Scenario Analysis using Vector Autoregression (VAR) Model on Economic Data with R

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Abstract
This paper is an econometrics self-assignment about employing the VAR model in R programming and conducting scenario analysis based on the model. The primary goal of the R code is to identify the relationships among several macroeconomic variables, including GDP, the unemployment rate, base money, M1, M2, and the inflation rate, and to provide predictions for these variables. However, exogenous events in an economy cannot be ignored. Consequently, the scenario analysis allows us to consider their effects on the predictions.

1. Introduction

Forecasting economic variables has always been important for different groups of people. Entrepreneurs need to forecast economic variables to make informed economic decisions. Policymakers need forecasts to understand macroeconomic changes and the effects of policies on them. Quantitative forecasting involves capturing the relationships among economic variables, and there has always been many debates about the possibility of such analysis and predictions. For instance, many Austrians argue against quantitative economic analyses.[1] However, among proponents of quantitative analyses, there are many debates about how they should be conducted.[2]

This paper explains an R code that focuses on identifying the relationships among economic data, including GDP, the unemployment rate, base money, M1, M2, and the inflation rate, using a VAR model. Additionally, due to the existence of exogenous events in the economy, a scenario adjustment variable is defined in the code in order to examine the effects of these events on the economic variables.

2. Methodology

In this research, a dataset was extracted from the Federal Reserve Economic Data (FRED) website. The data was then prepared and analyzed using R programming.

2.1. Data Preparation

Datasets: Economic data including the following indicators:

- **GDP (Gross Domestic Product):**
  - Billions of Dollars, Seasonally Adjusted Annual Rate
  - Quarterly
  - Q1 1947 – Q2 2024
- **DFF (Federal Funds Effective Rate):**
  - Percent, Not Seasonally Adjusted
  - Daily
  - 1/1/1955 – 1/1/2024
- **UNRATE (Unemployment Rate):**
  - Percent, Seasonally Adjusted
  - Monthly
  - Jan 1948 – Jan 2024
- **BOGMBASE (Monetary Base: Total):**
  - Billions of Dollars, Not Seasonally Adjusted
  - Monthly
  - Jan 1959 – Jan 2024
- **M2SL (M2 Money Stock):**

[1] For example, see Butler (2010, 22).
[2] For example, see Bernanke (2024, 16-18) and Adebayo et al. (2019).

    - Billions of Dollars, Seasonally Adjusted
    - Monthly
    - Jan 1959 – Jan 2024
- **M1SL (M1 Money Stock):**
    - Billions of Dollars, Seasonally Adjusted
    - Monthly
    - Jan 1959 – Jan 2024
- **PCEPI (Personal Consumption Expenditures: Chain-type Price Index):**
    - Percent Change from Year Ago, Seasonally Adjusted
    - Quarterly, Average
    - Q1 1960 – Q1 2024

Looking at these data, I understand that they have several issues:

1) **Different Frequencies:** The data are not set at the same frequency. The smallest common frequency among these data is quarterly. Thus, daily and monthly data, including DFF, UNRATE, BOGMBASE, M2SL, and M1SL, need to be converted to a quarterly frequency to ensure consistency and comparability.
2) **Inconsistency of Data Range:** Although GDP spans from 1947 to 2024, the other datasets do not cover the same period. Consequently, after realigning and converting all data to a quarterly frequency, I need to retain only the data within the common time range.

2.1.1. Data Refinement

To realign DFF and UNRATE, which are percentage values, I calculated the mean of the data for each quarter, considering the result as representative of the quarter. However, for cumulative data such as BOGMBASE, M2SL, and M1SL, I used the first value of each quarter to represent the entire quarter. In the next step, I combined all data into a single dataset. Each row represents one quarter and includes the values of all existing variables for that period.

The newly-created dataset contains some null values due to the "Inconsistency of Data Range." Therefore, incomplete rows need to be removed. Afterwards, both aforementioned problems are solved, and the resulting dataset is quarterly and free of any null values.

The final dataset spans from Q1 1960 to Q1 2024. Although the data is complete for this period, I preferred to use a more contemporary period for this analysis because the macroeconomic environment has changed significantly. Therefore, I selected a period that encompasses key events that have shaped the current macroeconomic landscape, including the dotcom bubble and its impact on the internet, which in turn affected the economy, the great recession of 2008 and its effects, recent fluctuations in GDP, inflation, and unemployment rate, and the Covid-19 pandemic. Consequently, the suitable period is from Q1 2000 to Q1 2024.

2.1.2. Augmented Dickey-Fuller (ADF) test

To ensure stationarity, I conducted the Augmented Dickey-Fuller (ADF) test on the selected variables. The results of the ADF test indicated the following:

- **GDP**
    - **Test Statistic:** 0.43843
    - **Lag Order:** 4
    - **p-value:** 0.99

The results of the Augmented Dickey-Fuller test for GDP indicate a test statistic of 0.43843 and a p-value of 0.99. Given the high p-value, I fail to reject the null hypothesis that the time series has a unit root. Consequently, I conclude that the GDP data is not stationary and may require differencing.

- **DFF**
    - **Test Statistic:** -2.7915
    - **Lag Order:** 4
    - **p-value:** 0.2491

The results of the Augmented Dickey-Fuller test for DFF indicate a test statistic of -2.7915 and a p-value of 0.2491. Given the p-value, I fail to reject the null hypothesis that the time series has a unit root. Consequently, I conclude that the DFF data is not stationary and may require differencing.

- **UNRATE**
  - **Test Statistic:** -2.3676
  - **Lag Order:** 4
  - **p-value:** 0.4245

The results of the Augmented Dickey-Fuller test for UNRATE indicate a test statistic of -2.3676 and a p-value of 0.4245. Given the p-value, I fail to reject the null hypothesis that the time series has a unit root. Consequently, I conclude that the UNRATE data is not stationary and may require differencing.

- **BOGMBASE**
  - **Test Statistic:** -3.4819
  - **Lag Order:** 4
  - **p-value:** 0.04743

The results of the Augmented Dickey-Fuller test for BOGMBASE indicate a test statistic of -3.4819 and a p-value of 0.04743. Given the p-value, I reject the null hypothesis that the time series has a unit root. Consequently, I conclude that the BOGMBASE data is stationary.

- **M2SL**
  - **Dickey-Fuller:** -1.9594
  - **Lag order:** 4
  - **p-value:** 0.5934

The results of the Augmented Dickey-Fuller test for M2SL indicate a test statistic of -1.9594 and a p-value of 0.5934. Given the p-value, I fail to reject the null hypothesis that the time series has a unit root. Consequently, I conclude that the M2SL data is not stationary and may require differencing.

- **M1SL**
  - **Test Statistic:** -1.7166
  - **Lag Order:** 4
  - **p-value:** 0.6938

The results of the Augmented Dickey-Fuller test for M1SL indicate a test statistic of -1.7166 and a p-value of 0.6938. Given the p-value, I fail to reject the null hypothesis that the time series has a unit root. Consequently, I conclude that the M1SL data is not stationary and may require differencing.

- **PCEPI**
  - **Test Statistic:** -2.1013
  - **Lag Order:** 4
  - **p-value:** 0.5346

The results of the Augmented Dickey-Fuller test for PCEPI indicate a test statistic of -2.1013 and a p-value of 0.5346. Given the p-value, I fail to reject the null hypothesis that the time series has a unit root. Consequently, I conclude that the PCEPI data is not stationary and may require differencing.

Then, I applied differencing to the variables GDP, DFF, UNRATE, M1SL, and PCEPI. However, differencing did not work well on M2SL. The results of the Augmented Dickey-Fuller Test for differenced M2SL are as follows:

- **Test Statistic:** -3.3271
- **Lag order:** 4
- **p-value:** 0.07104

Given the p-value, M2SL is still non-stationary. Therefore, I found Polynomial Detrending more applicable. Consequently, I used the lm() function to fit a quadratic polynomial and the residuals() function to remove the trend and obtain the detrended data. Finally, I conducted the Augmented Dickey-Fuller test again for the variables that had been non-stationary. The results confirmed that I now have stationary data.

3. Model Specification

A Vector Autoregression (VAR) model was specified using the 'vars' package in R, with the optimal lag length determined by the Akaike Information Criterion (AIC).

Since the data is quarterly, I anticipated that a one-year time frame would be appropriate for determining the causal relationships among variables. In addition, the ADF tests consistently used a lag order of 4, which further suggest that 4 is likely the suitable number of lag.

To evaluate whether 4 is suitable, I used the VARselect() function with lag.max set to 6. I set lag.max two numbers higher than the hypothesis to allow the AIC estimator to examine with more options. However, it indicated that the optimal lag length is 4.

Then, I fitted the VAR model using the VAR() function and incorporated all the data as inputs. I expected that the model would uncover the relationships between the variables. The results of this model are required for future tasks, such as forecasting.

To conduct a residual analysis, I used the serial.test() function. I found that the optimal number of lags for the Portmanteau test is 15. Using lags.pt = 15 resulted in the following:

- Chi-squared = 586.18
- Degrees of freedom = 539
- p-value = 0.07823

This high p-value indicates no significant serial correlation in the residuals, validating the model's suitability for forecasting.

The next check is the Stability Check. Therefore, I used the roots() function to analyze the stability of the model. In general, it is expected that all the roots (eigenvalues) be less than 1 to validate stability. However, in conducting the stability check for the VAR model in this research, I found that one of the eigenvalues was slightly above 1 (eigenvalue = 1.0147547). According to the stability criterion, this indicates potential instability. However, given the scope of this assignment and the focus on working with the VAR model, I decided to proceed without making additional adjustments.

Nevertheless, to obtain more accurate predictions, some actions can be effective. For instance, conducting BVAR modeling instead of VAR could help prevent over-parameterization and potentially solve the problem. Alternatively, using SVAR instead of VAR might be the solution, since it may better highlight shocks, like the financial crisis of 2008, and provide deeper insights. Another possible option could be Structural Break Analysis, by dividing the data into pre-QE and QE era periods. The QE era involves many changes in the economy, such as the generation of a large amount of excess reserves, a more active role of the Fed, and the elimination of required reserves in 2020.

However, finding the best solution requires more theoretical studies, conducting comprehensive analyses, and examining the results.

4. Scenario Adjustments

Before the forecasting section, there are some settings and adjustments to consider. Here, it is possible to command the program how many steps I need to forecast. The variable n_steps gets the number of steps as an input.

For example, if I want to see how variables will change in the next 8 steps (from Q2 2024 to Q1 2026, since each step is a quarter and the current data ends in Q1 2024), I simply set the n_steps input to 8. In this case, there are no additional adjustments needed, so I can set the adjustment inputs to 0.

However, this is not always the case. Monetary authorities might manually adjust the base money more or less than usual. Economic shocks might affect some variables, such as GDP or the unemployment rate. Consequently, I need to incorporate these changes into the program via the scenario adjustment section.

In the scenario_adjustment variable, if I add any value, for example, 0.5, to diff_GDP, diff_BOGMBASE, diff_M2SL, and diff_M1SL, it means that for each step, those variables would be 0.5 billion dollars more than the usual prediction. Therefore, the forecasts of other variables will be calculated based on these adjusted values.

Also, if I add any value, like 0.5, to other variables, since their data is in percentage terms, it means that those variables would be 0.5% more than the usual prediction. Similar to the previous adjustments, these new inputs will affect the calculation of the forecasts.

Negative numbers work the same way. However, they reduce the usual predicted values.

5. Forecasting

Finally, the last part of the code generates two series of predictions. The first one, called "baseline", is the usual set of predictions, regardless of the Scenario Adjustments. The second one, "scenario", consists of the predictions based on the adjusted values.

Then, the two series will be visualized, allowing us to compare the baseline predictions with the scenario predictions. However, it is noteworthy that the code illustrates the predicted values of only one variable at a time to avoid unnecessary overload.

6. Conclusion

The VAR model is a statistical tool used to analyze various quantitative data and discover the relationships between them. I employed it with R programming to analyze economic data, including GDP, the unemployment rate, base money, M1, M2, and the inflation rate, from 2000 to 2024. Then, I identified the relationships between these variables and used this analysis to forecast future changes.

However, since exogenous events can occur, it is necessary to consider their effects on economic variables. Consequently, by defining a scenario adjustment variable, we can intervene in the predictions based on these events and conduct scenario analysis.

This code is a simplified application of the VAR model and might not be completely accurate. Nevertheless, it demonstrates how to use the VAR model in a simple assignment.

7. References

Adebayo, Agunbiade D., Ayodeji Odusanya O., Funmi Adedotun A., and Gabriel Obadina O. 2019. "Comparison of Vector Autoregressive Model (VAR) and Bayesian Vector Autoregressive Model (BVAR) Models for Modelling Economic Growth." In 17th iSTEAMS Multidisciplinary Research Nexus Conference, 21st–23rd July, 2019, Ogun State, Nigeria.

Bernanke, Ben. Forecasting for Monetary Policy Making and Communication at the Bank of England: A Review. Bank of England, 2024.

Butler, Eamonn. Austrian Economics: A Primer. Adam Smith Institute, 2010.