# Portfolio choice theory and asset pricing 

Tutorials : Risk measures

## Exercise 1

Assume that the loss distribution of a portfolio follows a Gaussian law $L \sim \mathcal{N}\left(\mu, \sigma^{2}\right)$. Then, prove that

$$
\operatorname{Var}_{\alpha}(L)=\mu+\sigma \Phi^{-1}(\alpha),
$$

where $\Phi$ is the cdf of $\mathcal{N}(0,1)$ and $\Phi^{-1}(\alpha)$ is the $\alpha$-quantile of $\Phi$.

## Exercise 2

We consider a portfolio consisting in a long position of $\beta=10$ shares of a stock with initial price $S_{0}=100$. The intra-day log return of the asset is given by $\Delta_{1} Y_{t+1}=\log \left(S_{t+1} / S_{t}\right)$ for $t \geq 0$ are assumed to be iid according to a Gaussian law of mean 0 and standard deviation $\sigma=0.1$.
a. Compute the $\operatorname{VaR}_{\alpha}\left(L_{1}\right)$ where $L_{1}$ is the portfolio loss between today and tomorrow for $\alpha=99 \%$.
Hint: Use the fact that $\Phi^{-1}(\alpha) \approx 2.3$.
b. We keep the long position on the portfolio during 100 days. Compute $\operatorname{VaR}_{\alpha}\left(L_{100}\right)$ where $L_{100}$ is the portfolio loss during 100 days.

## Exercise 3

Let $L$ be a loss with law $\mathcal{N}\left(\mu, \sigma^{2}\right)$. As usual, we denote by $\Phi$ the $\operatorname{cdf}$ of $\mathcal{N}(0,1)$ and by $\phi$ its density. Prove that

$$
\mathrm{ES}_{\alpha}(L)=\mu+\sigma \frac{\phi\left(\Phi^{-1}(\alpha)\right)}{1-\alpha}
$$

## Exercise 4

Let $X=\left(X_{1}, X_{2}\right) \sim \mathcal{N}(\mu, \Sigma)$ with $\mu=\left(\mu_{1}, \mu_{2}\right)$ and

$$
\Sigma=\left(\begin{array}{cc}
\sigma_{1}^{2} & \rho \sigma_{1} \sigma_{2} \\
\rho \sigma_{1} \sigma_{2} & \sigma_{2}^{2}
\end{array}\right), \quad \rho \in(-1,1) .
$$

a. Show that

$$
\operatorname{Var}_{\alpha}\left(X_{1}+X_{2}\right) \leq \operatorname{Var}_{\alpha}\left(X_{1}\right)+\operatorname{VaR}_{\alpha}\left(X_{2}\right)
$$

b. What's the financial interpretation of this inequality?

## Exercise 5

Prove the following relations :
a. If $L$ follows a Laplace distribution (double exponential) with density $f(\ell)=$ $\frac{\lambda}{2} \exp (-\lambda|\ell|)$ then

$$
\operatorname{Var}_{\alpha}(L)=\left\{\begin{array}{l}
-\frac{1}{\lambda} \ln (2(1-\alpha)), \quad \text { if } \quad \alpha \geq 1 / 2, \\
\frac{1}{\lambda} \ln (2 \alpha), \quad \text { otherwise }
\end{array}\right.
$$

and

$$
\mathrm{ES}_{\alpha}(L)= \begin{cases}\frac{1}{\lambda}(1-\ln (2(1-\alpha))), & \text { if } \quad \alpha \geq 1 / 2, \\ \frac{1}{\lambda}\left(\frac{1}{2}+\alpha(1-\ln (2 \alpha))\right), & \text { otherwise } .\end{cases}
$$

b. If $L$ follows a Pareto distribution with index $p$ with density function $f(\ell)=$ $\frac{p}{\ell^{p+1}} \mathbf{1}_{\ell \geq 1}$, with $p>1$, then

$$
\operatorname{Var}_{\alpha}(L)=(1-\alpha)^{-\frac{1}{p}}, \quad \operatorname{ES}_{\alpha}(L)=\frac{p}{p-1}(1-\alpha)^{-\frac{1}{p}}
$$

Exercise 6 (Coherence and independence)
We could think that the risk of two independent risks aggregate together, namely, if $L_{1}$ and $L_{2}$ are two independent real-valued random variables and $\rho$ is a risk measure, then

$$
\rho\left(L_{1}+L_{2}\right)=\rho\left(L_{1}\right)+\rho\left(L_{2}\right) .
$$

In general, this is wrong.
Exhibit two independent random variables $L_{1}$ and $L_{2}$ as well as a risk measure $\rho$ such that

$$
\rho\left(L_{1}+L_{2}\right)<\rho\left(L_{1}\right)+\rho\left(L_{2}\right) .
$$

## Exercise 7 (Conditioning a Gaussian vector)

With the notation introduced in the course, we let $X=\left(X_{1}, X_{2}\right)$ be a Gaussian vector with mean $\mu=\left(\mu_{1}, \mu_{2}\right)$ and covariance matrix

$$
\Sigma=\left(\begin{array}{ll}
\Sigma_{1,1} & \Sigma_{1,2} \\
\Sigma_{2,1} & \Sigma_{2,2}
\end{array}\right)
$$

a. Prove that

$$
\mathbb{E}\left[X_{2} \mid X_{1}\right]=\mu_{2}+\Sigma_{2,1} \Sigma_{1,1}^{-1}\left(X_{1}-\mu_{1}\right)
$$

b. Deduce from the previous question that $X_{2}-\mathbb{E}\left[X_{2} \mid X_{1}\right]$ is independent of $X_{2}$.

Exercise 8 (Characteristic function of normal mixture)
a. Recall the definition of a normal mixture with non-negative weight random variable $W$ and parameters $\mu \in \mathbb{R}^{d}$ and $A \in \mathbb{R}^{d \times k}$.
b. Prove that the characteristic function of the normal mixture $X$ is given by

$$
\phi_{X}(u)=\mathbb{E}\left[\exp \left(i u^{T} X\right)\right]=\exp \left(i u^{T} \mu\right) F_{W}\left(\frac{1}{2} u^{T} \Sigma u\right),
$$

where for $\theta \in \mathbb{R}$

$$
F_{W}(\theta)=\int_{0}^{\infty} \exp (-\theta w) \mathbb{P}_{W}(d w)
$$

Exercise 9 (Stochastic representation of Elliptical distributions)
Prove that $X \sim E_{d}(\mu, \Sigma, \psi)$ if and only if

$$
X \stackrel{d}{=} \mu+R A S
$$

where $S$ is uniformly distributed on the unit sphere, $R \geq 0$ is a radial random vector independent of $S$ and $A \in \mathbb{R}^{d \times k}$ such that $\Sigma=A A^{T}$.

## Exercise 10

a. Let $X \sim \mathcal{N}_{d}(\mu, \Sigma)$. Prove that $X \sim E_{d}(\mu, \Sigma, \psi)$ for an explicit function $\psi$.
b. Let $X \sim E_{d}(\mu, \Sigma, \psi)$. Prove that for any $B \in \mathbb{R}^{d \times k}, b \in \mathbb{R}^{k}$, it holds

$$
B X+b \sim E_{k}\left(B \mu+b, B \Sigma B^{T}, \psi\right) .
$$

c. Prove that if $X=\left(X_{1}, X_{2}\right) \sim E_{d}(\mu, \Sigma, \psi), X_{1} \in \mathbb{R}^{k}$ and $X_{2} \in \mathbb{R}^{d-k}$ with $\mu=$ $\left(\mu_{1}, \mu_{2}\right)$ and $\Sigma=\left(\begin{array}{ll}\Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22}\end{array}\right)$ then

$$
X_{1} \sim E_{k}\left(\mu_{1}, \Sigma_{11}, \psi\right), \quad X_{2} \sim E_{d-k}\left(\mu_{2}, \Sigma_{22}, \psi\right)
$$

d. Prove that if $X \sim E_{d}(\mu, \Sigma, \psi)$ and $Y \sim E_{d}(\tilde{\mu}, \Sigma, \tilde{\psi})$ are independent then $X+Y \sim$ $E_{d}(\mu+\tilde{\mu}, \Sigma, \psi \tilde{\psi})$.

Exercise 11 (sub-additivity of VaR for elliptical distributions)
Let $X \sim E_{d}(\mu, \Sigma, \psi)$. Prove that for any $u, w \in \mathbb{R}^{d}$ and $\alpha \in(0,1)$,

$$
\operatorname{VaR}_{\alpha}\left(u^{T} X+w^{T} X\right) \leq \operatorname{VaR}_{\alpha}\left(u^{T} X\right)+\operatorname{VaR}_{\alpha}\left(w^{T} X\right)
$$

Exercise 12 (Correlation bounds)
Let $X_{1}, X_{2}$ be two $\log$-normal distributions: $\log \left(X_{1}\right) \sim \mathcal{N}(0,1)$ and $\log \left(X_{2}\right) \sim \mathcal{N}\left(0, \sigma^{2}\right)$ for some $\sigma>0$.
a. Compute the minimal and maximal correlation $\rho_{\min }, \rho_{\max }$ of the vector $\left(X_{1}, X_{2}\right)$.
b. What are the limits of $\rho_{\min }, \rho_{\max }$ when $\sigma \uparrow \infty$ ?

## Exercise 13 (The Clayton Copula)

The Clayton copula is defined by

$$
C\left(u_{1}, u_{2}\right)=\max \left(u_{1}^{-\theta}+u_{2}^{-\theta}-1,0\right)^{-\frac{1}{\theta}}, \quad \theta \geq-1 .
$$

a. For which value of $\theta$, does $C$ correspond to the minimal copula $C_{\min }\left(u_{1}, u_{2}\right)=$ $\max \left(u_{1}+u_{2}-1,0\right) ?$
b. Prove that when $C$ goes to $C_{\max }\left(u_{1}, u_{2}\right)=\min \left(u_{1}, u_{2}\right)$ when $\theta \rightarrow+\infty$.
c. To which copula $C$ converges when $\theta \rightarrow 0$ ?

