Operational Risk

A Discussion of Quantification Techniques

John Jordan

Federal Reserve Bank of Boston

March 10, 2004

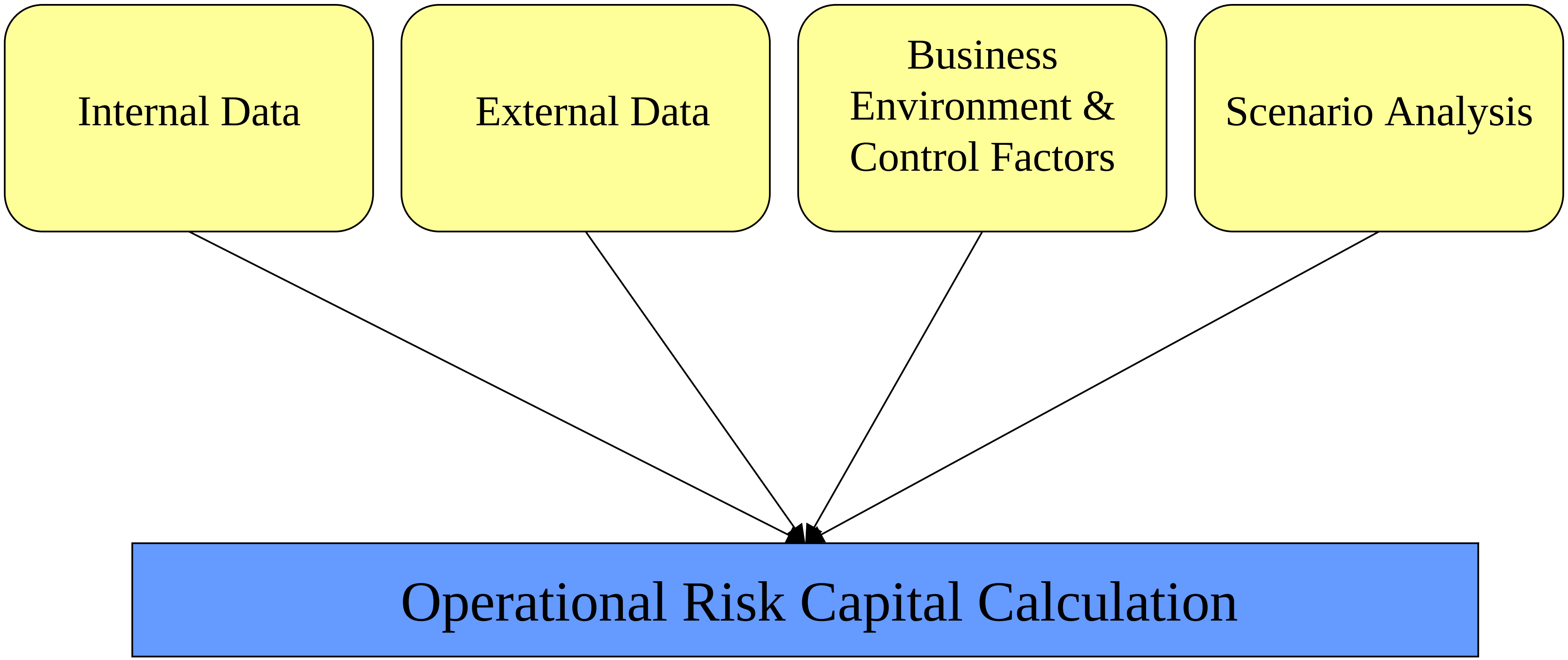
What is required in an AMA?

- Banks are expected to use internal models to determine operational risk capital requirements
- To qualify, however, banks must satisfy a number of supervisory standards beyond "model validation"
- OpRisk Supervisory Standards
  - Governance Structure
  - Data
  - Quantification

Data:
Required Elements of an AMA

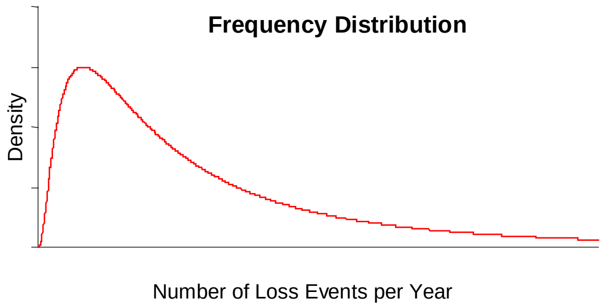
Internal Data	• OpLoss event tracking
External Data	• OpLoss events occurring at peers • vendor products • data consortia
Business Environment & Control Factors	• Key Risk Indicators • Risk and Control Self Assessments • Scorecards
Scenario Analysis	• Systematic process for obtaining expert opinions

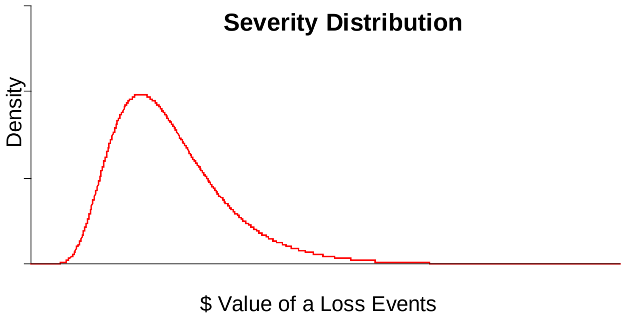
Quantification:
Significant flexibility in model design

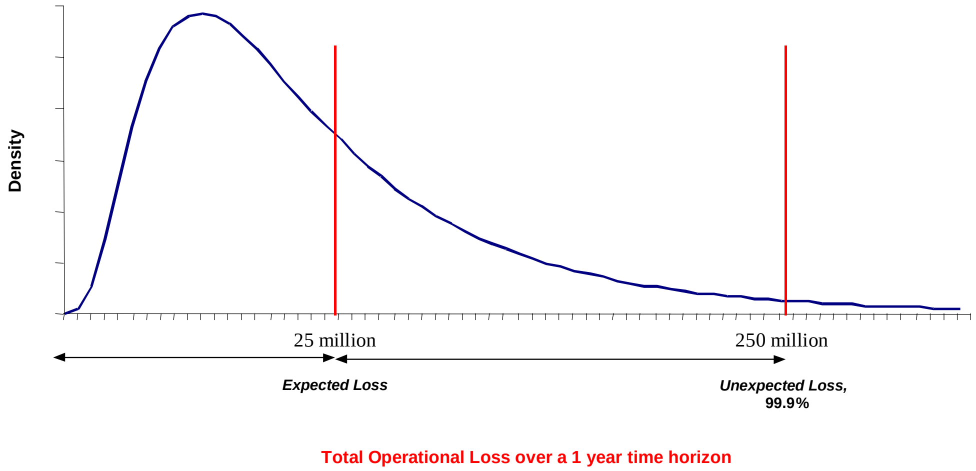


One Example of an AMA:
The Loss Distribution Approach

The Loss Distribution Approach

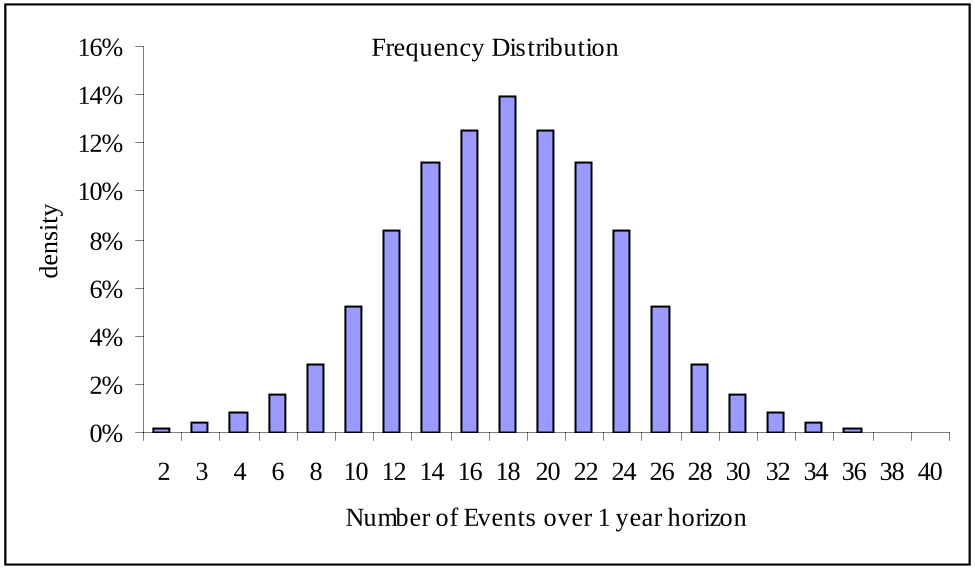






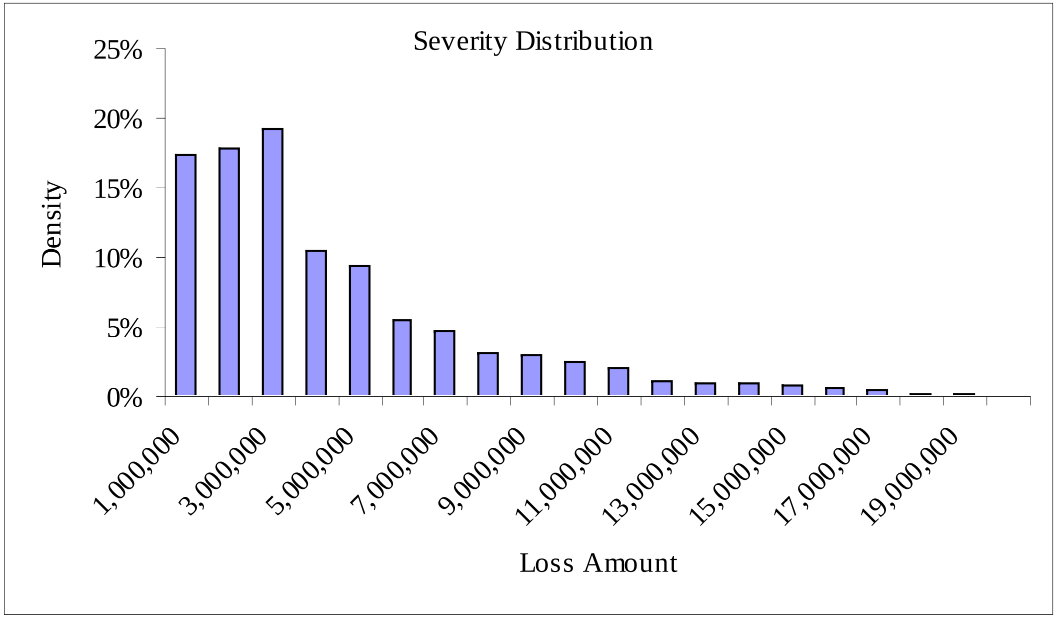
Step 1:
The Frequency Distribution

- Provides a range of the “number of events over a 1 year time horizon”
- “Shape” and “Location” of frequency distribution are determined by:
  - scale of operations
  - level of controls and sophistication of processes



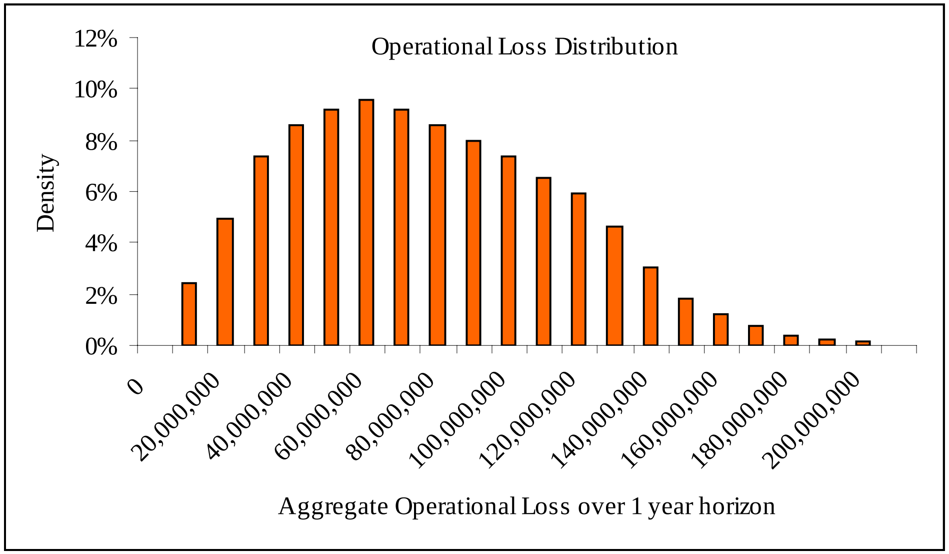
Step 2:
The Severity Distribution

- Provides the range of "loss amounts, given a loss event occurs"
- "Shape" and "Location" of severity distribution are determined by:
  - nature of underlying transaction (ex. size of trade)
  - controls and processes may play a "mitigation" role



Step 3:
The Aggregate Loss Distribution

- Provides the range "aggregate loss over a 1 year time horizon"
- Often construct using "monte carlo" simulation techniques:
  - Take a random draw from the frequency distribution, example: 22 events
  - Take 22 random draws from the severity distribution, example: 1st draw $5,000,000; 2nd draw $1,200,000; …; the 22nd draw $12,500,000
  - Sum the $ value of losses, example: $45,000,000 result is 1 observation in loss distribution
  - Repeat 100,000 (1,000,000, 10,000,000?) times

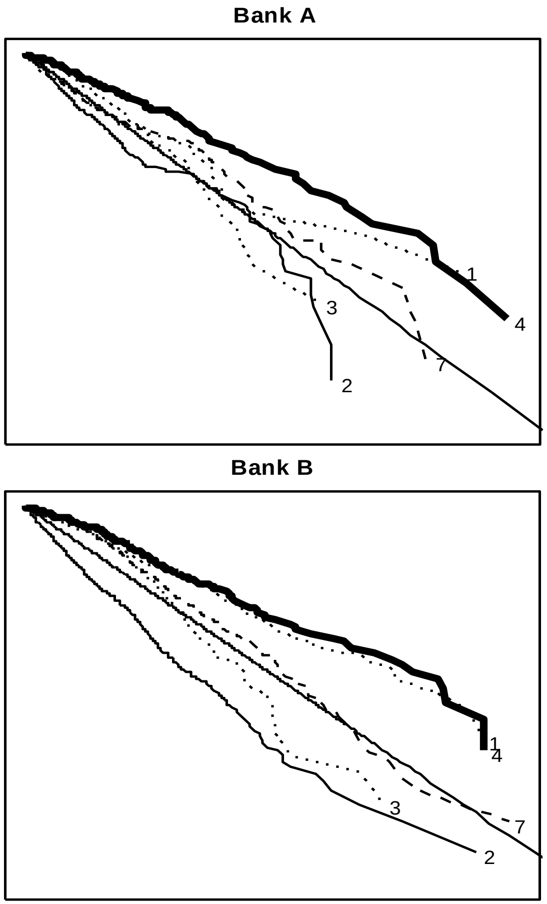


Using Internal Loss Event Data

Using Internal Loss Event Data in an LDA

- Loss Data Collection Exercise – sponsored by RMG/BCBS
  - 89 banks in 19 countries participated.
  - 47,269 losses above €10,000 occurring in 2001.
  - 22 banks had more than 500 observations
- Challenges:
  - Significant differences in the number of loss events across banks
  - A “handful” of banks contributed the majority of observations
  - Reason for differences:
    - Definition gaps
    - Capture gaps
    - Time Series gaps

Empirical Regularities in Internal Data



- Consistent cross-bank ordering of event types:
  - Internal Fraud (1)
  - Litigation (4)
  - Process Management (7)
  - External Fraud (2)
  - Employment Practices (3)

Severity Distributions with Internal Data

- We consider 9 common distributions.
  - Thin-tailed: Exponential, Gamma, Weibull, Lognormal
  - Fat-tailed: Pareto, Generalized Pareto, Burr, Loggamma, Loglogistic

- Goodness of fit:
  - Heavy-tailed distributions often fit well, as did the lognormal.
  - Other light-tailed distributions did not fit as well

Using External Loss Event Data

Using External Loss Event Data in an LDA

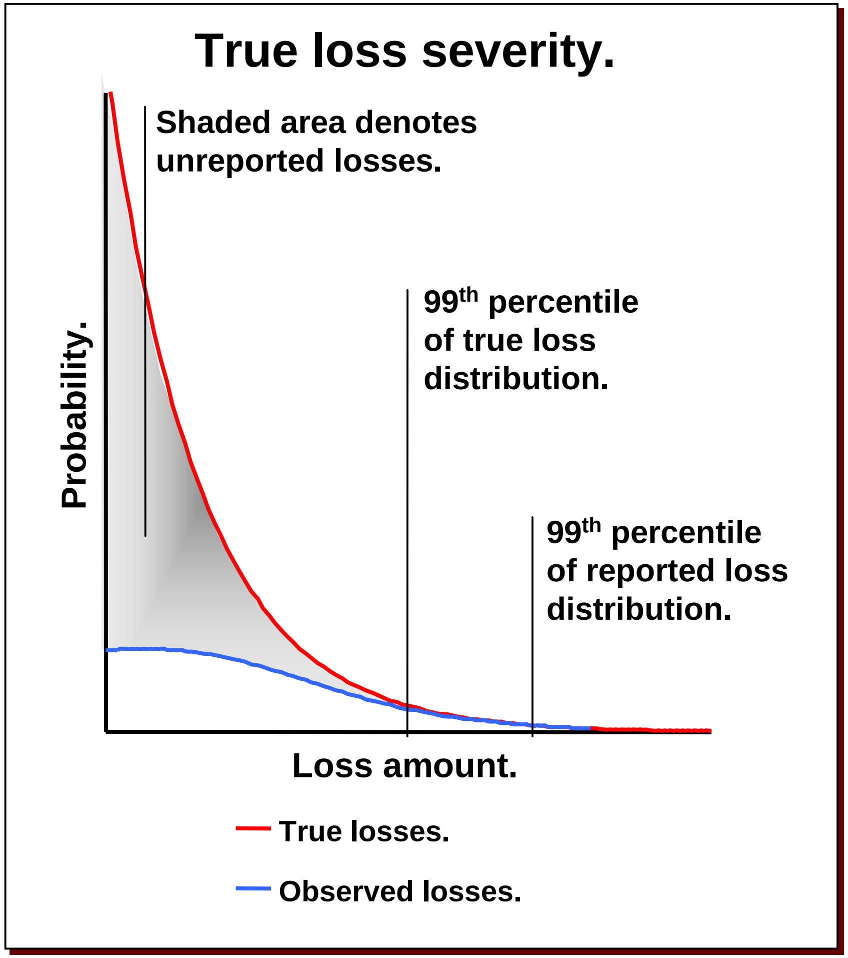
- Vendors OpRisk Analytics, OpVantage, AON, others?
- Collect data from public news sources
- Events over $1M from the past 10+ years
- Vendors provide scaling data
- Potential difficulties:
  - Business line classification
  - Non-finalized loss amounts
  - Non-monetary losses
  - Reporting bias

Summary Statistics of External Event Data

	% of Losses		3rd Qrt. ($B)	
	OpR	OpV	OpR	OpV
Corp. Fin.	6%	4%	23	23
T&S	9%	9%	44	27
Ret. Bank.	38%	39%	11	12
Com. Bank.	21%	16%	24	28
P&S	1%	1%	11	11
Agency Svc.	2%	3%	110	28
Asset Mgmt.	5%	6%	20	22
Ret. Brok.	17%	22%	12	13
Total			17	17

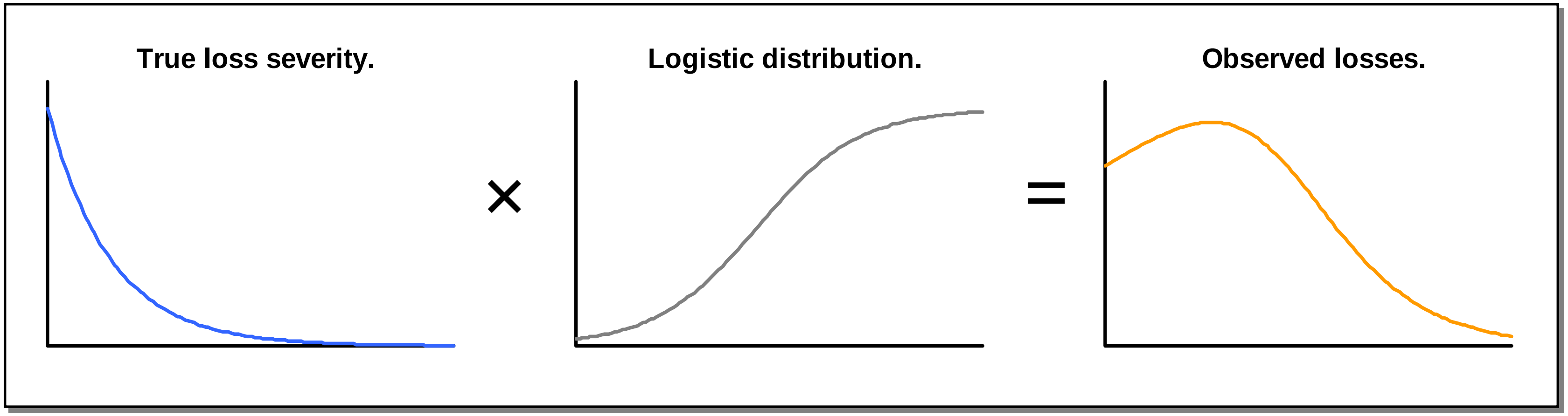
- Data in all business lines
- Apparent variation across business lines
- Similarity across databases
- Non-US losses are larger, less agreement across databases
- Only 2 event types with many observations
- 99.9th percentile of the empirical severity distribution is $1.3B. Are losses really that heavy-tailed?

Reporting Bias in External Data



- Not all losses are reported
- Reporting probability increases with loss amount
- Loss severity estimates are biased upwards
- Percentiles from the severity distribution also biased upwards
- Capital estimates will likely be too high

Correcting for Reporting Bias



- The observed loss distribution equals the “true” loss distribution times the reporting probability distribution.
- Extreme Value Theory (EVT) motivates choice of severity distribution.
- Normality motivates choice of reporting distribution.

An Example of the Monte Carlo Technique to Estimate an Aggregate Loss Distribution

Estimating an Aggregate Loss Distribution

- Monte Carlo Technique

- Frequency assumptions:
  - Poisson distribution
  - Parameter calibrated to published LDCE results

- Severity assumption:
  - Log-exponential distribution
  - Parameter based on severity distribution estimates using external data

Implications for Capital

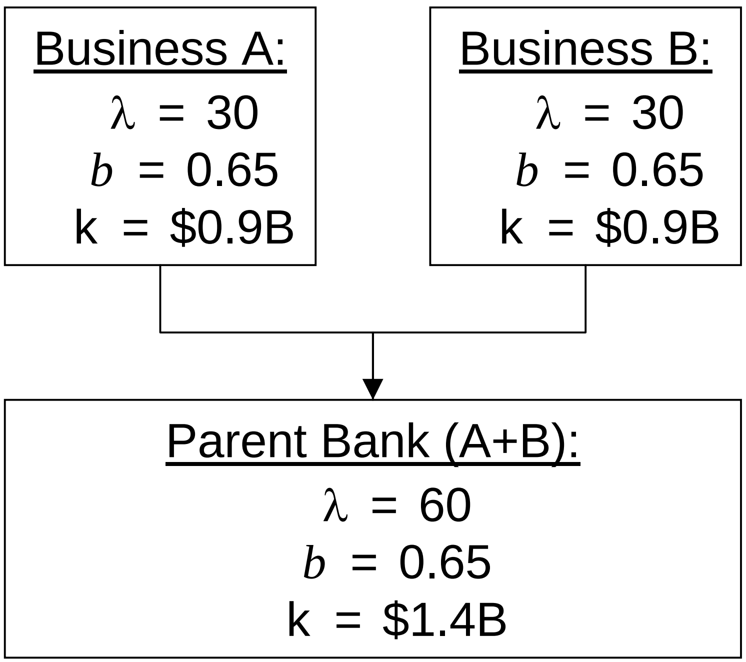
Table. 99.9 percentiles from simulated aggregate loss distributions.

	$\lambda = 30$ (Low freq.)	$\lambda = 60$ (Large bank.)	$\lambda = 100$ (High freq.)
b = 0.55 (Lower)	\$0.4B	\$0.6B	\$0.8B
b = 0.65 (Est.)	\$0.9B	<u>\$1.4B</u>	\$2.1B
b = 0.75 (Upper)	\$2.4B	\$4.0B	\$6.0B

Note. Additional capital required to cover losses below \$1 Million.

Other Issues

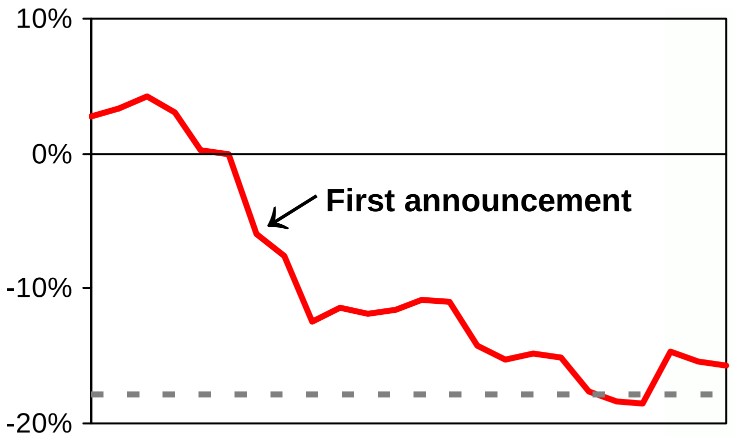
Diversification Effects



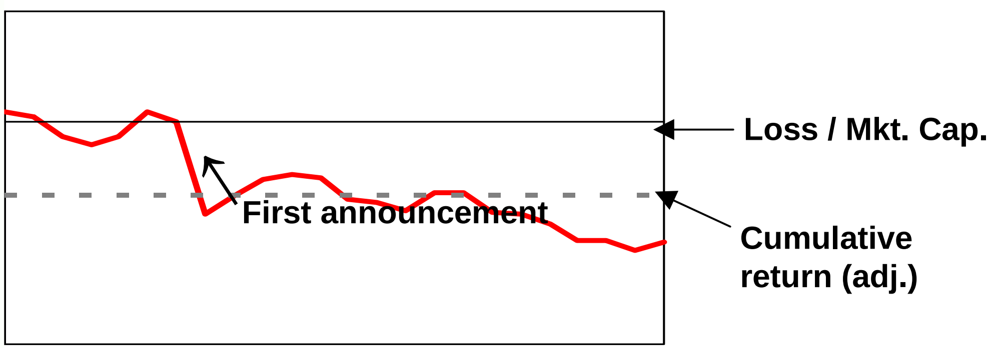
- If risks at A and B are independent, the top-tier banking organization may benefit from diversification effects
- Implications for top-tier vs. subsidiary legal entity capital requirements

Impact of Operational Events

Impact of Drysdale Failure on Chase Manhattan (1982).



Unauthorized MBS trading at Merrill Lynch (1987).



- Results extended to 60 events.
- Market impact is immediate, significant, and proportional to loss amount.
- The market seems to view even moderate losses as material.

Conclusion

Conclusion

- OpRisk estimates seem significant, but reasonable
- The proposed methods appear feasible
- Modeling choices yield reasonable results:
  - Initial results suggest stability across banks
  - Initial results suggest stability across internal data and external data methodologies
  - Initial results suggest estimated capital requirements consistent with Basel Committee's expectations
- The availability of industry-wide loss data will be a critical development in ensuring consistent application across industry