Quantifying Regulatory Capital for Operational Risk: Utopia or Not?

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Contents

A. The New Accord (Basel II)

- **1988**: Basel Accord (Basel I): minimum capital requirements against credit risk. One standardised approach

- **1996**: Amendment to Basel I: market risk.

- **1999**: First Consultative Paper on the New Accord (Basel II).

- **to date**: CP3: Third Consultative Paper on the New Basel Capital Accord. (`www.bis.org/bcbs/bcbscp3.htmcp3`)

- **end of 2003 (?)**: Revision of CP3

- **end of 2006 (?)**: full implementation of Basel II ([7])

What's new?

- **Rationale** for the New Accord: More flexibility and risk sensitivity
- **Structure** of the New Accord: Three-pillar framework:

❶ Pillar 1: minimal capital requirements (risk measurement)

❷ Pillar 2: supervisory review of capital adequacy

❸ Pillar 3: public disclosure

What's new? (cont'd)

- Two options for the measurement of credit risk:
  - Standard approach
  - Internal rating based approach (IRB)

- Pillar 1 sets out the minimum capital requirements:

$$\frac{\text{total amount of capital}}{\text{risk-weighted assets}} \geq 8\%$$

- MRC (minimum regulatory capital) $\stackrel{\text{def}}{=} 8\%$ of risk-weighted assets

- Explicit treatment of operational risk (*the risk of losses resulting from inadequate or failed internal processes, people and systems, or external events*)

What's new? (cont'd)

- **Notation**: C_{OP}: capital charge for operational risk
- **Target**: $C_{\mathrm{OP}} \approx 12\%$ of MRC
- **Estimated total losses** in the US (2001): $50b
- **Some examples**
  - 1977: Credit Suisse Chiasso-affair
  - 1995: Nick Leeson/Barings Bank, £1.3b
  - 2001: Enron (largest US bankruptcy so far)
  - 2003: Banque Cantonale de Vaudoise, KBV Winterthur

B. Risk measurement methods for OP risks

Pillar 1 regulatory minimal capital requirements for operational risk:
Three distinct approaches:

❶ Basic Indicator Approach

❷ Standardised Approach

❸ Advanced Measurement Approaches (AMA)

Basic Indicator Approach

- Capital charge:

$$\boxed{C_{\text{OP}}^{\text{BIA}} = \alpha \times GI}$$

- $C_{\text{OP}}^{\text{BIA}}$: capital charge under the Basic Indicator Approach

- GI: average annual gross income over the previous three years

- $\alpha = 15\%$ (set by the Committee)

Standardised Approach

- Similar to the BIA, but on the level of each business line:

$$C_{\mathrm{OP}}^{\mathrm{SA}} = \sum_{i=1}^{8} \beta_i \times GI_i$$

$\beta_i \in [12\%, 18\%]$, $i = 1, 2, \ldots, 8$.

- 8 business lines:

Corporate finance	Payment & Settlement
Trading & sales	Agency Services
Retail banking	Asset management
Commercial banking	Retail brokerage

Advanced Measurement Approaches (AMA)

- Allows banks to use their internally generated risk estimates

- Preconditions: Bank must meet qualitative and quantitative standards before using the AMA

- Risk mitigation via insurance allowed

- **AMA1**: Internal measurement approach

- **AMA2**: Loss distribution approach

Internal Measurement Approach

- Capital charge:

$$\boxed{C_{\mathrm{OP}}^{\mathrm{IMA}} = \sum_{i=1}^{8} \sum_{k=1}^{7} \gamma_{ik}\, e_{ik}}$$

e_{ik}: expected loss for business line i, risk type k

γ_{ik}: scaling factor

- 7 loss types:
  - Internal fraud
  - External fraud
  - Employment practices and workplace safety
  - Clients, products & business practices
  - Damage to physical assets
  - Business disruption and system failures
  - Execution, delivery & process management

C. Loss Distribution Approach

- For each business line/risk type cell (i, k) one models

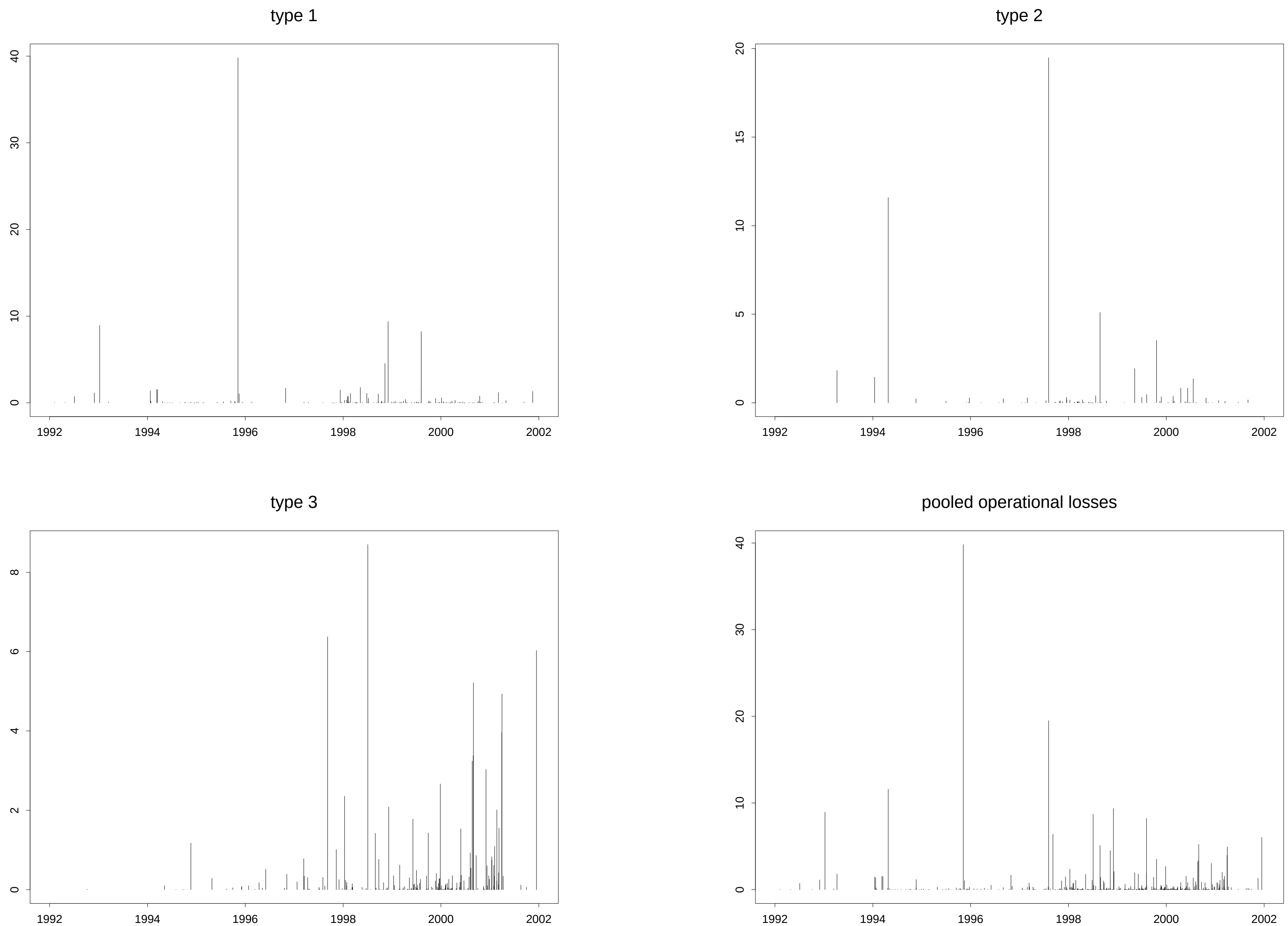
$L_{i,k}^{T+1}$: OP risk loss for business line/risk type cell (i, k) over the period $[T, T+1]$.

$$L_{i,k}^{t} = \sum_{\ell=1}^{N_{i,k}^{t}} X_{i,k}^{\ell}$$

$$C_{i,k}^{\text{OP}} = g(L_{i,k}^{t+1}) = \begin{cases} F_{L^{t+1}}^{\leftarrow}(\alpha) = \text{VaR}_{\alpha}(L^{t+1}) \\ \text{ES}_{\alpha}(L^{t+1}) = \mathbb{E}[L^{t+1} | L^{t+1} > \text{VaR}_{\alpha}(L^{t+1})] \end{cases}$$

$$C_{\text{OP}} = \sum_{i,k} g(L_{i,k}^{t+1}) \qquad \text{(perfect correlation)}$$

Some data


type 1
type 2
type 3
pooled operational losses
0
10
20
30
40
0
5
10
15
20
0
2
4
6
8
1992
1994
1996
1998
2000
2002

Modelling issues

- Stylized facts about OP risk losses
  - Loss occurrence times are irregularly spaced in time
    (selection bias, economic cycles, regulation, management interactions,. . .)
  - Loss amounts show extremes
- Large losses are of main concern!
- Repetitive vs non-repetitive losses
- **Warning flag**: Are observations in line with modeling assumptions?
- Example: "iid" assumption implies
  - NO structural changes in the data as time evolves
  - Irrelevance of which loss is denoted X_1, which one X_2,. . .

The Problem

- In-sample estimation of $\text{VaR}_\alpha(L^{t+1})$ (α large) impossible!
- Estimation of the (far-) tail of L_t via subcategories:

$$L = \sum_{\ell=1}^{N} Y_\ell\,, \qquad 1 - F_Y(x) \sim x^{-\alpha} h(x)\ , \qquad x \to \infty$$

$$\Rightarrow \quad 1 - F_L(x) \sim \mathbb{E}[N]\, x^{-\alpha} h(x)\ , \qquad x \to \infty$$

- Standard actuarial techniques:
  - Approximation (translated gamma/lognormal)
  - Inversion methods (FFT)
  - Recursive methods (Panjer)
  - Simulation

How accurate are VaR-estimates?

- **Assumptions**:
  - (L_m) iid $\sim F$
  - For some ξ, β and u large ($G_{\xi,\beta}$: GPD):

$$F_u(x) := \mathbb{P}[L - u \leq x | L > u] = G_{\xi,\beta(u)}(x)$$

- Tail- and quantile estimate:

$$\boxed{\begin{aligned} 1 - \hat{F}_L(x) &= \frac{N_u}{n}\left(1 + \hat{\xi}\,\frac{x-u}{\hat{\beta}}\right)^{-1/\hat{\xi}}, \quad x > u. \\ \widehat{\text{VaR}}_\alpha &= \hat{q}_\alpha = u - \frac{\hat{\beta}}{\hat{\xi}}\left(1 - \left(\frac{N_u}{n(1-\alpha)}\right)^{\hat{\xi}}\right) \end{aligned}} \tag{1}$$

How accurate are VaR-estimates? (cont'd)

- **Idea**: Comparison of estimated quantiles with the corresponding theoretical ones by means of a simulation study ([6]).

- **Simulation procedure**:

  ❶ Choose F and fix $\alpha_0 < \alpha < 1$, N_u ($\#$ of data points above u)

  ❷ Calculate $u = q_{\alpha_0}$ and the true value of the quantile q_α

  ❸ Sample N_u independent points of F above u by the rejection method. Record the total number n of sampled points this requires

  ❹ Estimate ξ, β by fitting the GPD to the N_u exceedances over u by means of MLE.

  ❺ Determine $\hat{q}_\alpha$ according to (1)

  ❻ Repeat N times the above to arrive at estimates of Bias$(\hat{q}_\alpha)$ and SE$(\hat{q}_\alpha)$

How accurate are VaR-estimates? (cont'd)

- **Accuracy** of the quantile estimate expressed in terms of bias and standard error:

$$\text{Bias}(\hat{q}_\alpha) = \mathbb{E}[\hat{q}_\alpha - q_\alpha], \qquad \text{SE}(\hat{q}_\alpha) = \mathbb{E}\big[(\hat{q}_\alpha - q_\alpha)^2\big]^{1/2}$$

$$\widehat{\text{Bias}} = \frac{1}{N}\sum_{j=1}^{N} \hat{q}_\alpha^j - q_\alpha \qquad \widehat{\text{SE}} = \Big(\frac{1}{N}\sum_{j=1}^{N}(\hat{q}_\alpha^j - q_\alpha)^2\Big)^{1/2}$$

- **Ideally**, $\widehat{\text{Bias}}$ AND $\widehat{\text{SE}}$ small

Example: Pareto distribution with $\theta = 2$

$u = F^{\leftarrow}(x_q)$	α	Goodness of $\widehat{\text{VaR}}_\alpha$
$q = 0.7$	0.99	A minimum number of **100 exceedances** (corresponding to 333 observations) is required to ensure accuracy wrt bias and standard error.
	0.999	A minimum number of **200 exceedances** (corresponding to 667 observations) is required to ensure accuracy wrt bias and standard error.
$q = 0.9$	0.99	Full accuracy can be achieved with the minimum number **25** of **exceedances** (corresponding to 250 observations).
	0.999	A minimum number of **100 exceedances** (corresponding to 1000 observations) is required to ensure accuracy wrt bias and standard error.

Example: Pareto distribution with $\theta = 1$

$u = F^{\leftarrow}(x_q)$	α	Goodness of $\widehat{\text{VaR}}_\alpha$
$q = 0.7$	0.99	For all number of exceedances up to **200** (corresponding to a minimum of 667 observations) the VaR estimates fail to meet the accuracy criteria.
	0.999	For all number of exceedances up to **200** (corresponding to a minimum of 667 observations) the VaR estimates fail to meet the accuracy criteria.
$q = 0.9$	0.99	A minimum number of **100 exceedances** (corresponding to 1000 observations) is required to ensure accuracy wrt bias and standard error.
	0.999	A minimum number of **200 exceedances** (corresponding to 2000 observations) is required to ensure accuracy wrt bias and standard error.

How accurate are VaR-estimates? (cont'd)

- Minimum number of observations increases as the tails become thicker ([6]).

- Large number of observations necessary to achieve targeted accuracy.

- **Remember**: The simulation study was done under idealistic assumptions. OP risk losses, however, typically do NOT fulfil these assumptions.

D. Conclusions

- OP risk $\neq$market risk, credit risk
- "Multiplicative structure" of OP risk losses ([5])
  $S \times T \times M$ (Selection-Training-Monitoring)
- Actuarial methods (including EVT) aiming to derive capital charges are of limited use due to
  - lack of data
  - inconsistency of the data with the modeling assumptions
- OP risk loss databases must grow
- Sharing/pooling internal operational risk data?

Conclusions (cont'd)

- Choice of risk measure?
- Heavy-tailed ruin estimation for general risk processes ([4])
- Alternatives?
  - Insurance. Example: FIORI, Swiss Re (Financial Institution Operating Risk Insurance)
  - Securitization / Capital market products
- OP risk charges can not be based on statistical modeling alone

▶ Pillar 2 (overall OP risk management such as analysis of causes, prevention, . . .) more important than Pillar 1

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