

Computer Handout 9: MA, AR and ARMA Models

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Econ 3342

This Computer Handout 9 will cover the estimation of MA, AR and ARMA models and how to select between competing models using AIC, SIC, the autocorrelation function and the partial autocorrelation function. For this exercise we will start with the same file as computer handout 8.

Artificial Data: MA(1) Process

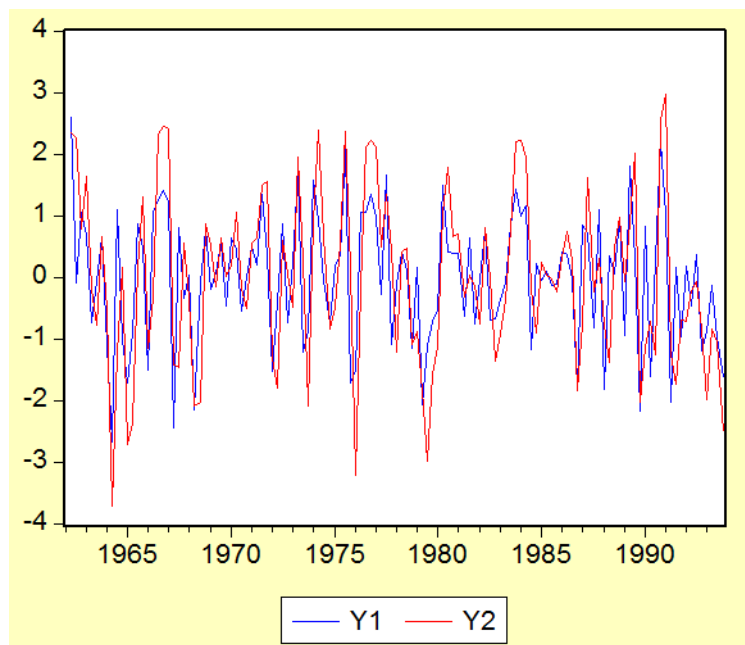
Lets generate an artificial MA(1) process.

Generate the random variable epsilon: `genr epsilon=nrnd`

Now, generate the following three MA(1) processes:

```
genr Y1=epsilon+0.08*epsilon(-1)
genr Y2=epsilon+0.98*epsilon(-1)
genr Y3=epsilon-0.98*epsilon(-1)
```

Graph Y1 and Y2. Notice that Y2 is more volatile than Y1. Recall the formula for the variance?



Now, let's look at the autocorrelation and the partial autocorrelation functions. Notice that even though the series have undistinguishable forms based on just looking at the graph, they have very characteristic autocorrelation and partial correlation functions.

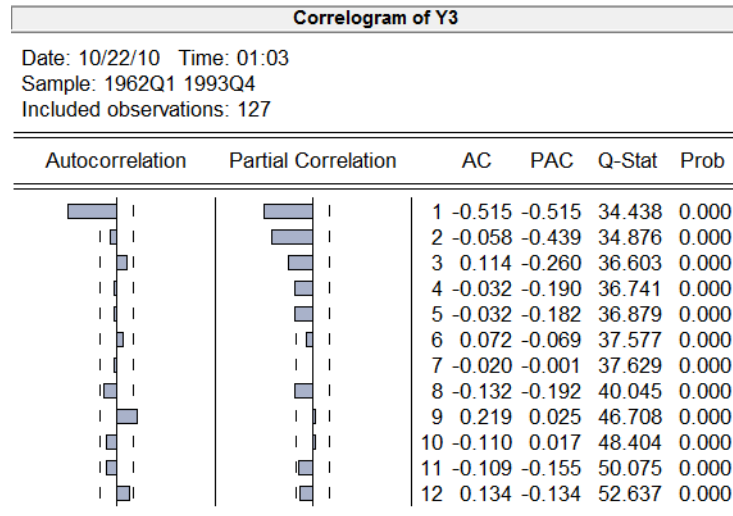
For Y1, the coefficient on the lagged epsilon is so small that based on the autocorrelation and the partial autocorrelation function, we conclude that it is white noise (all coefficients are within the bands). Moreover, the Ljung-Box Q-statistic reaches the same conclusion.

Correlogram of Y1						
Date: 10/22/10 Time: 01:00						
Sample: 1962Q1 1993Q4						
Included observations: 127						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1 -0.059	-0.059	0.4460	0.504	
		2 -0.104	-0.108	1.8631	0.394	
		3 0.069	0.057	2.4893	0.477	
		4 -0.014	-0.018	2.5157	0.642	
		5 -0.040	-0.029	2.7299	0.742	
		6 0.013	0.001	2.7513	0.839	
		7 -0.087	-0.093	3.7816	0.805	
		8 -0.140	-0.149	6.4704	0.595	
		9 0.099	0.063	7.8320	0.551	
		10 -0.132	-0.150	10.261	0.418	
		11 -0.150	-0.147	13.451	0.265	
		12 0.083	0.017	14.437	0.274	

For Y2, theretically speaking, $\rho(\tau) = \theta/(1+\theta^2) = 0.98/(1+0.98^2) = 0.499$. The simulated series gives un 0.358. Because $\theta > 0$, the coefficients of the partial autocorrelation function alternate signs. Ljung-Box Q-statistic rejects white noise.

Correlogram of Y2						
Date: 10/22/10 Time: 01:02						
Sample: 1962Q1 1993Q4						
Included observations: 127						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1 0.358	0.358	16.710	0.000	
		2 -0.150	-0.319	19.648	0.000	
		3 0.017	0.258	19.684	0.000	
		4 -0.011	-0.245	19.701	0.001	
		5 -0.050	0.164	20.034	0.001	
		6 -0.044	-0.205	20.298	0.002	
		7 -0.165	-0.056	24.010	0.001	
		8 -0.129	-0.051	26.301	0.001	
		9 -0.004	-0.007	26.304	0.002	
		10 -0.164	-0.263	30.092	0.001	
		11 -0.194	0.046	35.408	0.000	
		12 0.045	-0.021	35.698	0.000	

For Y3, we should have $\rho(\tau) = \theta/(1+\theta^2) = -0.98/(1+(-0.98)^2) = -0.499$. The simulated series gives un -0.515. Because $\theta < 0$, the coefficients of the partial autocorrelation function are all negative. Ljung-Box Q-statistic rejects white noise.



Artificial Data: AR(1) Process

Lets generate an artificial AR(1) process.

Generate the random variable epsilon: `genr epsilon=nrnd`

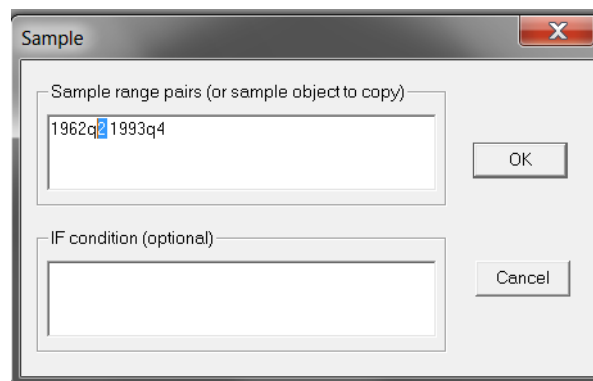
Now, generate the following four AR(1) processes. First you need to create the series:

```

genr Z1 = 0
genr Z2 = 0
genr Z3 = 0
genr Z4 = 0

```

Then modify the sample to exclude the first observation. (this is just a trick to make sure we eliminate the first observation)



Now, proceed to create the series:

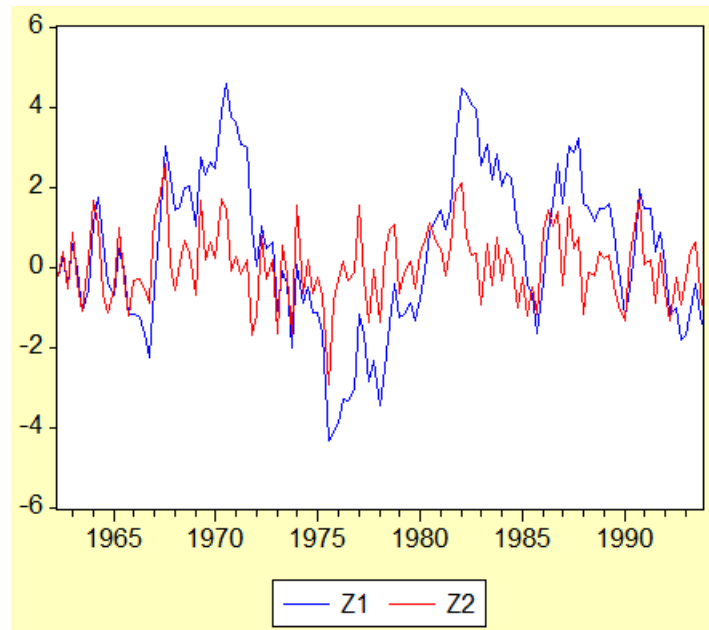
```

genr Z1 = +0.90*Z1(-1) + epsilon
genr Z2 = +0.20*Z2(-1) + epsilon
genr Z3 = -0.90*Z3(-1) + epsilon

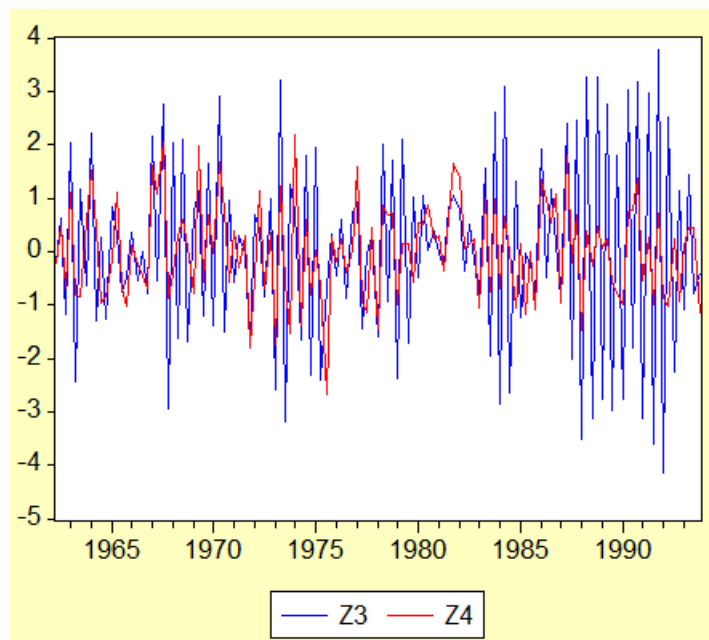
```

$$\text{genr } Z4 = -0.20 * Z4(-1) + \text{epsilon}$$

To see how a simple difference in the sign and the magnitude (size) of the autoregressive coefficient ϕ can have important differences in the series, let's graph Z1 and Z2:

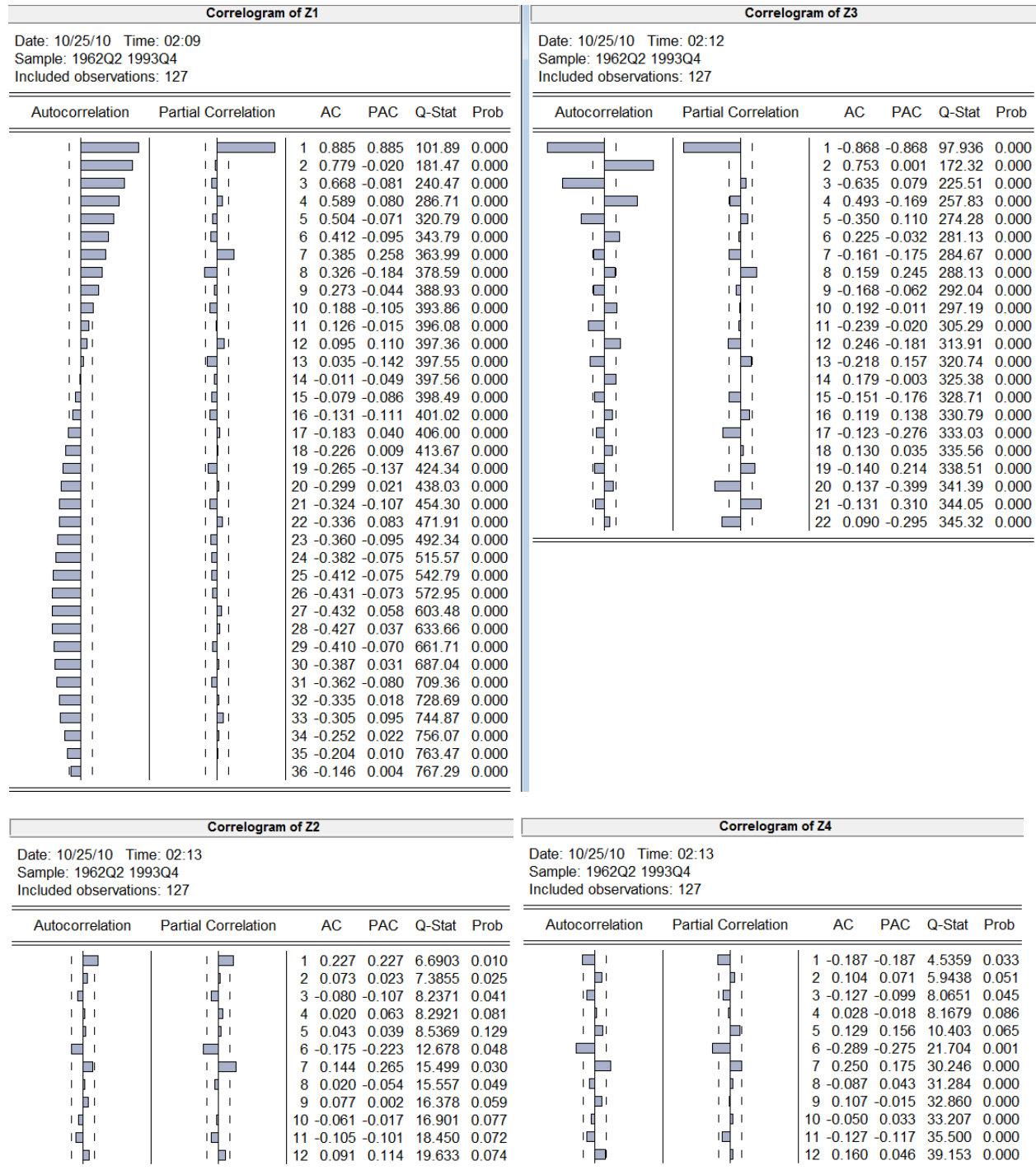


And a graph of Z3 and Z4:



First, notice how different are the Z1 and Z2 series (positive ϕ) when compared with the Z3 and Z4 series (negative ϕ). Second, notice how a larger ϕ (either positive or negative) generates a series with higher dispersion (variance).

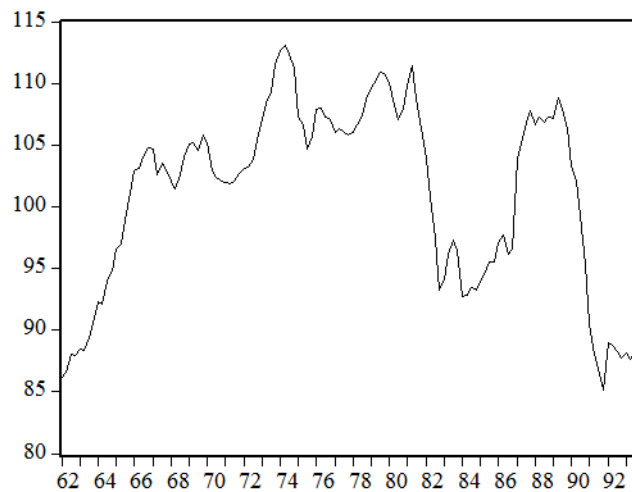
Now, let's see what the autocorrelation functions and the partial autocorrelation functions have to say:



Now, once you see the autocorrelation function and the partial autocorrelation function, can you guess whether the series is MA or AR?

Example: Canadian Employment

Consider the Canadian Employment series from the previous computer handout:

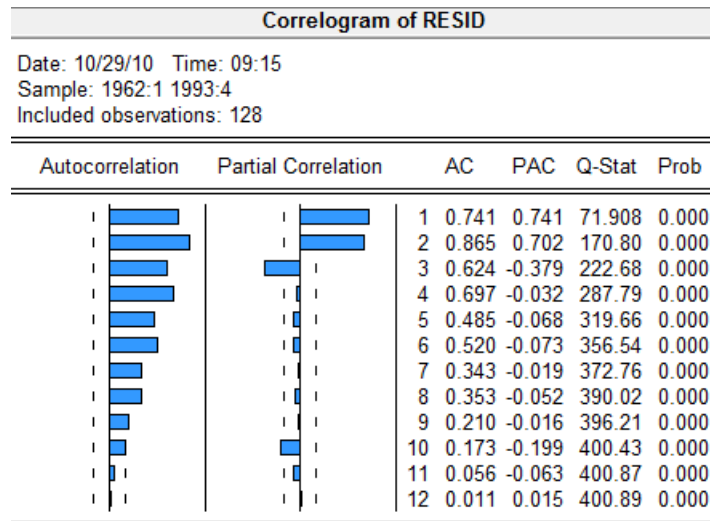


Let's estimate an MA(1) model: `ls caemp c ma(1)`

Dependent Variable: CAEMP
Method: Least Squares
Date: 10/29/10 Time: 09:12
Sample: 1962:1 1993:4
Included observations: 128
Convergence achieved after 11 iterations
Backcast: 1961:4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	100.9893	0.710258	142.1867	0.0000
MA(1)	0.937751	0.030321	30.92718	0.0000
R-squared	0.696454	Mean dependent var	101.0176	
Adjusted R-squared	0.694045	S.D. dependent var	7.499163	
S.E. of regression	4.148027	Akaike info criterion	5.698644	
Sum squared resid	2167.972	Schwarz criterion	5.743207	
Log likelihood	-362.7132	F-statistic	289.0938	
Durbin-Watson stat	0.439477	Prob(F-statistic)	0.000000	
Inverted MA Roots	-.94			

As soon as you estimated this model, you have to open the series: resid, to test if the regression residuals are White Noise.



Based on these results you reject the null hypothesis of White Noise error terms. This is because the autocorrelation and the partial autocorrelation for various values of the displacement fall outside the two-standard deviation bands. Moreover, the Q-statistic (Ljung-Box Q-statistic) which is the weighted sum of squared autocorrelations has large values when compared to the χ^2 distribution with the corresponding degrees of freedom (the p-values are below 0.05). Hence, you may want to try other specifications and also keep track of the AIC and SIC.

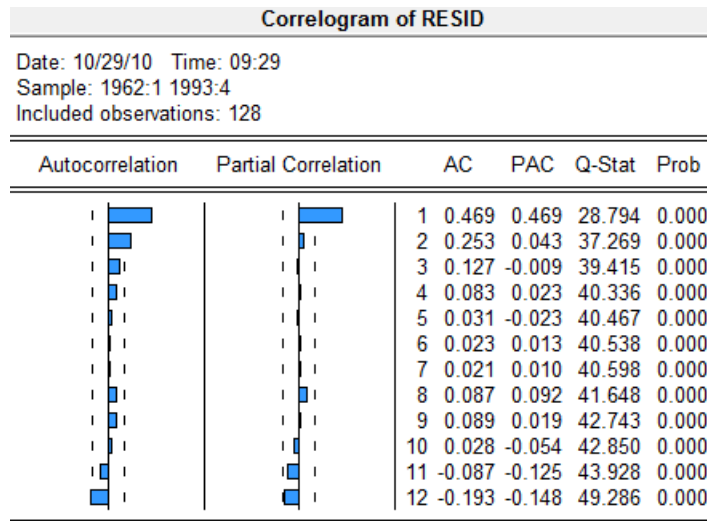
You should consider MA(q) of different order q.

For an AR(1) we have to type: `ls caemp c ar(1)`

Dependent Variable: CAEMP
Method: Least Squares
Date: 10/29/10 Time: 09:26
Sample: 1962:1 1993:4
Included observations: 128
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	101.7767	4.898049	20.77903	0.0000
AR(1)	0.970201	0.019320	50.21620	0.0000
R-squared	0.952411	Mean dependent var		101.0176
Adjusted R-squared	0.952033	S.D. dependent var		7.499163
S.E. of regression	1.642415	Akaike info criterion		3.845715
Sum squared resid	339.8886	Schwarz criterion		3.890278
Log likelihood	-244.1257	F-statistic		2521.666
Durbin-Watson stat	1.061546	Prob(F-statistic)		0.000000
Inverted AR Roots	.97			

With the corresponding correlogram:

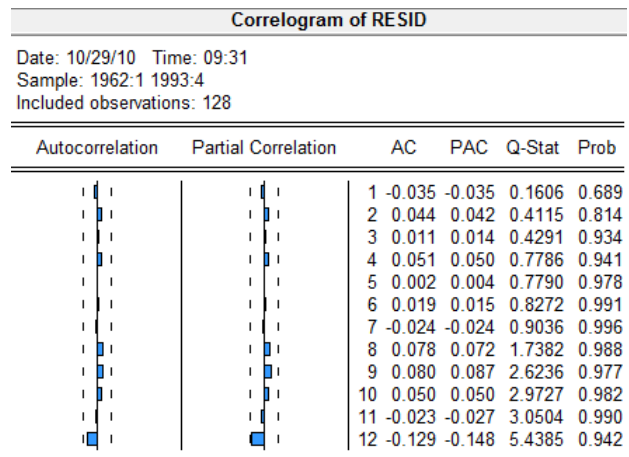


We still reject the null of White Noise errors.

For an AR(2): Is caemp c ar(1) ar(2)

Dependent Variable: CAEMP
Method: Least Squares
Date: 10/29/10 Time: 09:31
Sample: 1962:1 1993:4
Included observations: 128
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	101.2413	3.399620	29.78017	0.0000
AR(1)	1.438810	0.078487	18.33188	0.0000
AR(2)	-0.476451	0.077902	-6.116042	0.0000
R-squared	0.963372	Mean dependent var	101.0176	
Adjusted R-squared	0.962786	S.D. dependent var	7.499163	
S.E. of regression	1.446663	Akaike info criterion	3.599554	
Sum squared resid	261.6041	Schwarz criterion	3.666399	
Log likelihood	-227.3715	F-statistic	1643.837	
Durbin-Watson stat	2.067024	Prob(F-statistic)	0.000000	
Inverted AR Roots	.92	.52		



We finally have White Noise errors.

Now, you have to pick the most appropriate ARMA(p,q) for different orders of p and q based on the AIC and SIC. The result (not shown for all models) show that the ARMA(3,1) is the most appropriate:

Dependent Variable: CAEMP
Method: Least Squares
Date: 10/29/10 Time: 09:35
Sample: 1962:1 1993:4
Included observations: 128
Convergence achieved after 73 iterations
Backcast: 1961:4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	101.1376	3.539424	28.57458	0.0000
AR(1)	0.500389	0.087408	5.724751	0.0000
AR(2)	0.872158	0.066839	13.04857	0.0000
AR(3)	-0.443209	0.080958	-5.474587	0.0000
MA(1)	0.971171	0.034669	28.01281	0.0000
R-squared	0.964535	Mean dependent var	101.0176	
Adjusted R-squared	0.963381	S.D. dependent var	7.499163	
S.E. of regression	1.435042	Akaike info criterion	3.598545	
Sum squared resid	253.2996	Schwarz criterion	3.709952	
Log likelihood	-225.3069	F-statistic	836.2915	
Durbin-Watson stat	2.057495	Prob(F-statistic)	0.000000	
Inverted AR Roots	.93	.51	-.94	
Inverted MA Roots	-.97			

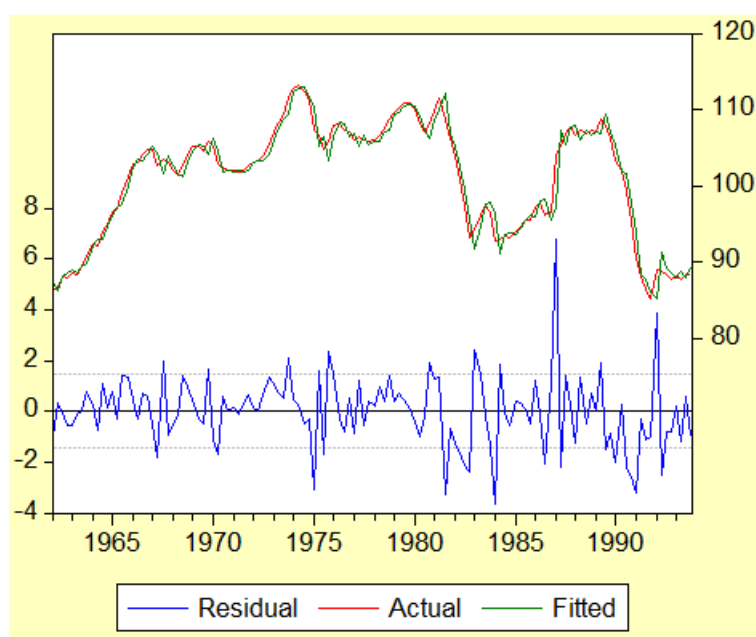
Correlogram of RESID

Date: 10/29/10 Time: 09:35
Sample: 1962:1 1993:4
Included observations: 128

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1		-0.032	-0.032	0.1384	0.710
2		0.042	0.041	0.3683	0.832
3		0.014	0.016	0.3937	0.942
4		0.048	0.047	0.7030	0.951
5		0.005	0.007	0.7070	0.983
6		0.013	0.010	0.7311	0.994
7		-0.017	-0.019	0.7723	0.998
8		0.064	0.060	1.3485	0.995
9		0.092	0.097	2.5236	0.980
10		0.039	0.041	2.7345	0.987
11		-0.017	-0.022	2.7736	0.993
12		-0.136	-0.153	5.4430	0.942

And we have White Noise errors.

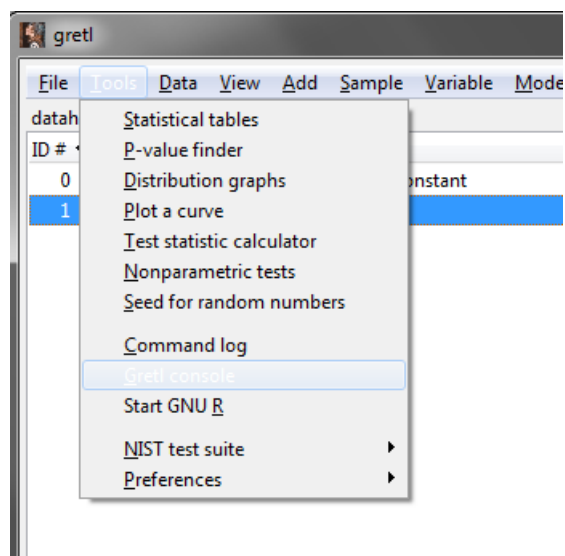
The actual, fitted (in-sample forecast), and residual (in-sample forecast errors) graph is:



In gretl

The command for the ARMA model is: arma 3 1 ; CAEMP 0

Go to "Tools" and then "gretl console"



To obtain:

```
gretl console: type 'help' for a list of commands
? arma 3 1 ; CAEMP 0
Function evaluations: 96
Evaluations of gradient: 32
```

```
Model 1: ARMA, using observations 1961:1-1994:4 (T = 136)
Estimated using Kalman filter (exact ML)
Dependent variable: CAEMP
Standard errors based on Hessian
```

	coefficient	std. error	z	p-value	
const	99.0506	3.22221	30.74	1.66e-207	***
phi_1	2.19046	0.224518	9.756	1.73e-022	***
phi_2	-1.49762	0.360611	-4.153	3.28e-05	***
phi_3	0.298463	0.145749	2.048	0.0406	**
theta_1	-0.781041	0.199694	-3.911	9.18e-05	***

```
Mean dependent var    100.2198    S.D. dependent var    7.997169
Mean of innovations   -0.034017    S.D. of innovations    1.413822
Log-likelihood        -242.0093    Akaike criterion       496.0187
Schwarz criterion      513.4946    Hannan-Quinn           503.1205
```

		Real	Imaginary	Modulus	Frequency
AR					
Root	1	1.0773	-0.0984	1.0817	-0.0145
Root	2	1.0773	0.0984	1.0817	0.0145
Root	3	2.8633	0.0000	2.8633	0.0000
MA					
Root	1	1.2803	0.0000	1.2803	0.0000

For the correlogram just go to “variable” and then “correlogram”:

