Term paper

MARTIN-LUTHER-UNIVERSITÄT
HALLE-WITTENBERG

As part of the course Applied Macroeconometrics

“Report of the macroeconomic effects of monetary policy shocks in Austria”

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Submitted on: 27 July 2023

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1. Abstract

This study investigates the macroeconomic effects of monetary policy shocks using two variables: the industrial production index and the unemployment rate. The analysis focuses on the interest rates surrounding European Central Bank (ECB) meetings from 1999 to 2021 as the monetary policy shock. The Vector Autoregression (VAR) model is employed to capture the dynamic relationships between multiple variables and their changes over time, allowing for a more comprehensive analysis of multivariate time series compared to univariate autoregressive models. The selection of appropriate lags for the time series is determined using the Akaike Information Criterion (AIC) method. Additionally, Cholesky decomposition is applied to decompose the covariance of the residual of the reduced form, thereby obtaining the impulse response matrix with the Lutz Kilian function. The results indicate that, during the period under consideration, contractionary monetary policy appears to impact the Austrian economy, leading to a reasonable decrease in the industrial production index in subsequent periods. Conversely, the unemployment rate rises in response to the monetary policy shock. Lastly, I explore various input lags and examine the data without removing the time trend.

2. Data Modification

The interest rates data encompass various values around ECB meetings between 1999 and 2021. To derive a single interest rate (the surprise) for each month, these values were aggregated. For the input macroeconomic variables, namely the Industrial Production Index (IPI) and the Unemployment Rate (Une), data were obtained from the OECD database. The observation period for the data spans from 1999 to 2021, resulting in a total of 276 data points (periods).

Figure 1 illustrates the historical trend of our input data over time. Prior to 2007, the interest rates remained relatively stable with minimal fluctuations. One of the reason for the fluctuations started near 2007-2008 is that, the financial crisis had a profound impact on the global economy, leading to increased volatility in the interest rate (OIS_6M). The turmoil in the financial markets lasting till 2013, during this period prompted significant fluctuations in interest rates as central banks and policymakers responded to the crisis.

Subsequently, the heightened volatility in the interest rate (OIS_6M) prompted a corresponding decline in the logarithm of the Industrial Production Index (logIPI) and a rise in the unemployment rate. Similarly, around 2020, there was a significant shift in both logIPI and Une, while the interest rate remained relatively unchanged. This notable change coincided with the global outbreak of the coronavirus pandemic, possibly serving as an additional contributing factor.

2.1 First-Difference Method

Figure 1 also illustrates a gradual and steady upward trend in both the log IPI and Une over time. In order to facilitate meaningful inference, I applied the first difference to the log IPI and Une datasets to eliminate the constant trend. By not taking the first difference, several issues may arise:

(i) Non-stationarity: Time series data in its original form may exhibit non-stationarity, wherein the mean, variance, or autocovariance changes over time. This non-stationarity can lead to model instability and produce unreliable results.

(ii) Autocorrelation: Time series data may display autocorrelation, where observations are correlated with past observations. This can result in high autocorrelation in the model, making estimation and inference difficult.

(iii) Higher-order dependencies: Time series data may exhibit higher-order dependencies, wherein observations are correlated with multiple past observations. Without differencing, these higher-order dependencies can interfere with model interpretation and prediction.

To avoid these issues, it is generally recommended to perform first differencing on the time series data before analysis, thereby eliminating non-stationarity and autocorrelation. First differencing involves computing the differences between consecutive observations, which makes the data more stationary and can improve the accuracy and reliability of the model. Additionally, first differencing helps to avoid the peculiar asymptotic properties of variance in the presence of random walks. As a result of applying the first differencing method, our datapoints are reduced by one (275 datapoints after differencing, rather than the original 276).

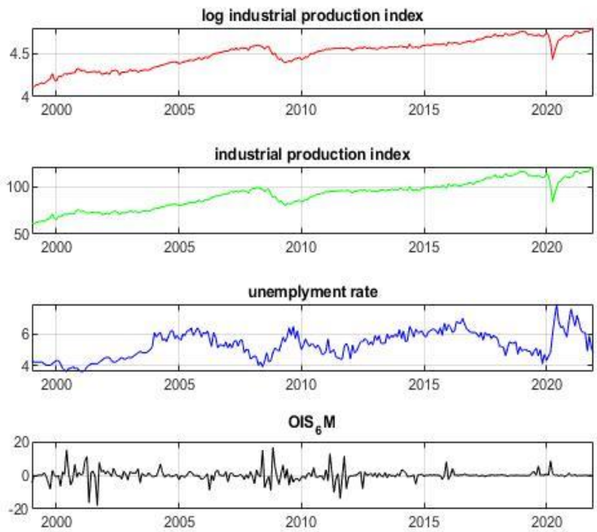

Fig 1. The red line is the log of IPI series to be explained by percentage.
The green line is the IPI series without taking logarithm
The blue line is the unemployment rate series
The black line is the MP shock (OIS_6M)

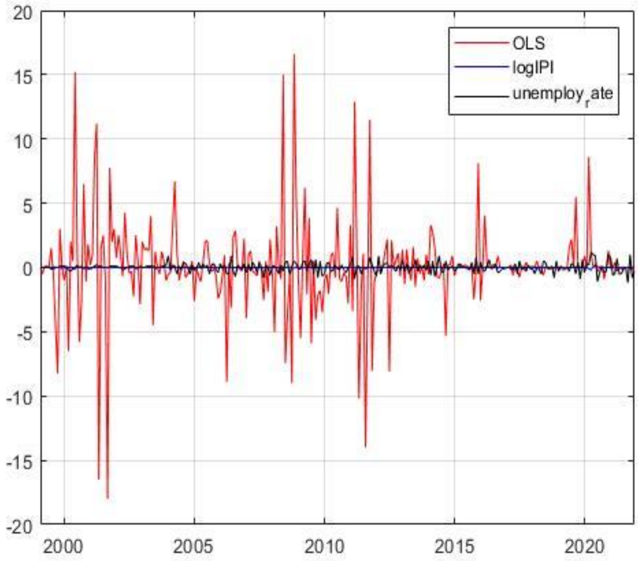

Fig 2. Applying the first difference method, the IPI and Une are centering the zero mean.

3. Akaike Information Criteria (AIC)

The Akaike Information Criterion (AIC) is a widely used statistical measure in model selection, aiming to strike a balance between model goodness of fit and complexity. It offers a means of comparing various models and identifying the most suitable one for a given dataset. The AIC value is computed by considering the log-likelihood of the model and the number of parameters in the model, following the formula:

$$AIC = -2 * loglikelihood + 2 * number\ of\ parameters \qquad \text{(Model 1.)}$$

The log-likelihood is a measure that assesses how well a model fits the observed data, where a higher log-likelihood indicates a better fit. On the other hand, the number of parameters in the model reflects its complexity, with a larger number of parameters indicating a more intricate model. The Akaike Information Criterion (AIC) takes both factors into account by penalizing models with a higher number of parameters, seeking to strike a balance between goodness of fit and model simplicity. Consequently, the AIC aims to identify the most appropriate model that provides a good fit to the data while being as parsimonious as possible.

Lower AIC values indicate a superior trade-off between fit and complexity, indicating a more suitable model. In the case of this multi-variable model, hereby obtained p = 22 for the industrial production index and unemployment rate data spanning from 1999 to 2021. This means that there are 22 parameters in the model

Example of VAR(22) model:

Structure form:

$$B * \begin{bmatrix} x_t \\ y_t \\ z_t \end{bmatrix} = A_0 + A_1 \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ z_{t-1} \end{bmatrix} + \cdots + A_{22} \begin{bmatrix} x_{t-22} \\ y_{t-22} \\ z_{t-22} \end{bmatrix} + \begin{bmatrix} u_{xt} \\ u_{yt} \\ u_{zt} \end{bmatrix} \quad \text{(Model 2.)}$$

xt : MP shock, yt : log industrial production index, zt : unemployment rate

Reduced form:

$$Y_t = B^{-1} * A_0 + B^{-1} * A_1 * Y_{t-1} + \cdots + B^{-1} A_{22} * Y_{t-22} + B^{-1} u_t \quad \text{(Model 3.)}$$

$$Y_t = \Phi_0 + \Phi_1 * Y_{t-1} + \cdots + \Phi_{22} * Y_{t-22} + \varepsilon_t \quad \text{(Model 4.)}$$

In MATLAB, the Φ matrixes are calculated using the reduced form approach. With 22 lags in the model, the calculated data will cover the period from period 1 to the end period minus 22 (275 - 22 = 253). The coefficient matrix has a size of 3 x 66, with an additional column for the intercept, resulting in a final size of 3 x 67.

The reduced form approach is commonly utilized in Vector Autoregression (VAR) modeling to analyze the dynamic relationships between multiple variables. In this case, the 3 x 66 coefficient matrix represents the relationships between the variables (x_t, y_t, and z_t) over the 22 lags, resulting in 66 parameters in each equation. The additional intercept column accounts for the constant term in the model, bringing the total to 67.

However, a limitation of the reduced form VAR is that it cannot identify the structural shocks and represent their effects through impulse response analysis due to contemporaneous correlation among the residuals. To overcome this limitation and obtain a more interpretable model, a recursively identified VAR or Structural VAR (SVAR) is applied by imposing restrictions on the model.

4. Prior Information for SVAR

The Structural VAR (SVAR) method imposes specific restrictions to determine all parameters of the structural form from the reduced form. In a reduced form, the residuals are correlated, whereas in the SVAR, the correlation of residuals is precisely set to zero. This necessitates the sequential ordering of variables. In this study, the monetary policy shock x_t is given precedence, resulting in a simultaneous effect on the industrial production index $y_t$and the unemployment rate z_t, but not vice versa.

The findings from Murat GUNDUZ (2020) indicate that sudden structural changes in the industrial production index have a long-term impact on the U.S. unemployment rate. Furthermore, Donald J. Mullineaux (1980) found that considering a long-distributed lag effect of uncertainty on these variables results in the inflation rate reducing unemployment, but it does not significantly increase industrial production. However, it is commonly observed that the unemployment rate has an intermediate relation in response to output changes. Consequently, it is assumed that the industrial production index has a simultaneous effect on the unemployment rate. This assumption is based on the observation that the unemployment rate has a more direct impulse on the industrial production index than the interest rate, indicating that industrial production is more actively responsive to changes in the interest rate.

To ensure that cov $(\varepsilon_{xt}, \varepsilon_{yt})$ = 0, cov $(\varepsilon_{xt}, \varepsilon_{zt})$ = 0, and cov $(\varepsilon_{yt}, \varepsilon_{zt})$ = 0, the variables are ordered accordingly. The monetary policy rate is placed as the first variable in the equation, followed by the industrial production rate y_t, and the last variable is the unemployment rate z_t. This sequential ordering allows for the calculation of the triangular VAR using Cholesky decomposition, leading to a recursive model known as the "semi-VAR structure."

By incorporating prior information and theoretical insights into the SVAR analysis, the study enhances the robustness and credibility of its findings. The appropriate ordering of variables and utilization of Cholesky decomposition enable a comprehensive analysis of the monetary policy shock's impact on the economy and the dynamic responses of the variables over time.

5. Cholesky Decomposition (Triangular VAR Model)

Cholesky decomposition plays a crucial role in obtaining the lower triangular matrix B in our Structural VAR (SVAR) model. It involves decomposing the covariance matrix of residuals, and the underlying assumption is that all eigenvalues of the matrix are non-negative, or positive semi-definite. Our covariance matrix (sigma) is symmetric and positive semi-definite, represented as sigma = PP', where P is the Cholesky decomposition of sigma and corresponds to a lower triangular matrix, the matrix, giving rise to a recursive structure in the VAR model.

In MATLAB, obtaining the lower triangular matrix B is achieved through the function "chol(sigma, 'lower')". This allows us to calculate the transformed residuals, obtained by multiplying the residual matrix with the inverse of B.

By performing Cholesky decomposition and evaluating the residuals, the SVAR analysis gains valuable insights into the dynamic interactions between the variables and their responses to the structural shocks

The residual of SVAR:

$$B^{-1} * u_t = \begin{bmatrix} c_{1,1} & 0 & 0 \\ c_{2,1} & c_{2,2} & 0 \\ c_{3,1} & c_{3,2} & c_{3,3} \end{bmatrix} * \begin{bmatrix} u_{xt} \\ u_{yt} \\ u_{zt} \end{bmatrix} = \begin{bmatrix} c_{1,1} * u_{xt} + 0 + 0 \\ c_{2,1} * u_{xt} + c_{2,2} * u_{yt} + 0 \\ c_{3,1} * u_{xt} + c_{3,2} * u_{yt} + c_{3,3} u_{zt} \end{bmatrix} \qquad \text{(Model 5.)}$$

6. Impulse Response Function

The objective is to analyze how the variables (x_t, y_t, z_t) respond to the shock (u_{xt}), which pertains to the changes in the parameters of our input variables following a residual shift. The impulse response function assumes that the shocks u_{yt} and u_{zt} are equal to zero, implying that

I solely focus on obtaining the shock associated with the interest rate in our VAR model. Through this analysis, I gain valuable insights into the dynamic responses of the variables to the monetary policy shock

6.1 Companion Form

To analyze the impulse response function (IRF), I employ the "irfvar()" function developed by Lutz Kilian. This function is instrumental in constructing the companion form matrix, which facilitates the transformation of the VAR model into a comprehensive structure. The companion form matrix possesses computational advantages and enables the derivation of unknown parameters within the model. Additionally, it allows for the acquisition of the special density matrix.

As a result of this process, I obtain a 66x66 matrix. The first three rows (1 to 3) consist of Φ_1 to Φ_{22} matrices, each with a size of 3x3, representing the dynamic relationships among the variables over the 22 lags. The last three rows (64 to 66) contain identical matrices, each of size 3x3, reflecting the parameters matrix.

Subsequently, I specify the number of periods for computing the IRF. Considering the optimal number of lags as 22, I set the number of periods to 30 to ensure comprehensive coverage of the dynamic changes. However, this value is adjustable and can be tailored to suit specific requirements. Upon applying the "irfvar()" function, I obtain the impulse response matrix of size 9x31.

Analyzing this matrix allows us to understand the short-term and long-term effects of the shock on each variable and draw valuable conclusions regarding the economic dynamics under consideration.

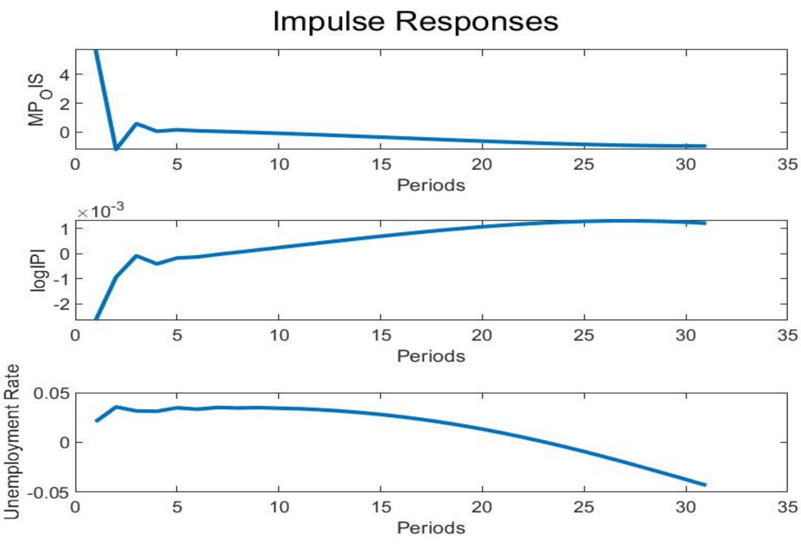

Fig 3. MP_OIS is the interest rate change (MP shock)
The second curve shows that how logIPI response to the MP shock
The third is the response of unemployment rate to the MP shock

6.2 Calculating Confidence Intervals with Bootstrapping

Calculating confidence intervals is essential for understanding how data points spread around the mean. In this case, I employed the bootstrapping method to obtain the standard error band. Bootstrapping involves creating numerous simulated samples by resampling from our single dataset, allowing us to assess the probable spread in our model. For this analysis, I performed 1000 resampling iterations, and the width of the purple region on the plot represents the 95 % confidence intervals of the standard error band.

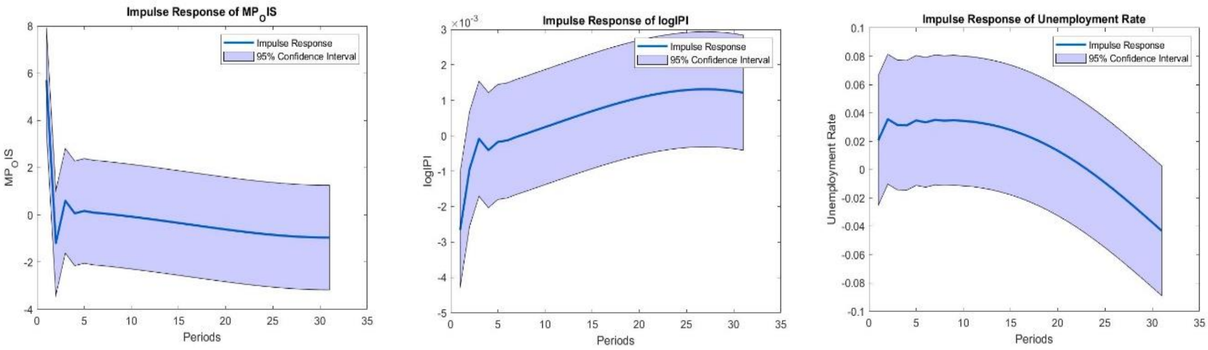

Fig 4. With the standard error band

7. Result

The first graph in Figure 3 reveals that the European Central Bank (ECB) implements a contractionary monetary policy. This policy stance is likely adopted to restrain excessive economic acceleration and to control inflation when it rises too rapidly. The high lending rates set by the banks prompt firms to reduce their investment activities and slow down their production processes. This reduction in economic activity can explain the observations in the second graph, which illustrates that a tight monetary policy shock leads to a decrease in the industrial production rate. Consequently, the unemployment rate may be affected due to the decline in production activities by firms.

Inter-temporally, the shock exhibits a pronounced impulse in the initial two periods, causing a significant drop of around 6 percent, which then gradually stabilizes and converges to a mean of zero. Furthermore, a slight negative deviation occurs thereafter. Concurrently, the log of Industrial Production Index (logIPI) demonstrates a response closely following the high-interest rate conditions, leading to a decline of approximately 0.3 percent. Simultaneously, the unemployment rate rises by approximately 4 percentage points in response to the shock.

However, as I move forward in time, the response of logIPI gradually recovers after the fifth period and continues to do so until the twenty-fifth period, eventually fading away. Similarly, the response of the unemployment rate remains persistently high for a span of 10 periods before gradually declining, taking around 20 months to return to its baseline level. From the twentieth to the thirtieth period, the unemployment rate exhibits a steady decline, reaching 5 percent.

8. Sensitivity Check

This sensitivity check allows us to assess the robustness of our findings and determine the most appropriate lag length for our model. By comparing the responses of the variables with different lag lengths and the historical trend.

8.1 Lag Lengths

Theoretically, the lag included up to the optimal p value determines the output variable, and lags after p should not have a significant effect or influence on the results. To validate this, I conducted a sensitivity check by changing the number of lags.

In the initial analysis, the optimal p value is determined to be 22. For Figure 5, I plotted the results with 21 lags. As anticipated, this change in the lag length resulted in a notable impact on the graph. The responses of the variables exhibited less bending after the tenth period, and there were slight alterations in the tail track, affecting the overall direction of the impact.

In contrast, for Figure 6, I used 23 lags, the results showed a little change, which aligns with our hypothesis. This observation confirms that lags beyond the optimal p value have little to no impact on the outcomes of the analysis.

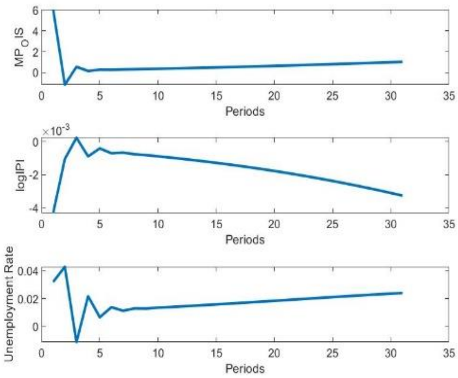

Fig 5. P = 21

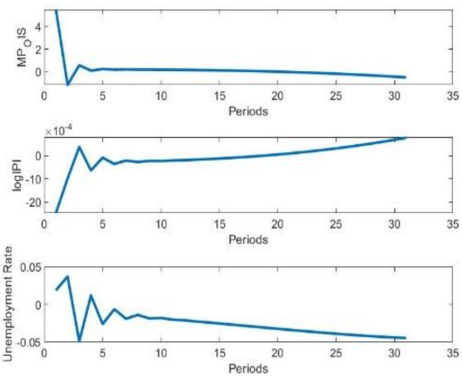

Fig 6. P = 23

8.2 Without Removing the Time Trend

By omitting the first difference section, the AIC analysis suggests that the optimal lag for our model is one. I proceed with this information for further analysis.

In Figure 7, I maintain the initial optimal lag of p = 22. As a result, I observe smooth curves for the three variables under consideration. This implies that the response of each variable to the monetary policy shock follows a consistent pattern over time.

In contrast, Figure 8 sets the optimal p equal to 1. As expected, the responses of the variables are approximately zero during the following 10 months, which shows limited impact in the initial period of the shock when considering only one lag. However, the responses of the variables take a response in late subsequent months.

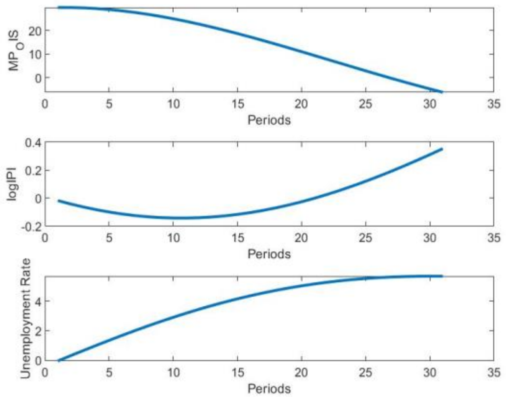

Fig 6. Without remove the time trend p = 22

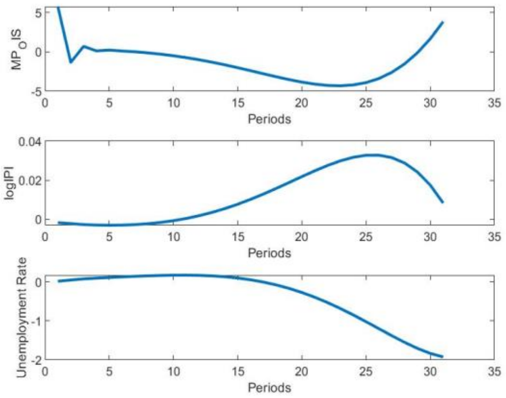

Fig 7. Without remove the time trend p = 1

9. Discussion

In any empirical study involving extensive calculations and data analysis, it is imperative to acknowledge the possibility of human errors and oversights, which cannot be entirely eliminated. As I manually utilized MATLAB for the computation of the VAR model, inherent risks of mistakes or confusion may be present. The involvement of different matrix forms, such as the companion form, reduced form, and structural form, introduces complexities that can potentially lead to errors during their transformations and operations. Furthermore, the proper handling of matrix transposition is a critical aspect that requires meticulous attention, as inaccuracies in this process may propagate through subsequent analyses.

For interpretation, there are several limitations, one of the main limitations of our study is the sample period used for analysis, which spans from 1999 to 2021. While this period provides a considerable time frame for analysis, it may not capture certain economic dynamics and events that occurred before 1999 or after 2021. Therefore, the generalizability of our findings to different time periods might be limited.

Moreover, like any empirical study, our analysis is based on certain assumptions and simplifications. For instance, the VAR model assumes linearity and stationarity of the variables, which may not fully capture the complexities of real-world economic dynamics. Additionally, I consider only a specific set of macroeconomic variables, leaving out potential influential factors that could affect the results.

10. Reference

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