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Multivariate Time Series Forecasting of KP-RI Financial Performance Using VARIMA and VARIMAX with a Dummy Variable

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Abstract

Cooperative financial performance is influenced by both internal financial dynamics and external policy interventions. However, the contribution of policy-intervention information to multivariate forecasting models in cooperative finance remains insufficiently explored. This study compares Vector Autoregressive Integrated Moving Average (VARIMA) and Vector Autoregressive Integrated Moving Average with Exogenous Variables (VARIMAX-Dummy) models for analyzing and forecasting monthly Interest Income (PHB) and Net Surplus (SHU) in a savings and loan cooperative during 2015–2024. The analysis employed stationarity testing, cointegration testing, model identification, Granger causality analysis, Impulse Response Function, Forecast Error Variance Decomposition, and out-of-sample forecasting evaluation. A pulse dummy variable representing mandatory savings policy adjustments was incorporated into the VARIMAX model. The results indicate bidirectional predictive relationships and stable dynamic responses in both models. Model identification indicated that VARIMA$(1, 1, 0)$ rovided the optimal endogenous dynamic structure, which was subsequently retained in the VARIMAX-Dummy, resulting in the VARIMAX$(1, 1, 0)$-Dummy specification. Forecasting evaluation showed that the VARIMAX-Dummy model achieved lower RMSE values for SHU (0.2129) and PHB (0.2088) than the corresponding VARIMA model (0.7434 and 0.6060). These findings demonstrate that incorporating policy-intervention information improves forecasting accuracy and enhances the representation of cooperative financial dynamics. The study highlights the value of exogenous policy variables in multivariate forecasting models for cooperative financial management.

Keywords: Forecast Error Variance Decomposition; Impulse Response Function; RMSE; VARIMA; VARIMAX.

1. Introduction

Membership-based microfinance institutions, such as KP-RI savings and loan cooperatives, play an important role in providing financial access to communities that are underserved by the formal banking sector. Their operational characteristics, which are grounded in collective values and economic democracy, make cooperatives an important subject of academic investigation.

In the financial system of KP-RI savings and loan cooperatives, monthly Interest Income (PHB) and Net Surplus (SHU) exhibit interdependent relationships. Interest income generated

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from loans to members constitutes one of the primary components of cooperative revenue [1]. Higher monthly interest income generally contributes to a greater SHU distributed to members. However, the internal dynamics of cooperatives are often influenced by social interactions, seasonal patterns, and community activities, making cooperative performance difficult to predict using conventional approaches.

Moreover, cooperative financial systems are not influenced solely by internal interactions among financial variables. External events and policy interventions may also generate structural shocks that cannot always be represented as endogenous components within the model. In the context of cooperatives, policy changes such as revisions to SHU distribution regulations, adjustments in savings interest rates, or managerial reforms may affect financial performance beyond the historical patterns of cooperative financial variables [1].

Multivariate time series analysis extends univariate approaches by considering the simultaneous interactions among several variables [2, 3]. One of the most widely used approaches is the Vector Autoregressive Integrated Moving Average (VARIMA) model, which is a multivariate extension of the ARIMA model for non-stationary data. VARIMA explains the relationship between current observations of a variable, its own historical values, and the historical values of other variables within the system [2].

Although VARIMA provides an effective framework for capturing endogenous relationships among variables, real-world financial systems are often influenced by external factors that originate outside the modeled system. To accommodate such external information, the Vector Autoregressive Integrated Moving Average with Exogenous Variables (VARIMAX) model extends VARIMA by incorporating exogenous variables into the model structure [4]. VARIMAX allows external variables, including policy interventions and dummy variables, to influence endogenous variables while preserving dynamic interrelationships among the endogenous variables.

In intervention analysis, dummy variables are commonly used to represent policy changes, structural breaks, institutional reforms, economic crises, or extraordinary events [5]. The inclusion of dummy variables enables the model to capture abrupt changes that cannot be explained solely by the historical behavior of endogenous variables. Consequently, the integration of dummy variables into the VARIMAX framework may improve both model interpretation and forecasting accuracy [5].

Before constructing a multivariate forecasting model, it is important to investigate whether long-run equilibrium relationships exist among the variables. This concept is referred to as cointegration. Cointegration occurs when non-stationary variables move together over time and maintain a stable long-run equilibrium relationship despite short-run fluctuations. The existence of cointegration determines whether variables should be modeled in levels or differences and is therefore a critical step in multivariate time series modeling [6].

In addition to long-run equilibrium analysis, understanding causal interactions among variables is also essential. One of the most widely used approaches is the Granger causality test. Granger causality evaluates whether past values of one variable contain useful information for predicting another variable. The concept of causal relationships among variables forms the basis of vector autoregressive systems and helps identify the direction of information flow among variables [7].

After estimating multivariate models, dynamic interactions among variables can be further analyzed through Impulse Response Functions (IRF). The IRF measures how shocks occurring in one variable propagate throughout the system over time [8]. impulse response functions are central tools in vector autoregressive analysis because they describe the dynamic responses of variables following structural shocks [8].

Another important tool in multivariate analysis is Forecast Error Variance Decomposition (FEVD). While IRF focuses on the direction and magnitude of responses to shocks, FEVD quantifies the proportion of forecast error variance attributable to innovations originating from each variable in the system. Therefore, FEVD provides information regarding the relative importance of variables in explaining fluctuations over different forecasting horizons [9]. The combination of IRF and FEVD allows a comprehensive understanding of dynamic interactions among variables in multivariate systems [9].

Despite these advantages, VARIMA is fundamentally linear and primarily focuses on endogenous relationships, which limits its ability to accommodate the influence of external factors and structural changes within the system [10]. The Vector Autoregressive Integrated Moving Average with Exogenous Variables (VARIMAX) model extends the VARIMA framework by incorporating external explanatory variables into the system. These exogenous variables may represent policy interventions, economic shocks, institutional reforms, or other factors that originate outside the endogenous system. By including such variables, VARIMAX is capable of capturing both internal dynamic interactions and external influences simultaneously. Previous studies have shown that the inclusion of exogenous variables can improve both model interpretation and forecasting performance [11, 12].

Recent developments in econometric modeling emphasize the importance of comparing alternative modeling approaches to identify the most appropriate multivariate forecasting models. Comparative analysis between the Vector Autoregressive Integrated Moving Average (VARIMA) model and the Vector Autoregressive Integrated Moving Average with Exogenous Variables and Dummy Variables (VARIMAX-Dummy) model is therefore conducted to examine dynamic relationships and forecasting performance within such complex cooperative financial data [5, 12]. While both approaches are capable of modeling multivariate time-series dynamics, their ability to capture external interventions and structural changes may differ substantially. To provide an overview of previous studies and to highlight the existing research gap, Table 1 presents a comparison of earlier studies related to the application of VARIMA and VARIMAX-based models in economic and financial time-series analysis.

Table 1: Comparison of Previous Studies on Models

Study	Model(s)	Key Metric(s)	Main Findings
Karim and Ahmed, (2023)	VARIMA	Standard Error	The VARIMA (2,1,2) model effectively captures the relationship between variables and provides good accuracy for short-term forecasting but is less stable for the long term.
Atmaja and Warsito, (2021)	VARIMAX-Dummy	MAE	The VARIMAX (0,1,2) model with dummy variables produced the best model with better prediction accuracy based on MAAE.
This Study	Comparative VARIMA and VARIMAX-Dummy	IRF, FEVD, RMSE	This study compares VARIMA and VARIMAX-Dummy models in forecasting KPRI evaluates both forecasting accuracy and dynamic intervariable relationships.

Although previous studies have examined VARIMA and VARIMAX models separately, several important gaps remain. First, limited research has compared VARIMA and VARIMAX-Dummy models in the context of cooperative financial performance. Second, previous studies have primarily focused on forecasting accuracy without simultaneously investigating dynamic relationships through Granger causality, IRF, and FEVD analyses. Third, empirical evidence regarding the impact of policy-related structural interventions on cooperative financial systems remains scarce. Consequently, the relative effectiveness of VARIMA and VARIMAX-Dummy models in capturing both dynamic interactions and forecasting performance within cooperative financial data remains insufficiently explored.

This study addresses these gaps by conducting a comparative analysis of VARIMA and VARIMAX-Dummy models using monthly financial data from a KP-RI savings and loan cooperative. The comparison is performed from two perspectives: (1) forecasting performance using Root Mean Square Error (RMSE), and (2) dynamic system analysis using Granger causality, Impulse Response Function (IRF), and Forecast Error Variance Decomposition (FEVD). The main contributions of this study are twofold. First, it provides empirical evidence on the effectiveness of incorporating policy dummy variables into a multivariate forecasting framework. Second, it integrates forecast evaluation and dynamic interaction analysis within a single comparative framework. These findings are expected to provide useful insights for cooperative managers and researchers in selecting appropriate forecasting models for financial decision-making under policy-related structural changes.

The remainder of this article is organized as follows. Section 2 presents the data, problem formulation, modeling methods, and evaluation procedures. Section 3 discusses the experimental results and model performance analysis. Finally, Section 4 concludes the study and outlines directions for future research.

2. Methods

This section describes the data, modeling framework, analytical procedures, and evaluation criteria employed in this study. The discussion begins with the data sources and observation period, followed by the specification of the VARIMA and VARIMAX models with dummy variables, as well as the model performance evaluation methods used to assess forecasting accuracy.

2.1. Data Collection

This study employs secondary data and supporting primary data obtained from the KP-RI Semeru Ngajum Savings and Loan Cooperative. The secondary data consist of monthly financial observations derived from annual financial accountability reports during the 2015–2024 management period. The analyzed variables are monthly Interest Income (PHB) and monthly Net Surplus (SHU), resulting in 120 observations from January 2015 to December 2024.

The monthly financial data were reconstructed from the cooperative's annual financial accountability reports. Each annual report contains monthly records of financial transactions and performance indicators. Monthly observations of Interest Income (PHB) and Net Surplus (SHU) were extracted from these reports and compiled into a continuous monthly time-series dataset. Data consistency was verified by comparing monthly aggregates with annual totals reported in each accountability report.

Supporting primary data were collected through interviews with the cooperative's financial management to identify policy changes related to mandatory savings contributions. This information was used to construct a dummy variable as an exogenous factor representing the implementation periods of mandatory savings policy adjustments.

A dummy variable was introduced to represent temporary changes in the mandatory savings regulation implemented by KP-RI Semeru Ngajum during the observation period. Based on information provided by the cooperative management, policy adjustments occurred during February 2015–April 2015, October 2015, October 2016–December 2016, February 2017–April 2017, July 2017, September 2017, June 2018–July 2018, August 2019–December 2019, April 2020, March 2021, March 2022, and June 2022.

The dummy variable was specified as a pulse dummy variable because the policy adjustments were implemented only during specific periods and were assumed to generate temporary effects on cooperative financial performance. Accordingly, the dummy variable was coded as 1 during the months in which the mandatory savings regulation adjustment was implemented and 0 otherwise. This specification allows the VARIMAX model to capture short-term structural disturbances associated with policy interventions without assuming permanent shifts in the underlying financial process.

The inclusion of the policy dummy variable was based on the assumption that adjustments to the mandatory savings regulation could temporarily influence the financial performance of the cooperative. Changes in mandatory savings contributions may affect the amount of funds available for lending activities, which in turn can influence Interest Income (PHB) and ultimately affect Net Surplus (SHU). Therefore, the dummy variable was incorporated as an exogenous variable in the VARIMAX model to represent temporary policy-related shocks that are not captured by the endogenous financial variables alone.

For consistency throughout the manuscript, Net Surplus is denoted by Y_t, Interest Income is denoted by X_t, and the policy-intervention dummy variable is denoted by D_t in all mathematical formulations. The labels SHU and PHB are used only in tables, figures, and software outputs to facilitate interpretation. Furthermore, the notation ∇ is used to represent first differencing, and all lagged variables are expressed using the subscript form $t-k$. Detailed descriptions of the research variables are presented in Table 2.

Table 2: Data Variable Description

No	Code	Nama Variabel	Unit	Scale
1	Z_{1t}	Net surplus (SHU)	Million in a Month	Rasio
2	Z_{2t}	Interest income (PHB)	Million in a Month	Rasio
3	D_t	The implementation of the policy changes (Dummy)	Dummy = 1, for months in which the mandatory savings regulation adjustment was implemented. Dummy = 0, for months in which no adjustment to the mandatory savings regulation was implemented.	Nominal

2.2. Stationarity Test

Stationarity is an essential assumption in time-series analysis, requiring the statistical properties of the data to remain constant over time. In this study, stationarity is evaluated in terms of both variance and mean. Variance stationarity is assessed using the Box–Cox transformation, where a parameter value of $\lambda \approx 1$ indicates stable variance; otherwise, an appropriate transformation is applied to stabilize the variance [13]. Mean stationarity is subsequently tested using the Augmented Dickey–Fuller (ADF) test [13]. If non-stationarity is detected, differencing is performed to remove trends, as expressed in Eq. (1):

$$\nabla W_t = W_t - W_{t-1} \tag{1}$$

The general ADF model is formulated in Eq. (2):

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

where α denotes the constant term, β is the parameter being tested, δ_i represents the autoregressive coefficient at lag i, and ε_t is the error term. The null hypothesis H_0 indicates non-stationarity, while H_1 indicates stationarity. The null hypothesis is rejected when the p-value is smaller than the significance level α, implying that the series is stationary. This procedure is important because VARIMA and VARIMAX models require stationary time-series data prior to estimation.

2.3. Vector Autoregressive Integrated Moving Average (VARIMA)

The Vector Autoregressive Integrated Moving Average (VARIMA) model is an extension of the ARIMA model designed for multivariate time-series analysis, enabling the modeling of dynamic relationships among multiple variables simultaneously [12]. Similar to ARIMA, the VARIMA model incorporates differencing to handle non-stationary data [12]. The general form of the VARIMA model is expressed in Eq. (3):

$$\Phi(B)(1-B)^d \mathbf{Z}_t = \Theta(B)\mathbf{a}_t \tag{3}$$

where $\mathbf{Z}_t$ denotes the multivariate time-series vector after differencing, $\Phi(B)$ and $\Theta(B)$ represent the autoregressive (AR) and moving average (MA) orders, respectively, $\mathbf{c}$ is the intercept vector,

Φ_i and Θ_j are the autoregressive and moving average coefficient matrices, and $\mathbf{a}_t$ denotes the white-noise error vector. Overall, the VARIMA model explains current changes in variables as functions of past observations and past error components, allowing the model to capture dynamic interactions within the system.

2.4. Vector Autoregressive Integrated Moving Average with Exogenous Variable (VARIMAX)

The Vector Autoregressive Integrated Moving Average with Exogenous Variables (VARIMAX) model extends the VARIMA framework by incorporating exogenous variables, such as dummy variables, to capture external influences and structural changes within the system [5]. The general form of the VARIMAX model is expressed in Eq. (4):

$$\Phi(B)(1-B)^d\mathbf{Z}_t = \mathbf{c} + \Psi(B)\mathbf{X}_t + \Theta(B)\mathbf{a}_t \tag{4}$$

where $\mathbf{Z}_t$ denotes the differenced multivariate time-series vector, $\Phi(B)$ and $\Theta(B)$ represent the autoregressive (AR) and moving average (MA) orders, respectively, and $\mathbf{X}_t$ denotes the number of exogenous variables included in the model. The parameter Ψ represents the effect of the exogenous dummy variable D_t, which captures policy interventions or specific events affecting the system. The terms Φ and Θ denote the autoregressive and moving average coefficient matrices, while $\mathbf{a}_t$ represents the white-noise error vector. By incorporating exogenous variables, the VARIMAX model is able to capture both internal dynamics and external shocks more comprehensively than the VARIMA model.

2.5. Akaike's Information Criterion (AIC)

Model order selection is an important step in multivariate time-series modeling, particularly in VARIMA and VARIMAX models, because the autoregressive (p) and moving average (q) orders determine the model's complexity and forecasting capability. In this study, AIC was used exclusively for selecting the optimal model structure and order, which balances model goodness of fit and complexity [12]. The AIC is defined as follows Eq. (5):

$$\text{AIC}(p,q) = \ln|\Sigma_a| + \frac{2k}{N} \tag{5}$$

where Σ_a denotes the residual covariance matrix, N is the number of observations, and k represents the number of estimated parameters. The model with the smallest AIC value is considered the most appropriate because it provides the optimal balance between model accuracy and parsimony. Accordingly, several VARIMA model specifications with different combinations of p and q are estimated and compared. The VARIMAX model was constructed by incorporating the policy-intervention dummy variable into the optimal VARIMA specification identified through the minimum AIC criterion. Because the primary objective of this study was to compare the forecasting performance and dynamic behavior of VARIMA and VARIMAX-Dummy while isolating the contribution of the exogenous policy variable, the autoregressive and moving-average orders selected for VARIMA were retained in the VARIMAX model. By maintaining the same endogenous model structure, any differences in parameter estimates, dynamic responses, and forecasting performance can be attributed primarily to the inclusion of the dummy variable rather than differences in model specification. The adequacy of the resulting VARIMAX model was subsequently evaluated through parameter significance testing, residual diagnostics, and out-of-sample forecasting performance measures.

2.6. IRF dan FEVD

Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) are important tools in multivariate time-series analysis, particularly in VAR and VARIMA models, for examining dynamic interactions among variables [14]. Based on the moving average representation, the model can be expressed as follows Eq. (6):

$$\mathbf{Z}_t = \sum_{i=0}^{\infty} \Psi_i \mathbf{a}_{t-i} \tag{6}$$

where Ψ_i denotes the impulse response coefficient matrix and $\mathbf{a}_t$ represents the shock vector. The Impulse Response Function (IRF) measures the response of a variable to shocks in another variable over future periods and is defined as Eq. (7) :

$$\mathrm{IRF}_h = \frac{\partial \mathbf{Z}_{t+h}}{\partial \mathbf{a}_t'} \tag{7}$$

Meanwhile, FEVD evaluates the contribution of each shock to the forecast error variance of the variables, formulated as Eq. (8):

$$\mathrm{FEVD}_{ij}(h) = \frac{\sum_{m=0}^{h-1} (\mathbf{e}_i' \Psi_m \Sigma_a \mathbf{e}_j)^2}{\sum_{m=0}^{h-1} \mathbf{e}_i' \Psi_m \Sigma_a \Psi_m' \mathbf{e}_i} \tag{8}$$

where Σ_a denotes the covariance matrix of the error terms. Together, IRF and FEVD provide insights into the magnitude and persistence of dynamic interactions among variables within the system [15].

2.7. Root Mean Squared Error (RMSE)

Model performance is evaluated using the Root Mean Squared Error (RMSE), which serves as the primary metric for assessing forecasting accuracy [16, 17]. RMSE measures the square root of the average squared differences between actual and predicted values, making it sensitive to large forecasting errors and useful for evaluating model stability. The RMSE is defined as follows Eq. (9):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \tag{9}$$

where y_t denotes the observed value, $\hat{y}_t$ represents the predicted value, and n is the number of observations. Lower RMSE values indicate better predictive accuracy; therefore, the optimal model is selected based on the smallest RMSE value [18, 19]. RMSE was employed solely to evaluate out-of-sample forecasting performance and to compare the predictive accuracy of the final VARIMA and VARIMAX models.

2.8. Data Analysis Procedure

The data were processed using R and Python software.

1. The multivariate time-series dataset consists of cooperative financial performance variables Y_t, X_t and the dummy variable (D_t). The dataset was divided into training data (90%) and testing data (10%). The dataset was initially divided into training data (90%) and testing data (10%). To evaluate the robustness of the forecasting results and address the limited size of the testing sample, an expanding-window rolling forecast procedure was subsequently performed. In each iteration, the model was re-estimated using all observations available up to time t, and a one-step-ahead forecast was generated for time t+1. This process was repeated throughout the testing period, and forecasting errors from all iterations were aggregated to calculate the RMSE values. The rolling forecast approach provides a more reliable assessment of out-of-sample forecasting performance by reducing dependence on a single train-test partition. For the VARIMAX model, the values of the exogenous dummy variable in the testing period were determined based on the actual implementation schedule

of mandatory savings policy adjustments obtained from cooperative management records. Because these policy interventions were administrative decisions with known implementation dates, the dummy-variable values were treated as predetermined information rather than forecasted variables. Consequently, no future information from the endogenous variables (SHU and PHB) was used in constructing the dummy-variable series, thereby minimizing the risk of data leakage during forecasting evaluation.

2. Data Preprocessing and Model Identification:
   (a) Variance stationarity was evaluated using the Box–Cox transformation, while mean stationarity was tested using the Augmented Dickey–Fuller (ADF) test. If non-stationarity was detected, differencing was applied until stationarity was achieved follows Eq. (1) and Eq. (2).
   (b) The Johansen cointegration test was applied to identify long-run relationships among variables [12]. The trace test statistic is formulated as Eq. (10):

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^{k} \ln(1 - \hat{\lambda}_i) \tag{10}$$

   while the maximum eigenvalue statistic is expressed Eq. (11):

$$\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{11}$$

   The null hypothesis states that the number of cointegration vectors is less than or equal to r, whereas the alternative hypothesis indicates the existence of more than r cointegration relationships.
   (c) The orders of the VARIMA model were identified using the Matrix Autocorrelation Function (MACF) and Matrix Partial Autocorrelation Function (MPACF) [12]. The MACF is expressed as ρ_k where ρ_k denotes the sample cross-correlation between variables in lag to k, which is calculated as Eq. (12):

$$\hat{\Gamma}_k = \frac{1}{T} \sum_{t=k+1}^{T} (\mathbf{Z}_t - \bar{\mathbf{Z}})(\mathbf{Z}_{t-k} - \bar{\mathbf{Z}})' \tag{12}$$

   The Matrix Partial Autocorrelation Function (MPACF), denoted as P_k, was used together with the Matrix Autocorrelation Function (MACF) to identify the VARIMA model order. The cut-off pattern of MACF was used to determine the moving average order (q), whereas the cut-off pattern of MPACF was used to determine the autoregressive order (p).
   (d) Based on the initial identification results, several VARIMA candidate models with different p and q combinations were estimated, and the optimal model was selected using the Akaike Information Criterion (AIC), where the model with the smallest AIC value was considered the best model follows as Eq. (5).
   (e) Granger causality testing was subsequently performed to examine causal relationships among variables using the following Eq. (13) [12]:

$$y_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i y_{t-i} + \sum_{j=1}^{n} \beta_j x_{t-j} + \varepsilon_t \tag{13}$$

   The null hypothesis states that x does not Granger-cause y (H_0), while the alternative hypothesis indicates the presence of causality (H_1). The test statistic is defined as Eq. (14):

$$F = \frac{(\text{RSS}_R - \text{RSS}_U)/m}{\text{RSS}_U/(T-k)} \tag{14}$$

H_0 is rejected when the p-value is smaller than the significance level α. The same procedure was applied to test the reverse direction of causality, namely whether y influences x, allowing the relationships among variables to be classified as unidirectional, bidirectional, or non-causal.

3. Parameter estimation was performed for both VARIMA and VARIMAX models based on Eq. (3) and Eq. (4).
4. Diagnostic checking was subsequently conducted to ensure that the models satisfied the assumptions of white-noise and normally distributed residuals [12]. The Ljung–Box test was applied to examine residual autocorrelation using the following Eq. (15):

$$Q(m) = T(T+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{T-k} \tag{15}$$

where the null hypothesis states that the residual autocorrelations are equal to zero (H_0). Residual normality was evaluated using the Jarque–Bera test, defined as Eq. (16) :

$$\mathrm{JB} = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{16}$$

where the null hypothesis assumes that the residuals are normally distributed. The null hypothesis was rejected when the p-value was smaller than the significance level α.
5. Furthermore, Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) analyses were performed for both VARIMA and VARIMAX models to evaluate dynamic interactions and the contribution of each variable to system fluctuations following Eq. (7) and Eq. (8).
6. Forecasting performance was finally assessed using the Root Mean Squared Error (RMSE), where the model with the smallest RMSE value was selected as the best forecasting model following Eq. (9).

3. Results and Discussion

This section presents the empirical results obtained from the implementation of the proposed methodology. To provide a systematic discussion, the analysis begins with descriptive statistics and data splitting, followed by stationarity testing, cointegration analysis, model identification, and Granger causality testing. Subsequently, the VARIMA and VARIMAX models are estimated and evaluated through diagnostic testing, dynamic analysis using Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD), and forecasting performance assessment using Root Mean Squared Error (RMSE).

3.1. Descriptive Statistics and Data Splitting

Descriptive statistics were used to provide an overview of the characteristics of the variables analyzed in this study, namely SHU, PHB, and the dummy variable D_t, which represents policy changes. The results indicate that SHU has a mean value of 38.30, with a minimum of 23.64 and a maximum of 49.67, suggesting relatively high variability during the observation period. In contrast, PHB has a lower mean value of 24.24, ranging from 15.91 to 29.18, indicating more stable fluctuations over time.

The dummy variable D_t shows that policy changes occurred in only 31 observations (25.83%), while the remaining 89 observations (74.17%) correspond to periods without policy changes. This finding indicates that policy interventions were relatively infrequent during the study period, supporting the inclusion of a dummy variable in the VARIMAX model to capture external effects on the system dynamics. Furthermore, the dataset was divided into training and testing sets using a 90:10 ratio, where 90% of the observations were used for model estimation and the remaining 10% for forecasting evaluation. As illustrated in Fig. 1, the split point is located around the beginning of 2024, ensuring that the temporal structure of the data was preserved. The time-series plots also reveal different movement patterns between SHU and PHB, with SHU exhibiting greater fluctuations, whereas PHB shows relatively smoother and more stable trends throughout the observation period.

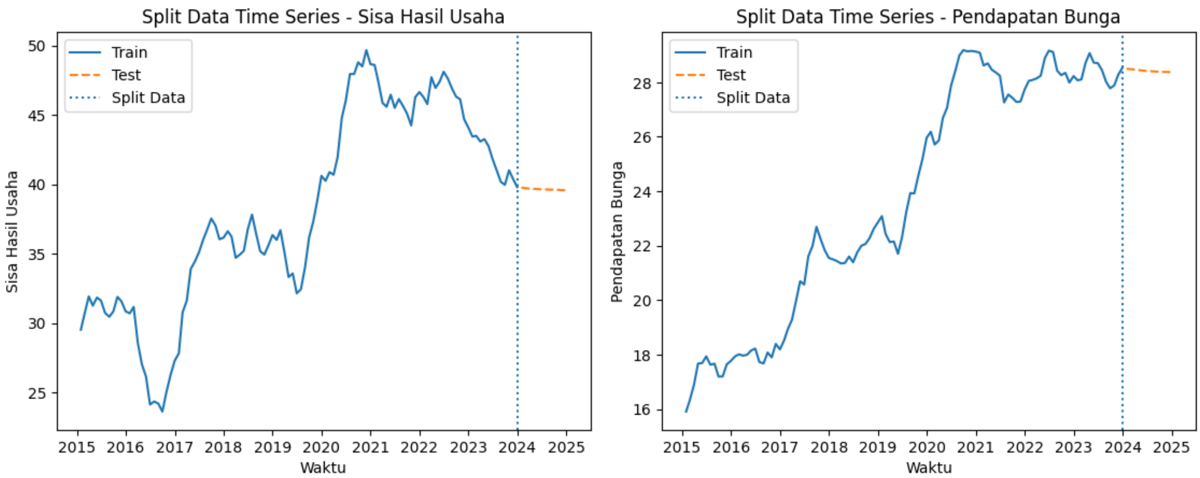

Fig. 1: Data Splitting

The split point between the training and testing datasets is indicated by the dashed vertical line around the beginning of 2024, preserving the temporal structure of the series while ensuring that model evaluation was conducted on unseen data. The time-series plot of SHU shows a gradual upward trend from 2015 to approximately 2021, followed by relatively stable movements with minor fluctuations until 2024. During the testing period, the series appears relatively flat or slightly declining, suggesting a slowdown in growth at the end of the observation period. In contrast, PHB exhibits greater fluctuations, with a substantial increase reaching its peak around 2021, followed by a gradual decline toward 2024. In the testing period, PHB remains at a lower level compared with its peak and tends to move relatively stable with a slight downward trend. Overall, the descriptive statistics and time-series visualization reveal distinct characteristics between SHU and PHB in terms of variability and movement patterns. Moreover, the relatively low frequency of policy changes supports the inclusion of dummy variables in the VARIMAX model to capture external influences on system dynamics.

In addition to the descriptive analysis, the monthly SHU and PHB series were examined for potential seasonal patterns before model estimation. Seasonality refers to recurring fluctuations that occur regularly within specific periods, such as monthly or annual cycles. Visual inspection of the time-series plots did not reveal any consistent repeating pattern across months or years. The SHU series was characterized primarily by long-term increases and decreases, while the PHB series displayed a gradual upward trend followed by relatively stable movements rather than cyclical fluctuations. The absence of strong seasonality was further supported by correlation analysis between the month variable and the financial variables. The correlation coefficient between month and SHU was 0.045, whereas the correlation coefficient between month and PHB was 0.086. Both values are close to zero, indicating that calendar month has only a negligible relationship with variations in SHU and PHB. These findings suggest that the dynamics of the financial variables are driven mainly by long-term trends and policy-related factors rather than seasonal effects. Therefore, seasonal differencing or seasonal model specifications were not considered necessary in the subsequent VARIMA and VARIMAX-Dummy analyses. This preliminary assessment supports the use of non-seasonal VARIMA and VARIMAX-Dummy models in the present study.

3.2. Pre-processing before testing parameter estimates

Prior to model estimation, stationarity testing was performed to verify that the data met the assumptions of multivariate time-series modeling. Variance stationarity was assessed using the Box–Cox transformation. The estimated Box–Cox parameters before transformation were λ for SHU and λ for PHB. Following the first Box–Cox transformation, both series yielded $\lambda = 1$ indicating that the variance had been stabilized and the data were stationary with respect to variance. Subsequently, stationarity in the mean was examined. After transformation, both variables satisfied the variance stationarity assumption. Mean stationarity was subsequently examined using the Augmented Dickey–Fuller (ADF) test before differencing and after differencing in Table 3 and Table 4.

Table 3: Result ADF before differencing

Variable	Statistics ADF	P-value	Decision
SHU	-2.3017	0.4515	non-stationary
PHB	-1.7311	0.6882	non-stationary

The results at the level form indicated that both variables were non-stationary, as the p-values exceeded the 5% significance level.

Table 4: Result ADF after differencing

Variable	Statistics ADF	P-value	Decision
SHU	-3.7389	0.0245	stationary
PHB	-4.1964	0.0100	stationary

The results in Table 4 show first-order differencing was applied. After differencing, both variables became stationary, with ADF p-values below 0.05, indicating that the transformed series were suitable for further analysis. To examine long-run relationships among variables, the Johansen cointegration test was performed using the trace test without linear trend and constant terms in the cointegration equation. The results of the Johansen cointegration test are presented in Table 5.

Table 5: Results of the Johansen cointegration test (Trace Test)

Hypothesis	Statistical Test	Critical Value(5%)	Decision
$r = 0$	14.42	19.96	Fail to Reject H_0
$r \leq 1$	6.71	9.24	Fail to Reject H_0

The results in Table 5 show that the trace statistics for both SHU and PHB were smaller than the corresponding critical values at the 5% significance level. This finding indicates the absence of cointegration between interest income and SHU, suggesting that no long-run equilibrium relationship exists between the variables. Consequently, the subsequent analysis focused on the differenced VARIMA framework without incorporating an error correction term, emphasizing short-run dynamic interactions. The next step is to identify the model to determine the autoregressive (AR) and moving average (MA) orders in the VARIMA model. This process uses the Matrix Partial Autocorrelation Function (MPACF) and Matrix Autocorrelation Function (MACF) obtained from stationary data. The MPACF and MACF results are presented in Table 6 and Table 7.

Table 6: Result MPACF

Variable	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
SHU	++	..	..	..	..
PHB	+-	..	..	..	..

The MPACF results in Table 6 showed a cut-off pattern at lag 1 for both variables, indicating an autoregressive order of 1.

Table 7: Result MACF

Variable	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
SHU	++	++	..	..	..	..
PHB	+-	+-	..	..	..	..

Meanwhile, the MACF results in Table 7 suggested moving average orders between 0 and 1. Based on these findings, several candidate VARIMA models, namely $AR(1)$, $MA(1)$, and $MA(2)$, were estimated and compared using the Akaike Information Criterion (AIC). The results of the AIC calculations for several candidate models are presented in Table 8.

Table 8: AIC Value Model Vector

Model	MA(0)	MA(1)	MA(2)
AR(1)	-145.6536	-3.740476	-3.738388

Based on Table 8, the Vector model with a combination of AR(1) and MA(0) produces a model with the smallest AIC value (-145.6536), indicating the best balance between model fit and complexity. The VARIMAX model employed the same autoregressive and moving-average orders selected for the optimal VARIMA model. Following the identification of the optimal VARIMA (1,1,0) specification based on the minimum AIC criterion, the same autoregressive and moving-average structure was retained for the VARIMAX model. This approach was adopted to ensure a fair comparison between VARIMA and VARIMAX-Dummy, as the primary objective of this study was to evaluate the contribution of the policy-intervention dummy variable to forecasting performance. By maintaining the same endogenous model structure, the only substantive difference between the two models is the inclusion of the exogenous policy variable. Consequently, any improvement in model fit, dynamic response analysis, or forecasting accuracy can be attributed primarily to the incorporation of the policy-intervention dummy variable rather than differences in model order specification. The adequacy of the resulting VARIMAX (1,1,0) model was subsequently evaluated through parameter significance testing, residual diagnostics, IRF–FEVD analysis, and comparison of model evaluation. Granger causality testing was subsequently conducted to examine the predictive relationships between SHU and PHB. Results Granger test show in Table 9.

Table 9: Result Granger Test

Relationship	F-Statistic	P-value	Decision
$SHU \rightarrow PHB$	18.892	0.00002164	H_0 Reject
$PHB \rightarrow SHU$	9.9158	0.00188	H_0 Reject

In Table 9 shows that both predictive directions are statistically significant, with p-values below 0.05. The results indicate that past values of SHU provide significant predictive information for PHB, while past values of PHB also provide significant predictive information for SHU. Therefore, a bidirectional predictive relationship exists between the two variables. This finding suggests strong short-run dynamic interdependence within the cooperative financial system. The presence of mutual predictive relationships supports the use of multivariate models such as VARIMA and VARIMAX, which are designed to capture the interconnected dynamics among financial performance variables.

3.3. Estimation of VARIMA and VARIMAX Dummy Models

After determining the optimal model order (1,1,0), parameter estimation was performed for the VARIMA (1,1,0) and VARIMAX-Dummy (1,1,0) models using the Maximum Likelihood Estimation (MLE) method. Parameter significance was evaluated through partial t-tests under the null hypothesis that the estimated parameters are not statistically significant. Parameters with p-values smaller than 0.05 were considered significant. The complete estimation results are presented in the appendix, while the summaries are reported in Table 10 and Table 11. The hypothesis used in parameter testing is as follows:

$$H_0 : \phi_{ij} = 0 \quad \text{(Parameter tidak signifikan)}$$
$$H_1 : \phi_{ij} \neq 0 \quad \text{(Parameter signifikan)}$$

The test decision is made by rejecting H_0 if the p-value is smaller than the significance level $\alpha = 0.05$.

Table 10: VARIMA Parameter Estimation Results

Parameter	Estimated	P-value	Decision
ϕ_{11}	0.23898	0.01164	H_0 Reject
ϕ_{12}	0.97579	0.00214	H_0 Reject
ϕ_{21}	0.11585	3.23e-05	H_0 Reject
ϕ_{22}	0.22275	0.0136	H_0 Reject

In Table 10 shows The VARIMA estimation results indicate that all autoregressive parameters are statistically significant. In the SHU equation, the lagged SHU variable has a coefficient of 0.23898 (ϕ_{11}), while the lagged PHB variable has a coefficient of 0.97579 (ϕ_{12}). Similarly, in the PHB equation, lagged SHU and lagged PHB have coefficients of 0.11585 (ϕ_{21}) and 0.22275 (ϕ_{22}), respectively. These findings confirm the existence of significant bidirectional dynamic interactions between SHU and PHB. The VARIMA (1,1,0) model can therefore be expressed as follows:

$$SHU_t = 0.23898 SHU_{t-1} + 0.97579 PHB_{t-1} + \varepsilon_{1,t}$$
$$PHB_t = 0.11585 SHU_{t-1} + 0.22275 PHB_{t-1} + \varepsilon_{2,t}$$

Next, the VARIMAX model is estimated by adding dummy variables as exogenous variables.

Table 11: VARIMAX Parameter Estimation Results

Parameter	Estimated	p-value	Decision
ϕ_{11}	0.3888	3.27e-06	H_0 Reject
ϕ_{12}	1.0799	4.75e-05	H_0 Reject
γ_1	0.8629	9.57e-11	H_0 Reject
ϕ_{21}	0.13045	5.54e-06	H_0 Reject
ϕ_{22}	0.23289	0.00909	H_0 Reject
γ_2	0.08409	0.04390	H_0 Reject

In Table 11 shows the VARIMAX nmodel nwas estimated by incorporating the dummy variable as an exogenous variable. The results demonstrate an improvement in model performance compared with VARIMA. In the SHU equation, lagged SHU, lagged PHB, and the dummy variable are all statistically significant, with coefficients of 0.3888, 1.0799, and 0.8629, respectively.

Similarly, in the PHB equation, lagged SHU, lagged PHB, and the dummy variable remain significant, with coefficients of 0.13045, 0.23289, and 0.08409, respectively. The significance of the dummy variable in both equations indicates that external policy changes contribute substantially to the dynamics of cooperative financial performance. The VARIMAX (1,1,0) model is formulated as follows:

$$SHU_t = 0.3888SHU_{t-1} + 1.0799PHB_{t-1} + 0.8629D_t + \varepsilon_{1,t}$$

$$PHB_t = 0.13045SHU_{t-1} + 0.23289PHB_{t-1} + 0.08409D_t + \varepsilon_{2,t}$$

3.4. Diagnostic Testing of VARIMA and VARIMAX Dummy

Diagnostic testing was conducted to verify whether the VARIMA and VARIMAX-Dummy models satisfied the assumptions of white-noise and multivariate normal residuals. Residual autocorrelation was evaluated using the Portmanteau autocorrelation test, with the H_0 stating that the residuals are independently distributed. The results presented in Table 12 with a hypothesis:

Table 12: Portmanteau Autocorrelation Test

Model	Lag	Test Statistics	P-value
VARIMA	1	0.9899	0.9113
	2	1.3269	0.9952
	3	2.6907	0.9974
	4	3.5171	0.9995
	5	4.2493	0.9999
	6	8.4284	0.9986
	7	10.6897	0.9987
	8	17.8978	0.9789
	9	19.9715	0.9859
	10	26.4035	0.9516
VARIMAX Dummy	1	2.3907	0.6643
	2	4.5240	0.8070
	3	13.1523	0.3581
	4	16.1429	0.4430
	5	16.5020	0.6850
	6	21.8482	0.5883
	7	25.4356	0.6040
	8	28.5677	0.6410
	9	31.8054	0.6684
	10	35.4019	0.6772

The results presented in Table 12 show that all p-values across the examined nlags are greater than 0.05 for both models. Therefore, the H_0 cannot be rejected, indicating that the residuals are free from autocorrelation and satisfy the white-noise assumption. Residual normality was subsequently examined using the multivariate Jarque–Bera test. H_0 states that the residuals follow a multivariate normal distribution. The results presented in Table 13 with a hypothesis:

Table 13: Residual Normality Test

Model	Type Test	Test Statistics	P-value	Decision
VARIMA	Skewness	0.11798	0.9427	Accept H_0
	Kurtosis	0.59669	0.7420	Accept H_0
VARIMAX Dummy	Skewness	4.3128	0.1157	Accept H_0
	Kurtosis	3.9701	0.1374	Accept H_0

As summarized in Table 13, all p-values for the skewness and kurtosis tests exceed the 5% significance level for both VARIMA and VARIMAX-Dummy models. Consequently, the H_0 cannot be rejected, indicating that the residuals are approximately multivariate normal. Overall, the diagnostic results confirm that both VARIMA and VARIMAX-Dummy models satisfy the assumptions of white-noise and multivariate normal residuals, indicating that the models are statistically adequate for dynamic analysis and forecasting purposes.

3.5. Analisis Impulse Response Function (IRF) dan Forecast Error Variance Decomposition (FEVD)

Dynamic system analysis was conducted using the Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD). The IRF analysis was employed to examine the response of a variable to shocks originating from other variables within the system, whereas FEVD was used to measure the contribution of each variable in explaining the forecast error variance. The IRF results are presented in Fig. 2.

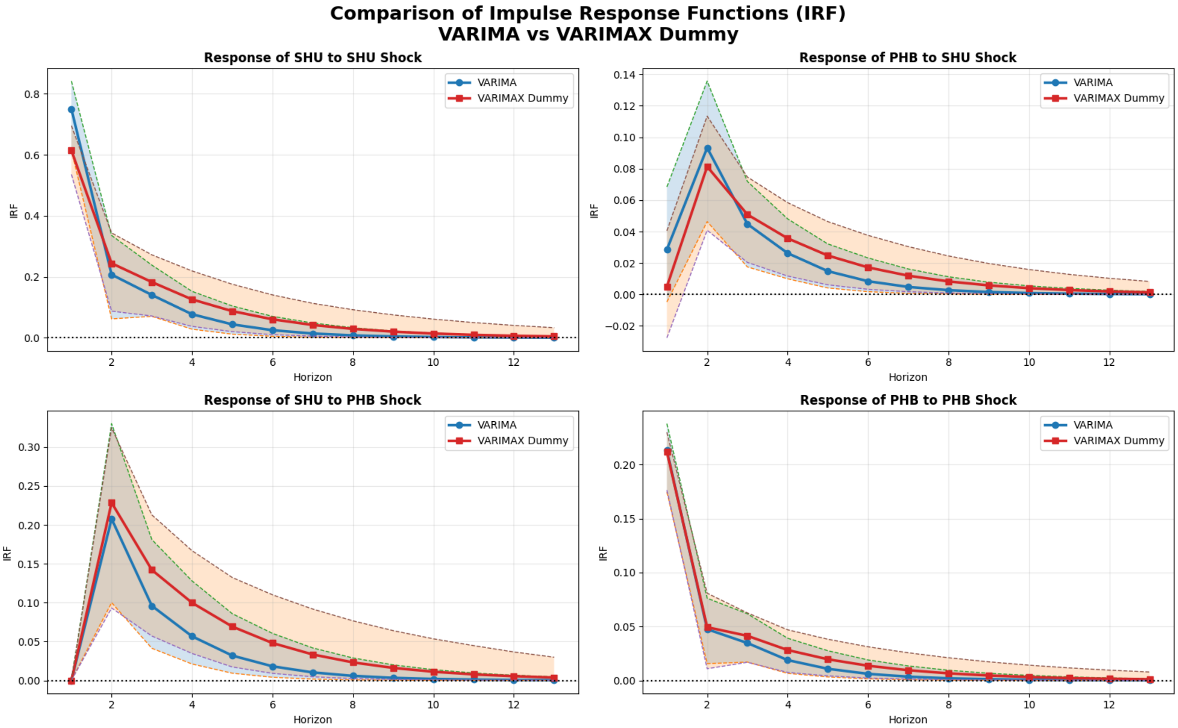

Fig. 2: Impulse Response Function (IRF)

Based on Fig. 2 the IRF results, the responses of the variables to shocks exhibit relatively consistent patterns in both models, characterized by strong initial responses that gradually decline and converge toward zero over time. The IRF results show that both VARIMA and VARIMAX-Dummy models produce positive responses that gradually decline and converge toward zero, indicating dynamic stability. Compared with VARIMA, the responses generated by the VARIMAX-Dummy model exhibit smoother adjustment paths and slower decay patterns. The smoother adjustment patterns observed in the VARIMAX-Dummy model indicate that the inclusion of the policy-intervention dummy variable helps capture temporary structural disturbances associated with mandatory savings adjustments. By explicitly incorporating policy-related information, nthe model is better able to distinguish between endogenous financial fluctuations and exogenous intervention effects. As a result, the dynamic responses become more stable and economically interpretable, suggesting that policy interventions contribute to short-run variations in SHU and PHB that are not fully explained by the endogenous variables alone. This finding supports the inclusion of the policy-intervention dummy variable as an exogenous component of the VARIMAX model. The ability to account for intervention-related shocks provides additional explanatory information that may contribute to the superior forecasting performance of VARIMAX-Dummy relative to the VARIMA model, as reflected in the lower RMSE values obtained during forecasting evaluation.

Nevertheless, the IRF results alone do not provide direct evidence regarding the magnitude of the dummy variable contribution because the responses are evaluated only for the endogenous variables. In addition, SHU responds positively to shocks in PHB during the initial periods before gradually declining toward equilibrium. These findings indicate that the relationships among variables are primarily short-run in nature and do not produce persistent long-term effects. Overall, the IRF analysis confirms that both models are dynamically stable, as all responses converge toward zero over time.

Table 14: Result FEVD

Model	SHU			PHB		
	Horizon	SHU (%)	PHB (%)	Horizon	SHU (%)	PHB (%)
VARIMA	1	100.00	0.00	1	1.77	98.23
	2	93.34	6.66	2	16.66	83.34
	3	92.27	7.73	3	19.09	80.91
	4	91.90	8.10	4	19.89	80.11
	5	91.79	8.21	5	20.14	79.86
	6	91.76	8.24	6	20.22	79.78
	7	91.74	8.26	7	20.24	79.76
	8	91.74	8.26	8	20.25	79.75
	9	91.74	8.26	9	20.25	79.75
	10	91.74	8.26	10	20.26	79.74
	11	91.74	8.26	11	20.26	79.74
	12	91.74	8.26	12	20.26	79.74
VARIMAX Dummy	1	100.00	0.00	1	0.05	99.95
	2	89.33	10.67	2	12.32	87.68
	3	86.66	13.34	3	15.85	84.15
	4	85.52	14.48	4	17.42	82.58
	5	85.00	15.00	5	18.14	81.86
	6	84.76	15.24	6	18.48	81.52
	7	84.65	15.35	7	18.64	81.36
	8	84.60	15.40	8	18.71	81.29
	9	84.57	15.43	9	18.75	81.25
	10	84.56	15.44	10	18.77	81.23
	11	84.55	15.45	11	18.78	81.22
	12	84.55	15.45	12	18.78	81.22

Table 14 indicates that the cross-variable contributions in the VARIMAX-Dummy model are larger than those observed in the VARIMA model. For example, the contribution of PHB to the forecast error variance of SHU increases from 8.26% in VARIMA to 15.45% in VARIMAX-Dummy by the twelfth horizon. Likewise, the contribution of SHU to PHB remains substantial, reaching 18.78% in the VARIMAX-Dummy model. These findings suggest that incorporating the policy dummy variable modifies the dynamic transmission mechanism between SHU and PHB and allows the model to capture additional variation that is not explained solely by endogenous variables. However, because FEVD was evaluated only for the endogenous variables, the results should be interpreted as indirect evidence of the contribution of the dummy variable rather than a direct measurement of its forecast variance contribution.

3.6. Comparison of Model Evaluation

The comparison between the VARIMA and VARIMAX-Dummy models was conducted using the Root Mean Squared Error (RMSE) metric to evaluate the forecasting accuracy of each model for the variables Net Surplus (SHU) and Interest Income (PHB). Forecasting performance was evaluated using an expanding-window rolling forecast procedure. At each forecasting origin, the VARIMA and VARIMAX-Dummy models were re-estimated using the available historical observations, and one-step-ahead forecasts were generated. The resulting forecast errors were accumulated across all forecasting horizons, and RMSE was computed from the aggregated errors. This approach provides a more robust evaluation of forecasting accuracy than a single holdout assessment because it utilizes multiple out-of-sample forecasts throughout the testing period.

To ensure a fair forecasting comparison, the exogenous dummy-variable values used in the testing period were specified according to the actual policy implementation schedule identified before model estimation. Therefore, the forecasting evaluation did not rely on information derived from future observations of SHU or PHB. The dummy variable was treated as an externally known intervention variable, consistent with the standard application of intervention analysis in VARIMAX models. RMSE was calculated on differenced-transformed data. The RMSE comparison results are presented in Table 15.

Table 15: Comparison of Model Evaluation

Model	RMSE	
	Z_{1t}	Z_{2t}
VARIMA	0.180136811	0.10121611
VARIMAX Dummy	0.067571092	0.07771696

Based on Table 15, the VARIMA model produced RMSE values of 0.180136811 for SHU and 0.10121611 for PHB. In contrast, the VARIMAX-Dummy model demonstrated substantially improved forecasting performance, with RMSE values decreasing to 0.067571092 for SHU and 0.07771696 for PHB. The considerable reduction in RMSE indicates that the VARIMAX-Dummy model provides more accurate predictions than the VARIMA model. These findings suggest that the inclusion of the dummy variable as an exogenous factor contributes significantly to improving the model's ability to capture the underlying dynamics of the data.

3.7. Discussion

Cooperatives play an important role as community-based financial institutions that support member welfare through savings, loans, and profit-sharing activities. The results of this study indicate that SHU (SHU) and PHB (PHB) have significant bidirectional relationships, meaning that changes in one variable directly influence the other in the short run. The IRF and FEVD analyses also confirm the existence of dynamic interactions between the variables, although the effects gradually decline over time and converge toward equilibrium. Furthermore, the VARIMAX-Dummy model produced lower RMSE values than the VARIMA model, indicating that the inclusion of policy-related dummy variables improves forecasting accuracy and better captures cooperative financial dynamics.

Despite its better performance, the VARIMAX-Dummy model still has several limitations. The model only uses two financial variables, namely SHU (SHU) and PHB (PHB), so it may not fully represent the complexity of cooperative performance. In addition, the dummy variable simplifies policy changes into binary categories and may not reflect the actual magnitude of policy impacts. The absence of cointegration also indicates that the model mainly captures short-run relationships and may be less suitable for long-term forecasting. Therefore, future research should incorporate additional macroeconomic and operational variables, as well as explore more advanced forecasting approaches to improve model accuracy and generalizability. The rolling forecast evaluation was conducted to assess the robustness of the forecasting results obtained from the relatively limited testing sample. The consistent superiority of the VARIMAX-Dummy model across multiple forecasting origins indicates that the improvement in forecasting accuracy was not driven by a specific train-test partition but rather by the inclusion of the policy-intervention dummy variable.

4. Conclusion

This study investigated the analysis and forecasting of cooperative financial performance by comparing VARIMA and VARIMAX-Dummy models within a multivariate time-series framework. Based on the model selection procedure using the Akaike Information Criterion (AIC), VARIMA$(1, 1, 0)$ was identified as the optimal endogenous dynamic structure for modeling Net Surplus (SHU, denoted by SHU_t) and Interest Income (PHB, denoted by PHB_t). To evaluate the contribution of policy-intervention information, the same autoregressive and moving-average orders were retained in the VARIMAX-Dummy model, resulting in a comparable VARIMAX$(1, 1, 0)$-Dummy specification.

Both models satisfied the stationarity requirements and provided an adequate representation of the dynamic relationships between the financial variables. Based on the RMSE values obtained from the out-of-sample rolling forecast procedure, the VARIMAX-Dummy model consistently achieved lower forecasting errors than the corresponding VARIMA model for both SHU and PHB. These results indicate that incorporating policy-intervention information improves forecasting accuracy and provides more stable forecasts.

The IRF and FEVD analyses further support the usefulness of the VARIMAX-Dummy model. Both models exhibited stable and convergent responses to shocks, while the FEVD results showed larger intervariable contributions after the inclusion of the dummy variable. These findings suggest that the policy-intervention dummy variable captures additional variation associated with external policy effects that cannot be fully explained by endogenous variables alone.

The main contribution of this study lies in demonstrating that policy-intervention information can enhance forecasting performance in multivariate time-series models of cooperative financial systems. From a practical perspective, the VARIMAX-Dummy model can serve as a useful analytical tool to support managerial decision-making and financial planning in cooperatives.

Several limitations should be acknowledged. First, the analysis was conducted using data from a single cooperative institution, which may limit the generalizability of the findings. Second, only two financial variables, namely SHU and PHB, were included in the model, while other relevant financial and macroeconomic factors were not considered. Third, the policy intervention was represented using a relatively simple dummy-variable specification that may not fully capture the complexity and duration of policy effects. Fourth, the Johansen cointegration analysis indicated no long-run equilibrium relationship between the variables, implying that the findings primarily reflect short-run dynamics. Finally, although forecasting performance was evaluated using an out-of-sample rolling forecast procedure, the testing period remained relatively limited compared with the overall sample size.

Future studies may address these limitations by incorporating additional financial and macroeconomic variables, such as inflation, interest rates, savings growth, loan distribution, and cooperative membership trends. If long-run equilibrium relationships are identified, Vector Error Correction Models (VECM) may be employed to capture both short-run and long-run dynamics. Furthermore, nonlinear and advanced forecasting approaches, including Long Short-Term Memory (LSTM) networks and Transformer-based models, may be explored to evaluate whether predictive performance can be further improved. Future research may also compare alternative validation strategies and seasonal forecasting specifications to assess the robustness and generalizability of forecasting results.

CRediT Authorship Contribution Statement

Tri Candra Nur Muhaimin: Conceptualization, Methodology, Data Curation, Formal Analysis, Writing – Original Draft. **Nurjannah**: Supervision, Validation, Editing. **Rahma Fitriani**: Supervision, Validation, Editing.

Declaration of Generative AI and AI-assisted technologies

The authors declare that no generative artificial intelligence (AI) tools were used in the design of the study, data collection, data analysis, statistical modeling, interpretation of results, or formulation of scientific conclusions. AI-assisted tools were used solely for language editing, grammar correction, formatting improvement, and enhancement of manuscript readability. All scientific content, methodological decisions, analyses, interpretations, and conclusions were developed, verified, and approved entirely by the authors. The authors take full responsibility for the accuracy, originality, and integrity of the work presented in this manuscript.

Declaration of Competing Interest

The authors declare that there are no known competing financial or personal interests that could have appeared to influence the work reported in this paper

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Data and Code Availability

The data used in this study consist of secondary data and supporting primary data. The secondary data were obtained from the annual financial cash reports of the KP-RI Semeru Ngajum Savings and Loan Cooperative during the 2015–2024 management period, which were subsequently transformed into monthly observations covering 120 months (January 1, 2015, to December 1, 2024). Supporting primary data were collected through interviews with the cooperative's financial management to identify changes in mandatory savings policies. This information was used to construct dummy variables as exogenous variables representing the periods before and after policy changes. Some of the data used in this study are not publicly available because they contain internal cooperative information. However, the data may be provided by the authors for academic purposes upon reasonable request and subject to approval from the relevant parties. The analysis code used in this study is also available from the authors upon reasonable request.

References

[1] H. Hamsyah, I. N. Latif, and C. K. Dewi. "Cooperative Financial Performance Analysis of Liquidity, Solvency, Profitability, and Activity Ratios: A Case Study of the Tirta Dharma PDAM Cooperative in Samarinda City Based on Ministerial Regulation Number 06/Per/M.KUKM/V/2006". In: *Indonesian Journal of Sustainable Policy and Technology* 1.1 (2023), pp. 30–45. DOI: 10.61656/ijospat.v1i1.119.

[2] M.-C. Düker, D. S. Matteson, R. S. Tsay, and I. Wilms. "Vector Autoregressive Moving Average Models: A Review". In: *WIREs Computational Statistics* 17 (2025). DOI: 10.1002/wics.70009.

[3] S. Almaghrabi, M. Rana, M. Hamilton, and M. Saiedur. "Multidimensional Dynamic Attention for Multivariate Time Series Forecasting". In: *Applied Soft Computing* 167.2 (2024), p. 112350. DOI: 10.1016/j.asoc.2024.112350.

[4] Y. Boddu, A. Manimaran, B. Arunkumar, and D. Ramkumar. "Design of an Iterative Dual Metaheuristic VARMAx Model Enhancing Efficiency of Time Series Predictions". In: *IEEE Access* 12 (2024), pp. 128071–128084. DOI: 10.1109/ACCESS.2024.3454540.

[5] D. D. Atmaja and B. Warsito. "Forecasting Stock Prices on the LQ45 Index Using the VARIMAX Method". In: *Media Statistika* 14.1 (2021), pp. 98–107. DOI: 10.14710/medstat.14.1.98-107.

[6] A. Bykhovskaya and V. Gorin. "Cointegration in Large VARs". In: *The Annals of Statistics* 50.3 (2021), pp. 1593–1617. DOI: 10.1214/21-AOS2164.

[7] S. Stramaglia, T. Scagliarini, Y. Antonacci, and L. Faes. "Local Granger Causality". In: *Physical Review E* 103.2 (2021), pp. 1–11. DOI: 10.1103/PhysRevE.103.L020102.

[8] M. Plagborg-Møller and C. K. Wolf. "Local Projections and VARs Estimate the Same Impulse Responses". In: *Econometrica* 89.2 (2021), pp. 955–980. DOI: 10.3982/ECTA17813.

[9] F. Fusari, J. Marlow, and A. Volpicella. "Estimation and Inference of the Forecast Error Variance Decomposition for Set-Identified SVARs". In: *Journal of Econometrics* 255 (2026), p. 106233. DOI: 10.1016/j.jeconom.2026.106233.

[10] B. Lim, S. Ö. Arık, N. Loeff, and T. Pfister. "Temporal Fusion Transformers for Interpretable Multi-Horizon Time Series Forecasting". In: *International Journal of Forecasting* 37.4 (2021), pp. 1748–1764. DOI: 10.1016/j.ijforecast.2021.03.012.

[11] R. D. Toscano, D. Lima, S. Murilo, F. Maciel, S. Marlon, and L. de Lima. "Time Series Forecasting with Exogenous Variables: A Literature Review to Identify Promising Gaps in Computational Research". In: *Revista Principia* 62.1 (2025), pp. 1–26. DOI: 10.18265/2447-9187a2025id8575.

[12] A. J. M. Karim and N. M. Ahmed. "Vector Autoregressive Integrating Moving Average (VARIMA) Model of COVID-19 Pandemic and Oil Price". In: *International Journal of Professional Business Review* 8.1 (2023), pp. 1–20.

[13] R. Abdalla, M. El-Diasty, A. Kostogryzov, and N. Makhutov. *Time Series Analysis: New Insights*. Norderstedt: Books on Demand, 2023.

[14] M. A., L. S., M. I., T. T., and R. B. N. "Modeling of COVID-19 in Indonesia Using Vector Autoregressive Integrated Moving Average". In: *Journal of Physics: Conference Series*. Vol. 1722. 1. 2021, pp. 1–7. DOI: 10.1088/1742-6596/1722/1/012079.

[15] A. Shojaie and E. B. Fox. "Granger Causality: A Review and Recent Advances". In: *Annual Review of Statistics and Its Application* 9 (2022), pp. 289–319. DOI: 10.1146/annurev-statistics-040120-010930.

[16] T. Fissler, R. Frongillo, J. Hlavinov, and B. Rudloff. "Forecast Evaluation of Quantiles, Prediction Intervals, and Other". In: *Electronic Journal of Statistics* 15 (2021), pp. 1034–1084. DOI: 10.1214/21-EJS1808.

[17] R. J. Hyndman and G. Athanasopoulos. *Forecasting: Principles and Practice*. 3rd. Melbourne: OTexts, 2021. https://otexts.com/fpp3/.

[18] R. D. Gidaro and J. L. Harvill. "Evaluating Approximations of Count Distributions and Forecasts for Poisson-Lindley Integer Autoregressive Processes". In: *arXiv preprint* (2024), pp. 1–40. DOI: 10.48550/arXiv.2405.20342.

[19] G. Buturac. "Measurement of Economic Forecast Accuracy: A Systematic Overview of the Empirical Literature". In: *Journal of Risk and Financial Management* 15.1 (2022), pp. 1–28. DOI: 10.3390/jrfm15010001.