Modeling

September 28, 2020

```
[1]: import pandas as pd
     import numpy as np
     %matplotlib notebook
     import matplotlib.pyplot as plt
     from datetime import datetime
     import statsmodels.api as sm
     from statsmodels.tsa.arima_model import ARIMA
[3]: # HIT (BA)
    hit_HT = pd.read_csv('./hit/hit_HT.csv')
    hit_HH = pd.read_csv('./hit/hit_HH.csv')
     hit_KT = pd.read_csv('./hit/hit_KT.csv')
    hit_LG = pd.read_csv('./hit/hit_LG.csv')
     hit_LT = pd.read_csv('./hit/hit_LT.csv')
    hit_NC = pd.read_csv('./hit/hit_NC.csv')
     hit_OB = pd.read_csv('./hit/hit_OB.csv')
     hit_SK = pd.read_csv('./hit/hit_SK.csv')
     hit_SS = pd.read_csv('./hit/hit_SS.csv')
     hit_WO = pd.read_csv('./hit/hit_WO.csv')
     ba_HT = hit_HT.iloc[:,[1,2]]
     ba_HH = hit_HH.iloc[:,[1,2]]
     ba_KT = hit_KT.iloc[:,[1,2]]
     ba_LG = hit_LG.iloc[:,[1,2]]
     ba LT = hit LT.iloc[:,[1,2]]
     ba_NC = hit_NC.iloc[:,[1,2]]
     ba_OB = hit_OB.iloc[:,[1,2]]
     ba_SK = hit_SK.iloc[:,[1,2]]
     ba_SS = hit_SS.iloc[:,[1,2]]
     ba_W0 = hit_W0.iloc[:,[1,2]]
[4]: # PIT (ER)
     pit_HT = pd.read_csv('./pit/pit_HT.csv')
     pit_HH = pd.read_csv('./pit/pit_HH.csv')
     pit_KT = pd.read_csv('./pit/pit_KT.csv')
     pit_LG = pd.read_csv('./pit/pit_LG.csv')
     pit_LT = pd.read_csv('./pit/pit_LT.csv')
```

```
pit_NC = pd.read_csv('./pit/pit_NC.csv')
     pit_OB = pd.read_csv('./pit/pit_OB.csv')
     pit_SK = pd.read_csv('./pit/pit_SK.csv')
     pit_SS = pd.read_csv('./pit/pit_SS.csv')
     pit_WO = pd.read_csv('./pit/pit_WO.csv')
     er_HT = pit_HT.iloc[:,[1,2]]
     er_HH = pit_HH.iloc[:,[1,2]]
     er_KT = pit_KT.iloc[:,[1,2]]
     er_LG = pit_LG.iloc[:,[1,2]]
     er_LT = pit_LT.iloc[:,[1,2]]
     er_NC = pit_NC.iloc[:,[1,2]]
     er_OB = pit_OB.iloc[:,[1,2]]
     er_SK = pit_SK.iloc[:,[1,2]]
     er_SS = pit_SS.iloc[:,[1,2]]
     er_WO = pit_WO.iloc[:,[1,2]]
[5]: # PIT (WLS)
     wls_HT = pit_HT.iloc[:,[1,3]]
     wls_HH = pit_HH.iloc[:,[1,3]]
     wls_KT = pit_KT.iloc[:,[1,3]]
     wls_LG = pit_LG.iloc[:,[1,3]]
     wls_LT = pit_LT.iloc[:,[1,3]]
     wls_NC = pit_NC.iloc[:,[1,3]]
     wls_OB = pit_OB.iloc[:,[1,3]]
     wls_SK = pit_SK.iloc[:,[1,3]]
     wls_SS = pit_SS.iloc[:,[1,3]]
     wls_W0 = pit_W0.iloc[:,[1,3]]
[6]: #
     def modeling(data,order,steps,trend='c'): # , arima ,
         data = data.iloc[:,1]
         model = ARIMA(data,order=order)
         model_fit = model.fit(trend=trend,full_output=True,disp=True)
         print("{}\n".format(model_fit.summary()))
         fore = model_fit.forecast(steps=steps)
         f = pd.DataFrame(fore[0])
         f.index = pd.RangeIndex(start=len(data), stop=len(data)+steps, step=1)
         model_fit.plot_predict()
         plt.plot(f)
         print(" ",f)
```

1

HH 10 HT 12 KT 9 LG 7 LT 9 NC 7 OB 12 SK 9 SS 11 WO 9

2 BA(hit)

 $HH\ 2,0,2\ HT\ 1,0,2\ KT\ 2,1,0\ LG\ 2,0,0\ LT\ 2,0,4\ NC\ 1,0,0\ OB\ 1,0,4\ SK\ 2,1,0\ SS\ 0,2,1\ WO\ 4,0,3$

[7]: # BA modeling(ba_HH,(2,0,2),10)

ARMA Model Results							
Dep. Variable: Model: Method: Date: Time: Sample:	Sun	ARMA(2 css., 27 Sep :	-mle 2020	Log S.D.	======================================	=====	112 384.622 0.008 -757.245 -740.934 -750.627
	coef	std err		z	P> z	[0.025	0.975]
ar.L1.BA	0.2348 0.3913 0.4922	0.240	1		0.000 0.103 0.032	-0.079	0.862
ma.L1.BA	0.0673).288 2.447	0.774		0.526 0.514
=========	======================================	 I1			======================================	======	Frequency
	1.0823 -1.8773 -0.1179 -0.1179	-	+0.000 +0.000 -1.868 +1.868	00j 86j	1.0823 1.8773 1.8723 1.8723		0.0000 0.5000 -0.2600 0.2600

<IPython.core.display.Javascript object>

0

112 0.230051

113 0.237423

114 0.233488

115 0.235576

116 0.234457

117 0.235047

118 0.234727

119 0.234892

<IPython.core.display.HTML object>

120 0.234799121 0.234843

```
[26]: # BA
```

modeling(ba_HT,(1,0,2),12,'c')

ARMA Model Results

ARMA MODEL RESULTS						
Dep. Variable Model: Method: Date: Time: Sample:		, 26 Sep 2	2) Log I	Observations: Likelihood of innovations		109 347.943 0.010 -685.887 -672.430 -680.430
				P> z	_	0.975]
	0.9280 0.1414	0.056 0.112 0.117	16.543 1.265		0.818 -0.078	1.038 0.361
	Real	Im	naginary	Modulus		Frequency
	1.0776 -1.4045 1.7527	+	0.0000j 0.0000j 0.0000j	1.0776 1.4045 1.7527		0.0000 0.5000 0.0000

<IPython.core.display.Javascript object>

0

109 0.286989

110 0.285649

111 0.283947

112 0.282368

113 0.280903

114 0.279544

115 0.278282

116 0.277111

117 0.276025

118 0.275017

<IPython.core.display.HTML object>

119 0.274081 120 0.273213

[27]: #KT BA

modeling(ba_KT,(2,1,0),9,'nc')

ARIMA Model Results

		AILTIA .	ites			
Dep. Variable:		D.1	BA No.	Observations:		110
Model:	I	RIMA(2, 1,	0) Log	Likelihood		355.761
Method:		css-m	le S.D.	of innovations		0.010
Date:	Sat	, 26 Sep 20	20 AIC			-705.523
Time:		01:02:	32 BIC			-697.421
Sample:			1 HQIC			-702.237
=========	=======	:=======	=======		======	=======
	coef	std err	z	P> z	[0.025	0.975]
ar.L1.D.BA	0.2161	0.098	2.216	0.027	0.025	0.407
ar.L2.D.BA	0.1811	0.097	1.861	0.063	-0.010	0.372
			Roots			
	Real	Ima	====== ginary	Modulus	======	Frequency
AR.1	1.8279	+0	 .0000j	1.8279		0.0000

+0.0000j AR.2 -3.0212 3.0212 0.5000

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

0

111 0.287613

112 0.288108

113 0.288326

114 0.288463

115 0.288532

116 0.288571

117 0.288592

118 0.288604

119 0.288610

[28]: #LG BA

 $modeling(ba_LG,(2,0,0),7)$

ARMA Model Results

=========		=======	========		=======	========
Dep. Variable:			BA No.	Observations:		113
Model:		ARMA(2,	0) Log	Likelihood		367.203
Method:		css-	mle S.D.	. of innovations	}	0.009
Date:	Sat	, 26 Sep 2	020 AIC			-726.407
Time:		01:02	:41 BIC			-715.497
Sample:			O HQIO	C		-721.980
=========	coef	std err	z	P> z	[0.025	0.975]
const	0.2787	0.005	61.489	0.000	0.270	0.288
ar.L1.BA	1.1319	0.128	8.839	0.000	0.881	1.383
ar.L2.BA	-0.3237	0.128	-2.521	0.012	-0.575	-0.072
			Roots			
========	Real	Im	aginary	Modulus		Frequency
AR.1	1.7484		 0.1799j	1.7576	;	-0.0163
AR.2	1.7484	+	0.1799j	1.7576	;	0.0163

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

0

113 0.272637

114 0.274004

115 0.275347

116 0.276423

117 0.277207

118 0.277746

119 0.278103

[42]: # BA

modeling(ba_LT,(2,0,4),9)

Dep. Variable:	ВА	No. Observations:	110
Model:	ARMA(2, 4)	Log Likelihood	377.968
Method:	css-mle	S.D. of innovations	0.008
Date:	Sat, 26 Sep 2020	AIC	-739.936
Time:	01:06:10	BIC	-718.333

	coef	std err	z	P> z	[0.025	0.975]
const	0.2668	0.006	45.199	0.000	0.255	0.278
ar.L1.BA	1.7050	0.139	12.262	0.000	1.433	1.978
ar.L2.BA	-0.8043	0.138	-5.815	0.000	-1.075	-0.533
ma.L1.BA	-0.5370	0.147	-3.647	0.000	-0.826	-0.248
ma.L2.BA	-0.1005	0.116	-0.866	0.387	-0.328	0.127
ma.L3.BA	-0.0451	0.102	-0.443	0.658	-0.245	0.154
ma.L4.BA	0.4827	0.091	5.301	0.000	0.304	0.661
			Roots			

	Real	Imaginary	Modulus	Frequency
AR.1	1.0600	-0.3461j	1.1151	-0.0502
AR.2	1.0600	+0.3461j	1.1151	0.0502
MA.1	0.9096	-0.6024j	1.0910	-0.0931
MA.2	0.9096	+0.6024j	1.0910	0.0931
MA.3	-0.8628	-0.9981j	1.3193	-0.3634
MA.4	-0.8628	+0.9981j	1.3193	0.3634

<IPython.core.display.HTML object>

0

110 0.264672

111 0.263119

112 0.260621

113 0.263019

114 0.265325

115 0.267327

116 0.268886

117 0.269935

118 0.270468

[57]: #NC BA

modeling(ba_NC,(1,0,0),7)

ARMA Model Results

Dep. Variable: BA No. Observations: 110 Model: ARMA(1, 0) Log Likelihood 387.947

Method:		css-	mle S.D.	of innovations		0.007
Date:	Sat	, 26 Sep 2	2020 AIC			-769.895
Time:		01:23	3:43 BIC			-761.793
Sample:			O HQIC			-766.609
_						
=========	coef	std err	z	P> z	[0.025	0.975]
const	0.2722	0.018	 15.150	0.000	0.237	0.307
ar.L1.BA	0.9666	0.030	32.672	0.000	0.909	1.025
			Roots			
==========		=======	=======	========	======	=======
	Real	In	naginary	Modulus		Frequency
AR.1	1.0345	+	-0.0000j	1.0345		0.0000

 $\verb| <IPython.core.display.Javascript| object> \\$

<IPython.core.display.HTML object>

0

- 110 0.283605
- 111 0.283224
- 112 0.282855
- 113 0.282498
- 114 0.282154
- 115 0.281821
- 116 0.281499

[56]: #OB BA

modeling(ba_OB,(1,0,4),12)

=======================================	=======			======			=======
Dep. Variable:		В	Α	No. Obse	rvations:		112
Model:		ARMA(1, 4)	Log Like	lihood		360.897
Method:		css-ml	е	S.D. of	innovations		0.010
Date:	Sat	, 26 Sep 202	0	AIC			-707.794
Time:		01:23:3	4	BIC			-688.764
Sample:			0	HQIC			-700.073
==========		========		======	=======	=======	=======
	coef	std err		Z	P> z	[0.025	0.975]
const	0.2846	0.007	 42.	242	0.000	0.271	0.298
COIID	0.2040	0.007	42.	Z T Z	0.000	0.211	0.230

ar.L1.BA	0.6462	0.134	4.827	0.000	0.384	0.909
ma.L1.BA	0.4539	0.123	3.687	0.000	0.213	0.695
ma.L2.BA	0.2091	0.104	2.008	0.045	0.005	0.413
ma.L3.BA	0.5663	0.105	5.418	0.000	0.361	0.771
ma.L4.BA	0.4175	0.110	3.812	0.000	0.203	0.632
			Roots			

Real Imaginary Modulus Frequency 1.5474 +0.0000j AR.1 1.5474 0.0000 MA.1 0.5428 -0.9918j -0.1703 1.1306 MA.2 0.5428 +0.9918j 1.1306 0.1703 MA.3 -0.6188j -1.2211 1.3689 -0.4253 MA.4 +0.6188j -1.22111.3689 0.4253

<IPython.core.display.HTML object>

0

112 0.259467

113 0.263392

114 0.268439

115 0.273813

116 0.277620

117 0.280081

118 0.281671

119 0.282698

120 0.283362

121 0.283791

122 0.284069

123 0.284248

[60]: #SK BA

modeling(ba_SK,(2,1,0),9,'nc')

ARIMA Model Results

Dep. Variable: D.BA No. Observations: 113 ARIMA(2, 1, 0) Log Likelihood Model: 346.393 Method: css-mle S.D. of innovations 0.011 Date: Sat, 26 Sep 2020 AIC -686.786 01:39:35 Time: BIC -678.604 Sample: 1 HQIC -683.466

<IPython.core.display.Javascript object>

========	========	========		.=======	=======	========
	coef	std err	z	P> z	[0.025	0.975]
ar.L1.D.BA	0.8073	0.107	7.513	0.000	0.597	1.018
ar.L2.D.BA	-0.2627	0.142	-1.850	0.064	-0.541	0.016
			Roots			
	======================================	Im:	======= aginary 	Modul	us 	Frequency

AR.1 1.5367 -1.2023j 1.9512 -0.1057
AR.2 1.5367 +1.2023j 1.9512 0.1057

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

0

114 0.219258

115 0.218620

116 0.218825

117 0.219158

118 0.219373

119 0.219460

120 0.219473

121 0.219460

122 0.219447

[19]: #SS BA

modeling(ba_SS,(0,2,1),11,'nC')

D.BA	No. Observations:	111
ARIMA(1, 1, 1)	Log Likelihood	387.744
css-mle	S.D. of innovations	0.007
Sat, 26 Sep 2020	AIC	-767.487
16:44:52	BIC	-756.649
1	HQIC	-763.091
	ARIMA(1, 1, 1) css-mle Sat, 26 Sep 2020	ARIMA(1, 1, 1) Log Likelihood css-mle S.D. of innovations Sat, 26 Sep 2020 AIC 16:44:52 BIC

	coef	std err	z	P> z	[0.025	0.975]
const ar.L1.D.BA	0.0036 0.9661	0.003 0.040	1.125 24.015	0.260	-0.003 0.887	0.010
ma.L1.D.BA	-0.8399	0.040	-11.882	0.000	-0.978	-0.701

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	1.0350	+0.0000j	1.0350	0.0000
MA.1	1.1906	+0.0000j	1.1906	0.0000

<IPython.core.display.HTML object>

0

112 0.292387

113 0.295782

114 0.299184

115 0.302594

116 0.306011

117 0.309434

118 0.312865

119 0.316302

120 0.319745

121 0.323194

122 0.326649

[69]: #WO BA

modeling(ba_WO,(4,0,3),9)

BA	No. Observations:	117
ARMA(4, 3)	Log Likelihood	411.833
css-mle	S.D. of innovations	0.007
Sat, 26 Sep 2020	AIC	-805.667
01:43:23	BIC	-780.807
0	HQIC	-795.574
	ARMA(4, 3) css-mle Sat, 26 Sep 2020	ARMA(4, 3) Log Likelihood css-mle S.D. of innovations Sat, 26 Sep 2020 AIC 01:43:23 BIC

=======	coef	std err	z	P> z	[0.025	0.975]
const	0.2678	0.001	321.423	0.000	0.266	0.269
ar.L1.BA	0.7107	0.073	9.680	0.000	0.567	0.855
ar.L2.BA	0.4449	0.108	4.126	0.000	0.234	0.656
ar.L3.BA	0.6768	0.099	6.833	0.000	0.483	0.871
ar.L4.BA	-0.9008	0.066	-13.661	0.000	-1.030	-0.772
ma.L1.BA	0.2300	0.097	2.374	0.018	0.040	0.420

ma.L2.BA	-0.4161	0.095	-4.373	0.000	-0.603	-0.230
ma.L3.BA	-0.8139	0.102	-7.958	0.000	-1.014	-0.613
			Roots			

Imaginary Modulus Frequency -0.6402 -0.8019j 1.0261 AR.2 -0.6402 +0.8019j 1.0261 0.3572 AR.3 1.0158 -0.1501j 1.0269 -0.0234 AR.4 +0.1501j 1.0158 1.0269 0.0234 MA.1 1.0000 -0.0000j 1.0000 -0.0000 MA.2 -0.7556 -0.8110j 1.1084 -0.3694

+0.8110j

1.1084

0.3694

<IPython.core.display.Javascript object>

-0.7556

<IPython.core.display.HTML object>

0

117 0.250726

MA.3

118 0.252510

119 0.254042

120 0.255702

121 0.258116

122 0.260001

123 0.262158

124 0.264667

125 0.266512

3 ER(PIT)

HH 201 HT 112 KT 010//414 LG 102 LT 100 NC 210 OB 211 SK 011 SS 010//302 WO 101

[71]: #HH ER modeling(er_HH,(2,0,1),10)

=======================================			
Dep. Variable:	ER	No. Observations:	110
Model:	ARMA(2, 1)	Log Likelihood	-44.164
Method:	css-mle	S.D. of innovations	0.354
Date:	Sat, 26 Sep 2020	AIC	98.328
Time:	01:44:40	BIC	111.830
Sample:	0	HQIC	103.804

=======	=======			=======	========
coef	std err	z	P> z	[0.025	0.975]
4.2368 1.9676	1.270	3.336 40.773	0.001	1.748 1.873	6.726 2.062
-0.9720	0.048	-20.345	0.000	-1.066	-0.878
-0.9144	0.137	-6.669	0.000	-1.183	-0.646
		Roots			
Real	Im	Imaginary		Modulus	
1.0122	-	0.0658j	1.014	3	-0.0103
1.0122	+	0.0658j	1.014	3	0.0103
1.0937	+	0.0000j 	1.093	7 	0.0000
	4.2368 1.9676 -0.9720 -0.9144 	4.2368 1.270 1.9676 0.048 -0.9720 0.048 -0.9144 0.137 Real Im 1.0122 - 1.0122 +	4.2368 1.270 3.336 1.9676 0.048 40.773 -0.9720 0.048 -20.345 -0.9144 0.137 -6.669 Roots Real Imaginary 1.0122 -0.0658j 1.0122 +0.0658j	4.2368 1.270 3.336 0.001 1.9676 0.048 40.773 0.000 -0.9720 0.048 -20.345 0.000 -0.9144 0.137 -6.669 0.000 Roots Real Imaginary Modulu 1.0122 -0.0658j 1.014 1.0122 +0.0658j 1.014	4.2368 1.270 3.336 0.001 1.748 1.9676 0.048 40.773 0.000 1.873 -0.9720 0.048 -20.345 0.000 -1.066 -0.9144 0.137 -6.669 0.000 -1.183 Roots Real Imaginary Modulus 1.0122 -0.0658j 1.0143 1.0122 +0.0658j 1.0143

<IPython.core.display.HTML object>

0

- 110 4.168585
- 111 4.116964
- 112 4.067313
- 113 4.019792
- 114 3.974548
- 115 3.931715
- 116 3.891412
- 117 3.853743
- 118 3.818799
- 119 3.786654

[74]: #HT ER

modeling(er_HT,(1,1,2),12,'NC')

			======			=======
Dep. Variable:		D.ER	No. Obs	servations:		108
Model:	A	RIMA(1, 1, 2)	Log Lil	kelihood		-74.501
Method:		css-mle	S.D. of	f innovation	S	0.479
Date:	Sat	, 26 Sep 2020	AIC			157.002
Time:		01:45:08	BIC			167.731
Sample:		1	HQIC			161.352
						=======
	coef	std err	Z	P> z	[0.025	0.975]

ar.L1.D.ER	-0.8058	0.169	-4.773	0.000	-1.137	-0.475
ma.L1.D.ER	1.1079	0.128	8.638	0.000	0.857	1.359
ma.L2.D.ER	0.6470	0.076	8.467	0.000	0.497	0.797
			Roots			

	Real	Imaginary	Modulus	Frequency			
AR.1	-1.2411	+0.0000j	1.2411	0.5000			
MA.1	-0.8562	-0.9014j	1.2432	-0.3709			
MA.2	-0.8562	+0.9014j	1.2432	0.3709			

<IPython.core.display.HTML object>

0

109 4.330714

110 4.674135

111 4.397421

112 4.620385

113 4.440730

114 4.585489

115 4.468848

116 4.562832

117 4.487104

118 4.548123

119 4.498956

120 4.538572

[11]: #KT ER

modeling(er_KT,(4,1,4),9,'nc')

C:\Users\user\Anaconda3\lib\site-packages\statsmodels\base\model.py:548: HessianInversionWarning: Inverting hessian failed, no bse or cov_params available

'available', HessianInversionWarning)

Dep. Variable:	D.ER	No. Observations:	111
Model:	ARIMA(4, 1, 4)	Log Likelihood	-26.198
Method:	css-mle	S.D. of innovations	0.295
Date:	Sat, 26 Sep 2020	AIC	70.396
Time:	16:37:02	BIC	94.782
Sample:	1	HOTC	80.288

========	========	========				=======
	coef	std err	Z	P> z	[0.025	0.975]
ar.L1.D.ER	-0.7634	0.102	-7.502	0.000	-0.963	-0.564
ar.L2.D.ER	-0.5596	0.117	-4.771	0.000	-0.790	-0.330
ar.L3.D.ER	-0.6014	0.127	-4.723	0.000	-0.851	-0.352
ar.L4.D.ER	-0.7099	0.106	-6.712	0.000	-0.917	-0.503
ma.L1.D.ER	0.6127	0.063	9.685	0.000	0.489	0.737
ma.L2.D.ER	0.5129	0.058	8.894	0.000	0.400	0.626
ma.L3.D.ER	0.6127	0.067	9.155	0.000	0.482	0.744
ma.L4.D.ER	1.0000	0.069	14.476	0.000	0.865	1.135
			Roots			

========		=======================================		
	Real	Imaginary	Modulus	Frequency
AR.1	0.4525	-1.0043j	1.1015	-0.1826
AR.2	0.4525	+1.0043j	1.1015	0.1826
AR.3	-0.8762	-0.6272j	1.0775	-0.4011
AR.4	-0.8762	+0.6272j	1.0775	0.4011
MA.1	0.4755	-0.8797j	1.0000	-0.1711
MA.2	0.4755	+0.8797j	1.0000	0.1711
MA.3	-0.7819	-0.6235j	1.0000	-0.3929
MA.4	-0.7819	+0.6235j	1.0000	0.3929

<IPython.core.display.Javascript object>

112 3.875421 113 3.809631 114 3.766659 115 3.670642 116 3.856234 117 3.840842 118 3.836983 119 3.805084 120 3.709103

[12]: #LG ER

#LG ER
modeling(er_LG,(1,0,2),7)

ARMA Model Results

<IPython.core.display.HTML object>

Dep. Variable:	ER	No. Observations:	113
Model:	ARMA(1, 2)	Log Likelihood	-40.403
Method:	css-mle	S.D. of innovations	0.343
Date:	Sat, 26 Sep 2020	AIC	90.805
Time:	11:30:18	BIC	104.442
Sample:	0	HQIC	96.339

						=======	
	coef	std err	z	P> z	[0.025	0.975]	
const	4.3780	0.260	16.836	0.000	3.868	4.888	
ar.L1.ER	0.8058	0.076	10.620	0.000	0.657	0.955	
ma.L1.ER	0.3068	0.108	2.844	0.004	0.095	0.518	
ma.L2.ER	0.3041	0.091	3.337	0.001	0.125	0.483	
Roots							

	Real	======================================	Modulus 	Frequency
AR.1	1.2410	+0.0000j	1.2410	0.0000
MA.1	-0.5045	-1.7418j	1.8133	-0.2949
MA.2	-0.5045	+1.7418j	1.8133	0.2949

<IPython.core.display.HTML object>

0

- 113 4.774576
- 114 4.698293
- 115 4.636097
- 116 4.585980
- 117 4.545595
- 118 4.513053
- 119 4.486832

[14]: #LT ER

modeling(er_LT,(1,0,0),9)

===========			
Dep. Variable:	ER	No. Observations:	110
Model:	ARMA(1, 0)	Log Likelihood	-36.496
Method:	css-mle	S.D. of innovations	0.334
Date:	Sat, 26 Sep 2020	AIC	78.992
Time:	11:31:06	BIC	87.093

Sample: 0 HQIC	82.278
----------------	--------

=========	========	========	========	.=======	=======	========
	coef	std err	Z	P> z	[0.025	0.975]
const	4.3589	0.382	11.401	0.000	3.610	5.108
ar.L1.ER	0.9216	0.045	20.657	0.000	0.834	1.009
			Roots			
	Real	Ima	Imaginary		us	Frequency
AR.1	1.0850	+(+0.0000j		50 	0.0000

<IPython.core.display.HTML object>

0

- 110 4.847453
- 111 4.809163
- 112 4.773873
- 113 4.741349
- 114 4.711374
- 115 4.683748
- 116 4.658287
- 117 4.634821
- 118 4.613195

ar.L2.D.ER

[17]: #NC ER

modeling(er_NC,(2,1,0),7,'nc')

0.2153

0.102

ARIMA Model Results

		=====					
Dep. Variable:			D.ER	No. O	bservations:		109
Model:		ARIMA((2, 1, 0)	Log L	ikelihood		-33.920
Method:			css-mle	S.D.	of innovations	1	0.330
Date:	Sa	t, 26	Sep 2020	AIC			73.839
Time:			11:31:58	BIC			81.913
Sample:			1	HQIC			77.114
===========		=====			=========	-	
	coef	std	err	Z	P> z	[0.025	0.975]
ar.L1.D.ER	0.1692	0.	102	 1.653	0.098	-0.031	0.370

2.102

0.036

0.015

0.416

Roots

Real	Imaginary	Modulus 	Frequency
AR.1 1.7979		1.7979	0.0000
AR.2 -2.5840		2.5840	0.5000

<IPython.core.display.HTML object>

0

110 3.933432

111 3.898275

112 3.877997

113 3.866998

114 3.860772

115 3.857351

116 3.855432

[20]: #OB ER

modeling(er_OB,(2,1,1),12,'NC')

==========			=======	.========		=======
Dep. Variable:	:	D.	ER No. Ob	servations:		111
Model:	I	ARIMA(2, 1,	1) Log Li	.kelihood		-57.156
Method:		css-m	· ·	of innovation	ıs	0.402
Date:	Sat	c, 26 Sep 20	20 AIC			122.312
Time:		_	21 BIC			133.150
Sample:			1 HQIC			126.709
1						
==========		.=======	========	:========	=======	=======
	coef	std err	z	P> z	[0.025	0.975]
ar.L1.D.ER	0.7220	0.153	4.720	0.000	0.422	1.022
ar.L2.D.ER	-0.7015	0.108	-6.519	0.000	-0.912	-0.491
ma.L1.D.ER	-0.5594	0.135	-4.139	0.000	-0.824	-0.295
			Roots			
===========					=======	
	Real	Ima	ginary	Modulu	ıs	Frequency
AR.1	0.5146		.0774j	1.194		-0.1791
AR.2	0.5146		.0774j	1.194	:0	0.1791
MA.1	1.7878	+0	.0000j	1.787	8	0.0000

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

0
112 4.246179
113 4.185770
114 4.125197
115 4.123841
116 4.165354

121 4.156683 122 4.172755 123 4.178580

117 4.196275 118 4.189478 119 4.162880 120 4.148446

[13]: #SK ER modeling(er_SK,(0,1,1),9,'NC')

==========	=======	:========				======	=======
Dep. Variable:		D.	ER No	Obs	servations:		113
Model:	A	RIMA(0, 1,	1) Log	g Lik	celihood		-39.492
Method:		css-m	nle S.I	of	innovations		0.343
Date:	Sat	, 26 Sep 20)20 AI	;			82.984
Time:		16:37:	48 BIG	;			88.439
Sample:			1 HQ	C			85.198
=========	=======	:=======					========
	coef	std err	2	:	P> z	[0.025	0.975]
ma.L1.D.ER	0.2533	0.105	2.420)	0.016	0.048	0.459
			Roots				
=========	=======	:=======				======	=======
	Real	Ima	aginary		Modulus		Frequency
MA.1	 -3.9473		0000÷		2 0472		0.5000
MA. I	-3.94/3	+(0.0000j		3.9473		0.5000

<IPython.core.display.Javascript object>

0
114 5.956982
115 5.956982
116 5.956982
117 5.956982
118 5.956982
119 5.956982
120 5.956982
121 5.956982
122 5.956982

[15]: #SS ER

modeling(er_SS,(3,0,2),11,'C')

		ARMA	Model Res	ults 		
Dep. Variable: Model: Method: Date: Time: Sample:		ARMA(3, css- , 26 Sep 2 16:38	2) Log 1 mle S.D. 020 AIC	Observations: Likelihood of innovations		111 -23.193 0.287 60.386 79.353 68.081
	coef	std err	z	P> z	[0.025	0.975]
const ar.L1.ER ar.L2.ER ar.L3.ER ma.L1.ER ma.L2.ER	4.7447 0.3011 -0.4125 0.8692 0.7992 0.9998	0.293 0.056 0.052 0.056 0.042 0.039	16.181 5.422 -7.953 15.587 19.195 25.313 Roots	0.000 0.000 0.000 0.000 0.000	4.170 0.192 -0.514 0.760 0.718 0.922	5.319 0.410 -0.311 0.978 0.881 1.077
	Real	Im	aginary	Modulus		Frequency
AR.1 AR.2 AR.3 MA.1 MA.2	-0.3149 -0.3149 1.1043 -0.3997 -0.3997	++ 	0.9709j 0.9709j 0.0000j 0.9168j 0.9168j	1.0207 1.0207 1.1043 1.0001 1.0001		-0.2999 0.2999 -0.0000 -0.3154 0.3154

<IPython.core.display.Javascript object>

0
111 6.036718
112 5.958781
113 5.813561
114 5.688741
115 5.643319
116 5.554905
117 5.438527
118 5.400473
119 5.360173
120 5.262579
121 5.216741

[27]: #WO ER

modeling(er_WO,(1,0,1),9)

		ARMA	Model Kest	11TS 		
Dep. Variable: Model: Method: Date: Time: Sample:	======= Sat	ARMA(1, css-r , 26 Sep 20	1) Log Inle S.D. D20 AIC	Dbservations: Likelihood of innovations	=====	117 -37.002 0.327 82.004 93.052 86.489
	coef	std err	z	P> z	[0.025	0.975]
ar.L1.ER	3.7488 0.9635 0.3425	0.985 0.033	3.805 29.261	0.000 0.000 0.000		5.680 1.028 0.535
	Real	Im:	aginary	Modulus		Frequency
AR.1 MA.1	1.0378 -2.9196		0.0000j 0.0000j	1.0378 2.9196		0.0000

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

```
117 5.194384
118 5.141680
119 5.090896
120 5.041965
121 4.994817
122 4.949388
123 4.905616
124 4.863439
```

125 4.822801

4 WLS

HH 302 HT 010//212 KT 010//414 LG 102 LT 103 NC 010/110 OB 411 SK 010/100 SS 010/100 WO 100

[30]: #HH WLS modeling(wls_HH,(3,0,2),10)

ARMA Model Results

WLS	No. Observations:	110
ARMA(3, 2)	Log Likelihood	156.282
css-mle	S.D. of innovations	0.057
Sat, 26 Sep 2020	AIC	-298.564
11:36:23	BIC	-279.661
0	HQIC	-290.897
	ARMA(3, 2) css-mle Sat, 26 Sep 2020	ARMA(3, 2) Log Likelihood css-mle S.D. of innovations Sat, 26 Sep 2020 AIC 11:36:23 BIC

=========		=======	=======	========		========
	coef	std err	Z	P> z	[0.025	0.975]
const	0.3988	0.144	2.769	0.006	0.117	0.681
ar.L1.WLS	0.3508	0.110	3.196	0.001	0.136	0.566
ar.L2.WLS	-0.0066	0.146	-0.045	0.964	-0.292	0.279
ar.L3.WLS	0.5745	0.115	4.985	0.000	0.349	0.800
ma.L1.WLS	0.3426	0.032	10.722	0.000	0.280	0.405
ma.L2.WLS	0.9555	0.079	12.038	0.000	0.800	1.111

=======	Real	Imaginary	Modulus	Frequency
AR.1	1.0382	-0.0000j	1.0382	-0.0000
AR.2	-0.5134	-1.1887j	1.2948	-0.3149
AR.3	-0.5134	+1.1887j	1.2948	0.3149
MA.1	-0.1793	-1.0072j	1.0230	-0.2780
MA.2	-0.1793	+1.0072j	1.0230	0.2780

Roots

<IPython.core.display.HTML object>

110 0.286332 111 0.300901 112 0.304992 113 0.301925 114 0.309193 115 0.314113 116 0.314029 117 0.318142 118 0.322412 119 0.323835

[16]: #HT WLS modeling(wls_HT,(2,1,2),12,'nc')

ARIMA Model Results

=======================================			
Dep. Variable:	D.WLS	No. Observations:	108
Model:	ARIMA(2, 1, 2)	Log Likelihood	164.589
Method:	css-mle	S.D. of innovations	0.053
Date:	Sat, 26 Sep 2020	AIC	-319.178
Time:	16:39:00	BIC	-305.768
Sample:	1	HQIC	-313.741

=========	========	========		========	========	=======
	coef	std err	Z	P> z	[0.025	0.975]
ar.L1.D.WLS	0.1407	0.042	3.329	0.001	0.058	0.224
ar.L2.D.WLS	-0.8400	nan	nan	nan	nan	nan
ma.L1.D.WLS	-0.1790	0.155	-1.152	0.249	-0.483	0.125
ma.L2.D.WLS	0.7419	0.150	4.960	0.000	0.449	1.035
Roots						

	Real	Imaginary	Modulus	Frequency
AR.1	0.0838	-1.0879j	1.0911	-0.2378
AR.2	0.0838	+1.0879j	1.0911	0.2378
MA.1	0.1206	-1.1547j	1.1610	-0.2334
MA.2	0.1206	+1.1547j	1.1610	0.2334

 $^{{\}tt C:\Users\setminus Anaconda3\lib\site-packages\statsmodels\base\model.py:548:}$

```
HessianInversionWarning: Inverting hessian failed, no bse or cov_params
     available
       'available', HessianInversionWarning)
     C:\Users\user\Anaconda3\lib\site-packages\statsmodels\tsa\arima_model.py:1490:
     RuntimeWarning: invalid value encountered in sqrt
       return np.sqrt(np.diag(-inv(hess)))
     C:\Users\user\Anaconda3\lib\site-
     packages\scipy\stats\_distn_infrastructure.py:1932: RuntimeWarning: invalid
     value encountered in less_equal
       cond2 = cond0 & (x <= _a)
     <IPython.core.display.Javascript object>
     <IPython.core.display.HTML object>
     109 0.669300
     110 0.682648
     111 0.682595
     112 0.671375
     113 0.669841
     114 0.679050
     115 0.681634
     116 0.674263
     117 0.671055
     118 0.676795
     119 0.680297
     120 0.675969
[17]: #KT WLS
      modeling(wls_KT,(4,1,4),9,'nc')
     C:\Users\user\Anaconda3\lib\site-packages\statsmodels\base\model.py:548:
     HessianInversionWarning: Inverting hessian failed, no bse or cov_params
     available
       'available', HessianInversionWarning)
                                  ARIMA Model Results
     Dep. Variable:
                                     D.WLS No. Observations:
                                                                                111
     Model:
                           ARIMA(4, 1, 4) Log Likelihood
                                                                          190.780
                                   css-mle S.D. of innovations
     Method:
                                                                             0.042
     Date:
                          Sat, 26 Sep 2020 AIC
                                                                           -363.560
                                  16:39:32
     Time:
                                           BIC
                                                                           -339.174
     Sample:
                                            HQIC
                                                                           -353.667
                                         1
```

Z

coef std err

P>|z|

[0.025

0.975]

ar.L1.D.WLS	-0.3149	0.096	-3.277	0.001	-0.503	-0.127
ar.L2.D.WLS	-0.0887	0.097	-0.913	0.361	-0.279	0.102
ar.L3.D.WLS	-0.3893	0.074	-5.292	0.000	-0.533	-0.245
ar.L4.D.WLS	-0.8091	0.087	-9.276	0.000	-0.980	-0.638
ma.L1.D.WLS	0.4172	0.064	6.487	0.000	0.291	0.543
ma.L2.D.WLS	0.2645	0.078	3.377	0.001	0.111	0.418
ma.L3.D.WLS	0.4171	0.065	6.391	0.000	0.289	0.545
ma.L4.D.WLS	0.9999	0.065	15.395	0.000	0.873	1.127
			Roots			

	Real	Imaginary	Modulus	Frequency
AR.1	0.6169	-0.8262j	1.0311	-0.1479
AR.2	0.6169	+0.8262j	1.0311	0.1479
AR.3	-0.8575	-0.6535j	1.0782	-0.3964
AR.4	-0.8575	+0.6535j	1.0782	0.3964
MA.1	0.5626	-0.8268j	1.0001	-0.1549
MA.2	0.5626	+0.8268j	1.0001	0.1549
MA.3	-0.7712	-0.6366j	1.0000	-0.3902
MA.4	-0.7712	+0.6366j	1.0000	0.3902

<IPython.core.display.Javascript object>

0

112 0.731450

113 0.739907

114 0.719804

115 0.707352

116 0.702117

117 0.705853

118 0.726253

119 0.731611

120 0.730896

[35]: #LG WLS

 $modeling(wls_LG,(1,0,2),7)$

ARMA Model Results

Dep. Variable: WLS No. Observations: 113 ARMA(1, 2) Log Likelihood Model: 161.686 S.D. of innovations Method: 0.057 css-mle

Date:	Sat, 26 Sep 2020	AIC	-313.373
Time:	11:40:46	BIC	-299.736
Sample:	0	HQIC	-307.839

========	========	========	========	=======	========	=======
	coef	std err	z	P> z	[0.025	0.975]
const	0.6066	0.047	12.980	0.000	0.515	0.698
ar.L1.WLS	0.7576	0.088	8.580	0.000	0.585	0.931
ma.L1.WLS	0.4890	0.081	6.017	0.000	0.330	0.648
ma.L2.WLS	0.6457	0.095	6.782	0.000	0.459	0.832
			Roots			

========						
	Real	Imaginary	Modulus	Frequency		
AR.1	1.3199	+0.0000j	1.3199	0.0000		
MA.1	-0.3786	-1.1854j	1.2444	-0.2992		
MA.2	-0.3786	+1.1854j	1.2444	0.2992		

<IPython.core.display.Javascript object>

0

- 113 0.596592
- 114 0.598490
- 115 0.600457
- 116 0.601947
- 117 0.603075
- 118 0.603931
- 119 0.604579

[37]: #LT WLS

modeling(wls_LT,(1,0,3),9)

ARMA Model Results

===========			
Dep. Variable:	WLS	No. Observations:	110
Model:	ARMA(1, 3)	Log Likelihood	192.675
Method:	css-mle	S.D. of innovations	0.041
Date:	Sat, 26 Sep 2020	AIC	-373.350
Time:	11:41:11	BIC	-357.147
Sample:	0	HQIC	-366.778

	coef	std err	z	P> z	[0.025	0.975]
const	0.5777	0.099	5.835	0.000	0.384	0.772
ar.L1.WLS	0.9494	0.037	25.675	0.000	0.877	1.022
ma.L1.WLS	-0.0277	0.099	-0.280	0.780	-0.221	0.166
ma.L2.WLS	0.1947	0.097	1.999	0.046	0.004	0.386
ma.L3.WLS	0.2718	0.088	3.090	0.002	0.099	0.444
			Roots			
========	Real	Ima	Imaginary		======= us	Frequency
AR.1	1.0533	+(+0.0000j		1.0533	
MA.1	0.5660	-1	-1.2924j		1.4109	
MA.2	0.5660	+1	l.2924j	1.4109		0.1843
MA.3	-1.8484	-(-0.0000j		84 	-0.5000

<IPython.core.display.Javascript object>

0

- 110 0.434011
- 111 0.417183
- 112 0.419772
- 113 0.427759
- 114 0.435342
- 115 0.442542
- 116 0.449377
- 117 0.455867
- 118 0.462028

[9]: #NC WLS

modeling(wls_NC,(1,1,0),7,'NC')

===========	======	=========		========	=======	=======
Dep. Variable:		D.WLS	No. Obs	ervations:		109
Model:	AR	IMA(1, 1, 0)	Log Lik	elihood		193.556
Method:		css-mle	S.D. of	${\tt innovations}$		0.041
Date:	Sat,	26 Sep 2020	AIC			-383.111
Time:		13:08:09	BIC			-377.728
Sample:		1	HQIC			-380.928
=============		=========				
	coef	std err	Z	P> z	[0.025	0.975]

ar.L1.D.WLS -0.1317 0.094 -1.394 0.163 -0.317 0.053 Roots Real Imaginary Modulus _____ +0.0000j 7.5924 <IPython.core.display.Javascript object> <IPython.core.display.HTML object> 110 0.562 111 0.562 112 0.562 113 0.562 114 0.562 115 0.562 116 0.562 [12]: #OB WLS modeling(wls_OB, (4,1,1),12,'nc') ARIMA Model Results Dep. Variable: D.WLS No. Observations: 111 Model: 160.125 ARIMA(4, 1, 1) Log Likelihood css-mle S.D. of innovations Method: 0.057 Date: Sat, 26 Sep 2020 AIC -308.249 Time: 13:09:16 BIC -291.992 Sample: HQIC -301.654 ______ z P>|z| [0.025 0.975] coef std err ar.L1.D.WLS 0.7943 0.159 4.981 0.000 0.482 1.107 ar.L2.D.WLS -0.4144 0.142 -2.913 -0.693 0.004 -0.136 ar.L3.D.WLS 0.7517 0.142 5.279 0.000 0.473 ar.L4.D.WLS -0.6329 0.128 -4.947 0.000 -0.884 1.031 -0.382 -5.271 ma.L1.D.WLS -0.7910 0.150 0.000 -1.085 -0.497Roots

Modulus

______ Imaginary

._____

AR.1	-0.4476	-0.9891j	1.0857	-0.3176
AR.2	-0.4476	+0.9891j	1.0857	0.3176
AR.3	1.0414	-0.5060j	1.1578	-0.0720
AR.4	1.0414	+0.5060j	1.1578	0.0720
MA.1	1.2643	+0.0000j	1.2643	0.0000

<IPython.core.display.HTML object>

0

- 112 0.469447
- 113 0.494425
- 114 0.501232
- 115 0.519926
- 116 0.530825
- 117 0.521045
- 118 0.518503
- 119 0.516900
- 120 0.502430
- 121 0.495881
- 122 0.497079
- 123 0.490883

[14]: #SK WLS

modeling(wls_SK,(1,0,0),9)

============			======	=====		======	
Dep. Variable:			WLS No	. Obs	ervations:		114
Model:		ARMA(1,	0) Lo	g Lik	elihood		156.880
Method:		css-	mle S.	D. of	innovations		0.061
Date:	Sat	, 26 Sep 2	020 AI	С			-307.759
Time:		13:12		С			-299.551
Sample:			O HQ	IC			-304.428
•							
=========		.=======		=====			========
	coef	std err		z	P> z	[0.025	0.975]
const	0.3089	0.049	6.34	6	0.000	0.214	0.404
ar.L1.WLS	0.8891	0.046	19.53	2	0.000	0.800	0.978
			Roots				
=========	=======		======	=====	=======		=======
	Real	Im	aginary		Modulus		Frequency

<ipy< th=""><th>thon.core</th><th>display.Ja</th><th>avascript o</th><th>bject</th><th>:></th><th></th><th></th><th></th></ipy<>	thon.core	display.Ja	avascript o	bject	: >			
<ipy< th=""><th>thon.core</th><th>display.H</th><th>TML object></th><th></th><th></th><th></th><th></th><th></th></ipy<>	thon.core	display.H	TML object>					
		0						
114	0.330332							
115	0.327959							
116	0.325850							
117	0.323975							
	0.322307							
	0.320824							
	0.319506							
121								
122	0.317292							
: # <i>SS</i>	WLS							
mod	${ t eling(wls_{oldsymbol{-}})}$	SS,(1,0,0)),11,'NC')					
mod	eling(wls_	SS,(1,0,0)						
mod					el Resul	ts		
			ARMA					
	Variable:		ARMA	===== WLS	No. Ob Log Li	servations: kelihood		1:
==== Dep.	======================================		ARMA ARMA(1,	===== WLS	No. Ob Log Li	servations:		1: 175.68
==== Dep. Mode Meth	======================================		ARMA ARMA(1, css- t, 26 Sep 2	WLS 0) mle	No. Ob Log Li S.D. o	servations: kelihood		175.68 0.04 -347.38
==== Dep. Mode Meth Date			ARMA ARMA(1,	WLS 0) mle 020	No. Ob Log Li S.D. o AIC BIC	servations: kelihood		175.68 0.04 -347.38 -341.94
==== Dep. Mode Meth			ARMA ARMA(1, css- t, 26 Sep 2	WLS 0) mle	No. Ob Log Li S.D. o	servations: kelihood		175.68 0.04 -347.38 -341.94
Dep. Mode Meth Date Time			ARMA 	WLS 0) mle 020 ::21	No. Ob Log Li S.D. o AIC BIC HQIC	servations: kelihood	=====	1175.68 0.04 -347.35 -341.94 -345.16
Dep. Mode Meth Date Time Samp		Sa-	ARMA(1, css- t, 26 Sep 2	WLS 0) mle 020 ::21 0	No. Ob Log Li S.D. o AIC BIC HQIC	servations: kelihood f innovations P> z	[0.025	115.68 0.04 -347.35 -341.94 -345.16
Dep. Mode Meth Date Time Samp		Sa-	ARMA(1, css-t, 26 Sep 2 13:14	WLS 0) mle 020 ::21 0	No. Ob Log Li S.D. o AIC BIC HQIC	p> z 0.000	[0.025	175.68 0.04 -347.38 -341.94 -345.16
Dep. Mode Meth Date Time Samp		Sa	ARMA(1, css-t, 26 Sep 2 13:14	WLS 0) mle 020 ::21 0 127 Rocesses	No. Ob Log Li S.D. o AIC BIC HQIC	p> z 0.000	[0.025 0.976	175.68 0.04 -347.38 -341.94 -345.16

0
111 0.385696
112 0.382420
113 0.379171
114 0.375950
115 0.372757
116 0.369591
117 0.366451
118 0.363338
119 0.360252
120 0.357192
121 0.354158

[19]: #WO WLS

modeling(wls_WO,(1,0,0),9)

ARMA Model Results

AND HOUSE RESULTS									
Dep. Variable:			WLS	No. O	bservations:		117		
Model:	ARMA(1, 0)		Log Likelihood			179.554			
Method:		css-	-mle	S.D.	of innovations		0.052		
Date:	Sat	, 26 Sep 2	2020	AIC			-353.109		
Time:		13:14	4:38	BIC			-344.822		
Sample:			0	HQIC			-349.744		
=======================================		=======		=====	=========		=======		
	coef	std err		Z	P> z	[0.025	0.975]		
const	0.6209	0.071	 8	 .744	0.000	0.482	0.760		
ar.L1.WLS	0.9385		24		0.000	0.863	1.014		
			Roo						
=======================================					==========		=======		
	Real	Real Imagina			Modulus		Frequency		
AR.1	1.0655	+0.000		0j 1.0655		0.0000			

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

0

117 0.480210

118 0.488853

119 0.496965

120 0.504579

- 121 0.511725
- 122 0.518432
- 123 0.524726
- 124 0.530634
- 125 0.536178