

# Credibility for the Chain Ladder Reserving Method

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# Introduction

- claims reserving still one of the basic actuarial tasks
- based on claims development triangles (or trapezoids) predict the ultimate claim
- problems often encountered in practise
  - scarce data  
data from individual triangle do not allow to make a reliable forecast;  
actuaries then often rely on industry-wide development patterns;  
question: when to rely on industry-wide data and to what extent
  - line of business with little data  
then one often considers the development of other similar lines  
question: how much to rely on the other lines and how much on the data of the line in question ?
- **credibility: answer to such kind of questions**  
how to combine portfolio information and individual data

# Introduction

- in the paper we concentrate on the Chain-Ladder reserving method, but the basic idea could also be transformed to other reserving methods
- **basic idea of the paper:**  
to use a Bayesian set-up and credibility to combine portfolio information with the individual triangle information
- **link to classical chain ladder**  
taking an non informative prior we arrive at the classical chain ladder estimate.  
However: the estimate of the mean square error differs from the ones found in the literature. The paper also throws a new light upon the estimation of the mean square error.

# classical chain ladder

At time  $I$ , observations (upper left trapezoid)

$$D_I = \{C_{ij} : 0 \leq i \leq I, 0 \leq j \leq J, i+j \leq I\}$$

Usually,

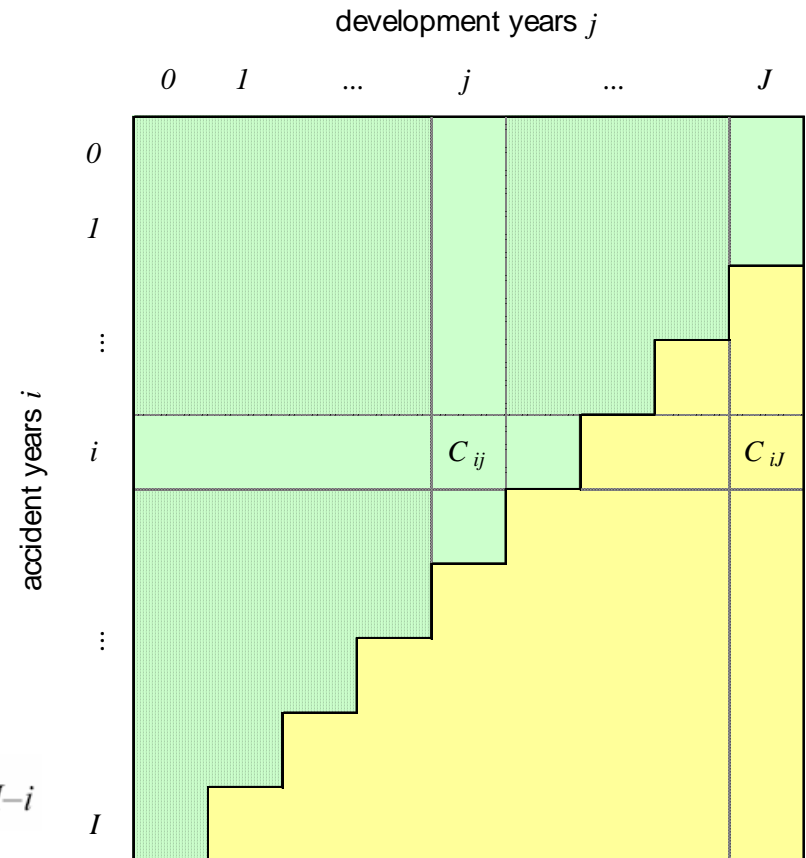
$C_{ij}$  = cumulative claims payments  
or incurred claims

$C_{i,J}$  = ultimate claim of accident year  $i$

want to estimate for each accident  
year  $i$  :

ultimate claim  $C_{i,J}$  and

the outstanding liabilities  $R_i = C_{i,J} - C_{i,I-i}$



# classical chain ladder

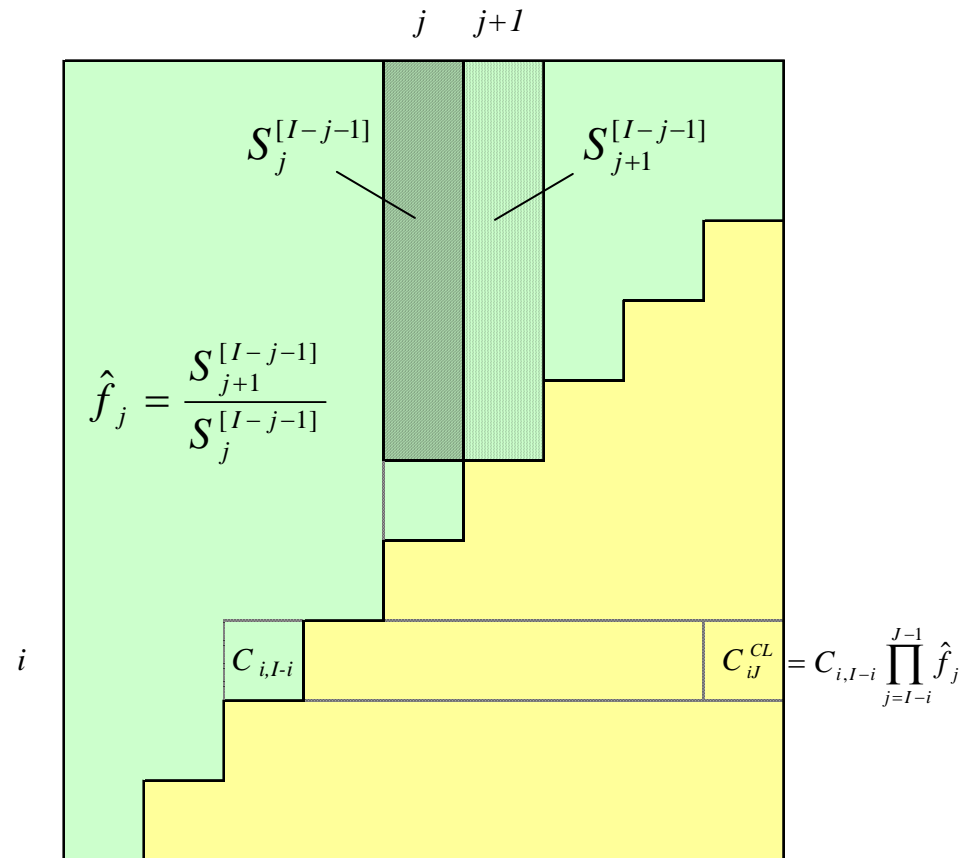
chain ladder algorithm:

$$C_{i,J}^{CL} = C_{i,I-i} \prod_{j=I-i}^{J-1} \hat{f}_j$$

where 
$$\hat{f}_j = \frac{S_{j+1}^{[I-j-1]}}{S_j^{[I-j-1]}}$$

$$S_j^{[k]} = \sum_{i=0}^k C_{i,j}$$

$$R_i^{CL} = C_{i,J}^{CL} - C_{i,I-i}$$



# classical chain ladder

## Model Assumptions of Mack

**M1**  $C_{i,j}$  belonging to different accident years are independent

**M2** There exist constants  $f_j > 0$  and  $\sigma_j^2 > 0$ , such that

$$E[C_{i,j+1} | C_{i,1}, \dots, C_{i,j}] = f_j C_{i,j},$$

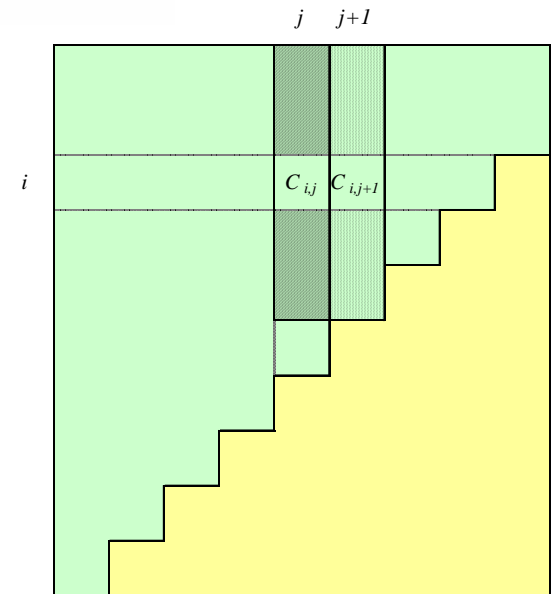
$$\text{Var}[C_{i,j+1} | C_{i,1}, \dots, C_{i,j}] = \sigma_j^2 C_{i,j}.$$

”individual” chain ladder ratios:  $Y_{i,j} = \frac{C_{i,j+1}}{C_{i,j}}$

model assumption M2 equivalent to

$$E[Y_{i,j+1} | C_{i,j}] = f_j, \quad \text{Var}[Y_{i,j+1} | C_{i,j}] = \frac{\sigma_j^2}{C_{i,j}}$$

$$\hat{f}_j = \frac{\sum_{i=0}^{I-j-1} C_{i,j} Y_{i,j}}{\sum_{i=0}^{I-j-1} C_{i,j}} = \frac{\sum_{i=0}^{I-j-1} C_{i,j+1}}{\sum_{i=0}^{I-j-1} C_{i,j}} = \frac{S_{j+1}^{[I-j-1]}}{S_j^{[I-j-1]}}$$



$$E[\hat{f}_j | B_j] = f_j,$$

$$\text{Var}(\hat{f}_j | B_j) = \frac{\sigma_j^2}{S_j^{[I-j-1]}}.$$

# classical chain ladder

point estimate:  $C_{i,J}^{CL} = C_{i,I-i} \prod_{j=I-i}^{J-1} \hat{f}_j$

mean square error

$$\begin{aligned}mse(R_i^{CL}) &= E\left[(C_{i,J}^{CL} - C_{i,J})^2 \mid \mathbf{D}_I\right] \\&= \underbrace{(C_{i,J} - E[C_{i,J} \mid \mathbf{D}_I])^2}_{\text{process variance}} + \underbrace{(C_{i,J}^{CL} - E[C_{i,J} \mid \mathbf{D}_I])^2}_{\text{estimation error}} \\&= C_{i,I-i} \Gamma_{I-i}^{CL} + C_{i,I-i}^2 \Delta_{I-i}^{CL}\end{aligned}$$

where  $\Gamma_{I-i}^{CL} = \sum_{j=I-i}^{J-1} \left\{ \prod_{m=I-i}^{j-1} f_m \cdot \sigma_k^2 \prod_{n=j+1}^{J-1} f_n^2 \right\}$

$$\Delta_{I-i}^{CL} = \left( \prod_{j=I-i}^{J-1} f_j - \prod_{j=I-i}^{J-1} \hat{f}_j \right)^2$$

# classical chain ladder

estimation of mean square error:

Mack (2003); Buchwalder, Bühlmann, Merz, Wüthrich (2006)

process variance:

$$\text{Mack and BMW} \quad \widehat{\Gamma}_{I-i}^{CL} = \sum_{j=I-i}^{J-1} \left\{ \prod_{m=I-i}^{j-1} \widehat{f}_m \cdot \widehat{\sigma}_k^2 \prod_{n=j+1}^{J-1} \widehat{f}_n^2 \right\}$$

estimation error:

$$\text{Mack} \quad \widehat{\Delta}_{I-i}^{CL}{}^{Mack} = \left( \prod_{l=I-i}^{j-1} \widehat{f}_l^2 \right) \left( \sum_{j=I-i}^{J-1} \frac{\widehat{\sigma}_j^2}{S_j^{[I-j-1]} \widehat{f}_j^2} \right)$$

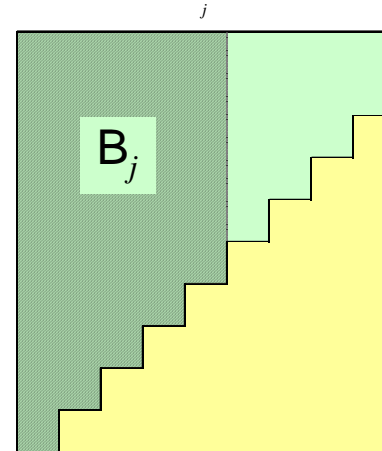
$$\text{BMW} \quad \widehat{\Delta}_{I-i}^{CL}{}^{BMW} = \prod_{j=I-i}^{J-1} \left( \widehat{f}_j^2 + \frac{\widehat{\sigma}_j^2}{S_j^{[I-j-1]}} \right) - \left( \prod_{j=I-i}^{J-1} \widehat{f}_j^2 \right)$$

# Bayes chain ladder

$f_j, j = 0, 1, \dots, J-1$ , realizations of independent r. v.  $F_j$

$$\mathbf{F} = (F_0, F_1, \dots, F_{J-1})'$$

$$B_j = \{C_{i,k}; i+k \leq I, k \leq j\}$$



## Model Assumptions

**B1** Conditionally, given  $\mathbf{F}$ , r.v.  $C_{i,j}$  belonging to different accident years  $i$  are independent.

**B2** Conditionally, given  $\mathbf{F}$  and  $B_j$ , the conditional distribution of  $Y_{i,j}$  depend only on  $C_{i,j}$  and

$$E[Y_{i,j} | \mathbf{F}, B_j] = F_j, \quad \text{Var}[Y_{i,j} | \mathbf{F}, B_j] = \frac{\sigma_j^2(F_j)}{C_{i,j}}.$$

**B3**  $\{F_0, F_1, \dots, F_{J-1}\}$  are independent with distributions  $U_j(f_j)$

# Bayes chain ladder

**Remark:**

$$\hat{F}_j = \frac{S_{j+1}^{[I-j-1]}}{S_j^{[I-j-1]}} \quad E[\hat{F}_j | \mathbf{F}, \mathbf{B}_j] = F_j, \quad \text{Var}[\hat{F}_j | \mathbf{F}, \mathbf{B}_j] = \frac{\sigma_j^2(F_j)}{S_j^{[I-j-1]}}.$$

**Theorem:**

A posteriori, given  $\mathbf{D}_I$ , the r.v.  $F_0, F_1, \dots, F_{J-1}$  are independent with posterior distributions  $U_j(f_j | \mathbf{D}_I)$

$$C_{i,J}^{Bayes} = C_{i,I-i} \prod_{j=I-i}^{J-1} F_j^{Bayes}, \quad \text{where } F_j^{Bayes} = \text{Bayes estimator of } F_j.$$

# Bayes chain ladder

**Theorem:**

$$\begin{aligned}
 mse\left(C_{i,J}^{Bayes}\right) &= E\left[\left(C_{i,J}^{Bayes} - C_{i,J}\right)^2 \mid \mathbf{D}_I\right] \\
 &= \underbrace{E\left[\text{Var}\left[C_{i,J} \mid \mathbf{F}, \mathbf{D}_I\right] \mid \mathbf{D}_I\right]}_{\text{"average" process variance}} + \underbrace{E\left[\left(C_{i,J}^{Bayes} - E\left[C_{i,J} \mid \mathbf{F}, \mathbf{D}_I\right]\right)^2 \mid \mathbf{D}_I\right]}_{\text{"average" estimation error}} \\
 &= C_{i,I-i} \Gamma_{I-i} + C_{i,I-i}^2 \Delta_{I-i}^B,
 \end{aligned}$$

where

$$\Gamma_{I-i} = \sum_{k=I-i}^{J-1} \left\{ \prod_{m=I-i}^{k-1} F_m^{Bayes} \cdot E\left[\sigma^2(F_k) \mid \mathbf{D}_I\right] \cdot \prod_{n=k+1}^{J-1} E\left[F_n^2 \mid \mathbf{D}_I\right] \right\},$$

$$\Delta_{I-i}^B = \text{Var}\left(\prod_{j=I-i}^{J-1} F_j \mid \mathbf{D}_I\right).$$

# Credibility for chain ladder

basic idea: replace  $F_j^{Bayes}$  by a credibility estimator  $F_j^{Cred}$

## Definition

credibility based predictor of  $C_{i,J}$  given  $D_I$ :  $C_{i,J}^{(Cred)} = C_{i,I-i} \prod_{j=I-i}^{J-1} F_j^{Cred}$

## Theorem

i) 
$$F_j^{Cred} = \alpha_j \hat{F}_j + (1 - \alpha_j) f_j,$$

where 
$$\hat{F}_j = \frac{S_{j+1}^{[I-j-1]}}{S_j^{[I-j-1]}}, \quad \alpha_j = \frac{S_j^{[I-j-1]}}{S_j^{[I-j-1]} + \frac{\sigma_j^2}{\tau_j^2}},$$

$$f_j = E[F_j], \quad \sigma_j^2 = E[\sigma_j^2(F_j)], \quad \tau_j^2 = \text{Var}[F_j].$$

ii) mean square error of  $F_j^{Cred}$

$$E\left[(F_j^{Cred} - F_j)^2 \mid \mathbf{B}_j\right] = \alpha_j \frac{\sigma_j^2}{S_j^{[I-j-1]}} = (1 - \alpha_j) \tau_j^2.$$

# Credibility for chain ladder

## Theorem

$$mse\left(R_i^{(Cred)}\right) \cong \underbrace{C_{i,I-i}\Gamma_{I-i}^{Cr}}_{\text{process variance}} + \underbrace{C_{i,I-i}^2\Delta_{I-i}^{Cr}}_{\text{estimation error}}$$

where

$$\Gamma_{I-i}^{Cr} = \sum_{k=I-i}^{J-1} \left\{ \prod_{m=I-i}^{k-1} F_m^{Cred} \cdot \sigma_k^2 \prod_{n=k+1}^{J-1} \left( (F_n^{Cred})^2 + \alpha_n \frac{\sigma_n^2}{S_n^{[I-n-1]}} \right) \right\}$$

$$\Delta_{I-i}^{Cr} = \prod_{j=I-i}^{J-1} \left( (F_j^{Cred})^2 + \alpha_j \frac{\sigma_j^2}{S_j^{[I-j-1]}} \right) - \prod_{j=I-i}^{J-1} (F_j^{Cred})^2.$$

# Credibility for chain ladder

## Link to classical chain ladder

For  $\tau_j^2 \rightarrow \infty$  (non informative prior)

- $F_j^{Cred} = \hat{f}_j$  and  $C_{i,J}^{(Cred)} = C_{i,J}^{CL}$
- mean square error:

process variance  $C_{i,I-i} \Gamma_{I-i}^{Cr}$  :

$$\Gamma_{I-i}^{Cr} = \sum_{k=I-i}^{J-1} \left\{ \prod_{m=I-i}^{k-1} \hat{f}_m \cdot \hat{\sigma}_k^2 \prod_{n=k+1}^{J-1} \left( \hat{f}_n^2 + \frac{\hat{\sigma}_n^2}{S_n^{[I-n-1]}} \right) \right\}$$

$$\Gamma_{I-i}^{Cr} \neq \widehat{\Gamma}_{I-i}^{CL} \quad (\text{of Mack and BMW})$$

estimation error  $C_{i,I-i}^2 \Delta_{I-i}^{Cr}$  :

$$\Delta_{I-i}^{Cr} = \prod_{j=I-i}^{J-1} \left( \hat{f}_j^2 + \frac{\hat{\sigma}_j^2}{S_j^{[I-j-1]}} \right) - \prod_{j=I-i}^{J-1} (\hat{f}_j)^2$$

$$\Delta_{I-i}^{Cr} = \widehat{\Delta}_{I-i}^{CL}{}^{BMW} \neq \widehat{\Delta}_{I-i}^{CL}{}^{Mack}$$

# Exact Credibility

Best reserve estimate would be the Bayes reserves  $R_i^{Bayes}$

Are the credibility reserves a good approximation ?

Are there reasonable Bayes models, where  $C_{i,j}^{Cred} = C_{i,j}^{Bayes}$  ?

The answer is yes !

basic assumptions:

- conditionally on  $\mathbf{F}$  and  $B_j$ , the r.v.  $Y_{0,j}, \dots, Y_{I,j}$  are independent with a distribution belonging to the one-parameter exponential dispersion family
- the a priori distribution of  $F_j$  belongs to the family of the natural conjugate priors

Then  $C_{i,j}^{Cred} = C_{i,j}^{Bayes}$

# Exact Credibility

of particular interest:

Tweedie models = subclass of the exponential family with  $V(\mu) = \mu^p$

Defined only for  $p$  outside the interval  $0 < p < 1$

include

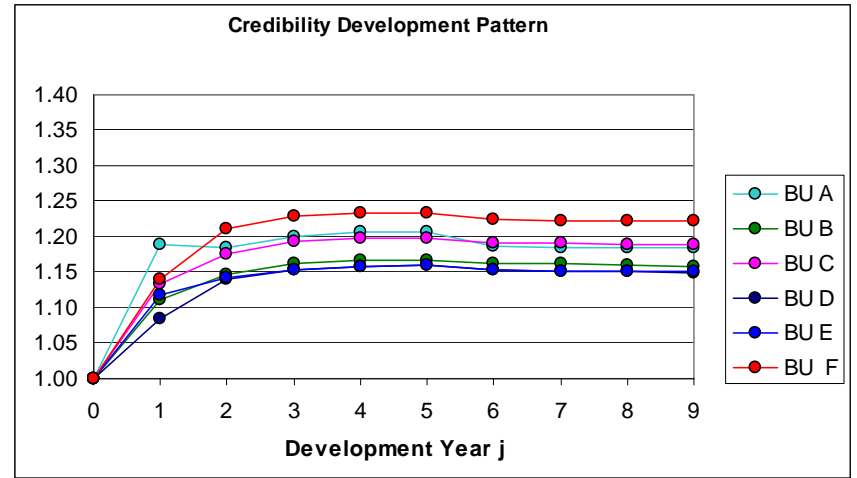
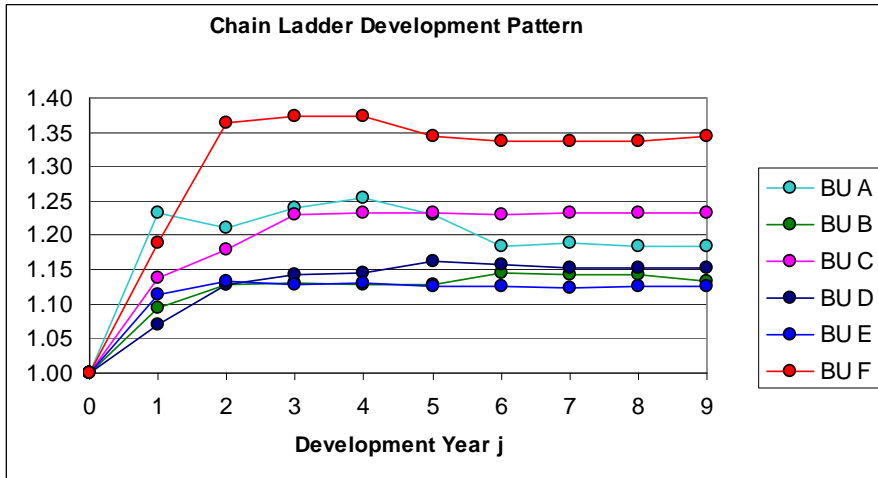
- $p = 0$  : Normal-distribution
- $p = 1$  : (Overdispersed) Poisson distribution
- $1 < p < 2$  : Compound Poisson with Gamma distributed claim amounts
- $p = 2$  : Gamma distribution

in particular, the case  $1 < p < 2$  often a reasonable assumption

# Numerical Example

table of results												
	j=	0	1	2	3	4	5	6	7	8	9	product
	$\sigma_j^2$	336.53	34.739	7.828	5.934	0.426	4.342	4.248	0.239	0.097	0.154	
<b>all BU</b>	$F_j^{CL}$	<b>2.111</b>	<b>1.119</b>	<b>1.031</b>	<b>1.013</b>	<b>1.004</b>	<b>1.001</b>	<b>0.993</b>	<b>0.998</b>	<b>1.000</b>	<b>0.999</b>	<b>2.452</b>
A	$F_j^{CL}$	2.270	1.233	0.982	1.024	1.012	0.981	0.962	1.003	0.996	1.000	2.686
	$F_j^{cred}$	2.111	1.189	0.996	1.015	1.004	1.001	0.984	0.998	1.000	0.999	2.499
B	$F_j^{CL}$	2.133	1.094	1.032	1.002	0.998	1.000	1.014	0.999	1.000	0.990	2.416
	$F_j^{cred}$	2.111	1.111	1.033	1.012	1.003	1.001	0.997	0.998	1.000	0.997	2.444
C	$F_j^{CL}$	2.189	1.138	1.037	1.042	1.003	1.000	0.999	1.002	1.000	1.000	2.700
	$F_j^{cred}$	2.111	1.134	1.036	1.016	1.004	1.001	0.994	0.998	1.000	0.999	2.509
D	$F_j^{CL}$	2.108	1.070	1.054	1.013	1.004	1.015	0.996	0.995	1.000	1.000	2.429
	$F_j^{cred}$	2.111	1.084	1.050	1.013	1.004	1.001	0.994	0.998	1.000	0.999	2.426
E	$F_j^{CL}$	1.930	1.114	1.018	0.995	1.002	0.997	0.999	0.997	1.002	1.000	2.172
	$F_j^{cred}$	2.111	1.119	1.021	1.010	1.004	1.001	0.995	0.998	1.000	0.999	2.429
F	$F_j^{CL}$	3.008	1.190	1.146	1.006	1.000	0.979	0.996	1.000	1.000	1.004	4.041
	$F_j^{cred}$	2.111	1.139	1.064	1.013	1.004	1.001	0.993	0.998	1.000	0.999	2.578

# Numerical Example



BU	estimated reserves		estimated mse <sup>1/2</sup>			
	CL	Cred	CL		Cred	
A	486	504	657	135.1%	498	98.9%
B	235	244	288	122.7%	402	164.3%
C	701	517	411	58.6%	520	100.6%
D	1'029	899	844	82.1%	729	81.1%
E	495	621	397	80.2%	596	95.9%
F	40	25	140	347.0%	149	595.8%
<b>sum</b>	<b>2'987</b>	<b>2'810</b>	<b>1'254</b>	<b>42.0%</b>	<b>1'261</b>	<b>44.9%</b>

Thank you for your attention

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