

8.3 Serially Correlated Errors

Consider the case where the error term is serially correlated.

8.3.1 Augmented Dickey-Fuller (ADF) Test

Consider the following AR(p) model:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t, \quad \epsilon_t \sim \text{iid}(0, \sigma^2),$$

which is rewritten as: $\phi(L)y_t = \epsilon_t$.

When the above model has a unit root, we have $\phi(1) = 0$, i.e., $\phi_1 + \phi_2 + \cdots + \phi_p = 1$.

The above AR(p) model is written as:

$$y_t = \rho y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_t,$$

where $\rho = \phi_1 + \phi_2 + \cdots + \phi_p$ and $\delta_j = -(\phi_{j+1} + \phi_{j+2} + \cdots + \phi_p)$.

The null and alternative hypotheses are:

$$H_0 : \rho = 1 \text{ (Unit root),}$$

$$H_1 : \rho < 1 \text{ (Stationary).}$$

Use the t test, where we have the same asymptotic distributions.

We can utilize the same tables as before.

Choose p by AIC or SBIC.

Use $N(0, 1)$ to test $H_0 : \delta_j = 0$ against $H_1 : \delta_j \neq 0$ for $j = 1, 2, \dots, p - 1$.

Reference

Kurozumi (2008) “Economic Time Series Analysis and Unit Root Tests: Development and Perspective,” *Japan Statistical Society*, Vol.38, Series J, No.1, pp.39 – 57.

Download the above paper from:

http://ci.nii.ac.jp/vol_issue/nels/AA11989749/ISS0000426576_ja.html

Example of ADF Test

```
. gen time=_n
. tsset time
    time variable:  time, 1 to 516
                delta: 1 unit
. gen sexpend=expend-112.expend
(12 missing values generated)
. corrgram sexpend
```

LAG	AC	PAC	Q	Prob>Q	$^{-1}$ [Autocorrelation]	0 [Partial Autocor]	1
1	0.7177	0.7184	261.14	0.0000	-----	-----	-----
2	0.7036	0.3895	512.6	0.0000	-----	-----	---
3	0.7031	0.2817	764.23	0.0000	-----	-----	--
4	0.6366	0.0456	970.94	0.0000	-----	-----	
5	0.6413	0.1116	1181.1	0.0000	-----	-----	
6	0.6267	0.0815	1382.2	0.0000	-----	-----	
7	0.6208	0.0972	1580	0.0000	-----	-----	
8	0.6384	0.1286	1789.5	0.0000	-----	-----	-
9	0.5926	-0.0205	1970.5	0.0000	-----	-----	
10	0.5847	-0.0014	2146.9	0.0000	-----	-----	
11	0.5658	-0.0185	2312.6	0.0000	-----	-----	
12	0.4529	-0.2570	2418.9	0.0000	-----	-----	--
13	0.5601	0.2318	2581.8	0.0000	-----	-----	-
14	0.5393	0.1095	2733.2	0.0000	-----	-----	
15	0.5277	0.0850	2878.4	0.0000	-----	-----	

. varsoc d.sexpend, exo(l.sexpend) maxlag(25)

Selection-order criteria

Sample: 39 - 516

Number of obs

=

478

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-4917.7				5.1e+07	20.5845	20.5914	20.6019
1	-4878.69	78.013	1	0.000	4.3e+07	20.4255	20.4358	20.4516
2	-4858.95	39.481	1	0.000	4.0e+07	20.3471	20.3608	20.382
3	-4858.46	.97673	1	0.323	4.0e+07	20.3492	20.3664	20.3928
4	-4855.44	6.0461	1	0.014	4.0e+07	20.3407	20.3613	20.3931
5	-4853.84	3.1904	1	0.074	4.0e+07	20.3383	20.3623	20.3993
6	-4851.58	4.5304	1	0.033	4.0e+07	20.333	20.3604	20.4027
7	-4847.61	7.942	1	0.005	3.9e+07	20.3205	20.3514	20.399
8	-4847.51	.20154	1	0.653	3.9e+07	20.3243	20.3586	20.4115
9	-4847.51	.00096	1	0.975	3.9e+07	20.3285	20.3662	20.4244
10	-4847.43	.16024	1	0.689	4.0e+07	20.3323	20.3735	20.437
11	-4831.38	32.094	1	0.000	3.7e+07	20.2694	20.3139	20.3828
12	-4818.46	25.834	1	0.000	3.5e+07	20.2195	20.2675	20.3416*
13	-4815.64	5.6341	1	0.018	3.5e+07	20.2119	20.2633	20.3427
14	-4813.98	3.321	1	0.068	3.5e+07	20.2091	20.264	20.3487
15	-4813.38	1.2007	1	0.273	3.5e+07	20.2108	20.2691	20.3591
16	-4810.57	5.6184	1	0.018	3.5e+07	20.2032	20.265	20.3603
17	-4808.7	3.7539	1	0.053	3.5e+07	20.1996	20.2647	20.3653
18	-4806.12	5.1557	1	0.023	3.4e+07	20.195	20.2616	20.3674
19	-4804.6	3.0319	1	0.082	3.4e+07	20.1908	20.2628	20.374
20	-4804.6	2.7e-05	1	0.996	3.5e+07	20.195	20.2704	20.3869
21	-4797.33	14.542	1	0.000	3.4e+07	20.1688	20.2476	20.3694
22	-4794.2	6.2571*	1	0.012	3.3e+07*	20.1598*	20.2422*	20.3692
23	-4793.42	1.5626	1	0.211	3.3e+07	20.1608	20.2465	20.3788
24	-4792.85	1.1533	1	0.283	3.3e+07	20.1625	20.2517	20.3893

```
| 25 | -4792.78 .13518 1 0.713 3.4e+07 20.1664 20.259 20.402 |
+-----+
Endogenous: D.sexpend
Exogenous: L.sexpend _cons
```

```
. dfuller sexpend, lags(22)
```

```
Augmented Dickey-Fuller test for unit root          Number of obs   =          481
```

```

          Test          ----- Interpolated Dickey-Fuller -----
          Statistic      1% Critical  5% Critical  10% Critical
                          Value       Value       Value
-----
Z(t)          -1.627          -3.442          -2.871          -2.570
-----
```

```
MacKinnon approximate p-value for Z(t) = 0.4689
```

```
. dfuller sexpend, lags(12)
```

```
Augmented Dickey-Fuller test for unit root          Number of obs   =          491
```

```

          Test          ----- Interpolated Dickey-Fuller -----
          Statistic      1% Critical  5% Critical  10% Critical
                          Value       Value       Value
-----
Z(t)          -2.399          -3.441          -2.870          -2.570
-----
```

```
MacKinnon approximate p-value for Z(t) = 0.1420
```

⇒ Unit root is detected.

8.4 Cointegration (共和分)

1. For a scalar y_t , when $\Delta y_t = y_t - y_{t-1}$ is a white noise (i.e., iid), we write $\Delta y_t \sim I(1)$.

2. Definition of Cointegration:

Suppose that each series in a $g \times 1$ vector y_t is $I(1)$, i.e., each series has unit root, and that a linear combination of each series (i.e. $a'y_t$ for a nonzero vector a) is $I(0)$, i.e., stationary.

Then, we say that y_t has a cointegration.

a is called the cointegrating vector.

3. Example:

Suppose that $y_t = (y_{1,t}, y_{2,t})'$ is the following vector autoregressive process:

$$y_{1,t} = \phi_1 y_{2,t} + \epsilon_{1,t},$$

$$y_{2,t} = y_{2,t-1} + \epsilon_{2,t}.$$

Then,

$$\Delta y_{1,t} = \phi_1 \epsilon_{2,t} + \epsilon_{1,t} - \epsilon_{1,t-1}, \quad (\text{MA}(1) \text{ process}),$$

$$\Delta y_{2,t} = \epsilon_{2,t},$$

where both $y_{1,t}$ and $y_{2,t}$ are $I(1)$ processes.

The linear combination $y_{1,t} - \phi_1 y_{2,t}$ is $I(0)$.

In this case, we say that $y_t = (y_{1,t}, y_{2,t})'$ is cointegrated with $a = (1, -\phi_1)$.

$a = (1, -\phi_1)$ is called the cointegrating vector, which is not unique.

Therefore, the first element of a is set to be one.

8.5 Spurious Regression (見せかけ回帰)

1. Suppose that $y_t \sim I(1)$ and $x_t \sim I(1)$.

For the regression model $y_t = x_t \beta + u_t$, OLS does not work well if we do not have the β which satisfies $u_t \sim I(0)$.

⇒ **Spurious regression** (見せかけ回帰)

2. Suppose that $y_t \sim I(1)$, y_t is a $g \times 1$ vector and $y_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix}$.
 $y_{2,t}$ is a $k \times 1$ vector, where $k = g - 1$.

Consider the following regression model:

$$y_{1,t} = \alpha + \gamma' y_{2,t} + u_t, \quad t = 1, 2, \dots, T.$$

OLSE is given by:

$$\begin{pmatrix} \hat{\alpha} \\ \hat{\gamma} \end{pmatrix} = \begin{pmatrix} T & \sum y'_{2,t} \\ \sum y_{2,t} & \sum y_{2,t} y'_{2,t} \end{pmatrix}^{-1} \begin{pmatrix} \sum y_{1,t} \\ \sum y_{1,t} y_{2,t} \end{pmatrix}.$$

Next, consider testing the null hypothesis $H_0 : R\gamma = r$, where R is a $m \times k$ matrix ($m \leq k$) and r is a $m \times 1$ vector.

The F statistic, denoted by F_T , is given by:

$$F_T = \frac{1}{m} (R\hat{\gamma} - r)' \left(s_T^2 \begin{pmatrix} 0 & R \end{pmatrix} \begin{pmatrix} T & \sum y'_{2,t} \\ \sum y_{2,t} & \sum y_{2,t} y'_{2,t} \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ R' \end{pmatrix} \right)^{-1} (R\hat{\gamma} - r),$$

where

$$s_T^2 = \frac{1}{T-g} \sum_{t=1}^T (y_{1,t} - \hat{\alpha} - \hat{\gamma}' y_{2,t})^2.$$

When we have the γ such that $y_{1,t} - \gamma y_{2,t}$ is stationary, OLSE of γ , i.e., $\hat{\gamma}$, is not statistically equal to zero.

When the sample size T is large enough, H_0 is rejected by the F test.

3. Phillips, P.C.B. (1986) “Understanding Spurious Regressions in Econometrics,” *Journal of Econometrics*, Vol.33, pp.95 – 131.

Consider a $g \times 1$ vector y_t whose first difference is described by:

$$\Delta y_t = \Psi(L)\epsilon_t = \sum_{s=0}^{\infty} \Psi_s \epsilon_{t-s},$$

for ϵ_t an i.i.d. $g \times 1$ vector with mean zero, variance $E(\epsilon_t \epsilon_t') = PP'$, and finite fourth moments and where $\{s\Psi_s\}_{s=0}^{\infty}$ is absolutely summable.

Let $k = g - 1$ and $\Lambda = \Psi(1)P$.

Partition y_t as $y_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix}$ and $\Lambda\Lambda'$ as $\Lambda\Lambda' = \begin{pmatrix} \Sigma_{11} & \Sigma'_{21} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$, where $y_{1,t}$ and Σ_{11} are scalars, $y_{2,t}$ and Σ_{21} are $k \times 1$ vectors, and Σ_{22} is a $k \times k$ matrix.

Suppose that $\Lambda\Lambda'$ is nonsingular, and define $\sigma_1^{*2} = \Sigma_{11} - \Sigma'_{21}\Sigma_{22}^{-1}\Sigma_{21}$.

Let L_{22} denote the Cholesky factor of Σ_{22}^{-1} , i.e., L_{22} is the lower triangular matrix satisfying $\Sigma_{22}^{-1} = L_{22}L'_{22}$.

Then, (a) – (c) hold.

- (a) OLSEs of α and γ in the regression model $y_{1,t} = \alpha + \gamma'y_{2,t} + u_t$, denoted by $\hat{\alpha}_T$ and $\hat{\gamma}_T$, are characterized by:

$$\begin{pmatrix} T^{-1/2}\hat{\alpha}_T \\ \hat{\gamma}_T - \Sigma_{22}^{-1}\Sigma_{21} \end{pmatrix} \rightarrow \begin{pmatrix} \sigma_1^* h_1 \\ \sigma_1^* L_{22} h_2 \end{pmatrix},$$

where
$$\begin{pmatrix} h_1 \\ h_2 \end{pmatrix} = \begin{pmatrix} 1 & \int_0^1 W_2^*(r)' dr \\ \int_0^1 W_2^*(r) dr & \int_0^1 W_2^*(r)W_2^*(r)' dr \end{pmatrix}^{-1} \begin{pmatrix} \int_0^1 W_1^*(r) dr \\ \int_0^1 W_2^*(r)W_1^*(r) dr \end{pmatrix}.$$

$W_1^*(r)$ and $W_2^*(r)$ denote scalar and g -dimensional standard Brownian motions, and $W_1^*(r)$ is independent of $W_2^*(r)$.

- (b) The sum of squared residuals, denoted by $\text{RSS}_T = \sum_{t=1}^T \hat{u}_t^2$, satisfies

$$T^{-2}\text{RSS}_T \rightarrow \sigma_1^{*2}H,$$

where
$$H = \int_0^1 (W_1^*(r))^2 dr - \left(\left(\begin{pmatrix} \int_0^1 W_1^*(r) dr \\ \int_0^1 W_2^*(r)W_1^*(r) dr \end{pmatrix}' \begin{pmatrix} h_1 \\ h_2 \end{pmatrix} \right) \right)^{-1}.$$

- (c) The F_T test satisfies:

$$T^{-1}F_T \rightarrow \frac{1}{m}(\sigma_1^* R^* h_2 - r^*)' \times \left(\sigma_1^{*2} H \begin{pmatrix} 0 & R^* \end{pmatrix} \begin{pmatrix} 1 & \int_0^1 W_2^*(r)' dr \\ \int_0^1 W_2^*(r) dr & \int_0^1 W_2^*(r)W_2^*(r)' dr \end{pmatrix}^{-1} \begin{pmatrix} 0 & R^* \end{pmatrix}' \right)^{-1}$$

$$\times(\sigma_1^* R^* h_2 - r^*),$$

where $R^* = RL_{22}$ and $r^* = r - R\Sigma_{22}^{-1}\Sigma_{21}$.

Summary: Spurious regression (見せかけの回帰)

Consider the regression model: $y_{1,t} = \alpha + y_{2,t}\gamma + u_t$ for $t = 1, 2, \dots, T$

and $y_t \sim I(1)$ for $y_t = (y_{1,t}, y_{2,t})'$.

(a) indicates that OLSE $\hat{\gamma}_T$ is not consistent.

(b) indicates that $s_T^2 = \frac{1}{T-g} \sum_{t=1}^T \hat{u}_t^2$ diverges.

(c) indicates that F_T diverges.

\Rightarrow It seems that the coefficients are statistically significant, based on the conventional t statistics.