

Replication: Identifying Aggregate Supply and Demand Shocks in South Africa

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Keywords: Econometrics, Time Series, VAR, SVAR, Blanchard-Quah

1. Introduction

The paper, *Identifying aggregate supply and demand shocks in South Africa*, is an application of a structural VAR method to identify supply and demand shocks for the South African economy since the 1960s. The aim of this paper is to replicate the paper by Du Plessis, Smit and Sturzenegger (2008), with

2. Data

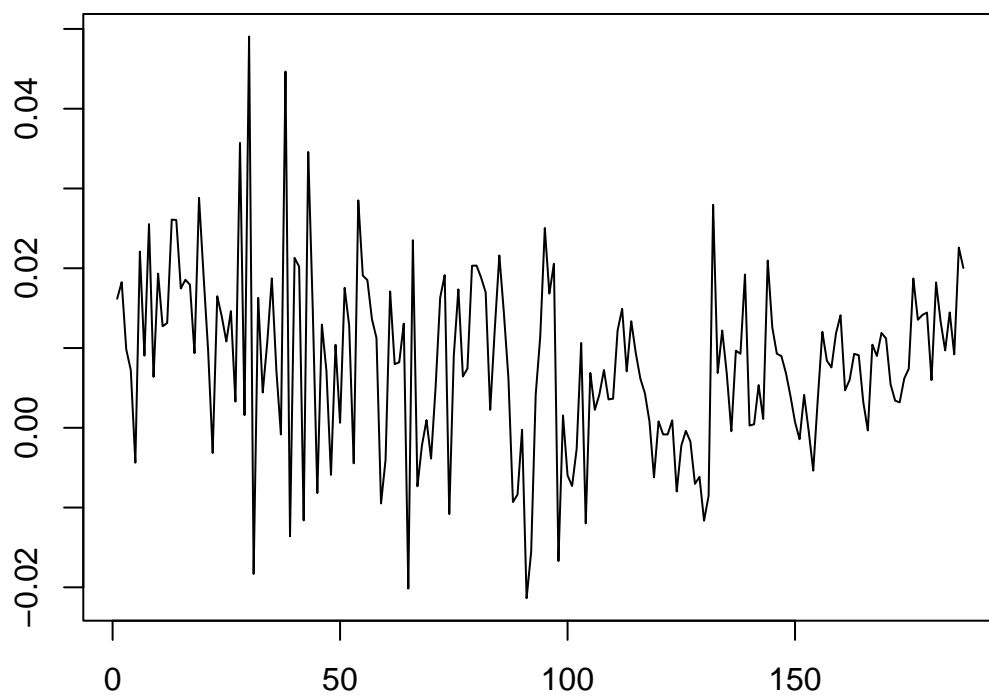
The data used is quarterly data from FRED, dating back to 1960 up until 2007. Unlike the original paper, the data used is not seasonally adjusted. The variables used in the model are the first difference of the log of GDP (y_t), the ratio of government consumption to GDP (g_t), as well the real interest rate (r_t). r_t is calculated using the monthly nominal interest rate as well as the monthly CPI data. Below is the equation used to calculate r_t .

$$r_t = ((1 + \text{Avg}(i_{mt-1}, i_{mt}, i_{mt+1})) / (1 + (\ln(CPI_{mt-2}) - \ln(CPI_{mt+1}))))^4 - 1) * 100$$

Figures 1, 2 and 3 represent the variables used. As seen in the Appendix, when an Augmented Dickey-Fuller test is conducted, it is evident that y_t is stationary, as the p-value is less than 0.05. However, both g_t and r_t are non-stationary. In the original paper (2007), r_t is stationary. This may be due to the data used for this paper not being seasonally adjusted.

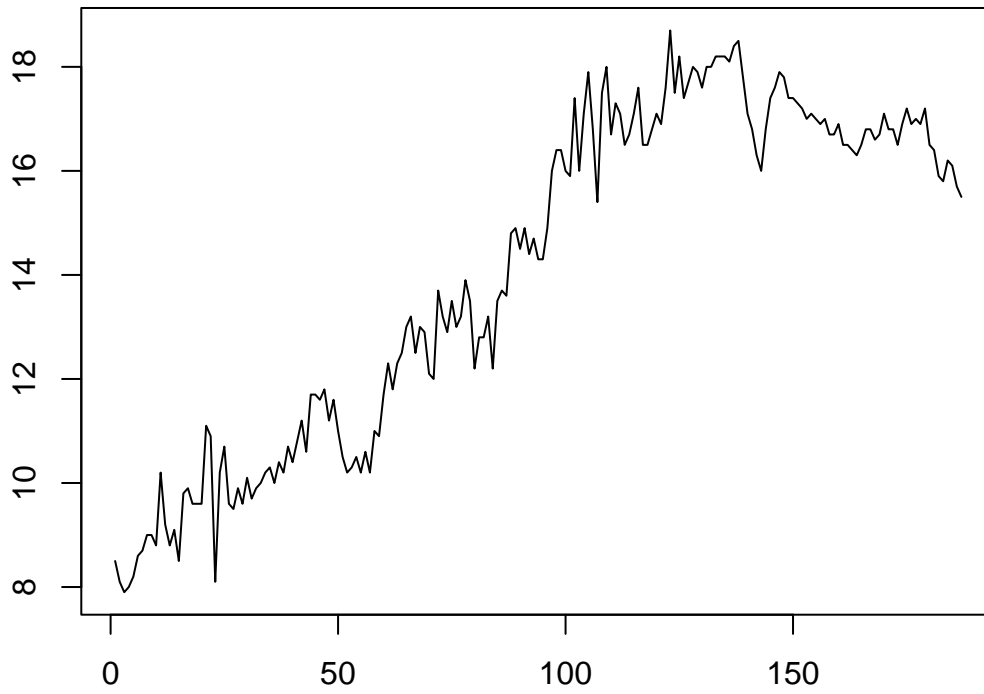
*Corresponding author: Samantha Scott
Email address: 20945043@sun.ac.za (Samantha Scott)

First difference of logged real GDP



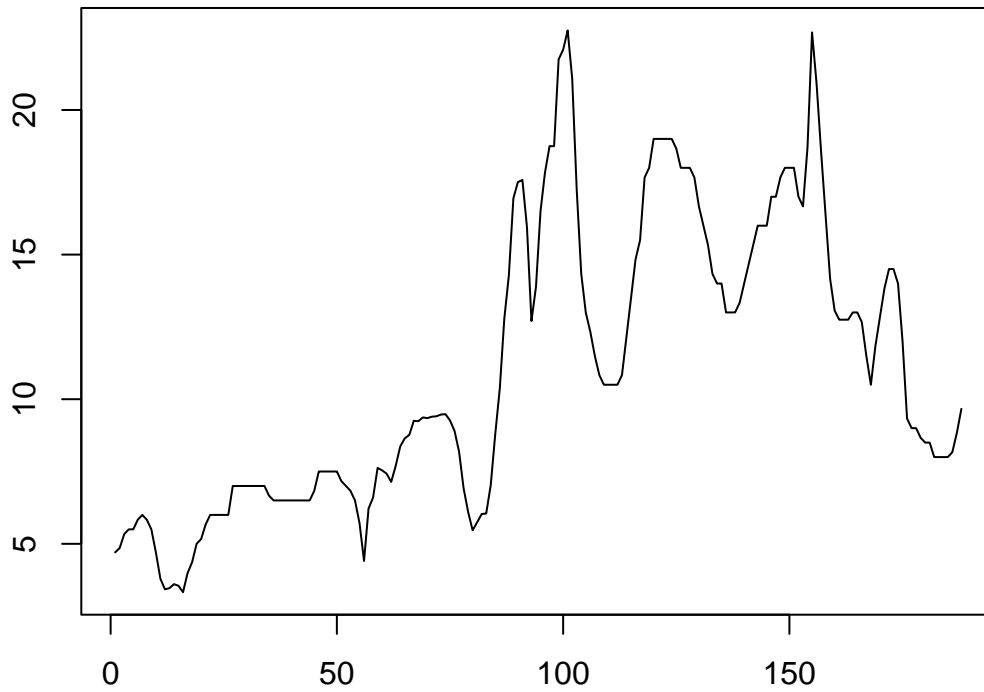
Time
Figure 1

Ratio of government expenditure to GDP



Time
Figure 2

Real interest rate



Time
Figure 3

3. Methodology

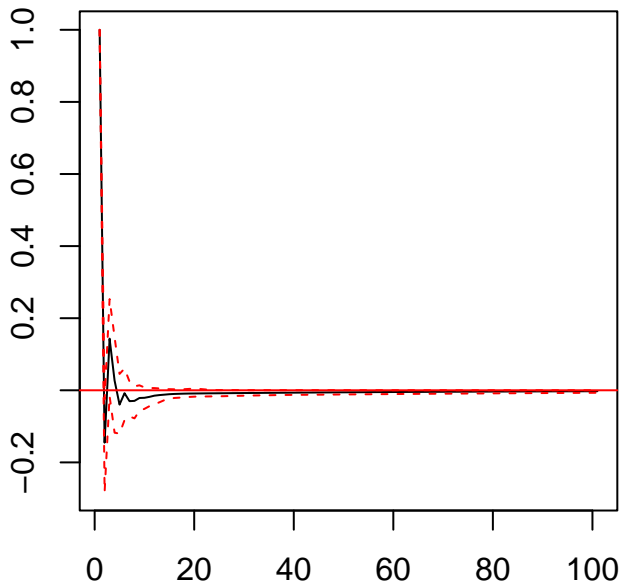
A structural VAR model is created to identify supply and demand shocks for the South African economy since the 1960s. The demand the variables, y_t , g_t and r_t are proxies for a supply shock, a fiscal shock and a monetary shock, respectively.

4. Results

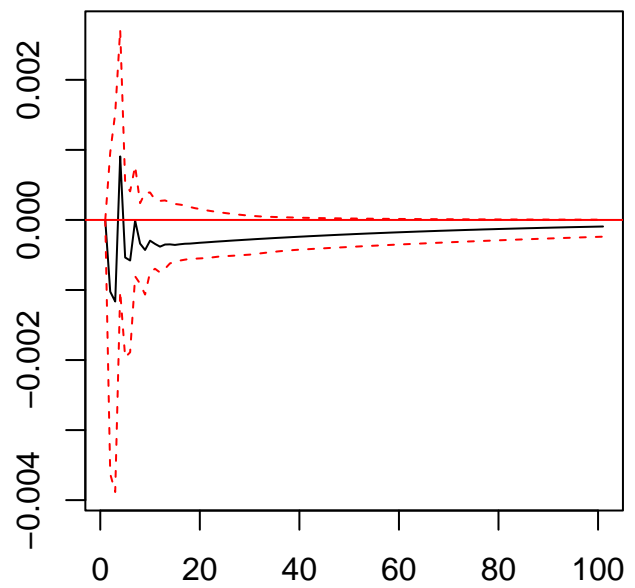
The results of the model are presented as impulse response functions.

4.1. Impulse Response of real GDP for each of the identified shocks

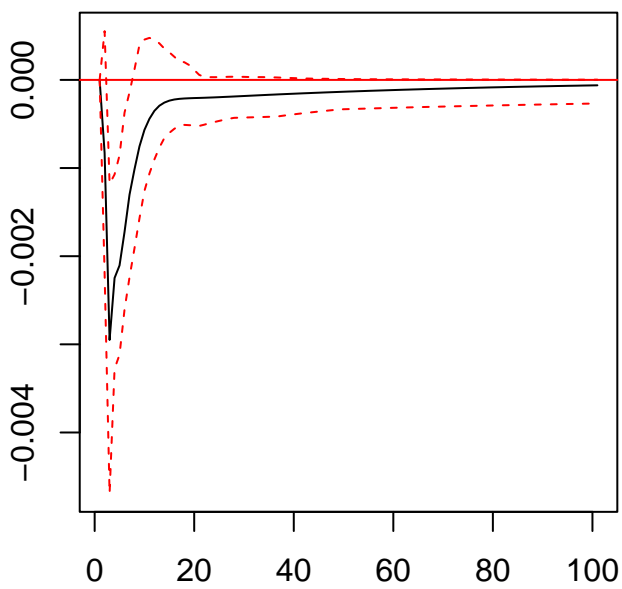
Supply Shock



Fiscal Shock



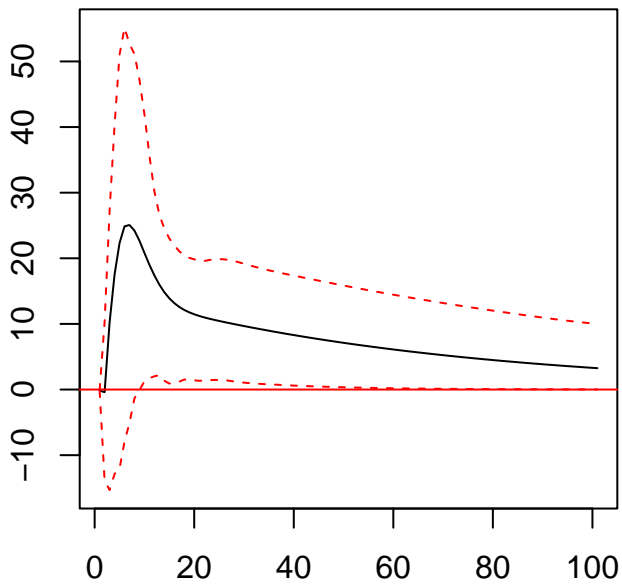
95 % Bootstrap CI, 100 runs
Monetary Shock



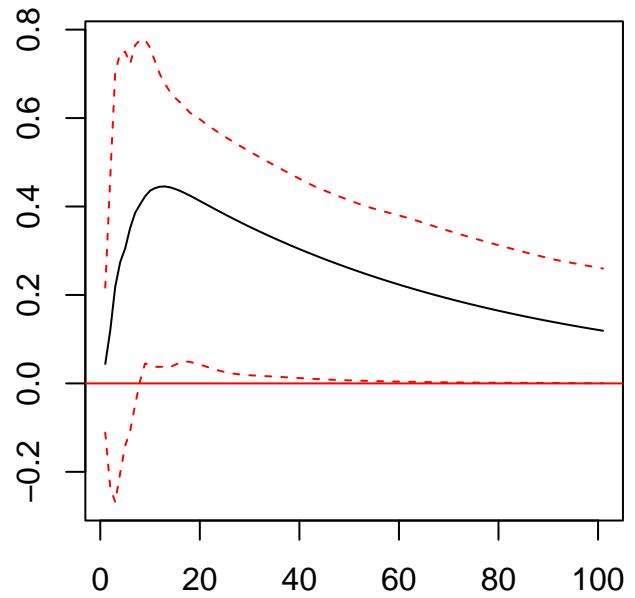
95 % Bootstrap CI, 100 runs

4.2. Impulse Response of the real interest rate for each of the identified shocks

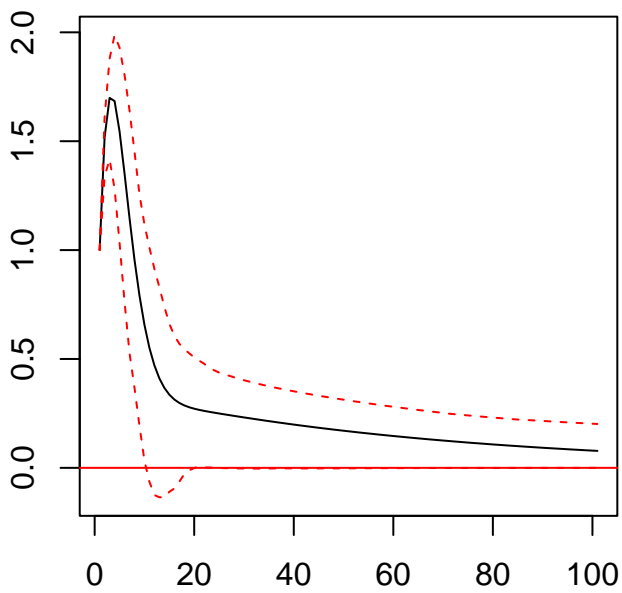
Supply Shock



Fiscal Shock



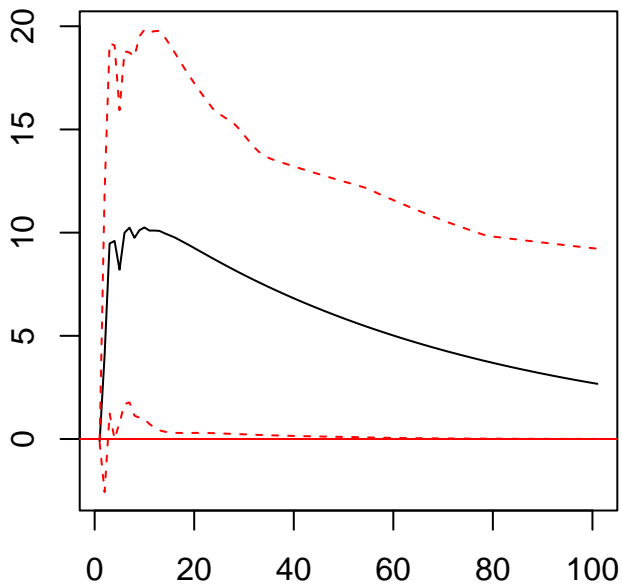
95 % Bootstrap CI, 100 runs
Monetary Shock



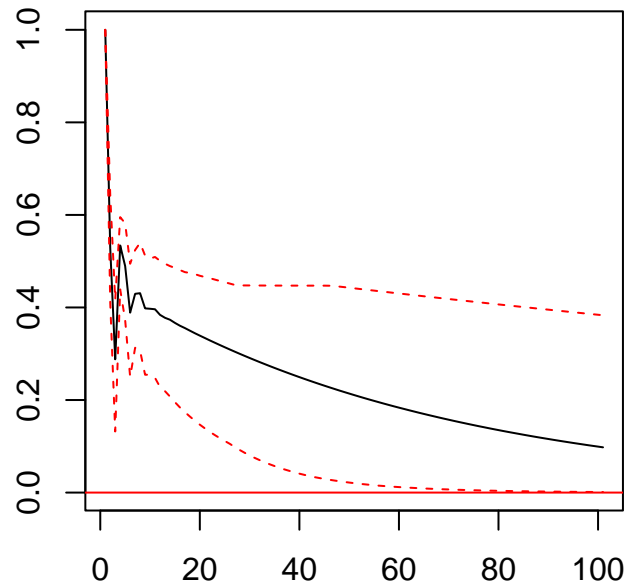
95 % Bootstrap CI, 100 runs

4.3. Impulse Response of the government consumption to real GDP for each of the identified shocks

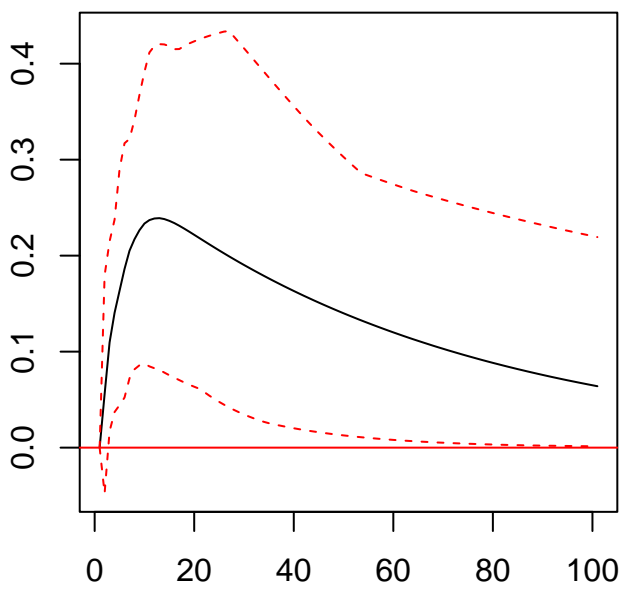
Supply Shock



Fiscal Shock



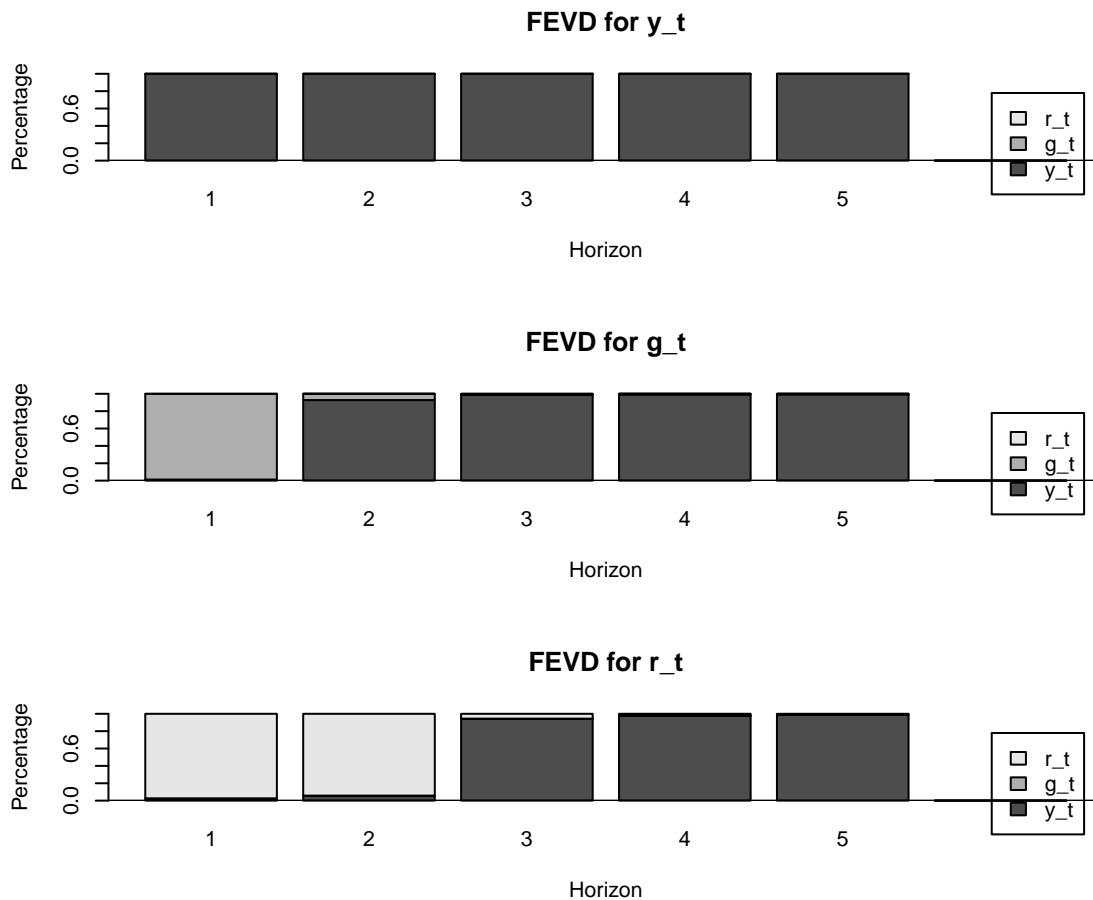
95 % Bootstrap CI, 100 runs
Monetary Shock



95 % Bootstrap CI, 100 runs

4.4. Variance Decomposition

“The variance decomposition indicates the amount of information each variable contributes to the other variables in the autoregression. It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables.”



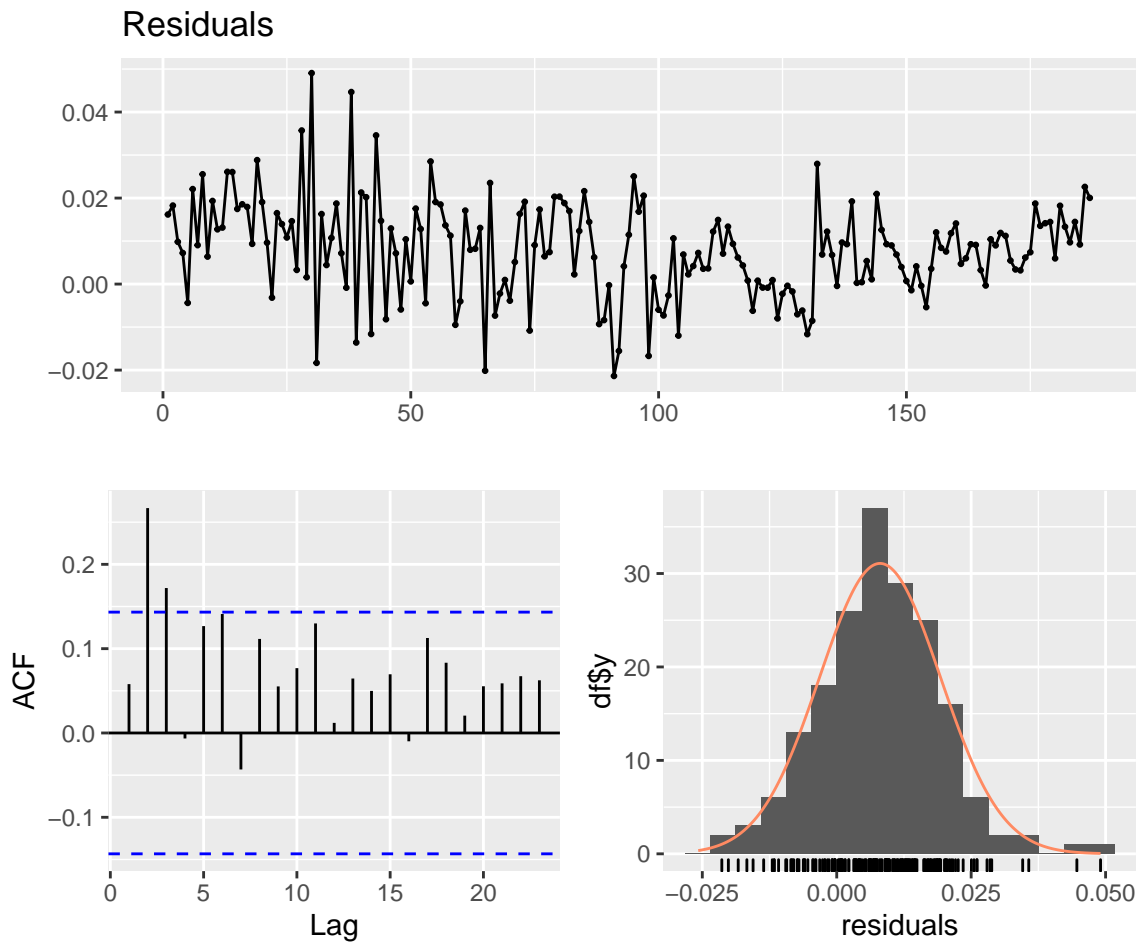
5. Robustness Checks

5.1. Residuals

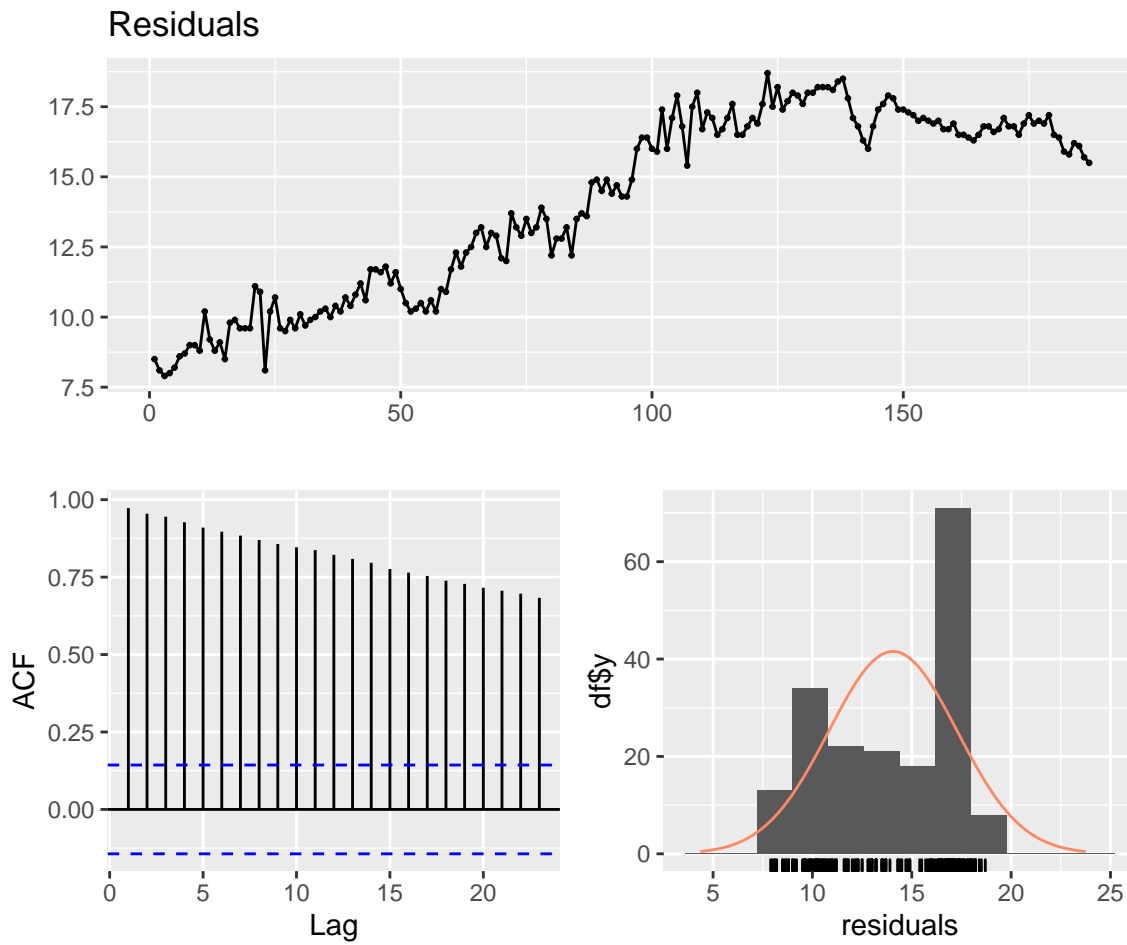
checking if residuals are white noise

“The residuals are the differences between the fitted model and the data. In a signal-plus-white noise model, if you have a good fit for the signal, the residuals should be white noise.”

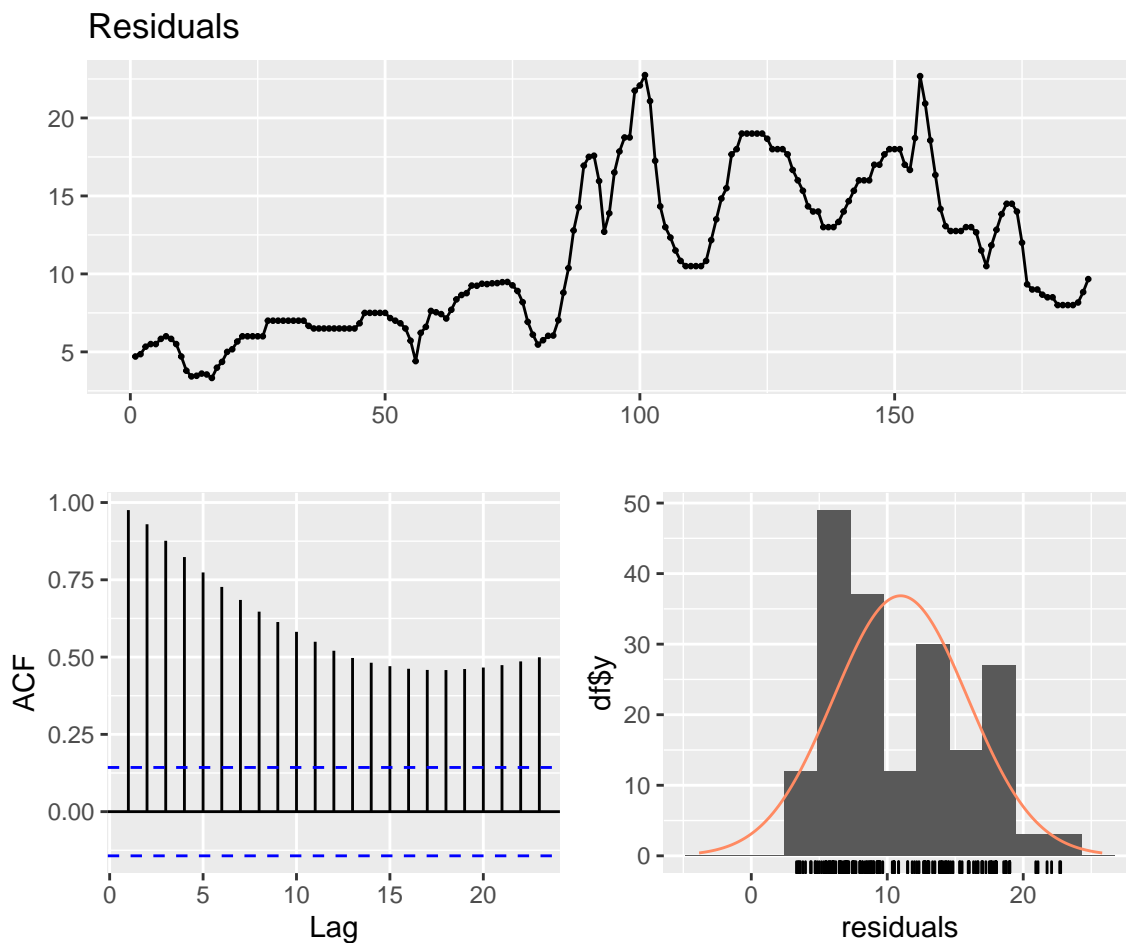
Below is a check for residuals for the y_t variable. This helps to determine whether the residual are white noise.



Below is a check for residuals for the g_t variable.



Below is a check for residuals for the r_t variable.



5.2. Lag Selection

“Lütkepohl (1993) indicates that overfitting (selecting a higher order lag length than the true lag length) causes an increase in the mean-squareforecast errors of the VAR and that underfitting the lag length often generates autocorrelated errors.”

The first set of Impulse Response Functions below are presented using a second SVAR model, where the number of lags selected is 6.

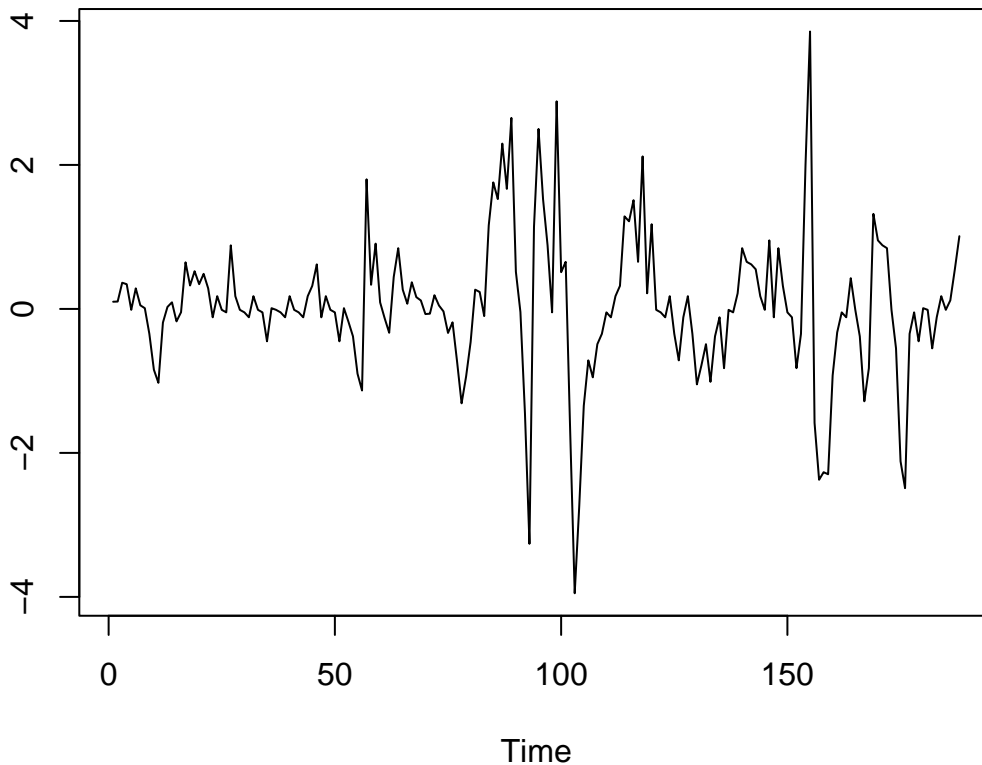
5.3. Reduced Sample (from last quarter, 1983)

As another robustness check, a smaller sample is used and the same method applied. As seen by the impulse response functions in the Appendix, using a smaller sample (1983+) does not significantly impact the results, as they are comparable to the impulse response functions of the larger sample (1960+).

5.4. *Removing seasonality and making Real Interest Rate Stationary*

For the last robustness check, the data used to calculate the real interest rate is seasonally adjusted. Further, the real interest rate data is differenced by 1, resulting in a stationary time series. As seen in the Appendix, the new, seasonally adjusted data that is differenced by 1 is stationary, with a p-value of 0.01 when an Aumented Dickey-Fuller test is conducted. The new real interest rate variable is depicted below:

Real interest rate: seasonally adjusted



6. Conclusion

7. Reference List

Du Plessis, S., Smit, B. and Sturzenegger, F., 2008. Identifying aggregate supply and demand shocks in South Africa. *Journal of African economies*, 17(5), pp.765-793.

Ozcicek, O. Lag Length Selection in Vector Autoregressive Models: Symmetric and Asymmetric Lags. Working Paper. https://www.lsu.edu/business/economics/files/workingpapers/pap97_27.pdf

8. Appendix

8.1. Forecast

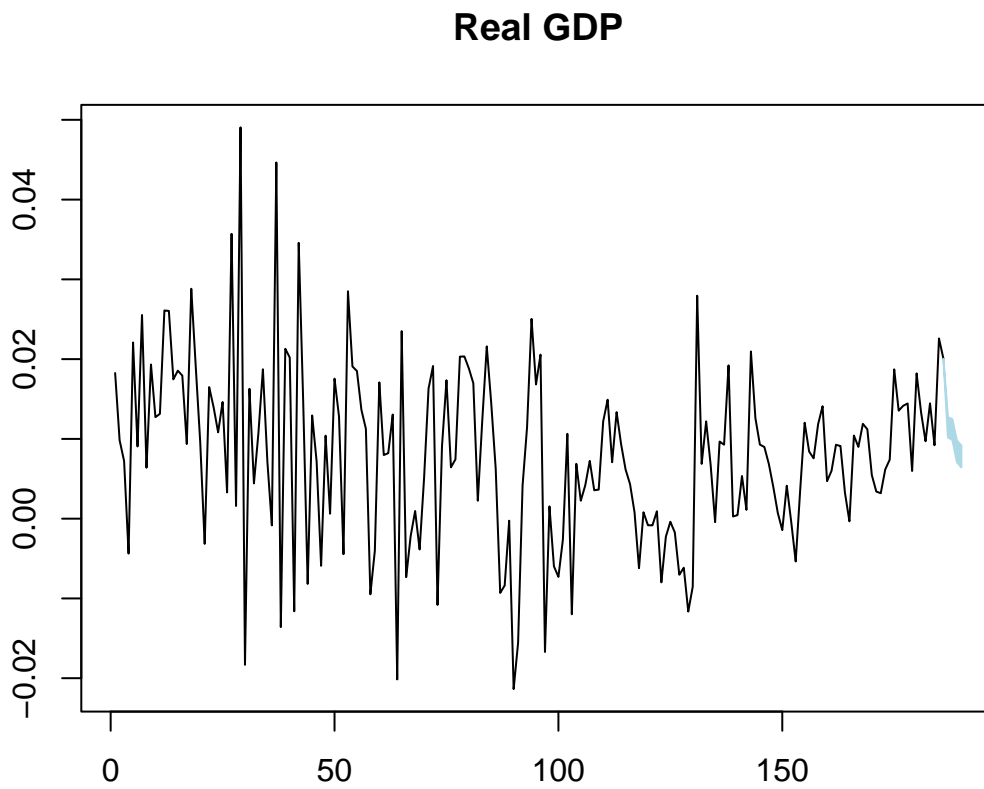


Figure 5

Government Consumption to GDP ratio

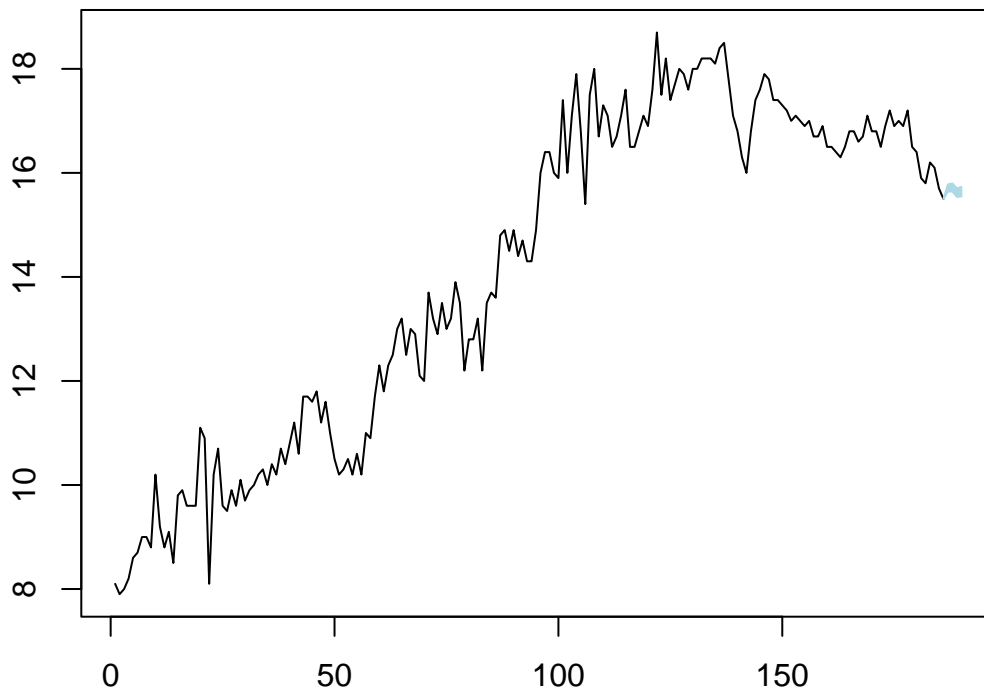


Figure 6

Real Interest Rate

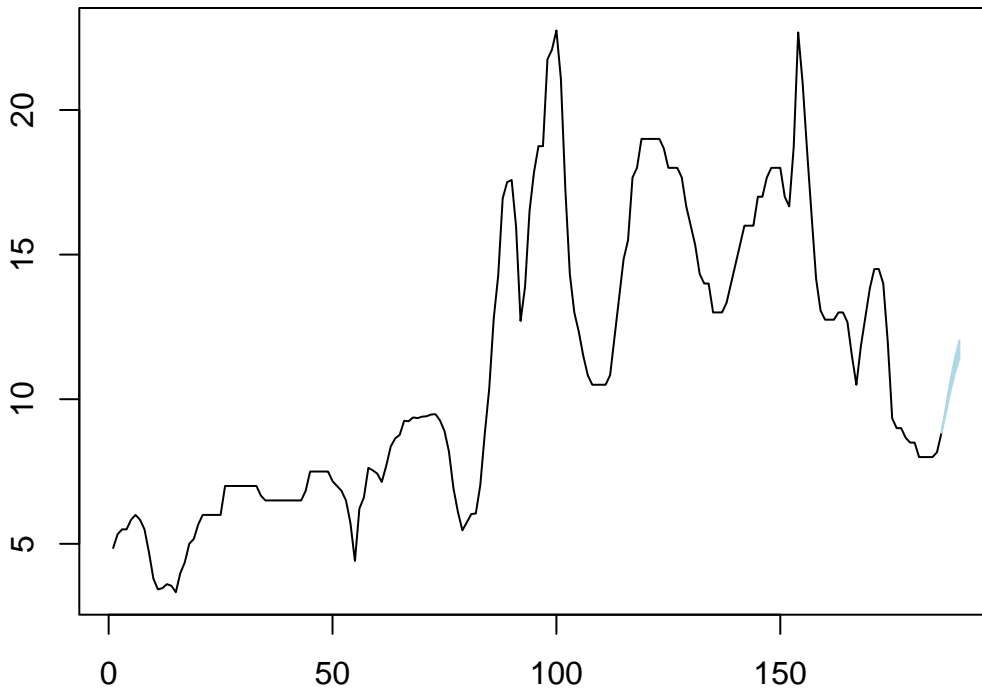


Figure 7

8.2. Testing for Stationarity

```
##
## Augmented Dickey-Fuller Test
##
## data:  real_gdp1
## Dickey-Fuller = -3.7922, Lag order = 5, p-value = 0.0208
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data:  rg83
## Dickey-Fuller = -3.5737, Lag order = 4, p-value = 0.03979
## alternative hypothesis: stationary
```

```
##
## Augmented Dickey-Fuller Test
##
## data: Real_interest1$Real_interest_rate
## Dickey-Fuller = -2.6335, Lag order = 5, p-value = 0.3112
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: ri83$Real_interest_rate
## Dickey-Fuller = -2.7977, Lag order = 4, p-value = 0.2473
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: ri_sa$seasonally_differenced
## Dickey-Fuller = -5.7783, Lag order = 5, p-value = 0.01
## alternative hypothesis: stationary

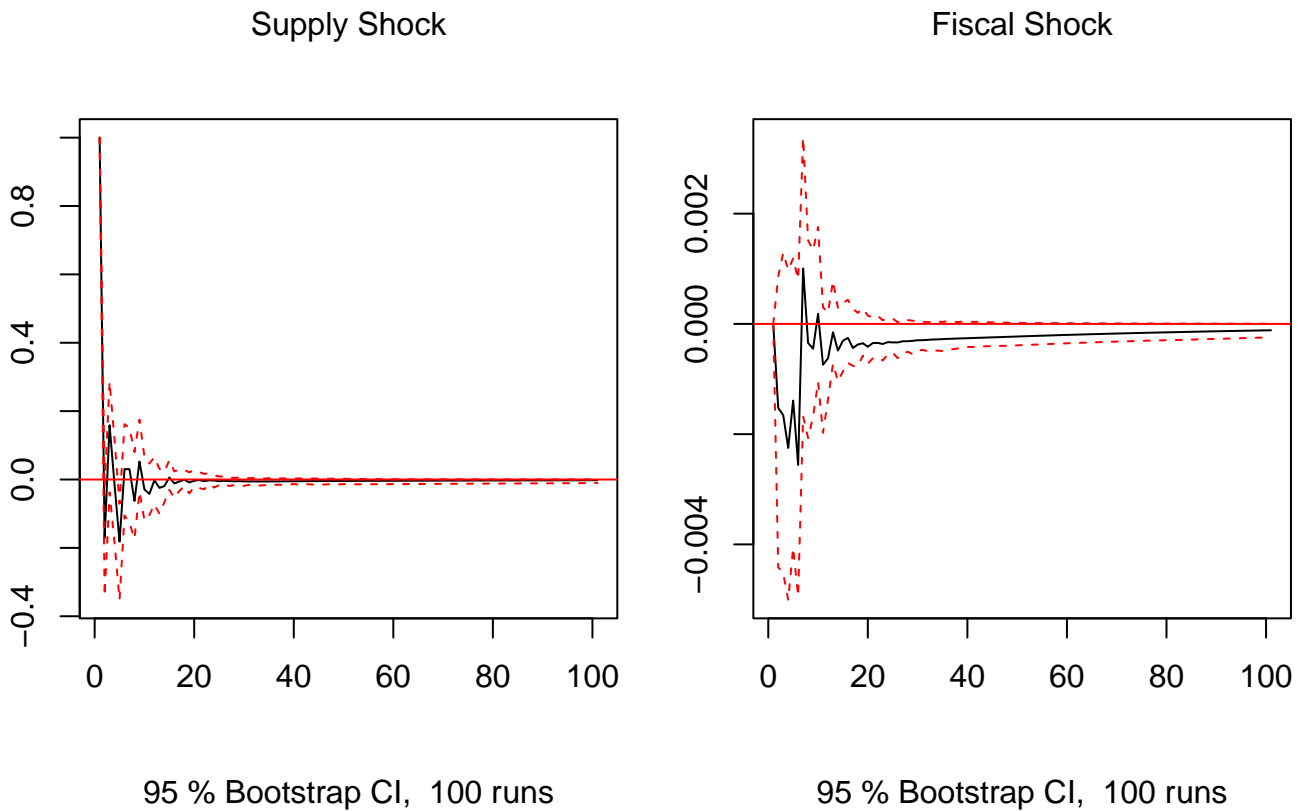
##
## Augmented Dickey-Fuller Test
##
## data: g_g_not_s$Value
## Dickey-Fuller = -0.66065, Lag order = 5, p-value = 0.9724
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: gg83$Value
## Dickey-Fuller = -2.3567, Lag order = 4, p-value = 0.4292
## alternative hypothesis: stationary
```

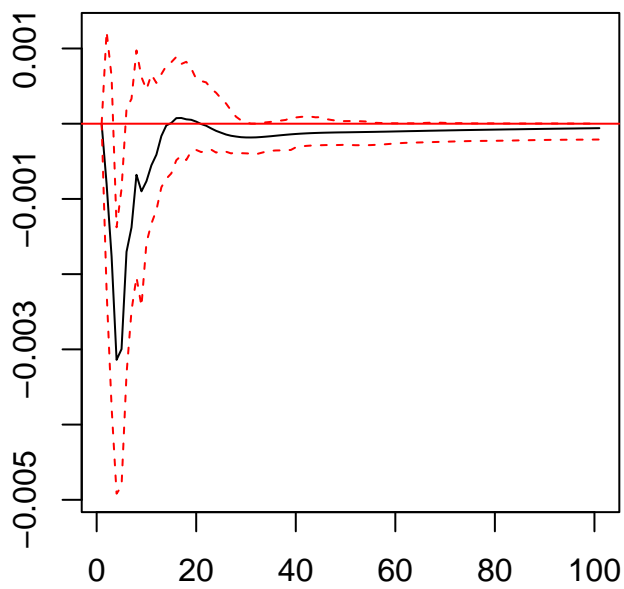
8.3. Lag Selection Impulse Response Functions

The set of Impulse Response Functions presented below are created using a second SVAR model, where the number of lags selected is 6.

Impulse Response of the real GDP for each of the identified shocks:



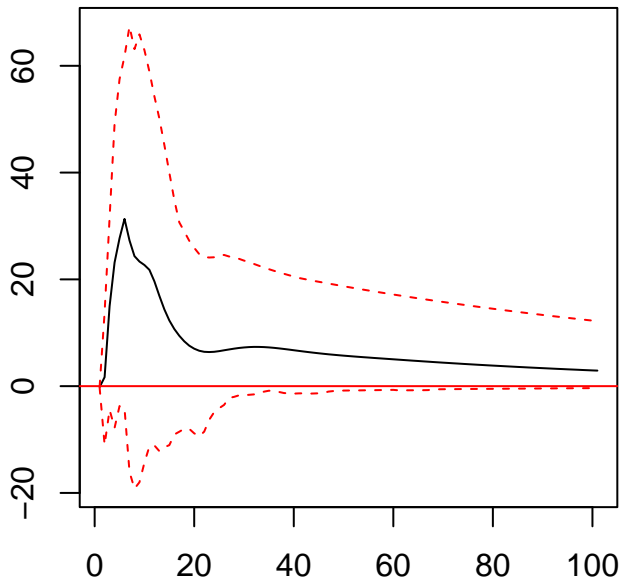
Monetary Shock



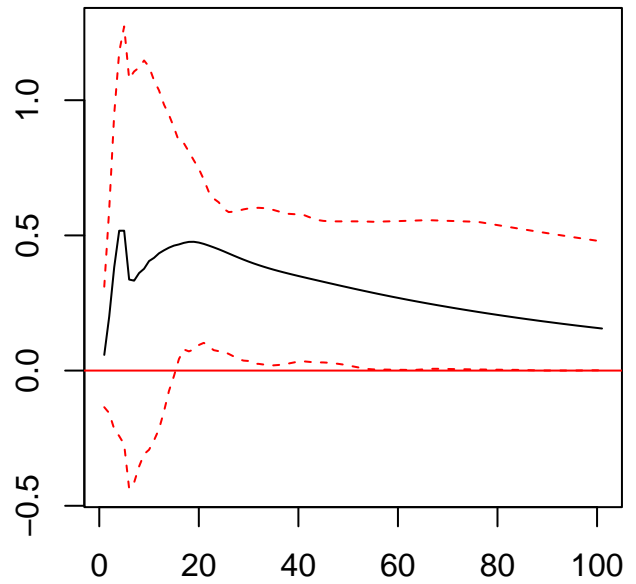
95 % Bootstrap CI, 100 runs

Impulse Response of the real interest rate for each of the identified shocks:

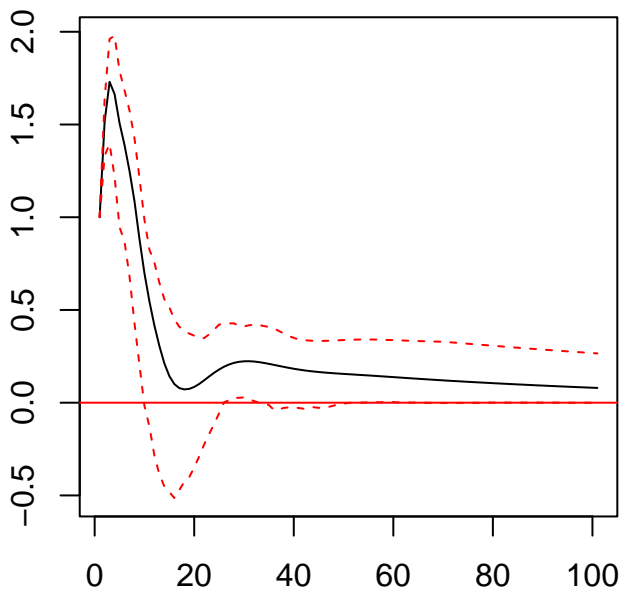
Supply Shock



Fiscal Shock



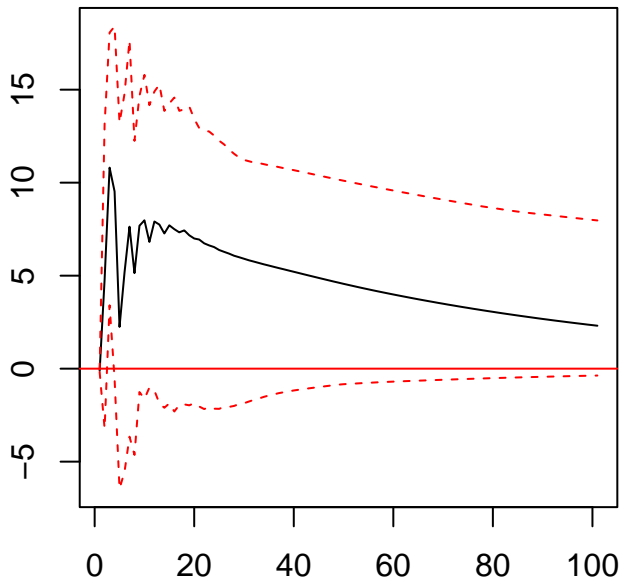
95 % Bootstrap CI, 100 runs
Monetary Shock



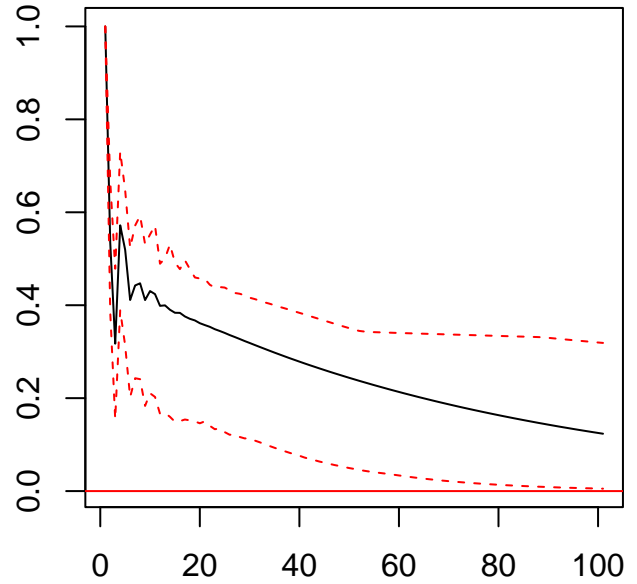
95 % Bootstrap CI, 100 runs

Impulse Response of the government consumption to real GDP for each of the identified shocks:

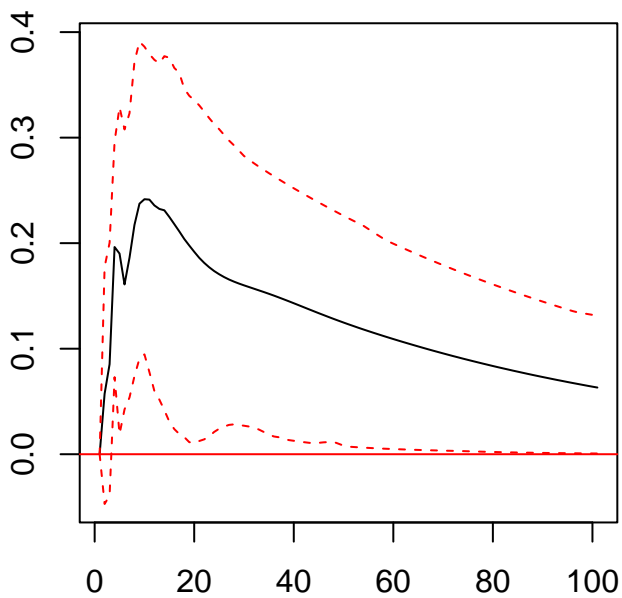
Supply Shock



Fiscal Shock



95 % Bootstrap CI, 100 runs
Monetary Shock



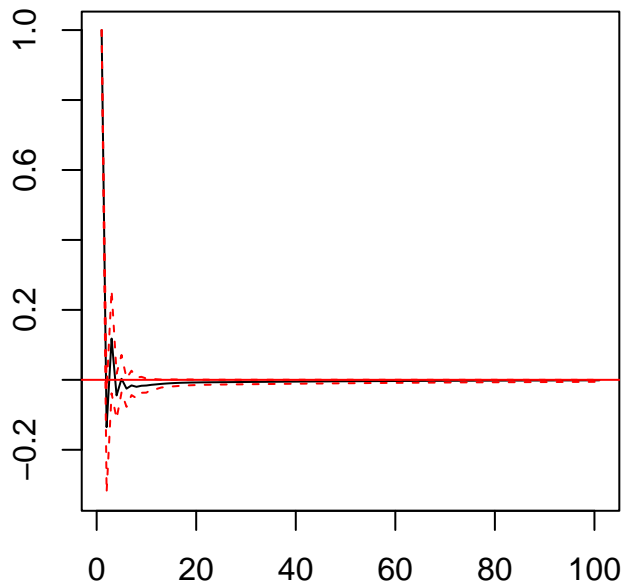
95 % Bootstrap CI, 100 runs

The set of Impulse Response Functions presented below are created using a third SVAR model, where

the number of lags selected is 2.

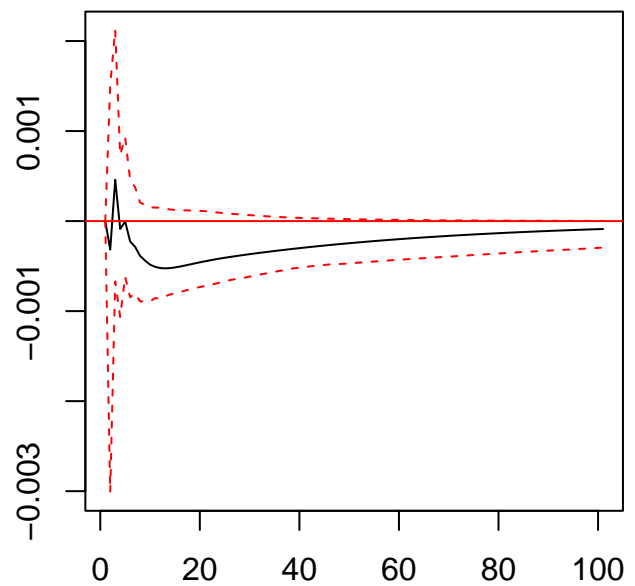
Impulse Response of the real GDP for each of the identified shocks:

Supply Shock



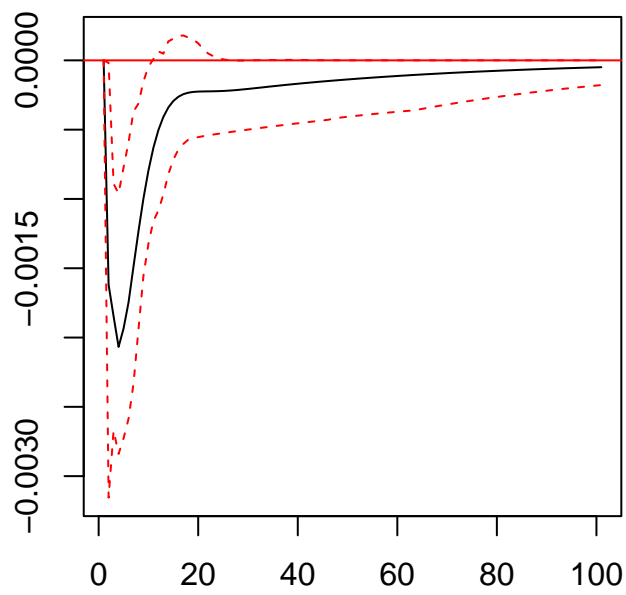
95 % Bootstrap CI, 100 runs

Fiscal Shock



95 % Bootstrap CI, 100 runs

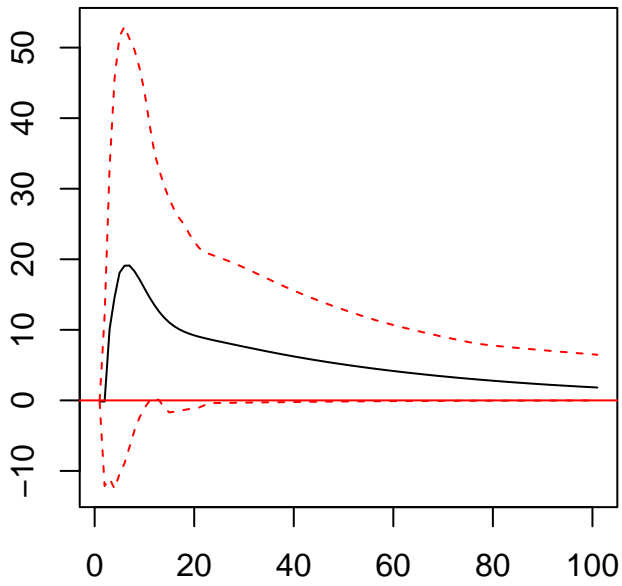
Monetary Shock



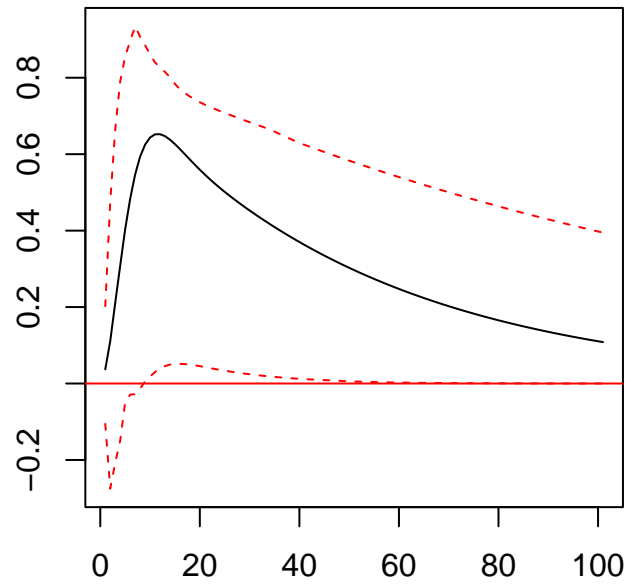
95 % Bootstrap CI, 100 runs

Impulse Response of the real interest rate for each of the identified shocks:

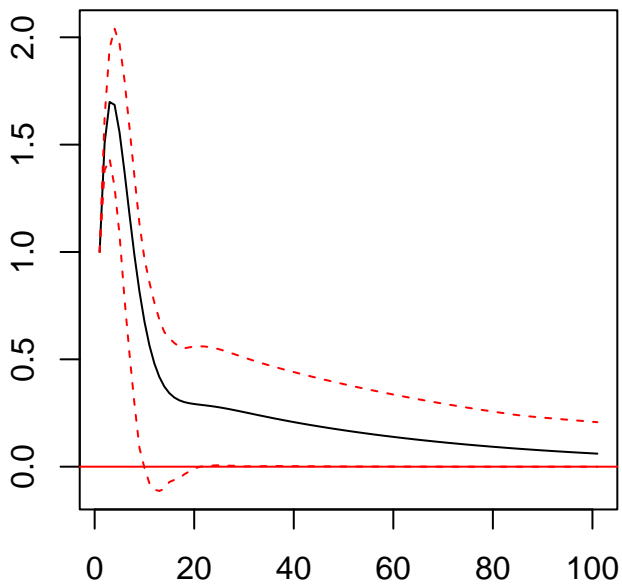
Supply Shock



Fiscal Shock



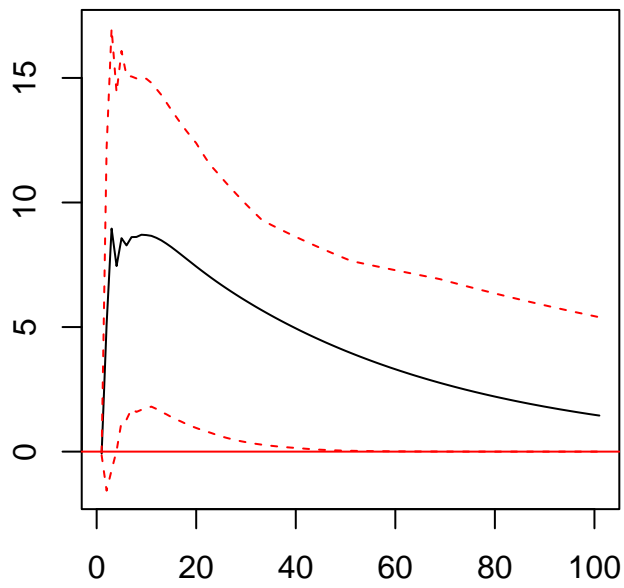
95 % Bootstrap CI, 100 runs
Monetary Shock



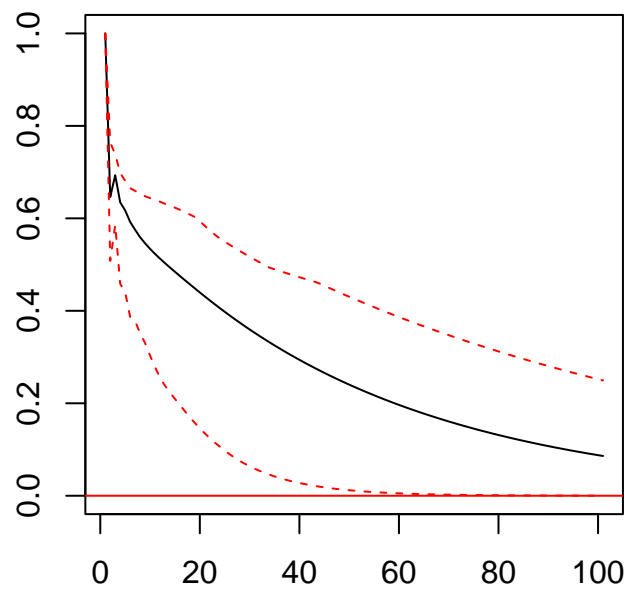
95 % Bootstrap CI, 100 runs

Impulse Response of the government consumption to real GDP for each of the identified shocks:

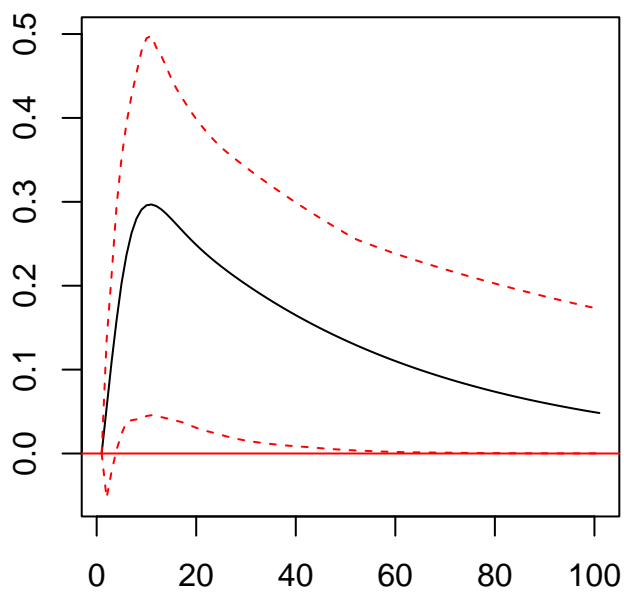
Supply Shock



Fiscal Shock



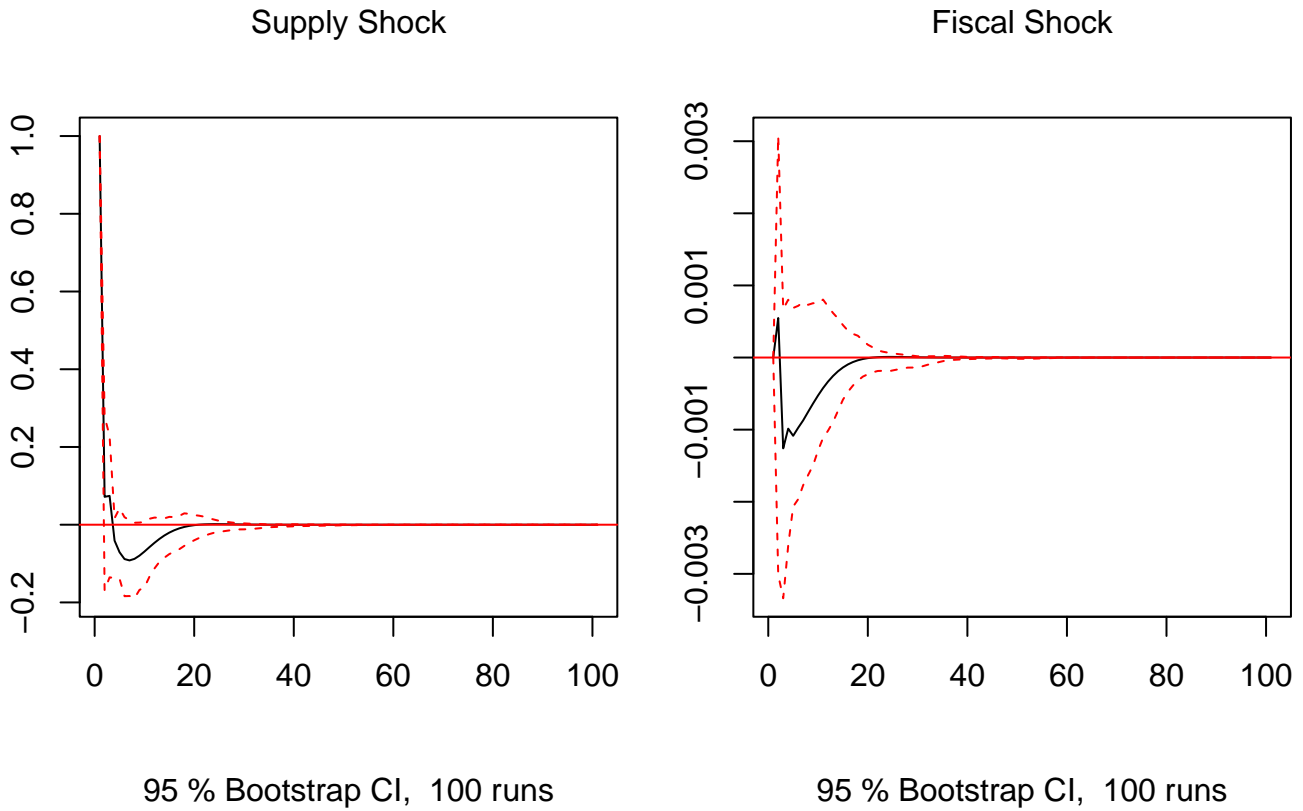
95 % Bootstrap CI, 100 runs
Monetary Shock



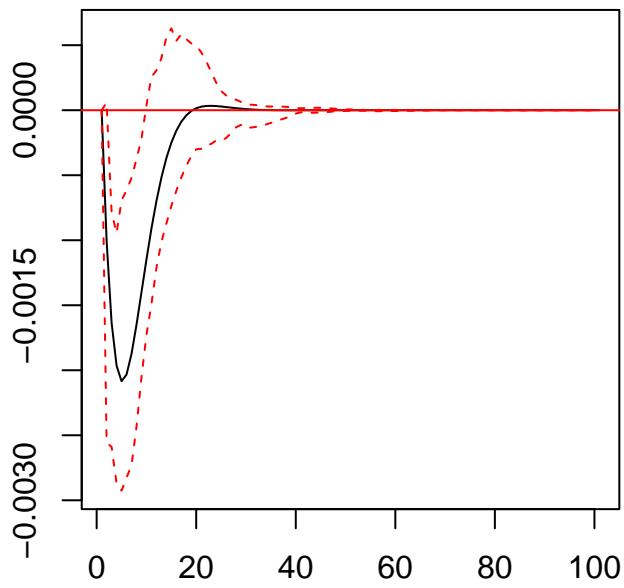
95 % Bootstrap CI, 100 runs

8.4. Reduced Sample Impulse Response Functions

Impulse Response of real GDP for each of the identified shocks:



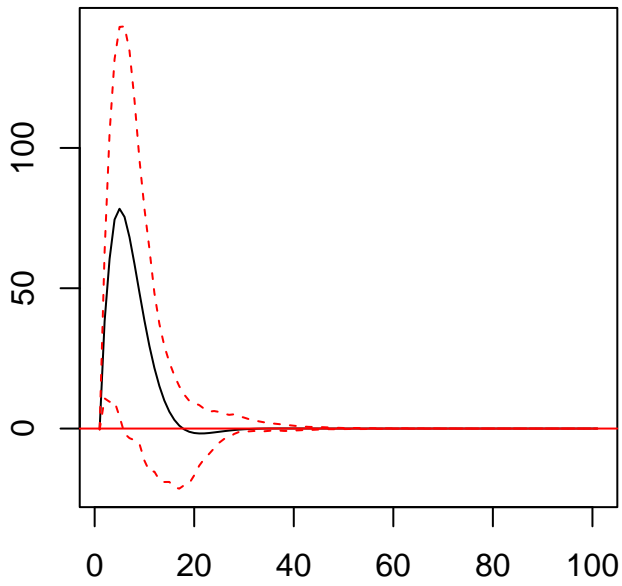
Monetary Shock



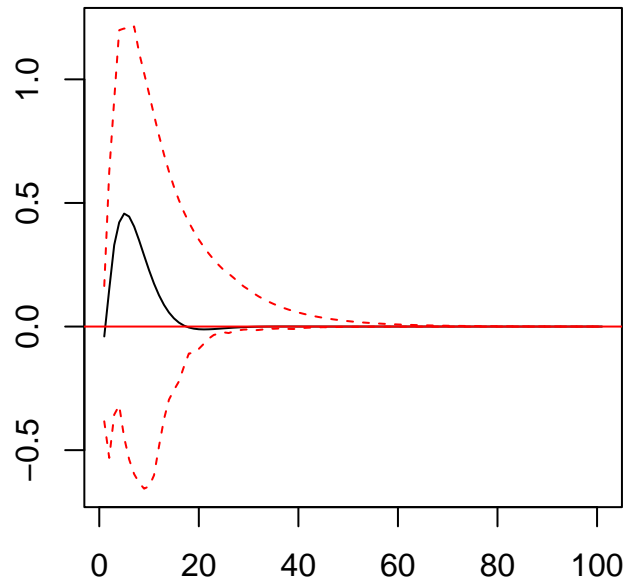
95 % Bootstrap CI, 100 runs

Impulse Response of the real interest rate for each of the identified shocks:

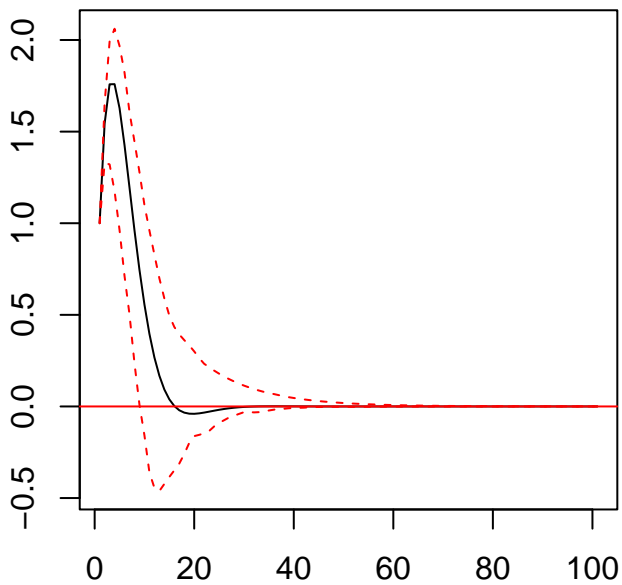
Supply Shock



Fiscal Shock



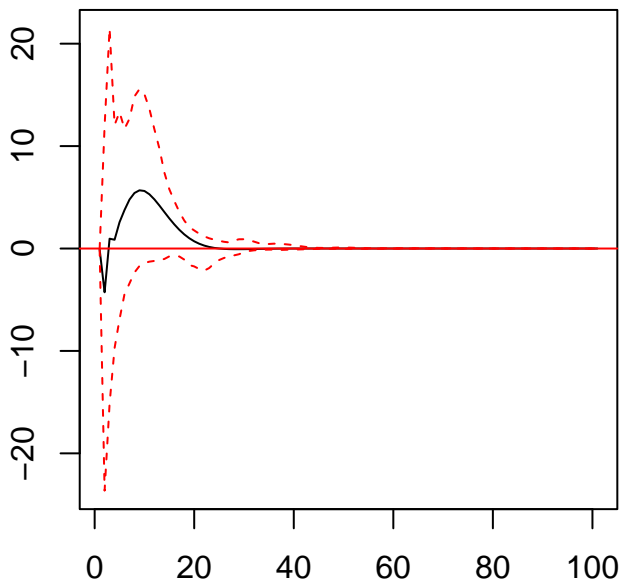
95 % Bootstrap CI, 100 runs
Monetary Shock



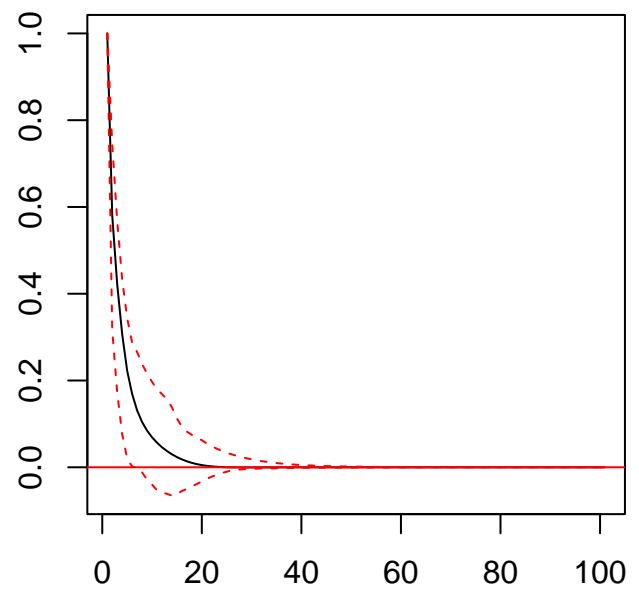
95 % Bootstrap CI, 100 runs

Impulse Response of the government consumption to real GDP for each of the identified shocks:

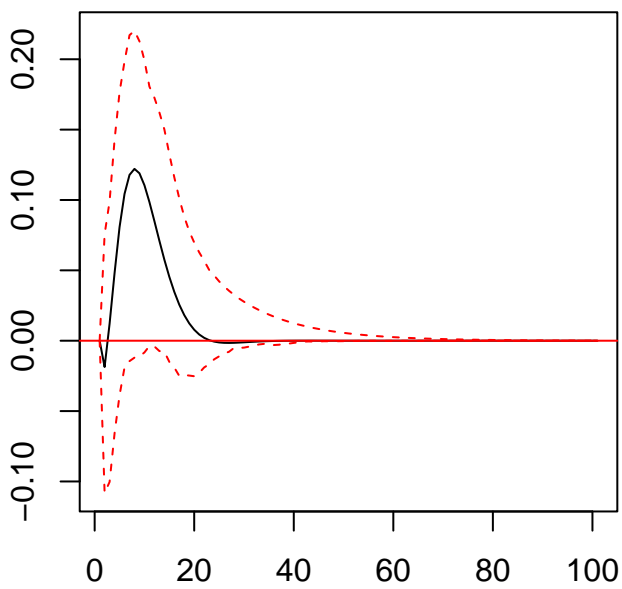
Supply Shock



Fiscal Shock



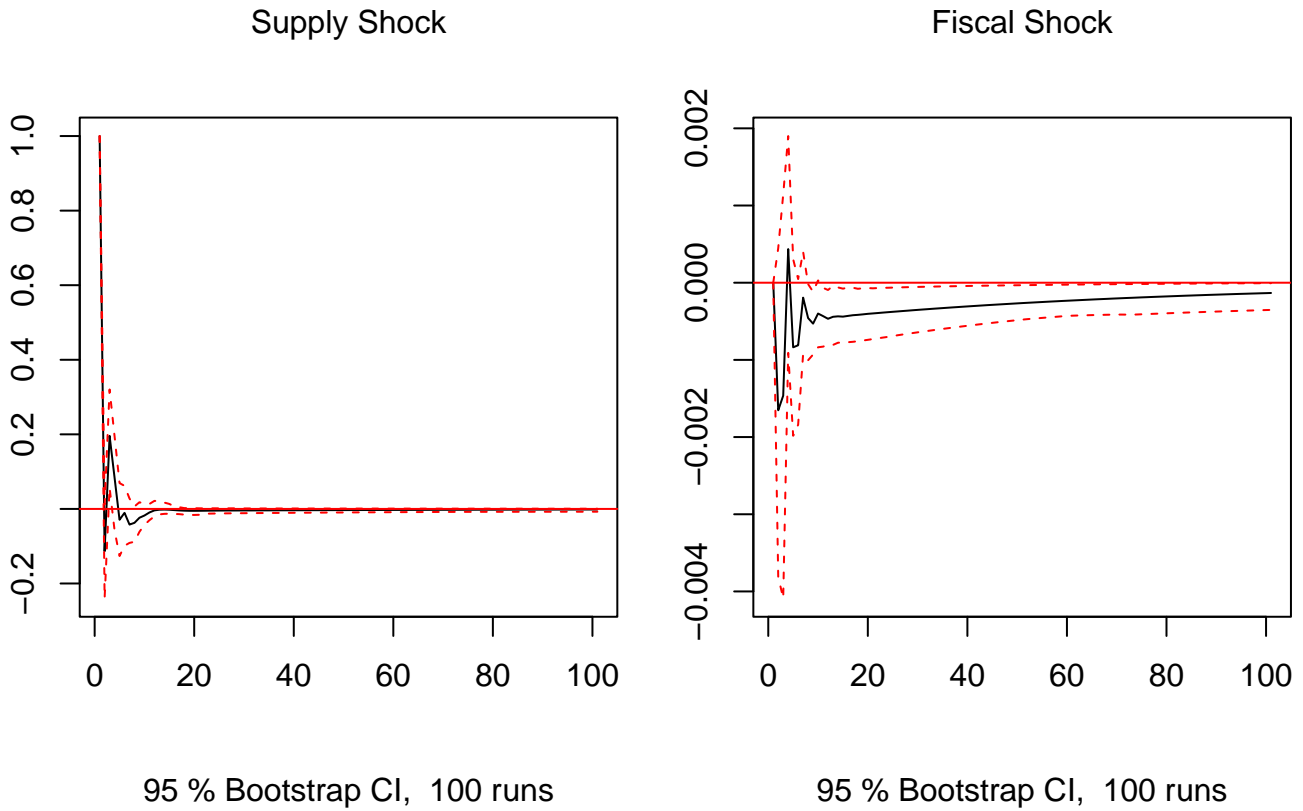
95 % Bootstrap CI, 100 runs
Monetary Shock



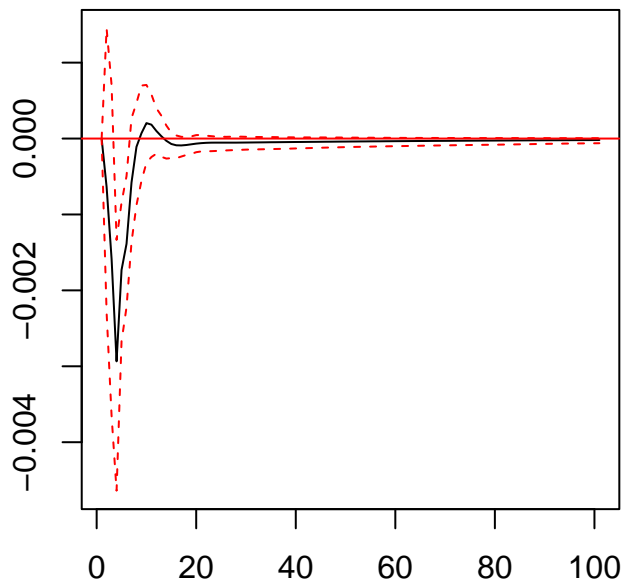
95 % Bootstrap CI, 100 runs

8.5. Removing Seasonality and Non-stationarity Impulse Response Functions

Impulse Response of real GDP for each of the identified shocks:



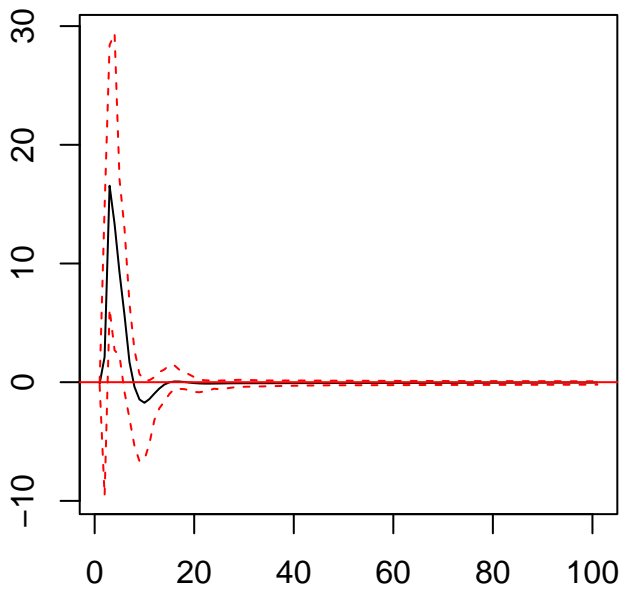
Monetary Shock



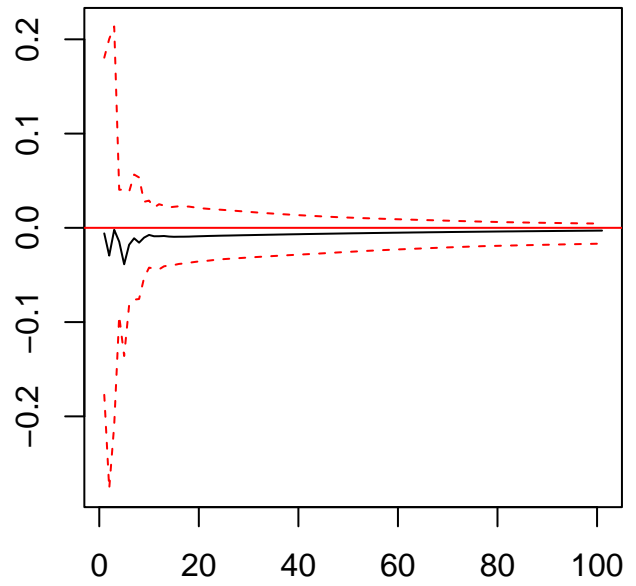
95 % Bootstrap CI, 100 runs

Impulse Response of the real interest rate for each of the identified shocks:

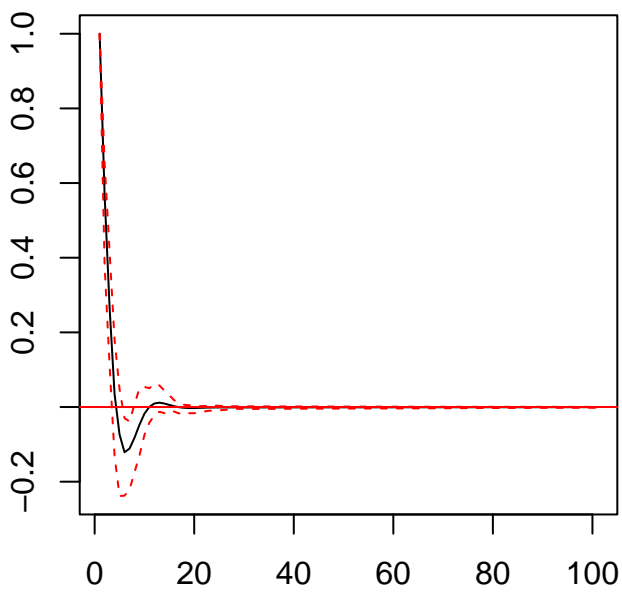
Supply Shock



Fiscal Shock



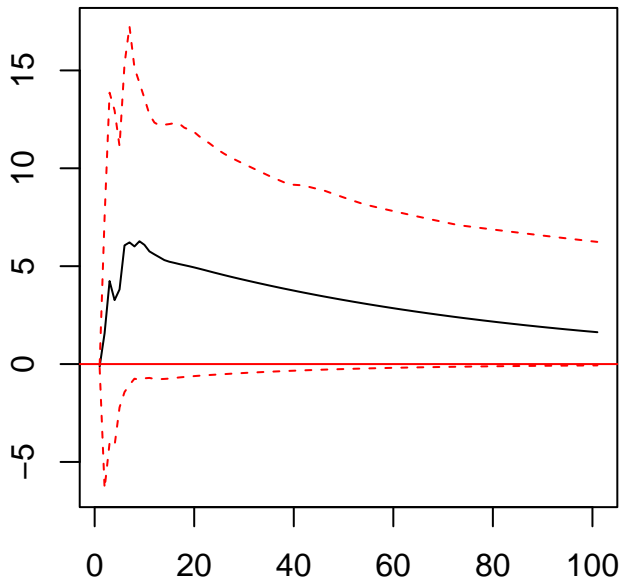
95 % Bootstrap CI, 100 runs
Monetary Shock



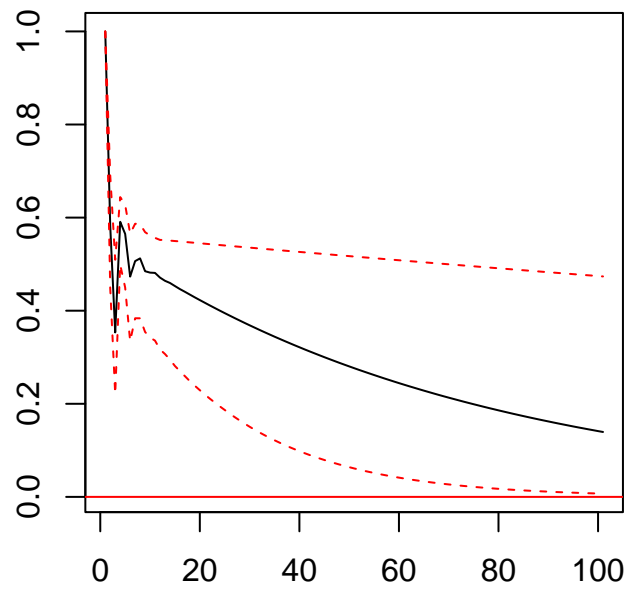
95 % Bootstrap CI, 100 runs

Impulse Response of the government consumption to real GDP for each of the identified shocks:

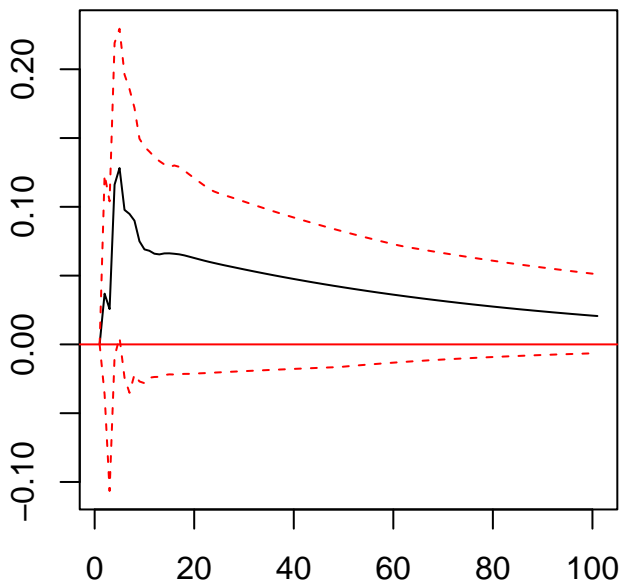
Supply Shock



Fiscal Shock



95 % Bootstrap CI, 100 runs
Monetary Shock



95 % Bootstrap CI, 100 runs