<Time series>

Projection onto the number of a suicide by time series analysis.

Kyungmin Yoon

kmin。yoon@samsung。com

2013.Fall semester

CONTENTS

Ⅰ. The background of analysis and goals on project

My contury, Korea, is dishonorably ranked 1st in the suicide rate over the OECD and keeps its ranking for 8 years.
It's becoming a terrible social problem and need to analyze its cause.
To find out main reason and help to take measure, this time series project is set.

Ⅱ. The selection of variable and definitions

1) Time periods of variable observation

: 1 JAN 2005 ~ 1 DEC 2010 (totally 72 observations)

2) Variable selection

(1) output variable

❑ **Suicide - the number of suicide**

(2) input variables

❑ **price - consumer price index**

➩ increasing consumer price can lead to economic difficultyties and can have a bad effect suicide rate. .

❑ **econ - economically inactive population(1,000 unit)**

➩ increasing economically inactive population can lead to economic difficultyties and can have a bad effect suicide rate.

❑ **ecopar - economic activity participation rate**

➩ this can help to look into economic situation

❑ **unemp - unemployment**

➩ increasing unemployment can lead to economic difficultyties in the society and can have a bad effect suicide rate.

❑ **div - the number of divorced people**

➩ increasing the number of divorced people can have a bad effect suicide rate. This is because a divorced person have a tendency of anxiety in the daily life and getting depressed and can have a bad effect suicide rate.

❑ **sun - the duration of sunshine**

➩ SAD(Seasonal Affective Disorder) begins from late fall with less sunchine and fades away when the spring comes. So it is also one of psychological reason lead to increase suicide rate.

3) Verifying correlation among variables

단순 통계량

변수	N	평균	표준편차	합	최소값	최대값
price	72	2.98472	0.96556	214.90000	1.60000	5.90000
sun	72	166.37500	34.93341	11979	73.70000	240.80000
econ	72	15237	571.53284	1097092	14265	16554
ecopar	72	61.34444	0.95059	4417	59.00000	62.70000
unemp	72	3.26806	0.37335	235.30000	2.70000	4.70000
divorce	72	10195	953.25894	734023	6364	12226

피어슨 상관 계수, N = 72
H0: Rho=0 가정하에서 Prob > |r|

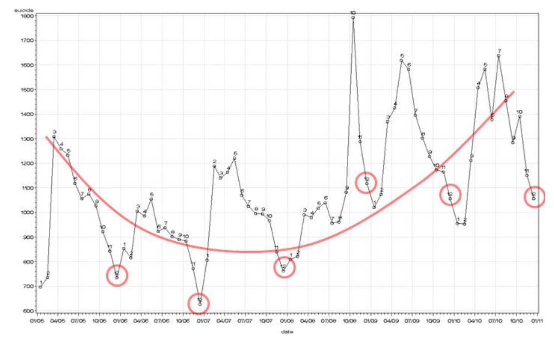
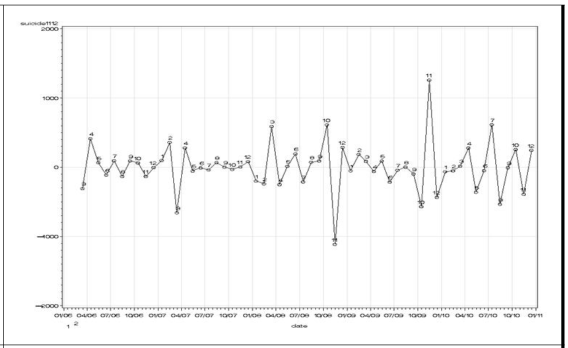
	price	sun	econ	ecopar	unemp	divorce
price	1.00000	0.09329 0.4357	0.17023 0.1528	-0.09301 0.4371	-0.20806 0.0795	-0.38804 0.0008
sun	0.09329 0.4357	1.00000	-0.19775 0.0959	0.24924 0.0348	-0.02488 0.8357	0.09184 0.4429
econ	0.17023 0.1528	-0.19775 0.0959	1.00000	-0.86854 <.0001	0.22426 0.0582	-0.26553 0.0242
ecopar	-0.09301 0.4371	0.24924 0.0348	-0.86854 <.0001	1.00000	-0.46185 <.0001	0.17556 0.1402
unemp	-0.20806 0.0795	-0.02488 0.8357	0.22426 0.0582	-0.46185 <.0001	1.00000	0.10319 0.3884
divorce	-0.38804 0.0008	0.09184 0.4429	-0.26553 0.0242	0.17556 0.1402	0.10319 0.3884	1.00000

Checked correlation of variables each other, we can conclude the correlation between Secon and ecopar is 0.9. That is the multicollinearity between two variables has a problem.
The ecopar variable increase correlation of most of variables, decide to eliminate ecopar variable.
See the correlation matirx without ecopar.

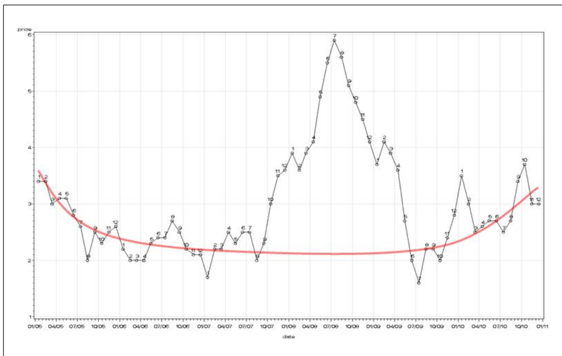
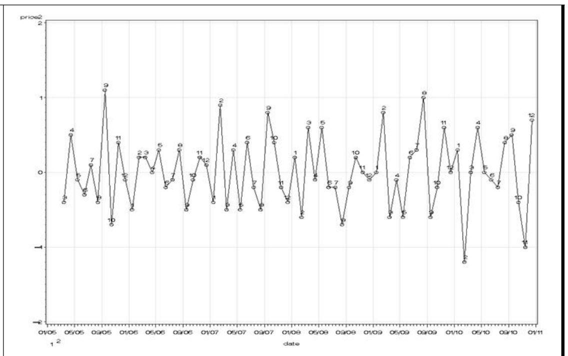
피어슨 상관 계수, N = 72
H0: Rho=0 가정하에서 Prob > |r|

	price	sun	econ	unemp	divorce
price	1.00000	0.09329 0.4357	0.17023 0.1528	-0.20806 0.0795	-0.38804 0.0008
sun	0.09329 0.4357	1.00000	-0.19775 0.0959	-0.02488 0.8357	0.09184 0.4429
econ	0.17023 0.1528	-0.19775 0.0959	1.00000	0.22426 0.0582	-0.26553 0.0242
unemp	-0.20806 0.0795	-0.02488 0.8357	0.22426 0.0582	1.00000	0.10319 0.3884
divorce	-0.38804 0.0008	0.09184 0.4429	-0.26553 0.0242	0.10319 0.3884	1.00000

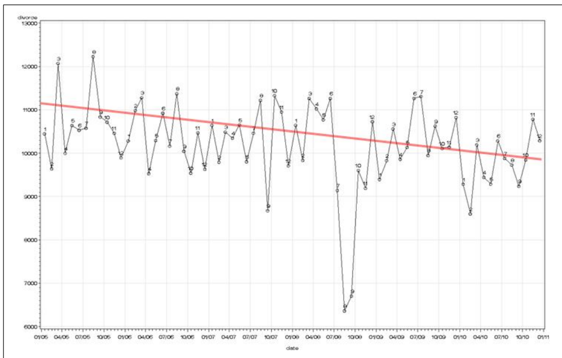
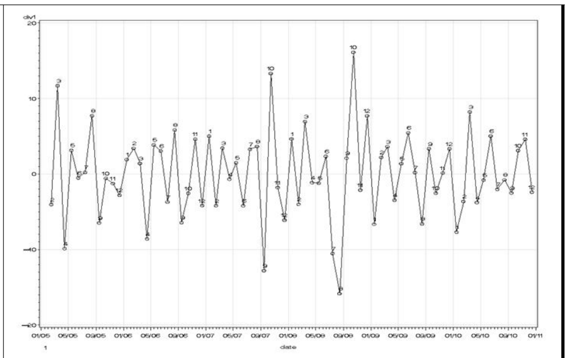
4) Stationary Process

	
Suicide	Suicide(1 1 12)

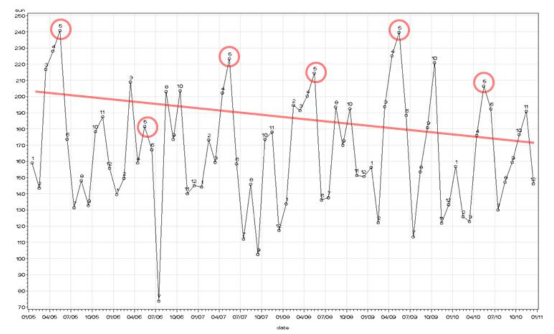
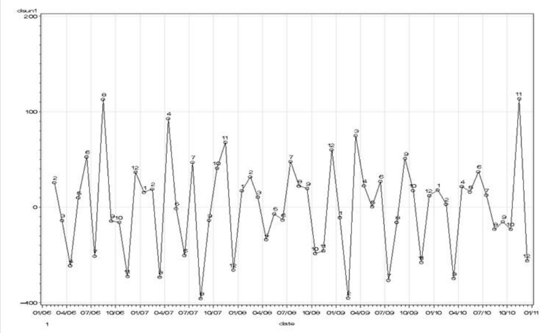
applied seasonal difference ond time and aseasonal difference twice because graph have a curve of secondary degree

	
price	price(1 1)

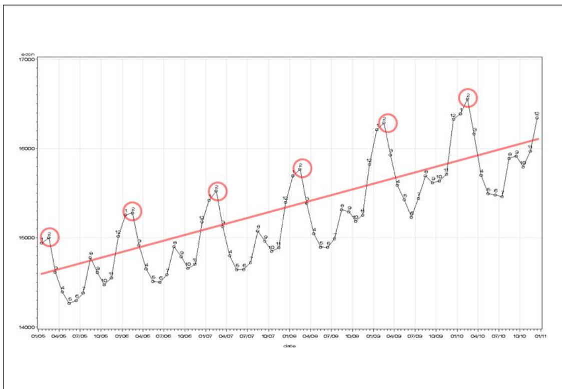
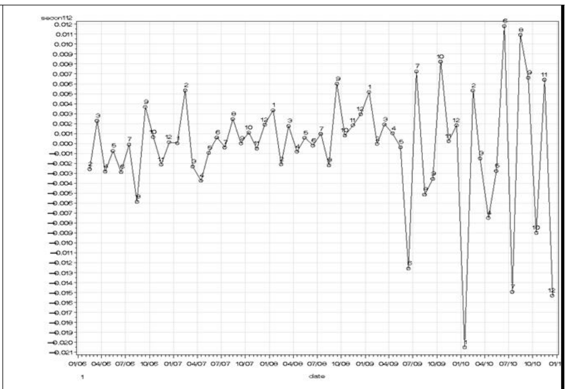
no seasonality is found, applied aseasonal twice difference because graph have a curve of secondary degree

	
Divorce	Div(1)

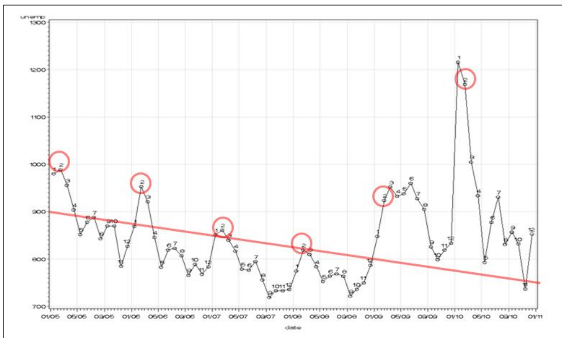
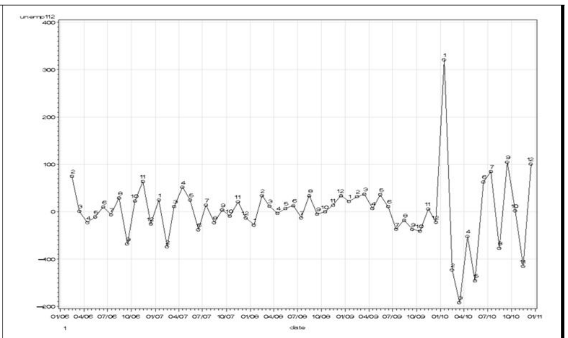
Took root converstion because variation have increasing trend and applied a difference.

	
Sun	Sun(1 12)

applied seasonal difference one time and aseasonal difference one time because it has decreasing trend.

	
Econ	Secon(1 12)

applied seasonal difference one time. Took log variation and after that applied difference because variation seems to increase.

	
Unemp	Unemp(1 12)

applied seasonal difference one time and applied aseasonal a difference one time

Ⅲ. ARIMA model fitting

❑ $\nabla_{12}\nabla^{2}suicide$'S Model fitting

Autocorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std Error
0	115145	1.00000	********************	0
1	-62752.068	-.54498	***********	0.131306
2	-2420.360	-.02102		0.165780
3	12320.988	0.10700	**	0.165826
4	-5404.636	-.04694	*	0.167012
5	1966.547	0.01708		0.167239
6	-7347.198	-.06381	*	0.167270
7	8381.154	0.07279	*	0.167689
8	1492.854	0.01297		0.168233
9	-7405.084	-.06431	*	0.168250
10	1490.580	0.01295		0.168673
11	25821.878	0.22426	****	0.168690
12	-50953.850	-.44252	*********	0.173754
13	30557.903	0.26539	*****	0.192206
14	3189.330	0.02770	*	0.198423
15	-7587.339	-.06589	*	0.198490
16	-2226.404	-.01934		0.198867
17	1934.011	0.01680		0.198899
18	9647.504	0.08379	**	0.198923
19	-22647.135	-.19668	****	0.199531
20	22938.298	0.19921	****	0.202846
21	-6575.654	-.05711	*	0.206192
22	-3199.903	-.02779	*	0.206464

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	-0.54498	***********
2	-0.45239	*********
3	-0.27933	******
4	-0.22329	****
5	-0.14832	***
6	-0.23429	*****
7	-0.19072	****
8	-0.10495	**
9	-0.11864	**
10	-0.16382	***
11	0.30827	******
12	-0.14267	***
13	-0.14460	***
14	-0.10976	**
15	-0.02717	*
16	-0.11146	**
17	-0.11074	**
18	-0.04903	*
19	-0.30857	******
20	-0.09813	**
21	-0.05896	*
22	-0.06006	*

< graph : the number of suicides ARIMA model's ACF, PACF >

Y's ACF and PACF are cut off and it means that Y satisfied stationary.

And 1,12 are cutoff in ACF, 3 is cutoff in PACF. So fitted model at p=3,q=1,Q=1

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	19.32	6	0.0037	-0.545	-0.021	0.107	-0.047	0.017	-0.064
12	38.54	12	0.0001	0.073	0.013	-0.064	0.013	0.224	-0.443
18	45.06	18	0.0004	0.265	0.028	-0.066	-0.019	0.017	0.084
24	52.73	24	0.0006	-0.197	0.199	-0.057	-0.028	-0.015	0.042
30	54.54	30	0.0040	0.020	-0.072	0.014	0.080	-0.059	-0.017
36	60.59	36	0.0063	0.083	-0.162	0.097	0.032	-0.010	-0.033
42	61.96	42	0.0241	-0.016	0.052	-0.015	-0.051	0.038	-0.007
48	63.68	48	0.0643	0.049	-0.045	0.001	0.002	-0.009	0.043
54	70.76	54	0.0626	-0.058	0.020	0.050	-0.076	0.037	0.008

< graph : the number of suicides ARIMA model's portmanteau test >

p-value of white-noise is under 0.05. It leads to reject H0 : CORR=0 and Y variable is proper for model.

❑ $\nabla_{12}\nabla^{2}suicide$'s model fitting

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.92214	0.05412	17.04	<.0001	1
MA2,1	0.61875	0.12475	4.96	<.0001	12

Variance Estimate	39377.71
Std Error Estimate	198.4382
AIC	780.257
SBC	784.3779
Number of Residuals	58

* AIC and SBC do not include log determinant.

< graph : the number of suicides ARIMA model's estimation >

Final model is ARIMA(0,2,1)*(0,1,1).$_{(12)}$

❑ $\nabla_{12}\nabla^{2}suicide$'s model fitting

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.96	4	0.7430	-0.160	-0.071	0.014	0.004	0.015	-0.029
12	3.62	10	0.9629	0.048	0.133	-0.043	0.034	0.017	-0.019
18	6.40	16	0.9831	0.113	0.069	-0.084	-0.025	0.022	0.092
24	11.00	22	0.9747	-0.080	0.170	0.101	0.049	-0.019	0.038
30	11.41	28	0.9977	0.027	-0.021	0.020	0.038	0.014	-0.020
36	13.88	34	0.9991	-0.045	-0.061	0.043	0.095	0.009	-0.028
42	19.60	40	0.9972	-0.063	0.049	0.010	-0.110	0.090	0.054
48	21.03	46	0.9994	0.027	-0.046	0.005	0.039	0.013	0.026
54	26.97	52	0.9984	-0.060	0.012	0.026	-0.080	0.013	0.018

< graph : the number of suicides ARIMA model's diagnosis >

Autocorrelation Plot of Residuals

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std Error
0	39377.713	1.00000	********************	0
1	-6297.979	-.15994	***	0.131306
2	-2796.365	-.07101	*	0.134623
3	548.920	0.01394		0.135268
4	159.969	0.00406		0.135292
5	597.855	0.01518		0.135295
6	-1147.308	-.02914	*	0.135324
7	1877.069	0.04767	*	0.135432
8	5254.038	0.13343	***	0.135721
9	-1704.070	-.04327	*	0.137964
10	1320.036	0.03352	*	0.138198
11	678.037	0.01722		0.138338
12	-760.610	-.01932		0.138375
13	4461.744	0.11331	**	0.138421
14	2734.921	0.06945	*	0.140011
15	-3319.959	-.08431	**	0.140604
16	-994.763	-.02526	*	0.141473
17	848.330	0.02154		0.141551
18	3638.188	0.09239	**	0.141607
19	-3138.506	-.07970	**	0.142643
20	6710.723	0.17042	***	0.143409
21	3973.823	0.10092	**	0.146859
22	1911.220	0.04854	*	0.148050
23	-736.021	-.01869		0.148324
24	1504.284	0.03820	*	0.148364

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	-0.15994	***
2	-0.09913	**
3	-0.01492	
4	-0.00319	
5	0.01629	
6	-0.02411	
7	0.04270	*
8	0.15017	***
9	0.01512	
10	0.05504	*
11	0.03215	*
12	-0.00690	
13	0.11723	**
14	0.11920	**
15	-0.05129	*
16	-0.05550	*
17	-0.00549	
18	0.07717	**
19	-0.05447	*
20	0.16710	***
21	0.11706	**
22	0.11450	**
23	0.06078	*
24	0.07778	**

< graph : the number of suicides ARIMA model's diagnosis >

All the p-value of Q-test are over 0.2. So correlation of residuals don't remain and it means that they become whit-noise status.

And there is no outlier point in the ACF,PACF of residuals, we can conclude that the model is rightly fitted.

Thus, final model of Y's ARIMA is as in the following.

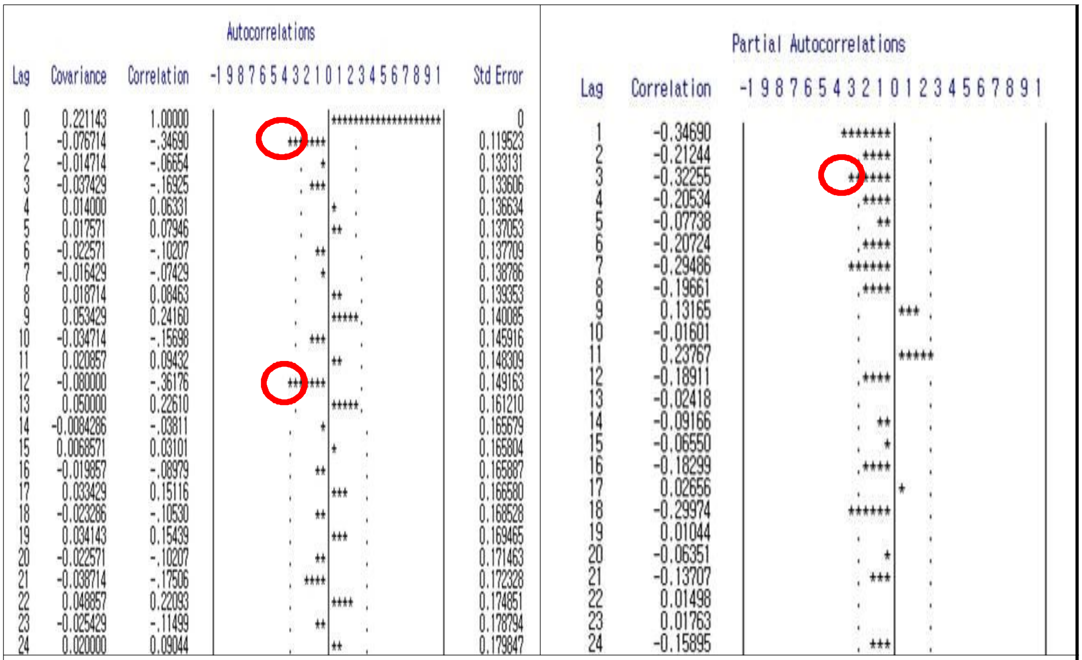
$$\nabla_{12}\nabla^2 suicide = (1-0.92214B)(1-0.61875B^{12})a_t$$

IV. Model fitting of transfer function

1) ARIMA model fitting of input variables

(1) Consumer price index (Price)

❑ $\nabla^2 price$'s model fitting



Autocorrelations

Lag	Covariance	Correlation	Std Error
0	0.221143	1.00000	0
1	-0.076714	-.34690	0.119523
2	-0.014714	-.06654	0.133131
3	-0.037429	-.16925	0.133606
4	0.014000	0.06331	0.136634
5	0.017571	0.07946	0.137053
6	-0.022571	-.10207	0.137709
7	-0.016429	-.07429	0.138786
8	0.018714	0.08463	0.139353
9	0.053429	0.24160	0.140085
10	-0.034714	-.15698	0.145916
11	0.020857	0.09432	0.148309
12	-0.080000	-.36176	0.149163
13	0.050000	0.22610	0.161210
14	-0.0084286	-.03811	0.165679
15	0.0068571	0.03101	0.165804
16	-0.019857	-.08979	0.165887
17	0.033429	0.15116	0.166580
18	-0.023286	-.10530	0.168528
19	0.034143	0.15439	0.169465
20	-0.022571	-.10207	0.171463
21	-0.038714	-.17506	0.172328
22	0.048857	0.22093	0.174851
23	-0.025429	-.11499	0.178794
24	0.020000	0.09044	0.179847

Partial Autocorrelations

Lag	Correlation
1	-0.34690
2	-0.21244
3	-0.32255
4	-0.20534
5	-0.07738
6	-0.20724
7	-0.29486
8	-0.19661
9	0.13165
10	-0.01601
11	0.23767
12	-0.18911
13	-0.02418
14	-0.09166
15	-0.06550
16	-0.18299
17	0.02656
18	-0.29974
19	0.01044
20	-0.06351
21	-0.13707
22	0.01498
23	0.01763
24	-0.15895

< graph : consumer price index ARIMA model's ACF, PACF >

The ACF and PACF of price variable is cutoff. So price satisfied stationary status. The model is fitted on p=3,q=1,Q=1.

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	12.89	6	0.0448	-0.347	-0.067	-0.169	0.063	0.079	-0.102
12	32.94	12	0.0010	-0.074	0.085	0.242	-0.157	0.094	-0.362
18	41.68	18	0.0012	0.226	-0.038	0.031	-0.090	0.151	-0.105
24	55.67	24	0.0003	0.154	-0.102	-0.175	0.221	-0.115	0.090
30	67.03	30	0.0001	-0.091	0.167	-0.091	0.008	-0.154	0.163
36	71.86	36	0.0004	-0.038	-0.018	0.085	-0.101	0.107	-0.059
42	77.97	42	0.0006	-0.076	-0.012	0.104	-0.081	0.112	-0.030
48	79.47	48	0.0029	-0.032	-0.003	-0.016	0.034	0.006	-0.067
54	94.64	54	0.0005	0.037	0.076	-0.110	0.139	-0.127	0.001
60	98.04	60	0.0014	0.054	-0.047	0.039	-0.031	0.011	0.033

< graph : consumer price index ARIMA model's portmanteau test >

p-value of white-noise is under 0.05. It leads to reject H0 : CORR=0 and consumer price variable is proper for model.

❑ $\nabla^2 price$'s model estimation

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.78960	0.09829	8.03	<.0001	12
AR1,1	-0.62306	0.11066	-5.63	<.0001	1
AR1,2	-0.53217	0.11976	-4.44	<.0001	2
AR1,3	-0.60926	0.12398	-4.91	<.0001	3
AR1,4	-0.49003	0.11373	-4.31	<.0001	4
AR1,5	-0.26480	0.10331	-2.56	0.0127	6

Variance Estimate	0.11466
Std Error Estimate	0.338615
AIC	52.77369
SBC	66.26466
Number of Residuals	70

* AIC and SBC do not include log determinant.

< graph : consumer price index ARIMA model's ARIMA model's estimation >

The final model is ARIMA(6,2,0)x(0,0,1)$_{(12)}$from lots of taking try and error..

It's p-value is under 0.05 so the model is right.

❑ $\nabla^2 price$'s model diagnosis

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	.	0	.	-0.073	-0.096	-0.041	-0.110	-0.118	0.073
12	5.96	6	0.4275	-0.010	0.020	0.088	-0.135	0.008	-0.038
18	9.09	12	0.6951	0.040	-0.108	-0.042	-0.077	0.102	0.048
24	18.76	18	0.4066	0.216	-0.131	-0.160	0.064	-0.029	0.037
30	24.30	24	0.4447	-0.066	0.081	-0.057	-0.109	-0.036	0.137
36	25.54	30	0.6984	-0.007	0.026	0.047	-0.076	0.014	-0.009
42	34.27	36	0.5509	-0.137	0.065	0.031	-0.057	0.155	0.043
48	34.57	42	0.7852	-0.017	0.009	-0.008	-0.022	-0.021	-0.009
54	39.29	48	0.8105	0.079	-0.010	-0.028	0.057	-0.034	-0.075
60	42.68	54	0.8668	0.029	-0.045	0.053	-0.012	0.008	0.048

< graph : consumer price index ARIMA model's ARIMA model's diagnosis >

Autocorrelation Plot of Residuals

Lag	Covariance	Correlation	Plot (-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1)	Std Error
0	0.114660	1.00000	********************	0
1	-0.0083780	-.07307	*	0.119523
2	-0.011040	-.09629	**	0.120159
3	-0.0047532	-.04146	*	0.121257
4	-0.012589	-.10979	**	0.121459
5	-0.013512	-.11785	**	0.122868
6	0.0083749	0.07304	*	0.124473
7	-0.0012006	-.01047		0.125083
8	0.0022855	0.01993		0.125096
9	0.010058	0.08772	**	0.125141
10	-0.015471	-.13493	***	0.126017
11	0.00096498	0.00842		0.128064
12	-0.0043663	-.03808	*	0.128072
13	0.0045940	0.04007	*	0.128234
14	-0.012434	-.10844	**	0.128412
15	-0.0047938	-.04181	*	0.129714
16	-0.0088168	-.07689	**	0.129906
17	0.011717	0.10219	**	0.130555
18	0.0055120	0.04807	*	0.131693
19	0.024782	0.21614	****	0.131943
20	-0.015056	-.13131	***	0.136907
21	-0.018388	-.16037	***	0.138695
22	0.0073000	0.06367	*	0.141319
23	-0.0033627	-.02933	*	0.141728
24	0.0042763	0.03730	*	0.141815

Partial Autocorrelations

Lag	Correlation	Plot (-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1)
1	-0.07307	*
2	-0.10217	**
3	-0.05758	*
4	-0.13034	***
5	-0.15484	***
6	0.01729	
7	-0.04924	*
8	-0.00789	
9	0.05906	*
10	-0.13582	***
11	0.00719	
12	-0.07026	*
13	0.03761	*
14	-0.13762	***
15	-0.11351	**
16	-0.12820	***
17	0.02987	*
18	0.00567	
19	0.21283	****
20	-0.14336	***
21	-0.14875	***
22	0.04002	*
23	0.01050	
24	0.04250	*

< graph : consumer price index ARIMA model's ARIMA model's diagnosis >

All the p-value of Q-test are over 0.2. And correlation of residuals doesn't remain and it means that they become whit-noise status.

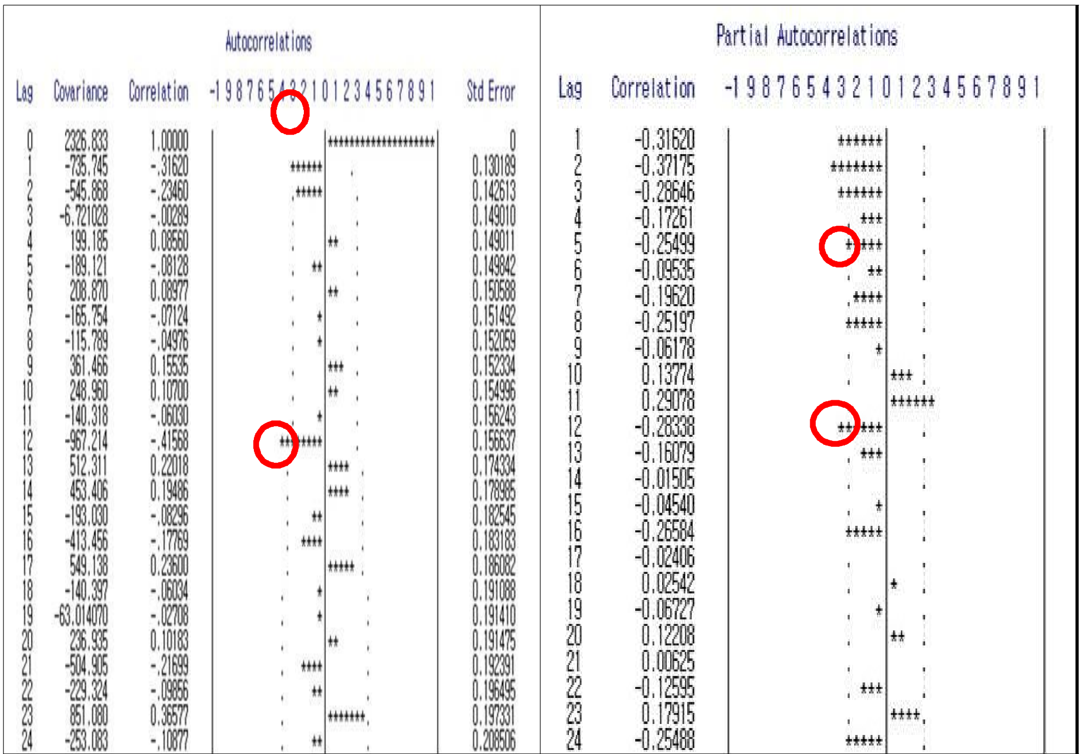
And there is no outlier point in the ACF,PACF of residuals, we can conclude that the model is rightly fitted.

Thus, final model of Price's ARIMA is as in the following.

$$\nabla^2 price = \frac{(1-0.78960B^{12})}{(1+0.62306B+0.53217B^2+60926B^3+0.49003B^4+0.26480B^6)}a_t$$

(2) Duration of sunshine(Sun)

❑ $\nabla_{12}\nabla sun$'s model fitting



Autocorrelations

Lag	Covariance	Correlation	Std Error
0	2326.833	1.00000	0
1	-735.745	-.31620	0.130189
2	-545.868	-.23460	0.142613
3	-6.721028	-.00289	0.149010
4	199.185	0.08560	0.149011
5	-189.121	-.08128	0.149842
6	208.870	0.08977	0.150588
7	-165.754	-.07124	0.151492
8	-115.789	-.04976	0.152059
9	361.466	0.15535	0.152334
10	248.960	0.10700	0.154996
11	-140.318	-.06030	0.156243
12	-967.214	-.41568	0.156637
13	512.311	0.22018	0.174334
14	453.406	0.19486	0.178985
15	-193.030	-.08296	0.182545
16	-413.456	-.17769	0.183183
17	549.138	0.23600	0.186082
18	-140.397	-.06034	0.191088
19	-63.014070	-.02708	0.191410
20	236.935	0.10183	0.191475
21	-504.905	-.21699	0.192391
22	-229.324	-.09856	0.196495
23	851.080	0.36577	0.197331
24	-253.083	-.10877	0.208506

Partial Autocorrelations

Lag	Correlation
1	-0.31620
2	-0.37175
3	-0.28646
4	-0.17261
5	-0.25499
6	-0.09535
7	-0.19620
8	-0.25197
9	-0.06178
10	0.13774
11	0.29078
12	-0.28338
13	-0.16079
14	-0.01505
15	-0.04540
16	-0.26584
17	-0.02406
18	0.02542
19	-0.06727
20	0.12208
21	0.00625
22	-0.12595
23	0.17915
24	-0.25488

< graph : Sunshine ARIMA model's ACF, PACF >

The ACF and PACF of price variable is cutoff. So price satisfied stationary status. The model is fitted on p=5,P=1,q=1,Q=1.

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	11.15	6	0.0839	-0.316	-0.235	-0.003	0.086	-0.081	0.090
12	27.75	12	0.0060	-0.071	-0.050	0.155	0.107	-0.060	-0.416
18	42.88	18	0.0008	0.220	0.195	-0.083	-0.178	0.236	-0.060
24	63.90	24	<.0001	-0.027	0.102	-0.217	-0.099	0.366	-0.109
30	65.95	30	0.0002	-0.095	0.018	0.050	0.011	-0.056	-0.055
36	80.93	36	<.0001	0.074	0.003	0.070	0.035	-0.251	0.158
42	91.22	42	<.0001	0.030	-0.026	-0.111	0.176	-0.098	-0.003
48	97.24	48	<.0001	0.043	-0.070	0.003	0.035	0.081	-0.081
54	108.72	54	<.0001	-0.001	-0.041	0.093	-0.083	0.074	-0.006

< graph : sunshine variable ARIMA model's portmanteau test >

p-value of white-noise is under 0.05. It leads to reject H0 : CORR=0 and sunshine variable is proper for model.

❑ $\nabla_{12}\nabla sun$'s model estimation

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.84740	0.07122	11.90	<.0001	1
MA2,1	0.73629	0.10717	6.87	<.0001	12
AR1,1	0.44979	0.15397	2.92	0.0050	23

Variance Estimate	914.7755
Std Error Estimate	30.24526
AIC	572.6578
SBC	578.8904
Number of Residuals	59

* AIC and SBC do not include log determinant.

< graph : sunshine ARIMA model's ARIMA model's estimation >

The final model is ARIMA ARIMA(23,1,1)x(0,1,1)$_{(12)}$from lots of taking try and error.. It's p-value is under 0.05 so the model is proper.

❑ $\nabla_{12}\nabla sun$'s model diagnosis

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	4.46	3	0.2157	0.176	-0.097	-0.146	0.058	-0.062	0.041
12	5.84	9	0.7559	-0.072	0.057	-0.023	-0.079	-0.061	-0.009
18	11.46	15	0.7194	0.079	0.174	-0.049	-0.009	0.109	0.130
24	18.01	21	0.6485	0.030	0.110	-0.180	-0.145	-0.038	-0.028
30	21.26	27	0.7741	-0.028	0.087	0.029	0.020	-0.110	-0.078
36	29.65	33	0.6346	0.128	0.172	0.026	-0.040	-0.061	0.097
42	40.50	39	0.4038	-0.021	-0.101	-0.085	0.059	-0.115	-0.145

< graph : sunshine ARIMA model's ARIMA model's diagnosis >

Autocorrelation Plot of Residuals

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std Error
0	914.776	1.00000	********************	0
1	160.656	0.17562	****	0.130189
2	-88.904032	-.09719	**	0.134144
3	-133.266	-.14568	***	0.135332
4	53.119604	0.05807	*	0.137965
5	-56.329426	-.06158	*	0.138378
6	37.647011	0.04115	*	0.138842
7	-66.319597	-.07250	*	0.139049
8	52.281422	0.05715	*	0.139688
9	-21.012727	-.02297		0.140084
10	-72.472341	-.07922	**	0.140148
11	-55.636681	-.06082	*	0.140905
12	-8.087479	-.00884		0.141349
13	72.004483	0.07871	**	0.141358
14	159.291	0.17413	***	0.142099
15	-44.959898	-.04915	*	0.145671
16	-8.671095	-.00948		0.145952
17	99.882665	0.10919	**	0.145962
18	118.938	0.13002	***	0.147340
19	27.738492	0.03032	*	0.149272
20	100.184	0.10952	**	0.149376
21	-164.870	-.18023	****	0.150731
22	-133.010	-.14540	***	0.154340
23	-34.988331	-.03825	*	0.156645
24	-25.329171	-.02769	*	0.156803

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	0.17562	****
2	-0.13210	***
3	-0.10833	**
4	0.09907	**
5	-0.12570	***
6	0.08120	**
7	-0.09935	**
8	0.07771	**
9	-0.04009	*
10	-0.10499	**
11	0.02036	
12	-0.06842	*
13	0.10796	**
14	0.12980	***
15	-0.12178	**
16	0.10745	**
17	0.09103	**
18	0.07974	**
19	0.06252	*
20	0.12094	**
21	-0.21498	****
22	-0.07557	**
23	0.04659	*
24	-0.12675	***

< diagnosis : sunshine ARIMA model's ARIMA model's diagnosis>

All the p-value of Q-test are over 0.2. And correlation of residuals doesn't remain and it means that they become whit-noise status.

And there is no outlier point in the ACF,PACF of residuals, we can conclude that the model is rightly fitted.

Thus, final model of Sun's ARIMA is as in the following.

$$\nabla_{12}\nabla sun = \frac{(1-0.84740B)(1-0.73629B^{12})}{(1-0.44979B^{23})}a_t$$

(3) economically inactive population(Secon)

❑ $\nabla_{12}\nabla secon$**'s model fitting**

Autocorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std Error
0	0.00003320	1.00000	********************	0
1	-0.0000135	-.40676	********	0.130189
2	1.72982E-6	0.05210	*	0.150192
3	5.20776E-6	0.15684	***	0.150498
4	-4.4942E-6	-.13536	***	0.153244
5	-1.2929E-6	-.03894	*	0.155257
6	1.79136E-7	0.00540		0.155422
7	1.23777E-6	0.03728	*	0.155425
8	-2.0625E-7	-.00621		0.155577
9	2.36901E-7	0.00713		0.155581
10p	-2.001E-7	-.00603		0.155587
11	9.68612E-6	0.29172	******	0.155591
12	-9.3275E-6	-.28092	******	0.164600
13	5.84528E-6	0.17605	****	0.172535
14	-3.8543E-6	-.11608	**	0.175553
15	-2.3853E-6	-.07184	*	0.176850
16	1.50638E-6	0.04537	*	0.177343
17	-1.9435E-6	-.05853	*	0.177540
18	1.22728E-6	0.03696	*	0.177867
19	5.89892E-7	0.01777		0.177997
20	-6.17E-7	-.01858		0.178027
21	9.9144E-7	0.02986	*	0.178060
22	-2.4475E-6	-.07371	*	0.178145
23	1.72089E-6	0.05183	*	0.178661
24	-1.5925E-6	-.04796	*	0.178916

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	-0.40676	*******
2	-0.13583	***
3	0.15341	***
4	-0.00047	
5	-0.12080	**
6	-0.11064	**
7	0.04189	*
8	0.07253	*
9	0.02282	
10	-0.04614	*
11	0.34980	*******
12	-0.01295	
13	0.04167	*
14	-0.18292	****
15	-0.07731	**
16	0.00176	
17	-0.01871	
18	-0.05155	*
19	0.00636	
20	-0.02124	
21	0.01172	
22	-0.22189	****
23	0.08341	**
24	-0.04762	*

< graph : Secon ARIMA model's ACF, PACF>

The ACF and PACF of Secon variable is cutoff. So price satisfied stationary status. The model is fitted on p=1,q=1.

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	13.32	6	0.0382	-0.407	0.052	0.157	-0.135	-0.039	0.005
12	25.85	12	0.0113	0.037	-0.006	0.007	-0.006	0.292	-0.281
18	30.36	18	0.0341	0.176	-0.116	-0.072	0.045	-0.059	0.037
24	31.54	24	[illegible]	0.018	-0.019	0.030	-0.074	0.052	-0.048
30	33.35	30	0.3077	-0.066	0.064	-0.073	-0.045	0.000	-0.025
36	39.67	36	0.3097	-0.063	0.051	-0.035	0.106	-0.146	0.056
42	40.18	42	0.5512	0.024	-0.036	-0.021	-0.023	0.003	-0.004
48	51.77	48	0.3288	0.037	0.017	0.076	-0.137	0.113	-0.048
54	52.70	54	0.5246	-0.008	0.009	-0.025	0.005	0.014	0.025

< graph : Secon variable ARIMA model's portmanteau test >

p-value of white-noise is under 0.05. It leads to reject H0 : CORR=0 and Secon variable is proper for model.

❑ $\nabla_{12}\nabla secon$'s model estimation

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	-0.45121	0.14052	-3.21	0.0022	11
AR1,1	-0.38347	0.10905	-3.52	0.0009	1
AR1,2	-0.63547	0.17684	-3.59	0.0007	12

Variance Estimate	0.000018
Std Error Estimate	0.004286
AIC	-473.04
SBC	-466.808
Number of Residuals	59

* AIC and SBC do not include log determinant.

< graph : Secon variable ARIMA model's ARIMA model's estimation >

The final model is ARIMA(1,1,11)*(1,1,0)$_{(12)}$from lots of taking try and error.. It's p-value is under 0.05 so the model is proper..

❑ $\nabla_{12}\nabla secon$'s model diagnosis

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.36	3	0.7140	0.014	0.022	0.099	-0.035	-0.086	-0.040
12	4.20	9	0.8981	0.094	-0.014	-0.064	0.139	0.060	-0.053
18	9.16	15	0.8691	-0.057	-0.038	-0.201	-0.043	-0.110	-0.032
24	10.89	21	0.9649	-0.045	0.024	-0.037	0.064	-0.096	0.022
30	14.86	27	0.9714	-0.042	0.047	-0.101	-0.089	-0.056	-0.095
36	18.44	33	0.9807	-0.066	0.031	0.051	0.056	-0.095	0.068
42	20.66	39	0.9930	0.043	0.025	-0.076	-0.011	0.032	0.050
48	25.91	45	0.9899	0.055	0.105	0.018	-0.014	0.077	0.006
54	27.05	51	0.9977	-0.031	0.016	-0.036	0.006	0.003	0.011

< graph : Secon variable ARIMA model's diagnosis >

Autocorrelation Plot of Residuals

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std Error
0	0.0001837	1.00000	|********************	0
1	2.56917E-7	0.01399	. | .	0.130189
2	4.05921E-7	0.02210	. | .	0.130214
3	1.82683E-6	0.09947	. |** .	0.130278
4	-6.4594E-7	-.03517	. *| .	0.131559
5	-1.5803E-6	-.08605	. **| .	0.131718
6	-7.4195E-7	-.04040	. *| .	0.132667
7	1.73498E-6	0.09447	. |** .	0.132876
8	-2.6372E-7	-.01436	. | .	0.134009
9	-1.1743E-6	-.06394	. *| .	0.134035
10	2.55557E-6	0.13915	. |*** .	0.134551
11	1.10086E-6	0.05994	. |* .	0.136969
12	-9.6951E-7	-.05279	. *| .	0.137413
13	-1.0468E-6	-.05700	. *| .	0.137756
14	-6.9025E-7	-.03758	. *| .	0.138155
15	-3.6981E-6	-.20136	. ****| .	0.138328
16	-7.9696E-7	-.04339	. *| .	0.143210
17	-2.017E-6	-.10982	. **| .	0.143433
18	-5.8175E-7	-.03168	. *| .	0.144851
19	-8.2581E-7	-.04496	. *| .	0.144968
20	4.49553E-7	0.02448	. | .	0.145204
21	-6.7819E-7	-.03693	. *| .	0.145274
22	1.16829E-6	0.06361	. |* .	0.145433
23	-1.7596E-6	-.09581	. **| .	0.145904
24	4.12315E-7	0.02245	. | .	0.146967

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	0.01399	. | .
2	0.02191	. | .
3	0.09893	. |** .
4	-0.03856	. *| .
5	-0.09037	. **| .
6	-0.04725	. *| .
7	0.10960	. |** .
8	0.00265	. | .
9	-0.07035	. *| .
10	0.11273	. |** .
11	0.06670	. |* .
12	-0.03810	. *| .
13	-0.09079	. **| .
14	-0.05749	. *| .
15	-0.17097	. ***| .
16	0.00603	. | .
17	-0.13040	. ***| .
18	-0.02929	. *| .
19	-0.03927	. *| .
20	0.02550	. |* .
21	-0.07917	. **| .
22	0.09016	. |** .
23	-0.11234	. **| .
24	0.04963	. |* .

< graph : Secon variable ARIMA model's diagnosis >

All the p-value of Q-test are over 0.2. And correlation of residuals doesn't remain and it means that they become whit-noise status.

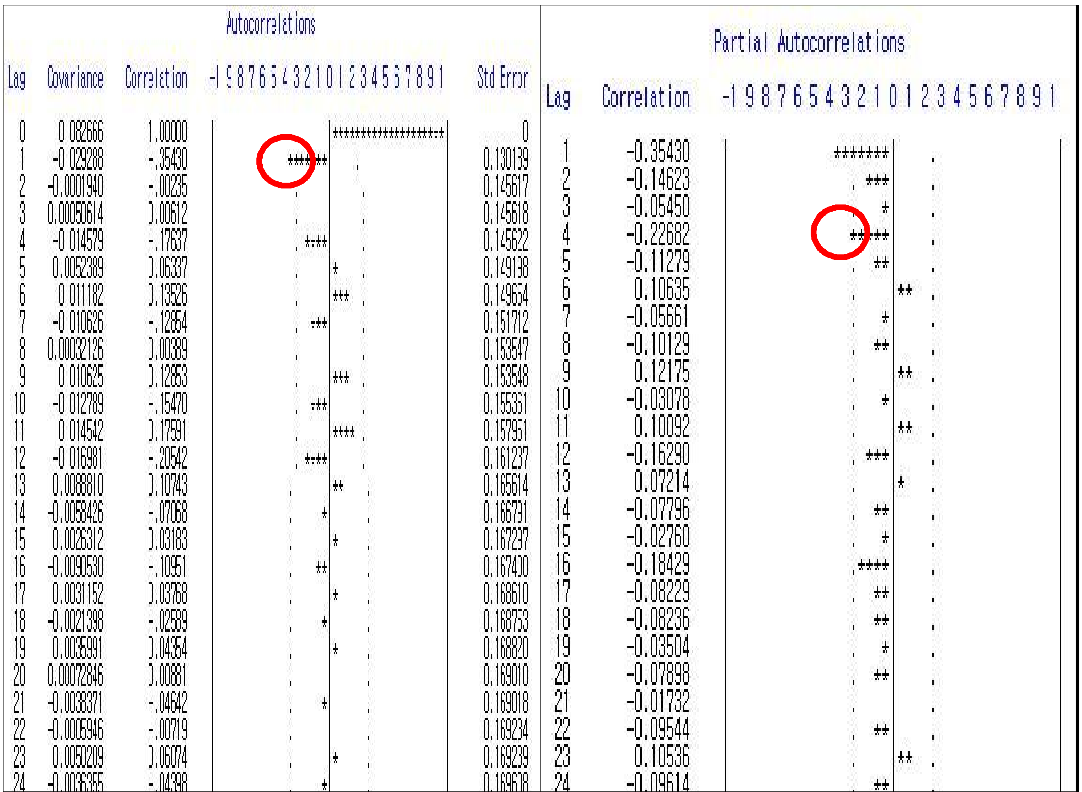
And there is no outlier point in the ACF,PACF of residuals, we can conclude that the model is rightly fitted.

Thus, final model of Secon's ARIMA is as in the following.

$$\nabla_{12}\nabla \mathrm{secon} = \frac{(1+0.45121B^{11})}{(1+0.38347B)(1+0.63547B^{12})}a_t$$

(4) The number of unemployment(Unemp)

❑ $\nabla_{12}\nabla unemp$'s model fitting



Autocorrelations

Lag	Covariance	Correlation	Std Error
0	0.082666	1.00000	0
1	-0.029288	-.35430	0.130189
2	-0.0001940	-.00235	0.145617
3	0.00050614	0.00612	0.145618
4	-0.014579	-.17637	0.145622
5	0.0052389	0.06337	0.149198
6	0.011182	0.13526	0.149654
7	-0.010626	-.12854	0.151712
8	0.00032126	0.00389	0.153547
9	0.010625	0.12853	0.153548
10	-0.012789	-.15470	0.155361
11	0.014542	0.17591	0.157951
12	-0.016981	-.20542	0.161237
13	0.0088810	0.10743	0.165614
14	-0.0058426	-.07068	0.166791
15	0.0026312	0.03183	0.167297
16	-0.0090530	-.10951	0.167400
17	0.0031152	0.03768	0.168610
18	-0.0021398	-.02589	0.168753
19	0.0035991	0.04354	0.168820
20	0.00072846	0.00881	0.169010
21	-0.0038371	-.04642	0.169018
22	-0.0005946	-.00719	0.169234
23	0.0050209	0.06074	0.169239
24	-0.0036355	-.04398	0.169608

Partial Autocorrelations

Lag	Correlation
1	-0.35430
2	-0.14623
3	-0.05450
4	-0.22682
5	-0.11279
6	0.10635
7	-0.05661
8	-0.10129
9	0.12175
10	-0.03078
11	0.10092
12	-0.16290
13	0.07214
14	-0.07796
15	-0.02760
16	-0.18429
17	-0.08229
18	-0.08236
19	-0.03504
20	-0.07898
21	-0.01732
22	-0.09544
23	0.10536
24	-0.09614

< graph : unemployment ARIMA model's ACF, PACF >

The ACF and PACF of unemployment variable is cutoff. So price satisfied stationary status.

The model is fitted on p=4, q=1

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	11.34	6	0.0785	-0.354	-0.002	0.006	-0.176	0.063	0.135
12	20.98	12	0.0507	-0.129	0.004	0.129	-0.155	0.176	-0.205
18	23.55	18	0.1703	0.107	-0.071	0.032	-0.110	0.038	-0.026
24	24.50	24	0.4331	0.044	0.009	-0.046	-0.007	0.061	-0.044
30	27.06	30	0.6199	0.016	0.030	-0.097	0.090	-0.054	0.028
36	34.18	36	0.5554	-0.082	0.106	0.039	0.020	-0.143	0.095
42	44.67	42	0.3602	-0.112	0.128	0.036	-0.116	0.099	-0.065
48	53.28	48	0.2785	0.062	-0.067	0.011	-0.051	0.125	-0.062
54	56.66	54	0.3762	0.025	-0.029	-0.054	0.052	-0.015	-0.002

< graph : unemployment variable ARIMA model's portmanteau test >

p-value of white-noise is under 0.05. It leads to reject H0 : CORR=0 and unemployment variable is proper for model.

❑ $\nabla_{12}\nabla unemp$'s model estimation

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.84775	0.15384	5.51	<.0001	12
AR1,1	-0.34768	0.12201	-2.85	0.0061	1
AR1,2	-0.27521	0.12320	-2.23	0.0295	4

Correlations of Parameter Estimates

Parameter	MA1,1	AR1,1	AR1,2
MA1,1	1.000	0.095	0.143
AR1,1	0.095	1.000	0.027
AR1,2	0.143	0.027	1.000

< graph : unemployment variable ARIMA model's ARIMA model's estimation >

The final model is ARIMA(4,1,0)*(0,1,1)$_{(12)}$from lots of taking try and error. It's p-value is under 0.05 so the model is proper.

❑ $\nabla_{12}\nabla unemp$'s model diagnosis

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.36	3	0.7140	0.014	0.022	0.099	-0.035	-0.086	-0.040
12	4.20	9	0.8981	0.094	-0.014	-0.064	0.139	0.060	-0.053
18	9.16	15	0.8691	-0.057	-0.038	-0.201	-0.043	-0.110	-0.032
24	10.89	21	0.9649	-0.045	0.024	-0.037	0.064	-0.096	0.022
30	14.86	27	0.9714	-0.042	0.047	-0.101	-0.089	-0.056	-0.095
36	18.44	33	0.9807	-0.066	0.031	0.051	0.056	-0.095	0.068
42	20.66	39	0.9930	0.043	0.025	-0.076	-0.011	0.032	0.050
48	25.91	45	0.9899	0.055	0.105	0.018	-0.014	0.077	0.006
54	27.05	51	0.9977	-0.031	0.016	-0.036	0.006	0.003	0.011

< graph : unemployment variable ARIMA model's diagnosis >

Autocorrelation Plot of Residuals

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std Error
0	0.055910	1.00000	********************	0
1	-0.0018590	-.03325	* (−)	0.130189
2	-0.0038447	-.06877	* (−)	0.130333
3	-0.0078543	-.14048	*** (−)	0.130946
4	-0.0014345	-.02566	* (−)	0.133476
5	0.0045223	0.08089	** (+)	0.133560
6	0.0070425	0.12596	*** (+)	0.134388
7	-0.0041294	-.07386	* (−)	0.136374
8	-0.0004837	-.00865		0.137050
9	0.0082151	0.14694	*** (+)	0.137060
10	0.00087463	0.01564		0.139704
11	0.0085732	0.15334	*** (+)	0.139734
12	-0.0023610	-.04223	* (−)	0.142557
13	0.0021620	0.03867	* (+)	0.142769
14	0.0037030	0.06623	* (+)	0.142946
15	-0.0018436	-.03298	* (−)	0.143466
16	-0.0081793	-.14629	*** (−)	0.143594
17	0.00060868	0.01089		0.146098
18	-0.0006942	-.01242		0.146112
19	0.00075742	0.01355		0.146130
20	0.0022176	0.03966	* (+)	0.146151
21	0.00082269	0.01471		0.146334
22	0.00045377	0.00812		0.146359
23	0.00073020	0.01306		0.146366
24	0.0017708	0.03167	* (+)	0.146386

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	-0.03325	* (−)
2	-0.06995	* (−)
3	-0.14613	*** (−)
4	-0.04330	* (−)
5	0.05861	* (+)
6	0.11079	** (+)
7	-0.06410	* (−)
8	0.01948	
9	0.18361	**** (+)
10	0.01809	
11	0.16681	*** (+)
12	0.01956	
13	0.10013	** (+)
14	0.10144	** (+)
15	-0.05084	* (−)
16	-0.14144	*** (−)
17	-0.03287	* (−)
18	-0.07076	* (−)
19	-0.09817	** (−)
20	-0.06244	* (−)
21	0.02714	* (+)
22	-0.01944	
23	-0.01613	
24	0.06345	* (+)

< graph : unemployment variable ARIMA model's diagnosis >

All the p-value of Q-test are over 0.2. And correlation of residuals doesn't remain and it means that they become whit-noise status.

And there is no outlier point in the ACF,PACF of residuals, we can conclude that the model is rightly fitted.

Thus, final model of unemployment's ARIMA is as in the following.

$$\nabla_{12}\nabla unemp = \frac{(1-0.84775B^{12})}{(1+0.34768B+0.27521B^{4})}a_t$$

(5) The number of divorced(divorce)

❑ $\nabla\sqrt{divorce}$'s model fitting

Autocorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std Error
0	32.265822	1.00000	********************	0
1	-11.364251	-.35221	*******	0.118678
2	-3.735561	-.11577	**	0.132585
3	3.600449	0.11159	**	0.134002
4	-8.487799	-.26306	*****	0.135304
5	5.373558	0.16654	***	0.142325
6	-1.690325	-.05239	*	0.145044
7	1.301519	0.04034	*	0.145310
8	-0.070572	-.00219		0.145468
9	2.338883	0.07249	*	0.145468
10	-8.296350	-.25713	*****	0.145976
11	2.164553	0.06709	*	0.152222
12	7.862276	0.24367	*****	0.152637
13	-10.030560	-.31087	******	0.158021
14	7.076469	0.21932	****	0.166412
15	-2.553707	-.07915	**	0.170435
16	-5.067779	-.15706	***	0.170952
17	9.260380	0.28700	******	0.172972
18	-4.549572	-.14100	***	0.179554
19	-1.170767	-.03629	*	0.181107
20	4.081500	0.12650	***	0.181209
21	-1.368877	-.04242	*	0.182449
22	-1.679928	-.05207	*	0.182588
23	1.954801	0.06058	*	0.182797
24	-0.069903	-.00217		0.183079

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	-0.35221	*******
2	-0.27379	*****
3	-0.04540	*
4	-0.32358	******
5	-0.07136	*
6	-0.16257	***
7	-0.00752	
8	-0.11197	**
9	0.12065	**
10	-0.32993	*******
11	-0.11657	**
12	0.07922	**
13	-0.20001	****
14	-0.06577	*
15	-0.10625	**
16	-0.24298	*****
17	0.00689	
18	-0.03966	*
19	-0.18785	****
20	-0.08810	**
21	0.00226	
22	-0.03913	*
23	-0.10137	**
24	0.01428	
25	-0.01895	

< graph : divorce variable ARIMA model's ACF, PACF >

The ACF and PACF of divorce variable is cutoff. So price satisfied stationary status. The model is fitted on p=16, q=13

The ARIMA Procedure

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	18.89	6	0.0044	-0.352	-0.116	0.112	-0.263	0.167	-0.052
12	30.68	12	0.0022	0.040	-0.002	0.072	-0.257	0.067	0.244
18	56.45	18	<.0001	-0.311	0.219	-0.079	-0.157	0.287	-0.141
24	59.08	24	<.0001	-0.036	0.126	-0.042	-0.052	0.061	-0.002
30	84.73	30	<.0001	-0.043	0.114	-0.197	0.103	0.148	-0.349
36	94.77	36	<.0001	0.192	0.061	-0.099	0.128	-0.089	-0.010
42	101.10	42	<.0001	-0.002	-0.037	0.013	0.131	-0.119	-0.066
48	112.95	48	<.0001	0.168	-0.154	0.086	0.017	-0.042	0.026
54	114.57	54	<.0001	-0.005	-0.030	0.015	0.054	-0.041	-0.013
60	118.70	60	<.0001	0.001	-0.013	0.038	0.003	-0.058	0.066

< graph : divorce variable ARIMA model's portmanteau test >

p-value of white-noise is under 0.05. It leads to reject H0 : CORR=0 and divorce variable is proper for model.

❑ $\nabla\sqrt{divorce}$'s model estimation

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.86869	0.05385	16.13	<.0001	1
MA1,2	-0.19162	0.05671	-3.38	0.0012	16
AR1,1	-0.29479	0.11967	-2.46	0.0163	4
AR1,2	-0.24639	0.11577	-2.13	0.0370	10

Variance Estimate	21.05991
Std Error Estimate	4.589108
AIC	421.7355
SBC	430.7863
Number of Residuals	71

* AIC and SBC do not include log determinant.

< graph : divorce variable ARIMA model's ARIMA model's estimation >

The final model is ARIMA(10,1,16) from lots of taking try and error.

It's p-value is under 0.05 so the model is proper

❑ $\nabla\sqrt{divorce}$'s model diagnosis

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	6.26	2	0.0438	0.205	-0.048	-0.032	-0.034	-0.028	-0.186
12	10.21	8	0.2509	-0.001	-0.107	-0.094	0.018	0.079	0.139
18	14.80	14	0.3918	-0.092	0.043	-0.069	-0.168	0.048	-0.061
24	17.64	20	0.6108	-0.027	0.006	0.084	0.066	0.011	0.119
30	26.82	26	0.4190	0.003	-0.063	-0.106	0.039	0.017	-0.238
36	29.89	32	0.5739	0.028	0.115	0.014	-0.013	-0.068	-0.057
42	35.01	38	0.6083	-0.134	-0.053	0.019	-0.031	-0.096	-0.028
48	38.92	44	0.6888	0.120	-0.032	0.045	0.047	0.027	0.005
54	40.21	50	0.8374	0.005	-0.004	-0.005	0.051	0.025	-0.036
60	41.89	56	0.9194	0.003	0.029	0.037	0.014	-0.034	0.024

< graph : divorce variable ARIMA model's diagnosis >

Autocorrelation Plot of Residuals

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1	Std Error
0	21.059910	1.00000	********************	0
1	4.315260	0.20490	****	0.118678
2	-1.004366	-.04769	*	0.123561
3	-0.672713	-.03194	*	0.123820
4	-0.724635	-.03441	*	0.123936
5	-0.582019	-.02764	*	0.124070
6	-3.909387	-.18563	****	0.124157
7	-0.029033	-.00138		0.128006
8	-2.258610	-.10725	**	0.128006
9	-1.981471	-.09409	**	0.129266
10	0.371397	0.01764		0.130227
11	1.666905	0.07915	**	0.130260
12	2.925285	0.13890	***	0.130936
13	-1.937493	-.09200	**	0.132995
14	0.911538	0.04328	*	0.133888
15	-1.444655	-.06860	*	0.134085
16	-3.533484	-.16778	***	0.134579
17	1.004311	0.04769	*	0.137493
18	-1.284808	-.06101	*	0.137726
19	-0.572426	-.02718	*	0.138106
20	0.123682	0.00587		0.138182
21	1.763479	0.08374	**	0.138185
22	1.380200	0.06554	*	0.138898
23	0.240774	0.01143		0.139333

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1	0.20490	****
2	-0.09361	**
3	-0.00219	
4	-0.03291	*
5	-0.01689	
6	-0.19043	****
7	0.08264	**
8	-0.16900	***
9	-0.03628	*
10	0.01444	
11	0.06450	*
12	0.06673	*
13	-0.12663	***
14	0.07772	**
15	-0.14542	***
16	-0.12139	**
17	0.11199	**
18	-0.10970	**
19	-0.02764	*
20	0.08443	**
21	0.01021	
22	-0.02446	
23	0.04467	*
24	0.04745	*
25	-0.03454	*
26	-0.05766	*

< graph : divorce variable ARIMA model's diagnosis >

All the p-value of Q-test are over 0.2. And correlation of residuals doesn't remain and it means that they become whit-noise status.

And there is no outlier point in the ACF,PACF of residuals, we can conclude that the model is rightly fitted.

Thus, final model of unemploymen's ARIMA is as in the following

$$\nabla \sqrt{divorce} = \frac{(1-0.86869B+0.19162B^{16})}{(1+0.29479B^{4}+0.24639B^{10})} a_t$$

2) After checking CCF, set the transfer function model with s,d,r.

(1) Consumer price index(Price)

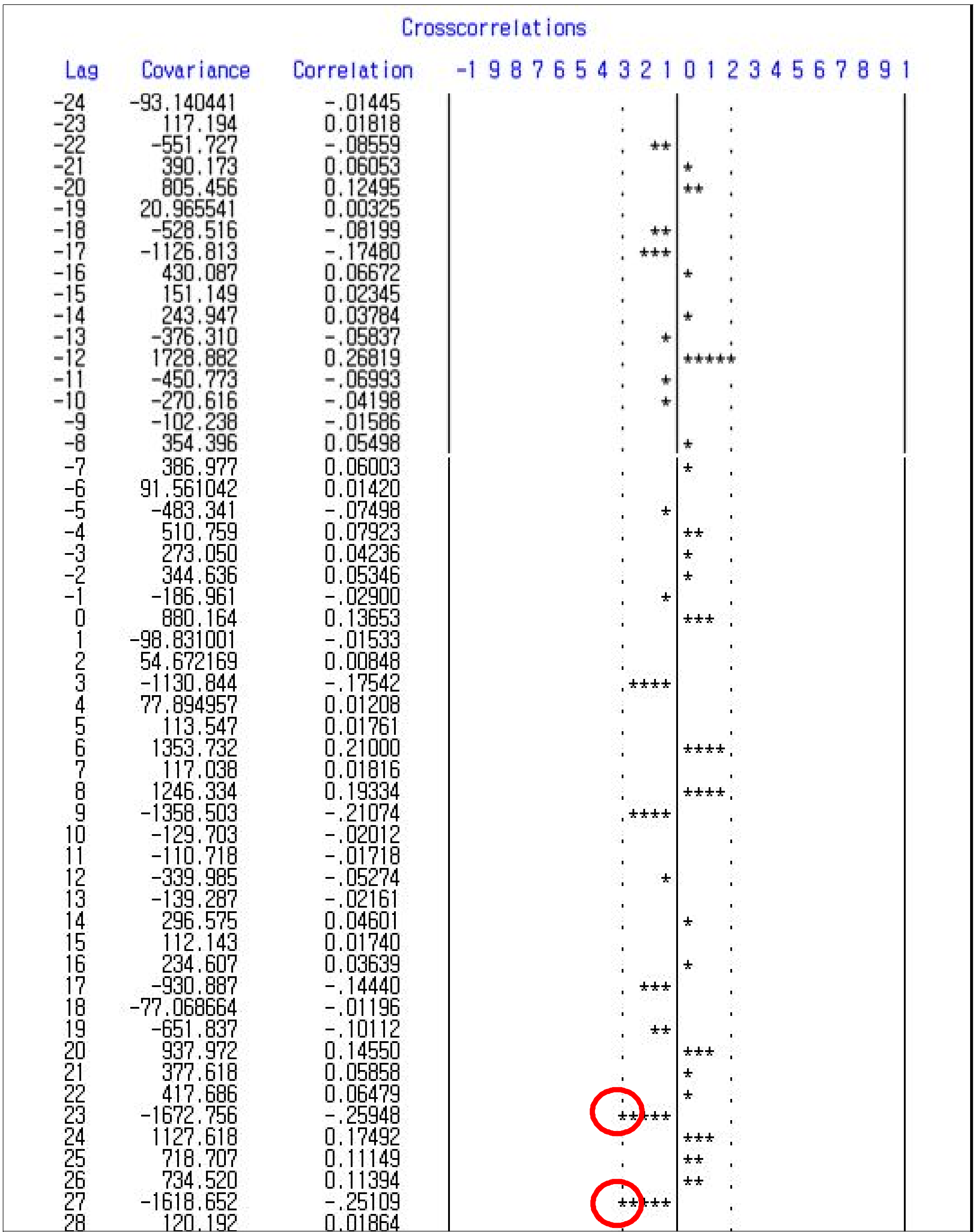
Crosscorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
-25	-8.358236	-.10370	**
-24	13.093543	0.16246	***
-23	-4.986596	-.06187	*
-22	3.858811	0.04788	*
-21	-10.408827	-.12915	***
-20	-0.262570	-.00326	
-19	-3.147220	-.03905	*
-18	-2.623153	-.03255	*
-17	3.142588	0.03899	*
-16	14.192301	0.17609	****
-15	-3.729338	-.04627	*
-14	-1.214435	-.01507	
-13	12.124072	0.15043	***
-12	-16.918578	-.20991	****
-11	-5.707663	-.07082	*
-10	14.493859	0.17983	****
-9	-10.390516	-.12892	***
-8	5.461681	0.06776	*
-7	9.368049	0.11623	**
-6	-8.576939	-.10642	**
-5	7.908368	0.09812	**
-4	10.048760	0.12468	**
-3	-28.939117	-.35906	*******
-2	-1.973849	-.02449	
-1	6.058756	0.07517	**
0	-3.342925	-.04148	*
1	-14.205313	-.17625	****
2	9.561512	0.11863	**
3	12.639188	0.15682	***
4	-9.679181	-.12009	**
5	19.081146	0.23675	*****
6	1.392727	0.01728	
7	-6.559747	-.08139	**
8	-2.746248	-.03407	*
9	2.205849	0.02737	*
10	-13.661455	-.16950	***
11	19.425658	0.24102	*****
12	-0.562923	-.00698	
13	1.522583	0.01889	
14	-1.177864	-.01461	
15	-9.324238	-.11569	**
16	1.639748	0.02034	
17	3.883041	0.04818	*
18	0.539160	0.00669	
19	-3.035850	-.03767	*
20	3.718474	0.04614	*
21	-22.274489	-.27637	******
22	12.179904	0.15112	***
23	-0.774736	-.00961	
24	-2.923919	-.03628	*

< graph : Price's Crosscorrelations >

I looked at the CCF of Suicide and Price, correlation that was meaningfully different from 0 appeared at lag5 for the first time, and it seemed to continue until cutting-off at lag21. Therefore although I set the condition as d=5, s=16 and r=0 at the beginning, I got to use 5$(6 16)price assumption by trial and error. Figure stood out at -3, but it was never given serious consideration because it was nonsense that increase of the number of suicides causes inflation

(2) Duration of sunshine(Sun)



Crosscorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
-24	-93.140441	-.01445	
-23	117.194	0.01818	
-22	-551.727	-.08559	**
-21	390.173	0.06053	*
-20	805.456	0.12495	**
-19	20.965541	0.00325	
-18	-528.516	-.08199	**
-17	-1126.813	-.17480	***
-16	430.087	0.06672	*
-15	151.149	0.02345	
-14	243.947	0.03784	*
-13	-376.310	-.05837	*
-12	1728.882	0.26819	*****
-11	-450.773	-.06993	*
-10	-270.616	-.04198	*
-9	-102.238	-.01586	
-8	354.396	0.05498	*
-7	386.977	0.06003	*
-6	91.561042	0.01420	
-5	-483.341	-.07498	*
-4	510.759	0.07923	**
-3	273.050	0.04236	*
-2	344.636	0.05346	*
-1	-186.961	-.02900	*
0	880.164	0.13653	***
1	-98.831001	-.01533	
2	54.672169	0.00848	
3	-1130.844	-.17542	****
4	77.894957	0.01208	
5	113.547	0.01761	
6	1353.732	0.21000	****
7	117.038	0.01816	
8	1246.334	0.19334	****
9	-1358.503	-.21074	****
10	-129.703	-.02012	
11	-110.718	-.01718	
12	-339.985	-.05274	*
13	-139.287	-.02161	
14	296.575	0.04601	*
15	112.143	0.01740	
16	234.607	0.03639	*
17	-930.887	-.14440	***
18	-77.068664	-.01196	
19	-651.837	-.10112	**
20	937.972	0.14550	***
21	377.618	0.05858	*
22	417.686	0.06479	*
23	-1672.756	-.25948	*****
24	1127.618	0.17492	***
25	718.707	0.11149	**
26	734.520	0.11394	**
27	-1618.652	-.25109	*****
28	120.192	0.01864	

< graph : Sun's Crosscorrelations >

Looked at the CCF of Sucide and Sun, correlation that was meaningfully different from 0 for the first time appeared at lag23,and it was exponentially decreased after continued at lag21 .

Therefore at the biginning I used 23$(4)/(1)sun by a process of trial and error.

(3) Economically inactive population(Secon)

Crosscorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
-27	0.276836	0.23585	|*****
-26	-0.101765	-.08670	**|
-25	0.075266	0.06412	|*
-24	-0.0080759	-.00688	|
-23	0.098720	0.08410	|**
-22	-0.167894	-.14304	***|
-21	-0.145411	-.12388	**|
-20	0.205409	0.17500	|***
-19	-0.124365	-.10595	**|
-18	-0.092032	-.07841	**|
-17	0.339106	0.28890	|******
-16	-0.272474	-.23213	*****|
-15	-0.024527	-.02090	|
-14	0.136470	0.11627	|**
-13	0.062326	0.05310	|*
-12	-0.047390	-.04037	*|
-11	-0.153319	-.13062	***|
-10	-0.081617	-.06953	*|
-9	0.195085	0.16620	|***
-8	-0.159372	-.13578	***|
-7	0.327052	0.27863	|******
-6	-0.087814	-.07481	*|
-5	0.168004	0.14313	|***
-4	-0.013775	-.01174	|
-3	-0.143857	-.12256	**|
-2	-0.144886	-.12344	**|
-1	-0.019606	-.01670	|
0	0.073856	0.06292	|*
1	0.081459	0.06940	|*
2	-0.030069	-.02562	*|
3	-0.080088	-.06823	*|
4	-0.0022104	-.00188	|
5	0.115510	0.09841	|**
6	-0.341357	-.29082	******|
7	0.163601	0.13938	|***
8	0.123245	0.10500	|**
9	0.158311	0.13487	|***
10	-0.296477	-.25258	*****|
11	-0.027995	-.02385	|
12	0.133778	0.11397	|**
13	-0.028020	-.02387	|
14	-0.0075801	-.00646	|
15	0.135956	0.11583	|**
16	-0.010489	-.00894	|
17	-0.075437	-.06427	*|
18	-0.019204	-.01636	|
19	0.088859	0.07570	|**
20	-0.034008	-.02897	*|
21	-0.031591	-.02691	*|
22	-0.012713	-.01083	|
23	-0.088114	-.07507	**|
24	0.018234	0.01553	|

< graph : Secon's Crosscorrelations >

By looking through CCF of Suicide and Secon, there are large correlation at lag -27, -17, -16, -7. So decided to remove this variable in this projection..

(4) Unemployments (Unemp)

Crosscorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
-34	-17.784013	-.29240	******
-33	6.408712	0.10537	**
-32	1.629496	0.02679	*
-31	7.308249	0.12016	**
-30	-3.720305	-.06117	*
-29	-3.906771	-.06423	*
-28	1.966924	0.03234	*
-27	4.006562	0.06588	*
-26	-3.055082	-.05023	*
-25	-1.078901	-.01774	
-24	0.883271	0.01452	
-23	-7.681671	-.12630	***
-22	0.0050890	0.00008	
-21	10.125451	0.16648	***
-20	-4.637207	-.07624	**
-19	4.316063	0.07096	*
-18	-3.143309	-.05168	*
-17	-5.862906	-.09640	**
-16	5.433035	0.08933	**
-15	23.294944	0.38301	********
-14	-25.085277	-.41245	********
-13	-1.017620	-.01673	
-12	-7.684066	-.12634	***
-11	13.729599	0.22574	*****
-10	-6.223196	-.10232	**
-9	6.947379	0.11423	**
-8	0.754787	0.01241	
-7	9.582066	0.15755	***
-6	-5.944412	-.09774	**
-5	-6.847942	-.11259	**
-4	-4.293780	-.07060	*
-3	4.102163	0.06745	*
-2	6.502038	0.10691	**
-1	-3.918940	-.06443	*
0	-7.232960	-.11892	**
1	0.671775	0.01105	
2	0.418875	0.00689	
3	14.331766	0.23564	*****
4	-9.177985	-.15090	***
5	-0.529976	-.00871	
6	7.313526	0.12025	**
7	-5.778136	-.09500	**
8	-3.872174	-.06367	*
9	-2.170120	-.03568	*
10	0.475104	0.00781	
11	9.525160	0.15661	***
12	-6.640029	-.10917	**
13	1.216480	0.02000	
14	1.507222	0.02478	
15	0.627177	0.01031	
16	-4.949711	-.08138	**
17	8.254835	0.13572	***
18	-3.066382	-.05042	*
19	-4.747846	-.07806	**
20	-0.691899	-.01138	
21	3.140435	0.05163	*

< graph : Unemp's Crosscorrelations >

By looking through CCF of Suicide and Unemp, there are large correlation at lag -34, -15, -14, -11. So decided to remove this variable in this projection.

(5) Divorce(Sdiv)

Crosscorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
-19	-193.519	-.17039	*** |
-18	19.593067	0.01725	|
-17	-18.844139	-.01659	|
-16	-80.726815	-.07108	* |
-15	10.659805	0.00939	|
-14	20.191864	0.01778	|
-13	-87.201904	-.07678	** |
-12	-66.128510	-.05822	* |
-11	122.302	0.10768	| **
-10	-41.248114	-.03632	* |
-9	-26.375244	-.02322	|
-8	-32.964278	-.02902	* |
-7	153.343	0.13501	| ***
-6	133.415	0.11747	| **
-5	-174.074	-.15327	*** |
-4	5.240597	0.00461	|
-3	-135.538	-.11934	** |
-2	-94.391211	-.08311	** |
-1	24.395825	0.02148	|
0	28.597268	0.02518	| *
1	-195.279	-.17194	*** |
2	-162.711	-.14326	*** |
3	97.575314	0.08591	| **
4	320.185	0.28192	| ******
5	-27.783880	-.02446	|
6	-141.167	-.12429	** |
7	36.710038	0.03232	| *
8	-31.734491	-.02794	* |
9	-2.402025	-.00211	|
10	-77.186570	-.06796	* |
11	148.430	0.13069	| ***
12	74.493328	0.06559	| *
13	198.030	0.17436	| ***
14	239.271	0.21067	| ****
15	-103.910	-.09149	** |
16	-173.726	-.15296	*** |
17	129.586	0.11410	| **
18	64.391148	0.05669	| *
19	-141.520	-.12461	** |
20	-249.130	-.21935	**** |
21	250.302	0.22039	| ****
22	28.848211	0.02540	| *
23	-221.561	-.19508	**** |
24	21.232346	0.01869	|
25	228.529	0.20121	| ****

< graph : Sdiv's Crosscorrelations >

By looking through CCF of Suicide and Sdiv, there are large correlation only at lag 4 and cutoff. So decided to remove this variable in this projection. Thus I used 4$sdiv with d=4, s=0, r=0.

3) i.i.d. assumption check and ARMA model fitting regarding N_t

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
NUM1	12.16871	131.95050	0.09	0.9273	0	price	5
NUM1,1	-108.39035	148.16201	-0.73	0.4712	6	price	5
NUM1,2	145.59280	167.67515	0.87	0.3935	16	price	5
NUM2	-2.65549	1.34989	-1.97	0.0604	0	sun	23
NUM1,1	2.81582	1.29785	2.17	0.0397	4	sun	23
DEN1,1	-0.22266	0.29505	-0.75	0.4575	1	sun	23
NUM3	6.96227	10.38893	0.67	0.5089	0	sdiv	4

Variance Estimate	99523.02
Std Error Estimate	315.4727
AIC	465.1732
SBC	475.4333
Number of Residuals	32

* AIC and SBC do not include log determinant.

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	19.44	6	0.0035	-0.547	-0.065	0.296	-0.276	0.213	-0.130
12	44.38	12	<.0001	-0.136	0.396	-0.361	-0.003	0.299	-0.339
18	56.72	18	<.0001	0.233	-0.095	-0.025	0.185	-0.263	0.130
24	63.44	24	<.0001	0.088	-0.197	0.152	-0.003	-0.047	-0.011
30	63.99	30	0.0003	-0.001	0.042	-0.018	-0.017	0.014	-0.006

Autocorrelation Plot of Residuals

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0	0 1 2 3 4 5 6 7 8 9 1	Std Error
0	99523.020	1.00000		********************	0
1	-54467.946	-.54729	***********		0.176777
2	-6474.310	-.06505	*		0.223541
3	29473.584	0.29615		******	0.224131
4	-27422.816	-.27554	******		0.236043
5	21159.766	0.21261		****	0.245889
6	-12951.352	-.13013	***		0.251569
7	-13522.328	-.13587	***		0.253664
8	39411.262	0.39600		********	0.255928
9	-35905.700	-.36078	*******		0.274409
10	-279.036	-.00280			0.288852
11	29742.016	0.29885		******	0.288852
12	-33731.380	-.33893	*******		0.298358
13	23169.775	0.23281		*****	0.310157
14	-9494.029	-.09540	**		0.315570
15	-2535.400	-.02548	*		0.316470
16	18380.888	0.18469		****	0.316534
17	-26148.621	-.26274	*****		0.319884
18	12925.560	0.12988		***	0.326558

Partial Autocorrelations

Lag	Correlation	-1 9 8 7 6 5 4 3 2 1 0	0 1 2 3 4 5 6 7 8 9 1
1	-0.54729	***********	
2	-0.52048	**********	
3	-0.08387	**	
4	-0.19814	****	
5	0.10462		**
6	-0.05705	*	
7	-0.29392	******	
8	0.10522		**
9	-0.04251	*	
10	-0.23240	*****	
11	-0.01513		
12	-0.15308	***	
13	-0.01161		
14	-0.06731	*	
15	0.03992		*
16	0.01214		
17	-0.03577	*	
18	-0.02969	*	

<graph : N_t's i.i.d assumption check>

All p-values are 0.05 regarding Q-test of Nt's residuals. so there are correlations of residuals. So p=2,q=1 and after taking lots of try and error, we can conclude ARMA(1,1) is final model.

2012년 12월 18일 화요일 오후

The ARIMA Procedure

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1,1	0.80122	0.14447	5.55	<.0001	1	suicide	0
AR1,1	-0.43920	0.20867	-2.10	0.0455	1	suicide	0
NUM1	131.50415	79.51677	1.65	0.1107	0	price	5
NUM1,1	-252.93052	72.48371	-3.49	0.0018	6	price	5
NUM2	-1.87638	1.04915	-1.79	0.0858	0	sun	23
NUM1,1	4.57374	1.05545	4.33	0.0002	4	sun	23
DEN1,1	-0.38003	0.19375	-1.96	0.0611	1	sun	23

Variance Estimate	43226.08
Std Error Estimate	207.9088
AIC	438.4869
SBC	448.7471
Number of Residuals	32

* AIC and SBC do not include log determinant.

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.72	4	0.6059	-0.074	-0.100	0.192	0.094	0.003	-0.103
12	7.05	10	0.7205	-0.106	0.190	-0.105	-0.066	0.147	-0.081
18	9.35	16	0.8984	0.169	0.058	0.014	0.030	-0.024	0.067
24	15.15	22	0.8558	0.103	-0.093	0.182	0.085	-0.010	0.020
30	16.46	28	0.9585	0.038	0.010	-0.023	-0.052	-0.018	-0.013

Autocorrelation Plot of Residuals

```
Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

  0    43226.078       1.00000   |                    |********************|            0
  1    -3177.707       -.07351   |               .   *|    .               |     0.176777
  2    -4335.404       -.10030   |               .  **|    .               |     0.177729
  3     8278.266       0.19151   |               .    |****.               |     0.179489
  4     4051.170       0.09372   |               .    |**  .               |     0.185765
  5      108.184       0.00250   |               .    |    .               |     0.187237
  6    -4467.742       -.10336   |               .  **|    .               |     0.187238
  7    -4592.075       -.10623   |              .   **|     .              |     0.189013
  8     8193.255       0.18954   |              .     |****  .              |     0.190869
  9    -4522.643       -.10463   |              .   **|     .              |     0.196664
 10    -2855.869       -.06607   |              .    *|     .              |     0.198395
 11     6355.221       0.14702   |              .     |***  .              |     0.199082
 12    -3517.743       -.08138   |              .   **|     .              |     0.202446
```

Partial Autocorrelations

```
Lag   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1     -0.07351    |               .    *|    .               |
  2     -0.10627    |               .   **|    .               |
  3      0.17851    |               .     |****.               |
  4      0.11510    |               .     |**  .               |
  5      0.05632    |               .     |*   .               |
  6     -0.12262    |               .   **|    .               |
  7     -0.17329    |               .  ***|    .               |
  8      0.13922    |               .     |*** .               |
  9     -0.06029    |               .    *|    .               |
 10      0.02837    |               .     |*   .               |
 11      0.10736    |               .     |**  .               |
 12     -0.09158    |               .   **|    .               |
```

< graph: N_t's ARMA model's fitting>

All the p-value of Q-test with repect to a_t are over 0.2. And correlation of residuals doesn't remain and it means that they become whit-noise status. And there is no outlier point in the ACF,PACF of residuals, we can conclude that the ARMA model is rightly fitted.

$$N_t = \frac{(1-0.80122B)}{(1+0.43920B)} a_t$$

V. Model comparison and prediction

1) Comparision between ARIMA Model and Transfer function model

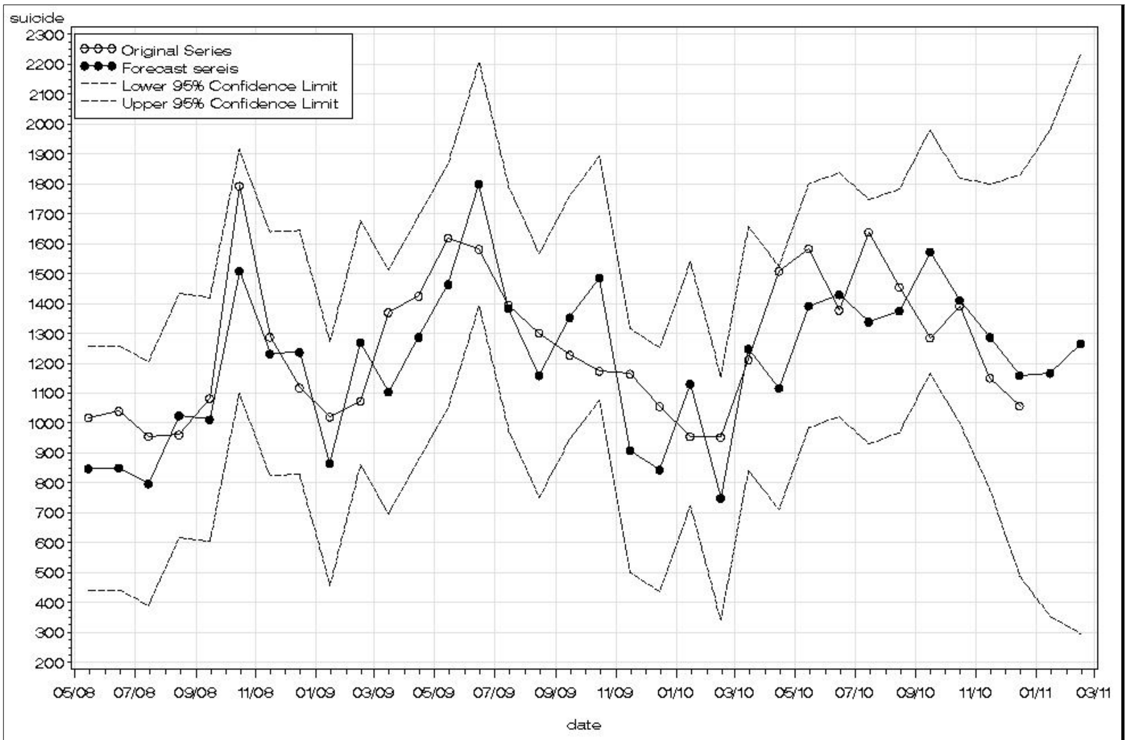
Variance Estimate 39377.71 Std Error Estimate 198.4382 AIC 780.257 SBC 784.3779 Number of Residuals 58 * AIC and SBC do not include log determinant.	Variance Estimate 43226.08 Std Error Estimate 207.9088 AIC 438.4869 SBC 448.7471 Number of Residuals 32 * AIC and SBC do not include log determinant.
<graph: ARIMA model's AIC, SBC>	<graph: Transfer function model's AIC, SBC>

The left of graph is CLS estimation result of output variable(the number of suicides) from Ⅲ and the right is CLS estimation of transfer function model from IV.

SSE slightly increased from 198.44 to 207.91, but AIC and SBC largely decreased.

So transfer function model is more proper than ARIMA model.

2) Prediction



<graph : predction of the number of suicides by time period>

The ARIMA Procedure

Forecasts for variable suicide

Obs	Forecast	Std Error	95% Confidence Limits		Actual	Residual
70	1410.4462	207.9088	1002.9524	1817.9400	1391.0000	-19.4462
71	1287.2611	261.0866	775.5407	1798.9814	1151.0000	-136.2611
72	1159.0146	342.1968	488.3213	1829.7079	1057.0000	-102.0146
73	1166.7297	414.9730	353.3976	1980.0618	.	.
74	1265.1271	495.1474	294.6560	2235.5982	.	.

The final graph of projection is above one with transfer function model. It seems that there is no need to take intervention analysis because there is no outlier observation from confidence interval.

VI. Conclusion and limits

1) The results of transfer function model fitting

❑ Model fitting

$$\nabla_{12}\nabla^2 suicide = (1-131.50415+252.93052B^6)B^5\nabla^2 price$$
$$+\frac{(1+1.87638-4.57374B^4)}{(1+0.38003B)}B^{23}\nabla_{12}\nabla sun+\frac{(1-0.80122B)}{(1+0.43920B)}a_t$$

❑ Specification

❍ 1st step

$$suicide_t-2suicide_{t-1}+suicide_{t-2}-suicide_{t-12}+suicide_{t-13}-suicide_{t-14}$$
$$=(131.504+252.913B^6)B^5(price_t-2price_{t-1}+price_{t-2})$$
$$+(-1.8764-4.57374B^4)B^{23}(1+(-0.38003B)+(-0.38003B)^2+(-0.38003B)^3+...)$$
$$(sun_t-sun_{t-1}-sun_{t-12}+sun_{t-13})$$
$$+(1-0.80122B)(1+(-0.4392B)+(-0.4392B)^2+(-0.4392B)^3+...)a_t$$

❍ 2nd step

$$suicide_t-2suicide_{t-1}+suicide_{t-12}+suicide_{t-13}-suicide_{t-14}$$
$$=131.504price_{t-5}-263.008price_{t-6}+131.504price_{t-7}+252.913price_{t-11}$$
$$-505.826price_{t-12}+252.913price_{t-13}+(-1.8764sun_{t-23}+0.713088sun_{t-24}$$
$$-0.270995sun_{t-25}+...)+a_t-1.24042a_{t-1}+0.54479a_{t-2}+...$$

❑ Interpretation

If consumer price index increase by 1%, the number of suicides increase by 131,504. And if duration of sunshine increase by 1 hour, the number of suicides decrease 1.8764.

2) Conclusion

I set total 6 variable at first, but only 2 variables that are price index and duration of sunshine finally remain.

The society has become a graying and the number of elder people's suicides increase. Most of elder people are reitred and they are vulnerable to economic situation of society.

So we can estimate that their suicides have positive correlation with consumer price index.

The duration of sunshine is lately going down and it is naturally leading to increase depression of elder people.

So we can estimate that their suicides have negative correlation with duration of sunshine.

Thus, we need to offer reemployment opportunity for elderly to solve suicides problem in the society.

3) Limits

❑ **Data collection**

A) Couldn't specify the number of suicide by age and just used total number of suicides.
Thus I couldn't set the number of suicide specified in the elder people evenif elders suicide becomes big issues in the society. It makes me feel something lacking.

B) I had trouble in collecting the suicide data because of lack of data and nonexistence of integrated suicide management organization.

Ⅷ. References

1) 박유성, 김기환 <SAS/ETS를 이용한 시계열자료분석> 자유아카데미
2) 고려대학교 통계학과 <2010년 2학기 시계열 분석 사례집>
3) 국가통계포털 KOSIS www.kosis.kr
4) 기상청 www.kma.go.kr
5) Naver 뉴스
6) 송태정외 2명 <자살, 이혼, 범죄 그리고 경제> LG 경제연구소
7) 김성진 <자살도 일조량 영향 받아> 연합뉴스

2) SAS CODES

```
%macro origin_p(d_set, t_year, t_start, t_unit, origin);

data arrange;
 set &d_set(keep=&origin);
 %if  &t_unit = 1  %then
    %do
             day = 15 year=resolve(&t_year);
t_mon=resolve(&t_start);
             year=year+int((_n_+t_mon-1)/12-0.001);
             month=MOD(_n_+t_mon-1,12);
             if month = 0 then month=12
             date=MDY(month,day,year);
             format date mmyys5.
     %end
  %else
    %do
             year=resolve(&t_year);
t_mon=resolve(&t_start);
             year=year+int((_n_+t_mon-1)/4-0.001);
             month=MOD(_n_+t_mon-1,4);
             if month=0 then month=4
             date=YYQ(year, month);
             format date yyq6.
    %end
run;

data anno;
 set arrange(keep=date &origin month);
   x=date; y=&origin;
   xsys='2' ysys='2'
   text=put(month,2.);
   size=1.0
   position='2'
run;

goptions reset=all ftext=swissx fontres=presentation;
 symbol1 v=circle cv=black i=join ci=black;
 proc gplot data=arrange;
  where &origin ne .
 plot &origin*date=1 /grid annotate=anno frame;
run;

%mend origin_p;


data aa;
input suicide price sun econ ecopar unemp divorce ;
cards
697.00  3.40  159.10  14940.00  60.60  3.90  10447.00
736.00  3.40  143.50  15000.00  60.50  4.00  9639.00
1309.00  3.00  216.90  14614.00  61.60  3.90  12071.00
1259.00  3.10  228.10  14393.00  62.30  3.60  9999.00
1233.00  3.10  240.80  14265.00  62.70  3.40  10636.00
1119.00  2.80  173.70  14297.00  62.70  3.40  10531.00
1056.00  2.60  131.40  14382.00  62.50  3.50  10578.00
1075.00  2.00  148.00  14777.00  61.50  3.40  12226.00
1027.00  2.50  132.70  14612.00  62.00  3.30  10836.00
922.00  2.30  178.50  14474.00  62.40  3.40  10717.00
843.00  2.50  187.60  14551.00  62.20  3.10  10459.00
735.00  2.60  155.80  15017.00  61.00  3.40  9896.00
853.00  2.20  139.50  15256.00  60.40  3.50  10282.00
816.00  2.00  149.60  15278.00  60.40  3.90  10985.00
1006.00  2.00  209.00  14919.00  61.40  3.70  11280.00
986.00  2.00  159.00  14652.00  62.10  3.30  9528.00
1055.00  2.30  181.60  14511.00  62.50  3.00  10295.00
924.00  2.40  167.20  14502.00  62.60  3.20  10923.00
938.00  2.40  73.70  14587.00  62.40  3.20  10164.00
902.00  2.70  203.20  14900.00  61.60  3.20  11375.00
890.00  2.50  173.60  14788.00  61.90  3.10  10047.00
884.00  2.20  203.60  14658.00  62.30  3.10  9543.00
772.00  2.10  140.10  14705.00  62.20  3.00  10471.00
627.00  2.10  145.00  15178.00  61.00  3.10  9631.00
806.00  1.70  144.20  15420.00  60.40  3.40  10643.00
1189.00  2.20  173.30  15525.00  60.20  3.40  9795.00
1141.00  2.20  159.40  15125.00  61.30  3.30  10487.00
1163.00  2.50  202.30  14799.00  62.10  3.20  10348.00
1221.00  2.30  223.40  14643.00  62.60  3.00  10653.00
1070.00  2.50  158.50  14643.00  62.60  2.90  9804.00
1025.00  2.50  112.10  14723.00  62.40  3.00  10462.00
996.00  2.00  145.90  15076.00  61.60  2.90  11220.00
994.00  2.30  102.60  14963.00  61.90  2.80  8673.00
967.00  3.00  173.60  14848.00  62.20  2.80  11329.00
840.00  3.50  178.10  14888.00  62.10  2.80  10949.00
762.00  3.60  117.30  15396.00  60.90  2.90  9709.00
809.00  3.90  133.80  15694.00  60.20  3.10  10645.00
821.00  3.60  194.70  15768.00  60.00  3.30  9836.00
991.00  3.90  191.40  15389.00  61.00  3.20  11263.00
980.00  4.10  200.40  15045.00  61.90  3.00  11023.00
1018.00  4.90  214.50  14895.00  62.30  2.90  10773.00
1040.00  5.50  136.20  14892.00  62.40  2.90  11264.00
956.00  5.90  137.60  14988.00  62.20  3.00  9141.00
961.00  5.60  193.60  15314.00  61.40  3.00  6364.00
1083.00  5.10  170.00  15291.00  61.50  2.70  6704.00
1793.00  4.80  192.60  15186.00  61.80  2.80  9603.00
1288.00  4.50  151.40  15255.00  61.60  2.80  9192.00
1118.00  4.10  150.70  15822.00  60.30  3.10  10727.00
1021.00  3.70  156.30  16212.00  59.30  3.30  9395.00
1074.00  4.10  122.10  16288.00  59.20  3.70  9828.00
1370.00  3.90  193.80  15927.00  60.10  3.70  10559.00
1425.00  3.60  225.20  15587.00  61.00  3.60  9861.00
1619.00  2.70  239.70  15426.00  61.50  3.60  10135.00
1582.00  2.00  188.40  15230.00  62.00  3.50  11265.00
1396.00  1.60  113.30  15440.00  61.50  3.50  11307.00
1302.00  2.20  153.50  15695.00  60.90  3.50  9948.00
1228.00  2.20  180.90  15616.00  61.20  3.20  10626.00
1174.00  2.00  221.00  15637.00  61.10  3.00  10111.00
1165.00  2.40  121.90  15712.00  61.00  3.10  10140.00
1056.00  2.80  133.30  16326.00  59.50  3.20  10824.00
955.00  3.50  156.90  16389.00  59.40  4.70  9284.00
953.00  3.00  125.90  16554.00  59.00  4.20  8600.00
1212.00  2.50  122.90  16163.00  60.00  3.80  10193.00
1508.00  2.60  176.00  15700.00  61.20  3.50  9445.00
1583.00  2.70  206.50  15495.00  61.80  2.90  9290.00
1378.00  2.70  192.40  15480.00  61.80  3.20  10285.00
```

```
1638.00  2.50  130.00  15461.00  61.90  3.40  9880.00
1455.00  2.70  147.20  15889.00  60.90  3.10  9727.00
1285.00  3.40  159.40  15914.00  60.90  2.90  9238.00
1391.00  3.70  176.50  15793.00  61.20  3.00  9846.00
1151.00  3.00  190.90  15971.00  60.80  2.70  10781.00
1057.00  3.00  146.20  16343.00  59.90  3.20  10289.00

run

%origin_p(aa, 2005,1,1,suicide)
%origin_p(aa, 2005,1,1,price)
%origin_p(aa, 2005,1,1,sun)
%origin_p(aa, 2005,1,1,econ)
%origin_p(aa, 2005,1,1,ecopar)
%origin_p(aa, 2005,1,1,unemp)
%origin_p(aa, 2005,1,1,divorce)

 /*입력변수간의 다중공선성 확인*/
proc corr data=aa;
var price sun econ ecopar unemp divorce;
run


/*ecopar이 correlation을 높이므로 제거*/
proc corr data=aa;
var price sun econ unemp divorce;
run


/*자살자수*/
data aa1;
 set aa;
 suicide12=dif12(suicide);
 suicide112=dif(suicide12);
 suicide1112=dif(suicide112);
run

%origin_p(aa1, 2005,1,1,suicide1112)

proc arima data=aa1;
 identify var=suicide(1 1 12) nlag=60
 estimate q=(1)(12) noconstant plot
run


/*소비자물가*/
data aa2;
 set aa1;
 price1=dif(price);
 price2=dif(price1);
run

%origin_p(aa2, 2005,1,1,price2)

proc arima data=aa2;
 identify var=price(1 1) nlag=60
 estimate p=(1 2 3 4 6) q=( 12) noconstant plot
run

/*일조시간*/
data aa3;
set aa2;
dsun=dif12(sun);
dsun1=dif1(dsun);
run

%origin_p(aa3, 2005,1,1,dsun1)

proc arima data=aa3;
identify var=sun(1 12) nlag=60
estimate p=(23) q=(1)(12) noconstant plot
run


/*비경제활동인구*/
data aa4;
 set aa3;
 secon=log(econ);
 secon12=dif12(secon);
 secon112=dif(secon12);
run

%origin_p(aa4, 2005,1,1,secon112)


proc arima data=aa4;
 identify var=secon(1 12) nlag=60
 estimate p=(1 12) q=(11) noconstant plot
run


/*실업률*/
data aa5;
 set aa4;
 unemp12=dif12(unemp);
 unemp112=dif(unemp12);
run

%origin_p(aa5, 2005,1,1,unemp112)

proc arima data=aa5;
 identify var=unemp(1 12) nlag=60
 estimate p=(1 4) q=(12) noconstant plot
run


/*이혼통계*/
data aa6;
set aa5;
sdiv=sqrt(divorce);
div1=DIF(sdiv);
run

%origin_p(aa6,2005,1,1,div1)

proc arima data=aa6;
identify var=sdiv(1) nlag=60
```

```
estimate p=(4 10) q=(1 16)  plot noconstant maxit=100
run


/*전이함수*/
proc arima data=aa6;

identify var=price(1 1) nlag=60
estimate p=(1 2 3 4 6) q=( 12) noconstant plot

identify var=sun(1 12) nlag=60
estimate p=(23) q=(1)(12) noconstant plot

identify var=secon(1 12) nlag=60
estimate p=(1 12) q=(11) noconstant plot

identify var=unemp(1 12) nlag=60
estimate p=(1 4) q=(12) noconstant plot

identify var=sdiv(1) nlag=60
estimate p=(4 10) q=(1 16)  plot noconstant maxit=100

/*Y와 각각의 X에 대하여 crosscorrelation 확인*/
identify var=suicide(1 1 12) crosscor=(price(1 1) sun(1 12)
secon(1 12) unemp(1 12) sdiv(1)) nlag=60

/*CCF에서 s,d,r 결정 후 모형에 적합*/
estimate input=(5$(6 16)price 23$(4)/(1)sun 4$sdiv)
noconstant plot

/*Nt가 i.i.d.하지 않으므로 Nt에 대해 ARMA모형 적합한 후
유의하지 않은 변수 제거*/
estimate p=(1) q=(1) input=(5$(6)price 23$(4)/(1)sun)
noconstant plot

run



 %macro fore_p(d_set, t_year, t_start, t_unit, origin);

data &d_set;
 set &d_set(keep=&origin forecast L95 U95);
 %if  &t_unit = 1  %then
    %do
            day = 15 year=resolve(&t_year);
t_mon=resolve(&t_start);
            year=year+int((_n_+t_mon-1)/12-0.001);
            month=MOD(_n_+t_mon-1,12);
            if month = 0 then month=12
            date=MDY(month,day,year);
            format date mmyys5.
      %end
   %else
    %do
            year=resolve(&t_year);
t_mon=resolve(&t_start);
            year=year+int((_n_+t_mon-1)/4-0.001);
            month=MOD(_n_+t_mon-1,4);
            if month=0 then month=4
            date=YYQ(year, month);
            format date yyq6.
    %end
run;

goptions reset=all ftext=swissx fontres=presentation;
symbol1 v=circle cv=black i=join ci=black;
symbol2 v=dot cv=black i=join ci=black;
symbol3 v=none i=join ci=black l=3
legend1 across=1 cborder=black mode=reserve
cframe=white
        position=(top inside left) label=none
        value=(tick=1 font=swissx 'Original Series'
               tick=2 font=swissx 'Forecast sereis'
               tick=3 font=swissx 'Lower 95% Confidence
Limit'
               tick=4 font=swissx 'Upper 95% Confidence
Limit');
proc gplot data=&d_set;
 where forecast ne .
 plot &origin*date=1
      forecast*date=2
      L95*date=3 u95*date=3 /grid overlay
legend=legend1 frame;
run;

%mend fore_p;

forecast lead=5 back=3 out=out2;
run

%fore_P(out2,2005,1,1,suicide)
```