Research Article

Forecasting Inflation in Lao PDR: A Comparison of ARIMA and VAR Models

Received: *July 14, 2024*
Revised: *August 8, 2024*
Accepted: *September 6, 2024*

Alounny Vorachakdaovy
Student in Master of Business Administration, Majoring in Finance,
Faculty of Economics and Business Management, National University of Laos

Dr.Piya Wongpit
Associate Professor of Finance and Banking Department,
Faculty of Economics and Business Management, National University of Laos
(Corresponding Author)

ABSTRACT

This study aims to use a univariate time series in the form of an Autoregressive Integrated Moving Average (ARIMA) model developed by Box and Jenkins and a multivariate time series model in the form of a Vector Autoregressive model (VAR) to forecast inflation for Lao PDR. Our focus is to use change in quarterly inflation data obtained from the Bank of Lao PDR over the period 2005: Q1 to 2023: Q3 to analyze the forecast performance of the two models using measures of accuracy such as RMSE and MAPE statistics. So, the best forecasting model for predicting inflation in Lao PDR will be selected based on different diagnostic and evaluation criteria. ARIMA model (1,1,3) was the best model, and the VAR model used a vector error correction model. The Impulse Response Function and Variance Decomposition analyses reveal consistent results, indicating that the variables experience sudden changes or shocks. However, the Var model had the least minimum square error and is the closest approximate to current inflation at 26.4 percent in Q3:2023 in Lao PDR. The study forecasted core inflation using VAR for the quarterly of 2023: Q3 to 2024: Q4 to be 28.8 percent.

Keywords: Inflation Forecasting, ARIMA and VAR

1. INTRODUCTION

Inflation results from the continuous rise in the prices of goods and services, leading to economic instability, higher living costs, and challenges in economic development and financial policy. It impacts household income and spending at the micro level and increases financial capital costs at the macro level due to higher wages, transportation costs, and commodity prices. Fluctuations in global oil, gold, and exchange rates directly affect price stability and are primary causes of inflation.

Lao PDR joined ASEAN in 1997 and faced economic challenges due to the Asian financial crisis, with growth dropping to 4 percent in 1998 but rebounding to 6 percent in 2000 despite high inflation (Asian Development Bank, 2006). In 2019, the COVID-19 pandemic led to economic slowdowns globally, including in Laos, impacting financial stability and significantly reducing tourism, transportation, and income processing.

Since the end of 2019, global economies have implemented loose monetary and currency policies to revive their economies, increasing the money supply and raising prices for goods and services. In response, the Bank of Lao PDR (BOL) has raised policy interest rates to combat inflation, which has weakened the Lao LAK and subsequently impacted Lao PDR's import prices. As domestic production remains weak and heavily reliant on imports, the impact on the cost of imported goods further contributes to inflation (Bank of Lao PDR, 2022).

In 2022, global economic and political instability, including the Russia-Ukraine conflict and rising inflation, severely impacted countries like Lao PDR, leading to increased living costs and economic difficulties for its citizens. The Lao LAK depreciated by 5.8 percent against the dollar and 4 percent against the Baht in first quarter of 2022, while the dollar index rose from 119.9 to 121.9, resulting in higher costs for imported goods, especially imported oil. Limited market intervention capabilities have further weakened the value of the Lao LAK, directly impacting the prices of imported goods (Lao Statistics Bureau, 2023).

In mid-2022, the Lao LAK depreciated significantly due to external imbalances, limited foreign exchange liquidity, and low foreign currency reserves, leading to a 32 percent drop against the Baht and a 43 percent drop against the Dollar by early 2023 (World Bank, 2023). By the first month of September 2023, the depreciation reached 33.7 percent over nine months. The product category with the highest increase was food and non-alcoholic beverages, which increased by 42.8 percent.

In 2024, the BOL aimed to reduce inflation to a single-digit level by the end of the year. However, mid-year reports indicated that inflation had reached 26% (Bank of Lao PDR, 2024). This significant gap between the target and actual inflation suggests that the BOL may have underestimated critical factors such as oil prices, gold prices, and other variables affecting their estimations. The incorrect forecast of inflation generates uncertainty for the economy, complicating the government’s use of monetary and fiscal policy. This uncertainty is particularly challenging for the private sector, especially

SMEs, which have limited resilience to economic fluctuations. Consequently, businesses may struggle to plan and invest effectively, potentially stifling growth and innovation within the sector. Additionally, consumers may face higher costs of living, reducing their purchasing power and overall economic well-being.

Various models have been used to forecast inflation, such as ARIMA, VAR, and ECM, which are appropriately used in certain contexts (Uko & Nkoro, 2012). However, the BOL currently relies mainly on a macroeconomic model to target inflation, which does not adequately reflect the current situation. Therefore, it is important to apply new techniques to forecast inflation to reduce uncertainty for the economy and businesses in general. The objectives of this study are to estimate univariate and multivariate time series models to forecast inflation of Lao PDR and to compare the forecasting results of the ARIMA and VAR models. This paper is divided into six sections, including this introduction as section one. Section two presents a brief literature review related to the study's focus, while section three discusses the methodology. Section four covers the empirical analysis. Section five compares the forecasting ability of the models and their stability. Section six provides a summary and concluding remarks.

Forecasting inflation benefits both the public and private sectors. Accurate inflation forecasting will help the government of Lao PDR implement policy interventions to ensure economic stability. For the private sector, especially businesses, accurate inflation forecasts allow for better risk management regarding finance and production costs. Therefore, it is crucial to use appropriate tools to analyze and forecast inflation effectively and this paper intends to reveal this result.

2. LITERATURE REVIEW

Several forecasting models have emerged to predict inflation. Among these, the ARIMA and VAR models are widely used for inflation forecasting. Marpaung et al. (2022) forecasted inflation in Central Java in Indonesia using the ARIMA method with data from January 2016 to April 2021. The best model found is ARIMA (3,0,3), which predicts a rise in inflation. The forecast of Iran's inflation, Jafarian-Namin et al. (2021) applied a Box-Jenkins methodology using ARIMA models, is applied to forecast Iran's yearly inflation rate from 1960 to 2019, with the non-seasonal ARIMA (1,0,0) model found to be the most suitable.

On the other hand, Nyoni (2019) forecasts that inflation in the Philippines will drop from 5.6 percent in 2018 to 0.3 percent in 2027 and supports the continued use of the current inflation-targeting policy. Alnaa and Ahiakpor (2011) used monthly inflation data from 2000:6 to 2010:12 to forecast the inflation rate of Ghana. They used the ARIMA model, and ARIMA (6,1,6) was the best-fitted model in this study. This paper completely ignores the importance of many variables that are influencing inflation. The standard in-sample and out-of-sample forecasting models Stovicek (2007) standard model selection criteria work for predicting Slovenian. It compares different seasonal adjustments and forecast lengths and shows that standard in-sample criteria are ineffective for out-of-sample forecasting. Monthly and quarterly data were analyzed, and models with a trend break in 1999 provided the best forecasts.

Klesbayev et al. (2022) researched the determinants of inflation in Kazakhstan from 2015 to 2021. Rising oil prices led to inflation and a stronger national currency. Central banks responded by lowering interest rates. Stationarity analysis showed that variables stabilized after their first difference. The VAR model used was VAR. SVAR analysis found that oil prices were influenced by both themselves and REER. REER is influenced by itself and oil prices. These factors mostly influenced CPI. In response, Gatawa et al. (2017) used the VAR model and the Granger Causality test to explain inflation and interest rates' negative long-term effects and how broad money positively affects growth. The study compares three forecasting models (VAR, Exponential Smoothing, and ARIMA) of Erkekoglu et al. (2020) using Turkish economic data from 1998 to 2017, finding ARIMA to be the most accurate, followed by VAR. Khan and Khan (2020) research focused on predicting multiple economic indicators of Bangladesh at once using VAR and ARIMA models leveraging their correlations. The study found that the VAR model provided better forecasts for highly correlated variables like GDP vs. GNP. In contrast, both models performed similarly for less correlated variables and concluded that checking correlations before forecasting is crucial for highly correlated variables. The VAR model is preferable, while either model can be used for less correlated variables. To forecast the inflation rate Sinaj (2014) used ARIMA and VAR models and obtained data from 17 years about CPI, M2, and interest rates. Results gained by this analysis indicate a significant relation between CPI, M2, and interest rates and a statistically significant autoregressive relation to the CPI with time delay. Bokhari and Feridun (2006) forecasted Pakistan's inflation rate using ARIMA and VAR models. Results indicate that the VAR model performs poorly than the ARIMA (2, 1, 2) model.

A comparative model analysis to forecast the inflation rate is absent in Lao PDR. This paper will contribute to forecasting the inflation rate by considering univariate and multivariate models.

3. METHODOLOGY

3.1 Data

The data for this study including inflation, broad money, and interest rate, are obtained from the Bank of the Lao PDR. In addition, macroeconomic factors include total imports from the International Monetary Fund (IMF), real effective exchange rates from Bruegal.org, crude oil prices, and gold prices from the World Bank. The improvement was extended to data. Due to this constraint, quarterly data are being used. The data spanned from 2005: Q1 to 2023: Q3.

3.2 Design

To explore the inflation forecasting model in Lao PDR, the study employed Autoregressive Integrated Moving Average (ARIMA) and Vector Auto Regression (VAR) techniques on the variable listed above.

In fitting ARIMA to the series, the study examines the autocorrelation properties. This approach is known as the Box-Jenkin (1976) method. This approach in time series analysis is a method for investigating an ARIMA (p, d, q) model that adequately represents the stochastic process from which the sample was derived. This method includes three steps: model identification, estimation, and diagnostic checking. Finally, this model can be used to forecast future time series values. If the estimated model adequately explains the process from which the data is derived, the residuals should behave like white noise and not exhibit autocorrelation. The residuals are tested using the Ljung-Box (1978, 1979) Q statistic. If the model is inadequate, it must return to the first phase to reconstruct a better model. After completing the above steps, the forecasting process is followed to project future time series values based on the most appropriate model deriving from the previous stages.

Through the VAR modeling, Sims (1980) proposed the vector autoregressive (VAR) model. VAR is considered one of the foremost successful, flexible, and practical multivariate time series analysis models. In order words, there should be no distinction between endogenous and exogenous variables; therefore, once this distinction is abandoned, all variables are treated as endogenous. The univariate time series model cannot ensure any economic reason for inflation. However, the VAR model has proven useful, especially for describing the dynamic behavior of economic and financial time series and forecasting. All variables in a VAR model enter the same way: each variable has an equation, and its evaluation is based on its own lagged values, the lagged values of another model variable, and an error term.

When there is no confidence that a variable is exogenous, each variable must be treated symmetrically. The time series y_t is affected by current and past values of x_t, and simultaneously, the time series x_t is a series that is affected by current and past values of the y_t series. In this case, the simple bivariable model is given by:

$$y_t = \beta_{10} - \beta_{12}x_t + \Pi_{11}y_{t-1} + \Pi_{12}x_{t-1} + \varepsilon_{yt} \tag{1}$$

$$x_t = \beta_{20} - \beta_{21}y_t + \Pi_{21}y_{t-1} + \Pi_{22}x_{t-1} + \varepsilon_{xt} \tag{2}$$

we assume that y_t and x_t are stationary, and ε_{yt} and ε_{xt} are uncorrelated white-noise error terms. Equations constitute a first-order VAR model because the longest lag length is unity. These equations are not reduced-form since they have a contemporaneous impact on x_t (given by β_{21}), and x_t has a contemporaneous impact on y_t (given by β_{12}). Rewriting the system using matrix algebra, we get:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \Pi_{11} & \Pi_{12} \\ \Pi_{21} & \Pi_{22} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{yt} \\ \varepsilon_{xt} \end{pmatrix} \quad (3)$$

The VAR model offers a straightforward approach. Firstly, the econometrician does not need to differentiate between endogenous and exogenous variables. Secondly, estimation is simplified as the usual OLS method can estimate each equation separately. Lastly, forecasts from VAR models often outperform those from more complex simultaneous equation models (Mahmoud, 1984; McNees, 1986). Using non-stationary time series in VAR modeling poses problems for statistical inference because standard tests assume all series are stationary. If the series are non-stationary, first or higher-order differencing is required. In a VAR model, endogenous variables are expressed as functions of their lags and the lags of other variables. Proper lag length selection is crucial; incorrect lag lengths can lead to inadequate model explanations and a loss of degrees of freedom due to unnecessary lags. Typically, systematic lags are used to estimate VAR models, with the same lag length applied across all variables in all model equations. Lag length is often chosen using statistical criteria such as the AIC, SIC, or HQ.

Impulse Response function

Akkaya (2021) reflects on the impact of a deviant shock on the present and future values of internal variables. The impulse response functions determine whether it can serve as an intermediary.

Variance Decomposition

The variance decomposition helps interpret a VAR model once it has been fitted. It indicates the amount of information each variable contributes to the other variables in the auto-regression. It determines how much of the forecast error variance of each variable can be explained by exogenous shocks to the other variables.

Forecasting

Ex-post point forecasts can be checked against the actual data and provide a means of evaluating a forecasting model. They are characterized as an Ex-ante point forecast that predicts the future values of spot prices beyond the original sample's period Ex-ante forecasts can be used for decision-making or policy-making in either short-term or long-term periods.

Model Comparison

To identify a model with superior forecasting capability, the comparison of two models is required. A model with a smaller adjusted Root Mean Square Error (RMSE), which estimates the standard deviation of random shocks, is preferred because it fits the available data better and tends to produce forecasts with smaller error variance. Another measure of the closeness of fit is the Mean Absolute

Percent Error (MAPE), which indicates the expected accuracy of a forecasting model. The following equations describe these measures:

$$RSME = \sqrt{\tfrac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \tag{4}$$

$$MAPE = \tfrac{100}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \tag{5}$$

3.3 Models Specification

Specifically the models, attention was given to various ways to explain inflation.

ARIMA Model

$$\Delta INF_t = \delta + \phi_1 \Delta INF_{t-1} + \phi_2 \Delta INF_{t-2} + \ldots + \phi_p \Delta INF_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} + \mu_t \tag{6}$$

Where ΔINF_t predictable the first difference at the time t of inflation, ϕ_1, $\phi_2, \ldots, \phi_p$ and θ_1, $\theta_2, \ldots, \theta_q$ coefficients to be estimated, δ is a constant mean of the process and μ_t is the stationary error term.

VAR Model

$$\begin{bmatrix} INF_t \\ M2_t \\ REER_t \\ RATE_t \\ OIL_t \\ GOLD_t \\ IM_t \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \\ \beta_{40} \\ \beta_{50} \\ \beta_{60} \\ \beta_{70} \end{bmatrix} + \begin{bmatrix} \prod_{11} & \prod_{12} & \prod_{13} & \prod_{14} & \prod_{15} & \prod_{16} & \prod_{17} \\ \prod_{21} & \prod_{22} & \prod_{23} & \prod_{24} & \prod_{25} & \prod_{26} & \prod_{27} \\ \prod_{31} & \prod_{32} & \prod_{33} & \prod_{34} & \prod_{35} & \prod_{36} & \prod_{37} \\ \prod_{41} & \prod_{42} & \prod_{43} & \prod_{44} & \prod_{45} & \prod_{46} & \prod_{47} \\ \prod_{51} & \prod_{52} & \prod_{53} & \prod_{54} & \prod_{55} & \prod_{56} & \prod_{57} \\ \prod_{61} & \prod_{62} & \prod_{63} & \prod_{64} & \prod_{65} & \prod_{66} & \prod_{67} \\ \prod_{71} & \prod_{72} & \prod_{73} & \prod_{74} & \prod_{75} & \prod_{76} & \prod_{77} \end{bmatrix} \begin{bmatrix} INF_{t-1} \\ M2_{t-1} \\ REER_{t-1} \\ RATE_{t-1} \\ OIL_{t-1} \\ GOLD_{t-1} \\ IM_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix} \tag{7}$$

Where INF_t represents inflation at time t, $M2_t$ is broad money at time t, and $RATE_t$ is the interest rate from the Bank of Lao PDR (BOL) at time t. $REER_t$ is the real-effect exchange rate from Bruegel. org. OIL_t is crude prices at time t and $GOLD_t$ is gold prices from the World Development Indicators (WDI) of the World Bank database, and IM_t is total imports from the International Monetary Fund (IMF). This study's balanced time series data convert the period from monthly to quarterly in EViews programs adjusted 2005: Q1 to 2023: Q3 of Lao PDR.

Table 1: Description of the selected variable

Variable	Definition and Measurement	Data Source
Inflation (INF)	Monthly changes of consumer price (percent)	BOL
Broad money (M2)	The amount of money supplied by a national economy (LAK)	BOL
Real-effect exchange rate (REER)	The weighted average of a country's currency to an index	Bruegel.org
Interest rate (RATE)	The cost of a loan to a borrower (percent)	BOL
Crude prices (OIL)	The spot price of a barrel	WDI
Gold prices (GOLD)	The gold spot price in troy ounces	WDI
Total import (IM)	The product price to bring from a foreign or external source (USD)	IMF

Note: BOL = Bank of Lao PDR, WDI = World Development Indicators database, IMF = International Monetary Fund

Based on the theoretical frameworks and existing literature, the effect of broad money, real-effect exchange rate, interest rate, crude prices, gold prices, and total import on inflation can be expected as follows:

- The expected effect of broad money is positive ($\beta_{20} > 0$) If the amount of broad money sense increases by 1 percent because the increase in the amount of money in the broad sense means an increase in the price of goods and services, which will reduce purchasing power and consumption.

- The expected effect of the Real-effect exchange rate is positive ($\beta_{30} > 0$) if the real-effect exchange rate increases by 1 percent, we have to import more goods and invest in the foreign currency of the trading partner countries, which will reduce the currency in the country and the budget deficit due to the smaller amount of goods.

- The expected effect of the interest rate is negative ($\beta_{40} < 0$) if the loans increase by 1 percent, which means that those who will borrow money and business people must borrow at a higher rate, making spending on goodwill and investments cost less.

- The expected effect of crude prices is positive ($\beta_{50} > 0$). Suppose the price of oil in the world market increases by 1 percent. In that case, the cost of production and transportation increases, and the value of the trading partner countries' currencies increases substantially, reducing domestic purchasing power and decreasing stock prices.

- The expected effect of gold prices is positive ($\beta_{60} > 0$) if the price of gold in the world market increases by 1 percent, the structural aspect of the price adjustment of gold is a leap higher. There are imports from abroad, especially gold bars, so the exchange rate for purchasing foreign currency compared to domestic currency decreases.
- The expected effect of total import is positive ($\beta_{70} > 0$) if the value of imported goods increases by 1percent. Most are brought from abroad because the domestic production base is still tiny, so they import consumer goods. In addition, foreign currency appreciation will weaken the value of money.

Table 2: Expected effects of the explanatory variable on Inflation

Variable	The expected sign of the coefficient	Author(s) who used the variable
Inflation (INF)		
Broad money (M2)	Positive	Gathingi (2014)
Real-effect exchange rate (REER)	Positive	Kelesbayev et al. (2022)
Interest rate (RATE)	Negative	Gatawa et al. (2017)
Crude prices (OIL)	Positive	Gathingi (2014)
Gold prices (GOLD)	Positive	Hapau (2022)
Total import (IM)	Positive	Khan and Khan (2020)

4. EMPIRICAL RESLT AND ANALYSIS

4.1 Inflation and its determinant

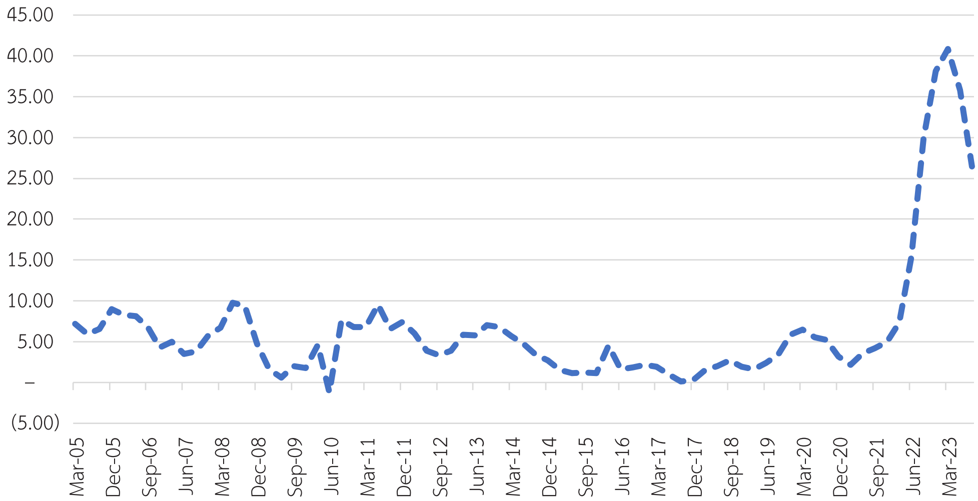


Figure 1: Changes in the Inflation Rate from 2005 to 2023 (%)

Source: Bank of Lao PDR

This section discusses inflation and its determinant variables in Lao PDR from 2005 to 2023. Figure 1 shows that at the end of the fourth quarter of 2005, the inflation rate was 8.9%, which is considered moderate, largely due to instability in crude oil prices in the world market. The inflation rate fell between 2007 and 2008 during the global financial crisis. Laos was affected by this crisis as global oil prices continued to rise, directly impacting domestic oil prices. Consequently, the inflation rate increased slightly, but compared to other countries, it remained relatively low, reaching 9.73% in the second quarter of 2008.

From 2009 to 2010, the inflation rate saw a significant decrease. By the second quarter of 2010, it was at 1.21%. This decrease can be attributed to a reduction in the global inflation rate and the appreciation of the Lao LAK against the USD and the THB, leading to lower prices for imported goods and an adequate supply of goods to meet societal needs. From 2011 to 2015, the inflation rate remained relatively stable, averaging 4.22%. This stability aligned with expectations, primarily due to reductions in oil, gold, and commodity prices in the world market. By the end of the fourth quarter of 2019, the inflation rate had slightly increased to 5.85%.

In 2020, the inflation rate continued to increase, reaching 6.44% due to the global spread of COVID-19. This pandemic caused disruptions that affected Laos by increasing the price of imported goods, weakening the exchange rate, and limiting domestic production capabilities. However, at the beginning of 2021, the inflation rate showed a downward trend, dropping to 2.13%. This decrease was mainly due to lower prices for non-alcoholic beverages and a reduction in the prices of domestically produced goods, which helped offset the rising prices of imported goods.

Despite this brief respite, the country experienced a sudden spike in the inflation rate in mid-2022, reaching 30%. This surge was driven by increased oil import costs and the devaluation of the LAK compared to major currencies. The weakening currency caused the inflation rate to continue rising, peaking at 41% in the first quarter of 2023.

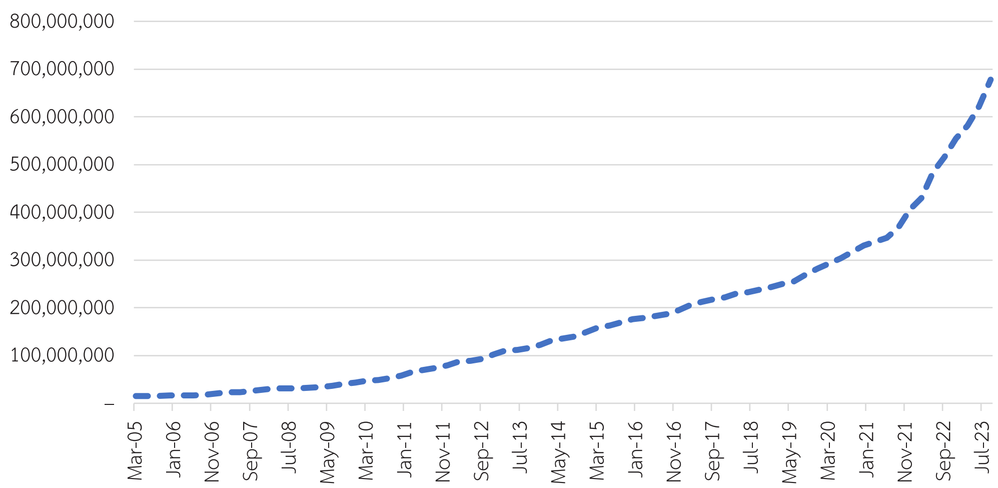


Figure 2: Broad Money (M2) from 2005 to 2023 (million LAK)

Source: Bank of Lao PDR

Figure 2 shows that M2 at the end of the fourth quarter of 2009 was 43,721,710 million LAK. This amount grew rapidly, reaching 221,568,770 million LAK by the end of the fourth quarter of 2017, accounting for 53.06% of GDP at that time. This increase in M2 facilitated the growth of the domestic credit sector and was supported by investment flows from abroad in sectors such as electricity, construction, mining, and quarrying.

From 2018 to 2019, M2 increased to 281,699,400 million LAK, driven primarily by investment in the Lao-China railway construction project and the “Vientiane-Vangvieng” highway construction project. Despite the global COVID-19 pandemic, the growth of M2 continued, reaching 331,090,080 million LAK in the fourth quarter of 2020, accounting for 64.82% of GDP at the end of 2020. This growth reflects the ongoing use of expansionary policies, despite budget constraints and the weakening of the LAK against the USD.

By the third quarter of 2022, M2 had grown to 484,026,100 million LAK. This increase was supported by funding for large-scale projects, improvements in commercial banking, increased foreign currency deposits, and more credit provided to the economic system, leading to rapid growth in the broad money.

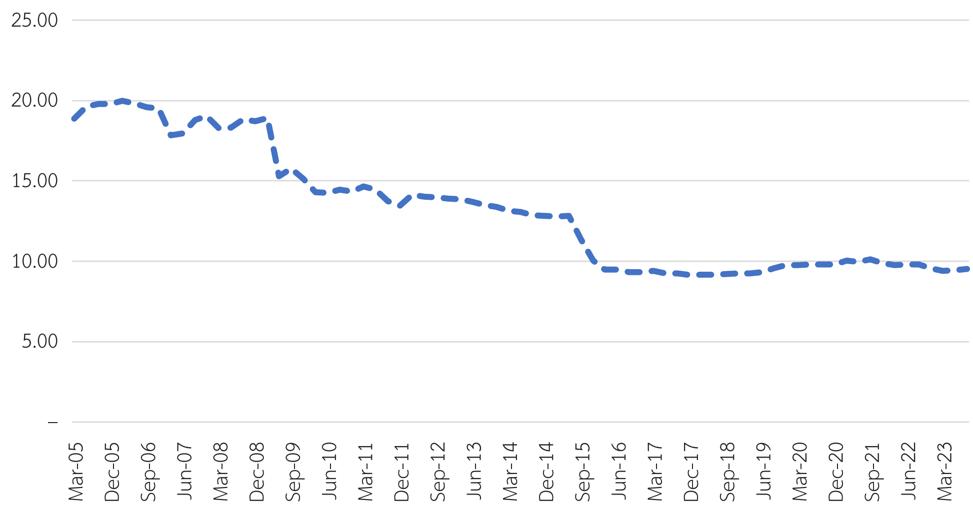


Figure 3: Lending rate from 2005 to 2023 (%)

Source: Bank of Lao PDR

Changes in lending rates from Figure 3 shows that during global and regional economic conditions not yet recovering from the effects of the international financial crisis, the BOL adopted a loose monetary policy to reduce lending rates and issued bonds for lending to the government and private sectors. In 2009, commercial banks adjusted loan interest rates according to the economic situation and loan demand. The average 1-year loan interest rate across the commercial banking system decreased from 19.8% in 2005 to 15.15%.

Overall, interest rates followed a continuous downward trend, falling to 9.2% by the end of 2018, in line with notifications issued by the Bank of the Lao PDR over time. Up to 2019, to align with basic economic conditions and capital management principles, the BOL allowed commercial banks to set interest rates according to market mechanisms under state management. However, the loan interest rate showed a tendency to increase, reaching 9.7%, and in 2020, the commercial bank loan interest rate rose by 10% due to concerns about the risk of non-performing loans and capital management principles during the COVID-19 epidemic.

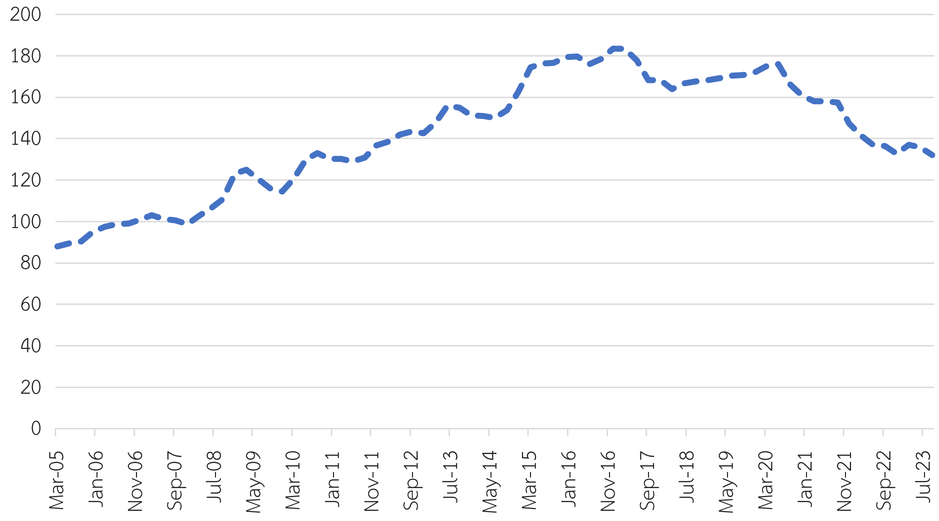


Figure 4: Change in Real Effective Exchange Rate from 2005 to 2023

Source: www.bruegel.org

Changes in the real exchange rate from Figure 4 show an increasing trend from 2005 to 2007, maintaining a relatively stable level of around 99. Despite the international financial crisis in 2009, the real exchange rate rose. From early 2010 to 2018, it reached levels of 130 and 168.

During this period, the exchange rate fluctuated upwards due to decreasing global market prices and the appreciation of major currencies. This led to higher demand for goods and increased prices and production costs within the economy.

From mid-2019 to the end of 2020, many countries were impacted by the COVID-19 pandemic, causing the real exchange rate to drop to 160 due to decreased international trade. In 2022, the real exchange rate stood at 133, reflecting a weakened currency compared to 2021. This trend of currency depreciation continued into the third quarter of 2023.

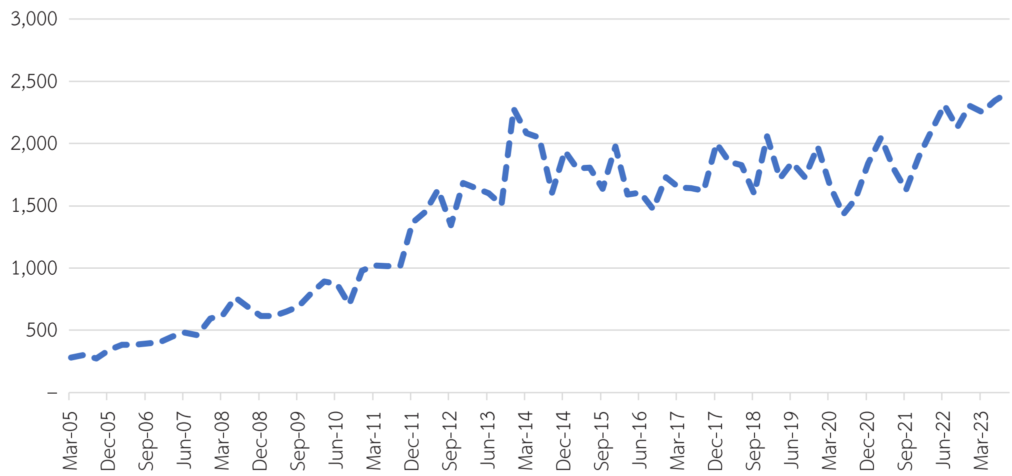


Figure 5: Changes in the Value of Imported Goods from 2005–2023 (unit: million USD)

Source: International Monetary Fund

Figure 5 shows that the Lao People's Democratic Republic relies heavily on imported goods, including consumer goods, production factor goods, mechanical tools, and more. A significant portion of imports between 2005 and 2013 consisted of oil for domestic consumption. During this period, the global market price of oil rose, compounded by the international financial crisis. Consequently, the value of imported goods increased from 344 million USD to 2,780 million USD.

Despite being affected by external factors, such as the weakening of the LAK against major currencies (notably the USD), the price of imported goods continued to rise. The domestic production base remains insufficient to meet local consumption needs, necessitating reliance on high-cost imports. Notably, in mid-2022, the value of imports rose further to 2,345 million USD.

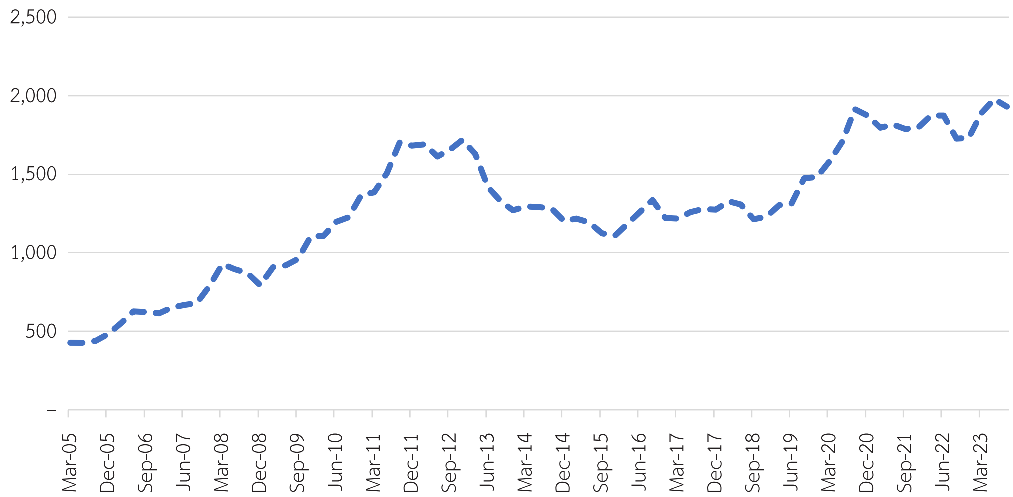


Figure 6: Changes in gold prices from 2005–2023 (unit: USD/ounce)

Source: World Development Indicator database

The price of gold in the world market affects the domestic gold price in the same direction, heavily influenced by the exchange rate with trading countries. From Figure 6, it is evident that from 2005 to 2011, the price of gold steadily increased from 486 USD per ounce to 1,700 USD per ounce, largely due to the weakening of the USD. By the end of 2015, however, the world market price of gold had decreased to 1,100 USD per ounce.

At the beginning of 2020, despite the COVID-19 pandemic causing many countries to implement lockdowns and halt work, the price of gold continued to rise. The appreciation of the USD pushed the gold price up to 1,876 USD per ounce. In 2022, the political conflict between Russia and Ukraine, coupled with an increase in US interest rates, caused the world market price of gold to rise further to 1,978 USD per ounce. This increase also impacted domestic gold prices due to the weakening of the LAK against major currencies.

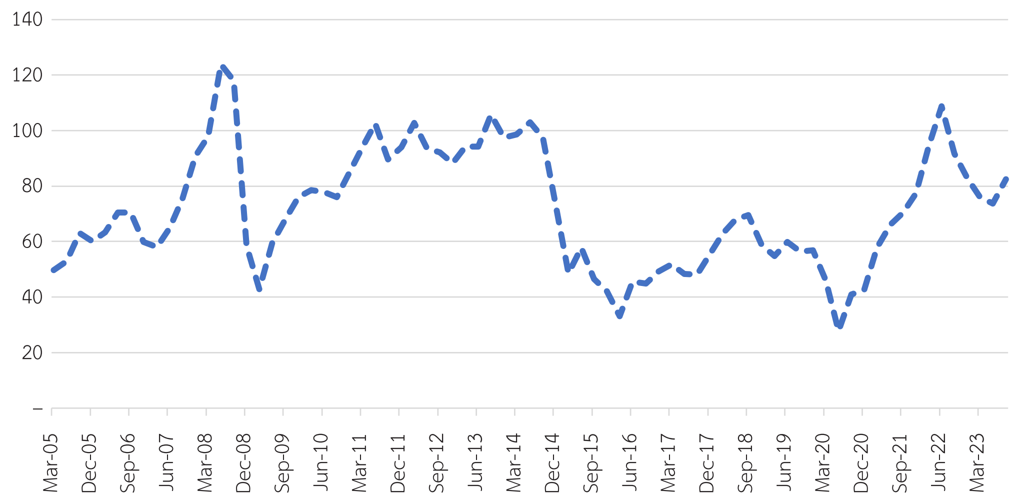


Figure 7: Changes in oil prices from 2005–2023 (Unit: USD/barrel)

Source: World Development Indicator database

Changes in oil prices from Figure 7 indicate that from 2005 to 2007, world oil prices remained relatively stable. However, in 2008, oil prices began to rise due to economic superpowers supporting agricultural production to replace energy sources, which led to reduced agricultural output, higher commodity prices, and international trade disputes. As a result, the price of oil increased to 120 USD per barrel. By the end of 2009, the price had dropped as major economies slowed their growth, reducing oil demand to 65 USD per barrel.

In early 2016, the global oil market experienced significant price uncertainty with a sharp decline, influenced by political tensions among major crude oil producers and the appreciation of major currencies. From late 2019 to early 2020, the outbreak of COVID-19 led to widespread lockdowns, causing global oil prices to plummet to 28 USD per barrel in the second quarter of 2020.

As the COVID-19 pandemic receded and the global economy began to recover in early 2022, the war between Russia and Ukraine decreased global crude oil supply, leading to an oil shortage crisis in many countries. This caused oil prices to rise, reaching 109 USD per barrel, affecting Laos due to its reliance on oil imports.

4.2 ARIMA Model

Table 3: Unit Root Test Using Augmented Dickey-Fuller (ADF)

Variable	ADF Test						
	In level		In First Difference		Critical Value		
	t-stat	Prob*	t-stat	Prob*	1percent	5percent	10percent
INF	−3.627	0.007	−6.107	0.000	−3.52	−2.90	−2.58
LM2	−0.948	0.776	−5.356	0.000	−3.52	−2.90	−2.58
RATE	−1.174	0.681	−8.741	0.000	−3.52	−2.90	−2.58
LREER	−2.150	0.225	−5.159	0.000	−3.52	−2.90	−2.58
LGOLD	−2.792	0.064	−6.406	0.000	−3.52	−2.90	−2.58
LOIL	−2.574	0.102	−7.310	0.000	−3.52	−2.90	−2.58
LIM	−2.281	0.180	−4.040	0.000	−3.52	−2.90	−2.58

Note: 95percent Critical level for ADF

The data must be stationary before we can identify a suitable ARIMA model. The table above revealed that the inflation variable is stationary in level while other variables are non-stationary.

Model Identification

Having achieved stationarity, the next is to identify the model. This is established by finding a suitable ARIMA form. This is achieved through the Box-Jenkin procedure, which involves plotting the correlogram and Partial correlogram of the stationary series. This is shown in Figure 8 below.

Autocorrelation	Partial Correlation	LAGs	AC	PAC	Q-Stat	Prob
. |*** |	. |*** |	1	0.385	0.385	11.561	
. |*. |	. | . |	2	0.178	0.035	14.059	
. | . |	.*| . |	3	0.011	−0.080	14.069	0.000
**| . |	**| . |	4	−0.296	−0.332	21.207	0.000
.*| . |	. |*. |	5	−0.078	0.192	21.710	0.000
.*| . |	. | . |	6	−0.071	−0.026	22.131	0.000
.*| . |	.*| . |	7	−0.116	−0.130	23.265	0.000
. | . |	.*| . |	8	−0.027	−0.068	23.328	0.001
. | . |	. |*. |	9	0.034	0.181	23.429	0.001
. | . |	. | . |	10	0.065	0.014	23.810	0.002

Figure 8: Correlogram and Partial Correlogram of the difference of INF (All items)

Sample: 2005: Q1 to 2023: Q3

Included observations: 75

Source: Eviews12

As shown in Figure 8 above, only lags 1 and 3 are statistically significantly different from zero. They are outside the 95 percent confidence bounds. This depicts a correlogram of a random walk; hence, the ARIMA model must be found.

Table 4: model Identification of Inflation using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

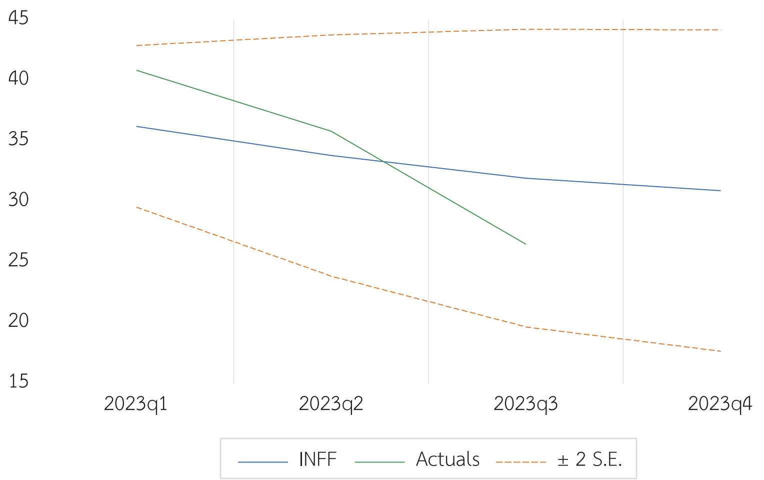
ARIMA	ACF and PACF (Number of lags)
Inflation (All items) (2005:Q1-2023:Q3)	1,3

Source: Eviews12

Table 4 above shows the correlated lags of ACF and PACF. This revealed that the model follows an AR process. Thus, the model is estimated using AR and MA terms, taking cognizance of the properties of the residuals. The best model is identity through this process.

Model Simulation

This is performed over a model's estimation. The main reason for this simulation is model validation and evaluation. A comparison of the actual with the simulated series for the same variable is often used to test a model's validity. This is because such a comparison allows an analyst or policymaker to determine how well a simulated series tracks the data. The duration of Ex-post forecasting is from Quarter 1, 2023, to Quarter 4, 2023. In Figure 9, the solid line represents the forecast value of the inflation. Meanwhile, the dotted lines above or below the forecasted inflation show the forecast with ±2 of standard errors.



Forecast: INFF	
Actual: INF	
Forecast sample: 2023Q1 2023Q4	
Included observations: 4	
Root Mean Squared Error	4.298932
Mean Absolute Error	4.038866
Mean Abs. Percent Error	12.54334
Theil Inequality Coef. 0.062402	
Bias Proportion	0.008592
Variance Proportion	0.958052
Covariance Proportion	0.033356
Theil U2 Coefficient	0.555210
Symmetric MAPE	12.18249

Figure 9: Historical Simulation Ex-post forecasting of the ARIMA Model

Source: Eviews12

The ARIMA model's ex-post forecasting ability, as indicated in Figure 9, shows that Forecasting is considered adequate, according to the research by Fulthon and Hubrich (2021), who said that macroeconomic data forecasting is when the value of the variable we can predict is compared to the actual value and is expected to move. So, short-term forecasting has a smaller prediction value than long-term forecasting. The RMSE, MAPE, MAE, and Theil Inequality Coefficient are suitable forecasting models.

The Lao PDR inflation series forecast using the Ex-ante forecasting by the ARIMA (1,1,3) model was conducted in the next step. The one-step-ahead static forecasts are more accurate than the dynamic forecasts. The duration of forecasts is from 2023: Q3 to 2024: Q4. The forecasts are plotted in Figure 10.

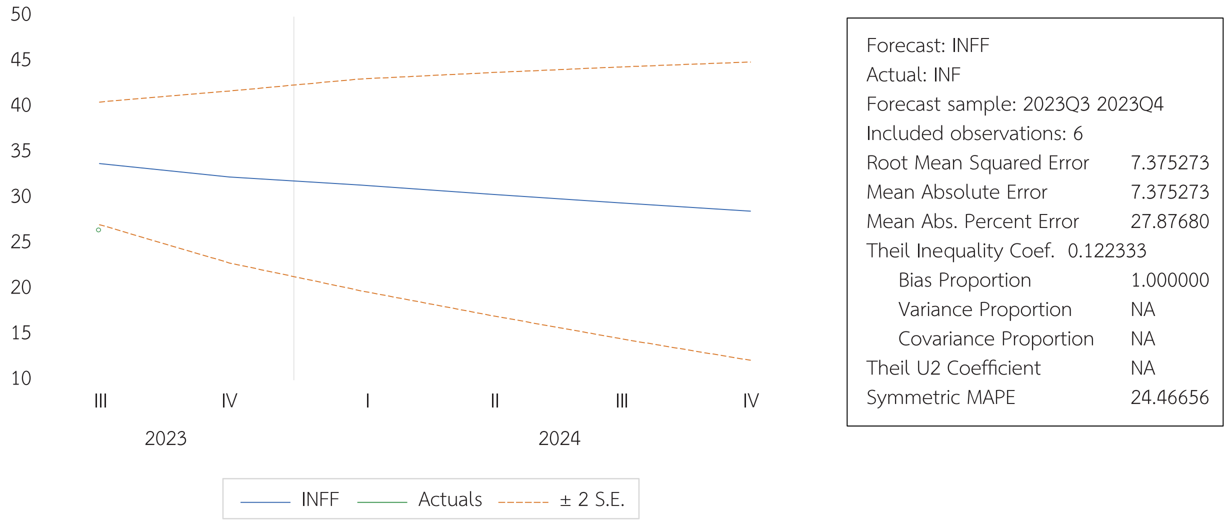


Figure 10: Ex-ante Forecasting of Inflation by ARIMA (1,1,3) model.

Source: Eviews12

In the forecasting stage, we calculated RMSE, MAPE, and Theil inequality coefficient values from the ARIMA (1,1,3) model. A small forecast error will be obtained if the actual and forecast values are closer. Thus, smaller RMSE, MAPE, and Theil inequality coefficients are preferred. The results show that the model is relevant for forecasting inflation in Lao PDR.

4.3 VAR Model

Lag Order Selection

Determining the optimum lag length is empirical. Several criteria, such as Hannan-Quinn information (HQ), Akaike Information Criteria (AIC), and Schwarz information Criteria (SIC), are used to detect the lag length—the model with lower values of these criteria. The optimum length of six lags was chosen using the Akaike Information Criteria. The lag specification criteria results are shown in Table 5.

Table 5: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−269.3961	NA	7.11e−06	8.011481	8.238130	8.101400
1	307.4484	1019.928	1.62e−12	−7.288358	−5.475170*	−6.569006*
2	351.3370	68.69529	1.96e−12	−7.140203	−3.740476	−5.791418
3	398.2867	63.96044	2.33e−12	−7.080774	−2.094507	−5.102555
4	470.2857	83.47715*	1.50e−12	−7.747413	−1.174607	−5.139761
5	534.6794	61.59390	1.45e−12	−8.193605	−0.034259	−4.956520
6	616.5060	61.66647	1.13e−12*	−9.145102*	0.600783	−5.278584

Source: Eviews12

VAR Stability Test

Figure 11 below shows that VAR satisfies the stability condition for Inflation. The values were within the bound.

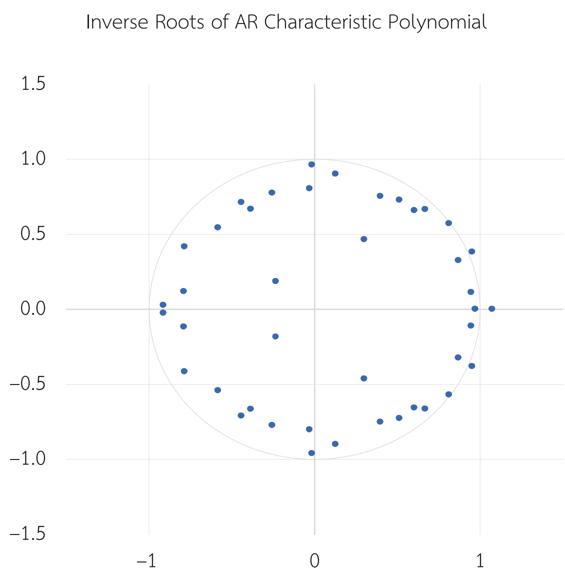


Figure 11: Inflation (All items)

Source: Eviews12

Impulse Response and Variance Decomposition

This aspect deals with impulse response function and variance decomposition. Figure 12 below shows the effects of an innovation in the variables in the model on Inflation (INF). The graphs in Figure 5 reveal that a positive shock to broad money (M2) increased INF from the first quarter of the first year, began to drop from the third quarter of the second year, and increased from the second quarter of last year onward. INF declined to the positive shock of interest rate (RATE) and increased from the second quarter of the second year to the last quarter of last year, causing a positive shock in gold prices (GOLD). Also, positive shock in the actual real effect exchange rate (REER) and crude prices (OIL) led to a decline in INF from the first quarter of the first year and started decreasing from the third quarter of last year. On the other hand, a negative shock to total import (IM) led to a decline in INF from the third quarter of the first year and later dropped in the last year.

Figure 12: Impulse Response of Inflation

Source: Eviews12

Variance decomposition estimates are computed to trace the effects of innovations in variables in the systems on INF. Table 6 below reveals that innovations in crude prices (OIL) are a major source of variation in prices in Lao PDR. Accounting for 18.16 percent shocks in prices after 3 years of 12 quarterly. Other factors include broad money, interest rate, total imports, and crude prices, accounting for 14.62, 10.007, 6.56, and 3.04 percent fluctuation in prices, respectively, while 45.22 percent variation is attributed to own shock. Little or none can be attributed to REER.

Table 6: Variance Decomposition of Inflation (All Items)

Period	S.E	INF	LM2	LREER	RATE	LOIL	LGOLD	LIM
1	1.797	100.000	0.000	0.000	0.000	0.000	0.000	0.000
2	3.007	96.356	2.208	0.140	0.585	0.389	0.173	0.146
3	3.844	94.831	4.004	0.112	0.524	0.262	0.170	0.093
4	4.271	89.537	8.050	0.909	0.552	0.483	0.365	0.100
5	4.565	78.353	12.970	0.845	4.674	0.426	0.412	2.316
6	5.053	67.899	17.640	0.813	4.403	0.494	1.536	7.212
7	5.362	67.042	16.618	0.854	4.486	0.449	1.966	8.582
8	5.617	67.052	15.148	0.886	4.316	1.028	2.052	9.515
9	5.770	65.162	14.643	1.372	4.095	3.644	1.945	9.136
10	6.253	55.486	16.878	2.851	5.574	9.266	2.023	7.919
11	6.683	48.851	15.556	2.496	7.630	16.165	2.309	6.989
12	6.949	45.228	14.623	2.369	10.007	18.168	3.041	6.560

Source: Eviews12

5. Comparative Forecasting Ability of ARIMA and VAR

The starting point in model appraisal and validation involves the performance of historical simulation to examine the closeness of the estimated model in tracking historical data. To compare the forecasting accuracy of the models and how well the simulated series tracks the actual data. Finally, we compare the accuracy of the predictions of the ARIMA and VAR models. The model with the slightest error is a better model for forecasting inflation. The estimated criteria in Table 7 below, in the ex-ante forecasting, suggest that the VAR prediction minimizes all the error criteria. Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the VAR model are better for forecasting inflation than the ARIMA model.

Table 7: Model Selection Based on Criteria

Criteria	ARIMA model	VAR model
RMSE (Root Mean Square Error)	7.375273	0.514959
MAPE (Mean Absolute Percentage Error)	27.87680	1.985063

The ex-ante forecasting comparison graph shown in Figure 13 also suggests that the deviation between the VAR model forecasted inflation and the ARIMA model forecasted inflation increased by 28.83 percent compared to the actual inflation.

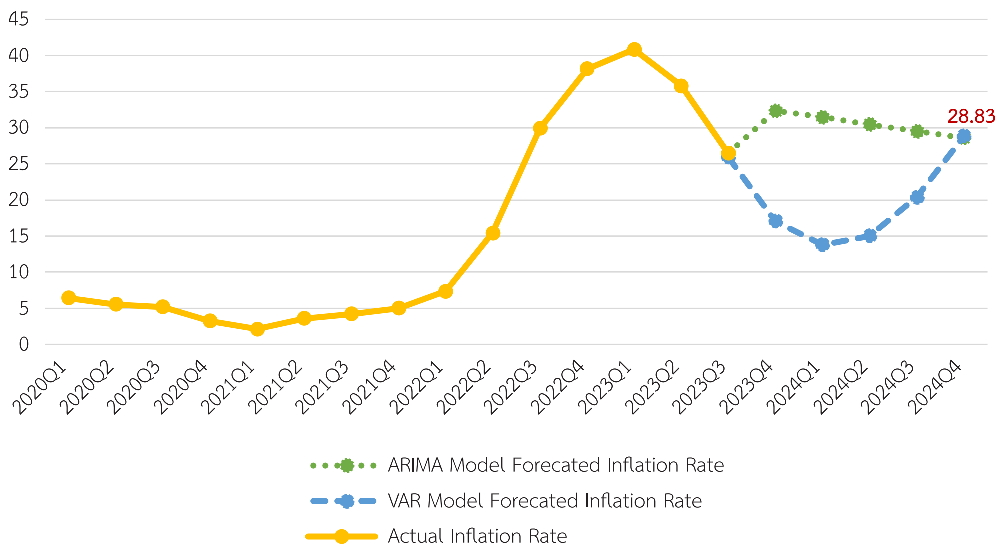


Figure 13: Ex-ante forecasting comparison graph

Forecasting the Ex-ante forecast found that the VAR model can forecast real-time data through multiple variables. This forecasting shows that inflation tends to increase according to the results of the study of GAUTAM and KANOUJIYA (2022) VAR is useful for understanding variable interactions through tools like impulse response and variable decomposition, so despite many forecasting models available, and VAR holds a unique position in multivariate forecasting, which has changed in the economy whether it is the inflation rate, the price of gold, the cost of oil that affects the forecasting of India and Gatawa et al. (2017) It found that broad money supply positively impacts growth, while inflation and interest rates negatively impact it, especially in the long run and in the short run, only inflation was not negatively related to development. The study also found that none of these factors directly cause economic growth. It recommended expansionary monetary policies and zero-interest finance to boost investment and control inflation.

Support for forecasting secondary data in Bangladesh with both ARIMA and VAR models by defining that the forecast can be compared, which is in line with the study of Khan and Khan (2020) found that the VAR model is the best compared to the ARIMA model because the forecast in the model comparison can be read according to the Root Mean absolute Error (RMSE) and Mean Absolute Percent Error (MAPE) with the smallest value that can explain the error and accuracy of the model Well, Sargolzaie, and Shahrami (2022) study the effect of oil conversion on the Inflation rate and the price of gold in Ehan than Gathingi (2014) found that the amount of money, crude price, and exchange rate all affect the exchange rate and also found that it is an essential variable in the economy in Kenya and can explain that the VAR model is the best compared to the ARIMA model. However, it differs from the studies of Erkekoglu et al. (2020) and Uko and Nkoro (2012), which tested the ARIMA model, Exponential Smoothing, VAR, and ECM and found that the results of the regression equation analysis of both of them are that the ARIMA model is more effective than the VAR model. Also, there are independent variables that are different from this research, namely GDP and GNI variables and different study cases.

6. CONCLUSION

This study analyses the determinants of changes in the inflation in Lao PDR and compares the forecasting of inflation in Lao PDR using quarterly data over the periods 2005:Q1 to 2023:Q3. Two methods that have been used increasingly in the literature in forecasting inflation, the Vector Autoregressive Method (VAR) and the Autoregressive Integrated Moving Average Method (ARIMA); the ADF Test shows that data at the 1st Difference level meets the criteria for both ARIMA and VAR models were used for this study. The current inflation in Lao, which is put at 26.4 percent in 2023:Q3, is expected to increase in the first quarter of 2022 following external factors that make the living of the Lao people encounter difficulties, especially the rapidly increasing cost of living and the high world market prices resulting in the inflation and the exchange rate of LAK for the purchase of goods from trading partner countries compared to foreign currencies. Also, there is an increase in the price of goods around the world, especially fuel that we have imported from abroad, and the price of food up to 52 percent compared to the year, which is a higher rate than the overall inflation that will affect households and impoverished households.

The ARIMA model was a univariate time series model employed in the study to forecast the Lao PDR inflation. The researchers selected the Automatic ARIMA Forecasting method based on the Box-Jenkins model to identify the most suitable model for the time series data. The ARIMA (1,1,3) model was appropriate for this purpose. The researchers examined the Correlogram graph to validate the model's suitability, focusing on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The results showed that ACF and PACF were close to the axis, indicating that the data followed a normal distribution and that the residuals were white noise. This validation step confirmed the model's reliability for accurate forecasting.

In the Vector Autoregression (VAR) model, determining the appropriate lag length is crucial for accurate forecasting. The study identifies the optimal lag length by selecting the smallest Akaike Information Criterion (AIC) value, which is found to be at level 6. The Impulse Response Function and Variance Decomposition analyses reveal consistent results, indicating that the variables experience sudden changes or shocks. The analysis focuses on the volatility of key economic indicators: inflation rate (INF), interest rate (RATE), total imports (IM), and gold prices (GOLD). Additionally, the crude prices (OIL) show an increasing trend. The variance decomposition analysis highlights that changes in inflation significantly influence its movement, accounting for 45.22 percent of the variation over the past year.

The result of our estimate from both ARIMA and VAR models predicts a similar upward trend in the inflation in Lao PDR, with an anticipated increase of 28.8 percent. However, the VAR model is deemed more effective than the ARIMA model, as evidenced by the lower and more consistent RMSE and MAPE values in Table 7. The effectiveness of the VAR model is further highlighted by its ability to account for various external factors influencing inflation. These factors include global oil prices, increased foreign currency inflows, enhanced business banking activities, rapid credit supply growth, high capital costs due to the weakening of the LAK, and rising gold prices driven by exchange rate pressures. This comprehensive approach underscores the robustness of the VAR model in forecasting inflation.

The VAR model indicates a more accurate forecast and highlights the significant impact of variables such as oil prices, gold prices, and the real exchange rate on inflation. Policymakers should closely monitor these variables and consider them when designing monetary policies. The BOL should continue to adjust policy interest rates in response to inflationary pressures, taking into account the influence of external factors like global oil and gold prices.

High inflation significantly impacts business risk. Therefore, it is important to strengthen the capacity of businesses, particularly by increasing agricultural productivity, promoting local industries, and reducing dependency on imports to help stabilize inflation. Businesses should prioritize investments in infrastructure and technology to support local production and improve self-sufficiency.

The significant depreciation of the Lao LAK has contributed to rising import prices and inflation. Policies aimed at stabilizing the exchange rate, such as managing foreign exchange reserves more effectively and implementing measures to attract foreign investment, can help mitigate this issue. Businesses should also diversify their markets to provide more stability to the exchange rate.

REFERENCES

Adebayo, F. A., Sivasamy, R., & Shangodoyin, D. K. (2014). Forecasting stock market series with ARIMA model. *Journal of Statistical and Econometric Methods, 3*(3), 65–77.

Ariyo, A. A., Adewumi, A. O., & Ayo, C. K. (2014, March). Stock price prediction using the ARIMA model. In *2014 UKSim-AMSS 16th international conference on computer modelling and simulation* (pp. 106–112). IEEE.

Adelekan, O. G., Abiola, O. H., & Constance, A. U. (2020). Modelling and forecasting inflation rate in Nigeria using ARIMA models. *KASU Journal of Mathematical Science, 1*(2), 127–143.

Akkaya, M. (2021). Vector Autoregressive Model and Analysis. *Handbook of Research on Emerging Theories, Models, and Applications of Financial Econometrics*, 197–214.

Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.

Bokharı, S. H., & Feridun, M. (2006). Forecasting inflation through econometric models: An empirical study on Pakistani data. *Doğuş Üniversitesi Dergisi, 7*(1), 39–47.

Cologni, A., & Manera, M. (2008). Curde prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. *Energy economics, 30*(3), 856–888.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association, 74*(366a), 427–431.

Dassanayake, W., Ardekani, I., Gamage, N., Jayawardena, C., & Sharifzadeh, H. (2021, December). Effectiveness of Stock Index Forecasting using ARIMA model: Evidence from New Zealand. In *2021 3rd International Conference on Advancements in Computing (ICAC)* (pp. 13–18). IEEE.

Enders, W., & Jones, P. (2016). Grain prices, curde prices, and multiple smooth breaks in a VAR. *Studies in Nonlinear Dynamics & Econometrics, 20*(4), 399–419.

Erkekoglu, H., Garang, A. P. M., & Deng, A. S. (2020). Comparative evaluation of forecast accuracies for ARIMA, exponential smoothing and VAR. *International Journal of Economics and Financial Issues, 10*(6), 206–216.

Fulton, C., & Hubrich, K. (2021). Forecasting US inflation in real time. *Econometrics, 9*(4), 36.

Gathingi, V. W. (2014). *Modeling inflation in Kenya using ARIMA and VAR models* (Doctoral dissertation, University of Nairobi).

Gatawa, N. M., Abdulgafar, A., & Olarinde, M. O. (2017). Impact of money supply and inflation on economic growth in Nigeria (1973-2013). *IOSR Journal of Economics and Finance (IOSR-JEF), 8*(3), 26–37.

GAUTAM, R. S., & KANOUJIYA, J. (2022). Multivariate Inflation Forecasting: A Case of Vector Auto Regressive (VAR) Model”. *Iconic Research and Engineering Journals, 5*(12), 11–14.

HĂPĂU, R. G. (2022). Exploring the Relationship between Exchange Rates, Gold Price and Inflation. An Multivariate Empirical Approach. *Fostering Recovery through Metaverse Business Modelling*, 818.

Hossain, M., Khanam, M., & Akhter, S. (2022). An Econometric Analysis to Forecast the Food Grain Production in Bangladesh by Using ARIMA and VAR Models. *Dhaka University Journal Science, 70*(1), 8–13.

Jafarian-Namin, S., Fatemi Ghomi, S. M. T., Shojaie, M., & Shavvalpour, S. (2021). Annual forecasting of inflation rate in Iran: Autoregressive integrated moving average modeling approach. *Engineering Reports, 3*(4), e12344.

Keynes, J. M. (1936). *The General Theory of Employment Terest and Money*. Macmillan and Company.

Kurz, H. D. (2016). David Ricardo (1772–1823). In *Handbook on the History of Economic Analysis Volume I*. Edward Elgar Publishing.

Khan, M. S., & Khan, U. (2020). Comparison of forecasting performance with VAR vs. ARIMA models using economic variables of Bangladesh. *Asian Journal of Probability and Statistics, 10*(2), 33–47.

Kelesbayev, D., Myrzabekkyzy, K., Bolganbayev, A., & Baimaganbetov, S. (2022). The effects of the curde price shock on inflation: the case of Kazakhstan. *International Journal of Energy Economics and Policy, 12*(3), 477–481.

LAO PDR ECONOMIC MONITOR REPORT. (2023). World Bank Group in Laos PDR. https://www.worldbank.org

McCallum, B. T. (1990). Inflation: theory and evidence. *Handbook of monetary economics, 2*, 963–1012.

Marpaung, G. N., Soesilowati, E., Rahman, Y. A., Tegar, Y. D., & Yuliani, R. (2022). Forecasting the Inflation Rate in Central Java Using ARIMA Model. *Efficient: Indonesian Journal of Development Economics, 5*(2), 163–173.

Nyoni, T. (2018). Modeling and forecasting inflation in zimbabwe: a generalized autoregressive conditionally heteroskedastic (GARCH) approach.

Nyoni, T. (2019). Modeling and forecasting inflation in Philippines using ARIMA models.

Pindyck, R. S., & Rubinfeld, D. L. (1988). Econometric models and economic forecasts.

Qasim, T. B., Ali, H., Malik, N., & Liaquat, M. (2021). Forecasting Inflation Applying ARIMA Model with GARCH Innovation: The Case of Pakistan. *Journal of Accounting and Finance in Emerging Economies, 7*(2), 313–324.

Sinaj, V. (2014). Models to forecast inflation in Albania. *International Journal of Scientific Research, 5*(1), 2229–5518.

Shahbaz, M. (2012). Does trade openness affect long run growth? Cointegration, causality and forecast error variance decomposition tests for Pakistan. *Economic Modelling, 29*(6), 2325–2339.

Sargolzaie, A., & Shahrami, M. (2022). The effect of oil shocks on inflation and gold prices.

Stoviček, K. (2007). Forecasting with ARMA Models: The case of Slovenian inflation. *Bank of Slovenia*.

Uko, A. K., & Nkoro, E. (2012). Inflation forecasts with ARIMA, vector autoregressive and error correction models in Nigeria. *European Journal of Economics, Finance & Administrative Science, 50*, 71–87.

Ulton, C., & Hubrich, K. (2021). Forecasting US inflation in real time. *Econometrics, 9*(4), 36.