

Estimation of variance of LLE

LE_{exp} and LE_C are asymptotically normal random variables, so their difference LLE is also random variable with $N(\mu; \Sigma)$, where the expectation $\mu = E(LLE) = E(LE_{\text{exp}}) - E(LE_C)$ and variance-covariance matrix Σ can be found by matrix multiplication:

$$\Sigma = G^T \cdot V \cdot G, \quad (1)$$

where

$$G = \left(\frac{\partial (LE_{\text{exp}} - LE_C)}{\partial \beta} \right) = \begin{pmatrix} \frac{\partial (LE_{\text{exp}} - LE_C)}{\partial \widehat{\beta}_{21}} \\ \frac{\partial (LE_{\text{exp}} - LE_C)}{\partial \widehat{\beta}_{22}} \\ \cdots \\ \frac{\partial (LE_{\text{exp}} - LE_C)}{\partial \widehat{\beta}_{2p_2}} \\ -\frac{\partial LE_C}{\partial \widehat{\beta}_{11}} \\ \cdots \\ -\frac{\partial LE_C}{\partial \widehat{\beta}_{1p_1}} \end{pmatrix}, \quad (2)$$

where p_1 is the number of parameters in vector β_1 , p_2 is the number of parameters in vector β_2 and β is a vector of $p = p_1 + p_2$ parameters:

$$\widehat{\beta} = (\widehat{\beta}_2 \ \widehat{\beta}_1)^T = (\widehat{\beta}_{21} \ \widehat{\beta}_{22} \ \dots \ \widehat{\beta}_{2p_2} \ \widehat{\beta}_{11} \ \widehat{\beta}_{12} \ \dots \ \widehat{\beta}_{1p_1})^T$$

$$\begin{aligned} \widehat{\frac{\partial LE_C}{\partial \beta}} &= -\frac{\partial \int_0^{t^*} \widehat{Cr}_{cancer}(u) du}{\partial \widehat{\beta}} - \frac{\partial \int_0^{t^*} \widehat{Cr}_{other}(u) du}{\partial \widehat{\beta}} \\ &= -\frac{\partial \int_0^{t^*} \widehat{R}(u) \cdot \widehat{S^*(a_0 + u)} \cdot \widehat{h^*(a_0 + u)} du}{\partial \widehat{\beta}} - \frac{\partial \int_0^{t^*} \widehat{R}(u) \cdot \widehat{S^*(a_0 + u)} \cdot \widehat{\lambda(u)} du}{\partial \widehat{\beta}} \end{aligned}$$

and

$$\widehat{\frac{\partial LE_{\text{exp}}}{\partial \beta}} = \frac{\partial \int_0^{t^*} \widehat{S^*(a_0 + u)} du}{\partial \widehat{\beta}} = \left(\frac{\partial \int_0^{t^*} \widehat{S^*(a_0 + u)}}{\partial \widehat{\beta}_{21}} \ \frac{\partial \int_0^{t^*} \widehat{S^*(a_0 + u)}}{\partial \widehat{\beta}_{22}} \ \dots \ \frac{\partial \int_0^{t^*} \widehat{S^*(a_0 + u)}}{\partial \widehat{\beta}_{2p_2}} \ 0_1 \ \dots \ 0_{p_1} \right)$$

Variance-covariance $p \times p$ matrix V can be presented as:

$$V = \begin{pmatrix} \sigma_{\beta_{21}}^2 & \sigma_{\beta_{21},\beta_{22}} & \dots & \sigma_{\beta_{21},\beta_{2p_2}} & 0 & 0 & \dots & 0 \\ \sigma_{\beta_{22},\beta_{21}} & \sigma_{\beta_{22}}^2 & \dots & \sigma_{\beta_{22},\beta_{2p_2}} & 0 & 0 & \dots & 0 \\ \dots & \dots \\ \sigma_{\beta_{2p_2},\beta_{21}} & \sigma_{\beta_{2p_2},\beta_{22}} & \dots & \sigma_{\beta_{2p_2}}^2 & 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & \sigma_{\beta_{11}}^2 & \sigma_{\beta_{11},\beta_{12}} & \dots & \sigma_{\beta_{11},\beta_{1p_1}} \\ 0 & 0 & \dots & 0 & \sigma_{\beta_{11},\beta_{12}} & \sigma_{\beta_{12}}^2 & \dots & \sigma_{\beta_{12},\beta_{1p_1}} \\ \dots & \dots \\ 0 & 0 & \dots & 0 & \sigma_{\beta_{1p_1},\beta_{11}} & \sigma_{\beta_{1p_1},\beta_{12}} & \dots & \sigma_{\beta_{1p_1}}^2 \end{pmatrix}, \quad (3)$$

where $V_2(\hat{\beta}_2)$ is the variance-covariance matrix from model for expected mortality:

$$V_2(\hat{\beta}_2) = \begin{pmatrix} \sigma_{\beta_{21}}^2 & \sigma_{\beta_{21},\beta_{22}} & \dots & \sigma_{\beta_{21},\beta_{2p_2}} \\ \sigma_{\beta_{22},\beta_{21}} & \sigma_{\beta_{22}}^2 & \dots & \sigma_{\beta_{22},\beta_{2p_2}} \\ \dots & & & \\ \sigma_{\beta_{2p_2},\beta_{21}} & \sigma_{\beta_{2p_2},\beta_{22}} & \dots & \sigma_{\beta_{2p_2}}^2 \end{pmatrix} \quad (4)$$

Variance-covariance matrix $V_1(\hat{\beta}_1)$ from model for excess mortality is then:

$$V_1(\hat{\beta}_1) = \begin{pmatrix} \sigma_{\beta_{11}}^2 & \sigma_{\beta_{11},\beta_{12}} & \dots & \sigma_{\beta_{11},\beta_{1p_1}} \\ \sigma_{\beta_{11},\beta_{12}} & \sigma_{\beta_{12}}^2 & \dots & \sigma_{\beta_{12},\beta_{1p_1}} \\ \dots & & & \\ \sigma_{\beta_{1p_1},\beta_{11}} & \sigma_{\beta_{1p_1},\beta_{12}} & \dots & \sigma_{\beta_{1p_1}}^2 \end{pmatrix} \quad (5)$$