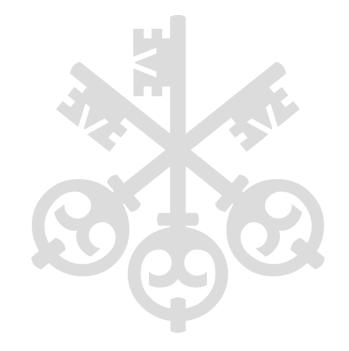


## **Operational Risk**

Presentation for QRM Students

Michael Amrein, Dr. sc. ETH Zurich, Actuary SAA Head AI, Monitoring & Surveillance Models Validation Model Risk Management & Control



Public

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- What is Operational Risk (Op Risk)?
- Applications of Operational Risk models in the banking industry
  - Op Risk Measurement Pillar 1 (Minimum Capital Requirements)
  - Op Risk Measurement Pillar 2 (Supervisory Review of Capital Adequacy)
  - Monitoring & Surveillance of Op Risks

# What is Operational Risk?



## Definition of Operational Risk (Op Risk)?

- Definition (Basel Committee): The risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes
  - Legal Risk financial loss that can result from lack of awareness or misunderstanding of, ambiguity in, or reckless indifference to, the way law and regulation apply to your business, its relationships, processes, products and services

but excludes

- Strategic Risk loss arising from a poor strategic business decision
- Reputational Risk damage to an organization through loss of its reputation or standing
- The seven Basel Op Risk categories
  - 1. <u>Internal Fraud</u> misappropriation of assets, tax evasion, intentional mismarking of positions, bribery
  - 2. <u>External Fraud</u> theft of information, hacking damage, third-party theft and forgery
  - 3. Employment Practices and Workplace Safety discrimination, workers compensation, ...
  - 4. <u>Clients, Products, and Business Practice</u> market manipulation, product defects, fiduciary breaches, ...
  - 5. <u>Damage to Physical Assets</u> natural disasters, terrorism, vandalism
  - 6. <u>Business Disruption and Systems Failures</u> utility disruptions, software failures, hardware failures
  - 7. Execution, Delivery, and Process Management data entry errors, accounting errors, ...

#### **WBS**

#### Examples of Op Risk Losses 1





In the course of 2014 and 2015, Barclays, Citi, JP Morgan, Royal Bank of Scotland and UBS were forced to pay more than \$ 5.6 bn\* to UK and US authorities

#### LIBOR Scandal



## **BNP** Paribas Sanctions Violations



Several banks and brokers pay settlements of close to \$ 9 bn to regulators in relation to the rigging of benchmark interest rates BNP Paribas was forced to pay \$ 9 bn to US authorities in June 2014 after admitting that it flouted sanctions against Cuba, Iran and Sudan



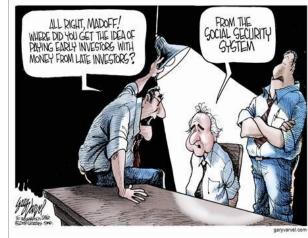
## Examples of Op Risk Losses 2

#### **UBS rogue trader scandal**



\$ 2 bn\* were lost as a result of unauthorized trading performed by Kweku Adoboli, a director of the bank's Global Synthetic Equities Trading team in London

#### Bernhard Madoff's Ponzi Scheme



Prosecutors estimated the size of the fraud to be \$ 64.8 bn, based on the amounts in the accounts of Madoff's 4800 clients as of November 30, 2008

## Residential mortgage-backed securities (RMBS)



Deutsche Bank agreed to pay a civil monetary penalty of \$ 3.1 bn and to provide \$ 4.1 bn in consumer relief in the US in connection with the bank's issuance and underwriting of RMBS and related securitization activities between 2005 and 2007

\* In English, 1bn = 1 billion = 10^9



# Op Risk Measurement – Pillar 1



- Banks must hold a regulatory minimum capital for Op Risk. Currently, there are three approaches.
- Basic Indicator Approach (BIA)
  - for regional, non-complex firms
  - not risk-sensitive
- The Standardized Approach (TSA)
  - expected for most financial services firms
  - not risk-sensitive
- Advanced Measurement Approach (AMA)
  - is currently in place at many of the global and systemically important banks
  - requires prior regulatory approval
  - involves complex statistical modelling, allows for flexibility

• The Regulatory Capital (RC) under the BIA equals 15% of the average annual gross income over the previous three years where it was positive, i.e.,

$$\mathrm{RC}_{t}^{\mathrm{BIA}} = 15\% \cdot \left(\sum_{k=1}^{3} \max\{\mathrm{GI}_{t-k}, 0\}\right) / \left(\sum_{k=1}^{3} \mathbb{I}_{\mathrm{GI}_{t-k} > 0}\right)$$

where  $GI_{t-k}$  is the annual gross income in year t - k.

• The TSA is similar to the BIA, but the calculation is performed separately for each business line with different weights, i.e., the Regulatory Capital (RC) is given by

$$\mathrm{RC}_{t}^{\mathrm{TSA}} = \frac{1}{3} \cdot \sum_{k=1}^{3} \max\{\sum_{b=1}^{8} \beta_{b} \mathrm{GI}_{t-k}^{b}, 0\}$$

where  $GI_{t-k}^{b}$  is the annual gross income in year t – k of business line b and  $\beta_{b}$  is its weight

 The 8 business lines and their weights are (note the sum of weights is equal 1.2 = 8x15%): Corporate finance (18%)
 Trading & sales (18%)
 Agency Services (15%)

Retail banking (12%)

Commercial banking (15%)

Agency Services (15%) Asset management (12%)

Retail brokerage (12%)



- Allows banks to use their internally generated risk estimates
- Supervisory Guidance:
  - Operational Risk Supervisory Guidelines for the Advanced Measurement Approaches, Basel Committee on Banking Supervision
  - Supervisory Guidance for Data, Modeling, and Model Risk Management Under the Operational Risk Advanced Measurement Approaches, FED
  - ... (and more)
- The Regulatory Capital is equal to the Op Risk loss that is exceeded only once in 1000 years, i.e., VaR<sub>0.999</sub>(L), where the random variable L is the total annual Op Risk loss.
- Common approach to model L, taken in large banks, is the Loss Distribution Approach (LDA)

### Typical LDA Setup within the AMA Framework

- Define Units of Measure (UoM)
  - A UoM typically combines business lines / loss event types, e.g., Investment Bank / Fraud
- For each UoM u,  $u \in \{1, 2, ..., U\}$ , we model the annual loss  $L_u$  as compound sum of
  - the annual loss frequency:  $N_u$  is number of losses in UoM u per year
  - the loss severity:  $X_{k,u}$  is the amount of the k-th loss in UoM u,

that is,  $L_u = \sum_{k=1}^{N_u} X_{k,u}$ ,

where we assume that  $\{X_{k,u}: k = 1, 2, ..., N_u\}$  are i.i.d and independent from  $N_u$ .

- The total annual Op Risk loss L is then  $L = \sum_{u=1}^{U} L_u$ .
- Very challenging problem! We need to estimate / justify
  - Segmentation into UoM
  - Frequency distribution, i.e., distribution of N<sub>u</sub>
  - Severity distribution, i.e., distribution of X<sub>1,u</sub>
  - Dependence between UoM via copula

More objective but backward-looking:

- Internal Operational Loss Event Data (ILD)
- External Operational Loss Event Data (ELD)
  - Data consortia, e.g., Operational Riskdata eXchange Association (homogeneous classification standards, data relevance)
  - Publicly available data, e.g., media or annual reports (reporting bias)

Forward-looking but more subjective:

- Scenario Analysis (SA)
  - Systematic process of obtaining expert opinions to derive reasoned assessments of the likelihood and loss impact of plausible, high-severity operational losses, typically developed through workshops
  - Expert biases (overconfidence, anchoring, ...) and subjectivity
- Business Environment and Internal Control Factors (BEICF)
  - Indicators designed to provide a forward-looking assessment of a banking organization's business risk factors and internal control environment (impact of discontinuing a line of business, a change in the internal control environment, ...)
  - Might be used to adjust operational risk exposure

#### **WBS**

- Frequency: Poisson, Negative Binomial,  $N \sim NB(r, p) \le P[N = n] = \binom{n+r-1}{n}p^n(1-p)^r$ ,  $n \in \mathbb{N}_0$
- Severity: Log-Normal, Log-Gamma, Generalized Pareto, ...
- Dependence
  - Dependence between annual losses  $L_u$ ,  $u \in \{1, 2, ..., U\}$  vs dependence on frequency / severity level
  - Copulas: t, Clayton, Gumbel, Frank, ...
- Use the four data elements (ILD, ELD, SA, BEICF)
  - Filtering ELD to remove non-relevant events
  - Scaling ELD to account for differences in size or business activities
  - Mixing data vs mixing distributions, e.g., fit distribution to ILD plus weighted ELD vs fit distributions to both ILD and ELD and mix the densities
  - Benchmarking, e.g., compare ILD based main model with ELD based challenger model
  - Build and own SA distribution vs SA based adjustments
  - Bayesian approach: use SA distributions as prior and calculate posterior given ILD and ELD
  - Parameter adjustments based on BEICF
  - ... (use your imagination)



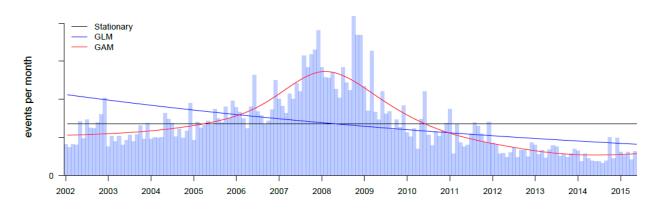
Model component	Modelling choice	Data elements used for calibration
Units of Measure	<ul> <li>Expert driven definition</li> <li>Often an internal risk category, e.g., External Fraud, Market Conduct, Suitability, Cross Border Business Conduct</li> </ul>	• None
Event Frequency (per UoM)	<ul> <li>Negative Binomial distribution</li> </ul>	• ILD
Event Severity (per UoM)	<ul> <li>Body: Continuous version of the empirical distribution</li> <li>Tail: Truncated lognormal distribution</li> <li>Truncation point is unknown, needs estimation</li> </ul>	<ul> <li>ILD</li> <li>Filtered and weighted ELD</li> </ul>
Dependence	<ul> <li>Mirrored Clayton copula to link annual UoM loss distributions</li> </ul>	• ILD
Expert Adjustments	<ul> <li>Frequency: adjustment of the expected number of events per year</li> <li>Severity: uniform scaling of the severity distribution</li> </ul>	• SA • BEICF
Capital Calculation		
Calculation of aumu	lative loss distribution (CLD) por LIoM via discretization of soverity di	stribution combined with

- Calculation of cumulative loss distribution (CLD) per UoM via discretization of severity distribution combined with Fast Fourier Transform
- Aggregation of UoM CLD's via copula using Monte Carlo simulation. To control the Monte Carlo simulation error, capital calculation is averaged over 100 repetitions with sample size 1'000'000



#### Some Insights into Frequency Calibration

- Several models were investigated for the event frequency
  - Poisson, Neg Bin (variance is a quadratic function of the mean), Neg Bin Linear (variance is a linear function of the mean)
  - no trend in mean over time, linear trend in mean (using a generalized linear model) and piecewise cubic trend in mean (using a generalized additive model)
- Akaike Information Criterion (AIC), Kolmogorov-Smirnoff (K-S) and Anderson-Darling (A-D) tests were used to evaluate goodness of fit



	AIC	K-S	A-D	$\lambda$ (Year)	$\sigma$	r
Poisson	7677	<0.01	<0.01	1624.25		
NegBin	1813	0.8	0.7	1624.25	39.55	41.07
Poisson GLM	6928	<0.01	<0.01	1212.77		
NBL GLM	1791	0.16	0.06	1212.77	41.23	29.42
NegBin GLM	1785	0.1	0.07	1055.36		
Poisson GAM	2468	<0.01	<0.01	657.1		
NBL GAM	1586	0.55	0.17	664.41	8.85	75.06
NegBin GAM	1576	0.36	0.21	664.41		

- Direct estimation of the copula is difficult: we had only 14 data points for a 15-dimensional copula
- An adapted permutation test (that reflects the copula in question) with test statistic maximum yearly loss over all UoM was chosen to analyse four one parameter copula families (mirrored-Clayton, Gumbel, t with v degrees of freedom and no correlation, equicorrelated Gaussian)
- The p-values quickly decrease monotonically as the parameters move away from independence

mirrored-Clayton		Gumbel		Student-t		Gaussian	
$\theta$	p-value	$\theta$	p-value	u (df)	p-value	ρ	p-value
0.00	0.2792	1.00	0.2723	1	0.0583	-0.06	0.3680
0.02	0.2306	1.02	0.2354	2	0.1081	-0.03	0.3286
0.04	0.2060	1.04	0.2006	3	0.1417	0.00	0.2745
0.06	0.1734	1.06	0.1736	4	0.1604	0.03	0.2307
0.08	0.1479	1.08	0.1540	5	0.1793	0.06	0.1970
0.10	0.1335	1.10	0.1308	6	0.1952	0.09	0.1596
0.12	0.1149	1.12	0.1193	7	0.2022	0.12	0.1400
0.14	0.1003	1.14	0.1033	8	0.2087	0.15	0.1207
0.16	0.0864	1.16	0.0893	9	0.2089	0.18	0.0954
0.18	0.0749	1.18	0.0777	10	0.2198	0.21	0.0761
0.20	0.0654	1.20	0.0707	11	0.2326	0.24	0.0674
0.22	0.0600	1.22	0.0650	12	0.2340	0.27	0.0523
0.24	0.0565	1.24	0.0514	13	0.2267	0.30	0.0484
0.26	0.0486	1.26	0.0506	14	0.2330	0.33	0.0346
0.28	0.0389	1.28	0.0407	15	0.2377	0.36	0.0318
0.30	0.0364	1.30	0.0413	Inf	0.2777	0.39	0.0239

# Criticism of the AMA and the new Standardized Measurement Approach (SMA)

#### **Main Criticisms**

- Comparability of AMA minimum capital figures is questionable due to the full methodological freedom within the LDA
- How reliable are the quantitative estimates? 1-in-1000-year loss vs 15 years of ILD!
  - Limited availability of data / high confidence levels → uncertainty / instability in estimates
  - Over-fitting and extrapolation issues

#### **Standardized Measurement Approach (SMA)**

- A simpler and more comparable approach will be implemented effective January 1, 2022, see Section *Minimum* capital requirements for operational risk in Basel III: Finalising post-crisis reforms from the Basel Committee on Banking Supervision
- The SMA combines the Business Indicator, a simple financial statement proxy of operational risk exposure, with bank-specific Internal Loss Multiplier (based on internal operational loss data) to provide some incentive for banks to improve their operational risk management
- Nevertheless, comparability of capital charges remains a concern because
  - the collection of operational loss data is still determined by individual bank rules (no common standard),
  - national regulators may grant exclusion of (parts of) the loss history from the calculation (due to backward-looking nature of the SMA).

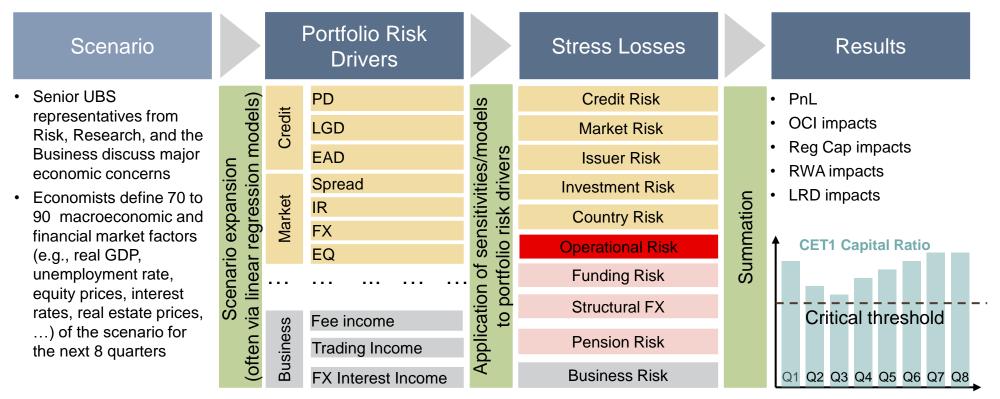


# Op Risk Measurement – Pillar 2



		Loans		
Position risks		Derivatives		
	Our dit	IB Loan Underwriting		
	Credit	Issuer		
		Settlement		
		Country (transfer) risk	Div	
sks	Market	Trading books	Diversification between risks	
	Widi Ket	Banking book	fica	
	Investment	Equity investments	tion	
	investment	Debt financial investments	bet	
Co	Operational risk			
nse	Funding risk			
que	Structural FX			
<b>Consequential risks</b>	Property & equipment risk			
l ris	Uncertain tax risk			
ks	Pension risk			
Business risk				
Liquidation cost				

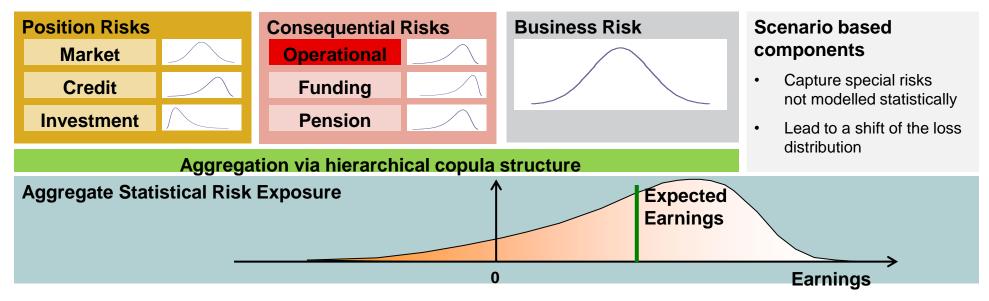
- In the Internal Capital Adequacy Assessment Process, a bank needs to assess (among other things) whether it considers its capital adequate to cover the level and nature of the risks to which it is exposed
- This includes the risk types from Pillar 1, but extends to every possible risk type and their aggregation / diversification



 Stress Testing: analysis to determine whether there is enough capital to withstand the impact of an unfavorable economic scenario, including the causality chain by which losses would arise if the scenario were to unfold Per UBS internal risk category *i*:

- Quarterly loss sums are related to the quarterly values/shocks of explanatory variables *j* via a generalized linear model with compound Poisson-Gamma distribution and log link function:  $E[Y_t^i | \mathbf{X}_t] = \exp(\beta_0 + \sum_{j=1}^n \beta_j X_t^j), Var[Y_t^i | \mathbf{X}_t] = \phi E[Y_t^i | \mathbf{X}_t]^p, p \in (1, 2), \phi > 0.$ 
  - Reasonable assumption: Poisson frequency and Gamma severity
  - Can handle positive mass at a zero quarterly loss
  - Tractable parameter estimation
  - Log-link is often a good choice and has proven to be more stable than considered alternatives
- Candidate models are identified via a stepwise variable selection approach out of a predefined set of drivers, i.e., transformations of equity indexes, interest rates, bond yields, price indices and macroeconomic drivers including lags up to six quarters, by minimizing the Root Mean Square Error using Cross Validation subject to expert given constraints.
- If no (or no economically meaningful) model can be identified for a risk category, a fallback approach, i.e., the historical average quarterly loss, is used.





- Economic Capital: amount of capital required to ensure solvency over a year with a pre-specified probability (e.g., 95% or 99.9%)
- A common approach to generate the annual loss distribution is to model risk types via their marginal loss distributions and then to aggregate them using copulas, see picture. For the Op Risk marginal distribution, the LDA can be used again (if there is already AMA LDA model).
- Another approach is to simulate many economic scenarios (risk drivers) consistently, and then to use methods similar to the ones used in Stress Testing to calculate the annual loss for each scenario.

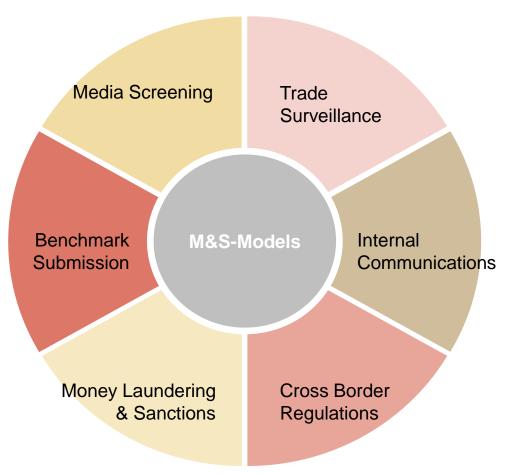


# Monitoring & Surveillance of Op Risks



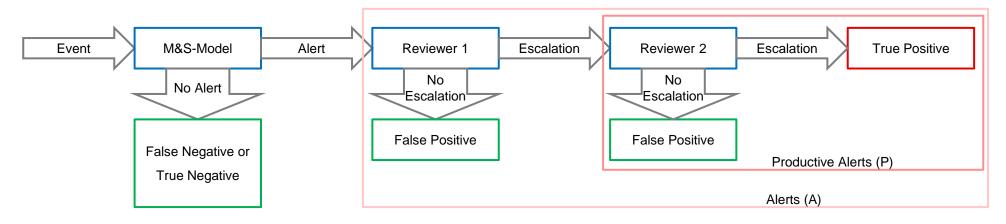
#### Monitoring & Surveillance (M&S) Models

- We use **alert generating** models to monitor many of our key operational risks in the bank
- Goals:
  - Detect improper client and employee practices at the earliest opportunity
  - Deal with ever more complex rules and increasing severity of noncompliance
  - Effective and efficient use of human resources



## Typical Characteristics of a M&S Model

• M&S-Models are embedded in a subject matter expert review process



• Essentially a binary classification problem: predict "fraud" (alert) or "non-fraud" (no alert)

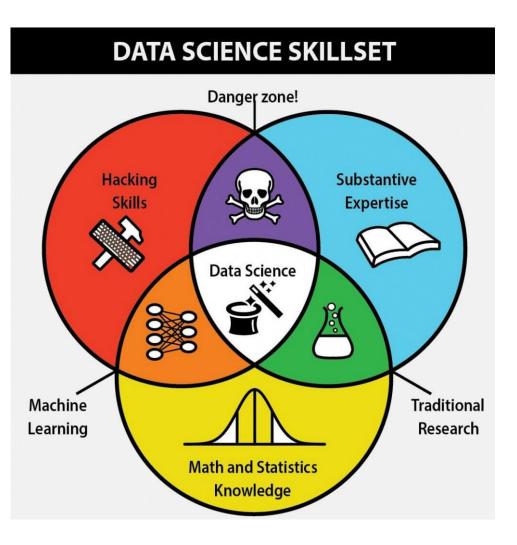
Prediction / Actual	"Fraud"	"Non-Fraud"
Alert	True Positives	False Positives – Type I Error
Non-Alert	False Negatives – Type II Error	True Negatives

 Often large amounts of data are being processed: Conversations (emails, chat streams, audio data) / trade data / client transaction data / media



## Modelling Techniques for M&S

- Often rule / lexical search based
- Use of Machine Learning is taking up speed in this area
  - Classification / supervised learning
    - Logistic Regression
    - Linear and quadratic discriminant analysis
    - Trees / Random Forests
    - Support Vector Machines
    - Artificial Neural Networks
    - ...
  - Clustering / unsupervised learning (for feature engineering and dimension reduction)
    - K-means / K-medoids
    - Nonparametric density estimation
    - Hierarchical clustering
    - Principal Component Analysis / Autoencoder



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