

## 1 Outline

In this lecture, we cover

- Errata in Value at Risk (VaR) materials (Lectures 19 and 20),
- two-period investment.

## 2 Errata: Value at Risk (VaR)

### 2.1 Lecture 19

Assume that we have likelihood weights  $p_i$  for each scenario  $\xi_i$  and the distribution  $\hat{P}_N$  with

$$\mathbb{P}_{\xi \sim \hat{P}_N} [\xi = \xi_i] = p_i, \quad i \in [N].$$

Fix some  $\alpha \in (0, 1)$ . In Lecture 19, we defined the **Value-at-Risk** at level  $\alpha$  or  $\alpha$ -**VaR** is the risk measure defined as

$$\text{VaR}_\alpha \left( g(x, \xi); \hat{P}_N \right) = \min \left\{ t : \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq t] > \alpha \right\}.$$

**There is a mistake in this definition. The correct definition is**

$$\text{VaR}_\alpha \left( g(x, \xi); \hat{P}_N \right) = \min \left\{ t : \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq t] \geq \alpha \right\}$$

where the lower bound on the probability is given by a **non-strict inequality**. We also considered the following example.

**Example 24.1.** Suppose that we have

$i$	1	2	3	4	5	6
$p_i$	0.05	0.15	0.1	0.4	0.2	0.1
$g(x, \xi_i)$	10	8	6	3	2	-2
$\mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq g(x, \xi_i)]$	1	0.95	0.8	0.7	0.3	0.1

Then

- $\text{VaR}_{0.98} \left( g(x, \xi); \hat{P}_N \right) = 10.$
- $\text{VaR}_{0.95} \left( g(x, \xi); \hat{P}_N \right) = \del{10} \rightarrow 8.$
- $\text{VaR}_{0.85} \left( g(x, \xi); \hat{P}_N \right) = 8.$
- $\text{VaR}_{0.8} \left( g(x, \xi); \hat{P}_N \right) = \del{8} \rightarrow 6.$

- $\text{VaR}_{0.7} \left( g(x, \xi); \hat{P}_N \right) = \text{b} \rightarrow 3.$
- $\text{VaR}_{0.6} \left( g(x, \xi); \hat{P}_N \right) = 3.$

When  $p_i = 1/N$  for  $i \in [N]$  and  $\alpha = 1 - k/N$ , then  $\text{VaR}_\alpha \left( g(x, \xi); \hat{P}_N \right)$  is **not the  $k$ th largest value but the  $(k+1)$ th largest value** among  $g(x, \xi_1), \dots, g(x, \xi_N)$ . Basically, if  $g(x, \xi_1) \geq \dots \geq g(x, \xi_N)$ , then

$$\text{VaR}_{1-k/N} \left( g(x, \xi); \hat{P}_N \right) = g(x, \xi_{k+1}), \quad k = 0, 1, \dots$$

## 2.2 Lecture 20

Assume that we can model any constraint of the form  $g(x, \xi_i) \leq b_i$ . Based on this, let us try to model

$$\text{VaR}_\alpha \left( g(x, \xi); \hat{P}_N \right) \leq 0.$$

This is equivalent to

$$\min \left\{ t : \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq t] > \alpha \right\} \leq 0 \rightarrow \min \left\{ t : \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq t] \geq \alpha \right\} \leq 0.$$

We may rewrite this as

$$t \leq 0$$

$$\mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq t] > \alpha \rightarrow \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq t] \geq \alpha$$

Without loss of generality, we can take  $t = 0$  and just consider

$$\mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq 0] > \alpha \rightarrow \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq 0] \geq \alpha.$$

This is because  $\mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq 0]$  never decreases as  $t$  increases.

Therefore,  $\text{VaR}_\alpha \left( g(x, \xi); \hat{P}_N \right) \leq 0$  is equivalent to a **chance constraint**.

$$\mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq 0] > \alpha \rightarrow \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq 0] \geq \alpha \Leftrightarrow \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) > 0] \leq 1 - \alpha.$$

To model this, we introduce binary variables  $z_i \in \{0, 1\}$  for  $i \in [N]$  for scenarios.

$$z_i = \begin{cases} 1, & \text{if } g(x, \xi_i) > 0 \\ 0, & \text{otherwise.} \end{cases}$$

Basically, we add implications

$$z_i = 0 \Rightarrow g(x, \xi_i) \leq 0, \quad i \in [N]$$

This can be modelled with the big-M technique:

$$g(x, \xi_i) \leq M z_i, \quad i \in [N].$$

We need to ensure that the probability  $g(x, \xi) > 0$  is no greater than  $1 - \alpha$ :

$$\sum_{i \in [N]} p_i z_i \leq 1 - \alpha.$$

In summary,

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & \text{VaR}_\alpha \left( g(x, \xi); \hat{P}_N \right) \leq 0 \\ & x \in \mathcal{X} \end{aligned}$$

is equivalent to

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & g(x, \xi_i) \leq Mz_i, \quad i \in [N] \\ & \sum_{i \in [N]} p_i z_i \leq 1 - \alpha \\ & x \in \mathcal{X}, \quad z \in \{0, 1\}^N \end{aligned}$$

### 3 Two-period investment

Let us consider a two-period investment problem. Here, we have three stages of decisions in the optimization model. Remember that  $r_{s,1}$  is the random return of stocks for period 1 and that  $r_{s,2}$  is the random return for period 2. Suppose that there are  $n$  outcomes for period 1:

$$r_{s,1}^{(1)}, \dots, r_{s,1}^{(n)}.$$

Next, under the  $i$ th outcome  $r_{s,1}^{(i)}$  for period 1, we assume that  $n$  outcomes for period 2:

$$r_{s,1}^{(i,1)}, \dots, r_{s,1}^{(i,n)}.$$

This is summarized as the following scenario tree. Since there are  $n$  outcomes for period 1 and  $n$

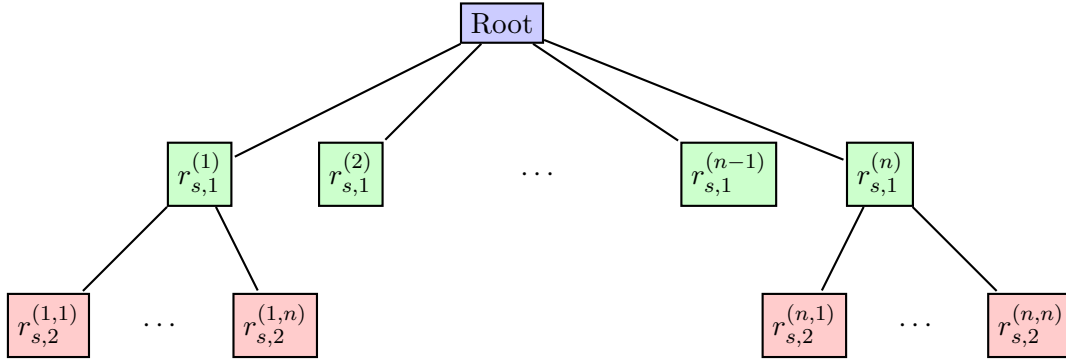


Figure 24.1: The scenario tree under  $n$  outcomes for each stage

outcomes for period 2, there are technically  $n \times n = n^2$  scenarios. Moreover, we assume that each outcome occurs with equal probability  $1/n$ . More specifically,

$$\begin{aligned} \mathbb{P} \left[ r_{s,1} = r_{s,1}^{(i)} \right] &= \frac{1}{n}, \quad i = 1, \dots, n \\ \mathbb{P} \left[ r_{s,2} = r_{s,2}^{(i,j)} \mid r_{s,1} = r_{s,1}^{(i)} \right] &= \frac{1}{n}, \quad i = 1, \dots, n, \quad j = 1, \dots, n \end{aligned}$$

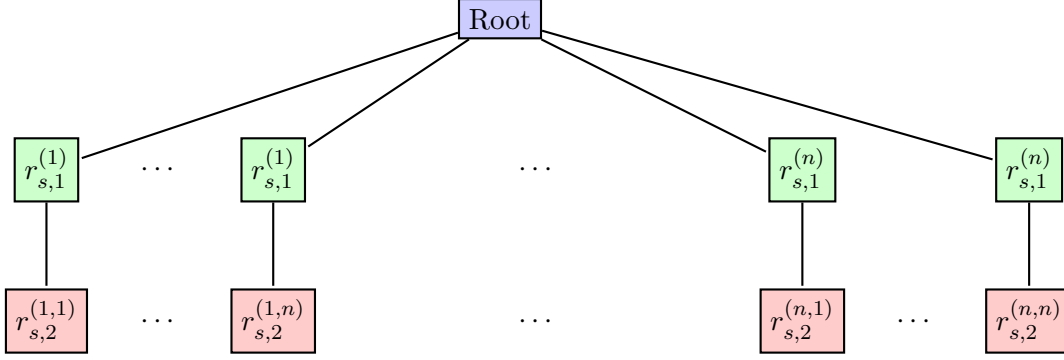


Figure 24.2: The scenario tree under  $n^2$  scenarios

**Decisions** The period 1 investment decision is given by

$$x_1 = (x_{s,1}, x_{o,1})$$

where  $x_{s,1}$  is for stocks and  $x_{o,1}$  is for savings. At the end of period 1, we observe a value among

$$r_{s,1}^{(1)}, \dots, r_{s,1}^{(n)},$$

each of which occurs with probability  $1/n$ . When the outcome is  $r_{s,1}^{(i)}$ , the period 2 investment decision is given by

$$x_2^{(i)} = (x_{s,2}^{(i)}, x_{o,2}^{(i)}), \quad i = 1, \dots, n.$$

After period 2, we observe

$$r_{s,2}^{(i,1)}, \dots, r_{s,2}^{(i,n)},$$

each of which occurs with probability  $1/n$ . When the outcome is  $r_{s,2}^{(i,j)}$ , the total wealth is

$$w_2^{(i,j)} = r_{s,2}^{(i,j)} x_{s,2}^{(i)} + x_{o,2}^{(i)}.$$

**Third-stage model** The third-stage is after period 2 where we collect the total reward from the two periods. Then the objective is to maximize the reward given by

$$\min \left\{ p \left( w_2^{(i,j)} - G \right), q \left( w_2^{(i,j)} - G \right) \right\}$$

where  $p$  is the borrowing rate and  $q$  is the interest rate. Then the third-stage model is given by

$$\begin{aligned} \max \quad & \min \left\{ p \left( w_2^{(i,j)} - G \right), q \left( w_2^{(i,j)} - G \right) \right\} \\ \text{s.t.} \quad & w_2^{(i,j)} = r_{s,2}^{(i,j)} x_{s,2}^{(i)} + x_{o,2}^{(i)}. \end{aligned}$$

We can represent this as the following linear program.

$$\begin{aligned} \max \quad & t^{(i,j)} \\ \text{s.t.} \quad & w_2^{(i,j)} = r_{s,2}^{(i,j)} x_{s,2}^{(i)} + x_{o,2}^{(i)} \\ & t^{(i,j)} \leq p \left( w_2^{(i,j)} - G \right) \\ & t^{(i,j)} \leq q \left( w_2^{(i,j)} - G \right) \end{aligned}$$

**Second-stage model** The second stage is after period 1 and before period 2. In the second stage, we prepare our second period investment plan. Assuming that the first period outcome is  $r_{s,1}^{(i)}$ , the wealth from period 1 would be

$$w_1^{(i)} = r_{s,1}^{(i)}x_{s,1} + x_{o,1}.$$

For period 2, we allocate the wealth to stocks and savings. Hence,

$$w_1^{(i)} = x_{s,2}^{(i)} + x_{o,2}^{(i)}.$$

Eliminating the term  $w_1^{(i)}$ , we can simply write

$$r_{s,1}^{(i)}x_{s,1} + x_{o,1} = x_{s,2}^{(i)} + x_{o,2}^{(i)}.$$

Moreover,

$$x_{s,2}^{(i)}, x_{o,2}^{(i)} \geq 0.$$

The objective is to maximize the expected third-stage value

$$\frac{1}{n} \sum_{j=1}^n Q_3(x_1, x_2^{(i)}, r_{s,1}^{(i)}, r_{s,2}^{(i,j)}).$$

Then the second-stage model is given by

$$\begin{aligned} \max \quad & \frac{1}{n} \sum_{j=1}^n Q_3(x_1, x_2^{(i)}, r_{s,1}^{(i)}, r_{s,2}^{(i,j)}) \\ \text{s.t.} \quad & r_{s,1}^{(i)}x_{s,1} + x_{o,1} = x_{s,2}^{(i)} + x_{o,2}^{(i)} \\ & x_{s,2}^{(i)}, x_{o,2}^{(i)} \geq 0. \end{aligned}$$

**First-stage model** Note that the initial budget is  $B$ . Hence, we have

$$B = x_{s,1} + x_{o,1}.$$

Moreover, for simplicity, we assume no short selling and no leverage. Then

$$x_{s,1}, x_{o,1} \geq 0.$$

The first stage objective is to maximize the expected second-stage value

$$\frac{1}{n} \sum_{i=1}^n Q_2(x_1, r_{s,1}^{(i)}).$$

Hence, the first-stage model is given by

$$\begin{aligned} \max \quad & \frac{1}{n} \sum_{i=1}^n Q_2(x_1, r_{s,1}^{(i)}) \\ \text{s.t.} \quad & x_{s,1} + x_{o,1} = B \\ & x_{s,1}, x_{o,1} \geq 0 \end{aligned}$$

**Aggregated model** The full model after aggregating the three stages is given as follows.

$$\begin{aligned}
\max \quad & \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n t^{(i,j)} \\
\text{s.t.} \quad & x_{s,1} + x_{o,1} = B \\
& x_{s,1}, x_{o,1} \geq 0 \\
& r_{s,1}^{(i)} x_{s,1} + x_{o,1} = x_{s,2}^{(i)} + x_{o,2}^{(i)}, \quad i = 1, \dots, n \\
& x_{s,2}^{(i)}, x_{o,2}^{(i)} \geq 0, \quad i = 1, \dots, n \\
& w_2^{(i,j)} = r_{s,2}^{(i,j)} x_{s,2}^{(i)} + x_{o,2}^{(i)}, \quad i = 1, \dots, n, j = 1, \dots, n \\
& t^{(i,j)} \leq p \left( w_2^{(i,j)} - G \right), \quad i = 1, \dots, n, j = 1, \dots, n \\
& t^{(i,j)} \leq q \left( w_2^{(i,j)} - G \right), \quad i = 1, \dots, n, j = 1, \dots, n
\end{aligned}$$