

Auto-correlation of Error Terms

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General Auto-correlation (1)

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{v}$$

$$\mathbf{E}(\mathbf{v}) = \mathbf{0}$$

$$\mathbf{V}(\mathbf{v}) = \sigma^2 \boldsymbol{\Sigma}$$

where

$\mathbf{0}$ is a $n \times 1$ column vector of zeroes

$\boldsymbol{\Sigma}$ is an $n \times n$ positive-definite symmetric matrix.

Covered Topics

- GLS
- Assumptions
- Detection, e.g.,
 - Durbin-Watson d-test
 - Breusch-Godfrey test
- Estimation Methods, e.g.,
 - Cochrane-Orcutt

General Auto-correlation (2)

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdot & \sigma_{1n} \\ \sigma_{12} & \sigma_{22} & \cdot & \sigma_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ \sigma_{1n} & \sigma_{2n} & \cdot & \sigma_{nn} \end{bmatrix}$$

where $\sigma^2 \sigma_{ij} = V(v_i, v_j)$ for $i, j = 1, \dots, n$

General Auto-correlation (3)

Sources of Auto-correlation

- Inertia (nature)
- Spill-over effect over geographical region, e.g., contagion, migration (nature)
- Spec. errors, e.g.,
 - Exclusion of auto-correlated independent variables
 - Incorrect functional form
 - Lagged terms

Generalized LS (1)

$$\Omega Y = \Omega X \beta + \Omega v$$

where Ω is an $n \times n$ symmetric matrix such that

$$\Omega \Omega = \Sigma^{-1}$$

Note that $E(\Omega v) = \mathbf{0}$ and $V(\Omega v) = \sigma^2 \mathbf{I}_n$

General Auto-correlation (4)

Effect of Ignoring Pure Auto-correlation

- OLS is unbiased but not the best
- Need new estimate of Σ , e.g.,
 - Newey-West formula

Generalized LS (2)

If Σ is known, apply OLS to BLU estimate β, σ^2

$$\begin{aligned}\hat{\beta} &= \left[(\Omega X)^T (\Omega X) \right]^{-1} (\Omega X)^T (\Omega Y) \\ &= \left[X^T \Sigma^{-1} X \right]^{-1} X^T \Sigma^{-1} Y\end{aligned}$$

$$\begin{aligned}\hat{\sigma}^2 &= \frac{1}{n-K} \left(\Omega(Y - X\hat{\beta}) \right)^T \left(\Omega(Y - X\hat{\beta}) \right) \\ &= \frac{1}{n-K} (Y - X\hat{\beta})^T \Sigma^{-1} (Y - X\hat{\beta})\end{aligned}$$

What if Σ is unknown? Need more assumptions?

Assumptions

$$Y_i = X_{1i}\beta_1 + X_{2i}\beta_2 + \dots + X_{Ki}\beta_K + v_i$$

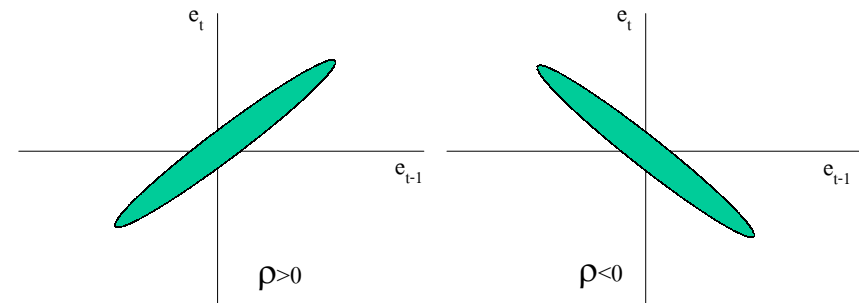
$$i = 1, \dots, n$$

In addition to CLRM assumptions

- ARMA error term (v)
- weakly stationary error term. Otherwise, estimation will be invalid. Why?

AR(1) error term --(2)

Graphical Test



where e is the OLS residual when auto-correlation has been ignored

AR(1) error term --(1)

$$Y_t = X_{1t}\beta_1 + X_{2t}\beta_2 + \dots + X_{Kt}\beta_K + \rho v_{t-1} + \varepsilon_t$$

$$-1 < \rho < 1, \quad t = 1, \dots, n$$

$\varepsilon_t \sim$ White Noise

$$H_0 : \rho = 0$$

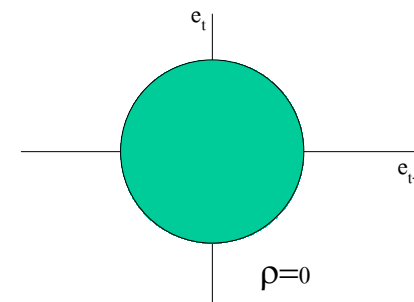
$$H_1 : \rho \neq 0$$

Accept \implies No auto-correlation

Reject \implies AR(1)

AR(1) error term --(3)

Graphical Test (cont'd)



Note that plot of e_t vs e_{t-1} cannot reveal higher AR in error terms

AR(p) error term --(1)

$$Y_t = X_{1t}\beta_1 + X_{2t}\beta_2 + \dots + X_{Kt}\beta_K + \rho v_t$$

$$v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \dots + \rho_p v_{t-p} + \varepsilon_t$$

~ stationary

$\varepsilon_t \sim$ White Noise

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_p = 0$$

$$H_1 : \rho_1 \neq \rho_2 \neq \dots \neq \rho_p \neq 0$$

Accept \implies No auto-correlation

Reject \implies AR(p) or lower

Durbin-Watson's d-test (1)

$$DW = \frac{\sum_{t=2}^n (e_t - e_{t-1})^2}{\sum_{t=1}^n e_t^2}$$

Note that t=2

DW statistic follows a special distribution. Need a special table to perform AR(1) test.

See Table D.5A-B (Gujarati)

Auto-correlation Tests

Statistical Tests

- Durbin-Watson's d-test. Good only for AR(1).
- DW's h-test (obsolete)
- BG's General Auto-correlation or Serial Correlation test
- Runs test (non-parametric). Not require normal error term nor ARMA form. Good for small sample.

Durbin-Watson's d-test (2)

$$DW = \frac{\sum_{t=2}^n (e_t^2 - 2e_{t-1}e_{t-1} + e_{t-1}^2)}{\sum_{t=1}^n e_t^2}$$

$$= \frac{\sum_{t=2}^n e_t^2}{\sum_{t=1}^n e_t^2} - 2 \frac{\sum_{t=2}^n e_{t-1}e_{t-1}}{\sum_{t=1}^n e_t^2} + \frac{\sum_{t=2}^n e_{t-1}^2}{\sum_{t=1}^n e_t^2}$$

$$\approx 1 - 2\hat{\rho} + 1 = 2(1 - \hat{\rho})$$

$$\implies 0 \leq DW \leq 4$$

Durbin-Watson's d-test (3)

Given significant level(α) and sample size (n),
read d_L and d_U from DW tables.

Criterion:

$$0 \leq DW \leq d_L \implies \rho > 0 \text{ pos. auto-corr.}$$

$$d_L \leq DW \leq d_U \implies \rho \geq 0 \text{ indecisive}$$

$$d_U \leq DW \leq 4 - d_L \implies \rho = 0 \text{ zero auto-corr.}$$

$$4 - d_L \leq DW \leq 4 - d_U \implies \rho \leq 0 \text{ indecisive}$$

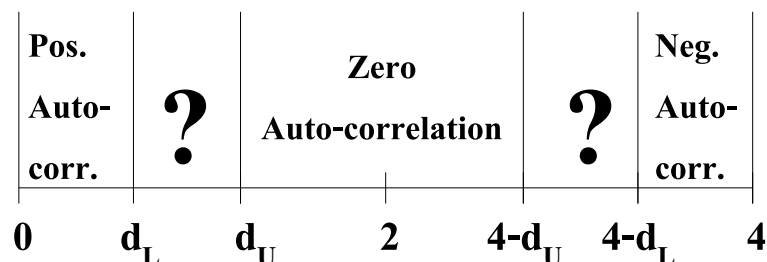
$$4 - d_U \leq DW \leq 4 \implies \rho < 0 \text{ neg. auto-corr.}$$

Durbin-Watson's d-test (4)

Notes

- DW is invalid if there are lagged dependent variables as explanatory variables (AR Model). Their existence is equivalent to higher AR of error terms
- Good only for AR(1). DW statistic is usually an item in the OLS report.
- DW can be used to roughly estimate ρ but no SE given.

Durbin-Watson's d-test (4)



Note that the conclusion is not simply
“Accept” or “Reject”.

Breusch-Godfrey's test (1)

Step 1 Run OLS by ignoring
auto-correlation

\implies residual \hat{v}_t

Step 2 run OLS for

$$\hat{v}_t = X_{1t}\beta_1 + X_{2t}\beta_2 + \dots + X_{Kt}\beta_K + \rho_1\hat{v}_{t-1} + \rho_2\hat{v}_{t-2} + \dots + \rho_p\hat{v}_{t-p} + \varepsilon'_t$$

Breusch-Godfrey's test (2)

Step 3 Do F-Test or χ^2 test for

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_p = 0$$

$$H_1 : \rho_1 \neq \rho_2 \neq \dots \neq \rho_p \neq 0$$

Accept $H_0 \Rightarrow$ no AR(p) auto-corr.

Reject \Rightarrow AR(p) or lower

Note that BG test also gives estimate for ρ 's and their SE's but still not the best estimates.

Cochrane-Orcutt Method (1)

For AR(p) error term

Step 1 Run OLS by ignoring auto-correlation

\Rightarrow residual \hat{v}_t

Step 2 run OLS for

$$\hat{v}_t = \rho_1 \hat{v}_{t-1} + \rho_2 \hat{v}_{t-2} + \dots + \rho_p \hat{v}_{t-p} + \varepsilon'_t$$

$\Rightarrow \hat{\rho}_1, \hat{\rho}_2, \dots, \hat{\rho}_p$

Step 3 Transform Y and X 's

Breusch-Godfrey's test (3)

$$\begin{aligned} F_{cal} &= \frac{(RSS_R - RSS_U) \div p}{RSS_U \div (n - K - p)} \\ &= \frac{(TSS_U - RSS_U) \div p}{RSS_U \div (n - K - p)} \\ &= \frac{n - K - p}{p} R^2 \sim F(p, n - K - p) \end{aligned}$$

$$\chi^2_{cal} = (n - p)R^2 \sim \chi^2(p)$$

Cochrane-Orcutt Method (2)

Step 3 Transform Y and X 's

$$Y_t^* = Y_t - \hat{\rho}_1 Y_{t-1} - \hat{\rho}_2 Y_{t-2} - \dots - \hat{\rho}_p Y_{t-p}$$

$$X_{kt}^* = X_{kt} - \hat{\rho}_1 X_{k,t-1} - \hat{\rho}_2 X_{k,t-2} - \dots - \hat{\rho}_p X_{k,t-p}$$

$$k = 1, \dots, K$$

Step 4 Run OLS for

$$Y_t^* = X_{1t}^* \beta_1 + X_{2t}^* \beta_2 + \dots + X_{Kt}^* \beta_K + v_t^*$$

$$v_t^* \approx v_t - \rho_1 v_{t-1} - \rho_2 v_{t-2} - \dots - \rho_p v_{t-p}$$

$= \varepsilon_t$

Cochrane-Orcutt Method (3)

$$V(\mathbf{v}_t^*) \approx V(\boldsymbol{\varepsilon}_t) = \sigma^2$$

==> OLS is almost BLUE

Step 5 Re-calculate \hat{v}_t using new $\hat{\boldsymbol{\beta}}$

$$\hat{v}_t = Y_t - X_{1t}\hat{\beta}_1 - X_{2t}\hat{\beta}_2 - \dots - X_{Kt}\hat{\beta}_K$$

If solution does not significantly change, stop. Otherwise, go back to Step 2

MA Part Estimation (2)

$$\hat{\gamma}_1(\theta_1, \theta_2 + \theta_2\theta_3 + \dots + \theta_{q-1}\theta_q) = (\theta_1^2 + \theta_2^2 + \dots + \theta_q^2)$$

$$\hat{\gamma}_2(\theta_1, \theta_3 + \theta_2\theta_4 + \dots + \theta_{q-2}\theta_q) = (\theta_1^2 + \theta_2^2 + \dots + \theta_q^2)$$

⋮

$$\hat{\gamma}_q(\theta_1, \theta_q) = (\theta_1^2 + \theta_2^2 + \dots + \theta_q^2)$$

q unknown q equations ==> solve for $\hat{\boldsymbol{\theta}}$

Add as step 4.1 in Cochrane-Orcutt

MA Part Estimation (1)

Note that

$$\mathbf{v}_t^* = \boldsymbol{\varepsilon}_t + \theta_1\boldsymbol{\varepsilon}_{t-1} + \theta_2\boldsymbol{\varepsilon}_{t-2} + \dots + \theta_q\boldsymbol{\varepsilon}_{t-q}$$

$$\text{Cov}(\mathbf{v}_t^*, \mathbf{v}_t^*) = \sigma^2(\theta_1^2 + \theta_2^2 + \dots + \theta_q^2)$$

$$\text{Cov}(\mathbf{v}_t^*, \mathbf{v}_{t-1}^*) = \sigma^2(\theta_1\theta_2 + \theta_2\theta_3 + \dots + \theta_{q-1}\theta_q)$$

⋮

$$\text{Cov}(\mathbf{v}_t^*, \mathbf{v}_{t-q}^*) = \sigma^2(\theta_1\theta_q)$$