

SIMPLE EXAMPLE OF THE EFFECTS OF SPATIAL AUTOCORRELATION

Given the simple spatial model:

$$(1) \quad Y(s) = \mu + \varepsilon(s), \quad s \in \{s_1, \dots, s_n\}$$

suppose it is assumed that $\varepsilon(s) \underset{iid}{\sim} N(0, \sigma^2)$ so that in matrix form we have:

$$(2) \quad Y = \mu \cdot 1 + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I)$$

[with $1 = (1, \dots, 1)'$]. Then it is well known that the *sample-mean estimator*,

$$(3) \quad \bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$$

is the *minimum-variance linear unbiased estimator* for μ , and in particular, that this minimum variance is given by

$$(4) \quad \text{var}(\bar{Y}) = \frac{\sigma^2}{n}$$

But suppose that in reality there is *positive spatial autocorrelation* among the residuals in (2) so that in fact:

$$(5) \quad \text{cov}(\varepsilon) = \begin{bmatrix} \text{cov}(\varepsilon_1, \varepsilon_1) & \cdots & \text{cov}(\varepsilon_1, \varepsilon_n) \\ \vdots & \ddots & \vdots \\ \text{cov}(\varepsilon_n, \varepsilon_1) & \cdots & \text{cov}(\varepsilon_n, \varepsilon_n) \end{bmatrix} = \begin{pmatrix} \sigma^2 & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \cdots & \sigma^2 \end{pmatrix} \geq \sigma^2 I$$

with $\sigma_{ij} > 0$ for many distinct (i, j) pairs. Then [as in expression (4.10.3) of the NOTEBOOK] it follows that since $\text{cov}(Y) = \text{cov}(\varepsilon)$, the true variance of \bar{Y} is given by

$$(6) \quad \begin{aligned} \text{var}(\bar{Y}) &= \text{var}\left(\frac{1}{n} \sum_{i=1}^n Y_i\right) = \frac{1}{n^2} \left(\sum_{i=1}^n \text{var}(Y_i) + \sum_i \sum_{j \neq i} \text{cov}(Y_i, Y_j) \right) \\ &= \frac{1}{n^2} \sum_{i=1}^n \text{var}(Y_i) + \frac{1}{n^2} \sum_i \sum_{j \neq i} \text{cov}(Y_i, Y_j) = \frac{1}{n^2} \sum_{i=1}^n \sigma^2 + \frac{1}{n^2} \sum_i \sum_{j \neq i} \sigma_{ij} \\ &= \frac{1}{n^2} (n\sigma^2) + \frac{1}{n^2} \sum_i \sum_{j \neq i} \sigma_{ij} = \frac{\sigma^2}{n} + \frac{1}{n^2} \sum_i \sum_{j \neq i} \sigma_{ij} \end{aligned}$$

which together with the positive spatial dependencies shows that:

$$(7) \quad \text{var}(\bar{Y}) \gg \frac{\sigma^2}{n} \Rightarrow \sigma(\bar{Y}) \gg \frac{\sigma}{\sqrt{n}}$$

Hence if we consider, say, a 95% confidence interval for the true mean, μ , then the *actual* interval is given by

$$(8) \quad CI_{\text{actual}} = [\bar{Y} \pm (1.96)\sigma(\bar{Y})]$$

rather than the *assumed* interval

$$(9) \quad CI_{\text{assumed}} = \left[\bar{Y} \pm (1.96)\frac{\sigma}{\sqrt{n}} \right]$$

So for any given estimate, \bar{y} , this implies from (7) that

