

Week 3 Risk Models

$$S = X_1 + X_2 + \dots + X_N$$

$$\text{if } N=0, S=0$$

Distribution of S

$$\left\{ \underbrace{S \leq x}_{\text{CDF}} \text{ and } \underline{N=0} \right\} \text{ i.e. no claims}$$

$$\left\{ S \leq x \text{ and } N=1 \right\} \text{ i.e. 1 claim of amount } \leq x$$

$$\left\{ S \leq x \text{ and } N=2 \right\} \text{ i.e. 2 claims which total } \leq x$$

⋮

$$\left\{ S \leq x \text{ and } N=r \right\} \text{ i.e. } r \text{ claims which total } \leq x$$

⋮

mutually exclusive and exhaustive

$$\{S \leq x\} = \bigcup_{n=0}^{\infty} \{S \leq x \text{ and } N=n\}$$

$$\underline{P}\{S \leq x\} = \sum_{n=0}^{\infty} \underline{P}(S \leq x \text{ and } N=n)$$

Traverse all N

$$= \sum_{n=0}^{\infty} P(N=n) P(S \leq x | N=n)$$

E.g. Compound distribution S :

slide 6 $P(N=0) = 0.6$, $P(N=1) = 0.3$, $P(N=2) = 0.1$

X claim amount $X = \begin{cases} 1 & p=0.5 \\ 2 & p=0.5 \end{cases}$

$S \sim ?$

A: $S: 0, 1, 2, 3, 4$

$S=0$, ~~$P(N=0)$~~

CDF

$$P(S \leq 0) = P(N=0) = 0.6$$

$$P(S \leq 1) = P(S \leq 0) + P(S=1) = 0.6 + P(N=1) \cdot P(X=1) \\ = 0.6 + 0.3 \times 0.5 = 0.75$$

$$P(S \leq 2) = P(S \leq 1) + P(S=2) = 0.75 + P(N=1) \cdot P(X=2) \\ + P(N=2) \cdot P(X_1=1) \cdot P(X_2=1)$$

$$P(S \leq 3) = P(S \leq 2) + P(S=3) = 0.925 + P(N=2) \times P(X_1=1) \times P(X_2=2)$$

$N=1$ upper limit is $2 < 3$ X
 $X_1=1, X_2=2$
 $X_1=2, X_2=1$

$$+ P(N=2) \times P(X_1=2) \times P(X_2=1)$$

$$P(S \leq 4) = P(S \leq 3) + P(S=4) = 0.975 + P(N=2) \cdot P(X_1=2) \cdot P(X_2=2) \\ = 1$$

Moments of Compound distributions

$$E(S), \text{Var}(S)$$

The law of total expectation

$$E(S) = E[E(S|N)]$$

Proof: RHS = $E[E(S|N)] = E\left[\int_0^{\infty} s f(s|N) ds\right]$

$$E(S) = \int_0^{\infty} s f(s) ds$$

$$E(S|N) = \int_0^{\infty} s f(s|N) ds$$

N discrete

$$= \sum_{\text{all } n} P(N=n) \int_0^{\infty} s f(s|N=n) ds$$

$$= \int_0^{\infty} s \underbrace{\sum_{\text{all } n} P(N=n) f(s|N=n)}_{f(s)} ds$$

$$= \int_0^{\infty} s f(s) ds = E(S) = \text{LHS}$$

The law of total variance

$$\text{Var}(S) = E[\text{Var}(S|N)] + \text{Var}[E(S|N)]$$

Proof: LHS = $\text{Var}(S) = E(S^2) - [E(S)]^2 = E[E(S^2|N)] - [E[E(S|N)]]^2$
 use the law of total expectation

$$= E[\text{Var}(S|N) + (E(S|N))^2] - [E[E(S|N)]]^2$$

$$= E[\text{Var}(S|N)] + E[E(S|N)^2] - [E[E(S|N)]]^2$$

$$= E[\text{Var}(S|N)] + \text{Var}(E(S|N)) \quad \text{① \& \textcircled{2}}$$

$$= \text{RHS}$$

$\text{Var}(S) = E(S^2) - [E(S)]^2$
 $\text{Var}(S|N) \text{ ②} = E(S^2|N) - [E(S|N)]^2$
 $E[E(S|N)]^2 \text{ ①} = E[E(S^2|N)]$
 Linearity of E func

~~$$E[E(S|N)]^2 = E[E(S|N)]^2$$

$$= E[E(S|N)]^2$$~~

~~$$E[E(S)] = E[E(S)]^2$$~~

The mean $E(S)$

$$E(S) = E(E(S|N))$$

$$E(S|N=n) = \sum_{i=1}^n E(X_i) = nm_1$$

$$E(S|N) = Nm_1 \quad (*)$$

$$\begin{aligned} E(S) &= E[E(S|N)] = E[Nm_1] \\ &= E(N) \cdot m_1 \end{aligned}$$

$$E(S) = E(N) \cdot E(X)$$

Q: $X \sim \text{Pareto}(\alpha, \lambda)$, $\alpha = 3$, $\lambda = 400$

$N \sim \text{Poisson}(50)$

Find $E(S)$

$$A: E(S) = E(N) \cdot E(X) = 50 \times \frac{400}{3-1} = 10,000$$

fix $n \leftarrow \text{constant}$

$N = \text{r.v.}$

$$\begin{cases} m_1 = E(X) \\ m_2 = E(X^2) \end{cases}$$

$$S = \sum_{i=1}^N X_i$$

$$E(X) = \frac{\lambda}{\alpha-1}$$

The variance $\text{Var}(S)$

$$\text{Var}(S | N=n) = \text{Var} \left[\sum_{i=1}^n X_i \right] \stackrel{\text{independence}}{=} \sum_{i=1}^n \text{Var}(X_i) \stackrel{\text{identity}}{=} n(m_2 - m_1^2)$$

fix n $E(X^2)$ $E(X)$

$$\text{Var}(S | N) \stackrel{(**)}{=} N(m_2 - m_1^2) \quad (**)$$

$$\begin{aligned} \text{Var}(S) &= E(\text{Var}(S | N)) + \text{Var}[E(S | N)] \\ &= E[N(m_2 - m_1^2)] + \text{Var}(Nm_1) \\ &= E(N)(m_2 - m_1^2) + \text{Var}(N)m_1^2 \end{aligned}$$

$$\boxed{\text{Var}(S) = E(N) \text{Var}(X) + \text{Var}(N) [E(X)]^2}$$

MGF of S

$$M_S(t) = E(e^{tS})$$

$$M_S(t) = E \left[\underbrace{E(e^{tS} | N)} \right] \quad \leftarrow \quad E(X) = E \left[\underbrace{E(X | N)} \right]$$

$$E(e^{tS} | N=n) = E \left[e^{tX_1 + tX_2 + \dots + tX_n} \right]$$

independence $\prod_{i=1}^n$

$$= \prod_{i=1}^n E(e^{tX_i})$$

$\{X_i\}_{i=1}^n$ independent
identical

identity $\prod_{i=1}^n$

$$= \prod_{i=1}^n M_X(t) = [M_X(t)]^n$$

$$E(e^{tS} | N) = [M_X(t)]^N \quad \leftarrow \quad N: \text{r.v.}$$

func of N

$$M_S(t) = E \left[E(e^{tS} | N) \right] = E \left[[M_X(t)]^N \right]$$

$$= E \left[\exp \{ \ln [M_X(t)]^N \} \right] = E \left[\exp \{ N \ln M_X(t) \} \right]$$

Def of $M_N(t)$
 \downarrow
 $E(e^{Nt}) \triangleq M_N(t)$

$$M_S(t) = M_N(\ln M_X(t))$$

$$= M_N(\ln M_X(t))$$

Q: slide 18

A: a)
$$\underline{E(S) = E(N) \cdot E(X)}$$

$$E(S) = E(N) \cdot B$$

$$\text{Var}(S) = \cancel{E[\text{Var}(S|N)]} + \text{Var}[E(S|N)]$$

$$\text{Var}(S) = E(N) \text{Var}(X) + \text{Var}(N) [E(X)]^2$$

$$\text{Var}(S) = E(N) \times 0 + \text{Var}(N) \cdot B^2$$

$$= \text{Var}(N) \cdot B^2$$

b)
$$S: \begin{matrix} N=0 & 1 & 2 \\ 0, & B, & 2B, \dots, \end{matrix} S = BN$$

$$P(S \leq s) = P(BN \leq s) = P(N \leq \frac{s}{B})$$

The Compound Poisson distribution

$$N \sim \text{Poisson}(\lambda)$$

Facts of N : $E(N) = \text{Var}(N) = \lambda$

$$M_N(t) = e^{\lambda(e^t - 1)}$$

$$\checkmark \boxed{E(S)} = E(N) \cdot E(X) = \boxed{\lambda \cdot m_1}$$

$$\checkmark \boxed{\text{Var}(S)} = E(N) \cdot \text{Var}(X) + \text{Var}(N) \cdot [E(X)]^2 \\ = \lambda (m_2 - m_1^2) + \lambda m_1^2$$

$$\boxed{= \lambda m_2}$$

$$m_2 \neq \text{Var}(X)$$

$$\boxed{M_S(t)} \stackrel{\text{formulae}}{=} M_N(\ln M_X(t)) \\ = e^{\lambda (e^{\ln M_X(t)} - 1)}$$

$$\boxed{=} e^{\lambda (M_X(t) - 1)}$$

$$\boxed{\text{skew}(S)} = E([S - E(S)]^3) = \boxed{\lambda m_3}$$

$$m_1 = E(X)$$

$$\underline{m_2 = E(X^2)}$$

$$M_N(t) \stackrel{\text{def}}{=} e^{\lambda (e^t - 1)} \\ \ln M_X(t)$$

$$E(N) = \text{Var}(N) = \lambda$$

Sums of independent Compound Poisson r.v.s

$$A = S_1 + S_2 + \dots + S_n$$

$S_i \sim \text{Compound Poisson } (\lambda_i)$

CDF: $F_i(x)$

① $A \sim \text{Compound Poisson } (\Lambda)$

$$\Lambda = \sum_{i=1}^n \lambda_i$$

②
$$F(x) = \frac{1}{\Lambda} \sum_{i=1}^n \lambda_i F_i(x)$$

The Compound Binomial distribution $N \sim \text{Bin}(n, p)$

Facts of (Bin) N :

$$E(N) = np$$

$$\text{Var}(N) = np(1-p)$$

$$M_N(t) = (pe^t + 1 - p)^n$$

	mean	Var
Normal	μ	σ^2
Poisson	λ	λ

$$E(S) = E(N) \cdot E(X) = np m_1$$

$$\begin{aligned} \text{Var}(S) &= E(N) \text{Var}(X) + \text{Var}(N) (E(X))^2 = np(m_2 - m_1^2) + np(1-p)m_1^2 \\ &= np m_2 - np^2 m_1^2 \end{aligned}$$

$$\begin{aligned} M_S(t) &\stackrel{\text{formulae}}{=} M_N(\underbrace{\ln M_X(t)}) \\ &= (pe^{\ln M_X(t)} + 1 - p)^n \\ &= (pM_X(t) + 1 - p)^n \end{aligned}$$

$$M_N(t) = (pe^t + 1 - p)^n$$

Skew(S) Slide. 26

Example Slide. 27

$$A: (a) M_X(t) = \left(1 - \frac{t}{0.2}\right)^{-10}, \quad M_N(t) = (0.99 + 0.01e^t)^{100}$$

$$\boxed{M_S(t) = M_N(\underbrace{\ln M_X(t)})} = (0.99 + 0.01e^{\ln(1 - \frac{t}{0.2})^{-10}})^{100} = \dots$$

Slide 28

$$(b) E(S) = E(N) \cdot E(X) = np \cdot m_1 = 100 \times 0.01 \times \frac{10}{0.2} = 50$$

$$\text{Gamma: mean} = \frac{\alpha}{\beta}, \quad \text{Var} = \frac{\alpha}{\beta^2}$$

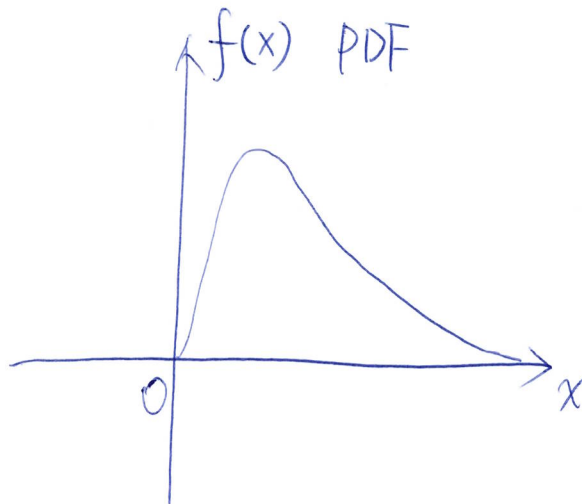
$$\begin{aligned} \text{Var}(S) &= E(N) \cdot \text{Var}(X) + \text{Var}(N) \cdot (E(X))^2 = np(m_2^2 - m_1^2) + np(1-p)m_1^2 \\ &= \underline{np m_2} - np^2 m_1^2 \end{aligned}$$

$$m_2 = E(X^2) = \text{Var}(X) + (E(X))^2 = \frac{\alpha}{\beta^2} + \left(\frac{\alpha}{\beta}\right)^2 = \frac{\alpha(\alpha+1)}{\beta^2}$$

\uparrow Var \uparrow E

$$\text{Var}(S) = 100 \times 0.01 \times \frac{10 \times (10+1)}{0.2^2} - 100 \times 0.01^2 \times \left(\frac{10}{0.2}\right)^2 = 2725$$

X_i



Positively - skewed