

# Efficient Simulation of Ruin Probabilities When Claims are Mixtures of Heavy and Light Tails

Eleni Vatamidou

jointed work with Hansjörg Albrecher, Martin Bladt

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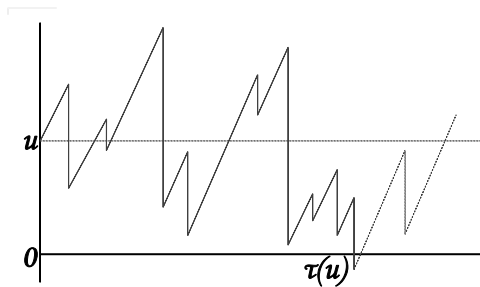


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## Insurance company with:

- 2 opposing cash flows
  - incoming cash premiums
  - outgoing claims, and
- an initial capital.

Question of interest: What is the probability of bankruptcy?



# Ruin probability for the Cramér-Lundberg risk model

- $\lambda$ : Poisson arrival rate ( $N(t)$ )
- $U_k$ : i.i.d. claim sizes ( $G$ )
- $c = 1$ : premium rate
- $u$ : initial capital.

## Risk reserve process

$$R(t) = u + ct - \sum_{k=1}^{N(t)} U_k.$$

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Claim surplus:  $M = \sup_{0 \leq t < \infty} (u - R(t))$

Ruin probability

$$\psi(u) = \mathbb{P}(M > u).$$

## PK formula

If  $\rho = \lambda \mathbb{E}U < 1$  (safety loading condition) then

$$\psi(u) = 1 - (1 - \rho) \sum_{k=0}^{\infty} \rho^k (G^e)^{*k}(u),$$

where  $G^e(u) = \int_0^u (1 - G(x)) dx / \mathbb{E}U$  (stationary excess claim size distribution).

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## Ways to calculate the ruin probability:

- closed-form solutions (e.g. algebraic, analytic/Laplace transforms)
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# Corrected phase-type approximations

## Combining the best of 2 worlds

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high accuracy

computationally tractable

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## Fitting distributions to data

- ① higher order statistics for tail probabilities (r.v.  $C$ )
- ② remaining data set phase-type distribution (r.v.  $B$ )

## Claim size distribution

$$G(x) = (1 - \epsilon)F_p(x) + \epsilon F_h(x), \quad x \geq 0.$$

# New series expansion for the ruin probability

## Theorem

We have

$$\psi(u) = \frac{1-\rho}{1-\rho^\bullet} \psi^\bullet(u) + \frac{1-\rho}{1-\rho^\bullet} \sum_{k=1}^{\infty} \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^k \mathcal{A}_k(u),$$

where  $\mathcal{A}_k(u) = \mathbb{P}(M_0^\bullet + M_1^\bullet + \dots + M_k^\bullet + C_1^e + \dots + C_k^e > u)$  and  $M_k^\bullet \stackrel{\mathcal{D}}{=} M^\bullet$ . This expansion converges for all values of  $u$ .

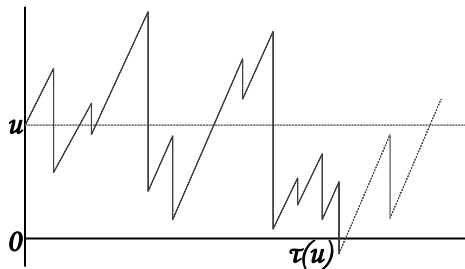
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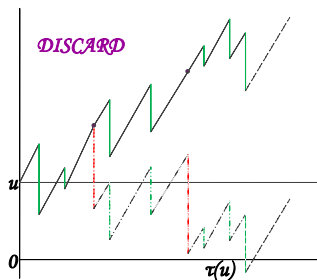
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$$\begin{aligned} \varphi(u) &:= \frac{1-\rho}{1-\rho^\bullet} \sum_{k=2}^{\infty} \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^k \mathcal{A}_k(u) = \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^2 \mathbb{E} \mathcal{A}_{N+2}(u) \\ &= \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^2 \mathbb{P}(M_0^\bullet + M_1^\bullet + \dots + M_{N+2}^\bullet + C_1^e + \dots + C_{N+2}^e > u), \end{aligned}$$

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**Simulate:**

$$V \stackrel{\text{D}}{=} M_0^\bullet + M_1^\bullet + C_1^e + \sum_{k=2}^{N+2} (M_k^\bullet + C_k^e), \quad N \sim \text{Geom} \left( \frac{1-\rho}{1-\rho^\bullet} \right).$$

## Idea of the control variate techniques:

- 1 We must simulate a r.v.  $Z(u)$  such that  $\varphi(u) = \mathbb{E}Z(u)$ .
- 2 We find another r.v.  $W(u)$  that has a known expectation  $\mathbb{E}W(u)$  and is strongly correlated with  $Z(u)$ .
- 3 We simulate them together, i.e. we take  $(Z^{(i)}(u), W^{(i)}(u))$ ,  $i = 1, 2, \dots, \kappa$ , are independent copies of  $(Z(u), W(u))$ .
- 4 We calculate

$$\hat{\varphi}_\kappa(u) := \hat{z}_\kappa(u) + \hat{\alpha}_\kappa(\hat{w}_\kappa(u) - \mathbb{E}W(u)),$$

where

$$\hat{z}_\kappa(u) = \frac{\sum_{i=1}^{\kappa} Z^{(i)}(u)}{\kappa}, \quad \hat{w}_\kappa(u) = \frac{\sum_{i=1}^{\kappa} W^{(i)}(u)}{\kappa},$$
$$\hat{\alpha}_\kappa = -\frac{\sum_{i=1}^{\kappa} (Z^{(i)}(u) - \hat{z}_\kappa(u))(W^{(i)}(u) - \hat{w}_\kappa(u))}{\sum_{i=1}^{\kappa} (W^{(i)}(u) - \hat{w}_\kappa(u))^2}.$$



# Control variate: max of heavy tails

$$\varphi(u) = \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^2 \mathbb{P}(\underbrace{M_0^\bullet + M_1^\bullet + \dots + M_{N+2}^\bullet + C_1^e + \dots + C_{N+2}^e}_{\stackrel{\text{D}}{=}V} > u)$$

Obviously:  $Z(u) = \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^2 \mathbb{1}_{\{V>u\}}$ .

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**Obviously:**  $Z(u) = \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^2 \mathbb{1}_{\{V > u\}}$ .

**We define:**  $V_n := \max\{C_1^e, \dots, C_{N+2}^e\} \mathbb{1}_{\{N+2 \leq n\}}$ , for fixed  $n$ .

**Control variate:**  $W_n(u) = \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^2 \mathbb{1}_{\{V_n > u\}}$ , for fixed  $n$ .

$$\varphi_n(u) = \mathbb{E} W_n(u) = \left( \frac{1-\rho}{1-\rho^\bullet} \right) \sum_{k=2}^n \left( \frac{\epsilon\theta}{1-\rho^\bullet} \right)^k \mathbb{P}(\max\{C_1^e, \dots, C_k^e\} > u)$$

# Alternative control variate: Conditional Monte Carlo

$$V \stackrel{\mathcal{D}}{=} \underbrace{M_0^\bullet}_{=X_0^*} + \underbrace{M_1^\bullet + C_1^e}_{=X_1} + \sum_{k=2}^{N+2} \underbrace{(M_k^\bullet + C_k^e)}_{=X_k} \stackrel{\mathcal{D}}{=} X_0^* + \sum_{k=1}^{N+2} X_k$$

If:  $m_k := \max\{X_1, \dots, X_k\}$ ,  $\bar{F}_X$  is the c.c.d.f. of  $X_k$ 's, and  $S_\ell = \sum_{k=1}^{\ell} X_k$ ,  $S_0 = 0$

Now:  $Z^*(u) = \left(\frac{\epsilon\theta}{1-\rho^\bullet}\right)^2 (N+2)\bar{F}_X(m_{N+1} \vee (u - X_0^* - S_{N+1}))$ .

AK control variate:  $W^*(u) = \left(\frac{\epsilon\theta}{1-\rho^\bullet}\right)^2 (N+2)\bar{F}_X(u)$

$$\varphi^*(u) = \left(\frac{\epsilon\theta}{1-\rho^\bullet}\right)^2 \left(\frac{\epsilon\theta}{1-\rho} + 2\right)\bar{F}_X(u)$$

- Mixture claim size distribution
  - PH:  $\overline{F}_p(u) = \overline{F}_p^e(u) = e^{-\mu u}$ , and  $\mu_B = 1/\mu$  ( $\mu = 3$ )
  - HT: shifted Pareto with shape  $a > 1$  and scale  $b > 0$ , i.e.  
 $\overline{F}_h(u) = (1 + u/b)^{-a}$  and  $\overline{F}_h^e(u) = (1 + u/b)^{-(a-1)}$ ,  $u \geq 0$ ,  
with  $\mu_C = b/(a-1)$  ( $b = 1$ )
  - Perturbation parameter:  $\epsilon \in \{0.1, 0.7\}$ .
- Focus on  $\rho \in \{0.9, 0.99, 0.999\}$ .
- Order of  $\varphi_n(u)$  equal to  $n = 100$
- Number of simulations is  $\kappa = 10,000$ .

# Figures for 1st control variate (max of heavy tails)

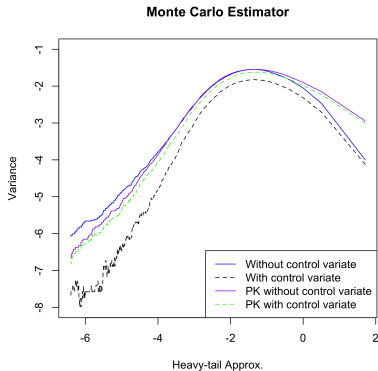
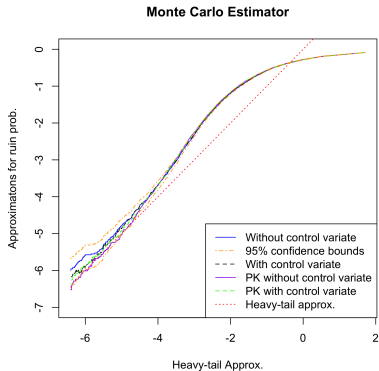


Figure: Plotted in a log-log scale. Model parameters:  $a = 2$ ,  $\epsilon = 0.1$ , and  $\rho = 0.99$ .

# Figures for 2nd control variate (AK estimator)

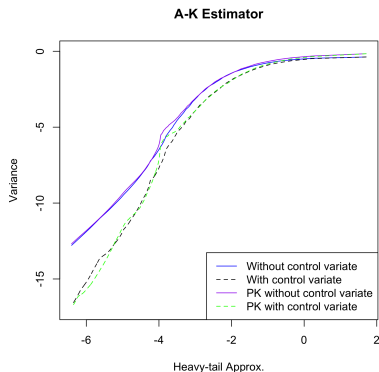
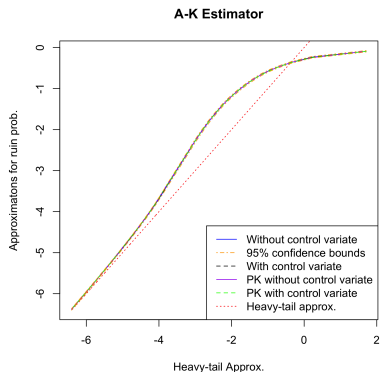


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# Conclusions

- We introduced an alternative series expansion for the PK formula in the Cramér-Lundberg model for mixture claim sizes
- Significant improvement of simulation algorithms based on this series
- Proposed a control variate technique: fast and preferable in the heavy traffic regime
- Variance reduction is better with AK conditional Monte Carlo technique but the method is significantly slower
- For other mixtures that the 2nd term of the ruin probability cannot be evaluated, it can also be simulated
- Extension to the Sparre Andersen model, which also has a PK-type formula with respect to the ladder height distribution

Ευχαριστώ