

Révision

* Credibilité de stabilité: tien compte de l'expérience individuelle s_i et seulement si elle est stable dans le temps

↳ 2 types: Partiel et Complète

L'idée: est ce que l'expérience est utile?

↳ On cherche le nombre minimum pour dire que c'est stable

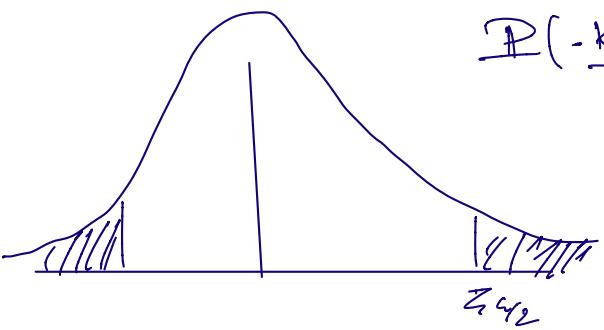
{ Complète: l'expérience du contrat, en fonction de la taille (+ c'est mieux)
Partiel: forte attention à l'expérience individuelle

Credibilité:

$$P((1-K)\bar{E}[s] \leq s \leq (1+K)\bar{E}[s]) \geq p$$

$$P\left(\frac{-K\bar{E}[s]}{\sigma_s} \leq Z(0,1) \leq \frac{K\bar{E}[s]}{\sigma_s}\right) \geq p$$

$$\bar{E}[s] \geq \left(\frac{z_{\alpha/2}}{K}\right) \sqrt{\text{Var}(s)}$$



• La taille est liée à la fréquence est non biaisée

$$\bar{E}[s] \geq \left(\frac{z_{\alpha/2}}{K}\right) \sqrt{\text{Var}(s)}$$

s: loi Composée:

$$S = \sum_{i=1}^n X_i$$

$$N \sim \text{Poi}(\lambda) \quad X_i \sim f_X(x)$$

$$\mathbb{E}[S] = \lambda \mathbb{E}[X]$$

$$\mathbb{E}[\text{Var}(X|N)] + \text{Var}(\mathbb{E}[X|N])$$

$$\text{Var}(S) = \lambda \mathbb{E}[X^2]$$

$$\text{Var}(X)\mathbb{E}[N] + \mathbb{E}[X]\text{Var}(N)$$

$$\mathbb{E}[S] \geq \left(\frac{\sum \epsilon_{ik}}{k} \right) \sqrt{\text{Var}(S)} \Rightarrow \lambda \mathbb{E}[X] \geq \left(\frac{\sum \epsilon_{ik}}{k} \right) \sqrt{\lambda \mathbb{E}[X^2]}$$

$$\lambda \mathbb{E}[X^2] \geq \left(\frac{\sum \epsilon_{ik}}{k} \right)^2 \mathbb{E}[X^2] \rightarrow \lambda \geq \left(\frac{\sum \epsilon_{ik}}{k} \right)^2 \frac{\mathbb{E}[X^2]}{\mathbb{E}^2[X]}$$

$$\lambda \geq \left(\frac{\sum \epsilon_{ik}}{k} \right)^2 \left(\frac{\text{Var}(S) + \mathbb{E}^2(X)}{\mathbb{E}^2[X]} \right) \rightarrow \lambda \geq \left(\frac{\sum \epsilon_{ik}}{k} \right)^2 \left(1 + \text{CV}(X)^2 \right)$$

$$\text{CV}(X) = \frac{\sigma_x}{\mu_x}$$

s: $\mathbb{P}(X=1) \rightarrow \text{Var}(X)=0 \rightarrow \lambda \geq \left(\frac{\sum \epsilon_{ik}}{k} \right)^2 (1+0)$

$$\text{Var}(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2 = 0$$

↑
k tout en haut pour une période

* En fonction de nombre d'année d'expérience:

$$W = \frac{1}{n} \sum_{i=1}^n S_i$$

$$\mathbb{E}[W] = \mathbb{E}[S]$$

$$\text{Var}(W) = \frac{\text{Var}(S)}{n}$$

$$\mathbb{E}[S] \geq \left(\frac{\sum \epsilon_{ik}}{k} \right) \sqrt{\frac{\text{Var}(S)}{n}}$$

$$n \geq \left(\frac{\sum \epsilon_{ik}}{k} \right)^2 \frac{\text{Var}(S)}{\mathbb{E}^2[S]}$$

on est intéressé par # années d'expérience

* Credibilité partielle n'importe l'expérience individuelle.

$$\pi = zS + (1-z)m$$

$$z = \min \left\{ \sqrt{\frac{n}{n_0}}, 1 \right\}$$

n_0 : credibilité complète

$$z = \min \left\{ \left(\frac{n}{n_0} \right)^{2/3}, 1 \right\}$$

2: #5

$$N \sim \text{Poi}(266) \quad X \sim \text{Pareto}(3, 0.05) \quad S = \sum_{i=1}^t X_i$$

a) on cherche le k .

$$\mathbb{E}(S) \geq \left(\frac{z_{4k}}{k} \right) \sqrt{\text{Var}(S)} \quad \text{Var}(X) = 0.001975$$

$$\lambda \mathbb{E}[X] \geq \left(\frac{z_{4k}}{k} \right)^2 (\text{Var}(X) \cdot \lambda + \mathbb{E}[X]^2)$$

$$\lambda \mathbb{E}[X]^2 \geq \left(\frac{z_{4k}}{k} \right)^2 \left(1 + \frac{\text{Var}(X)}{\mathbb{E}[X]^2} \right)$$

$$k \geq \sqrt{\frac{(z_{4k})^2}{\lambda} (1+3)} = 0.205625$$

b)

$$n=10 \\ W = \sum_{i=1}^{10} \frac{S_i}{10}$$

$$\mathbb{E}[W]^2 \geq \left(\frac{z_{4k}}{k} \right)^2 \frac{\lambda \mathbb{E}[X]^2}{10}$$

$$\lambda \geq \frac{(1.64r)^2}{k^2} \frac{\mathbb{E}[X]^2}{10 \mathbb{E}[X]^2}$$

$$k \geq \sqrt{\frac{(1.64r)^2}{10.2056} \cdot (1+3)} = 0.0650$$

2: #8

$$H \sim \text{BinNeg}(r, \theta = 0.01) \quad X \sim \text{Gamma}(\alpha=0.01, \lambda=1)$$

$$\begin{array}{c} \xrightarrow{\quad} \\ 0.98\#(S) \quad \mathbb{E}[S] \rightarrow 1.98\mathbb{E}[S] \end{array}$$

$K = 0.05$

$$\mathbb{P}(0.98\mathbb{E}[S] \leq S \leq 1.98\mathbb{E}[S]) \geq 19/20 = 0.95$$

$$S = \sum_{i=1}^N X_i \quad \mathbb{E}[S] = \mathbb{E}[N]\mathbb{E}[X] = r \cdot \frac{1-0.01}{0.01} \times 0.02 = 1.98r$$

$$\begin{aligned} \text{Var}(S) &= \mathbb{E}[\text{Var}(\sum_i X_i)] + \text{Var}(\mathbb{E}[\sum_i X_i]) \\ &= \text{Var}(X)\mathbb{E}[N] + \mathbb{E}^2[X]\text{Var}(N) \\ &= 0.02 \cdot r \cdot \frac{1-0.01}{0.01} + (0.02)^2 \cdot r \cdot \frac{1-0.01}{0.01^2} \\ &= 1.98r + 3.96r = 5.94r \end{aligned}$$

$$1.98r \geq \left(\frac{1.96}{0.05}\right) \sqrt{5.94r} \rightarrow (1.98)^2 r \geq \left(\frac{1.96}{0.05}\right)^2 5.94$$

$$r \geq 2328.24$$

2: #11

$$A: \$10 \quad \mathbb{P}(X = \$10) = 1$$

$$B: X \sim \text{Gamma} \quad \frac{\alpha}{\lambda} = \$10$$

$$\lambda \geq \left(\frac{\sum_{i=1}^n \alpha_{i,2}}{K}\right)^2 (1 + CV(X)) = 1000$$

$$\left(\frac{\sum_{i=1}^n \alpha_{i,2}}{K}\right)^2 = 1000 \quad \checkmark$$

$$\left(1 + \frac{\alpha/\beta^2}{(\$10)^2}\right) = 3 \rightarrow \left(1 + \frac{\$10/\beta}{\$10^2}\right) = 3 \quad \alpha = \$10\beta$$

$$A: \lambda \geq 1000$$

$$B: \lambda \geq 3000$$

$$\lambda \geq \left(\frac{\sum_{i=1}^n \alpha_{i,2}}{K}\right)^2 (1 + CV(X)^2) = 3000$$

$$\frac{1}{\$10\beta} = 2 \rightarrow \beta = 0.01 \quad X \sim \text{Gamma}(1/2, 0.01)$$

2: #13

$$\text{frequency} = 6494 \quad q = 0.04 \quad CV(x) = 2$$

$$nq \geq \left(\frac{\sum_{i=1}^k n_i}{K} \right)^2 + q \frac{(1-q)}{q} \quad n \geq \left(\frac{\sum_{i=1}^k n_i}{K} \right)^2 \frac{1-q}{q} = 6494$$

$$(nqE(x))^2 \geq \left(\frac{6494}{24} \right) (E(N)Var(x) + E^2(x)Var(\mu)) \quad \left(\frac{\sum_{i=1}^k n_i}{K} \right)^2 = \frac{6494}{24}$$

$$(nqE(x))^2 \geq \left(\frac{6494}{24} \right) (nqVar(x) + E^2(x)n(1-q)q)$$

$$CV(x) = \frac{\sigma}{E(x)^2}$$

$$nq \geq \left(\frac{6494}{24} \right) \left(\frac{Var(x)}{E(x)^2} + \frac{E^2(x)(1-q)}{E^2(x)} \right)$$

$$\sqrt{E(x)} = \sigma$$

$$n \geq \left(\frac{6494}{24} \right) (4 + (1-q)) / q$$

$$n \geq 33 \times 82.$$

2: #16

$$a) \quad \lambda \geq \left(\frac{1.641}{0.05} \right)^2 = 1082.41$$

$$b) \quad \lambda \geq \left(\frac{1.96}{0.041} \right)^2 \left(1 + \frac{1/4}{1/4} \right) = 4802$$

$$c) \quad \min \left(\sqrt{\frac{\lambda}{4802}}, 1 \right) = 2$$

#17

$$\lambda \geq \left(\frac{\sum_{i=1}^k n_i}{K} \right)^2 = 3000$$

$$Z = 0.5 \quad \lambda \geq 3000 (1 + 3) = 12000$$

$$0.5 = \sqrt{\frac{\lambda}{12000}} \rightarrow (\lambda = 3000) \checkmark$$

#18

$$N \sim \mathcal{P}_0$$

$$X \sim LN \quad CV(X) = 3$$

$$n = 1 \quad \lambda > 1000$$

$$S_1 = 6.75 \text{ M\$}$$

$$m = 8 \text{ M\$}$$

$$\therefore 5\% \text{ de mycar} \quad K = 5\% \quad P = 0.95$$

$$\lambda \geq 17336.4$$

$$Z = \min \left(\sqrt{\frac{n}{n_0}}, 1 \right) = \min \left(\sqrt{\frac{1000}{17336.4}}, 1 \right)$$

$$\pi_1 = 2S_1 + m(1-Z) = 2.48 \text{ M\$} \quad \checkmark$$

#19

$$\lambda = 0.035 \quad n > 103400$$

$$Z = 0.67 = \sqrt{\frac{n}{103400}} \rightarrow n = 46461 \quad \checkmark$$

#20

n pour crédit-completé

10% 10%

$$K = 0.05 \\ P = 0.9$$

$$n \geq \left(\frac{1.645}{0.05} \right)^2 0.128$$

$$n \geq \left(\frac{1.645}{0.1} \right)^2 0.17 = \dots \quad n = 9.86 \quad \checkmark$$

Chapitre 3

Porte feuille dc I contrat:

Θ_i	S_{i1}								
1	S_{11}, \dots, S_{1n}								
2	S_{21}, \dots, S_{2n}								
:	:								
I	S_{I1}, \dots, S_{In}								

Θ_i (inconnu) : niveau de risque

- 1. $S_i | \Theta_i \sim f(x | \Theta_i)$
- 2. $\Theta_1, \dots, \Theta_I$: identiquement distribuer
- 3. Contrat IL

- * iid seulement lorsque on connaît Θ_i sinon Dépendants
- * Voici graph (...)

* Meilleur prévision: $\mu(\Theta_i) = \mathbb{E}[S_{it} | \Theta_i = \Theta] = \int_{-\infty}^{\infty} x \int_{-\infty}^{\infty} f(x | \Theta_i) dx$

* Prisme collective: $m = \mathbb{E}[\mu(\Theta_i)] = \int_{-\infty}^{\infty} \mu(\Theta) u(\Theta) d\Theta$

$$m = \mathbb{E}[\mu(\Theta)] = \mathbb{E}[\mathbb{E}[S_{it} | \Theta_i]] = \mathbb{E}[S_{it}]$$

meilleur prévision: $\mathbb{E}[(\mu(\Theta_i) - g(x_{i1}, \dots, x_{in}))^2]$

$$g(x_{i1}, \dots, x_{in}) = \mathbb{E}[\mu(\Theta_i) | x_{i1}, \dots, x_{in}]$$

Prisme Bayésienne: $B_{i,n+1} = \mathbb{E}[\mu(\Theta_i) | S_{i1} = x_{i1}, \dots, S_{in} = x_{in}]$

$$B_{i,n+1} = \mathbb{E}[\mu(\Theta_i) | S_{i1} = x_{i1}, \dots, x_{in}] = \int_{-\infty}^{\infty} \mu(\Theta) u(\Theta | x_{i1}, \dots, x_n) d\Theta$$

$$\mu(\Theta) = \mathbb{E}[S_{it} | \Theta]$$

$$= \int_{-\infty}^{\infty} \mathbb{E}[S_{it} | \Theta] u(\Theta | x_{i1}, \dots, x_n) d\Theta$$

• distribution à postériori: $u(\theta | x_1, \dots, x_n)$

$$u(\theta | x_1, \dots, x_n) = \frac{u(x_1, \dots, x_n | \theta) u(\theta)}{\int_{-\infty}^{\infty} u(x_1, \dots, x_n | \theta) u(\theta) d\theta}$$

$$m = \int_{-\infty}^{\infty} \mu(\theta) u(\theta) d\theta$$

$$B_{i,n+1} = \int_{-\infty}^{\infty} \mu(\theta) u(\theta | x_1, \dots, x_n) d\theta$$

* distribution prédictive

$$B_{i,n+1} = \mathbb{E}[\mu(\theta) | S_1, \dots, S_n] = \mathbb{E}[S_{i,n+1} | S_1, \dots, S_n]$$

$$f(x | x_1, \dots, x_n) = \int_{-\infty}^{\infty} f(x | \theta) u(\theta | x_1, \dots, x_n) d\theta$$

$$f(x | x_1, \dots, x_n) = \frac{f(x, x_1, \dots, x_n)}{f(x_1, \dots, x_n)} = \frac{\int_{-\infty}^{\infty} f(x | \theta) f(x_1, \dots, x_n | \theta) u(\theta) d\theta}{\int_{-\infty}^{\infty} f(x_1, \dots, x_n | \theta) u(\theta) d\theta}$$

(constante)

$$\cdot f(x | x_1, \dots, x_n) = \int_{-\infty}^{\infty} f(x | \theta) u(\theta | x_1, \dots, x_n) d\theta$$

$$f(x) = \int_{-\infty}^{\infty} f(x | \theta) u(\theta) d\theta$$

$$B_{i,n+1} = \int_{-\infty}^{\infty} x f(x | x_1, \dots, x_n) dx$$

** Si distribution à postériori \hat{u} et de même type que à priori
 Lors la distribution prédictive est de même type marginale

* Distribution qui donnent une prime linéaire:

- $SID \sim Po(\theta)$ (\oplus n Gamma(α, λ) ; $\rightarrow SID \sim \sum Po_i(\theta)$)
- $SID \sim Exp(\theta)$ (\oplus n Gamma(α, λ) ; $\rightarrow SID \sim \text{Gamma}(n, \theta)$, \oplus Gamma(α, λ)
- $SID \sim N(\theta, \sigma^2)$ (\oplus n $N(\mu_i, \sigma_i^2)$)
- $SID \sim \text{Bin}(\theta)$, \oplus Beta(a, b) $\rightarrow SID \sim \text{Bin}(n, \theta)$ \oplus Beta(a, b)
- $SID \sim Geo(\theta)$, \oplus Beta(a, b) $\rightarrow SID \sim \text{Bin}(\theta)$ \oplus Beta(a, b)

* Démo Exp - Gamma

$$f(x|\theta) = \theta e^{-\theta x} \quad f(\theta) = \frac{\theta^{\alpha-1} e^{-\theta} \beta^{\alpha}}{\Gamma(\alpha)}$$

$$U(\theta|x_1, \dots, x_n) = \frac{U(x_1, \dots, x_n|\theta) U(\theta)}{\int U(x_1, \dots, x_n|\theta) U(\theta) d\theta} \quad \mu(\theta) = \left(\frac{1}{\theta} \right)$$

~~$$\propto \frac{\theta^n e^{\sum x_i \theta} \theta^{\alpha-1} e^{-\theta} \beta^{\alpha}}{\Gamma(\alpha)}$$~~

~~$$\propto \theta^{n+\alpha-1} e^{-\theta(\sum x_i + \beta)}$$~~

$$U(\theta|x_1, \dots, x_n) \sim \text{Gamma}(n + \alpha, \sum x_i + \beta)$$

$$f(x) = \int \theta e^{-\theta x} \frac{\theta^{\alpha-1} e^{-\theta} \beta^{\alpha}}{\Gamma(\alpha)} d\theta = \int \frac{\theta^{\alpha+1-1} e^{-\theta(x+\beta)}}{\Gamma(\alpha)} \beta^{\alpha} d\theta$$

$$f(x) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} \frac{\Gamma(\alpha+1)}{(x+\beta)^{\alpha+1}} = \frac{\alpha \beta^{\alpha}}{(x+\beta)^{\alpha+1}}$$

$$f(x | x_1, \dots, x_n) \sim \text{Pareto}(\alpha + n, \sum x_i + \beta)$$

$$R_{i,n+1} = \mathbb{E}[S_{i,n+1} | x_1, \dots, x_n] = \frac{\sum x_i + \beta}{n + \alpha - 1}$$

$$B_{i,n+1} = \mathbb{E}[M(\theta) | x_1, \dots, x_n] = \int M(\theta) u(\theta | x_1, \dots, x_n) d\theta$$

$$= \int \frac{1}{\theta} \frac{\theta^{n+\alpha-1} e^{\theta(\sum x_i + \beta)}}{\Gamma(\alpha+n)} (\sum x_i + \beta)^{\alpha}$$

$$= \frac{\sum x_i + \beta}{(\alpha+n-1)}$$

\hat{m} chose

* Si $u(\theta | x_1, \dots, x_n)$ appartient à la \hat{m} ème famille que $u(\theta)$, on dit
que $u(\theta)$ et $f(x|\theta)$ sont conjuguées naturelles

Chapitre 4

$$m = \mathbb{E}[\mu(\Theta_i)]$$

$$s^2 = \mathbb{E}[\text{Var}(S|\Theta_i)]$$

$$\alpha = \text{Var}(\mathbb{E}[S|\Theta_i])$$

$$\text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$$

$$= \mathbb{E}[(X - \mathbb{E}[X|\Theta] + \mathbb{E}[X|\Theta] - \mathbb{E}[X])(Y - \mathbb{E}[Y|\Theta] + \mathbb{E}[Y|\Theta] - \mathbb{E}[Y])]$$

$$= \mathbb{E}[(X - \mathbb{E}[X|\Theta])(Y - \mathbb{E}[Y|\Theta])] + \mathbb{E}[(X - \mathbb{E}[X|\Theta])(\mathbb{E}[Y|\Theta] - \mathbb{E}[Y])]$$

$$+ \mathbb{E}[(\mathbb{E}[X|\Theta] - \mathbb{E}[X])(Y - \mathbb{E}[Y|\Theta])] + \mathbb{E}[(\mathbb{E}[X|\Theta] - \mathbb{E}[X])(\mathbb{E}[Y|\Theta] - \mathbb{E}[Y])]$$

$$= \mathbb{E}[\text{Cov}(X, Y|\Theta)] + 0 + 0 + \text{Cov}(\mathbb{E}[X|\Theta], \mathbb{E}[Y|\Theta])$$

$$\text{Cov}(S_k, S_u) = \mathbb{E}[\text{Cov}(S_k, S_u|\Theta_i)] + \text{Cov}(\mathbb{E}[S_k|\Theta_i], \mathbb{E}[S_u|\Theta_i])$$

$$\text{Cov}(S_k, S_u) = \mathbb{E}[\sigma^2(\Theta_i)] \mathbf{1}_{\{k=u\}} + \text{Var}(\mu(\Theta_i))$$

$$\cdot \text{Cov}(S_k, S_u) = \alpha + s^2 \mathbf{1}_{\{k=u\}}$$

$$\left\{ \begin{array}{l} \alpha = \text{Var}(\mathbb{E}[S_k|\Theta_i]) \\ s^2 = \mathbb{E}[\text{Var}(S_k|\Theta_i)] \end{array} \right.$$

$$\begin{aligned} \text{Cov}(\mu(\Theta_i), S_u) &= \text{Cov}(\mathbb{E}[\mu(\Theta_i)|\Theta_i], \mathbb{E}[S_u|\Theta_i]) \\ &\quad + \mathbb{E}[\text{Cov}(\mathbb{E}[S|\Theta_i], S_u|\Theta_i)] \end{aligned}$$

$$\text{Cov}(\mu(\Theta_i), S_u) = \text{Cov}(\mu(\Theta_i), \mu(\Theta_i)) + \mathbb{E}[0]$$

$$\text{Cov}(\mu(\Theta_i), S_u) = a = \text{Var}(\mu(\Theta_i))$$

Les contacts (Θ_i, S_i) sont II, Θ_i sont identiquement distribuer

$$\pi_{i,n+1}^B = z \bar{S}_i + (1-z)m$$

$$z = \frac{n}{n+k}, k = \frac{s^2}{a}$$

$$\mathbb{E}[(\mu(\Theta_i) - c_0 - \sum_{t=1}^n c_t S_{it})^2]$$

$$c_0: \frac{\partial}{\partial c_0} (\dots) = 0 \rightarrow c_0 = \mathbb{E}[\mu(\Theta_i)] - \sum_{t=1}^n c_t \mathbb{E}[S_{it}]$$

c_u :

$$\frac{\partial}{\partial c_u} (\dots) = 0$$

$$\mathbb{E}[(\mu(\Theta_i) - \mathbb{E}[\mu(\Theta_i)]) \sum_{t=1}^n c_t \mathbb{E}[S_{it}] - \sum_{t=1}^n c_t S_{it}](\mathbb{E}[S_u] - S_u)]$$

$$\mathbb{E}[(\mu(\Theta_i) - \mathbb{E}[\mu(\Theta_i)]) (\mathbb{E}[S_u] - S_u)] = -\mathbb{E}[(\sum c_t \mathbb{E}[S_t] - \sum c_t S_t)(\mathbb{E}[S_u] - S_u)]$$

$$+\mathbb{E}[(\mu(\Theta_i) - \mathbb{E}[\mu(\Theta_i)]) (S_u - \mathbb{E}[S_u])] = +\mathbb{E}[(\sum c_t S_t - \sum c_t \mathbb{E}[S_t])(S_u - \mathbb{E}[S_u])]$$

$$\text{Cov}(\mu(\Theta_i), S_u) = \text{Cov}(\sum_{t=1}^n c_t S_t, S_u)$$

$$\mathbb{E}[\text{Cov}(\mu(\Theta_i), S_u | \Theta_i)] + \text{Cov}(\mathbb{E}[\mu(\Theta_i)], \mathbb{E}[S_u | \Theta_i]) = \text{Var}(\mu(\Theta_i)) = a$$

$$a = \sum_{t=1}^n c_t \text{Co}(S_t, S_0)$$

$$a = \sum_{t=1}^n c_t (a + s^2 \mathbb{A}_{\{a=t\}})$$

$$a = a \sum_{t=1}^n c_t + c_u s^2 \quad c_1 = c_2 = c_3 = \dots = c_n$$

$$a = a n c_u + c_u s^2 \rightarrow c_u = \frac{a}{a n + s^2}$$

$$c_0 = \mathbb{E}[u(\theta_i)] - \sum_{t=1}^n c_t \mathbb{E}[s_t]$$

$$c_0 = m - \sum \frac{a}{a n + s^2} m = m \left(1 - \frac{n a}{a n + s^2} \right)$$

$$\pi_{i,n+1}^B = \sum_{t=1}^n \frac{a}{a n + s^2} s_t + m \left(1 - \frac{n}{n + s^2/a} \right)$$

$$\pi_{i,n+1}^B = \frac{n}{n + s^2/a} \bar{s}_i + m \left(1 - \frac{n}{n + s^2/a} \right)$$

$$\pi_{i,n+1}^B = \frac{n}{n + s^2/a} \bar{s}_i + m \left(1 - \frac{n}{n + s^2/a} \right)$$

$$z = \frac{n}{n + s^2/a} \quad \mathbb{E}[\pi_{i,n+1}^B] = m$$

Dès $n \rightarrow \infty$ $\pi_{i,n+1}^B = u(\theta_i)$ on accorde plus à la prime individuelle

* meilleure approximation de la prime de risque $\mu(\Theta_i)$, est aussi meilleure approximation Bayes $B_{i,n+1}$

$$\mathbb{E}[(\mu(\Theta_i) - c_0 - \sum c_t S_t)^2] = \mathbb{E}[(\mu(\Theta_i) - B_{i,n+1})^2] + \mathbb{E}[(B_{i,n+1} - c_0 - \sum c_t S_t)^2]$$

$$\mathbb{E}[(\mu(\Theta_i) - \pi_{i,n+1}^B)^2] \geq \mathbb{E}[(\mu(\Theta_i) - B_{i,n+1})^2]$$

\hookrightarrow Qd $\pi_{i,n+1}^B = B_{i,n+1} \rightarrow$ égalité meilleur scénario

\hookrightarrow La prime de crédibilité ne sera jamais meilleure que la prime Bayes

* Approche paramétrique :

\hookrightarrow on trouve juste les diff moment puis:

$$m = \mathbb{E}[\mu(\Theta_i)]$$

$$S^2 = \mathbb{E}[\text{Var}(S_i | \Theta_i)] \quad K = \frac{S^2}{a} \quad Z = \frac{n}{n+K}$$

$$a = \text{Var}(\mathbb{E}[S_i | \Theta_i])$$

* Approche non-paramétrique

Θ_i :

		S_i:	
S _{1,1}	S _{1,2}	...	S _{1,n}
S _{2,1}	-S _{2,n}
:		...	
S _{I,1}	S _{I,n}

L'idée est de trouver m, a, S^2

$$\hat{m} = \frac{1}{I_n} \sum_{j=1}^I \sum_{t=1}^n S_{jt}$$

$$\mathbb{E}[\hat{m}] = \hat{m} \rightarrow \text{sans Bias}$$

$$S^2 = \mathbb{E}[\text{Var}(S|\Theta)] \rightarrow \hat{S}^2 = \frac{1}{I} \sum_{j=1}^I \sum_{t=1}^n (S_{jt} - \bar{S}_j)^2$$

$$\mathbb{E}[(S_{jt} - \bar{S}_j)^2] = \mathbb{E}[\mathbb{E}[(S_{jt} - \bar{S}_j)^2 | \Theta_i]]$$

$$\hookrightarrow \mathbb{E}[(S_{jt} - \bar{S}_j)^2 | \Theta_i] = \text{Var}(S_{jt} - \bar{S}_j | \Theta_i)$$

$$= \text{Var}(S_{jt} | \Theta_i) + \text{Var}(\bar{S}_j | \Theta_i) - 2 \text{Cov}(S_{jt}, \bar{S}_j | \Theta_i)$$

$$= \text{Var}(S_{jt} | \Theta_i) + \frac{\text{Var}(S_{jt} | \Theta)}{n} - \frac{2}{n} \text{Var}(S_{jt})$$

$$= \text{Var}(S_{jt} | \Theta) \left(\frac{n-1}{n} \right)$$

$$\hookrightarrow \mathbb{E}[\text{Var}(S_{jt} | \Theta_i)] \frac{n-1}{n} = S^2 \frac{n-1}{n}$$

$$\hookrightarrow \mathbb{E}[\hat{S}^2] = \frac{1}{I(n-1)} \sum_{j=1}^I \sum_{t=1}^n S^2 \frac{n-1}{n} = \frac{I \bar{S}^2}{I-1} = S^2 \checkmark \text{ sans bras}$$

$$0 = \text{Var}(\mathbb{E}[S | \Theta]) \rightarrow \hat{a} = \frac{1}{I-1} \sum_{j=1}^I (\bar{S}_j - \bar{\bar{S}})^2$$

$$\bar{\bar{S}} = \bar{\bar{\Sigma}} \sum S_{jt} - \frac{1}{In}$$

$\mathbb{E}[\hat{a}]$:

$$\mathbb{E}[(\bar{S}_j - \bar{\bar{S}})^2] = \text{Var}(\bar{S}_j) + \text{Var}(\bar{\bar{S}}) - 2 \text{Cov}(\bar{S}_j, \bar{\bar{S}})$$

$$\frac{1}{I} \text{Cov}(\bar{S}_j, \sum_{i \neq j} \bar{S}_i) = \frac{1}{I} \text{Var}(\bar{S}_j)$$

$$\hookrightarrow \text{Var}(\bar{S}_j) + \frac{1}{I} \text{Var}(\bar{S}_j) - \frac{2}{I} \text{Var}(\bar{S}_j) = \text{Var}(\bar{S}_j) \left(\frac{I-1}{I} \right)$$

$$\mathbb{E}[\hat{a}] = \text{Var}(\bar{S}_j) = \mathbb{E}[\text{Var}(\bar{S}_j | \Theta_i)] + \text{Var}(\mathbb{E}[\bar{S}_j | \Theta_i]) =$$

$$\mathbb{E}[\hat{a}] = \frac{S^2}{n} + a$$

donc : $\hat{\alpha}_i = \frac{1}{I-1} \sum_{j=1}^I (\bar{s}_j - \bar{s}) - \frac{s^2}{n}$ pour tenir le pas

$$\pi_{i,n+1}^B = \hat{z} \bar{s}_i + \hat{m} (1-\hat{z}), \quad \hat{z} = \frac{n}{n + \frac{s^2}{\hat{\alpha}}}$$

- Ad $n \rightarrow \infty \rightarrow$ on accorde $\eta(\theta_i)$
- s^2 petit \rightarrow expérience stable dans le portefeuille
 $\hookrightarrow \bar{s}_i$ sera utile, plus besoin de m
- $\alpha \rightarrow \infty$: hétérogène, meilleure approximation primaire individuel
- $\alpha = 0 \rightarrow \bar{s}_1 = \bar{s}_2 = \dots = \bar{s}_I$: la p'm $\bar{s}_i = m$, plus besoin de l'exp' individuel \rightarrow (IARDI)