

EMHW5

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Problem 1: VAR implementation

Use the data on quarterly excess stock market returns, the market Dividend / Price ratio, and the difference between the 10-yr Treasury yield and the Fed Funds rate in the excel spreadsheet “MktRet_DP_TermSpread.xlsx”. The interest rate data is from the FRED data depository, available online from the St. Louis Fed.

```
#import data and library
library(ggplot2)
library(expm)
library(lmtest)
library(sandwich)
library(vars)
library(DataAnalytics)
library(readxl)
HW5data = read_excel("MktRet_DP_TermSpread.xlsx")
```

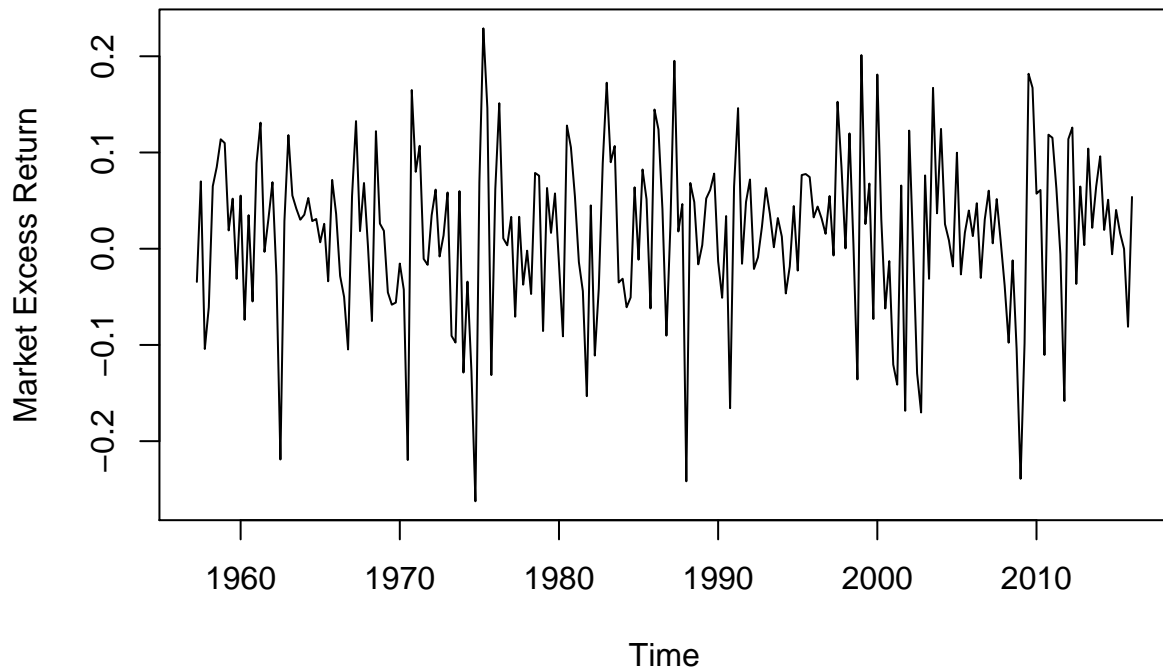
1

Plot each series. Give the sample mean, standard deviation, and first order autocorrelation of each series. From the first-order autocorrelation, calculate the half-life of each series (see ARMA notes for exact half-life formula).

Plot each Series.

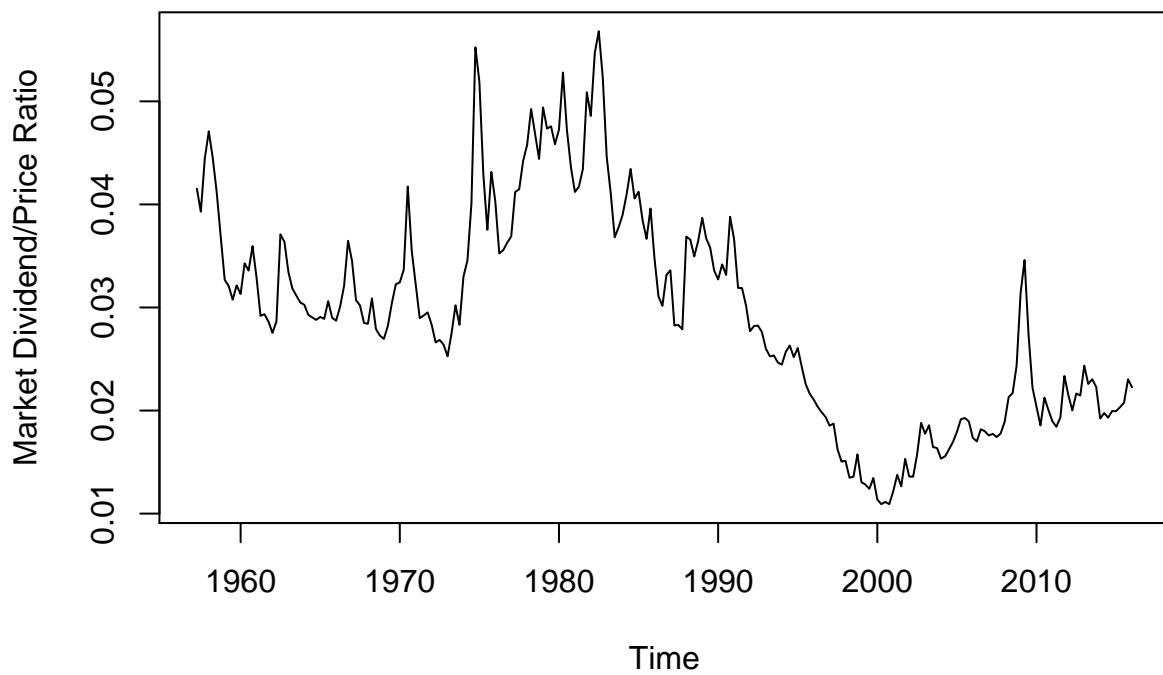
```
plot(x = HW5data$Date, y = HW5data$MktExRet, xlab = 'Time', ylab = 'Market Excess Return', main = 'Time Series')
```

Time Series of Market Excess Return



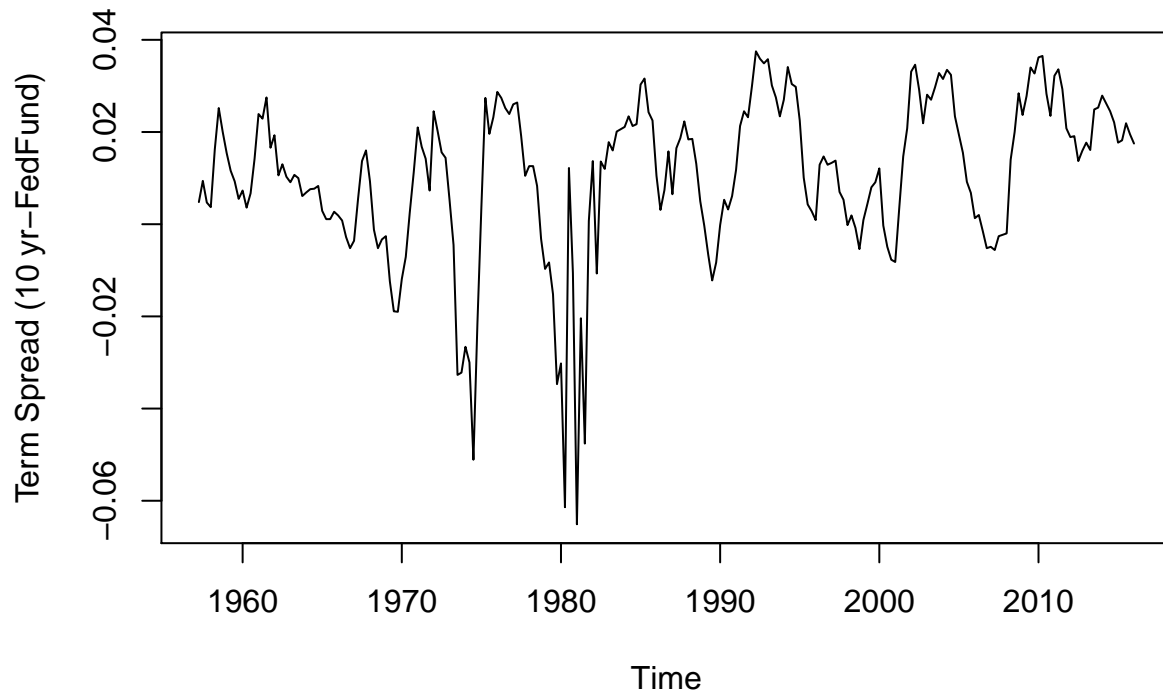
```
plot(x = HW5data$Date,y = HW5data$Mkt_DP,xlab = 'Time',ylab = 'Market Dividend/Price Ratio',main = 'Time
```

Time Series of Market Dividend/Price Ratio



```
plot(x = HW5data$Date,y = HW5data$y10minFedFunds,xlab = 'Time',ylab = 'Term Spread (10 yr-FedFund)',main = 'Time
```

Time Series of Term Spread



Recall

the formula for half life is:

$$h = \frac{\ln(0.5)}{\ln(\phi_1)}$$

```
#compute descriptive stats
```

```
desrp_data=descStat(HW5data[,-1])
```

```
##           Mean Median    SD   IQR SE Mean 95% CI-L 95% CI-U NMissing
## MktExRet    0.016  0.026 0.084 0.096  0.005    0.005    0.027        0
## Mkt_DP      0.029  0.029 0.010 0.016  0.001    0.028    0.031        0
## y10minFedFunds 0.011  0.013 0.017 0.021  0.001    0.008    0.013        0
## Number of Observations = 236
```

```
#compute 1st order acf
```

```
Phi_1=apply(X = HW5data[,-1],MARGIN = 2 , FUN = acf,lag.max=1,plot=F)
```

```
Phi_1=c(Phi_1$MktExRet$acf[2],Phi_1$Mkt_DP$acf[2],Phi_1$y10minFedFunds$acf[2])
```

```
desrp_data=cbind(desrp_data,Phi_1)
```

```
HalfLife=log(0.5)/log(desrp_data[,9])
```

```
desrp_data=cbind(desrp_data,HalfLife)
```

```
desrp_data
```

```
##           Mean Median    SD   IQR SE Mean 95% CI-L 95% CI-U NMissing
## MktExRet    0.016  0.026 0.084 0.096  0.005    0.005    0.027        0
## Mkt_DP      0.029  0.029 0.010 0.016  0.001    0.028    0.031        0
## y10minFedFunds 0.011  0.013 0.017 0.021  0.001    0.008    0.013        0
##           Phi_1   HalfLife
## MktExRet    0.06960754  0.2601042
## Mkt_DP      0.95807815 16.1852221
## y10minFedFunds 0.80344922  3.1673510
```

2

Recall from the slides, the VAR(1) Model would follow the following hypothesis:

$$\vec{y}_t = \vec{\phi}_0 + \Phi_1 y_{t-1} + \vec{\epsilon}_t$$

where

$$\vec{y}_t = \begin{pmatrix} R_t^E \\ DP_t \\ SPD_t \end{pmatrix}$$

$\vec{\phi}_0$ is the 3 by 1 constant coeff vector,

Φ

the 3 by 3 slop coeff matrix, and $\vec{\epsilon}_t$ is 3 by 1 residual vector. Perform the VAR(1) regression, and the OLS coefficients and R-sq of each regression would be:

```
Model_var1=VAR(y = HW5data[,-1],p = 1,type='const')
summary(Model_var1)
```

```
##
## VAR Estimation Results:
## =====
## Endogenous variables: MktExRet, Mkt_DP, y10minFedFunds
## Deterministic variables: const
## Sample size: 235
## Log Likelihood: 2262.805
## Roots of the characteristic polynomial:
## 0.9407 0.7953 0.07442
## Call:
## VAR(y = HW5data[, -1], p = 1, type = "const")
##
##
## Estimation results for equation MktExRet:
## =====
## MktExRet = MktExRet.l1 + Mkt_DP.l1 + y10minFedFunds.l1 + const
##
##              Estimate Std. Error t value Pr(>|t|)
## MktExRet.l1    0.04852    0.06554   0.740  0.45987
## Mkt_DP.l1      1.45092    0.54218   2.676  0.00798 **
## y10minFedFunds.l1 1.04958    0.33379   3.144  0.00188 **
## const         -0.03827    0.01805  -2.121  0.03501 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.08239 on 231 degrees of freedom
## Multiple R-Squared: 0.06072, Adjusted R-squared: 0.04852
## F-statistic: 4.977 on 3 and 231 DF,  p-value: 0.002297
##
##
## Estimation results for equation Mkt_DP:
## =====
## Mkt_DP = MktExRet.l1 + Mkt_DP.l1 + y10minFedFunds.l1 + const
##
##              Estimate Std. Error t value Pr(>|t|)
## MktExRet.l1    -0.0022822  0.0021906  -1.042  0.298577
```

```

## Mkt_DP.l1          0.9402772  0.0181216  51.887  < 2e-16 ***
## y10minFedFunds.l1 -0.0388263  0.0111566  -3.480  0.000599 ***
## const              0.0021214  0.0006032   3.517  0.000526 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.002754 on 231 degrees of freedom
## Multiple R-Squared:  0.9298, Adjusted R-squared:  0.9289
## F-statistic: 1021 on 3 and 231 DF, p-value: < 2.2e-16
##
##
## Estimation results for equation y10minFedFunds:
## =====
## y10minFedFunds = MktExRet.l1 + Mkt_DP.l1 + y10minFedFunds.l1 + const
##
##              Estimate Std. Error t value Pr(>|t|)
## MktExRet.l1    -0.014836   0.008060  -1.841   0.0669 .
## Mkt_DP.l1       0.010477   0.066677   0.157   0.8753
## y10minFedFunds.l1  0.821641   0.041050  20.016  <2e-16 ***
## const           0.001872   0.002220   0.844   0.3998
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01013 on 231 degrees of freedom
## Multiple R-Squared:  0.6516, Adjusted R-squared:  0.647
## F-statistic: 144 on 3 and 231 DF, p-value: < 2.2e-16
##
##
## Covariance matrix of residuals:
##              MktExRet      Mkt_DP y10minFedFunds
## MktExRet      0.0067882 -2.058e-04   1.130e-04
## Mkt_DP        -0.0002058  7.583e-06  -4.058e-06
## y10minFedFunds 0.0001130 -4.058e-06   1.027e-04
##
## Correlation matrix of residuals:
##              MktExRet      Mkt_DP y10minFedFunds
## MktExRet      1.0000 -0.9073      0.1353
## Mkt_DP        -0.9073  1.0000     -0.1454
## y10minFedFunds 0.1353 -0.1454      1.0000

```

The HC White robust standard error would be:

```
coeftest(x=Model_var1,vcov.=vcovHC(Model_var1))
```

```

##
## t test of coefficients:
##
##              Estimate Std. Error t value Pr(>|t|)
## MktExRet:(Intercept) -0.03827466  0.01997553 -1.9161 0.0565896
## MktExRet:MktExRet.l1  0.04851912  0.07487925  0.6480 0.5176512
## MktExRet:Mkt_DP.l1    1.45092240  0.58947110  2.4614 0.0145720
## MktExRet:y10minFedFunds.l1 1.04958093  0.40866889  2.5683 0.0108503

```

```
## Mkt_DP:(Intercept)          0.00212138  0.00060034  3.5336 0.0004949
## Mkt_DP:MktExRet.l1         -0.00228220  0.00239071 -0.9546 0.3407722
## Mkt_DP:Mkt_DP.l1           0.94027718  0.01990206 47.2452 < 2.2e-16
## Mkt_DP:y10minFedFunds.l1   -0.03882632  0.01785154 -2.1750 0.0306485
## y10minFedFunds:(Intercept) 0.00187225  0.00192781  0.9712 0.3324747
## y10minFedFunds:MktExRet.l1 -0.01483615  0.00807623 -1.8370 0.0674925
## y10minFedFunds:Mkt_DP.l1    0.01047743  0.07634819  0.1372 0.8909668
## y10minFedFunds:y10minFedFunds.l1 0.82164129  0.09298732  8.8361 2.557e-16
##
## MktExRet:(Intercept)      .
## MktExRet:MktExRet.l1      .
## MktExRet:Mkt_DP.l1        *
## MktExRet:y10minFedFunds.l1 *
## Mkt_DP:(Intercept)        ***
## Mkt_DP:MktExRet.l1        .
## Mkt_DP:Mkt_DP.l1          ***
## Mkt_DP:y10minFedFunds.l1   *
## y10minFedFunds:(Intercept) .
## y10minFedFunds:MktExRet.l1 .
## y10minFedFunds:Mkt_DP.l1   .
## y10minFedFunds:y10minFedFunds.l1 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3

To test the stationarity of the VAR(1) Model, we need to check all the eigenvalues of the slope matrix

$$\Phi_1$$

is smaller than 1 in modulus sense.

```
# grab the slope coeff matrix
est_coeff=coef(Model_var1)
Phi=rbind(est_coeff$MktExRet[-4,1],est_coeff$Mkt_DP[-4,1],est_coeff$y10minFedFunds[-4,1])
#compute the eigenvalues of the Phi matrix
lambdas=eigen(x=Phi,only.values = T)$values
lambdas
```

```
## [1] 0.94071594 0.79530199 0.07441967
```

All eigenvalues are smaller than 1. Therefore the VAR(1) model is stationary, which is consistent with the summary of the library function.

4

Recall our first regression would be the following hypothesis:

$$R_t^E = \phi_{0,R} + \phi_{1,R}R_{t-1}^E + \phi_{DP,R}DP_{t-1} + \phi_{SPD,R}SPD_{t-1} + \epsilon_{R,t}$$

Taking conditional Variance of above at time t-1:

$$Var_{t-1}(R_t^E) = Var(\epsilon_{R,t})$$

Therefore:

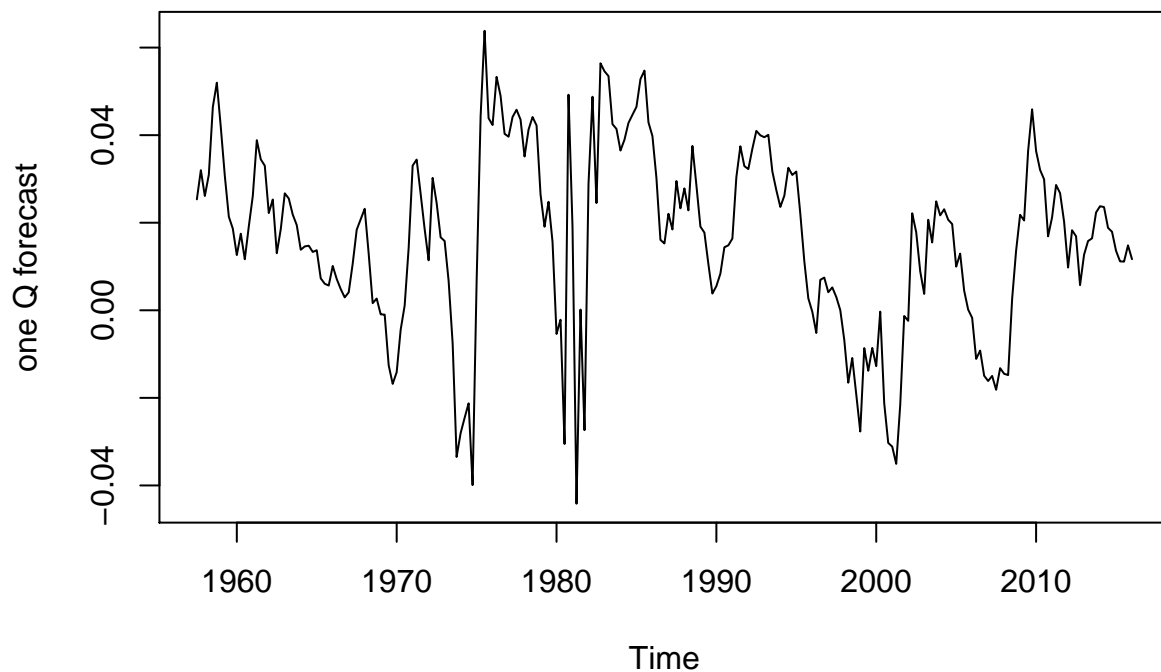
$$\sigma_{t-1}^2(R_t^E) = \hat{\sigma}(\epsilon_{R,t}) = \hat{\sigma}(\epsilon_{R,t}) = 0.08239$$

5

Plot the one-quarter ahead expected return series

```
plot(y=Model_var1$varresult$MktExRet$fitted.values,type='l',x = HW5data$Date[-1],ylab='one Q forecast',;
```

1 Q ahead forecasting

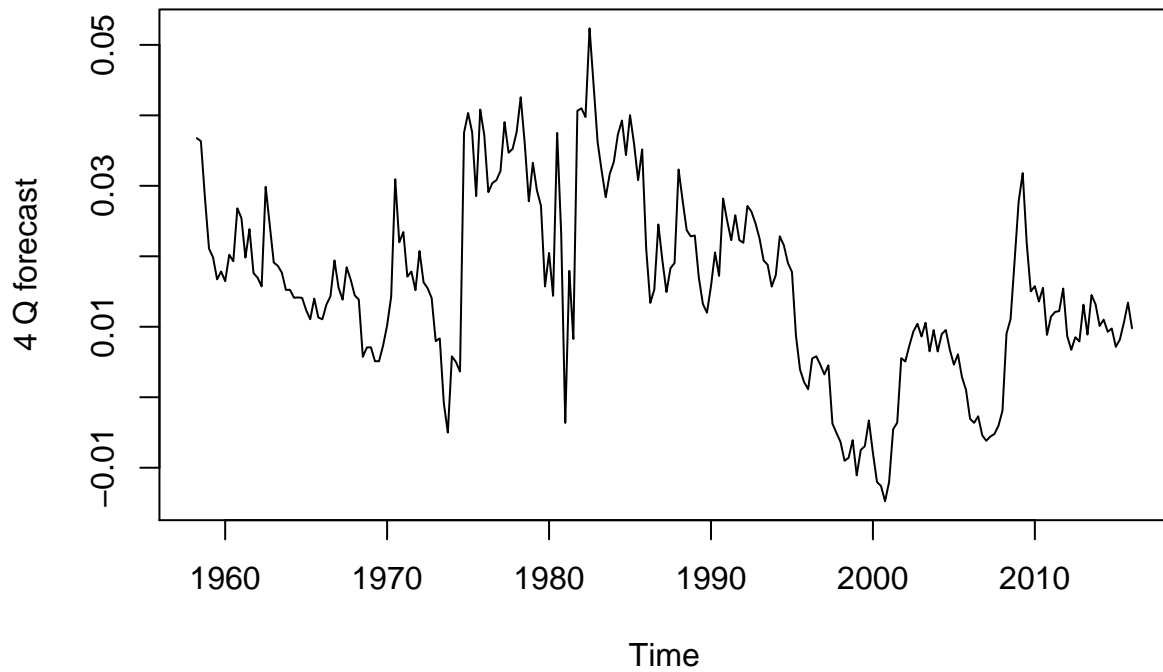


Plot the four-quarter ahead expected return series. Recall the prediction h-period formula for VAR(1) model:

$$E_t(\vec{y}_{t+h}) = (I - \Phi_1^h)\vec{\mu} + \Phi_1^h\vec{y}_t$$

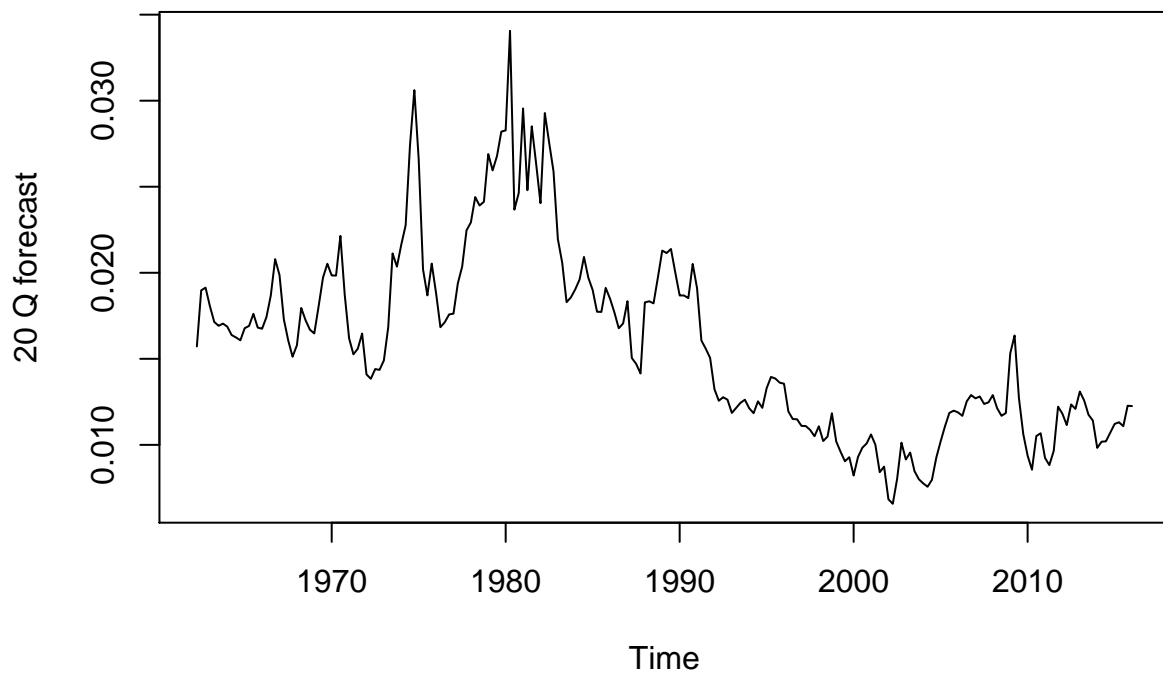
```
mu=colMeans(HW5data[,-1])
Y_t4=HW5data[-1:-4,-1]
Forecast_4=t(matrix(rep((diag(3)-Phi%^4)%*%mu,nrow(Y_t4)),nrow = 3)+(Phi%^4)%*%t(Y_t4))
plot(y=Forecast_4[,1],type='l',x = HW5data$Date[-1:-4],ylab='4 Q forecast',xlab='Time',main='4 Q ahead f
```

4 Q ahead forecasting



```
mu=colMeans(HW5data[, -1])
Y_t20=HW5data[-1:-20, -1]
Forecast_20=t(matrix(rep((diag(3)-Phi~%20)*%mu,nrow(Y_t20)),nrow = 3)+(Phi~%20)*%t(Y_t20))
plot(y=Forecast_20[,1],type='l',x = HW5data$Date[-1:-20],ylab='20 Q forecast',xlab='Time',main='20 Q ahead forecasting')
```

20 Q ahead forecasting



For longer horizons, the predictive power of term spread and the DP-ratios diminished because long horizon

conditional expectation converges to unconditional expectation

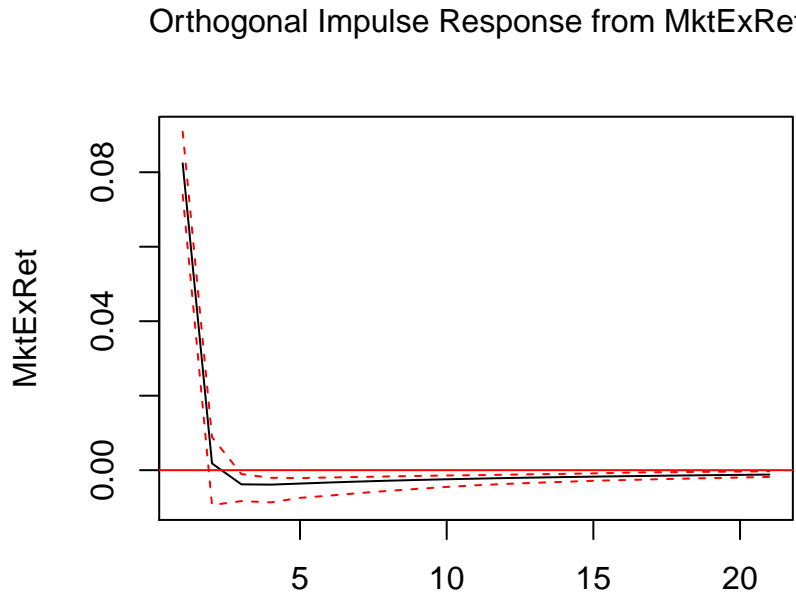
$$E(R_t^E)$$

, which is a constant.

6

The plot of impulse-response function of Excess Return itself, with orthogonalized shock version, with 95% bootstrapping confidence bands.

```
IR_MktEX=irf(x = Model_var1,impulse = 'MktExRet',response = 'MktExRet',n.ahead = 20,ortho = T)
plot(IR_MktEX)
```

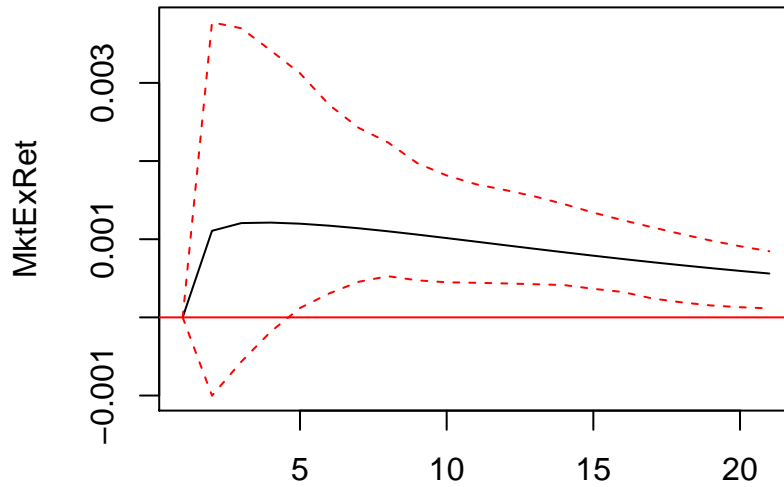


95 % Bootstrap CI, 100 runs

The plot of impulse-response function of Market Dividend Pirce Ratio, with orthogonalized shock version, with 95% bootstrapping confidence bands.

```
IR_MktDP=irf(x = Model_var1,impulse = 'Mkt_DP',response = 'MktExRet',n.ahead = 20,ortho = T)
plot(IR_MktDP)
```

Orthogonal Impulse Response from Mkt_DP

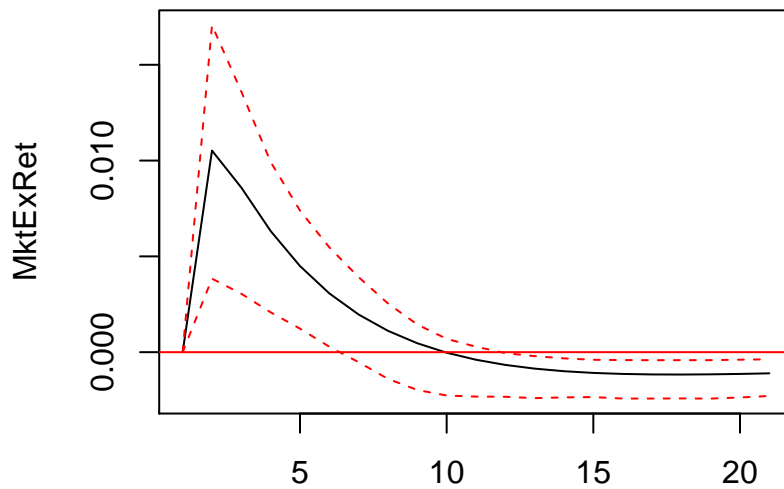


95 % Bootstrap CI, 100 runs

The plot of impulse-response function of Market Dividend Pirce Ratio, with orthogonalized shock version, with 95% bootstrapping confidence bands.

```
IR_spd=irf(x = Model_var1,impulse = 'y10minFedFunds',response = 'MktExRet',n.ahead = 20,ortho = T)
plot(IR_spd)
```

Orthogonal Impulse Response from y10minFedFunds



95 % Bootstrap CI, 100 runs

7

To perform an out-of-sample test, we first need to split our data in to a 80% training set and 20% test set. Then, we fit our VAR(1) model on the training set, predict the t+1 observation, compare with the

underground truth, and then roll over.

```
# compute the out-of-sample prediction and absolute error
Split_idx=round(nrow(HW5data)*0.8)
Prediction_test=data.frame(matrix(0,nrow =(nrow(HW5data)-Split_idx),ncol = 3))
colnames(Prediction_test)=c('Prediction','Observation','absError')
Prediction_test$Observation=HW5data$MktExRet[(Split_idx+1):nrow(HW5data)]
for (t in 1:(nrow(HW5data)-Split_idx)){
  #fit the model
  Model=VAR(y = HW5data[1:Split_idx,-1],p = 1,type = 'const')
  Prediction_test$Prediction[t]=predict(object = Model,n.ahead = 1)[[1]][[1]][1]
  Split_idx=Split_idx+1
}
Prediction_test$absError=abs(Prediction_test$Observation-Prediction_test$Prediction)
Prediction_test$Date=HW5data$Date[(round(nrow(HW5data)*0.8)+1):nrow(HW5data)]
```

```
Prediction_test=as.zoo(Prediction_test)
plot.zoo(Prediction_test[,-4],plot.type = 'single',col=c('blue','black','red'),main = 'VAR(1) out of sample test for Excess Returns')
legend(x = 0,y = -0.1,legend = c('Prediction','Observed','AbsError'),col=c(3, 4, 6),fill = F)
```

VAR(1) out of sample test for Excess Returns

