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# INFLATION DYNAMICS IN THE USA AND EU: VAR ANALYSIS AND FORECASTING

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***Abstract:*** *This paper aims to analyze the relationship between the inflation rate in the USA and the inflation rate in the EU and to make short-term forecasts of their future movements. The Vector Autoregression (VAR) model was used to study the dynamic relationships among multiple variables. The VAR model was fitted on the data with a maximum lag of 5, and the diagnostic checks were performed to ensure it was correctly specified. The results are presented and discussed and the paper concludes by suggesting that future research should focus on addressing the problem of non-stationarity in the residuals and on testing the robustness of the model.*

***Keywords:*** *VAR, inflation, forecasting*

***JEL classification:*** *E31, E37*

# DINAMIKA INFLACIJE U SAD I EU: VAR ANALIZA I PROGNOZIRANJE

***Sažetak:*** *Cilj ovog istraživanja je analiza odnosa između stope inflacije u Sjedinjenim Američkim Državama i stope inflacije u Evropskoj uniji, kao i kratkoročna prognoza njihovih budućih kretanja. U istraživanju je korišćen model Vektorske Autoregresije (VAR) kako bi se ispitali dinamički odnosi između odabranih varijabli. VAR model je prilagođen podacima sa maksimalnim zakašnjenjem od 5, a izvršene su dijagnostičke provere kako bi se osiguralo da je model ispravno specificiran. Zaključak istraživanja se odnosi na sugestiju da se buduća istraživanja trebaju fokusirati na rešavanje problema ne-stacionarnosti reziduala i testiranje robustnosti modela.*

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***Ključne reči:*** *VAR, inflacija, prognoziranje*

## 1. INTRODUCTION

Inflation is a critical macroeconomic variable that has a significant impact on the economy and the well-being of individuals. Understanding the factors that drive inflation and the ability to predict its movements are crucial for policymakers and investors. The main objective of this paper is to study the relationship between the inflation rate in the USA and the inflation rate in the EU and to make short-term forecasts of their future movements.

To achieve this goal, the Vector Autoregression (VAR) model is used. VAR is a multivariate time series model that allows the dynamic relationship between multiple variables to be examined. It is widely used in various fields, including time dependence modelling in multivariate time series. In this research, a VAR model with a maximum lag of 5 is used to estimate the short-run dynamics of the relationship between the inflation rate in the USA and the inflation rate in the EU, as well as the long-run relationship between them. The VAR model is used to make short-term forecasts of the inflation rates in both the USA and the EU.

Diagnostic checks on the VAR model are performed to ensure that it is correctly specified. This includes testing for residuals' stationarity, as well as testing for correlation between the residuals. Python libraries like pandas, statsmodels and matplotlib are used to implement the VAR model and perform the diagnostic checks.

## 2. THEORETICAL BACKGROUND

The Vector Autoregression (VAR) model is a powerful and versatile tool for multivariate time series analysis. It is an extension of the univariate autoregressive model, and has been widely used in various fields, including finance, psychology, and medicine analysis (Zivot & Wang, 2006; Halsbeck, Bringmann, & Waldorp, 2020; Khan, Saeed, & Ali, 2020). VAR model has gained significant attention in recent years for its usefulness in describing the dynamic behaviour of financial time series and for forecasting their future values (Russel, Pratama, Wamiliana, & Usman, 2022). As a regression model, VAR has been widely applied in various fields, including modelling time dependence in multivariate time series data (Davis, Zang, & Zheng, 2013).

One of the key features of the VAR model is that each variable is predicted by a linear combination of all the variables at previous time points. The main assumption of this model is that its parameters remain constant or stationary over time. This feature has led to its widespread use in many areas of psychological research, as evidenced by studies such as Haselbeck, Bringmann & Waldorp (2021). Overall, the VAR model has proven to be a valuable tool for understanding and predicting the behaviour of complex systems and processes (Brandt & Sandler, 2017).

Previous research on inflation analysis in Indonesia has provided insight into the relationships between various economic indicators and inflation. Specifically, Idah, Kusuma and Syela (2017) have found that foreign exchange reserves have a negative, but not statistically significant, relationship with inflation, while money supply has a positive and significant relationship with inflation. Additionally, the exchange rate of the rupiah to the USA dollar has been found to have a negative and significant relationship with inflation. Furthermore, research on exchange rates in Mexico (Aleem & Lahiani, 2014) has revealed that a monthly inflation rate of 0.79% acts as a threshold, above which the exchange rate pass-through to domestic prices is statistically significant and below which it is not. These findings indicate that the relationship between exchange rates and inflation is complex and contingent on various factors. Additional research has focused on the relationship between inflation and energy prices in the Indonesian market. The study uses VAR modelling, and the best model is found to be VAR with order 3. Further analysis, including Granger causality, impulse response function, and forecasting, will be conducted based on the best model VAR(3) (Usman, Paujiah, Russel , Nairobi, & Pratama, 2022).

Moreover, the use of a Factor-Augmented Vector Autoregressive (FAVAR) approach has shown that monetary policy explains inflation fluctuations rather than stimulating output (Suresh & Jithin, 2020). Another variant of the VAR approach is the structural VAR. This approach was to examine the impact of world crude oil prices on inflation in Vietnam (Thac, 2018).

Another variant of the VAR model that has been used to model inflation and money supply is the Spatial Vector Autoregression (SVAR) model. Non-restricted SVAR models have been found to have better predictive power than restricted ones (Sumarminingsih, Suharsono, Ruchjana, & Stiawan, 2019). Additionally, research using VAR has been conducted to investigate the explanatory power of bank credit on inflation rates in Jordan, and it was concluded that there is a positive effect of bank credit on the inflation rate (Al-Oshaibat & Banikhalid, 2019).

The above-mentioned research demonstrates the versatility of the VAR model in analyzing the relationships between different economic variables and the usefulness of various VAR approaches in understanding the mechanisms driving these relationships. As evidenced by this body of research, VAR models have proven to be a valuable tool in analyzing the relationships between different economic variables and forecasting their future values.

Providing a review of the forecasting capabilities of inflation using the VAR model (Ferrentino & Vota, 2019), this paper represents a continuation of research on the monetary policy instrument, i.e., inflation, enriching the body of research that has confirmed the usefulness of VAR in forecasting various economic variables like GDP growth, inflation and exchange rate, inflation and unemployment, economic growth forecasting (Dinh, 2020); (Ha, Stocker, & Yilmazkuday, 2020); (Iyer & Gupta, 2019); (Sasongko & Huruta, 2019); (Karlsson, Mazur, & Nguyen, 2023).

By utilizing a Vector Autoregression (VAR) model, it is possible to estimate the dynamic relationship between the inflation rate in the United States and the inflation rate in the European Union over time. The VAR model provides the capability to estimate the short-term dynamics of the relationship as well as the long-term relationship between the two inflation rates. Furthermore, the VAR model can be used to make short-term forecasts of the inflation rates in both the United States and the European Union.

It is important to note that the VAR model assumes that the inflation rates in the USA and the EU are stationary. If this assumption is not met, it can lead to biased or inefficient parameter estimates (Holden, 1995). To test the assumption of stationarity, one can use the unit root test (Phillips, 2001).

A possible null hypothesis that could be tested using a VAR model is that there is no causal relationship between the inflation rate in the USA and the EU. This hypothesis could be tested by examining the coefficients of the lagged values of the inflation rates in the VAR model. If the coefficients are not statistically significant, it would suggest that there is no causal relationship between the two variables.

## 3. METHODOLOGY

Vector Autoregression (VAR) is a statistical model used to analyze the dynamic relationships among multiple time series variables. A VAR model is a generalization of the univariate autoregression model and can be used to analyze the relationship between multiple variables over time (Hashimzade & Thornton, 2015).

The basic VAR model is specified as:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-} + \cdots + \beta_p Y_{t-p} + \varepsilon_t \tag{1}$$

Where:

$\alpha$ – is the intercept

$\beta_1, \beta_2\ until\ \beta_p$ – are the coefficients of the lags of $Y$until order $p$

Implementing VAR models to analysis enables (Baltagi, 2020):

- investigation of dynamic relationships among multiple variables.
- short-term forecasts of the variables included in the model.
- testing hypotheses of the causal relationships among the variables included in the model.

The major limitation of the VAR models is that they assume the variables included in the model to be stationary, which may not be the case in practice (Brockwell & Davis, 2016).

The process of using the VAR model typically involves several steps (Aoki, 2011; Luetkepohl, 2006). The first step in using a VAR model is to determine which variables to include in the model and how many lags of each variable to use. Once the variables and lags have been selected, the next step is to estimate the VAR model. This can be done using a variety of estimation techniques, such as maximum likelihood or OLS. After the VAR model is estimated, it is important to check for diagnostic issues such as multicollinearity, autocorrelation, and heteroscedasticity.

Structural specification and estimation follow. Identifying the causal relationships among the variables included in the model is of importance. This is done by imposing certain restrictions on the coefficients of the lagged values of the variables in the VAR model. The VAR model can be used to make short-term forecasts of the variables included in the model, as well as to test hypotheses about the causal relationships among the variables included in the model.

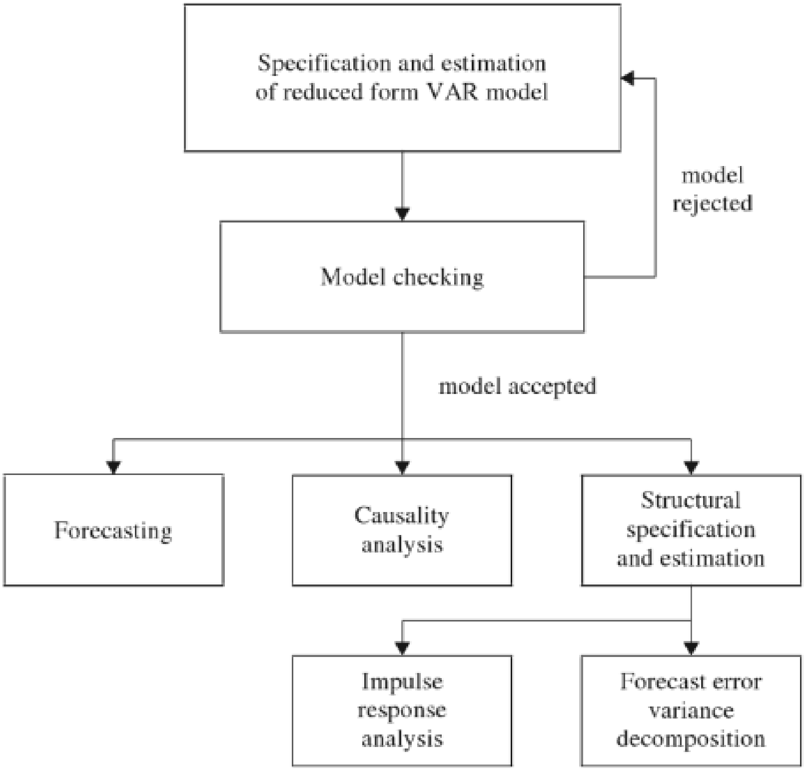


*Figure 1.* VAR Analysis Process

*Note*. Luetkepohl, H. (2006). Structural vector autoregressive analysis for cointegrated variables. *Modern Econometric Analysis*, 73-86.

The VAR model implementation process is presented in Figure 1. Some important parameters need to be introduced when talking about the VAR Model or statistical models in general:

1. The p-value is used to determine the significance of the results. If the p-value is less than a predetermined level of significance (often 0.05), the null hypothesis is rejected, and the result is considered statistically significant. The smaller the p-value, the stronger the evidence against the null hypothesis, indicating that the alternative hypothesis is more likely to be true (Dodhe, 2010).

2. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are measures of the relative quality of statistical models. They are used to compare different models and select the best one based on their

ability to fit the data. Lower AIC and BIC values generally indicate a better quality model in terms of goodness of fit and parsimony. AIC measures the relative quality of a statistical model compared to other models and balances the trade-off between the model's goodness of fit and the number of parameters. The BIC is similar to AIC but places a stronger emphasis on penalizing models with more parameters, as it assumes that models with fewer parameters are more likely to be true. In general, a model with lower AIC and BIC values is preferred as it indicates a better balance between model fit and complexity (Schwarz, 1978).

3. The Augmented Dickey-Fuller (ADF) test is a statistical test used to test the null hypothesis that a time series is non-stationary (French, 2016). In terms of the values, a smaller ADF test statistic value indicates stronger evidence against the null hypothesis of non-stationarity and, thus, provides more evidence that the time series is stationary. A negative ADF test statistic value provides stronger evidence of stationarity than a positive value. Therefore, in general, smaller and more negative ADF test statistic values are considered better and provide stronger evidence of stationarity.

4. Mean Absolute Error (MAE) is a commonly used metric to evaluate the performance of a predictive model. In regression problems, the MAE measures the average absolute difference between the predicted values and the true values. The smaller the MAE value, the better the model's accuracy in predicting the target variable (Baltagi, 2020).

5. Correlation is a statistical measure that indicates the strength and direction of the linear relationship between two variables (Hashimzade & Thornton, 2015). Correlation ranges from -1 to 1, where -1 indicates a perfect negative linear relationship, +1 indicates a perfect positive linear relationship, and 0 indicates no linear relationship between the two variables.

6. Log-likelihood is a measure of the goodness of fit of a statistical model to a set of data (Baltagi, 2020). The log-likelihood is used in model selection and evaluation, with higher values indicating a better fit of the model to the data. The log-likelihood is often used in conjunction with information criteria such as the AIC and the BIC to compare different models and determine the best model for a given set of data.

## 4. RESULTS AND DISCUSSION

Before considering the results obtained, it is important to note the steps required to make a forecast using the VAR model. VAR is used to analyze the relationship between the inflation rate in the USA and in the EU, and one can expect to estimate the dynamic relationship between the two variables over time. Using the VAR model, it is possible to estimate the short-run dynamics of the relationship between the two inflation rates, as well as the long-run relationship between them. Likewise, by using the VAR model, it is possible to make short-run forecasts of inflation rates in the USA and the EU. The VAR model assumes that inflation rates in the USA and the EU are stationary. If this assumption is not met, this can lead to biased or inefficient parameter estimates, as will be shown below.

The Python model is suitable for forecasting due to its ease of use, accessibility, and availability of numerous libraries that support statistical modelling and time series analysis. Some of the most popular libraries for VAR modelling in Python are Statsmodels, Scikit-learn and pandas.

To use Python for VAR modelling, the following steps are required (McKinney, 2012; French, 2016):

- Importing the necessary libraries and data: Necessary libraries and data should be imported, including those for data analysis and modelling, such as Pandas and Statsmodels. The data should then be loaded into a pandas data frame.
- Preprocessing and Cleaning: Preprocessing and cleaning of the data should be conducted, which involves checking the quality of the data and making necessary modifications, such as handling missing values, converting data types, and transforming the data if needed.
- Creating the VAR model: A VAR model should then be created using the statsmodels library by passing the data as input and specifying the order of the model.
- Fitting the Model: The model should be fitted using the fit() function to estimate the model parameters based on the provided data.
- Model Diagnostics: Model diagnostics should be performed to check the accuracy and stability of the model, including a residual analysis, a stability test and other statistical tests.
- Forecasting: Finally, future predictions can be made for a specified time horizon using the predict() function.

By following these steps, one can implement a VAR model for forecasting inflation using Python.

The VAR model is fitted on the data with a maximum lag of 5, and the summary of the results is presented in Table. 1. Then, the Augmented Dickey-Fuller test is applied to the 'Inflation USA' and 'Inflation EU' columns of the data frame and the ADF statistic and p-value are printed for each of them.

Table 1

*Summary of Regression Results Using the VAR model*

| | |
|---|---|
| **Model:** | VAR |
| **Method:** | OLS |
| **Number of Equations:** | 2,0000 |
| **Nobs:** | 283,0000 |
| **Log Likelihood:** | -111,4720 |
| **AIC:** | -4,7325 |
| **BIC:** | -4,4491 |

*Note.* Author's calculation.

Table 2

*Correlation matrix, ADF Statistics and p-value*

| **Correlation matrix:** | | | | |
|---|---|---|---|---|
| | **Inflation USA** | **Inflation EU** | **ADF Statistic** | **p-value** |
| **Inflation USA** | 1,0000 | 0,5803 | -2,3889 | 0,1448 |
| **Inflation EU** | 0,5803 | 1,000 | -1,8686 | 0,3468 |

*Note.* Author's calculation.


*Figure 2.* Inflation rate of USA and EU from 1999 to 2022

*Note*. Author's calculation.

The VAR model that has been implemented is a multivariate time series model that is used to model the relationship between multiple variables. The coefficients are presented in Table 1, and the output portrays the estimated relationship between the variables in the model. In this case, the log-likelihood is relatively low, indicating that the model does not fit the data very well. The AIC and BIC values are also relatively high, suggesting that this is not the best model for the data. The significance of each coefficient, indicated by the ADF statistic and p-value (see Table 2), is provided in the output. An ADF test was conducted to test for stationarity in the residuals. The ADF statistic and p-value suggest that the residuals are non-stationary, which is not desirable for a time series model. For this model, correlation coefficients are presented in Table 2, with a correlation coefficient of 0.58, indicating a moderate positive correlation between the two variables. A correlation coefficient of 0.58 tells that as one variable increases, the other variable also tends to increase, but not as strongly as it would if the correlation was closer to 1.

To summarize, the VAR model performed provided results with several problems identified, such as non-stationarity of residuals, high correlation between residuals, and high values of AIC and BIC (see Table 1). To achieve sound results, adjustment of the model by first and second differencing is required. A unit root test, known as a Dickey-Fuller test, was performed for the two-time series in the same dataset. The first and second-order differences of the time series were tested by the ADF test to check for stationarity.

Table 3

*Augmented Dickey-Fuller Test Results for the 2nd Order Differentiation*

| **Augmented Dickey-Fuller Test for the dataset Inflation USA 2nd Order Diff** | |
|---|---|
| ADF test statistics | -8,16E+06 |
| p-value | 9,13E-07 |

| **Augmented Dickey-Fuller Test for the dataset Inflation EU 2nd Order Diff** | |
|---|---|
| ADF test statistics | -1,40E+07 |
| p-value | 4,02E-20 |

*Note.* Author's calculation.

The results of the Augmented Dickey-Fuller test indicate that both the Inflation USA and Inflation EU time series are non-stationary when tested on their raw data. However, after taking the first-order difference of the time series, both of them become stationary as the p-value is less than 0.05, which suggests that they are stationary (See Table 3). Also, a second-order difference of both time series is also stationary. Now that the data are stationary, it is possible to forecast the inflation in the USA and EU using the VAR model. The first step was to create a VAR model with the training data and select the optimal lag order using the AIC and BIC criteria (by selecting the lowest values of both parameters). The next step was to forecast the values using the selected lag order and calculate the forecasted values by cumulatively summing the differences. Finally, the forecasted values are plotted against the actual values for the test data to evaluate the accuracy of the model. The forecast is presented in Figure 3.

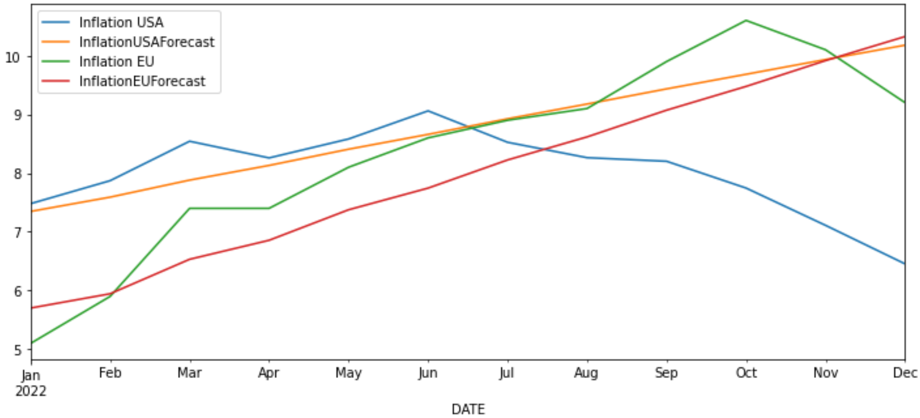


*Figure 3.* Forecast of inflation for the 12 months of 2022

*Note*. Author's calculation.

One way to assess the performance of the model is to compare these results with other models or benchmarks, such as the MAE values. The MAE values indicate the average error in the forecast for each of the two series (USA inflation and EU inflation). A lower MAE value generally indicates a more accurate forecast. In this case, the forecast for inflation in the EU has a slightly lower MAE value than the forecast for inflation in the USA, suggesting that the forecast for inflation in the EU may be more accurate. However, these values should be compared with the range of data and the specific requirements of the use case to determine whether the forecast is considered accurate enough.

Table 4

*Mean Absolute Error of forecasting models*

| | |
|---|---|
| MAE Inflation USA: | 8,7506 |
| MAE Inflation EU: | 7,9572 |

*Note.* Author's calculation.

# 5. CONCLUSION

This paper offers a detailed analysis of the relationship between the inflation rate in the USA and the EU using the Vector Autoregression (VAR) model. The VAR model was used to estimate the short-run dynamics of the relationship between the two inflation rates, as well as the long-run relationship between them. The model was also used to make short-run forecasts of inflation rates in the USA and the EU.

The results of the VAR model showed that there is a positive relationship between the inflation rate in the USA and the inflation rate in the EU. However, the model also showed that the residuals are non-stationary, which is not desirable for a time series model. Additionally, the model showed that the inflation rate in the USA and the inflation rate in the EU have a moderate positive correlation.

Based on these findings, it could be suggested that future research focus on addressing the problem of non-stationarity in the residuals by adjusting the model through first and second differencing or by using other models such as structural VAR or Vector Error Correction Model (VECM). Additionally, further research could be done to explore the impact of other macroeconomic variables on the inflation rate in the USA and the inflation rate in the EU and to test the robustness of the model.

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