ECON423 Assignment 3 - d2tsai 20567329

November 29, 2018

1 ECON 423 Assignment 3

```
20567329
In [65]: # Importing necessary packages
    import numpy as np
    from arch import arch_model
    import matplotlib.pyplot as plt
```

import pandas as pd

1.1 Monte Carlo Simulation

1.1.1 Part 1

Diana Tsai

```
In [66]: n = 2100
     a1 = 0.69
     b1 = 0.24
     mu = 1
     errors = np.random.normal(0, 1, n)
```

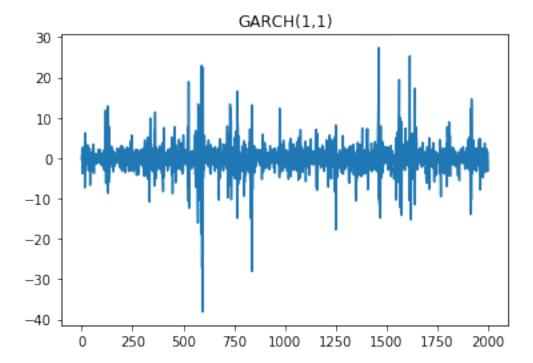
1.1.2 Part 2

```
In [67]: np.random.seed(323)
    a1 = 0.69
    b1 = 0.31

    epsilon = np.random.normal(size=n)
    x = np.zeros_like(epsilon)
    sigma_sqr = np.zeros_like(epsilon)

for i in range(1, n):
        sigma_sqr[i] = mu + a1*(x[i-1]**2) + b1*sigma_sqr[i-1]
        x[i] = epsilon[i] * np.sqrt(sigma_sqr[i])

# drop first 500 observations
    sigma_sqr = sigma_sqr[100:]
    x = x[100:]
```



1.1.3 Part 3

ARCH(1)

Out[68]: <class 'statsmodels.iolib.summary.Summary'>

Constant Mean - ARCH Model Results

===========			===========
Dep. Variable:	у	R-squared:	-0.000
Mean Model:	Constant Mean	Adj. R-squared:	-0.000
Vol Model:	ARCH	Log-Likelihood:	-4796.20
Distribution:	Normal	AIC:	9598.40
Method:	Maximum Likelihood	BIC:	9615.21
		No. Observations:	2000
Date:	Wed, Nov 28 2018	Df Residuals:	1997
Time:	21:21:41	Df Model:	3

Mean Model

=========	coef	std err	t	P> t	95.0% Conf. Int.
mu	-0.0129	4.818e-02 Volati	-0.268	0.789	[-0.107,8.152e-02]
	coef	std err	t	P> t	95.0% Conf. Int.
omega alpha[1]	2.9117 0.9003	0.224 6.028e-02			[2.473, 3.351] [0.782, 1.018]

 ${\tt Covariance\ estimator:\ robust}$

11 11 11

GARCH(1,1)

Out[69]: <class 'statsmodels.iolib.summary.Summary'>

11 11 11

Constant Mean - GARCH Model Results

=========			======		=============	==		
Dep. Variable):		y R-	squared:	-0.00	00		
Mean Model:		Constant M	ean Ad	j. R-squared	: -0.00	00		
Vol Model:		GA	RCH Lo	g-Likelihood	: -4692.3	36		
Distribution:		Nor	mal AI	C:	9392.7	72		
Method:	Max	imum Likelih	ood BI	C:	9415.1	12		
			No	. Observatio	ns: 200	00		
Date:	V	ed, Nov 28 2	018 Df	Residuals:	199	96		
Time:		21:21	:41 Df	Model:		4		
Mean Model								
		std err			95.0% Conf. Int.			
mu		3.913e-02		7 0.633	[-9.536e-02,5.802e-02]]		
=========	·=======		======		======================================			
	coei			t P> t 	95.0% Conf. Int.			
omega	1.1233				[0.879, 1.367]			
alpha[1]	0.7213	5.111e-02	14.11	3.088e-45	[0.621, 0.822]			
beta[1]	0.2787	3.078e-02	9.05	1.380e-19	[0.218, 0.339]			

Covariance estimator: robust

11 11 11

GARCH(2,2)

In [70]: garch22 = arch_model(x, p=2, q=2)

garch22_resid = garch22.fit(disp='off')

garch22_resid.summary()

Out[70]: <class 'statsmodels.iolib.summary.Summary'>

11 11 11

Constant Mean - GARCH Model Results

Dep. Variable: R-squared: -0.000 Mean Model: Constant Mean Adj. R-squared: -0.000 Vol Model: GARCH Log-Likelihood: -4691.69 Distribution: Normal AIC: 9395.38 Method: Maximum Likelihood BIC: 9428.99 No. Observations: 2000

Date: Wed, Nov 28 2018 Df Residuals: 1994
Time: 21:21:41 Df Model: 6

Mean Model

coef std err t P>|t| 95.0% Conf. Int.
----mu -0.0202 3.933e-02 -0.513 0.608 [-9.729e-02,5.690e-02]
Volatility Model

=========						======
	coef	std err	t	P> t	95.0% Con	f. Int.
omega alpha[1] alpha[2] beta[1]	1.1415 0.7379 0.0000 0.2312	0.388 5.377e-02 0.252 0.307			-	0.843]
beta[2]	0.0310	7.332e-02	0.422		[-0.113,	

Covariance estimator: robust

11 11 1

1.1.4 Part 4

(i)

In [71]: $x_half1 = x[:1000]$ $x_half2 = x[1000:]$

(ii)

```
arch1_residp4 = arch1p4.fit(disp='off')
      arch1_paramp4 = arch1_residp4.params
      arch1_residp4.summary()
Out[72]: <class 'statsmodels.iolib.summary.Summary'>
                     Constant Mean - ARCH Model Results
      ______
                              y R-squared:
      Dep. Variable:
                                                       -0.000
      Mean Model:
                    Constant Mean Adj. R-squared:
                                                       -0.000
      Vol Model:
                            ARCH Log-Likelihood:
                                                    -2373.51
      Distribution:
                           Normal AIC:
                                                      4753.03
                 Maximum Likelihood BIC:
      Method:
                                                      4767.75
                                 No. Observations:
                                                        1000
      Date:
                   Wed, Nov 28 2018 Df Residuals:
                                                         997
                         21:21:41 Df Model:
      Time:
                                                          3
                           Mean Model
      _____
                             t P>|t| 95.0% Conf. Int.
                coef std err
      _____
              -0.1023 6.262e-02 -1.634 0.102 [ -0.225,2.040e-02]
                        Volatility Model
      _____
                coef std err t
                                      P>|t| 95.0% Conf. Int.
      _____
               2.3566 0.238
                              9.884 4.906e-23 [ 1.889, 2.824]
               1.0000 8.528e-02 11.726 9.367e-32 [ 0.833, 1.167]
      alpha[1]
      ______
      Covariance estimator: robust
In [73]: garch11p4 = arch_model(x_half1, p=1, q=1)
      garch11_residp4 = garch11p4.fit(disp='off')
      garch11_paramp4 = garch11_residp4.params
      garch11_residp4.summary()
Out[73]: <class 'statsmodels.iolib.summary.Summary'>
                    Constant Mean - GARCH Model Results
      ______
      Dep. Variable:
                              y R-squared:
                                                       -0.000
      Mean Model:
                    Constant Mean Adj. R-squared:
                                                       -0.000
      Vol Model:
                           GARCH Log-Likelihood:
                                                     -2332.16
      Distribution:
                           Normal ATC:
                                                      4672.33
      Method:
                 Maximum Likelihood
                                 BIC:
                                                      4691.96
                                 No. Observations:
                                                        1000
```

In [72]: arch1p4 = arch_model(x_half1, p=1, q=0)

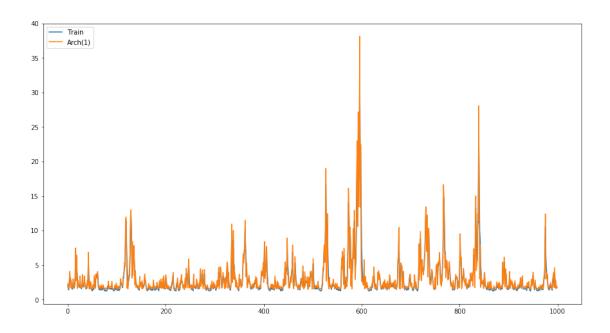
Date: Wed, Nov 28 2018 Df Residuals: 996 Time: 21:21:42 Df Model: 4 Mean Model ______ coef std err t P>|t| 95.0% Conf. Int. ______ -1.143 0.253 [-0.169,4.462e-02] -0.0624 5.462e-02 Volatility Model _____ coef std err t P>|t| 95.0% Conf. Int. _____ 1.0029 0.169 5.950 2.678e-09 [0.673, 1.333] 0.7146 7.091e-02 10.077 6.965e-24 [0.576, 0.854] 0.2854 4.684e-02 6.094 1.104e-09 [0.194, 0.377] alpha[1] beta[1] ______ Covariance estimator: robust In [74]: garch22p4 = arch_model(x_half1, p=2, q=2) garch22_residp4 = garch22p4.fit(disp='off') garch22_paramp4 = garch22_residp4.params garch22_residp4.summary() Out[74]: <class 'statsmodels.iolib.summary.Summary'> Constant Mean - GARCH Model Results ______ Dep. Variable: R-squared: -0.000 Mean Model: Constant Mean Adj. R-squared: -0.000 Vol Model: GARCH Log-Likelihood: -2331.75Distribution: Normal AIC: 4675.50 Method: Maximum Likelihood BIC: 4704.94 No. Observations: 1000 Date: Wed, Nov 28 2018 Df Residuals: 994 Time: 21:21:42 Df Model: 6 Mean Model ______ P>|t| 95.0% Conf. Int. coef std err _____ -0.0622 5.476e-02 -1.136 0.256 [-0.170,4.514e-02] mıı Volatility Model ______ coef std err t P>|t| 95.0% Conf. Int. omega 1.0499 0.290 3.617 2.979e-04 [0.481, 1.619] alpha[1] 0.7371 7.690e-02 9.584 9.303e-22 [0.586, 0.888] alpha[2] 0.0170 0.171 9.973e-02 0.004 -----

```
beta[1] 0.1976 0.214 0.922 0.357 [-0.222, 0.618]
beta[2] 0.0484 6.430e-02 0.752 0.452 [-7.767e-02, 0.174]
```

Covariance estimator: robust

(iii)

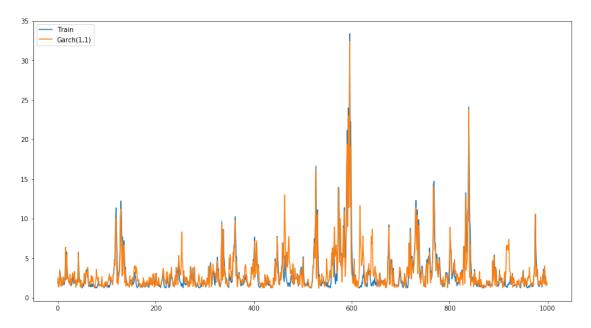
```
In [124]: omegaarch1=arch1_paramp4[1]
          alphaarch1=arch1_paramp4[2]
          n=1000
          e=np.random.normal(loc=0,scale=1,size=n)
          rtAR=np.zeros_like(e)
          xtAR=np.zeros_like(e)
          sigstAR=np.zeros_like(e)
          for x in range(0,n):
              sigstAR[x]=omegaarch1+alphaarch1*(x_half1[x-1]**2)
          testdfarch1=pd.DataFrame(np.sqrt(sigma_sqr[:1000]))
          ardfarch1=pd.DataFrame(np.sqrt(sigstAR))
          plt.figure(figsize=(15,8))
          plt.plot(testdfarch1)
          plt.plot(ardfarch1)
          plt.legend(['Train', 'Arch(1)'], loc='upper left')
          plt.show()
          rmse=1/n*(ardfarch1-testdfarch1)**2
          rmse=rmse.values.sum()
          print('RMSE:',rmse)
```



RMSE: 0.7888461682561507

```
In [125]: omegagarch11=garch11_paramp4[1]
          alphagarch11=garch11_paramp4[2]
          betagarch11=garch11_paramp4[3]
          n=1000
          sigsqrhalf1=sigma_sqr[1000:]
          e=np.random.normal(loc=0,scale=1,size=n)
          rtAR=np.zeros_like(e)
          xtAR=np.zeros_like(e)
          sigstGARCH11=np.zeros_like(e)
          for x in range(0,n):
              sigstGARCH11[x]=omegagarch11+alphagarch11*
              (x_half1[x-1]**2)+betagarch11*(sigsqrhalf1[x-1])
          testdfgarch11=pd.DataFrame(np.sqrt(sigma_sqr[:1000]))
          ardfgarch11=pd.DataFrame(np.sqrt(sigstGARCH11))
          plt.figure(figsize=(15,8))
          plt.plot(testdfgarch11)
          plt.plot(ardfgarch11)
          plt.legend(['Train', 'Garch(1,1)'], loc='upper left')
          plt.show()
          rmse=1/n*(ardfgarch11-testdfgarch11)**2
```

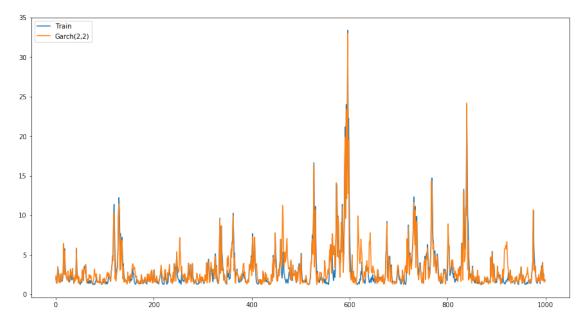
```
rmse=rmse.values.sum()
print('RMSE:',rmse)
```



RMSE: 1.9855503140086266

```
In [153]: omegagarch22=garch22_paramp4[1]
          alphagarch22=garch22_paramp4[2]
          alpha2garch22=garch22_paramp4[3]
          betagarch22=garch22_paramp4[4]
          beta2garch22=garch22_paramp4[5]
          n=1000
          e=np.random.normal(loc=0,scale=1,size=n)
          sigstGARCH22=np.zeros_like(e)
          for x in range(0,n):
              sigstGARCH22[x] = omegagarch22 + alphagarch22 * (x_half1[x-1] * * 2)
              +alpha2garch22*(x_half1[x-2]**2)+betagarch22
              *(sigsqrhalf1[x-1])+beta2garch22*(sigsqrhalf1[x-2])
          testdfgarch22=pd.DataFrame(np.sqrt(sigma_sqr[:1000]))
          ardfgarch22=pd.DataFrame(np.sqrt(sigstGARCH22))
          plt.figure(figsize=(15,8))
          plt.plot(testdfgarch22)
          plt.plot(ardfgarch22)
          plt.legend(['Train', 'Garch(2,2)'], loc='upper left')
```

```
plt.show()
rmse=1/n*(ardfgarch22-testdfgarch22)**2
rmse=rmse.values.sum()
print('RMSE:',rmse)
```



RMSE: 1.585339355839273

1.2 Empirical Application

1.2.1 Part 1

Constant Mean - ARCH Model Results

	Dep. Variable: Mean Model: Vol Model: Distribution: Method: Date: Time:	ARCH Log Normal AIG Maximum Likelihood BIG No Thu, Nov 29 2018 Df 03:36:38 Df Mean Mode			R-squared Likelihood Observation esiduals: odel:	ns:	-0.000 -0.000 -9253.98 18514.0 18533.2 : 4527 4524		
		coef	std err	t	P> t		Conf.		
	mu		2.675e-02 Volatili	0.973 ty Model	0.330	[-2.640e-02	,7.846	;-02]	
		coef	std err	t	P> t	95.0% Conf	. Int.		
	omega alpha[1]	2.7574 0.3037	0.195 5.280e-02	14.142 5.752	2.092e-45 8.799e-09	[2.375, [0.200,	3.140] 0.407]		
	Covariance est	imator:	robust						
In [104]:	<pre>arch2cok = arc arch2cok_res = arch2cokparam arch2cok_res.s</pre>	arch2co	ok.fit(disp='of cok_res.params		0)				
Out[104]:	<pre><class """<="" 'statsm="" pre=""></class></pre>	odels.io	olib.summary.Su	mmary'>					
			Constant Mean			-			
	Dep. Variable: Mean Model: Vol Model: Distribution: Method: Date: Time:	Max N	Return Constant Mean ARC Norma Timum Likelihoo Wed, Nov 28 201 23:35:3	n R-sq n Adj. H Log- l AIC: d BIC: No. 8 Df R	uared: R-squared Likelihood Observation esiduals: odel:	ns:	-92 18 18	-0.000 -0.000 202.10 3412.2 3437.9 4527 4523 4	
	========	coef	std err	t	P> t	95.0%	Conf.		
	mu	0.0313	2.763e-02		0.257	[-2.286e-02	,8.544	;-02]	

Volatility Model

========	coef	std err	 t	P> t	95.0% Con	if. Int.
omega alpha[1] alpha[2]	*	0.210 4.305e-02 3.777e-02	5.689	1.274e-08	[2.021, [0.161, [6.799e-02,	0.329]

Covariance estimator: robust

11 11 11

Out[105]: <class 'statsmodels.iolib.summary.Summary'>

Constant Mean - GARCH Model Results

Dep. Variable:	Return			R-squared:		-0.000
Mean Model:		Constant Mean			R-squared:	-0.000
Vol Model:		GARCH			ikelihood:	-9100.95
Distribution:		No	rmal	AIC:		18209.9
Method:	Max	imum Likeli	hood	BIC:		18235.6
				No. O	bservation	is: 4527
Date:	W	ed, Nov 28	2018	Df Re	siduals:	4523
Time:		23:3	5:33	Df Mo	del:	4
			Mean	Model		
=======================================	======		=====		=======	
	coef	std err		t	P> t	95.0% Conf. Int.
mu	0.0412					[-1.242e-02,9.476e-02]
		Vo	latili	ty Mod	el 	
	coef	std err		t	P> t	95.0% Conf. Int.
omega	0.0214	2.677e-02		.800	0.424	[-3.105e-02,7.387e-02]
alpha[1]	0.0263	1.615e-02	1	.629	0.103	[-5.337e-03,5.796e-02]
beta[1]	0.9683	2.312e-02	41	.888	0.000	[0.923, 1.014]
=======================================	======		=====			

Covariance estimator: robust

11 11 11

garch12cokparam = garch12cok_res.params garch12cok_res.summary()

Out[106]: <class 'statsmodels.iolib.summary.Summary'>

Constant Mean - GARCH Model Results

==========		=========			=======================================
Dep. Variable:		Return	R-squar	red:	-0.000
Mean Model:		Constant Mean	Adj. R-	squared:	-0.000
Vol Model:		GARCH	Log-Lik	celihood:	-9094.15
Distribution:		Normal	AIC:		18198.3
Method:	Max	imum Likelihood	BIC:		18230.4
			No. Obs	ervations	s: 4527
Date:	W	ed, Nov 28 2018	Df Resi	duals:	4522
Time:		23:35:34	Df Mode	el:	5
		Mea	n Model		
==========	:======			.======	
	coef	std err	t	P> t	95.0% Conf. Int.
mu	0.0396		1.469 lity Model		[-1.322e-02,9.240e-02]
	coef	std err	t	P> t	95.0% Conf. Int.

 0.0325
 3.709e-02
 0.877
 0.380
 [-4.016e-02, 0.105]

 0.0416
 2.168e-02
 1.920
 5.483e-02
 [-8.616e-04,8.413e-02]

 0.3774
 0.110
 3.435
 5.916e-04
 [0.162, 0.593]

 omega alpha[1] beta[1] beta[2] 0.5728 0.123 4.660 3.164e-06 [0.332, 0.814] ______

Covariance estimator: robust

In [107]: garch22cok = arch_model(cok["Return"], p=2, q=2) garch22cok_res = garch22cok.fit(disp='off') garch22cokparam = garch22cok_res.params garch22cok_res.summary()

Out[107]: <class 'statsmodels.iolib.summary.Summary'>

Constant Mean - GARCH Model Results

______ Dep. Variable: Return R-squared: -0.000 Constant Mean Adj. R-squared: Mean Model: -0.000 Vol Model: GARCH Log-Likelihood: -9098.98 Distribution: Normal AIC: 18210.0 Method: Maximum Likelihood BIC: 18248.5 No. Observations: 4527

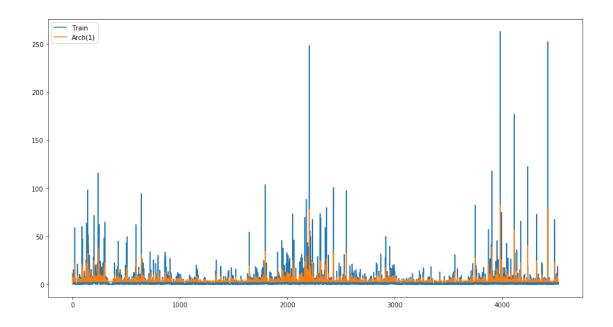
coef std err t P> t 95.0% Conf. Int mu 0.0426 2.664e-02 1.600 0.110 [-9.602e-03,9.483e-02 Volatility Model coef std err t P> t 95.0% Conf. Int.	Date: Time:			5:36 Df M Mean Model	odel:		4521 6
mu 0.0426 2.664e-02 1.600 0.110 [-9.602e-03,9.483e-02		coef	std err	t	P> t	95.0% C	
			2.664e-02	1.600	0.110		.483e-02]
		coef	std err	t	P> t	95.0% Con	f. Int.
omega 0.2226 0.108 2.053 4.010e-02 [1.005e-02, 0.435] alpha[1] 0.1024 7.672e-02 1.335 0.182 [-4.794e-02, 0.253] alpha[2] 3.5277e-12 9.539e-02 3.698e-11 1.000 [-0.187, 0.187] beta[1] 0.5059 0.845 0.599 0.549 [-1.151, 2.163] beta[2] 0.3336 0.829 0.402 0.687 [-1.291, 1.958]	alpha[1] alpha[2] beta[1]	0.1024 3.5277e-12 0.5059	7.672e-02 9.539e-02 0.845	1.335 3.698e-11 0.599	0.182 1.000 0.549	[-4.794e-02, [-0.187, [-1.151,	0.253] 0.187] 2.163]

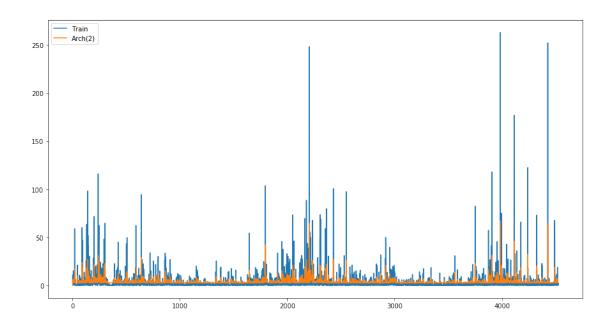
1.2.2 Part 2

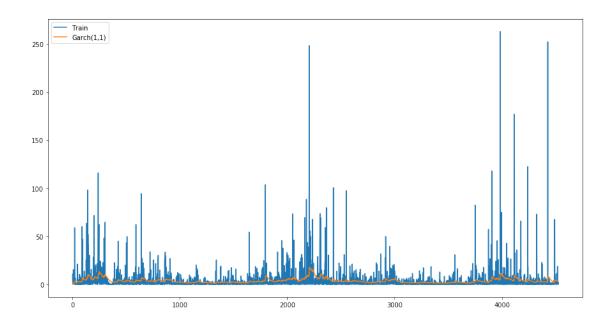
11 11 11

We can look at the AIC (Akaike's Information Criteria) and BIC(Bayesian Information Criteria) of the models to determine which one is the "best" model for the sample data. AIC measures the quality of the model based on the amount of information lost. BIC attempts to select the "true" model from a set of candidate models. GARCH(1,2) has the lowest BIC and AIC and hence is the "best" model.

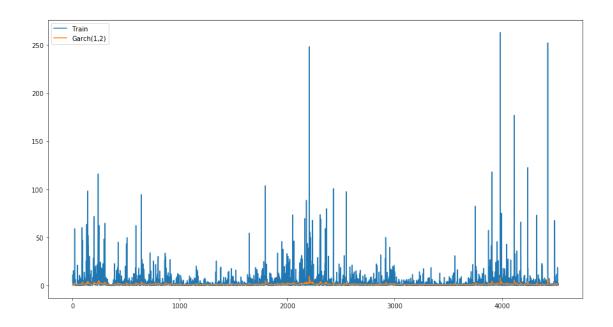
1.2.3 Part 3



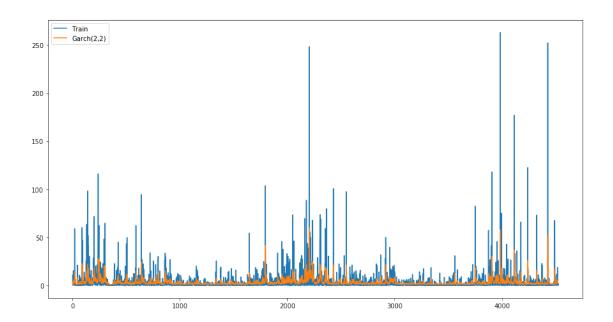




```
In [237]: omegagarch12cok=garch12cokparam[1]
          alphagarch12cok=garch12cokparam[2]
          betagarch12cok=garch12cokparam[3]
          beta2garch12cok=garch12cokparam[4]
          n=len(cok["Return"])
          e=np.random.normal(loc=0,scale=1,size=n-1)
          vargarch12cok=np.zeros_like(e)
          for x in range(1,n-1):
              vargarch12cok[x]=omegagarch12cok+alphagarch11cok* \
              (list(cok["Return"])[x-1]**2)+betagarch12cok*vargarch12cok[x-1] \
              +beta2garch12cok*vargarch12cok[x-2]
          plt.figure(figsize=(15,8))
          plt.plot(np.square(cok["Return"]))
          plt.plot(vargarch12cok)
          plt.legend(['Train', 'Garch(1,2)'], loc='upper left')
          plt.show()
```



```
In [238]: omegagarch22cok=garch22cokparam[1]
          alphagarch22cok=garch22cokparam[2]
          alpha2garch22cok=garch22cokparam[3]
          betagarch22cok=garch22cokparam[4]
          beta2garch22cok=garch22cokparam[5]
          n=len(cok["Return"])
          e=np.random.normal(loc=0,scale=1,size=n-1)
          vargarch22cok=np.zeros_like(e)
          for x in range(1,n-1):
              vargarch22cok[x]=omegagarch22cok+alphagarch22cok \
              *(list(cok["Return"])[x-1]**2)+alphagarch22cok \
              *(list(cok["Return"])[x-2]**2)+betagarch22cok \
              *vargarch12cok[x-1]+beta2garch22cok*vargarch22cok[x-2]
          plt.figure(figsize=(15,8))
          plt.plot(np.square(cok["Return"]))
          plt.plot(vargarch22cok)
          plt.legend(['Train', 'Garch(2,2)'], loc='upper left')
          plt.show()
```



1.2.4 Part 4

```
In [239]: varARCH1cokpred60 = arch1cok_res.forecast(horizon=60)
          varARCH1cokpred60 = varARCH1cokpred60.variance.dropna().head().T
          varARCH2cokpred60 = arch2cok_res.forecast(horizon=60)
          varARCH2cokpred60 = varARCH2cokpred60.variance.dropna().head().T
          vargarch11cokpred60 = garch11cok_res.forecast(horizon=60)
          vargarch11cokpred60 = vargarch11cokpred60.variance.dropna().head().T
          vargarch12cokpred60 = garch12cok_res.forecast(horizon=60)
          vargarch12cokpred60 = vargarch12cokpred60.variance.dropna().head().T
          vargarch22cokpred60 = garch22cok_res.forecast(horizon=60)
          vargarch22cokpred60 = vargarch22cokpred60.variance.dropna().head().T
In [274]: def realized_variance(returns, k):
              .....
              Returns is a numpy array. This is for the out-of-sample section.
              Returns should include the k-1 data points before the prediction range.
              Then if want to predict after time T, should use
                  realized_variance(returns[T-k-+1:], k)
              sq returns = returns**2
              realized_variance = pd.Series(sq_returns).rolling(k).sum()[k-1:]
              c = np.var(returns) / np.mean(realized_variance)
```

```
return sigmasq_t
                        def MSE_1(rv, preds):
                                  return np.mean((np.sqrt(rv) - preds)**2)
                        MSE 1(realized variance(cok["Return"][-60-5+1:], 5), varARCH1cokpred60[varARCH1cokpred60]
Out [274]: 7.22890897875777
In [275]: MSE_1(realized_variance(cok["Return"][-60-5+1:], 5), varARCH2cokpred60[varARCH2cokpred60]
Out [275]: 7.167660262570629
In [276]: MSE_1(realized_variance(cok["Return"][-60-5+1:], 5), vargarch11cokpred60[vargarch11cokpred60]
Out[276]: 5.121325224938479
In [277]: MSE_1(realized_variance(cok["Return"][-60-5+1:], 5), vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60]]
Out [277]: 8.253181411946402
In [278]: MSE_1(realized_variance(cok["Return"][-60-5+1:], 5), vargarch22cokpred60[vargarch22cokpred60[vargarch22cokpred60]]
Out [278]: 8.252735646950587
       Looking at these MSE results, GARCH(1,1) has the smallest number and hence is better.
In [279]: def MAE_1(rv, preds):
                                  return np.mean(np.abs(np.sqrt(rv) - np.sqrt(preds)))
                        MAE_1(realized_variance(cok["Return"][-60-5+1:], 5), varARCH1cokpred60[varARCH1cokpred60]
Out [279]: 0.953969511653309
In [281]: MAE_1(realized_variance(cok["Return"] [-60-5+1:], 5), varARCH2cokpred60[varARCH2cokpred60]
Out [281]: 0.9497613961086594
In [282]: MAE_1(realized_variance(cok["Return"][-60-5+1:], 5), vargarch11cokpred60[vargarch11cokpred60]
Out [282]: 0.9042371759517865
In [283]: MAE_1(realized_variance(cok["Return"][-60-5+1:], 5), vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[vargarch12cokpred60[var
Out [283]: 0.9575990138183529
In [284]: MAE_1(realized_variance(cok["Return"][-60-5+1:], 5), vargarch22cokpred60[vargarch22cokpred60[vargarch22cokpred60]]
Out [284]: 0.957586258811187
```

sigmasq_t = c * realized_variance

Looking at these MAE Results, GARCH(1,1) has the smallest number and hence is better.