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FINANCIAL ECONOMETRICS
Problem Set-3

Q1.

a.

```
. dfuller cpi, lags(2) trend regress

Augmented Dickey-Fuller test for unit root

Variable: cpi                               Number of obs  = 234
                                            Number of lags =   2

H0: Random walk with or without drift

                                       Dickey-Fuller
                   Test         -------- critical value ---------
              statistic           1%           5%          10%
-----------------------------------------------------------------
 Z(t)            -2.132       -3.995       -3.432       -3.132
-----------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.5282.

Regression table
------------------------------------------------------------------------------
       D.cpi | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         cpi |
         L1. |  -.0272293    .012772    -2.13   0.034     -.052395   -.0020636
         LD. |   .5050387   .0639478     7.90   0.000     .3790375      .63104
        L2D. |  -.1913743   .0648277    -2.95   0.003    -.3191093   -.0636393
             |
      _trend |   .0097025   .0047602     2.04   0.043     .0003231    .0190819
       _cons |   4.829998   2.121071     2.28   0.024     .6506869    9.009309
------------------------------------------------------------------------------
```

```
. dfuller usdeuro, lags(2) regress

Augmented Dickey-Fuller test for unit root

Variable: usdeuro                           Number of obs  = 234
                                            Number of lags =   2

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test         -------- critical value ---------
              statistic           1%           5%          10%
-----------------------------------------------------------------
 Z(t)            -1.719       -3.465       -2.881       -2.571
-----------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.4216.

Regression table
------------------------------------------------------------------------------
   D.usdeuro | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     usdeuro |
         L1. |  -.0182886   .0106417    -1.72   0.087    -.0392563    .0026791
         LD. |   .3186636   .0653924     4.87   0.000      .189819    .4475083
        L2D. |   -.056484   .0655479    -0.86   0.390    -.1856351    .0726672
             |
       _cons |   .0223861   .0129809     1.72   0.086    -.0031905    .0479627
------------------------------------------------------------------------------
```

The tests do not reject a unit root at the 10% significant level for either variable.

b.

```
. estimates stats m1 m2 m3 m4

Akaike's information criterion and Bayesian information criterion
```

Model	N	ll(null)	ll(model)	df	AIC	BIC
m1	233	.	-194.9392	3	395.8784	406.2315
m2	233	.	-189.4545	4	386.9091	400.7132
m3	233	.	-189.435	5	388.8701	406.1253
m4	233	.	-190.5328	4	389.0657	402.8698

AIC selects Model 2 (386.9091). BIC selects Model 2 (400.7132).

c.

```
. estimates stats m1 m2 m3 m4

Akaike's information criterion and Bayesian information criterion
```

Model	N	ll(null)	ll(model)	df	AIC	BIC
m1	233	.	507.2147	3	-1008.429	-998.0763
m2	233	.	507.8574	4	-1007.715	-993.9107
m3	233	.	508.0733	5	-1006.147	-988.8914
m4	233	.	507.9372	4	-1007.874	-994.0702

AIC selects Model 1 (-1008.429). BIC selects Model 1 (-998.0763).

d.

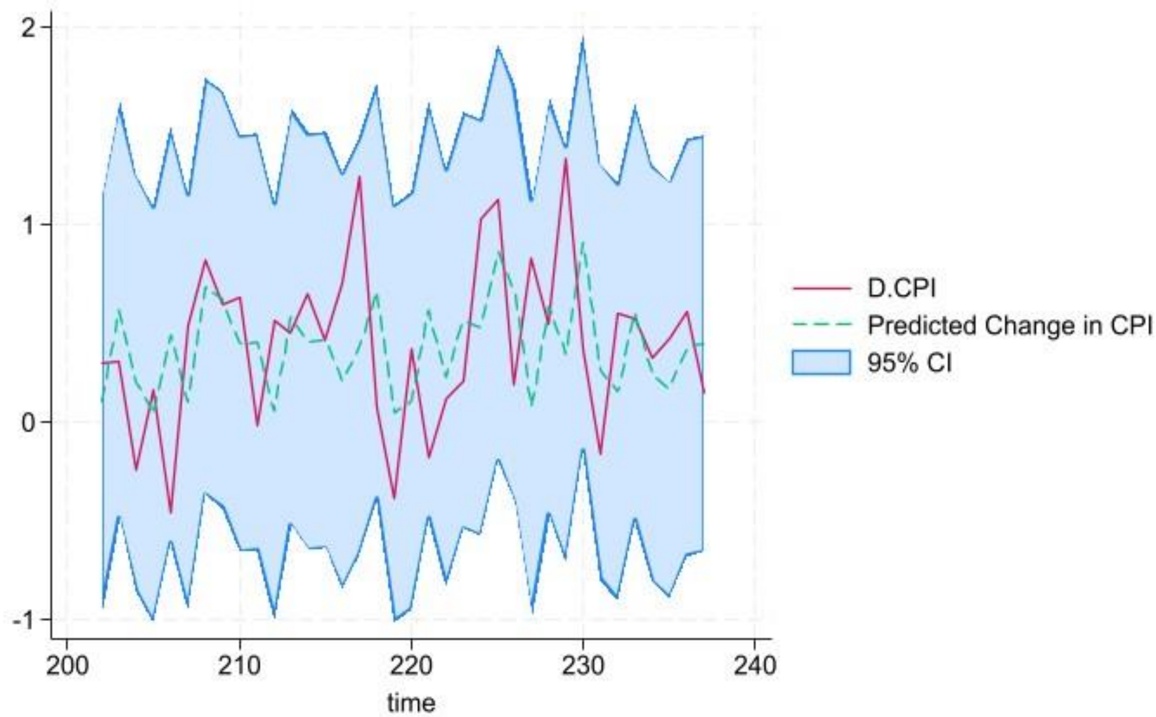
```
. varsoc y1 y2, maxlag(6)

Lag-order selection criteria

   Sample: 8 thru 237                           Number of obs = 230
```

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	284.237				.000295	-2.45423	-2.44217	-2.42434
1	321.93	75.386	4	0.000	.00022	-2.74722	-2.71104*	-2.65753*
2	328.338	12.816*	4	0.012	.000215*	-2.76815*	-2.70786	-2.61867
3	329.794	2.9129	4	0.572	.00022	-2.74604	-2.66162	-2.53676
4	330.841	2.094	4	0.718	.000226	-2.72036	-2.61182	-2.45129
5	333.997	6.3115	4	0.177	.000227	-2.71302	-2.58036	-2.38416
6	335.467	2.9398	4	0.568	.000233	-2.69102	-2.53424	-2.30236

```
   * optimal lag
   Endogenous: y1 y2
    Exogenous: _cons
```

AIC selects a VAR(2)

e.



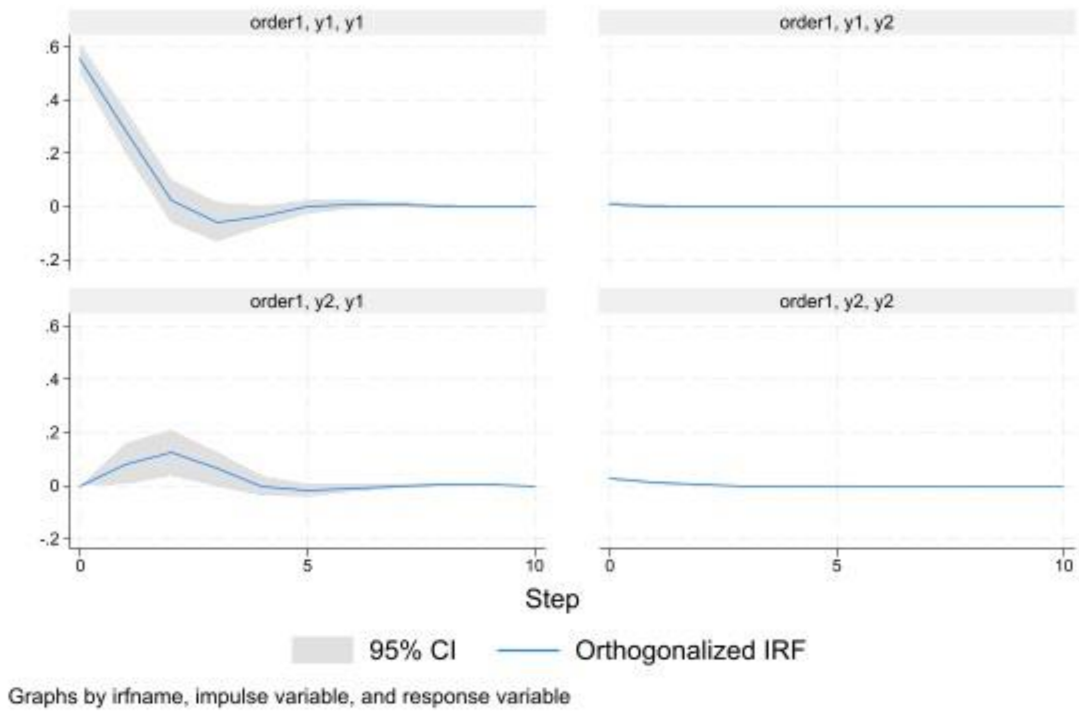
f.

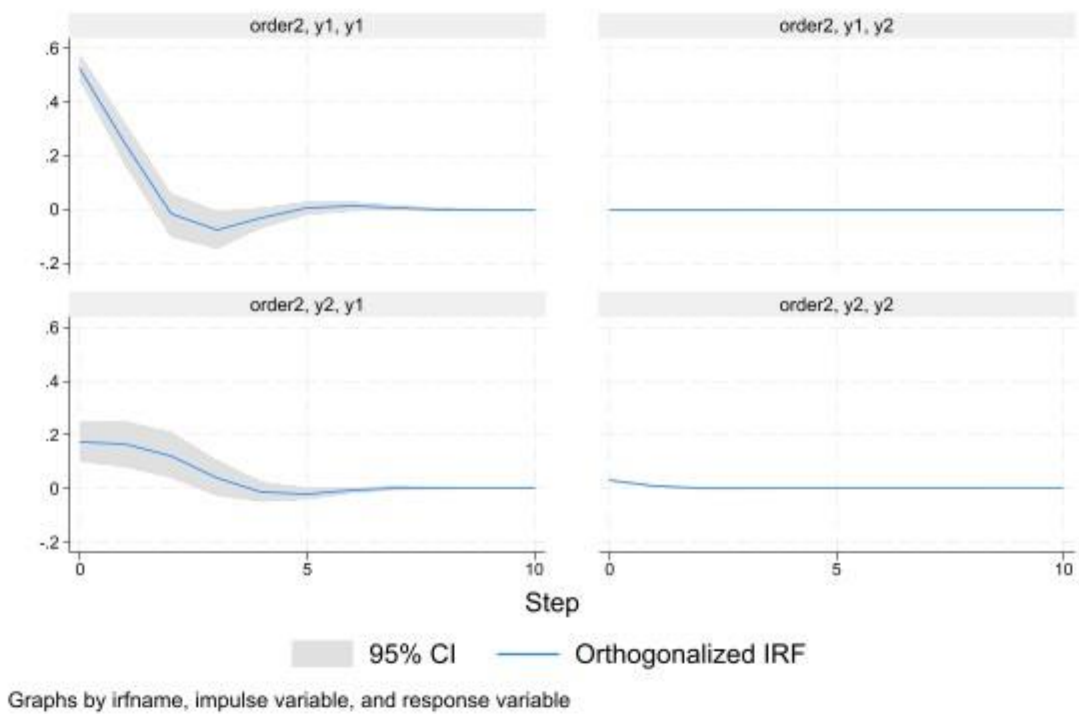
```
. vargranger
```

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
y1	y2	8.9601	2	0.011
y1	ALL	8.9601	2	0.011
y2	y1	.88437	2	0.643
y2	ALL	.88437	2	0.643

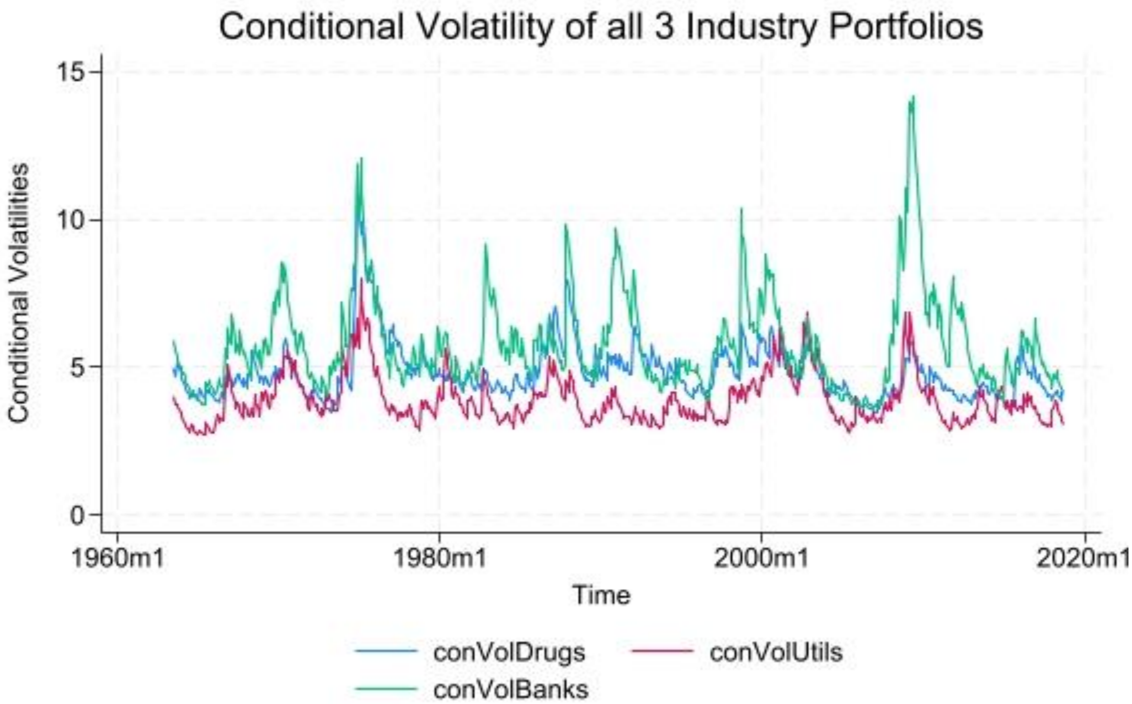
g.


order1, y1, y1
order1, y1, y2
order1, y2, y1
order1, y2, y2
.6
.4
.2
0
-.2
0
5
10
Step
95% CI
Orthogonalized IRF
Graphs by irfname, impulse variable, and response variable


order2, y1, y1
order2, y1, y2
order2, y2, y1
order2, y2, y2
.6
.4
.2
0
-.2
0
5
10
Step
95% CI
Orthogonalized IRF
Graphs by irfname, impulse variable, and response variable

Q2.

a.



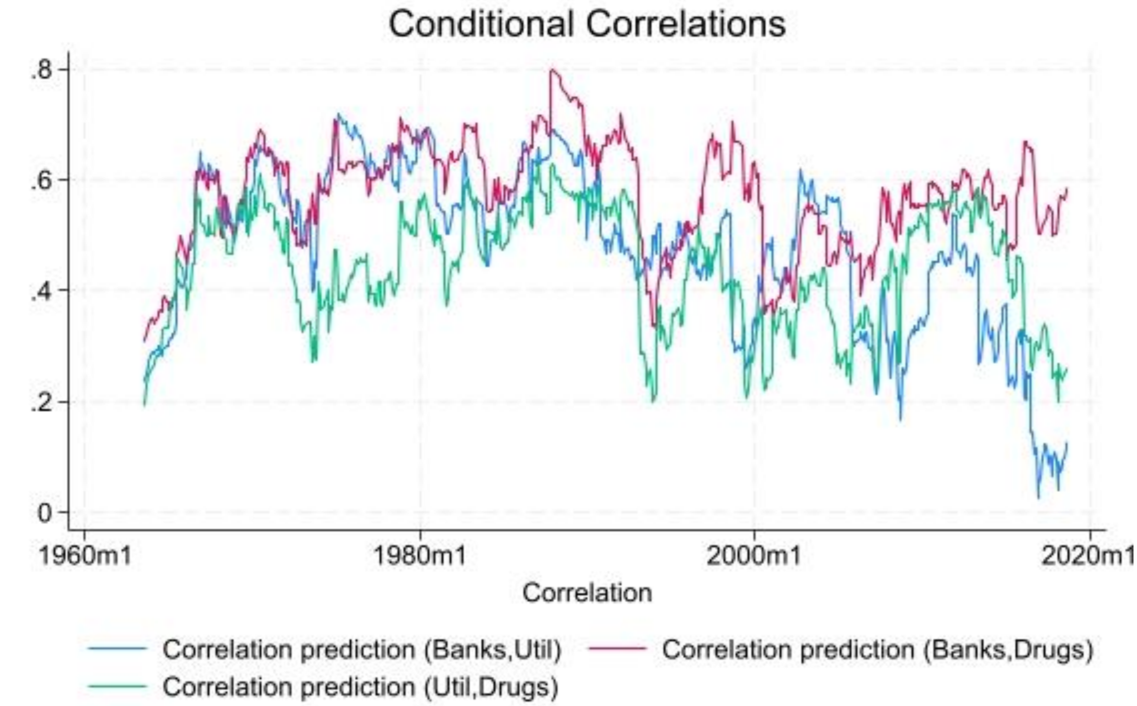
Conditional Volatility of all 3 Industry Portfolios
Conditional Volatilities
15
10
5
0
1960m1
1980m1
2000m1
2020m1
Time
conVolDrugs
conVolUtils
conVolBanks

b.

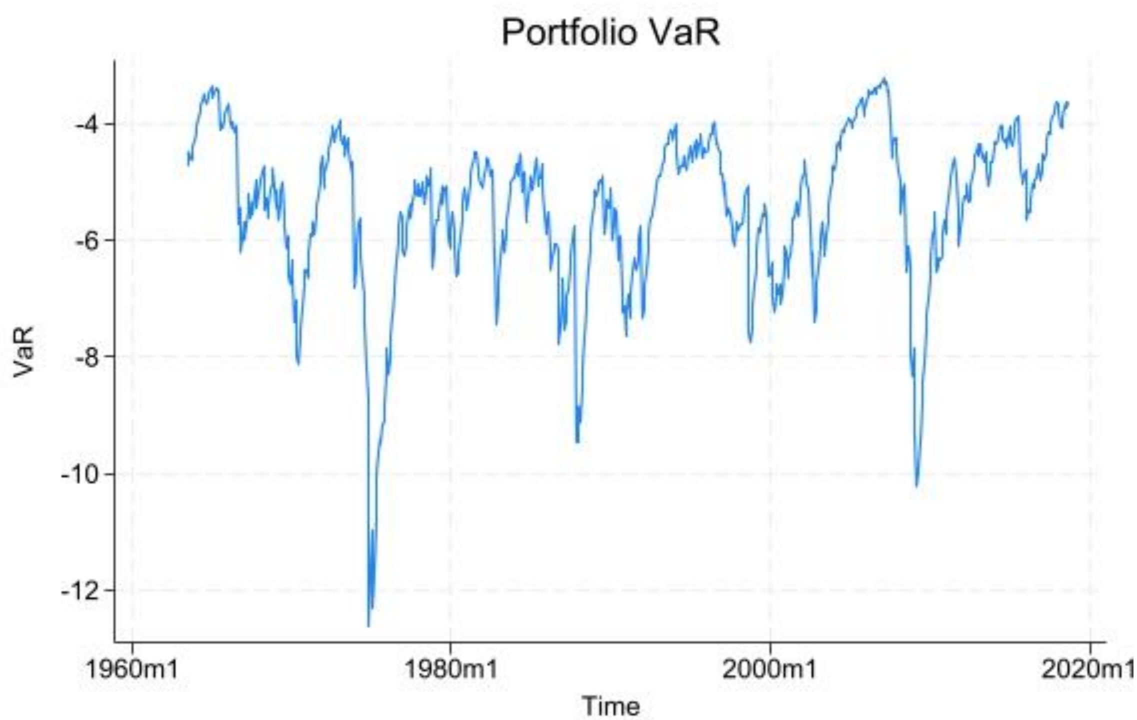
```
Sample: 1 thru 663                                    Number of obs = 663
Distribution: Gaussian                                Wald chi2(.)  =   .
Log likelihood = -5615.428                            Prob > chi2   =   .
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Drugs						
_cons	1.231964	.1725749	7.14	0.000	.8937234	1.570205
ARCH_Drugs						
arch L1.	.0799133	.0172312	4.64	0.000	.0461409	.1136858
garch L1.	.8780659	.0263463	33.33	0.000	.826428	.9297037
_cons	1.054416	.4396656	2.40	0.016	.1926873	1.916145
Util						
_cons	.945712	.1344151	7.04	0.000	.6822633	1.209161
ARCH_Util						
arch L1.	.1047558	.0256416	4.09	0.000	.0544991	.1550125
garch L1.	.8170652	.0392431	20.82	0.000	.7401502	.8939802
_cons	1.163961	.3771213	3.09	0.002	.4248172	1.903106
Banks						
_cons	1.008646	.1952552	5.17	0.000	.6259533	1.39134
ARCH_Banks						
arch L1.	.106573	.0194248	5.49	0.000	.0685011	.1446449
garch L1.	.8363687	.0287276	29.11	0.000	.7800636	.8926738
_cons	1.895741	.6609275	2.87	0.004	.6003469	3.191135
corr(Drugs,Util)	.4154742	.0800977	5.19	0.000	.2584855	.5724629
corr(Drugs,Banks)	.5765296	.0646339	8.92	0.000	.4498495	.7032097
corr(Util,Banks)	.4340148	.0818921	5.30	0.000	.2735093	.5945204
/Adjustment						
lambda1	.0358398	.0078648	4.56	0.000	.0204249	.0512546
lambda2	.9390758	.0134624	69.76	0.000	.91269	.9654615

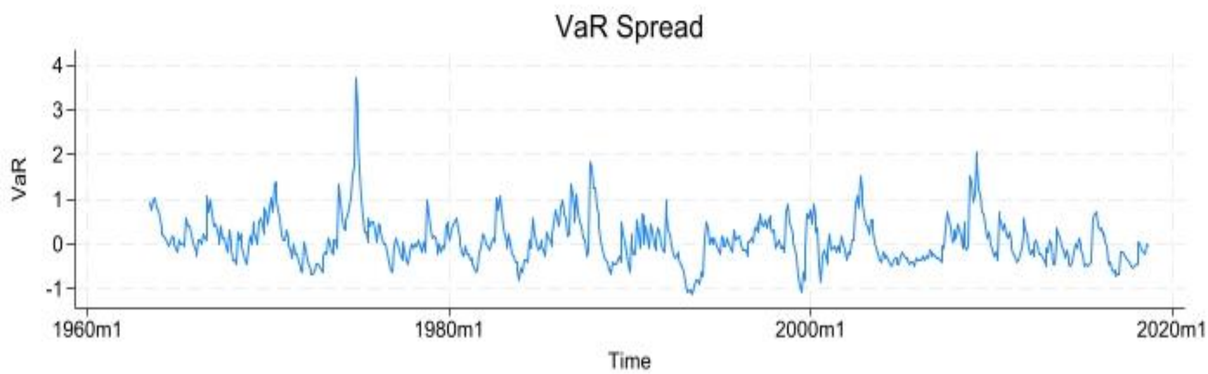
c.


Conditional Correlations
.8
.6
.4
.2
0
1960m1
1980m1
2000m1
2020m1
Correlation
Correlation prediction (Banks,Util)
Correlation prediction (Banks,Drugs)
Correlation prediction (Util,Drugs)

d.


Portfolio VaR
-4
-6
-8
-10
-12
VaR
1960m1
1980m1
2000m1
2020m1
Time

e.



It appears that GARCH(1,1) volatility model is more volatile than the dynamic conditional correlation model. The DCC model is a multivariate model that possesses the characteristics of GARCH models while also having a parametric model for correlations. On the other hand, GARCH is a univariate model and does not account for correlations between holdings in the portfolio. The difference in structure between the models should explain this spread.

f.

```
. summarize hit1

    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
        hit1 |        663    .0558069    .2297218          0          1

.
. egen aHat1=mean(hit1)

. egen tOne1=sum(portfolioReturns-VaR < 0)

.
. gen logNum1 = (tOne1*log(0.05))+((_N-tOne1)*log(0.95))

. gen logDenom1 = (tOne1*log(aHat1))+((_N-tOne1)*log(1-aHat1))

. gen UC1=-2*(logNum1-logDenom1)

.
. gen pval1=1-chi2(1,UC1)

.
. disp UC1[_N]
.4543457

. disp pval1[_N]
.50027841
```

```
. summarize hit2

    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
        hit2 |        663    .0603318    .2382804          0          1

.
. egen aHat2=mean(hit2)

. egen tOne2=sum(portfolioReturns-VaR2 < 0)

.
. gen logNum2 = (tOne2*log(0.05))+((_N-tOne2)*log(0.95))

. gen logDenom2 = (tOne2*log(aHat2))+((_N-tOne2)*log(1-aHat2))

. gen UC2=-2*(logNum2-logDenom2)

.
. gen pval2=1-chi2(1,UC2)

.
. disp UC2[_N]
1.4017334

. disp pval2[_N]
.23643357
```

There is no significant difference between both tests.

STATA CODE

Q1.

a.
```
gen time=_n
tsset time

dfuller cpi, lags(2) trend regress
dfuller usdeuro, lags(2) regress
```

b.
```
arima cpi if time >=5, arima(1,1,0)
  estimates store m1
arima cpi if time >=5, arima(2,1,0)
  estimates store m2
arima cpi if time >=5, arima(3,1,0)
  estimates store m3
arima cpi if time >=5, arima(1,1,1)
  estimates store m4

estimates stats m1 m2 m3 m4
```

c.
```
arima usdeuro if time >=5, arima(1,1,0)
  estimates store m1
arima usdeuro if time >=5, arima(2,1,0)
  estimates store m2
arima usdeuro if time >=5, arima(3,1,0)
  estimates store m3
arima usdeuro if time >=5, arima(1,1,1)
  estimates store m4

estimates stats m1 m2 m3 m4
```

d.
```
gen y1=D.cpi
gen y2=D.usdeuro
label variable y1 “D.CPI”
label variable y2 “D.usdeuro”

varsoc y1 y2, maxlag(6)
```

e.
```
quietly var y1 y2 if time<=201, lags(1/2)
  predict y1for, equation(#1)
  label variable y1for “Predicted Change in CPI”
  predict res, equation(#1) residuals
  egen sdf=sd(res)
  gen lcl = y1for – 1.96*sdf
  gen hcl = y1for + 1.96*sdf
twoway (rarea lcl hcl time, fintensity(inten20)) ///
(line y1 y1for time, lpattern(solid dash)) in -36/1, ///
```

```
legend(order(2 3 1) label(1 “95% CI”))
```

f.
```
quietly var y1 y2 if time<=201, lags(1/2)
vargranger
```

g.
```
irf create order1, set(myExamp) step(10) replace
irf graph oirf

erase myExamp.irf

quietly var y1 y2 if time<=201, lags(1/2)

irf create order2, set(myExamp) step(10) replace
irf graph oirf

erase myExamp.irf
```

Q2.

a.
```
clear all
ssc install tsmktim
import excel "\\apporto. com\dfs \CLT\Users \rkamath1_clt\Documents \industry.×lsx",
sheet("49_Industry Portfolios") firstrow
gen time=_n
tsset time

arch Drugs, garch(1) arch(1)
predict conVar1, variance
gen conVolDrugs = sqrt(conVar1)

arch Util, garch (1) arch (1)
predict conVar2, variance
gen conVolUtils = sqrt (conVar2)

arch Banks, garch(1) arch(1)
predict conVar3, variance
gen conVolBanks = sqrt (conVar3)

tsline conVolDrugs conVolUtils conVolBanks, lpattern (solid) xtitle("Time") ytitle("Conditional
Volatilities") title("Conditional Volatility of all 3 Industry Portfolios")
```

b.
```
mgarch dcc (Drug Util Banks), arch(1) garch(1)
```

c.
```
predict rho*, correlation
tsline rho_Banks_Util rho_Banks_Drugs rho_Util_Drugs, Ipattern (solid) xtitle("Correlation")
title("Conditional Correlations")
```

d.
```
predict m*, xb
predict s*, variance
gen m_Hat = (m_Drugs+m_Banks+m_Util)/3
gen v_Hat = (s Drugs _Drugs+s _Util_Util+s _Banks _Banks +
2*(s_Util_Drugs+s_Banks_Drugs+s_Banks_Uti))/9
gen VaR = (m_Hat - (1.645 * sqrt(v_Hat)))
tsline VaR, xtitle ("Time") ytitle("VaR") title("Portfolio VaR") name (VAR1)
```

e.
```
gen portfolioReturns = (Drugs + Util + Banks)/3
arch portfolioReturns, garch(1) arch(1)
predict me, xb
predict conVar, variance
gen VaR2 = (me - (1.645 * sqrt(conVar)))
tsline VaR2, pattern(solid) xtitle("Time") ytitle("Conditional Volatility") title("VaR from GARCH")
name (VAR2)
graph combine VAR1 VAR2, row(2) col(1)
```

```
gen VaR_spread = VaR - VaR2
tsline VaR_spread, lpattern(solid) xtitle ("Time") ytitle("VaR") title("VaR Spread") name
(VARspread)
graph combine VAR1 VARspread, row(2) col(1)
```

f.
```
generate hit1 = (portfolioReturns-VaR < 0)
summarize hit1

egen aHat1=mean (hit1)
egen tOne1=sum(portfolioReturns-VaR < 0)

gen LogNum1 = (tOne1*log (0.05))+((_N-tOne1)*log(0.95))
gen logDenom1 = (tOne1*log(aHat1))+((_N-tOne1)*log(1-aHat1))
gen UC1=-2* (logNum1-logDenom1)

gen pval1=1-chi2(1, UC1)

disp UC1[_N]
disp pval1[_N]

generate hit2 = (portfolioReturns-VaR2 < 0)
summarize hit2

egen aHat2-mean (hit2)
egen tOne2=sum(portfolioReturns-VaR2 < 0)

gen logNum2 = (tOne2*log(0.05))+((_N-tOne2)*log(0.95))
gen logDenom2 = (tOne2*log(aHat2))+((_N-tOne2)*log(1-aHat2))
gen UC2=-2* (logNum2-logDenom2)

gen pval2=1-chi2(1,UC2)

disp UC2[_N]
disp pval2[_N]
```