



## Econometrics 2, Class 1

Problem Set #7  
October 31, 2005



## Problem Set #7

- We start with a multiple choice test.
- You get the rest of the hour to answer the questions (in groups if you wish).
- Give reasons for your answers.
- Again, you are welcome to present your answers!



7.1 Questionnaire 1-5

Table 7.1: Questionnaire		(a)	(b)
1	Consider the AR(2) process, $Y_t = \delta + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \epsilon_t$ . When is the maximum likelihood estimator identical to the OLS estimator? (a) when $\epsilon_t \sim N(0, \sigma^2)$ ; (b) always.		
2	Consider the AR(1) process, $Y_t = 5 + 0.8 \cdot Y_{t-1} + \epsilon_t$ . What is the mean, $E[Y_t]$ ? (a) $E[Y_t] = 5$ ; (b) $E[Y_t] = 25$ .		
3	Minimizing an information criteria, e.g. AIC, HQ or SC, will give the same result as maximizing $R^2$ . (a) correct; (b) wrong.		
4	Is a finite moving average process always stationary? (a) yes; (b) no.		
5	Can the moving average model be estimated by OLS? (a) yes; (b) no.		



Questionnaire 6-10

6	For a stationary process, the autocorrelations, $\rho_1, \rho_2, \dots$ , are always zero? (a) yes; (b) no.		
7	Choose the correct orders for the following ARIMA model for $Y_t$ : $\Delta Y_t = \delta + \theta_1 \Delta Y_{t-1} + \epsilon_t + \alpha_1 \epsilon_{t-1} + \alpha_2 \epsilon_{t-2}$ . (a) ARIMA(1,1,2); (b) ARIMA(2,0,1).		
8	Why are unit roots important in time series analysis? (a) the usual asymptotic results do not hold; (b) it is important for forecasting.		
9	For an ARMA(2,0) model which one is correct: (a) the two first ACFs are significant while all PACFs are insignificant; (b) the ACF converges exponential to zero while the first two PACFs are significant.		
10	Consider the model $y_t = \theta y_{t-1} + \epsilon_t + \alpha \epsilon_{t-1}$ . The optimal forecast for $y_{T+3 T}$ is: (a) $y_{T+3 T} = \hat{\theta}^3 y_T + \hat{\theta}^2 \hat{\alpha} \hat{\epsilon}_T$ ; (b) $y_{T+3 T} = \hat{\theta}^3 y_T$ .		



## 7.2 ARIMA Models for Danish Time Series

We have quarterly observations of the following variables over the last approximately 30 years:

EFKRKS	Effective (nominal) exchange rate (1980=100).
ENL	Current account (current prices).
FIPMXE	Business machinery investments (constant prices).
FY	Total GDP (constant prices).
IBZ	Bond yield (pro anno yield in ratio).
KP	House price index (1995=1).
PCP	Consumption deflator (1995=1).
UNR	Unemployment rate (in ratio).
TT	Terms of trade, export price/import price, (1995=1).

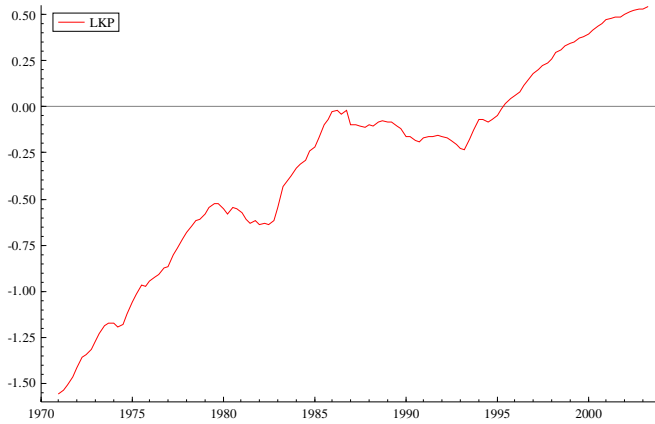


### (1) Choose a time series for analysis

- I choose the house price index ( $kp$ )!
- I decide to transform this variable by taking the natural logarithm.
- I call the new variable  $lkp$ . (Use the Calculator in GiveWin.)
- Usually it is a good idea to transform all real variables (which don't cross zero!).
- This often helps to remove heteroskedasticity, where the residuals increase with the value of the variable. This happens because the error or change in the value of an outcome variable is often a **percent** of the value rather than an **absolute** value. For the same percent error, a bigger value of the variable means a bigger absolute error, so residuals are bigger too.
- $\log(Y * \text{error}) = \log(Y) + \log(\text{error})$ . The percent error therefore becomes the same additive error, regardless of the value of  $Y$ .



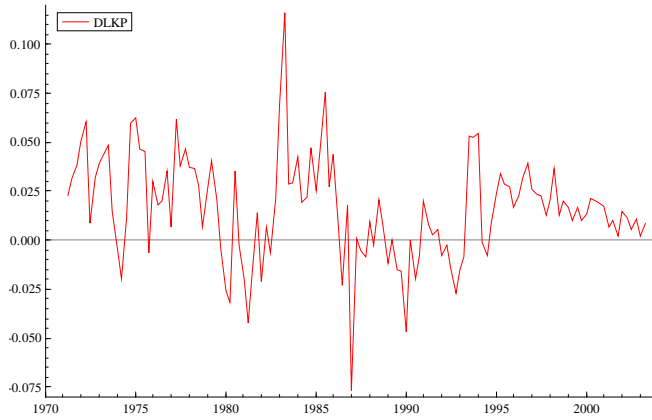
## (2) Graph of the time series



This does not look very stationary!



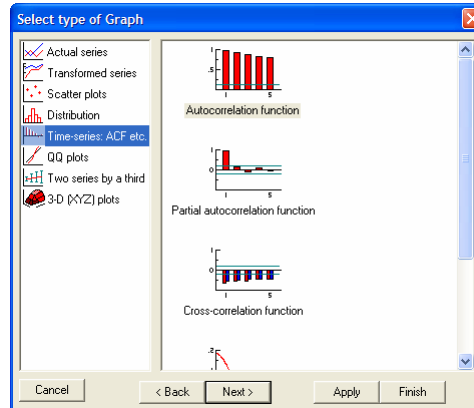
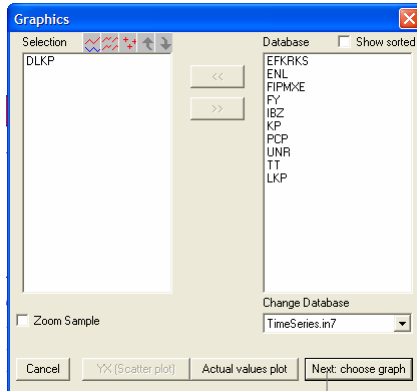
## Graph of first differences



That looks much better!



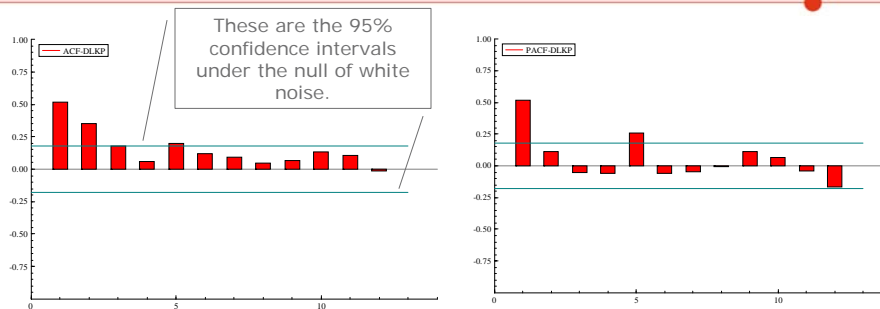
### (3) Draw the ACF and the PACF



Go to the usual graphics menu, select the variable you want to analyze and click here.



### ACF and PACF



Remember: An AR(p) should have exponentially declining ACF and p significant PACF. An MA(q) should have q significant ACF and exponentially declining PACF.

This looks like an AR(2) process!

In the "old days" these graphs were used to decide which model to estimate (there wasn't time to estimate more than one!) Now these are often used to decide on the maximum number of lags to include.



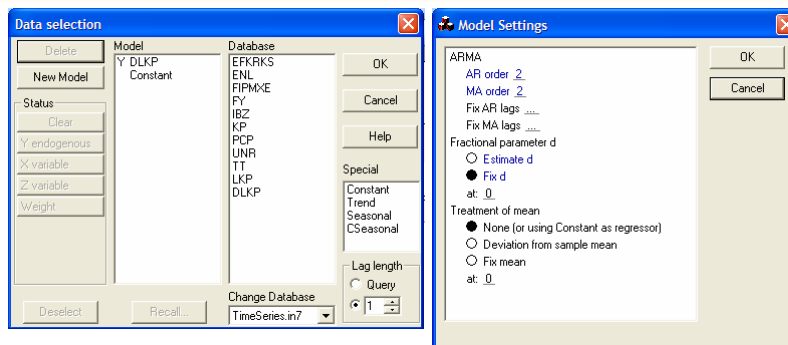
#### (4) Estimate the relevant ARMA models

The relevant models are:

- ARMA(2,2)
- ARMA(2,1)
- ARMA(2,0)
- ARMA(1,2)
- ARMA(1,1)
- ARMA(1,0)
- ARMA(0,2)
- ARMA(0,1)
- ARMA(0,0)



#### GiveWin – Package – Time Series Models; Model – Formulate...



... and choose to estimate with maximum likelihood.

We start with the general model.



## ARMA(2,2)

---- Maximum likelihood estimation of ARFIMA(2,0,2) model ----  
The estimation sample is: 1971 (2) - 2003 (2)  
The dependent variable is: DLKP (TimeSeries.in7)

	Coefficient	Std.Error	t-value	t-prob
AR-1	0.436914	0.1534	2.85	0.005
AR-2	-0.332963	0.2559	-1.30	0.196
MA-1	-0.00854203	0.1329	-0.0643	0.949
MA-2	0.592704	0.2632	2.25	0.026
Constant	0.0163153	0.003418	4.77	0.000

This is the fractional parameter,  $d$ , which we set equal to 0 (only relevant for ARFIMA models).

log-likelihood	308.745105			
no. of observations	129	no. of parameters	6	
AIC.T	-605.490211	AIC	-4.69372256	
mean(DLKP)	0.0163011	var(DLKP)	0.000689048	
sigma	0.0220417	sigma <sup>2</sup>	0.000485838	

This is standard output. Already it looks like the data might best be described by an AR(1) process!

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):  
Strong convergence

Used starting values:

1.0994	-0.39438	0.14397	-0.31449	0.016301
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This is to do with how PcGive solved the maximum likelihood FOCs.



## ARMA(2,1)

---- Maximum likelihood estimation of ARFIMA(2,0,1) model ----  
The estimation sample is: 1971 (2) - 2003 (2)  
The dependent variable is: DLKP (TimeSeries.in7)

	Coefficient	Std.Error	t-value	t-prob
AR-1	0.311203	0.3735	0.833	0.406
AR-2	0.188492	0.2006	0.939	0.349
MA-1	0.141988	0.3721	0.382	0.703
Constant	0.0162866	0.004437	3.67	0.000

log-likelihood	307.198497			
no. of observations	129	no. of parameters	5	
AIC.T	-604.396993	AIC	-4.68524801	
mean(DLKP)	0.0163011	var(DLKP)	0.000689048	
sigma	0.0223349	sigma <sup>2</sup>	0.000498848	

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):  
Strong convergence

Used starting values:

0.010966	0.34352	0.58537	0.016301
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### ARMA(2,0)

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---- Maximum likelihood estimation of ARFIMA(2,0,0) model ----
The estimation sample is: 1971 (2) - 2003 (2)
The dependent variable is: DLKP (TimeSeries.in7)

      Coefficient  Std.Error  t-value  t-prob
AR-1          0.452642    0.08697    5.20    0.000
AR-2          0.114135    0.08698    1.31    0.192
Constant      0.0162902    0.004485    3.63    0.000

log-likelihood    307.138871
no. of observations    129    no. of parameters          4
AIC.T             -606.277742    AIC             -4.69982746
mean(DLKP)        0.0163011    var(DLKP)       0.000689048
sigma             0.0223454    sigma^2         0.000499317

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):
Strong convergence
Used starting values:
      0.45623    0.11419    0.016301

```



### ARMA(1,2)

```

---- Maximum likelihood estimation of ARFIMA(1,0,2) model ----
The estimation sample is: 1971 (2) - 2003 (2)
The dependent variable is: DLKP (TimeSeries.in7)

      Coefficient  Std.Error  t-value  t-prob
AR-1          0.310253    0.1870    1.66    0.100
MA-1          0.136802    0.1693    0.808    0.421
MA-2          0.296248    0.1395    2.12    0.036
Constant      0.0162804    0.004025    4.05    0.000

log-likelihood    308.113642
no. of observations    129    no. of parameters          5
AIC.T             -606.227285    AIC             -4.69943631
mean(DLKP)        0.0163011    var(DLKP)       0.000689048
sigma             0.0221682    sigma^2         0.00049143

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):
Strong convergence
Used starting values:
      0.51767    0.14440    -0.81381    0.016301

```



### ARMA(1,1)

---- Maximum likelihood estimation of ARFIMA(1,0,1) model ----  
 The estimation sample is: 1971 (2) - 2003 (2)  
 The dependent variable is: DLKP (TimeSeries.in7)

	Coefficient	Std.Error	t-value	t-prob
AR-1	0.642722	0.1195	5.38	0.000
MA-1	-0.178087	0.1504	-1.18	0.239
Constant	0.0162970	0.004476	3.64	0.000
log-likelihood	306.973644			
no. of observations	129	no. of parameters	4	
AIC.T	-605.947288	AIC	-4.6972658	
mean(DLKP)	0.0163011	var(DLKP)	0.000689048	
sigma	0.0223746	sigma^2	0.000500624	

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):  
 Strong convergence  
 Used starting values:  
 0.67794      -0.32739      0.016301



### ARMA(1,0)

---- Maximum likelihood estimation of ARFIMA(1,0,0) model ----  
 The estimation sample is: 1971 (2) - 2003 (2)  
 The dependent variable is: DLKP (TimeSeries.in7)

	Coefficient	Std.Error	t-value	t-prob
AR-1	0.511624	0.07500	6.82	0.000
Constant	0.0162915	0.004022	4.05	0.000
log-likelihood	306.282782			
no. of observations	129	no. of parameters	3	
AIC.T	-606.565565	AIC	-4.70205864	
mean(DLKP)	0.0163011	var(DLKP)	0.000689048	
sigma	0.0224964	sigma^2	0.000506088	

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):  
 Strong convergence  
 Used starting values:  
 0.51504      0.016301



### ARMA(0,2)

---- Maximum likelihood estimation of ARFIMA(0,0,2) model ----  
 The estimation sample is: 1971 (2) - 2003 (2)  
 The dependent variable is: DLKP (TimeSeries.in7)

	Coefficient	Std.Error	t-value	t-prob
MA-1	0.379976	0.07905	4.81	0.000
MA-2	0.381201	0.09196	4.15	0.000
Constant	0.0163014	0.003458	4.71	0.000
log-likelihood	306.706537			
no. of observations	129	no. of parameters	4	
AIC.T	-605.413074	AIC	-4.6931246	
mean(DLKP)	0.0163011	var(DLKP)	0.000689048	
sigma	0.0224149	sigma^2	0.000502426	

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):  
 Strong convergence  
 Used starting values:  
 -0.069181      -0.28445      0.016301



### ARMA(0,1)

---- Maximum likelihood estimation of ARFIMA(0,0,1) model ----  
 The estimation sample is: 1971 (2) - 2003 (2)  
 The dependent variable is: DLKP (TimeSeries.in7)

	Coefficient	Std.Error	t-value	t-prob
MA-1	0.402465	0.07256	5.55	0.000
Constant	0.0163039	0.002902	5.62	0.000
log-likelihood	300.421515			
no. of observations	129	no. of parameters	3	
AIC.T	-594.843029	AIC	-4.61118627	
mean(DLKP)	0.0163011	var(DLKP)	0.000689048	
sigma	0.0235537	sigma^2	0.000554777	

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):  
 Strong convergence  
 Used starting values:  
 -0.23243      0.016301



## ARMA(0,0)

---- Maximum likelihood estimation of ARFIMA(0,0,0) model ----  
 The estimation sample is: 1971 (2) - 2003 (2)  
 The dependent variable is: DLKP (TimeSeries.in7)

	Coefficient	Std.Error	t-value	t-prob
Constant	0.0163011	0.002311	7.05	0.000
log-likelihood	286.529809			
no. of observations	129	no. of parameters	2	
AIC.T	-569.059617	AIC		-4.41131486
mean(DLKP)	0.0163011	var(DLKP)		0.000689048
sigma	0.0262497	sigma^2		0.000689048

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):  
 Strong convergence  
 Used starting values:  
 0.016301



## (5) Model – Progress...

GiveWin gives them all a number. You can identify them by the value given for the maximum of the log-likelihood function. ARFIMA(6) turns out to be the ARMA(1,0) model.

These are the information criteria. Only use the first two. AIC is not consistent and does not punish enough for extra variables, so will often recommend a model that is too large. In this case all three are smallest for the ARMA(1,0) model.

Progress to date				log-likelihood	SC	HQ	AIC
Model	T	p					
Arfima( 1)	129	5	EML	308.74511	-4.5984	-4.6642	-4.7092
Arfima( 2)	129	4	EML	307.19850	-4.6121	-4.6647	-4.7008
Arfima( 3)	129	3	EML	307.13887	-4.6488	-4.6883	-4.7153
Arfima( 4)	129	4	EML	308.11364	-4.6263	-4.6789	-4.7149
Arfima( 5)	129	3	EML	306.97364	-4.6463	-4.6857	-4.7128
Arfima( 6)	129	2	EML	306.28278	-4.6732	-4.6995	-4.7176
Arfima( 7)	129	3	EML	306.70654	-4.6421	-4.6816	-4.7086
Arfima( 8)	129	2	EML	300.42151	-4.5824	-4.6087	-4.6267
Arfima( 9)	129	1	EML	286.52981	-4.4046	-4.4178	-4.4268

cont...



cont...

```

Tests of model reduction (please ensure models are nested for test validity)
Arfima( 1) --> Arfima( 2): Chi^2( 1) = 3.0932 [0.0786]
Arfima( 1) --> Arfima( 3): Chi^2( 2) = 3.2125 [0.2006]
Arfima( 1) --> Arfima( 4): Chi^2( 1) = 1.2629 [0.2611]
Arfima( 1) --> Arfima( 5): Chi^2( 2) = 3.5429 [0.1701]
Arfima( 1) --> Arfima( 6): Chi^2( 3) = 4.9246 [0.1774]
Arfima( 1) --> Arfima( 7): Chi^2( 2) = 4.0771 [0.1302]
Arfima( 1) --> Arfima( 8): Chi^2( 3) = 16.647 [0.0008] **
Arfima( 1) --> Arfima( 9): Chi^2( 4) = 44.431 [0.0000] **

Arfima( 2) --> Arfima( 3): Chi^2( 1) = 0.11925 [0.7298]
Arfima( 2) --> Arfima( 5): Chi^2( 1) = 0.44971 [0.5025]
Arfima( 2) --> Arfima( 6): Chi^2( 2) = 1.8314 [0.4002]
Arfima( 2) --> Arfima( 7): Chi^2( 1) = 0.98392 [0.3212]
Arfima( 2) --> Arfima( 8): Chi^2( 2) = 13.554 [0.0011] **
Arfima( 2) --> Arfima( 9): Chi^2( 3) = 41.337 [0.0000] **

Arfima( 3) --> Arfima( 6): Chi^2( 1) = 1.7122 [0.1907]
Arfima( 3) --> Arfima( 8): Chi^2( 1) = 13.435 [0.0002] **
Arfima( 3) --> Arfima( 9): Chi^2( 2) = 41.218 [0.0000] **

Arfima( 4) --> Arfima( 5): Chi^2( 1) = 2.2800 [0.1311]
Arfima( 4) --> Arfima( 6): Chi^2( 2) = 3.6617 [0.1603]
Arfima( 4) --> Arfima( 7): Chi^2( 1) = 2.8142 [0.0934]
Arfima( 4) --> Arfima( 8): Chi^2( 2) = 15.384 [0.0005] **
Arfima( 4) --> Arfima( 9): Chi^2( 3) = 43.168 [0.0000] **

Arfima( 5) --> Arfima( 6): Chi^2( 1) = 1.3817 [0.2398]
Arfima( 5) --> Arfima( 8): Chi^2( 1) = 13.104 [0.0003] **
Arfima( 5) --> Arfima( 9): Chi^2( 2) = 40.888 [0.0000] **

Arfima( 6) --> Arfima( 9): Chi^2( 1) = 39.506 [0.0000] **

Arfima( 7) --> Arfima( 8): Chi^2( 1) = 12.570 [0.0004] **
Arfima( 7) --> Arfima( 9): Chi^2( 2) = 40.353 [0.0000] **

Arfima( 8) --> Arfima( 9): Chi^2( 1) = 27.783 [0.0000] **
    
```



(6) Re-estimate ARMA(1,0);  
Test – Test Summary

```

---- Maximum likelihood estimation of ARFIMA(1,0,0) model ----
The estimation sample is: 1971 (2) - 2003 (2)
The dependent variable is: DLKP (TimeSeries.in7)

      Coefficient  Std.Error  t-value  t-prob
AR-1          0.511624    0.07500    6.82    0.000
Constant      0.0162915    0.004022    4.05    0.000

log-likelihood  306.282782
no. of observations  129  no. of parameters  3
AIC.T          -606.565565  AIC              -4.70205864
mean(DLKP)     0.0163011  var(DLKP)        0.000689048
sigma          0.0224964  sigma^2          0.000506088

BFGS using numerical derivatives (eps1=0.0001; eps2=0.005):
Strong convergence
Used starting values:
    0.51504    0.016301

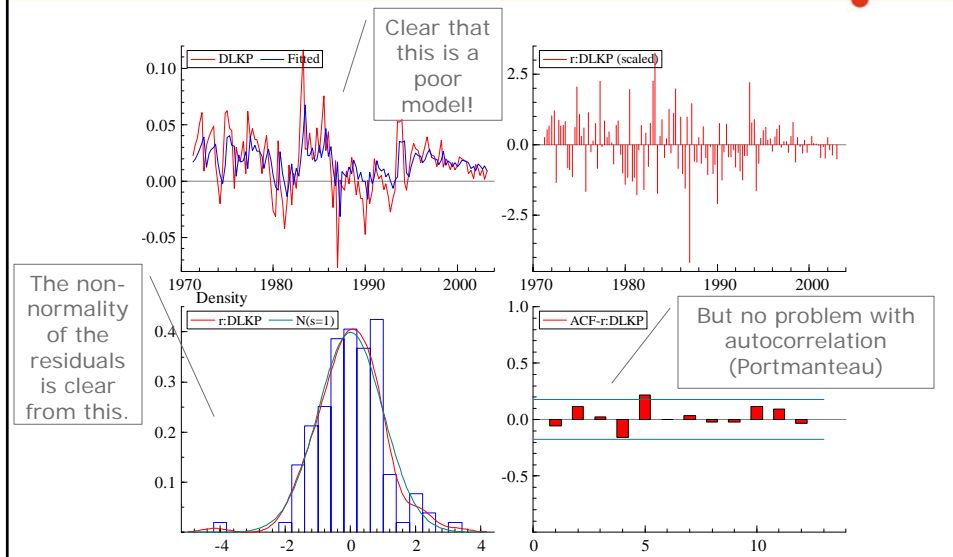
Descriptive statistics for residuals:
Normality test:  Chi^2(2) = 20.973 [0.0000]**
ARCH 1-1 test:  F(1,125) = 3.9632 [0.0487]*
Portmanteau(12): Chi^2(11) = 15.567 [0.1580]
    
```

Rejects null of normality  
for the residuals!

This is a test for whether there  
is autocorrelation in the  
residuals. Accepts null of no  
autocorrelation.



### Test – Graphic Analysis



### (7) Model – Estimate...; Test – Forecast...

**Estimate Model**

Maximum Likelihood  
Non-linear Least Squares  
Modified Profile Likelihood  
Starting values only  
NLS with stationarity imposed

Selection sample 1971 2 to 2003 2  
Estimation sample 1971 2 to 2003 2  
Less forecasts 20 T=129

OK Cancel Help Options...

**Forecast**

Forecast  
Number of forecasts 20  
 Naive forecasts only  
 Undo data transformations

**Options**

Use error bars  
 Use error bands  
 Use error fans  
Critical value to use for error bars: 2  
Number of pre-forecast observations to graph: 200  
 Write results instead of graphing

OK Cancel

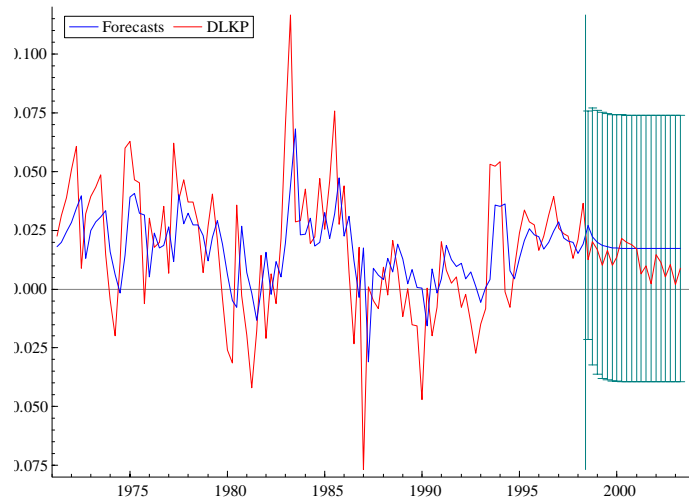
Put this equal to 20.

We will see how well the model forecasts for the last 20 periods.

Remember to change this!



## The forecasts



With 95% certainty we will stay within the historical range of the variable, minus extremes.

The "problem" is, that we start the forecast close to the historic mean.



## (8) Try yourselves with a new time series...

... if you have time!



## Next time

- We learn how to test for unit roots!