







# Reinsurance - Single risk

An insurance company faces a risk  $X$  over a period.

Reinsurance:

- $f(X)$  ! reinsurer
- $R_f(X) = X - f(X)$  ! insurer
- The insurer pays premium  $(f(X))$  to the reinsurer
- Total risk exposure  $S^f(X) = X - f(X) + (f(X))$

To minimize

$$(S^f(X))$$

Three factors

- the optimization objective or  $S^f(X)$
- is a the premium principle
- $f$  is the ceded loss function

- Value-at-Risk:  $\text{VaR}_\alpha(X) = (F_X)_L^{-1}(\alpha)$  (Solvency II);
- Expected Shortfall (ES): (Swiss Solvency Test) For  $\alpha \in [0; 1)$ ,

$$\text{ES}_\alpha(X) = \frac{1}{1-\alpha} \int_{\text{VaR}_\alpha(X)}^{\infty} \text{VaR}_t(X) dt;$$

- Range-Value-at-Risk (RVar) (Cont-Deguest-Scandolo'10 QF): For  $0 < \alpha < \beta < 1$ ,

$$R_{\alpha;\beta}(X) = \frac{1}{\beta - \alpha} \int_{\text{VaR}_\alpha(X)}^{\text{VaR}_\beta(X)} \text{VaR}_t(X) dt;$$

Clearly,  $R_{0;\alpha}(X) = \text{ES}_\alpha(X)$  and  $\lim_{\beta \rightarrow 0} R_{\alpha;\beta}(X) = \text{VaR}_\alpha(X)$ .

# Example of premium principles

- **Expectation principle:**

$$\pi(X) = (1 + \theta)E(X)$$

for  $X \geq X$  with  $\theta > 0$ ;

- **Standard deviation principle:**

$$\pi(X) = E(X) + \theta \sqrt{\text{Var}(X)}$$

for  $X \geq X$  with  $\theta > 0$ ;

- **Wang's principle:**

$$\pi_g(X) = \int_0^{\infty} g(P(X > x)) dx$$

for  $X \geq X_g$ , where  $g : [0; 1] \rightarrow [0; 1]$  with  $g(0) = 0$  and  $g(1) = 1$ , and  $g$  is increasing.

Book: **Young' 04**, eleven widely used premium principles.

# Loss function

Both  $f$  and  $R_f$  are **non-negative** and **increasing** on  $\mathbb{R}_+$  ( $\mathbb{R}_+ = [0, \infty)$ )  
Lipschitz-continuous, i.e.,

$$0 \leq f(y) - f(x) \leq y - x; \quad 0 \leq x - y; \quad 0 \leq f(x) - x; \quad x \geq 0:$$

Examples:

- Quota-share:  $f(x) = ax$  with  $0 \leq a \leq 1$ ;

- Stop-loss:  $f(x) = (x - c)_+$  with  $c > 0$ ;

- Limited stop-loss:

$$f(x) = (x - a)_+ - (x - b)_+ = \min((x - a)_+; b - a) \text{ with } 0 \leq a \leq b.$$

(Cai-Chi'20 STRF: review)

# Multiple risks

An insurance company usually has many lines of business and each line generates a risk  $X_i$ .

Life insurance and non-life insurance.

- Reinsurance for each business  $X_i$ :  $f_i(X_i) + \rho_i(f_i(X_i))$
- The total risk:  $S^f = \sum_{i=1}^n X_i + f_i(X_i) + \rho_i(f_i(X_i))$ , where  $f = (f_1, \dots, f_n)$
- The task is to minimize  $\rho(S^f)$ .



- **Cai-Wei'12 IME**:  $\pi(X) = E(u(X))$ ,  $\pi_i(X) = (1 + \beta_i)E(X)$ , and  $(X_1; \dots; X_n)$  are **positive dependence through stochastic ordering**
- **Cheung-Sung-Yam'14 JRI**:  $\pi$ : convex risk measure,  $\pi_i(X) = (1 + \beta_i)E(X)$ ,  $(X_1; \dots; X_n)$  are **comonotonic** (the worst case scenario)
- **Bernard-Liu-Vanduehl'20 JEBO**:  $\pi(X) = E(u(X))$ , general premium principle, and **some specific dependence structure**  $\pi_i(x) = a_i x$   
Quota-Share policy



# Conditions on premium principle

We impose the following conditions on  $\pi$ :

- (i) **Distribution invariance:** For  $Y, Z \in \mathcal{X}$ ,  $\pi(Y) = \pi(Z)$

Limited stop loss policy:

## Theorem

For  $n = 2$ , suppose that  $F_1^{-1}$  and  $F_2^{-1}$  are continuous over  $(0; 1)$ , then

$$\begin{aligned} & \inf_{(f_1; f_2) \in \mathcal{D}^2} \sup_{(X_1; X_2) \in \mathcal{E}_2(F)} \text{VaR} (S_2^f(X_1; X_2)) \\ &= \inf_{(a_1; a_2; b_1; b_2) \in \mathcal{A}} \inf_{t \in [0; 1]} L_1(a_1; a_2; b_1; b_2; t); \end{aligned}$$

where

$$L_1(a_1; a_2; b_1; b_2; t) = \text{VaR}_{1-t}(X_1 |_{a_1; b_1}(X_1)) + \text{VaR}_{1-t};$$





## Theorem

Suppose  $F_1^{-1}(\cdot); \dots; F_n^{-1}(\cdot)$  are all continuous over  $(0; 1)$  and  $\alpha \in (0; 1)$ . If each of  $F_1; \dots; F_n$  is **convex beyond its  $\alpha$ -quantile**, then

$$\begin{aligned} & \inf_{F_1, \dots, F_n \in \mathcal{F}_\alpha} \sup_{(X_1, \dots, X_n) \in \mathcal{E}_n(F)} \text{VaR}_\alpha(S_n^f(X_1; \dots; X_n)) \\ &= \inf_{(a; b; c; d) \in \mathcal{A}_\alpha} \inf_{(h_1; \dots; h_n)} H(a; b; c; d; \cdot); \end{aligned}$$

where

$$H(a; b; c; d; \cdot) = \sum_{i=1}^n f R_{i; \alpha}(X_i) - R_{i; \alpha}(h_{a_i; b_i; c_i; d_i}(X_i)) + g_i(h_{a_i; b_i; c_i; d_i}(X_i)).$$

Additionally, if  $g_i$  are continuous,  $(h_{a_1; b_1; c_1; d_1}; \dots; h_{a_n; b_n; c_n; d_n})$  is the optimal ceded loss functions for the worst case scenario provided

$$(a; b; c; d) = \arg \inf_{(a; b; c; d) \in \mathcal{A}_\alpha} \inf_{(h_1; \dots; h_n)} H(a; b; c; d; \cdot)$$



# Concave distributions on tail part

To guarantee that  $X = f(X)$  has a concave distribution on its tail part,

$D_2^n = \{f = (f_1, \dots, f_n) : f \in D; f_i \text{ is concave for } i = 1, \dots, n\}$

$$g_{a,b}(x) := a \min(x, b) + a$$

# Concave tail distributions

## Theorem

Suppose  $F_1^{-1}(\cdot); \dots; F_n^{-1}(\cdot)$  are all continuous over  $(0; 1)$  and  $\mathcal{L}(0; 1)$ .  
 If each of  $F_1; \dots; F_n$  is **concave beyond its-quantile**, then

$$\inf_{F \in \mathcal{D}_n^{\text{D}}(X_1; \dots; X_n)} \sup_{E \in \mathcal{E}_n(F)} \text{VaR} (S_n^f(X_1; \dots; X_n)) \\
 = \inf_{(a; b) \in \mathcal{A}_2} \inf_{\mathcal{L}(1 - a; 1 - b)} G(a; b; \cdot);$$

- We extend the result (Theorem 1) of [Blanchet-Lam-Liu-Wang 20'](#) on convolution bounds on RVaR aggregation from marginal with decreasing densities in the tail part to those with concave distribution in the tail part.
- We obtain similar results on the optimal reinsurance problems.

We solve

$$\min_{f \in \mathcal{D}^2(X_1; X_2)} \max_{2E_2} \text{VaR} S_2^f(X_1; X_2) ; \quad (1)$$

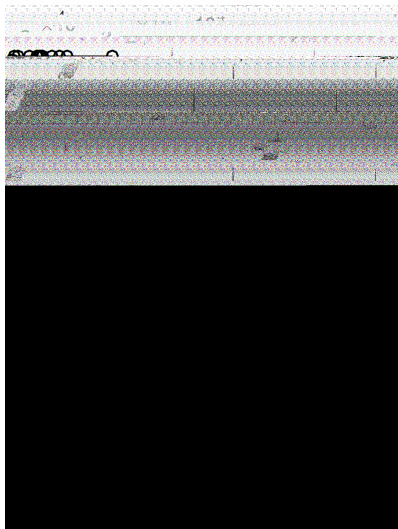
The optimal copula is  $C_{opt} = C_{G}^{-1} \circ G^{-1} \circ G \circ G^{-1}$  with  $G^{-1}(x) = \max\{0, x - 1\}$  and  $G(x) = \min\{x, 1\}$ .  
The optimal copula is  $C_{opt} = C_{G}^{-1} \circ G^{-1} \circ G \circ G^{-1}$  with  $G^{-1}(x) = \max\{0, x - 1\}$  and  $G(x) = \min\{x, 1\}$ .





# Example: Exponential marginals

- $X_i \sim \text{Exp}(\lambda_i)$  with  $E(X_i) = \lambda_i^{-1} > 0$
- $\lambda_1 = 8000$ ,  $\lambda_2 = 3000$ ,  $\alpha_1 = 0.8$ ,  $\alpha_2 = 0.3$ ,  $\beta = 0.95$  and  $n = 200$



- Our main results show that finding the optimal ceded loss functions for the worst case reinsurance models with dependence uncertainty boils down to finding the minimiser of a deterministic function.





Thank You!