

① "Problems a-c are done in RStudio code"

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② (i) The investor will move up from Point A until the tangent, or move to the left of Point A until the tangent (Point G). These represent the Efficient Frontier.

(ii) Portfolio Z cannot be on the Efficient Frontier because the point lies below the Efficient Frontier. It has a higher standard deviation than Portfolio X with a lower expected return.

(iii)  $E(R) = 15\% = 0.15$   
 $\sigma^2 = 60\% = 0.60$   
 $P = 0.5$   
 $n = 25$

$$\bar{R}_p = \sum_{i=1}^n x_i \bar{R}_i = \frac{1}{n} \sum_{i=1}^n \bar{R}_i \Rightarrow \frac{1}{25} \sum_{i=1}^{25} \bar{R}_i = \frac{(25)(0.15)}{(25)} \rightarrow \boxed{\bar{R}_p = 0.15}$$

$$\sigma_p^2 = \sum_{i=1}^n x_i^2 \sigma_i^2 + \sum_{i=1}^n \sum_{j \neq i}^n x_i x_j \sigma_{ij} \Rightarrow$$

$$\frac{1}{(25)^2} \cdot (25) \cdot (0.60)^2 + \frac{1}{(25)^2} \cdot (25)(25-1)(0.5)(0.60)^2 = (0.0144) + (0.1728) \rightarrow$$

$$\boxed{\sigma_p^2 = 0.1872} \rightarrow \boxed{\sigma_p = \sqrt{0.1872} = 0.4327}$$

(iv) We have the formula...  $\sigma_p^2 = \frac{1}{n}(\sigma^2) + \frac{1}{n}(n-1)(P)(\sigma^2) \rightarrow$  we need  $\sigma_p^2 < (0.43)^2$  for an unknown (n)  $\rightarrow$

$$\frac{1}{n}(0.36) + \frac{n-1}{n}(0.18) < (0.43)^2 \rightarrow (0.36) + (n-1)(0.18) < 0.1849(n) \rightarrow$$

$$n = 36.7347 \rightarrow \boxed{n = 37}$$

(v)  $\sigma_p = \sigma \sqrt{P} (?) \rightarrow \sigma_p = (0.6)\sqrt{0.5} = 0.4243 \rightarrow$

if  $n=25 \rightarrow \sigma_p = 0.4327$   
 $n=37 \rightarrow \sigma_p = 0.4300$   
 $n=100 \rightarrow \sigma_p = 0.4264$

$\rightarrow$  Yes, it is true that if (n) increases, then  $\sigma_p = \sigma \sqrt{P}$ . The reason is because the more you increase your sample size ("diversify"), the closer it'll be till it reaches the true minimum risk.

③ "Exercise 3 done in RStudio"

④ Equal Weight Portfolio  $\rightarrow \sigma_p^2 = \frac{1}{n}(\bar{\sigma}_i^2 - \bar{\sigma}_{ij}^2) + \bar{\sigma}_{ij}$  for  $\bar{\sigma}_i^2 = 50$  &  $\bar{\sigma}_{ij} = 10 \rightarrow$

n	$\sigma_p^2 = \frac{1}{n}(\bar{\sigma}_i^2 - \bar{\sigma}_{ij}^2) + \bar{\sigma}_{ij}$
5	18.0
10	14.0
20	12.0
50	10.8
100	10.4

\*  $(\bar{\sigma}_i^2 - \bar{\sigma}_{ij}^2) = ((50)^2 - (10)) = 4000$

$\leftarrow$  Answers



⑤  $X_k = \frac{E \sum_{j=1}^m V_{kj} (CE_j - A) + \sum_{j=1}^m V_{kj} (B - AE_j)}{D}$  for  $k=1, \dots, m \rightarrow$  we need equations...

⑥  $0 = \sum_{j=1}^m x_j \sigma_{ij} - \lambda_1 E_i - \lambda_2$  for  $i=1, \dots, m$  |  $A = \sum_{j=1}^m \sum_{k=1}^m V_{kj} E_j$  |  $E = B\lambda_1 + A\lambda_2$   
 ⑦  $0 = E - \sum_{i=1}^m x_i E_i$  |  $B = \sum_{j=1}^m \sum_{k=1}^m V_{kj} E_j E_k$  |  $1 = A\lambda_1 + C\lambda_2$   
 ⑧  $0 = 1 - \sum_{i=1}^m x_i$  |  $C = \sum_{j=1}^m \sum_{k=1}^m V_{kj}$   
 $D = BC - A^2$

$\lambda_1 = \frac{(CE - A)}{D}$        $\lambda_2 = \frac{(B - AE)}{D}$

$X_k = \lambda_1 \sum_{j=1}^m V_{kj} E_j + \lambda_2 \sum_{j=1}^m V_{kj}$  for  $k=1, \dots, m$

$\rightarrow$  we would simply plug the  $(\lambda_1) \neq (\lambda_2)$  to our  $(X_k) \rightarrow \left[ \frac{CE - A}{D} \right] \cdot \sum_{j=1}^m V_{kj} E_j + \left[ \frac{B - AE}{D} \right] \cdot \sum_{j=1}^m V_{kj} \rightarrow$

$X_k = \frac{E \cdot \sum_{j=1}^m V_{kj} (CE_j - A) + \sum_{j=1}^m V_{kj} (B - AE_j)}{D}$  for  $k=1, \dots, m$  ✓ frontier portfolio

ii) say  $\bar{E} = \frac{A}{C} \rightarrow$  multiply eq. ⑥ by  $(x_i) \rightarrow \sum_{j=1}^m \sum_{k=1}^m x_i x_j \sigma_{ij} = \lambda_1 \sum_{i=1}^m x_i E_i + \lambda_2 \sum_{i=1}^m x_i$

$\rightarrow \sigma^2 = \lambda_1 E + \lambda_2 \rightarrow \sigma^2 = \lambda_1 E + \lambda_2 \rightarrow \sigma^2 = \frac{CE^2 - 2AE + B}{D} \rightarrow$   
 (from definition of  $\sigma^2$ )

$\frac{\partial \sigma^2}{\partial E} = \frac{2[CE - A]}{D} = 0 \rightarrow \bar{E} = \frac{A}{C} \rightarrow \bar{\sigma}^2 = \frac{1}{C} \rightarrow$  we define  $(\bar{x}_k)$  as the proportion of min.-variance portfolio...  $\rightarrow$

$\bar{x}_k = \frac{\sum_{j=1}^m V_{kj}}{\sum_{j=1}^m \sum_{k=1}^m V_{kj}}$  for  $k=1, \dots, m \rightarrow$  we know that  $C = \sum_{j=1}^m \sum_{k=1}^m V_{kj} \rightarrow \bar{x}_k = \frac{\sum_{j=1}^m V_{kj}}{C}$  for  $k=1, \dots, m$  ✓ min. risk portfolio