

Ex 1. Dense initial data: $Y_{ij} = Y_m$... claims per policy in m -th cell

$N_{ij} = N_m$... number of policies in m -th cell

and after change: $Y_m^{(k)} = Y_m$... ~~sd~~ claims per policy unchanged

$N_m^{(k)} = k \cdot N_m$... nr. of policies multiplied by k

First, let's review the effect of change on point estimates.

MLE of β is obtained from (2.19). After change,

both sides ~~multiplied~~ multiply by $k \Rightarrow$ solution (the MLE) remains unchanged. Consequently, risk factors e^{β_1} and expected claims per policy

$e^{(\beta)_m}$ do not change as well. Hence, the

change in exposure does not affect the point estimates.

Let's see, how it affects their variabilities.

(a) Covariance matrix of MLE can be approximated by the inverse of Fisher information matrix.

$$\text{var}(\beta_{MLE}) \approx [J(\hat{\beta})]^{-1}, \text{ where}$$

$$(J\hat{\beta})_{jir} = -E\left(\frac{\partial^2 \ell}{\partial \beta_j \partial \beta_r}\right) = -E\left(\frac{\partial}{\partial \beta_r} \left[\sum_m \frac{Y_m - \exp\{(\beta)_m\}}{N_m} \right] \right)$$

$$= \sum_m N_m \cdot \exp\{(\beta)_m\} \cdot R_{mrr} \cdot R_{mrr}$$

after the change, the point estimate $\hat{\beta}$ is unaffected and so

$$\left(J^{(k)}(\hat{\beta}) \right)_{j,r} = \sum_m k \cdot \sigma_m \cdot \exp\{(\mathbf{Z}\hat{\beta})_m\} \cdot Z_{m,r} \cdot R_{m,e} = k \cdot \left[J(\hat{\beta}) \right]_{j,r}$$

In result $\text{var}(\beta_{MLE}^{(k)}) \approx \frac{1}{k} \text{var}(\beta)$.

In particular, variances of MLE of each β_2 is k -times lower after k -times increase in nr. of policies.

(b) For variance of risk factors, we can use linear approximation of exp. function by Taylor polynomial at point estimate $\hat{\beta}_2$:

$$e^{\beta_{MLE,2}} \approx e^{\hat{\beta}_2} + e^{\hat{\beta}_2} \cdot (\beta_{MLE,2} - \hat{\beta}_2)$$

↑ the estimator as random variable
 ↑ point estimate, fixed value

This implies $\text{var}(e^{\beta_{MLE,2}}) \approx (e^{\hat{\beta}_2})^2 \cdot \text{var}(\beta_{MLE,2})$,

and $\text{var}(e^{\beta_{MLE,2}^{(k)}}) \approx \frac{1}{k} \text{var}(e^{\beta_{MLE,2}})$

(c) $EY_m = e^{(\mathbf{Z}\beta_{MLE})_m}$

$$\text{var}(\mathbf{Z}\beta_{MLE})_m = \text{var}(Z_{m,1}\beta_{MLE}) = Z_{m,1} \cdot \text{var}(\beta_{MLE}) \cdot Z_{m,1}^T$$

$$\Rightarrow \text{var}(\mathbf{Z}\beta_{MLE}^{(k)})_m = Z_{m,1} \cdot \text{var}(\beta_{MLE}^{(k)}) \cdot Z_{m,1}^T \approx \frac{1}{k} Z_{m,1} \cdot \text{var}(\beta_{MLE}) \cdot Z_{m,1}^T = \frac{1}{k} \text{var}(\mathbf{Z}\beta_{MLE}^{(k)})_m \quad (2)$$

Similarly to (b), we conclude

$$\begin{aligned} \underline{\underline{\text{var}(\tilde{E}Y_m^{(k)})}} &= \text{var}\left(\frac{1}{K} \sum_{i=1}^K (Z_{MLE}^{(k)})_m\right) \approx \frac{1}{K} \cdot \text{var}\left(\sum_{i=1}^K (Z_{MLE})_m\right) = \\ &= \underline{\underline{\frac{1}{K} \text{var}(EY_m^3)}} \end{aligned}$$

After the change, the variance of the estimated expected nr. of claims per policy decreased approximately K -times.

To conclude, increasing number of policies K -times did not change point estimates, but it ~~also~~ decreased variances of the estimator approx. K -times.