



Econometrics 2, Class 1

Problem Set #3
September 26, 2005



Practical information

- Remember to send me an e-mail! (Last reminder!)
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- You might want to look at what we went through last time again, now that you have had some more of the relevant material covered during the lectures.
- Heino has talked to the nerds in the computer basement, and they have promised to install GiveWin etc. ASAP.



3.1 The Frisch-Waugh-Lovell Theorem

- This should be repetition.
- In Econometrics 1 (Wooldridge pp. 78-79), we demonstrated that the OLS estimator $\hat{\beta}_1$ from the regression $y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i$ can be derived in the following way:
 1. Regress x_1 on x_2 and save the residuals, $\hat{\eta}_1$. These residuals are the part of x_1 that is uncorrelated with x_2 . (I.e. the effects of x_2 have been *partialled out*.)
 2. Regress y on $\hat{\eta}_1$ to obtain $\hat{\beta}_1$. So $\hat{\beta}_1$ measures the sample relationship between y and x_1 after x_2 has been partialled out.
- Another (more general) way of interpreting the FWL theorem is that the determination of the coefficients in a standard regression model via ordinary least squares and a method involving projection matrices are equivalent.
- This is what the exercise demonstrates (on the blackboard).

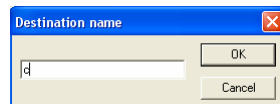
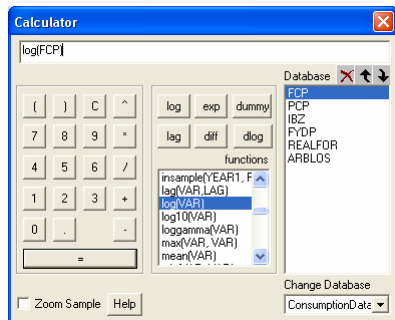


3.2 Time series regressions for private consumption

- Data set for aggregate private consumption in Denmark for period 1971:1 – 2002:2 (in quarters).
- Data file ConsumptionData.In7 contains observations for:
 - FCP Private sector aggregate consumption, constant prices
 - PCP Deflator for private consumption, 1995=100
 - FYDP Private disposable income, constant prices
 - REALFOR Private wealth including owner occupied housing, constant prices
 - ARBLOS Expected income loss from changes in unemployment
 - IBZ Average bond rate, fractions, p.a.
- All variables, except interest rate, are seasonally adjusted.
- Taken from Danish Central Bank's MONA model.



(1) Load data into GiveWin, construct variables



Use the calculator. Here is the output you should get in GiveWin:

$c = \log(\text{FCP});$
 $y = \log(\text{FYDP});$
 $w = \log(\text{REALFOR});$
 $p = \log(\text{PCP});$
 $dp = \text{diff}(p, 1);$
 $r = 1/4 * \text{IBZ};$

When we use the log-log model, we can interpret the coefficients as the percentage change in the dependent variable, given a 1% change in the independent variable (elasticity).

This helps stabilize the variables, since absolute changes in the variables (measured in kroner) will be increasing over time, even if the percentage change is not.



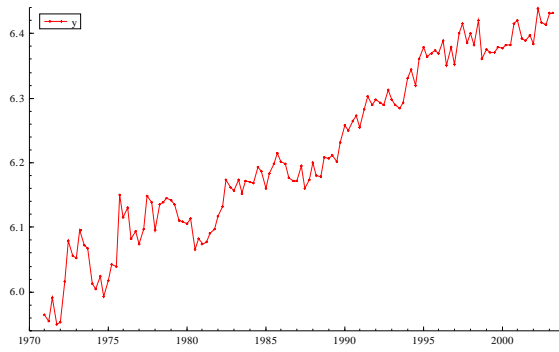
Time series graph of c_t (Tools – Graphics)



Non-stationary!



Time series graph of y_t



Non-stationary!



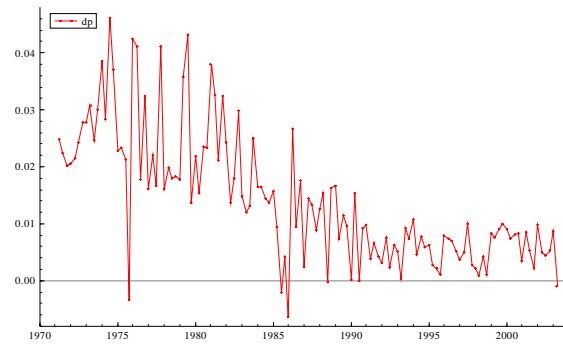
Time series graph of w_t



Non-stationary!



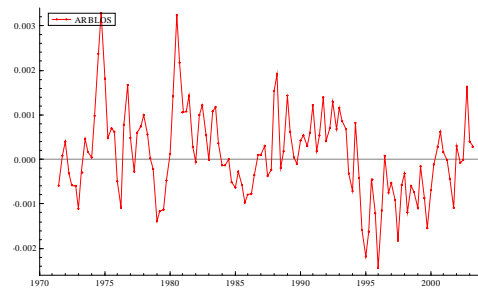
Time series graph of π_t



Non-stationary!



Time series graph of $ARBLOS_t$



Looks stationary!



(2) Construct new transformed variables

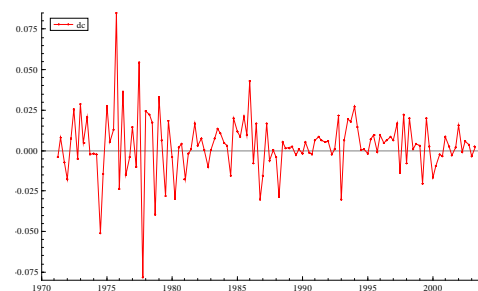
```
dc = diff(c, 1);  
dy = diff(y, 1);  
dw = diff(w, 1);  
ddp = diff(dp, 1);  
ECM = c-0.536566-0.263579*y-0.482082*w+2.12642*dp;
```

Taking first differences is one possible way of making the variables stationary.

Don't worry too much about *ECM*. Just think about it as a variable accounting for the deviation from the equilibrium value of *c* in period *t*.



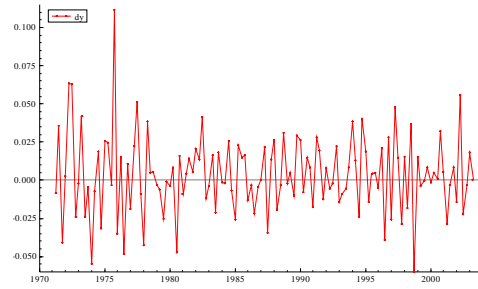
Time series graph of dc_t



Looks stationary!



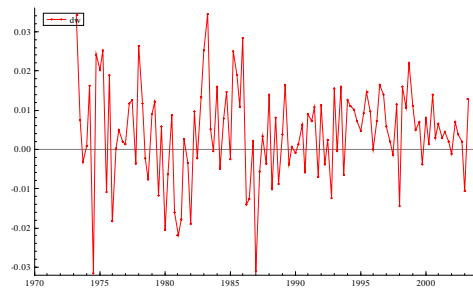
Time series graph of dy_t



Looks stationary!



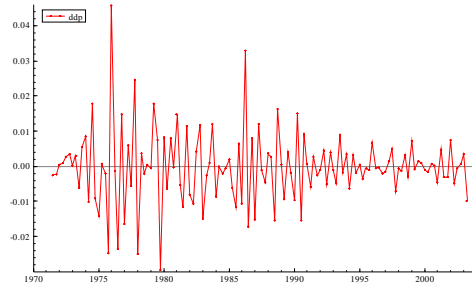
Time series graph of dw_t



Looks stationary!



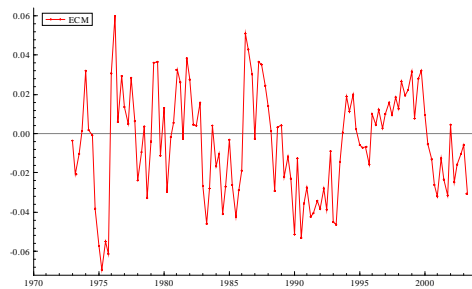
Time series graph of dn_t



Looks stationary!



Time series graph of ECM_t



Looks stationary!



(3) Why is it important that the included variables are stationary?

See lecture note "Linear Regression with Time Series Data":

ASSUMPTION 1 (Stationarity and weak dependence) Consider a time series y_t and the $k \times 1$ vector time series x_t . We assume that $z_t = (y_t, x_t)'$ has a joint stationary distribution. We also assume that the process z_t is weakly dependent, so that z_t and z_{t+k} becomes approximately independent for $k \rightarrow \infty$.

A minimal requirement for an estimator is that it is consistent, so that the estimator converges to the true value as we get more and more observations.

RESULT 1 (Consistency) Consider a data set, y_t and x_t , that obeys Assumption 1. If the regressors, x_t , are predetermined so that the moment condition (5) holds, then the OLS estimator in (7) is a consistent estimator of the true value, i.e. $\hat{\beta} \rightarrow \beta$ as $T \rightarrow \infty$.



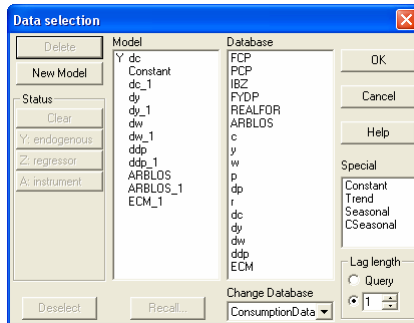
(4) "General to specific" or "specific to general"?

- See lecture note again.
- If we start with a model which is missing some important explanatory variables, then OLS gives inconsistent estimators; the distributions of our standard tests are wrong, so we cannot check for significance.
- We could use a misspecification test, but it is difficult to see how to use constructively the information that a model is misspecified.
- However, if we include too many variables, then their coefficients will be consistent with a true value of 0, if we have enough observations.
- So general to specific is best!



(5) Specify model in PcGive

$$\Delta c_t = \beta_1 + \beta_2 \cdot \Delta c_{t-1} + \beta_3 \cdot \Delta y_t + \beta_4 \cdot \Delta y_{t-1} + \beta_5 \cdot \Delta w_t + \beta_6 \cdot \Delta w_{t-1} + \beta_7 \cdot \Delta \pi_t + \beta_8 \cdot \Delta \pi_{t-1} + \beta_9 \cdot \text{ARBLOS}_t + \beta_{10} \cdot \text{ARBLOS}_{t-1} + \beta_{11} \cdot \text{ECM}_{t-1} + \epsilon_t,$$



Interpret the signs and magnitudes of the coefficients!

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EQ( 1) Modelling dc by OLS (using ConsumptionData.in7)
The estimation sample is: 1973 (3) to 2003 (2)

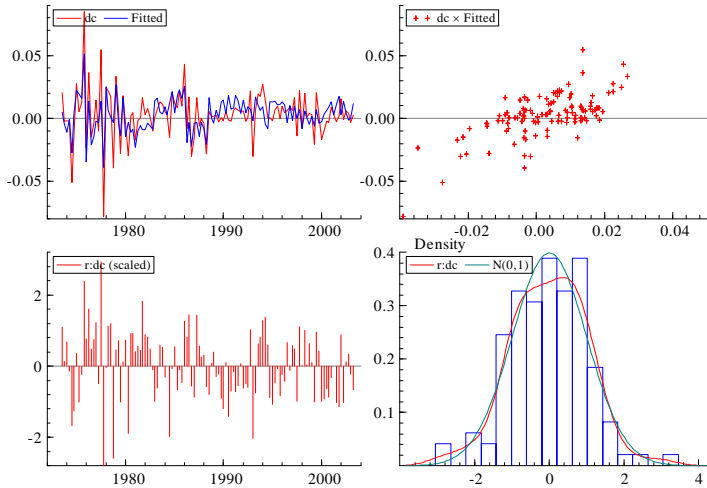
      Coefficient   Std. Error   t-value   t-prob   Part.R^2
dc_1          -0.148550   0.09209   -1.61    0.110   0.0233
Constant      0.00131848   0.001492   0.884    0.379   0.0071
dy             0.164134   0.06100    2.69    0.008   0.0623
dy_1          -0.0406634   0.06169   -0.659   0.511   0.0040
dw             0.281942   0.1209    2.33    0.022   0.0475
dw_1          -0.0252974   0.1262   -0.201   0.841   0.0004
ddp           -0.540210   0.1741   -3.10    0.002   0.0811
ddp_1         0.189334   0.1632    1.16    0.249   0.0122
ARBLOS        -4.43844     1.804    -2.46    0.015   0.0526
ARBLOS_1     -0.644997     1.832   -0.352   0.725   0.0011
ECM_1         -0.331333    0.06190   -5.35    0.000   0.2081

sigma         0.0140012   RSS              0.0213676361
R^2           0.490032   F(10,109) =     10.47 [0.000]**
log-likelihood 347.73   DW              1.94
no. of observations 120   no. of parameters 11
mean(dc)      0.00310834   var(dc)         0.000349166
    
```

N.B. Some of the coefficients are insignificant!



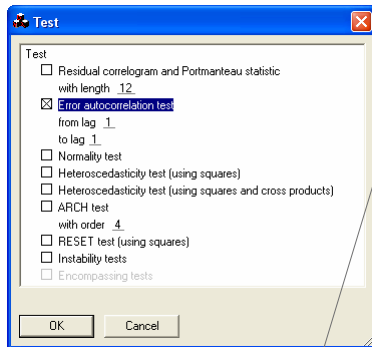
(6) Are the residuals well behaved? (Test - Graphic Analysis...)



Residuals should be $N(0, 1)$. Looks good!



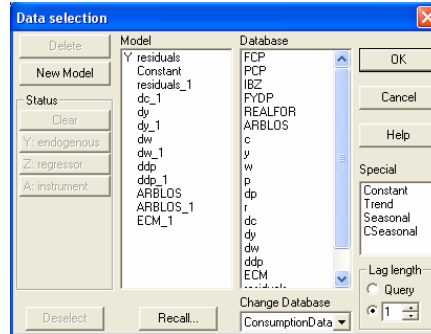
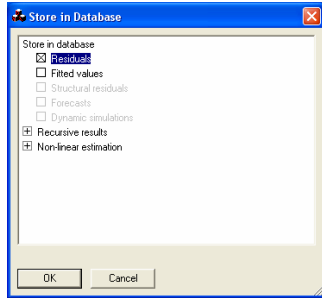
(7) LM test for no autocorrelation in the residuals. (Test - Test...)



Use this one! The distribution is as given, the p-value is in parentheses.
The null hypothesis is *no autocorrelation*. This is clearly accepted!

Testing for error autocorrelation from lags 1 to 1
 $\chi^2(1) = 0.99127 [0.3194]$ and F-form $F(1, 108) = 0.89957 [0.3450]$

Test – Store Residuals etc. in Database... Breusch-Pagan LM test



Remember to look at the dataset and set the first (missing) values of *residual* to 0.

From lecture note p. 12:

$$\hat{\epsilon}_t = x_t' \delta + \gamma \hat{\epsilon}_{t-1} + u_t,$$

Two methods for testing for no autocorrelation



Is this significant? (no)

$$T \cdot R^2 \rightarrow \chi^2(1). \\ = 120 \cdot 0.00826 \\ = 0.99$$

Critical value is 3.84

Null hypothesis of *no* autocorrelation is accepted.

(N.B. Identical to PcGive automatic statistic!)

EQ (2) Modelling residuals by OLS (using ConsumptionData.in7)
The estimation sample is: 1973 (3) to 2003 (2)

	Coefficient	Std. Error	t-value	t-prob	Part. R ²
residuals_1	0.370016	0.3901	0.948	0.345	0.0083
Constant	0.000194610	0.001507	0.129	0.897	0.0002
dc_1	-0.227580	0.2570	-0.885	0.378	0.0072
dy	-0.00810739	0.06162	-0.132	0.896	0.0002
dy_1	0.0168384	0.06422	0.262	0.794	0.0006
dw	0.00342751	0.1210	0.0283	0.977	0.0000
dw_1	0.0302281	0.1302	0.232	0.817	0.0005
d dp	-0.0440648	0.1803	-0.244	0.807	0.0006
d dp_1	-0.0679481	0.1783	-0.381	0.704	0.0013
ARBLOS	0.140799	1.811	0.0777	0.938	0.0001
ARBLOS_1	-1.59951	2.491	-0.642	0.522	0.0038
ECM_1	-0.108258	0.1299	-0.834	0.406	0.0064

sigma	0.0140076	RSS	0.0211911269
R ²	0.00826059	F(11,108) =	0.08178 [1.000]
log-likelihood	348.227	DW	2.01
no. of observations	120	no. of parameters	12
mean(residuals)	-5.71917e-019	var(residuals)	0.000178064



(8) More misspecification tests
(remember to go back to the original model!)

You can look these tests up in PcGive's help.

<p>AR 1-5 test: F(5, 104) = 1.1531 [0.3374] ARCH 1-4 test: F(4, 101) = 1.0383 [0.3913] Normality test: Chi²(2) = 2.7733 [0.2499] hetero test: F(20, 88) = 1.8510 [0.0268]* hetero-X test: F(65, 43) = 1.3338 [0.1585] RESET test: F(1, 108) = 0.028427 [0.8664]</p>	<p>Null is no autocorrelation: Not rejected</p>	<p>Null is normality: Not rejected</p>	<p>We will use this later. It is a type of heteroskedasticity</p>
	<p>Null is correct specification: Not rejected</p>		<p>Maybe problems with heteroskedasticity</p>



(9) General to specific!

Remember to remove just one at a time, and re-estimate the model each time. Start with the smallest t-value. Continue until all coefficients are significant. You must have a very good reason before you remove the constant!

You will end up with this:

	Coefficient	Std. Error	t-value	t-prob	Part. R ²
dc_1	-0.188834	0.08054	-2.34	0.021	0.0464
Constant	0.00136215	0.001400	0.973	0.333	0.0083
dy	0.164554	0.05374	3.06	0.003	0.0766
dw	0.268310	0.1182	2.27	0.025	0.0436
ddp	-0.613797	0.1586	-3.87	0.000	0.1170
ARBLOS	-4.99805	1.338	-3.74	0.000	0.1099
ECM_1	-0.297180	0.05203	-5.71	0.000	0.2240
sigma	0.0138659	Rss		0.0217257253	
R ²	0.481486	F(6, 113) =	17.49	[0.000]**	
log-likelihood	346.732	DW		1.94	
no. of observations	120	no. of parameters		7	
mean(dc)	0.00310834	var(dc)		0.000349166	
AR 1-5 test:	F(5, 108) =	0.61041	[0.6921]		
ARCH 1-4 test:	F(4, 105) =	1.1020	[0.3596]		
Normality test:	Chi ² (2) =	2.7957	[0.2471]		
hetero test:	F(12, 100) =	1.8084	[0.0566]		
hetero-X test:	F(27, 85) =	1.6348	[0.0463]*		
RESET test:	F(1, 112) =	0.0045531	[0.9463]		

No big problems here!



(10) Effect of the interest rate on consumption?

- In theory, there could be a life-cycle effect: If the interest rate is high, then agents will save for future consumption.
- However, you can show yourselves that neither the bond rate nor the real bond rate explain much in this data.



(11) Forecasting! (Test – Forecast...)

Our preferred model is the one we reached in (9).

Estimate Model dialog box:

- Method: Ordinary Least Squares
- Selection sample: 1973 2 to 2003 2
- Estimation sample: 1973 3 to 2003 2
- Less forecasts: 18
- T=120 (sub sample)
- Recursive estimation, initialization: 16

Forecast dialog box:

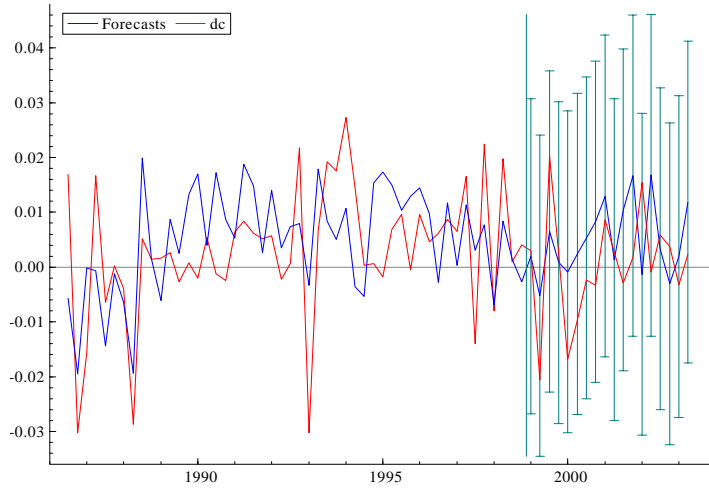
- Number of forecasts: 18
- Forecast type: Dynamic forecasts, h-step forecasts
- h = 1
- Forecast standard errors: Use error bars, Use error bands, Use error fans
- Critical value to use for error bars: 2
- Number of pre-forecast observations to graph: 50
- Write results instead of graphing
- Transformations

Change this!

Change this so you get more of the data in the graph (the default is 5).



The results!



With 95% certainty we can say that consumption will either rise or fall by 3%! (Poor forecasting, despite high explanatory power of model!)



Next time

- There will be a test!
- But don't worry: it is multiple choice, you get to answer in groups etc.
- Nobody will be forced to present their answers, but volunteers would be nice!
- Remember to bring your notes etc.
- We will also go through an old exam exercise.