



↳ Démonstration que (E) est équivalent à (E')

Soit A en plf solution de (E) tel que $\text{Var}[V_1(a_0^A, a^A)] < \sigma^2$

Soit $\delta = \sqrt{\frac{\sigma^2}{\text{Var}[V_1^A]}}$ et considérons le plf B : $(a_0^B, \delta a^A)$ avec a_0^B choisi tq $V_0^B = r$

$$\delta = 1 + \varepsilon, \quad \varepsilon > 0$$

$$EV_1^A = (r - a_0^A p_0)(1 + u) + a^A \text{diag}(p_0) \mu$$

$$\begin{aligned} EV_1^B &= (r - \delta a_0^A p_0)(1 + u) + \delta a^A \text{diag}(p_0) \mu \\ &= EV_1^A + \varepsilon (a^A \text{diag}(p_0) \mu - a_0^A p_0 (1 + u)) \\ &= EV_1^A - r(1 + u) \end{aligned}$$

$$\begin{aligned} \text{Var } V_1^B &= \text{Var} \left(a_0^B (1 + u) + \delta \sum_{i=1}^N a_i^A p_{i0} y_i \right) \\ &= \delta^2 \left(\text{Var} \left(\sum_{i=1}^N a_i^A p_{i0} y_i \right) \right) \\ &= \delta^2 \left(\text{Var} \left(a_0^A (1 + u) + \sum_{i=1}^N a_i^A p_{i0} y_i \right) \right) \\ &= \delta^2 \text{Var } V_1^A = \sigma^2 \end{aligned}$$

Réécriture (E')

$$\begin{aligned} \max \quad & w^A \tilde{\mu} \\ \text{s.c.} \quad & w^A \Omega w^A - \sigma^2 = 0 \end{aligned}$$

← on enlève $v(1+u)$ car constant ne sert à rien dans l'optimisation

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On introduit le lagrangien

$$\mathcal{L}(w, \lambda) = w^A \tilde{\mu} - \frac{\lambda}{2} (w^A \Omega w^A - \sigma^2)$$

$$= \sum_{i=1}^N w_{A,i} \tilde{\mu}_i - \frac{\lambda}{2} \left(\sum_{i=1}^N (w_{A,i}^2 \Omega_{i,i}) + \sum_{i \neq j} w_{A,i} w_{A,j} \Omega_{i,j} \right) - \sigma^2$$

$$\frac{\partial \mathcal{L}(w, \lambda)}{\partial w_{A,i}} = \tilde{\mu}_i - \frac{\lambda}{2} \left(2 w_{A,i} \Omega_{i,i} + 2 \sum_{j \neq i} w_{A,j} \Omega_{i,j} \right)$$

$$\frac{\partial \mathcal{L}(w, \lambda)}{\partial \lambda} = \frac{1}{2} (w^A \Omega w^A - \sigma^2)$$

forme quadratique :

$$\begin{aligned} w^A \Omega w^A &= \sum_{i=1}^N \sum_{j=1}^N w_{A,i} \Omega_{i,j} w_{A,j} \\ &= \sum_{i=1}^N w_{A,i}^2 \Omega_{i,i} + \sum_{i=1}^N \sum_{j \neq i} w_{A,i} \Omega_{i,j} w_{A,j} \end{aligned}$$

$$\begin{aligned} \frac{\partial \mathcal{L}(u_k, \lambda)}{\partial u_k} &= 0 \\ \frac{\partial \mathcal{L}(u_k, \lambda)}{\partial \lambda} &= 0 \end{aligned} \quad (\Rightarrow) \quad \begin{cases} \tilde{\mu} - \lambda \Omega u_k = 0 \\ u_k' \Omega u_k - \sigma^2 = 0 \end{cases}$$

On pose $\Omega = R^2$ et $R = \Omega^{1/2}$

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Soit (a, μ) un n° quelconque

$$\begin{aligned} S(a) &= \frac{u_k' \tilde{\mu}}{\sqrt{u_k' \Omega u_k}} = \frac{u_k' \Omega^{1/2} \Omega^{-1/2} \tilde{\mu}}{\sqrt{u_k' \Omega u_k}} \\ &= \frac{(\Omega^{1/2} u_k)' (\Omega^{-1/2} \tilde{\mu})}{\sqrt{(\Omega^{1/2} u_k)' (\Omega^{1/2} u_k)}} \\ &= \frac{\text{Tr}(Y X')}{\sqrt{\text{Tr}(X X')}} \end{aligned}$$

on pose $X := \Omega^{1/2} u_k \in \mathbb{R}^n$ et $Y := \Omega^{-1/2} \tilde{\mu} \in \mathbb{R}^n$

Cauchy-Schwarz

$$\text{Tr}(Y X') \leq \sqrt{\text{Tr}(Y Y')} \sqrt{\text{Tr}(X X')}$$

$$\begin{aligned} &\leq \sqrt{\text{Tr}(Y Y')} \\ &\leq \sqrt{(\Omega^{-1/2} \tilde{\mu})' (\Omega^{-1/2} \tilde{\mu})} = (\tilde{\mu}' \Omega^{-1} \tilde{\mu})^{1/2} \\ &\quad \text{shared du modèle} \end{aligned}$$

$X, Y \in \mathbb{R}^n$
alors $\exists a, b$ et une v.a ε tels que $Y = a + bX + \varepsilon$
avec $E\varepsilon = 0$ et $\text{Cov}(\varepsilon, X) = 0$
 $b = \frac{\text{Cov}(X, Y)}{\text{Var } X}$, $a = E(Y) - E[X]$
 $\varepsilon = Y - a - bX$

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$$z = Y - (1+b) \varepsilon$$

$$z(a_m^*) = \tilde{\mu}' \Omega^{-1} z$$

$$E(z(a_m^*)) = \frac{\tilde{\mu}' \Omega^{-1} \tilde{\mu}}{\tilde{\mu}' \Omega^{-1} e}$$

si $\text{Var } z = \Omega$
alors $\text{Var}(a'z) = a'a$

Pf de marché
efficient

$$z_i = \alpha_i + \beta_i z(a_m^*) + \varepsilon_i \quad \forall i$$

$$\rightarrow \alpha = E[z(a_m^*)] - b E[z(a_m^*)]$$

$$\alpha = \tilde{\mu} - b \frac{\tilde{\mu}' \Omega^{-1} \tilde{\mu}}{\tilde{\mu}' \Omega^{-1} e}$$

$$\begin{aligned} \rightarrow \beta &= \frac{\text{Cov}(X, Y)}{\text{Var}(X)} = \frac{\text{Cov}(z(a_m^*), z)}{\text{Var}(z(a_m^*))} \\ &= \frac{\text{Cov}(\tilde{\mu}' \Omega^{-1} z, z)}{\tilde{\mu}' \Omega^{-1} e \text{Var}(z(a_m^*))} \end{aligned}$$

$$\text{Var}(z(a_m^*)) = \text{Var}\left(\frac{\tilde{\mu}' \Omega^{-1} z}{\tilde{\mu}' \Omega^{-1} e}\right)$$

$$= \frac{(\tilde{\mu}' \Omega^{-1}) \Omega (\Omega^{-1} \tilde{\mu})}{(\tilde{\mu}' \Omega^{-1} e)^2}$$

$$\bullet \text{Var}(z(a_m^*)) = \frac{\tilde{\mu}' \Omega^{-1} \tilde{\mu}}{(\tilde{\mu}' \Omega^{-1} e)^2}$$

$$\bullet \text{Cov}(\tilde{\mu}' \Omega^{-1} z, z) = \tilde{\mu}' \Omega^{-1} \text{Var}(z) = \tilde{\mu}' \Omega^{-1} \Omega = \tilde{\mu}$$

$$\beta = \frac{\tilde{\mu}' \Omega^{-1} e \tilde{\mu}}{\tilde{\mu}' \Omega^{-1} \tilde{\mu}} \Rightarrow \boxed{\alpha = 0}$$

Markowitz

- $y_i = \frac{p_{i,1}}{p_{i,0}}$ rendement $Y = (y_1, \dots, y_N)'$. $E(Y) = \mu \in \mathbb{R}^N$. $\text{Var}(Y) = \Omega$
- Valeur en t $V_t = d_0 r_t^{\text{ASR}} + a' r_t \rightarrow a = (a_1, \dots, a_N)'$ et $r_t = (r_{1,t}, \dots, r_{N,t})'$
- $V_0 = d_0 + a' p_0$ • $V_1 = d_0(1+i) + a' \text{diag}(p_0) Y$
- $Ua = \text{diag}(p_0) a$ $E(V_1) = d_0(1+i) + a' \text{diag}(p_0) \mu$ $\text{Var}(V_1) = a' \text{diag}(p_0) \Omega \text{diag}(p_0) a$

• Problème d'optimisation à résoudre:

$$(E') \rightarrow \begin{cases} \max_{(d_0, a)} & d_0(1+i) + a' \text{diag}(p_0) \mu \\ \text{s.c} & a' \text{diag}(p_0) \Omega \text{diag}(p_0) a = \sigma^2 \text{ et } d_0 + a' p_0 = v \end{cases}$$

on pose $v = d_0 + w'a' e$ avec $e = (1, \dots, 1)'$

$$\hookrightarrow (E') \begin{cases} \max_{w_a} & (v - w'a' e)(1+i) + w'a' \mu \\ \text{s.c} & w'a' \Omega w_a = \sigma^2 \end{cases} \quad \begin{cases} v = d_0 + w'a' e \\ \sigma^2 = w'a' \Omega w_a \end{cases}$$

on pose $\tilde{\mu} = \mu - (1+i)e$ entree on les pos de $v(2+i)$

$$\hookrightarrow (E') \begin{cases} \max_{w_a} & v(1+i) + w'a' \tilde{\mu} \\ \text{s.c} & w'a' \Omega w_a - \sigma^2 = 0 \end{cases} \Rightarrow \begin{cases} \tilde{\mu} - \lambda \Omega w_a = 0 \\ w'a' \Omega w_a - \sigma^2 = 0 \end{cases} \Rightarrow \begin{cases} w_a = \frac{1}{\lambda} \Omega^{-1} \tilde{\mu} \\ a = \frac{1}{\lambda} (\text{diag}(p_0))^{-1} \Omega^{-1} \tilde{\mu} \\ d_0 = v - \frac{1}{\lambda} \tilde{\mu}' \Omega^{-1} e \\ \lambda = \frac{1}{\sigma} (\tilde{\mu}' \Omega^{-1} \tilde{\mu})^{1/2} \end{cases}$$

$$w_a = \frac{1}{\lambda} \Omega^{-1} \tilde{\mu} \rightarrow a = \frac{1}{\lambda} (\text{diag}(p_0))^{-1} \Omega^{-1} \tilde{\mu}$$

$$d_0 = v - \frac{1}{\lambda} \tilde{\mu}' \Omega^{-1} e \quad \lambda = \frac{1}{\sigma} (\tilde{\mu}' \Omega^{-1} \tilde{\mu})^{1/2}$$

$$E[V_1] = v(1+i) + \frac{1}{\lambda} \tilde{\mu}' \Omega^{-1} \tilde{\mu} \quad \text{Var}(V_1) = \sigma = \frac{(\tilde{\mu}' \Omega^{-1} \tilde{\mu})^{1/2}}{\lambda}$$

$$E[V_1] = v(1+i) + \sqrt{\text{Var}(V_1)} (\tilde{\mu}' \Omega^{-1} \tilde{\mu})^{1/2}$$

on écrit $P = \alpha_0(\lambda) P_0 + \alpha^*(\lambda) P^*$

• $P_0 = ASR$

• $\alpha^*(\lambda) = \frac{1}{\lambda}$

• $\alpha_0(\lambda) = 1 - \frac{1}{\lambda} \tilde{\mu}' \Sigma^{-1} \tilde{e}$

• $P^* = (\text{diag}(P_0))^{-1} \Sigma^{-1} \tilde{\mu}$

Théorème de séparation en 2 fonds:

Tout portefeuille efficient est la combinaison linéaire entre P_0 (1 ASR) et P^* qui ne contient que des actifs risqués.

Sharpe $S(a) = \frac{E[V_1(a, a) - V(1+r)]}{\sqrt{\text{Var}[V_1(a, a)]}} = \frac{w_a' \tilde{\mu}}{(w_a' \Sigma w_a)^{1/2}}$

$S = \frac{1}{\lambda} \frac{\tilde{\mu}' \Sigma^{-1} \tilde{\mu}}{\sigma} = \frac{\tilde{\mu}' \Sigma^{-1} \tilde{\mu}}{(\tilde{\mu}' \Sigma^{-1} \tilde{\mu})^{1/2}} = S$

BAPM

• on note $z = y - (1+r)e$ valeur rentabilité net

$z(\alpha^*) = \frac{\tilde{\mu}' \Sigma^{-1} z}{\tilde{\mu}' \Sigma^{-1} e}$ pour un pft efficient

on a $z = \beta z(\alpha_m^*) + \varepsilon$

$\beta = \frac{\text{Cov}(z, z(\alpha_m^*))}{\text{Var}(z(\alpha_m^*))}$ • $E[\varepsilon] = 0$ • $\text{Cov}[\varepsilon, z(\alpha_m^*)] = 0$

Et: $E[z_i] = \beta_i E[z(\alpha_m^*)]$

$\text{Var}[z_i] = \beta_i^2 \text{Var}[z(\alpha_m^*)] + \sigma_i^2$ avec $\sigma_i^2 = E[\varepsilon_i^2]$

↑
Risque idiosyncratique

on prend a un pft rq: $z(a) = w_a' z = \sum_i w_{a,i} z_i = \sum_i w_{a,i} (\beta_i z(\alpha_m^*) + \varepsilon_i)$

on pose $\rightarrow \beta(a) = \sum_i w_{a,i} \beta_i$ $\varepsilon(a) = \sum_i w_{a,i} \varepsilon_i = w_a' \varepsilon$

$\hookrightarrow E[z(a)] = \beta(a) E[z(\alpha_m^*)]$

$\hookrightarrow V[z(a)] = \beta(a)^2 \text{Var}[z(\alpha_m^*)] + \text{Var}[w_a' \varepsilon]$
 $= \beta(a)^2 \text{Var}[z(\alpha_m^*)] + w_a' \text{Var}[\varepsilon] w_a$

$V[z(a)] = \beta(a)^2 \text{Var}[z(\alpha_m^*)] + \bar{w}_a' \text{Var}[\varepsilon] \bar{w}_a$

on pose $\bar{w}_a = \frac{w_a}{\sum w_a}$