

# Math Finance - II

## Week - 1

### Utility theory.

"How to make a choice under risk"

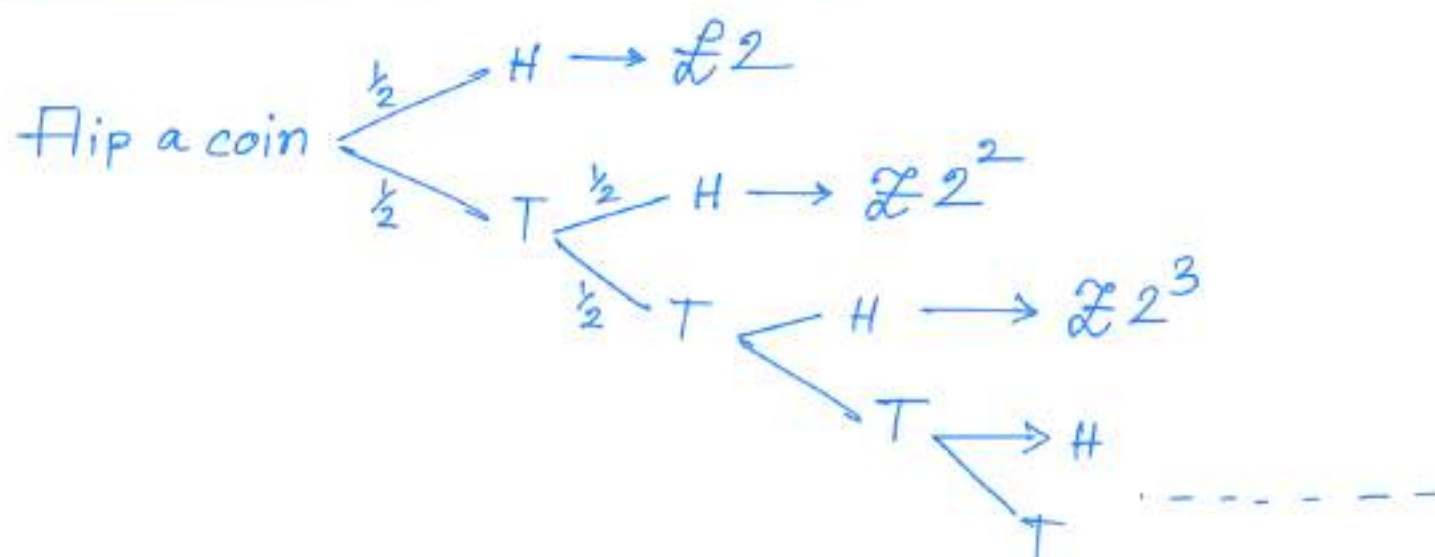


How much you will be willing to pay.

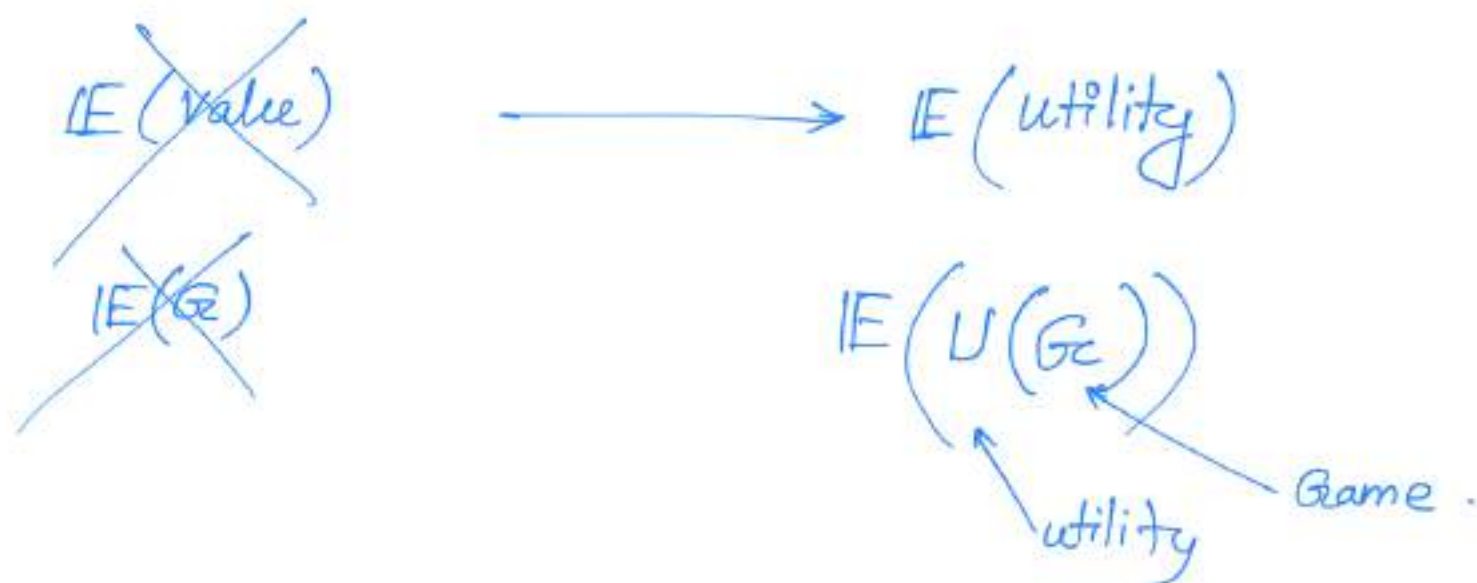
$$\begin{aligned} E(\text{Value}) &= \frac{1}{2} \times £0 + \frac{1}{2} £10 \\ &= £5 \end{aligned}$$

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New Game: (Bernoulli 1738)



$$\begin{aligned} E(\text{Game}) &= £2 \cdot \frac{1}{2} + £2^2 \cdot \frac{1}{4} + £2^3 \cdot \frac{1}{8} + \dots \\ &= 1 + 1 + \dots = \infty \end{aligned}$$



More formally

We will denote  $U$  for utility fn.

$$U : [0, \infty) \longrightarrow \mathbb{R}$$

$$w \longmapsto U(w)$$

↙ Income/wealth ↘

We want to max Exp utility :

$$\max_{\Theta_1} E(U(L)) \quad L = \text{lottery.}$$

$\Theta_1 =$  set of all feasible strategies.

Axioms of Utility func:

① More-is-better (Monotonicity)

$w_1, w_2 \longrightarrow$  wealth level

$$w_1 > w_2$$

Side note:  
Sometimes this  
break down in pract



$$\Rightarrow U(w_1) \geq U(w_2)$$



② strictly increasing.

$$w_1 > w_2 \Rightarrow U(w_1) > U(w_2)$$

③ Completeness.

Bundle  $A, B, C$ .

$$A \succ B ; B \succ A$$

$\succ$  denotes preference.

$$\Rightarrow \boxed{A \equiv B}$$

④ Mix - is - better (Convexity).

⑤ Rationality (Transitivity).

$$A \succ B , B \succ C$$

$$\Rightarrow \boxed{A \succ C}$$

⑥ Consistency

$A \succ B$ . if there is another bundle  $C$   
and  $\alpha \in (0, 1)$

$$\alpha A + (1-\alpha)C \succ \alpha B + (1-\alpha)C$$

Under the axiom 1-6:

Theorem:

If any preference satisfies Ax 1-6 then  
 $\exists$  a real valued func.<sup>U</sup> (unique upto affine  
(there exists) transformation); and defined on the all possible  
bundles such that:

Any two bundles A and B.

$$A \succ B \iff E(U(A)) \geq E(U(B)).$$

Affine transformation

$$U_1, U_2$$

$$U_1 = a + bU_2.$$

Imp

Remark: Utility func are ordinal, and  
not cardinal.

If  $U_2 = aU_1 + b$  with  $a > 0$  then.

$$U_1 \equiv U_2.$$

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Utility function on wealth.

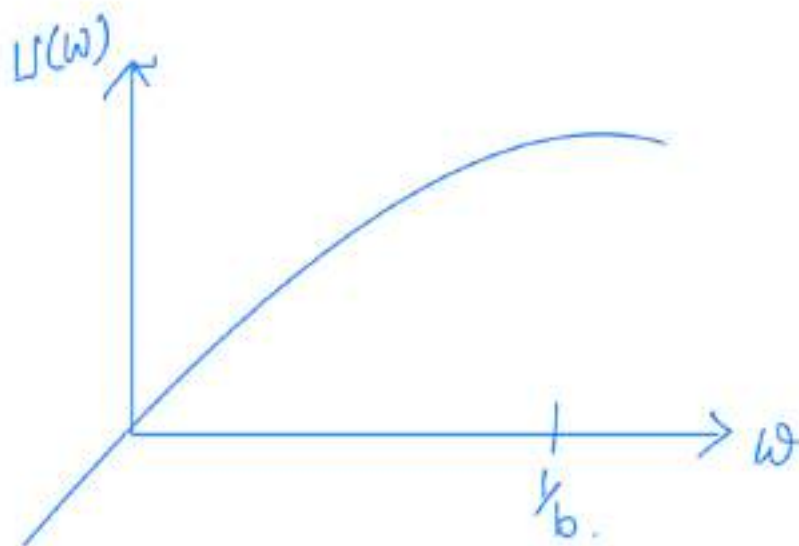
$$U : [0, \infty) \longrightarrow \mathbb{R}$$

$$w \longmapsto U(w).$$

(can be thought of income)

Ex: Quadratic utility

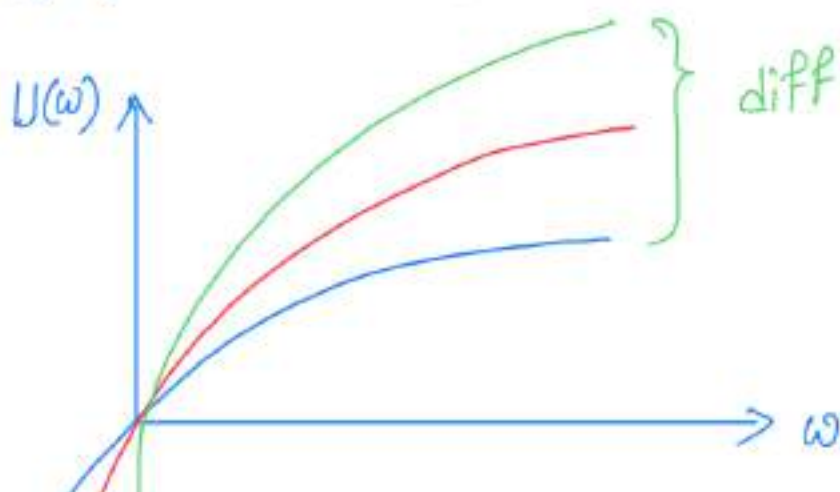
$$U(w) = w - \frac{b}{2} w^2 \quad ; \quad \frac{b > 0}{\text{constant}}.$$



Not strictly increasing on  $[0, \infty)$   
But strictly increasing on  $[0, \frac{1}{b}]$

Ex: Exponential Utility

$$U(w) = -e^{-\gamma w} \quad \text{for } \gamma > 0$$



More difficult mathematically than Quadratic.

But

$$W \sim N(\mu, \sigma)$$

↳ End of period wealth.

$$\boxed{E(U(W)) = -e^{-r\mu + \frac{1}{2}r^2\sigma^2}}$$

Sometime the exp utility is denoted as:

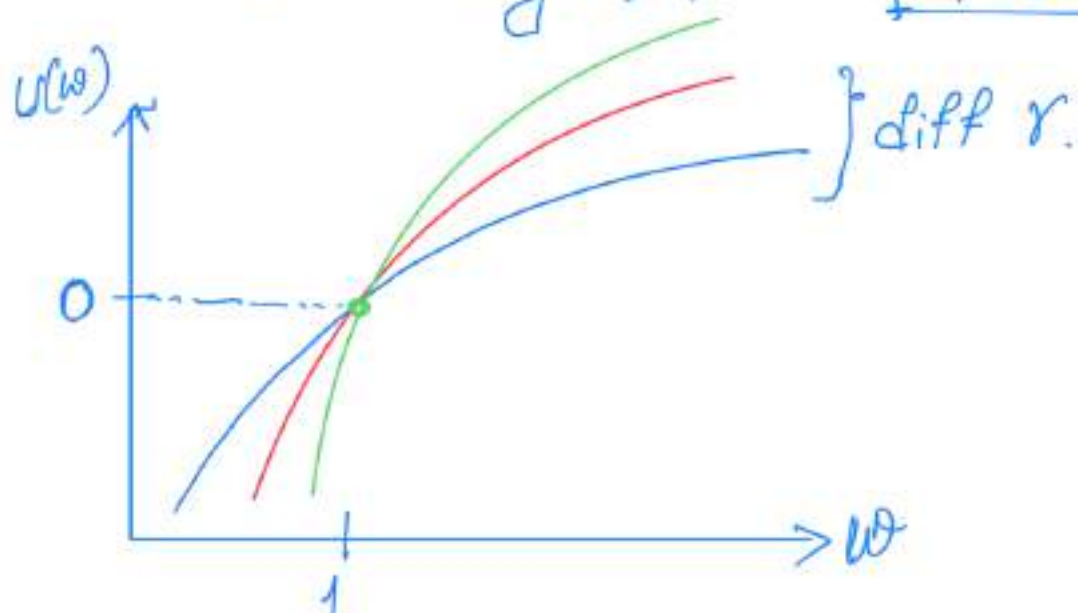
$$U(w) = \frac{1 - e^{-r w}}{r} \quad (\text{HW})$$

Ex: Power Utility.

$$U(w) = \frac{w^{1-\gamma} - 1}{1-\gamma} \quad \text{for } \gamma > 0, \gamma \neq 1.$$

for  $\gamma = 1$  by taking  $\lim_{\gamma \uparrow 1}$  we get

$$U(w) = \log(w); \quad \boxed{w > 0}$$



## Risk - Aversion :

"A strictly risk-averse investor is unwilling to accept a fair game."

### Notation :

$W_0$  = Wealth at time  $t=0$

$W_1/W$  = Wealth at time  $t=1$  /  
end of period wealth.

### Def<sup>n</sup> (fair game) :

A game is fair  $\iff E(W) = E(W_0)$   
 $= W_0$

*Annotations:*  
- A green arrow labeled "a RV" points from the left side of the equation to  $E(W)$ .  
- A green arrow labeled "Not a RV" points from the right side of the equation to  $E(W_0)$ .

### Example :

L lottery : start with  $W_0$

$$W_1 = \begin{cases} W_0 + h_0 & \text{with prob } p \\ W_0 + h_1 & \text{with prob } (1-p) \end{cases}$$

When is the lottery fair :

We need to have

$$E(W) = W_0$$

$$\Leftrightarrow (W_0 + h_0)p + (W_0 + h_1)(1-p) = W_0$$

$$\Leftrightarrow \boxed{h_0p + h_1(1-p) = 0}$$

"A strictly risk-averse investor is unwilling to accept a fair game."

$$\Leftrightarrow E(U(W)) < E(U(W_0))$$

$$\Leftrightarrow E(U(W)) < U(W_0) \quad \text{def of fair game.}$$

$$\Leftrightarrow E(U(W)) < U(E(W))$$

$$\Leftrightarrow pU(W_0 + h_0) + (1-p)U(W_0 + h_1) < U(p(W_0 + h_0) + (1-p)(W_0 + h_1))$$

————— (\*)

(\*) has to be true for all fair gam.

$$\Leftrightarrow (*) \text{ is true for any } h_0, h_1 \in \mathbb{R}; \text{ and } p \in [0, 1] \\ \text{with } ph_0 + (1-p)h_1 = 0.$$

$$\Leftrightarrow U \text{ has to be concave. (can also be seen using Jensen's ineq.)}$$

Lemma! A strict risk-averse investor always has concave utility func.

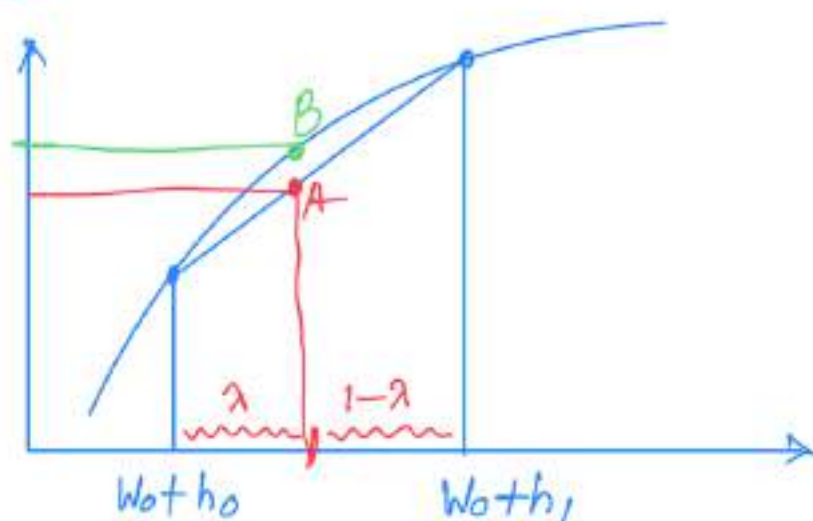
Def<sup>n</sup> (Risk-aversion)

A investor is risk-averse iff the utility fn is concave.

$$\Rightarrow \frac{d^2 U}{dW^2} \leq 0 \quad ; \quad \frac{dU}{dW} > 0$$

(concave) ; (strictly increasing U)

Risk-averse  
U



B is above A

$$B: U(\lambda(W_0 + h_0) + (1-\lambda)(W_0 + h_1))$$

$$A: \lambda U(W_0 + h_0) + (1-\lambda) U(W_0 + h_1)$$

two other type of investor.

Risk-seeking :  $\frac{d^2 U}{dW^2} \geq 0$  ;  $\frac{dU}{dW} > 0$

(convex)

(increasing)

Risk - Neutral :  $\frac{dU^2}{d\omega} = 0$  ;  $\frac{dU}{d\omega} > 0$

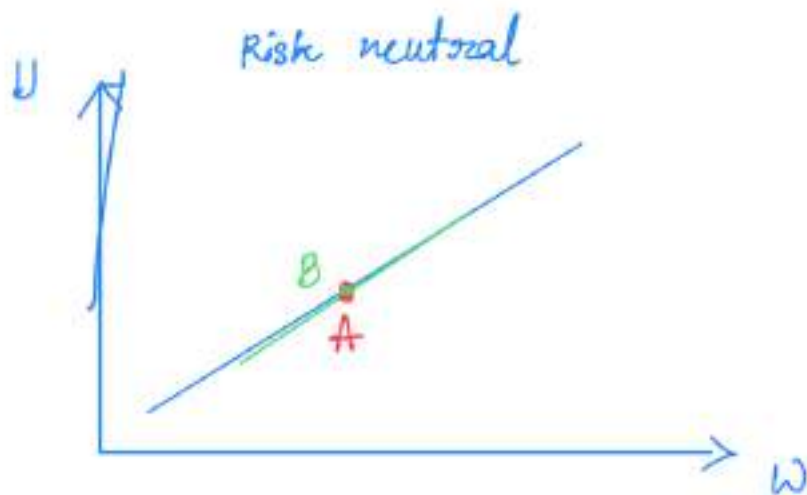
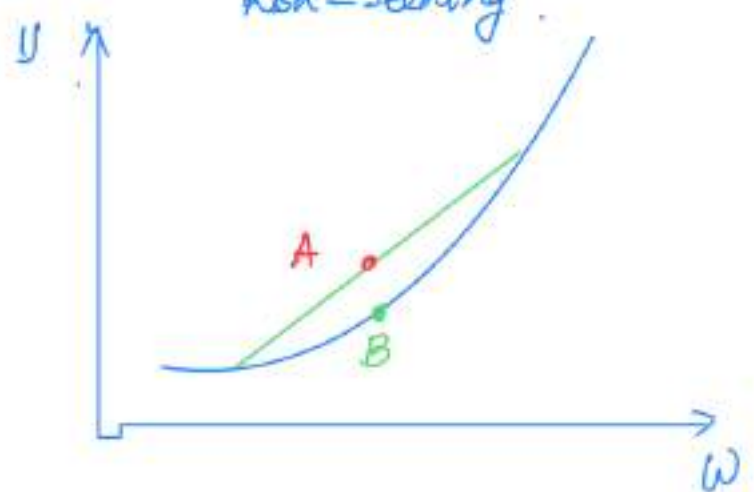
(convex)

(increasing)



linear utility fn.

Risk-seeking



# Math - Finance - II

## Week - 2

### Reminder:

Please submit the "Tutorial 1: suggestion" by tomorrow!

### Note:

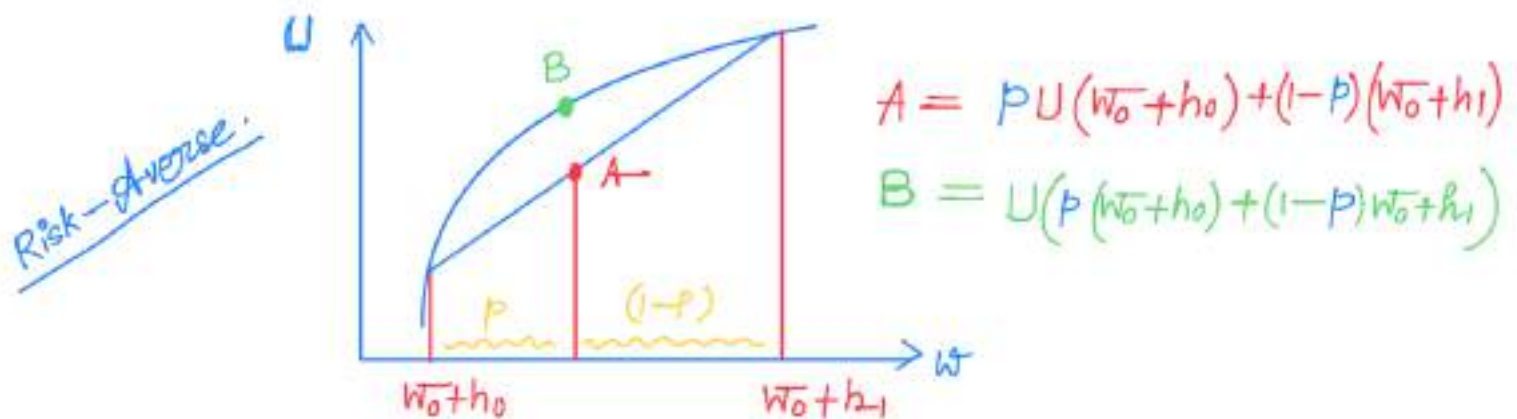
Please use the keats discussion forum / Q and A board for any qn/comments/feedback for the course (class/hw/notes/tutorial)

### correction:

We want to maximize exp utility:

$$\max_{\theta} E(L) \longrightarrow \text{should have been } E(U(L))$$

Recap: A rational investor should max exp utility!



### Lottery:

start with  $W_0$

$$\text{End of period wealth } W = \begin{cases} W_0 + h_0 & \text{w.p. } P \\ W_0 + h_1 & \text{w.p. } 1-P. \end{cases}$$

Def<sup>n</sup>: (Marginal utility):

Marginal utility at a given wealth level  $w^*$  is the slope of utility func at  $w^*$

$$\left. \frac{dU(w)}{dw} \right|_{w^*}$$

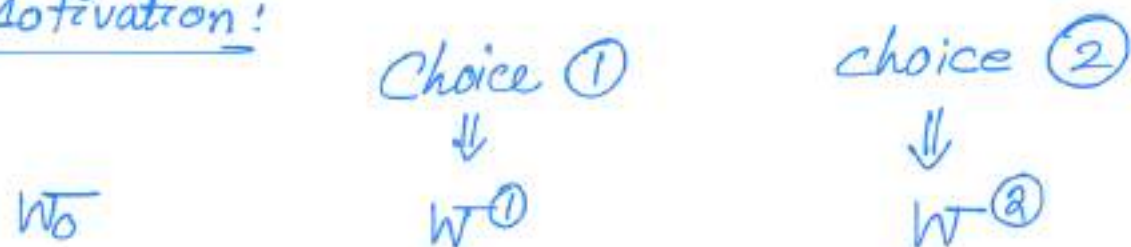
Notation! A diminishing marginal utility means utility func increases at a decreasing rate.

$$\left. \begin{array}{l} U' > 0 \\ U'' < 0 \end{array} \right\} \text{--- Risk-averse.}$$

Notation! Increasing marginal utility.

$$\left. \begin{array}{l} U' > 0 \\ U'' > 0 \end{array} \right\} \text{--- Risk-seeking.}$$

Motivation!



The investor has utility func  $U$ .

$$E U(w^{①}) \stackrel{\text{①}}{\geq} E U(w^{②}) \quad \text{②}$$

say:  $E U(W^{(1)}) > E U(W^{(2)})$

$\Rightarrow$  We prefer choice ① over choice ②.

"We can not say how much we prefer ① over ②."

Goal! We want a monetary unit; to say how much we prefer ① over ②.

Certainly Equivalent  $\therefore$

For any distribution of end-of-period wealth  $W$ ,  
and for any valid utility function  $U$ ,  $\exists!$  constant  
(there exists unique)

$W_c$  st

$$U(W_c) = E(U(W))$$

Note!  $W_c$  has same unit (say £) with  $W_0$  and  $W$ .

Now we can prefer choice ① over ② by

$$\pounds W_c^{(1)} - \pounds W_c^{(2)}$$

Lemma! For a risk averse investor  $W_c \leq E(W)$ .

Proof! Since this is a risk averse person:

$$\Rightarrow E(U(W)) \leq U(E(W)).$$

Hint: think of  $U$  to be concave and apply Jensen's Inequality.

$$\Rightarrow U(W_C) \leq U(E(W))$$

$$\stackrel{?}{\Rightarrow} W_C \leq E(W) \quad (\text{this is true since } U \text{ is strictly increasing}). \quad \square$$

The opposite direction is in HW2.

Ex!

$$W_0 = \frac{1}{2} 10.$$
$$W = \begin{cases} \pounds 15 & \text{wp } \frac{1}{2} \\ \pounds 5 & \text{wp } \frac{1}{2} \end{cases}$$

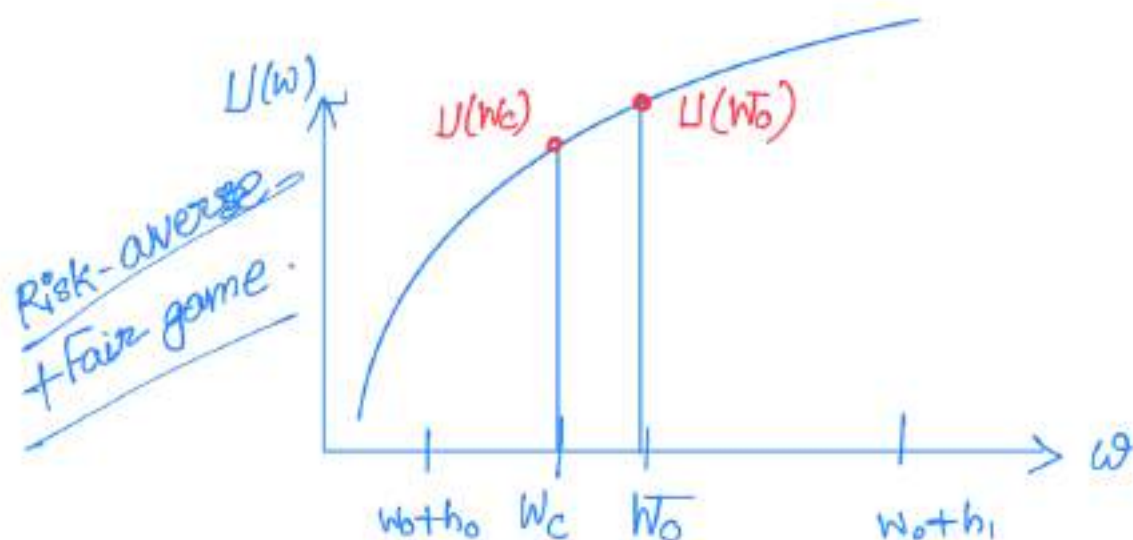
The investor is risk averse.  
Can you show  $W_C \leq W_0$

Sol!

$$W_C \leq E(W) \text{ (lemma)}$$
$$= 15 \times \frac{1}{2} + 5 \times \frac{1}{2}$$
$$= 10$$
$$= W_0$$

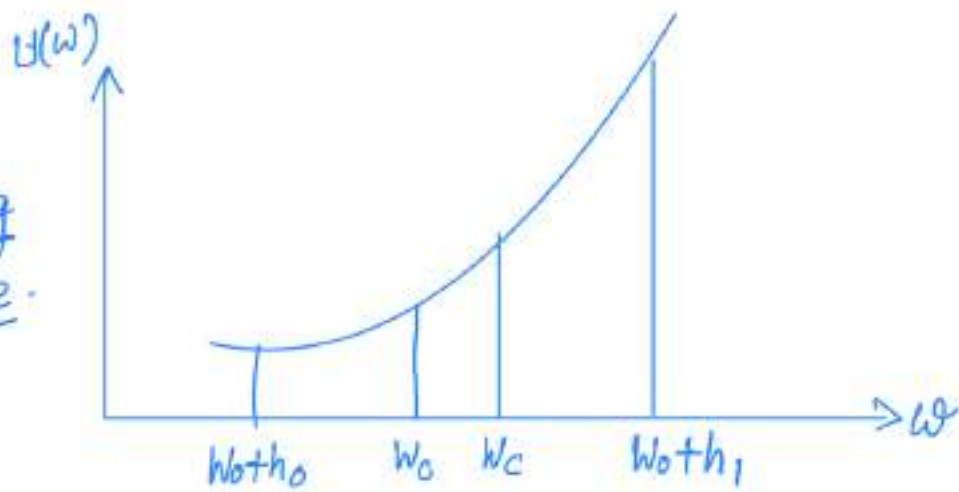
Lemma! For a fair game ( $E(W) = W_0$ ); and risk-averse person one has:

$$W_C \leq W_0$$



Simply:

Risk-seeking  
+ Fair game.



Def<sup>n</sup>: (Risk-premium)

= the difference between exp. monetary value of the lottery and the certainty equivalent.

Mathematically:  $R_p := E(W) - W_c$   
Risk-premium

Remark! The risk-premium is the max amount a investor is willing to pay to avoid taking risk.

Remark!

Risk-averse :  $R_p \geq 0$

Risk-seeking :  $R_p \leq 0$

Risk-neutral :  $R_p = 0$ .

Coefficient of Risk-aversion.

Def<sup>n</sup> The absolute risk-aversion <sup>(ARA)</sup> coefficient is defined

as:

$$\gamma^a(w) = - \frac{U''(w)}{U'(w)}$$

Ex:  $U(w) = -e^{-\bar{\gamma}w}$

$$\Rightarrow \gamma^a(w) = \bar{\gamma}$$

exponential utility is  
const. abs. risk aversion  
func.

Def<sup>n</sup>: The relative risk-aversion coefficient is given as:

$$\gamma^r(w) = -w \frac{U''(w)}{U'(w)} = w \gamma^a(w)$$

Ex: The power utility  $\Rightarrow \gamma^r(w) \equiv \text{const.}$

**Example 6.** Consider an investor with the option of buying shares of an asset. The investor's initial wealth is  $W_0$  and each share costs  $P_0$ . If the investor buys  $\theta$  shares, the end-of-period wealth is  $W = W_0 - \theta P_0 + \theta P_1$ . Assume further  $P_1 \sim \mathcal{N}(P_0 + \mu, \sigma)$  and that the investor uses exponential utility. What is the optimal number of shares to purchase?

$W_0$  = initial wealth.

$P_0$  = stock price now.

$P_1$  = stock price at end of wealth period

$$P_1 \sim \mathcal{N}(P_0 + \mu, \sigma)$$

$$W = W_0 - \theta P_0 + \theta P_1$$

$\theta$  = amount of share we buy.

Goal: find the optimal  $\theta$ .

$$E(U(W)) = E(U(W_0 - \theta P_0 + \theta P_1))$$

$$U(W) = -e^{-\gamma W}$$

$$= E(U(W_0 - \theta P_0 + \theta (P_0 + \mu + \sigma Z)))$$

where  $Z \sim N(0,1)$ .

$$= E(-e^{-\gamma(W_0 - P_0\theta + \theta P_0 + \theta\mu + \theta\sigma Z)})$$

$$= -e^{-\gamma W_0 - \gamma\theta\mu} E(e^{-\gamma\theta\sigma Z})$$

$$\stackrel{\text{(MGF)}}{=} -e^{-\gamma W_0 - \gamma\theta\mu} \times e^{-\frac{\gamma^2\theta^2\sigma^2}{2}} \quad \text{--- ①}$$

We want to find  $\theta^*$  st. ① is maximized.

$$\theta^* = \operatorname{argmax}_{\theta} \left[ -e^{-\gamma W_0 - \gamma\theta\mu} \times e^{-\frac{\gamma^2\theta^2\sigma^2}{2}} \right]$$

$$= \operatorname{argmin}_{\theta} \left[ e^{-\gamma W_0 - \gamma\theta\mu} \times e^{-\frac{\gamma^2\theta^2\sigma^2}{2}} \right]$$

$$= \operatorname{argmin}_{\theta} \left[ e^{-\gamma W_0 - \gamma\theta\mu + \frac{\gamma^2\theta^2\sigma^2}{2}} \right]$$

$$= \operatorname{argmin}_{\theta} \left[ -\gamma W_0 - \gamma\theta\mu + \frac{\gamma^2\theta^2\sigma^2}{2} \right]$$

$$= \operatorname{argmin}_{\theta} \left[ \underbrace{-r\theta\mu + \frac{r^2\theta^2\sigma^2}{2}} \right]$$

quadratic on  $\theta$ .

$$\theta^* \stackrel{HW}{=} \frac{\mu}{r\sigma^2}$$

if  $\mu > 0 \Rightarrow$  investor buys the asset.

Recall:

$$P_1 \sim N(P_0 + \mu, \sigma)$$

$\mu = 0 \Rightarrow \theta^* = 0$  (on an average  $E(P_1) = P_0$   
 $\Rightarrow$  fair game.

exp utility  $\Rightarrow$  risk averse.

$\Rightarrow$  We don't accept fair game.

$\Rightarrow \theta^* = 0$ )

Week - 3  
Math - Finance - II

Reminder:

Please submit "tutorial 2: suggestion" by tomorrow.

Jan 23

Utility fn on multiple goods:

Previously:  $U: \mathbb{R}_+ \rightarrow \mathbb{R}$

Now:  $U: \mathbb{R}_+^n \rightarrow \mathbb{R}$

Notation:

→  $p_1, \dots, p_n$  — price for good  $i$

→  $x_1, \dots, x_n$  — quantity of good  $i$

→  $I/m$  — the total income/budget

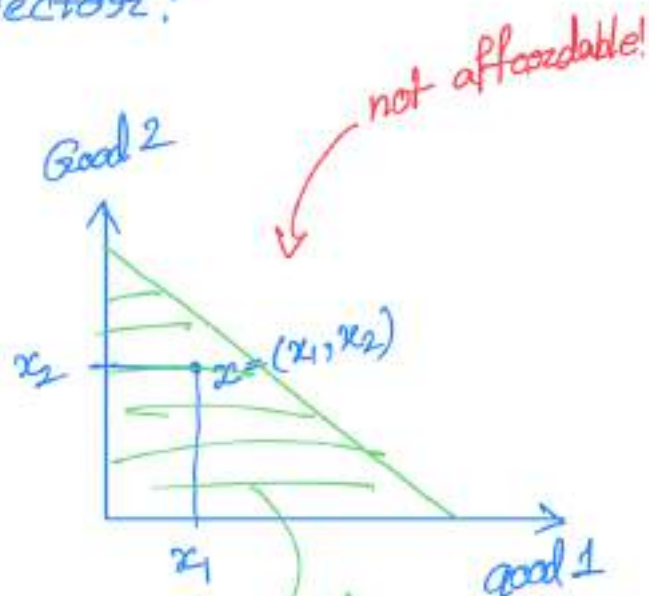
Def<sup>n</sup>

A consumer bundle is a vector:

$$x = (x_1, \dots, x_n) \in \mathbb{R}^n.$$

Affordable:

$$x_1 p_1 + x_2 p_2 \leq m \quad \text{or not.}$$



Affordable. 0

Jan 30

Note:  $x_i \in \mathbb{R}_+$  not just integer.

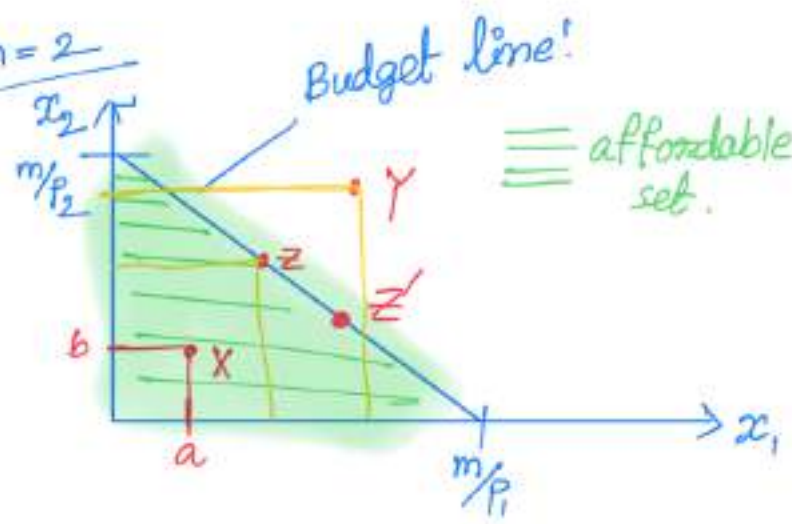
Budget Constraint:  $p_1 x_1 + p_2 x_2 + \dots + p_n x_n \leq m$ .

Affordable consumption:

Bundle:  $(x_1, \dots, x_n) \in \mathbb{R}_+^n$  st.  $\underbrace{\sum_{i=1}^n p_i x_i}_{\text{total cost of bundle}} \leq m$ . income

Budget line:  $p_1 x_1 + \dots + p_n x_n = m$ .  $(x_1, \dots, x_n)$

take  $n=2$



$\equiv$  affordable set.

Budget line:

$$p_1 x_1 + p_2 x_2 = m$$

$$x_2 = \frac{m}{p_2} - \frac{p_1}{p_2} x_1$$

slope =  $-\frac{p_1}{p_2}$

"More is better"  $\implies Y \succ Z \succ X$

$\implies Y \succ X$

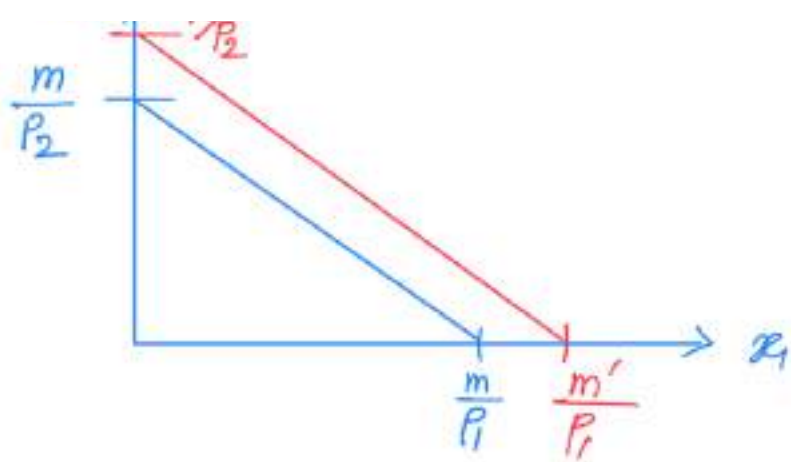
We can't afford  $Y$  }  $\implies$  We chose  $Z$ .  
 $Z \succ X$

if  $EU(Z) > EU(\bar{Z})$  we chose  $Z$ .

Case-1

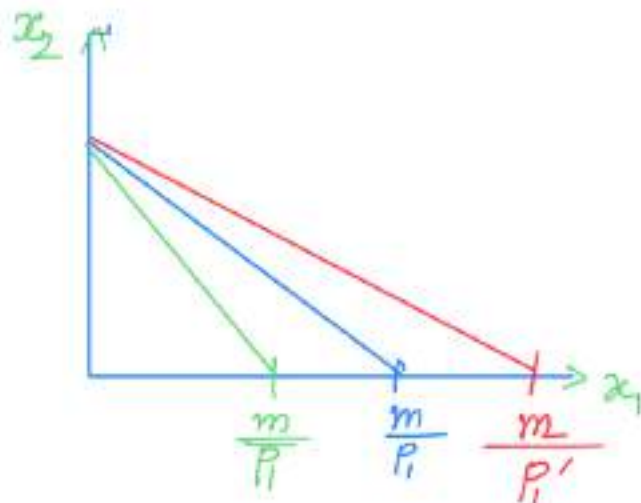
what happens when the budget/income  $\uparrow$

$x_2 \propto m$



New income  $m' > m$ .

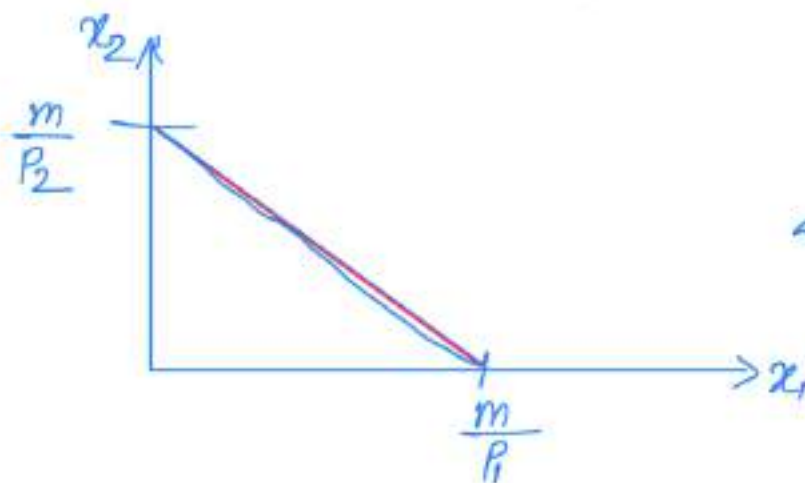
$P_1 \uparrow$  or  $P_1 \downarrow$



$$\bar{P}_1 > P_1$$

$$P_1' < P_1$$

What happens when there is a perfect inflation:



$$\sum P_i x_i = m$$

$$\Leftrightarrow \sum (\alpha P_i) x_i = \alpha m$$

Budget line do not need to be straightline.

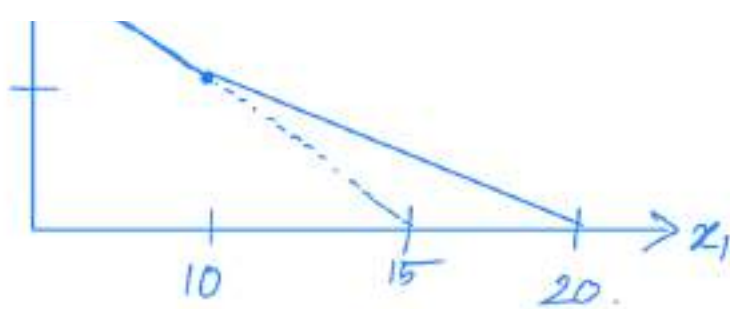
Ex! Quantity discount:

income  $m = 30$

$P_2 = 2$

$$P_1 = \begin{cases} 2 & \text{for } x_1 < 10 \\ 1 & \text{for } x_1 \geq 10 \end{cases} \left. \begin{array}{l} \text{if } x_1 > 10 \\ \text{we still pay} \\ \text{at 2 for the} \\ \text{first 10 unit} \end{array} \right\}$$





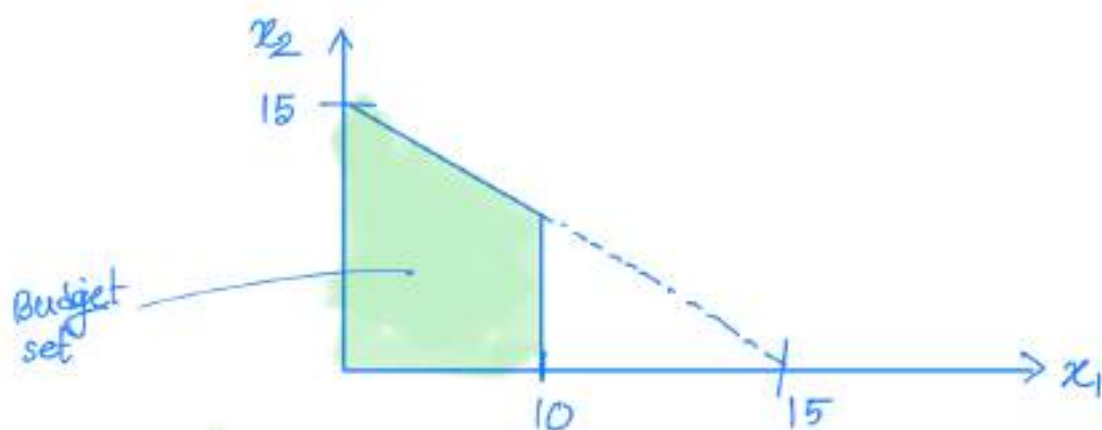
Ex:

Rationing

$$m = 30$$

$P_1 = 2 \rightarrow$  One is not allowed to buy good 1 more than 10 unit.

$$P_2 = 2$$

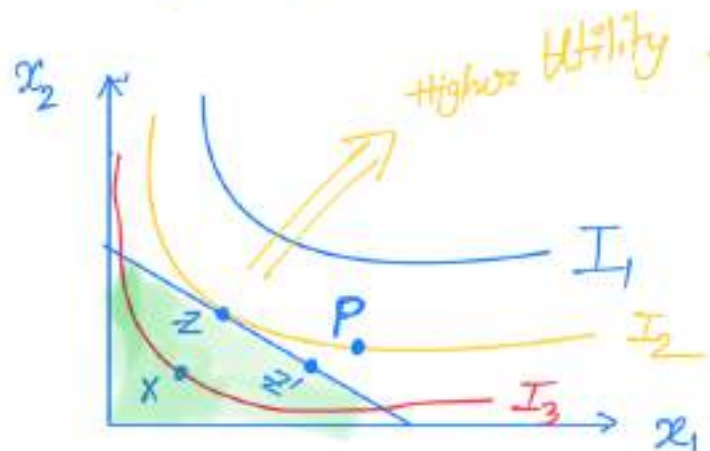


Defn (Indifference Curves)

This is the set of all bundles which consumer is indifferent to.

Let's denote the IC by  $I_1$

$$\left. \begin{array}{l} (x_1, \dots, x_n) \in I_1 \\ (\bar{x}_1, \dots, \bar{x}_n) \in I_1 \end{array} \right\} \Rightarrow U((x_1, \dots, x_n)) = U(\bar{x}_1, \dots, \bar{x}_n)$$

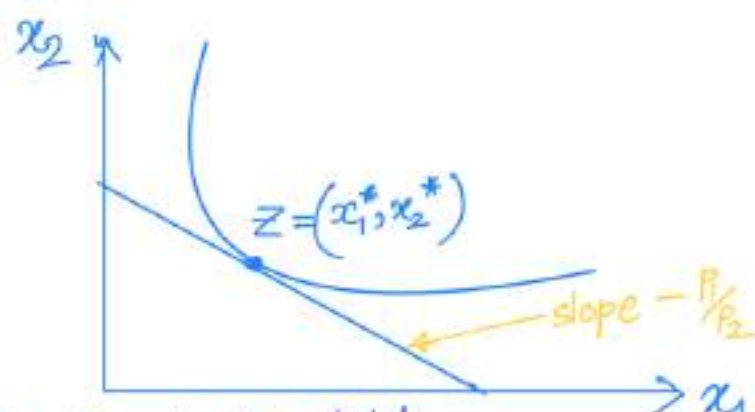


$I_1$  gives us bundles with more utility than  $I_2$ .

$I_1$  is not affordable.

Goal: To find the optimal bundle given  $(P_1, \dots, P_n, m)$ .

The optimal bundle should be tangent point of IC and budget set.



$z$  gives the optimal bundle.

$z$  represents the best utility you can get given  $m$ .

Note: • the optimal bundle can not be interior of Budget set.

• Tangency condition:

$$MRS(x_1^*, x_2^*) = \text{abs slope of budget line.}$$

(Marginal rate of substitution)

The MRS is defined as

$$MRS \Big|_{(x_1, x_2)} = \frac{\frac{dU}{dx_1}}{\frac{dU}{dx_2}} = \frac{\text{Marginal utility of } x_1}{\text{Marginal utility of } x_2}$$

$$\Rightarrow \left. \begin{array}{l} \frac{\frac{dU}{dx_1}}{\frac{dU}{dx_2}} \\ \text{MRS} \end{array} \right\} \text{at optimal} = \frac{P_1}{P_2}$$

$= (x_1^*, x_2^*)$

for the ...

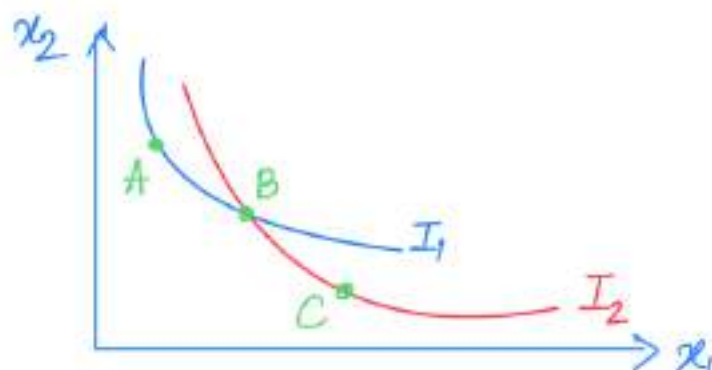
For the 2 goods.

$$\frac{1}{P_1} \frac{dU}{dx_1} = \frac{1}{P_2} \frac{dU}{dx_2} = \dots = \frac{1}{P_n} \frac{dU}{dx_n} = \lambda$$

"Marginal utility per pound spend is same for all goods."

Lemma: The two IC can never intersect

Idea of proof:



$$U(A) = U(B)$$

$$U(B) = U(C)$$

transitivity:

$$A \sim C$$

Ex:  $U(x_1, x_2) = \sqrt{x_1 x_2}$

$$U(x_1, x_2, x_3) = \sqrt{x_1} + \sqrt{x_2} + \sqrt{x_3}$$

$$U(x_1, x_2) = \ln x_1 + \frac{4}{5} x_2^2$$

Cobb-douglas utility fn:

$$U(x_1, x_2) = A x_1^\alpha x_2^{(1-\alpha)}$$

$$\alpha \in (0, 1)$$

$$A > 0$$

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Mathematical formulation (Primal problem)

$$(P) \quad \max_{x_1, \dots, x_n} U(x_1, \dots, x_n)$$

$$\text{st } P_1 x_1 + P_2 x_2 + \dots + P_n x_n \leq m$$

Lagrange Formulation:

$$\mathcal{L}(x_1, \dots, x_n, \lambda) = U(x_1, \dots, x_n) + \lambda(m - P_1 x_1 - P_2 x_2 - \dots - P_n x_n)$$

Solving P  $\iff \max_{x_1, \dots, x_n, \lambda} \mathcal{L}$

Now we take derivative of  $\mathcal{L}$  and equate to 0.

FOC:

①  $\frac{\partial \mathcal{L}}{\partial x_i} = 0 \iff \frac{\partial U}{\partial x_i} - \lambda P_i = 0 \quad \forall i=1, \dots, n.$

②  $\frac{\partial \mathcal{L}}{\partial \lambda} = 0 \iff P_1 x_1 + \dots + P_n x_n = m.$

$\frac{\partial U}{\partial x_i} \times \frac{1}{P_i} = \lambda$

We have  $n+1$  unknown }  $\implies (x_1^*, x_2^*, \dots, x_n^*, \lambda^*)$   
 $n+1$  equations }

What does this  $\lambda^*$  means:

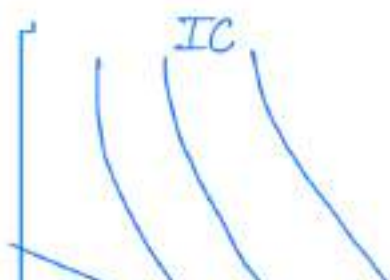
$$\lambda^* = \frac{dU}{dx_i} \times \frac{1}{P_i}$$

$\lambda^*$  is known as shadow price.

$$\lambda^* = \frac{dU}{dm}$$

"Additional utility one can get by relaxing budget by 1 unit."

What about:



$\longleftarrow$  corner solution.



"We will always assume the optimal solution  $(x_1^* \dots x_n^*)$  is an interior solution"

### Indirect utility fn:

This gives a function which tells us what is the max utility one can get given  $(p_1 \dots p_n, m)$

$$\begin{aligned}
 V(p_1, \dots, p_n, m) &= U(x_1^*, \dots, x_n^*, m) \\
 &= U\left(x_1^*(p_1, \dots, p_n, m), x_2^*(p_1, \dots, p_n, m), \dots, x_n^*(p_1, \dots, p_n, m)\right)
 \end{aligned}$$

### Marshallian demand for

this denotes the optimal quantity you consume for  $i$ th good.

$$M_i(p_1, \dots, p_n, m) = x_i^* = x_i^*(p_1, \dots, p_n, m)$$

### Properties of indirect utility:

1. Homogeneous of degree 0 in  $(p_1, \dots, p_n, m)$ , i.e.,  $V(tp_1, \dots, tp_n, tm) = V(p_1, \dots, p_n, m)$ .
2. Increasing in  $m$ , decreasing in each  $p_i$ .
3. Quasi-concave in  $(p_1, \dots, p_n, m)$ .

## Dual formulation of utility prob.

⇒ Also known as Expenditure Minimizing problem.

$$(D) \quad \min_{(x_1, \dots, x_n)} P_1 x_1 + P_2 x_2 + \dots + P_n x_n.$$

Subject to  $U(x_1, \dots, x_n) \geq \bar{u}$

To solve this we again use Lagrangian Formulation!

$$\mathcal{L}(x_1, \dots, x_n, \lambda) = P_1 x_1 + \dots + P_n x_n + \lambda (\bar{u} - U(x_1, \dots, x_n))$$

$$\text{Solving (D)} \iff \text{Solving } \min_{(x_1, \dots, x_n, \lambda)} \mathcal{L}(x_1, \dots, x_n, \lambda)$$

We do the same step as (P).

The first order condition (FOC)

$$(1) \quad \frac{\partial \mathcal{L}}{\partial x_i} = 0 \iff P_i - \lambda \frac{dU}{dx_i} = 0 \quad \forall i=1, \dots, n.$$

$$(2) \quad \frac{\partial \mathcal{L}}{\partial \lambda} = 0 \iff \bar{u} = U(x_1, \dots, x_n).$$

Week - 4  
Math Finance - II

Reminder: Please submit "Tutorial 3 suggestion" by tomorrow.

$$\mathcal{L}(x_1, \dots, x_n, \lambda) = p_1 x_1 + p_2 x_2 + \dots + p_n x_n + \lambda (\bar{u} - U(x_1, \dots, x_n))$$

FOC:

$$\textcircled{1} \quad \frac{\partial \mathcal{L}}{\partial x_i} = 0 \quad \Rightarrow \quad p_i - \lambda \frac{\partial U}{\partial x_i} = 0$$

$\forall i = 1, \dots, n$

$$\Rightarrow \frac{1}{p_i} \frac{\partial U}{\partial x_i} = \lambda$$

$$\textcircled{2} \quad \frac{\partial \mathcal{L}}{\partial \lambda} = 0 \quad \Rightarrow \quad \bar{u} = U(x_1, \dots, x_n)$$

$$\textcircled{1} \Rightarrow \frac{1}{p_i} \frac{\partial U}{\partial x_i} = \frac{1}{p_j} \frac{\partial U}{\partial x_j}$$

$$\Leftrightarrow \frac{\frac{\partial U}{\partial x_i}}{\frac{\partial U}{\partial x_j}} = \frac{p_i}{p_j} \quad \forall i, j \in \{1, \dots, n\}$$

*Marginal utility for i*

Defn: Expenditure func:

min level of income/cost required to achieve given level of utility  $\bar{u}$ .

$$e(p_1, \dots, p_n, \bar{u}) := \sum_{i=1}^n p_i \underbrace{x_i^h(p_1, \dots, p_n, \bar{u})}$$

$x^h$  is the solution of (2).

Def<sup>n</sup> Hicksian Demand Func

$H_i(p_1, \dots, p_n, \bar{u})$  = the optimal level of good  $i$  we consume when prices  $(p_1, \dots, p_n)$  and we achieve at least utility level  $\bar{u}$ .

$$:= x_i^h(p_1, \dots, p_n, \bar{u})$$

Ex! Cobb-Douglas utility -

$$U(x_1, x_2) = \sqrt{x_1 x_2}$$

Dual problem:

$$\min p_1 x_1 + p_2 x_2$$

$$\text{st } U(x_1, x_2) \geq \bar{u} \iff \sqrt{x_1 x_2} \geq \bar{u} \\ \iff x_1 x_2 \geq \bar{u}^2$$

$$\mathcal{L}(x_1, x_2, \lambda) = p_1 x_1 + p_2 x_2 + \lambda \left( \underbrace{\bar{u}^2 - x_1 x_2}_{\bar{u} - \sqrt{x_1 x_2}} \right)$$

FOC:

$$\frac{\partial \mathcal{L}}{\partial x_1} = 0 \iff p_1 - \lambda x_2 = 0 \iff x_2 = \frac{p_1}{\lambda}$$

$$\frac{\partial \mathcal{L}}{\partial x_2} = 0 \iff p_2 - \lambda x_1 = 0 \iff x_1 = \frac{p_2}{\lambda}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 0 \iff \bar{u}^2 = x_1 x_2$$

$$\textcircled{1} + \textcircled{2} \implies \boxed{\frac{p_1}{x_1} = \frac{p_2}{x_2}} (= \lambda) \quad \textcircled{*}$$

$x_2 = x_1 p_2 / p_1$

Replacing  $\textcircled{*}$  in  $\textcircled{3}$  we get:

$$\rightarrow x_1 \left( \frac{p_2 x_1}{p_1} \right) = \bar{u}^2$$

$$\Rightarrow \boxed{x_1^{**} = \sqrt{\bar{u}^2 \frac{p_2}{p_1}}}$$

This gives us the optimal level of good 1 we want to consume.

$$\boxed{\begin{aligned} x_2^{**} &= x_1^{**} \times \frac{p_2}{p_1} \\ &= \bar{u} \sqrt{\frac{p_1}{p_2}} \end{aligned}}$$

Hicksian Demand

$$h_1(p_1, p_2, \bar{u}) = \bar{u} \sqrt{\frac{p_2}{p_1}}$$

$$h_2(p_1, p_2, \bar{u}) = \bar{u} \sqrt{\frac{p_1}{p_2}}$$

$$e(p_1, p_2, \bar{u}) = \sum p_i x_i^h$$

$$= P_1 \left( \bar{u} \sqrt{\frac{P_2}{P_1}} \right) + P_2 \left( \bar{u} \sqrt{\frac{P_1}{P_2}} \right)$$

$$= 2\bar{u} \sqrt{P_1 P_2}$$

Primal-Dual relationship (interior sol)

- Links indirect utility with expenditure func.

Imp

$$\bar{u} = V(P_1, P_2, \dots, P_n, m)$$

$$m = e(P_1, \dots, P_n, \bar{u})$$

- Links Marshallian and Hicksian demands

Imp

$$M_i(P_1, \dots, P_n, m) = H_i(P_1, \dots, P_n, V(P_1, \dots, P_n, m))$$

$$H_i(P_1, \dots, P_n, \bar{u}) = M_i(P_1, \dots, P_n, e(P_1, \dots, P_n, \bar{u}))$$

Sec 3.5 in notes

2025 May exam Qn.

7

1. (a) Bill is risk-neutral. What is the absolute risk aversion for Bill? How does he rank the following lotteries?

$$L1 = \begin{pmatrix} \text{£}24 & \text{£}12 & \text{£}48 & \text{£}6 \\ \frac{1}{6} & \frac{2}{6} & \frac{1}{6} & \frac{2}{6} \end{pmatrix}, \quad L2 = \begin{pmatrix} \text{£}180 & \text{£}0 & \text{£}90 \\ \frac{1}{20} & \frac{17}{20} & \frac{2}{20} \end{pmatrix}$$

(Note: The first line denotes the possible outcome of the lottery and the second line denotes the corresponding probability)

What are the risk premiums associated with lottery L1 and L2 respectively for Bill? [10+10+10%]

- (b) Suppose an agent consumes three goods,  $\{x_1, x_2, x_3\}$  and the corresponding prices are  $\{p_1, p_2, p_3\}$  respectively. Her utility is  $U(x_1, x_2, x_3) = \sqrt{x_1} + \sqrt{x_2} + \sqrt{x_3}$ . The agent has income  $M$ .
- (b-1) Calculate the indirect utility function. [40%]

(b-2) Write in detail the primal and the dual consumer problem associated with the above utility. [30%]

1. (a) Consider a lottery which has probability density  $f(w) = \frac{2}{3}w$  for  $1 \leq w \leq 2$ . If the client has log utility (i.e.  $U(w) = \log(w)$ ), calculate the expected utility (i.e.  $\mathbb{E}(U(\text{Lottery}))$ ) and the certainty equivalence of this lottery. [40%]
- (b) An agent chooses a consumption bundle  $x = (x_1, x_2)$  to maximise her utility. Her utility function is

$$U(x_1, x_2) = \left(x_1 - \frac{1}{2}x_1^2\right) + \left(x_2 - \frac{1}{2}x_2^2\right)$$

where we assume  $0 \leq x_1 \leq 1$  and  $0 \leq x_2 \leq 1$ . The agent has income  $M = 1$ . Suppose the prices are  $p_1 = 3$  and  $p_2 = 2$ .

- (b-1) Solve for the agent's optimal consumption. [40%]
- (b-2) Furthermore, solve the agent's optimal consumption if her income doubles. [20%]

↑  
2025 Aug exam Qn.

# Week - 4

## Mathematical Finance II

### Portfolio Optimization.

Markowitz in 1952.

"One should consider risk and return together."

Goal: Given an initial capital  $V(0)$  and  $N$  many securities: how we allocate the capital  $V(0)$  so that the return of the portfolio is "optimal".

Assumptions:

① only consider single period model.

⇒ two time period

$t=0$  (initial time)       $t=1$  (terminal time)

② Each investment is measured by two quantity only

→ Mean  
→ Var/sd. (this means we ignore more informative shape of the distribution)

Remark: for Normal dis; this gives full knowledge of the dist.

③ The risk of a portfolio is measured by sd.

risk  $\neq$  var as we want the unit of risk to be same as unit of security.

Additional assumption:

- investor is rational
- No arbitrage.
- everyone has same information.
- market is liquid.
- no transaction cost
- no tax.
- same borrow/lend limit for all.

Def<sup>n</sup>: (short selling)

selling something which you do not own at time  $t=0$

"Short selling is Risky"

short selling 1 unit of Stock A.  $S(0)$  (= known)

We agree to sell at time  $t=1$ .

$S(1)$  is unknown:

The total loss/gain =  $S(1) - S(0)$

---

Stock A		Stock B	
Position	Price	Position	Price



## Risk and returns of a portfolio

Def<sup>n</sup>: (Exp return) this is nothing but

$$\mu_i = E(K_i) = E\left(\frac{S_i(1) - S_i(0)}{S_i(0)}\right) = \frac{E(S_i(1)) - S_i(0)}{S_i(0)}$$

↳ exp return of security  $i$ .

Def<sup>n</sup>: (Risk) the risk of security  $i$  is given by

$$\begin{aligned}\sigma_i &= \text{sd}(K_i) = \sqrt{\text{Var}(K_i)} \\ &= \sqrt{E(K_i^2) - (E(K_i))^2}\end{aligned}$$

▣ How to connect this to portfolio risk and exp return?

Lemma: The portfolio risk + exp return:

$$\mu_V = w_1 \mu_1 + \dots + w_n \mu_n$$

Assume  
 $n=2$

$$\sigma_V = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1 w_2 \underbrace{\text{Cov}(K_1, K_2)}$$

$$\rho_{K_1, K_2} \sigma_1 \sigma_2$$

↳ the correlation coefficient between  $K_1$  and  $K_2$

(sometimes written as  $\rho_{12}$ )

$$\sigma_V = \text{sd}(K_V)$$

$$\Leftrightarrow \sigma_V^2 = \text{Varz}(K_V)$$

$$= \text{Varz}(\omega_1 K_1 + \omega_2 K_2)$$

$$= E\left((\omega_1 K_1 + \omega_2 K_2)^2\right) - \left\{E(\omega_1 K_1 + \omega_2 K_2)\right\}^2$$

$$= E\left(\underbrace{\omega_1^2 K_1^2}_{\text{wavy}} + \underbrace{\omega_2^2 K_2^2}_{\text{wavy}} + \underbrace{2\omega_1 \omega_2 K_1 K_2}_{\text{wavy}}\right) - \left\{\underbrace{\omega_1 E(K_1)}_{\mu_1} + \underbrace{\omega_2 E(K_2)}_{\mu_2}\right\}^2$$

$$= \omega_1^2 \left\{E(K_1^2) - \mu_1^2\right\} + \omega_2^2 \left\{E(K_2^2) - \mu_2^2\right\} + 2\omega_1 \omega_2 (E(K_1 K_2) - \mu_1 \mu_2)$$

$$= \omega_1^2 \sigma_1^2 + \omega_2^2 \sigma_2^2 + 2\omega_1 \omega_2 \text{Cov}(K_1, K_2)$$

$$\Rightarrow \omega_1, \omega_2 \geq 0$$

Lemma: If shortselling not allowed then:

$$\sigma_V \leq \max\{\sigma_1, \sigma_2\}.$$

Proof:

$$\sigma_V^2 = \omega_1^2 \sigma_1^2 + \omega_2^2 \sigma_2^2 + 2 \underbrace{\omega_1 \omega_2}_{\text{+ve}} \underbrace{\rho_{12}}_{|\rho_{12}| \leq 1} \underbrace{\sigma_1 \sigma_2}_{\text{+ve}}$$

$$\leq \omega_1^2 \sigma_1^2 + \omega_2^2 \sigma_2^2 + 2\omega_1 \omega_2 \sigma_1 \sigma_2$$

$$= (\omega_1 \sigma_1 + \omega_2 \sigma_2)^2$$

$$\begin{aligned} &\leq \left( \omega_1 \max\{\sigma_1, \sigma_2\} + \omega_2 \max\{\sigma_1, \sigma_2\} \right)^2 \\ &= \left( \max\{\sigma_1, \sigma_2\} \right)^2 \underbrace{(\omega_1 + \omega_2)}_{=1}^2 \\ &= \left( \max\{\sigma_1, \sigma_2\} \right)^2 \end{aligned}$$

$$\iff \sigma_v \leq \max\{\sigma_1, \sigma_2\}.$$

# Week - 5

## Math - Finance - II

Reminder: Please submit "Tutorial-4 suggestion" by tomorrow.

Note: Next week the class is on Wed (Not Friday)

Revisit of last class:

Lemma:

$\Rightarrow w_1, w_2 \geq 0$   
If shortselling not allowed then:

$$\sigma_V \leq \max\{\sigma_1, \sigma_2\}$$

-  $\sigma_1, \sigma_2$  say risk of stock A, B.  
V - portfolio containing stock A, B.

Proof:

$$\sigma_V^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + \underbrace{2w_1w_2}_{+ve} \underbrace{\rho}_{|\rho| \leq 1} \underbrace{\sigma_1 \sigma_2}_{+ve}$$

$$\leq w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1w_2 \sigma_1 \sigma_2 \cdot 1$$

$$= (w_1 \sigma_1 + w_2 \sigma_2)^2$$

wlog  $\sigma_1 \leq \sigma_2$

$$\leq \left( w_1 \overbrace{\max\{\sigma_1, \sigma_2\}}^{\sigma_2} + w_2 \overbrace{\max\{\sigma_1, \sigma_2\}}^{\sigma_2} \right)^2$$

$$= \left( \overbrace{\max\{\sigma_1, \sigma_2\}}^{\sigma_2} \right)^2 \left( \underbrace{w_1 + w_2}_{=1} \right)^2$$

$$= \left( \max \{ \sigma_1, \sigma_2 \} \right)^2$$

$$\Leftrightarrow \sigma_v \leq \max \{ \sigma_1, \sigma_2 \}.$$

13<sup>th</sup> Feb The above phenomena is call diversification.

Take away: We can reduce risk by having 2 security over having 1 security.

**Example 4.** Suppose that there are  $n$  assets, all of which are mutually uncorrelated, i.e., the return of each asset  $K_i$  is uncorrelated with that of any other asset  $K_j$  in the group. Suppose that the expected rate of return and variance of each of these assets is  $\mu$  and  $\sigma^2$ , respectively. A portfolio is created by taking equal portions of each of these assets; that is,  $w_i = 1/n$  for each  $i$ . Calculate the expected rate of return and the risk of this portfolio.

We have  $n$  stocks

Each  $i^{\text{th}}$  stock:

$$\mu_i = \mu$$

$$\sigma_i = \sigma$$

$\implies$  the stocks are uncorrelated

$$\text{Cov}(K_i, K_j) = 0 \quad \forall i \neq j$$

$$\text{Cov}(K_i, K_i) = \text{Var}(K_i) = \sigma_i^2$$

$$\text{Portfolio } V = \begin{pmatrix} \frac{1}{n} \text{ unit of stock 1} \\ \vdots \\ \frac{1}{n} \text{ unit of stock } n \end{pmatrix}$$

$$\implies \omega_1 = \omega_2 = \dots = \frac{1}{n}$$

What is the risk of the portfolio  $V$ .

$$\sigma_V = \text{sd}(K_V)$$

$$\iff \sigma_V^2 = \text{Var}(K_V)$$

$$= \text{Var}\left(\sum_{i=1}^n \omega_i K_i\right)$$

$$= \sum_{i=1}^n \sum_{j=1}^n \omega_i \omega_j \text{Cov}(K_i, K_j)$$

$$= \sum_{i=1}^n \frac{1}{n} \cdot \frac{1}{n} \sigma^2$$

$$= \frac{1}{n} \sigma^2$$

$$\begin{cases} \text{Cov}(K_i, K_j) = 0 \quad \forall i \neq j \\ \text{Cov}(K_i, K_i) = \text{Var}(K_i) = \sigma_i^2 \end{cases}$$

$$\left[ \sigma_V = \frac{1}{\sqrt{n}} \sigma \right] \xrightarrow[\text{theoretically.}]{\text{as } n \rightarrow \infty} 0.$$

individual risk.

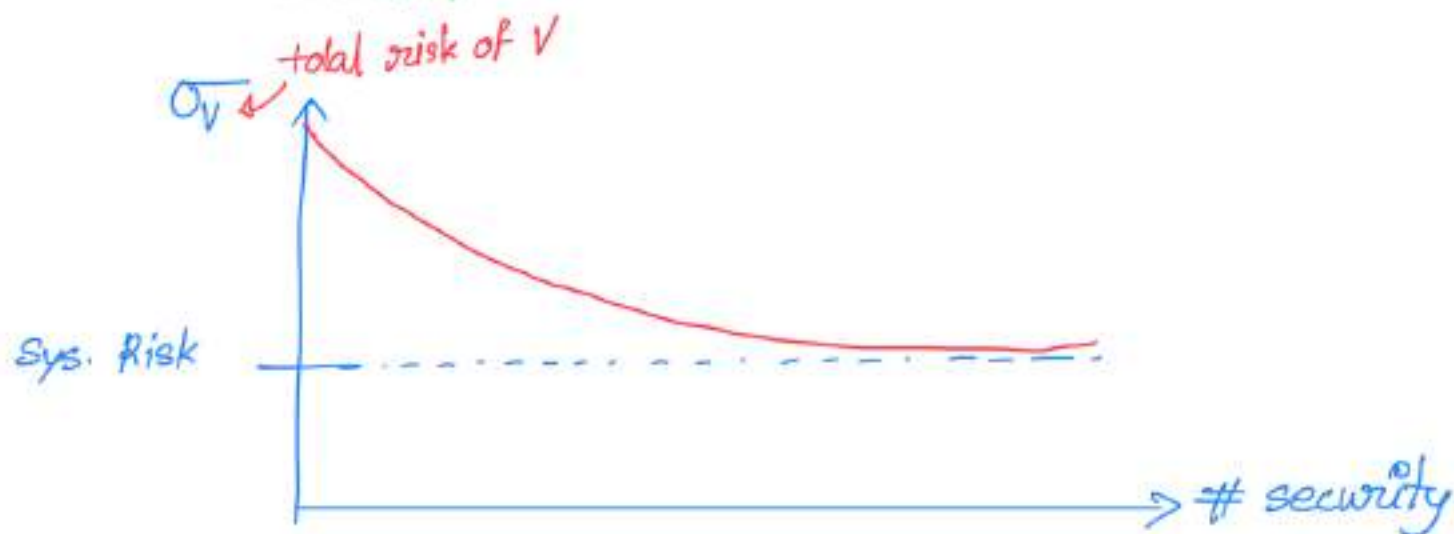
Can we always make the (risk of  $V$ )  $\rightarrow 0$   
by choosing appropriate weights.

$\Rightarrow$  No.

Type of Risk.

Diversifiable risk: (Ex: Internal/external business risk, financial risk (company specific)).  
 $\hookrightarrow$  we can make this risk  $\downarrow 0$   
by choosing correct portfolio weights.

Systematic risk. (Ex: Market risk, interest rate risk, Inflation risk)  
 $\hookrightarrow$  can not be diversified.



Ex 5 of lecture note:

$\hookrightarrow$   $n$  stock

weights  $\frac{1}{n}$  for each stock  $i$

each stock  $i$  has

$$\mu_i = \mu$$

$$\sigma_i = \sigma$$

$$\sigma_v^2 = \text{Varz}(K_v)$$

$$= \text{Varz}\left(\sum_{i=1}^n w_i K_i\right)$$

$$= \sum_{i=1}^n \sum_{j=1}^n w_i w_j \text{Cov}(K_i, K_j)$$

$$= \sum_{i=1}^n \sum_{j=1}^n \frac{1}{n^2} \text{Cov}(K_i, K_j)$$

$$= \sum_{i=1}^n \frac{1}{n^2} \sigma^2 + \sum_{i \neq j=1}^n \frac{1}{n^2} \text{Cov}(K_i, K_j)$$

$$\rho_{ij} \sigma_i \sigma_j =: \sigma_{ij}$$

$$= \frac{1}{n} \left( \sum_{i=1}^n \frac{1}{n} \sigma^2 \right) + \frac{n^2 - n}{n^2} \left( \sum_{i=1}^n \sum_{j(\neq i)=1}^n \frac{1}{n^2 - n} \sigma_{ij} \right)$$

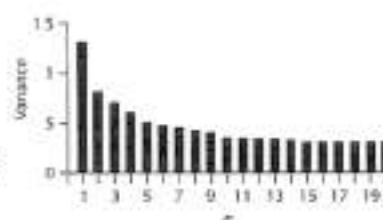
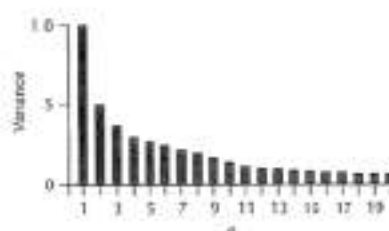
avg variance
avg covariance,

$\downarrow n \rightarrow \infty$   
 $\downarrow$   
 0

$\downarrow$   
 Avg cov.

$\hookrightarrow$  systematic risk.

**Homework:** Show that when all the assets are positively correlated and at least two of the assets are not perfectly correlated, the risk of the portfolio is still lower than  $\sigma$  but higher than the uncorrelated case. Also, show that if the assets are negatively correlated, then the risk decreases even further from the uncorrelated case.



Let's go back to  $n=2$ .

Goal: Find the 'best' portfolio weights.

The portfolio risk  $\sigma_V$  has a formula.

$$\sigma_V^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1w_2 \underbrace{\sigma_1 \sigma_2 \rho_{12}}_{\text{pre fixed}}$$

$$w_1 + w_2 = 1 \Rightarrow w_2 = 1 - w_1$$

$$\sigma_V^2 = w_1^2 \sigma_1^2 + (1-w_1)^2 \sigma_2^2 + 2w_1(1-w_1) \sigma_1 \sigma_2 \rho_{12}$$

f:  $w_1 \longmapsto w_1^2 \sigma_1^2 + (1-w_1)^2 \sigma_2^2 + 2w_1(1-w_1) \sigma_1 \sigma_2 \rho_{12}$   
 $\sigma_V^2$

Case-1  $\rho_{12} = +1$

say we want  $\sigma_V \equiv 0 \iff \sigma_V^2 = 0$  ①

$$\iff w_1^2 \sigma_1^2 + (1-w_1)^2 \sigma_2^2 + 2w_1(1-w_1) \sigma_1 \sigma_2 \rho_{12} = 0$$

$$\iff (w_1 \sigma_1 + (1-w_1) \sigma_2)^2 = 0$$

$$\iff |w_1 \sigma_1 + (1-w_1) \sigma_2| = 0$$

$$[\sigma_V = 0] \iff \text{if } \sigma_1 \neq \sigma_2 \text{ then } w_1 = \frac{-\sigma_2}{\sigma_1 - \sigma_2}, w_2 = \frac{\sigma_1}{\sigma_1 - \sigma_2}$$

→ We always need shortselling.

Case 2  $\rho_{12} = -1$

then  $\sigma_V = |\omega_1 \sigma_1 - \omega_2 \sigma_2|$

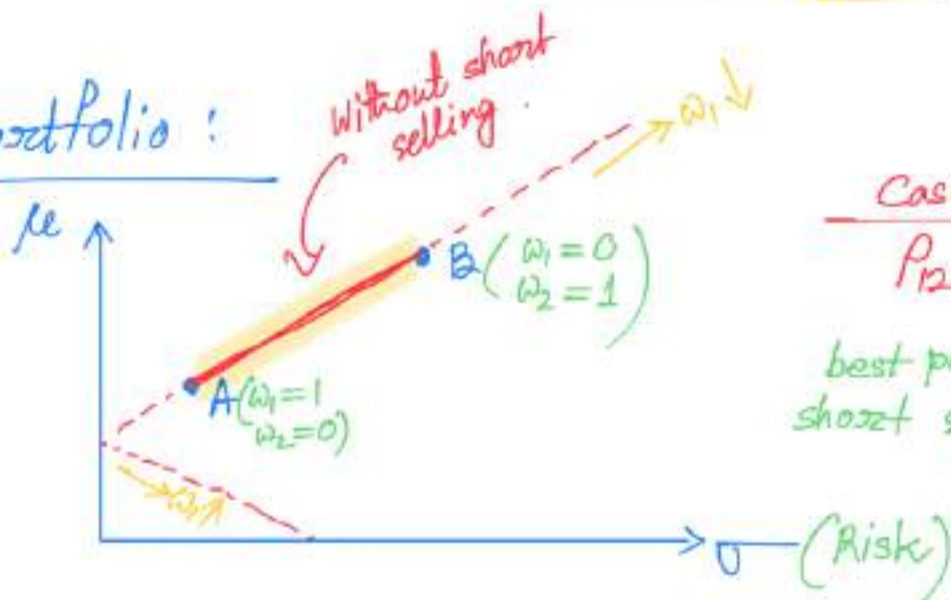
Furthermore,

$\sigma_V = 0 \iff$

$\omega_1 = \frac{\sigma_2}{\sigma_1 + \sigma_2}, \omega_2 = \frac{\sigma_1}{\sigma_1 + \sigma_2}$

→ We do not need shortselling for the best portfolio

Draw portfolio:



Case - 1

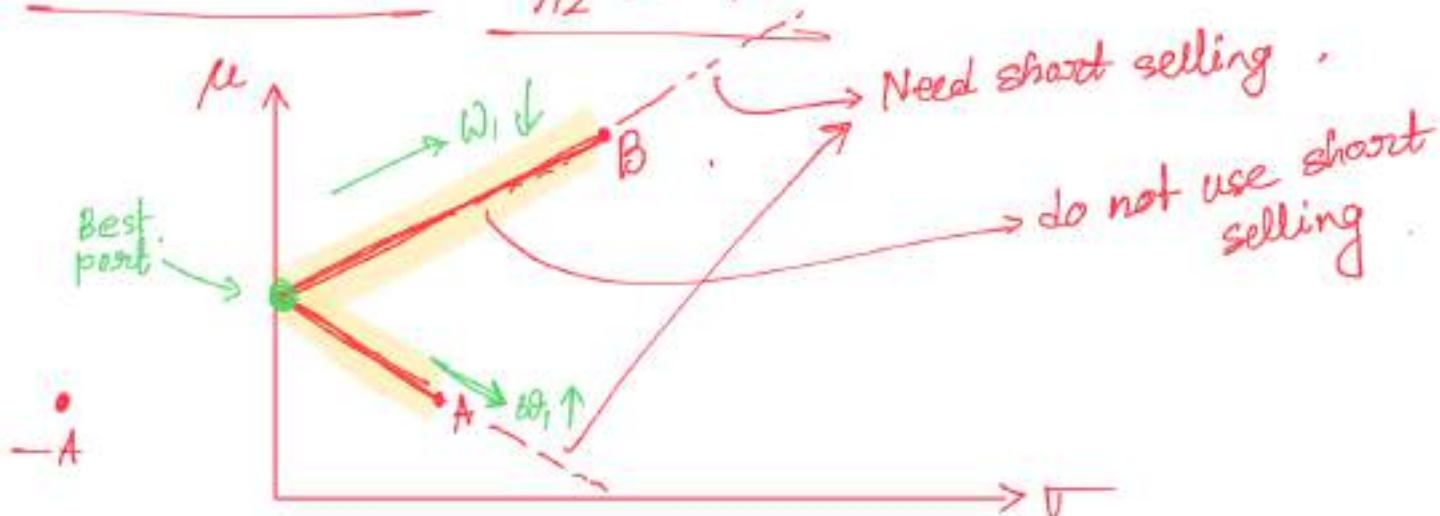
$\rho_{12} = +1$

best port without shorts selling =  $\left\{ \begin{matrix} \omega_1 = 1 \\ \omega_2 = 0 \end{matrix} \right\}$

We start from security A and B.

then each portfolio constructed from A and B can be uniquely represented in  $\sigma - \mu$  plane.

For case 2  $\rho_{12} = -1$



Case - 3  $\rho_{12} \in (-1, +1)$

$$f: \omega_1 \mapsto \sqrt{\sigma_1^2 \omega_1^2 + \sigma_2^2 (1-\omega_1)^2 + 2\sigma_1 \sigma_2 \omega_1 (1-\omega_1) \rho_{12}}$$

$\Rightarrow$  Equiv func:

$$g: \omega_1 \mapsto \sigma_1^2 \omega_1^2 + \sigma_2^2 (1-\omega_1)^2 + 2\sigma_1 \sigma_2 \omega_1 (1-\omega_1) \rho_{12}$$

Need to take  $g'$

$$\Rightarrow g' \equiv 0$$

$$\Rightarrow \omega_1^* ; \omega_2^* = 1 - \omega_1^*$$

We can also say  $g'' > 0$ .

Theorem: if  $\rho_{12} \in (-1, +1)$  then the  $\sigma_V^{\min}$  may not be  $\equiv 0$ .

Furthermore the weight of  $\sigma_V^{\min}$  is given as.

$$\omega_1^{\min} = \frac{\sigma_2^2 - \rho_{12} \sigma_1 \sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\sigma_1 \sigma_2 \rho_{12}}$$

$$\omega_2^{\min} = \frac{\sigma_1^2 - \rho_{12} \sigma_1 \sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\sigma_1 \sigma_2 \rho_{12}}$$

Short selling is allowed.

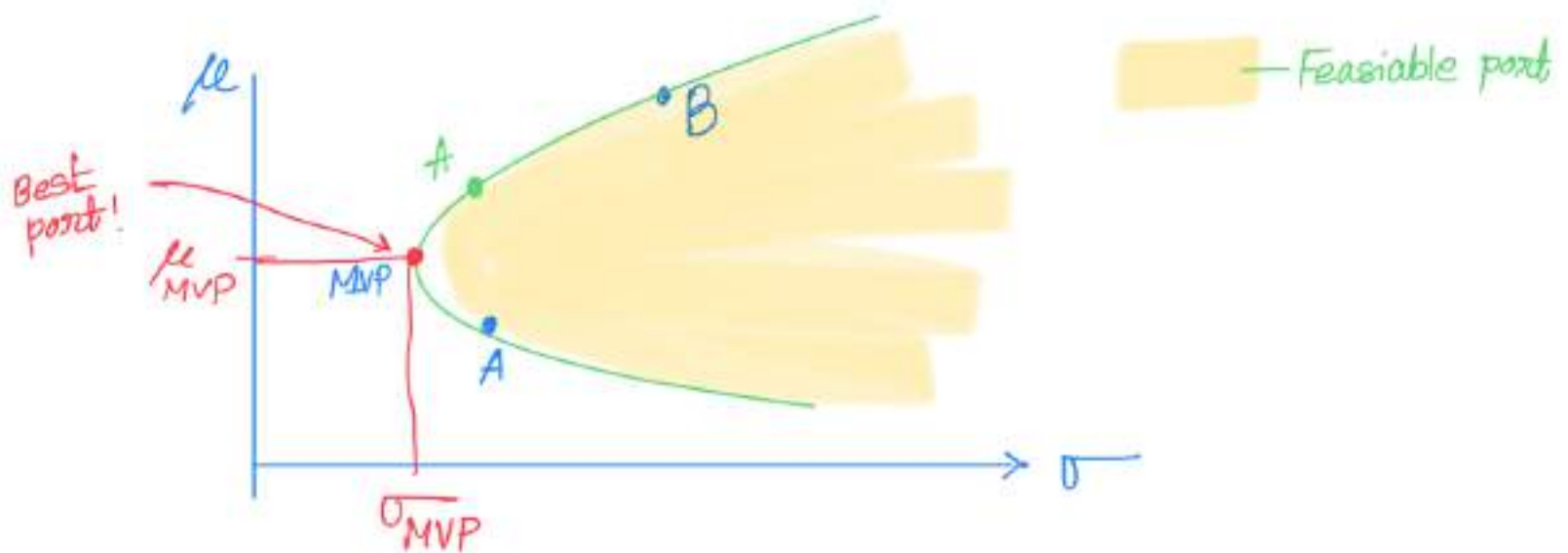
If we do not allow short selling:

$$\begin{pmatrix} w_1^{\min} \\ w_2^{\min} \end{pmatrix} = \begin{cases} (0, 1) \\ (w_1^{\min}, w_2^{\min}) \\ (1, 0) \end{cases}$$

$$w_1^{\min} < 0$$

$$\text{if } 0 \leq w_1^{\min} \leq 1$$

$$\text{if } w_1^{\min} > 1$$



### Min Variance Port (MVP)

the portfolio with the smallest possible risk among all feasible portfolio.

Notation

$$w_{MVP} = (w_1^{MVP}, w_2^{MVP}, \dots, w_N^{MVP})$$

Def<sup>n</sup> (feasible set)

The set of all portfolios which can be constructed by investing ONLY in security 1, ..., security N.

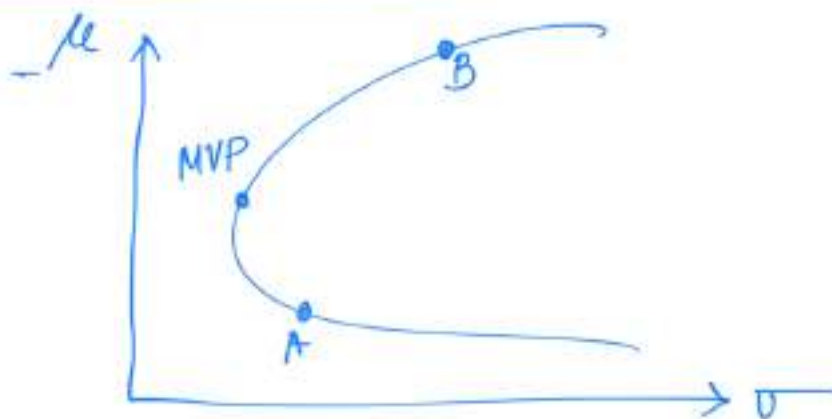
Theorem:  $\sigma_1 \neq \sigma_2$ .

Then

$$\mu_{MVP} = \frac{\mu_1 \sigma_2^2 + \mu_2 \sigma_1^2 - (\mu_1 + \mu_2) \rho_{12} \sigma_1 \sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho_{12} \sigma_1 \sigma_2}$$

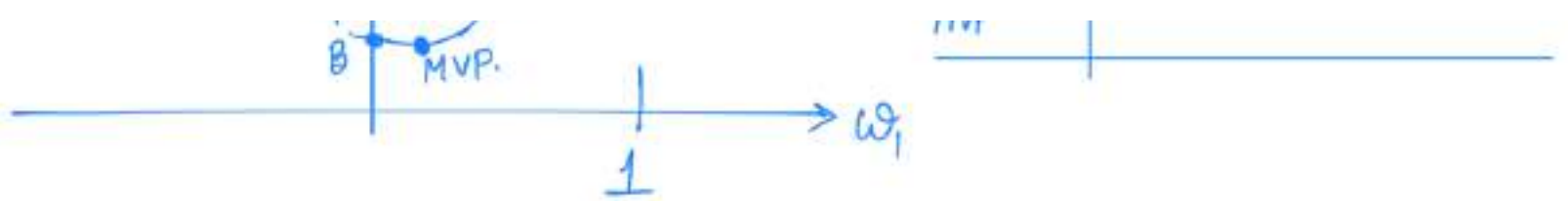
$$\left( \mu_{MVP} = \sum_{i=1}^n w_i \mu_i \right)$$

$$\frac{2}{\sigma_{MVP}^2} = \frac{\sigma_1^2 \sigma_2^2 (1 - \rho_{12}^2)}{\sigma_1^2 + \sigma_2^2 - 2\sigma_1 \sigma_2 \rho_{12}}$$



What if we want to explore:  $w_1$  vs  $\frac{2}{\sigma_{MVP}^2}$





Theorem: (shape of feasible set) Assume  $\rho_2 \in (-1, +1)$   
 and  $\rho_1 \neq \rho_2$  then each point  $V$  on feasible  
 set

$$x = b_V$$

$$y = \rho_V$$

$$\Rightarrow x^2 - A^2 (y - \rho_{MVP})^2 = D_{MVP}^2$$

known constant!

## Def<sup>n</sup> (Feasible set)

The set of all portfolios which can be constructed by investing ONLY in security 1, ..., security N.

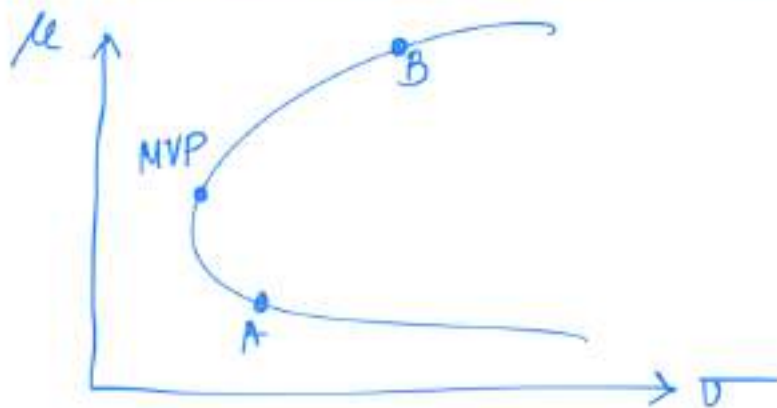
Theorem:  $\sigma_1 \neq \sigma_2$ .

Then

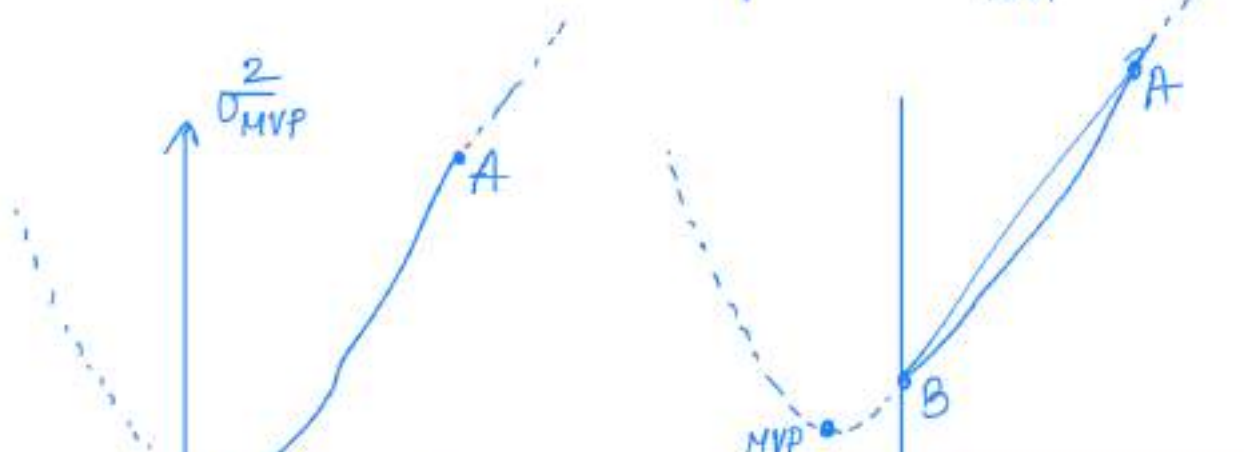
$$\mu_{MVP} = \frac{\mu_1 \sigma_2^2 + \mu_2 \sigma_1^2 - (\mu_1 + \mu_2) \rho_{12} \sigma_1 \sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho_{12} \sigma_1 \sigma_2}$$

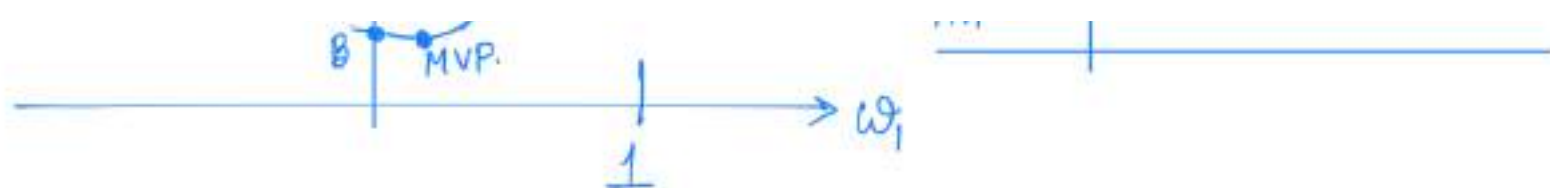
$$\left( \mu_{MVP} = \sum_{i=1}^n w_i \mu_i \right)$$

$$\frac{2}{\sigma_{MVP}^2} = \frac{\sigma_1^2 \sigma_2^2 (1 - \rho_{12}^2)}{\sigma_1^2 + \sigma_2^2 - 2\sigma_1 \sigma_2 \rho_{12}}$$



What if we want to explore:  $w_1$  Vs  $\frac{2}{\sigma_{MVP}^2}$





Theorem: (shape of feasible set) Assume  $\rho_{12} \in (-1, +1)$   
 and  $\mu_1 \neq \mu_2$  then each part  $V$  on feasible

**Remark 3.** Suppose  $\sigma_1 \leq \sigma_2$ , then we summarize the different cases as follows:

Cases	Is there a portfolio with $\sigma_V < \sigma_1 (\leq \sigma_2)$ ?	short selling needed?
1) $-1 \leq \rho_{12} < \frac{\sigma_1}{\sigma_2}$	yes	no
2) $\rho_{12} = \frac{\sigma_1}{\sigma_2}$	no	
3) $\frac{\sigma_1}{\sigma_2} < \rho_{12} \leq 1$	yes	yes

Week - 6

Maths Finance - II

Notation:

$N$  many securities.

Covariance matrix.

$$C_{N \times N} = \begin{bmatrix} \text{Cov}(K_1, K_1) & \dots & \text{Cov}(K_1, K_N) \\ \vdots & & \vdots \\ \text{Cov}(K_N, K_1) & \dots & \text{Cov}(K_N, K_N) \end{bmatrix}$$

the  $(i, j)^{\text{th}}$  element is  $C_{ij}$

$$C_{ij} = \text{Cov}(K_i, K_j) = \text{Cov}(K_j, K_i) = C_{ji}$$

Properties

→  $C$  is symmetric.

→  $C$  is square  $N \times N$  matrix.

→ the diagonals are variance.

$$C_{ii} = \text{Cov}(K_i, K_i) = \text{Var}(K_i) = (\sigma_i)^2$$

→  $C$  is always +ve semi definite

$$(X \subseteq X' \geq 0 \quad \forall X \in \mathbb{R}^n)$$

Similarly one can denote the correlation coefficients in matrix format.

$$\Sigma_{N \times N} = \begin{pmatrix} \rho_{11} & \rho_{12} & \dots & \rho_{1N} \\ \vdots & & & \\ \rho_{N1} & \dots & \dots & \rho_{NN} \end{pmatrix}$$

where  $\rho_{ij} :=$  correlation coefficient of  $K_i$  and  $K_j$

$$\left( = \frac{\text{Cov}(K_i, K_j)}{\sigma_i \sigma_j} = \frac{C_{ij}}{\sqrt{C_{ii} C_{jj}}} \right)$$

Now; a portfolio  $V$  consists of security 1,  $\dots$ ,  $N$  can always be UNIQUELY represented as

$$\omega_V = \begin{pmatrix} \omega_1 & \omega_2 & \dots & \omega_N \end{pmatrix}$$

$\omega_V$   
 $1 \times N$

$\omega_i$  represents weights of security  $i$

Remember:  $\omega_1 + \omega_2 + \dots + \omega_N = 1$ ;  $\omega_i \in \mathbb{R}$

Recall:

The exp. return of a portfolio  $V$  ( $\omega_V = (\omega_1, \dots, \omega_N)$ ) is given by:

$$K_V = \omega_1 K_1 + \omega_2 K_2 + \dots + \omega_N K_N$$

$$= \begin{pmatrix} \omega_1 & \dots & \omega_N \end{pmatrix}_{1 \times N} \begin{pmatrix} k_1 \\ \vdots \\ k_N \end{pmatrix}_{N \times 1}$$

$$= \omega_V K^T$$

where  $K := (k_1 \dots k_N)$

↳ vectors of individual returns.

### Notations:

- returns vectors  $K = (k_1 \dots k_N)_{1 \times N}$
- Mean/Exp returns vector  $\mu = (\mu_1 \dots \mu_N)_{1 \times N}$
- Cov matrix  $\mathbb{C}$

$$\mathbb{C} = \begin{bmatrix} \text{Cov}(k_i, k_j) \end{bmatrix} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1N} \\ \sigma_{21} & \sigma_2^2 & & \vdots \\ \vdots & & \ddots & \vdots \\ \sigma_{N1} & \dots & \dots & \sigma_N^2 \end{bmatrix}_{N \times N}$$

- Unit vectors:  $\mathcal{U}$

Either  $\mathcal{U} := (1 \ 1 \ \dots \ 1)_{1 \times N}$

or  $\mathcal{U} := \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$

depending on situation we might need row/column

Theorem: The expected return and risk of the portfolio  $V$  ( $w_V = (w_1 \dots w_N)$ ) is given by:

$$\mu_V = \sum_{i=1}^N w_i \mu_i = (\mu_1 \dots \mu_N) \begin{pmatrix} w_1 \\ \vdots \\ w_N \end{pmatrix} = \mu w^T$$

$(= w \mu^T)$

$$\sigma_V^2 = \sum_{i=1}^N \sum_{j=1}^N w_i w_j \text{Cov}(K_i, K_j)$$

$$= (w_1 \dots w_N) \begin{pmatrix} \sigma_1^2 & & \sigma_{1N} \\ & \ddots & \\ \sigma_{N1} & & \sigma_N^2 \end{pmatrix} \begin{pmatrix} w_1 \\ \vdots \\ w_N \end{pmatrix}$$

$1 \times N$                        $N \times N$                        $N \times 1$

$$= (w \Sigma w^T)_{1 \times 1}$$

Risk:  $\sigma_V = \sqrt{w \Sigma w^T}$

**Example 1.** Given  $w_1 = 50\%$ ,  $w_2 = -25\%$ ,  $w_3 = 75\%$ ;  $\mu_1 = 10\%$ ,  $\mu_2 = 7\%$ ,  $\mu_3 = 12\%$ ;  $\sigma_1 = 1$ ,  $\sigma_2 = 0.5$ ,  $\sigma_3 = 2$ ; and  $\rho_{12} = -0.5$ ,  $\rho_{13} = 0.5$ ,  $\rho_{23} = 0$ , find the expected return  $\mu_V$  and the risk  $\sigma_V$  of the portfolio.

$$w_V = \left( \cancel{50\%} \quad \cancel{-25\%} \quad 75\% \right) = \left( \frac{50}{100} \quad -\frac{25}{100} \quad \frac{75}{100} \right)$$

$$\mu_{1 \times 3} = (\mu_1 \quad \mu_2 \quad \mu_3) = \left( \frac{10}{100} \quad \frac{7}{100} \quad \frac{12}{100} \right)$$

$$C_{3 \times 3} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \vdots & \sigma_2^2 & \sigma_{23} \\ \vdots & \vdots & \sigma_3^2 \end{bmatrix} = \begin{bmatrix} 1^2 & -0.25 & 1 \\ -0.25 & (0.5)^2 & 0 \\ 1 & 0 & 2^2 \end{bmatrix}$$

$$\sigma_{12} = \text{Cov}(K_1, K_2) = \rho_{12} \sigma_1 \sigma_2$$

$$\mu_V = \mu w^T = 0.1225$$

$$\sigma_V = \sqrt{\sigma_V^2} = \sqrt{w C w^T} = \dots \approx 1.7984$$

**Example 2.** An investor holds a portfolio of three assets with weights  $w_1 = 0.5$ ,  $w_2 = -0.25$ ,  $w_3 = 0.75$ . The assets have expected returns and standard deviations

$$\mu_1 = 10\%, \quad \mu_2 = 7\%, \quad \mu_3 = 12\%, \quad \sigma_1 = 1, \quad \sigma_2 = 0.5, \quad \sigma_3 = 2,$$

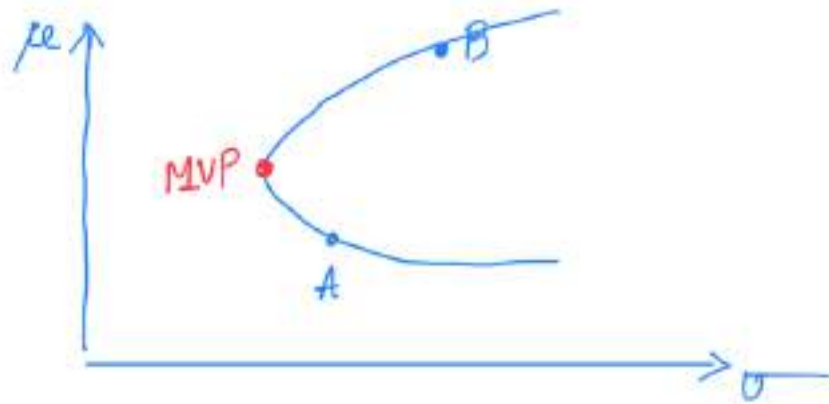
and correlations  $\rho_{13} = 0.5$ ,  $\rho_{23} = 0$ , while  $\rho_{12}$  is unknown. The portfolio standard deviation is observed to be  $\sigma_V = 1.824$ .

(a) Find the covariance  $\text{Cov}(K_1, K_2)$  and correlation coefficient  $\rho_{1,2}$ .

(b) Compute the expected return  $\mu_V$  of the portfolio.

# Min Var Portfolio

Port N=2



as long as  $|\rho_{AB}| \neq 1$

From last class:

$$w_1^{\min} = \frac{\sigma_2^2 - \rho_{12} \sigma_1 \sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho_{12} \sigma_1 \sigma_2} = \frac{\sigma_{22} - \sigma_{12}}{\sigma_{11} + \sigma_{22} - 2\sigma_{12}}$$

$$w_2^{\min} = 1 - w_1^{\min}$$

$$= \frac{\sigma_1^2 - \rho_{12} \sigma_1 \sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho_{12} \sigma_1 \sigma_2} = \frac{\sigma_{11} - \sigma_{12}}{\sigma_{11} + \sigma_{22} - 2\sigma_{12}}$$

(Remember  $\sigma_{12} = \sigma_{21}$ )

①  $\det(C) \mathcal{U} C^{-1}$   
 $1 \times N$   $N \times N$   $N \times N$

②  $(\det C) \mathcal{U} C^{-1} \mathcal{U}^T$

$$C = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$$

$$\sigma_{ij} := \text{Cov}(k_i, k_j)$$

$$\sigma_{ij} = \sigma_{ji}$$

$$C^{-1} = \frac{1}{(\det C)} \begin{bmatrix} \sigma_{22} & -\sigma_{12} \\ -\sigma_{12} & \sigma_{11} \end{bmatrix}$$

$$\textcircled{1}: \det(C) u C^{-1} = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} \sigma_{22} & -\sigma_{12} \\ -\sigma_{12} & \sigma_{11} \end{bmatrix}$$

$$= \begin{bmatrix} \sigma_{22} - \sigma_{12} & \sigma_{11} - \sigma_{12} \end{bmatrix}$$

$$\textcircled{2}: \det(C) u C^{-1} u^T = \begin{bmatrix} \sigma_{22} - \sigma_{12} & \sigma_{11} - \sigma_{12} \end{bmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$= \sigma_{11} + \sigma_{22} - 2\sigma_{12}$$

$$\frac{\textcircled{1}}{\textcircled{2}} = \frac{\begin{bmatrix} \sigma_{22} - \sigma_{12} & \sigma_{11} - \sigma_{12} \end{bmatrix}}{\sigma_{11} + \sigma_{22} - 2\sigma_{12}}$$

$$= \begin{bmatrix} \frac{\sigma_{22} - \sigma_{12}}{\sigma_{11} + \sigma_{22} - 2\sigma_{12}} & \frac{\sigma_{11} - \sigma_{12}}{\sigma_{11} + \sigma_{22} - 2\sigma_{12}} \end{bmatrix}$$

$$= \begin{bmatrix} \omega_1^{\min} & \omega_2^{\min} \end{bmatrix} = \omega_{MVP} \left( \begin{array}{l} = \frac{\textcircled{1}}{\textcircled{2}} \\ = \frac{u C^{-1}}{u C^{-1} u^T} \end{array} \right)$$

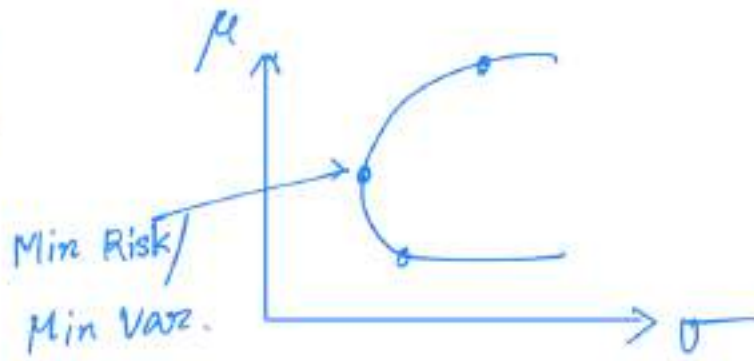
Theorem: (N security).

Assume  $\det C \neq 0$ . Then the MVP weights are given by:

Imp

$$\omega_{MVP} = \frac{u C^{-1}}{u C^{-1} u^T}$$

Proof:



We want to min Risk

↕  
min var.

Solve:

$$\min_{\omega_v} \omega_v^T C \omega_v$$

$$\text{st } \sum_{i=1}^N \omega_i = 1 \iff u \omega_v^T = 1$$

The Lagrange problem:

$$\mathcal{L}(\omega_v, \lambda) = \omega_v^T C \omega_v - \lambda (u \omega_v^T - 1)$$

FOC:

$$\frac{\partial \mathcal{L}}{\partial \omega_v} = 0 \iff 2 \omega_v^T C - \lambda u = 0$$

$$\iff \omega_v = \frac{\lambda u C^{-1}}{2} \quad (*)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 0 \iff u \omega_v^T = 1$$

↪ replacing (\*) we get

$$\frac{\lambda}{2} u C^{-1} u^T = 1$$

$$\Leftrightarrow \lambda = \frac{2}{u C^{-1} u^T} \quad \text{--- (**)}$$

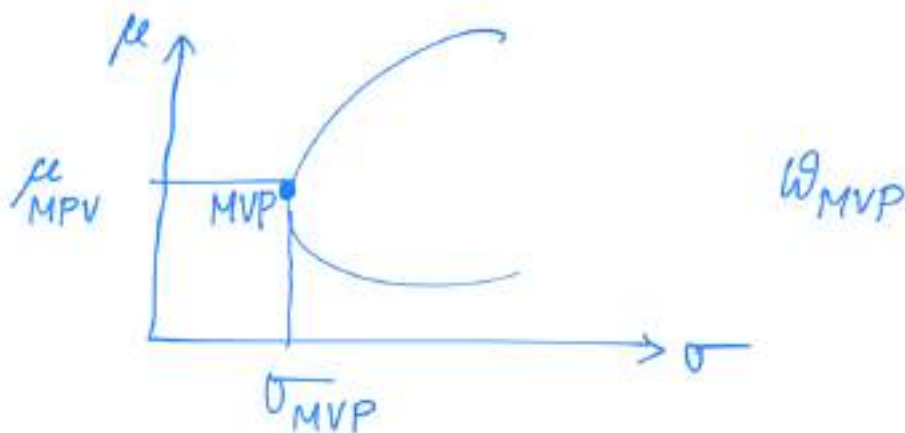
replacing  $\lambda$  in (\*) we get

$$\omega^* = \omega_{MVP} = \frac{u C^{-1}}{u C^{-1} u^T}$$

Sometimes  $\omega_{MVP}$  is written as.

$$\omega_{MVP} = \frac{C^{-1} u^T}{u C^{-1} u^T} \quad \leftarrow \text{column vector instead of row vec.}$$

The two followup Qn.

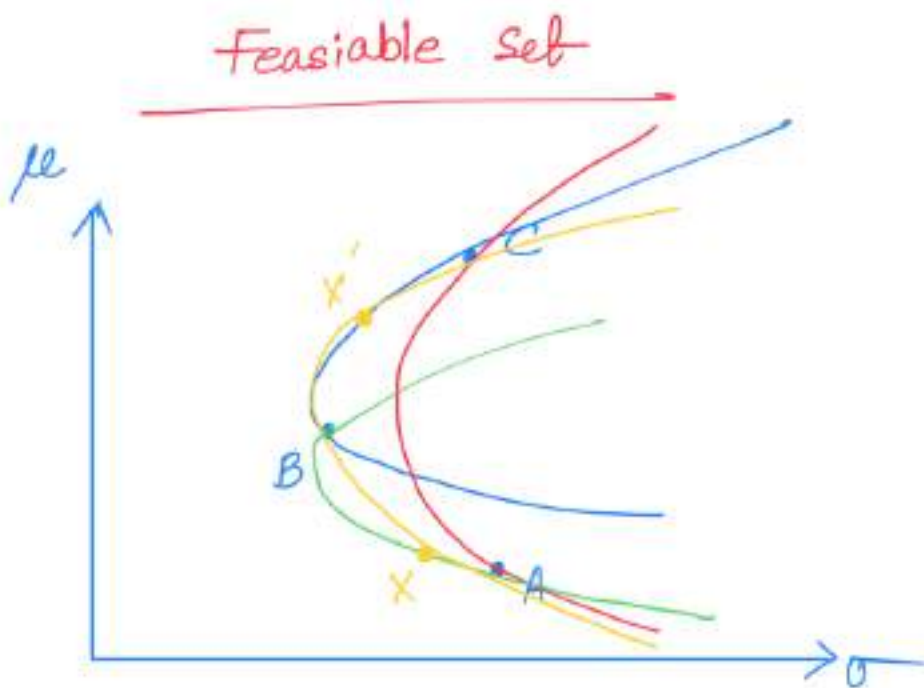


Imp Theorem:

$$\mu_{MVP} = \frac{u C^{-1} \mu^T}{u C^{-1} u^T}$$

$$\sigma_{MVP} = \sqrt{\sigma_{MVP}^2} = \sqrt{\frac{1}{u C^{-1} u^T}}$$

$$\begin{aligned}
 \left( \text{Proof: } \sigma_{MVP}^2 &= w_{MVP}^T C w_{MVP} \right. \\
 &= \left( \frac{u C^{-1}}{u C^{-1} u^T} \right) C \left( \frac{u C^{-1}}{u C^{-1} u^T} \right)^T \\
 &= \frac{\cancel{u C^{-1}} C \overset{C^{-1}}{\cancel{(C^{-1})^T}} u^T}{(u C^{-1} u^T)^2} \\
 &= \frac{\cancel{u C^{-1}} u^T}{(u C^{-1} u^T)^{\cancel{2}}} = \frac{1}{u C^{-1} u^T} \left. \right)
 \end{aligned}$$



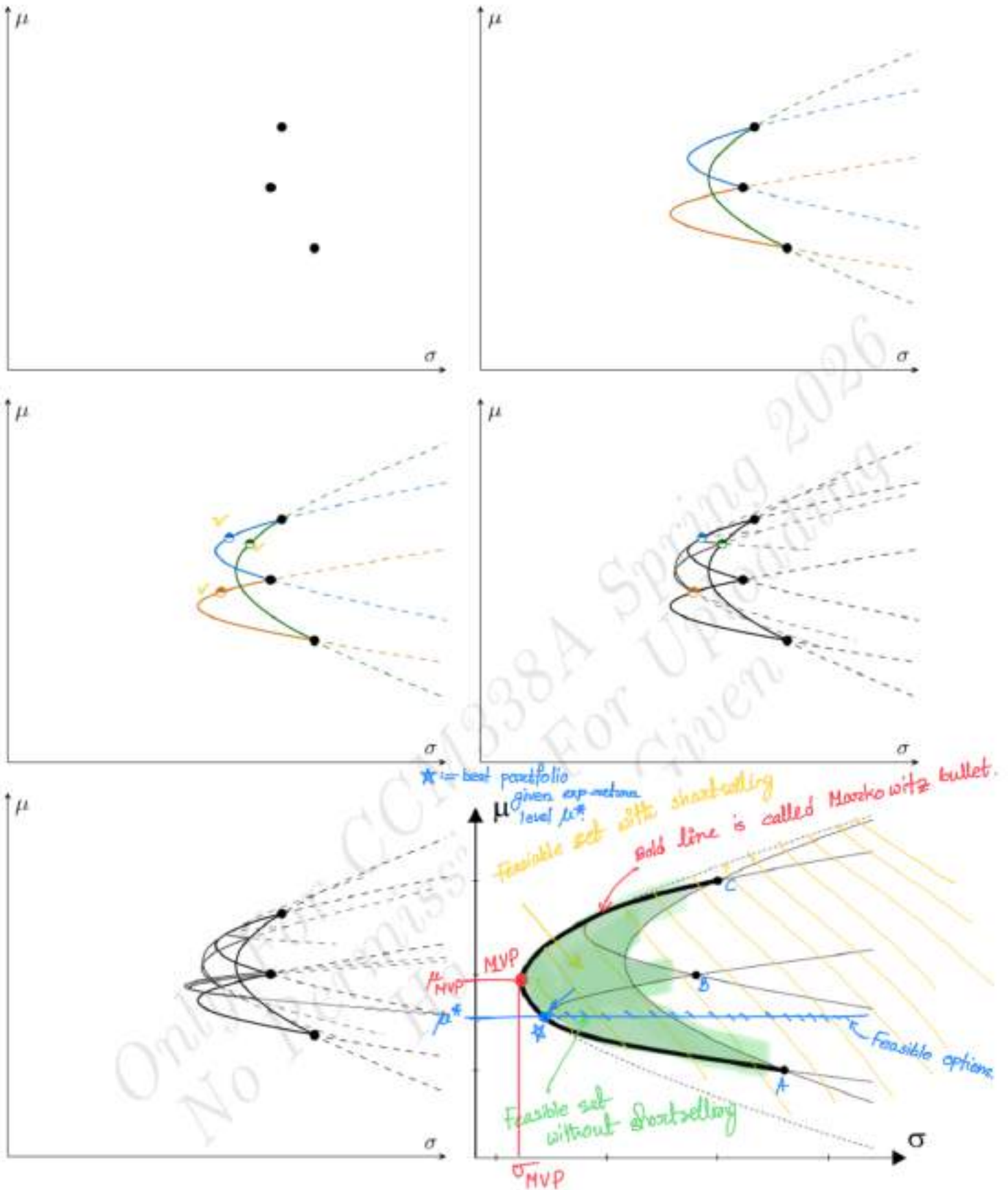


Figure 1: The feasible set and the Markowitz bullet without short selling

Assumption:

We need at least 3 securities above.

+ all securities has different exp return ( $\mu_1 \neq \mu_2 \neq \mu_3$ )

+  $P_{AB}, P_{BC}, P_{CA} \notin \{-1, +1\}$

Under the assumptions the feasible set will always look like above.

Note: The solid line is called Markowitz bullet, this is also the left most points of feasible set.

Imp  
Note: Markowitz bullet is also known as minimum variance Line (MVL).

Def<sup>n</sup>: (MVL)

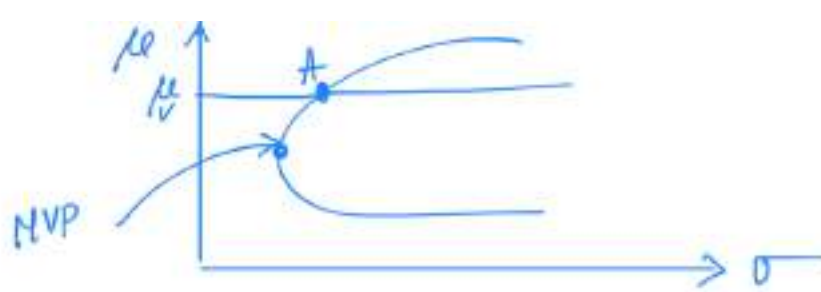
set of all portfolio with min risk given the expected return  $\mu^*$ .

**Theorem 2.4** (Weights of portfolios on the minimal variance line). Assume that  $\det C \neq 0$ . Fix a level of expected return  $\mu_V$ . Then a portfolio has the smallest risk among all portfolios with expected return  $\mu_V$  if and only if it has the weights

$$w_{\mu_V}^{\min} = \frac{\begin{vmatrix} 1 & uC^{-1}\mu^T \\ \mu_V & \mu C^{-1}\mu^T \end{vmatrix} uC^{-1} + \begin{vmatrix} uC^{-1}u^T & 1 \\ \mu C^{-1}u^T & \mu_V \end{vmatrix} \mu C^{-1}}{\begin{vmatrix} uC^{-1}u^T & uC^{-1}\mu^T \\ \mu C^{-1}u^T & \mu C^{-1}\mu^T \end{vmatrix}}, \quad (6)$$

*(Assump)*  $\mu_V \geq \mu_{MVP}$

where we have used the usual notation for the determinant of a  $2 \times 2$  matrix.



Proof:

Solve:

$$\min_w w^T C w$$

$$\text{st } w^T u = 1$$

$$\mu w^T = \mu_V \quad \leftarrow$$

Similarly to a previous case, we will use the **Lagrange multipliers method**. To this end, define

$$\mathcal{L}(w, \lambda) := w^T C w - \lambda_1 (w^T u - 1) - \lambda_2 (\mu w^T - \mu_V).$$

Then,

$$\nabla_w \mathcal{L} = 0 \Leftrightarrow 2w^T C - \lambda_1 u - \lambda_2 \mu = 0 \Leftrightarrow w = \frac{1}{2} (\lambda_1 u + \lambda_2 \mu) C^{-1} \quad (7)$$

which, in conjunction with the constraints ( $w^T u = 1$  and  $\mu w^T = \mu_V$ ), leads to the system with unknowns only involving  $\lambda$ :

$$\begin{cases} \lambda_1 u^T C^{-1} u + \lambda_2 \mu^T C^{-1} u = 2 \\ \lambda_1 \mu^T C^{-1} u + \lambda_2 \mu^T C^{-1} \mu = 2\mu_V \end{cases} \quad (8)$$

whose solution can be immediately determined, e.g., by Cramer's rule. Then, we derive immediately  $w_{\mu_V}^{\min}$  by substituting in (7).  $\square$

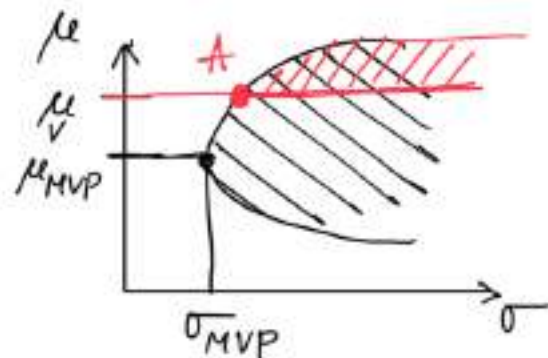
Week - 7  
Math - Finance - II

Reminder: Please submit "Tutorial-5 suggestion" by Friday.

Recap:

The last theorem from last class:

Theorem (Weights of portfolio on the MVL)



Weights of A

$$w_{\mu_v}^{\min} = \frac{\begin{vmatrix} 1 & uC^{-1}\mu^T \\ \mu_v & \mu C^{-1}\mu^T \end{vmatrix} C^{-1}u^T + \begin{vmatrix} uC^{-1}u^T & 1 \\ \mu C^{-1}u^T & \mu_v \end{vmatrix} C^{-1}\mu^T}{\begin{vmatrix} uC^{-1}u^T & uC^{-1}\mu^T \\ \mu C^{-1}u^T & \mu C^{-1}\mu^T \end{vmatrix}}$$

A  $\in \mathbb{R}$   
B  $\in \mathbb{R}$   
C  $\in \mathbb{R}$

} - scalar.

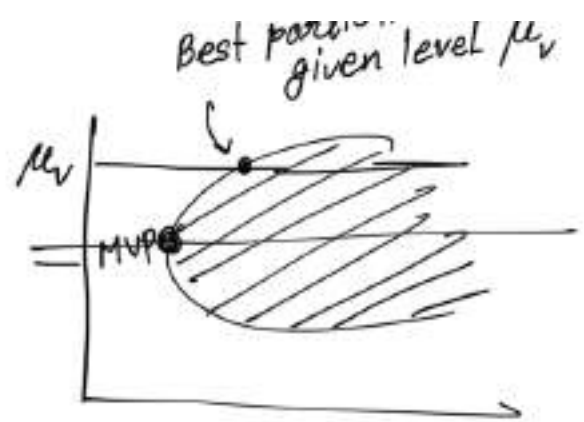
Note:  $\mu C^{-1}u^T = uC^{-1}\mu^T$

Assump:  $A > 0$  and  $C > 0$ .

$$w_{\mu_v}^{\min} = \frac{\begin{vmatrix} 1 & B \\ \mu_v & C \end{vmatrix} C^{-1}u^T + \begin{vmatrix} A & 1 \\ B & \mu_v \end{vmatrix} C^{-1}\mu^T}{\begin{vmatrix} A & B \\ B & C \end{vmatrix}}$$

$$\hookrightarrow = \frac{(C - \mu_v B) C^{-1}u^T + (A\mu_v - B) C^{-1}\mu^T}{AC - B^2}$$

To do:  
 "Two fund theorem"



▣ Finding MVP from  $\omega_{\mu_v}^{\min}$ .

chose  $\mu_v := \frac{B}{A}$

$$\begin{aligned} \omega_{\mu_v}^{\min} &= \frac{(C - \cancel{\mu_v B}) \mathbb{C}^{-1} u^T + (A \cancel{\mu_v} - B) \mathbb{C}^{-1} \mu^T}{AC - B^2} \\ &= \frac{(C - \frac{B^2}{A}) \mathbb{C}^{-1} u^T}{AC - B^2} \\ &= \frac{(AC - \cancel{B^2}) \mathbb{C}^{-1} u^T}{(\cancel{AC - B^2}) A} = \frac{\mathbb{C}^{-1} u^T}{A} \\ &= \frac{\mathbb{C}^{-1} u^T}{u \mathbb{C}^{-1} u^T} = \omega_{MVP} \end{aligned}$$

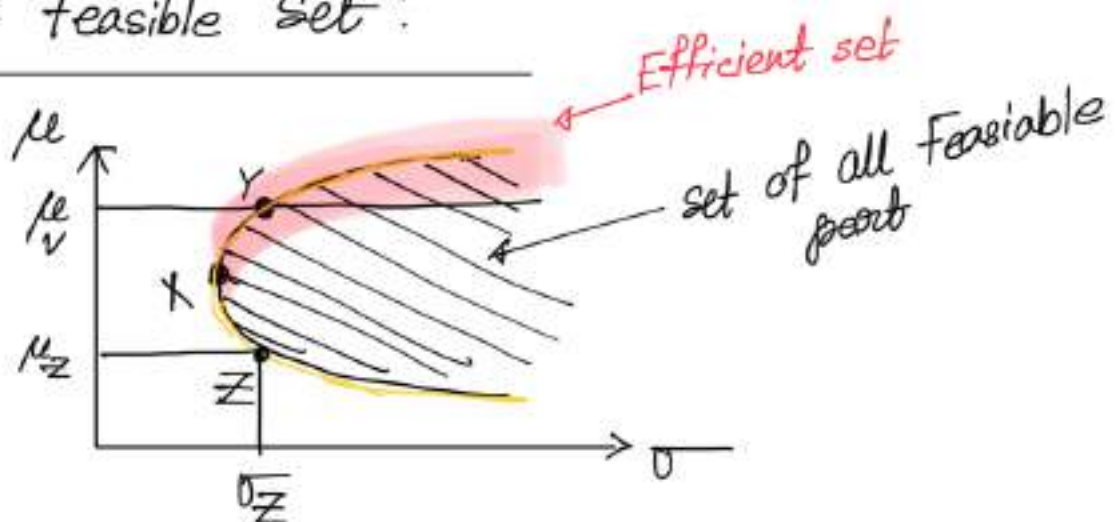
Finding second efficient portfolio:

chose  $\mu_v := \frac{C}{B}$

$$\begin{aligned} \omega_{\mu_v}^{\min} &= \frac{(C - \cancel{\mu_v B}) \mathbb{C}^{-1} u^T + (A \cancel{\mu_v} - B) \mathbb{C}^{-1} \mu^T}{AC - B^2} \\ &= \frac{(\frac{AC}{B} - B) \mathbb{C}^{-1} \mu^T}{AC - B^2} \quad \mathbb{C}^{-1} \mu^T \end{aligned}$$

$$\begin{aligned}
 &= \frac{1}{(AC - B^2)} = \frac{1}{B} \\
 &= \frac{C^{-1} \mu^T}{\mu C^{-1} \mu^T} = w \quad \text{(second eff point)} \\
 &= \mu C^{-1} \mu^T
 \end{aligned}$$

Prop. of Feasible set:



→ Any security can be uniquely represented in  $\sigma$ - $\mu$  plane.

→  $x :=$  Best portfolio i.e. the point with Min risk  
 $=$  MVP.

→ We learnt how to construct the best point (Y)  
 given exp returns  $\mu_V$ .

→ The yellow line  $:=$  Markowitz Bullet  
 also known as Min Variance Line (MVL)

→ Any portfolio which are efficient has to be on  
 MVL, but not all points in MVL are efficient  
 portfolios.

**Theorem 2.5** (Risk associated to the best portfolio given expected return  $\mu_V$ ). Assume that  $\det \mathbb{C} \neq 0$ . Fix a level of expected return  $\mu_V$ . Then the portfolio that has the smallest risk among all portfolios with expected return  $\mu_V$  has risk/variance as follows.

$$\sigma_{w_V}^2 = \sigma_{\text{MVP}}^2 + \frac{(\mu_V - \mu_{\text{MVP}})^2}{\psi \sigma_{\text{MVP}}^2}, \quad \text{with,}$$

$$\text{const} \rightarrow \psi = AC - B^2 = u^\top \mathbb{C}^{-1} u \mu^\top \mathbb{C}^{-1} \mu - (u^\top \mathbb{C}^{-1} \mu)^2.$$



*Proof.* We will skip the proof, as this is computationally heavy. □

$$\sigma_A^2 = \sigma_{MVP}^2 + \underbrace{\text{Const} \times (\mu_A - \mu_{MVP})^2}_{\substack{\text{compensation} \\ \text{for extra exp} \\ \text{returns}}}$$

Additionally:

Lemma:

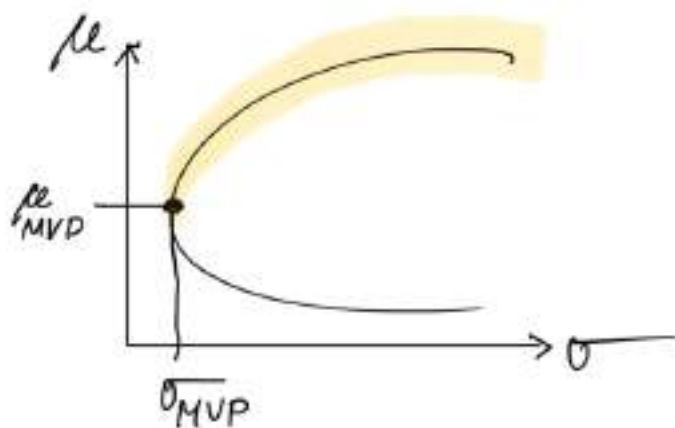
$$w_A = \text{Const}^{(1)} \mu_A + \text{Const}^{(2)}$$

↳ weights of best portfolio at exp return level  $\mu_V$  depends linearly on  $\mu_V$ .

Note: The above lemma is very useful in practice as once the  $\text{const}^{(1)}$  and  $\text{const}^{(2)}$  are estimated it is very easy to find  $w_{\mu_V}^{\min}$ .

The portfolio  $w_{\mu_V}^{\min}$  is known as "target return portfolio".

## Two fund theorem



— set of all efficient port.

Theorem: Chose any two arbitrarily distinct portfolio on the MVL, say  $V_1^{MVL}$  and  $V_2^{MVL}$ , and these has weights denoted as  $w_1$  and  $w_2$  and exp return  $\mu_1$  and  $\mu_2$  ( $\mu_1 \neq \mu_2$ ).

Then a portfolio  $V$  is on MVL iff its weight vector ( $w$ ) can be written as a affine combination of  $w_1$  and  $w_2$ .

Mathematically:  $w = \alpha w_1 + (1-\alpha) w_2$  for some  $\alpha \in \mathbb{R}$ .

↑  
weight of  $V$

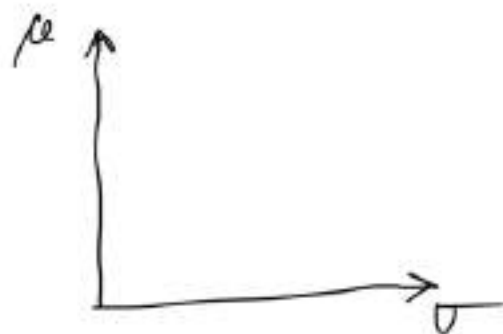
In other words:

one can construct two efficient funds/portfolios, st any other efficient portfolio is just a combination of these two funds.

Two distinct portfolio:

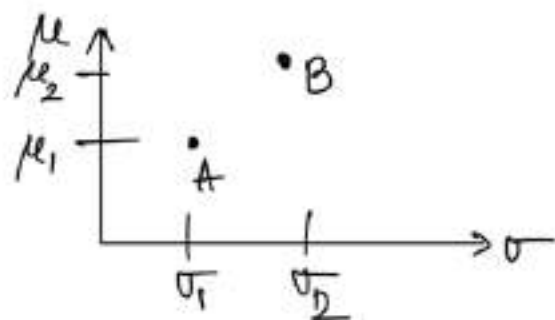
$$V_1 = (\sigma_1, \mu_1)$$

$$V_2 = (\sigma_2, \mu_2)$$

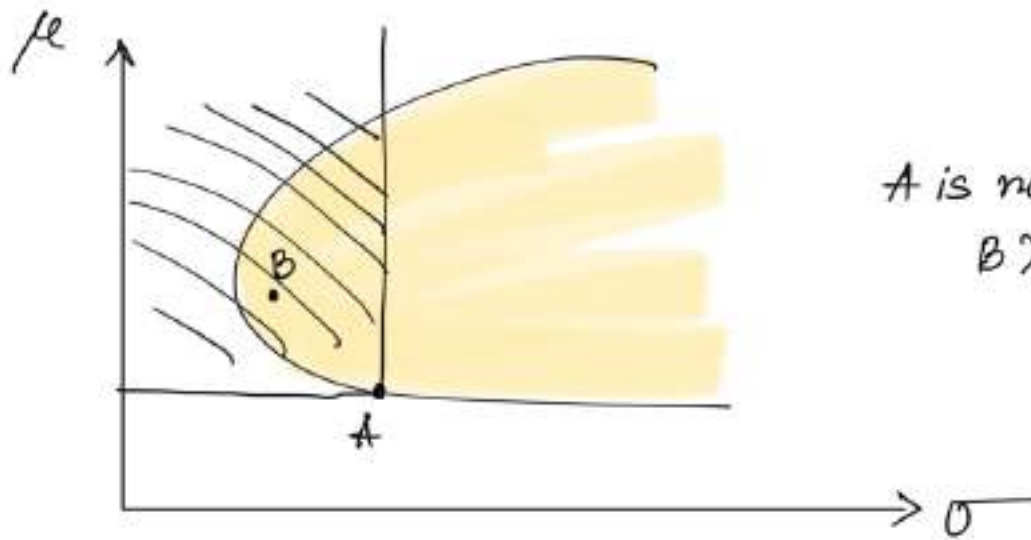


- If  $\mu_1 = \mu_2 \rightarrow$  the one with lower risk.
- If  $\sigma_1 = \sigma_2 \rightarrow$  the one with better exp returns.
- If  $\sigma_1 \leq \sigma_2$  and  $\mu_1 \geq \mu_2 \rightarrow$  the portf  $(\sigma_1, \mu_1)$
- If  $\sigma_1 \leq \sigma_2$  and  $\mu_1 \leq \mu_2 \rightarrow$  No obvious best

$\searrow$  depends on the level of risk-aversion.



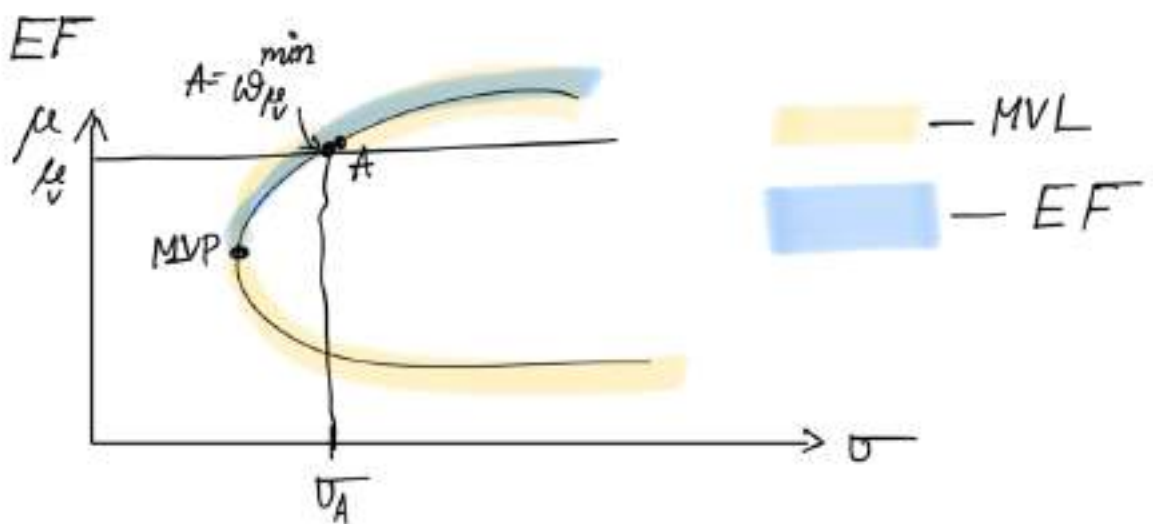




A is not on EF as  $B \succ A$ .

So:

The EF



What is the mathematical representation of EF:

$$\left\{ \left( \sigma_{\mu_V}^{\min}, \mu_V \right) \mid \mu_V \geq \mu_{MVP} \right\}$$

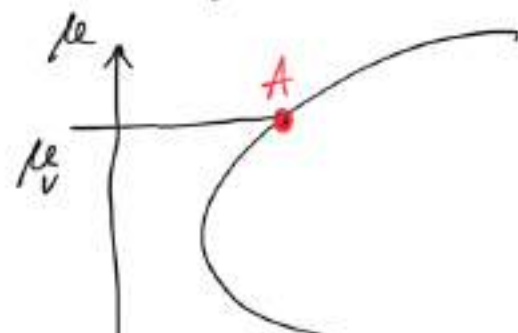
Qn: Say security A dominates security B.  
Do we get rid of security B from optimal port?

→ No (Diversification)

Qn: I fix the level of exp returns  $\mu_V$ .

Case-I

My exp returns =  $\mu_V \Rightarrow A$

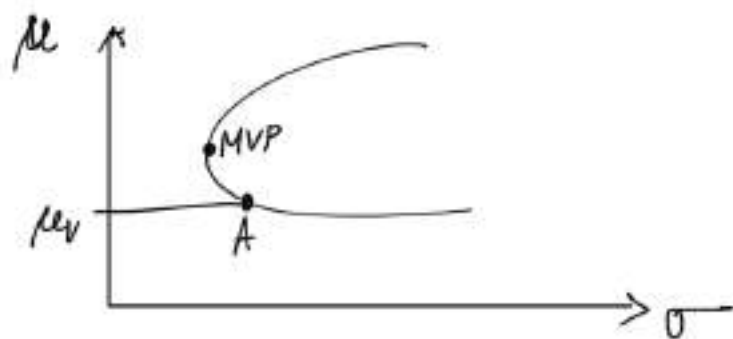


...-II

Case My exp return is at least  $\mu_v$

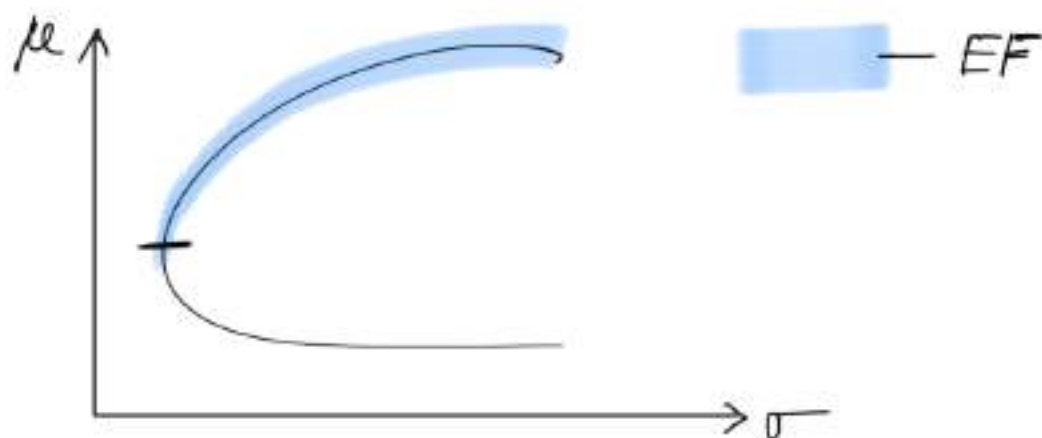


$\Rightarrow A$



Lemma: The EF is the set of all portfolios whose weights  $w_{EF}$  are given by:

$$w_{EF} = \text{Cont}^{(1)} \mu_{EF} + \text{Cont}^{(2)}$$



Goal! I want to choose the best possible port from EF.

Recall! In utility theory we had Quadratic utility for:

$$U(w) = w - \frac{b}{2} w^2 ; b > 0.$$

We were max  $E(U(w))$ .

Now we will define Performance criteria of a port.

$\mu, \sigma, \gamma, \dots$

$$:= \mathbb{E}(K_V) - \frac{\gamma}{2} \text{Var}[r_V]$$

$$= \omega_V^T \mu - \frac{\gamma}{2} \omega_V^T \mathbb{C} \omega_V.$$

Once we fix the level (of risk-aversion)  $\gamma$  the we can construct a portfolio which is on EF as well as gives the highest Performance criteria.

**Theorem 3.1.** The weights associated to the portfolio with the best portfolio performance criteria is given by (No need to remember the formulas):

$$\omega_{\text{best-performance}} = \frac{\mathbb{C}^{-1}u}{u^T \mathbb{C}^{-1}u} + \frac{1}{\gamma} \left( \frac{u^T \mathbb{C}^{-1}u \mathbb{C}^{-1}\mu - \mu^T \mathbb{C}^{-1}u \mathbb{C}^{-1}u}{u^T \mathbb{C}^{-1}u} \right).$$

Furthermore, the expected return and the variance of this optimal portfolio is given by

$$\mu_{\text{best-performance}} = \frac{u^T \mathbb{C}^{-1}\mu}{u^T \mathbb{C}^{-1}u} + \frac{1}{\gamma} \left( \frac{\mu^T \mathbb{C}^{-1}\mu u^T \mathbb{C}^{-1}u - (u^T \mathbb{C}^{-1}\mu)^2}{u^T \mathbb{C}^{-1}u} \right)$$

$$= \mu_{MVP} + \frac{1}{\gamma} \psi \sigma_{MVP}^2.$$

$$\sigma_{\text{best-performance}}^2 = \sigma_{MVP}^2 + \frac{1}{\gamma^2} \left( \frac{\mu^T \mathbb{C}^{-1}\mu u^T \mathbb{C}^{-1}u - (u^T \mathbb{C}^{-1}\mu)^2}{u^T \mathbb{C}^{-1}u} \right)$$

$$= \sigma_{MVP}^2 + \frac{1}{\gamma^2} \psi \sigma_{MVP}^2.$$

Where  $\psi := \mu^T \mathbb{C}^{-1}\mu u^T \mathbb{C}^{-1}u - (u^T \mathbb{C}^{-1}\mu)^2$  is a scalar value. Note that this  $\psi$  is the same constant which appears in Theorem 2.5. This is a consequence of  $\psi = \psi^T$  (since  $\psi$  is scalar) and  $\mathbb{C}^{-1} = (\mathbb{C}^{-1})^T$  (Since  $\mathbb{C}$  is symmetric).

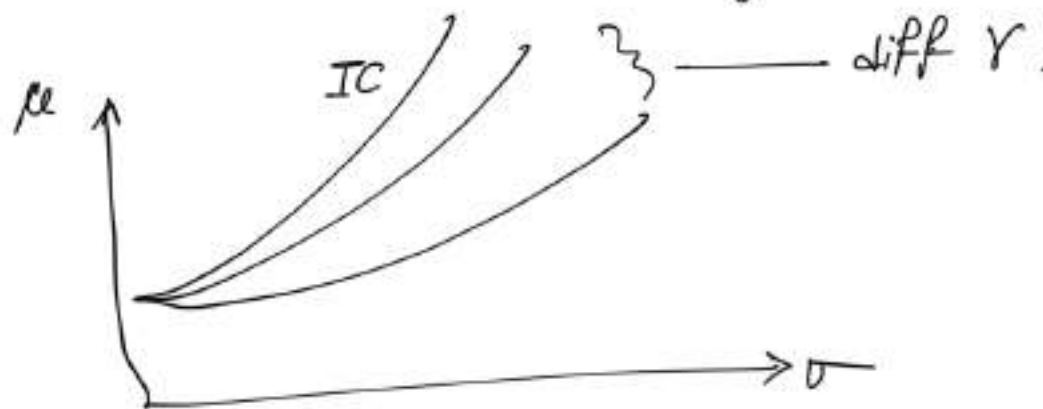
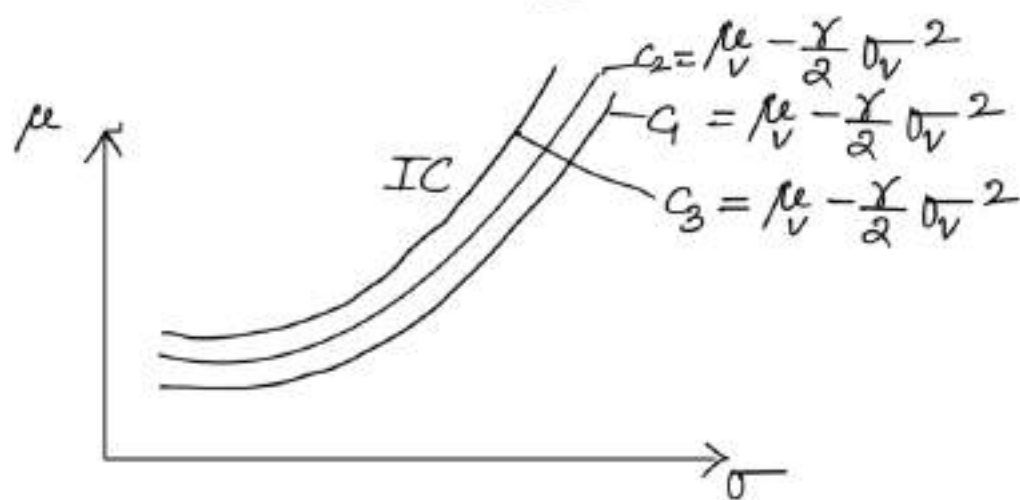
*Proof.* Proof using the Lagrange multiplier. □

## Indifference Curve:

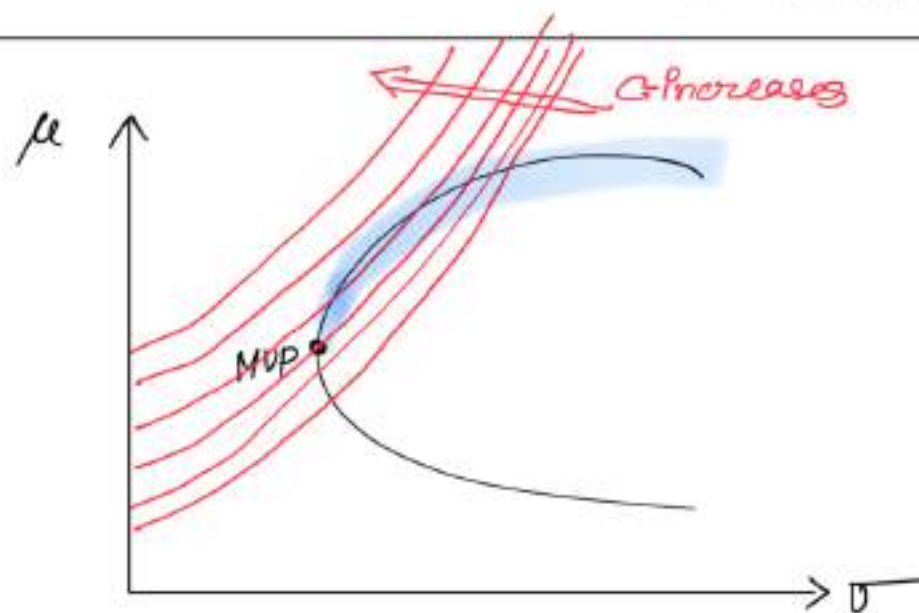
Def<sup>n</sup>: An indifference curve is a collection of portfolios which an investor is indifferent to.

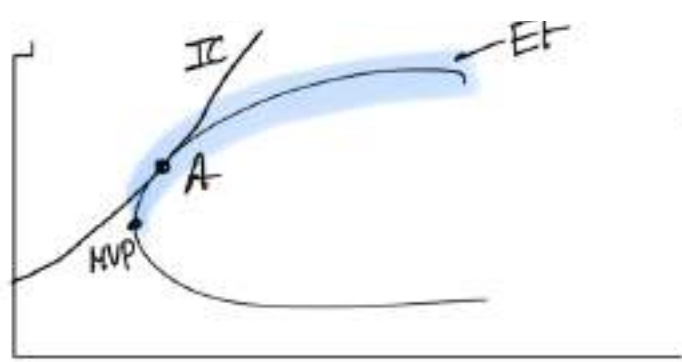
i.e. for all the portfolios;

$$\mu_V - \frac{\gamma}{2} \sigma_V^2 = C_0$$



Which portfolio on EF gives me best performance criteria.





A → Max performance  
criteria  
on EF.

# Week - 8

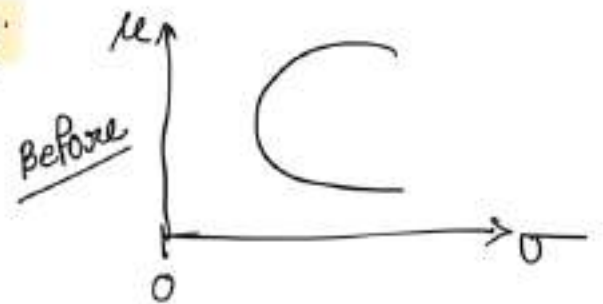
## Math - Finance - II

Reminder: Please submit "Tutorial-7 suggestion" by Friday.

Class Test: 11<sup>th</sup> March (Wed)

Recap: Until week 7:

MVP, EF, Feasible Set, Exp return and risk of a portfolio for  $N$ -Risky security.



Add a Risk-free asset

Framework:  $N$ -risky asset + 1 Risk free.

Notations:

$R / R_{rf} / R_f / \mu_{RF}$  — a risk free asset.

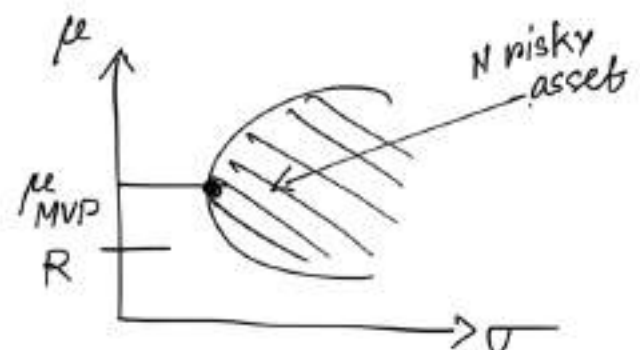
$R$  is not a Random variable.

$$\boxed{E(K_R) = K_R = R}$$

$\mu_R$

Exp rate of return = Rate of return!

Assump:  $R < \mu_{MVP}$



↳ Bond will not give better exp return than  $N$  risky asset\* (best).

### Step-1

What is the feasible set when we have 1 Risky asset ( $V$ )  
+ 1 RF ( $R$ )

Take a new portfolio  $P$  with  $\omega = (\omega_f, \omega_1)$  with  
 $\omega_f$  representing weight of RF  
 $\omega_1$  Risky asset  $V$ .

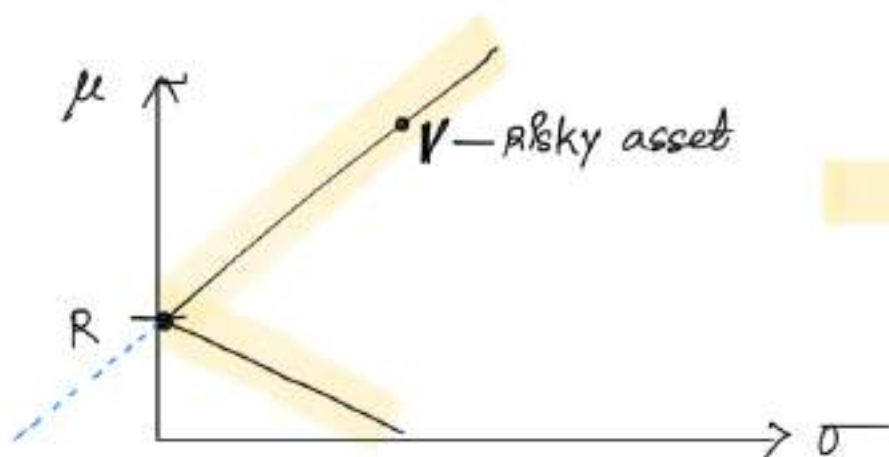
Note:  $\omega_f + \omega_1 = 1$

$$\mu_p = \omega_f \mu_f + \omega_1 \mu_1 = (1 - \omega_1) \mu_f + \omega_1 \mu_1$$

$$\begin{aligned} \sigma_p^2 &= \omega_f^2 \underbrace{\sigma_f^2}_0 + \omega_1^2 \sigma_1^2 + 2 \omega_f \omega_1 \underbrace{\text{Cov}(K_f, K_1)}_0 \text{ (HW)} \\ &= \omega_1^2 \sigma_1^2 \end{aligned}$$

$$\Leftrightarrow \sigma_p = |\omega_1 \sigma_1|$$

$\mu_p$  is linear on  $\omega_1$   
 $\sigma_p$  is also "linear" on  $\omega_1$  } —  $\sigma_p$  is "linear" on  $\mu_p$ .

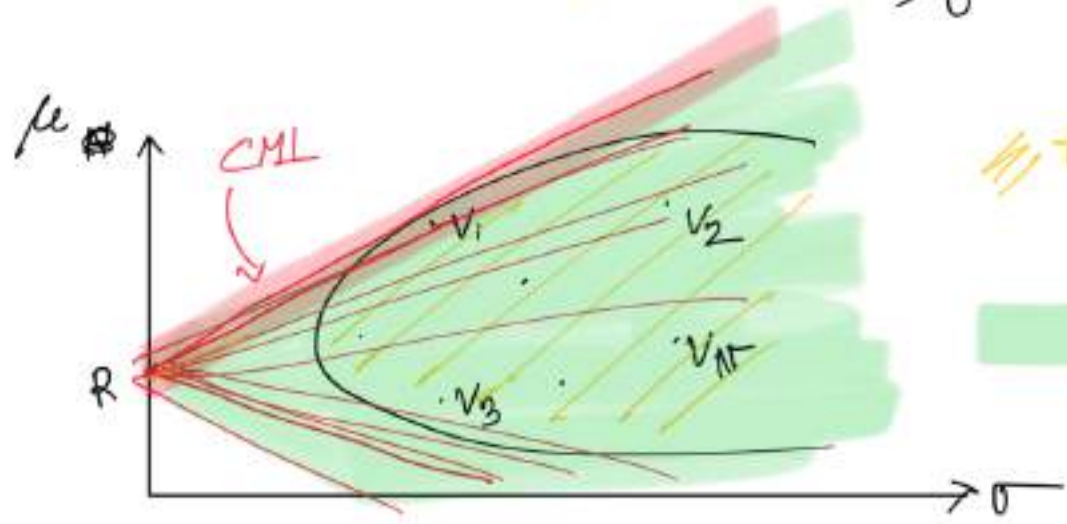
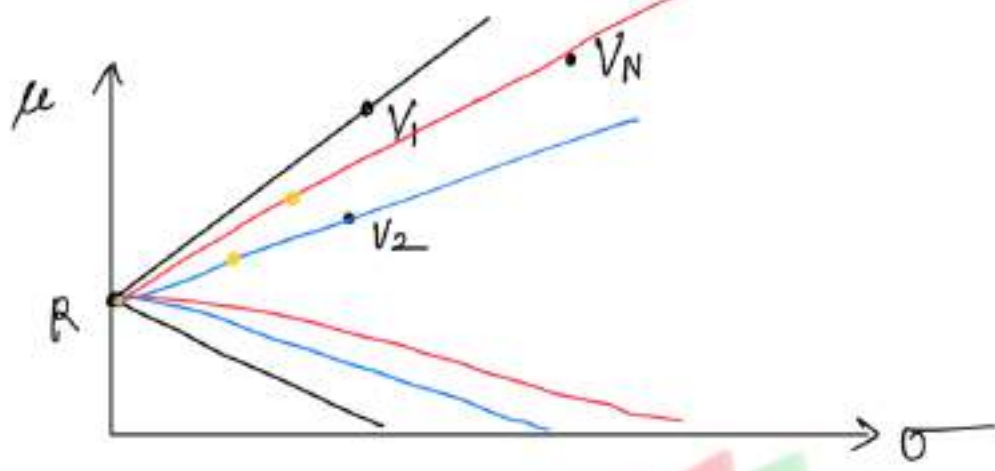


— The set of all efficient points for step-1.

### Step-2 ( $R, V_1, V_2, \dots, V_N$ )

$N$ -Risky asset + 1 RF. (one should not have more than 1 RF in a market)

→ we overcome the one with lower interest

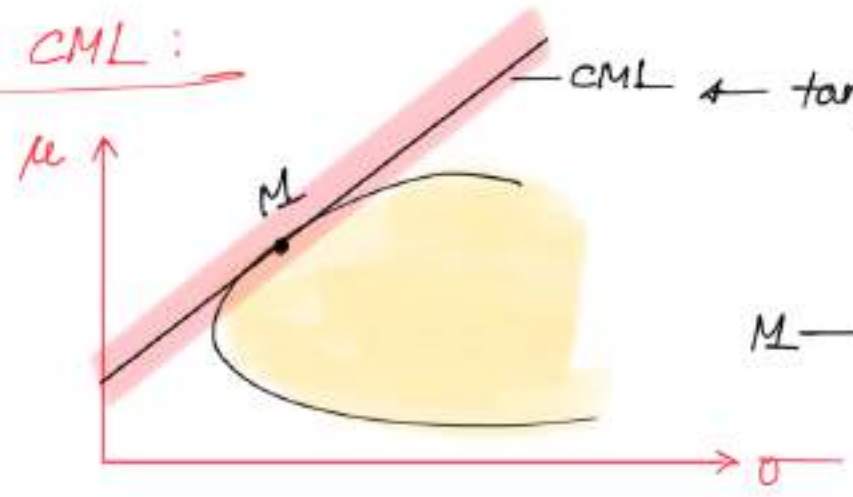


Feasible set with just N-Risky asset

Feasible point with N-risky + 1 RF.

set of all efficient point (under RF) (CML)

What is CML:



CML ← tangent to the old feasible set (No-RF)

M — Market portfolio.

M is the only efficient point which can be constructed just from the N-risky asset.

Definition 10 (CML, Market Portfolio). The half-line that starts at the risk-free asset and runs through the market portfolio M is called the Capital Market Line (CML). The portfolio M corresponding to the tangency point  $(\sigma_M, \mu_M)$  is called the market portfolio.

Theorem: (One Fund theorem).

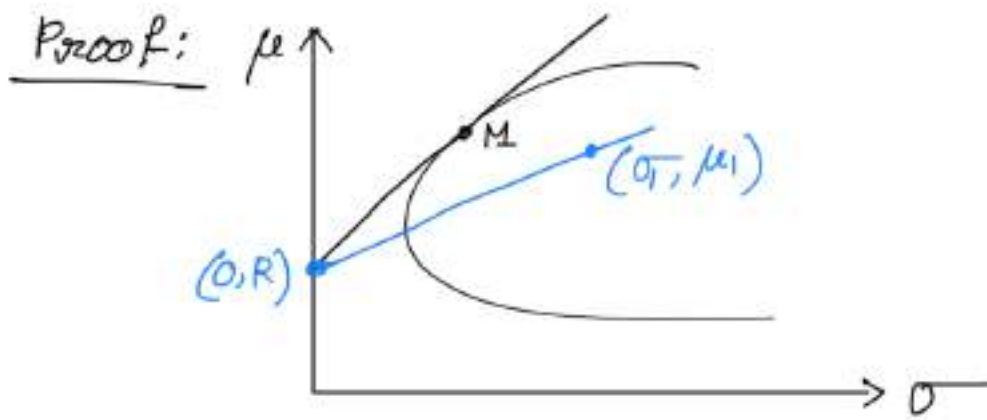
Assume (N-risky + 1 RF). Then there exists a unique single fund (Market port M) st any efficient port

single fund (minimum variance portfolio) can be constructed as a linear combination of  $M$  and  $R$ .

Qn: How to construct  $M$ :

**Theorem 5.2.** Consider a market that consists of one risk-free security with return  $R$ , and  $n$  risky securities with expected return  $\mu = (\mu_1, \dots, \mu_n)$  and covariance matrix  $C$ . Assume that  $R < \mu_{MVP}$ , and if  $C$  is invertible, then the market portfolio  $M$  exists and its weights are given by

$$w_M = \frac{(\mu - Ru)C^{-1}}{(\mu - Ru)C^{-1}u^T}$$



$$\sigma_1 = \frac{1}{\sqrt{wCw^T}}$$

$$\mu_1 = \mu w^T$$

$$\max_w \text{slop of the line.} = \frac{\mu w^T - R}{\sqrt{wCw^T}}$$

$$\text{st } uw^T = 1$$

*Proof.* We look for the  $V$  (or equivalently,  $w$ ) that satisfies:

$$\max_w \frac{\mu w^T - R}{\sqrt{wCw^T}} \text{ subject to the constraint } uw^T = 1.$$

To this end, we define the Lagrangian  $\mathcal{L}(w, \lambda) := \frac{\mu w^T - R}{\sqrt{wCw^T}} - \lambda(uw^T - 1)$ .

By calculating the FOC, we derive

$$\begin{aligned} \nabla \mathcal{L} = 0 &\Leftrightarrow \frac{\mu[wCw^T]^{-\frac{1}{2}} - (\mu w^T - R)[wCw^T]^{-\frac{3}{2}}wC}{wCw^T} - \lambda u = 0 \\ &\Leftrightarrow \mu - \lambda[wCw^T]^{\frac{1}{2}}u = \frac{\mu w^T - R}{wCw^T}wC. \end{aligned} \quad (10)$$

By multiplying with  $w^T$  on the right and using the constraint, we get

$$\lambda = \frac{R}{[wCw^T]^{\frac{1}{2}}}.$$

Plug in back to (10), we have

$$\mu - Ru = \gamma wC, \quad (11)$$

where  $\gamma := \frac{\mu w^T - R}{wCw^T}$  (observe that  $\gamma$  depends on  $w$ ).

Multiplying by  $C^{-1}u^T$  on the right, we get

$$\gamma = (\mu - Ru)C^{-1}u^T. \quad (12)$$

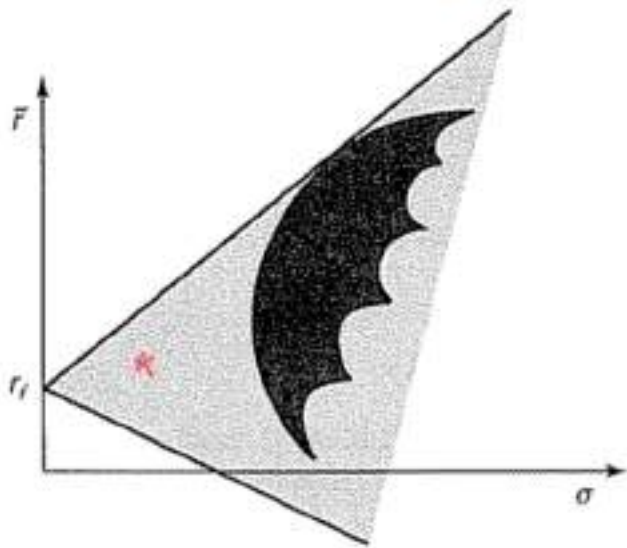
Note that the RHS is independent of  $w$  now.

To solve  $w$  from (11), we have to make sure that  $\gamma \neq 0$ . Recall that

$$\begin{aligned} \mu_{\text{MVE}} = w_{\text{MVE}}\mu^T &= \frac{uC^{-1}\mu^T}{uC^{-1}u^T} = \frac{\mu C^{-1}u^T}{uC^{-1}u^T} \stackrel{\text{Assumption}}{>} R \\ &\Leftrightarrow \mu C^{-1}u^T - RuC^{-1}u^T > 0 \Leftrightarrow \gamma > 0. \end{aligned}$$

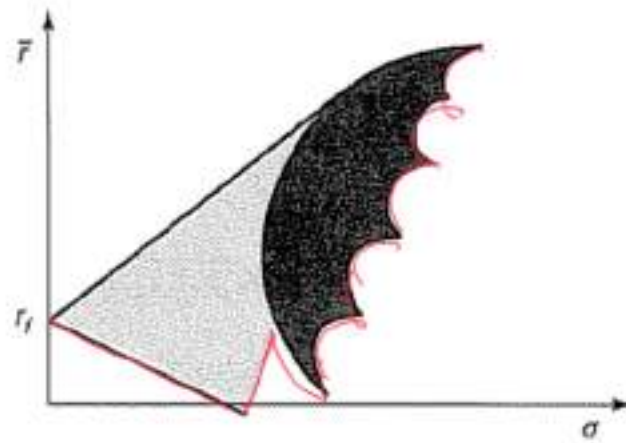
Combine (11) and (12) to get the required form.  $\square$

With short-selling



(a)

Without short selling



(b)

FIGURE 6.13 Effect of a risk-free asset. Inclusion of a risk-free asset adds lines to the feasible region (a) If both borrowing and lending are allowed, a complete infinite triangular region is obtained (b) If only lending is allowed, the region will have a triangular front end, but will curve for larger  $\sigma$

Does the market port always exists?

→ if  $C$  is invertible and  $R < \mu_{MVP}$  then Yes.

→ And it's unique (given  $C$ )



No way of drawing a tangent to the Markowitz bullet.

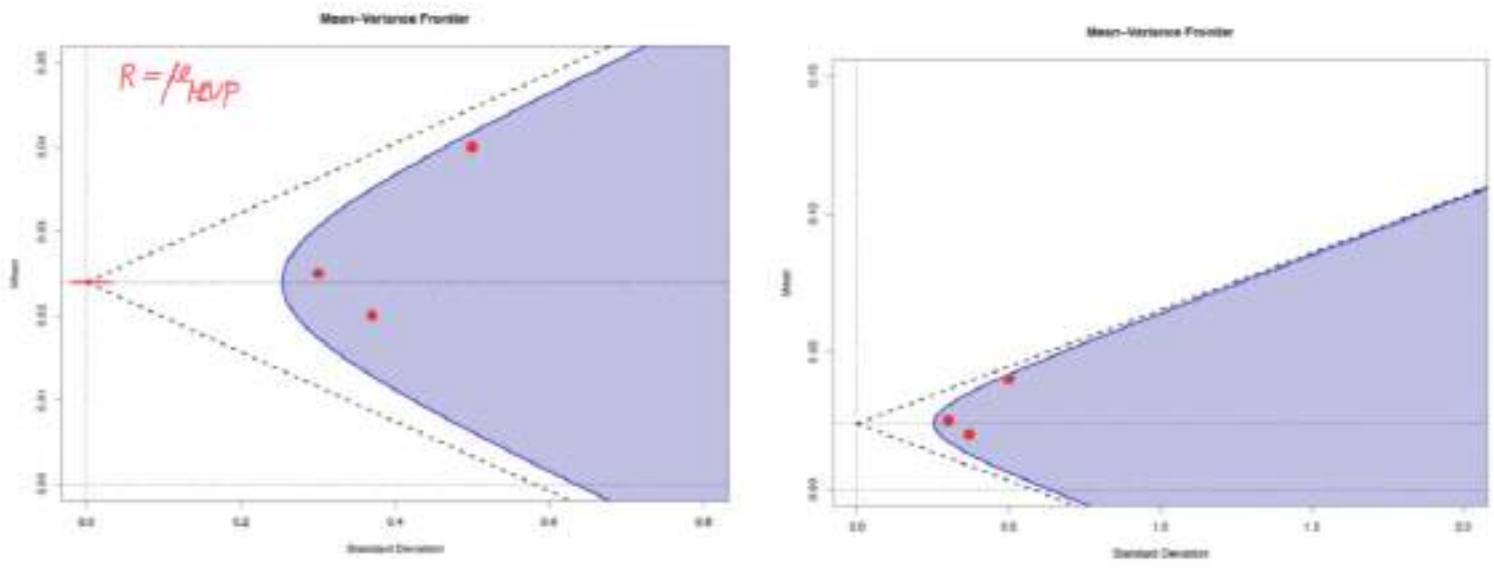


Figure 5: Left/ Right: Non-existence of tangency portfolio.

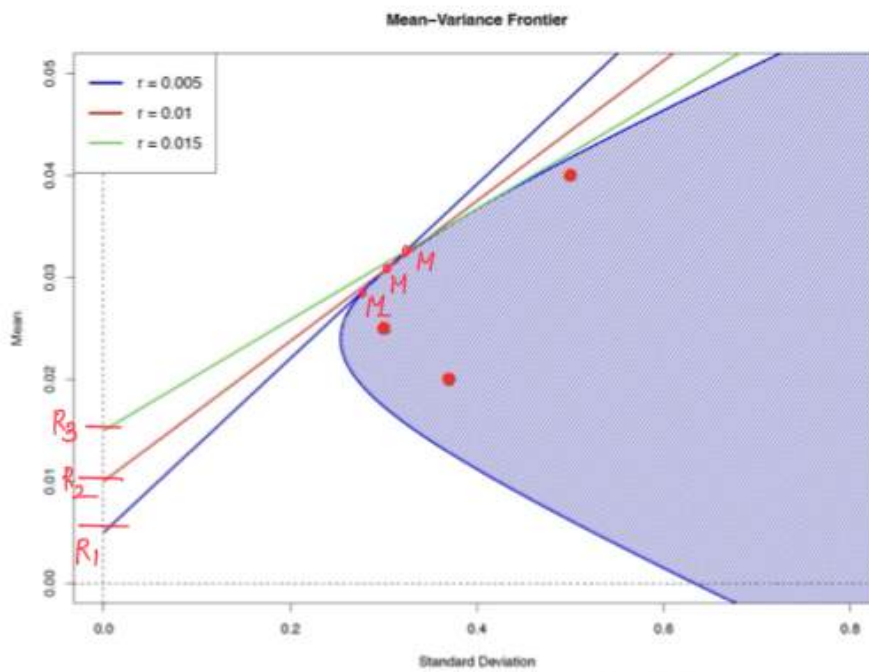


Figure 6: Market portfolio for various risk-free returns  $R$ .

Why the name Market portfolio?

- It contains every risky asset (N many).
- The weights of asset  $i$  is equal to their relative shares in the market.

---

## Capital Market line (CML)

---

Assumptions:

- No transaction cost
- • Every investor has access to same RF  $R$ .
- MVP • every investor has the same exp return ( $\mu$ ) and same cov matrix ( $\Sigma$ ).
- $R < \mu_{MVP}$
- all assets are inf. divisible.

☑ What happens under all the assumptions?

- One fund theorem says: everyone in the market will invest in single risky fund  $M$  and RF asset  $R$ .
- The single risky asset is  $M$ .
- Everyone has access to the same  $M$ .

Theorem: The CML satisfies.

$$\mu_v = R + \frac{\mu_M - R}{\sigma_M} \sigma_v$$

← CML  
(set of all efficient points).

↙ Risk-premium.

$$\text{Risk-premium} : \frac{\mu_M - R}{\sigma_M} \sigma$$

↳ The extra return one gets for taking Risk.

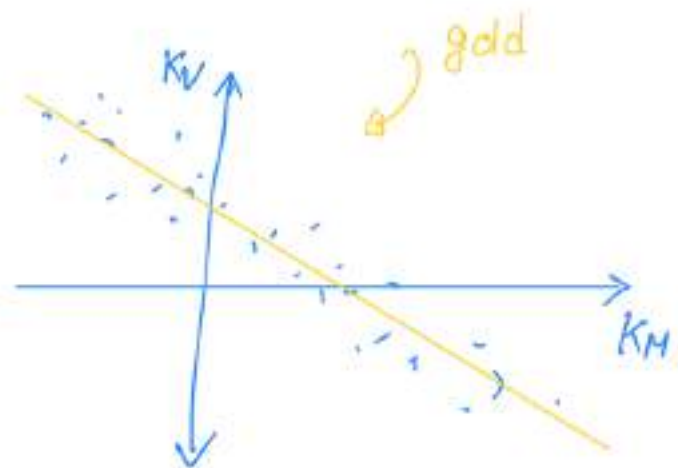
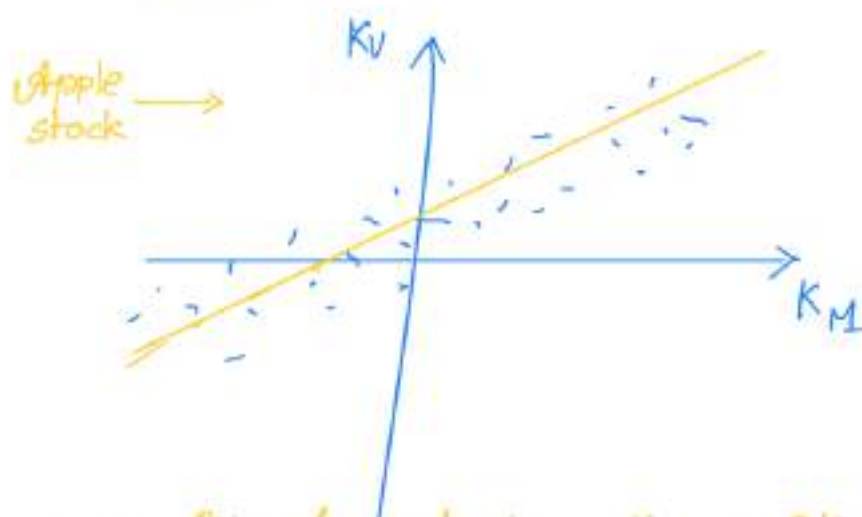
$$\text{Price of Risk} : \frac{\mu_M - R}{\sigma_M}$$

→ If we increase risk then the total exp-return also increases.

## Capital Asset Pricing Model (CAPM)

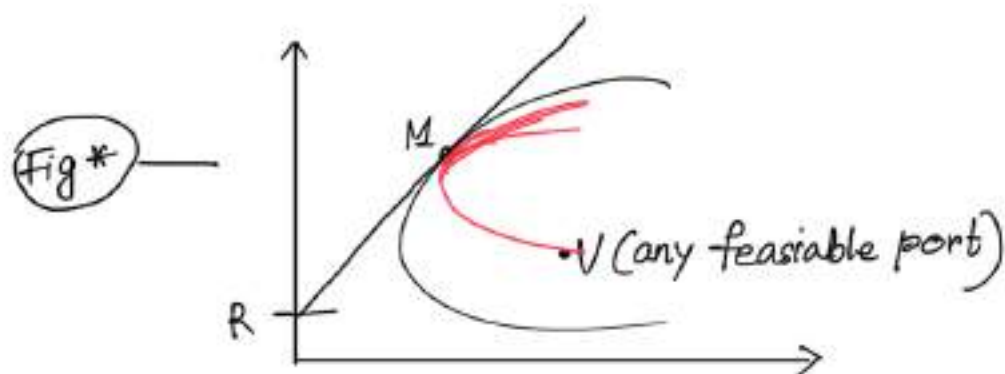
☑ CML only gives the risk-exp return relationship for EP.

It does not show how the  $\mu$  of an individual asset relates to its  $\sigma$ .



We will characterize this with beta of a portfolio.

Note: CAPM is applicable to any feasible portfolio.



(Please see the details on lecture note).

Is CML still tangent to the Red curve?

→ Yes.

Def<sup>n</sup> (Beta of a portfolio)

Beta factor of port V is given by

$$\beta_V = \frac{\text{Cov}(K_V, K_M)}{\sigma_M^2}$$

Using the arguments from fig (\*) one can construct the eq for CAPM: (See lecture note).

Theorem: Suppose  $R < \mu_{MVP}$ . Under the assumption that Market portfolio is efficient, then the expected return  $\mu_V$  for any feasible portfolio V is given by CAPM:

$$\mu_V = R + \beta_V (\mu_M - R)$$

Remark:  $\beta_M = 1$   $\beta_V = \frac{\text{Cov}(K_V, K_M)}{\sigma_M^2}$

$$\beta_R = 0$$

## Summarizing assumptions of CAPM:

- All investors select portfolios by mean-variance optimization. ←
- All investors have the same investment horizon. ←
- All investors use the same mean return vector and covariance matrix. ↗
- Individual investors may have different levels of risk aversion.
- Assets are infinitely divisible. ←
- No taxes and transaction costs.
- The market is in equilibrium.

Spring  
2020

Week - 9

Game Theory

Remember to submit "Tutorial Suggestion" on KEATS by today.

What is a game?

Def<sup>n</sup>

A game in strategic form (Normal form) is a tuple  $G = (N, \{S_i\}_{i \in N}, \{u_i\}_{i \in N})$  where

$N :=$  set of all players in the game. (for us 2-players)

say  $N = \{1, 2\} / \{P_1, P_2\}$

$S_i :=$  set of all actions/strategies for player  $i$ .

$$S := \prod_{i \in N} S_i \times S_2 \times \dots \times S_n$$

↳ set of all strategies in the game  $G$ .

$$u_i : S \longrightarrow \mathbb{R} \quad \forall i \in N$$

↳ the utility/payoff for player  $i$ .

Example: (Matching Pennies)



We toss a coin  $\begin{matrix} \swarrow H \\ \searrow T \end{matrix}$

P1: wants to guess what P2 is going to say (Match)

P2: wants to guess the opposite of P1 (miss-match)

We use a matrix to represent the game:

P2

		P2	
		h	t
P1	H	1,0	0,1
	T	0,1	1,0

$G = (N, \{S_i\}_{i \in N}, \{u_i\}_{i \in N})$

$$N = \{1, 2\} / \{P1, P2\} / \{\text{Row, Column}\}$$

$$S_1 = \{H, T\}$$

$$S_2 = \{h, t\}$$

set of all

The strategy for the game

$$S = S_1 \times S_2$$

$$= \{H, T\} \times \{h, t\}$$

$$= \{H \times h, H \times t, T \times h, T \times t\}$$

$$u_1: S \rightarrow \mathbb{R}$$

$$H \times h \mapsto 1$$

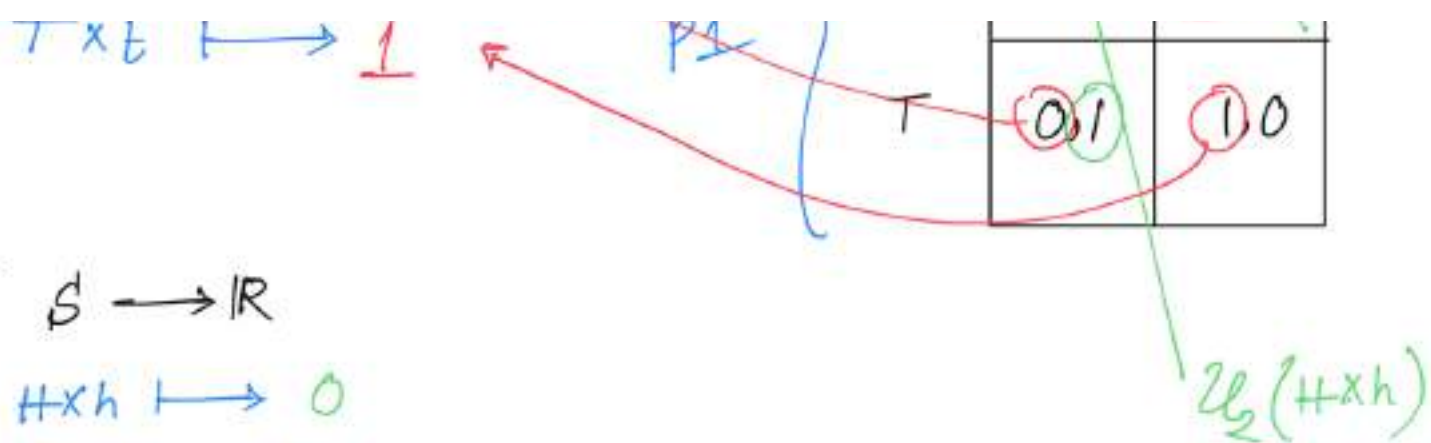
$$H \times t \mapsto 0$$

$$T \times h \mapsto 0$$

$$T \times t \mapsto 1$$

		P2	
		h	t
P1	H	1,0	0,1
	T	0,1	1,0

$u_1(H \times h)$



$u_2: S \rightarrow \mathbb{R}$

- $H \times h \mapsto 0$
- $H \times b \mapsto 1$
- $T \times h \mapsto 1$
- $T \times b \mapsto 0$

Def<sup>n</sup> (Finite Game)

We say a game  $G$  if  $N$  and  $S$  both are finite.

↑ # players.  
 ↑ set of all strategies.

Def<sup>n</sup>: (Pure) Nash-Equilibrium (NE)

are element of  $S$   
 (last ex:  $H \times b$   
 Not st. profile  $h \times T$   
 or  $h \times h$

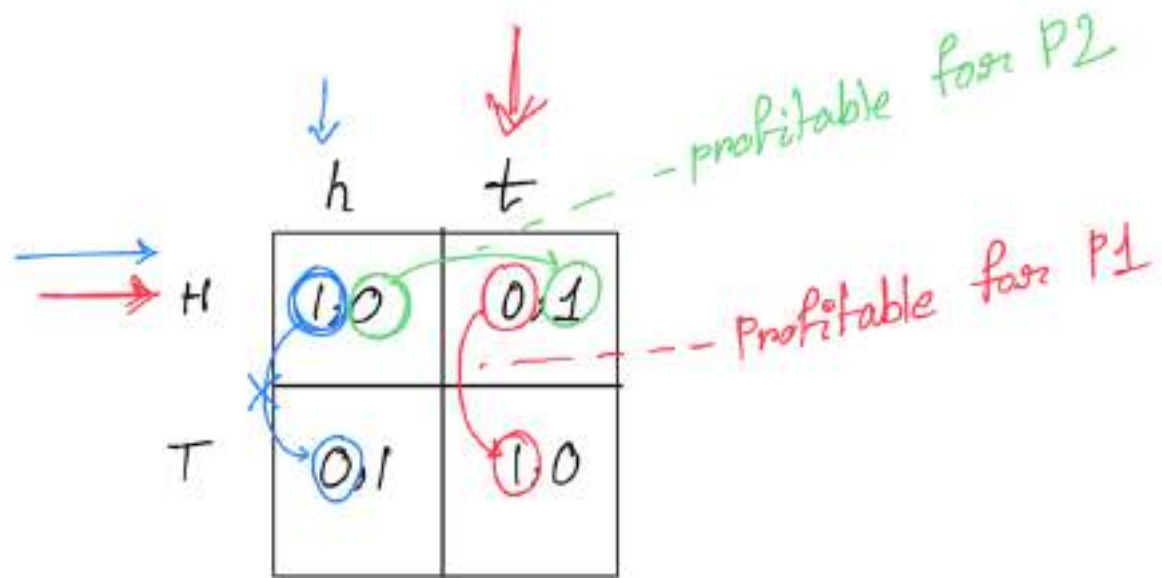
A strategy profile  $s^* \in S$  is a Nash Equilibrium (NE) if

$u_i(s_i^*, s_{-i}^*) \geq u_i(s_i, s_{-i}^*) \quad \forall s_i \in S_i$

$s^* = s_1^* \times s_2^* \dots \times s_n^*$   
 $s_{-i}^* = s_1^* \times \dots \times s_{i-1}^* \times \dots \times s_{i+1}^* \dots \times s_n^*$

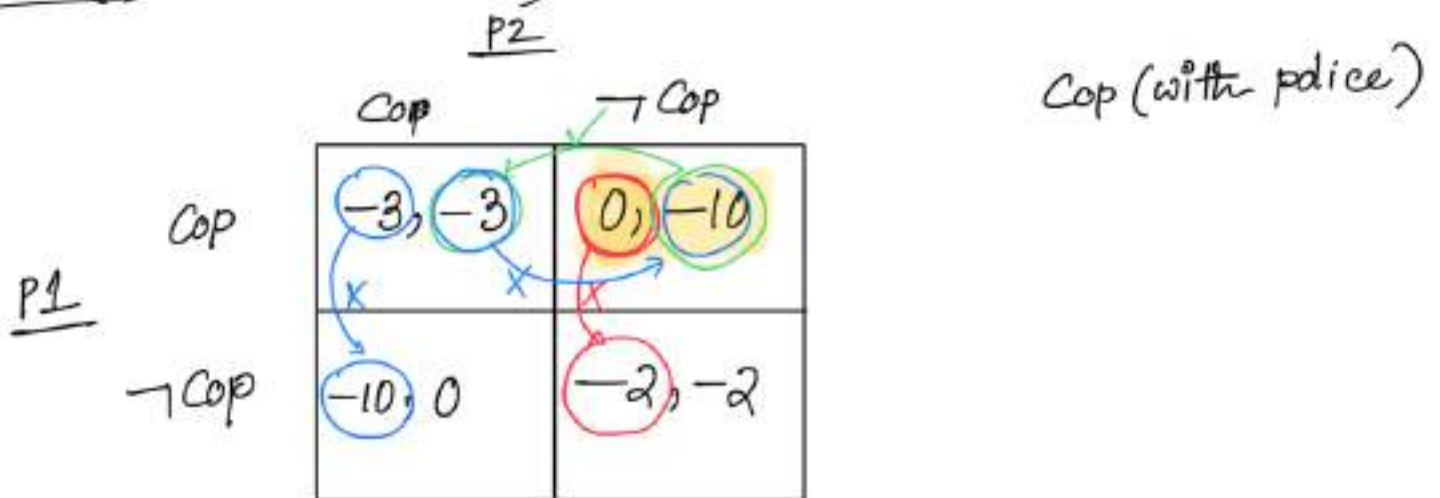
$(t_i, s_{-i}^*) := s_1^* \times s_2^* \dots \times s_{i-1}^* \times t_i \times s_{i+1}^* \dots \times s_n^*$

Nothing but saying "no player has any incentive to move (to a different strategy)"



This game does not have a (pure) NE

EX 2: (Prisoners' dilemma)



$(C, C)$  is a Pure NE ✓✓  
No other pure NE (check)

- Split or steal
  - Stage Hunt
  - Battle of sexes.
- } (HW) try to find pure NE

Remark: for a finite game  $G$  one can have NO pure NE, or have 1 pure NE, or have  $> 1$  pure NE.

Def<sup>n</sup>: (Dominated strategy).

A strategy  $s_i \in S_i$  for player  $i$  in a game  $G$

dominated (also known as strictly dominated) if  $\exists t_i \in S_i$

st:

$$u_i(s_{-i}, t_i) > u_i(s_{-i}, s_i)$$

Def<sup>n</sup>: (**Weakly** dominated strategy)  $\leftarrow$  unless explicitly mentioned we will not use.

A strategy  $s_i \in S_i$  for player  $i$  in a game  $G$   
dominated (also known as strictly dominated) if  $\exists t_i \in S_i$

st:

$$u_i(s_{-i}, t_i) \geq u_i(s_{-i}, s_i)$$

Imp Theorem: (Dominance Principal)

Let  $G = (N, \{S_i\}_{i \in N}, \{u_i\})$ .

Let  $d_j \in S_j$  be a dominated strategy of player  $j$ .

Define:

$$G' = (N, \{S'_i\}_{i \in N}, \{u'_i\}_{i \in N})$$

$$S'_i = \begin{cases} S_i & \text{for } i \neq j \\ S_j \setminus \{d_j\} & i = j \end{cases}$$

and  $u'_i$  is the restriction of  $u_i$  to  $S'_i$ .

Then every pure NE of  $G$  is in  $S'$ .

$\rightarrow$  if  $c \in S'$  is a pure NE in  $G'$   $\rightarrow$   $c$  is a pure

$\Rightarrow$  If  $SE$  is a pure NE  $\rightarrow$   $SE$  is a NE in  $G$ .

Theorem: Fix a <sup>finite</sup> game  $G$ . and let  $G_1$  be a game that is

- ① is the result of repeated elimination of dominated strategies from  $G$ .
- ② NO dominated strategies left.

Say  $G_2$  be another such game.

Then:  $G_1 = G_2$

and  $NE$  of  $G_1 = NE$  of  $G_2 = NE$  of  $G$ .

Example:

$G^* =$

	P2 $\rightarrow$	X	Y	Z	
P1 $\downarrow$					
A		4, 3	5, 1	6, 2	$Z > Y$ $2 > 1$ $6 > 4$ $8 > 6$
B		2, 1	8, 4	3, 6	
C		3, 0	9, 6	2, 8	

}  $Z > Y$  dominates st.

$\Downarrow$

	P2	X	Z	
P1				
A		4, 3	6, 2	4 > 3 6 > 2
B		2, 1	3, 6	
C		3, 0	2, 8	

$$\Downarrow$$

	X	Z
A		
B		

$$\Downarrow$$

	X	Z
A	4,3	6,2

$3 > 2$

$$\Downarrow$$

	X
A	4,2

$\Downarrow$

the pure NE is  $(A, X)$

(theorem)  $\implies (A, X)$  is pure NE of  $G^*$ .

HW: Reverify  $(A, X)$  is the <sup>only</sup> pure NE of  $G^*$  just from the def<sup>n</sup> of pure NE.

---

Remark:

- Every game may not be reduced to  $1 \times 1$  game.
- We can have games where we have no dominated strategy to start with.

Ex:

$P_1 \backslash P_2$	X	Y	Z
A	3, 3	2, -2	5, -5
B	4, -4	3, -3	6, -6
C	1, -1	4, -4	3, -3

$A \times B$   
 $Z \times X$

We can not reduce further.

Def<sup>n</sup> (Dominant strategy): (please see Note)

$$u_i(s_i, s_i) > u_i(s_{-i}, t_i); \quad \forall t_i \in S_i$$

$\Leftrightarrow S_i$  is dominant.

Theorem: If player  $i$  has a dominant strategy  $d_i \in S_i$   
then ~~every~~ for every NE in the game  $G$

say  $S^*$  is NE

$$\text{then } S^* = S_1^* \times S_2^* \times \dots \times S_n^*$$

$$\text{and } S_i^* \equiv d_i$$

# Mixed NE / NE

Notation: Given a set  $X$ ; we denote  $\Delta X$  the set of all prob. distribution over  $X$ .

$$S = S_1 \times S_2 \\ = \{H, T\} \times \{h, t\}$$

	$h$	$t$
$H$	1, 0	0, 1
$T$	0, 1	1, 0

$$\Delta S = \left\{ (p, 1-p) \times (q, 1-q) \mid p, q \in [0, 1] \right\}$$

$$\Delta S_1 = \left\{ (p, 1-p) \mid p \in [0, 1] \right\}$$

$$\Delta S_2 = \left\{ (q, 1-q) \mid q \in [0, 1] \right\}$$

Now  $(p, 1-p)$  represent  
P1 chooses H w.p.  $p$   
P1 chooses T w.p.  $(1-p)$

for ex: take  $p=0, q=0$

$$\Rightarrow \left\{ (0, 1) \times (0, 1) \right\} \Rightarrow \text{our old } (T, t)$$

Week - 10

Math - Finance - II

HW 10 : (Week 10 + Week 11)

Mixed NE

Recall: Given a finite set  $(X)$  we denote  $(\Delta X)$  to be the distribution over  $X$ .

say  $S_1 = \{H, T\}$   $S_2 = \{H, T\}$

$$\rightarrow \Delta S_1 = \left\{ (p, 1-p) \mid p \in [0, 1] \right\}$$

$\swarrow$   $\searrow$   $\swarrow$   $\searrow$

#      T       $\swarrow$  prob of #

$\Delta S := \Delta S_1 \times \Delta S_2$  for Player 1

$$= \left\{ (p, 1-p); (q, 1-q) \mid p, q \in [0, 1] \right\}$$

$\rightarrow p :=$  prob of H for player 1.

$q :=$  2.

$\downarrow$        $\downarrow$   
h      t

$\rightarrow$ H	1, 0	0, 1
$\rightarrow$ T	0, 1	1, 0

For example:

$$\sigma = \left\{ \left( \frac{1}{5}, \frac{4}{5} \right); \left( \frac{2}{3}, \frac{1}{3} \right) \right\}$$

$\swarrow$   $\swarrow$   $\swarrow$   $\swarrow$

sum upto 1

Remember: A pure strategy was  $(T, h)$

$\uparrow$   
p1 choses T w.p 1

This is  $\sigma = \{(0, 1); (1, 0)\}$   
 $(0, 1)$

---

▣ Linking NE of  $G_C$  to a pure NE of  $\hat{G}_C$ .

$G_C = (N, \{S_i\}, \{u_i\})$  is finite game.

Define  $\hat{G}_C = (\hat{N}, \{\hat{S}_i\}, \{\hat{u}_i\})$

$$\hat{N} = N$$

$$\hat{S}_i = \Delta S_i \quad (\text{Note not finite anymore})$$

$$\hat{u}_i : \Delta S_1 \times \Delta S_2 \times \dots \times \Delta S_N \longrightarrow \mathbb{R}$$

$$\sigma = \sigma_1 \times \sigma_2 \times \dots \times \sigma_N \longmapsto \underbrace{E_{\sigma_1 \sigma_2 \dots \sigma_N}(u_i(s))}_{\sigma}$$

“this is exp payoff  
when exp is taken  
wrt the mixed strategy  
 $\sigma$ ”

Then any pure NE of  $\hat{G}_C$   
is a NE of the game  $G_C$ .

How to calculate  $u_i(\sigma)$  for any  $\sigma \in \Delta S_1 \times \Delta S_2 \dots \Delta S_N$ .

Example:

	h	t
H prob $p$ to choose $\frac{1}{3}$	1, 0	0, 1
T prob $(1-p)$ $\frac{2}{3}$	0, 1	1, 0

prob  $q=1$  (pointing to h)  
 prob  $1-q=0$  (pointing to t)

Say  $\sigma = \left\{ \left( \frac{1}{3}, \frac{2}{3} \right); (1, 0) \right\}$

payoff for (H, h)      prob of H for P1  
 prob of h of P2

$u_1(\sigma) = 1 \times \frac{1}{3} \times 1$

$+ 0 \times \frac{1}{3} \times 0 + 0 \times \frac{2}{3} \times 1 + 1 \times \frac{2}{3} \times 0$

Player 1

$= \begin{bmatrix} \frac{1}{3} & \frac{2}{3} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

P1's strategy

P2's strategy

the first components of payoff matrix

$$u_2(\sigma) = \left(\frac{1}{3} \quad \frac{2}{3}\right) \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix}.$$

---

Key Theorem (Nash 1950)

Every finite game has a NE.

- Note:
- A game may not have a pure NE
  - A game can have more than 1 NE. Even more than 1 pure NE

Proof: The proof is by Brouwer's fixed point theorem.

**Theorem 4.2** (Brouwer's Fixed Point Theorem). Let  $X$  be a compact convex subset of  $\mathbb{R}^d$ . Let  $T: X \rightarrow X$  be continuous. Then  $T$  has a fixed point, i.e., there exists an  $x \in X$  such that  $T(x) = x$ .

A simple application: If you are in a room and hold a map of the room horizontally, then there is a point in the map that is exactly above the point it represents.

---

How to find set of all NE of a Game.

---

### Best Response

Let  $\sigma$  be any NE in the game  $G$ .

We say  $s_i \in S_i$  is a best response to  $\sigma_{-i}$  if

$$\forall t_i \in S_i : u_i(\sigma_{-i}, s_i) \geq u_i(\sigma_{-i}, t_i)$$

Note: It is not difficult to generalize this to  $\Delta S_i$ .

**Proposition 4.3.** Let  $G = (N, \{S_i\}_{i \in N}, \{u_i\}_{i \in N})$  be a finite strategic game. Then,  $\sigma^* = (\sigma_1^*, \dots, \sigma_N^*)$  is a mixed Nash equilibrium of  $G$  if and only if for every player  $i$ , every pure strategy  $s_i$  in the support of  $\sigma_i^*$  (i.e., any  $s_i$  to which  $\sigma_i^*$  assigns positive probability) is a best response to  $\sigma_{-i}^*$ .

*Proof.* Suppose  $s_i \in S_i$  is in the support of  $\sigma_i^*$ , but is not a best response to  $\sigma_{-i}^*$ , and let  $t_i \in S_i$  be some best response to  $\sigma_{-i}^*$ . We will prove the claim by showing that  $t_i$  is a profitable deviation for  $i$ .

Let  $C = u_i(\sigma_{-i}^*, t_i)$ . Then  $u_i(\sigma_{-i}^*, r_i) \leq C$  for any  $r_i \in S_i$ , and  $u_i(\sigma_{-i}^*, s_i) < C$ . It follows that

$$\begin{aligned} u_i(\sigma^*) &= \sum_{r_i \in S_i} \sigma_i^*(r_i) u_i(\sigma_{-i}^*, r_i) \\ &< C \end{aligned}$$

and so  $t_i$  is indeed a profitable deviation, since it yields utility  $C$  for  $i$ .

It follows that if  $\sigma^*$  is an equilibrium then  $u_i(\sigma_{-i}^*, s_i)$  is the same for every  $s_i$  in the support of  $\sigma_i^*$ . That is,  $i$  is indifferent between all the pure strategies in support of her mixed strategy.  $\square$

It simply says a NE is something like NO Profitable deviation

Def<sup>n</sup>: (Completely mixed strategy)

We say  $\sigma_i \in \Delta S_i$  is a completely mixed strategy

↳ strategy for Player i?

if each  $s_i \in S_i$  are assigned strictly +ve prob.

Ex:  $\sigma_i = \left(\frac{1}{3} \quad \frac{2}{3}\right)$  is a completely mixed <sup>(CM)</sup> st.

$\sigma_i = (0 \quad 1)$  is a pure strategy.

A strategy does not have to be either pure or CM

↳  $\sigma_i = \left(\frac{1}{3} \quad 0 \quad 0 \quad 0 \quad \frac{1}{3} \quad \frac{1}{3}\right)$

☑ Often a strategy is called "Randomized Strategy" if it is not a pure strategy.

$$\sigma = \sigma_1 \times \sigma_2$$

$$= \left\{ \left(\frac{1}{3}, \frac{2}{3}\right); (1, 0) \right\}$$

•  $\sigma$  as a strategy profile is Not CM

..... is CM

- $\sigma_1$ : P1's strategy is  $\dots$
- $\sigma_2$ : P2's strategy is pure strategy.

Example: set of all NE

Take

$$G = \begin{array}{c|cc} & A & B \\ \hline a & 1,1 & 1,0 \\ \hline b & 0,1 & 4,4 \end{array}$$

Qn: We want to calculate set of all NE in  $G$ .

Step-1 : check for row/column domination.

For this game NO domination.

if  $a \succ b$   
 or  $b \succ a$   
 or  $A \succ B$   
 or  $B \succ A$  }  $\Rightarrow$  domination.

Step-2 Find set of all pure st (one can skip)

$$\begin{array}{c|cc} & A & B \\ \hline a & 1,1 & 1,0 \\ \hline b & 0,1 & 4,4 \end{array}$$

*(Note: In the original image, the cells (1,1) and (1,0) are circled in green, and the cell (0,1) is circled in yellow. There are also arrows and 'x' marks indicating comparisons between these cells.)*

- take  $(a, A) = \{(1, 0); (1, 0)\}$ 
  - Best response.
  - No profitable deviation
  - ⇒ pure NE
- $(b, B) \Rightarrow$  pure NE
- $(a, B) \Rightarrow$  NOT pure NE
- $(b, A) \Rightarrow$  NOT pure NE.

Step-3 Find all NE using best response.

From Nash's theorem we know  $\exists \sigma^*$  which is a NE of the game.

Assume  $\sigma^*$  is a NE of the game  $G$ .

$$\sigma^* = \left\{ (p^* \ 1-p^*); (q^* \ 1-q^*) \right\}$$

		$\downarrow q^*$	$\downarrow 1-q^*$
		A	B
$\xrightarrow{p^*}$	a	1, 1	1, 0
$\xrightarrow{1-p^*}$	b	0, 1	4, 4

Now: fix player 1.

then  $\sigma_1^* = (p^* \ 1-p^*)$  is a best response to  $\sigma_{-1}^*$

$$\Rightarrow u_1(\sigma^*) \geq u_1(\sigma_{-1}^*, x) \quad \forall x \in \Delta S_1$$

$$\Leftrightarrow (p^* \ 1-p^*) \begin{bmatrix} 1 & 1 \\ 0 & 4 \end{bmatrix} \begin{bmatrix} q^* \\ 1-q^* \end{bmatrix} \geq (p \ 1-p) \begin{bmatrix} 1 & 1 \\ 0 & 4 \end{bmatrix} \begin{bmatrix} q^* \\ 1-q^* \end{bmatrix}$$

$\forall p \in [0, 1]$

$$\Leftrightarrow (p^* - p) (1 - 4(1 - q^*)) \geq 0 \quad \forall p \in [0, 1].$$

$$\Leftrightarrow \begin{cases} \text{Either } 1 - 4(1 - q^*) = 0 \Rightarrow q^* = \frac{3}{4} ; p^* \in [0, 1] \\ \text{or } p^* = 1 \text{ and } 1 - 4(1 - q^*) > 0 \Rightarrow q^* \geq \frac{3}{4} \\ \text{or } p^* = 0 \text{ and } 1 - 4(1 - q^*) < 0 \Rightarrow q^* \leq \frac{3}{4}. \end{cases}$$

Let's repeat for player 2

$$u_2(\sigma^*) \geq u_2(\sigma_{-2}^*, y) \quad \forall y \in \Delta S_2.$$

$$\Leftrightarrow \begin{cases} \text{Either } 1 - 4(1 - p^*) = 0 \Rightarrow p^* = \frac{3}{4} \text{ and } q^* \in [0, 1] \\ \text{or } q^* = 1 \text{ and } p^* \geq \frac{3}{4} \\ \text{or } q^* = 0 \text{ and } p^* \leq \frac{3}{4} \end{cases}$$

say  $p^* = 0 \Rightarrow q^* = 0.$

$$p^* = 1 \implies q^* = 1$$

$$q^* = \frac{3}{4} \implies p^* = \frac{3}{4}$$

and no other feasible options.

so set of all NE:  $\rightarrow$  NE (mixed/general NE)

$\rightarrow$  Pure NE

①  $\{(0, 1); (0, 1)\}$

$\rightarrow$  Randomized NE

②  $\{(1, 0); (1, 0)\}$

$\rightarrow$  Completely mixed NE

③  $\left\{ \left( \frac{3}{4}, \frac{1}{4} \right); \left( \frac{3}{4}, \frac{1}{4} \right) \right\}$

Another consequence:

(Support prop):

If  $\sigma^*$  is a NE; and  $s_i \in S_i$  is assigned  $> 0$  prob on  $\sigma^*$

similarly say  $s'_i \in S_i$  is also assigned  $> 0$  prob on  $\sigma^*$

Then:  $u_i(\sigma_{-i}^*, s_i) = u_i(\sigma_{-i}^*, s'_i)$

**Proposition 4.4** (Support Property). In any mixed equilibrium  $\sigma^*$ , all pure strategies  $s_i$  (for both players) that receive positive probability under  $\sigma^*$  yield equal expected payoffs:

$$u_i(\sigma_{-i}, s_i) = u_i(\sigma_{-i}, s'_i) \quad \text{for all } s_i, s'_i \in \text{Supp}(\sigma_i^*).$$

Otherwise, the player could shift probability towards the more profitable pure strategy.

This leads to the so-called Indifference Principle, often used to compute mixed equilibria in  $2 \times 2$  games.

Note: (Added after class),

there might have been some confusion with notation during class. The following three terms are all the same.

$$u_i(\sigma^*) = u_i((\sigma_1^* \dots \sigma_n^*)) = u_i(\sigma_{-i}^*, \sigma_i)$$

Zero-Sum Games

finite.

A two player game  $G = (\{P_1, P_2\}, \{S_1, S_2\}, \{u_1, u_2\})$

is called zero-sum if  $u_1 + u_2 = 0$

$$\begin{cases} u_1 : S_1 \times S_2 \rightarrow \mathbb{R} \\ u_2 : S_1 \times S_2 \rightarrow \mathbb{R} \end{cases}$$

$$u_1 + u_2 = 0 \iff \forall s_1 \times s_2 \in S_1 \times S_2$$

$$u_1(s_1, s_2) = -u_2(s_1, s_2)$$

Example:

$$G = \begin{array}{|c|c|} \hline 1, -1 & -1, 1 \\ \hline 2, -2 & 4, -4 \\ \hline 3, -3 & -2, 2 \\ \hline \end{array}$$

a zero-sum  
game

1	-1
2	4
3	-3

standard notation.

Remark:

This is a game with co-operative component.

4, 3	0, 0
0, 0	3, 4

A zero-sum game can never have a co-operative

component.

$\Leftrightarrow P1$ 's Gain =  $P2$ 's loss.

and  $P1$ 's loss =  $-P2$ 's gain.

(\*) Player 1's perspective:

$P1$  knows  $P2$  will try to max  $P2$ 's profit.

$\Rightarrow P1$  will try to prepare for worst possible outcome.

"Worst possible outcome" = given  $P1$ 's strategy

$P2$  will choose the strategy  $\sigma_2 \in \Delta S_2$

which gives  $\max u_2 \Leftrightarrow \min u_1$ .

$$u_g(\sigma_1) = \min_{\sigma_2 \in \Delta S_2} u_1(\{\sigma_1, \sigma_2\})$$

↑  
The guaranteed payoff  $P1$  will receive  
by playing the strategy  $\sigma_1 \in \Delta S_1$

Now  $P1$  will try to maximize their own payoff.

$$\sigma_1^* = \operatorname{argmax}_{\sigma_1 \in \Delta S_1} u_g(\sigma_1)$$

$$= \operatorname{argmax}_{\sigma_1 \in \Delta S_1} \min_{\sigma_2 \in \Delta S_2} u_1(\{\sigma_1, \sigma_2\})$$

\* Same argument can be done from a P2's perspective.

$$\sigma_2^* = \arg \min_{\sigma_2 \in \Delta S_2} \max_{\sigma_1 \in \Delta S_1} u_1(\{\sigma_1, \sigma_2\})$$

should be  $\underline{v}$

$$\overline{v} = \max_{\sigma_1 \in \Delta S_1} \min_{\sigma_2 \in \Delta S_2} u_1(\{\sigma_1, \sigma_2\}) \geq \min_{\sigma_2 \in \Delta S_2} \max_{\sigma_1 \in \Delta S_1} u_1(\{\sigma_1, \sigma_2\}) = \underline{v}$$

→ should be  $\leq$ 
→ should be  $\overline{v}$

The one in typed note was correct.

Theorem: (Von-Neumann) In a zero-sum game

$$\overline{v} = \underline{v}$$

$\overline{v} = \underline{v}$  is also known as value of the game.

### Notations for zero-sum game

• A zero-sum game is always represented by matrix.

$$A = (a_{ij})_{i=1, j=1}^{m, n}$$

• P1 — always represents row player.

• P2 — always the column player.

•  $S_1 = \{1, \dots, m\}$

•  $S_2 = \{1, \dots, n\}$

•  $S = \{i \in S_1 \vee j \in S_2 \mid i \in \{1, \dots, m\}\}$

$$P = P_1 \wedge P_2 = \{ (i, j) \mid i \in \{1, \dots, m\}, j \in \{1, \dots, n\} \}$$

- $a_{ij}$  is the payoff P1 gets when P1 plays  $i \in S_1$   
P2 plays  $j \in S_2$

- $(-a_{ij})$  ----- P2 -----

- $u =$  utility of player 1 ( $= u_1$ )

we write  $-u$  to represent  $u_2$ .

- The strategy of P1 will be written as  $x = (x_1 \dots x_m)$   
with  $x_1 + x_2 \dots + x_m = 1$

- The strategy of P2 will be written as  $y = (y_1 \dots y_n)$   
with  $y_1 + \dots + y_n = 1$

- $u(x, y) \stackrel{\text{(from last class)}}{=} x A y^T = \sum_{i=1}^m \sum_{j=1}^n x_i a_{ij} y_j$

$1 \times m$        $m \times n$        $1 \times n$

Imp

Theorem: Take  $G$  to be finite zero sum game with payoff matrix  $A_{m \times n}$ .

Then:

①  $\dots$  NE of the game  $G$ : denote it as  $\sigma^* = (x^*, y^*)$

① Every NE  $\sigma^* = (x^*, y^*)$  is a min-max strategy.

② And they matches with value of the game.

Mathematically;

every NE  $\sigma^* = (x^*, y^*)$ ; we have.

$$\begin{array}{ccc} \max_x \min_y u(x, y) & = & u(x^*, y^*) \\ \parallel & & \parallel \\ \min_y \max_x u(x, y) & = & v \end{array}$$

Note:

- A game can have more than 1 NE
- but the payoff from each NE are the same.
- payoff from any NE matches with value of the game ( $v$ )
- The value of the game is unique

Remark:

$$v(G) = \max \min = \min \max.$$

Theorem: if  $\sigma^* = (x^*, y^*)$  is a NE then:

$$\begin{array}{ccc} \text{Minimum entry of } x^*A & = & \text{max entry of } Ay^* \\ \underbrace{(1 \times m) \times (m \times n)}_{= 1 \times n} & & \underbrace{(m \times n)(1 \times n)^T}_{= n \times 1} \end{array}$$

Proposition: if  $\sigma^* = (x^*, y^*)$  is a NE of the game  $A = (a_{ij})$

then:  $x^* A \geq v [1 \ 1 \ 1 \ \dots \ 1]_{1 \times n}$

$$A(y^*)^T \leq v \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}_{m \times 1}$$

Findin 1 NE in a game  $A$  is a linear-problem and can be completed in polynomial time by solving a convex optimization problem.

(Primal)  $\max_{x \in \mathbb{R}^m, v \in \mathbb{R}} v$   
 s.t.  $\sum_{i=1}^m x_i A_{ij} \geq v, \quad j = 1, \dots, n,$   
 $\sum_{i=1}^m x_i = 1, \quad \leftarrow \text{valid strategy.}$   
*we assign  $\geq 0$  prob.  $\rightarrow x_i \geq 0, \quad i = 1, \dots, m.$*

The dual formulation (again a convex optimization problem) of the above problem is as follows:

(Dual)  $\min_{y \in \mathbb{R}^n, w \in \mathbb{R}} w$   
 s.t.  $\sum_{j=1}^n y_j A_{ij} \leq w, \quad i = 1, \dots, m,$   
 $\sum_{j=1}^n y_j = 1,$   
 $y_j \geq 0, \quad j = 1, \dots, n.$

"Symmetric game is a fair game"

Def<sup>n</sup>: A fair game is a game with value of the game  $v = 0$ .

Def<sup>n</sup>: A symmetric game is a game with anti-symmetric payoff matrix, i.e.

$$A = -A^T$$

Theorem: A symmetric game is always a fair game. i.e.  $v = 0$ .

Proof: A simple consequence of the lemma below.

Lemma: For any payoff matrix  $A$  one has

$$v(A) = -v(-A^T)$$

Proof: 
$$v(-A^T) = \max_{x \in S_1} \min_{y \in S_2} x(-A^T)y$$

$$= \max_x \min_y -x A^T y$$

$$= \max_x - \left( \max_y x A^T y \right)$$

$$= - \min_x \max_y \underbrace{(x A^T y)^T}_{y A x^T}$$

$$= - \min_{\alpha} \max_{\beta} \beta A \alpha^T$$

$$= - \min_y \max_x x A y^T$$

$$= - v(A)$$

---

Saddel point:

- This is another way to find value of the game  $v$

→ Look at the min entry of the column maxima.

if they coincide then this gives value of the game.

$A = \begin{pmatrix} 6 & 8 & 6 \\ 4 & 12 & 2 \end{pmatrix}_{2 \times 3}$

Row minima: 6 ✓, 2  
 Column maxima: 6, 12, 6  
 Value of the game: 6 ✓

Note: We can have 0, 1, > 1 saddle points.

Theorem: every saddle point has same matrix entry = value of the game.

The saddle point corresponds to pure NE.

Ex: Above game.

$\{(1, 0); (1, 0, 0)\}$  is a pure NE

$\{(1, 0); (0, 0, 1)\}$  is a pure NE.

We may not have saddle point:  $\begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix}$

Rock - Paper - Scissors.

R P S

R < P

R > S

P > R

$$A = \begin{matrix} & R & & \\ & P & & \\ & S & & \end{matrix} \begin{pmatrix} 0 & -1 & 1 \\ 1 & 0 & -1 \\ -1 & 1 & 0 \end{pmatrix} \quad r \sim s$$

$A = -A^T \Rightarrow$  symmetric game.

$$\Rightarrow v = 0.$$

Say  $x^* = (x_1^* \ x_2^* \ x_3^*)$  is optimal for P1.

$$\Rightarrow x^* A \geq v \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}$$

$$\Rightarrow \begin{pmatrix} x_1^* & x_2^* & x_3^* \end{pmatrix} \begin{bmatrix} 0 & -1 & 1 \\ 1 & 0 & -1 \\ -1 & 1 & 0 \end{bmatrix} \geq \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}$$

$$\Rightarrow \begin{cases} x_2^* - x_3^* \geq 0 \\ -x_1^* + x_3^* \geq 0 \\ x_1^* - x_2^* \geq 0 \end{cases} + \left( x_1^* + x_2^* + x_3^* = 1 \right).$$

We simply check for equality:

$$x_1^* = x_2^* = x_3^* = \frac{1}{3}.$$

P2

... is the same as:

We get a NE of the game

$$\left\{ \left( \frac{1}{3} \ \frac{1}{3} \ \frac{1}{3} \right); \left( \frac{1}{3} \ \frac{1}{3} \ \frac{1}{3} \right) \right\}$$

