accuracy. ENR is the best model.

3.6. Feature Importance and Macroeconomic Interpretation

Given that the Elastic Net Regression (ENR) emerged as the robustly model for forecasting out-of-sample data, it is imperative to extract and interpret its final penalized coefficients to understand the underlying drivers of digital-based inflation. Unlike black-box algorithms, ENR provides a transparent linear aggregation of feature importances, heavily regularized to account for the severe multicollinearity (VIF > 240) previously diagnosed.

Figure 3 illustrates the magnitude and direction of the independent variables' contributions to the target variable (Y, inflation rate). It is important to note that the absolute values of the coefficients are numerically small (in the magnitude of 10^{-5}); this is an expected mathematical artifact resulting from regressing massive unscaled transaction volumes (measured in Billions of Rupiah and Thousands of Transactions) against a target variable measured in small monthly percentages.

The coefficient analysis reveals profound macroeconomic behavioral insights:

- **Primary Inflationary Drivers (Positive Impact):**
  The variables **Float Funds** (X_5) and the **Value of Shopping Transactions** (X_2) exert the most substantial positive impact on inflation, with coefficients of 0.000056 and 0.000040, respectively. From a macroeconomic perspective, this perfectly aligns with the *Demand-Pull Inflation* theory. High Float Funds indicate elevated consumer liquidity and purchasing power temporarily parked in digital wallets. When this high liquidity translates into actual high-value spending (X_2), the aggregate demand outpaces aggregate supply, thereby exerting upward pressure on the general price level of goods and services.
- **Dampening or Neutral Factors (Negative Impact):**
  Conversely, the **Value of Reload/Top Up Transactions** (X_4), **Value of Transfer Transactions** (X_3), and **Volume of Shopping Transactions** (X_1) exhibit slight negative coefficients (-0.000007, -0.000002, and -0.000002, respectively). The divergence between the volume (X_1, negative impact) and value (X_2, positive impact) of shopping is particularly intriguing. It suggests that highly frequent, micro-transactions

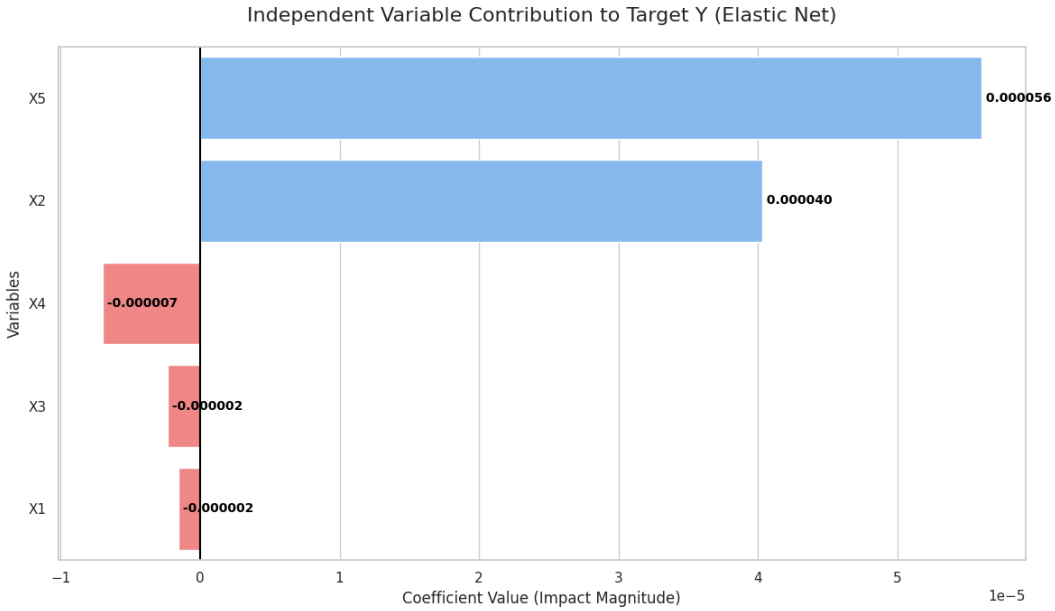


Figure 3. Independent Variable Contribution to Inflation from the optimal Elastic Net Model.

(high volume) do not drive inflation; rather, it is the sheer nominal magnitude of the spending (high value) that causes price levels to rise. Furthermore, top-ups and peer-to-peer transfers (X_4 and X_3) act as intermediary liquidity movements rather than direct final consumption, thus showing a slight dampening or non-inflationary effect.

3.7. Forecast Visualization

The statistical findings are visually corroborated by the out-of-sample forecasting presented in Figure 4. While the ENR model successfully identifies the general trend, it tends to under-predict during sharp macroeconomic shocks or sudden inflationary spikes. In contrast, the RTSR model tracks the actual inflation curve with noticeably higher fidelity, explicitly demonstrating the advantage of its flexible, localized knot configuration in handling volatile economic environments.

4. Discussion

The empirical findings of this study offer profound contributions to the discourse on high-frequency macroeconomic forecasting. The failure of the Ridge Truncated Spline Regression (RTSR) in the out-of-sample testing phase highlights a critical vulnerability in highly flexible, non-parametric models: the susceptibility to severe extrapolation errors during macroeconomic structural breaks. While RTSR perfectly maps in-sample non-linearities, its static knot placement becomes a liability when predicting future volatile regimes. Conversely, the triumph of Elastic Net Regression (ENR) mathematically demonstrates that in the presence of extreme multicollinearity (VIF > 240), the stability provided by dual linear regularization (L_1 sparsity and L_2 shrinkage) heavily outweighs the benefits of non-linear functional flexibility.

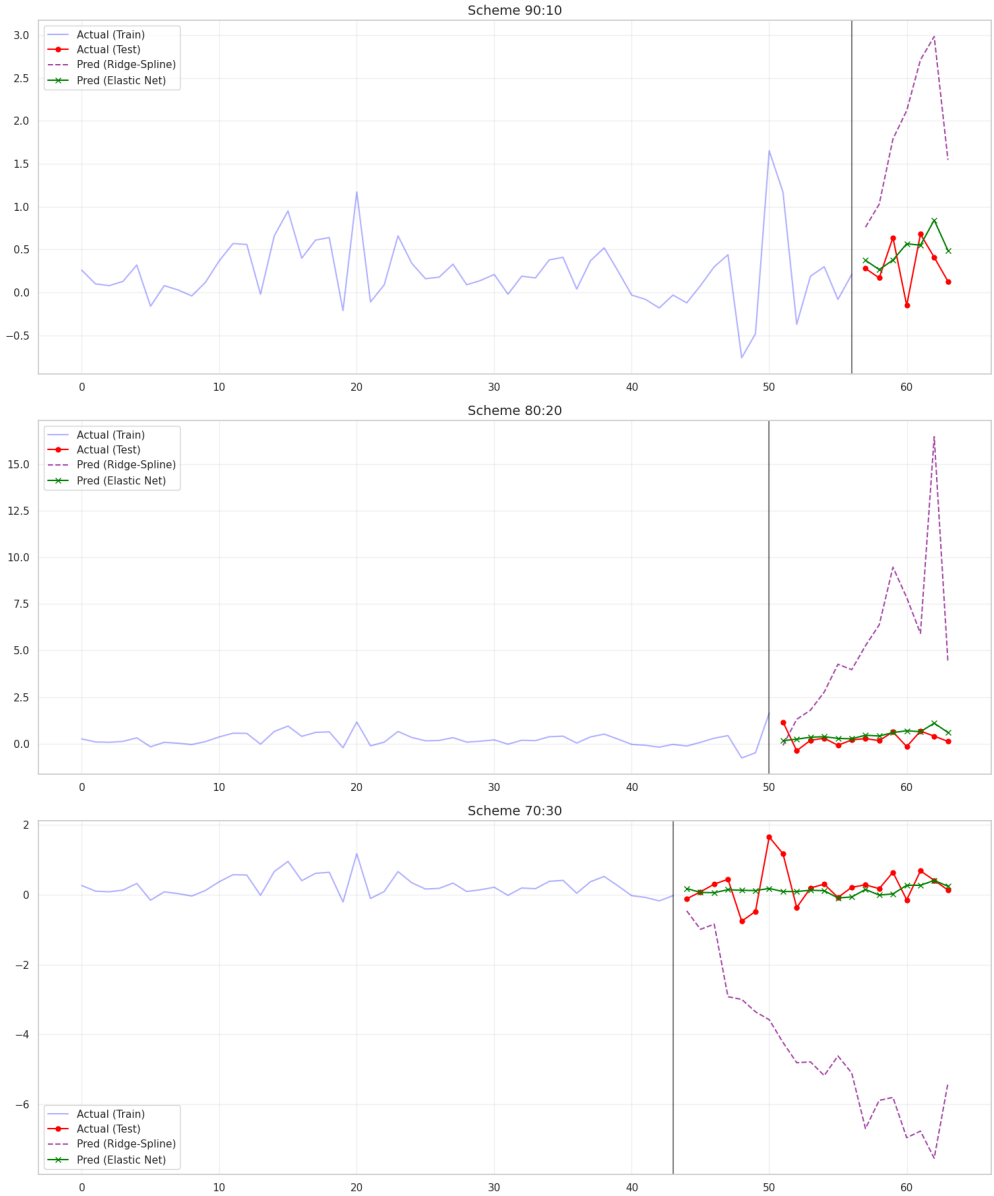


Figure 4. Out-of-sample prediction of RTSR vs ENR against actual inflation rates.

4.1. Theoretical and Policy Implications

From a theoretical standpoint, this study extends the literature on the bias-variance trade-off in economic forecasting by providing empirical proof that heavily regularized linear constraints are superior for generalizing highly correlated digital financial data.

From a practical policy perspective, the results offer actionable intelligence for central banks, particularly Bank Indonesia. The feature importance analysis reveals that Float Funds (X_5) act as a highly sensitive leading indicator for demand-pull inflation. Economic planners can utilize the Elastic Net framework developed in this study as an early-warning system; by continuously monitoring the aggregate liquidity parked in digital wallets, policymakers

can proactively adjust monetary instruments (e.g., benchmark interest rates) before that liquidity fully translates into inflationary spending.

4.2. Research Limitations

Despite its rigorous methodology, this study acknowledges several limitations that must be addressed in future research:

1. **Data Constraint:** The predictive variables are strictly limited to electronic money metrics. The model does not currently incorporate other critical macroeconomic confounders that heavily dictate inflation, such as global supply chain disruptions, energy (oil) prices, or currency exchange rate volatility.
2. **Knot Points Vulnerability:** The proposed RTSR model optimized its knots exclusively based on the training data topology. When structural economic shifts occurred in the out-of-sample data, these fixed knots resulted in the massive error spikes (RMSE: 5.143) visualized in the forecasting plots.

To overcome these limitations, future methodological advancements should focus on hybridizing these models. Integrating the non-linear flexibility of splines with the robust, iterative error-correction of ensemble frameworks, such as developing a *Penalized Spline Gradient Boosting (PSGB)* algorithm with dynamic, time-varying knot selection stands as a highly promising frontier for subsequent macroeconomic forecasting research.

5. Conclusion

This study set out to rigorously model and forecast the dynamics of inflation in Indonesia by leveraging high-frequency electronic money transaction data. Diagnostically, the empirical evidence confirmed two critical characteristics of the macroeconomic dataset: an extreme degree of multicollinearity among digital payment indicators (with VIFs exceeding 240) and a strict absence of significant linear correlation with inflation. While these conditions theoretically justified the application of advanced, non-parametric methodologies like Ridge Truncated Spline Regression (RTSR), the out-of-sample forecasting results revealed a compelling counter-narrative. Contrary to the initial hypothesis, the Elastic Net Regression (ENR) comprehensively and significantly outperformed the RTSR model across all time-series validation schemes. The Diebold-Mariano test confirmed that ENR's predictive superiority was statistically highly significant ($p < 0.001$). The fundamental reason for this performance disparity lies in the bias-variance trade-off inherent in macroeconomic forecasting. While RTSR exhibited high flexibility in fitting in-sample non-linearities, its localized knot placements extrapolated erratically during out-of-sample structural shifts, leading to severe overfitting and inflated error metrics. Conversely, the dual regularization framework of ENR—combining L_1 sparsity and L_2 shrinkage—provided the essential algorithmic stability required to filter out noise, effectively suppressing multicollinearity while maintaining robust generalizability during volatile economic periods.

The primary policy implication of this research for central banks and economic planners is that when utilizing highly correlated, high-frequency digital transaction data for macroeconomic nowcasting or forecasting, heavily regularized linear models (such as Elastic Net) should be prioritized over highly flexible non-parametric splines to prevent catastrophic extrapolation errors. Future research should focus on mitigating the out-of-sample vulnerabilities of spline regressions, potentially by integrating them within ensemble frameworks (e.g., Penalized Spline Gradient Boosting) or employing dynamic, time-varying knot selection algorithms that can robustly adapt to sudden macroeconomic regime shifts.

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