# Financial Theory – Lecture 5

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#### Agenda

- Mean-variance analysis with only risky assets.
- Choice under uncertainty.

The lecture is based on

• Chapter 7 in the course book.

We consider a market with N risky assets.

By a "risky asset" we mean an asset whose rate of return has a strictly positive standard deviation.

The rate of return of these assets are collected in the vector  $\mathbf{r}$ .

Recall the notation

$$\mu = E[r]$$

and

$$\Sigma = \mathsf{Var}[r].$$

The first goal for us is to find the portfolio with mean  $\bar{\mu}$  that has the smallest variance.

Mathematically we formulate this problem as

$$\min_{oldsymbol{\pi}} \quad \mathsf{Var}[r(oldsymbol{\pi})] \\ \mathsf{s.t.} \quad \sum_{i=1}^{N} \pi_i = 1 \qquad \Leftrightarrow \qquad \substack{\min_{oldsymbol{\pi}} \quad oldsymbol{\pi} \cdot \Sigma oldsymbol{\pi} \\ \mathsf{s.t.} \quad oldsymbol{\pi} \cdot \mathbf{1} = 1 \\ \mathcal{E}[r(oldsymbol{\pi})] = \overline{\mu}. \end{cases}$$

The Lagrangian of this problem is

$$L(\boldsymbol{\pi}) = \boldsymbol{\pi} \cdot \boldsymbol{\Sigma} \boldsymbol{\pi} + \lambda_1 (1 - \boldsymbol{\pi} \cdot \boldsymbol{1}) + \lambda_2 (\overline{\mu} - \boldsymbol{\pi} \cdot \boldsymbol{\mu}).$$

Here  $\lambda_1$  and  $\lambda_2$  are the (Lagrangian) multipliers.

We need to be able to take the derivative of functions like

$$f(x) = x \cdot a$$
 and  $g(x) = x \cdot Ax$ 

where  $\boldsymbol{a}$  is a vector and  $\boldsymbol{A}$  is a matrix.

Since

$$f(x) = x \cdot a = \sum_{i=1}^{N} x_i a_i$$

we have

$$\frac{\partial f}{\partial x_i} = a_i, \ i = 1, \dots, N.$$

We write this as

$$\frac{\partial f}{\partial \mathbf{x}} = \mathbf{a}.$$

We also have

$$g(\mathbf{x}) = \mathbf{x} \cdot A\mathbf{x} = \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j A_{ij}.$$

If the matrix A is symmetric then

$$\frac{\partial \mathbf{g}}{\partial x_i} = 2(A\mathbf{x})_i,$$

where  $(Ax)_i$  is the element of row i of Ax.

We write this as

$$\frac{\partial \mathbf{g}}{\partial \mathbf{x}} = 2A\mathbf{x}.$$

Let us return to the Lagrangian:

$$L(\boldsymbol{\pi}) = \boldsymbol{\pi} \cdot \boldsymbol{\Sigma} \boldsymbol{\pi} + \lambda_1 (1 - \boldsymbol{\pi} \cdot \boldsymbol{1}) + \lambda_2 (\overline{\mu} - \boldsymbol{\pi} \cdot \boldsymbol{\mu}).$$

The first-order condition with respect to  $\pi$  is

$$\frac{\partial L}{\partial \boldsymbol{\pi}} = 2\boldsymbol{\Sigma}\boldsymbol{\pi} - \lambda_1 \mathbf{1} - \lambda_2 \boldsymbol{\mu} = 0.$$

This can be written

$$2\Sigma \boldsymbol{\pi} = \lambda_1 \mathbf{1} + \lambda_2 \boldsymbol{\mu} \quad \Leftrightarrow \quad \Sigma \boldsymbol{\pi} = \frac{\lambda_1}{2} \mathbf{1} + \frac{\lambda_2}{2} \boldsymbol{\mu}.$$

How do we solve for  $\pi$ ? Multiply both sides with  $\Sigma^{-1}$ !

$$\underbrace{\Sigma^{-1}\Sigma}_{=I}\pi = \Sigma^{-1}\left(\frac{\lambda_1}{2}\mathbf{1} + \frac{\lambda_2}{2}\mu\right)$$

Since  $I\pi = \pi$  we get

$$oldsymbol{\pi} = rac{\lambda_1}{2} \Sigma^{-1} \mathbf{1} + rac{\lambda_2}{2} \Sigma^{-1} oldsymbol{\mu}.$$

We need to find the Lagrange multipliers  $\lambda_1$  and  $\lambda_2 \longrightarrow$  use the constraints.

Portfolio weights sum to 1:

$$1 = \pi \cdot \mathbf{1} = \mathbf{1} \cdot \pi$$

$$= \mathbf{1} \cdot \left(\frac{\lambda_1}{2} \Sigma^{-1} \mathbf{1} + \frac{\lambda_2}{2} \Sigma^{-1} \mu\right)$$

$$= \frac{\lambda_1}{2} \mathbf{1} \cdot \Sigma^{-1} \mathbf{1} + \frac{\lambda_2}{2} \mathbf{1} \cdot \Sigma^{-1} \mu$$

Expected rate of return equal to  $\bar{\mu}$ :

$$\begin{split} \bar{\mu} &= \pi \cdot \mu = \mu \cdot \pi \\ &= \mu \cdot \left(\frac{\lambda_1}{2} \Sigma^{-1} \mathbf{1} + \frac{\lambda_2}{2} \Sigma^{-1} \mu\right) \\ &= \frac{\lambda_1}{2} \mu \cdot \Sigma^{-1} \mathbf{1} + \frac{\lambda_2}{2} \mu \cdot \Sigma^{-1} \mu \end{split}$$

Now introduce the parameters

$$A = \mu \cdot \Sigma^{-1} \mu$$

$$B = \mu \cdot \Sigma^{-1} \mathbf{1} = \mathbf{1} \cdot \Sigma^{-1} \mu$$

$$C = \mathbf{1} \cdot \Sigma^{-1} \mathbf{1}$$

$$D = AC - B^{2}.$$

Using these, the two equations above can be written

$$\begin{cases} 1 = \frac{\lambda_1}{2}C + \frac{\lambda_2}{2}B \\ \bar{\mu} = \frac{\lambda_1}{2}B + \frac{\lambda_2}{2}A \end{cases}$$

We want to solve for  $\lambda_1$  and  $\lambda_2$ .

The solution is given by

$$\begin{cases} \lambda_1 = 2\frac{A - B\bar{\mu}}{D} \\ \lambda_2 = 2\frac{C\bar{\mu} - B}{D} \end{cases}$$

Inserting them in the expression for  $\pi$  results in

$$\pi(\bar{\mu}) = \frac{A - B\bar{\mu}}{D}\Sigma^{-1}\mathbf{1} + \frac{C\bar{\mu} - B}{D}\Sigma^{-1}\mu.$$

These are the portfolio weights in the portfolio with mean rate of return  $\bar{\mu}$  whose rate of return has the smallest variance.

Using the optimal weights from the previous slide we can calculate the standard deviation of this portfolio:

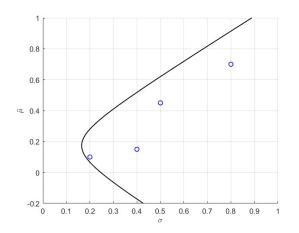
$$\sigma(\bar{\mu}) = \operatorname{Std}[r(\pi(\bar{\mu}))]$$

$$= \sqrt{\pi(\bar{\mu}) \cdot \Sigma \pi(\bar{\mu})}$$

$$= \dots$$

$$= \sqrt{\frac{C\bar{\mu}^2 - 2B\bar{\mu} + A}{D}}.$$

This is called the mean-variance frontier or the portfolio frontier.



An example with four assets (N = 4).

A portfolio whose mean and standard devition is on the mean-variance frontier is called a frontier portfolio.

We say that a portfolio is on the portfolio frontier if its standard deviation and mean is on the frontier.

The variance  $\sigma^2$  for a given  $\bar{\mu}$  is

$$\sigma^2 = \frac{C\bar{\mu}^2 - 2B\bar{\mu} + A}{D}.$$

This can be written

$$\frac{\sigma^2}{1/C} - \frac{\left(\bar{\mu} - B/C\right)^2}{D/C^2} = 1.$$

Mathematically this is an equation of a hyperbola in the  $(\sigma, \bar{\mu})$ -plane.

Let us now turm to the problem of finding the portfolio with the smallest variance, not taking its expected rate of return into account.

The minimum-variance portfolio (MVP)  $\pi_{\min}$  solves the problem

$$\begin{array}{lll} \min \limits_{\boldsymbol{\pi}} & \mathsf{Var}[r(\boldsymbol{\pi})] \\ \mathrm{s.t.} & \sum_{i=1}^{N} \pi_i = 1 \end{array} \quad \Leftrightarrow \quad \begin{array}{ll} \min \limits_{\boldsymbol{\pi}} & \boldsymbol{\pi} \cdot \boldsymbol{\Sigma} \boldsymbol{\pi} \\ \mathrm{s.t.} & \boldsymbol{\pi} \cdot \boldsymbol{1} = 1. \end{array}$$

To solve this problem we again set up the Lagrangian

$$L(\boldsymbol{\pi}) = \boldsymbol{\pi} \cdot \boldsymbol{\Sigma} \boldsymbol{\pi} + \lambda (1 - \boldsymbol{\pi} \cdot \boldsymbol{1})$$

and proceed as above

In this case we get (check this!)

$$\pi_{\min} = \frac{1}{C} \Sigma^{-1} \mathbf{1} = \frac{1}{\mathbf{1} \cdot \Sigma^{-1} \mathbf{1}} \Sigma^{-1} \mathbf{1}.$$

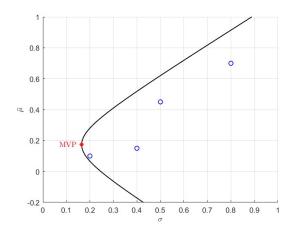
The standard deviation and mean of this portfolio is

$$\sigma_{\min} = \frac{1}{\sqrt{C}}$$

and

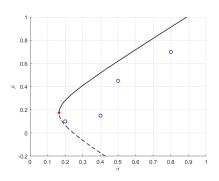
$$\mu_{\mathsf{min}} = \frac{B}{C}$$

respectively.



Looking at the mean-variance frontier, we see that for standard deviations larger than  $\sigma_{\mbox{min}}=1/\sqrt{\mbox{C}}$  there are two portfolios having this standard deviation.

Since an investor wants to maximise the expected return and minimise the standard deviation, no rational investor will hold a portfolio on the half of the mean-variance frontier that is below the MVP.



Recall the general formula

$$\pi(\bar{\mu}) = \underbrace{\frac{A - B\bar{\mu}}{D}}_{\text{Scalar}} \underbrace{\Sigma^{-1} \mathbf{1}}_{\text{Vector}} + \frac{C\bar{\mu} - B}{D} \Sigma^{-1} \mu.$$

Note that

$$\pi_{\min} = \frac{1}{C} \Sigma^{-1} \mathbf{1} \Leftrightarrow \Sigma^{-1} \mathbf{1} = C \pi_{\min}.$$

**Conclusion:** The vector  $\Sigma^{-1}\mathbf{1}$  is up to a scaling equal to the MVP.

We can write the general optimal weight vector as

$$\pi(\bar{\mu}) = \frac{(A - B\bar{\mu})C}{D}\pi_{\mathsf{min}} + \frac{C\bar{\mu} - B}{D}\Sigma^{-1}\mu.$$

We have seen that  $\pi(\bar{\mu})$  can be written as a constant, depending on the chosen level  $\bar{\mu}$ , times the MVP plus another constant, also depending on  $\bar{\mu}$ , times the vector  $\Sigma^{-1}\mu$ .

Define the portfolio

$$\pi_{\mathsf{slope}} = \frac{1}{B} \Sigma^{-1} \mu = \frac{1}{\mathbf{1} \cdot \Sigma^{-1} \mu} \Sigma^{-1} \mu.$$

**Note:** 1) We want a portfolio that is proportional to  $\Sigma^{-1}\mu$ .

2) We multiply with  $1/\mathbf{1} \cdot \Sigma^{-1} \mu$  so that  $\pi_{\text{slope}}$  is a portfolio, i.e. its elements sum to 1.

Using that

$$\pi_{\mathsf{slope}} = \frac{1}{B} \Sigma^{-1} \mu \quad \Leftrightarrow \quad \Sigma^{-1} \mu = B \pi_{\mathsf{slope}}$$

we get

$$\pi(\bar{\mu}) = \frac{(A - B\bar{\mu})C}{D} \pi_{\min} + \frac{C\bar{\mu} - B}{D} \Sigma^{-1} \mu$$

$$= \frac{(A - B\bar{\mu})C}{D} \pi_{\min} + \frac{(C\bar{\mu} - B)B}{D} \pi_{\text{slope}}$$

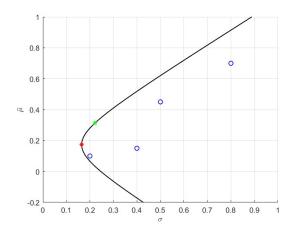
$$= a_{\min}(\bar{\mu})\pi_{\min} + a_{\text{slope}}(\bar{\mu})\pi_{\text{slope}}.$$

We have

$$a_{\min}(\bar{\mu}) + a_{\text{slope}}(\bar{\mu}) = \frac{(A - B\bar{\mu})C}{D} + \frac{(C\bar{\mu} - B)B}{D}$$
$$= \frac{AC - BC\bar{\mu} + BC\bar{\mu} - B^2}{D}$$
$$= \frac{AC - B^2}{D} = 1.$$

The interpretation is that for each  $\bar{\mu}$ , the optimal portfolio  $\pi(\bar{\mu})$  can be written as a combination of the two portfolios  $\pi_{\min}$  and  $\pi_{\text{slope}}$ .

This is called two-fund separation: Any portfolio on the mean-variance frontier is the combination of the two portfolios  $\pi_{\min}$  and  $\pi_{\text{slope}}$ .



More generally:

If the constant  $B \neq 0$ , then any two frontier portfolios  $\pi_1$  and  $\pi_2$  can be used to span the frontier, i.e. there exists a number w such that

$$\pi(\bar{\mu}) = w\pi_1 + (1-w)\pi_2.$$

Is there any economic interpretation of  $\pi_{slope}$ ?

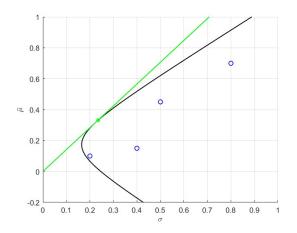
Yes!

Consider a straight line

$$\bar{\mu} = k\sigma$$

in the  $(\bar{\mu}, \sigma)$ -plane for some k.

The portfolio  $\pi_{slope}$  represents the frontier portfolio with the largest slope of this line.



#### Mean-variance analysis with portfolio constraints

So far we have allowed short-selling. Let us look at the problem where short-selling is not allowed.

$$\min_{\boldsymbol{\pi}} \quad \mathsf{Var}[r(\boldsymbol{\pi})]$$
s.t. 
$$\sum_{i=1}^{N} \pi_i = 1$$

$$\sum_{i=1}^{N} \pi_i \mu_i = \bar{\mu}$$

$$\pi_i \geq 0, i = 1, 2, \dots, N$$

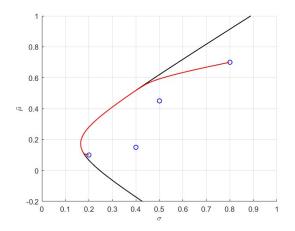
$$\min_{\boldsymbol{\pi}} \quad \boldsymbol{\pi} \cdot \boldsymbol{\Sigma} \boldsymbol{\pi}$$
s.t. 
$$\boldsymbol{\pi} \cdot \mathbf{1} = 1$$

$$\boldsymbol{\pi} \cdot \boldsymbol{\mu} = \bar{\mu}$$

$$\boldsymbol{\pi} \geq \mathbf{0}.$$

These type of problems are in general much harder to solve than when there are only equility constraints.

# Mean-variance analysis with portfolio constraints



#### Mean-variance analysis with portfolio constraints

#### Different types of constraints:

- No short-selling in one or several assets.
- Maximum fraction invested in one or several assets.
- Maximum fraction invested in a sector or country.

# Choice under uncertainty

We know that a rational investor will choose a portfolio on the upper efficient frontier. But which portfolio will be chosen?

The choice depends on the investor's attitude towards risk.

An investor has initial wealth  $W_0$  and invests in an asset with rate of return r. Then the future wealth is

$$W=W_0(1+r).$$

Given axioms of investor behaviour, one can show the existence of a utility function representing the investor's risk preferences such that

is the utility of getting the cash flow W.

# Choice under uncertainty

Let *u* be such a utility function.

In general it is

- 1) increasing, u'(x) > 0, and
- 2) concave,  $u''(x) \leq 0$ .

#### **Examples of utility functions**

- $u(x) = \ln x$ .
- $u(x) = -e^{-x}$ .
- $u(x) = \sqrt{x}$ .
- u(x) = x.

# Choice under uncertainty

How can we measure the level of attitude towards risk of an investor?

It is possible to show that the coefficient of absolute risk aversion

$$\mathsf{ARA}(x) = -\frac{u''(x)}{u'(x)}$$

is a good measure of this.

As an alternative the coefficient of relative risk aversion

$$\mathsf{RRA}(x) = -\frac{x \, u''(x)}{u'(x)}$$

can be used.

# CARA utility functions

lf

$$u(x) = -e^{-ax}$$

then

$$u'(x) = ae^{-ax}$$
 and  $u''(x) = -a^2e^{-ax}$ ,

SO

$$ARA(x) = -\frac{-a^2e^{-ax}}{ae^{-ax}} = a.$$

These are known as CARA utility functions for constant absolute risk aversion.

# CRRA utility functions

lf

$$u(x) = \begin{cases} \frac{x^{1-\gamma} - 1}{1-\gamma} & \text{if } \gamma > 0, \gamma \neq 1 \\ & \text{ln } x & \text{if } \gamma = 1 \end{cases}$$

then

$$u'(x) = x^{-\gamma}$$
 and  $u''(x) = -\gamma x^{-\gamma - 1}$ ,

SO

$$RRA(x) = -\frac{x \cdot \left(-\gamma x^{-\gamma - 1}\right)}{x^{-\gamma}} = \gamma.$$

These are known as CRRA utility functions for constant relative risk aversion.

# CARA utility and normally distributed rates of returns

Consider a market with N risky assets such that:

- 1) The rates of return vector  $\mathbf{r}$  has a multivariate normal distribution.
- 2) The investor has a CARA utility function with parameter a > 0.

This means that

$$W = W_0\big((1+r(\boldsymbol{\pi})\big) = W_0 + W_0\boldsymbol{\pi}\cdot\boldsymbol{r}$$

is normally distributed with mean

$$E[W_0 + W_0 \boldsymbol{\pi} \cdot \boldsymbol{r}] = W_0 + W_0 E[\boldsymbol{\pi} \cdot \boldsymbol{r}] = W_0 + W_0 \boldsymbol{\pi} \cdot \boldsymbol{\mu}$$

and variance

$$Var[W_0 + W_0 \pi \cdot \mathbf{r}] = W_0^2 Var[\pi \cdot \mathbf{r}] = W_0^2 \pi \cdot \Sigma \pi.$$

# CARA utility and normally distributed rates of returns

One can show (see the book!) that in this model an investor is indifferent between portfolios that have the same value of

$$\pi \cdot \mu - \frac{a}{2}W_0\pi \cdot \Sigma \pi$$
.

Hence, indifference curves are given by

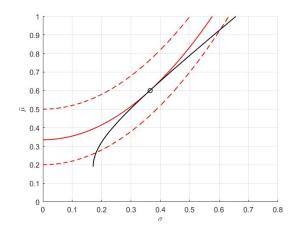
$$\boldsymbol{\pi} \cdot \boldsymbol{\mu} - \frac{\mathsf{a}}{2} W_0 \boldsymbol{\pi} \cdot \boldsymbol{\Sigma} \boldsymbol{\pi} = K$$

or

$$\pi \cdot \mu = K + \frac{a}{2}W_0\pi \cdot \Sigma\pi,$$

where we let the level of utility K vary.

# CARA utility and normally distributed rates of returns



Utility increases in the north-west direction.