

# TP 6 Correction

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The model of the ordinary least squares is considered under the following hypotheses :

- H1 : The model is linear in  $x_{i,t}$
- H2 : the values  $x_{i,t}$  are observed without error
- H3 :  $\mathbb{E}[u] = 0$  the mean of the error is equal to zero
- H4 :  $\mathbb{E}[u^t u] = \sigma^2 I_n$ , the variance of the error is constant
- H5 :  $\mathbb{E}[u_t u_{t+1}] = 0$ , the errors are not correlated
- H6 :  $Cov(x_{i,t}, u_t) = 0$ , the error is independent of the explanatory variable

## 1 Autocorrelation in the error

The violation of hypothesis H5 concerns time series where the off-diagonal elements of the covariance matrix of the errors are nonzero. In this case, the obtained OLS estimators are unbiased but no longer have a minimal variance. Thus, we must identify new estimators and techniques for detecting possible autocorrelation of the errors.

### Exercise 1

We consider a model

$$i3t = \beta_0 + \beta_1 inf t + \beta_2 def t + u_t$$

for  $t = 1, \dots, n$ . From TP5, we know that the error term is an AR(1) process :

$$u_t = \rho u_{t-1} + e_t$$

with  $|\rho| < 1$  (stability condition), and such that  $e_t$  are independent, zero mean random variables with variance  $\sigma_e^2$ . Thus, the form of  $u_t$  implies the autocorrelation in the error term.

### 1.1 Data transformation

We write the model in matrix form :

$$\begin{aligned} Y &= X\beta + u \\ u_t &= \rho u_{t-1} + e_t \end{aligned}$$

Note that  $e$  are zero mean random variables with constant variance  $\sigma_e^2$ . Thus,  $Var(u_t) = \frac{\sigma_e^2}{1-\rho^2} = \sigma_u^2$  and  $\mathbb{E}[u_t u_{t-i}] = \rho^i \sigma_u^2$ . The covariance matrix of residuals  $u$  (for AR(1) model) is of the form :

$$\Omega_u = \mathbb{E}[u^t u] = \frac{\sigma_e^2}{1 - \rho^2} \cdot \begin{pmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T-1} \\ \rho & 1 & & & \\ \rho^2 & & & & \\ \cdots & & & & \\ \cdots & & & & \\ \rho^{T-1} & & & & 1 \end{pmatrix}$$

Since  $\Omega_u$  is symmetric and positive definite, there exists matrix  $P$  such that  $\Omega_u^{-1} = P^\top P$  (Choleski decomposition). The model  $PY = PX + Pu$  has independent and homoskedastic errors. The matrix  $P$  for the covariance  $\Omega_u$  of AR(1) process is of the form :

$$P = \begin{pmatrix} \sqrt{1 - \rho^2} & 0 & 0 & \cdots & 0 \\ -\rho & 1 & 0 & & 0 \\ 0 & -\rho & 1 & & 0 \\ \cdots & & & & 0 \\ \cdots & & & & 0 \\ 0 & & & -\rho & 1 \end{pmatrix}$$

We multiply  $Y$  by matrix  $P$ , ie.  $Y \mapsto PY$  and compute  $y_t - \rho y_{t-1}$  for  $t = 2 \dots T$  and we take  $\sqrt{1 - \rho^2} y_1$  for the first observation. Code :

```
y = intdef(:, 2);
[n, k] = size(intdef)
X = [ones(n, 1), intdef(:, [3, 6])];
```

```
y_ = [y(2 : n)]
y_lag = [y(1 : n - 1)]
new_y = [sqrt(1 - rho^2) * y(1);
y_ - rho * y_lag]
```

```
X_ = [X(2 : n, :)]
X_lag = [X(1 : n - 1, :)]
new_X = [sqrt(1 - rho^2) * X(1, :);
X_ - rho * X_lag]
P = zeros(n, n);
v = repmat(1, 1, n)
P = P + diag(v, 0)
v = repmat(-rho, 1, n - 1)
P = P + diag(v, -1)
P(1, 1) = sqrt(1 - rho^2)
```

```
new_y_bis = P * y
new_X_bis = P * X
```

We perform OLS estimation for transformed data :

$$\begin{aligned}[n, k] &= \text{size}(\text{new\_X}) \\ \text{beta} &= \text{inv}(\text{new\_X}' * \text{new\_X}) * \text{new\_X}' * \text{new\_y} \\ u &= \text{new\_y} - \text{new\_X} * \text{beta};\end{aligned}$$

## 2 Granger causality

Consider two series  $y_t$  and  $z_t$  such that

$$y_t = \delta_0 + \alpha_1 y_{t-1} + \gamma_1 z_{t-1} + \alpha_2 y_{t-2} + \gamma_2 z_{t-2} + \dots$$

and

$$z_t = \eta_0 + \beta_1 y_{t-1} + \rho_1 z_{t-1} + \beta_2 y_{t-2} + \rho_2 z_{t-2} + \dots,$$

where each equation contains an error that has zero expected value given past information on  $y$  and  $z$ . Such equations allow us to test whether, after controlling for past  $y$ , past  $z$  help to forecast  $y_t$ .

Generally, we say that  $z$  **Granger causes**  $y$  if

$$E(y_t | I_{t-1}) \neq E(y_t | J_{t-1}), \quad (1)$$

where  $I_{t-1}$  contains past information on  $y$  and  $z$ , and  $J_{t-1}$  contains only information on past  $y$ . When (1) holds, past  $z$  is useful, in addition to past  $y$ , for predicting  $y_t$ .

### Exercise 2

We consider a model

$$i3_t = \beta_0 + \beta_1 \text{inf}_{t-1} + \beta_2 \text{inf}_{t-2} + \beta_3 \text{def}_{t-1} + \beta_4 \text{def}_{t-2} + u_t$$

for  $t = 1 \dots n$ . Code :

$$\begin{aligned}y &= \text{intdef}(:, 2); \\ [n, k] &= \text{size}(\text{intdef}) \\ X &= [\text{intdef}(:, [3, 6])]; \\ y &= \text{intdef}(3 : n, 2); \\ X\_lag &= [X(2 : n - 1, :)] \\ X\_lag2 &= [X(1 : n - 2, :)] \\ X &= [X\_lag X\_lag2] \\ [n, k] &= \text{size}(X) \\ \text{beta} &= \text{inv}(X' * X) * X' * y\end{aligned}$$

We want to test the significance of inflation and budget deficit (Granger causality test) :  $H_0 : \beta_1 = \beta_2 = 0$  and  $H_0 : \beta_3 = \beta_4 = 0$ . Code :

$$\begin{aligned}SSR0 &= u' * u; \\ X &= X(:, [2, 4]); \\ \text{beta1} &= \text{inv}(X' * X) * X' * y;\end{aligned}$$

$$u1 = y - X * beta1;$$

$$SSR1 = u1' * u1;$$

$$F = ((SSR1 - SSR0)/SSR0) * ((n - k)/2);$$

$$p = fdis\_prb(F, 2, n - k)$$

$$X = [X\_lagX\_lag2];$$

$$X = X(:, [1, 3]);$$

$$beta1 = inv(X' * X) * X' * y;$$

$$u1 = y - X * beta1;$$

$$SSR1 = u1' * u1;$$

$$F = ((SSR1 - SSR0)/SSR0) * ((n - k)/2);$$

$$p = fdis\_prb(F, 2, n - k)$$

We obtain respectively  $p = 1.1491^{-14}$  and  $p = 1.4639^{-4}$  thus, we strongly reject  $H_0$  each time.