

## FORMULARY – RISK MODELS

### Review of mathematical statistics

$$f_{Y_r}(y) = \frac{n!}{(r-1)! (n-r)!} (F_X(y))^{r-1} (1-F_X(y))^{n-r} f_X(y)$$

$$(M-m)\left(2f(m)\sqrt{n}\right) \stackrel{\circ}{\sim} n(0;1)$$

Normal populations:  $Z = \frac{\bar{X} - \mu}{\sigma / \sqrt{n}} \sim N(0,1)$ ;  $T = \frac{\bar{X} - \mu}{S / \sqrt{n}} \sim t_{(n-1)}$ ;  $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2(n-1)$  where  
 $S^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$

Large samples:  $Z = \frac{\bar{X} - \mu}{\sqrt{\text{var}(\bar{X})}} \stackrel{\circ}{\sim} N(0,1)$ ;  $Z = \frac{\bar{X} - \mu}{\sqrt{\hat{\text{var}}(\bar{X})}} \stackrel{\circ}{\sim} N(0,1)$

### Complete data

$$S_n(x) = r_j / n, \quad y_{j-1} \leq x < y_j, \quad j = 2, 3, \dots, k$$

$$S_n(x) = 1 - \frac{c_j F_n(c_{j-1}) - c_{j-1} F_n(c_j)}{c_j - c_{j-1}} - \frac{F_n(c_j) - F_n(c_{j-1})}{c_j - c_{j-1}} x, \quad c_{j-1} \leq x < c_j$$

$$S(x) = e^{-H(x)}$$

$$\hat{H}(x) = \sum_{i=1}^{j-1} (s_i / r_i), \quad y_{j-1} \leq x < y_j, \quad j = 2, 3, \dots, k$$

### Modified Data

$$S_n(x) = \prod_{i=1}^{j-1} \left( \frac{r_i - s_i}{r_i} \right), \quad y_{j-1} \leq x < y_j, \quad j = 2, 3, \dots, k$$

Greenwood's formula:  $\hat{\text{var}}(S_n(x)) \approx S_n(x)^2 \times \sum_{i:y_i \leq x} \frac{s_i}{r_i(r_i - s_i)}$

$$U = \exp \left( z_{\alpha/2} \frac{\sqrt{\hat{\text{var}}(S_n(x))}}{S_n(x) \times \ln S_n(x)} \right) \quad \left( (S_n(x))^{1/U}; (S_n(x))^U \right)$$

$$\hat{H}(x) = \sum_{i=1}^{j-1} (s_i / r_i), \quad y_{j-1} \leq x < y_j, \quad j = 2, 3, \dots, k$$

$$\hat{\text{var}}(\hat{H}(x)) = \sum_{i:y_i \leq x} (s_i / r_i^2)$$

$$U = \exp \left( z_{\alpha/2} \frac{\sqrt{\hat{\text{var}}(\hat{H}(x))}}{\hat{H}(x)} \right) \quad \left( U^{-1} \hat{H}(x); U \hat{H}(x) \right)$$

Kernel estimation:  $\hat{f}(x) = \sum_{j=1}^k p(y_j) k_{y_j}(x)$

## Maximum likelihood

(Mild regularity conditions)

$\hat{\theta}$  maximum likelihood estimator of  $\theta$ .  $\hat{\theta} \stackrel{\circ}{\sim}$  normal with mean  $\theta$  and variance  $I(\theta)^{-1}$ .  $I(\theta) \approx I(\hat{\theta}) \approx -H(\hat{\theta})$ ;

One parameter:  $I(\theta) = -n E\left(\frac{\partial^2}{\partial \theta^2} \ln f(X|\theta)\right) = -E(\ell''(\theta|X_1, X_2, \dots, X_n))$ ;

$k$  parameters:  $I(\theta)_{r,s} = -E\left(\frac{\partial^2}{\partial \theta_r \partial \theta_s} \ell(\theta|X_1, X_2, \dots, X_n)\right) \quad r, s = 1, 2, \dots, k$

Joint confidence interval:  $c = \ell(\hat{\theta}) - 0.5 \times q_\alpha$  and  $q_\alpha$  quantile of a  $\chi^2_{(r)}$

## Bayesian estimation

$$f_{Y|X}(y|x) = \int f_{Y|\Theta}(y|\theta) \pi_{\Theta|X}(\theta|x) d\theta \quad \text{or} \quad f_{Y|X}(y|x) = \sum_\theta f_{Y|\Theta}(y|\theta) \pi_{\Theta|X}(\theta|x)$$

Under regulatory conditions,  $\theta|x \stackrel{\circ}{\sim}$  normal

## Model selection

Kolmogorov-Smirnov

$\alpha$	0.10	0.05	0.01
Aprox. crit. value	$1.22/\sqrt{n}$	$1.36/\sqrt{n}$	$1.63/\sqrt{n}$

Anderson-Darling

$$A^2 = -n F^*(u) + n \sum_{j=0}^k (1 - F_n(y_j))^2 (\ln(1 - F^*(y_j)) - \ln(1 - F^*(y_{j+1}))) + \\ + n \sum_{j=1}^k (F_n(y_j))^2 (\ln F^*(y_{j+1}) - \ln F^*(y_j))$$

$$\text{No ties and no censoring: } A^2 = -n - \sum_{j=1}^n \frac{2j-1}{n} (\ln F^*(y_j) + \ln(1 - F^*(y_{n+1-j})))$$

$\alpha$	0.10	0.05	0.01
Aprox. crit. value	1.933	2.492	3.857

Chi-squared:  $Q = \sum_{j=1}^k \frac{(O_j - E_j)^2}{E_j} \quad Q \stackrel{\circ}{\sim} \chi^2_{(k-1)}$

Likelihood ratio:  $\lambda(x_1, x_2, \dots, x_n) = \frac{\sup_{\theta \in \Theta_0} L(\theta|x_1, x_2, \dots, x_n)}{\sup_{\theta \in \Theta} L(\theta|x_1, x_2, \dots, x_n)}$  and  $-2 \ln \lambda(x_1, x_2, \dots, x_n) \stackrel{\circ}{\sim} \chi^2_{(r)}$

## Simulation

Box-Muller formulae:  $(U_1, U_2)$  independent uniform variables, then  $Z_1 = \sqrt{-2 \ln U_1} \cos(2\pi U_2)$  and  $Z_2 = \sqrt{-2 \ln U_1} \sin(2\pi U_2)$  are independent  $n(0;1)$  random variables.