Integrating External Data Into Operational Risk Management

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The views expressed in this paper do not necessarily reflect those of the Federal Reserve System.

Outline

- Overview of operational risk
- The need for external data
- Adjusting for external data bias
- Integrating into self-assessments and scenarios.
- Technical paper can be found in a Federal Reserve Bank of Boston working paper `http://ssrn.com/abstract=395083`

Operational risk

- “The risk of loss resulting from inadequate or failed internal processes, people, and systems or from external events.”
- A variety of loss types:
  - Fraud.
  - Discrimination and wrongful termination.
  - Sales practices.
  - Damage to physical assets.
  - Systems problems, data entry, paperwork.
  - Compliance, regulatory, antitrust.

Importance of Operational Risk.

- More than 100 losses exceeding $100 Million over the last decade.
- Banks recognize the importance of oprisk:
  - On average, they hold 15% of their capital for Op Risk.
- Cause for regulatory concern.
  - deposit insurance.
  - Systemic issues.

Integrating external data into LDA

- Set frequency and severity based on self assessments and scenarios
- External data provides a cross-check for limited data from internal losses
- Because the tail is important for capital calculation - these choices are important in evaluating capital for operational risk

Business line risk assessments

- Compare internal loss experience with external loss experience in the same business line
- How do business mix and control environment impact loss experience
- How would changes in business impact future loss experience

Scenario

- Make loss analysis forward looking and tailored to bank
- Ask business lines for frequency of loss, by size of loss
- Model large losses, with help of specialists
- Compare results with external loss experience - are frequency and severity estimates consistent with industry experience?

Data strategies for LDA.

- High frequency low severity events.
  - Internal data should suffice.
- Low frequency low severity events.
- High frequency high severity events.
- Low frequency high severity events.
  - Internal data insufficient.
  - Need for external data.

External data.

- Vendors are OpRisk Analytics, OpVantage.
- 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.
  - Intentional actions and fraudulent firms.

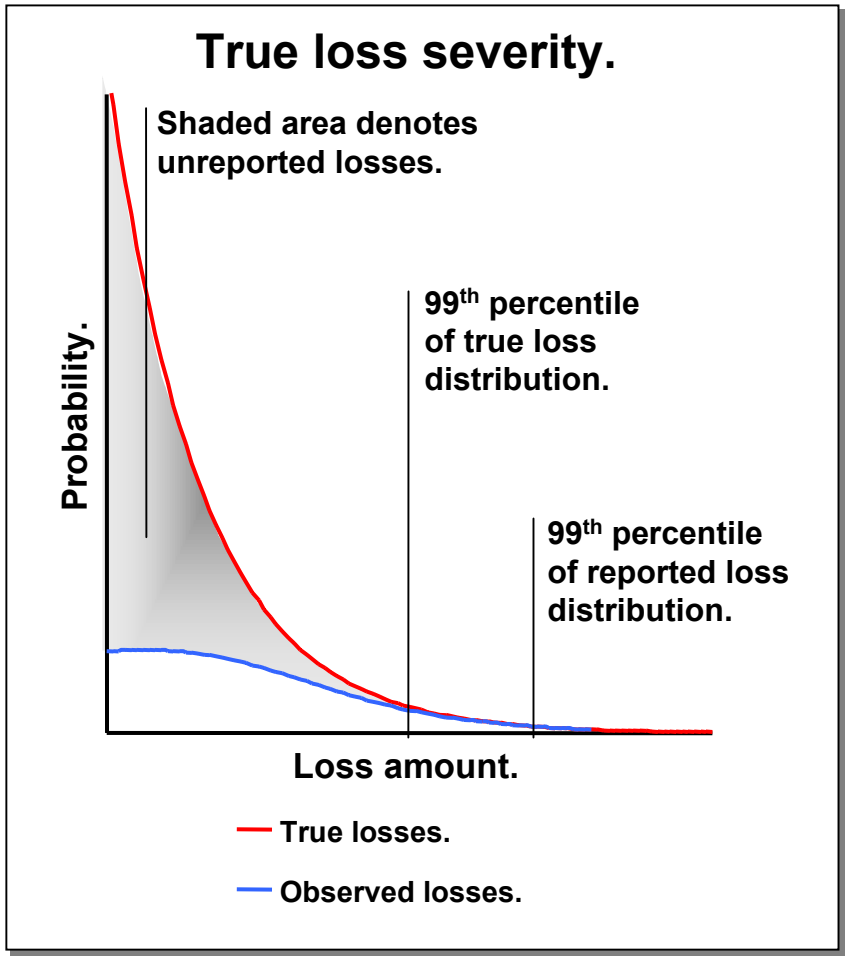
Basic statistics for U.S. losses.

	% 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

- Most business lines are well populated.
- Apparent variation across business lines.
- Similarity across databases.
- Non-US losses are larger, less agreement across databases.
- Only 2 event types with many observations.

The 99.9th percentiles are $1.4B and $1.2B.
Are losses really that heavy-tailed?

Reporting bias.



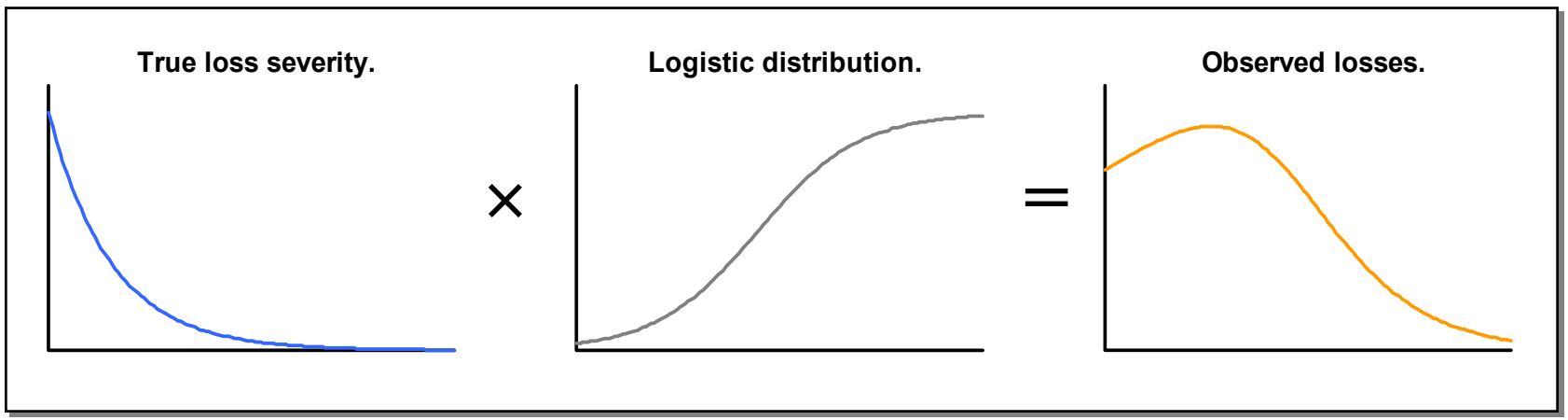
- Not all losses are reported.
- Reporting probability increases with loss amount.
- Loss severity estimates are biased upwards.
- Percentiles from the severity distribution also biased upwards.
- Capital estimates will likely be too high.

Stochastic truncation.

- Assume that loss x is observed only if it exceeds an unobserved (random) truncation point y.
- Density of observed losses equals the “true” density times the probability of being observed:

$$f(x \mid x > y) \sim f(x)\,\mathrm{G}(x).$$

- many factors influence reporting



Modeling the loss distribution.

- We use extreme value theory (EVT)
- EVT shows that “excesses” over a high threshold converge to a generalized pareto distribution, as the threshold increases, regardless of the underlying distibution

$$\mathrm{GPD}(x) = \begin{cases} 1 - (1 + \xi x/b)^{-1/\xi} & \xi > 0 \\ 1 - \exp(-x/b) & \xi = 0 \end{cases}$$

Model specification.

- Parameters:

  b ~ tail thickness parameter.

  τ ~ the $ loss with a 50% reporting probability.

  β ~ rate of increase in reporting probability.

Model results.

Table 3. Results for model 1.

	OpR	OpV
Exponential b	0.64	0.66
	(0.08)	(0.07)
Logistic β	0.78	0.82
	(0.10)	(0.09)
Logistic τ	4.45	4.46
	(0.36)	(0.32)
exp(τ)	\$86M	\$86M

- Data sets have remarkably similar parameter estimates.
- 99th and 99.9th percentiles are about \$20M and \$90M, respectively.
- The estimates of τ seem reasonable.

Sensitivity to threshold choice.

Results are not overly sensitive to threshold choice.

Table 4. Estimation results for various POT thresholds.

	Threshold value				
	$1M	$2M	$3M	$5M	$10M
OpRisk Analytics:	0.62	0.70	0.67	0.67	0.65
	(0.08)	(0.09)	(0.10)	(0.13)	(0.12)
OpVantage:	0.66	0.77	0.81	0.61	0.69
	(0.07)	(0.09)	(0.10)	(0.10)	(0.11)

Implications for capital

Including losses under $1 Million may yield capital estimates of about $2 Billion.

Table. 99.9 percentiles from simulated aggregate loss distributions.

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

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

Implications for supervision

- External data important for supervisors to understand modeling
- Distinguishing bank from industry results will require modeling of external data
- Best practices is an important component of bank supervision - bank supervisors will need to continue to work with external and internal operational risk data