VAR Stocks Model

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1.Install packages:ONLY if you have not installed

```
#install.packages('vars')
#install.packages('tseries')
#install.packages('psych')
```

2.Load libraries

```
library(vars)#VAR modellibrary(tseries)#ADF testlibrary(psych)#Neat Descriptives
```

3.Load data

4. Creating dataframe based on returns

```
#1.Get returns of stock market prices
DAX_re <- diff(ts(df$DAX))
SMI_re <- diff(ts(df$SMI))
CAC_re <- diff(ts(df$CAC))
FTSE_re <- diff(ts(df$FTSE))

#2.Bind them into a dataframe
df_re <-cbind(DAX_re,SMI_re,CAC_re,FTSE_re)

#3.Renaming columns in df_re
colnames(df_re) <- c('DAX','SMI','CAC','FTSE')</pre>
```

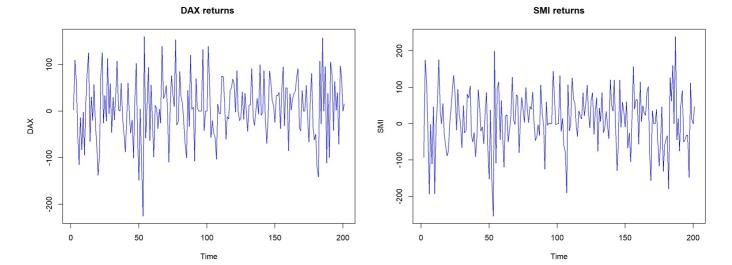
5. Exploratory data annalysis

6.Visualization

```
#i.Plots:DAX,SMI returns

par(mfrow=c(1,2))
plot(DAX_re,type='l',col="blue",
        ylab='DAX',
        main='DAX returns ')

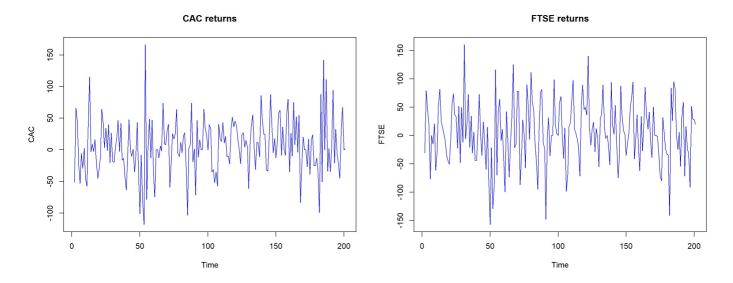
plot(SMI_re,type='l',col="blue",
        ylab='SMI',
        main='SMI returns')
```



```
par(mfrow=c(1,1))

#i.plots:CAC,FTSE returns
par(mfrow=c(1,2))
plot(CAC_re,type='l',col="blue",
    ylab='CAC',
    main='CAC returns')

plot(FTSE_re,type='l',col="blue",
    ylab='FTSE',
    main='FTSE returns')
```

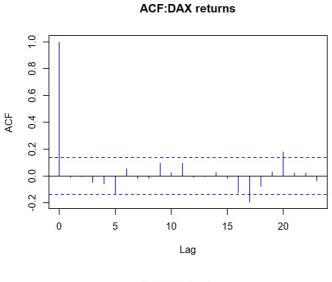


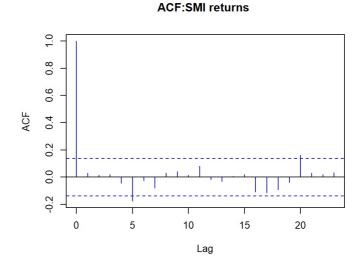
par(mfrow=c(1,1))

7.Stationarity

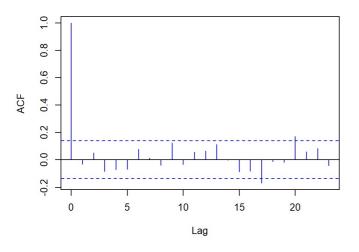
i.ACF plots

```
#i.Visual inspection :ACF PLOTS
par(mfrow=c(2,2))
acf(DAX_re,main='ACF:DAX returns',col='blue')
acf(SMI_re,main='ACF:SMI returns ',col='blue')
acf(CAC_re,main='ACF:CAC returns',col='blue')
acf(FTSE_re,main='ACF:FTSE returns ',col='blue')
```

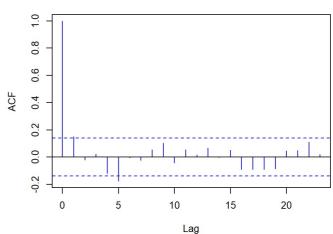








ACF:FTSE returns



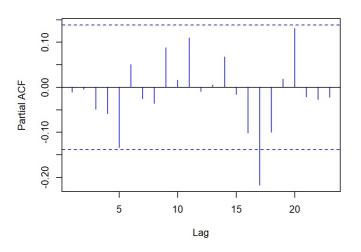
par(mfrow=c(1,1))

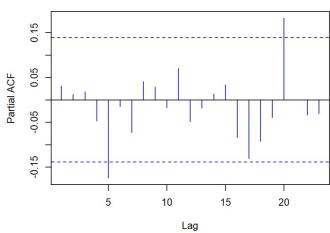
ii.PACF plots

```
par(mfrow=c(2,2))
pacf(DAX_re,main='PACF:DAX returns',col='blue')
pacf(SMI_re,main='PACF:SMI returns ',col='blue')
pacf(CAC_re,main='PACF:CAC returns',col='blue')
pacf(FTSE_re,main='PACF:FTSE returns ',col='blue')
```

PACF:DAX returns

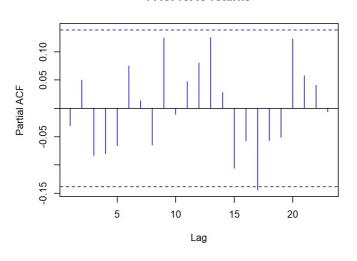
PACF:SMI returns

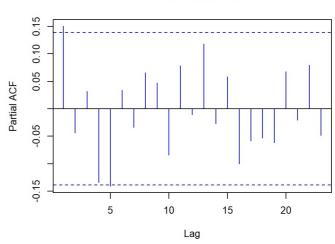




PACF:CAC returns

PACF:FTSE returns





par(mfrow=c(2,2))

iii.Statistical test

```
#ho:time series is non-stationary
#h1:time series is stationary
adf.test(SMI_re,k=10) #stationary
```

Warning in adf.test(SMI_re, k = 10): p-value smaller than printed p-value

```
##
## Augmented Dickey-Fuller Test
##
## data: SMI_re
## Dickey-Fuller = -4.1854, Lag order = 10, p-value = 0.01
## alternative hypothesis: stationary
```

```
adf.test(DAX_re,k=10) #stationary
```

```
##
## Augmented Dickey-Fuller Test
##
## data: DAX_re
## Dickey-Fuller = -3.7667, Lag order = 10, p-value = 0.02188
## alternative hypothesis: stationary
```

```
adf.test(SMI_re,k=10) #stationary
```

Warning in adf.test(SMI_re, k = 10): p-value smaller than printed p-value

```
##
## Augmented Dickey-Fuller Test
##
## data: SMI_re
## Dickey-Fuller = -4.1854, Lag order = 10, p-value = 0.01
## alternative hypothesis: stationary
```

```
adf.test(DAX_re,k=10) #stationary
```

```
##
## Augmented Dickey-Fuller Test
##
## data: DAX_re
## Dickey-Fuller = -3.7667, Lag order = 10, p-value = 0.02188
## alternative hypothesis: stationary
```

8.Lag selection

```
optimal <-VARselect(df_re, type="const")
optimal$selection</pre>
```

```
## AIC(n) HQ(n) SC(n) FPE(n)
## 1 1 1 1
```

9.VAR Model

```
#i.VAR model
model <-VAR(df_re, p = 1, type = c("const"),
    season = NULL, exogen = NULL, lag.max = NULL,
    ic = c("AIC"))
#ii.VAR model results
summary(model)</pre>
```

10:DIAGNOSTICS

i.Autocorrelation

ii.Heteroskedasticity

```
##
## ARCH (multivariate)
##
## data: Residuals of VAR object model
## Chi-squared = 602.74, df = 500, p-value = 0.001069
```

iii.normality

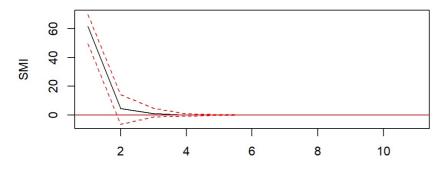
11.Granger causality

```
#verdict:p-value <0.05 reject null</pre>
#Conclude: There is instantaneous causality
#i.If DAX granger causes SMI, CAC, FTSE
DAX granger <- causality(model,cause='DAX')</pre>
DAX_granger
#ii.If SMI granger causes DAX, CAC, FTSE
#verdict:p-value <0.05 reject null</pre>
DAX_granger <- causality(model,cause='SMI')</pre>
DAX_granger
#iii.If CAC granger causes SMI,FTSE,DAX
#verdict:p-value <0.05 reject null</pre>
DAX granger <- causality(model,cause='CAC')</pre>
DAX_granger
#iv.If FTSE granger causes SMI,CAC,DAX
#verdict:p-value <0.05 reject null</pre>
DAX granger <- causality(model,cause='FTSE')</pre>
DAX granger
```

12.IMPULSE RESPONSE FUNCTIONS: Case of DAX variable

```
#i.IRF:Impact of a schock to DAX on other variables
DAX_SMI <- irf(model,impulse='DAX',response='SMI',n.ahead=10)
DAX_CAC <- irf(model,impulse='DAX',response='CAC',n.ahead=10)
DAX_FTSE <- irf(model,impulse='DAX',response='FTSE',n.ahead=10)
#ii.Plots of irf
plot(DAX_SMI)</pre>
```

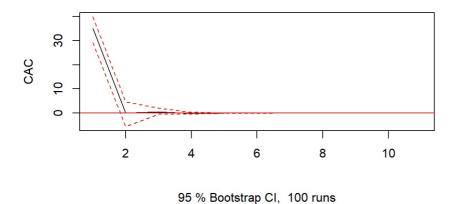
Orthogonal Impulse Response from DAX



95 % Bootstrap CI, 100 runs

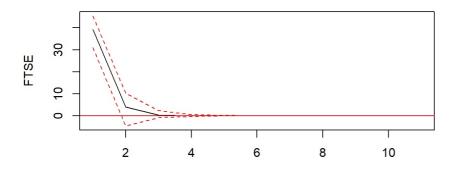
plot(DAX_CAC)

Orthogonal Impulse Response from DAX



plot(DAX_FTSE)

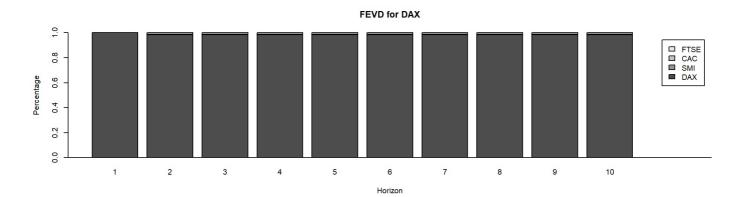
Orthogonal Impulse Response from DAX

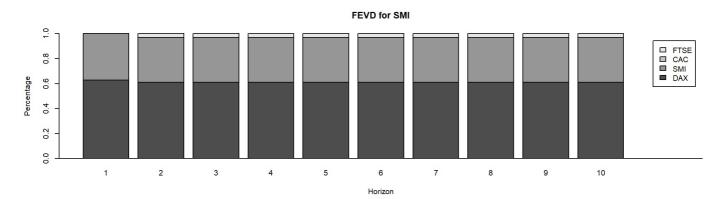


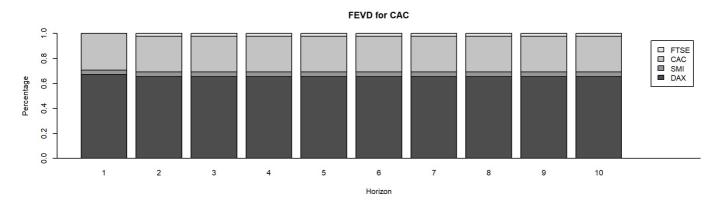
95 % Bootstrap CI, 100 runs

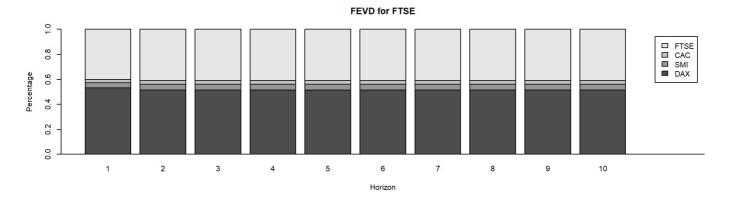
13.VARIANCE DECOMPOSITION

var_fevd <- fevd(model,n.ahead=10)
plot(var_fevd)</pre>







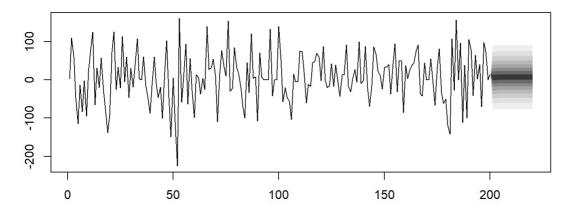


14.FORECASTING

#i.forecast for each variable
forecast <- predict(model,n.ahead=20,ci=0.95)</pre>

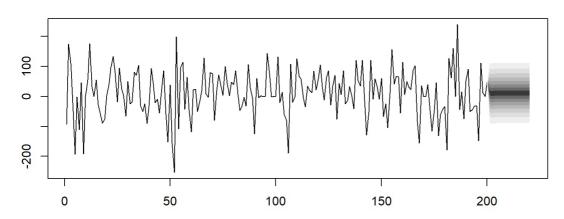
#ii.fancharts for each
fanchart(forecast,names='DAX')

Fanchart for variable DAX



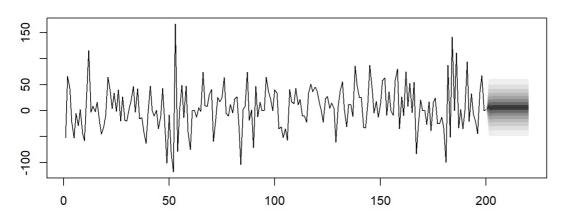
fanchart(forecast,names='SMI')

Fanchart for variable SMI



fanchart(forecast,names='CAC')

Fanchart for variable CAC



fanchart(forecast,names='FTSE')

Fanchart for variable FTSE

