

# Finance, Insurance, and Stochastic Control (I)

Jin Ma

The logo for the Department of Mathematics at the University of Southern California. It features the letters "USC" in a gold serif font, followed by the text "Department of Mathematics" in a white serif font, and "University of Southern California" in a gold sans-serif font, all set against a dark red rectangular background.

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**Part I. Ruin Problems (vs. Credit Risks)**

**Part II. Equity-Linked Insurance Problems**

**Part III. Reinsurance Problems**

**Part IV. A New Stochastic Control Problem**

- 1 Introduction
- 2 Basic Insurance Models
- 3 Ruin Problems
- 4 Lundberg Bounds
- 5 Lundberg Bounds for General Reserve Models
- 6 Ruin Probability and Large Deviation

## Definition (Credit Default Swap (CDS))

A CDS is a contract where

- the “protection buyer” “ $A$ ” pays rates “ $R$ ” at times  $T_{a+1}, \dots, T_b$  (the “premium leg”) in exchange for a single protection payment  $L_{GD}$  (Loss Given Default, the “protection leg”).
- The buyer receives the protection leg by the protection seller “ $B$ ” at the default time  $\tau$  of a reference entity “ $C$ ”, provided that  $T_a < \tau < T_b$ .
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In terms of “Term Life Insurance”:

- Time of death (default) —  $\tau$  (of the insured “ $C$ ”)
- Death benefit —  $L_{GD}$ , payable at the moment of death
- Premium — an annuity (e.g. monthly) at (leveled) rate  $R$
- Coverage period (term) —  $[T_a, T_b]$ , where  $a < b$  are two ages.

# Credit Risk vs. Actuarial Problems

	<b>Credit Risk</b>	<b>Actuarial Science</b>
$\tau$	Default time	Ruin time, Future life time ( $\tau = T(x)$ )
$P\{\tau > t\}$	Survival Proba.	Survival Probability ( ${}_t p_x = P\{T(x) > t\}$ )
$\Lambda(t) = -\ln {}_t p_x$	Hazard Process	Hazard Process
$\lambda(t) = \Lambda'(t)$	Default Intensity	“Force of Mortality” ( $\mu(x+t) = -({}_t p_x)' / {}_t p_x$ )
	Structure	Ruin Problems
	Reduced form	Life Contingencies

# Basel II Accord

From Wikipedia, the free encyclopedia

## Basel II (Bank for International Settlements Basel Accord)

**Basel II** is the second of the Basel Accords, which are recommendations on banking laws and regulations issued by the Basel Committee on Banking Supervision (Basel, Switzerland). The purpose of Basel II, which was initially published in June 2004, is to create an international standard that banking regulators can use when creating regulations about **how much capital banks need to put aside** to guard against the types of financial and operational risks banks face. ....

In practice, Basel II attempts to accomplish this by setting up rigorous risk and capital management requirements designed to **ensure that a bank holds capital reserves appropriate to the risk the bank exposes itself to** through its lending and investment practices.....

# An Example in Risk Management

- Recall that the definition of “Value at Risk” of a r.v.  $Z$ :

$$\text{VaR}_\alpha(Z) \triangleq \inf\{x : \mathbb{P}\{x + Z < 0\} \leq \alpha\}.$$



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- Define

$$\psi(x, T) = \mathbb{P}\{V_t^\pi < 0 : \exists t \in [0, T]\}. \quad (1)$$

Then

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- Assume now that  $\psi(x, T) \sim e^{-r^*x}$  for some  $r^* \in \mathbb{R}$ , then

$$\text{VaR}_\alpha(\inf_{t \geq 0} Q_t^\pi) \sim -\frac{\log \alpha}{r^*}!$$

## Note

- In Actuarial Sciences, the quantity  $\psi(x, T)$  (or  $\psi(x) = \mathbb{P}\{V_t^h < 0 : \exists t > 0\}$ ) is called “*Ruin Probability*”. The estimate  $\psi(x, T) \sim e^{-r^*x}$  is called the *Lundberg bound*, with *Lundberg exponent*  $r^*$ .

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- Define the “Average VaR” by

$$\rho(Z) \triangleq AVaR_\alpha(Z) \triangleq \frac{1}{\alpha} \int_0^\alpha VaR_u(Z) du.$$

Then  $\rho$  is a “*Coherent Risk Measure*” (Cheridito-Delbaen-Kupper, '04).

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- The Lundberg bound also implies that

$$\rho\left(\inf_{t \geq 0} Q_t\right) \sim (1 - \log \alpha) / r^*.$$

(The equality can hold if the Lundberg bound is sharp!)

## Wiener-Poisson Space

- $(\Omega, \mathcal{F}, P)$  — a complete probability space
- $W = \{W_t\}_{t \geq 0}$  — a  $d$ -dimensional Brownian motion
- $\mu(dt dz)$  — a Poisson random measure on  $(0, \infty) \times \mathbb{R}_+$ , with Lévy measure  $\nu(dz)$ .
- $\mathbf{F}^W = \{\mathcal{F}_t^W : t \geq 0\}$ ,  $\mathbf{F}^\mu \triangleq \{\mathcal{F}_t^\mu : t \geq 0\}$ ,  $\mathbf{F} = \overline{\mathbf{F}^W \otimes \mathbf{F}^\mu}^P$ ,

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## Main Elements

- Claim Process
- Premium Process
- Reserve Process (= Premium - Claim)



- **Claim Process:**  $S_t = \int_0^t \int_{\mathbb{R}_+} f(s, z, \cdot) \mu(dsdz), t \geq 0$   
(may assume  $d \leq f(s, z, \omega) \leq L$ , where  $d$  and  $L$  are the *deductible* and *benefit limit*, respectively)
- **Premium Process:**  $C_t = \int_0^t c_s ds, t \geq 0$

- **Claim Process:**  $S_t = \int_0^t \int_{\mathbb{R}_+} f(s, z, \cdot) \mu(ds dz), t \geq 0$   
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- **Premium Process:**  $C_t = \int_0^t c_s ds, t \geq 0$

## Compound Poisson Case:

- $f(t, z) \equiv z$
- $S_t = \sum_{k=1}^{N_t} \Delta S_{T_k}$ , where  $N_t$  is standard Poisson.
- $\nu(dz) = \lambda F_{U_1}(dz)$ , and  $E[S_t] = \int_0^t \int_{\mathbb{R}_+} z \nu(dz) ds = \lambda E[U_1] t$ .
- $c_t = E\{\Delta S_t | \mathcal{F}_t^\mu\} = \int_{\mathbb{R}_+} z \nu(dz) = \lambda E[U_1], t \geq 0,$

## Example

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- Add interest income:  $X_t = x + \int_0^t [r_s X_s + c_s(1 + \rho_s)] ds - S_t$
- Reserve with Investment

$$X_t = x + \int_0^t \left\{ X_s [r_s + \langle \pi_s, \mu_s - r_s \mathbf{1} \rangle] + c_s(1 + \rho_s) \right\} ds \\ + \int_0^t X_s \langle \pi_s, \sigma_s dW_s \rangle - \int_0^t \int_{\mathbb{R}_+} f(s, z) \mu(ds dz), \quad (2)$$

◀ General

Consider the simplest Cramér-Lundberg model:

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## Ruin Problem

Find/estimate the “ruin probabilities”:

$$\psi(x, T) = P\{X_t < 0 : \exists t \in (0, T]\}; \quad (\text{Finite horizon})$$

$$\psi(x) = P\{X_t < 0 : \exists t > 0\}. \quad (\text{Infinite horizon}).$$



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## Thinking finance?

Default probability? Structure model? ...

- **Direct Calculation:** (e.g, vi IDE)
  - Lundberg ('26), Cramér ('35), Segerdahi ('42)...
- **Bounds:**
  - Lundberg ('26, 32, 34), Cremér ('55), Gerber ('76), Feller ('71) ...
- **Asymptotics:** (e.g.,  $\lim_{u \rightarrow \infty} \psi(u)e^{\gamma u} = ?$   $\lim_{u \rightarrow \infty} \psi(u, T)e^{\gamma u} = ?$ )
  - Teugels-Veraverbeke ('73), Djehiche ('93), Asmussen-klüppelberg ('96)...
- **Approximations** (of claim size dist.):
  - De Vylder ('78), Daley Rolski ('84)...

# Existing ways/methods of studying ruin probabilities

One of most notable discovery in ruin theory is that the ruin probability satisfies a differential or integro-differential equation.

## Main Result (Feller (1971), Gerber (1990))

Assume **classical Cramér-Lundberg model**. Let  $\psi(x)$  be the infinite horizon ruin probability with initial capital  $x$ , and  $\varphi(x) = 1 - \psi(x)$  be the corresponding non-ruin probability. Then

$$\varphi(x) = \varphi(0) + \frac{\lambda}{c(1 + \rho)} \int_0^x \varphi(x - z) \bar{F}_Z(z) dz, \quad (4)$$

where  $F$  is the jump size distribution and  $\bar{F} = 1 - F$ , and  $\lambda$  is the intensity of jump frequency.

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More general model— Reinhard (1984), Asmusson (1989) (Hidden Markovian), Asmusson-Petersen (1988) (reserve dependent premium) ...

# Ruin Probability via Differential Equations

Assume that the risk reserve satisfies the following SDE:

$$X_t = x + \int_0^t b(s, X_s) ds - \int_0^t \int_{\mathbb{R}_+} f(s, z) N_p(dz ds), \quad (5)$$

where  $b : [0, \infty) \times \mathbb{R} \mapsto \mathbb{R}$  is some (deterministic!) measurable function (could be Lipschitz..., if you wish). Then  $X$  is (strong) Markov.

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Then,  $\forall 0 < t < T$ ,

$$\mathbf{1}_{\{\tau < T\}} = \mathbf{1}_{\{\tau < t\}} + \mathbf{1}_{\{t \leq \tau\}} \mathbf{1}_{\{\inf_{t \leq s < T} X_s < 0\}}. \quad (6)$$

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Define  $M_t \triangleq P\{\tau < T | \mathcal{F}_t^X\} = E\{\mathbf{1}_{\{\tau < T\}} | \mathcal{F}_t^X\}$ ; and

$$\Psi(t, r) \triangleq P\left\{ \inf_{t \leq s < T} X_s < 0 \mid X_t = r \right\}. \quad (7)$$



# Ruin Probability via Differential Equations

Taking conditional expectations  $E\{\cdot | \mathcal{F}_t^X\}$  on both sides of (6) and using the Markovian Property of  $X$ :

$$\begin{aligned} M_t &= \mathbf{1}_{\{\tau \leq t\}} + \mathbf{1}_{\{\tau > t\}} P \left\{ \inf_{t \leq s < T} X_s < 0 \mid X_t \right\} \\ &= \mathbf{1}_{\{\tau < t\}} + \mathbf{1}_{\{\tau \geq t\}} \Psi(t, X_t). \end{aligned} \quad (8)$$

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Setting  $t = t \wedge \tau$  in (8), we obtain that

$$M_{t \wedge \tau} = \Psi(t \wedge \tau, X_{t \wedge \tau}). \quad (9)$$

Thus by Optional Sampling  $t \mapsto \Psi(t \wedge \tau, X_{t \wedge \tau})$  is an (UI)  $\mathbf{F}^X$ -mg!

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Now denote  $\Phi(t, r) = 1 - \Psi(t, r)$  (*non-ruin probability*), and assume that  $\Phi(\cdot, \cdot) \in C^{1,1}$ .

Applying Itô (BV version) to get

$$\begin{aligned} & \Phi(t \wedge \tau, X_{t \wedge \tau}) - \Phi(0, x) \\ &= \int_0^{t \wedge \tau} \partial_t \Phi(s, X_s) ds + \int_0^{t \wedge \tau} \partial_r \Phi(s, X_s) b(s, X_s) ds \\ & \quad + \int_0^{t \wedge \tau} \int_{\mathbb{R}_+} [\Phi(s, X_{s-} - f(s, z)) - \Phi(s, X_{s-})] N_p(dz ds) \\ &= \int_0^{t \wedge \tau} \partial_t \Phi(s, X_s) ds + \int_0^{t \wedge \tau} \partial_r \Phi(s, X_s) b(s, X_s) ds \\ & \quad + \int_0^{t \wedge \tau} \int_{\mathbb{R}_+} [\Phi(s, X_{s-} - f(s, z)) - \Phi(s, X_{s-})] \nu(dz) ds + M_{t \wedge \tau}^*, \end{aligned}$$

where

$$M_t^* = \int_0^{t \wedge \tau} \int_{\mathbb{R}_+} [\Phi(s, X_{s-} - f(s, z)) - \Phi(s, X_{s-})] \tilde{N}_p(dz ds)$$

is an martingale with zero mean.

Thus

$$\begin{aligned} & \int_0^{t \wedge \tau} \partial_t \Phi(s, X_s) ds + \int_0^{t \wedge \tau} \partial_r \Phi(s, X_s) b(s, X_s) ds \\ & + \int_0^{t \wedge \tau} \int_{\mathbb{R}_+} [\Phi(s, X_{s-} - f(s, z)) - \Phi(s, X_{s-})] \nu(dz) ds \\ = & \Phi(t \wedge \tau, X_{t \wedge \tau}) - \Phi(0, x) - M_{t \wedge \tau}^* \end{aligned}$$

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Similarly, for any  $t' \in [0, T)$  and  $\tau' = \inf\{t \geq t' \mid X_t < 0\}$ , one shows that

$$\begin{aligned} & \int_{t'}^{t \wedge \tau'} \partial_t \Phi(s, X_s) ds + \int_{t'}^{t \wedge \tau'} \partial_r \Phi(s, X_s) b(s, X_s) ds \quad (10) \\ & = \int_{t'}^{t \wedge \tau'} \int_{\mathbb{R}_+} [\Phi(s, X_{s-}) - \Phi(s, X_{s-} - f(s, z))] \nu(dz) ds. \end{aligned}$$

# Ruin Probability via Differential Equations

Since  $t'$  is arbitrary and  $\tau' \geq t'$ , we can “differentiating” (10) to get the following IPDE:

$$[\partial_t \Phi + \partial_r \Phi b](t, r) = \int_{\mathbb{R}_+} [\Phi(t, r) - \Phi(t, r - f(t, z))] \nu(dz). \quad (11)$$



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## Remark

- Since  $\Phi(t, X_t) = 0$  for  $X_t < 0$ , the RHS in (11) is actually

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- In the compound Poisson case  $f(t, z) \equiv z$ ,  $\nu(dz) = \lambda F_Z(dz)$ , where  $Z$  is the jump size. Thus (11) becomes

$$[\partial_t \Phi + \partial_r \Phi b](t, r) = \Phi(t, r) \lambda - \lambda \int_{\{r \geq z\}} \Phi(t, r - z) F_Z(dz).$$

## Infinite horizon case

Assume  $b(t, r) = b(r)$ . Denote  $\psi(r) = \lim_{t \rightarrow \infty} \Psi(t, r)$  and  $\varphi(r) = 1 - \psi(r)$ . Then

$$\varphi'(r)b(r) = \varphi(r)\lambda - \lambda \int_{\{r \geq z\}} \varphi(r - z)F_Z(dz). \quad (12)$$

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$$\varphi'(r)b(r) = \varphi(r)\lambda - \lambda \int_{\{r \geq z\}} \varphi(r - z)F_Z(dz). \quad (12)$$

## Example

If  $b(r) = c(1 + \rho) \triangleq \beta$  and  $Z \sim \exp\{\delta\}$  Then (12) becomes

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- Differentiating:  $\varphi''(r)\beta = (\lambda - \delta\beta)\varphi'(r)$ .
- Solving:  $\varphi(r) = c_1 - c_2 e^{-(\delta - \lambda/\beta)r}$ , where  $c_1, c_2 \in \mathbb{R}$ .

Denoting  $\beta = c(1 + \rho)$  again, and integrate (13) from 0 to  $x$ :

$$\begin{aligned}\frac{\beta}{\lambda}(\varphi(x) - \varphi(0)) &= \frac{\beta}{\lambda} \int_0^x \varphi'(r) dr \\ &= \int_0^x \varphi(r) dr - \int_0^x \int_0^u \varphi(u - z) F_Z(dz) du \\ &= \dots\dots\dots \\ &= \int_0^x \varphi(r) dr - \int_0^x \int_0^{x-u} F_Z(dz) \varphi(u) du \\ &= \int_0^x [1 - F_Z(x - u)] \varphi(u) du.\end{aligned}$$
$$\Rightarrow \varphi(x) = \varphi(0) + \frac{\lambda}{\beta} \int_0^x \varphi(x - z) \bar{F}_Z(z) dz. \quad (14)$$

## An Evidence

Recall IDE (14). By Expected Value Principle  $c = \frac{dE[S_t]}{dt} = \lambda\mu$ , denoting  $F_I(x) = \mu^{-1} \int_0^x \bar{F}(z) dz$  (14) becomes

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Solving (15) by Laplace transforms and using the initial value  $\varphi(0) = \frac{\rho}{1+\rho}$  we have

$$\varphi(x) = \frac{\rho}{1+\rho} \sum_{n=0}^{\infty} \left( \frac{1}{1+\rho} \right)^n F_I^{n*}(x). \quad (16)$$



## Example

If  $Z \sim \exp(\delta)$ , then we see that

$$\psi(x) = 1 - \varphi(x) = \frac{1}{1 + \rho} \exp \left\{ -\frac{\rho}{\delta(1 + \rho)} x \right\} \leq e^{-Rx}.$$

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## Remark

A primitive method for the Lundberg bound is to consider  $\psi_n(x)$ , the ruin probability up to  $(n + 1)$ -st claim. By an inductual argument one proves that, there exists an  $R > 0$  such that

$$\psi_n(x) \leq e^{-Rx}, \quad \forall n. \quad (17)$$

Letting  $n \rightarrow \infty$  one derives the (upper) bound for (infinite horizon) ruin probability  $\psi(x)$ . The constant  $R$  is called “*Lundberg coefficient*” or “*adjustment coefficients*”.

# Exponential Martingale Approach (Gerber, (1973))

- Consider the classical model  $X_t = x + ct - S_t$ , where  $ct = E[S_t] = \lambda\mu t$ . Denote  $Q_t = ct - S_t$  (*profit process*).

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- For any given  $x$  and  $r > 0$ , consider the  $\mathbf{F}^P$ -adapted process

$$M_t^x \triangleq \frac{e^{-r(x+Q_t)}}{e^{t\theta(r)}}, \quad t \geq 0, \quad (18)$$

where  $\theta(\cdot)$  is a function to be determined.

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where  $\theta(\cdot)$  is a function to be determined.

- **Suppose that  $\{M_t^x\}$  is an  $\mathbf{F}^P$ -martingale(!)** Then, by optional sampling, for any given time  $t_0 > 0$  and stopping time  $\tau_x \triangleq \inf\{t \geq 0 : X_t = x + Q_t < 0\}$ , one has

$$\begin{aligned} e^{-rx} &= M_0^x = E \left\{ M_{t_0 \wedge \tau_x}^x \middle| \mathcal{F}_0^P \right\} = E \left\{ M_{t_0 \wedge \tau_x}^x \right\} \quad (19) \\ &\geq E \left\{ M_{\tau_x}^x \middle| \tau_x \leq t_0 \right\} P\{\tau_x \leq t_0\}. \end{aligned}$$

# Exponential Martingale Approach (Gerber, (1973))

- But on the set  $\{\tau_x \leq t_0\}$  one must have  $X_{\tau_x} = x + Q_{\tau_x} \leq 0$ .  
Thus

$$\begin{aligned} P\{\tau_x \leq t_0\} &\leq \frac{e^{-rx}}{E\{M_{\tau_x}^x | \tau_x \leq t_0\}} \leq \frac{e^{-rx}}{E\{e^{-\tau_x \theta(r)} | \tau_x \leq t_0\}} \\ &\leq e^{-rx} \sup_{0 \leq t \leq t_0} e^{t\theta(r)}. \end{aligned}$$

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## Question

How to determine  $\theta$ ?



## Analysis

- Denote  $\hat{f}(s) = \int_0^\infty e^{-sx} dF(x) = E[e^{-sU_1}]$ . Then

$$\begin{aligned} E \left[ e^{sS_t} \right] &= \sum_{n=0}^{\infty} E \left[ e^{s \sum_{k=1}^{N_t} U_k} \mid N_t = n \right] P(N_t = n) \\ &= \sum_{n=0}^{\infty} \hat{f}^n(-s) \frac{(\lambda t)^n}{n!} e^{-\lambda t} = e^{\lambda(\hat{f}(-s)-1)t} \end{aligned}$$

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- Thus to make  $M^x$  a martingale, one need only choose

$$E \left[ e^{-sQ_t} \right] = e^{-sct} E \left[ e^{sS_t} \right] = e^{-sct + \lambda[\hat{f}(-s)-1]t} \triangleq e^{t\theta(s)}, \quad (21)$$

where  $\theta(s) \triangleq \lambda[\hat{f}(-s) - 1] - sc$ .

# Exponential Martingale Approach (Gerber, (1973))

- With this choice of  $\theta$ , and using (21) and the fact that  $Q$  has independent increments, we have

$$E[M_t^x | \mathcal{F}_s^P] = M_s^x E \left\{ \frac{e^{-r(Q_t - Q_s)}}{e^{(t-s)\theta(r)}} \middle| \mathcal{F}_s^P \right\} = M_s^x.$$

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- Recall (20). Clearly the sharp estimate of ruin probability is obtained by minimizing the RHS w.r.t.  $r$ . Namely, choosing  $r^* \triangleq \sup\{r : \theta(r) \leq 0\}$  would give the best estimate

$$\psi(x) \leq e^{-r^*x}. \quad (22)$$

$r^*$  is thus called *Lundberg coefficient*.

# Another look at Exponential Martingales

Consider the more general model:

$$X_t = x + \int_0^t b(s, X_s) ds - \int_0^t \int_{\mathbb{R}_+} f(s, z) N_p(ds dz). \quad (23)$$

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- For any  $g \in C^{1,1}([0, T] \times \mathbb{R})$ , applying Itô's formula to get

$$\begin{aligned} g(t, X_t) &= g(0, x) + \int_0^t \{ \partial_t g + \partial_x g b \} (s, X_s) ds \\ &+ \int_0^t \int_{\mathbb{R}_+} [g(s, X_{s-} + f(s, z)) - g(s, X_{s-})] \nu(dz) ds + mg \end{aligned}$$

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- Thus  $M_t \triangleq g(t, X_t)$  is a mg (or local mg)  $\iff g$  satisfies

$$\partial_t g + \partial_x g b + \int_{\mathbb{R}_+} [g(t, x - f(t, z)) - g(t, x)] \nu(dz) = 0. \quad (24)$$

# Another look at Exponential Martingales

In the compound Poisson case  $b(t, x) = \beta$ ,  $f \equiv z$ , and  $\nu(dz) = \lambda F_U(dz)$ . The equation (24) becomes

$$[\partial_t g + \partial_x g]\beta + \lambda \left\{ \int_{\mathbb{R}_+} [g(t, x - z) - g(t, x)] F_U(dz) \right\} = 0.$$

If  $g = g(x)$ , then

$$g'(x)\beta + \lambda \left\{ \int_{\mathbb{R}_+} g(x - z) F_U(dz) - g(x) \right\} = 0. \quad (25)$$

Setting  $g(x) = \varphi(x)$  for  $x \geq 0$  and  $g(x) = 0$  for  $x < 0$  we see that the integral becomes  $\int_0^x g(x - z) F_U(dz)$  and we recover (14) for the infinite horizon ruin probability.



- Assume  $g(t, x) = e^{-sx - \theta t}$ , where  $s$  and  $\theta$  are parameters. Then (25) reads

$$[-\theta - \beta s]g(t, x) + \lambda \left\{ \int_{\mathbb{R}_+} [e^{sz} F_U(dz) - 1]g(t, x) \right\} = 0.$$

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- Denoting  $\hat{m}_U(s) = \int_{\mathbb{R}_+} e^{sz} F_U(dz)$ , then the above becomes

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- Thus (since  $g(t, x) > 0!$ )

$$\theta = \theta(s) = -\beta s + \lambda [\hat{m}_U(s) - 1]. \quad (26)$$

We obtain the *adjustment coefficient*  $\theta = \theta(s)$ , and

$$M_t = g(t, X_t) = \exp\{-sX_t - \theta(s)t\}$$

is a martingale!

- Consider the reserve equation with interest:  $X_0 = x$

$$dX_t = [r_t X_t + c_t(1 + \rho_t)]dt - \int_{\mathbb{R}_+} f(t, z) N_p(dzdt).$$

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- Denote  $\Gamma_t \triangleq e^{-\int_0^t r_s ds}$ , and  $\tilde{X}_t = \Gamma_t X_t$ . Then  $\tilde{X}$  satisfies

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- Assume  $\beta = c(1 + \rho)$  is constant, and  $r_t$  is deterministic, Then for  $g \in C^{1,1}(\mathbb{R}_+ \times \mathbb{R})$ , we have

$$\begin{aligned} g(t, \tilde{X}_t) &= g(0, x) + \int_0^t [\partial_t g + \partial_x g \Gamma_s \beta](s, \tilde{X}_s) ds \\ &\quad + \int_0^t \int_{\mathbb{R}_+} [g(\cdot, \cdot - \Gamma_s f) - g](s, \tilde{X}_{s-}) \nu(dz) ds + mg \end{aligned}$$

- Thus  $M_t = g(t, \tilde{X}_t)$  is a martingale if and only if

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- Thus  $M_t = g(t, \tilde{X}_t)$  is a martingale if and only if

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- Assume  $a(0) = 1$ . We can solve the ODE

$$a'(t) + \theta(s \Gamma_t) a(t) = 0, \quad t \geq 0$$

to get  $a(t) = e^{-\int_0^t \theta(s \Gamma_u) du}$ .

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- Thus  $\tilde{M}_t \triangleq g(t, \tilde{X}_t) = \exp\{-s \tilde{X}_t - \int_0^t \theta(s \Gamma_u) du\}$  is a mg.

## Question:

Can we find an exponential martingale that leads to the Lundberg bound for the general reserve model (2)?

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Recall the exponential martingale

$$\tilde{M}_t = \exp \left\{ -s\Gamma_t X_t - \int_{\mathbb{R}_+} \theta(s\Gamma_u) du \right\} \triangleq \exp \{ -I_s(t, X_t) - K_t^s \}.$$

where  $I_s(t, x) \triangleq sx\Gamma_t$  and  $K_t^s = \int_{\mathbb{R}_+} \theta(s\Gamma_u) du$ . Define

- $\beta_t = -\int_0^t r_s ds, t \geq 0$
- $I_\delta(t, x) \triangleq \delta x e^{-\int_0^t r_s ds} = \delta x \Gamma_t = \delta x e^{\beta_t}, \delta \in \mathbb{R}$ .
- $\tilde{X}_t = e^{\beta_t} X_t = \Gamma_t X_t$  (discounted risk reserve).

- In general, we replace  $s$  by a parameter  $\delta$ , and look for a possible exponential mgf  $M^\delta = \exp\{I_\delta + K^\delta\}$ , where  $I_\delta(t, X_t) = \delta \tilde{X}_t$ , and  $\tilde{X}$  satisfies:

$$d\tilde{X}_t = \Gamma_t(\tilde{b}(t, \beta_t, \tilde{X}_t) + \eta_t)dt + \langle \hat{\sigma}_t, dW_t \rangle - \int_{\mathbb{R}^+} \Gamma_t f(t, x) N_p(dt dx),$$

where  $\tilde{b}(t, \beta_t, \tilde{X}_t) = b(t, e^{-\beta_t} \tilde{X}_t) = b(t, X_t)$ .

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where  $\tilde{b}(t, \beta_t, \tilde{X}_t) = b(t, e^{-\beta_t} \tilde{X}_t) = b(t, X_t)$ .

- To “decompose  $K^\delta$ ”, define  $m_t^f(\gamma) \triangleq \int_{\mathbb{R}^+} [e^{\gamma f(t,z)} - 1] \nu(dz)$ . Then  $m^f(\gamma)$  is increasing in  $\gamma$  and integrable for all  $\gamma \leq \delta_0$ .

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- In compound Poisson case,  $f \equiv z$  and  $\nu(dz) = \lambda F_U(dz)$ , then  $m_t^f(\gamma) \triangleq \lambda \int_{\mathbb{R}^+} [e^{\gamma z} - 1] F_U(dz) = \lambda(\hat{m}_U(\gamma) - 1)$ , again.

- Now define  $K_t^\delta = -V_t^\delta + \frac{1}{2}Y_t^\delta + Z_t^\delta$ , where

$$V_t^\delta = \delta \int_0^t e^{\beta_s} [\tilde{b}(s, \beta_s, \tilde{X}_s) + \eta_s] ds;$$

$$Y_t^\delta = \delta^2 \int_0^t e^{2\beta_s} |\hat{\sigma}_s|^2 ds; \quad Z_t^\delta \triangleq \int_0^t m_s^f(\delta e^{\beta_s}) ds.$$

- Define also  $Z_t^{\delta,0} \triangleq \int_0^t m_s^f(\delta) ds$ , and

$$\begin{cases} \mathcal{D} = \{\delta \geq 0 : Z_t^\delta < \infty, P\text{-a.s.}, \forall t \geq 0\}; \\ \mathcal{D}_0 = \{\delta \geq 0 : Z_t^{\delta,0} < \infty, P\text{-a.s.}, \forall t \geq 0\}. \end{cases}$$

- Since  $\gamma \geq 0$  and  $\beta_s \leq 0$ , the monotonicity of  $m^f(\cdot)$  shows that  $\mathcal{D}_0 \subseteq \mathcal{D}$ .



## Theorem (M. Sun (02))

The process  $M_t^\delta \triangleq \exp\{-\delta\tilde{X}_t - K_t^\delta\}$ ,  $t \geq 0$ , enjoys the following properties:

- For every  $\delta \in \mathcal{D}$ ,  $\{M_t^\delta : t \geq 0\}$  is an  $\mathbf{F}$ -local martingale.
- If the processes  $\pi$ ,  $\sigma$ ,  $\mu$ , and  $r$  are all bounded and  $\mathbf{F}^W$ -adapted, and that  $f(\cdot, \cdot, \cdot)$  is deterministic, then for every  $\delta \in \mathcal{D}_0$ ,  $\{M_t^\delta : t \geq 0\}$  is an  $\mathbf{F}$ -martingale.
- If  $r$  is also deterministic, then (ii) holds for all  $\delta \in \mathcal{D}$ .
- If  $\pi$  is allowed to be  $\mathbf{F}$ -adapted, then (ii) and (iii) hold for all  $\delta$  such that  $2\delta \in \mathcal{D}$  and  $\mathcal{D}_0$ , respectively.

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**Proof:** Define  $F^\delta(x, v, y, z) \triangleq \exp(-\delta x + v - \frac{1}{2}y - z)$ , and applying Itô's formula to  $F^\delta(\tilde{X}_t, V_t^\delta, Y_t^\delta, Z_t^\delta) \dots$

## Example

- **Classical Model**  $\pi_t \equiv 0, r_t \equiv 0, \rho \equiv 0, \mu_t \equiv 0, \sigma_t \equiv 0,$ 
  - $S_t$  is Compound Poisson
  - $K_t^\delta = t(\int_0^\infty (e^{\delta x} - 1)\lambda F(dx) - c\delta) (= \theta(\delta)t!)$
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- **Discounted Risk Reserve**  $\pi_t = \rho_t = \mu_t = \sigma_t \equiv 0, r > 0$ 
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- **Perturbed risk reserve**  $\pi_t \equiv 1, \rho_t = r_t = \mu_t \equiv 0, \sigma_t \equiv \varepsilon,$ 
  - $X_t = x + ct + \varepsilon W_t - S_t$
  - $K_t^\delta = t(-c\delta + \frac{1}{2}\delta^2\varepsilon^2 + \int_0^\infty (e^{\delta x} - 1)\lambda F(dx)) \triangleq k(\delta)t$
  - $\tilde{\delta} \triangleq \sup\{\delta > 0 : k(\delta) = 0\}$  (Delbaen-Haezendonck (1987), ...)

# Ruin Probability via “Rate Functions”

Extending the idea of the function  $I_\delta(t, x) = \delta x \beta_t$ , we can consider a more general “rate function”:  $I \in C^{1,2}(\mathbb{R}_+ \times \mathbb{R})$ . Define

- $M_t^I \triangleq \exp\{-I(t, X_t) - K_t^I\}$ ,  $K_t^I \triangleq -V_t^I + \frac{1}{2} Y_t^I + Z_t^I$ , and
- $Z_t^I \triangleq \int_0^t \int_{\mathbb{R}^+} [\exp\{I(s, X_s) - I(s, X_s - f(s, x))\} - 1] v(dx) ds$
- $V_t^I \triangleq \int_0^t \{\partial_x I(s, X_s) b(s, X_s) + \partial_t I(s, X_s)\} ds$
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## Definition

A function  $I \in C^{1,2}(\mathbb{R}_+ \times \mathbb{R})$  is called a “rate function” if  $Z_t^I < \infty$ ,  $\forall t \geq 0$ ,  $P$ -almost surely.

Suppose that we can find  $I$  such that  $M^I$  is a local martingale, and that  $I(t, x) \leq 0$ , for all  $t$  and  $x \leq 0$ .

- Let  $\tau \triangleq \inf\{t, X_t < 0\}$ , and apply Optional Sampling to supermartingale (nonnegative loc mg)  $M_t^I$ :

$$\begin{aligned} e^{-I(0,x)} &\geq E\{e^{-I(\tau, X_\tau) - K_\tau^I} | \tau < T\} P\{\tau < T\} \\ &\geq E\left\{\inf_{0 \leq t \leq T} e^{-K_t^I}\right\} \psi(x, T). \end{aligned}$$

- Applying Jensen's inequality we have

$$\psi(x, T) \leq \frac{e^{-I(0,x)}}{E\left\{\inf_{0 \leq t \leq T} e^{-K_t^I}\right\}} \leq e^{-I(0,x)} E\left\{\sup_{0 \leq t \leq T} e^{K_t^I}\right\}.$$

- One can let  $T \rightarrow \infty$  to obtain the bound for  $\psi(x)$ .



## Theorem

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$$\psi(x, T) \leq e^{-I(0, x)} E \sup_{0 \leq t \leq T} \exp(K_t^I),$$

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## Question:

How to find a rate function?

Assume Compound Poisson ( $f(t, x) = x$ , and  $v(dx) = \lambda F(dx)$ ), and  $\pi \equiv 0$ ,  $\mu \equiv 0$ ,  $\sigma \equiv 0$ ,  $r_t = r$  (constant),  $\rho(t, x) \equiv \rho(x)$  is an increasing function in  $x$ . Then

- $X_t = x + \int_0^t \rho(X_s) ds + \int_0^t \int_{\mathbb{R}^+} x \mu(dx ds)$ ,  $t \geq 0$ ,  
where  $\rho(x) \triangleq rx + c(1 + \rho(x))$ .

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- Consider the Rate function of the form:  $I(x) = \int_0^x \gamma(y) dy$ ,  $x \geq 0$ ,  $\gamma(\cdot) > 0$ , increasing. Then

$$\begin{aligned} K_t^I &= \int_0^t \left\{ -[\gamma \rho](X_s^+) + \int_{\mathbb{R}^+} \left[ e^{\int_{X_s^+ - x}^{X_s^+} \gamma(y) dy} - 1 \right] \lambda F(dx) \right\} ds \\ &\leq \int_0^t \left\{ -[\gamma \rho](X_s^+) + \int_{\mathbb{R}^+} \left[ e^{\gamma(X_s^+)x} - 1 \right] \lambda F(dx) \right\} ds. \end{aligned}$$

- Let  $\gamma$  be the non-decreasing solution to the **Lundberg equation**:

$$-\gamma p(y) + \int_{\mathbb{R}^+} [e^{\gamma x} - 1] \lambda F(dx) = 0, \quad y \geq 0.$$

(such solution exists if the so-called **net profit condition**:  $\inf_{x \geq 0} p(x) > \lambda E[U_1]$  holds and  $\rho$  is monotone.)

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- One can show that if  $p(\cdot) \in C^1$ , then  $I$  can be extended so that  $I(\cdot) \in C^2(\mathbb{R})$ ,  $I(0) = 0$ , and  $I(x) \leq 0$  for  $x < 0$ .



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- Thus  $K_t'(X^+) \leq 0$ ,  $\forall t \geq 0$ , and we have

$$\psi(x, T) \leq e^{-I(x)} \quad \text{and} \quad \psi(x) \leq e^{-I(x)}.$$

This is the Asmussen and Nielsen bound (1995).

# Can We Do Better?

Assume now  $\rho(x) \equiv 0$ , and  $F(x) = 1 - e^{-\theta x}$ ,  $x \geq 0$ . Then the Asmussen-Nielsen bound tells us:

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Denote  $K^I(X^+) = \int_0^t \mathcal{L}[I](X_s^+) ds$ , where  $\mathcal{L}$  is an ID operator:

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Setting  $\mathcal{L}[I](y) = 0$ , we see that  $b$  must satisfy

$$e^{\theta y} [ry + c] b'(y) + \int_0^y b(z) \lambda \theta e^{-\theta z} dz + \int_y^\infty \lambda \theta e^{-\theta x} dx = \lambda e^{\theta y} b(y).$$

Solving this equation to get

$$b(y) = C_1 \int_0^y e^{-\theta z} \left( \frac{rz}{c} + 1 \right)^{\frac{\lambda}{r} - 1} dz + C_2.$$

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Determining the constant  $C_1$  and  $C_2$ , and working a little more to get

$$I(y) = -\log \left( \frac{\int_y^\infty e^{-\theta z} \left( 1 + \frac{rz}{c} \right)^{\left(\frac{\lambda}{r}\right)-1} dz}{\frac{c}{\lambda} + \int_0^\infty e^{-\theta z} \left( 1 + \frac{rz}{c} \right)^{\left(\frac{\lambda}{r}\right)-1} dz} \right).$$

Extend  $I$  carefully for  $x < 0$ , one has

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But it is known that in this case  $\psi(x) = e^{-I(x)}$ ,  $x \geq 0$  (Segerdahi (1942)), we have obtained the **SHARPEST** bound!



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## Example

Assume that the claim sizes  $U_k$  are of Pareto  $(a, b)$  distribution:

$$F(z) = \frac{b}{a} \int_0^z \left(\frac{a}{z}\right)^{b+1} \mathbf{1}_{[a, \infty)}(z) dz.$$

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We show that the rate function technique still works in this case!

Assume that  $X_t = x + ct - \sum_{k=1}^{N_t} U_k$ , where  $U_k \sim \text{Pareto}(1, 2)$  and  $\lambda = 1$ . (i.e.,  $F_U(dz) = 2z^{-3} \mathbf{1}_{[1, \infty)}(z)$ .) Note that the Net Profit Condition implies that  $c - E[U_1] = c - 2 > 0$ .

# Large Claim Case

We assume that the rate function  $I \in C^2$  takes the following form:

$$I(y) = \begin{cases} \ln(y + \beta) - \ln \beta & y \geq 0, \\ 0 & y \leq -1, \end{cases}$$

Then the process  $K^I(X^+)$  takes the form:

$$K_t^I = \int_0^t \underbrace{\left\{ -\frac{c}{X_s^+ + \beta} + \int_0^\infty \{e^{I(X_s^+) - I(X_s^+ - x)} - 1\} F(dx) \right\}}_{\Gamma^I(X_s^+)} ds.$$

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Can we find  $I$  such that  $\Gamma^I(y) \leq 0$ ,  $y \geq 0$ , (Hence  $K^I \leq 0$ )?

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- First choosing  $Y > 0$  such that  $\frac{\ln y}{y} \leq \frac{(c-1)}{8}$ ,  $\forall y \geq Y$ .
- Then define  $\beta \triangleq \max\{Y, \frac{4}{c-1}, 2\}$  and  $\varepsilon \triangleq (\beta + 1)^2$ , such that  $I(y) \geq -\ln(1 + \varepsilon)$ , for  $y \in [-1, 0]$

The idea of finding  $\Gamma^I$  can be developed further. Consider

$$X_t = x + \int_0^t p(X_s) ds + \int_0^t \langle \alpha X_s, \sigma dW_s \rangle - \sum_{k=1}^{N_t} U_k, \quad t \geq 0,$$

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## Purpose

Find  $I \in C^2(\mathbb{R})$ , such that

$$\begin{aligned} \Gamma^I(y) &\triangleq -I'(y)\{ry + C\} + \frac{1}{2}(I'(y)^2 - I''(y))y^2|\sigma^T \alpha|^2 \\ &\quad + \int_{\mathbb{R}_+} [e^{I(y)-I(y-x)} - 1] \lambda \theta e^{-\theta x} dx \leq 0, \end{aligned}$$

and  $I(y) \sim k \ln y + C$  for some constant  $k, C$ , as  $y \rightarrow \infty$ .

Consider the following two-parameter family:

$$I_{\beta,k}(y) = k(\ln(y + \beta) - \ln 2\beta)1_{[\beta,\infty)}(y).$$

Suppose that  $r > |\sigma^T \alpha|^2 / 2 > 0$ . Then, for  $k = 2 \frac{r}{|\sigma^T \alpha|^2} - 1 > 0$ , one can find  $\beta = \frac{k}{\delta}$  large enough, such that

$$\begin{aligned} \Gamma^I(y) &= -I'(y)\{ry + C\} + \frac{1}{2}(I'(y)^2 - I''(y))y^2|\sigma^T \alpha|^2 \\ &\quad + \int_{\mathbb{R}_+} [e^{I(y)-I(y-x)} - 1]\lambda\theta e^{-\theta x} dx \leq 0, \quad \forall y \geq \beta. \end{aligned}$$

Consequently,  $\psi(x) \leq e^{-I(x)} = K(x + \beta)^{-k}$ , for  $x$  large.

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$$I_{\beta,k}(y) = k(\ln(y + \beta) - \ln 2\beta)1_{[\beta,\infty)}(y).$$

Suppose that  $r > |\sigma^T \alpha|^2 / 2 > 0$ . Then, for  $k = 2 \frac{r}{|\sigma^T \alpha|^2} - 1 > 0$ , one can find  $\beta = \frac{k}{\delta}$  large enough, such that

$$\begin{aligned} \Gamma^I(y) &= -I'(y)\{ry + C\} + \frac{1}{2}(I'(y)^2 - I''(y))y^2|\sigma^T \alpha|^2 \\ &\quad + \int_{\mathbb{R}_+} [e^{I(y)-I(y-x)} - 1] \lambda \theta e^{-\theta x} dx \leq 0, \quad \forall y \geq \beta. \end{aligned}$$

Consequently,  $\psi(x) \leq e^{-I(x)} = K(x + \beta)^{-k}$ , for  $x$  large.

**Note:** This result coincides with those of Nyrhinen (1999) and Kalashnikov-Norberg (2000).

# Ruin Problem via Storage Processes

An important observation made by Asmussen-Petersen (1988) is that the ruin probability of the risk process:

$$X_t = x + \int_0^t b(X_s) ds - S_t,$$

where  $S$  is a compound Poisson, and  $b(\cdot)$  is deterministic. Then the following relation hold:

$$P\{\tau < T\} = \psi(x, T) = P\{Y_T > x\},$$

where  $Y_t \triangleq -\int_0^t b(Y_s) ds + S_T - S_{T-t}$  is called a “*storage process*”.

Such a relation has proved to be very useful when Large Deviation method is used to study the asymptotics of ruin probabilities.

# A Natural Extension

Consider the risk reserve process

$$X_t = x + \int_0^t b(s, \cdot, X_s) ds + \Lambda_t^\pi - S_t, \quad 0 \leq t \leq T, \quad (27)$$

where  $b(t, \omega, x) = c(1 + \rho(t, x)) + r_t(\omega)x$ , and

$$\Lambda_t^\pi = \int_0^t \langle \pi_s, \mu_s - r_s \mathbf{1} \rangle ds + \int_0^t \langle \pi_s, \sigma_s dw_s \rangle.$$

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## Need

A “storage” process that solves a “reflected SDE”:

$$Y_t = - \int_0^t b(T - s, \cdot, Y_s) ds + \xi_t^\pi + K_t \geq 0, \quad (28)$$

where  $\xi_t^\pi \triangleq -\Lambda_T^\pi + \Lambda_{T-t}^\pi + S_T - S_{T-t}$ ,  $K \nearrow$ , and  $\int_0^\infty Y_t dK_s = 0$ .

## Definition

A pair of processes  $(Y, K)$  is the solution of (28) if

- i)  $(Y, K) \in \mathbb{D}^2$  and  $(Y, K)$  satisfies (28);
- ii)  $Y_t \geq 0, \forall t \geq 0$ ;
- iii)  $K$  is increasing, with “jump set”  $\mathcal{S}_K = \{t : \Delta K_t \neq 0\}$ ;
- iv)  $\int_0^\infty Y_s dK_s = 0$ ;
- v)  $\Delta K_t = |Y_t + \Delta \xi_t^\pi|, \forall t \in \mathcal{S}_K = \{t \geq 0 : Y_t + \Delta \xi_t^\pi < 0\}$ .



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## Warning:

The solution of SDEDR (28) is not adapted! It is solved pathwisely as an ODE with reflection. Further, since  $\xi_t^\pi$  has only upward jump by definition,  $K$  is always continuous!

The reflected SDE is solved by using the solution to the “**Discontinuous Skorohod Problem (DSP)**” (cf. e.g., Dupuis-Ishii (90) or Ma (92)).

## An important property of DSP (Dupuis-Ishii (90))

For any  $Y \in D$ , the *solution mapping* of  $\text{DRP}(Y)$ , as a mapping  $\Gamma : D \rightarrow D$  such that  $\Gamma(Y) = X$ , where  $(X, K)$  is the solution to  $\text{DRP}(Y)$ , is **Lipschitz** under the uniform topology in  $\mathbb{D}$ , that is, there exists a constant  $C > 0$ , such that, for any  $Y^1, Y^2 \in D$ , it holds that

$$\sup_{0 \leq s \leq t} |\Gamma(Y^1)_s - \Gamma(Y^2)_s| \leq C \sup_{0 \leq s \leq t} |Y_s^1 - Y_s^2|, \quad \forall t \geq 0. \quad (29)$$

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The reflected SDE is then  $Y_t = \Gamma(Z)_t = Z_t + K_t$ , and  $Z$  satisfies

$$Z_t = - \int_0^t b(s, \Gamma(Z)_s, \cdot) ds + \xi_t, \quad t \geq 0,$$

# Ruin Probability via Storage Process

Let  $Y$  be the storage proc. Set  $\tilde{Y}_t = Y_{T-t}$ ,  $J_t = K_T - K_{T-t}$ , then

$$\tilde{Y}_t = Y_T + \int_0^t b(s, \tilde{Y}_s, \cdot) ds + \Lambda_t - S_t - J_t.$$

$$\implies X_t - \tilde{Y}_t = x - Y_T + \int_0^t \alpha_s (X_s - Y_s) ds + J_t.$$

where  $\alpha_s \triangleq \frac{b(s, X_s, \cdot) - b(s, \tilde{Y}_s, \cdot)}{(X_s - \tilde{Y}_s)} \mathbf{1}_{\{X_s - \tilde{Y}_s \neq 0\}}$ .

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$$X_t - \tilde{Y}_t = (x - Y_T) e^{\int_0^t \alpha_s ds} + \int_0^t e^{\int_s^t \alpha_s ds} dJ_s \geq (x - Y_T) e^{\int_0^t \alpha_s ds}.$$

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Thus  $x \geq Y_T \implies X_t \geq \tilde{Y}_t \geq 0, \forall t \implies \tau \geq T$

$$\implies P\{\tau < T\} \leq P\{Y_T > x\}.$$

# Ruin Probability via Storage Process

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$$X_t - \tilde{Y}_t = (x - Y_T) e^{\int_0^t \alpha_s ds} + \int_0^t e^{\int_v^t \alpha_s ds} dJ_v \geq (x - Y_T) e^{\int_0^t \alpha_s ds}.$$

Thus  $x \geq Y_T \implies X_t \geq \tilde{Y}_t \geq 0, \forall t \implies \tau \geq T$

$$\implies P\{\tau < T\} \leq P\{Y_T > x\}.$$

With some more work, one can show that the equality holds.

To consider the Large Deviation problem, we now emphasize the dependence of the coefficients on the initial reserve  $x$ :

$$dX_t = b(t, x, X_t)ds + d\Lambda_t(x) - dS_t, \quad X_0 = x, \quad (30)$$

where  $S_t$  is compound Poisson, and  $d\Lambda_t(x) = \sigma_t(x)dW_t$ .



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## Example

- (“perturbed risk reserve”)  $b(t, x, X_t) = r_t X_t + c_t$  and  $\sigma_t(x) = \varepsilon$ .
- (Buy-and-hold)  $\pi_t \equiv f(x)$ . That is,

$$b(t, x, X_t) = r_t X_t + c(1 + \rho(t, X_t)),$$
$$\sigma_t(x) = \sigma_t^T f(x).$$

# Relation with Large Deviation

Recall the Lundberg bounds

$$\psi(x, T) \leq e^{-\delta x} E \sup_{0 \leq t \leq T} \exp(\tilde{K}_t^\delta), \quad (31)$$

$$\psi(x) \leq e^{-\delta x} E \sup_{t \geq 0} \exp(\tilde{K}_t^\delta). \quad (32)$$

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Denote the **adjustment coefficient** by

$$\tilde{\delta} = \sup\{\delta \in \mathcal{D} : E \sup_{t \geq 0} \exp(\tilde{K}_t^\delta) < \infty\},$$

$$\tilde{\delta}_T = \sup\{\delta \in \mathcal{D} : E \sup_{0 \leq t \leq T} \exp(K_t^\delta) < \infty\}.$$

Then for all  $\varepsilon > 0$  it holds that

$$\lim_{x \rightarrow \infty} \psi(x) e^{(\tilde{\delta} - \varepsilon)x} = 0, \quad \lim_{x \rightarrow \infty} \psi(x, T) e^{(\tilde{\delta}_T - \varepsilon)x} = 0,$$

$$\lim_{x \rightarrow \infty} \psi(x) e^{(\tilde{\delta} + \varepsilon)x} = \infty, \quad \lim_{x \rightarrow \infty} \psi(x, T) e^{(\tilde{\delta}_T + \varepsilon)x} = \infty.$$

- Consider the reflected “random” DE

$$Y_t(x) = - \int_0^t b(T-s, x, Y_s(x)) ds + \xi_t(x) + K_t(x), \quad (33)$$

where  $\xi_t(x) \triangleq -\Lambda_T(x) + \Lambda_{T-t}(x) + S_T - S_{T-t}$ , and  $K_t(x)$  is the *reflecting* process.





- By definition of the storage process we have

$$\psi(1/\varepsilon, T) = P\{Y_T(1/\varepsilon) > 1/\varepsilon\} = P\{\varepsilon Y_T(1/\varepsilon) > 1\}.$$

Thus the asymptotic ruin is

$$\lim_{\varepsilon \rightarrow 0} \varepsilon \log P\{\varepsilon Y_T(1/\varepsilon) > 1\} = -\tilde{\delta}_T.$$

— A problem of (*Sample-Path*) *Large Deviation* for the (perturbed) storage process  $Y_t^\varepsilon \triangleq \varepsilon Y_t(1/\varepsilon)$ !

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