

2 Basics concepts in risk management

2.1 Risk management for a financial firm

2.2 Modelling value and value change

2.3 Risk measurement

2.1 Risk management for a financial firm

2.1.1 Assets, liabilities and the balance sheet

A stylized balance sheet for a **bank** is:

Assets Investments of the firm		Liabilities Obligations from fundraising	
Cash (and central bank balance)	£10M	Customer deposits	£80M
Securities	£50M	Bonds issued	
- bonds, stocks, derivatives		- senior bond issues	£25M
Loans and mortgages	£100M	- subordinated bond issues	£15M
- corporates		Short-term borrowing	£30M
- retail and smaller clients		Reserves (for losses on loans)	£20M
- government			
Other assets	£20M	Debt (sum of above)	£170M
- property			
- investments in companies		Equity	£30M
Short-term lending	£20M		
Total	£200M	Total	£200M

A stylized balance sheet for an **insurer** is:

Assets		Liabilities	
Investments		Reserves for policies written	£80M
- bonds	£50M	(technical provisions)	
- stocks	£5M	Bonds issued	£10M
- property	£5M		
Investments for unit-linked contracts	£30M	Debt (sum of above)	£90M
Other assets	£10M	Equity	£10M
- property			
Total	£100M	Total	£100M

- Balance sheet equation: $\text{Assets} = \text{Liabilities} = \text{Debt} + \text{Equity}$.
If equity > 0 , the company is *solvent*, otherwise *insolvent*.
- Valuation of the items on the balance sheet is a non-trivial task.
 - Amortized cost accounting* values a position a *book value* at its inception and this is carried forward/progressively reduced over time.

- ▶ *Fair-value accounting* values assets at prices they are sold and liabilities at prices that would have to be paid in the market. This can be challenging for non-traded or illiquid assets or liabilities.

There is a tendency in the industry to move towards fair-value accounting. Market consistent valuation in Solvency II follows similar principles.

2.1.2 Risks faced by a financial firm

- Decrease in the value of the investments on the asset side of the balance sheet (e.g. losses from securities trading or credit risk)
- *Maturity mismatch* (large parts of the assets are relatively illiquid (long-term) whereas large parts of the liabilities are rather short-term obligations. This can lead to a default of a solvent bank or a bank run).
- The prime risk for an insurer is *insolvency* (risk that claims of policy holders cannot be met). On the asset side, risks are similar to those of a bank. On the liability side, the main risk is that reserves are insufficient

to cover future claim payments. Note that the **liabilities of a life insurer are of a long-term nature** and subject to multiple categories of risk (e.g. interest rate risk, inflation risk and longevity risk).

- So risk is found on **both sides** of the balance sheet and thus RM should not focus on the asset side alone.

2.1.3 Capital

- There are different notions of **capital**. One distinguishes:

Equity capital

- Value of **assets** — **debt**;
- Measures the firm's value to its shareholders;
- Can be split into *shareholder capital* (initial capital invested in the firm) and *retained earnings* (accumulated earnings not paid out to shareholders).

Regulatory capital — Capital required according to **regulatory rules**;

- For European insurance firms: MCR + SCR;
- A regulatory framework also specifies the **capital quality**. One distinguishes *Tier 1 capital* (i.e. shareholder capital + retained earnings; **can act in full as buffer**) and *Tier 2 capital* (includes other positions on the balance sheet).

Economic capital

- Capital required to control the probability of **becoming insolvent** (typically over one year);
- **Internal assessment** of risk capital;
- Aims at a holistic view (assets and liabilities) and works with fair values of balance sheet items.

- **All of these notions** refer to items on the liability side that entail no obligations to outside creditors; they **can thus serve as buffer against losses**.

2.2 Modelling value and value change

2.2.1 Mapping of risks

To start of we set up a general mathematical model for (changes in) value caused by financial risks. For this we work on a *probability space* $(\Omega, \mathcal{F}, \mathbb{P})$ and consider a risk or loss as a *random variable* $X : \Omega \rightarrow \mathbb{R}$ (or: L).

- Consider a *portfolio* of assets and possibly liabilities. The *value* of the portfolio at time t (*today*) is denoted by V_t (a random variable; assumed to be known at t ; its *df* is typically *not trivial to determine!*).
- We consider a given *time horizon* Δt and *assume*:
 - 1) the *portfolio composition remains fixed* over Δt ;
 - 2) there are *no intermediate payments* during Δt

\Rightarrow *Fine for small Δt but unlikely to hold for large Δ .*

- The *change* in value of the portfolio is then given by

$$\Delta V_{t+1} = V_{t+1} - V_t$$

and we define the (random) *loss* by the *sign-adjusted* value change

$$L_{t+1} = -\Delta V_{t+1}$$

(as QRM is mainly concerned with losses).

Remark 2.1

- 1) The *distribution of L_{t+1}* is called *loss distribution* (df F_L or simply F).
- 2) Practitioners often consider the *profit-and-loss (P&L) distribution* which is the distribution of $-L_{t+1} = \Delta V_{t+1}$.
- 3) For longer time intervals, $\Delta V_{t+1} = V_{t+1}/(1 + r) - V_t$ (r = *risk-free interest rate*) would be more appropriate, but we will *mostly neglect* this issue.

- V_t is typically modelled as a function f of time t and a d -dimensional random vector $\mathbf{Z} = (Z_{t,1}, \dots, Z_{t,d})$ of risk factors, that is,

$$V_t = f(t, \mathbf{Z}_t) \quad (\text{mapping of risks})$$

for some measurable $f : \mathbb{R}_+ \times \mathbb{R}^d \rightarrow \mathbb{R}$. The choice of f and \mathbf{Z}_t is problem-specific (but typically known).

- It is often convenient to work with the risk-factor changes

$$\mathbf{X}_{t+1} = \mathbf{Z}_{t+1} - \mathbf{Z}_t.$$

We can rewrite L_{t+1} in terms of \mathbf{X}_t via

$$\begin{aligned} L_{t+1} &= -(V_{t+1} - V_t) = -(f(t+1, \mathbf{Z}_{t+1}) - f(t, \mathbf{Z}_t)) \\ &= -(f(t+1, \mathbf{Z}_t + \mathbf{X}_{t+1}) - f(t, \mathbf{Z}_t)). \end{aligned}$$

We see that the loss df is determined by the loss df of \mathbf{X}_{t+1} . We will thus also write $L_{t+1} = L(\mathbf{X}_{t+1})$, where $L(\mathbf{x}) = -(f(t+1, \mathbf{Z}_t + \mathbf{x}) - f(t, \mathbf{Z}_t))$ is known as loss operator.

- If f is differentiable, its **first-order (Taylor) approximation** ($f(\mathbf{y}) \approx f(\mathbf{y}_0) + \nabla f(\mathbf{y}_0)(\mathbf{y} - \mathbf{y}_0)$ for $\mathbf{y} = (t+1, Z_{t,1} + X_{t+1,1}, \dots, Z_{t,d} + X_{t+1,d})$ and $\mathbf{y}_0 = (t, Z_{t,1}, \dots, Z_{t,d})$) is

$$f(t+1, \mathbf{Z}_t + \mathbf{X}_{t+1}) \approx f(t, \mathbf{Z}_t) + f_t(t, \mathbf{Z}_t) \cdot 1 + \sum_{j=1}^d f_{z_j}(t, \mathbf{Z}_t) \cdot X_{t+1,j}$$

We can thus approximate L_{t+1} by the **linearized loss**

$$L_{t+1}^{\Delta} = - \left(\underbrace{f_t(t, \mathbf{Z}_t)}_{=: c_t} + \sum_{j=1}^d \underbrace{f_{z_j}(t, \mathbf{Z}_t)}_{=: b_{t,j}} X_{t+1,j} \right) = -(c_t + \mathbf{b}'_t \mathbf{X}_{t+1}),$$

a linear function of $X_{t+1,1}, \dots, X_{t+1,d}$ (indices denote partial derivatives). The **approximation is best if the risk-factor changes are small in absolute value**.

Example 2.2 (Stock portfolio)

Consider a **portfolio** \mathcal{P} of d **stocks** $S_{t,1}, \dots, S_{t,d}$ ($S_{t,j}$ = value of stock j at time t) and denote by λ_j the **number of shares** of stock j in \mathcal{P} . In finance and risk management, one typically uses **logarithmic prices as risk factors**, i.e. $Z_{t,j} = \log S_{t,j}$, $j \in \{1, \dots, d\}$. Then

$$V_t = f(t, \mathbf{Z}_t) = \sum_{j=1}^d \lambda_j S_{t,j} = \sum_{j=1}^d \lambda_j e^{Z_{t,j}}.$$

- The one-period ahead loss is then given by

$$\begin{aligned} L_{t+1} &= -(V_{t+1} - V_t) = -\sum_{j=1}^d \lambda_j (e^{Z_{t,j} + X_{t+1,j}} - e^{Z_{t,j}}) \\ &= -\sum_{j=1}^d \lambda_j e^{Z_{t,j}} (e^{X_{t+1,j}} - 1) = -\sum_{j=1}^d \underbrace{\lambda_j S_{t,j}}_{=: w_{t,j}} (e^{X_{t+1,j}} - 1) \quad (1) \end{aligned}$$

which is non-linear in $X_{t+1,j}$ (here: $L(\mathbf{x}) = -\sum_{j=1}^d w_{t,j} (e^{x_j} - 1)$).

- With $f_{z_j}(t, \mathbf{Z}_t) = \lambda_j e^{Z_{t,j}} = \lambda_j S_{t,j} = w_{t,j}$, the **linearized loss** is

$$\begin{aligned} L_{t+1}^\Delta &= -\left(f_t(t, \mathbf{Z}_t) + \sum_{j=1}^d f_{z_j}(t, \mathbf{Z}_t) X_{t+1,j}\right) = -\left(0 + \sum_{j=1}^d w_{t,j} X_{t+1,j}\right) \\ &= -\mathbf{w}_t' \mathbf{X}_{t+1}. \end{aligned}$$

- Note that $L_{t+1}^\Delta = -(c_t + \mathbf{b}_t' \mathbf{X}_{t+1})$ for $c_t = 0$ and $\mathbf{b}_t = \mathbf{w}_t$.
- If $\boldsymbol{\mu} = \mathbb{E} \mathbf{X}_{t+1}$ and $\Sigma = \text{cov} \mathbf{X}_{t+1}$ are known, then **expectation** and **variance of the (linearized) one-period ahead loss** are

$$\begin{aligned} \mathbb{E} L_{t+1}^\Delta &= -\sum_{j=1}^d w_{t,j} \mathbb{E}(X_{t+1,j}) = -\mathbf{w}_t' \boldsymbol{\mu}, \\ \text{var } L_{t+1}^\Delta &= \text{var}(\mathbf{w}_t' \mathbf{X}_{t+1}) = \mathbf{w}_t' \text{cov}(\mathbf{X}_{t+1}) \mathbf{w}_t = \mathbf{w}_t' \Sigma \mathbf{w}_t. \end{aligned}$$

Example 2.3 (European call option)

Consider a portfolio consisting of a European call option on a non-dividend-paying stock S_t with maturity T and strike (exercise price) K . The Black–Scholes formula says that today's value is

$$V_t = C^{\text{BS}}(t, S_t; r, \sigma, K, T) = S_t \Phi(d_1) - K e^{-r(T-t)} \Phi(d_2), \quad (2)$$

where

- t is the time in years;
- Φ is the df of $N(0, 1)$;
- r is the continuously compounded risk-free interest rate;
- $d_1 = \frac{\log(S_t/K) + (r + \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}$ and $d_2 = d_1 - \sigma\sqrt{T-t}$; and
- σ is the annualized volatility of S_t (standard deviation).

While (2) assumes r, σ to be constant, this is often not true in real markets. Hence, besides $\log S_t$, we consider r_t, σ_t as risk factors, so

$$\mathbf{Z}_t = (\log S_t, r_t, \sigma_t) \Rightarrow \mathbf{X}_{t+1} = (\log(S_{t+1}/S_t), r_{t+1} - r_t, \sigma_{t+1} - \sigma_t).$$

This implies that the mapping f (in terms of the risk factors) is given by

$$V_t = C^{\text{BS}}(t, e^{Z_{t,1}}; Z_{t,2}, Z_{t,3}, K, T) =: f(t, \mathbf{Z}_t)$$

and the linearized one-day ahead loss (omitting the arguments of C^{BS}) is

$$\begin{aligned} L_{t+1}^{\Delta} &= -\left(f_t(t, \mathbf{Z}_t) + \sum_{j=1}^3 f_{z_j}(t, \mathbf{Z}_t) X_{t+1,j}\right) \\ &= -(C_t^{\text{BS}} \Delta t + C_{S_t}^{\text{BS}} S_t X_{t+1,1} + C_{r_t}^{\text{BS}} X_{t+1,2} + C_{\sigma_t}^{\text{BS}} X_{t+1,3}). \end{aligned}$$

If our risk management horizon is 1d (as opposed to 1y), we need to introduce $\Delta t := 1/250$ here. Note that the “Greeks” enter (C_t^{BS} is the *theta* of the option; $C_{S_t}^{\text{BS}}$ the *delta*; $C_{r_t}^{\text{BS}}$ the *rho*; $C_{\sigma_t}^{\text{BS}}$ the *vega*).

For portfolios of derivatives, L_{t+1}^{Δ} can be a rather poor approximation to $L_{t+1} \Rightarrow$ higher-order (Taylor) approximations such as the *delta-gamma-approximation* (second-order) can be used.

2.2.2 Valuation methods

Fair value accounting

The *fair value* of an asset/liability is an *estimate of the price* which would be *received/paid* on an *active market*. One distinguishes:

- Level 1** *Mark-to-market*. *Fair value* of an investment is *determined from quoted prices* for the *same instrument*; see Example 2.2.
- Level 2** *Mark-to-model with objective inputs*. The *fair value* of an instrument is determined *using quoted prices* in active markets *for similar instruments* or by using valuation techniques/models with inputs based on observable market data; see Example 2.3.
- Level 3** *Mark-to-model with subjective inputs*. The *fair value* of an instrument is determined using valuation techniques/models for which *some inputs are not observable* in the market (e.g. determining default risk of portfolios of loans to companies for which no CDS spreads are available).

Risk-neutral valuation

- ... is **widely used** for pricing financial products, e.g. derivatives
- **value** of a financial instrument **today** = **expected discounted values of future cash flows**; the expectation is **taken w.r.t. the risk-neutral pricing measure Q** (also called *equivalent martingale measure (EMM)*; it turns discounted prices into martingales, so fair bets) as opposed to the real world/**physical measure \mathbb{P}** .
- An **risk-neutral pricing measure** is a **probability measure Q** such that the **expectation of the discounted payoff w.r.t. Q** equals V_0 (fair bet).
- **Risk-neutral valuation at t of a claim H at T** is done via the **risk-neutral pricing rule**

$$V_0^H = \mathbb{E}_{Q,t}(e^{-r(T-t)}H), \quad t < T,$$

where $\mathbb{E}_{Q,t}(\cdot)$ denotes expectation w.r.t. Q given the information up to and including time t .

- **\mathbb{P} is estimated from historical data**; **Q is calibrated to market prices**.

Example 2.4 (European call option continued)

- Suppose that options with strike K or maturity T are not traded, but other options on the same stock are.
- Under \mathbb{P} the stock price (S_t) is assumed to follow a geometric Brownian motion (GBM) (the so-called *Black–Scholes model*) with dynamics $dS_t = \mu S_t dt + \sigma S_t dW_t$ for constants $\mu \in \mathbb{R}$ (drift) and $\sigma > 0$ (volatility), and a standard Brownian motion (W_t) .
- Under the EMM \mathbb{Q} , $(e^{-rt}S_t)$ is a martingale and S_t follows a GBM with drift r and volatility σ .
- The European call option payoff is $H = (S_T - K)^+ = \max\{S_T - K, 0\}$ and the risk-neutral valuation formula may be shown to be

$$V_t = E_t^{\mathbb{Q}}(e^{-r(T-t)}(S_T - K)^+) = C^{\text{BS}}(t, S_t; r, \sigma, K, T), \quad t < T; \quad (3)$$

- One typically uses quoted prices $C^{\text{BS}}(t, S_t; r, \sigma, K^*, T^*)$ (for different K^*, T^*) to infer the unknown σ . Then plug this so-called *implied volatility* into (3).

2.2.3 Loss distributions

Having determined the mapping f (may involve *valuation models*, e.g. Black–Scholes, or numerical approximation), we can identify the following **key statistical tasks of QRM**:

- 1) Find a statistical **model for \mathbf{X}_{t+1}** (typically a model for forecasting \mathbf{X}_{t+1} , estimated based on historical data);
- 2) Compute/derive the **df $F_{L_{t+1}}$** (requires the df of $f(t+1, \mathbf{Z}_t + \mathbf{X}_{t+1})$);
- 3) Compute a **risk measure from $F_{L_{t+1}}$** .

There are **three general methods** to approach these challenges.

1) Analytical method

Idea: Choose $F_{\mathbf{X}_{t+1}}$ and f such that $F_{L_{t+1}}$ can be determined explicitly.

Prime example: *Variance-covariance method*, see RiskMetrics (1996):

Assumption 1 $\mathbf{X}_{t+1} \sim N(\boldsymbol{\mu}, \Sigma)$ (e.g. if (\mathbf{Z}_t) is a Brownian motion, (S_t) a geometric Brownian motion)

Assumption 2 $F_{L_{t+1}^\Delta}$ is a good approximation to $F_{L_{t+1}}$.

$$L_{t+1}^\Delta = -(c_t + \mathbf{b}_t' \mathbf{X}_{t+1}) \underset{\text{Ass. 1}}{\Rightarrow} L_{t+1}^\Delta \sim N(-c_t - \mathbf{b}_t' \boldsymbol{\mu}, \mathbf{b}_t' \Sigma \mathbf{b}_t).$$

Advantages:

- $F_{L_{t+1}^\Delta}$ explicit (\Rightarrow typically explicit risk measures)
- Easy to implement

Drawbacks: Assumption 1 is unlikely to be realistic for daily (probably also weekly/monthly) data. Stylized facts about \mathbf{X}_{t+1} suggest that $F_{\mathbf{X}_{t+1}}$ is leptokurtic (thinner body, heavier tail than $N(\boldsymbol{\mu}, \Sigma)$). Thus, $\mathbf{X}_{t+1} \sim N(\boldsymbol{\mu}, \Sigma)$ underestimates the tail of $F_{L_{t+1}}$ and thus risk measures such as VaR.

When dynamic models for \mathbf{X}_{t+1} are considered, different estimation methods are possible depending on whether we focus on conditional distributions $F_{\mathbf{X}_{t+1} | (\mathbf{X}_s)_{s \leq t}}$ or the equilibrium distribution $F_{\mathbf{X}}$ in a stationary model.

2) Historical simulation

Idea: Estimate $F_{L_{t+1}}$ by its *empirical distribution function (edf)*

$$\hat{F}_{L_{t+1},n}(x) = \frac{1}{n} \sum_{i=1}^n I_{\{\tilde{L}_{t-i+1} \leq x\}}, \quad x \in \mathbb{R}, \quad (4)$$

based on

$$\tilde{L}_k = L(\mathbf{X}_k) = -(f(t+1, \mathbf{Z}_t + \mathbf{X}_k) - f(t, \mathbf{Z}_t)), \quad (5)$$

$k \in \{t-n+1, \dots, t\}$. $\tilde{L}_{t-n+1}, \dots, \tilde{L}_t$ show what would happen to the current portfolio if the past n risk-factor changes were to recur.

Advantages: ■ Easy to implement

■ No estimation of the distribution of \mathbf{X}_{t+1} required

Drawbacks: ■ Sufficient data for all risk-factor changes required

■ Only past losses considered (“driving a car by looking in the back mirror”)

3) Monte Carlo method

Idea: Take any model for \mathbf{X}_{t+1} , simulate \mathbf{X}_{t+1} , compute the corresponding losses as in (5) and estimate $F_{L_{t+1}}$ (typically via edf as in (4)).

Advantages: ■ Quite general (applicable to any model of \mathbf{X}_{t+1} which is easy to sample)

Drawbacks: ■ Unclear how to find an appropriate model for \mathbf{X}_{t+1} (any result is only as good as the chosen $F_{\mathbf{X}_{t+1}}$)

- Computational cost (every simulation requires to evaluate the mapping f ; expensive, e.g. if the latter contains derivatives which are priced via Monte Carlo themselves \Rightarrow Nested Monte Carlo simulations)

So-called *economic scenario generators* (i.e. economically motivated dynamic models for the evolution and interaction of risk factors) used in insurance also fall under the heading of Monte Carlo methods.

2.3 Risk measurement

- A *risk measure* for a financial position with (random) loss L is a *real number* which measures the “riskiness of L ”. In the Basel or Solvency context, it is often interpreted as the amount of *capital required to make a position with loss L acceptable* to an (internal/external) regulator.
- Some *reasons for using risk measures* in practice:
 - ▶ To *determine the amount of capital to hold* as a buffer against unexpected future losses on a portfolio (in order to satisfy a regulator/manager concerned with the institution’s solvency).
 - ▶ As a *tool for limiting* the amount of *risk of a business unit* (e.g. by requiring that the daily 95% value-at-risk (i.e. the 95%-quantile) of a trader’s position should not exceed a given bound).
 - ▶ To determine the *riskiness* (and *thus fair premium*) of an *insurance contract*.

2.3.1 Approaches to risk measurement

Existing risk measurement approaches grouped into three categories:

1) Notional-amount approach

- oldest approach; “standardized approaches” of Basel II (e.g. OpRisk)
- *risk of a portfolio* = summed notational values of the securities times their riskiness factor
- Advantages: ► simplicity
- Drawbacks: ► No differentiation between long and short positions and no netting: the risk of a long position in corporate bonds hedged by an offsetting position in credit default swaps is counted as twice the risk of the unhedged bond position.

- ▶ **No diversification** benefits: risk of a portfolio of loans to many companies = risk of a portfolio where the whole amount is lent to a single company.
- ▶ Problems for **portfolios of derivatives**: **notional** amount of the underlying **can** widely **differ from the economic value** of the derivative position.

2) Risk measures based on loss distributions

- Most modern **risk measures are characteristics** of the underlying **loss distribution** over some predetermined time horizon Δt .
- Examples: variance, **value-at-risk**, **expected shortfall** (see later)
- **Advantages:** ▶ **Makes sense on all levels** (from single portfolios to the overall position of a financial institution).
▶ Loss distributions **reflect netting** and **diversification**.

- Drawbacks:
- ▶ Estimates of loss distributions are typically based on past data.
 - ▶ It is difficult to estimate loss distributions accurately (especially for large portfolios).
 - ⇒ Risk measures should be complemented by information from scenarios (forward-looking).

3) Scenario-based risk measures

- Typically considered in stress testing.
- One considers possible future risk-factor changes (*scenarios*; e.g. a 20% drop in a market index).
- *Risk of a portfolio* = maximum (weighted) loss under all scenarios.

- If $\mathcal{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ denote the risk-factor changes (**scenarios**) with corresponding **weights** $\mathbf{w} = (w_1, \dots, w_n)$, the risk is

$$\psi_{\mathcal{X}, \mathbf{w}} = \max_{1 \leq i \leq n} \{w_i L(\mathbf{x}_i)\}, \quad (6)$$

where $L(\mathbf{x})$ denotes the loss the portfolio would suffer if the hypothetical scenario \mathbf{x} were to occur. Many risk measures are of the form (6); see *CME SPAN: Standard Portfolio Analysis of Risk* (2010).

- Mathematical interpretation of (6):
 - ▶ Assume $L(\mathbf{0}) = 0$ (okay if Δt small) and $w_i \in [0, 1] \ \forall i$.
 - ▶ $w_i L(\mathbf{x}_i) = w_i L(\mathbf{x}_i) + (1 - w_i) L(\mathbf{0}) = \mathbb{E}_{\mathbb{P}_i}(L(\mathbf{X}_i))$ where $\mathbf{X}_i \sim \mathbb{P}_i = w_i \delta_{\mathbf{x}_i} + (1 - w_i) \delta_{\mathbf{0}}$ ($\delta_{\mathbf{x}}$ the Dirac measure at \mathbf{x}) is a probability measure on \mathbb{R}^d .

Therefore, $\psi_{\mathcal{X}, \mathbf{w}} = \max\{\mathbb{E}_{\mathbb{P}}(L(\mathbf{X})) : \mathbf{X} \sim \mathbb{P} \in \{\mathbb{P}_1, \dots, \mathbb{P}_n\}\}$. Such a risk measure is known as a **generalized scenario**; they play an important role in the theory of **coherent risk measures**.

- **Advantages:**
 - ▶ Useful for portfolios with few risk factors.
 - ▶ Useful complementary information to risk measures based on loss distributions (past data).
- **Drawbacks:**
 - ▶ Determining scenarios and weights.

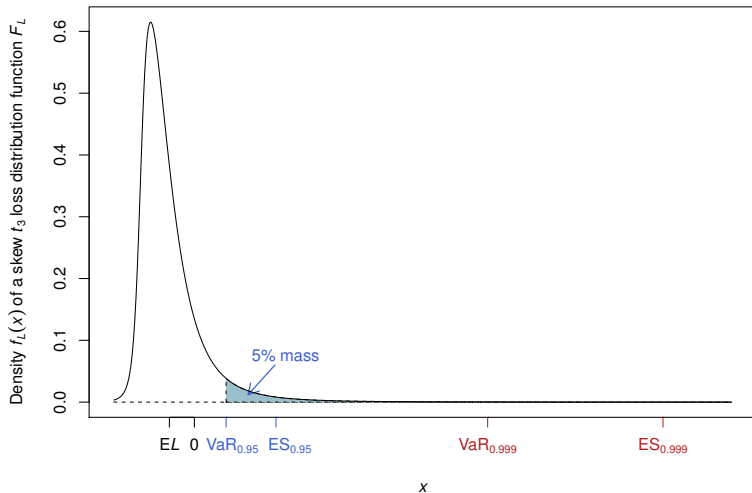
2.3.2 Value-at-risk

Definition 2.5 (Value-at-risk)

For a loss $L \sim F_L$, *value-at-risk (VaR)* at confidence level $\alpha \in (0, 1)$ is defined by $\text{VaR}_\alpha = \text{VaR}_\alpha(L) = F_L^{\leftarrow}(\alpha) = \inf\{x \in \mathbb{R} : F_L(x) \geq \alpha\}$.

- VaR_α is simply the α -quantile of F_L . As such, $F_L(x) < \alpha$ for all $x < \text{VaR}_\alpha(L)$ and $F_L(\text{VaR}_\alpha(L)) = F_L(F_L^{\leftarrow}(\alpha)) \geq \alpha$.
- Known since 1994: Weatherstone 4¹⁵ report (J.P. Morgan; RiskMetrics)
- VaR is the most widely used risk measure (by Basel II or Solvency II)

- $\text{VaR}_\alpha(L)$ is **not** a **what if** risk measure: It **does not** provide information about the **severity** of losses which occur with probability $\leq 1 - \alpha$.



Example 2.6 (VaR_α for $N(\mu, \sigma^2)$ and $t_\nu(\mu, \sigma^2)$)

1) Let $L \sim N(\mu, \sigma^2)$. Then

$$F_L(x) = \mathbb{P}(L \leq x) = \mathbb{P}((L - \mu)/\sigma \leq (x - \mu)/\sigma) = \Phi((x - \mu)/\sigma).$$

This implies that

$$\text{VaR}_\alpha(L) = F_L^{\leftarrow}(\alpha) = F_L^{-1}(\alpha) = \mu + \sigma\Phi^{-1}(\alpha).$$

Check: $F_L(\text{VaR}_\alpha(L)) = \Phi(((\mu + \sigma\Phi^{-1}(\alpha)) - \mu)/\sigma) = \alpha$.

2) Let $L \sim t_\nu(\mu, \sigma^2)$, so $(L - \mu)/\sigma \sim t_\nu$ and thus, as above,

$$\text{VaR}_\alpha(L) = \mu + \sigma t_\nu^{-1}(\alpha).$$

Note that $X \sim t_\nu = t_\nu(0, 1)$ has density

$$f_X(x) = \frac{\Gamma((\nu + 1)/2)}{\sqrt{\nu\pi}\Gamma(\nu/2)} (1 + x^2/\nu)^{-\frac{\nu+1}{2}}.$$

Furthermore, if $\nu > 1$, $\mathbb{E}X$ exists and $\mathbb{E}X = 0$; and if $\nu > 2$, $\text{var } X$ exists and $\text{var } X = \frac{\nu}{\nu-2}$.

Choices of parameters $\Delta t, \alpha$:

- Δt should reflect the time period over which the **portfolio is held (unchanged)** (e.g. insurance contracts: $\Delta t = 1 \text{ y}$)
- Δt **should be** relatively **small** (more risk-factor change data is available).
- Typical choices:
 - ▶ For limiting traders: $\alpha = 0.95$, $\Delta t = 1 \text{ d}$
 - ▶ According to **Basel II**:
 - **Market risk**: $\alpha = 0.99$, $\Delta t = 10 \text{ d}$ (2 trading weeks)
 - **Credit risk** and **operational risk**: $\alpha = 0.999$, $\Delta t = 1 \text{ y}$
 - ▶ According to Solvency II: $\alpha = 0.995$, $\Delta t = 1 \text{ y}$
- **Backtesting often needs** to be carried out at **lower confidence levels** in order to have sufficient statistical power to detect poor models.
- Be cautious with strictly **interpreting $\text{VaR}_\alpha(L)$** (and other risk measure) **estimates** (considerable **model/liquidity risk**).

Interlude: Generalized inverses

$T \nearrow$ means that T is *increasing*, i.e. $T(x) \leq T(y)$ for all $x < y$. $T \uparrow$ means that T is *strictly increasing*, i.e. $T(x) < T(y)$ for all $x < y$.

Definition 2.7 (Generalized inverse)

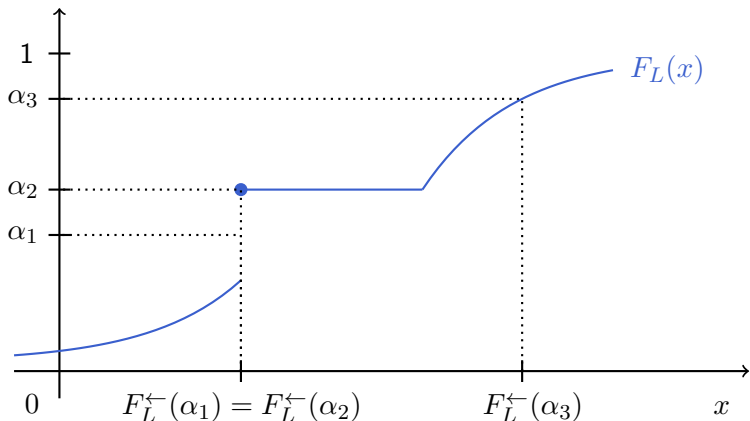
For any increasing function $T : \mathbb{R} \rightarrow \mathbb{R}$, with $T(-\infty) = \lim_{x \downarrow -\infty} T(x)$ and $T(\infty) = \lim_{x \uparrow \infty} T(x)$, the *generalized inverse* $T^{\leftarrow} : \mathbb{R} \rightarrow \bar{\mathbb{R}} = [-\infty, \infty]$ of T is defined by

$$T^{\leftarrow}(y) = \inf\{x \in \mathbb{R} : T(x) \geq y\}, \quad y \in \mathbb{R},$$

with the convention that $\inf \emptyset = \infty$. If T is a df, $T^{\leftarrow} : [0, 1] \rightarrow \bar{\mathbb{R}}$ is the *quantile function* of T .

- If T is *continuous and \uparrow* , then $T^{\leftarrow} \equiv T^{-1}$ (ordinary inverse).
- There are *rules for working with T^{\leftarrow}* similar to T^{-1} ; see Proposition A.15.

How to determine F_L^{\leftarrow} from F_L :



\Rightarrow Flat parts of F_L correspond to jumps of F_L^{\leftarrow} ; Jumps of F_L correspond to flat parts of F_L^{\leftarrow} .

2.3.3 VaR in risk capital calculations

1) VaR in regulatory capital calculations for the trading book

For banks using the *internal model (IM)* approach for market risk in Basel II, the daily risk capital formula is

$$RC^t = \max \left\{ VaR_{0.99}^{t,10}, \frac{k}{60} \sum_{i=1}^{60} VaR_{0.99}^{t-i+1,10} \right\} + c.$$

- $VaR_{\alpha}^{s,10}$ denotes the 10-day VaR_{α} calculated at day s ($t = \text{today}$).
- $k \in [3, 4]$ is a multiplier (or *stress factor*).
- $c = \text{stressed VaR charge}$ (calculated from data from a volatile market period) + *incremental risk charge (IRC;* $VaR_{0.999}$ -estimate of the annual distribution of losses due to defaults and downgrades) + *charges for specific risks.*

The averaging tends to lead to smooth changes in the capital charge over time unless $VaR_{0.99}^{t,10}$ is very large.

2) The Solvency Capital Requirement in Solvency II

The *Solvency Capital Requirement (SCR)* is the amount of capital that enables the insurer to meet its obligations over $\Delta t = 1$ y with $\alpha = 0.995$. Let $V_t = A_t - B_t$ denote the equity capital. The insurer wants to determine the minimum amount of extra capital x_0 to put aside to be solvent in Δt with probability $(\geq)\alpha$. So

$$\begin{aligned}x_0 &= \inf\{x \in \mathbb{R} : \mathbb{P}(V_{t+1} + x(1+r) \geq 0) \geq \alpha\} \\&= \inf\left\{x \in \mathbb{R} : \mathbb{P}\left(-\left(\frac{V_{t+1}}{1+r} - V_t\right) \leq x + V_t\right) \geq \alpha\right\} \\&= \inf\{x \in \mathbb{R} : \mathbb{P}(L_{t+1} \leq x + V_t) \geq \alpha\} \\&= \inf\{x \in \mathbb{R} : F_{L_{t+1}}(x + V_t) \geq \alpha\} \\&= \inf\{z - V_t \in \mathbb{R} : F_{L_{t+1}}(z) \geq \alpha\} = \text{VaR}_\alpha(L_{t+1}) - V_t\end{aligned}$$

and thus $\text{SCR} = V_t + x_0 = \text{VaR}_\alpha(L_{t+1})$ (available capital now + capital required to be solvent in Δt with probability $\geq \alpha$). If $x_0 < 0$, the company is already well capitalized.

2.3.4 Other risk measures based on loss distributions

1) Variance (or standard deviation)

- $\text{var}_\alpha(L)$ (or standard deviation) has a long history as a risk measure in finance (due to Markowitz).
- Drawbacks:
 - ▶ $\mathbb{E}(L^2) < \infty$ required (not justifiable for non-life insurance or operational risk)
 - ▶ no distinction between positive/negative deviations from the mean (var, or standard deviation, is only a good risk measure if F_L is roughly symmetric around $\mathbb{E}L$, but F_L is typically skewed in credit and operational risk)

2) Expected shortfall

Let $x_+ = \max\{x, 0\}$.

Definition 2.8 (Expected shortfall)

For a loss $L \sim F_L$ with $\mathbb{E}(L_+) < \infty$, *expected shortfall (ES)* at confidence level $\alpha \in (0, 1)$ is defined by

$$\text{ES}_\alpha = \text{ES}_\alpha(L) = \frac{1}{1 - \alpha} \int_\alpha^1 \text{VaR}_u(L) \, du. \quad (7)$$

- ES_α is the **average over VaR_u** for all $u \geq \alpha \Rightarrow \text{ES}_\alpha \geq \text{VaR}_\alpha$.
- Besides VaR, ES is the **most important risk measure** in practice.
- ES_α looks further into the tail of F_L , it is a “what if” risk measure (VaR_α is **frequency**-based; ES_α is **severity**-based).
- ES_α is more difficult to estimate and backtest than VaR_α (the variance of estimators is typically larger; larger sample size required).
- $\text{ES}_\alpha(L) < \infty$ requires $\mathbb{E}(L_+) < \infty$.
- **Subadditivity** and **elicitability** (see the appendix). One can show:
 - ▶ In contrast to VaR_α , ES_α is **subadditive** (see later).

- In contrast to ES_α (see Gneiting (2011) or Kou and Peng (2014)), VaR_α exists if $\mathbb{E}|L| = \infty$ and is elicitable (i.e., minimizes a certain expected functional (expected scoring function); see Gneiting (2011). This can be used for backtesting).

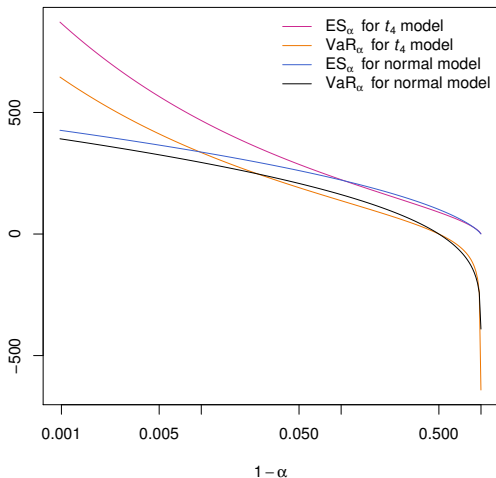
Example 2.9 (A comparison of VaR and ES for stock returns)

- Consider Example 2.2 with a portfolio consisting of a single stock $V_t = S_t = 10\,000$. In this case, $L_{t+1}^\Delta = -S_t X_{t+1}$, where $X_{t+1} = \log(S_{t+1}/S_t)$.
- Let $\sigma = 0.2/\sqrt{250}$ (annualized volatility of 20%) and assume
 - 1) $X_{t+1} \sim \text{N}(0, \sigma^2) \Rightarrow L_{t+1}^\Delta \sim \text{N}(0, S_t^2 \sigma^2)$;
 - 2) $X_{t+1} \sim t_\nu(0, \sigma^2 \frac{\nu-2}{\nu})$, $\nu > 2$ (so that $\text{var } X_{t+1}$ is also σ^2). Then

$$X_{t+1} = \sqrt{\sigma^2 \frac{\nu-2}{\nu}} Y \quad \text{for } Y \sim t_\nu.$$

$$\Rightarrow L_{t+1}^\Delta = -S_t \sqrt{\sigma^2 \frac{\nu-2}{\nu}} Y \sim t_\nu(0, S_t^2 \sigma^2 \frac{\nu-2}{\nu}) \quad (\text{var}(L_{t+1}^\Delta) = S_t^2 \sigma^2).$$

Consider $\nu = 4$ and note that $\text{VaR}_\alpha^{t_4} \geq \text{VaR}_\alpha^{\text{normal}}$ and $\text{ES}_\alpha^{t_4} \geq \text{ES}_\alpha^{\text{normal}}$ only hold for sufficiently large α .



\Rightarrow The t_4 model is not always “riskier” than the normal model.

Example 2.10 (Example 2.6 continued; ES_α for $N(\mu, \sigma^2)$ and $t_\nu(\mu, \sigma^2)$)

1) Let $\tilde{L} \sim N(0, 1)$. Then $\text{VaR}_\alpha(\tilde{L}) = 0 + 1 \cdot \Phi^{-1}(\alpha)$ and thus

$$\text{ES}_\alpha(\tilde{L}) = \frac{1}{1 - \alpha} \int_\alpha^1 \Phi^{-1}(u) du \stackrel{x = \Phi^{-1}(u)}{=} \frac{1}{1 - \alpha} \int_{\Phi^{-1}(\alpha)}^\infty x \varphi(x) dx,$$

where $\varphi(x) = \Phi'(x) = \exp(-x^2/2)/\sqrt{2\pi}$. Note that $x\varphi(x) = -\varphi'(x)$, so that

$$\text{ES}_\alpha(\tilde{L}) = \frac{-[\varphi(x)]_{\Phi^{-1}(\alpha)}^\infty}{1 - \alpha} = \frac{-(0 - \varphi(\Phi^{-1}(\alpha)))}{1 - \alpha} = \frac{\varphi(\Phi^{-1}(\alpha))}{1 - \alpha}.$$

This implies that $L \sim N(\mu, \sigma^2)$ has expected shortfall

$$\text{ES}_\alpha(L) = \mu + \sigma \text{ES}_\alpha(\tilde{L}) = \mu + \sigma \frac{\varphi(\Phi^{-1}(\alpha))}{1 - \alpha}.$$

2) Let $L \sim t_\nu(\mu, \sigma^2)$, $\nu > 1$. Similarly as above, one obtains that

$$\text{ES}_\alpha(L) = \mu + \sigma \frac{f_{t_\nu}(t_\nu^{-1}(\alpha))(\nu + t_\nu^{-1}(\alpha)^2)}{(1 - \alpha)(\nu - 1)},$$

where f_{t_ν} denotes the density of t_ν ; see Example 2.6.

By l'Hôpital's Rule (case "0/0"), one can show that

$$1 \leq \lim_{\alpha \uparrow 1} \frac{\text{ES}_\alpha(L)}{\text{VaR}_\alpha(L)} = \frac{\nu}{\nu - 1}.$$

- In finance, often $\nu \in (3, 5)$. With $\nu = 3$, $\text{ES}_\alpha(L)$ is 50% larger than $\text{VaR}_\alpha(L)$ (in the limit for large α).
- For $\nu \uparrow \infty$, $\lim_{\alpha \uparrow 1} \frac{\text{ES}_\alpha(L)}{\text{VaR}_\alpha(L)} \downarrow 1$; for $\nu \downarrow 1$, $\lim_{\alpha \uparrow 1} \frac{\text{ES}_\alpha(L)}{\text{VaR}_\alpha(L)} \uparrow \infty$.

Conclusion:

For losses with *heavy tails* (power-like), the difference between using VaR and ES as risk measures for computing risk capital can be huge (for large α as required by Basel II).

Proposition 2.11 ($\text{ES}_\alpha(L)$ under continuity)

If F_L is continuous, $\text{ES}_\alpha(L) = \mathbb{E}(L \mid L > \text{VaR}_\alpha(L))$.

Proof. If F_L is continuous, we know that

$$\begin{aligned}
 F_{L|L > \text{VaR}_\alpha(L)}(x) &= \mathbb{P}(L \leq x \mid L > \text{VaR}_\alpha(L)) \\
 &= \frac{\mathbb{P}(L \leq x, L > \text{VaR}_\alpha(L))}{\mathbb{P}(L > \text{VaR}_\alpha(L))} = \frac{\mathbb{P}(\text{VaR}_\alpha(L) < L \leq x)}{\mathbb{P}(L > \text{VaR}_\alpha(L))} \\
 &= \frac{F_L(x) - F_L(\text{VaR}_\alpha(L))}{1 - F_L(\text{VaR}_\alpha(L))} I_{\{x \geq \text{VaR}_\alpha(L)\}} \\
 &\stackrel{\text{(Gl4)}}{=} \frac{F_L(x) - \alpha}{1 - \alpha} I_{\{x \geq \text{VaR}_\alpha(L)\}} \quad \text{for all } \alpha \in (0, 1)
 \end{aligned}$$

and thus, since $dF_{L|L > \text{VaR}_\alpha(L)}(x) = dF_L(x)/(1 - \alpha)$,

$$\begin{aligned}
 \mathbb{E}(L \mid L > \text{VaR}_\alpha(L)) &= \int_{\text{VaR}_\alpha(L)}^{\infty} x dF_{L|L > \text{VaR}_\alpha(L)}(x) = \frac{1}{1 - \alpha} \int_{\text{VaR}_\alpha(L)}^{\infty} x dF_L(x) \\
 &= \frac{1}{1 - \alpha} \int_{\alpha}^1 \text{VaR}_z(L) dz = \text{ES}_\alpha(L),
 \end{aligned}$$

where we used the substitution $x = \text{VaR}_z(L)$ ($F_L(x) = z$, $dF_L(x) = dz$). □

2.3.5 Coherent and convex risk measures

- Artzner et al. (1999) (coherent risk measures) and Föllmer and Schied (2002) (convex risk measures) propose **axioms of a good risk measure**.
- Assume that **risk measures** ϱ are defined on a **linear space of random variables** \mathcal{M} (including constants; we can thus add rvs, multiply them with constants etc.), so $\varrho : \mathcal{M} \rightarrow \mathbb{R}$.
- There are **two possible interpretations** of elements of \mathcal{M} :
 - 1) **Elements of \mathcal{M} are random variables** V_{t+1} : $\tilde{\varrho}(V_{t+1})$ denotes the amount of **additional capital** that needs to be added to a position with future value V_{t+1} to make it acceptable to a regulator.
 - 2) **Elements of \mathcal{M} are losses** $L_{t+1} = -(V_{t+1} - V_t)$: $\varrho(L_{t+1})$ denotes the **total amount of capital** necessary to back a position with loss L .
- 1) and 2) are **related via** $\varrho(L_{t+1}) = V_t + \tilde{\varrho}(V_{t+1})$ (total capital = available capital + additional capital). **We focus on 2) and drop “ $t + 1$ ”.**

Axioms of coherence

Axiom 1 (**monotonicity**) $L_1, L_2 \in \mathcal{M}$, $L_1 \leq L_2$ (a.s., i.e. almost surely)
 $\Rightarrow \varrho(L_1) \leq \varrho(L_2)$

Interpr.: Positions which lead to a higher loss in every state of the world require more risk capital.

Criticism: none

Axiom 2 (**translation invar.**) $\varrho(L + l) = \varrho(L) + l$ for all $L \in \mathcal{M}$, $l \in \mathbb{R}$

Interpr.:

- By adding $l \in \mathbb{R}$ to a position with loss L , we alter the capital requirements accordingly.
- If $\varrho(L) > 0$, and $l = -\varrho(L)$, then $\varrho(L - \varrho(L)) = \varrho(L + l) = \varrho(L) + l = 0$ so that adding $\varrho(L)$ to a position with loss L makes it acceptable.

Criticism: Most people believe this to be reasonable.

Axiom 3 (**subadditivity**) $\varrho(L_1 + L_2) \leq \varrho(L_1) + \varrho(L_2)$ for all $L_1, L_2 \in \mathcal{M}$

- Interpr.:**
- Reflects the idea of **diversification**
 - Using a non-subadditive (that is, a **superadditive**) ϱ encourages institutions to legally break up into subsidiaries to reduce regulatory capital requirements.
 - Subadditivity makes decentralization possible: Assume $L = L_1 + L_2$ and that we want to bound $\varrho(L)$ by M . Choose M_j such that $\varrho(L_j) \leq M_j$, $j \in \{1, 2\}$, and $M_1 + M_2 \leq M$. Then $\varrho(L) \leq_{\text{subadd.}} \varrho(L_1) + \varrho(L_2) \leq M_1 + M_2 \leq M$.

Criticism: **VaR is ruled out** under certain scenarios (see later).
VaR is monotone, translation invariant, and positive homogeneous, but in general **not subadditive**.

Axiom 4 (positive homogeneity) $\varrho(\lambda L) = \lambda \varrho(L)$ for all $L \in \mathcal{M}$, $\lambda > 0$

Interpr.: (or motivation): $\lambda = n \in \mathbb{N}$ and subadditivity imply $\varrho(nL) \leq n\varrho(L)$, but n times the same loss L means no diversification, so equality should hold.

Criticism: If $\lambda > 0$ is large, liquidity risk plays a role and one should rather have $\varrho(\lambda L) > \lambda \varrho(L)$ (also to penalize concentration or risk), but this contradicts subadditivity. This has led to convex risk measures, i.e. risk measures ϱ satisfying

$$\varrho(\lambda L_1 + (1 - \lambda)L_2) \leq \lambda \varrho(L_1) + (1 - \lambda)\varrho(L_2)$$

for all $L_1, L_2 \in \mathcal{M}$, $0 \leq \lambda \leq 1$.

Definition 2.12 (Coherent risk measure)

A risk measure ϱ which satisfies Axioms 1–4 is called *coherent*.

Example 2.13 (Generalized scenario risk measures)

Let $L(x)$ denote the hypothetical loss under scenario x (risk-factor change).

The generalized scenario risk measure

$$\psi_{\mathcal{X},w}(L) = \max\{\mathbb{E}_{\mathbb{P}}(L(\mathbf{X})) : \mathbf{X} \sim \mathbb{P} \in \{\mathbb{P}_1, \dots, \mathbb{P}_n\}\}$$

is coherent. Monotonicity, translation invariance, positive homogeneity are clear (by monotonicity and linearity of $\mathbb{E}_{\mathbb{P}}(\cdot)$); for subadditivity, note that

$$\begin{aligned}\psi_{\mathcal{X},w}(L_1 + L_2) &= \max\{\underbrace{\mathbb{E}_{\mathbb{P}}(L_1(\mathbf{X}) + L_2(\mathbf{X}))}_{=\mathbb{E}_{\mathbb{P}}(L_1(\mathbf{X})) + \mathbb{E}_{\mathbb{P}}(L_2(\mathbf{X}))} : \mathbf{X} \sim \mathbb{P} \in \{\mathbb{P}_1, \dots, \mathbb{P}_n\}\} \\ &\leq \psi_{\mathcal{X},w}(L_1) + \psi_{\mathcal{X},w}(L_2).\end{aligned}$$

One can show that all coherent risk measures can be represented as generalized scenarios via

$$\varrho(L) = \sup\{\mathbb{E}_{\mathbb{P}}(L) : \mathbb{P} \in \mathcal{P}\}$$

for a suitable set \mathcal{P} of probability measures.

Definition 2.14 (Convex risk measure)

A risk measure ρ which is **monotone**, **translation invariant** and **convex** is called a **convex risk measure**.

- Justification: Again diversification but they don't have to be positive homogeneous.
- Any coherent risk measure is also a convex risk measure. The **converse is not true in general**, but for positive homogeneous risk measures, convexity and subadditivity are equivalent.

Theorem 2.15 (Coherence of ES)

ES is a coherent risk measure.

Proof. **Monotonicity**, **translation invariance** and **positive homogeneity** follow from VaR. **Subadditivity** is more involved but can be shown in various ways; see later. □

Superadditivity scenarios for VaR

Under the following scenarios, VaR_α is typically **superadditive**:

- 1) L_1, L_2 have **skewed** distributions;
- 2) **Independent, light-tailed** L_1, L_2 and **small** α ;
- 3) L_1, L_2 have **special dependence**;
- 4) L_1, L_2 have **heavy tailed** distributions.

Exercise 2.16 (Skewed loss distributions)

Consider a portfolio of **two independently defaultable zero-coupon bonds** (maturity $T = 1y$, nominal/face value 100, paid interest of 5%, default probability $p = 0.009$, no recovery). The **loss of bond j** (from the money lender's/investor's perspective) is thus

$$L_j = \begin{cases} -5, & \text{with prob. } 1 - p = 0.991, \\ 100, & \text{with prob. } p = 0.009, \end{cases} \quad j \in \{1, 2\}.$$

Set $\alpha = 0.99$. Then $\text{VaR}_\alpha(L_j) = -5$, $j \in \{1, 2\}$.

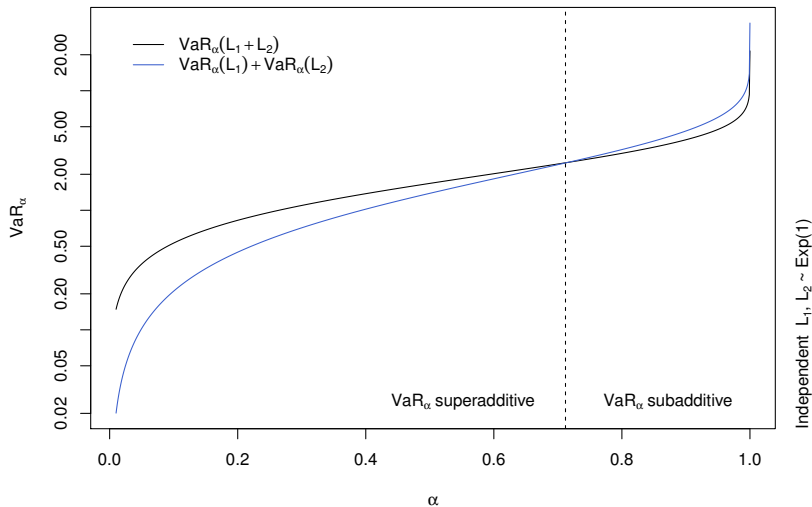
The loss $L_1 + L_2$ is given by

$$L_1 + L_2 = \begin{cases} -10, & \text{with prob. } (1 - p)^2 = 0.982081, \\ \mathbf{95}, & \text{with prob. } 2p(1 - p) = 0.017838, \\ 200, & \text{with prob. } p^2 = 0.000081. \end{cases}$$

Therefore, $\text{VaR}_\alpha(L_1 + L_2) = \mathbf{95} > -10 = \text{VaR}_\alpha(L_1) + \text{VaR}_\alpha(L_2)$. Hence **VaR_α is superadditive.**

Exercise 2.17 (Independent, light-tailed L_1, L_2 and small α)

If $L_1, L_2 \stackrel{\text{ind.}}{\sim} \text{Exp}(1)$, VaR_α is superadditive $\iff \alpha < 0.71$.



Exercise 2.18 (Special dependence)

Let $\alpha \in (0, 1)$, $L_1 \sim U(0, 1)$ and define $L_2 \stackrel{\text{a.s.}}{=} \begin{cases} L_1, & \text{if } L_1 < \alpha, \\ 1 + \alpha - L_1, & \text{if } L_1 \geq \alpha. \end{cases}$

One can show that $L_2 \sim U(0, 1)$. Also, $L_1 + L_2 = \begin{cases} 2L_1, & \text{if } L_1 < \alpha, \\ 1 + \alpha, & \text{if } L_1 \geq \alpha, \end{cases}$
from which one can show that

$$F_{L_1+L_2}(x) = \begin{cases} 0, & \text{if } x < 0, \\ x/2, & \text{if } x \in [0, 2\alpha), \\ \alpha, & \text{if } x \in [2\alpha, 1 + \alpha), \\ 1, & \text{if } x \geq 1 + \alpha. \end{cases}$$

For all $\varepsilon \in (0, \frac{1-\alpha}{2})$, we thus obtain that

$$\text{VaR}_{\alpha+\varepsilon}(L_1 + L_2) = 1 + \alpha > \underset{\varepsilon \in (0, \frac{1-\alpha}{2})}{2(\alpha + \varepsilon)} = \text{VaR}_{\alpha+\varepsilon}(L_1) + \text{VaR}_{\alpha+\varepsilon}(L_2).$$

Remark 2.19 (Special case of comonotone risks; elliptical risks)

- Note that $L_1 \stackrel{\text{a.s.}}{=} L_2$ does not lead to the largest $\text{VaR}_\alpha(L_1 + L_2)$ since

$$\text{VaR}_\alpha(L_1 + L_2) \stackrel[\text{hom.}]{\text{pos.}} 2 \text{VaR}_\alpha(L_1) = \text{VaR}_\alpha(L_1) + \text{VaR}_\alpha(L_2),$$

so “only” equality.

- VaR_α is subadditive and thus coherent for a certain class of multivariate distributions (strictly including the multivariate normal and t); see later.

Exercise 2.20 (Heavy tailed loss distributions)

Let $L_1, L_2 \stackrel{\text{ind.}}{\sim} F(x) = 1 - x^{-1/2}$, $x \in [1, \infty)$. By deriving the distribution function

$$F_{L_1+L_2}(x) = 1 - 2\sqrt{x-1}/x, \quad x \geq 2,$$

of $L_1 + L_2$ (via the density convolution formula; tedious), one can show (via solving a quadratic equation) that VaR_α is superadditive for all $\alpha \in (0, 1)$.