# Course 2023-2024 in Financial Risk Management Tutorial Session 4

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<sup>&</sup>lt;sup>1</sup>The opinions expressed in this presentation are those of the authors and are not meant to represent the opinions or official positions of Amundi Asset Management.

### Agenda

- Tutorial Session 1: Market Risk
- Tutorial Session 2: Credit Risk
- Tutorial Session 3: Counterparty Credit Risk and Collateral Risk
- Tutorial Session 4: Operational Risk & Asset Liability Management Risk
- Tutorial Session 5: Copulas, EVT & Stress Testing

#### Exercise

We consider a sample of n individual losses  $\{x_1, \ldots, x_n\}$ . We assume that they can be described by different probability distributions:

- (i) X follows a log-normal distribution  $\mathcal{LN}(\mu, \sigma^2)$ .
- (ii) X follows a Pareto distribution  $\mathcal{P}(\alpha, x^-)$  defined by:

$$\Pr\left\{X \le x\right\} = 1 - \left(\frac{x}{x_{-}}\right)^{-\alpha}$$

with  $x > x_-$  and  $\alpha > 0$ .

(iii) X follows a gamma distribution  $\Gamma(\alpha, \beta)$  defined by:

$$\Pr\left\{X \le x\right\} = \int_0^x \frac{\beta^{\alpha} t^{\alpha - 1} e^{-\beta t}}{\Gamma(\alpha)} dt$$

with x > 0,  $\alpha > 0$  and  $\beta > 0$ .

(iv) The natural logarithm of the loss X follows a gamma distribution: In  $X \sim \Gamma(\alpha; \beta)$ .

### Question 1

We consider the case (i).

(i) X follows a log-normal distribution  $\mathcal{LN}\left(\mu,\sigma^2\right)$ .

#### Question 1.a

Show that the probability density function is:

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^2\right)$$

The density of the Gaussian distribution  $Y \sim \mathcal{N}\left(\mu, \sigma^2\right)$  is:

$$g(y) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2\right)$$

Let  $X \sim \mathcal{LN}(\mu, \sigma^2)$ . We have  $X = \exp Y$ . It follows that:

$$f(x) = g(y) \left| \frac{\mathrm{d}y}{\mathrm{d}x} \right|$$

with  $y = \ln x$ . We deduce that:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{y-\mu}{\sigma}\right)^2\right) \times \frac{1}{x}$$
$$= \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{\ln x - \mu}{\sigma}\right)^2\right)$$

#### Question 1.b

Calculate the two first moments of X. Deduce the orthogonal conditions of the generalized method of moments.

For  $m \ge 1$ , the non-centered moment is equal to:

$$\mathbb{E}\left[X^{m}\right] = \int_{0}^{\infty} x^{m} \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^{2}\right) dx$$

By considering the change of variables  $y = \sigma^{-1} (\ln x - \mu)$  and  $z = y - m\sigma$ , we obtain:

$$\mathbb{E}[X^{m}] = \int_{-\infty}^{\infty} e^{m\mu + m\sigma y} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y^{2}} dy$$

$$= e^{m\mu} \times \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y^{2} + m\sigma y} dy$$

$$= e^{m\mu} \times e^{\frac{1}{2}m^{2}\sigma^{2}} \times \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y - m\sigma)^{2}} dy$$

$$= e^{m\mu + \frac{1}{2}m^{2}\sigma^{2}} \times \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}z^{2}\right) dz$$

$$= e^{m\mu + \frac{1}{2}m^{2}\sigma^{2}}$$

We deduce that:

$$\mathbb{E}\left[X\right] = e^{\mu + \frac{1}{2}\sigma^2}$$

and:

$$\operatorname{var}(X) = \mathbb{E}[X^{2}] - \mathbb{E}^{2}[X]$$

$$= e^{2\mu + 2\sigma^{2}} - e^{2\mu + \sigma^{2}}$$

$$= e^{2\mu + \sigma^{2}} \left(e^{\sigma^{2}} - 1\right)$$

We can estimate the parameters  $\mu$  and  $\sigma$  with the generalized method of moments by using the following empirical moments:

$$\begin{cases} h_{i,1}(\mu,\sigma) = x_i - e^{\mu + \frac{1}{2}\sigma^2} \\ h_{i,2}(\mu,\sigma) = \left(x_i - e^{\mu + \frac{1}{2}\sigma^2}\right)^2 - e^{2\mu + \sigma^2} \left(e^{\sigma^2} - 1\right) \end{cases}$$

### Question 1.c

Find the maximum likelihood estimators  $\hat{\mu}$  and  $\hat{\sigma}$ .

The log-likelihood function of the sample  $\{x_1, \ldots, x_n\}$  is:

$$\ell(\mu, \sigma) = \sum_{i=1}^{n} \ln f(x_i)$$

$$= -\frac{n}{2} \ln \sigma^2 - \frac{n}{2} \ln 2\pi - \sum_{i=1}^{n} \ln x_i - \frac{1}{2} \sum_{i=1}^{n} \left(\frac{\ln x_i - \mu}{\sigma}\right)^2$$

To find the ML estimators  $\hat{\mu}$  and  $\hat{\sigma}$ , we can proceed in two different way.

#1  $X \sim \mathcal{LN}(\mu, \sigma^2)$  implies that  $Y = \ln X \sim \mathcal{N}(\mu, \sigma^2)$ . We know that the ML estimators  $\hat{\mu}$  and  $\hat{\sigma}$  associated to Y are:

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} y_i$$

$$\hat{\sigma} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{\mu})^2}$$

We deduce that the ML estimators  $\hat{\mu}$  and  $\hat{\sigma}$  associated to the sample  $\{x_1, \ldots, x_n\}$  are:

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} \ln x_{i}$$

$$\hat{\sigma} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\ln x_{i} - \hat{\mu})^{2}}$$

#2 We maximize the log-likelihood function. The first-order conditions are  $\partial_{\mu} \ell(\mu, \sigma) = 0$  and  $\partial_{\sigma} \ell(\mu, \sigma) = 0$ . We deduce that:

$$\partial_{\mu} \ell(\mu, \sigma) = \frac{1}{\sigma^2} \sum_{i=1}^{n} (\ln x_i - \mu) = 0$$

and:

$$\partial_{\sigma} \ell(\mu, \sigma) = -\frac{n}{\sigma} + \sum_{i=1}^{n} \frac{(\ln x_{i} - \mu)^{2}}{\sigma^{3}} = 0$$

We finally obtain:

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} \ln x_i$$

and:

$$\hat{\sigma} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\ln x_i - \hat{\mu})^2}$$

#### Question 2

We consider the case (ii).

(ii) X follows a Pareto distribution  $\mathcal{P}(\alpha, x^-)$  defined by:

$$\Pr\left\{X \le x\right\} = 1 - \left(\frac{x}{x_{-}}\right)^{-\alpha}$$

with  $x \ge x_-$  and  $\alpha > 0$ .

#### Question 2.a

Calculate the two first moments of X. Deduce the GMM conditions for estimating the parameter  $\alpha$ .

The probability density function is:

$$f(x) = \frac{\partial \Pr\{X \le x\}}{\partial x}$$
$$= \alpha \frac{x^{-(\alpha+1)}}{x_{-}^{-\alpha}}$$

For  $m \ge 1$ , we have:

$$\mathbb{E}[X^{m}] = \int_{x_{-}}^{\infty} x^{m} \alpha \frac{x^{-(\alpha+1)}}{x_{-}^{-\alpha}} dx$$

$$= \frac{\alpha}{x_{-}^{-\alpha}} \int_{x_{-}}^{\infty} x^{m-\alpha-1} dx$$

$$= \frac{\alpha}{x_{-}^{-\alpha}} \left[ \frac{x^{m-\alpha}}{m-\alpha} \right]_{x_{-}}^{\infty}$$

$$= \frac{\alpha}{\alpha - m} x_{-}^{m}$$

We deduce that:

$$\mathbb{E}\left[X\right] = \frac{\alpha}{\alpha - 1} x_{-}$$

and:

$$\operatorname{var}(X) = \mathbb{E}[X^{2}] - \mathbb{E}^{2}[X]$$

$$= \frac{\alpha}{\alpha - 2} x_{-}^{2} - \left(\frac{\alpha}{\alpha - 1} x_{-}\right)^{2}$$

$$= \frac{\alpha}{(\alpha - 1)^{2} (\alpha - 2)} x_{-}^{2}$$

We can then estimate the parameter  $\alpha$  by considering the following empirical moments:

$$h_{i,1}(\alpha) = x_i - \frac{\alpha}{\alpha - 1} x_-$$

$$h_{i,2}(\alpha) = \left(x_i - \frac{\alpha}{\alpha - 1} x_-\right)^2 - \frac{\alpha}{(\alpha - 1)^2 (\alpha - 2)} x_-^2$$

The generalized method of moments can consider either the first moment  $h_{i,1}(\alpha)$ , the second moment  $h_{i,2}(\alpha)$  or the joint moments  $(h_{i,1}(\alpha), h_{i,2}(\alpha))$ . In the first case, the estimator is:

$$\hat{\alpha} = \frac{\sum_{i=1}^{n} x_i}{\sum_{i=1}^{n} x_i - nx_-}$$

#### Question 2.b

Find the maximum likelihood estimator  $\hat{\alpha}$ .

The log-likelihood function is:

$$\ell(\alpha) = \sum_{i=1}^{n} \ln f(x_i) = n \ln \alpha - (\alpha + 1) \sum_{i=1}^{n} \ln x_i + n\alpha \ln x_-$$

The first-order condition is:

$$\partial_{\alpha} \ell(\alpha) = \frac{n}{\alpha} - \sum_{i=1}^{n} \ln x_{i} + \sum_{i=1}^{n} \ln x_{-} = 0$$

We deduce that:

$$n = \alpha \sum_{i=1}^{n} \ln \frac{x_i}{x_-}$$

The ML estimator is then:

$$\hat{\alpha} = \frac{n}{\sum_{i=1}^{n} (\ln x_i - \ln x_-)}$$

#### Question 3

We consider the case (iii). Write the log-likelihood function associated to the sample of individual losses  $\{x_1, \ldots, x_n\}$ . Deduce the first-order conditions of the maximum likelihood estimators  $\hat{\alpha}$  and  $\hat{\beta}$ .

(iii) X follows a gamma distribution  $\Gamma(\alpha, \beta)$  defined by:

$$\Pr\left\{X \le x\right\} = \int_0^x \frac{\beta^{\alpha} t^{\alpha - 1} e^{-\beta t}}{\Gamma\left(\alpha\right)} dt$$

with  $x \ge 0$ ,  $\alpha > 0$  and  $\beta > 0$ .

The probability density function of (iii) is:

$$f(x) = \frac{\partial \Pr\{X \le x\}}{\partial x} = \frac{\beta^{\alpha} x^{\alpha - 1} e^{-\beta x}}{\Gamma(\alpha)}$$

It follows that the log-likelihood function is:

$$\ell(\alpha,\beta) = \sum_{i=1}^{n} \ln f(x_i) = -n \ln \Gamma(\alpha) + n\alpha \ln \beta + (\alpha - 1) \sum_{i=1}^{n} \ln x_i - \beta \sum_{i=1}^{n} x_i$$

The first-order conditions  $\partial_{\alpha} \ell(\alpha, \beta) = 0$  and  $\partial_{\beta} \ell(\alpha, \beta) = 0$  imply that:

$$n\left(\ln\beta - \frac{\Gamma'(\alpha)}{\Gamma(\alpha)}\right) + \sum_{i=1}^{n} \ln x_i = 0$$

and:

$$n\frac{\alpha}{\beta} - \sum_{i=1}^{n} x_i = 0$$

#### Question 4

We consider the case (iv). Show that the probability density function of X is:

$$f(x) = \frac{\beta^{\alpha} (\ln x)^{\alpha - 1}}{\Gamma(\alpha) x^{\beta + 1}}$$

What is the support of this probability density function? Write the log-likelihood function associated to the sample of individual losses  $\{x_1, \ldots, x_n\}$ .

(iv) The natural logarithm of the loss X follows a gamma distribution: In  $X \sim \Gamma(\alpha; \beta)$ .

Let  $Y \sim \Gamma(\alpha, \beta)$  and  $X = \exp Y$ . We have:

$$f_X(x) |dx| = f_Y(y) |dy|$$

where  $f_X$  and  $f_Y$  are the probability density functions of X and Y. We deduce that:

$$f_X(x) = \frac{\beta^{\alpha} y^{\alpha - 1} e^{-\beta y}}{\Gamma(\alpha)} \times \frac{1}{e^y}$$

$$= \frac{\beta^{\alpha} (\ln x)^{\alpha - 1} e^{-\beta \ln x}}{x\Gamma(\alpha)}$$

$$= \frac{\beta^{\alpha} (\ln x)^{\alpha - 1}}{\Gamma(\alpha) x^{\beta + 1}}$$

The support of this probability density function is  $[0, +\infty)$ .

The log-likelihood function associated to the sample of individual losses  $\{x_1, \ldots, x_n\}$  is:

$$\ell(\alpha, \beta) = \sum_{i=1}^{n} \ln f(x_i)$$

$$= -n \ln \Gamma(\alpha) + n\alpha \ln \beta + (\alpha - 1) \sum_{i=1}^{n} \ln (\ln x_i) - (\beta + 1) \sum_{i=1}^{n} \ln x_i$$

#### Question 5

We now assume that the losses  $\{x_1, \ldots, x_n\}$  have been collected beyond a threshold H meaning that  $X \ge H$ .

#### Question 5.a

What becomes the generalized method of moments in the case (i).

(i) X follows a log-normal distribution  $\mathcal{LN}\left(\mu,\sigma^2\right)$ .

Using Bayes' formula, we have:

$$\Pr\{X \le x \mid X \ge H\} = \frac{\Pr\{H \le X \le x\}}{\Pr\{X \ge H\}}$$
$$= \frac{\mathbf{F}(x) - \mathbf{F}(H)}{1 - \mathbf{F}(H)}$$

where  $\mathbf{F}$  is the cdf of X. We deduce that the conditional probability density function is:

$$f(x \mid X \ge H) = \partial_x \Pr\{X \le x \mid X \ge H\}$$
$$= \frac{f(x)}{1 - \mathbf{F}(H)} \times \mathbb{1}\{x \ge H\}$$

For the log-normal probability distribution, we obtain:

$$f(x \mid X \ge H) = \frac{1}{1 - \Phi\left(\frac{\ln H - \mu}{\sigma}\right)} \times \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^{2}} dx$$
$$= \varphi \times \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^{2}} dx$$

We note  $\mathcal{M}_m(\mu, \sigma)$  the conditional moment  $\mathbb{E}[X^m \mid X \geq H]$ . We have:

$$\mathcal{M}_{m}(\mu,\sigma) = \varphi \times \int_{H}^{\infty} \frac{x^{m-1}}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^{2}} dx$$

$$= \varphi \times \int_{\ln H}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x - \mu}{\sigma}\right)^{2} + mx} dx$$

$$= \varphi \times e^{m\mu + \frac{1}{2}m^{2}\sigma^{2}} \times \int_{\ln H}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\frac{\left(x - \left(\mu + m\sigma^{2}\right)\right)^{2}}{\sigma^{2}}} dx$$

$$= \frac{1 - \Phi\left(\frac{\ln H - \mu - m\sigma^{2}}{\sigma}\right)}{1 - \Phi\left(\frac{\ln H - \mu}{\sigma}\right)} e^{m\mu + \frac{1}{2}m^{2}\sigma^{2}}$$

The first two moments of  $X \mid X \geq H$  are then:

$$\mathcal{M}_1\left(\mu,\sigma
ight) = \mathbb{E}\left[X \mid X \geq H
ight] = rac{1 - \Phi\left(rac{\ln H - \mu - \sigma^2}{\sigma}
ight)}{1 - \Phi\left(rac{\ln H - \mu}{\sigma}
ight)}e^{\mu + rac{1}{2}\sigma^2}$$

and:

$$\mathcal{M}_{2}(\mu,\sigma) = \mathbb{E}\left[X^{2} \mid X \geq H\right] = \frac{1 - \Phi\left(\frac{\ln H - \mu - 2\sigma^{2}}{\sigma}\right)}{1 - \Phi\left(\frac{\ln H - \mu}{\sigma}\right)} e^{2\mu + 2\sigma^{2}}$$

We can therefore estimate  $\mu$  and  $\sigma$  by considering the following empirical moments:

$$\begin{cases}
h_{i,1}(\mu,\sigma) = x_i - \mathcal{M}_1(\mu,\sigma) \\
h_{i,2}(\mu,\sigma) = (x_i - \mathcal{M}_1(\mu,\sigma))^2 - (\mathcal{M}_2(\mu,\sigma) - \mathcal{M}_1^2(\mu,\sigma))
\end{cases}$$

#### Question 5.b

Calculate the maximum likelihood estimator  $\hat{\alpha}$  in the case (ii).

(ii) X follows a Pareto distribution  $\mathcal{P}(\alpha, x^-)$  defined by:

$$\Pr\left\{X \le x\right\} = 1 - \left(\frac{x}{x_{-}}\right)^{-\alpha}$$

with  $x \ge x_-$  and  $\alpha > 0$ .

We have:

$$f(x \mid X \ge H) = \frac{f(x)}{1 - \mathbf{F}(H)} \times \mathbb{1} \{x \ge H\}$$

$$= \left(\alpha \frac{x^{-(\alpha+1)}}{x_{-}^{-\alpha}}\right) / \left(\frac{H^{-\alpha}}{x_{-}^{-\alpha}}\right)$$

$$= \alpha \frac{x^{-(\alpha+1)}}{H^{-\alpha}}$$

The conditional probability function is then a Pareto distribution with the same parameter  $\alpha$  but with a new threshold  $x_- = H$ . We can then deduce that the ML estimator  $\hat{\alpha}$  is:

$$\hat{\alpha} = \frac{n}{\left(\sum_{i=1}^{n} \ln x_i\right) - n \ln H}$$

#### Question 5.c

Write the log-likelihood function in the case (iii).

(iii) X follows a gamma distribution  $\Gamma(\alpha, \beta)$  defined by:

$$\Pr\left\{X \le x\right\} = \int_0^x \frac{\beta^{\alpha} t^{\alpha - 1} e^{-\beta t}}{\Gamma\left(\alpha\right)} dt$$

with  $x \ge 0$ ,  $\alpha > 0$  and  $\beta > 0$ .

# Estimation of the loss severity distribution

The conditional probability density function is:

$$f(x \mid X \geq H) = \frac{f(x)}{1 - \mathbf{F}(H)} \times \mathbb{1} \{x \geq H\}$$

$$= \left(\frac{\beta^{\alpha} x^{\alpha - 1} e^{-\beta x}}{\Gamma(\alpha)}\right) / \int_{H}^{\infty} \frac{\beta^{\alpha} t^{\alpha - 1} e^{-\beta t}}{\Gamma(\alpha)} dt$$

$$= \frac{\beta^{\alpha} x^{\alpha - 1} e^{-\beta x}}{\int_{H}^{\infty} \beta^{\alpha} t^{\alpha - 1} e^{-\beta t} dt}$$

We deduce that the log-likelihood function is:

$$\ell(\alpha, \beta) = n\alpha \ln \beta - n \ln \left( \int_{H}^{\infty} \beta^{\alpha} t^{\alpha - 1} e^{-\beta t} dt \right) + (\alpha - 1) \sum_{i=1}^{n} \ln x_{i} - \beta \sum_{i=1}^{n} x_{i}$$

#### Exercise

We consider a dataset of individual losses  $\{x_1, \ldots, x_n\}$  corresponding to a sample of T annual loss numbers  $\{N_{Y_1}, \ldots, N_{Y_T}\}$ . This implies that:

$$\sum_{t=1}^{T} N_{Y_t} = n$$

If we measure the number of losses per quarter  $\{N_{Q_1}, \dots, N_{Q_{4T}}\}$ , we use the notation:

$$\sum_{t=1}^{4T} N_{Q_t} = n$$

#### Question 1

We assume that the annual number of losses follows a Poisson distribution  $\mathcal{P}(\lambda_Y)$ . Calculate the maximum likelihood estimator  $\hat{\lambda}_Y$  associated to the sample  $\{N_{Y_1}, \ldots, N_{Y_T}\}$ .

We have:

$$\Pr\{N=n\}=e^{-\lambda_Y}\frac{\lambda_Y^n}{n!}$$

We deduce that the expression of the log-likelihood function is:

$$\ell\left(\lambda_{Y}\right) = \sum_{t=1}^{T} \ln \Pr\left\{N = N_{Y_{t}}\right\} = -\lambda_{Y}T + \left(\sum_{t=1}^{T} N_{Y_{t}}\right) \ln \lambda_{Y} - \sum_{t=1}^{T} \ln\left(N_{Y_{t}}!\right)$$

The first-order condition is:

$$\frac{\partial \ell (\lambda_Y)}{\partial \lambda_Y} = -T + \frac{1}{\lambda_Y} \left( \sum_{t=1}^T N_{Y_t} \right) = 0$$

We deduce that the ML estimator is:

$$\hat{\lambda}_{Y} = \frac{1}{T} \sum_{t=1}^{T} N_{Y_{t}} = \frac{n}{T}$$

#### Question 2

We assume that the quarterly number of losses follows a Poisson distribution  $\mathcal{P}(\lambda_Q)$ . Calculate the maximum likelihood estimator  $\hat{\lambda}_Q$  associated to the sample  $\{N_{Q_1}, \ldots, N_{Q_{4T}}\}$ .

Using the same arguments, we obtain:

$$\hat{\lambda}_Q = \frac{1}{4T} \sum_{t=1}^{4T} N_{Q_t} = \frac{n}{4T} = \frac{\hat{\lambda}_Y}{4}$$

#### Question 3

What is the impact of considering a quarterly or annual basis on the computation of the capital charge?

Considering a quarterly or annual basis has no impact on the capital charge. Indeed, the capital charge is computed with a one-year time horizon. If we use a quarterly basis, we have to find the distribution of the annual loss number. In this case, the annual loss number is the sum of the four quarterly loss numbers:

$$N_Y = N_{Q_1} + N_{Q_2} + N_{Q_3} + N_{Q_4}$$

We know that each quarterly loss number follows a Poisson distribution  $\mathcal{P}\left(\hat{\lambda}_{Q}\right)$  and that they are independent. Because the Poisson distribution is infinitely divisible, we obtain:

$$\mathcal{N}_{Q_1} + \mathcal{N}_{Q_2} + \mathcal{N}_{Q_3} + \mathcal{N}_{Q_4} \sim \mathcal{P}\left(4\hat{\lambda}_Q
ight)$$

We deduce that the annual loss number follows a Poisson distribution  $\mathcal{P}\left(\hat{\lambda}_{Y}\right)$  in both cases.

#### Question 4

What does this result become if we consider a method of moments based on the first moment?

Since we have  $\mathbb{E}\left[\mathcal{P}\left(\lambda\right)\right]=\lambda$ , the MM estimator in the case of annual loss numbers is:

$$\hat{\lambda}_Y = rac{1}{T} \sum_{t=1}^T N_{Y_t} = rac{n}{T}$$

The MM estimator is exactly the ML estimator.

#### Question 5

Same question if we consider a method of moments based on the second moment.

Since we have  $var(\mathcal{P}(\lambda)) = \lambda$ , the MM estimator in the case of annual loss numbers is:

$$\hat{\lambda}_{Y} = \frac{1}{T} \sum_{t=1}^{T} N_{Y_{t}}^{2} - \frac{n^{2}}{T^{2}}$$

If we use a quarterly basis, we obtain:

$$\hat{\lambda}_{Q} = \frac{1}{4} \left( \frac{1}{T} \sum_{t=1}^{4T} N_{Q_{t}}^{2} - \frac{n^{2}}{4T^{2}} \right)$$

$$\neq \frac{\hat{\lambda}_{Y}}{4}$$

There is no reason that  $\hat{\lambda}_Y = 4\hat{\lambda}_Q$  meaning that the capital charge will not be the same.

#### Exercise

In what follows, we consider a debt instrument, whose remaining maturity is equal to m. We note t the current date and T = t + m the maturity date.

#### Question 1

We consider a bullet repayment debt. Define its amortization function  $\mathbf{S}(t, u)$ . Calculate the survival function  $\mathbf{S}^{\star}(t, u)$  of the stock. Show that:

$$\mathbf{S}^{\star}\left(t,u\right) = \mathbb{1}\left\{t \leq u < t+m\right\} \cdot \left(1 - \frac{u-t}{m}\right)$$

in the case where the new production is constant. Comment on this result.

By definition, we have:

$$\mathbf{S}(t,u) = \mathbb{1}\left\{t \le u < t + m\right\} = \begin{cases} 1 & \text{if } u \in [t,t+m[\\ 0 & \text{otherwise} \end{cases}$$

This means that the survival function is equal to one when u is between the current date t and the maturity date T = t + m. When u reaches T, the outstanding amount is repaid, implying that  $\mathbf{S}(t, T)$  is equal to zero. It follows that:

$$\mathbf{S}^{\star}(t, u) = \frac{\int_{-\infty}^{t} \operatorname{NP}(s) \mathbf{S}(s, u) \, \mathrm{d}s}{\int_{-\infty}^{t} \operatorname{NP}(s) \mathbf{S}(s, t) \, \mathrm{d}s}$$
$$= \frac{\int_{-\infty}^{t} \operatorname{NP}(s) \cdot \mathbb{1} \left\{ s \le u < s + m \right\} \, \mathrm{d}s}{\int_{-\infty}^{t} \operatorname{NP}(s) \cdot \mathbb{1} \left\{ s \le t < s + m \right\} \, \mathrm{d}s}$$

For the numerator, we have:

$$1 \{ s \le u < s + m \} = 1 \Rightarrow u < s + m$$
$$\Leftrightarrow s > u - m$$

and:

$$\int_{-\infty}^{t} \mathrm{NP}(s) \cdot \mathbb{1} \left\{ s \le u < s + m \right\} \, \mathrm{d}s = \int_{u-m}^{t} \mathrm{NP}(s) \, \, \mathrm{d}s$$

For the denominator, we have:

$$1 \{ s \le t < s + m \} = 1 \Rightarrow t < s + m$$
$$\Leftrightarrow s > t - m$$

and:

$$\int_{-\infty}^{t} \text{NP}(s) \cdot \mathbb{1} \left\{ s \le t < s + m \right\} ds = \int_{t-m}^{t} \text{NP}(s) ds$$

We deduce that:

$$\mathbf{S}^{\star}(t,u) = \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \frac{\int_{u-m}^{t} \mathrm{NP}(s) \, \mathrm{d}s}{\int_{t-m}^{t} \mathrm{NP}(s) \, \mathrm{d}s}$$

In the case where the new production is a constant, we have NP(s) = c and:

$$\mathbf{S}^{\star}(t,u) = \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \frac{\int_{u-m}^{t} \mathrm{d}s}{\int_{t-m}^{t} \mathrm{d}s}$$

$$= \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \frac{\left[s\right]_{u-m}^{t}}{\left[s\right]_{t-m}^{t}}$$

$$= \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \left(\frac{t-u+m}{t-t+m}\right)$$

$$= \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \left(1 - \frac{u-t}{m}\right)$$

The survival function  $S^*(t, u)$  corresponds to the case of a linear amortization.

#### Question 2

Same question if we consider a debt instrument, whose amortization rate is constant.

If the amortization is linear, we have:

$$\mathbf{S}(t,u) = \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \left(1 - \frac{u - t}{m}\right)$$

We deduce that:

$$\mathbf{S}^{\star}(t,u) = \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \frac{\int_{u-m}^{t} \operatorname{NP}(s)\left(1 - \frac{u-s}{m}\right) ds}{\int_{t-m}^{t} \operatorname{NP}(s)\left(1 - \frac{t-s}{m}\right) ds}$$

In the case where the new production is a constant, we obtain:

$$\mathbf{S}^{\star}(t,u) = \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \frac{\int_{u-m}^{t} \left(1 - \frac{u-s}{m}\right) ds}{\int_{t-m}^{t} \left(1 - \frac{t-s}{m}\right) ds}$$

For the numerator, we have:

$$\int_{u-m}^{t} \left(1 - \frac{u-s}{m}\right) ds = \left[s - \frac{su}{m} + \frac{s^2}{2m}\right]_{u-m}^{t}$$

$$= \left(t - \frac{tu}{m} + \frac{t^2}{2m}\right) - \left(u - m - \frac{u^2 - mu}{m} + \frac{(u-m)^2}{2m}\right)$$

$$= \left(t - \frac{tu}{m} + \frac{t^2}{2m}\right) - \left(u - \frac{m}{2} - \frac{u^2}{2m}\right)$$

$$= \frac{m^2 + u^2 + t^2 + 2mt - 2mu - 2tu}{2m}$$

$$= \frac{(m-u+t)^2}{2m}$$

For the denominator, we use the previous result and we set u=t:

$$\int_{t-m}^{t} \left(1 - \frac{t-s}{m}\right) ds = \frac{(m-t+t)^2}{2m}$$
$$= \frac{m}{2}$$

We deduce that:

$$\mathbf{S}^{*}(t,u) = \mathbb{1} \{t \leq u < t + m\} \cdot \frac{\frac{(m-u+t)^{2}}{2m}}{\frac{m}{2}}$$

$$= \mathbb{1} \{t \leq u < t + m\} \cdot \frac{(m-u+t)^{2}}{m^{2}}$$

$$= \mathbb{1} \{t \leq u < t + m\} \cdot \left(1 - \frac{u-t}{m}\right)^{2}$$

The survival function  $S^*(t, u)$  corresponds to the case of a parabolic amortization.

#### Question 3

Same question if we assume<sup>a</sup> that the amortization function is exponential with parameter  $\lambda$ .

<sup>a</sup>By definition of the exponential amortization, we have  $m = +\infty$ .

If the amortization is exponential, we have:

$$\mathbf{S}(t,u) = e^{-\int_t^u \lambda \, \mathrm{d}s} = e^{-\lambda(u-t)}$$

It follows that:

$$\mathbf{S}^{\star}\left(t,u\right) = \frac{\int_{-\infty}^{t} \mathrm{NP}\left(s\right) e^{-\lambda\left(u-s\right)} \, \mathrm{d}s}{\int_{-\infty}^{t} \mathrm{NP}\left(s\right) e^{-\lambda\left(t-s\right)} \, \mathrm{d}s}$$

In the case where the new production is a constant, we obtain:

$$\mathbf{S}^{\star}(t,u) = \frac{\int_{-\infty}^{t} e^{-\lambda(u-s)} \, \mathrm{d}s}{\int_{-\infty}^{t} e^{-\lambda(t-s)} \, \mathrm{d}s}$$

$$= \frac{\left[\lambda^{-1} e^{-\lambda(u-s)}\right]_{-\infty}^{t}}{\left[\lambda^{-1} e^{-\lambda(t-s)}\right]_{-\infty}^{t}}$$

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

$$= \mathbf{S}(t,u)$$

The stock amortization function is equal to the flow amortization function.

#### Question 4

Find the expression of  $\mathcal{D}^{\star}\left(t\right)$  when the new production is constant.

We recall that the liquidity duration is equal to:

$$\mathcal{D}(t) = \int_{t}^{\infty} (u - t) f(t, u) du$$

where f(t, u) is the density function associated to the survival function  $\mathbf{S}(t, u)$ . For the stock, we have:

$$\mathcal{D}^{\star}\left(t\right) = \int_{t}^{\infty} \left(u - t\right) f^{\star}\left(t, u\right) du$$

where  $f^*(t, u)$  is the density function associated to the survival function  $S^*(t, u)$ :

$$f^{\star}(t, u) = \frac{\int_{-\infty}^{t} \text{NP}(s) f(s, u) ds}{\int_{-\infty}^{t} \text{NP}(s) \mathbf{S}(s, t) ds}$$

In the case where the new production is constant, we obtain:

$$\mathcal{D}^{\star}\left(t\right) = \frac{\int_{t}^{\infty} \left(u - t\right) \int_{-\infty}^{t} f\left(s, u\right) \, \mathrm{d}s \, \mathrm{d}u}{\int_{-\infty}^{t} \mathbf{S}\left(s, t\right) \, \mathrm{d}s}$$

Since we have  $\int_{-\infty}^{t} f(s, u) ds = \mathbf{S}(t, u)$ , we deduce that:

$$\mathcal{D}^{\star}\left(t\right) = \frac{\int_{t}^{\infty} \left(u - t\right) \mathbf{S}\left(t, u\right) du}{\int_{-\infty}^{t} \mathbf{S}\left(s, t\right) ds}$$

#### Question 5

Calculate the durations  $\mathcal{D}(t)$  and  $\mathcal{D}^{\star}(t)$  for the three previous cases.

In the case of the bullet repayment debt, we have:

$$\mathcal{D}(t) = m$$

and:

$$\mathcal{D}^{\star}(t) = \frac{\int_{t}^{t+m} (u-t) du}{\int_{t-m}^{t} ds}$$

$$= \frac{\left[\frac{1}{2} (u-t)^{2}\right]_{t}^{t+m}}{\left[s\right]_{t-m}^{t}}$$

$$= \frac{m}{2}$$

In the case of the linear amortization, we have:

$$f(t,u) = \mathbb{1}\left\{t \leq u < t + m\right\} \cdot \frac{1}{m}$$

and:

$$\mathcal{D}(t) = \int_{t}^{t+m} \frac{(u-t)}{m} du$$

$$= \frac{1}{m} \left[ \frac{1}{2} (u-t)^{2} \right]_{t}^{t+m}$$

$$= \frac{m}{2}$$

For the stock duration, we deduce that

$$\mathcal{D}^{\star}(t) = \frac{\int_{t}^{t+m} (u-t) \left(1 - \frac{u-t}{m}\right) du}{\int_{t-m}^{t} \left(1 - \frac{t-s}{m}\right) ds}$$

$$= \frac{\int_{t}^{t+m} \left(u - t - \frac{u^{2}}{m} + 2\frac{tu}{m} - \frac{t^{2}}{m}\right) du}{\int_{t-m}^{t} \left(1 - \frac{t}{m} + \frac{s}{m}\right) ds}$$

$$= \frac{\left[\frac{u^{2}}{2} - tu - \frac{u^{3}}{3m} + \frac{tu^{2}}{m} - \frac{t^{2}u}{m}\right]_{t}^{t+m}}{\left[s - \frac{st}{m} + \frac{s^{2}}{2m}\right]_{t-m}^{t}}$$

The numerator is equal to:

$$(*) = \left[\frac{u^2}{2} - tu - \frac{u^3}{3m} + \frac{tu^2}{m} - \frac{t^2u}{m}\right]_t^{t+m}$$

$$= \frac{1}{6m} \left[3mu^2 - 6mtu - 2u^3 + 6tu^2 - 6t^2u\right]_t^{t+m}$$

$$= \frac{1}{6m} \left(m^3 - 3mt^2 - 2t^3\right) + \frac{1}{6m} \left(3mt^2 + 2t^3\right)$$

$$= \frac{m^2}{6}$$

The denominator is equal to:

$$(*) = \left[s - \frac{st}{m} + \frac{s^2}{2m}\right]_{t-m}^{t}$$

$$= \frac{1}{2m} \left[s^2 - 2s(t-m)\right]_{t-m}^{t}$$

$$= \frac{1}{2m} \left(t^2 - 2t(t-m) - (t-m)^2 + 2(t-m)^2\right)$$

$$= \frac{1}{2m} \left(t^2 - 2t^2 + 2mt + t^2 - 2mt + m^2\right)$$

$$= \frac{m}{2}$$

We deduce that:

$$\mathcal{D}^{\star}\left(t\right)=\frac{m}{3}$$

For the exponential amortization, we have:

$$f(t,u) = \lambda e^{-\lambda(u-t)}$$

and $^2$ :

$$\mathcal{D}(t) = \int_{t}^{\infty} (u - t) \lambda e^{-\lambda(u - t)} du = \int_{0}^{\infty} v \lambda e^{-\lambda v} dv = \frac{1}{\lambda}$$

For the stock duration, we deduce that:

$$\mathcal{D}^{\star}(t) = \frac{\int_{t}^{\infty} (u - t) e^{-\lambda(u - t)} du}{\int_{-\infty}^{t} e^{-\lambda(t - s)} ds} = \frac{\int_{0}^{\infty} v e^{-\lambda v} dv}{\int_{0}^{\infty} e^{-\lambda v} dv} = \frac{1}{\lambda}$$

We verify that  $\mathcal{D}(t) = \mathcal{D}^{\star}(t)$  since we have demonstrated that  $\mathbf{S}^{\star}(t, u) = \mathbf{S}(t, u)$ .

<sup>&</sup>lt;sup>2</sup>We use the change of variable v = u - t.

#### Question 6

Calculate the corresponding dynamics dN(t).

In the case of the bullet repayment debt, we have:

$$dN(t) = (NP(t) - NP(t - m)) dt$$

In the case of the linear amortization, we have:

$$f(s,t) = \frac{\mathbf{1}\left\{s \leq t < s + m\right\}}{m}$$

It follows that:

$$\int_{-\infty}^{t} \text{NP}(s) f(s, t) ds = \frac{1}{m} \int_{-\infty}^{t} \mathbf{1} \{s \le t < s + m\} \cdot \text{NP}(s) ds$$
$$= \frac{1}{m} \int_{t-m}^{t} \text{NP}(s) ds$$

We deduce that:

$$dN(t) = \left(NP(t) - \frac{1}{m} \int_{t-m}^{t} NP(s) ds\right) dt$$

For the exponential amortization, we have:

$$f(s,t) = \lambda e^{-\lambda(t-s)}$$

and:

$$\int_{-\infty}^{t} NP(s) f(s, t) ds = \int_{-\infty}^{t} NP(s) \lambda e^{-\lambda(t-s)} ds$$
$$= \lambda \int_{-\infty}^{t} NP(s) e^{-\lambda(t-s)} ds$$
$$= \lambda N(t)$$

We deduce that:

$$dN(t) = (NP(t) - \lambda N(t)) dt$$

#### Exercise

We recall that the outstanding balance of a CAM (constant amortization mortgage) at time t is given by:

$$N(t) = \mathbf{1} \{t < m\} \cdot N_0 \cdot \frac{1 - e^{-i(m-t)}}{1 - e^{-im}}$$

where  $N_0$  is the notional, i is the interest rate and m is the maturity.

#### Question 1

Find the dynamics dN(t).

We deduce that the dynamics of N(t) is equal to:

$$dN(t) = \mathbb{1} \{t < m\} \cdot N_0 \frac{-ie^{-i(m-t)}}{1 - e^{-im}} dt$$

$$= -ie^{-i(m-t)} \left( \mathbb{1} \{t < m\} \cdot N_0 \frac{1}{1 - e^{-im}} \right) dt$$

$$= -\frac{ie^{-i(m-t)}}{1 - e^{-i(m-t)}} N(t) dt$$

#### Question 2

We note  $\tilde{N}(t)$  the modified outstanding balance that takes into account the prepayment risk. Let  $\lambda_p(t)$  be the prepayment rate at time t. Write the dynamics of  $\tilde{N}(t)$ .

The prepayment rate has a negative impact on dN(t) because it reduces the outstanding amount N(t):

$$d\tilde{N}(t) = -\frac{ie^{-i(m-t)}}{1 - e^{-i(m-t)}}\tilde{N}(t) dt - \lambda_{p}(t)\tilde{N}(t) dt$$

#### Question 3

Show that  $\tilde{N}(t) = N(t) \mathbf{S}_{p}(t)$  where  $\mathbf{S}_{p}(t)$  is the prepayment-based survival function.

It follows that:

$$d \ln \tilde{N}(t) = -\left(\frac{ie^{-i(m-t)}}{1 - e^{-i(m-t)}} + \lambda_p(t)\right) dt$$

and:

$$\ln \tilde{N}(t) - \ln \tilde{N}(0) = \int_0^t \frac{-ie^{-i(m-s)}}{1 - e^{-i(m-s)}} ds - \int_0^t \lambda_p(s) ds$$

$$= \left[ \ln \left( 1 - e^{-i(m-s)} \right) \right]_0^t - \int_0^t \lambda_p(s) ds$$

$$= \ln \left( \frac{1 - e^{-i(m-t)}}{1 - e^{-im}} \right) - \int_0^t \lambda_p(s) ds$$

We deduce that:

$$ilde{N}(t) = \left(N_0 \frac{1 - e^{-i(m-t)}}{1 - e^{-im}}\right) e^{-\int_0^t \lambda_p(s) ds}$$

$$= N(t) \mathbf{S}_p(t)$$

where  $\mathbf{S}_{p}\left(t\right)$  is the survival function associated to the hazard rate  $\lambda_{p}\left(t\right)$ .

#### Question 4

Calculate the liquidity duration  $\tilde{\mathcal{D}}(t)$  associated to the outstanding balance  $\tilde{N}(t)$  when the hazard rate of prepayments is constant and equal to  $\lambda_p$ .

We have:

$$\tilde{N}(t,u) = \mathbf{1}\left\{t \leq u < t+m\right\} \cdot N(t) \frac{1 - e^{-i(t+m-u)}}{1 - e^{-im}} e^{-\lambda_p(u-t)}$$

this implies that:

$$\tilde{\mathbf{S}}(t,u) = \mathbf{1}\{t \le u < t+m\} \cdot \frac{e^{-\lambda_p(u-t)} - e^{-im+(i-\lambda_p)(u-t)}}{1 - e^{-im}}$$

and:

$$\tilde{f}(t,u) = \mathbf{1}\left\{t \leq u < t+m\right\} \cdot \frac{\lambda_p e^{-\lambda_p(u-t)} + (i-\lambda_p) e^{-im+(i-\lambda_p)(u-t)}}{1-e^{-im}}$$

It follows that:

$$\begin{split} \tilde{\mathcal{D}}(t) &= \frac{\lambda_{p}}{1 - e^{-im}} \int_{t}^{t+m} (u - t) e^{-\lambda_{p}(u - t)} \, \mathrm{d}u + \\ &\frac{(i - \lambda_{p}) e^{-im}}{1 - e^{-im}} \int_{t}^{t+m} (u - t) e^{(i - \lambda_{p})(u - t)} \, \mathrm{d}u \\ &= \frac{\lambda_{p}}{1 - e^{-im}} \int_{0}^{m} v e^{-\lambda_{p} v} \, \mathrm{d}v + \frac{(i - \lambda_{p}) e^{-im}}{1 - e^{-im}} \int_{0}^{m} v e^{(i - \lambda_{p})v} \, \mathrm{d}v \\ &= \frac{\lambda_{p}}{1 - e^{-im}} \left( \frac{m e^{-\lambda_{p} m}}{-\lambda_{p}} - \frac{e^{-\lambda_{p} m} - 1}{\lambda_{p}^{2}} \right) + \\ &\frac{(i - \lambda_{p}) e^{-im}}{1 - e^{-im}} \left( \frac{m e^{(i - \lambda_{p}) m}}{(i - \lambda_{p})} - \frac{e^{(i - \lambda_{p}) m} - 1}{(i - \lambda_{p})^{2}} \right) \\ &= \frac{1}{1 - e^{-im}} \left( \frac{e^{-im} - e^{-\lambda_{p} m}}{i - \lambda_{p}} + \frac{1 - e^{-\lambda_{p} m}}{\lambda_{p}} \right) \end{split}$$

because we have:

$$\int_{0}^{m} v e^{\alpha v} dv = \left[\frac{v e^{\alpha v}}{\alpha}\right]_{0}^{m} - \int_{0}^{m} \frac{e^{\alpha v}}{\alpha} dv$$

$$= \left[\frac{v e^{\alpha v}}{\alpha}\right]_{0}^{m} - \left[\frac{e^{\alpha v}}{\alpha^{2}}\right]_{0}^{m}$$

$$= \frac{m e^{\alpha m}}{\alpha} - \frac{e^{\alpha m} - 1}{\alpha^{2}}$$