

Discrete framework:

We will mostly carry out these models/methods in their discrete version. This is simpler and importantly allows us to use linear algebra to calculate.

Again  $\Omega$  is outcomes of real world, say

$$\Omega = \{\omega_1, \omega_2, \dots, \omega_n\}$$

Then there are  $2^n$  subsets of  $\Omega$ ,  $\mathcal{A}$  (this is our  $\sigma$ -algebra)

Let  $P$  be a probability measure on  $\Omega$ ,  $P: \mathcal{A} \rightarrow [0, 1]$ .

Define  $p_i = P(\omega_i)$ .

Let  $S(1) : \Omega \rightarrow [0, \infty)$

i.e. for each real world outcome  $\omega_i$

+ there is an associated price  $S(\omega_i)$  of the stock.

i.e. if  $\omega_i$  occurs  $S(1) = S(1; \omega_i) = S^{(\omega_i)}(1)$ .

$$E(S(1)) = \sum_{i=1}^n S^{(\omega_i)}(1) p_i = \underbrace{P^T \cdot S(1)}_{P_i} = S(1)^T \cdot P.$$

$$\text{where } S(1) = \begin{pmatrix} S^{(\omega_1)}(1) \\ S^{(\omega_2)}(1) \\ \vdots \\ S^{(\omega_n)}(1) \end{pmatrix}, P = \begin{pmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{pmatrix} = \langle S(1), p \rangle.$$

~~$$K^{(\omega_i)}(1) = \frac{S^{(\omega_i)}(1) - S(1)}{S(1)}, E(K(1)) = (K(1), P)$$~~

EXAMPLE: 2 SECURITIES, 1 time step. EG (1)

Now we consider eg of 2 securities,

Suppose there are 2 securities  $S_1$  &  $S_2$   
& 3 outcomes,  $\Omega = \{\omega_1, \omega_2, \omega_3\}$ .

Suppose  $S_1(0) = S_2(0) = \$100$

then

Notation:  $S_i(\omega_j) = S_i^{(\omega_j)}(1)$

Value ~~outcom~~ of  $i$ th security  
under outcome  $\omega_j$

Let  $S_1(0) = S_2(0) = \$100$

Let

$$S_1^{\omega_1}(1) = 120 \quad S_2^{\omega_1}(1) = 110 \quad P(\omega_1) = \frac{1}{4}$$

$$S_1^{\omega_2}(1) = \cancel{120} \quad S_2^{\omega_2}(1) = 115 \quad P(\omega_2) = \frac{1}{4}$$

$$S_1^{\omega_3}(1) = 105 \quad S_2^{\omega_3}(1) = 110 \quad P(\omega_3) = \frac{1}{2}$$

Let us organize this info as:

outcome	$S_1(1)$	$S_2(1)$	$P$
$\omega_1$	120	110	$\frac{1}{4}$

$\omega_2$	$\cancel{120}$	115	$\frac{1}{4}$
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$\omega_3$	105	110	$\frac{1}{2}$
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Let us find the expectation + Variance of  
 $S_i + K_i$ ,

$$E(S_1) = \frac{1}{4} 120 + \frac{1}{4} 120 + \frac{1}{2} 105 = \frac{\cancel{120}}{4} + \frac{105}{2} = \cancel{120} + 52.5 = 112.5$$

$$E(S_2) = \frac{1}{4} 110 + \frac{1}{4} 115 + \frac{1}{2} 110 = \frac{445}{4} = \cancel{111.25}$$

$$E(S_1^2) = \frac{1}{4} 120^2 + \frac{1}{4} 120^2 + \frac{1}{2} 105^2 = \cancel{120^2 + 120^2} = 12712.5$$

$$E(S_2^2) = \frac{1}{4} 110^2 + \frac{1}{4} 115^2 + \frac{1}{2} 110^2 = \frac{49525}{4} = 12381.25$$

$$\text{Var}(S_1) = E(S_1^2) - (E S_1)^2 = \cancel{12712.5} - (112.5)^2 = \cancel{5625}$$

$$\text{Var}(S_2) = E(S_2^2) - (E S_2)^2 = 12381.25 - (\cancel{111.25})^2 = 4 \frac{11}{16} = 4.6875$$

$$(7.5)^2 = \text{Var}(S_1) ; (2.17)^2 \approx \text{Var}(S_2)$$

$$E(K_1) = \frac{E S_{1(0)} - S_{1(0)}}{S_{1(0)}} = \frac{12.5}{100} = .125$$

$$E(K_2) = \frac{E S_{2(0)} - S_{2(0)}}{S_{2(0)}} = \frac{111.25}{100} = .1125$$

$$\text{Var}(K_1) = \frac{\text{Var } S_{1(0)}}{S_{1(0)}} = \frac{56.25}{100} = .5625 ; \text{Var } K_2 = \frac{\text{Var } S_{2(0)}}{S_{2(0)}} = \frac{4.6875}{100} = \cancel{.04688}$$

~~Now~~ let us consider buying into Port. @  $t=0$ .

w/  $x_i$  many  $S_i$ :

Value of Port. is (at time  $t=0$ )

$$V(0) = x_1 S_1(0) + x_2 S_2(0)$$

Value of Port @ time  $t=1$

$$V(1) = x_1 S_1(0)(1+K_1) + x_2 S_2(0)(1+K_2)$$

$$= \underbrace{x_1 S_1(0) + x_2 S_2(0)}_{V(0)} + x_1 S_1(0) K_1 + x_2 S_2(0) K_2$$

Find Return of  $V$  -  $K_V$

$$K_V = \frac{V(1) - V(0)}{V(0)} = \frac{x_1 S_1(0) K_1 + x_2 S_2(0) K_2}{V(0)}$$

$$= \left( \frac{x_1 S_1(0)}{V(0)} \right) K_1 + \left( \frac{x_2 S_2(0)}{V(0)} \right) K_2$$

these are weights:

$$\cancel{W_i} = \frac{x_i S_i(0)}{V(0)}$$

Now return on the portfolio is

$$K_v = w_1 K_1 + w_2 K_2 .$$

a random variable,

of course

$$\mathbb{E} K_v = w_1 \mathbb{E} K_1 + w_2 \mathbb{E} K_2 .$$

And

$$\begin{aligned} \text{Var } K_v &= \mathbb{E}(K_v^2) - (\mathbb{E} K_v)^2 \\ &= \mathbb{E}(w_1^2 K_1^2 + 2w_1 w_2 K_1 K_2 + w_2^2 K_2^2) \\ &\quad \left\{ (w_1 \mathbb{E} K_1)^2 + 2w_1 w_2 \mathbb{E} K_1 \mathbb{E} K_2 + (w_2 \mathbb{E} K_2)^2 \right\} \\ &= w_1^2 (\mathbb{E} K_1^2 - (\mathbb{E} K_1)^2) + w_2^2 (\mathbb{E} K_2^2 - (\mathbb{E} K_2)^2) \\ &\quad + 2w_1 w_2 (\mathbb{E} K_1 K_2 - \mathbb{E} K_1 \mathbb{E} K_2) \end{aligned}$$

$$= w_1^2 \text{Var } K_1 + w_2^2 \text{Var } K_2 + 2w_1 w_2 \text{Cov } K_1 K_2$$

$$= w_1^2 \cancel{C_1} + w_2^2 \cancel{C_2} + 2w_1 w_2 \cancel{C_{12}} .$$

$$C_i = \text{Var } K_i$$

~~Note~~

~~$$(w_1^2 C_1 + w_2^2 C_2 + 2w_1 w_2 C_{12})$$~~

~~(w\_1^2 C\_1 + w\_2^2 C\_2)~~

$$C_{12} = \text{Cov}(K_1, K_2)$$

Now Alternatively we can find K chart,

EC(1)

outcome	$K_1$	$K_2$	P
$\omega_1$	.20	.10	$\frac{1}{4}$

$\omega_2$	.20	.15	$\frac{1}{4}$
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$\omega_3$	.05	.10	$\frac{1}{2}$
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And find  $E K_1 = \dots = .125$

(as above)  $E K_2 = \dots = .1125$

$$\text{Var } K_1 = \dots = .5625$$

$$\text{Var } K_2 = \dots = .04688$$

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Working in K is helpful because we are interested in ~~return~~ return, we don't care as much about  $S_i(\Theta)$ .

Now let us return to EC(1)

\* if  $x_1, x_2 > 0$  then

$$\text{Cov}(x_1 S_{1(0)}, x_2 S_{2(0)}) > 0$$

But if  $x_2 < 0 < x_1$  then

$$\text{Cov}(x_1 S_{1(0)}, x_2 S_{2(0)}) < 0.$$

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ie covariance is similar to EC(2)

$\therefore$  Buy stock 1 & short sell stock 2.

Again  $\frac{x_i S_{i(0)}}{\sqrt{v(0)}} = w_i \quad \text{and} \quad w_1 = s$   
 $w_2 = -s$

let us set  $w_1 = \cancel{-0.01} + w_2 = \cancel{1.01}$ .

find

$$\sigma_v^2 + \mu v.$$

$$\sum = \begin{pmatrix} .5625 & 9.375 \times 10^{-4} \\ 9.375 \times 10^{-4} & .04688 \end{pmatrix}$$

$$\mu = \begin{pmatrix} .125 \\ .1125 \end{pmatrix}$$

But

$$\begin{aligned} (\bar{w}_1, \bar{w}_2) & \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \end{pmatrix} \\ &= (\bar{w}_1, \bar{w}_2) \begin{pmatrix} c_{11}w_1 + c_{12}w_2 \\ c_{21}w_1 + c_{22}w_2 \end{pmatrix} \\ &= c_{11}\bar{w}_1^2 + c_{12}\bar{w}_1\bar{w}_2 + c_{21}\bar{w}_1\bar{w}_2 + c_{22}\bar{w}_2^2 \\ &= \text{Var } K_V \end{aligned}$$

Recall  $\Sigma = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix}$  is called covariance matrix.  
It is diagonalizable & semi positive definite (non neg eigenvalues)

We know it has non neg eigenvalues

because: if  $(\bar{w}_1, \bar{w}_2)$  is an eigen vector then

$$(\bar{w}_1, \bar{w}_2) \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} \begin{pmatrix} \bar{w}_1 \\ \bar{w}_2 \end{pmatrix} = \bar{\lambda} (\bar{w}_1, \bar{w}_2) \begin{pmatrix} \bar{w}_1 \\ \bar{w}_2 \end{pmatrix} = \bar{\lambda} \left| \begin{pmatrix} \bar{w}_1 \\ \bar{w}_2 \end{pmatrix} \right|^2 = \text{Var } K_V \geq 0$$

$$\therefore \bar{\lambda} \geq 0.$$

Moreover  $\text{Var } K_V > 0$  if "each rv has some independent randomness" -  $K_2$  is not  $\perp\!\!\!\perp$  of  $K_1$ .

We will generally make the assumption that  
 $\Sigma$  is positive definite ie  $\bar{\lambda} > 0$   
ie  $\text{Var } K_1 > 0 \wedge (w_1, w_2)$  ie  $K_2$  not a fl of  $K_1$ .

Let us calculate  $\text{cov}(K_1, K_2)$ .

Recall:

	$\sum$	$K_1$	$K_2$	$P$
$w_1$	.2	.1	.4	
$w_2$	.2	.15	.4	
$w_3$	.05	.1	.2	

$$\mu_1 = \mathbb{E} K_1 = .125 \quad \mu_2 = \mathbb{E} K_2 = .1125.$$

$$\text{cov} = \mathbb{E} K_1 K_2 - \mathbb{E} K_1 \mathbb{E} K_2 = \mathbb{E} \{(K_1 - \mu_1)(K_2 - \mu_2)\}.$$

$$\mathbb{E} K_1 K_2 = \frac{1}{4} (.2)(.1) + \frac{1}{4} (.2)(.15) + \frac{1}{2} (.05)(.1) = .015$$

$$\mathbb{E} K_1 \mathbb{E} K_2 = .01406$$

$$\text{cov}(K_1, K_2) = .0009375 = 1.375 \times 10^{-4}$$

Also let us recall the correlation coefficient

$$\rho_{12} = \frac{\text{cov}(K_1, K_2)}{\sigma_1 \sigma_2} = \frac{\text{cov}(K_1, K_2)}{\sqrt{\text{Var } K_1 \text{Var } K_2}} = .005773.$$

Now we can find risk on any portfolio  $w = \begin{pmatrix} w_1 \\ w_2 \end{pmatrix}$   
 $\{ \text{let } w_1 = s \rightarrow w_1 + w_2 = 1 \Rightarrow w_2 = 1 - s \}$ .

Covariance matrix  $\Sigma_{K,K} = \begin{pmatrix} 0.5625 & 9.375 \times 10^{-4} \\ 9.375 \times 10^{-4} & 0.04688 \end{pmatrix}$

Let us take  $w_1 = w_2 = \frac{1}{2}$ .

$$\sigma_v^2 = \text{Var } K_v = \left( \frac{1}{2} \ 1 \right) \sum \begin{pmatrix} 1/2 \\ 1/2 \end{pmatrix} = \frac{1}{4} C_1 + \frac{1}{4} \cdot 2 \cdot C_{12} + \frac{1}{4} C_2$$

~~$\therefore \sigma_v^2 = 0.1528$~~

$$\mu_v = E(K_v) = \frac{1}{2}(0.125) + \frac{1}{2}(0.1125) = 0.1188.$$

Thus we have constructed a portfolio  $w$   
 so that

$$C_2 < \sigma_v^2 < C_1 ; \quad \mu_2 < \mu_v < \mu_1$$

This may be useful if the risk of  $S_1$  is too high  
 & return of  $S_2$  is too low.

Note here, if  $V(0) = \$100$  we have bought  $\frac{1}{2}$  of each stock  
 @ \\$100/stock at time 0.  $V(0) = \$100 ; V(1) = V(0)(1 + K_v)$

Consider an Alternative system... EC(2)

$$S_1(0) = S_2(0) = 100.$$

$\omega_i$	$S_{1(i)}$	$S_{2(i)}$	$P$		$\omega_i$	$K_1$	$K_2$	$P$
$\omega_1$	125	105	1/4	1 <sup>st</sup>				
$\omega_2$	110	110	1/2	→				
$\omega_3$	105	115	1/4					

~~Handwritten notes~~

$$\mu_1 = .125 ; \mu_2 = .10$$

$$C_1 = \text{Var } K_1 = \mathbb{E} K_1^2 - (\mathbb{E} K_1)^2 = 5.625 \times 10^{-3}$$

$$\mathbb{E} K_1^2 = .02125$$

$$C_2 = \text{Var } K_2 = 1.125 \times 10^{-3}$$

$$\mathbb{E} K_2^2 = .01125$$

$$C_{12} = \text{cov } K_1 K_2 = .01 - .0125 = -.0025 = -2.5 \times 10^{-3}$$

$$\begin{aligned} \mathbb{E} K_1 K_2 &= \frac{1}{4} (.25)(.05) + \frac{1}{2} (.1)(.1) + \frac{1}{4} (.05)(.15) \\ &= .01 \end{aligned}$$

$$\rho_{12} = \frac{-2.5 \times 10^{-3}}{\sqrt{(5.625 \times 10^{-3})(1.125 \times 10^{-3})}} = \frac{-2.5}{\sqrt{5.625 \times 1.125}} = -\frac{2.5}{2.05156} = -.9938.$$

Now consider a portfolio of  $w_1 = w_2 = \frac{1}{2}$ .

$$\Sigma_K = \Sigma_{K_1 K_2} = \begin{pmatrix} 5.625 & -2.5 \\ -2.5 & 1.125 \end{pmatrix} \times 10^{-3}$$

~~Handwritten note~~

$$\sigma_v^2 = \text{Var } K_v = \frac{1}{4} C_1 + \frac{1}{4} 2C_{12} + \frac{1}{4} C_2$$

$$= \left\{ \frac{1}{4} 5.625 + \frac{1}{4} 2(-2.5) + \frac{1}{4} (1.125) \right\} \times 10^{-3}$$

$$= 4.375 \times 10^{-4}$$

$$\mu_v = \mathbb{E} K_v = \frac{1}{2}(0.125) + \frac{1}{2}(0.1) = 0.1125$$

We have

$$\mu_2 < \mu_v < \mu_1$$

$$\sigma_v^2 < \sigma_2^2 < \sigma_1^2$$

" " "

$C_2 \quad C_1$

Here if e.g.  $V_0 = 200$  then  $x_1 = x_2 = 1$ .

$$V_0 = x_1 S_1(0) + x_2 S_2(0) \rightarrow V_1 = \frac{x_1 S_1(0)}{V_0} = \frac{1}{2}.$$