

Introduction to VARs and Structural VARs:

Estimation & Tests Using Stata

Bar-Ilan University 26/5/2009

Avichai Snir

Background: VAR

- **Background:**
- **Structural simultaneous equations**
 - Lack of Fit with the data
 - Lucas Critique (1976)
- **VAR: Vector Auto Regressions**
 - Simple
 - Non Structural
 - All Variables are treated identically
 - Better Fit with the Data

Simple VAR: Sims (1980)

- **Symmetric**
 - Lags of the dependent variables
 - Same Number of Lags

$$\begin{aligned}y_{1,t} &= \alpha_0 + \alpha_1 y_{1,t-1} + \alpha_2 y_{2,t-1} + \alpha_3 y_{3,t-1} + \alpha_4 y_{1,t-2} + \alpha_2 y_{2,t-2} + \alpha_3 y_{3,t-2} + \dots + \varepsilon_{1,t} \\y_{2,t} &= \beta_0 + \beta_1 y_{1,t-1} + \beta_2 y_{2,t-1} + \beta_3 y_{3,t-1} + \beta_4 y_{1,t-2} + \beta_2 y_{2,t-2} + \beta_3 y_{3,t-2} + \dots + \varepsilon_{2,t} \\y_{3,t} &= \gamma_0 + \gamma_1 y_{1,t-1} + \gamma_2 y_{2,t-1} + \gamma_3 y_{3,t-1} + \gamma_4 y_{1,t-2} + \gamma_2 y_{2,t-2} + \gamma_3 y_{3,t-2} + \dots + \varepsilon_{3,t}\end{aligned}$$

$$E(\varepsilon_{i,t}, \varepsilon_{j,\tau}) = \begin{cases} \sigma_{i,j} & \text{if } t = \tau \\ 0 & \text{if } t \neq \tau \end{cases}$$

$$i, j \in (1, 2, 3)$$

Simple VAR: Matrix Form

- In Matrix Form:

$$\mathbf{y}_t = \alpha + \Gamma_{t-1}\mathbf{y}_{t-1} + \Gamma_{t-2}\mathbf{y}_{t-2} + \dots + \varepsilon_t$$

or Simply :

$$[\mathbf{I} - \Gamma(L)]\mathbf{y}_t = \mathbf{A} + \varepsilon_t$$

- \mathbf{y}_t is a vector of the Dependent Variables
- Γ_{t-i} is a Matrix of Coefficients
- $\Gamma(L)$ is a Matrix in Lagged Variables
- ε_t is a Vector of White Noise Errors
- \mathbf{A} is a Matrix of exogenous variables (constant,...)

Covariance Matrix

$$\boldsymbol{\varepsilon}_t \times \boldsymbol{\varepsilon}_t' = \begin{pmatrix} \varepsilon_{1,1} \\ \varepsilon_{1,2} \\ \varepsilon_{1,3} \\ \vdots \\ \varepsilon_{2,1} \\ \varepsilon_{2,2} \\ \varepsilon_{2,3} \\ \vdots \\ \varepsilon_{3,1} \\ \varepsilon_{3,2} \\ \varepsilon_{3,3} \\ \vdots \end{pmatrix} \times \begin{pmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \varepsilon_{1,3} & \dots & \varepsilon_{2,1} & \varepsilon_{2,2} & \varepsilon_{2,3} & \dots & \varepsilon_{3,1} & \varepsilon_{3,2} & \varepsilon_{3,3} & \dots \end{pmatrix} =$$

$$\begin{pmatrix} \sigma_{1,1} & 0 & 0 & \dots & \sigma_{1,2} & 0 & \dots & \sigma_{1,3} & 0 & \dots \\ 0 & \sigma_{1,1} & 0 & \dots & 0 & \sigma_{1,2} & \dots & 0 & \sigma_{1,3} & \dots \\ 0 & 0 & \sigma_{1,1} & \dots & 0 & 0 & \dots & 0 & 0 & \dots \\ \vdots & & & \vdots & & & \vdots & & & \vdots \\ \sigma_{2,1} & 0 & 0 & \dots & \sigma_{2,2} & 0 & \dots & \sigma_{2,3} & 0 & \dots \\ 0 & \sigma_{2,1} & 0 & \dots & 0 & \sigma_{2,2} & \dots & 0 & \sigma_{2,3} & 0 \\ & 0 & \sigma_{2,1} & \dots & 0 & 0 & \dots & 0 & \sigma_{2,3} & 0 \\ \vdots & & & \vdots & & & \vdots & & & \vdots \\ \sigma_{3,1} & 0 & 0 & \dots & \sigma_{3,2} & 0 & \dots & \sigma_{3,3} & 0 & \dots \\ 0 & \sigma_{3,1} & 0 & \dots & 0 & \sigma_{3,2} & \dots & 0 & \sigma_{3,3} & 0 \\ \vdots & & & \vdots & & & \vdots & & & \vdots \end{pmatrix}$$

Contemporary Variance Matrix

$$\Omega = \begin{pmatrix} \sigma_{1,1} & \sigma_{1,2} & \sigma_{1,3} \\ \sigma_{2,1} & \sigma_{2,2} & \sigma_{2,3} \\ \sigma_{3,1} & \sigma_{3,2} & \sigma_{3,3} \end{pmatrix}$$

Issues Before Estimation

- **Stationarity:**
 - Constant expected value
 - Constant Variance
 - Constant Covariances
- **Granger Exogeneity:**
 - Order of variables
- **Lag Length**
 - Optimal lag length

Testing Stationarity

- We have data on Canada 1966Q1-2002Q1
 - GDP
 - Consumer Price Index (CPI)
 - Household Consumption (consumption)

Consumption	CPI	GDP	Descriptor
36.91	18.04	62.53	1966Q1
37.47	18.24	64.58	1966Q2
38.46	18.41	65.47	1966Q3

Declare: Time Series

- **Define and format: time variable**
 - `date(var_name, "dmy")` or
 - `Quarterly(var_name, "yq")`
 - `format: format var_name %d`
- **Declare database as time series**
 - Menu: statistics → time series → setup & utilities → declare dataset to be time series data

```
. generate time2 = quarterly(descriptor, "yq")
. format time2 %tq
. list time2 if _n<=3
```

	time2
1.	1966q1
2.	1966q2

Declaring Time series



Declare Time Series

tsset - Declare dataset to be time-series data

Time variable: Panel ID variable: (optional)

Clear all settings

Display format for the time variable:

<input type="radio"/> None specified	<input type="radio"/> Daily
<input type="radio"/> Weekly	<input type="radio"/> Monthly
<input checked="" type="radio"/> Quarterly	<input type="radio"/> Half-yearly
<input type="radio"/> Yearly	<input type="radio"/> Generic
<input type="radio"/> <input type="text" value="%tw"/>	<input type="button" value="Help format..."/>

Transformations

- **Convenience**

- taking logs: `gen var_name=log(var_name)`

```
gen log_gdp=ln(gdp_sa)
```

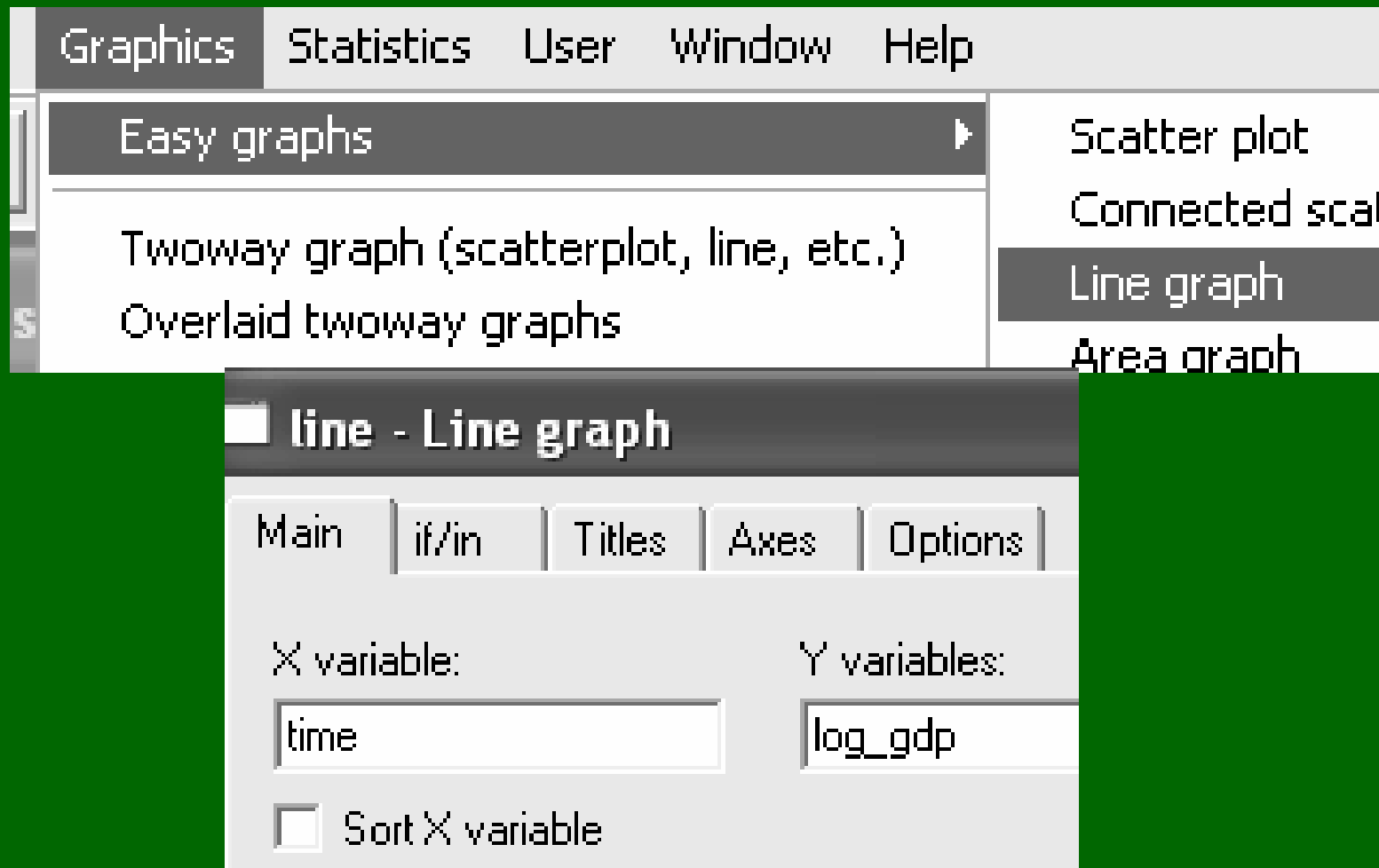
```
gen log_cons=log(household_cons)
```

```
gen log_cpi=log(cpi)
```

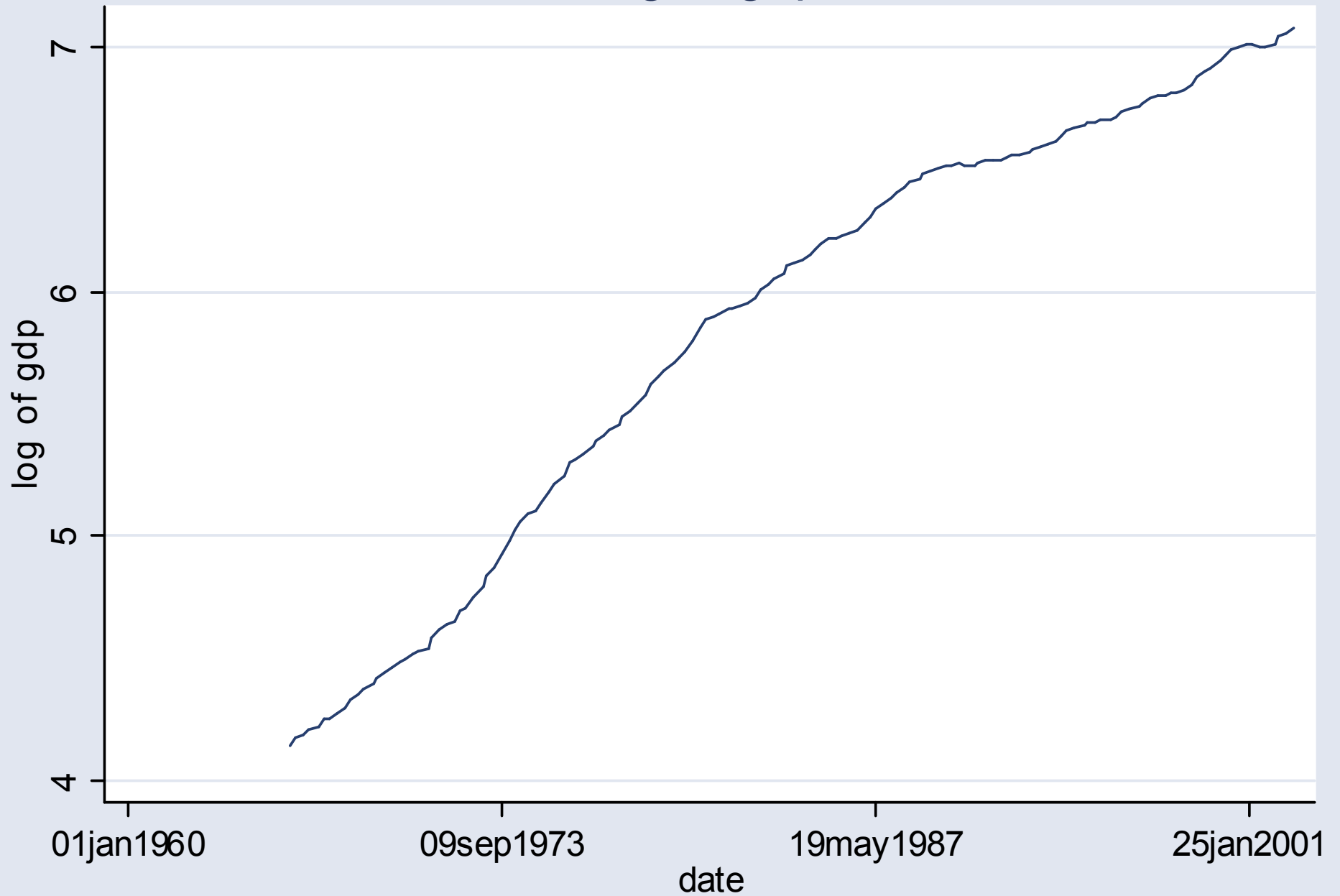
- **Differences are in percentage**

Plots

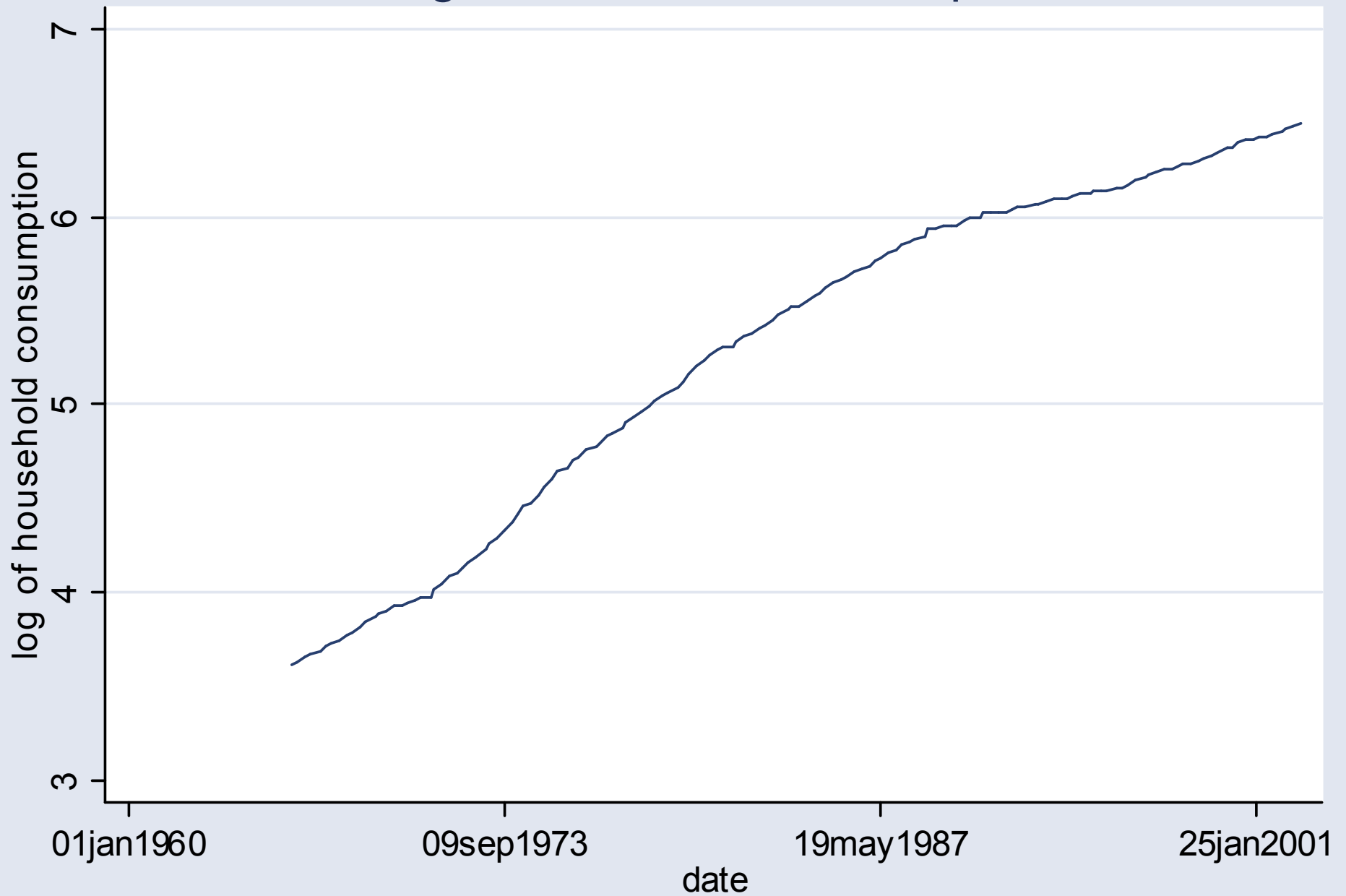
- Menu: Graphics → easy graphs → line graph
- Follow the wizard...



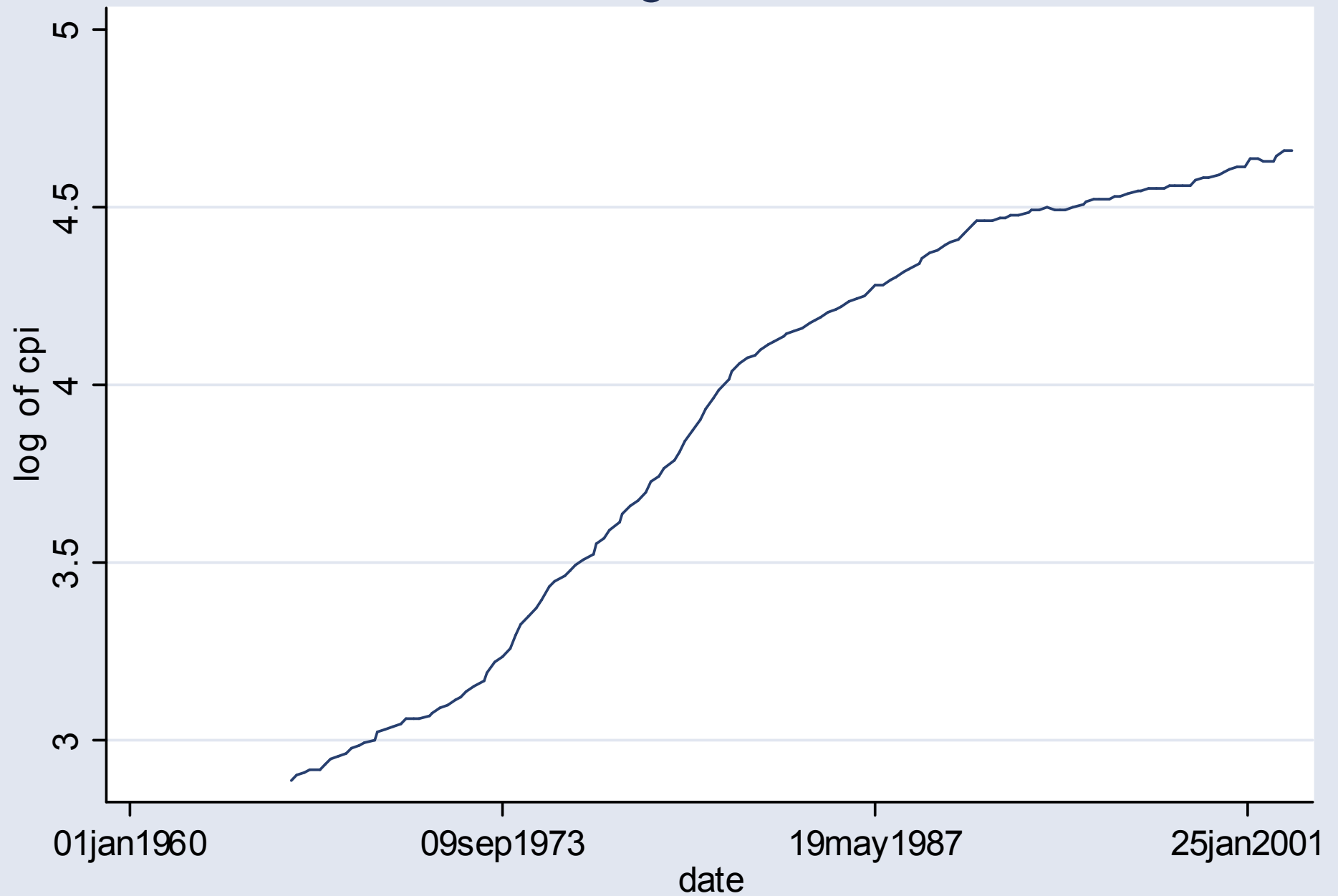
log of gdp



Log of household consumption



log of CPI



Stationarity

- Data don't look stationary
- Formal test required
- Common tests (Greene, 636-646):
 - Dickey Fuller:
 - H0: Variable has a unit root
 - Philips Peron
 - H0: Variable has a unit root
 - Dickey Fuller – GLS
 - H0: Variable has a unit root

Testing:

- **Menu: Statistics → Time Series → Tests**
- **Choose a test and follow the menu**
 - **Augmented Dickey Fuller**
 - **DF-GLS for a Unit root**
 - **Phillips-Peron unit root**

Choosing a test

The image shows a screenshot of the Stata software interface. The 'Statistics' menu is open, and the 'Time series' option is selected. A sub-menu is displayed for 'Time series', with 'Tests' highlighted. The 'Tests' sub-menu is also open, showing three options: 'Augmented Dickey-Fuller unit-root test', 'Perform DF-GLS test for a unit root', and 'Phillips-Perron unit roots test'. The 'Perform DF-GLS test for a unit root' option is highlighted. In the background, a command window shows the following code:

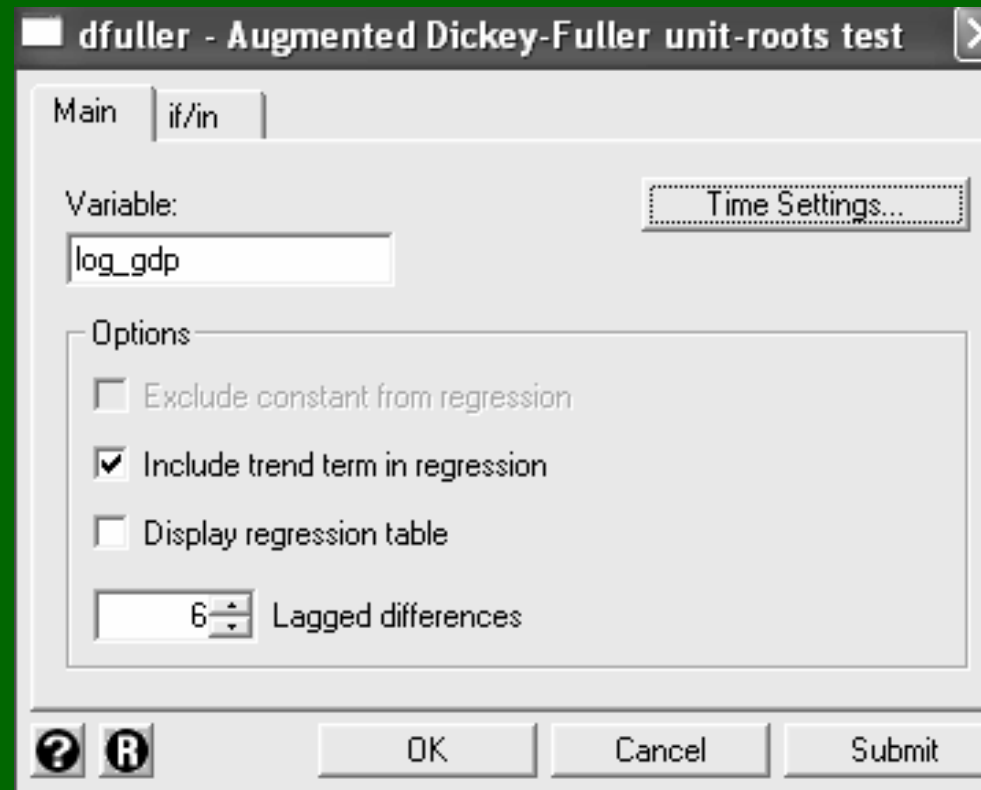
```
use "log of gdp" dta, clear  
xtset year  
xtreg log of gdp, fe  
estat ic  
estat ic, ytitle(log of gdp)
```

Statistics User Window Help

- Summaries, tables, & tests ▶
- Linear regression and related ▶
- Binary outcomes ▶
- Ordinal outcomes ▶
- Count outcomes ▶
- Categorical outcomes ▶
- Selection models ▶
- Generalized linear models (GLM) ▶
- Nonparametric analysis ▶
- Time series ▶**
 - Setup & utilities ▶
 - ARIMA models
 - ARCH/GARCH ▶
 - Prais-Winsten regression
 - Regression with Newey-West std. errors
 - Smoothers/univariate forecasters ▶
 - Tests ▶**
 - Augmented Dickey-Fuller unit-root test
 - Perform DF-GLS test for a unit root**
 - Phillips-Perron unit roots test
 - Graphs ▶
- ANOVA/MANOVA ▶
- Cluster analysis ▶
- Other multivariate analysis ▶

Running a Test

- **Augmented Dickey-Fuller Test**
 - 6 lags
 - Including Trend



Result

- Cannot reject the null at 5%

Result

Critical Values

Augmented Dickey-Fuller test for unit root		Number of obs =		141
		Interpolated Dickey-Fuller		
Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	
Z(t)	-1.074	-4.026	-3.445	-3.145

* MacKinnon approximate p-value for Z(t) = 0.9330

Create First Differences

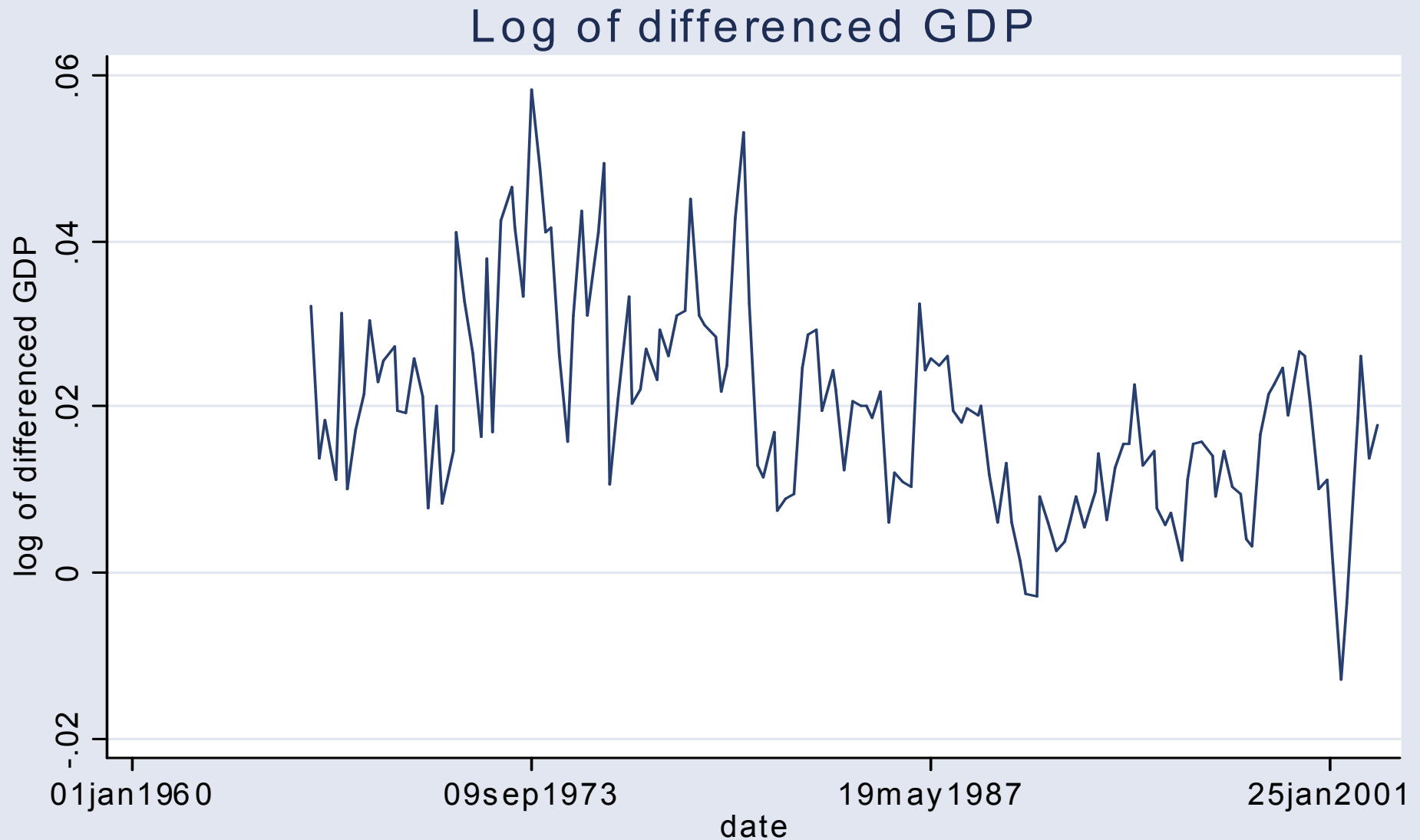
- **Cannot Reject Unit root: Data is I(1)**
- **Create First Differences of the data:**

```
. gen y=log_gdp-log_gdp[_n-1]
(1 missing value generated)

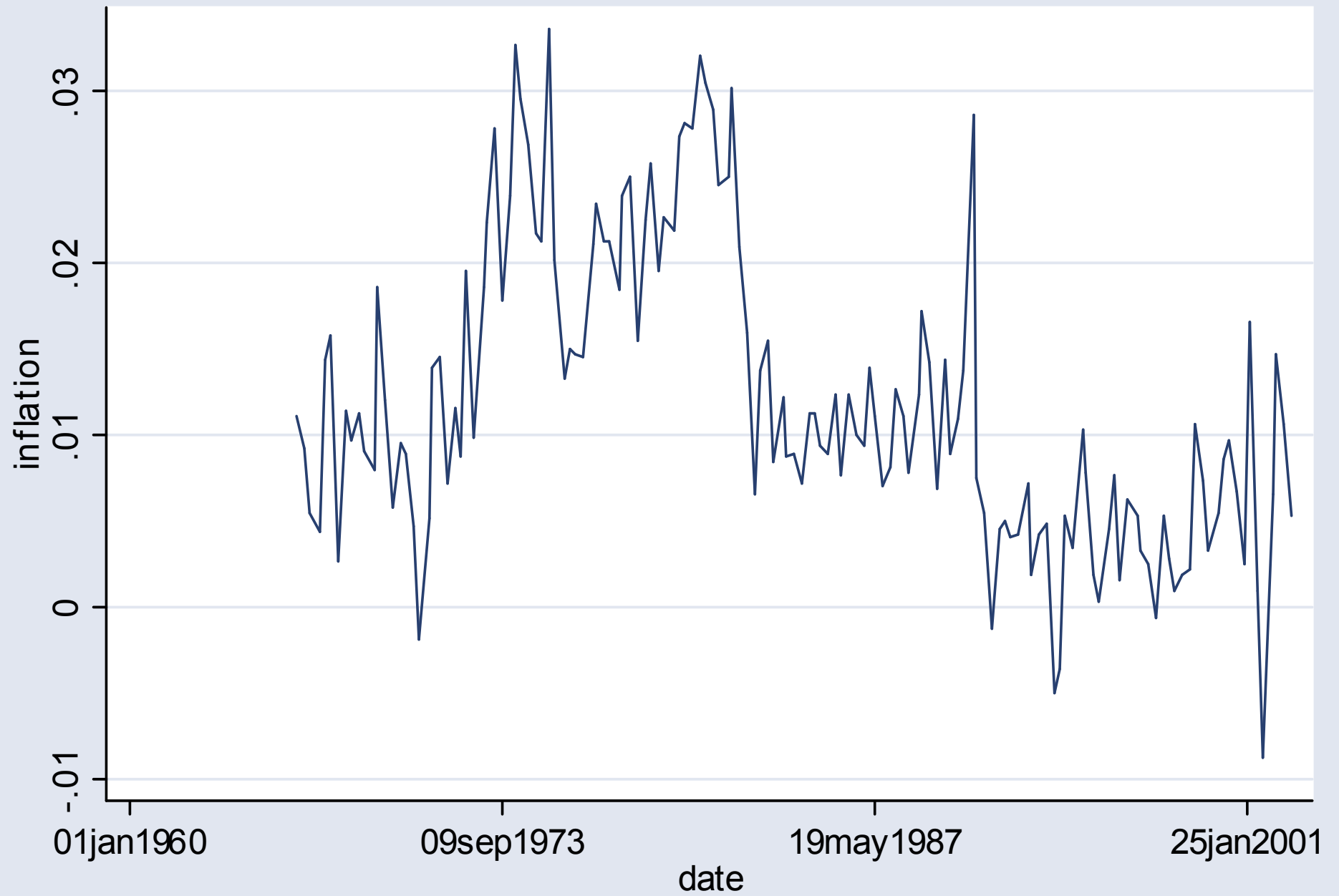
. gen inflation=log_cpi-log_cpi[_n-1]
(1 missing value generated)

. gen dcons=log_cons-L.log_cons
(1 missing value generated)
```

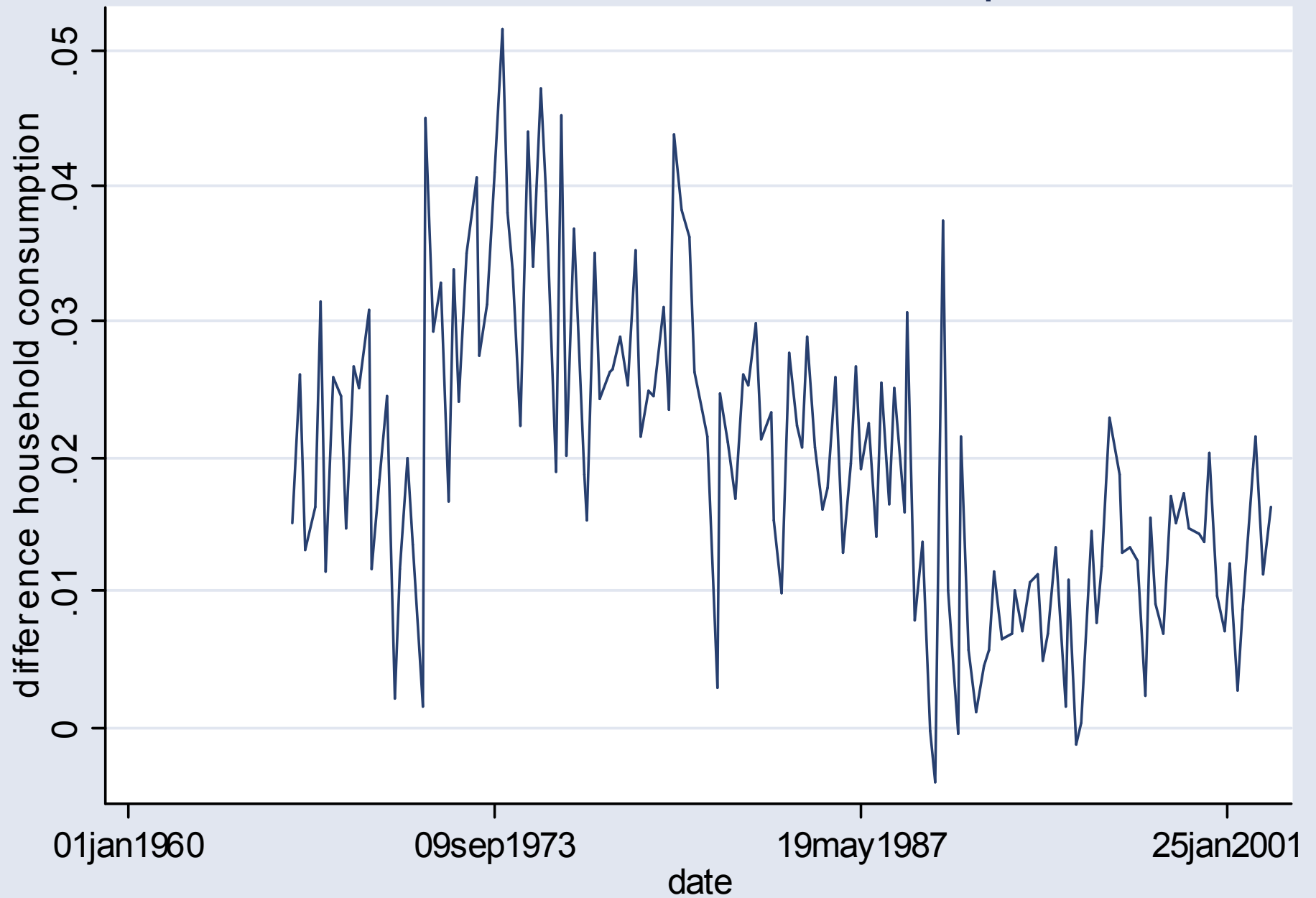
Check the new graphs



Inflation



Log differenced household consumption



Is it stationary now? (PP test)

```
. pperron y, lags(6)
```

```
Phillips-Perron test for unit root
```

```
Number of obs = 146
```

```
Newey-West lags = 6
```

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-49.247	-19.953	-11.061
Z(t)	-5.403	-3.495	-2.577

The differenced data seems to be stationary

Granger Causality

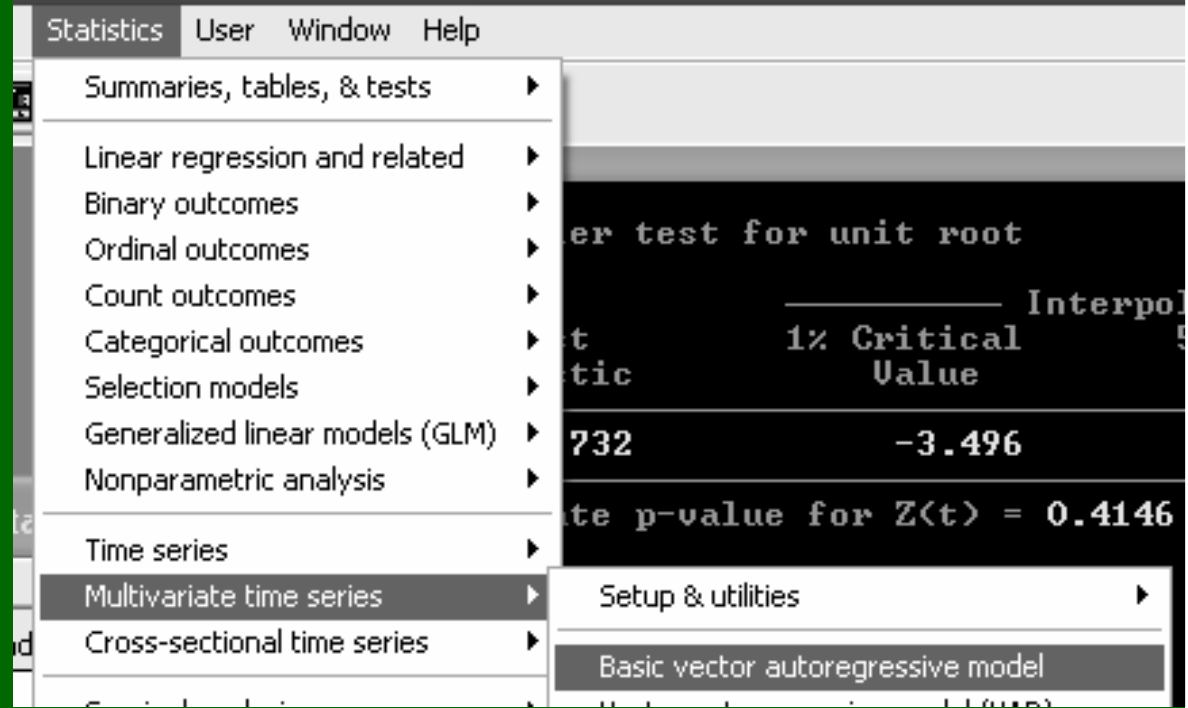
- **X Does not Granger Cause Y if:**

$$E(y_t | y_{t-1}, y_{t-2}, \dots, x_{t-1}, x_{t-2}, \dots) = E(y_t | y_{t-1}, y_{t-2}, \dots)$$

- **Test (Greene, p.592):**
 - Regress Y on lags of X and Y
 - Regress Y on lags of Y
 - Test if the restricted model is significantly outperformed by the non restricted model
 - Either χ^2 or F test

Granger Test

- Run simple VAR between the variables of interest
- Menu: Statistics → multivariate time series → Basic Vector Autoregression Model
- Choose
 - Variables
 - Lag Length



Granger Test: Running VAR

varbasic - Fit a simple VAR and graph IRFs

Main | if/in

Dependent variables:

Lags

Include lags 1 to:

Supply list of lags: (e.g. "1 3 8")

Graph

DIRFs

IRFs

FEVDs

No graph

Horizon for DIRFs, IRFs, and FEVDs

Periods

Testing in Stata

- **Statistics** → multivariate time series → var diagnostics and tests → **Granger causality test**

The screenshot shows the Stata software interface with the 'Statistics' menu open. The menu items are as follows:

- Summaries, tables, & tests
- Linear regression and related
- Binary outcomes
- Ordinal outcomes
- Count outcomes
- Categorical outcomes
- Selection models
- Generalized linear models (GLM)
- Nonparametric analysis
- Time series
 - Multivariate time series
 - Setup & utilities
 - Basic vector autoregressive model
 - Vector autoregressive model (VAR)
 - Structural vector autoregressive model
 - VAR diagnostics and tests**
 - Granger causality tests**
 - LM statistics for residual autocorrelation
 - VAR dynamic forecasts
 - Cross-sectional time series
- Survival analysis
- Observational/Epi. analysis
- Survey data analysis
- ANOVA/MANOVA

The background shows a terminal window with the following output:

```
Interpolated Dickey-Fuller
-----
t      1% Critical      5% Critical      10% Critical
Statistic      Value      Value      Value
-----
-2.785      -3.496      -2.887      -2.577
p-value for Z(t) = 0.0604
lags(4) trend
Number of obs = 14
Interpolated Dickey-Fuller
-----
5% Critical      10% Critical
Value      Value
-----
-3.444      -3.144
Granger causality tests
LM statistics for residual autocorrelation
Test for normally distributed disturbances
```

Granger Test

- Choose variables

vargranger - Pairwise Granger causality test

Options

Use currently active var or svar results

Use:

inflation y

0 Separator every N lines

? R OK Cancel Submit

Granger Test: Results

- We can reject that Inflation Granger Cause Household Consumption
- We cannot reject that Household Consumption Granger Cause Inflation

Granger causality Wald tests				
Equation	Excluded	chi2	df	Prob > chi2
dcons	inflation	2.4424	4	0.6550
dcons	ALL	2.4424	4	0.6550
inflation	dcons	22.7235	4	0.0001
inflation	ALL	22.7235	4	0.0001

Optimal Lag Length

- Sometimes, we have theory to guide us
- Often, we do not
- Three common tests (Greene, 589):
 - Likelihood Ratio Test (LR)
 - Akaike Information Criterion
 - Bayesian (Schwartz) Information Criterion

•

Likelihood Ratio (LR) test

General to simple approach: Run VAR with p lags. Use the LR test. If the test rejects the null, then stop. Otherwise run $p-1$ lags and compare with $p-2$...

$$\lambda = T \left(\ln |W_{res}| - \ln |W_{unres}| \right) \rightarrow \chi^2 \left(M^2 \right)$$

W_{res} – *restricted covariance matrix*

W_{unres} – *unrestricted covariance matrix*

M – *Number of equations*

Information Criteria

- **Two information Criteria: Akaike (AIC) and Bayesian (BIC). Find the information criteria for lag length 1 to p. Choose the lag length that minimizes the information criteria that you chose.**

$$\lambda = \ln(|W|) + \frac{(pM^2 + M)IC(T)}{T}$$

W – The covariance Matrix, *p* – number of lags,

T – number of observations *M* – number of equations,

IC(T) – 2 for AIC, *T* for BIC,

Tests in Stata

- **Menu: Statistics** → multivariate time series → var diagnostics and tests → **Lag-Order Selection statistics**

The screenshot shows the Stata Statistics menu with the following structure:

- Statistics
- User
- Window
- Help
- Summaries, tables, & tests
- Linear regression and related
- Binary outcomes
- Ordinal outcomes
- Count outcomes
- Categorical outcomes
- Selection models
- Generalized linear models (GLM)
- Nonparametric analysis
- Time series
- Multivariate time series**
 - Setup & utilities
 - Basic vector autoregressive model
 - Vector autoregressive model (VAR)
 - Structural vector autoregressive model
 - VAR diagnostics and tests**
 - Granger causality tests
 - LM statistics for residual autocor
 - Test for normally distributed dist
 - Lag-order selection statistics**
 - VAR dynamic forecasts
 - IRF & variance decomposition analysis
 - Manage IRF results and files
- Cross-sectional time series
- Survival analysis
- Observational/Epi. analysis
- Survey data analysis
- ANOVA/MANOVA
- Cluster analysis
- Other multivariate analysis

The background of the menu items is a table with the following data:

4805	.1529651	-0.27	0.786	-.3412866
4125	.0893092	1.59	0.111	-.0326303
7091	.0087489	4.24	0.000	.0199435

Running test

- Choose Variables
- Choose maximum lags

varsoc - Obtain lag-order selection statistics

Main | by/if/in

Dependent variables:

Use VAR or SVAR results: Maximum lag order

Exogenous variables:

Constraints on exogenous variables:

Exclude constant

Lutkepohl information criteria

Confidence level Separator every N

? R OK Cancel

Lag Length: Results

		LR				AIC			BIC
Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC	
0	389.636	.	.	.	8.66e-07	-5.44557	-5.42019	-5.38312	
1	1482.751	2186.231	9	0.000	2.02e-13	-20.7148	-20.6133	-20.465	
2	1533.067	100.631	9	0.000	1.13e-13	-21.2967	-21.1191*	-20.8596*	
3	1542.128	18.123	9	0.034	1.13e-13	-21.2976	-21.0438	-20.6731	
4	1551.512	18.768	9	0.027	1.13e-13	-21.303	-20.9731	-20.4912	
5	1562.889	22.755	9	0.007	1.09e-13	-21.3365	-20.9305	-20.3373	
6	1575.778	25.778*	9	0.002	1.03e-13*	-21.3912*	-20.9091	-20.2047	

We go with the LR and AIC and say 6
(why not?)

Run Simple VAR

- We run a simple VAR (not structural, no assumptions on order of variables) between Household Consumption, Inflation and GDP
- To do so:
- Menu: Statistics → multivariate time series → Basic Vector Autoregression Model

Simple VAR

- **Choose**
 - Variables
 - Lag Length
- **Choose how to plot the response functions:**
 - Irf (simply uses the covariance matrix, minimum order)
 - Orf (orthogonalized the Covariance matrix to set order)
 - FEVD: Variance Decomposition Tables (In a graph form)

Simple VAR

varbasic - Fit a simple VAR and graph IRFs

Main | if/in

Dependent variables:

y dcon inflation

Lags

Include lags 1 to:

Supply list of lags: (e.g. "1 3 8")

Graph

DIRFs

IRFs

FEVDs

No graph

Horizon for DIRFs, IRFs, and FEVDs

Periods

Results: Table of Coefficients

Model Lag Order Selection Statistics

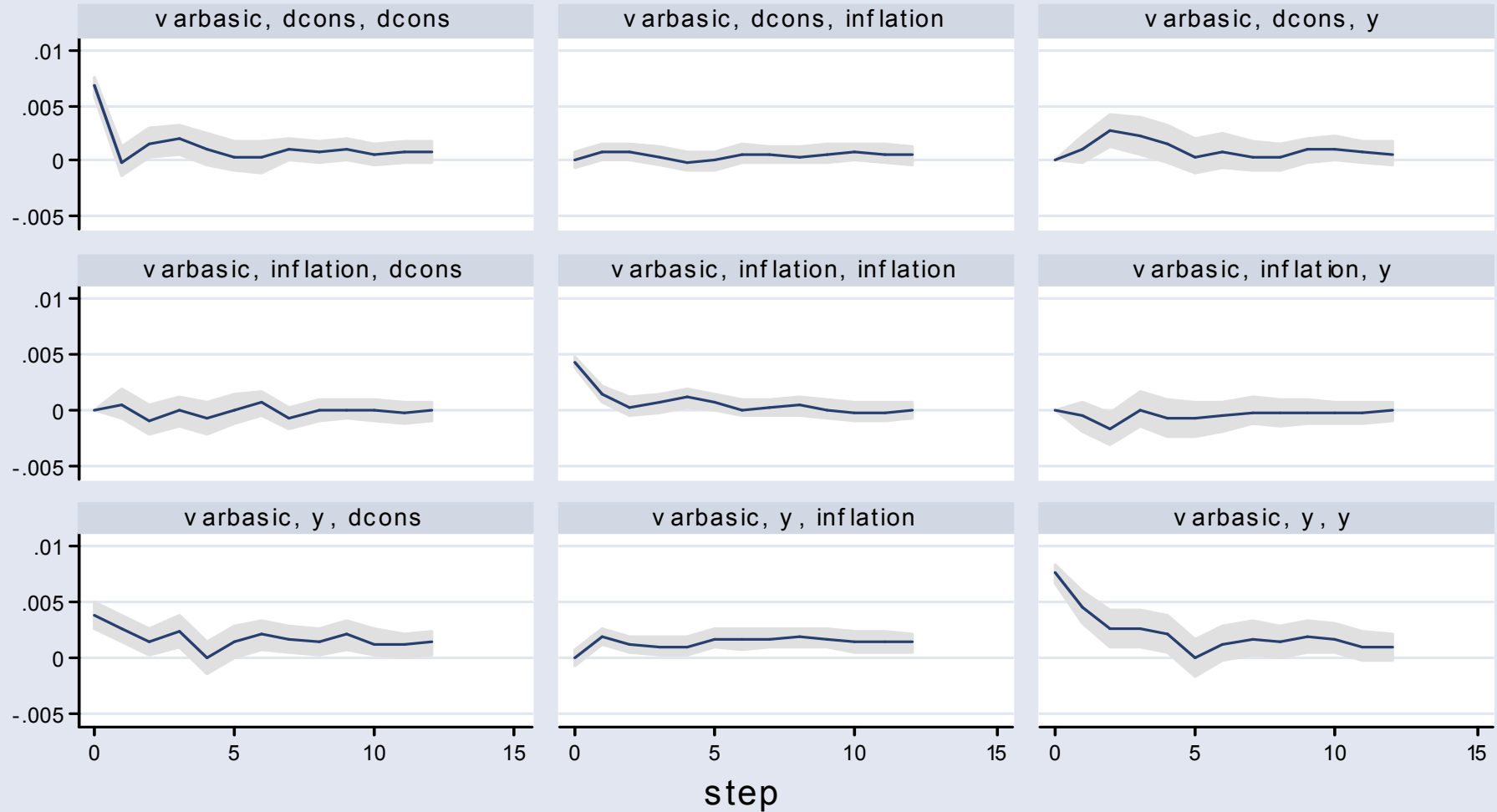
FPE	AIC	HQIC	SBIC	LL	Det(Sigma_ml)
1.144e-13	-21.290209	-20.8058	-20.098157	1557.9597	5.073e-14

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y						
y	L1	.5240169	.094267	5.56	0.000	.3392569 .7087769
	L2	-.1716709	.1008584	-1.70	0.089	-.3693498 .026008
	L3	.1312994	.0988067	1.33	0.184	-.0623581 .3249569
	L4	-.0964825	.098346	-0.98	0.327	-.2892371 .0962721
	L5	-.0531829	.0987135	-0.54	0.590	-.2466577 .1402919
	L6	.2467331	.0968582	2.55	0.011	.0568944 .4365717

dcons

—more—

Impulse Response Function



Graphs by irfname, impulse variable, and response variable

Simple VAR: Variance Decomposition Table

step	(9) fevd	(9) Lower	(9) Upper
0	0	0	0
1	.997849	.982572	1.01313
2	.821666	.707423	.935909
3	.758885	.620901	.896868
4	.729669	.579145	.880193
5	.714909	.555406	.874413
6	.653683	.482896	.82447
7	.594682	.41942	.769945
8	.543658	.364066	.723249
9	.501872	.316881	.686863
10	.463959	.277265	.650654
11	.44034	.252745	.627934

5% lower and upper bounds reported

- 1) irfname = varbasic, impulse = y, and response = y
- 2) irfname = varbasic, impulse = y, and response = dcons
- 3) irfname = varbasic, impulse = y, and response = inflation
- 4) irfname = varbasic, impulse = dcons, and response = y
- 5) irfname = varbasic, impulse = dcons, and response = dcons
- 6) irfname = varbasic, impulse = dcons, and response = inflation
- 7) irfname = varbasic, impulse = inflation, and response = y
- 8) irfname = varbasic, impulse = inflation, and response = dcons
- 9) irfname = varbasic, impulse = inflation, and response = inflation

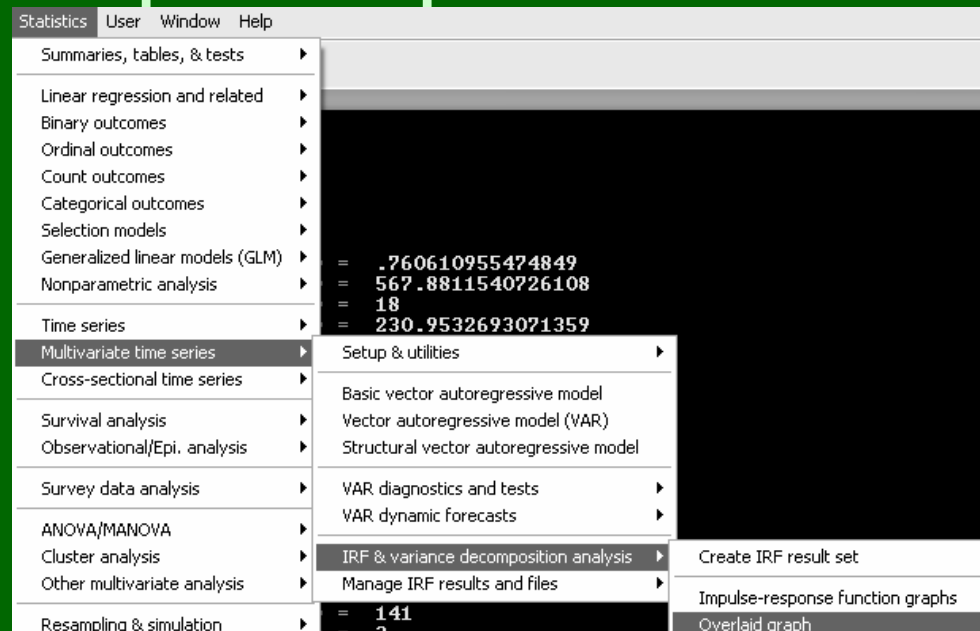
Generating After Estimation

- generate after estimation:

- Choose:

- Menu: Statistics → Multivariate time series → IRF & Variance Decomposition Analysis

- Choose the table or impulse response function that you need



To get the results

- **If you want to use some of the results:**
 - Coefficients
 - Number of observations
 - Etc...
- **Stata keeps them under the ereturn command**
- **To get them type e(variable_name)**
- **To see all the variables that you can choose from:**
 - ereturn list

Examples

```
. ereturn list
```

```
scalars:
```

```
      e(r2_3) = .760610955474849
      e(l1_3) = 567.8811540726108
      e(df_m3) = 18
      e(chi2_1) = 230.9532693071359
      e(chi2_2) = 161.690542764445
      e(chi2_3) = 447.9993849956065
      e(l1) = 1557.959742978141
      e(detsig_m1) = 5.07253323216e-14
```

```
. matrix list e($sigma)
```

```
symmetric e($sigma)[3,3]
```

	y	dcons	inflation
y	.00005872		
dcons	.00002995	.00006185	
inflation	9.504e-07	1.555e-06	.00001859

More than simple VAR

- **More than a simple VAR:**
 - Adding Exogenous Variables
 - Constraining blocks of variables to equal zero
- **Use Menu: Statistics → multivariate time series → Vector Autoregression Model**
- **Generating Impulse Responses:**
 - Menu: Statistics → Multivariate time series → IRF & Variance Decomposition Analysis

More than simple VAR

- **Adding constraints on the A or B matrix**
 - A: y Matrix, B: errors matrix
 - Short and long run constraints
- **skip lags**
- **Menu: Statistics → multivariate time series → Structural Autoregression Model**
- **Stata runs the VAR with the restrictions**
- **Caveat 1: Too many constraints can lead to failures in the convergence process**
- **Caveat 2: You need enough constraints to allow identification.**

Structural VAR

```
matrix A=[0,..,0\,..,..\,0,..]
```

Defining a matrix of constraints: the '.' imply a free parameter

sva - Estimate structural vector autoregressions

Main | by/if/in | Options | Max options

Dependent variables:

Example...

Time Se

y inflation dcons

Short-run constraints

Suppress the constant term

Short-run A constraints

Previously defined constraints:

Equality constraint matrix:

A

Cross-parameter constraint matrix:

Short-run B constraints

Previously defined constraints:

Equality constraint matrix:

Cross-parameter constraints:

Lags

Include lags 1 to:

6

Supply list of lags: (e.g. 1 2 3)

Using the constraints: Forcing the values in the constrained matrix



OK

Cancel

Structural VAR: Results

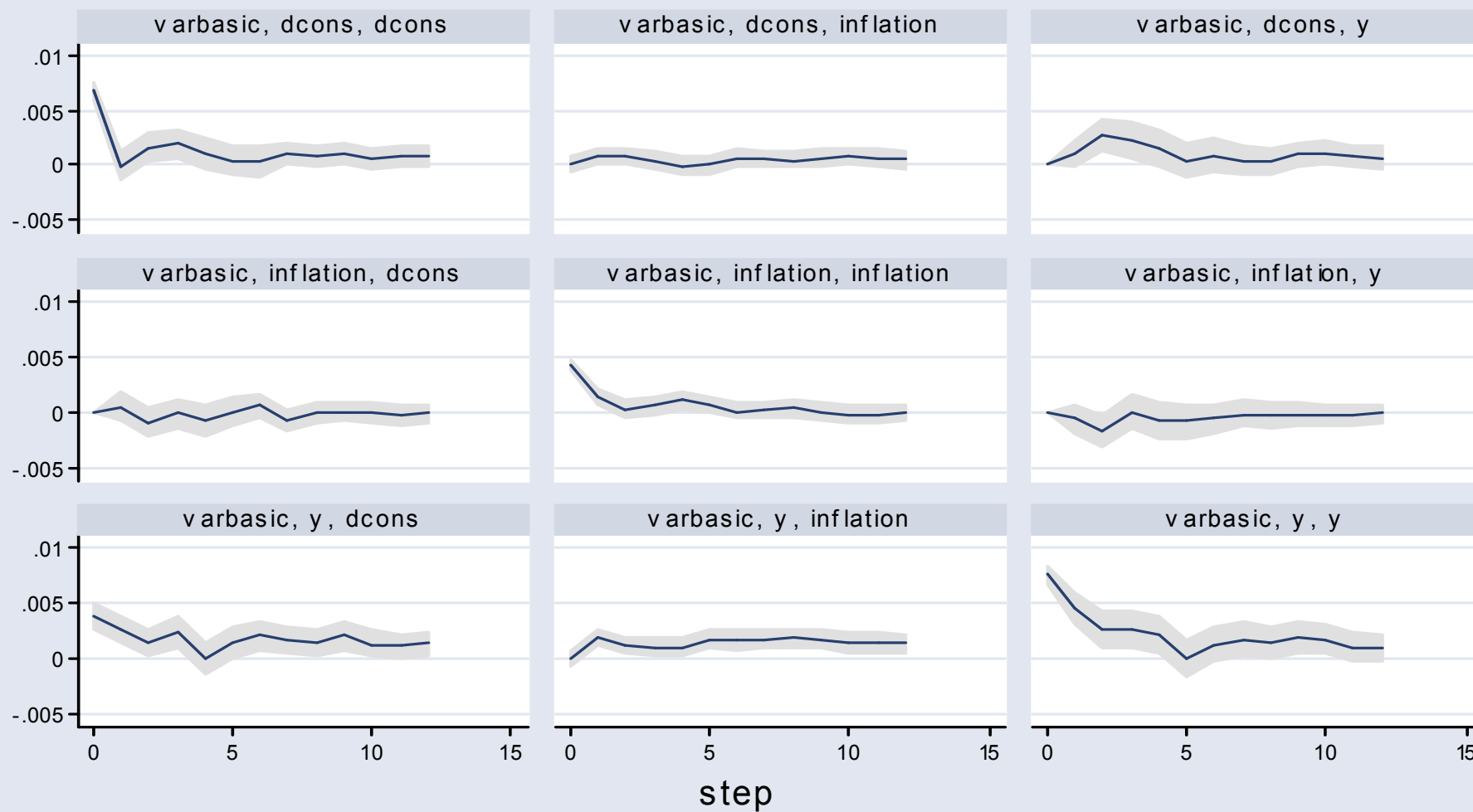
Equation	Obs	Parms	RMSE	R-sq	chi2	P
y	141	19	.008238	0.6209	230.9533	0.0000
inflation	141	19	.004635	0.7606	447.9994	0.0000
lcons	141	19	.008455	0.5342	161.6905	0.0000

VAR Model lag order selection statistics

FPE	AIC	HQIC	SBIC	LL	Det(Sigma_ml)
1.144e-13	-21.290209	-20.8058	-20.098157	1557.9597	5.073e-14

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
a_2_1 _cons	22.33818	270.0692	0.08	0.934	-506.9877	551.664
a_3_1 _cons	148.7274	41.47564	3.59	0.000	67.43667	230.0182
a_1_2 _cons	231.9367	13.81163	16.79	0.000	204.8664	259.007
a_2_2 _cons	-10.76834	19.54312	-0.55	0.582	-49.07215	27.53546
a_2_3						

Structural VAR: Results



Graphs by irfname, impulse variable, and response variable

Structural VARs

- **Structural VAR: VAR that is the result of a structural model**
- **Goal: Obtaining the Structural parameters out of the Estimated Reduced Form**
- **Required: Number of Constraints**

Model: Inflation and GDP

- Assume we have a simple model of the form:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 \pi_{t-1} + \varepsilon_t$$

$$\pi_t = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 \pi_{t-1} + \nu_t$$

y_t – GDP

π_t – inflation

ν_t, ε_t – White noise, independent random variables

We can write it:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 \pi_{t-1} + \varepsilon_t$$

$$\pi_t - \beta_1 y_t = \beta_0 + \beta_2 y_t + \beta_3 \pi_{t-1} + u_t$$

In Matrix Form:

$$\begin{pmatrix} 1 & 0 \\ -\beta_1 & 1 \end{pmatrix} \begin{pmatrix} y_t \\ \pi_t \end{pmatrix} = \begin{pmatrix} \alpha_{0t} \\ \beta_0 \end{pmatrix} + \begin{pmatrix} y_{t-1} \\ \pi_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \nu_t \end{pmatrix}$$

OR:

$$\begin{pmatrix} y_t \\ \pi_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ -\beta_1 & 1 \end{pmatrix}^{-1} \begin{pmatrix} \alpha_{0t} \\ \beta_0 \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ -\beta_1 & 1 \end{pmatrix}^{-1} \begin{pmatrix} y_{t-1} \\ \pi_{t-1} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ -\beta_1 & 1 \end{pmatrix}^{-1} \begin{pmatrix} \varepsilon_t \\ \nu_t \end{pmatrix}$$

Inverting the Matrix gives

$$\begin{pmatrix} 1 & 0 \\ -\beta_1 & 1 \end{pmatrix}^{-1} = \begin{pmatrix} 1 & 0 \\ \beta_1 & 1 \end{pmatrix}$$

So we can substitute this in the equations:

We find:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 \pi_{t-1} + \varepsilon_t$$

$$\pi_t = (\beta_1 \alpha_0 + \beta_0) + (\beta_1 \alpha_1 + \beta_2) y_{t-1} + (\beta_1 \alpha_2 + \beta_3) \pi_{t-1} + (\beta_1 \varepsilon_t + \nu_t)$$

So we can write in VAR form:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 \pi_{t-1} + \varepsilon_t$$

$$\pi_t = \theta_0 + \theta_1 y_{t-1} + \theta_2 \pi_{t-1} + \eta_t$$

Almost there

- After estimating the VAR we can find:

$$(\beta_1 \alpha_0 + \beta_0) = \theta_0$$

$$(\beta_1 \alpha_1 + \beta_2) = \theta_1$$

$$(\beta_1 \alpha_2 + \beta_3) = \theta_2$$

So we have three equations and four unknowns...

Hakuna Matata

- We also have the covariance matrix:

$$\begin{pmatrix} \sigma_{\varepsilon,\varepsilon} & \sigma_{\varepsilon,\eta} \\ \sigma_{\varepsilon,\eta} & \sigma_{\eta,\eta} \end{pmatrix} = \begin{pmatrix} \sigma_{\varepsilon,\varepsilon} & \beta_1 \sigma_{\varepsilon,\varepsilon} \\ \beta_1 \sigma_{\varepsilon,\varepsilon} & (\beta_1 \sigma_{\varepsilon,\varepsilon} + \nu_t)^2 \end{pmatrix}$$

- So we have a fourth equation:

$$\beta_1 \sigma_{\varepsilon,\varepsilon} = \sigma_{\varepsilon,\eta}$$

Run the VAR

- Note that because we assume that the “real” covariance matrix has the triangular form:

$$\begin{pmatrix} \sigma_{\varepsilon,\varepsilon} & 0 \\ \beta_1\sigma_{\varepsilon,\varepsilon} & \sigma_{\varepsilon,\varepsilon} \end{pmatrix}$$

- We can use the OIRF that Stata gives us (Cholesky factorization) to watch the Structural impulse functions.

Run the VAR (1 lag)

vardbasic - FIT a simple VAR and graph IRFs

Main | if/in

Dependent variables:

y inflation

Lags

Include lags 1 to:

Supply list of lags: (e.g. "1 3 8")

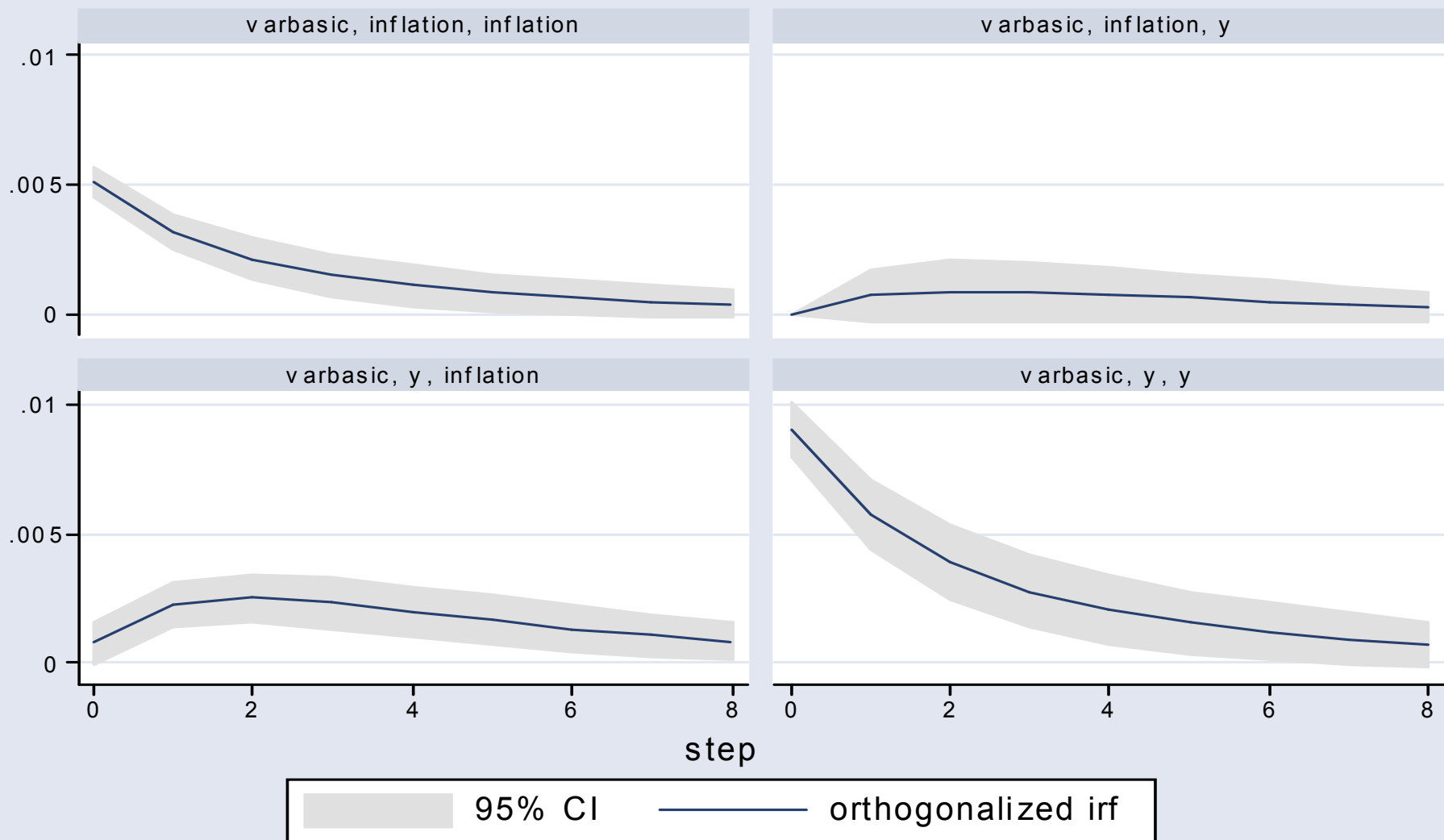
Graph

DIRFs
 IRFs
 FEVDs
 No graph

Horizon for DIRFs, IRFs, and FEVDs

Periods

Study the Impulse Responses



Graphs by irfname, impulse variable, and response variable

Get the coefficients

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
y inflation	L1	.622347	.070297	8.85	0.000	.4845675	.7601266
	L1	.1421922	.0999996	1.42	0.155	-.0538034	.3381978
	_cons	.0057446	.0015036	3.82	0.000	.0027976	.0086916
inflation y	L1	.1950256	.040598	4.80	0.000	.1154549	.2745962
	L1	.6247529	.0577519	10.82	0.000	.5115613	.7379445
	_cons	.0005972	.0008684	0.69	0.492	-.0011047	.0022992

α_1
 α_2
 α_0

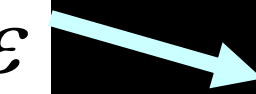
θ_1
 θ_2
 θ_0

Get the Errors matrix

```
. matrix list e(Sigma)
```

```
symmetric e(Sigma)[2,2]
```

$$\sigma_{\varepsilon, \varepsilon}$$



```
y inflation
```

```
y
```

```
.00008145
```

```
inflation
```

```
7.018e-06
```

```
.00002716
```

$$\beta_1 \sigma_{\varepsilon, \varepsilon}$$



We find:

$$\beta_1 = \frac{\text{cov}(\varepsilon, \eta)}{\sigma_{\varepsilon, \varepsilon}} = \frac{0.000007018}{0.00008145} = 0.086$$

$$\beta_0 = \theta_0 - \beta_1 \alpha_0 = 0.0005972 - 0.086 \times 0.0574 = -0.0043$$

$$\beta_2 = \theta_1 - \beta_1 \alpha_1 = 0.195 - 0.086 \times 0.622 = 0.142$$

$$\beta_3 = \theta_2 - \beta_1 \alpha_2 = 0.625 - 0.086 \times 0.142 = 0.614$$

Conclusion

- **Enough restrictions**
- **Exact Identification**
- **Possible to deduce the Structural Parameters**

To test a restricted Model

- Run a non restricted model
- Test the null by using the LR test on the difference between the restricted and unrestricted model

$$\lambda = T(\ln|W_{res}| - \ln|W_{unres}|) \rightarrow \chi^2(M)$$

W_{res} – restricted covariance matrix

W_{unres} – unrestricted covariance matrix

M – Number of restrictions

Caveat

- **With the data we used, it is likely that the variables are cointegrated (consumption and GDP)**
- **One should (theoretically) check for that option**