Interest Rates, Indexes and Inflation modelling using VAR

Applied Macroeconometrics

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Assignment 2 for ECON F240. Use of Vector Autoregressive Models to model and forecast financial variables.

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1 Description of the Dataset

The aim of the study is to study the movements of Index Prices, the rate of Inflation in a country, and the interest rates of 10 Year Government Securities.

For the purpose of this study we will be studying the time movement of these 3 specifics:

1. BSE SENSEX / NIFTY 50 Index
2. Indian Inflation Rate (CPI)
3. 10 Year Government Securities Interest Rate (Bond Rates)

1.1 Some background theory for the study

Here is some background theory on each variable:

1. Interest Rates on 10-Year Government Securities (G-Secs): G-Secs are long-term debt instruments issued by the government to raise funds. The interest rate on G-Secs is determined by market forces and reflects the government's cost of borrowing. It is influenced by factors such as inflation expectations, monetary policy, and the overall economic outlook. Changes in G-Sec rates can impact borrowing costs for the government, businesses, and individuals, affecting investment and spending decisions.
2. BSE Sensex Index Rates: The BSE Sensex is a stock market index that tracks the performance of the 30 largest and most actively traded stocks on the Bombay Stock Exchange (BSE). The Sensex is considered a barometer of the Indian stock market and is used to gauge investor sentiment and overall market performance. Changes in the Sensex reflect changes in the prices of its constituent stocks, which are influenced by factors such as company earnings, economic indicators, and global market trends.
3. Inflation Rate: Inflation is the rate at which the general level of prices for goods and services rises, leading to a decrease in purchasing power. The inflation rate is influenced by factors such as demand and supply dynamics, monetary policy, and external factors like oil prices and exchange rates. High inflation can erode the value of money, reduce consumer purchasing power, and impact investment decisions and economic growth.

1.1.1 Correlation

The possible correlation between interest rates on 10-year Government Securities (G-Secs), the BSE Sensex index rates, and the inflation rate can be complex and multifaceted. Here are some potential ways in which these variables may be correlated:

1. Interest Rates and Inflation: Generally, there is a positive correlation between interest rates and inflation. When inflation is high, central banks may raise interest rates to control inflation, leading to a positive correlation between interest rates on G-Secs and the inflation rate.
2. Interest Rates and Stock Market: The relationship between interest rates and stock market performance can be more nuanced. In some cases, rising interest rates may be perceived negatively by investors, leading to a negative correlation between interest rates and stock market returns. However, in other cases, rising interest rates may signal a strong economy, which can be positive for stock market performance.
3. Stock Market and Inflation: The relationship between the stock market and inflation can also vary. Inflation can erode the purchasing power of money, which may negatively impact stock market returns. However, moderate inflation can be indicative of a growing economy, which can be positive for stock market performance.
4. Overall Economic Conditions: Changes in interest rates, stock market performance, and inflation are often driven by broader economic conditions. For example, during periods of economic growth, interest rates may rise, and stock markets may perform well, while inflation remains moderate.
5. Policy Factors: Central bank policies and government actions can also influence the correlation between these variables. For example, if a central bank adopts an expansionary monetary policy to stimulate economic growth, this may lead to lower interest rates and higher inflation, which could impact stock market performance.

Overall, the correlation between interest rates on G-Secs, the BSE Sensex index rates, and the inflation rate can be influenced by a variety of factors, including economic conditions, policy decisions, and market sentiment. A VAR modeling approach can help to better understand these relationships and their implications for investors and policymakers.

1.2 Objective

One of the primary objectives is to quantify the degree and direction of causality between these variables. By analyzing historical data and employing VAR modeling techniques, the research aims to identify whether changes in one variable lead to changes in the others and the strength of these relationships.

Furthermore, the study intends to examine how changes in one variable affect the others over time. By conducting scenario analyses and sensitivity tests, the research seeks to understand the ripple effects of economic shocks or policy changes on interest rates, stock market performance, and inflation dynamics.

Additionally, the research aims to assess the impact of major economic events or policy changes on these variables. By studying historical data and identifying key events, such as economic downturns, policy rate changes, or major policy announcements, the study aims to evaluate how these events have influenced the relationships between interest rates, stock market performance, and inflation.

Ultimately, the research aims to provide valuable insights into the implications of these relationships for monetary policy, investment decisions, and economic forecasting in India. By better understanding the dynamics between these variables, policymakers, investors, and economists can make more informed decisions and better navigate the complex economic landscape.

1.3 Importing the Data

```r
# | echo: false
library(vars)
library(quantmod)
```

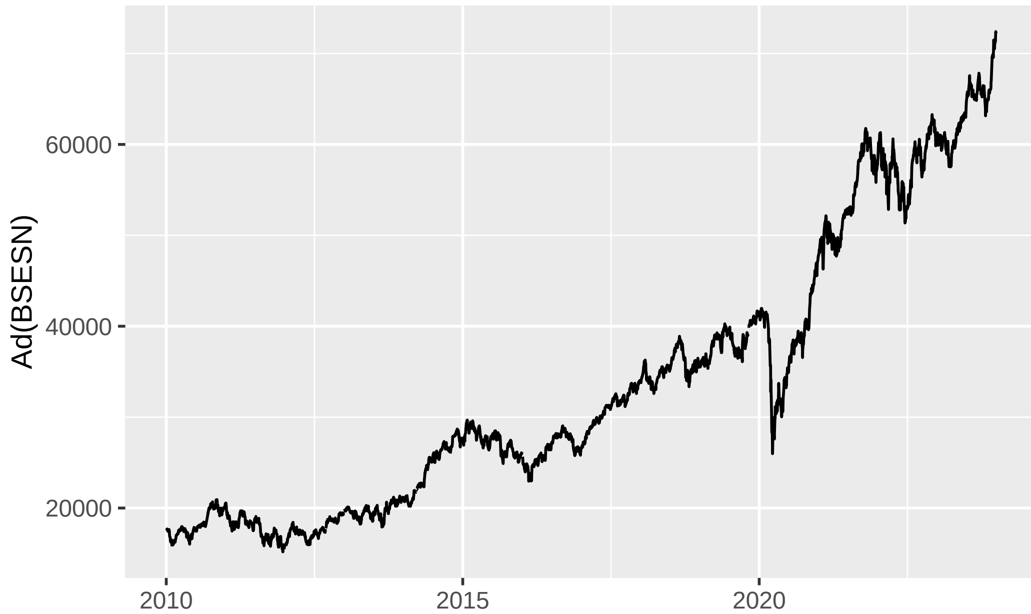
1.3.1 BSE SENSEX 30 Index Prices

From 2010 to 2024 start

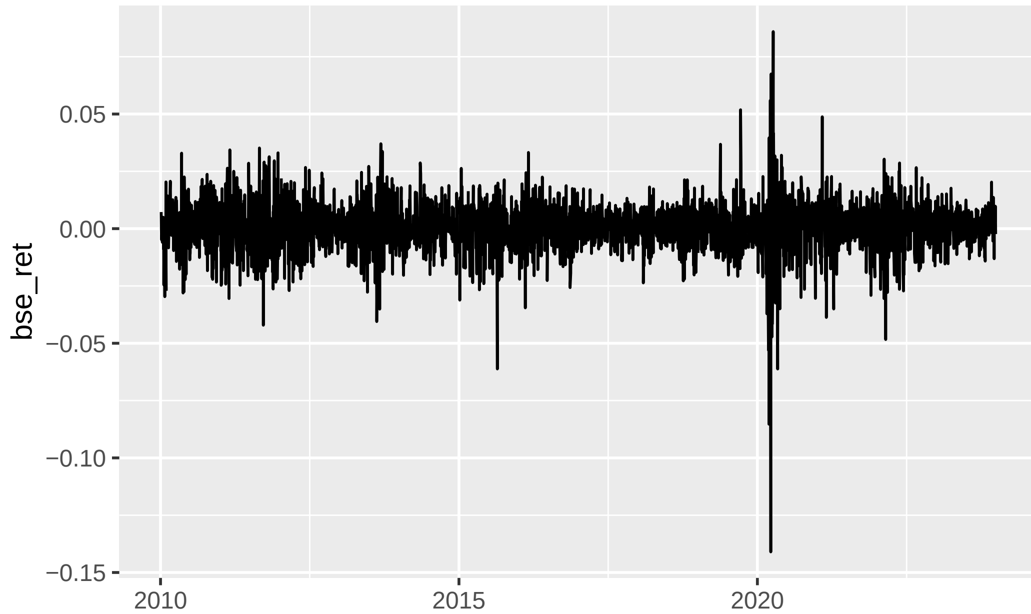
```r
getSymbols('^BSESN', from='2010-01-01', to='2024-01-01')
```

```
[1] "BSESN"
```

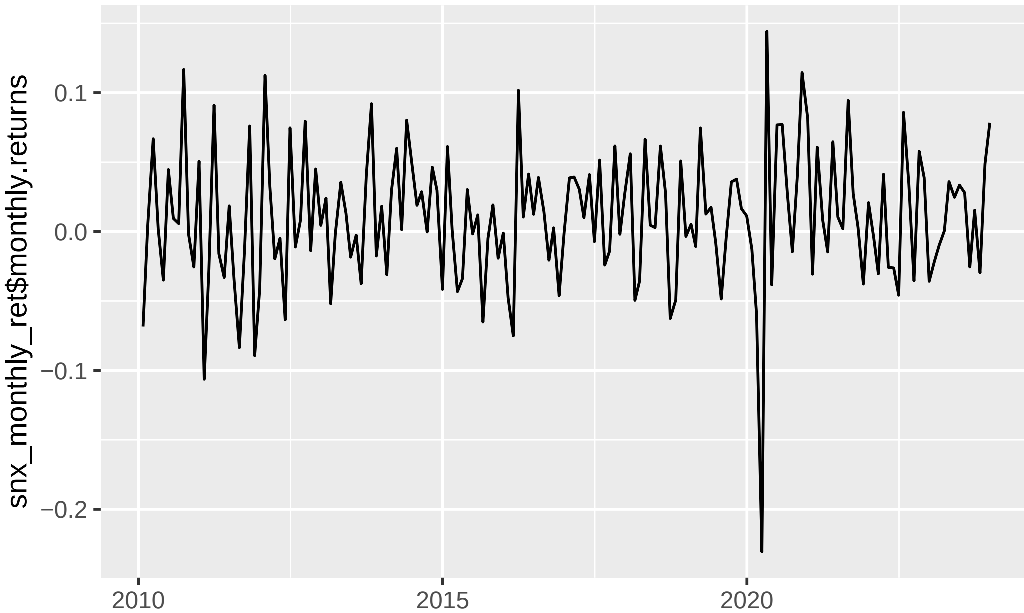
```r
BSESN <- align.time(BSESN, n = 1)
BSESN<-align.time(BSESN,n=1)

library(ggplot2)
ggplot(data=BSESN,aes(x=index(BSESN), y=Ad(BSESN))) +
  geom_line() +
  xlab("")
```




```
bse_ret<-diff(log(Ad(BSESN)))
ggplot(data=bse_ret,aes(x=index(bse_ret),y=bse_ret)) +
  geom_line() +
  xlab("")
```




```r
snx_monthly_ret <- monthlyReturn(Ad(BSESN))
ggplot(data=snx_monthly_ret,aes(x=index(snx_monthly_ret),
                                y=snx_monthly_ret$monthly.returns)) +
  geom_line() +
  xlab("")
```



1.3.2 Monthly CPI-Consumer Price Index (Inflation)

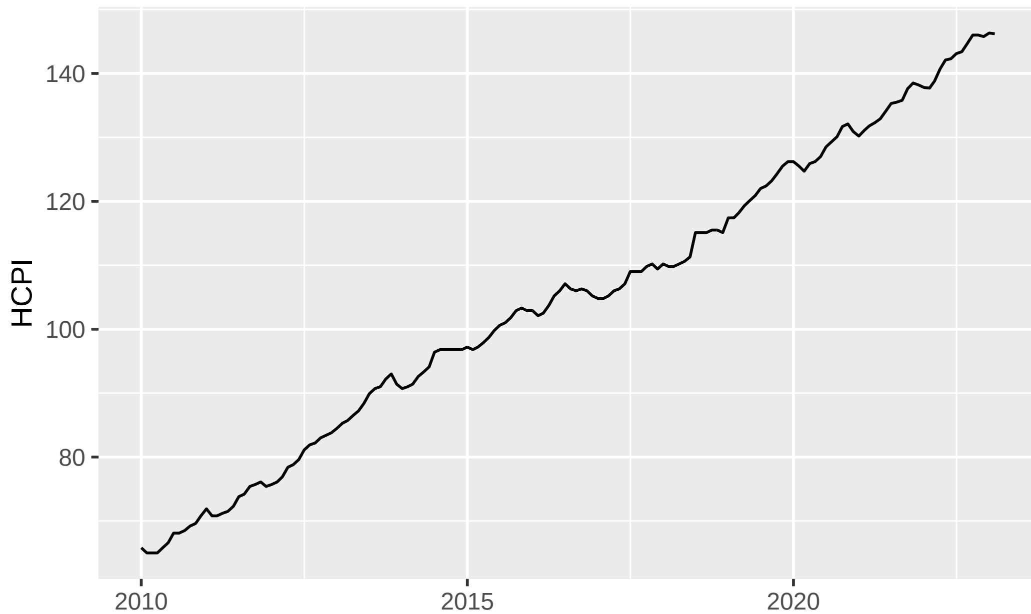
```
library(readxl)
hcpi_monthly <- read_excel("Data/india_hcpi_mothly.xlsx")
head(hcpi_monthly)
```

```
# A tibble: 6 x 1
   HCPI
  <dbl>
1  65.8
2  65
3  65
4  65
5  65.8
6  66.6
```

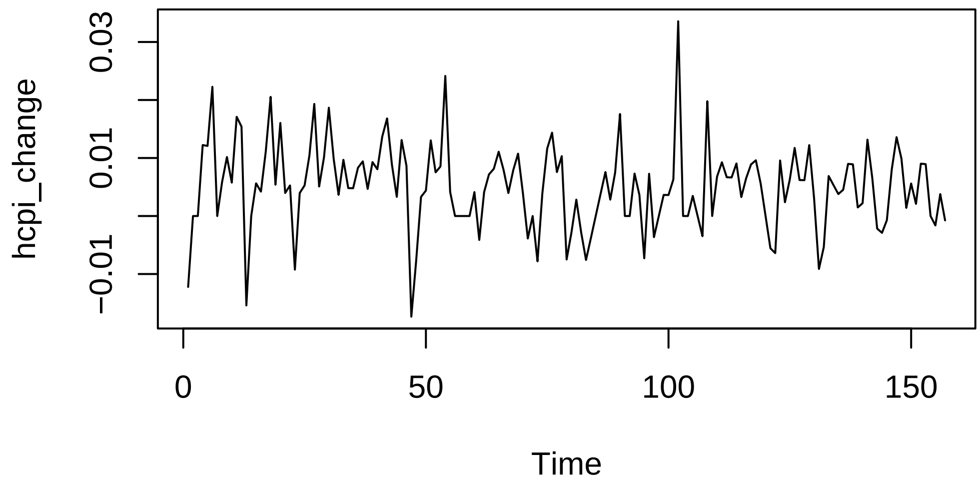
```
start_date <- as.Date("2010-01-01")
end_date <- as.Date("2023-02-01")
dates <- seq(start_date, end_date, by = "1 month")
```

```
hcpi_monthly$Date <- dates
```

```
ggplot(data=hcpi_monthly,aes(x=dates,y=HCPI))+
  geom_line() +
  xlab("")
```




```
hcpi_change<-diff(log(hcpi_monthly$HCPI))
ts.plot(hcpi_change)
```

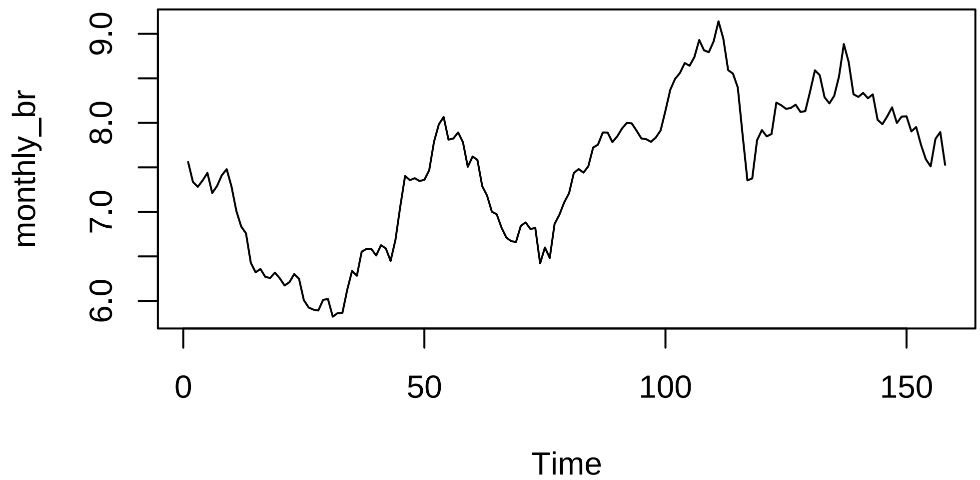


1.3.3 10 Year Government Security Rate

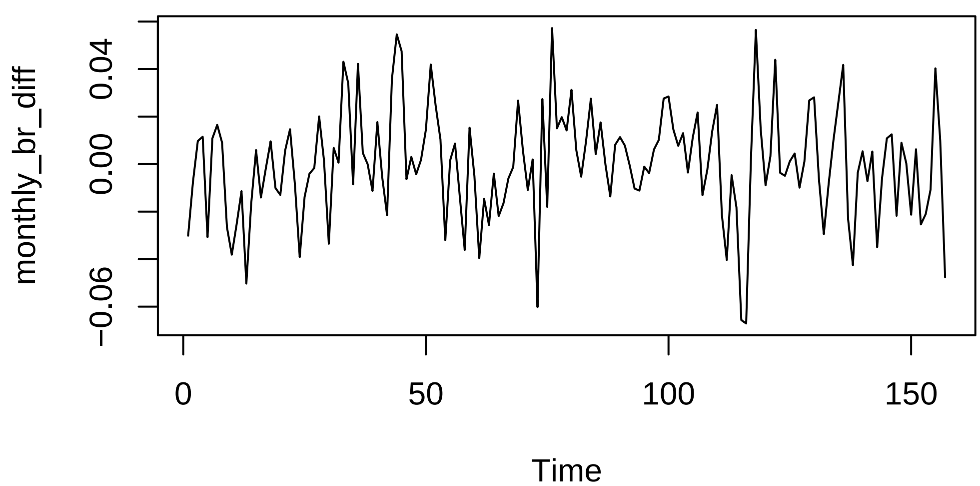
```
bond_rate<-read.csv("Data/bond_rate.csv")
head(bond_rate)
```

```
      Date  Open  High   Low Close
1 02/28/23 7.450 7.461 7.437 7.461
2 02/27/23 7.408 7.448 7.408 7.445
3 02/24/23 7.391 7.466 7.380 7.408
4 02/23/23 7.425 7.425 7.383 7.383
5 02/22/23 7.389 7.429 7.389 7.429
6 02/21/23 7.372 7.389 7.372 7.389
```

```
bond_rate$group <- rep(1:(nrow(bond_rate) %/% 21), each = 21,
                       length.out = nrow(bond_rate))

monthly_br <- tapply(bond_rate$Close, bond_rate$group, mean)

ts.plot(monthly_br)
```




```
monthly_br_diff<-diff(log(monthly_br))
ts.plot(monthly_br_diff)
```



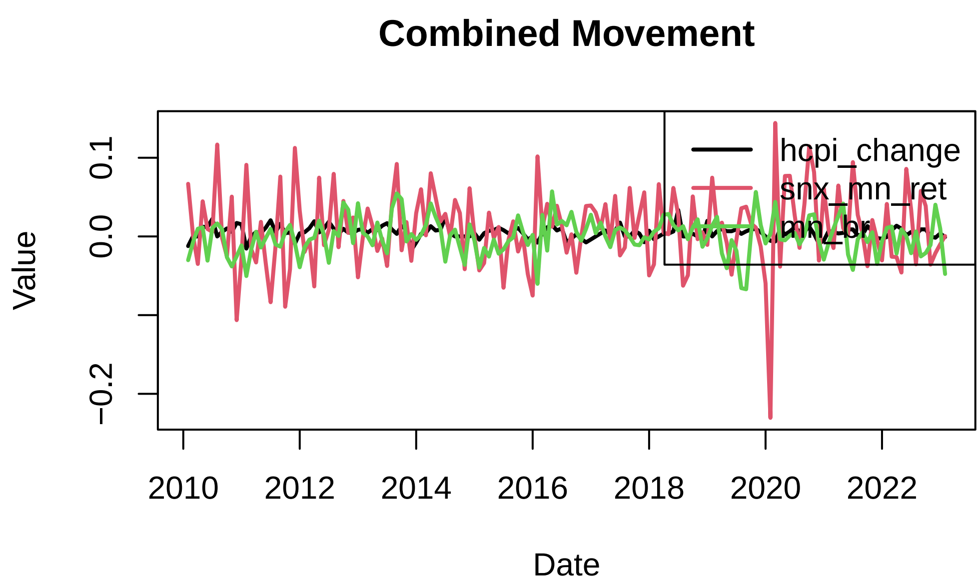
Some minor Adjustments:

```
snx_mn_ret<-snx_monthly_ret[2:length(hcpi_monthly$HCPI)+1]
mn_br<-monthly_br_diff[1:length(hcpi_monthly$HCPI)-1]
```

2 Model Fitting

Data Together:

```
hcpi_ts <- ts(hcpi_change, start = c(2010, 02, 01), frequency = 12)
snx_mn_ret_ts <- ts(snx_mn_ret, start = c(2010, 02), frequency = 12)
mn_br_ts <- ts(mn_br, start = c(2010, 02), frequency = 12)

# Plot the time series
ts.plot(hcpi_ts, snx_mn_ret_ts, mn_br_ts, col = 1:3, lwd = 2,
        main = "Combined Movement", xlab = "Date", ylab = "Value")
legend("topright", legend = c("hcpi_change", "snx_mn_ret", "mn_br"),
       col = 1:3, lwd = 2)
```



2.1 Stationarity and Seasonality Tests

```r
library(fUnitRoots)
adfTest(hcpi_change, type="c")
```

```
Title:
 Augmented Dickey-Fuller Test

Test Results:
  PARAMETER:
    Lag Order: 1
  STATISTIC:
    Dickey-Fuller: -8.2783
  P VALUE:
    0.01

Description:
 Wed Apr 24 11:42:06 2024 by user: rish
```

```r
adfTest(snx_mn_ret, type="c")
```

```
Title:
 Augmented Dickey-Fuller Test

Test Results:
  PARAMETER:
    Lag Order: 1
  STATISTIC:
    Dickey-Fuller: -10.6159
  P VALUE:
    0.01

Description:
 Wed Apr 24 11:42:06 2024 by user: rish
```

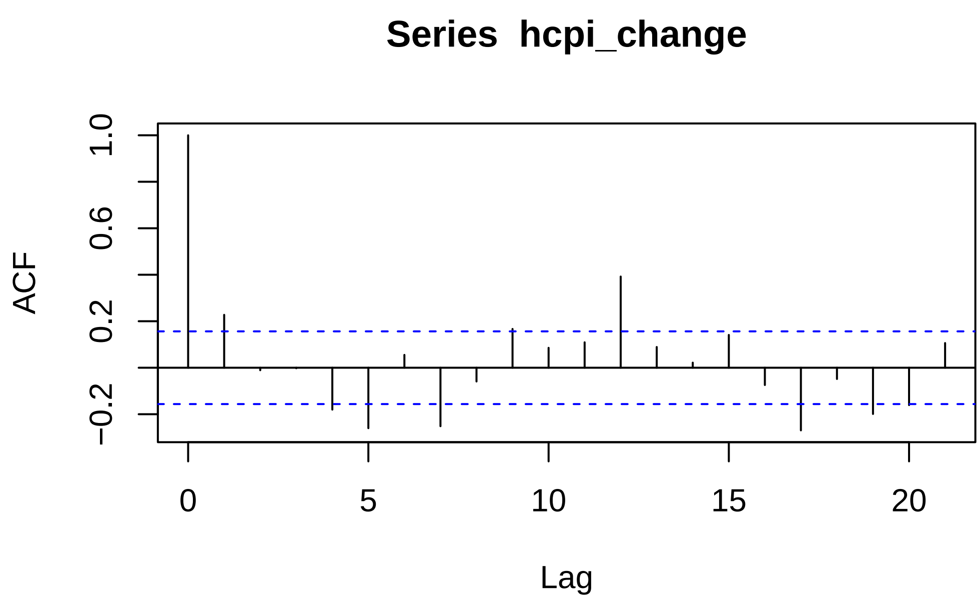
```r
adfTest(mn_br, type="c")
```

```
Title:
```

```
 Augmented Dickey-Fuller Test

Test Results:
  PARAMETER:
    Lag Order: 1
  STATISTIC:
    Dickey-Fuller: -8.4445
  P VALUE:
    0.01

Description:
 Wed Apr 24 11:42:06 2024 by user: rish
```

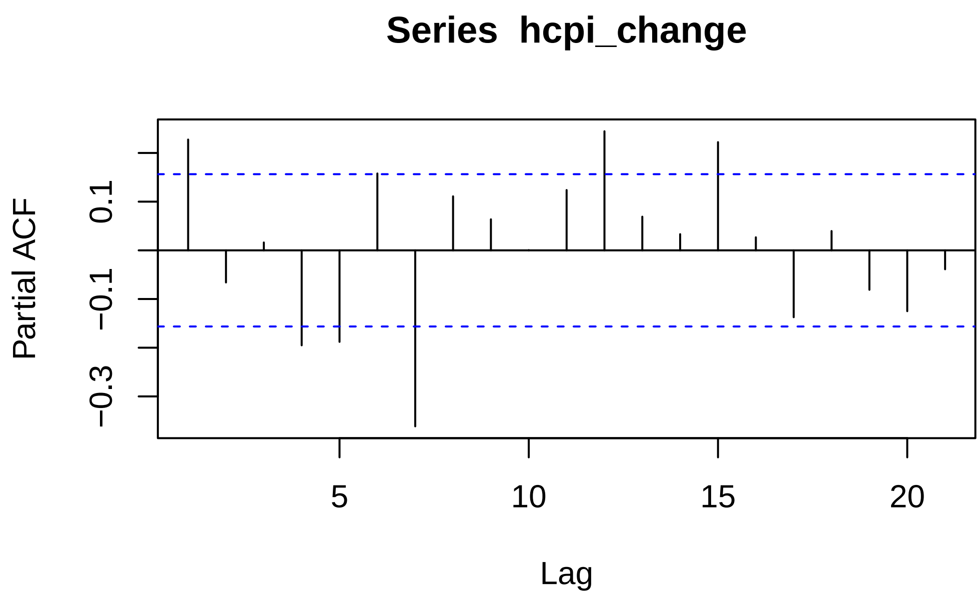
The p-value for all our variables are very low hence we can reject NULL hypothesis of them being non-stationary.

```r
acf(hcpi_change)
```



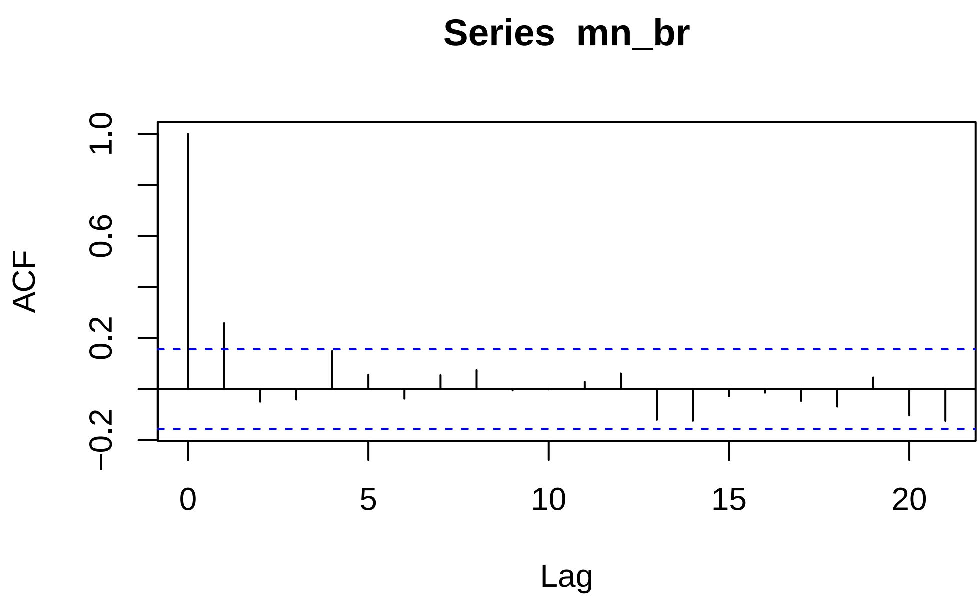
There seems to be some seasonality present

```r
pacf(hcpi_change)
```



Series hcpi_change
Partial ACF
−0.3
−0.1
0.1
5
10
15
20
Lag

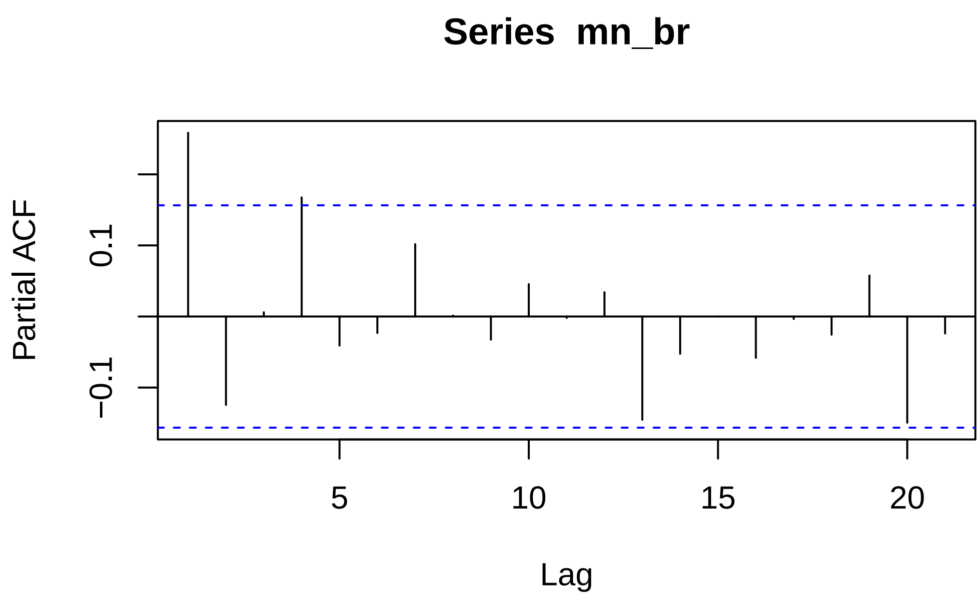

```r
acf(mn_br)
```



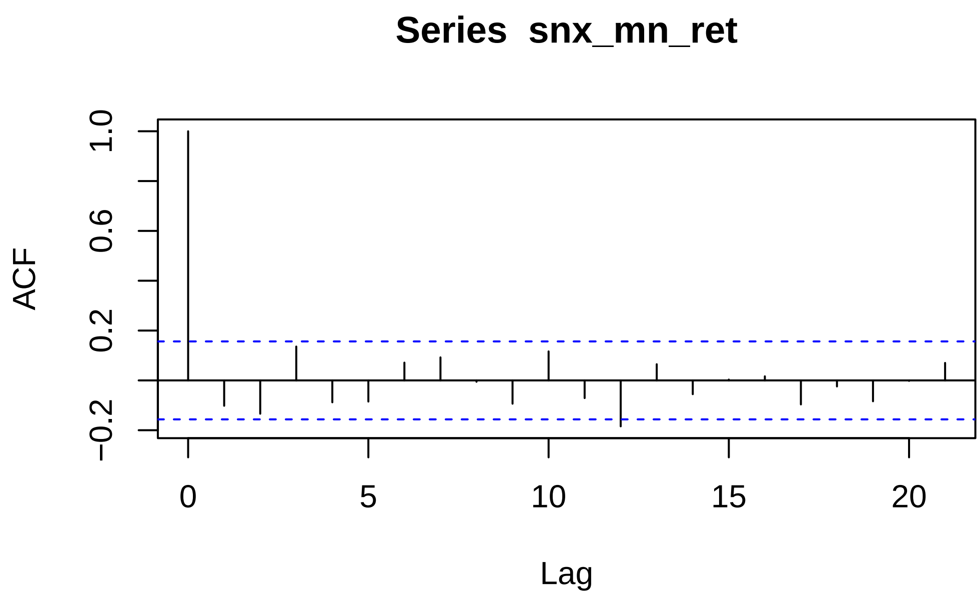
Series mn_br
ACF
−0.2
0.2
0.6
1.0
0
5
10
15
20
Lag

No seasonality in Bond Rates

```
pacf(mn_br)
```




```
acf(snx_mn_ret)
```

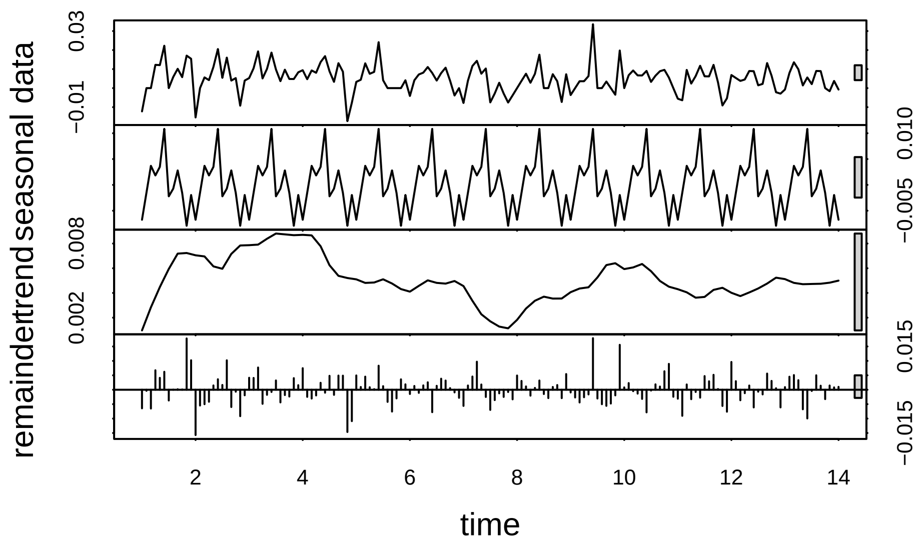


No seasonality here.

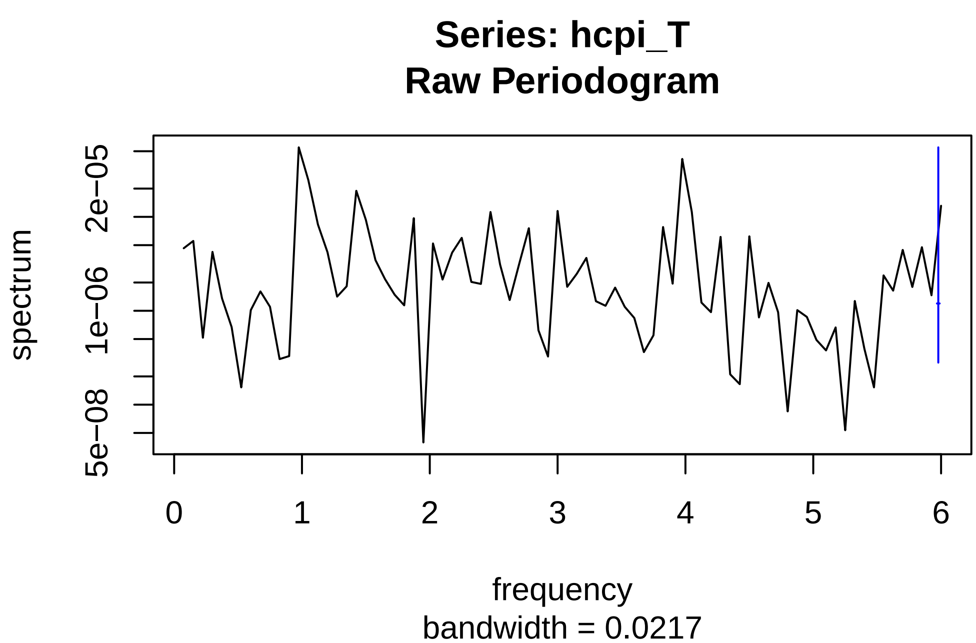
So, there is a seasonality component in CPI.

2.1.1 Quantitative Assessment for Seasonality in CPI

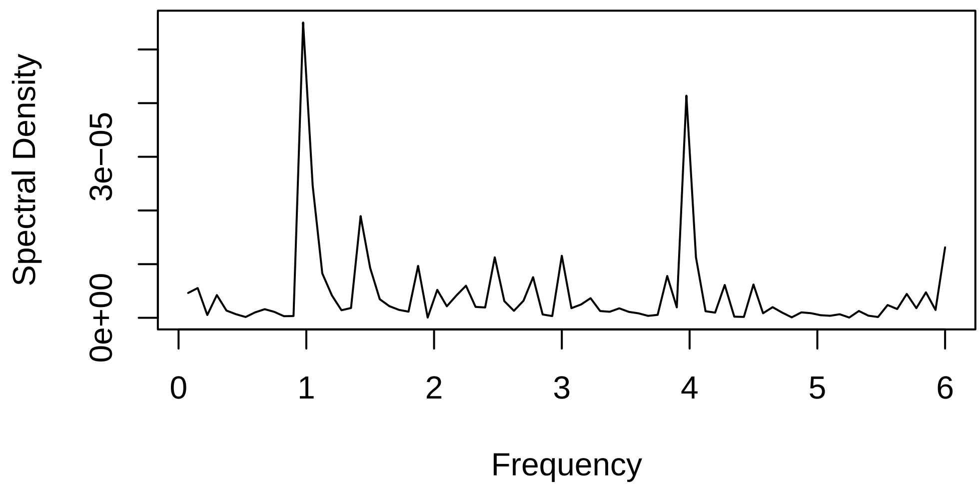
```
hcpi_T <- ts(hcpi_change, frequency = 12)
stl_result <- stl(hcpi_T, s.window = "periodic")
plot(stl_result)
```




```
spec_pgram <- spec.pgram(hcpi_T)
```



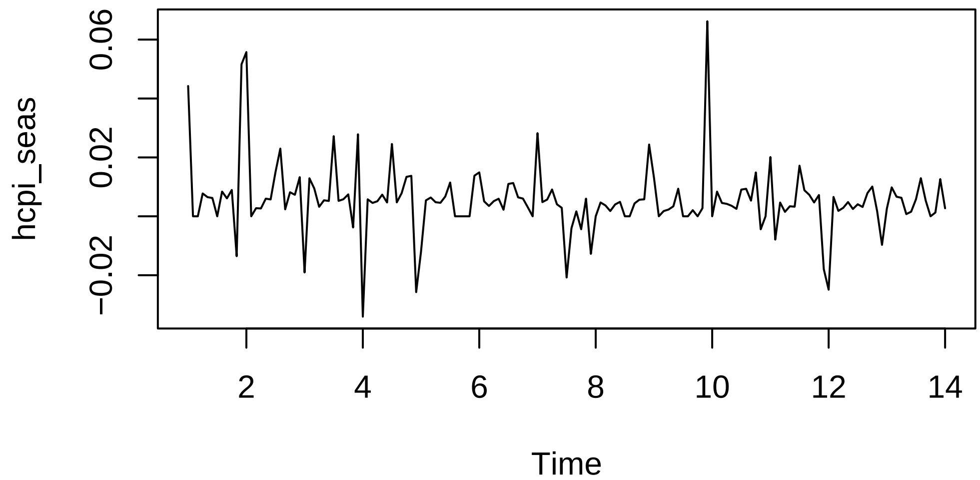
```
plot(spec_pgram$freq, spec_pgram$spec, type = "l", xlab = "Frequency", ylab = "Spectral De
```



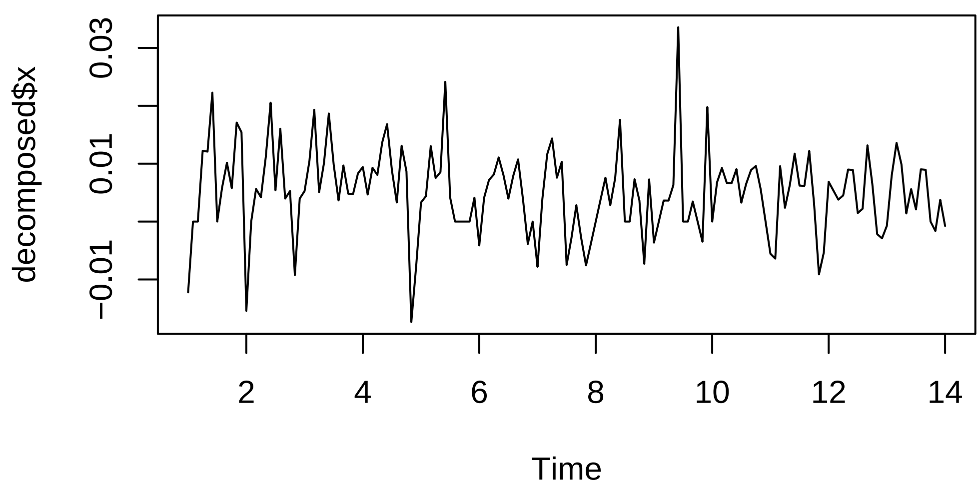
The periodogram has peaks at Freq=1 and 4, indicating yearly or quarterly seasonality.

```
hcpi_change_new<-diff(hcpi_change,lag=12)
hcpi_new_ts <- ts(hcpi_change_new, start = c(2010, 02, 01), frequency = 12)
```

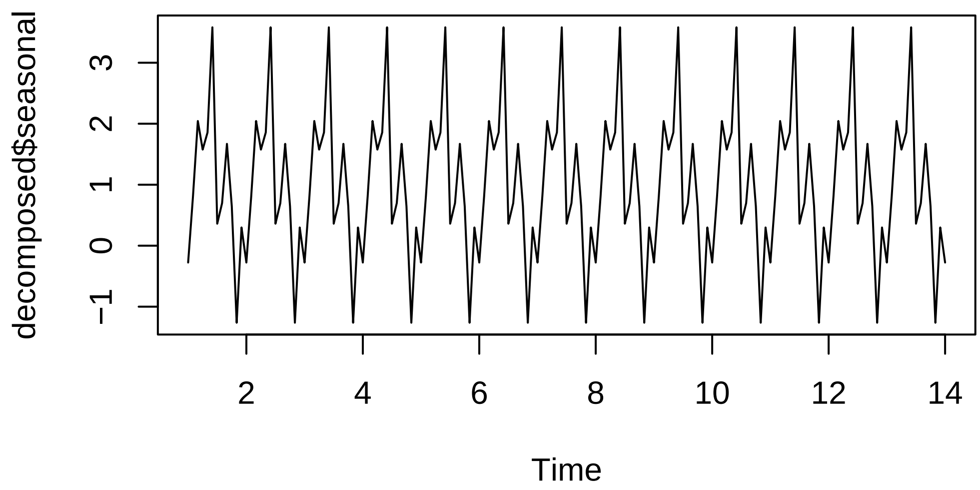
```
decomposed <- decompose(hcpi_T, type = "multiplicative")

# Extract the seasonally adjusted component
hcpi_seas <- decomposed$x / decomposed$seasonal
ts.plot(hcpi_seas)
```




```
ts.plot(decomposed$x)
```



```
ts.plot(decomposed$seasonal)
```



2.2 Models

3 Models, 1 normal VAR 1 seasonal VAR with yearly seasonality, and one seasonality decomposed data run Seasonal VAR model.

```
df_list<-list(snx_mn_ret_ts,mn_br_ts,hcpi_ts)
df_2d <- data.frame(Values = df_list)
colnames(df_2d)<-c("SNX","BR","CPI")
df_list_2<-list(snx_mn_ret_ts[13:length(snx_mn_ret_ts)],
                mn_br_ts[13:length(snx_mn_ret_ts)],hcpi_new_ts)
df_2d_2 <- data.frame(Values = df_list_2)
colnames(df_2d_2)<-c("SNX","BR","CPI")
df_list_3<-list(snx_mn_ret_ts,mn_br_ts,hcpi_seas)
df_2d_3 <- data.frame(Values = df_list_3)
colnames(df_2d_3)<-c("SNX","BR","CPI")
```

```
basic_model<-VARselect(df_2d, lag.max=14)
summary(basic_model)
```

```
          Length Class  Mode
selection  4      -none- numeric
criteria  56      -none- numeric
```

Seasonal Model:

```r
basic_2<-VARselect(df_2d_2, lag.max=14)
summary(basic_2)
```

```
          Length Class  Mode
selection  4      -none- numeric
criteria  56      -none- numeric
```

```r
basic_3<-VARselect(df_2d_3, lag.max=14)
summary(basic_3)
```

```
          Length Class  Mode
selection  4      -none- numeric
criteria  56      -none- numeric
```

The optimal lag here is 4.

Therefore:

$$\mathsf{SNX}_t = \alpha_{\mathsf{SNX},0} + \sum_{i=1}^{4} \alpha_{\mathsf{SNX},i}\mathsf{SNX}_{t-i} + \sum_{i=1}^{4} \beta_{\mathsf{SNX},i}\mathsf{BR}_{t-i} + \sum_{i=1}^{4} \gamma_{\mathsf{SNX},i}\mathsf{CPI}_{t-i} + \epsilon_{\mathsf{SNX},t}$$

$$\mathsf{BR}_t = \alpha_{\mathsf{BR},0} + \sum_{i=1}^{4} \alpha_{\mathsf{BR},i}\mathsf{SNX}_{t-i} + \sum_{i=1}^{4} \beta_{\mathsf{BR},i}\mathsf{BR}_{t-i} + \sum_{i=1}^{4} \gamma_{\mathsf{BR},i}\mathsf{CPI}_{t-i} + \epsilon_{\mathsf{BR},t}$$

$$\mathsf{CPI}_t = \alpha_{\mathsf{CPI},0} + \sum_{i=1}^{4} \alpha_{\mathsf{CPI},i}\mathsf{SNX}_{t-i} + \sum_{i=1}^{4} \beta_{\mathsf{CPI},i}\mathsf{BR}_{t-i} + \sum_{i=1}^{4} \gamma_{\mathsf{CPI},i}\mathsf{CPI}_{t-i} + \epsilon_{\mathsf{CPI},t}$$

In these equations, $\alpha_{SNX,i}$, $\alpha_{BR,i}$ and $\alpha_{CPI,i}$ represent the coefficients for the lag i of SNX, BR, and CPI respectively in the equation for each variable. Similarly, $\beta_{SNX,i}$, $\beta_{BR,i}$, and $\beta_{CPI,i}$ represent the coefficients for the lag i of the other variables in the system. The error terms are represented by $\epsilon_{SNX,t}$, $\epsilon_{BR,t}$, and $\epsilon_{CPI,t}$ for SNX, BR, and CPI respectively.

```r
m1<-VAR(df_2d,p=4,ic=("AIC"))
summary(m1)
```

```
VAR Estimation Results:
=========================
Endogenous variables: SNX, BR, CPI
Deterministic variables: const
Sample size: 153
Log Likelihood: 1174.66
Roots of the characteristic polynomial:
0.7115 0.7115 0.6836 0.6633 0.6633 0.6282 0.6282 0.6092 0.6092 0.5568 0.3383 0.3383
Call:
VAR(y = df_2d, p = 4, ic = ("AIC"))


Estimation results for equation SNX:
====================================
SNX = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 +

        Estimate Std. Error t value Pr(>|t|)
SNX.l1 -0.092293   0.083411  -1.106   0.2704
BR.l1   0.263479   0.182486   1.444   0.1510
CPI.l1  0.228524   0.580869   0.393   0.6946
SNX.l2 -0.140557   0.084771  -1.658   0.0995 .
BR.l2  -0.138628   0.190875  -0.726   0.4689
CPI.l2 -0.030330   0.590568  -0.051   0.9591
SNX.l3  0.076215   0.085027   0.896   0.3716
BR.l3  -0.043952   0.193912  -0.227   0.8210
CPI.l3 -0.188513   0.592232  -0.318   0.7507
SNX.l4 -0.099143   0.084636  -1.171   0.2434
BR.l4   0.319634   0.186398   1.715   0.0886 .
CPI.l4 -0.543827   0.562280  -0.967   0.3351
const   0.014271   0.006587   2.167   0.0320 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.04868 on 140 degrees of freedom
Multiple R-Squared: 0.08997,    Adjusted R-squared: 0.01196
F-statistic: 1.153 on 12 and 140 DF,  p-value: 0.3228
```

```
Estimation results for equation BR:
===================================
BR = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 + 

         Estimate Std. Error t value Pr(>|t|)
SNX.l1  0.0360584  0.0381801   0.944 0.346578
BR.l1   0.2939061  0.0835305   3.519 0.000586 ***
CPI.l1  0.0920305  0.2658852   0.346 0.729766
SNX.l2  0.0271100  0.0388027   0.699 0.485922
BR.l2  -0.1143688  0.0873706  -1.309 0.192676
CPI.l2  0.1712807  0.2703246   0.634 0.527368
SNX.l3  0.0105067  0.0389200   0.270 0.787592
BR.l3  -0.0487009  0.0887605  -0.549 0.584101
CPI.l3 -0.0470304  0.2710866  -0.173 0.862518
SNX.l4 -0.0405306  0.0387409  -1.046 0.297274
BR.l4   0.2016858  0.0853212   2.364 0.019461 *
CPI.l4 -0.2988185  0.2573761  -1.161 0.247610
const   0.0001309  0.0030150   0.043 0.965423
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.02228 on 140 degrees of freedom
Multiple R-Squared: 0.1421, Adjusted R-squared: 0.06858
F-statistic: 1.933 on 12 and 140 DF,  p-value: 0.03524


Estimation results for equation CPI:
====================================
CPI = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 +

         Estimate Std. Error t value Pr(>|t|)
SNX.l1  0.0273097  0.0118910   2.297  0.02312 *
BR.l1  -0.0160542  0.0260152  -0.617  0.53817
CPI.l1  0.2475202  0.0828088   2.989  0.00331 **
SNX.l2  0.0115608  0.0120849   0.957  0.34041
BR.l2   0.0001887  0.0272112   0.007  0.99448
CPI.l2 -0.0948188  0.0841914  -1.126  0.26200
SNX.l3  0.0033077  0.0121215   0.273  0.78535
BR.l3  -0.0382369  0.0276441  -1.383  0.16881
CPI.l3  0.0884108  0.0844287   1.047  0.29683
SNX.l4  0.0021873  0.0120657   0.181  0.85641
BR.l4  -0.0132881  0.0265729  -0.500  0.61782
```

```
CPI.l4 -0.1830954  0.0801586  -2.284  0.02387 *
const   0.0044896  0.0009390   4.781 4.36e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.006939 on 140 degrees of freedom
Multiple R-Squared: 0.1552, Adjusted R-squared: 0.08274
F-statistic: 2.143 on 12 and 140 DF,  p-value: 0.01777



Covariance matrix of residuals:
           SNX         BR        CPI
SNX  0.0023695 -1.130e-05 -2.850e-05
BR  -0.0000113  4.965e-04  4.607e-06
CPI -0.0000285  4.607e-06  4.816e-05

Correlation matrix of residuals:
         SNX       BR      CPI
SNX  1.00000 -0.01042 -0.08438
BR  -0.01042  1.00000  0.02980
CPI -0.08438  0.02980  1.00000
```

```r
m2<-VAR(df_2d_2,p=4,ic=("AIC"),season=12)
summary(m2)
```

```
VAR Estimation Results:
=========================
Endogenous variables: SNX, BR, CPI
Deterministic variables: const
Sample size: 141
Log Likelihood: 1097.734
Roots of the characteristic polynomial:
0.7973 0.7973 0.7821 0.7821 0.7575 0.5856 0.5096 0.5096 0.447 0.447 0.3638 0.2139
Call:
VAR(y = df_2d_2, p = 4, season = 12L, ic = ("AIC"))


Estimation results for equation SNX:
====================================
```

```
SNX = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 +

        Estimate Std. Error t value Pr(>|t|)
SNX.l1 -0.095147   0.090667  -1.049   0.2961
BR.l1   0.194679   0.203360   0.957   0.3404
CPI.l1 -0.048461   0.570224  -0.085   0.9324
SNX.l2 -0.119292   0.091024  -1.311   0.1926
BR.l2  -0.068457   0.213217  -0.321   0.7487
CPI.l2 -1.360614   0.563662  -2.414   0.0173 *
SNX.l3  0.069411   0.090507   0.767   0.4447
BR.l3  -0.055341   0.217588  -0.254   0.7997
CPI.l3  0.365239   0.570181   0.641   0.5231
SNX.l4 -0.015013   0.089570  -0.168   0.8672
BR.l4   0.328970   0.207007   1.589   0.1147
CPI.l4 -0.863995   0.568448  -1.520   0.1312
const   0.010101   0.004504   2.243   0.0268 *
sd1     0.002557   0.020193   0.127   0.8995
sd2     0.020133   0.020928   0.962   0.3380
sd3     0.024421   0.020964   1.165   0.2464
sd4     0.025181   0.021085   1.194   0.2348
sd5     0.034632   0.020370   1.700   0.0918 .
sd6     0.009833   0.020303   0.484   0.6291
sd7     0.013724   0.020102   0.683   0.4961
sd8     0.032458   0.020442   1.588   0.1150
sd9     0.017789   0.020350   0.874   0.3838
sd10    0.016168   0.020438   0.791   0.4305
sd11    0.018596   0.020258   0.918   0.3605
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.04851 on 117 degrees of freedom
Multiple R-Squared: 0.1554, Adjusted R-squared: -0.01067
F-statistic: 0.9358 on 23 and 117 DF,  p-value: 0.5521


Estimation results for equation BR:
===================================
BR = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 +

         Estimate Std. Error t value Pr(>|t|)
SNX.l1  0.0296898  0.0388966   0.763 0.446820
BR.l1   0.3272141  0.0872429   3.751 0.000276 ***
```

```
CPI.l1  0.0983014  0.2446302   0.402 0.688537
SNX.l2 -0.0133600  0.0390500  -0.342 0.732870
BR.l2  -0.1601888  0.0914718  -1.751 0.082526 .
CPI.l2 -0.0506831  0.2418152  -0.210 0.834349
SNX.l3  0.0356493  0.0388280   0.918 0.360437
BR.l3   0.0040629  0.0933469   0.044 0.965358
CPI.l3  0.2856258  0.2446118   1.168 0.245314
SNX.l4 -0.0311855  0.0384263  -0.812 0.418689
BR.l4   0.2101825  0.0888076   2.367 0.019589 *
CPI.l4 -0.7601036  0.2438684  -3.117 0.002300 **
const   0.0007333  0.0019323   0.379 0.705015
sd1    -0.0120979  0.0086630  -1.397 0.165204
sd2     0.0119983  0.0089783   1.336 0.184022
sd3    -0.0065928  0.0089936  -0.733 0.464993
sd4     0.0123645  0.0090455   1.367 0.174273
sd5    -0.0023683  0.0087389  -0.271 0.786867
sd6    -0.0122864  0.0087103  -1.411 0.161028
sd7     0.0030871  0.0086241   0.358 0.721018
sd8    -0.0054476  0.0087699  -0.621 0.535694
sd9     0.0087216  0.0087302   0.999 0.319849
sd10    0.0054243  0.0087682   0.619 0.537359
sd11   -0.0026310  0.0086906  -0.303 0.762628
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.02081 on 117 degrees of freedom
Multiple R-Squared: 0.3096, Adjusted R-squared: 0.1738
F-statistic: 2.281 on 23 and 117 DF,  p-value: 0.002213


Estimation results for equation CPI:
====================================
CPI = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 +

         Estimate Std. Error t value Pr(>|t|)
SNX.l1  0.0127469  0.0144802   0.880    0.381
BR.l1  -0.0079032  0.0324783  -0.243    0.808
CPI.l1  0.1409729  0.0910697   1.548    0.124
SNX.l2  0.0194229  0.0145373   1.336    0.184
BR.l2  -0.0220624  0.0340527  -0.648    0.518
CPI.l2 -0.1345068  0.0900218  -1.494    0.138
SNX.l3  0.0074539  0.0144547   0.516    0.607
```

```
BR.l3  -0.0441857  0.0347507  -1.272    0.206
CPI.l3 -0.1845339  0.0910628  -2.026    0.045 *
SNX.l4 -0.0064703  0.0143052  -0.452    0.652
BR.l4  -0.0383458  0.0330608  -1.160    0.248
CPI.l4 -0.0765153  0.0907861  -0.843    0.401
const  -0.0003907  0.0007193  -0.543    0.588
sd1     0.0019857  0.0032250   0.616    0.539
sd2     0.0005435  0.0033424   0.163    0.871
sd3     0.0003311  0.0033481   0.099    0.921
sd4     0.0002097  0.0033674   0.062    0.950
sd5    -0.0005357  0.0032533  -0.165    0.869
sd6    -0.0006219  0.0032426  -0.192    0.848
sd7     0.0004939  0.0032105   0.154    0.878
sd8     0.0001796  0.0032648   0.055    0.956
sd9    -0.0009678  0.0032500  -0.298    0.766
sd10   -0.0012919  0.0032642  -0.396    0.693
sd11   -0.0013227  0.0032353  -0.409    0.683
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.007748 on 117 degrees of freedom
Multiple R-Squared: 0.1988, Adjusted R-squared: 0.04126
F-statistic: 1.262 on 23 and 117 DF,  p-value: 0.2093



Covariance matrix of residuals:
           SNX         BR        CPI
SNX  2.353e-03 -4.942e-05 -9.819e-06
BR  -4.942e-05  4.331e-04  1.098e-05
CPI -9.819e-06  1.098e-05  6.003e-05

Correlation matrix of residuals:
         SNX       BR      CPI
SNX  1.00000 -0.04895 -0.02612
BR  -0.04895  1.00000  0.06810
CPI -0.02612  0.06810  1.00000
```

R-squared is improved in our Seasonal Model.

```r
m3<-VAR(df_2d_3,p=4,ic=("AIC"),season=12)
summary(m3)
```

```
VAR Estimation Results:
=========================
Endogenous variables: SNX, BR, CPI
Deterministic variables: const
Sample size: 153
Log Likelihood: 1123.149
Roots of the characteristic polynomial:
0.7766 0.7294 0.7294 0.696 0.696 0.6907 0.6907 0.6553 0.6553 0.5603 0.5462 0.5462
Call:
VAR(y = df_2d_3, p = 4, season = 12L, ic = ("AIC"))


Estimation results for equation SNX:
====================================
SNX = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 +

        Estimate Std. Error t value Pr(>|t|)
SNX.l1 -0.094842   0.086254  -1.100   0.2736
BR.l1   0.270139   0.195645   1.381   0.1697
CPI.l1  0.712631   0.375524   1.898   0.0600 .
SNX.l2 -0.113580   0.086285  -1.316   0.1904
BR.l2  -0.066909   0.208028  -0.322   0.7482
CPI.l2 -0.121891   0.364014  -0.335   0.7383
SNX.l3  0.090307   0.086491   1.044   0.2984
BR.l3  -0.095736   0.211324  -0.453   0.6513
CPI.l3 -0.294559   0.360127  -0.818   0.4149
SNX.l4 -0.106151   0.086725  -1.224   0.2232
BR.l4   0.415564   0.206398   2.013   0.0462 *
CPI.l4  0.113039   0.348364   0.324   0.7461
const   0.008990   0.005919   1.519   0.1312
sd1     0.003091   0.019976   0.155   0.8773
sd2     0.020170   0.020162   1.000   0.3190
sd3     0.019850   0.020563   0.965   0.3362
sd4     0.019310   0.020549   0.940   0.3491
sd5     0.029832   0.019865   1.502   0.1356
sd6     0.008801   0.019775   0.445   0.6570
sd7     0.019901   0.019565   1.017   0.3110
sd8     0.026596   0.019979   1.331   0.1855
sd9     0.014305   0.019755   0.724   0.4703
```

```
sd10    0.017611   0.019737   0.892   0.3739
sd11    0.006000   0.019662   0.305   0.7607
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.04918 on 129 degrees of freedom
Multiple R-Squared: 0.144,  Adjusted R-squared: -0.00866
F-statistic: 0.9433 on 23 and 129 DF,  p-value: 0.5421


Estimation results for equation BR:
===================================
BR = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 + 

         Estimate Std. Error t value Pr(>|t|)
SNX.l1  0.0276540  0.0381820   0.724 0.470213
BR.l1   0.3379145  0.0866065   3.902 0.000153 ***
CPI.l1  0.0732408  0.1662335   0.441 0.660248
SNX.l2  0.0274930  0.0381959   0.720 0.472956
BR.l2  -0.1449086  0.0920879  -1.574 0.118032
CPI.l2  0.0271551  0.1611382   0.169 0.866438
SNX.l3  0.0247817  0.0382871   0.647 0.518613
BR.l3  -0.0040304  0.0935471  -0.043 0.965701
CPI.l3 -0.1049733  0.1594176  -0.658 0.511403
SNX.l4 -0.0295169  0.0383905  -0.769 0.443381
BR.l4   0.1954913  0.0913663   2.140 0.034266 *
CPI.l4 -0.1655061  0.1542105  -1.073 0.285163
const   0.0006181  0.0026201   0.236 0.813877
sd1    -0.0144693  0.0088428  -1.636 0.104219
sd2     0.0126482  0.0089250   1.417 0.158844
sd3    -0.0041272  0.0091025  -0.453 0.651012
sd4     0.0120095  0.0090966   1.320 0.189099
sd5    -0.0041612  0.0087935  -0.473 0.636864
sd6    -0.0096040  0.0087537  -1.097 0.274623
sd7     0.0022950  0.0086608   0.265 0.791444
sd8    -0.0042640  0.0088443  -0.482 0.630537
sd9     0.0067627  0.0087448   0.773 0.440739
sd10    0.0030485  0.0087371   0.349 0.727726
sd11   -0.0026998  0.0087038  -0.310 0.756917
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.02177 on 129 degrees of freedom
Multiple R-Squared: 0.2453, Adjusted R-squared: 0.1107
F-statistic: 1.823 on 23 and 129 DF,  p-value: 0.01915


Estimation results for equation CPI:
====================================
CPI = SNX.l1 + BR.l1 + CPI.l1 + SNX.l2 + BR.l2 + CPI.l2 + SNX.l3 + BR.l3 + CPI.l3 + SNX.l4 +

        Estimate Std. Error t value Pr(>|t|)
SNX.l1 -0.010399   0.019481  -0.534   0.5944
BR.l1  -0.054745   0.044187  -1.239   0.2176
CPI.l1  0.032312   0.084813   0.381   0.7038
SNX.l2 -0.032938   0.019488  -1.690   0.0934 .
BR.l2   0.028548   0.046984   0.608   0.5445
CPI.l2 -0.117267   0.082214  -1.426   0.1562
SNX.l3  0.021637   0.019534   1.108   0.2701
BR.l3  -0.105639   0.047728  -2.213   0.0286 *
CPI.l3 -0.015620   0.081336  -0.192   0.8480
SNX.l4 -0.048993   0.019587  -2.501   0.0136 *
BR.l4  -0.088633   0.046616  -1.901   0.0595 .
CPI.l4 -0.064489   0.078679  -0.820   0.4139
const   0.006948   0.001337   5.197 7.69e-07 ***
sd1    -0.009186   0.004512  -2.036   0.0438 *
sd2    -0.008475   0.004554  -1.861   0.0650 .
sd3    -0.008050   0.004644  -1.733   0.0854 .
sd4    -0.010781   0.004641  -2.323   0.0217 *
sd5    -0.007658   0.004487  -1.707   0.0903 .
sd6    -0.007354   0.004466  -1.647   0.1021
sd7    -0.004026   0.004419  -0.911   0.3640
sd8    -0.005787   0.004512  -1.282   0.2020
sd9    -0.007973   0.004462  -1.787   0.0763 .
sd10   -0.006973   0.004458  -1.564   0.1202
sd11   -0.010937   0.004441  -2.463   0.0151 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.01111 on 129 degrees of freedom
Multiple R-Squared: 0.2104, Adjusted R-squared: 0.0696
F-statistic: 1.494 on 23 and 129 DF,  p-value: 0.08345
```

```
Covariance matrix of residuals:
           SNX         BR        CPI
SNX  2.419e-03 -2.824e-05 -1.672e-05
BR  -2.824e-05  4.740e-04 -1.282e-05
CPI -1.672e-05 -1.282e-05  1.234e-04

Correlation matrix of residuals:
         SNX       BR      CPI
SNX  1.00000 -0.02638 -0.03060
BR  -0.02638  1.00000 -0.05299
CPI -0.03060 -0.05299  1.00000
```

SEASON VAR(4) lag=12

$$
\begin{aligned}
\mathsf{SNX}_t = {} & \alpha_1 + \beta_{11}\mathsf{SNX}_{t-1} + \beta_{12}\mathsf{SNX}_{t-2} + \beta_{13}\mathsf{SNX}_{t-3} + \beta_{14}\mathsf{SNX}_{t-4} + \\
& \gamma_{11}\mathsf{BR}_{t-1} + \gamma_{12}\mathsf{BR}_{t-2} + \gamma_{13}\mathsf{BR}_{t-3} + \gamma_{14}\mathsf{BR}_{t-4} \\
& + \\
& \delta_{11}\mathsf{CPI}_{t-1} + \delta_{12}\mathsf{CPI}_{t-2} + \delta_{13}\mathsf{CPI}_{t-3} + \delta_{14}\mathsf{CPI}_{t-4} + \varepsilon_{1t} \\
\mathsf{BR}_t = {} & \alpha_2 + \beta_{21}\mathsf{SNX}_{t-1} + \beta_{22}\mathsf{SNX}_{t-2} + \beta_{23}\mathsf{SNX}_{t-3} + \beta_{24}\mathsf{SNX}_{t-4} + \\
& \gamma_{21}\mathsf{BR}_{t-1} + \gamma_{22}\mathsf{BR}_{t-2} + \gamma_{23}\mathsf{BR}_{t-3} + \gamma_{24}\mathsf{BR}_{t-4} \\
& + \\
& \delta_{21}\mathsf{CPI}_{t-1} + \delta_{22}\mathsf{CPI}_{t-2} + \delta_{23}\mathsf{CPI}_{t-3} + \delta_{24}\mathsf{CPI}_{t-4} + \varepsilon_{2t} \\
\mathsf{CPI}_t = {} & \alpha_3 + \beta_{31}\mathsf{SNX}_{t-1} + \beta_{32}\mathsf{SNX}_{t-2} + \beta_{33}\mathsf{SNX}_{t-3} + \beta_{34}\mathsf{SNX}_{t-4} + \\
& \gamma_{31}\mathsf{BR}_{t-1} + \gamma_{32}\mathsf{BR}_{t-2} + \gamma_{33}\mathsf{BR}_{t-3} + \gamma_{34}\mathsf{BR}_{t-4} \\
& + \\
& \delta_{31}\mathsf{CPI}_{t-1} + \delta_{32}\mathsf{CPI}_{t-2} + \delta_{33}\mathsf{CPI}_{t-3} + \delta_{34}\mathsf{CPI}_{t-4} + \varepsilon_{3t}
\end{aligned}
$$

The coefficients:

```r
m1$varresult
```

```
$SNX

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
```

```
  SNX.l1     BR.l1    CPI.l1    SNX.l2     BR.l2    CPI.l2    SNX.l3     BR.l3
-0.09229   0.26348   0.22852  -0.14056  -0.13863  -0.03033   0.07622  -0.04395
  CPI.l3    SNX.l4     BR.l4    CPI.l4     const
-0.18851  -0.09914   0.31963  -0.54383   0.01427


$BR

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
    SNX.l1       BR.l1      CPI.l1      SNX.l2       BR.l2      CPI.l2
 0.0360584   0.2939061   0.0920305   0.0271100  -0.1143688   0.1712807
    SNX.l3       BR.l3      CPI.l3      SNX.l4       BR.l4      CPI.l4
 0.0105067  -0.0487009  -0.0470304  -0.0405306   0.2016858  -0.2988185
     const
 0.0001309


$CPI

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
    SNX.l1       BR.l1      CPI.l1      SNX.l2       BR.l2      CPI.l2
 0.0273097  -0.0160542   0.2475202   0.0115608   0.0001887  -0.0948188
    SNX.l3       BR.l3      CPI.l3      SNX.l4       BR.l4      CPI.l4
 0.0033077  -0.0382369   0.0884108   0.0021873  -0.0132881  -0.1830954
     const
 0.0044896
```

```
m2$varresult
```

```
$SNX

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
   SNX.l1      BR.l1     CPI.l1     SNX.l2      BR.l2     CPI.l2     SNX.l3
```

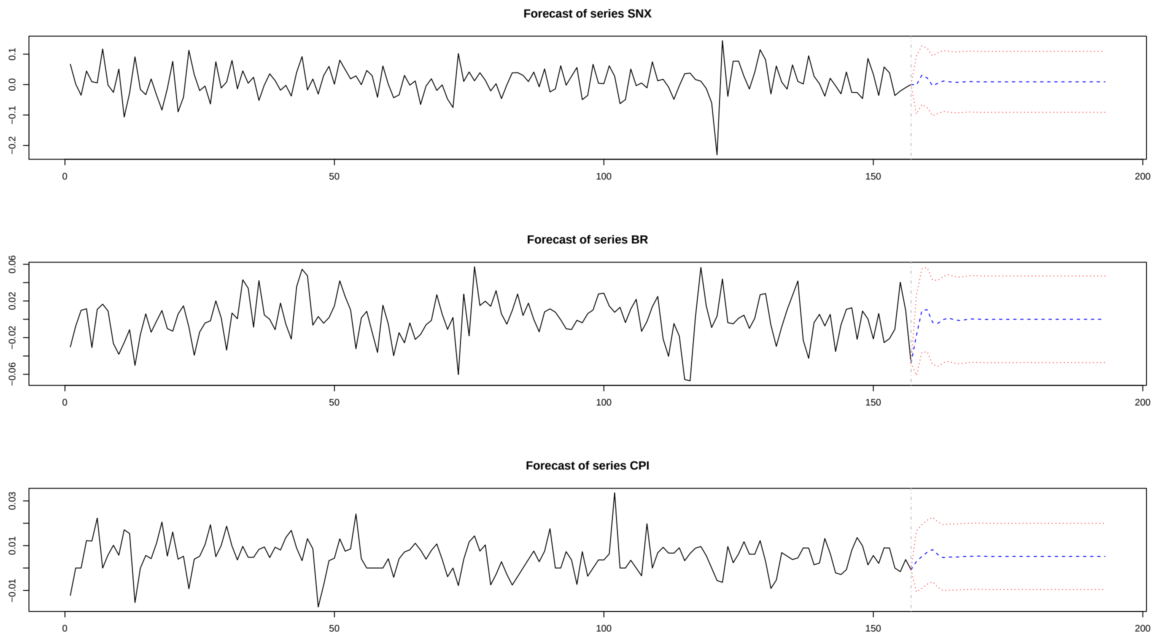
```
-0.095147   0.194679  -0.048461  -0.119292  -0.068457  -1.360614   0.069411
    BR.l3     CPI.l3     SNX.l4      BR.l4     CPI.l4      const        sd1
-0.055341   0.365239  -0.015013   0.328970  -0.863995   0.010101   0.002557
      sd2        sd3        sd4        sd5        sd6        sd7        sd8
 0.020133   0.024421   0.025181   0.034632   0.009833   0.013724   0.032458
      sd9       sd10       sd11
 0.017789   0.016168   0.018596


$BR

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
    SNX.l1       BR.l1      CPI.l1      SNX.l2       BR.l2      CPI.l2
 0.0296898   0.3272141   0.0983014  -0.0133600  -0.1601888  -0.0506831
    SNX.l3       BR.l3      CPI.l3      SNX.l4       BR.l4      CPI.l4
 0.0356493   0.0040629   0.2856258  -0.0311855   0.2101825  -0.7601036
     const         sd1         sd2         sd3         sd4         sd5
 0.0007333  -0.0120979   0.0119983  -0.0065928   0.0123645  -0.0023683
       sd6         sd7         sd8         sd9        sd10        sd11
-0.0122864   0.0030871  -0.0054476   0.0087216   0.0054243  -0.0026310


$CPI

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
    SNX.l1       BR.l1      CPI.l1      SNX.l2       BR.l2      CPI.l2
 0.0127469  -0.0079032   0.1409729   0.0194229  -0.0220624  -0.1345068
    SNX.l3       BR.l3      CPI.l3      SNX.l4       BR.l4      CPI.l4
 0.0074539  -0.0441857  -0.1845339  -0.0064703  -0.0383458  -0.0765153
     const         sd1         sd2         sd3         sd4         sd5
-0.0003907   0.0019857   0.0005435   0.0003311   0.0002097  -0.0005357
       sd6         sd7         sd8         sd9        sd10        sd11
-0.0006219   0.0004939   0.0001796  -0.0009678  -0.0012919  -0.0013227
```

```r
m3$varresult
```

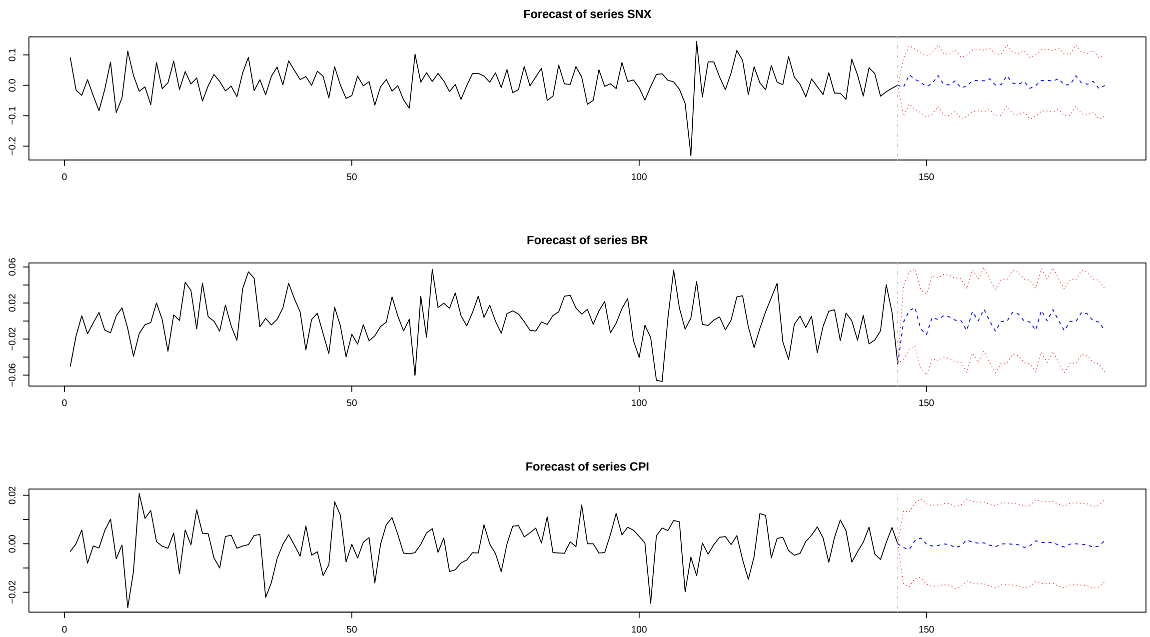
```
$SNX

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
   SNX.l1      BR.l1     CPI.l1     SNX.l2      BR.l2     CPI.l2     SNX.l3
-0.094842   0.270139   0.712631  -0.113580  -0.066909  -0.121891   0.090307
    BR.l3     CPI.l3     SNX.l4      BR.l4     CPI.l4      const        sd1
-0.095736  -0.294559  -0.106151   0.415564   0.113039   0.008990   0.003091
      sd2        sd3        sd4        sd5        sd6        sd7        sd8
 0.020170   0.019850   0.019310   0.029832   0.008801   0.019901   0.026596
      sd9       sd10       sd11
 0.014305   0.017611   0.006000


$BR

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
    SNX.l1       BR.l1      CPI.l1      SNX.l2       BR.l2      CPI.l2
 0.0276540   0.3379145   0.0732408   0.0274930  -0.1449086   0.0271551
    SNX.l3       BR.l3      CPI.l3      SNX.l4       BR.l4      CPI.l4
 0.0247817  -0.0040304  -0.1049733  -0.0295169   0.1954913  -0.1655061
     const         sd1         sd2         sd3         sd4         sd5
 0.0006181  -0.0144693   0.0126482  -0.0041272   0.0120095  -0.0041612
       sd6         sd7         sd8         sd9        sd10        sd11
-0.0096040   0.0022950  -0.0042640   0.0067627   0.0030485  -0.0026998


$CPI

Call:
lm(formula = y ~ -1 + ., data = datamat)

Coefficients:
   SNX.l1      BR.l1     CPI.l1     SNX.l2      BR.l2     CPI.l2     SNX.l3
-0.010399  -0.054745   0.032312  -0.032938   0.028548  -0.117267   0.021637
    BR.l3     CPI.l3     SNX.l4      BR.l4     CPI.l4      const        sd1
-0.105639  -0.015620  -0.048993  -0.088633  -0.064489   0.006948  -0.009186
      sd2        sd3        sd4        sd5        sd6        sd7        sd8
```

```
-0.008475  -0.008050  -0.010781  -0.007658  -0.007354  -0.004026  -0.005787
      sd9       sd10       sd11
-0.007973  -0.006973  -0.010937
```

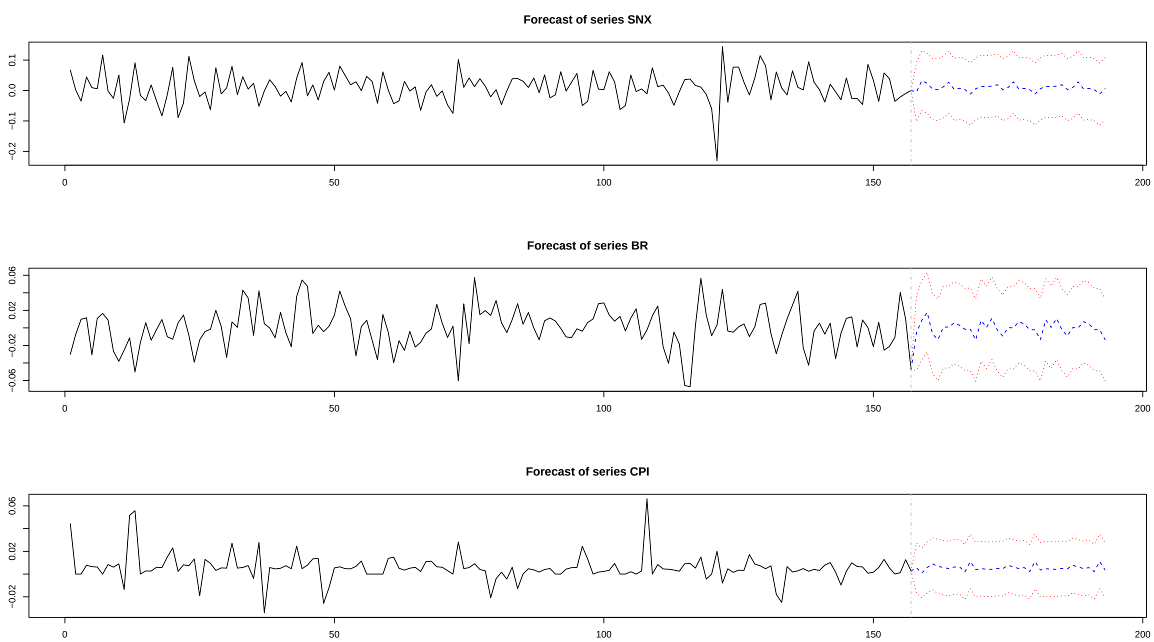
```r
plot(predict(m1,n.ahead=36))
```




```r
plot(predict(m2,n.ahead=36))
```



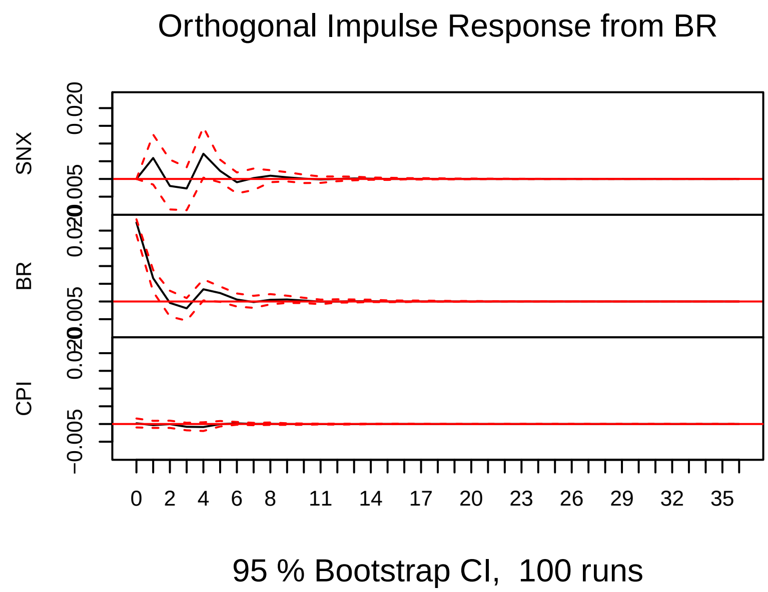

```r
plot(predict(m3,n.ahead=36))
```



3 Impulse response function

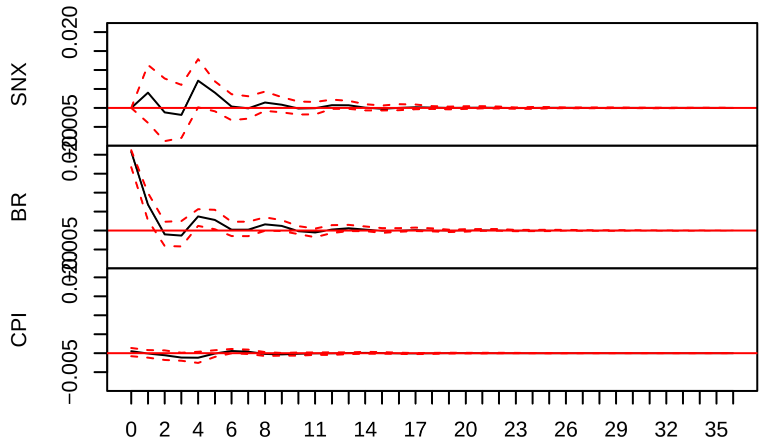
Checking impacts of shocks in Interest Rates on rest 2

```r
ir<-irf(m1, impulse="BR", response=c("SNX","BR","CPI"),n.ahead=36)
plot(ir)
```




```r
ir<-irf(m2, impulse="BR", response=c("SNX","BR","CPI"),n.ahead=36)
plot(ir)
```

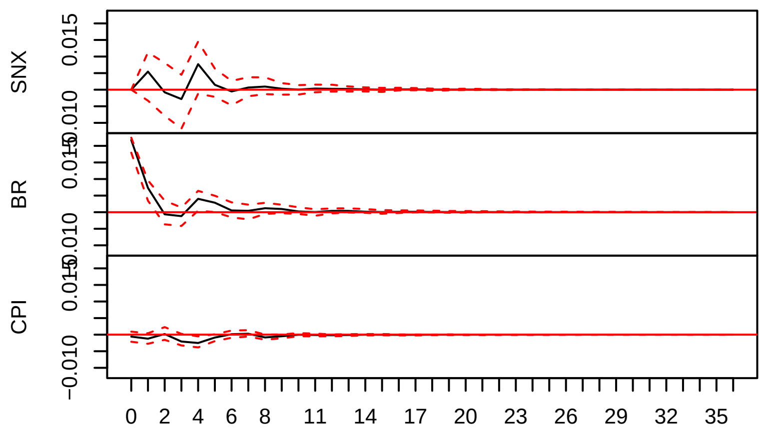
Orthogonal Impulse Response from BR



95 % Bootstrap CI, 100 runs

```r
ir<-irf(m3, impulse="BR", response=c("SNX","BR","CPI"),n.ahead=36)
plot(ir)
```

Orthogonal Impulse Response from BR



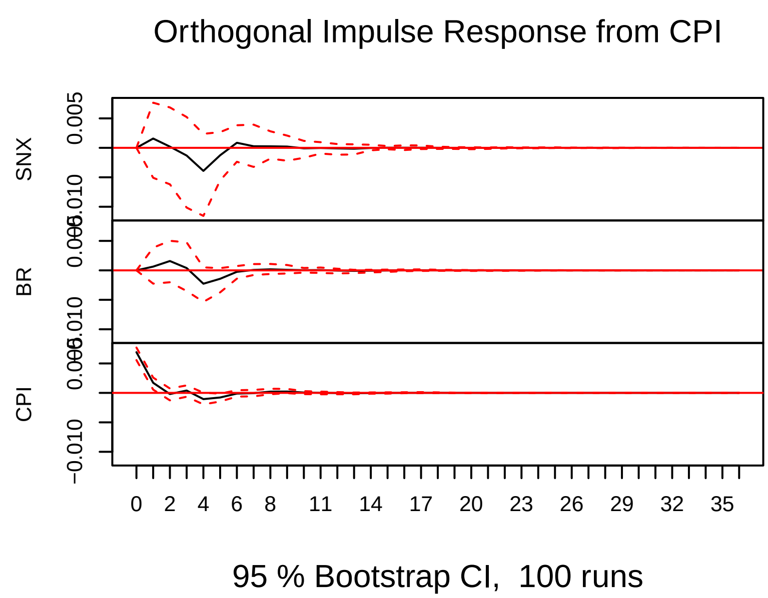
95 % Bootstrap CI, 100 runs

From the plots, shocks in Interest Rates generate high volatility in index prices for around 6-7 months.

Inflation Rate(being endogenous) does still remain quite stable instead of shocks in Interest Rates.

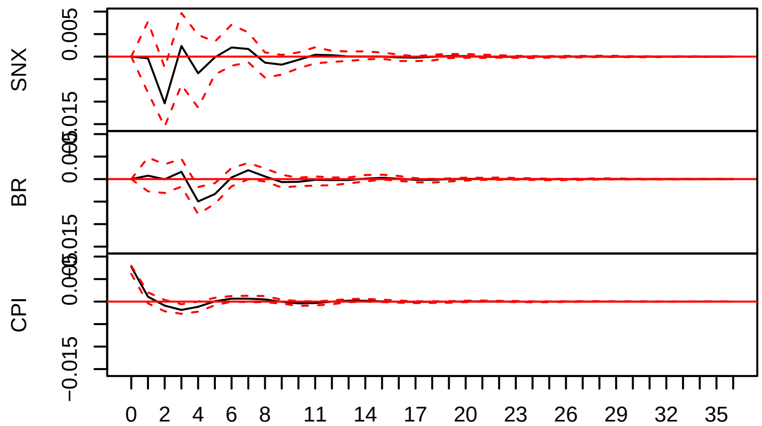
Checking impacts of shocks in CPI on the rest of 2.

```
ir2<-irf(m1, impulse="CPI", response=c("SNX","BR","CPI"),n.ahead=36)
plot(ir2)
```




```
ir2<-irf(m2, impulse="CPI", response=c("SNX","BR","CPI"),n.ahead=36)
plot(ir2)
```

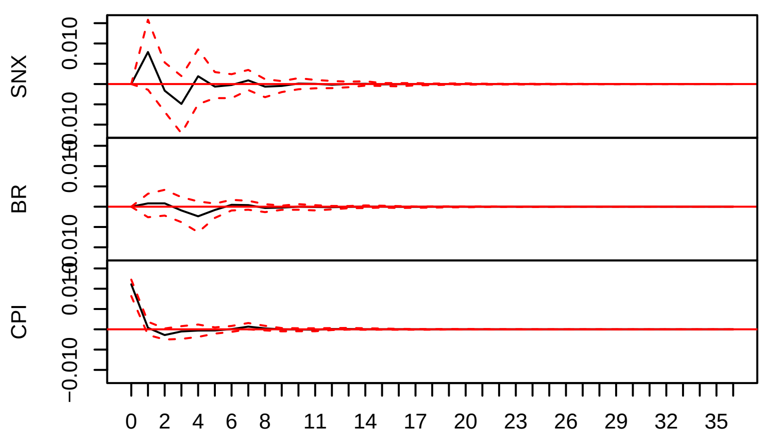
Orthogonal Impulse Response from CPI



95 % Bootstrap CI, 100 runs

```r
ir2<-irf(m3, impulse="CPI", response=c("SNX","BR","CPI"),n.ahead=36)
plot(ir2)
```

Orthogonal Impulse Response from CPI



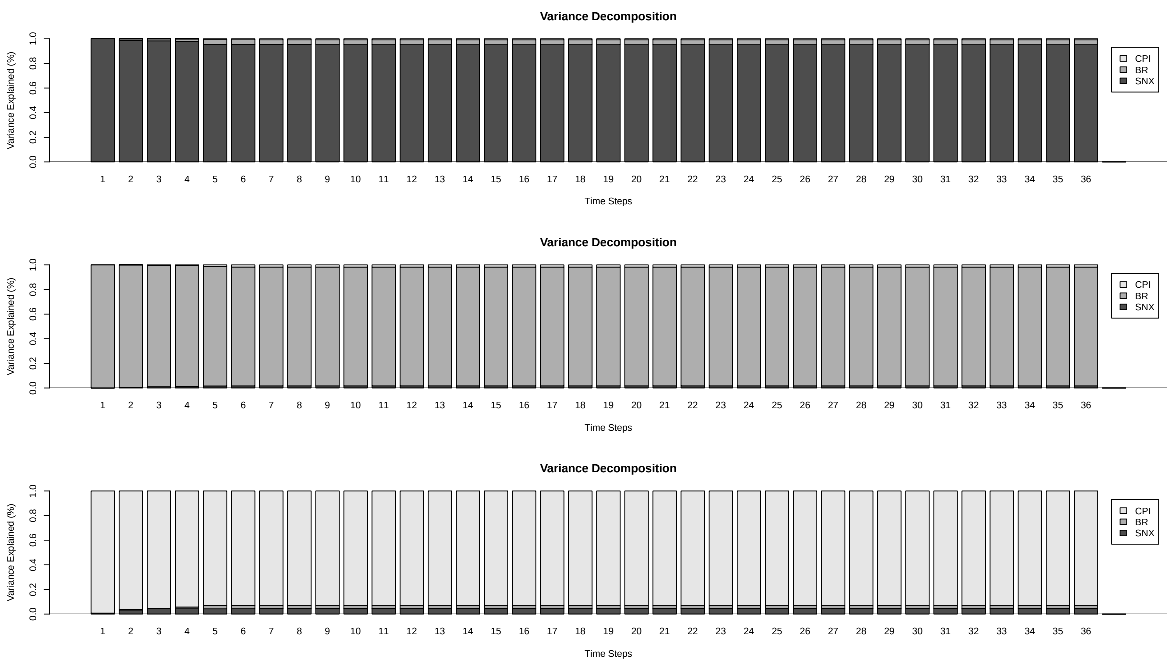
95 % Bootstrap CI, 100 runs

From the plots, shocks in CPI - Inflation, generates volatility in index prices for around 7-9 months.

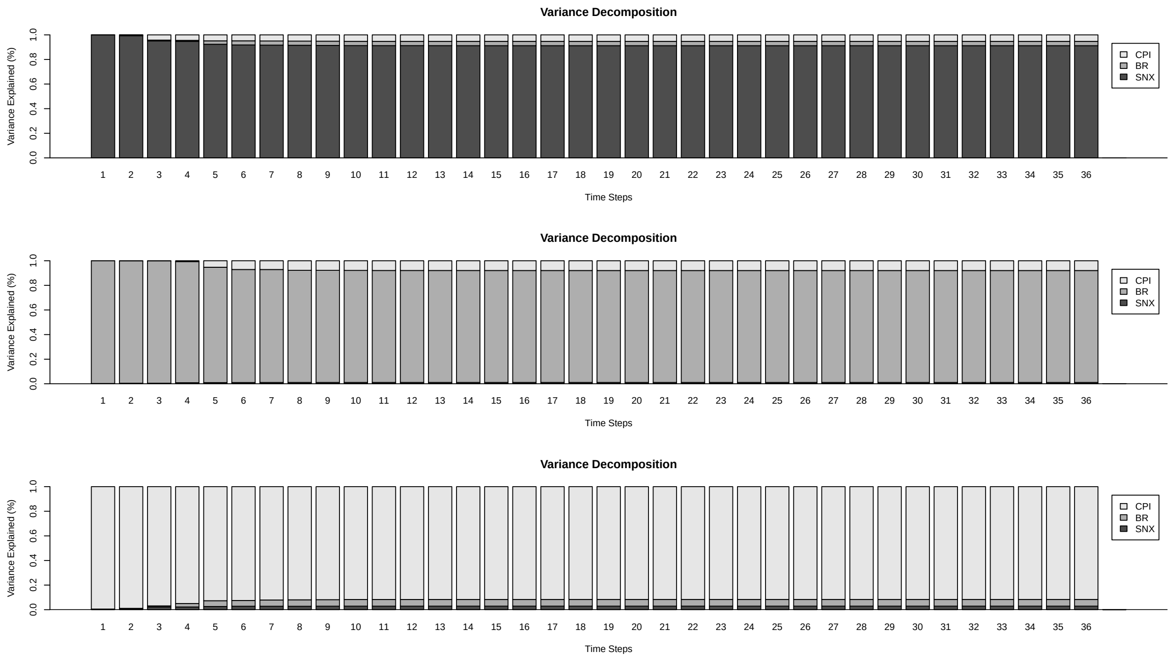
Even the Interest Rates adjust accordingly (effectiveness of monetary policies).

3.1 Variance Decomposition Analysis:

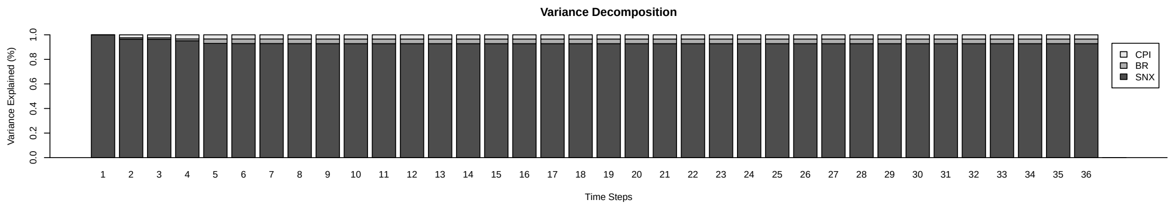
```r
fevd_result <- fevd(m1, n.ahead = 36)
plot(fevd_result, main = "Variance Decomposition",
     ylab = "Variance Explained (%)", xlab = "Time Steps")
```

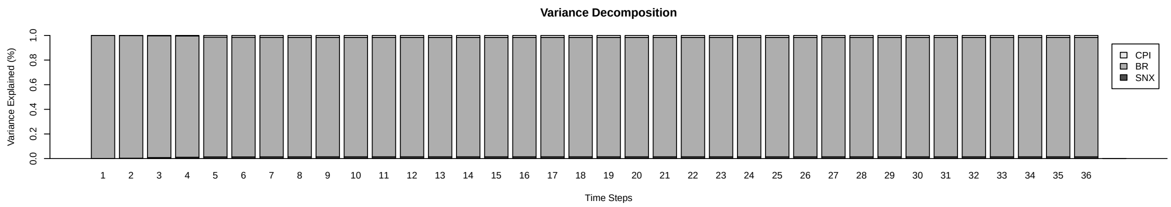


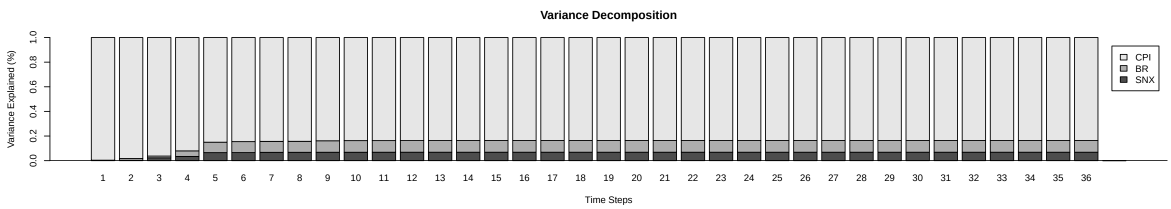

```r
fevd_result <- fevd(m2, n.ahead = 36)
plot(fevd_result, main = "Variance Decomposition",
     ylab = "Variance Explained (%)", xlab = "Time Steps")
```




```r
fevd_result <- fevd(m3, n.ahead = 36)
plot(fevd_result, main = "Variance Decomposition",
     ylab = "Variance Explained (%)", xlab = "Time Steps")
```







3.2 Variance Co-variance Matrix

```r
summary(m1)$covres
```

```
              SNX            BR           CPI
SNX  2.369459e-03 -1.130245e-05 -2.850225e-05
BR  -1.130245e-05  4.964561e-04  4.607230e-06
CPI -2.850225e-05  4.607230e-06  4.815543e-05
```

```r
summary(m2)$covres
```

```
              SNX            BR           CPI
SNX  2.353442e-03 -4.942387e-05 -9.819081e-06
BR  -4.942387e-05  4.331447e-04  1.098154e-05
CPI -9.819081e-06  1.098154e-05  6.002896e-05
```

```r
summary(m3)$covres
```

```
                 SNX               BR             CPI
SNX  2.418919e-03 -2.824292e-05 -1.671628e-05
BR  -2.824292e-05  4.740048e-04 -1.281560e-05
CPI -1.671628e-05 -1.281560e-05  1.233881e-04
```

error correlation:

```r
summary(m1)$corres
```

```
               SNX           BR          CPI
SNX  1.00000000 -0.01042095 -0.08437853
BR  -0.01042095  1.00000000  0.02979730
CPI -0.08437853  0.02979730  1.00000000
```

```r
summary(m2)$corres
```

```
               SNX           BR          CPI
SNX  1.00000000 -0.04895179 -0.02612394
BR  -0.04895179  1.00000000  0.06810300
CPI -0.02612394  0.06810300  1.00000000
```

```r
summary(m3)$corres
```

```
               SNX           BR          CPI
SNX  1.00000000 -0.02637592 -0.03059795
BR  -0.02637592  1.00000000 -0.05299208
CPI -0.03059795 -0.05299208  1.00000000
```

```r
t(chol(summary(m1)$covres))
```

```
                 SNX            BR          CPI
SNX  0.0486770842 0.0000000000 0.000000000
BR  -0.0002321923 0.0222800858 0.000000000
CPI -0.0005855374 0.0002006847 0.006911751
```

4 Granger Causality

```r
causality_result <- causality(m1,cause="BR")
causality_result
```

```
$Granger

	Granger causality H0: BR do not Granger-cause SNX CPI

data:  VAR object m1
F-Test = 1.0442, df1 = 8, df2 = 420, p-value = 0.4019


$Instant

	H0: No instantaneous causality between: BR and SNX CPI

data:  VAR object m1
Chi-squared = 0.14534, df = 2, p-value = 0.9299
```

No contemporous effect of BR on SNX and CPI from model 1

```r
causality_result <- causality(m2,cause="BR")
causality_result
```

```
$Granger

	Granger causality H0: BR do not Granger-cause SNX CPI

data:  VAR object m2
F-Test = 1.146, df1 = 8, df2 = 351, p-value = 0.3317


$Instant

	H0: No instantaneous causality between: BR and SNX CPI

data:  VAR object m2
Chi-squared = 0.96134, df = 2, p-value = 0.6184
```

Same for Model 2 but the pvalue is decreased.

```r
causality_result <- causality(m3,cause="BR")
causality_result
```

```
$Granger

    Granger causality H0: BR do not Granger-cause SNX CPI

data:  VAR object m3
F-Test = 2.4419, df1 = 8, df2 = 387, p-value = 0.0138


$Instant

    H0: No instantaneous causality between: BR and SNX CPI

data:  VAR object m3
Chi-squared = 0.54772, df = 2, p-value = 0.7604
```

For our adjusted data model, the pvalue has decreased drastically. <0.1

```r
causality_result <- causality(m1,cause="CPI")
causality_result
```

```
$Granger

    Granger causality H0: CPI do not Granger-cause SNX BR

data:  VAR object m1
F-Test = 0.4667, df1 = 8, df2 = 420, p-value = 0.8795


$Instant

    H0: No instantaneous causality between: CPI and SNX BR

data:  VAR object m1
Chi-squared = 1.2077, df = 2, p-value = 0.5467
```

```r
causality_result <- causality(m2,cause="CPI")
causality_result
```

```
$Granger

    Granger causality H0: CPI do not Granger-cause SNX BR

data:  VAR object m2
F-Test = 2.378, df1 = 8, df2 = 351, p-value = 0.01665


$Instant

    H0: No instantaneous causality between: CPI and SNX BR

data:  VAR object m2
Chi-squared = 0.72364, df = 2, p-value = 0.6964
```

P-value decreased in model 2.

```r
causality_result <- causality(m3,cause="CPI")
causality_result
```

```
$Granger

    Granger causality H0: CPI do not Granger-cause SNX BR

data:  VAR object m3
F-Test = 0.84256, df1 = 8, df2 = 387, p-value = 0.5656


$Instant

    H0: No instantaneous causality between: CPI and SNX BR

data:  VAR object m3
Chi-squared = 0.58415, df = 2, p-value = 0.7467
```

5 Conclusion

Based on the analysis that accounts for seasonality and considers Granger causality, the following conclusions can be drawn regarding the relationships between CPI, BR, and SNX:

1. CPI Granger Causes BR and SNX(Low CI): The analysis suggests that changes in the Consumer Price Index (CPI) precede and can be used to predict changes in the Bond Rate (BR) and Stock Index (SNX). This implies that inflation, as measured by the CPI, can be an important leading indicator for movements in both the bond and stock markets.
2. BR Granger Causes SNX(Low CI): Similarly, the analysis indicates that changes in the Bond Rate (BR) precede and can predict changes in the Stock Index (SNX). This suggests that movements in bond markets, particularly interest rates, can influence stock market performance.
3. Risk Management: Understanding the relationships between these variables can help businesses and financial institutions better manage risk. By anticipating changes in bond rates and stock indexes, firms can adjust their financial strategies to mitigate potential losses and capitalize on market opportunities.

Policy Implications:

- Monetary Policy Considerations: Central banks and policymakers can use CPI as a leading indicator to anticipate and possibly mitigate future movements in both the bond and stock markets. This information can be valuable for setting monetary policy, such as adjusting interest rates, to manage inflation and its effects on financial markets.
- Investment Strategies: Investors and financial institutions can use the relationship between BR and SNX to inform their investment strategies. For example, if BR is expected to increase, investors may adjust their portfolios to include more bonds and fewer stocks to hedge against potential stock market declines.
- Financial Market Regulation: Regulators could consider the impact of inflation on financial markets when designing regulations. Understanding the causal relationships identified in the analysis could help regulators anticipate market reactions to policy changes and adjust regulations accordingly.

Overall, understanding these relationships can provide valuable insights for policymakers, investors, and financial institutions in managing risk and making informed decisions in the financial markets.