

## Excess-of-Loss Reinsurance - Insurer's Perspective

### 1. Distribution of “Effective” Claim Size, $Y$ :

- Expected Claim Size

· If  $X \sim f_X(x; \theta)$ ,

$$\begin{aligned} E_\theta(Y) &= E_\theta\{XI_{(X \leq M)}\} + E\{MI_{(X > M)}\} \\ &= \int_0^\infty xI_{(x \leq M)}f_X(x; \theta)dx + MPr_\theta(X > M) \\ &= \int_0^M xf_X(x; \theta)dx + M \int_M^\infty f_X(x; \theta)dx \\ &= \int_0^\infty xf_X(x; \theta)dx - \int_M^\infty xf_X(x; \theta)dx + M \int_M^\infty f_X(x; \theta)dx \\ &= E_\theta(X) - \int_M^\infty (x - M)f_X(x; \theta)dx \\ &= E_\theta(X) - \int_0^\infty yf_X(y + M; \theta)dy, \end{aligned}$$

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### 1. Distribution of “Effective” Claim Size, $Y$ (*Continued*):

- Moment Generating Function

- If  $X$  has mgf  $m_X(t)$ ,

$$\begin{aligned} m_Y(t) &= \int_0^M e^{tx} f_X(x; \theta) dx + e^{tM} Pr_{\theta}(X > M) \\ &= m_X(t) - e^{tM} \int_0^{\infty} (e^{ty} - 1) f_X(y + M; \theta) dy \end{aligned}$$

## Excess-of-Loss Reinsurance - Insurer's Perspective

### 2. Modelling Claim Sizes:

- Key Issues
  - Choose family for  $X$ -distribution,  $f_X(x; \theta)$ .
  - Are  $X_i$  values recorded? Usually not.
  - The  $Y_i$  values are *Right-Censored*.
  - $Y_i$ 's not continuous;  $Pr(Y_i = M) = Pr(X_i > M) > 0$ .
  - Modelling  $Y$  distribution directly very difficult (but possible)

## Excess-of-Loss Reinsurance - Insurer's Perspective

### 2. Modelling Claim Sizes (*Continued*):

- Estimate  $X$  distribution parameters using  $Y$  data?
  - $\bar{x}$ ,  $\hat{x}_p$  generally not calculable from  $y$ 's
  - MOM, MOP not feasible
  - MLE concepts still feasible

## Excess-of-Loss Reinsurance - Insurer's Perspective

### 2. Modelling Claim Sizes (*Continued*):

- MLEs of  $X$  distribution parameters using  $Y$  data
  - Likelihood concept:

$$L(\theta) = \prod_i Pr_{\theta}(i^{\text{th}} \text{ data point observed})$$

“Product of chances of observing each data point”

- For  $n$  uncensored (i.e.,  $Y_i = X_i < M$ );  
and  $m$  censored (i.e.,  $Y_i = M$ ) observations:
  - Contribution to likelihood of  $n$  uncensored observations

$$L(\theta; x_1, \dots, x_n) = \prod_{i=1}^n f_X(x_i; \theta)$$

where  $X_i \sim f_X(x; \theta)$  is underlying *pdf* for claim model

- Contribution to likelihood of  $m$  censored observations

$$\{Pr_{\theta}(Y_i = M)\}^m = \{Pr_{\theta}(X > M)\}^m = \{1 - F_X(M; \theta)\}^m$$

- Likelihood of  $\theta$  based on  $Y_i$ 's:

$$\begin{aligned} L_1(\theta; y_1, \dots, y_{n+m}) &= \prod_{i=1}^n f_X(x_i; \theta) \prod_{j=1}^m \{1 - F_X(M; \theta)\} \\ &= L(\theta; x_1, \dots, x_n) \{1 - F_X(M; \theta)\}^m \end{aligned}$$

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### 2. Modelling Claim Sizes (*Continued*):

- Log-likelihood:

$$\begin{aligned}l_1(\theta) &= \ln\{L_1(\theta; y_1, \dots, y_{n+m})\} \\&= \ln\{L(\theta; x_1, \dots, x_n)\} + m \ln\{1 - F_X(M; \theta)\}\end{aligned}$$

- MLE Theorem still holds! Can create confidence intervals as:

$$\hat{\theta}_1 \pm 1.96\sqrt{I_1^{-1}(\hat{\theta}_1)}$$

where  $\hat{\theta}_1$  solves  $\frac{\partial}{\partial \theta} l_1(\theta) = 0$  and

$$I_1(\theta) = -E_{\theta} \left\{ \frac{\partial^2}{\partial \theta \partial \theta^T} l_1(\theta) \right\}$$

[NOTE:  $n$  and  $m$  are *random*, though  $n + m$  is considered fixed]

## Excess-of-Loss Reinsurance - Reinsurer's Perspective

1. All claim information known
  - No change to original claim modelling
  - Uncommon

## Excess-of-Loss Reinsurance - Reinsurer's Perspective

### 2. Information regarding claims below retention level unknown

- Total number of claims unknown
- Leads to *truncated* datasets; only observe  $Z$  if  $Z > 0$ .
- Estimate distribution parameters of  $f_X(x; \theta)$  based observed  $Z_i$ 's:
  - Use conditional distribution, which has *CDF*:

$$\begin{aligned} Pr_{\theta}(Z \leq z | Z > 0) &= Pr_{\theta}(X \leq z + M | X > M) \\ &= \frac{Pr_{\theta}(M < X \leq z + M)}{Pr_{\theta}(X > M)} \\ &= \frac{F_X(z + M; \theta) - F_X(M; \theta)}{1 - F_X(M; \theta)} \end{aligned}$$

- And *pdf*:

$$f_{Z|Z>0}(z; \theta) = \frac{f_X(z + M; \theta)}{1 - F_X(M; \theta)}$$