

VAR's: Estimation, forecasting and hypothesis tests

A. Principles of forecasting

Suppose we want to forecast y_{1t} based on:

$$y_{1,t-1}, y_{1,t-2}, \dots, y_{1,t-p}$$

$$y_{2,t-1}, y_{2,t-2}, \dots, y_{2,t-p}$$

\vdots

$$y_{n,t-1}, y_{n,t-2}, \dots, y_{n,t-p}$$

deterministic functions of t

$$(1, t, \cos(\pi t/6), \text{seasonal dummies})$$

Let $\mathbf{y}_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$
 $(n \times 1)$
 $\mathbf{x}_t = (1, \mathbf{y}'_{t-1}, \mathbf{y}'_{t-2}, \dots, \mathbf{y}'_{t-p})'$
 $(k \times 1)$
 $k = np + 1$

Suppose we consider linear forecast

$$\hat{y}_{1t|t-1} = \boldsymbol{\beta}' \mathbf{x}_t$$

Best forecast: value of $\boldsymbol{\beta}$ that minimizes

$$E(y_{1t} - \boldsymbol{\beta}' \mathbf{x}_t)^2$$

Proposition: If \mathbf{y}_t is covariance-stationary and $E(\mathbf{x}_t \mathbf{x}_t')$ is nonsingular, then optimal forecast uses

$$\boldsymbol{\beta}^* = E(\mathbf{x}_t \mathbf{x}_t')^{-1} E(\mathbf{x}_t y_{1t})$$

Definition: The optimal linear forecast,

$$\hat{y}_{1t|t-1} = \boldsymbol{\beta}^* \mathbf{x}_t,$$

is called the "population linear projection" of y_{1t} on \mathbf{x}_t

Definition: Ordinary least squares (OLS) estimate is given by

$$\hat{\beta} = \left(\sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \right)^{-1} \left(\sum_{t=1}^T \mathbf{x}_t y_t \right)$$

Proposition: If \mathbf{y}_t is ergodic, then

$$\hat{\beta} \xrightarrow{p} \beta^*$$

Proof: (Law of Large Numbers)

$$\hat{\beta} = \left(T^{-1} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \right)^{-1} \left(T^{-1} \sum_{t=1}^T \mathbf{x}_t y_t \right)$$

$$\xrightarrow{p} E(\mathbf{x}_t \mathbf{x}_t')^{-1} E(\mathbf{x}_t y_t)$$

Example 1: Single equation estimation

y_{1t} = real GDP growth

y_{2t} = inflation

y_{3t} = fed funds rate

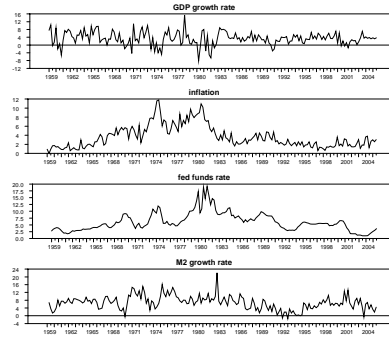
y_{4t} = rate of growth of M2

Example 1: Single equation estimation

- cal 1947 1 4
- all 0 2006:4
- open data gdp_data.prn 1947 1570.5 15.105
- 1947.25 1568.7 15.329
- data(org=obs) 1947:1
- 2005:3 datex gdplev 1947.5 1568 15.597
- pricelev 1947.75 1590.9 15.989
- open data fed_data.prn
- data(org=obs) 1959:1
- 2005:3 date2 fedfunds
- M2

- set gdpch = 400*log(gdplev(t)/gdplev(t-1))
- set inflation =
- 400*log(pricelev(t)/pricelev(t-1))
- set mgrow = 400*log(M2(t)/M2(t-1))
- smpl 1959:1 2005:3

- spgraph(vfields=4)
- graph(header='GDP growth rate',dates) 1
- # gdpch
- graph(samesize,header='inflation',dates) 1
- # inflation
- graph(samesize,header='fed funds rate',dates) 1
- # fedfunds
- graph(samesize,header='M2 growth rate',dates) 1
- # mgrow
- spgraph(done)

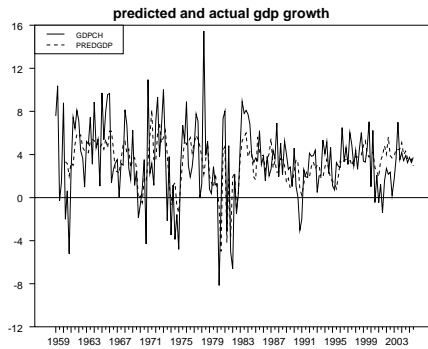


- linreg gdpch
- # constant gdpch{1 to 4} inflation{1 to 4} fedfunds{1 to 4} mgrow{1 to 4}

- Linear Regression - Estimation by Least Squares
- Dependent Variable GDPCH
- Quarterly Data From 1959:01 To 2005:03
- Usable Observations 182 Degrees of Freedom 165
- Total Observations 187 Skipped/Missing 5
- Centered R**2 0.325262 R Bar **2 0.259833
- Uncentered R**2 0.650477 T x R**2 118.387
- Mean of Dependent Variable 3.2792963257
- Std Error of Dependent Variable 3.4090248280
- Standard Error of Estimate 2.9328850575
- Sum of Squared Residuals 1419.2994355
- Regression F(16,165) 4.9712
- Significance Level of F 0.00000003
- Log Likelihood -445.15280
- Durbin-Watson Statistic 1.917563

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	2.08223813	0.811822124	2.56489	0.01121177
2. GDPCH{1}	0.118067740	0.079053976	1.49351	0.13721407
3. GDPCH{2}	0.203099131	0.080898608	2.51082	0.01300744
4. GDPCH{3}	-0.039822886	0.074458465	-0.53483	0.59348496
5. GDPCH{4}	0.027637404	0.069555777	0.39734	0.69162910
6. INFLATION{1}	0.171477187	0.211777736	0.80970	0.41927673
7. INFLATION{2}	-0.006036365	0.233560625	-0.02584	0.97941223
8. INFLATION{3}	-0.313409525	0.239203890	-1.31022	0.19194273
9. INFLATION{4}	0.027459910	0.217167797	0.12645	0.89953317
10. FEDFUNDS{1}	0.141392094	0.206817956	0.68366	0.49515192
11. FEDFUNDS{2}	-1.012059455	0.228892546	-4.41862	0.00001786
12. FEDFUNDS{3}	0.424541703	0.240408102	1.76592	0.07925855
13. FEDFUNDS{4}	0.247841364	0.219214781	1.13059	0.25986970
14. MGROW{1}	0.077751053	0.089888624	0.86496	0.38831579
15. MGROW{2}	0.086579388	0.094657441	0.91466	0.36170479
16. MGROW{3}	0.103284358	0.091678316	1.12660	0.26154944
17. MGROW{4}	0.002496693	0.085254375	0.02931	0.97665382

- prj predgdp 1960:2 2005:4
- graph(header='predicted and actual gdp growth',dates,key=uyleft) 2
- # gdpch
- # predgdp



```

• print(dates) 2005:1
  2005:4 gdpch
  predgdp

```

ENTRY	GDPCH	PREDGDP
2005:01	3.73397424782	3.426152642086
2005:02	3.25601091600	3.576184537927
2005:03	3.73391574327	2.933814021196
2005:04	NA	2.721240915629

I.

- A. Principles of forecasting
- B. Hypothesis testing

So far we assumed:

\mathbf{y}_t is stationary and ergodic

$E(\mathbf{x}_t \mathbf{x}_t')$ is nonsingular

and concluded:

OLS gives consistent estimate of optimal forecast weights

Suppose we want to go further and test a hypothesis, e.g.

$H_0 : y_{2,t-1}, y_{2,t-2}, \dots, y_{2,t-p}$
do not help forecast y_{1t}

Stronger assumptions for hypothesis testing:

$$\varepsilon_t = y_{1t} - \beta^{*'} \mathbf{x}_t$$

$$E(\varepsilon_t | \mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \dots, \mathbf{y}_1) = 0$$

$$E(\varepsilon_t^2) = \sigma^2$$

$$E(\varepsilon_t^4) < \infty$$

Then: all usual OLS t or F tests on $\hat{\beta}$ are valid for drawing conclusions about β^*

Example 2: Checking for lag length

H_0 : need $p - 1$ lags

H_A : need p lags

H_0 : coeffs on $y_{1,t-p}, y_{2,t-p}, \dots, y_{n,t-p}$ are all zero

- linreg gdpch
- # constant gdpch{1 to 5} inflation{1 to 5} fedfunds{1 to 5} mgrow{1 to 5}
- exclude
- # gdpch{5} inflation{5} fedfunds{5} mgrow{5}

- Null Hypothesis : The Following Coefficients Are Zero
- GDPCH Lag(s) 5
- INFLATION Lag(s) 5
- FEDFUNDS Lag(s) 5
- MGROW Lag(s) 5
- F(4,160)= 0.81118 with Significance Level 0.51974009

- linreg gdpch
- # constant gdpch{1 to 4} inflation{1 to 4} fedfunds{1 to 4} mgrow{1 to 4}
- exclude
- # gdpch{4} inflation{4} fedfunds{4} mgrow{4}

- Null Hypothesis : The Following Coefficients Are Zero
- GDPCH Lag(s) 4
- INFLATION Lag(s) 4
- FEDFUNDS Lag(s) 4
- MGROW Lag(s) 4
- F(4,164)= 0.39151 with Significance Level 0.81451782

Example 3: Granger-causality

If coeffs on $y_{2,t-1}, y_{2,t-2}, \dots, y_{2,t-p}$

are all zero, then we say that

“ y_2 does not Granger-cause y_1 ”

- linreg gdpch
 - # constant gdpch{1 to 4}
 - # inflation{1 to 4}
 - # mgrow{1 to 4}
 - exclude
 - # inflation{1 to 4}
- Null Hypothesis : The Following Coefficients Are Zero
 - INFLATION Lag(s) 1 to 4
 - F(4,164)= 0.71171 with Significance Level 0.58502790

- exclude
- # mgrow{1 to 4}

- Null Hypothesis : The Following Coefficients Are Zero
- MGROW Lag(s) 1 to 4
- F(4,164)= 1.97125 with Significance Level 0.10126036

- exclude
- # fedfunds{1 to 4}

- Null Hypothesis : The Following Coefficients Are Zero
- FEDFUNDS Lag(s) 1 to 4
- F(4,164)= 6.18029 with Significance Level 0.00011739

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9. INFLATION(4)	0.027459910	0.217167797	0.12645	0.89953317
10. FEDFUNDS(1)	0.141392084	0.206817856	0.68366	0.49515192
11. FEDFUNDS(2)	-1.012059455	0.228992546	-4.41962	0.00001786
12. FEDFUNDS(3)	0.424541703	0.240408102	1.76592	0.07925855
13. FEDFUNDS(4)	0.247841364	0.219214781	1.13059	0.25986970
14. MGROW(1)	0.077751053	0.089898624	0.86496	0.38831579
15. MGROW(2)	0.086579388	0.094657441	0.91466	0.36170479
16. MGROW(3)	0.103284358	0.091678316	1.12660	0.26154944
17. MGROW(4)	0.002498693	0.085254375	0.02931	0.97665382

What if one of our variables (say y_{2t}) were something like stock returns?

- linreg gdpch
 - # constant gdpch{1 to 4}
 - # stockch{1 to 4}
 - exclude
 - # stockch{1 to 4}
- Null Hypothesis : The Following Coefficients Are Zero
 - STOCKCH Lag(s) 1 to 4
 - F(4,172)= 6.85095 with Significance Level 0.00003857
- linreg stockch
 - # constant gdpch{1 to 4}
 - # stockch{1 to 4}
 - exclude
 - # gdpch{1 to 4}
- Null Hypothesis : The Following Coefficients Are Zero
 - GDPCH Lag(s) 1 to 4
 - F(4,172)= 0.91726 with Significance Level 0.45522372

GDP \Rightarrow stocks	stocks \Rightarrow GDP
inflation \Rightarrow stocks	stocks \Rightarrow inflation
fed funds \Rightarrow stocks	stocks \Rightarrow fed funds
money growth \Rightarrow stocks	stocks \Rightarrow money growth

Efficient markets theory:

(1) No variable should forecast stock returns (equivalent to no variable should Granger-cause y_2)

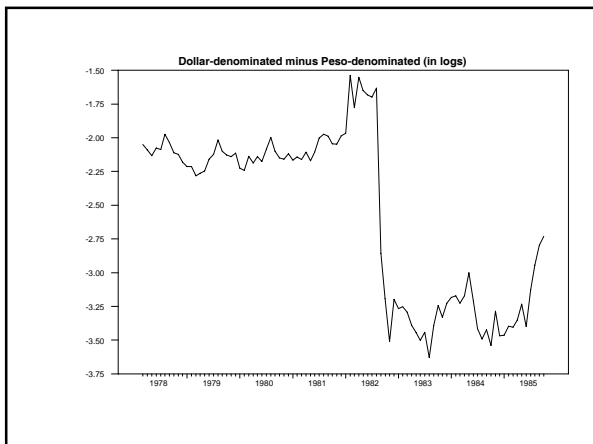
(2) Stock returns reflect forecast of future fundamentals (y_2 Granger-causes GDP and fed funds rate)

Summary: VAR's can be useful for making statements about forecasting

Interpreting statements about forecasting as statements about causation can be problematic

- Variables that can have strong forecasting components:
- stock returns
 - interest rates
 - exchange rates
 - commodity prices

Testing for structural stability



Chow test:

(1) Estimate model over whole sample:

$$y_t = \mathbf{x}_t' \boldsymbol{\beta} + \varepsilon_t \quad \mathbf{x}_t = (k \times 1)$$

save residual sum of squares RSS_0

(2) Estimate model with different coefficients before and after date t_1 ,

$$y_t = \mathbf{x}_t' \boldsymbol{\beta}_1 (\delta_{[t \leq t_1]}) + \mathbf{x}_t' \boldsymbol{\beta}_2 (\delta_{[t > t_1]}) + \varepsilon_t$$

save RSS_1

(3) Calculate $F(t_1) = \frac{(T-2k)(RSS_0 - RSS_1)}{k RSS_1}$

(4) Conclude stable if $F(t_1)$ is below $F(k, T - 2k)$ critical value

Example 4: Testing for structural stability

```

• set dum = 1
• set dum 1947:1 1985:4 = 0

• procedure somlags
  • set gdp1 = gdpch(t-1)*dum(t)
  • set gdp2 = gdpch(t-2)*dum(t)
  • set gdp3 = gdpch(t-3)*dum(t)
  • set gdp4 = gdpch(t-4)*dum(t)
  • set inf1 = inflation(t-1)*dum(t)
  • set inf2 = inflation(t-2)*dum(t)
  • set inf3 = inflation(t-3)*dum(t)
  • ...
  • set mgrow3 = mgrow(t-3)*dum(t)
  • set mgrow4 = mgrow(t-4)*dum(t)
• end

```

```

• @somlags
• linreg gdpch
• # constant gdpch{1 to 4}
  inflation{1 to 4} fedfunds{1 to 4}
  mgrow{1 to 4} $
• dum gdp1 gdp2 gdp3 gdp4
  inf1 inf2 inf3 inf4 ff1 ff2 ff3 ff4
  mgrow1 mgrow2 mgrow3
  mgrow4
• exclude
• # dum gdp1 gdp2 gdp3 gdp4
  inf1 inf2 inf3 inf4 ff1 ff2 ff3 ff4
  mgrow1 mgrow2 mgrow3
  mgrow4

• Null Hypothesis : The Following Coefficients Are Zero
• DUM
• GDP1
• GDP2
• ...
• MGROW3
• MGROW4
• F(17,147)= 0.93285 with Significance Level 0.53706567

```

Andrews (1993):

(1) Do above calculation for each possible t_1 between first 15% and last 15% of sample.

(2) Compare biggest $kF(t_1)$ found with critical value from $\pi_0 = 0.15$ row of Table 1 in Andrews (1993)

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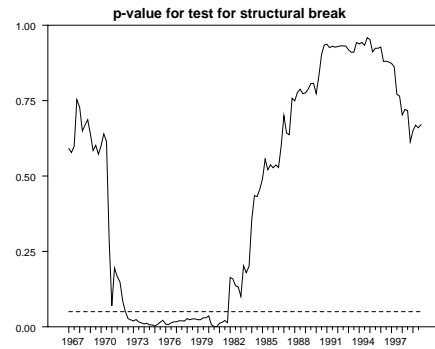
• do time=1967:1,1999:4
• set dum = 1
• set dum 1960:3 time = 0
• @somlags

• linreg(noprint) gdpch
• # constant gdpch{1 to 4} inflation{1 to 4} fedfunds{1 to 4} mgrow{1 to 4} $
• dum gdp1 gdp2 gdp3 gdp4 inf1 inf2 inf3 inf4 ff1 ff2 ff3 ff4 mgrow1 mgrow2
  mgrow3 mgrow4
• exclude(noprint)
• # dum gdp1 gdp2 gdp3 gdp4 inf1 inf2 inf3 inf4 ff1 ff2 ff3 ff4 mgrow1 mgrow2
  mgrow3 mgrow4

• set qmork time time = %cdstat
• set qcmork time time = %signif
• end do time
• smpl 1967:1 1999:4
• print(dates) / qmork qcmork

```

- set hq 1967:1 1999:4 = 0.05
- graph(header='p-value for test for structural break') 2
- # qcmork
- # hq



- Maximum value for F-statistic (1980:4) = 2.919
- k = 17
- (2.919)(17) = 49.62

p ₁₇	k	p = 16				p = 17				p = 18			
		10%	5%	1%	0.5%	10%	5%	1%	0.5%	10%	5%	1%	0.5%
.50	1.00	23.86	26.93	32.80	34.76	27.58	31.43	28.99	26.87	34.41			
.40	1.08	23.52	28.17	34.21	36.77	29.52	33.57	27.85	30.78	36.62			
.48	1.17	26.22	28.65	35.89	37.65	30.58	36.79	28.56	31.57	37.70			
.47	1.27	26.83	29.75	35.87	36.16	31.29	37.58	29.32	32.24	38.65			
.40	1.49	27.75	28.99	36.88	39.14	32.18	38.28	30.38	33.17	39.31			
.40	2.25	29.39	32.28	36.56	30.82	33.74	39.66	32.11	33.18	40.99			
.35	3.45	38.55	33.40	39.18	31.96	34.86	40.81	35.40	36.23	41.84			
.30	5.44	51.65	34.41	40.29	33.99	35.83	41.75	34.33	37.09	42.69			
.20	9.00	52.33	38.39	41.87	33.80	36.70	42.46	38.27	37.94	43.68			
.20	16.00	33.21	35.93	41.79	34.50	37.49	43.27	36.87	38.77	44.69			
.15	32.11	33.90	36.86	42.49	35.39	38.12	43.95	36.85	39.55	44.84			
.10	61.00	34.72	37.48	43.18	36.18	39.05	44.52	37.64	40.58	45.69			
.05	161.00	35.81	38.81	44.28	37.24	40.05	45.39	38.68	41.58	46.49			

49.62 > 38.12 so reject H0 (conclude regression is unstable)

Why is regression unstable?

- set dum = 1
- set dum 1960:3 1980:4 = 0
- @somlags
- FF1 1.155880251
0.443524075 2.60613
- FF2 -0.054742093
0.470867495 -0.11626
- FF3 -0.943361249
0.598965882 -3.24453
- FF4 2.167587438 0.747385701
2.90023

- Alternative idea: use average fed funds rate over quarter rather than third month of quarter
- open data fed_data_avg.prn
- data(org=obs) 1959:1 2005:3 date2 fedfunds M2

- Maximum value for F-statistic (1980:4) = 2.204
- $k = 17$
- $(2.204)(17) = 37.47$
- $37.47 < 38.12$ (we could accept H_0)

- A. Principles of forecasting
- B. Hypothesis testing
- C. Maximum likelihood and quasi-MLE

Suppose we make an even stronger assumption:

$$\varepsilon_t | \mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \dots, \mathbf{y}_1 \sim N(0, \sigma^2)$$

Then the sample conditional log likelihood would be

$$\begin{aligned} & \sum_{t=1}^T \log f(y_{1t} | \mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \dots, \mathbf{y}_{t-p}) \\ &= -\frac{T}{2} \log(2\pi\sigma^2) - \frac{\sum_{t=1}^T (y_{1t} - \boldsymbol{\beta}' \mathbf{x}_t)^2}{2\sigma^2} \end{aligned}$$

Observe: value of $\boldsymbol{\beta}$ that maximizes log likelihood is OLS estimate $\hat{\boldsymbol{\beta}}$

One option: maximize likelihood function even if we don't believe distributional assumption
= quasi-maximum likelihood estimation

MLE (or quasi-MLE) of σ^2 turns out to be

$$\hat{\sigma}^2 = T^{-1} \sum_{t=1}^T (y_{1t} - \hat{\boldsymbol{\beta}}' \mathbf{x}_t)^2$$

If distributional assumption is wrong (e.g., true $\varepsilon_t \sim$ Student t), then MLE is still consistent but no longer efficient

If convinced of Student t errors, better to choose (β, σ, ν) to maximize $\sum_{t=1}^T q_t$

$$q_t = \log \Gamma\left(\frac{\nu+1}{2}\right) - \log \Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2} \log(\sigma^2 \nu \pi) - \frac{\nu+1}{2} \log\left(1 + \frac{(y_t - \beta' \mathbf{x}_t)^2}{\nu \sigma^2}\right)$$

Estimation, Forecasting, and Hypothesis Testing

- A. Principles of forecasting
- B. Hypothesis testing
- C. Maximum likelihood and quasi-MLE
- D. Viewing as a vector system

So far we've just considered forecasting y_{1t} , the first element of the vector \mathbf{y}_t , using

$$y_{1t} = \boldsymbol{\pi}'_1 \mathbf{x}_t + \varepsilon_{1t}$$

$$\mathbf{x}_t = (1, \mathbf{y}'_{t-1}, \mathbf{y}'_{t-2}, \dots, \mathbf{y}'_{t-p})'$$

(k×1)

$$k = np + 1$$

$$\varepsilon_{1t} = \text{error forecasting variable 1}$$

Obviously we could set up analogous model to forecast second variable:

$$y_{2t} = \boldsymbol{\pi}'_2 \mathbf{x}_t + \varepsilon_{2t}$$

$$\mathbf{x}_t = (1, \mathbf{y}'_{t-1}, \mathbf{y}'_{t-2}, \dots, \mathbf{y}'_{t-p})'$$

(k×1)

Stack these in a vector system:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{nt} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\pi}'_1 \\ \boldsymbol{\pi}'_2 \\ \vdots \\ \boldsymbol{\pi}'_n \end{bmatrix} \mathbf{x}_t + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix}$$

$$\mathbf{y}_t = \mathbf{\Pi}' \mathbf{x}_t + \boldsymbol{\varepsilon}_t$$

$(n \times 1) \quad (n \times k)(k \times 1) \quad (n \times 1)$

$$\mathbf{\Pi}' \mathbf{x}_t = \begin{bmatrix} \mathbf{c} & \Phi_1 & \Phi_2 & \cdots & \Phi_p \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{y}_{t-1} \\ \mathbf{y}_{t-2} \\ \vdots \\ \mathbf{y}_{t-p} \end{bmatrix}$$

$$\mathbf{y}_t = \mathbf{c} + \Phi_1 \mathbf{y}_{t-1} + \Phi_2 \mathbf{y}_{t-2} + \cdots + \Phi_p \mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t$$

called a vector autoregression (VAR)

If all (possibly complex) scalars z satisfying

$$|1_n - \Phi_1 z - \Phi_2 z^2 - \cdots - \Phi_p z^p| = 0$$

also satisfy $\|z\| > 1$, then \mathbf{y}_t is covariance-stationary

Example: if $p = 1$ and all eigenvalues of Φ_1 are less than unity in modulus, then VAR is covariance-stationary

Suppose we make the distributional assumption that $\boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, \boldsymbol{\Omega})$

$$\begin{aligned} & \log f(\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_T | \mathbf{y}_0, \mathbf{y}_{-1}, \dots, \mathbf{y}_{-p+1}) \\ &= \sum_{t=1}^T \log f(\mathbf{y}_t | \mathbf{y}_{t-1}, \mathbf{y}_{t-2}, \dots, \mathbf{y}_{t-p}) \\ &= \frac{-Tn}{2} \log(2\pi) - \frac{T}{2} \log |\boldsymbol{\Omega}| \\ &\quad - (1/2) \sum_{t=1}^T (\mathbf{y}_t - \mathbf{\Pi}' \mathbf{x}_t)' \boldsymbol{\Omega}^{-1} (\mathbf{y}_t - \mathbf{\Pi}' \mathbf{x}_t) \end{aligned}$$

Result 1: the i th row of the MLE of Π' is given by

$$\hat{\pi}'_i = \left(\sum_{t=1}^T y_{it} \mathbf{x}'_t \right) \left(\sum_{t=1}^T \mathbf{x}_t \mathbf{x}'_t \right)^{-1}$$

Example 5: full system VAR estimation

- system
- variables gdpch inflation fedfunds mgrow
- lags 1 to 4
- det constant
- end(system)
- VAR/System - Estimation by Least Squares
- Dependent Variable GDPCH
- Quarterly Data From 1960:04 To 2005:03
- smpl 1960:4 2005:3
- estimate(sigma)

- F-Tests, Dependent Variable GDPCH
- Variable F-Statistic Signif
- GDPCH 2.3850 0.0534125
- INFLATION 0.8099 0.5205103
- FEDFUNDS 6.2796 0.0001005
- MGROW 2.4071 0.0515927

- F-Tests, Dependent Variable INFLATION
- Variable F-Statistic Signif
- GDPCH 1.0176 0.3999723
- INFLATION 69.0846 0.0000000
- FEDFUNDS 2.7173 0.0316318
- MGROW 0.2443 0.9127549

- F-Tests, Dependent Variable FEDFUNDS
- Variable F-Statistic Signif
- GDPCH 4.5979 0.0015233
- INFLATION 3.9117 0.0046364
- FEDFUNDS 260.0742 0.0000000
- MGROW 0.1242 0.9736087

- F-Tests, Dependent Variable MGROW
- Variable F-Statistic Signif
- GDPCH 0.6692 0.6142184
- INFLATION 1.2023 0.3119016
- FEDFUNDS 0.7263 0.5751938
- MGROW 16.3988 0.0000000

Result 2: the MLE of Ω is given by

$$\hat{\Omega} = T^{-1} \sum_{t=1}^T \hat{\varepsilon}_t \hat{\varepsilon}'_t$$

- estimate(sigma)
- Covariance\Correlation Matrix of Residuals
- GDPCH INFLATION FEDFUNDS MGROW
- GDPCH 7.66 -0.109 0.135 0.044
- INFLATION -0.309 1.035 0.201 -0.066
- FEDFUNDS 0.314 0.172 0.706 -0.449
- MGROW 0.317 -0.176 -0.982 6.768

Result 3: the maximized value for the log likelihood is given by

$$-(Tn/2)[1 + \log(2\pi)] - (T/2) \log |\hat{\Omega}|$$

Application: full-sample test of

$$H_0 : p - 1 \text{ lags}$$

$$H_A : p \text{ lags}$$

Let

$$\hat{\Omega}(p-1) = T^{-1} \sum_{t=1}^T \hat{\epsilon}_t(p-1) \hat{\epsilon}_t'(p-1)$$

$$\hat{\Omega}(p) = T^{-1} \sum_{t=1}^T \hat{\epsilon}_t(p) \hat{\epsilon}_t'(p)$$

$$\hat{\epsilon}_t(s) = \text{residuals from VAR with } s \text{ lags}$$

then twice likelihood ratio is

$$T[\log |\hat{\Omega}(p-1)| - \log |\hat{\Omega}(p)|] \approx \chi^2(n^2)$$

Sims small-sample correction:

$$(T-k)[\log |\hat{\Omega}(p-1)| - \log |\hat{\Omega}(p)|] \approx \chi^2(n^2)$$

Example 5 (continued): testing for lag length

- smpl 1960:4 2005:3
- estimate(sigma)
- compute logdet4 = %logdet
- compute tee = %nobs

- system
- variables gdpch inflation fedfunds mgrow
- lags 1 to 5
- det constant
- end(system)
- estimate
- compute logdet5 = %logdet

Reject H0 p=4 in favor of HA p=5

- compute test_chi = tee*(logdet4 - logdet5)
- cdf chisqr test_chi 16
- Chi-Squared(16)= 36.351987 with Significance Level 0.00258480
- compute test_sims = (tee - 21.0)*(logdet4 - logdet5)
- cdf chisqr test_sims 16
- Chi-Squared(16)= 32.110922 with Significance Level 0.00967250

Accept H0 p=5 over HA p=6

- system
- variables gdpch
inflation fedfunds
mgrow
- lags 1 to 6
- det constant
- end(system)
- estimate
- compute logdet6 =
%logdet
- Chi-Squared(16)=
28.972206 with
Significance Level
0.02412421
- Chi-Squared(16)=
24.948288 with
Significance Level
0.07074229

Akaike information criterion:

$$\text{minimize } \log |\hat{\Omega}(p)| + 2pn^2/T$$

Schwarz criterion:

$$\text{minimize } \log |\hat{\Omega}(p)| + (pn^2/T) \log T$$

Choose p=5 by AIC and p <=4 by Schwarz

- compute aic4 = logdet4 +
2*4.0*16/tee
- compute aic5 = logdet5 +
2*5.0*16/tee
- compute sic4 = logdet4 +
(4.0*16/tee)*log(tee)
- compute sic5 = logdet5 +
(5.0*16/tee)*log(tee)
- compute aic6 = logdet6 +
2.0*6*16/tee
- compute sic6 = logdet6 +
(6.0*16/tee)*log(tee)
- display 'aic for lags 4 5 6' aic4
aic5 aic6
- display 'schwarz for lags 4 5 6'
sic4 sic5 sic6
- aic for lags 4 5 6 4.02517
4.00099 4.01781
- schwarz for lags 4 5 6
5.16044 5.42008
5.72072

Rule of thumb:

$p \geq 4$ for quarterly data

use lags 1 – 6 and 11 – 13 for monthly