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Portfolio Management

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Laws of Returns of Financial Assets

Returns and Rate of Returns

- Return of an investment W_0 : $R_T = \frac{W_T}{W_0} - 1$
- Return of an (investment in an) asset P_t : $R_T = \frac{P_T + Div(0, T)}{P_0} - 1$
- Different ways to define a rate of return:
 - monetary rate: $1 + r \times T = 1 + R_T$
 - actuarial rate: $(1 + r)^T = 1 + R_T$
 - exponential rate: $\exp(r \times T) = 1 + R_T$
- Different ways to define T : 30/360, Act/360, Act/Act, Act/365
- For modelization, exponential rates make calculations simpler:
 - time scale properties: $\exp(\frac{r}{\lambda} \lambda T) = \exp(rT)$
 - simplicity to compound interests: $\exp(rT_1)\exp(rT_2) = \exp(r(T_1 + T_2))$
 - well suited for modelization in continuous time
 $dP_t = rP_t dt \implies P_T = P_0 e^{rT}$
 - enable to conserve the property of normality when assuming the independence of the returns

- **Probabilist** definitions for a r.v X
 - Expectation: $E[X]$
 - Variance: $Var[X] = E[X^2] - E[X]^2$
 - Standard deviation: $\sigma[X] = \sqrt{Var[X]}$
 - Skew: $Skew[X] = E \left[\left(\frac{X - E(X)}{\sigma(X)} \right)^3 \right]$
 - Kurtosis: $Kur[X] = E \left[\left(\frac{X - E(X)}{\sigma(X)} \right)^4 \right]$ (some authors subtract 3 in the definition, others call this new quantity the excess kurtosis)

- **Empirical** definitions for a sample $x = (x_1, x_2, \dots, x_n)$
 - Sample Mean: $\bar{x} = \hat{E}(x) = \frac{1}{n} \sum_{i=1}^{i=n} x_i$
 - Sample Variance : $\widehat{Var}(x) = \frac{1}{n} \sum_{i=1}^{i=n} (x_i - \bar{x})^2$
 - Sample Standard Deviation: $\hat{\sigma}(x) = \sqrt{\widehat{Var}(x)}$
 - Sample Skew: $\widehat{Skew}(x) = \frac{1}{n} \sum_{i=1}^{i=n} \left(\frac{x_i - \bar{x}}{\hat{\sigma}(x)}\right)^3$
 - Sample Kurtosis: $\widehat{Kur}(x) = \frac{1}{n} \sum_{i=1}^{i=n} \left(\frac{x_i - \bar{x}}{\hat{\sigma}(x)}\right)^4$
- **Remark:** the empirical quantities can be obtained from the probabilist definitions by taking $P(X_i = x_i) = \frac{1}{n}$ instead of P_X in the expectations, and therefore can be called "plug-in" estimators.

- **Properties** skewness:

- anti-symmetry: $Skew(-X) = -Skew(X)$
- scale invariance: if $\lambda > 0$, $Skew(\lambda X) = Skew(X)$
- location invariance: $\forall \lambda$, $Skew(X + \lambda) = Skew(X)$
- for $X \sim N(m, \sigma^2)$, $Skew(X) = 0$

- **Properties** kurtosis:

- symmetry: $Kur(-X) = Kur(X)$
- scale invariance: if $\lambda \neq 0$, $Kur(\lambda X) = Kur(X)$
- location invariance: $\forall \lambda$, $Kur(X + \lambda) = Kur(X)$
- for $X \sim N(m, \sigma^2)$, $Kur(X) = 3$

- **Definition:** if $Kur(X) > 3$ the distribution is leptokurtic if
 $Kur(X) < 3$ the distribution is platykurtic

Remark: (calculation trick): integration by parts proves that for any integer $n > 0$

$$\int_{-\infty}^{+\infty} x^n e^{-\frac{x^2}{2}} dx = n \int_{-\infty}^{+\infty} x^{n-2} e^{-\frac{x^2}{2}} dx$$

- **Remark:** the properties above are true for the empirical quantities as well
- **Exercise:** demonstrate the properties above
- **Remark:** for a mixture of normal distributions we have kurtosis > 3

Theorem (admitted) and the Berra and Jarque test

Let X_1, X_2, \dots, X_n be i.i.d $N(m, \sigma^2)$ and $X = (X_1, X_2, \dots, X_n)$ then asymptotically:

- $\sqrt{n}\widehat{Skew}(X) \sim N(0, 6)$
- $\sqrt{n}[\widehat{Kur}(X) - 3] \sim N(0, 24)$

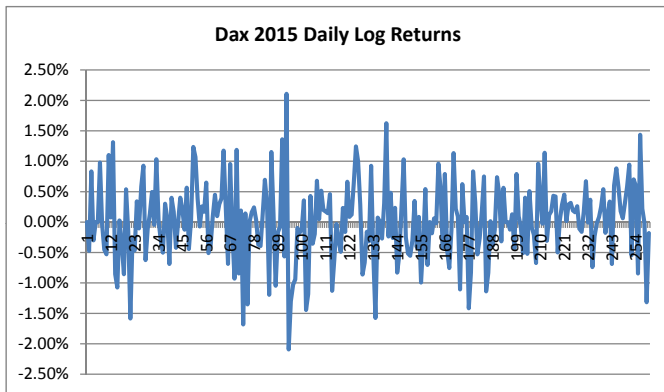
Let $\widehat{BJ}(X) = \frac{n}{6}[\widehat{Skew}(X)]^2 + \frac{n}{24}[\widehat{Kur}(X) - 3]^2$ then asymptotically:

- $\widehat{BJ}(X) \sim \chi^2(2)$

Let $\chi_{1-\alpha}^2(2)$ be such that $P(\chi^2 > \chi_{1-\alpha}^2(2)) = 1 - \alpha$

Then for n large enough the Berra and Jarque test rejects at confidence level α the normality hypothesis iff: $\widehat{BJ}(x) > \chi_{1-\alpha}^2(2)$

Goodness of Fit Tests



Remark: the DAX is a total return index, i.e it is calculated with dividends reinvested

Example: We calculate the daily log returns of the DAX for year 2015

- number of daily returns 255, $x = (x_1, x_2, \dots, x_{252})$
- $\bar{x} = 0.02\%$, $\hat{\sigma}(x) = 0.63\%$
- $\widehat{Skew}(x) = -0.15$, $\widehat{Kur}(x) = 3.56$ (fat tails)
- $\widehat{BJ}(x) = 4.32$, $\chi_{5\%}^2(2) = 5.99$

So we accept the normality hypothesis at confidence level 95%

Remarks: The Berra and Jarque's test is very sensitive to outliers.

Here, $\frac{n}{6}[\widehat{Skew}(X)]^2 = 0.94$ and $\frac{n}{24}[\widehat{Kur}(X) - 3]^2 = 3.38$

The volatility is defined as $vol \frac{1}{\sqrt{T}} = \hat{\sigma}(x)$. Here $T = \frac{1}{260}$ as we have here 260 observations in a year, so the estimate of the volatility is 10%.

Further Statistical Tests

Theorem of Parzen Rosenblatt (admitted)

Let X be a random variable of density function $f(x)$

Let X_i be i.i.d variables of the same law as X

Let K be positive of integral 1 and $(h_n)_{n \in \mathbb{N}}$ such that $h_n \rightarrow 0$ and $nh_n \rightarrow \infty$

Let $f_n(x)$ be defined by $f_n(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{h_n} K\left(\frac{X_i - x}{h_n}\right)$ then $f_n(x)$ is a density

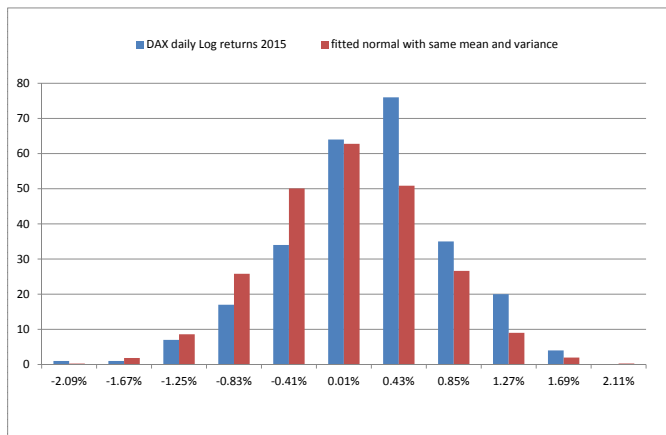
and $\sqrt{nh_n}[f_n(x) - f(x)] \xrightarrow{\text{Law}} N\left(0, f(x) \int_{-\infty}^{+\infty} K^2(x) dx\right)$

Exemples of Kernels

- Rectangular Kernel $K(u) = \frac{1}{2} \mathbf{1}_{|u| < 1}$
- Gaussian Kernel $K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right)$

Remark: "visual test" where the estimated density is usually compared to the density of a normal distribution with the same mean and variance as the empirical mean and variance of the sample.

Tests Based on Density Function Estimates



histogram for the 260 observations fitted into 10 buckets

Tests Based on Cumulative Distribution Function Estimates

Let X and $(X_i)_{i \in [1, n]}$ be i.i.d r.v with the same laws

Let $F_n(x) = \frac{1}{n} \sum_{i=1}^n 1_{X_i \leq x}$ and $\|F_n(x) - F(x)\|_\infty = \sup_x |F_n(x) - F(x)|$

Law of Large Numbers and Central Limit Theorem

$\forall x, F_n(x) \rightarrow F(x)$ p.s and $\sqrt{n}(F_n(x) - F(x)) \xrightarrow{Law} N(0, F(x)[1 - F(x)])$

Glivenko Cantelli Theorem (admitted)

$\|F_n(x) - F(x)\|_\infty \rightarrow 0$ p.s (which is stronger than the Law of Large Numbers)

Kolmogorov Smirnov Theorem (admitted)

$\sqrt{n}\|F_n(x) - F(x)\|_\infty \xrightarrow{Law} K$ when n is large
 K is the Kolmogorov's law and is independant from F

Tests Based on Cumulative Distribution Function Estimates

Several Goodness of fit tests are based on Kolmogorov Smirnov's theorem with F being a normal cdf with the same mean and variance as the sample observed. Amongst these tests (available in SAS and with excel extended libraries):

- Kolmogorov Smirnov's test
- Cramer von Mises's test
- Anderson Darling's test

Remark: The CLT result is not well adapted to test the normality hypothesis as it is not optimal to test an hypothesis based on the value of the empirical repartition function on one single point. The Kolmogorov Smirnov result is much more interesting for this matter.

Definition:

if Z is a random variable the α quantile of Z is the smallest number $q_Z(\alpha)$ such that $P(Z \leq q_Z(\alpha)) \geq \alpha$

if $z = (z_1, z_2, \dots, z_n)$ is a sample with frequency (f_1, f_2, \dots, f_n) the α quantile of z , $\hat{q}_z(\alpha)$ is the quantile of the r.v Z defined by $P(Z = z_i) = f_i$

Remark 1: if we have 10 observations: $\{z_i = i\}_{i \in [1,10]}$:

$$\hat{q}_z(1) = 10 \text{ and } \forall i \in \{1, \dots, 9\} \forall \alpha \in]\frac{i}{10}, \frac{i+1}{10}] \hat{q}_z(\alpha) = i + 1$$

Remark 2: if $Z \sim N(0, 1)$: $q_Z(0.5) = 0$ and $q_Z(97.5\%) = 1.96$

Tests Based on Order Statistics

Exercise 1: Show that if F_Z is invertible then: $q_Z(\alpha) = F_Z^{-1}(\alpha)$

Exercise 2: Show that if F_Z is invertible then: $F_Z(Z) \sim U([0, 1])$

Exercise 3: Show that if $Z_1 \sim N(m_1, \sigma_1^2)$ and $Z_2 \sim N(m_2, \sigma_2^2)$ then: $\{(q_{Z_1}(\alpha), q_{Z_2}(\alpha)), \alpha \in [0, 1]\}$ is a line.

Theorem: order statistics (admitted) and QQ-Plot test

Let $N \sim N(0, 1)$ and $z(n) = (z_1, z_2, \dots, z_n)$ be a sample for the r.v Z we want to test. Then when n is large:

- $\hat{q}_{z(n)}\left(\frac{i}{n}\right) \approx q_Z\left(\frac{i}{n}\right)$ and

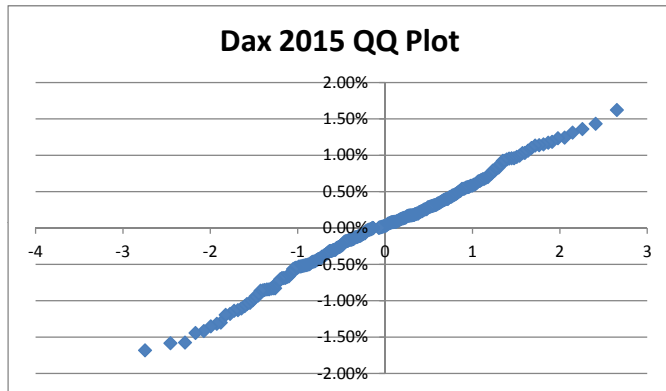
if Z is a normal Law:

- The points $(q_{N(0,1)}\left(\frac{i}{n}\right), \hat{q}_{z(n)}\left(\frac{i}{n}\right))$ should be "concentrated" around a line (called the Henry's line)

Tests Based on Order Statistics

Remark 1: The test can be used "visually" but can also be quantified through the Shapiro-Wilk test

Example: QQ plot DAX daily returns for 2015



(Reminder) Definition

- if $X \sim N(0, 1)$ then $X^2 \sim \chi^2(1)$
- if $X_i \sim N(0, 1)$ i.i.d then $\sum_{i=1}^{i=n} X_i^2 \sim \chi^2(n)$

(Reminder) Theorem and Definition

If $X_1 \sim N(M_1, Id_{\mathbb{R}^d})$ and $X_2 \sim N(M_2, Id_{\mathbb{R}^d})$ then:

$\|M_1\| = \|M_2\| \implies \|X_1\|^2$ and $\|X_2\|^2$ have the same law and this law is called $\chi^2(d, \|M_1\|^2)$

Parameter Estimations and Confidence Intervals

demonstration:

$$\|M_1\| = \|M_2\| \implies \exists A \text{ orthonormal such that } AM_1 = M_2$$

Let's consider AX_1 then:

- X_1 has a Normal law $\implies AX_1$ has a Normal law
- $E[AX_1] = AE[X_1]$
- $Var[AX_1] = Cov(AX_1, AX_1) = ACov(X_1, X_1)A' = AId_{\mathbb{R}^d}A' = Id_{\mathbb{R}^d}$

so, AX_1 and X_2 are both normal with the same mean and variance

so, $AX_1 \sim X_2$ and consequently $\|AX_1\|^2 \sim \|X_2\|^2$.

As $\|AX_1\|^2 = \|X_1\|^2$ (because A is orthonormal) by transitivity

$\|X_1\|^2 \sim \|X_2\|^2$. Q.E.D

Exercise: Show that $cov(AX, BY) = Acov(X, Y)B'$ (when A and B are matrices with the adequate dimensions) starting from the definition $cov(X, Y) = E(XY') - E(X)E(Y)'$

Parameter Estimations and Confidence Intervals

(Reminder) Definition

- if $X \sim N(m, 1)$ and $Z \sim \chi^2(d)$ then $\frac{X}{\sqrt{\frac{Z}{d}}}$ is called a Student Law and is noted $t(m, d)$. If $m = 0$ we simply note $t(d)$

Theorem: Student Law for Confidence Intervals

Let $X = (X^1, X^2, \dots, X^n)$ with $X_i \sim N(m, \sigma^2)$ i.i.d

Let $\bar{X} = \frac{1}{n} \sum_{i=1}^n X^i$ and $\hat{\sigma}(X) = \sqrt{\frac{1}{n} \sum_{i=1}^n (X^i - \bar{X})^2}$ then:

- \bar{X} and $\hat{\sigma}(X)$ are independant
- $\sqrt{n}(\frac{\bar{X}-m}{\sigma}) \xrightarrow{Law} N(0, 1)$
- $n(\frac{\hat{\sigma}(X)}{\sigma})^2 \xrightarrow{Law} \chi^2(n-1)$ that we can write as $\frac{\|X-\bar{X}\|^2}{\sigma^2} \approx \chi^2(n-1)$
- $\frac{\bar{X}-m}{\frac{\hat{\sigma}(X)}{\sqrt{n-1}}} \xrightarrow{Law} t(n-1)$ that we can write as $m \approx \bar{X} - \frac{\hat{\sigma}(X)}{\sqrt{n-1}} t(n-1)$

Parameter Estimations and Confidence Intervals

Sketch of the proof: we just need to show the result for $X^i \sim N(0, 1)$ i.i.d

Let $h : \mathbb{R}^n \rightarrow \mathbb{R}^n \times \mathbb{R}^n$ be defined by $h : \begin{pmatrix} X^1 \\ \vdots \\ X^n \end{pmatrix} \rightarrow \begin{pmatrix} \bar{X}1_n \\ X - \bar{X}1_n \end{pmatrix}$ then:

- X Gaussian and h linear $\Rightarrow h(X)$ is Gaussian
- $\forall i \text{ Cov}(\bar{X}, X^i - \bar{X}) = 0 \Rightarrow \bar{X}1_n$ and $X - \bar{X}1_n$ are independent because for Gaussian vectors zero covariance means independence
- $\langle X - \bar{X}1_n, 1_n \rangle = 0 \Rightarrow X - \bar{X}1_n \in (\mathbb{R}1_n)^\perp$

Note that $\forall u \in (\mathbb{R}1_n)^\perp$

$$\begin{aligned} \text{Var}(\langle u, X - \bar{X}1_n \rangle) &= \text{Var}(\langle u, X \rangle - \bar{X} \langle u, 1_n \rangle) \\ &= \text{Var}(\langle u, X \rangle) = u' \text{Var}(X) u = \|u\|^2 \end{aligned}$$

so if we call $\begin{pmatrix} 0 \\ Z \end{pmatrix}$ the components of $X - \bar{X}1_n$ in an orthonormal basis of

\mathbb{R}^n whose first vector is in $\mathbb{R}1_n$ we have $Z \sim N(0, Id_{\mathbb{R}^{n-1}})$

and so $\|X - \bar{X}1_n\|_n^2 = \|Z\|_{n-1}^2 \sim t(n-1)$ Q.E.D.

Example: GDAX returns for 2015

- $\bar{X} = 0.02\%$
- $\frac{\hat{\sigma}(X)}{\sqrt{n}} = 0.04\%$

So at confidence level 95% the expected daily rate of return is in the interval $[-0.06\%, 0.09\%]$

Remarks:

- $t(n - 1)$ is a symmetric distribution
- from $\frac{\sqrt{n-1}(\bar{X}-m)}{\hat{\sigma}(X)} \xrightarrow{Law} t(n - 1)$ and the law of large numbers and CLT we can deduct that $t(n - 1) \xrightarrow{Law} N(0, 1)$ (which means that when n is large the law/shape of a student distribution is very similar to the normal distribution)

Utility Functions

Definition: Utility functions

A utility function is any function $u : \mathbb{R} \rightarrow \mathbb{R}$ such that u is continuous, strictly increasing and two times differentiable.

Remark: based on the definition u is invertible

Definition: Preferred Investment and Risk Premium

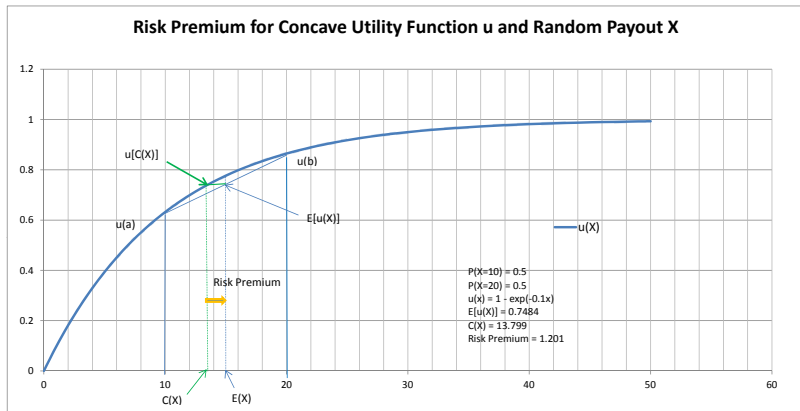
If X and Y are two random payoffs:

- $X \succ Y$ (X is preferred to Y for u) $\Leftrightarrow E[u(X)] > E[u(Y)]$

Let $C_u(X)$ be the constant defined by $u[C_u(X)] = E[u(X)]$

- $C_u(X)$ is called the certain equivalent to X
- $\Pi^u(X) = E[X] - C_u(X)$ is called the risk premium for X

Preferred investments



Properties (exercise)

- u convex $\Leftrightarrow \forall X, u(E[X]) \leq E[u(X)] \Leftrightarrow \forall X, \Pi^u(X) \leq 0 \Leftrightarrow$ risk taker
- u concave $\Leftrightarrow \forall X, u(E[X]) \geq E[u(X)] \Leftrightarrow \forall X, \Pi^u(X) \geq 0 \Leftrightarrow$ risk adverse
- u affine $\Leftrightarrow \forall X, u(E[X]) = E[u(X)] \Leftrightarrow \forall X, \Pi^u(X) = 0 \Leftrightarrow$ risk neutral

Theorem: Risk Aversion Measure

Let u and v be two utility functions strictly concave or convex then:

$$(\forall X \text{ discrete r.v, } \Pi^u(X) \geq \Pi^v(X)) \Leftrightarrow (\forall a, -\frac{u''(a)}{u'(a)} \geq -\frac{v''(a)}{v'(a)})$$

Remarks:

- $-\frac{u''}{u'}$ defines the risk aversion/concavity of u
- $\forall \lambda \neq 0, \lambda u$ and u have the same risk aversion
- the concavity measure we arrive at here differs from the geometric definition of curvature which is given by $\frac{u''}{(1+u'^2)^{3/2}}$

Demonstration theorem:

Let u be a utility function two times differentiable and strictly convex or concave (i.e. $u'' \neq 0$).

Demonstration \Rightarrow :

Let X_h^a be defined by: $P(X_h^a = a) = \frac{1}{2}$ and $P(X_h^a = a + h) = \frac{1}{2}$

Let $C_u^a(h) = C_u(X_h^a)$ i.e. $u(C_u^a(h)) = E[u(X_h^a)] = \frac{1}{2}u(a) + \frac{1}{2}u(a + h)$

by derivation on h of $u(C_u^a(h)) = \frac{1}{2}u(a) + \frac{1}{2}u(a + h)$ we obtain:

- $C_u^a(0) = a$ from $u(C_u^a(0)) = \frac{1}{2}u(a) + \frac{1}{2}u(a)$
- $C_u^{a'}(0) = \frac{1}{2}$ from $u'(C_u^a(0))C_u^{a'}(0) = \frac{1}{2}u'(a)$
- $C_u^{a''}(0) = \frac{1}{4} \frac{u''(a)}{u'(a)}$ from deriving $u'(C_u^a(h))C_u^{a'}(h) = \frac{1}{2}u'(a + h)$

Preferred investments

$$\begin{aligned} \text{Now, } \Pi^u \geq \Pi^v &\Rightarrow \forall a, \forall h, \Pi^u(X_h^a) \geq \Pi^v(X_h^a) \\ &\Rightarrow \forall h, E[X] - C_u^a(h) \geq E[X] - C_v^a(h) \\ &\Rightarrow -C_u^{a''}(0) \geq -C_v^{a''}(0) \text{ (as in 0 the value and first derivatives are equal)} \\ &\Rightarrow -\frac{u''(a)}{u'(a)} \geq -\frac{v''(a)}{v'(a)} \text{ (and this is true for all } a\text{). Q.E.D} \end{aligned}$$

Demonstration \Leftarrow

Let X be a discrete variable with $P(X = a_i) = p_i$

$$\Pi^u(X) \geq \Pi^v(X) \Leftrightarrow C_v(X) - C_u(X) \geq 0$$

$$\Leftrightarrow v^{-1}[E(v(X))] - u^{-1}[E(u(X))] \geq 0$$

$$\Leftrightarrow v^{-1}\left(\sum_{i=1}^{i=n} p_i v(a_i)\right) - u^{-1}\left(\sum_{i=1}^{i=n} p_i u(a_i)\right) \geq 0$$

$$\Leftrightarrow \sum_{i=1}^{i=n} p_i v(a_i) \geq v \circ u^{-1}\left(\sum_{i=1}^{i=n} p_i u(a_i)\right) \text{ (as } v \text{ is increasing)}$$

which should be true if $v \circ u^{-1}$ is convex.

Preferred investments

Let's calculate $(v \circ u^{-1})''$ to prove that $v \circ u^{-1}$ is convex

$$(v \circ u^{-1})' = (v' \circ u^{-1})(u^{-1})'$$

$$(v \circ u^{-1})'' = (v'' \circ u^{-1})[(u^{-1})']^2 + (v' \circ u^{-1})(u^{-1})''$$

$$\text{Now, } (u^{-1})' = \frac{1}{u' \circ u^{-1}} \text{ and } \left(\frac{1}{u' \circ u^{-1}}\right)' = -\frac{(u'' \circ u^{-1})(u^{-1})'}{(u' \circ u^{-1})^2} = -\frac{(u'' \circ u^{-1})}{(u' \circ u^{-1})^3}$$

$$\text{so, } (v \circ u^{-1})'' \geq 0 \Leftrightarrow \frac{(v'' \circ u^{-1})}{(u' \circ u^{-1})^2} - (v' \circ u^{-1}) \frac{(u'' \circ u^{-1})}{(u' \circ u^{-1})^3} \geq 0$$

$$\Leftrightarrow (v'' \circ u^{-1}) \geq (v' \circ u^{-1}) \frac{(u'' \circ u^{-1})}{(u' \circ u^{-1})}$$

$$\Leftrightarrow -\frac{(v'' \circ u^{-1})}{(v' \circ u^{-1})} \leq -\frac{(u'' \circ u^{-1})}{(u' \circ u^{-1})} \text{ Q.E.D as we assumed here } -\frac{v''}{v'} \leq -\frac{u''}{u'}$$

Remarks:

If there is aversion to risk we use u concave to modelize

For $u(a) = 1 - \exp(-\lambda a)$ (which is often used) $-\frac{u''}{u'} = \lambda$

Gaussian Laws and Mean Variance Implications

When investing W_0 the utility function criteria picks strategies π which maximizes: $E[u(W_T^\pi)]$ where $\frac{W_T^\pi}{W_0} = 1 + R_T^\pi$

If we assume $R_T^\pi \sim N(m_\pi, \sigma_\pi^2)$ then: $E[u(W_T^\pi)] = E[u(W_0 + W_0 R_T^\pi)]$
 $= E[u(W_0 + m_\pi W_0 + \sigma_\pi W_0 Z)]$ with $Z \sim N(0, 1)$

If we define $U(m, \sigma) = E[u(W_0 + mW_0 + \sigma W_0 Z)]$ then:

$$\max_{\pi} E[u(W_T^\pi)] = \max_{\pi} U(m_\pi, \sigma_\pi)$$

So in practice the model consists in maximizing $\max_{\pi} U(m_\pi, \sigma_\pi)$ where U is derived from a utility function.

Remarks: For the DAX, if we suppose that we are in an equilibrium where therefore investors are indifferent between investing into a 1 year zero coupon bond which yields approx 0% or into the DAX, which is expected to return approx $0.02\% \times 260$, then the Risk Premium is 5.20%...

Gaussian Laws and Mean Variance Implications

From now on we will modelize directly with a function U and we will assume that U is increasing in m and decreasing in σ which means that:

- if the investor has the choice between two strategies with the same expected returns he prefers the one with the less variance on the returns
- if the investor has the choice between two strategies with the same variance on the returns he prefers the one with the higher expected returns

In practice an investor will define the level of risks he accepts and based on this will find the efficient portfolio (that maximizes the expected return. Based on this we make the following definition

Definition: Efficient investment strategy

An investment strategy π_e is efficient iff for all π :

$$E[R^\pi] \geq E[R^{\pi_e}] \Rightarrow \sigma(R^\pi) \geq \sigma(R_e^\pi)$$

Proposition:

$$\pi_e \text{ is a solution of } \begin{cases} \min_{\pi} \sigma(R^\pi) \\ E[R^\pi] = E[R^{\pi_e}] \end{cases}$$

Demonstration: If the solution of the constraint minimization was less than $\sigma(R^{\pi_e})$ then we could find π such that $\sigma(R^\pi) < \sigma(R^{\pi_e})$ and

$E[R^\pi] = E[R^{\pi_e}]$ but the contraposition of

$E[R^\pi] \geq E[R^{\pi_e}] \Rightarrow \sigma(R^\pi) \geq \sigma(R_e^\pi)$ implies that

$\sigma(R^\pi) < \sigma(R_e^\pi) \Rightarrow E[R^\pi] < E[R^{\pi_e}]$

So π_e is solution of the constraint problem. QED

Remarks: Definitions and Geometric interpretation

If we note:

- $\mathcal{E} = \{\pi_e \text{ efficient}\}$ and
- $\mathcal{E}(\sigma, m) = \left\{ \begin{pmatrix} \sigma(R^{\pi_e}) \\ E(R^{\pi_e}) \end{pmatrix}, \pi_e \in \mathcal{E} \right\}$

Then any point $\begin{pmatrix} \sigma(R^\pi) \\ E(R^\pi) \end{pmatrix}$ is on the right of $\mathcal{E}(\sigma, m)$

Markowitz: The mean variance framework

Notations and Definitions

We note:

- S_t^i : the value of asset i at time t . Here we consider only two periods (0 and T)
- q_i : the number of shares i held ($q_i > 0$) or shorted ($q_i < 0$) at time 0
- R_T^i the return of asset i between 0 and T , i.e $R_T^i = \frac{S_T^i}{S_0^i} - 1$
- $R_T = \begin{pmatrix} R_T^1 \\ \vdots \\ R_T^n \end{pmatrix}$ the vector of returns of the n shares between 0 and T .

Definition:

At inception,

An investment portfolio is a portfolio for which $\sum_{i=1}^{i=n} q_i S_0^i > 0$

A self financing portfolio is a portfolio for which $\sum_{i=1}^{i=n} q_i S_0^i = 0$

Theorem and Definition:

If for an investment portfolio we define: $\forall i \pi_i = \frac{q_i S_0^i}{x_0}$ and $x_0 = \sum_{i=1}^{i=n} q_i S_0^i$

then :

- $(x_0, \pi_1, \dots, \pi_n)$ defines in a unique way the investment portfolio
- x_0 is the initial value of the portfolio
- $\sum_{i=1}^{i=n} \pi_i = 1$
- π_i is the percentage of the value of the portfolio invested in asset i at time 0 and (π_1, \dots, π_n) is called the allocation.

Theorem and Definition:

All self financing portfolios can be represented by a $(n+1)$ -uplet $(x_0, \pi_1, \dots, \pi_n)$ such that :

- $\forall i \ q_i = \frac{x_0 \pi_i}{S_0^i}$
- $\sum_{i=1}^{i=n} \pi_i = 0$
- $x_0 > 0$

The representation is not unique as $\forall \lambda > 0 \ (\frac{1}{\lambda}x_0, \lambda\pi_1, \dots, \lambda\pi_n)$ represents the same self financing portfolio as $(x_0, \pi_1, \dots, \pi_n)$.

For any chosen representation $(x_0, \pi_1, \dots, \pi_n)$ of the self financing portfolio, x_0 is called the Notional and (π_1, \dots, π_n) the allocation.

Notations and Definitions

From now on we will describe investment portfolios and self financing

portfolios by pairs (x_0, π) where $\pi = \begin{pmatrix} \pi_1 \\ \vdots \\ \pi_n \end{pmatrix}$

Theorem and Definition:

We note $W_t(x_0, \pi)$ the value at time t of the portfolio (x_0, π) and we have:

- $W_0(x_0, \pi) = x_0$
- $W_T(x_0, \pi) = \sum_{i=1}^{i=n} x_0 \pi_i \frac{S_T^i}{S_0^i}$

Remark:

$\pi^i < 0$ means that the portfolio has a short position in asset i

S^i is called a risky asset iff R_T^i is not deterministic i.e. $Var(R_T^i) \neq 0$

Example: when we consider various allocations (x_0, π) between two shares $S_0^1 = 100$ $S_0^2 = 50$ we get the following table:

x_0	π_1	π_2	q^1	q^2	W_0
100	1	-1	1	-2	0
1000	1	-1	10	-20	0
100	0.5	0.5	0.5	1	100
1000	0.5	0.5	5	10	1000

Theorem and Definition:

We define the return of a portfolio (x_0, π) as: $R_T = \frac{W_T(x_0, \pi) - W_0(x_0, \pi)}{x_0}$

- For an investment portfolio this definition corresponds to the definition of the return of an asset
- For a self financing portfolio this quantity equals $\frac{W_T(x_0, \pi)}{x_0}$

Proposition

For any investment or self financing portfolio (x_0, π) the return R_T verifies:

$$R_T = \sum_{i=1}^{i=n} \pi_i R_T^i.$$

As this expression depends only on π and not on x_0 we note it R_T^π .

Proposition:

For any investment or self-financing portfolio (x_0, π) we have:

- $R_T^\pi = \pi' R_T$
- $E(R_T^\pi) = E(\pi' R_T) = \pi' E[R_T]$
- $Cov(R_T^{\pi_1}, R_T^{\pi_2}) = Cov(\pi_1' R_T, \pi_2' R_T) = \pi_1' Cov[R_T, R_T] \pi_2$

Exercise: demonstrate the proposition

Notations: from now on we note:

- $\sigma^\pi = \sigma(R_T^\pi)$
- $m^\pi = E(R_T^\pi)$

Markowitz's Framework

We are going to consider two cases, each based on the existence or not of a risk-free investment strategy:

First case:

There are n risky assets $(S^i)_{i \in [1, n]}$ and no risk-free asset.

Second case:

There are n risky assets $(S^i)_{i \in [1, n]}$ and one risk-free asset S^0 .

Remarks:

In both cases it is natural to assume that the R_T^i are such as :

- (H1) there is no way to build a risk-free investment portfolio based on the $(S^i)_{i \in [1, n]}$
- (H2) there is no way to build a risk-free self-financing portfolio (other than zero) based on the $(S^i)_{i \in [1, n]}$

Comments:

The reason why we assume (H1) in the first case is because otherwise we could build a risk-free asset. The reason why we assume (H1) in the second case is because otherwise we could build a second risk-free asset and then:

- either this second risk-free asset has the same return as the risk-free asset and in this case one risky asset could be replicated (and then should be disregarded).
- or this second risk-free asset has a different return from the risk-free asset, in which case there would be some arbitrage opportunities.

The reason why we assume (H2) is because for a risk-free self-financing strategy:

- if the return is different from zero there are some arbitrage opportunities
- if the return is different is zero one risky asset can be replicated (and then should be be disregarded)

We Note :

- $\Sigma = \text{Cov}[R_T, R_T]$
- $M = E[R_T]$

Proposition:

(H1) and (H2) $\implies \Sigma$ is invertible

Demonstration:

If Σ was not invertible we could find $\pi \neq 0$ such that $\pi' \Sigma \pi = 0$ and then there would be two cases:

either $\pi' \mathbf{1}_n = 0$ in which case we could find a self-financing portfolio made of the risky assets without risk or

$\pi' \mathbf{1}_n \neq 0$ in which case we could find an investment portfolio made of the risky assets without risk.

in both cases this would be in contradiction with (H1) or (H2).

Markowitz: Optimization without a risk-free asset

Optimization without a risk-free asset

From the utility framework and in the context of normal distributions assumptions the efficient investment portfolios (x_0, π) are the solutions of

$$(P) \begin{cases} \min_{\pi} \pi' \Sigma \pi \\ \pi' M = m \text{ where } 1_n \text{ is the vector of } \mathbb{R}^n \text{ with components equal to } 1 \\ \pi' 1_n = 1 \end{cases}$$

We define a new scalar product in \mathbb{R}^n by $\langle x, y \rangle_{\Sigma^{-1}} = x' \Sigma^{-1} y$

We can write (P) as

$$(P) \begin{cases} \min_{\pi} \langle \Sigma \pi, \Sigma \pi \rangle_{\Sigma^{-1}} \\ \langle \Sigma \pi, M \rangle_{\Sigma^{-1}} = m \\ \langle \Sigma \pi, 1_n \rangle_{\Sigma^{-1}} = 1 \end{cases}$$

(P) can be solved either by writing its Lagrangien or geometrically by noticing that $\Sigma \pi$ must be in $\text{Vect}(M, 1_n)$ in order to minimize its $\langle, \rangle_{\Sigma^{-1}}$ norm while satisfying the constraints. We note \mathcal{F} all the investment portfolios solutions of (P) for any possible value of m .

We note:

- $a = \langle 1_n, 1_n \rangle_{\Sigma^{-1}}$ and
- $b = \langle M, 1_n \rangle_{\Sigma^{-1}}$

Excluding for now the case $M - \frac{b}{a}1_n = 0$ and noticing that $\langle M - \frac{b}{a}1_n, 1_n \rangle_{\Sigma^{-1}} = 0$ we get that $M - \frac{b}{a}1_n$ and 1_n form an orthogonal basis of $\text{Vect}(M, 1_n)$. So we can write:

$$\Sigma \pi_e = \lambda 1_n + \nu (M - \frac{b}{a}1_n) \text{ or } \pi_e = \lambda \Sigma^{-1} 1_n + \nu \Sigma^{-1} (M - \frac{b}{a}1_n)$$

We can now renormalize this decomposition.

We note:

- $\pi_a = \frac{1}{a} \Sigma^{-1} 1_n$ which satisfies $\pi_a' 1_n = 1$ and
- $\omega_{a,b} = \frac{\Sigma^{-1} (M - \frac{b}{a}1_n)}{\|M - \frac{b}{a}1_n\|_{\Sigma^{-1}}}$ which satisfies $\omega_{a,b}' 1_n = 0$ and $\text{var}[R_T^{\omega_{a,b}}] = 1$

Proposition: Building Blocks

- $\pi_a' \mathbf{1}_n = 1$ (so π_a is an investment portfolio).
- $m^{\pi_a} = \frac{b}{a}$
- $\sigma^{\pi_a} = \frac{1}{\sqrt{a}}$
- $\omega_{a,b}' \mathbf{1}_n = 0$ (so $\omega_{a,b}$ is a self-financing portfolio).
- $m^{\omega_{a,b}} = \|M - \frac{b}{a} \mathbf{1}_n\|_{\Sigma^{-1}}$
- $\sigma^{\omega_{a,b}} = 1$
- $\text{cov}(R^{\pi_a}, R^{\omega_{a,b}}) = 0$

Demonstration:

$$\pi_a' \mathbf{1}_n = \mathbf{1}_n' \pi_a = \frac{1}{a} \mathbf{1}_n' \Sigma^{-1} \mathbf{1}_n = 1$$

$$m^{\pi_a} = M' \pi_a = \frac{1}{a} M' \Sigma^{-1} \mathbf{1}_n = \frac{b}{a}$$

$$\sigma^{\pi_a} = [\pi_a' \Sigma \pi_a]^{\frac{1}{2}} = \left[\frac{1}{a^2} \mathbf{1}_n' \Sigma^{-1} \Sigma \Sigma^{-1} \mathbf{1}_n \right]^{\frac{1}{2}} = \left[\frac{a}{a^2} \right]^{\frac{1}{2}} = \frac{1}{\sqrt{a}}$$

$$\omega_{a,b}' \mathbf{1}_n = \frac{1}{\|M - \frac{b}{a} \mathbf{1}_n\|_{\Sigma^{-1}}} \mathbf{1}_n' \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) = 0$$

$$m^{\omega_{a,b}} = M' \omega_{a,b} = M' \frac{\Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n)}{\|M - \frac{b}{a} \mathbf{1}_n\|_{\Sigma^{-1}}}$$

using $\mathbf{1}_n' \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) = 0$ we get:

$$M' \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) = (M - \frac{b}{a} \mathbf{1}_n)' \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) \text{ and so}$$

$$m^{\omega_{a,b}} = \frac{\|M - \frac{b}{a} \mathbf{1}_n\|_{\Sigma^{-1}}^2}{\|M - \frac{b}{a} \mathbf{1}_n\|_{\Sigma^{-1}}} = \|M - \frac{b}{a} \mathbf{1}_n\|_{\Sigma^{-1}}$$

$$(\sigma^{\omega_{a,b}})^2 = \frac{1}{\|M - \frac{b}{a} \mathbf{1}_n\|_{\Sigma^{-1}}^2} (M - \frac{b}{a} \mathbf{1}_n)' \Sigma^{-1} \Sigma \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) = 1$$

$$\text{cov}(R^{\pi_a}, R^{\omega_{a,b}}) = \frac{1}{a} \mathbf{1}_n' \Sigma^{-1} \Sigma \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) \frac{1}{\|M - \frac{b}{a} \mathbf{1}_n\|_{\Sigma^{-1}}^2} = 0 \text{ Q.E.D}$$

Proposition

- a) $\mathcal{F} = \{\pi_a + \lambda\omega_{a,b}, \lambda \in \mathbb{R}\}$
- b) $R^{\pi_a + \lambda\omega_{a,b}} = R^{\pi_a} + \lambda R^{\omega_{a,b}}$
- c) $m^{\pi_a + \lambda\omega_{a,b}} = m^{\pi_a} + \lambda m^{\omega_{a,b}}$
- d) $(\sigma^{\pi_a + \lambda\omega_{a,b}})^2 = (\sigma^{\pi_a})^2 + \lambda^2$
- e) $\min_{\pi \in \mathcal{E}} \sigma^\pi = \sigma^{\pi_a}$

Demonstration:

a) We know that a solution of (P) is of the form $\alpha\pi_a + \beta\omega_{a,b}$ as it must be in $\text{Vect}(\pi_a, \omega_{a,b})$. The condition $\pi' \mathbf{1}_n = 1$ implies $\alpha\pi_a' \mathbf{1}_n = 1$ which implies $\alpha = 1$. So the solutions of (P) are all of the forms $\pi_a + \lambda\omega_{a,b}$. Reciprocally the investment portfolio $\pi_a + \lambda\omega_{a,b}$ is the solution of (P) for $m = m^{\pi_a} + \lambda m^{\omega_{a,b}}$.

Optimization without a risk-free asset

b) $R^{\pi_a + \lambda \omega_{a,b}} = (\pi_a + \lambda \omega_{a,b})' R_T = \pi_a' R_T + \lambda \omega_{a,b}' R_T = R^{\pi_a} + \lambda R^{\omega_{a,b}}$.
Q.E.D

c) by definition $m^{\pi_a + \lambda \omega_{a,b}} = E[R^{\pi_a + \lambda \omega_{a,b}}]$ so c) is derived from b) by taking expectations on both side of equality b).

d) by definition $(\sigma^{\pi_a + \lambda \omega_{a,b}})^2 = \text{Var}[R^{\pi_a + \lambda \omega_{a,b}}]$ and according to b) this quantity equals $\text{Var}[R^{\pi_a} + \lambda R^{\omega_{a,b}}]$. As the covariance between these two variables is zero, the expression is $\text{Var}[R^{\pi_a}] + \lambda^2 \text{Var}[R^{\omega_{a,b}}]$ and as seen previously $\text{Var}[R^{\omega_{a,b}}] = 1$. Q.E.D

e) this results from d)

Corollary

If $\pi_e \in \mathcal{F}$

- $(\sigma^{\pi_e})^2 = (\sigma^{\pi_a})^2 + \left(\frac{m^{\pi_e} - m^{\pi_a}}{m^{\omega_{a,b}}}\right)^2$
- $m^{\pi_e} = m^{\pi_a} + m^{\omega_{a,b}} \sqrt{(\sigma^{\pi_e})^2 - (\sigma^{\pi_a})^2}$ if $m^{\pi_e} > m^{\pi_a}$
- $m^{\pi_e} = m^{\pi_a} - m^{\omega_{a,b}} \sqrt{(\sigma^{\pi_e})^2 - (\sigma^{\pi_a})^2}$ if $m^{\pi_e} < m^{\pi_a}$
- $\pi_e = \pi_a + \frac{m^{\pi_e} - m^{\pi_a}}{m^{\omega_{a,b}}} \omega_{a,b}$

Demonstration:

Trivial when writing π_e as $\pi_a + \lambda \omega_{a,b}$ and eliminating λ between the equations.

Optimization without a risk-free asset

Remarks:

- The frontier $\mathcal{F}(\sigma, m)$ is an hyperbole
- For all assets and investment portfolios: (σ, m) is on or inside the hyperbole
- Geometrically: the line $y = a + bx$ is above the hyperbole $y = a + b\sqrt{x^2 - 1}$ and is "asymptotically tangent" as:
 - $a + bx - (a + b\sqrt{x^2 - 1}) \xrightarrow{x \rightarrow \infty} 0$ (points of the curves converging) and
 - $b / [b \frac{x}{\sqrt{x^2 - 1}}] \xrightarrow{x \rightarrow \infty} 1$ (slopes of the curves converging)

Definitions:

We note:

- $\mathcal{F}^+ = \{\pi_a + \lambda \omega_{a,b}, \lambda \geq 0\}$
- $\mathcal{F}^- = \{\pi_a + \lambda \omega_{a,b}, \lambda \leq 0\}$
- $\mathcal{F}^+(\sigma, m) = \{(\sigma^\pi, m^\pi), \pi \in \mathcal{F}^+\}$ and call it the Efficient Frontier
- $\mathcal{F}^-(\sigma, m) = \{(\sigma^\pi, m^\pi), \pi \in \mathcal{F}^-\}$ and call it the Inefficient Frontier

Two Funds Theorem:

All the efficient portfolios can be built from two fixed distinct efficient investment portfolios π_1 and π_2 .

For this reason to analyse the efficient frontier we just need to analyse a model based on two risky assets!

Demonstration:

Let $\pi_1 = \pi_a + \lambda_1 \omega_{a,b}$ and $\pi_2 = \pi_a + \lambda_2 \omega_{a,b}$ be distinct on \mathcal{F}

Let $\pi = \pi_a + \lambda \omega_{a,b}$ be on \mathcal{F} .

For any $\alpha \in \mathbb{R}$, $\alpha \pi_1 + (1 - \alpha) \pi_2$ is an investment portfolio (as $\alpha \pi_1' \mathbf{1}_n + (1 - \alpha) \pi_2' \mathbf{1}_n = 1$) and if we choose $\alpha = \frac{\lambda - \lambda_2}{\lambda_1 - \lambda_2}$ we get $\alpha \pi_1 + (1 - \alpha) \pi_2 = \pi_a + \lambda \omega_{a,b} = \pi$. Q.E.D

Exercise 1:

We consider 2 risky assets S^1, S^2 :

- $m_1 = 5\%$, $\sigma_1 = 15\%$
- $m_2 = 20\%$, $\sigma_2 = 30\%$

We note ρ the correlation between R^1 and R^2 .

a) Plot \mathcal{F} for: $\rho = -1$, $\rho = 0$, $\rho = 0.5$, $\rho = 1$.

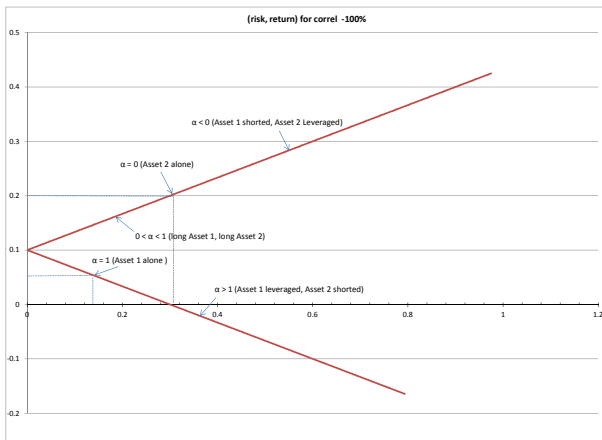
b) What is the portfolio of minimum standard deviation in each case?

If we consider the portfolio $\pi_\alpha = \alpha\pi_1 + (1 - \alpha)\pi_2$

c) In which region of $\mathcal{F}(\sigma, m)$ is $(\sigma^{\pi_\alpha}, m^{\pi_\alpha})$ in the following cases:

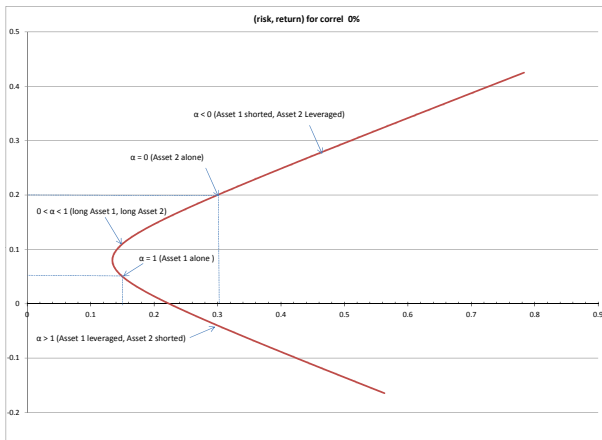
- $\alpha < 0$
- $0 \leq \alpha \leq 1$
- $\alpha > 1$

Optimization without a risk-free asset



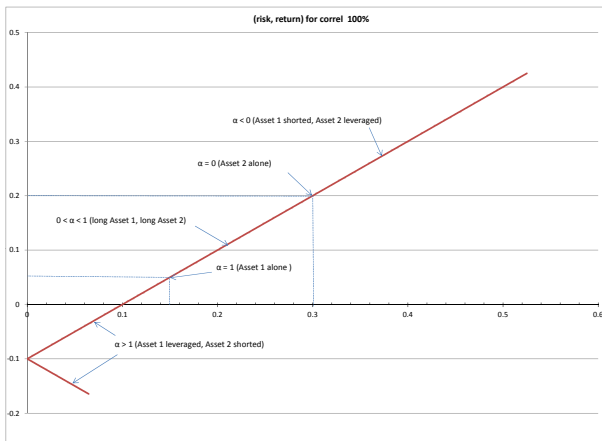
Note that Σ is not invertible here and a risk-free asset can be constructed

Optimization without a risk-free asset



Note that Σ is invertible here and we obtain the "usual" hyperbole

Optimization without a risk-free asset



Note that Σ is not invertible here and a risk-free asset can be constructed

Proposition:

$$\mathcal{F} = \left\{ \frac{1}{b-ma} \Sigma^{-1} (M - m \mathbf{1}_n), m \neq \frac{b}{a} \right\} \cup \left\{ \frac{1}{a} \Sigma^{-1} \mathbf{1}_n \right\}$$

Demonstration:

We know that $\mathcal{F} = \left\{ \frac{1}{a} \Sigma^{-1} \mathbf{1}_n + \lambda \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n), \lambda \in \mathbb{R} \right\}$

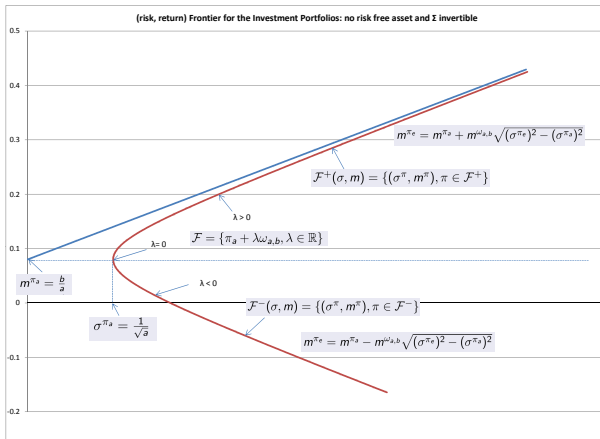
for $\lambda = 0$ we obtain the portfolio $\frac{1}{a} \Sigma^{-1} \mathbf{1}_n$

for $\lambda \neq 0$ we can write λ in the form $\lambda = \frac{1}{b-ma}$ and by doing so we obtain

$$\begin{aligned} & \frac{1}{a} \Sigma^{-1} \mathbf{1}_n + \frac{1}{b-ma} \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) \\ &= \frac{1}{b-ma} \Sigma^{-1} (M - m \mathbf{1}_n) + \frac{1}{b-ma} \Sigma^{-1} (m - \frac{b}{a}) \mathbf{1}_n + \frac{1}{a} \Sigma^{-1} \mathbf{1}_n \\ &= \frac{1}{b-ma} \Sigma^{-1} (M - m \mathbf{1}_n) + \frac{1}{b-ma} \Sigma^{-1} (am - b) \frac{1}{a} \mathbf{1}_n + \frac{1}{a} \Sigma^{-1} \mathbf{1}_n \\ &= \frac{1}{b-ma} \Sigma^{-1} (M - m \mathbf{1}_n) \text{ Q.E.D} \end{aligned}$$

Remarks: We will demonstrate later that the parameter m can be interpreted geometrically, by showing that the tangent to \mathcal{F} at point (σ, m) intersects the axe $\{\sigma = 0\}$ at point $(0, m)$.

Optimization without a risk-free asset



Remarks: We have assumed so far that $M - \frac{b}{a}1_n \neq 0$. We analyse here what would happen if this was not the case.

If $M - \frac{b}{a}1_n = 0$ then all portfolios would have the same returns equal to $\frac{b}{a}$. In this case (P) would be a problem of minimizing, for an investment portfolio, the standard deviation of the return, i.e to solve:

$$(P) \begin{cases} \min_{\pi} \langle \Sigma \pi, \Sigma \pi \rangle_{\Sigma^{-1}} \\ \langle \Sigma \pi, 1_n \rangle_{\Sigma^{-1}} = 1 \end{cases}$$

As previously, geometrically we see that the solution should verify $\Sigma \pi_e \in \text{Vect}(1_n)$, so $\pi_e = \lambda \Sigma^{-1} 1_n$. The only π_e of this form satisfying $(\pi_e)' 1_n = 1$ is $\pi_e = \frac{1}{a} \Sigma^{-1} 1_n$

Markowitz: Optimization with a risk-free asset

Optimization with a risk-free asset

We note $\Pi = \begin{pmatrix} \pi^0 \\ \pi \end{pmatrix}$ the allocation between the risk-free asset and the n risky assets.

We note $\Pi_0 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ the risk-free asset of return r_0 .

For any investment portfolios Π we must have $\pi^0 + (\pi)'1_n = 1$.

Replacing π^0 by $1 - \pi'1_n$ the problem we have to solve, to find the efficient portfolios, can now be written as:

$$(Q) \begin{cases} \min_{\pi} \pi' \Sigma \pi \\ \pi' M + (1 - \pi'1_n)r_0 = m \end{cases}$$

Which we can also write as:

$$(Q) \begin{cases} \min_{\pi} \langle \Sigma \pi, \Sigma \pi \rangle_{\Sigma^{-1}} \\ \langle \Sigma \pi, M - r_0 1_n \rangle_{\Sigma^{-1}} = m - r_0 \end{cases}$$

Geometrically, the solution has to be of the form $\Sigma\pi = \lambda(M - r_0\mathbf{1}_n)$ or equivalently $\pi = \lambda\Sigma^{-1}(M - r_0\mathbf{1}_n)$.

Note that $\mathbf{1}'_n\Sigma^{-1}(M - r_0\mathbf{1}_n) = (b - r_0a)$.

Until the end of this section we will consider that $b - r_0a \neq 0$

To renormalize the problem we define: $\pi_M = \frac{1}{b - r_0a}\Sigma^{-1}(M - r_0\mathbf{1}_n)$

Note that $\Pi_M = \begin{pmatrix} 0 \\ \pi_M \end{pmatrix}$ is an investment portfolio as $\pi'_M\mathbf{1}_n = 1$

With these notations we now state:

Theorem: Capital Market Line

The portfolios solutions of (Q) are the portfolios: $\lambda\Pi_M + (1 - \lambda)\Pi_0$ with $\lambda \in \mathbb{R}$. We note $\mathcal{C} = \{\lambda\Pi_M + (1 - \lambda)\Pi_0, \lambda \in \mathbb{R}\}$

Corollaries and "Market Portfolio"

① The portfolios Π of \mathcal{C} (i.e the solutions of (Q)) verify:

- $m^\Pi = \lambda m^{\Pi_M} + (1 - \lambda)m^{\Pi_0}$
- $\sigma^\Pi = |\lambda|\sigma^{\Pi_M}$

so their risk parameters (σ, m) are on a cone (i.e $\mathcal{C}(\sigma, m)$ is a cone).

② All the efficient portfolios are built by allocating money only between Π_0 and Π_M . For this reason to study optimal investments we just need to use a model with one single risky asset!

③ CAPM/MEDAF: if all the market participants are allocating efficiently and with the same parameters, then:

- all the risky investments are in Π^M and
- in Π^M the weight in risky asset i is the % of the total Market Capitalization of risky assets that asset i represents.

For this reason Π^M should be/is called the (risky) "Market Portfolio".

Corollaries:

- 1 Usually in the model $\frac{b}{a} > r_0$ otherwise all the efficient portfolios would short Π_M which practically would not make sense.
- 2 Assuming $\frac{b}{a} > r_0$ we define:
 - $\mathcal{C}^+ = \{\lambda m^{\Pi_M} + (1 - \lambda)m^{\Pi_0}, \lambda \geq 0\}$ and call it the Cone Efficient Frontier (or Capital Market Line)
 - $\mathcal{C}^- = \{\lambda m^{\Pi_M} + (1 - \lambda)m^{\Pi_0}, \lambda \leq 0\}$ and call it the Cone Inefficient Frontier
 - All the assets and portfolios we can build have their risk parameters (σ, m) within the cone $\mathcal{C}(\sigma, m)$ and in particular $\mathcal{F}(\sigma, m)$ is included in $\mathcal{C}(\sigma, m)$.

Demonstration:

Straightforward when writing $\Pi_e = \lambda \Pi_M + (1 - \lambda) \Pi_0$

Exercise:

Draw \mathcal{F} and \mathcal{C} in a model where there are two risky assets and a risk free asset and see what happens when you are changing the correlation

Lemma: Tangent Portfolio

The "Market Portfolio" Π_M , which has no allocation in the risk-free asset, is also a solution of the mean/variance optimization problem (P) where there was no risk-free asset. So we can write $\Pi_M \in \mathcal{F}$

Demonstration:

Geometrically: it is obvious as otherwise there would be some portfolios more efficient (above) than those on the Capital Market Line.

Algebraically:

$$\begin{aligned}\pi_M &= \frac{1}{b-r_0a} \Sigma^{-1} (M - r_0 \mathbf{1}_n) = \frac{1}{b-r_0a} \Sigma^{-1} [(M - \frac{b}{a} \mathbf{1}_n) + (\frac{b}{a} \mathbf{1}_n - r_0 \mathbf{1}_n)] \\ &= \frac{1}{b-r_0a} (\frac{b}{a} - r_0) \Sigma^{-1} \mathbf{1}_n + \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) \\ &= \frac{1}{a} \Sigma^{-1} \mathbf{1}_n + \frac{1}{b-r_0a} \Sigma^{-1} (M - \frac{b}{a} \mathbf{1}_n) \\ &= \pi_a + \lambda \omega_{a,b} \text{ which is the form of the portfolios of } \mathcal{F}. \text{ Q.E.D}\end{aligned}$$

Until the end of this section we assume that $\frac{b}{a} > r_0$

Theorem: Tangent Portfolio

$\mathcal{C}(\sigma, m)$ is tangent to $\mathcal{F}(\sigma, m)$ at the point $(\sigma^{\Pi_M}, m^{\Pi_M})$

Demonstration:

We know that Π_M is on \mathcal{C} and that Π_M is on \mathcal{F} .

Geometrically: If a line and an hyperbole have a contact point either they are tangent on this contact point or they cross each other. The situation where they cross each other is not possible here as it would imply that some portfolios of \mathcal{F} are more efficient than any portfolios of \mathcal{C} .

Remark:

Equivalently, we can say that the tangent to the Efficient Frontier \mathcal{F} at the point Π_M intersects the $\sigma = 0$ axis at the point $\begin{pmatrix} 0 \\ r_0 \end{pmatrix}$

Corollary: Geometry of the Efficient Frontier

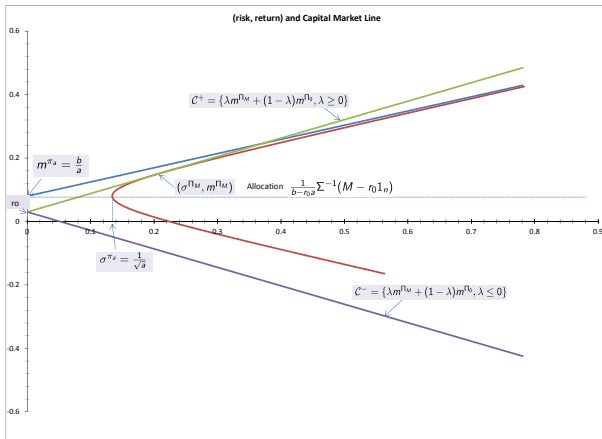
- For any risky efficient investment portfolio $\pi = \frac{1}{b-ma}\Sigma^{-1}(M - m\mathbf{1}_n)$ of \mathcal{F} , the tangent to $\mathcal{F}(\sigma, m)$ at (σ^π, m^π) intersects the $\{\sigma = 0\}$ axis at the point $\begin{pmatrix} 0 \\ m \end{pmatrix}$.
- For the risky efficient investment portfolio $\pi = \frac{1}{a}\Sigma^{-1}\mathbf{1}_n$ of \mathcal{F} , the tangent to $\mathcal{F}(\sigma, m)$ at (σ^π, m^π) is parallel to the $\{\sigma = 0\}$ axis.

These results mean that there is a bijection between $\mathcal{F} - \{\frac{1}{a}\Sigma^{-1}\mathbf{1}_n\}$ and $\mathbb{R} - \{\frac{b}{a}\}$ and that is it the tangents to the the $\mathcal{F}(\sigma, m)$ curve which establish the bijection between the portfolios and their parameters m .

Demonstration:

This result for a portfolio of parameter m corresponds to the result of the preceding corollary when taking $r_0 = m$. Q.E.D

More Geometric Properties



Security Market Line

Theorem: Security Market Line

Let Π_M be the Market Portfolio as defined previously

Let Π_P be any investment portfolio composed of the risk-free and risky assets. Then:

- $m_P - r_0 = (m_M - r_0)\rho(R_P, R_M)\frac{\sigma_P}{\sigma_M}$ (SML equation) and
- $R_P - r_0 = (R_M - r_0)\rho(R_P, R_M)\frac{\sigma_P}{\sigma_M} + \epsilon$ with ϵ normal independent from R_M and centered.

Demonstration:

Let Π_P be an investment portfolio then:

$$\text{cov}(R_M, R_P) = \pi_M' \Sigma \pi_P = \frac{1}{b-r_0a} (M - r_0 \mathbf{1}_n)' \pi_P = \frac{m_P - r_0}{b - r_0 a}$$

If we apply the same calculation to Π_P then:

$$\text{cov}(R_M, R_M) = \frac{m_M - r_0}{b - r_0 a}$$

From this we get:

$$\text{cov}(R_M, R_P) = \frac{m_P - r_0}{m_M - r_0} \text{cov}(R_M, R_M)$$

From which we get : $m_P - r_0 = (m_M - r_0)\rho(R_M, R_P)\frac{\sigma_P}{\sigma_M}$

We now want to show a relationship for the r.v and not only for their expectations.

$\left(\begin{array}{c} (R_P - r_0) - (R_M - r_0)\rho(R_M, R_P)\frac{\sigma_P}{\sigma_M} \\ R_M \end{array} \right)$ is Gaussian because it is an affine

transformation of the vector of the returns of the risky assets which is assumed to be a Gaussian vector. Thus, to show that the first variable that we call ϵ is independent from the second one we just need to show that the covariance is zero.

$$\begin{aligned} \text{Indeed, } \text{cov}(\epsilon, R_M) &= \text{cov}(R_P - R_M\rho(R_M, R_P)\frac{\sigma_P}{\sigma_M}, R_M) \\ &= \text{cov}(R_P, R_M) - \rho(R_M, R_P)\frac{\sigma_P}{\sigma_M}\text{cov}(R_M, R_M) = 0 \end{aligned}$$

The fact that ϵ is centered i.e $E(\epsilon) = 0$, results from the previous result.

Q.E.D

Definition:

The quantity $\rho(R_M, R_P) \frac{\sigma_P}{\sigma_M}$ is noted $\beta_{P,M}$ and is called the beta of the asset Π_P (in respect to the Market Portfolio Π_M).

Remarks:

The equation: $m_P - r_0 = (m_M - r_0)\beta_{P,M}$ (SML)

- is valid for all investment portfolios and not only for efficient ones.
- shows that only the risk correlated with the "Market Portfolio/Market Risk" is remunerated.
- is used in capital budgeting / CAPM to determine the price an asset should have based on its expected returns and beta with the sector.

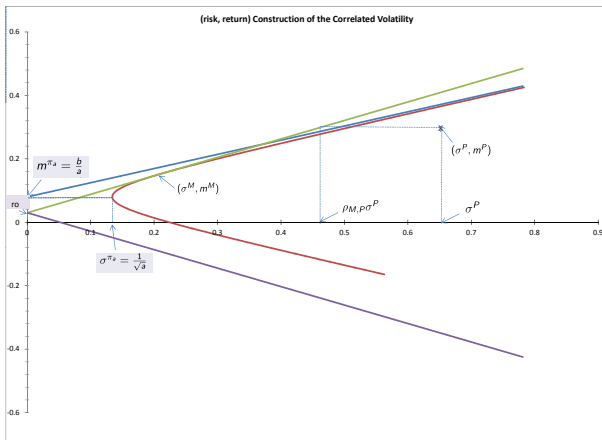
Definition:

When we write $R_P = r_0 + (R_P - r_0)\beta_{R_P, R_M} + \epsilon$ we have

$$\sigma_M^2 = \sigma_P^2 \beta_{P, M}^2 + \sigma_\epsilon^2$$

- $\sigma_P |\beta_{P, M}|$ is called the systematic risk. It cannot be reduced by diversification in the model and thus is remunerated.
- σ_ϵ is called the idiosyncratic risk. It can be reduced by diversification in the model, and thus is not remunerated.

Security Market Line



We can read on the graph, for any portfolio, the portion of the volatility correlated with the movements of the Market Portfolio.

Security Market Line and "Arbitrage" Detections

Remarks: The (β, m) of the assets we consider investing it according to the SML should be on a line.

- The beta will usually be calculated in relation to a broader index to which these stocks belong
- The expected returns will be based either on some historical estimates or some analysts predictions

In practice, the points will not be perfectly aligned and a regression line will be calculated.

- The assets over the line will look cheap
- The assets below the line will look expensive

In "pair-trading", strategies will be considered consisting in:

- Selling assets lying below the line
- Buying assets lying above the line (usually in the same sector)

Exercise: Show that if we consider an investment portfolio Π_P with risk parameters (σ_P, m_P) and if we call in the $\{(\sigma, m)\}$ plane, (x, m_P) the intersection of the SML and the line $\{m = m_P\}$ then $x = \beta_{P,M}\sigma_M$. Conclude that we can read in the $\{(\sigma, m)\}$ plane the decomposition between systematic risk and idiosyncratic risk.

Performance Indicators

Definition: Sharp Ratio

The Sharpe Ratio of an investment portfolio P is defined as: $\frac{m_P - r_0}{\sigma_P}$

Remarks:

Under the Markowitz's framework:

- The Ratio should be maximal for portfolios belonging to the CML
- All the portfolios belonging to the CML have the same Ratio
- Wealth should be allocated:
 - First by determining a portfolio with the maximum Sharpe Ratio that can be built
 - Then by allocating all the wealth between this portfolio and the risk free asset
- The Sharpe Ratio is independent from the leverage has $\lambda \Pi_P + (1 - \lambda) \Pi_0$ has the same Sharpe Ratio as Π_P for any $\lambda > 0$. So the indicator is really "intrinsic to the fund".
- The Sharpe Ratio is usually estimated by: $\frac{\hat{m}_P - r_0}{\hat{\sigma}_P}$

Remarks: An investor choosing a mutual fund to represent a large portion of his/her wealth should be concerned by the full risk of the fund and should look at the Sharpe Ratio.

Exercise 1: Show that the Sharpe Ratio is independent from the leverage

Exercise 2: How do you read in a $\{(\sigma, m)\}$ representation the Sharpe Ratio of a fund as the slope of a particular line?

Definition: Jensen Index

The Jensen Index of an investment portfolio P is defined as:

$$m_P - [r_0 + \beta_{M,P}(m_M - r_0)]$$

Remarks:

Under the Markowitz's framework this quantity should be zero according to the SML

In practice all the portfolios considered for investment are represented in the (β, m) plane where:

- the *beta* are estimated historically
- the expected returns are either historical estimates or analyst predictions

Then a regression line is calculated and the portfolios above the line could be considered for addition to the investment portfolio as:

- their systematic risk is remunerated more than expected
- their idiosyncratic risk should disappear via diversification

Remarks:

A large pension fund which allocates money amongst many asset managers may assume that the idiosyncratic risk is going to be reduced/cancelled through diversification and in this case may be concerned only by the remuneration of the non diversifiable risk and by the Jensen Index of each Asset Manager's funds.

Exercise 1: Show that the Jensen Ratio is dependent on leverage

Exercise 2: How do you read in a $\{(\beta, m)\}$ representation the Jensen Ratio of a fund as the distance above a particular line ?

Definition: Treynor Index

The Treynor Index of an investment portfolio P is defined as: $\frac{m_P - r_0}{\beta_{P,M}}$

Remarks:

Under the Markowitz's framework the Treynor Index should be constant according to the SML.

The Treynor Index is similar to the Jensen index in its objectives to detect funds for which there is an excess of remuneration of the systematic risk.

The excess is usually called the α !

Compared to the Jensen Index the advantage of the Treynor Index is that it does not depend on leverage and thus is a more intrinsic measure.

Remarks:

Show that the Treynor Index does not depend on leverage.

Factor Model

Factor Model

We revisit here the SML equation for risky assets and investment portfolios: $r^i(t) = r_0 + b^i(r_M(t) - r_0) + \epsilon^i(t)$ because:

- in practice the $\epsilon^i(t)$ appear to be correlated and to represent a significant portion of the variance of the assets.
- by adding additional factors we aim at identifying better the common sources of risks (even when they may not be remunerated) and to end up with smaller non explained residual idiosyncratic risks.
- we want to determine the remuneration of each individual source of risks through a non arbitrage argument.

The factor decomposition of the returns in a K-factor model of risky assets is expressed as:

$$r^i(t) = a^i + \sum_{j=1}^{j=K} \beta_j^i f^j(t) + \epsilon^i(t) \text{ for all assets } i \text{ in } \{1, \dots, N\} \text{ and all instants } t \text{ in } \{1, \dots, T\}$$

Factor Model

We can write matricially : $R(t) = A + BF(t) + E(T)$

$$\text{with } R(t) = \begin{pmatrix} r^1(t) \\ \vdots \\ r^N(t) \end{pmatrix} \quad A = \begin{pmatrix} a^1 \\ \vdots \\ a^N \end{pmatrix} \quad B = \begin{pmatrix} \beta_1^1 & \vdots & \beta_K^1 \\ \vdots & \vdots & \vdots \\ \beta_1^N & \vdots & \beta_K^N \end{pmatrix} \quad F(t) = \begin{pmatrix} f^1(t) \\ \vdots \\ f^K(t) \end{pmatrix}$$

$$\text{and } E(t) = \begin{pmatrix} \epsilon^1(t) \\ \vdots \\ \epsilon^N(t) \end{pmatrix}$$

We make the following assumptions:

$F(t)$ normal centered, $\text{Var}[F(t)] = \Sigma_F$ def positive independent from t .

$F(t)$ independent from $F(t')$ for $t \neq t'$.

A and B independent from t

$E(t)$ normal centered and $\text{Var}[E(t)] = \text{diag}(\sigma_i^2)$ independent from t .

$E(t)$ independent from $E(t')$ for $t \neq t'$.

$E(\cdot)$ independent from $F(\cdot)$

Remark 1 :

We assume that Σ_F is symmetric strictly positive.

If Σ_F was not strictly positive we could find $u = \begin{pmatrix} u^1 \\ \vdots \\ u^N \end{pmatrix} \neq 0$ such that

$u' \text{Var}[F(t)]u = 0$ and in this case we would have $\text{Var}[u'F(t)] = 0$ and so $u'F(t) = \text{Cte}$ which would mean that some of the factors would be redundant (could be "cointegrated").

Remark 2:

$$\begin{aligned} \text{Var}(R(t)) &= \text{cov}(BF(t) + E(t), BF(t) + E(t)) \\ &= \text{cov}(BF(t), BF(t)) + \text{cov}(E(t), E(t)) \\ &= B\text{cov}(F(t), F(t))B' + \text{diag}(\sigma_i^2) \\ &= B\Sigma_F B' + \text{diag}(\sigma_i^2) \end{aligned}$$

Remark 3:

If in the SML equation the $\epsilon^i(t)$ are independent, we are in presence of a one-factor model as it can be rewritten as:

$$r^i(t) = r_0 + b^i(m_M - r_0) + b^i(r_M(t) - m_M) + \epsilon^i(t)$$

which corresponds to a one factor model with:

$$a^i = r_0 + b^i(m_M - r_0), f^1(t) = (r_M(t) - m_M) \text{ and } \beta_1^i = b^i.$$

We note that:

- $r^i(t)$ represents the return of asset i over the period $[t - 1, t]$
- $f^1(t)$ represents the excess of the return of the factor (the market portfolio) compared to its expectation over the period $[t - 1, t]$
- $\epsilon^i(t)$ is a random variable relative to the period $[t - 1, t]$.

Remark 4:

With our hypothesis, a factor model is a "Markowitz model", i.e a model where the returns of the risky assets follow a Gaussian law. Here the vector of the returns $R(t)$ over the period $[t - 1, t]$ follows the normal law of:

- expectation $R(t) = \begin{pmatrix} a^1 \\ \vdots \\ a^N \end{pmatrix}$
- variance-covariance matrix $\Sigma = B\Sigma_F B' + \text{diag}(\sigma_i^2)$

Remark 5:

Factor models were introduced by Charles Spearman in 1904 in psychometrics.

Remark 6:

In financial econometrics, the factors used are either:

- Macroeconomics factors: ex GDP, inflation rate, unemployment rate..etc, in this case the $F(t)$ are "exogene" i.e given and observable.
- Fundamental factors: ex market cap, leverage, book/price ...etc which are as well exogene.
- Statistical factors: in this case the $F(t)$ are "endogene" / hidden factors and the aim is to determine these $F(t)$ as well as the corresponding sensibilities (i.e B).

Numerical Example:

Consider a two-periods 3 factors model with 3 assets where:

$A = \begin{pmatrix} 5\% \\ 4\% \\ 6\% \end{pmatrix}$ is the vector of expected returns for the assets

$B = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}$ defines the decomposition of the returns on the factors

$P = \begin{pmatrix} 100\% & 0 & 50\% \\ 0 & 100\% & 0 \\ 50\% & 0 & 100\% \end{pmatrix}$ is the matrix of correlation for the factors

$\sigma_1 = 15\%$, $\sigma_2 = 10\%$, $\sigma_3 = 10\%$ are the standard deviations for the factors
 $\sigma(\epsilon_1) = 5\%$ $\sigma(\epsilon_2) = 5\%$ $\sigma(\epsilon_3) = 5\%$ are the standard deviations for the residuals in the factor model

Assuming that for the risk free rate $r_0 = 2\%$, we find after calculating the implied law for the risky assets and applying Markowitz's results that:

- a) the investment portfolio of minimum variance has a return of expected value 3.84% and standard deviation 10.69%
- b) the tangent portfolio has an allocation between the three risky assets of $\begin{pmatrix} 0.684 \\ 0.353 \\ -0.037 \end{pmatrix}$ and has a return of expected value 4.61% and standard deviation 12.74%
- c) the return of the investment portfolio follows the equation
- $$r_M = 0.046 + 0.647F_1 + 0.353F_2 + 0.316F_3 + 0.684\epsilon_1 + 0.353\epsilon_2 - 0.037\epsilon_3$$
- d) from c) we can derive the β of the three risky assets with the tangent portfolio and find: $\beta_1 = 1.15$, $\beta_2 = 0.77$, $\beta_3 = 1.53$
- e) we can verify that for the three assets the SML is satisfied as:
- $$5\% = 2\% + 1.15 \times (4.6\% - 2\%)$$
- $$4\% = 2\% + 0.77 \times (4.6\% - 2\%)$$
- $$6\% = 2\% + 1.53 \times (4.6\% - 2\%)$$

f) the residual e_i of the returns of the tree risky assets after regression on the tangent portfolio, defined by $r^i = r_0 + \beta_i(r_M - r_0) + e_i$ have a variance-covariance matrix of:

$$\begin{pmatrix} 0.004 & -0.007 & 0.001 \\ -0.007 & 0.013 & -0.002 \\ 0.001 & -0.002 & 0.012 \end{pmatrix}$$

the standard deviations of the residuals e_i in the SML model are:

$$\sigma(e_1) = 5.98\% \quad \sigma(e_2) = 11.39\% \quad \sigma(e_3) = 10.92\%$$

As we can see on this example the 3-factors model enables a better explanation of the common sources of risks than the (one factor) SML model as the residuals have lower variances in the 3-factors model than in the SML model and are uncorrelated (proving that all common sources of risks have been identified).

Reminder: Diagonalisation Theorem

If Σ is symmetric definite positive in $(\mathbb{R}^K, \langle . \rangle)$ we can find V_1, V_2, \dots, V_K in \mathbb{R}^K such that:

- $\langle V_i, V_j \rangle = \delta_{i,j}$
- $\Sigma V_i = \lambda_i V_i$

and if we note V the matrix whose vectors columns are the V_i then:

- $V' \Sigma V = \text{diag}(\lambda_i)$
- $V' V = Id_K$

Here the λ_i are the (positive) eigenvalues of Σ and the V_i are the eigenvectors.

Standard Form Theorem

We can re-write the factor model in the form:

$$R(t) = A + DH(t) + E(t)$$

with $\text{Var}[H(t)] = Id_K$

This form is called the Standard Form of the Factor Model

demonstration:

$$A + BF(t) + E(t) = A + BV \text{diag}(\sqrt{\lambda_i}) \text{diag}\left(\frac{1}{\sqrt{\lambda_i}}\right) V' F(t) + E(t)$$

and $\text{Var}[V' F(t)] = V' \Sigma_F V = \text{diag}(\lambda_i)$

so $\text{Var}\left[\text{diag}\left(\frac{1}{\sqrt{\lambda_i}}\right) V' F(t)\right] = \text{diag}\left(\frac{1}{\sqrt{\lambda_i}}\right) \text{diag}(\lambda_i) \text{diag}\left(\frac{1}{\sqrt{\lambda_i}}\right) = Id_K$. Q.E.D

Fundamental APT Theorem

Let $r^i(t) = a^i + \sum_{j=1}^{j=K} b_j^i f^j(t) + \epsilon^i(t)$ or in matrix terms

$R(t) = A + BF(t) + E(t)$ be a K -factor model.

If there is no arbitrage in the reduced model $R(t) = A + BF(t)$ where the "diversifiable" risk $E(t)$ is neglected then:

there exist $\alpha^0, \lambda_1, \lambda_2, \dots, \lambda_K$ such that

$$\forall i \in \{1, 2, \dots, N\}, a^i = \alpha^0 + \sum_{j=1}^K b_j^i \lambda^j$$

or matrixially $A = \alpha^0 \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} + B \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_K \end{pmatrix}$

Remarks:

No arbitrage means that:

- all investment portfolios with no risk (i.e fixed returns) should have the same return. We note r_0 this return.
- all self financing portfolios with no risk (i.e fixed returns) should have a return of zero.

Lemma 1

If there is no arbitrage and if we call r_0 the risk free rate then:

$$\forall \pi \in \mathbb{R}^K \quad \pi' B = [0, 0, \dots, 0] \implies \pi' (A - r_0 \mathbf{1}_K) = 0$$

Demonstration Lemma 1:

Let $\pi \in \mathbb{R}^K$ be such that $\pi' B = [0, 0, \dots, 0]$.

- if $\pi' 1_K \neq 0$ then $\tilde{\pi} = \frac{\pi}{\pi' 1_K}$ is an investment portfolio which is without risk in the reduced model as $R^{\tilde{\pi}} = \tilde{\pi}' A + \tilde{\pi}' B = \tilde{\pi}' A$ therefore we should have $\tilde{\pi}' A = r_0$ that we can also write $\tilde{\pi}' (A - r_0 1_K) = 0$ as $\tilde{\pi}' 1_K = 0$
- if $\pi' 1_K = 0$ then π is a self-financing portfolio without risk which should therefore satisfy $\pi' A = 0$ that we can also write $\tilde{\pi}' (A - r_0 1_K) = 0$ as $\tilde{\pi}' 1_K = 0$. Q.E.D

Lemma 2:

If

$$\forall \pi \in \mathbb{R}^K \quad \pi' B = [0, 0, \dots, 0] \implies \pi' (A - r_0 \mathbf{1}_K) = 0 \quad (1)$$

then

$$\exists \lambda_1, \lambda_2, \dots, \lambda_K, \quad A - r_0 \mathbf{1}_K = \sum_{i=1}^{i=K} \lambda_i b_i \quad (2)$$

Demonstration Lemma 2:

We note $B = [b_1, b_2, \dots, b_K]$ and $\text{Vect}\{b_1, b_2, \dots, b_K\}$ the vector space generated by b_1, b_2, \dots, b_K .

$$(1) \iff \text{Vect}\{b_1, b_2, \dots, b_K\}^\perp \subset \text{Vect}\{A - r_0 \mathbf{1}_K\}^\perp$$

$$\implies \text{Vect}\{A - r_0 \mathbf{1}_K\} \subset \text{Vect}\{b_1, b_2, \dots, b_K\}$$

$$\implies A - r_0 \mathbf{1}_K \in \text{Vect}\{b_1, b_2, \dots, b_K\}$$

This proves Lemma 2.

Lemma 1 and Lemma 2 together proves the theorem.

Remarks:

In the previous numerical example we have $\lambda_1 = 5\%$, $\lambda_2 = 3\%$, $\lambda_3 = 1\%$

Lemma:

Let $x = \begin{pmatrix} x_1 \\ \cdots \\ x_d \end{pmatrix}$ and $y = \begin{pmatrix} y_1 \\ \cdots \\ y_d \end{pmatrix}$ be in R^d then $x'y = Tr(xy')$

demonstration: trivial

Proposition:

Let $Z = \begin{pmatrix} Z_1 \\ \vdots \\ Z_d \end{pmatrix}$ be a random variable in R^d then:

$E[\|Z - E[Z]\|^2] = Tr[Var(Z)] = \sum_{i=1}^d \lambda_i$ where Tr is the trace operator and the λ_i are the eigenvalues of $Var[Z]$

demonstration:
$$\begin{aligned} E [\|Z - E[Z]\|^2] &= E \left[(E - E[Z])'(Z - E[Z]) \right] \\ &= E \left[\text{Tr} \left((E - E[Z])(Z - E[Z])' \right) \right] = \text{Tr} \left(E \left[(Z - E[Z])(Z - E[Z])' \right] \right) \\ &= \text{Tr} [\text{Var}(Z)] \text{ Q.E.D} \end{aligned}$$

Definition:

We call $E [\|Z - E[Z]\|^2]$ the dispersion of Z and in dimension 1 this definition corresponds to the usual definition of variance.

Proposition:

Let Z be a random variable in R^d , we note $Var(Z)$ the matrix of variance covariance of Z and $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n \geq 0$ the eigenvalues of $Var(Z)$. For any $k \leq d$ we note H_k a sub-vector space of dimension k of R^d and $(x_i^{H_k})$ an orthonormal basis of H_k . Then for any $k \in [1, d]$:

$$\max_{H_k} \max_{(x_i^{H_k})} \sum_{i=1}^{i=k} (x_i^{H_k})' Var(Z) x_i^{H_k} = \sum_{i=1}^{i=k} \lambda_i$$

demonstration: we solve the maximization problem :

$$(P) \begin{cases} \sum_{i=1}^{i=k} x_i' Var(Z) x_i \\ x_i' x_j = \delta_{i,j} \end{cases}$$

Using the Lagrange multipliers $\lambda_{i,j}$ we obtain the following k equations:

$$\frac{\partial L}{\partial x_i} = 2x_i' \text{Var}(Z) - 2\lambda_{i,i}x_i' - \sum_{j \neq i} \lambda_{i,j}x_j' = 0$$

As the x_i are independent, necessarily we must have:

$$2x_i' \text{Var}(Z) - 2\lambda_{i,i}x_i' = 0 \text{ that we can write also as } (\text{Var}(Z) - \lambda_{i,i}Id)x_i = 0$$

So the maximum is attained for the x_i being the eigenvectors of $\text{Var}(Z)$ and in fact corresponding to the k largest values $\lambda_1, \lambda_2, \dots, \lambda_k$. Q.E.D

Corollary:

Let p_{H_k} be the orthogonal projection on H_k then:

$$\max_{H_k} E[\|p_{H_k}(Z - EZ)\|^2] = \sum_{i=1}^{i=k} \lambda_i$$

demonstration: Let (x_i) be an orthonormal basis of H_k then

$$p_{H_k}(Z - EZ) = \sum_{i=1}^{i=k} x_i'(Z - EZ)x_i \text{ and}$$

$$\|p_{H_k}(Z - EZ)\|^2 = \sum_{i=1}^{i=k} (x_i'(Z - EZ))^2 = \sum_{i=1}^{i=k} x_i'(Z - EZ)(Z - EZ)'x_i \text{ so}$$

$$E[\|p_{H_k}(Z - EZ)\|^2] = \sum_{i=1}^{i=k} x_i'E[(Z - EZ)(Z - EZ)']x_i = \sum_{i=1}^{i=k} x_i'\text{Var}(Z)x_i$$

So the result follows from the previous proposition.

Exercise 1:

Show that $\min_{H_k} E[\|p_{H_k}(Z - EZ)\|^2] = \sum_{i=n-k+1}^{i=n} \lambda_i$

Exercise 2:

Let Φ be a linear application from R^d to R^d whose matrix is symmetric and positive, H be a sub-space of R^d of dimension k and p_H be the orthogonal projection on H .

Let $\Phi|_H$ be the restriction of Φ to H defined by $\Phi|_H(x) = p_H[\Phi(x)]$

a) show that $\Phi|_H$ is a linear application from H to H whose matrix is symmetric and positive

b) show that $\max \lambda_{\Phi|_H} \leq \max \lambda_{\Phi}$ and $\min \lambda_{\Phi|_H} \geq \min \lambda_{\Phi}$

c) study the case where $Mat_{\Phi} = \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix}$ and $H = Vect(e_1 + e_2)$

Factor Model - Principal Components Analysis - Numerical Example

We consider an economy with two risky assets whose returns r_1 and r_2 follow the following one factor model:

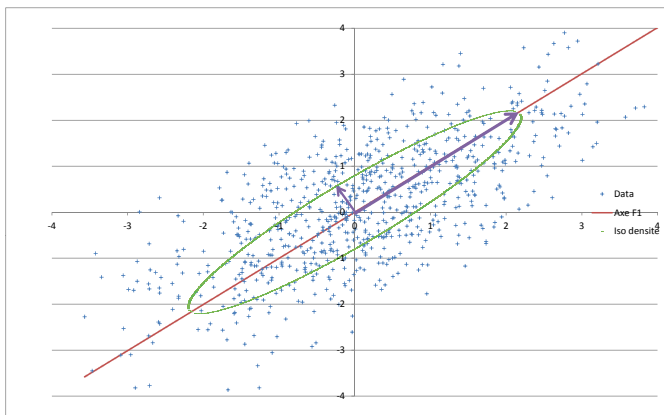
$$\begin{pmatrix} r_1 \\ r_2 \end{pmatrix} = \begin{pmatrix} 1 & 0.6 & 0 \\ 1.2 & 0 & 0.6 \end{pmatrix} \begin{pmatrix} f \\ e_1 \\ e_2 \end{pmatrix}$$

with f , e_1 and e_2 being independent of variance 1.

We assume we have 800 observations of this model (that we simulate here).

We plot on the graph below the 800 observations of $\begin{pmatrix} r_1 \\ r_2 \end{pmatrix}$

Factor Model - Numerical Example



in red the axis corresponding to the eigenvector of maximum eigenvalue.

Factor Model - Principal Components Analysis - Numerical Example

We have the following results:

- the theoretical eigenvalues are 2.80 and 0.36. From our sample and empirical variance-covariance matrix we obtain 3.06 and 0.57
- the theoretical measure of dispersion is 3.16 and from our sample 3.63
- $\begin{pmatrix} 1.20 \\ 1.44 \end{pmatrix}$ and $\begin{pmatrix} 1.20 \\ -1.00 \end{pmatrix}$ are theoretical eigenvectors
- $\begin{pmatrix} 1.24 \\ 1.25 \end{pmatrix}$ and $\begin{pmatrix} 1.25 \\ -1.24 \end{pmatrix}$ are empirical eigenvectors
- on the graph the red line corresponds to the axe generated by the sample eigenvector of the highest eigenvalue

Factor Model - Numerical Example

We have the following results:

- the green ellipse on the chart represents points for which the density function derived from the sample variance-covariance matrix is constant
- the lengths of the axis (in purple) of the ellipse are proportional to the eigenvalues
- when we project the points on the red axis, the dispersion of the points projected is 3.06 which is what we expected, as we have projected on an axe corresponding to the maximum eigenvalue

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The End