Implications of Alternative Operational Risk Modeling Techniques

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

Outline

- What is operational risk and why is it important?
- How are banks measuring operational risk?
- The LDCE Data
- Objectives of this paper
- Apparent regularities and a puzzle.
- A solution using Extreme Value Theory.
- Implications for capital.

Operational risk

- The risk of loss from failed processes, people, and systems or from external events.
- 7 loss types including Fraud, Business Practices, Errors, System Failures, Physical Damage.
- Well-known losses: Daiwa, Allfirst, Bankers Trust, Drexel, Kidder Peabody, Keystone, ...
- Consequences include failure/cost to taxpayers, reputational damage, systemic impact.

Operational Risk Under Basel II

- Basel II takes more granular approach than Basel I, including a separate charge for operational risk.
- In U.S., operational risk will be estimated based on internal models.
- Capital is 99.9th percentile of the aggregate loss distribution.

The Loss Distribution Approach

- Severity distribution:
  - The distribution of loss amounts
  - e.g., Lognormal or Pareto
- Frequency distribution:
  - The number of losses per year.
  - e.g., Poisson distribution.
- Aggregate loss distribution
  - Usually obtained via Monte Carlo simulation

The LDCE data

- A unique dataset containing loss experience from multiple institutions.
- One year's loss data for 89 global banks.
- We selected 6 banks whose data seem "complete."

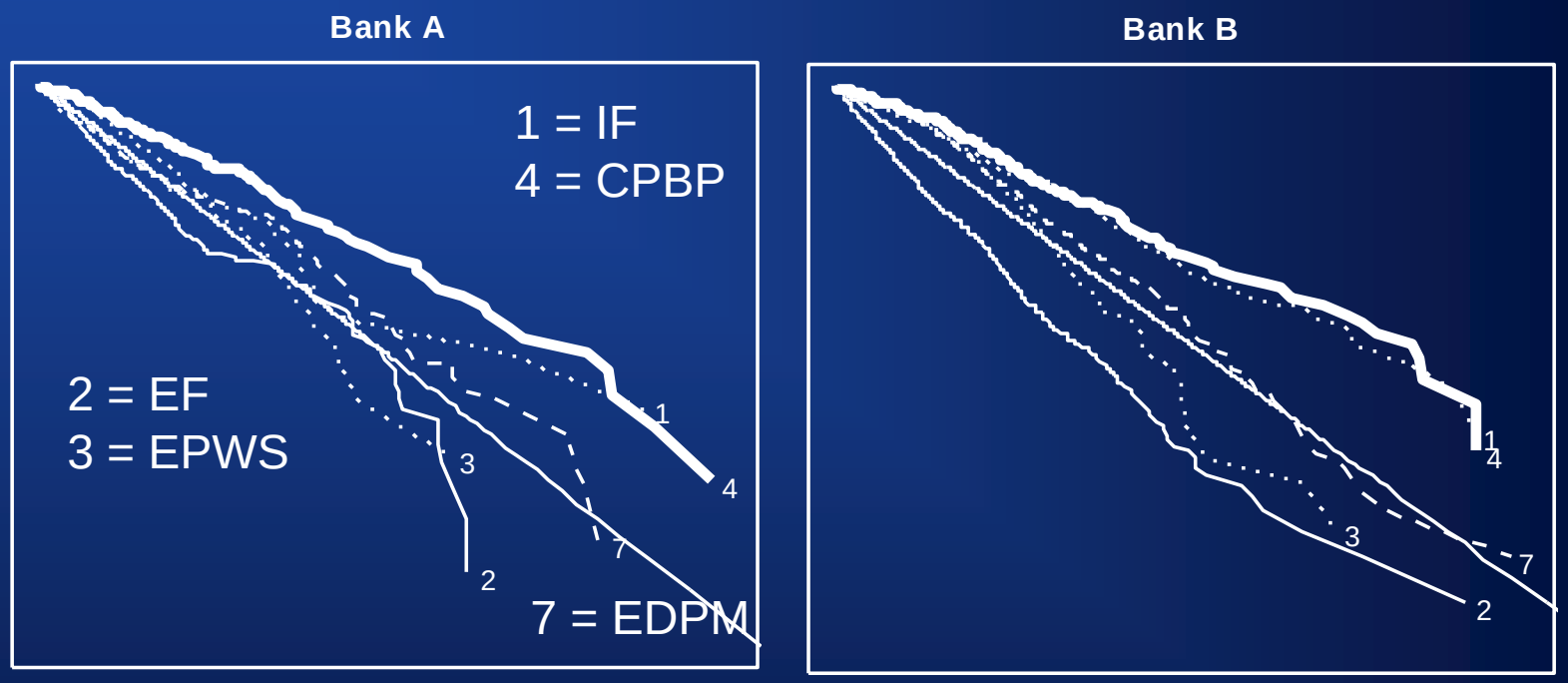
Questions addressed.

- What distributions fit OpLoss data? Are they consistent across banks?
- Is the risk-ordering of Business Lines and Event Types consistent across banks?
- Do parameter estimates appear reasonable and consistent?
- Do capital estimates appear reasonable and consistent?

Our objectives

- Our main question: Do operational losses display similar statistical properties across different institutions?
- The answer is of interest for multiple reasons: scientific reasons, policy, implementation.

Descriptive analysis: tail plots.



- Consistent cross-bank ordering of event types.

Parametric analysis.

- We consider 9 common distributions.
  - Light-Tailed (e.g., Lognormal)
  - Heavy-Tailed (e.g., Pareto)
- We evaluate goodness of fit (GF):
  - Statistical GF: Chisquare tests by business line and event type.
  - Heuristic GF: we consider the “reasonableness” of parameter estimates.

Severity fit results for GPD

	A	B	C	D	E	F
All BL, ET	X	X			X	X
ET1 – Int. Frd.	X	X	NA	X	NA	X
ET2 – Ext. Frd.	X				X	X
ET3 – EPWS			NA		NA	
ET4 - CPBP	X	X	NA	NA	NA	X
ET7 - EDPM	X	X				
BL2 – T&S	NA	X	X		NA	
BL3 - RetBnk	X	X			X	X
BL5 – P&S	NA		NA	NA	X	X
BL7 – AsstMgt	NA		X	NA		X

EPWS is the only event type with a good fit and reasonable estimates across all banks.

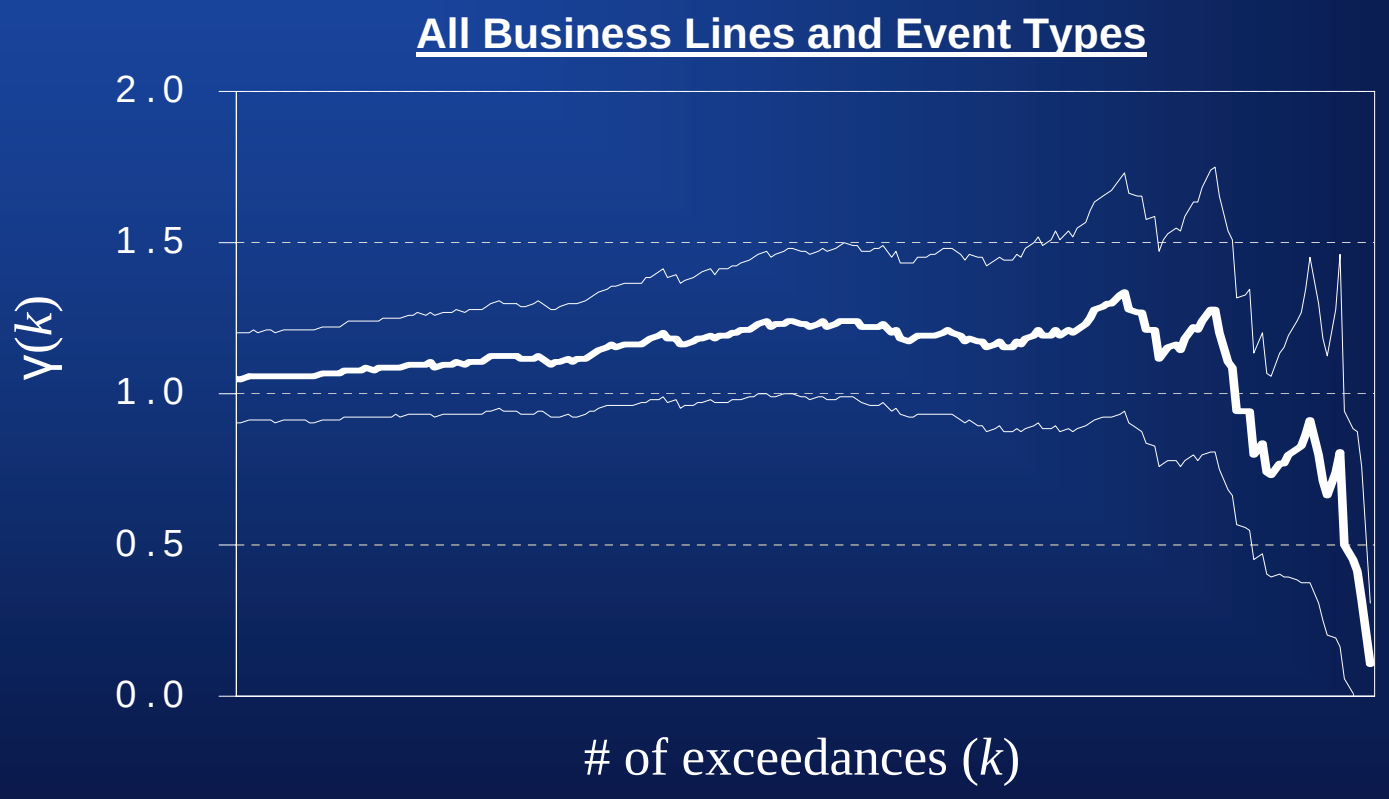
The heavy tail “puzzle”

- Operational losses are often well fit by heavy-tailed distributions.
- But tail parameter often exceeds 1, which implies certain unusual properties.
- Potential answer to puzzle:
  - Extreme value theory: the behavior of small and medium sized losses may not be informative about the behavior of very large losses.

Extreme Value Theory (EVT)

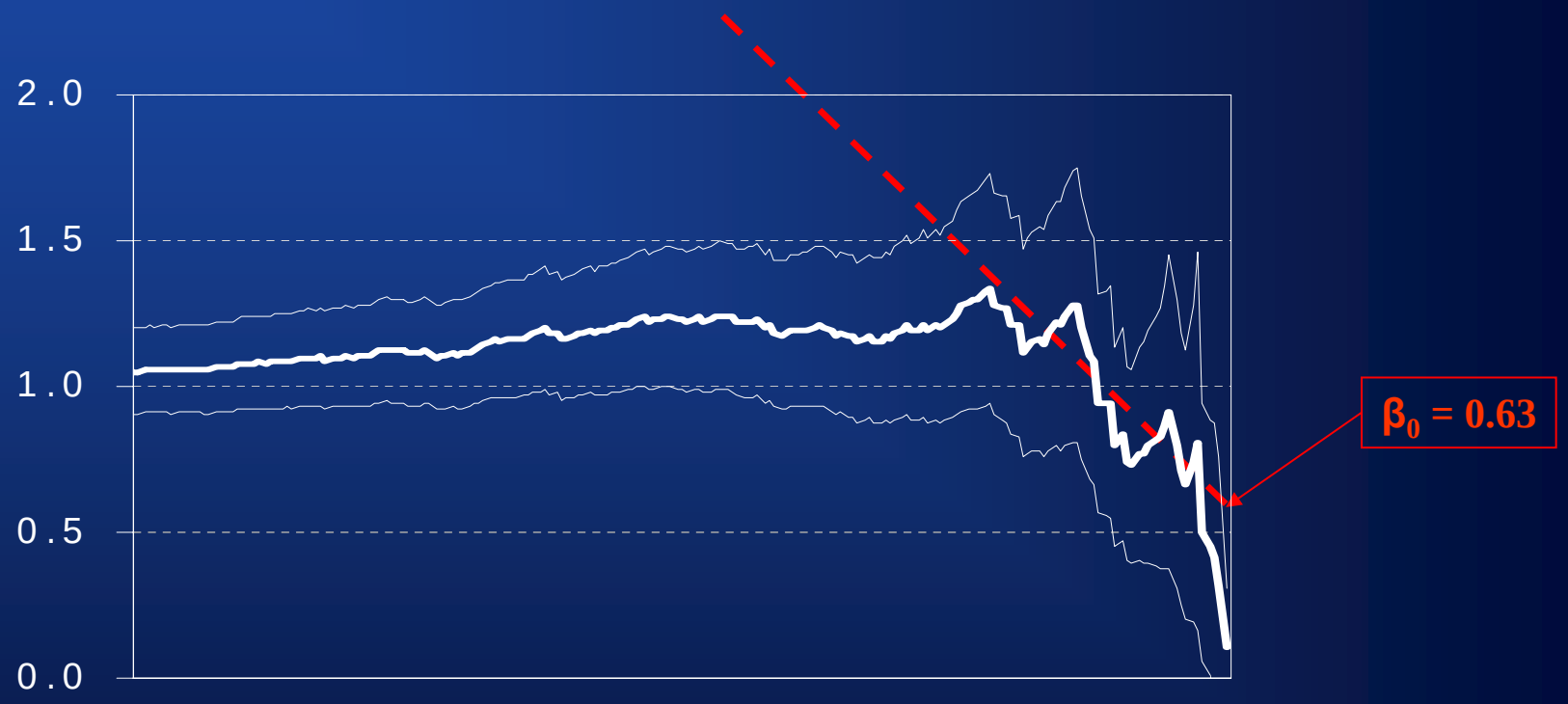
- Excess losses over a high threshold converge to GPDγ,b(x) as the threshold increases.
- The tail parameter γ is estimated via the regression technique of Huisman et. al. (2001).

The Hill plot (Bank F)



- Rule of thumb: identify a value of k for which the plot is stable to the right.

Huisman et. al. (2001)



- Bias of $\gamma(k)$ is roughly linear in k.
- Propose a regression-based estimator.

Choosing the unit of analysis

- For high thresholds, no significant variation in γ across business lines or event types.
  - We estimate severity at the aggregate, bank-wide level.
- Results do not mean there is no risk variation across event types (or business lines).
  - Results apply only to tail, based on limited data.
  - There are other potential sources of risk variation.

EVT Results

Estimates of tail parameter γ

Bank ID	Full Data	EVT
A	1.28	0.82
B	0.87	0.63
C	0.99	0.86
D	0.92	0.50
E	0.97	0.55
F	1.01	0.63
Median	0.98	0.63

- All banks' EVT estimates imply a finite mean.
- Tail thickness estimates are roughly consistent across banks.

Implications for capital

99.9th percentiles of the simulated aggregate loss distribution.

	Poisson Frequency	N.B. Frequency
EVT Severity	46.8 bps.	40.0 bps.

- The 99.9th percentile is divided by assets, and reported as a cross-bank median.
- 60 bps. would be consistent with results of Basel Committee survey documenting what industry considers “reasonable.”

Conclusions.

- Caveat
  - Results are based on only 1 year of data, and are intended only as a “proof of concept.”
- Implementing LDA seems workable even on current data.
- Results are reasonable and consistent across banks.
- Operational Risk is economically significant.

Conclusions

- Our results show that applying the same methods to different banks' data can yield similar results across banks.
- However, Basel purposely allows variation in methods across banks.
- It is important to understant the extent to which banks using varying methods can still arrive at consistent results.