Executive summary

- Operational risk is the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events
  - This definition includes legal risk, but excludes strategic and reputational risk
- In the post-crisis environment, operational risks with unusual severities emerge regarding litigations
  - Litigations with regulators
  - Litigations with clients
- New risks emerge from the technological transition: cyber risk
- Regulators have recently published new guidelines and measurement standards for the capital charge measurement. OR capital charges are now often larger than market risk capital charges in large banks
- The Loss Distribution Approach (LDA) is the reference approach for measuring operational risk, but the range of practices is large and data are scarce
  - Modelling choices (model risk): severities, correlations, structure of the model
  - Calibration and validation issues
  - Few analytical results
- Agenda
  - Context: emerging risks and regulation
  - New results on OR correlations
  - New results from classification invariance
EMERGING RISK AND REGULATION

Operational risk is expensive

**Rogue Trading**
- Barings (1995): $1.3 MM
- Allied Irish Banks (2002): $691M
- Société Générale (2008): €4.9 MM
- Caisses d’Epargne (2008): €938 M
- Merrill Lynch (2009): $456 M
- UBS (2011): $2.3 MM
- Credit Suisse (2012): $2.85 MM

**Reg. Rules Breach 2012-2014**
- OFAC
- BNPP: $9 MM
- HSBC: $1.9 MM
- Libor
- UBS: $1.53 MM
- Rabobank: $1.07 MM

**Client litigations 2012-2014**
- Subprimes
  - BoA: $17 MM
  - JP Morgan: $13 MM
- Payment Protection Insurance
  - Lloyds: $8.3MM
  - RBS: $2.67 MM
  - HSBC: $1.7MM
  - Barclays: $3.1MM

**Terrorist Attacks**
- New-York (2001)
- London (2005)

**Systems Failure**
- Knight capital (2012): $440M

**Fraud**
- Madoff (2008)
- "Madoff du var" (2011)

**Natural Disaster**
- Fukushima (2011)
- Katrina (2005)
- Sandy (2012)
How do banks measure and manage operational risk?

- Internal losses collection
  - Most of the advanced banks have started to collect data between 2000 and 2005
  - Useful for high frequency and low severity risk
- External loss data
  - Several providers + one consortium gathering up to 70 large banks around the world (ORX)
  - External data are not representative of the bank’s risk => scaling issue
- Scenario analysis
  - Represent high severity low frequency risk or losses arising from multiple simultaneous events
- Environment and internal control factors
  - Quantification must embed the internal risk profile of the bank
  - Capture key risk factors in a forward-looking approach
- OR management
  - Key Risk Indicators (KRI)
  - Risk and Controls Self Assessment (RCSA)
  - Action and remediation plans
  - Insurance contracts

Requirements from regulation

- The Basel regulation allows banks to use one of the 3 approaches
  - Basic approach: capital charge proportional to the bank’s gross income
  - Standard approach: capital charge proportional to the business lines’ gross income
  - Advanced approach (AMA): Loss distribution Approach (LDA) or Scenario Based Approach (SBA)
- In the AMA approach, the capital charge is equal to the 99.9% loss over 1 year
- Measurement of the capital charge must include the use of internal / external data, scenario analysis and Environment and internal control factors
- EBA has issued guidelines regarding AMA frameworks
  - The AMA perimeter should include OR linked to credit risk
  - Internal models will be constrained by the regulation
- BCBS publications
  - Consultative paper about the revision to the simpler approaches (basic and standard)
  - Review of the AMA framework expected in 2015
NEW RESULTS ON THE CORRELATION PROBLEM

Sound correlations vs. noise
Study based on ORX datas
Cell risk modeling

• Aggregate losses computed from the OpRisk SAS Database are compliant with lognormal tails
  • For a lognormal distribution, the parameters are linked to measurable quantities
  • The implied parameters are in a stable range of values for all confidence levels

<table>
<thead>
<tr>
<th>Confidence level</th>
<th>Average</th>
<th>SD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>95%</td>
<td>98%</td>
<td>41%</td>
</tr>
<tr>
<td>97.5%</td>
<td>99%</td>
<td>39%</td>
</tr>
<tr>
<td>99%</td>
<td>107%</td>
<td>44%</td>
</tr>
<tr>
<td>99.5%</td>
<td>112%</td>
<td>46%</td>
</tr>
<tr>
<td>99.9%</td>
<td>124%</td>
<td>48%</td>
</tr>
<tr>
<td>All</td>
<td>107%</td>
<td>42%</td>
</tr>
</tbody>
</table>

• Cell loss correlations are proportional to the number of events correlation (Frachot et al., 2004). The correlation upper bounds depend on cells frequencies

• Loss correlation upper-bounds from OpRisk SAS Database
  • Average = 1.33%
  • Standard deviation = 1.61%
  • Maximum = 11.27%

• The copula parameters are much lower than 10% on average

Analytical model: assumptions and definitions

ASSUMPTIONS
• Cell losses are lognormal
• One factor model
• Gaussian copula: pair-wise correlations may be different to each other
• We assume that the parameters are not dependent on the number of cells; the number of cells goes to infinity

DEFINITIONS
• Cell loss

• Correlation

• Bank’s loss

• Bank’s capital charge

• Stand-alone cell capital charge
Homogeneous portfolio

- The bank’s loss is still lognormal

\[ L = \frac{1}{N} \sum_{i=1}^{N} x_i \]

- Negative diversification appears when individual cell risk is larger than a given threshold

\[ \frac{\partial^2 \log L}{\partial \log x_i^2} = \frac{1}{x_i^2} - \frac{1}{N} \]

Cell risk dispersion

- Analytical model with individual cell risk dispersion

\[ L = \frac{1}{N} \sum_{i=1}^{N} x_i \exp(-\lambda x_i) \]

- Closed-form solution for the bank’s loss when the number of cells goes to infinity

\[ L = \frac{1}{\sqrt{2\pi}} \int_{0}^{\infty} \exp\left(-\frac{x^2}{2}\right) dx \]

![Graph of lognormal distribution](image)

![Graph of cell risk dispersion](image)
Correlation dispersion is not critical

- Analytical model with correlation dispersion

\[ \begin{align*}
\Delta^2 &= \sum_i \Delta_i^2 \\
\text{As the correlation parameters are linked to the beta, their variances are linked as well,}
\end{align*} \]

\[ \Delta^2 = \Delta_1^2 \quad \text{to} \quad \Delta^2 = \sqrt{\Delta_1^2 + \Delta_2^2} - \Delta_2^2 \]

NEW RESULTS ON THE CLASSIFICATION PROBLEM
Classification invariance (1/2)

ASSUMPTIONS

• Homogeneous risk portfolio
• The shapes of the distributions don’t change with the number N of cells
• The parameters scale with the number of cells
• The number of cells goes to infinity
• Cells risks are independent to each other

LOGNORMAL CASE

Bank’s loss

$L_N = \sum_{i=1}^{N} z_i \phi(x_i)$

Casymptotic classification invariance

\[
\lim_{N \to \infty} E[L_N] = \lim_{N \to \infty} e^{\mu_N + \sigma_N^2/2} = a \\
\lim_{N \to \infty} \text{var}[L_N] = \lim_{N \to \infty} e^{2\mu_N + 2\sigma_N^2} (e^{\sigma_N^2} - 1) = b
\]

Scaling of the parameters

\[
\mu_N \sim -\frac{3}{2} \ln N \quad \text{and} \quad \sigma_N \sim \sqrt{\ln N}
\]

Lindeberg’s criterion

\[
\lim_{N \to \infty} \sum_{i=1}^{N} \left( \frac{\mu_{y_i}}{\sigma_{y_i}} - \mu_{y_i} \right)^2 \mathbb{P}(y_i \geq |\mu_{y_i}|) = 0
\]

Domain of attraction of the normal distribution

\[
\sigma_N < \sqrt{\frac{\ln N}{2}}
\]

Classification invariance (2/2)

• Domain of attraction of the bank’s operational loss in the general case: Ben Arous, Bogachev, Molchanov Theorem
• There is a competition between the attraction of the normal distribution fixed point for the sum of i.i.d random variables and the divergence of the volatility parameter $\sigma_N$
  - If the divergence is slow: domain of attraction of the normal distribution (Lindeberg’s condition satisfied)
  - If the divergence is fast: domain of attraction of the fully asymmetric Levy distribution.
• Surprising results
  - Fat tail (power law) distributions emerge from the classification invariance requirement
  - Distributions with finite variance are not in the domain of attraction of the normal distribution
  - Negative diversification occurs, even for uncorrelated cell risks
  - For correlated cell risks, classification invariance generates decorrelation among cells. The correlation parameter scales as:

\[
\rho_N \sim K / \ln N
\]
Conclusions

- Average cell risk, cell risk dispersion and average correlations are critical parameters
- Regarding correlations
  - they are very noisy
  - they seem low
  - Correlation dispersion is not a critical parameter
- Diversification / negative diversification effects are not driven by correlations but by the shape of cell risk distributions
  - Power laws and fat tails appear naturally when we require the classification invariance
  - Negative diversification may appear for large numbers of cells in the model
- Analytical models have some virtues
  - Avoid the black box feeling of the full statistical / Monte-Carlo approach
  - They embed very few specifications and lead to general results
- The portfolio approach for operational risk is still unexplored, and we need to rethink the current approach to take into account the scarcity of data