# *AMA Implementation at Citigroup Where We Are and Outstanding Questions*

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Rudi Dekoker
Co-Head of Risk Analytics
rudi.dekoker@citigroup.com

Jay Newberry
Head of Operational Risk
jay.newberry@citigroup.com

# Overview

**Policy and Implementation**

**Analytics**

- ❖ Observations on Operational Risk Losses
- ❖ Implications and Challenges for Operational Risk Modelling
- ❖ Citigroup's Implementation Choices

# *Citigroup Operational Risk Management*

- Industry trends continue to drive many financial institutions toward increased scale and diversity. The resulting diversity in the earnings stream adds value, but can be accompanied by complexity, which can add to operational risk.
- Good operational risk management is critical for an institution seeking to benefit from this diversity while managing its risks effectively.
  - It involves risk identification, assessment, control, monitoring, measurement and reporting.
- Citigroup's operational risk framework and risk capital calculation methodology is intended to be fully supportive of our efforts to implement AMA. However, the foremost objective is to achieve proper risk management, which is reflected in multiple key measures including, ultimately, shareholder value.
  - Risk capital is an important tool for Citigroup that is used to measure and allocate risk across diverse products and geographies.

# AMA Readiness Plan

- Our overall approach to AMA readiness includes project planning under which every business has conducted a gap analysis and developed plans to close identified gaps. Our efforts to execute the plan are currently built around managing the following work streams:
  - Data quality / maintenance
  - Disclosure, reporting and home-host
  - Scenario analysis / external data
  - Business and control environment factors
  - Analytics
  - Testing and verification
  - Regulatory interface
- Our focus is on both measurement and management use, and many of these work streams have elements supportive of both.

# Where We Are: Areas of Significant Progress

- Overall Operational Risk Framework implementation, globally.
- Loss data collection, globally.
- Comprehensive reporting of global operational risks for management, senior management, and the Board.
- A comprehensive AMA plan.
- Modeling, based on incorporating superior elements of multiple alternative approaches into an integrated framework.
  - Citigroup has been conducting R&D for operational risk capital calculations for several years and is now harvesting these efforts.
  - The objective is to model within the constraints of what is required by established standards, feasible, and can be assessed based on empirical work.

## *Outstanding Issues*

- Appropriate definition of "significance" should reflect the small number of subsidiaries that meet this standard in the context of total Citigroup.
- Need to exclude routine and annually predictable operational risk losses from capital requirements, consistent with risk (economic) capital principles.
- Methodologies for reflecting business environment and internal control factors for capital modeling and for management.
- Use test for legal vehicles when management practices are structured around global product lines.
- Partial use of less advanced approaches, for non-significant subsidiaries.
- Validation of loss data absent a standard of reconciliation to the general ledger.
- Basel requirements related to capturing data on credit related "boundary" events, in the absence of any impact on operational risk capital or management benefits in excess of the collection costs.

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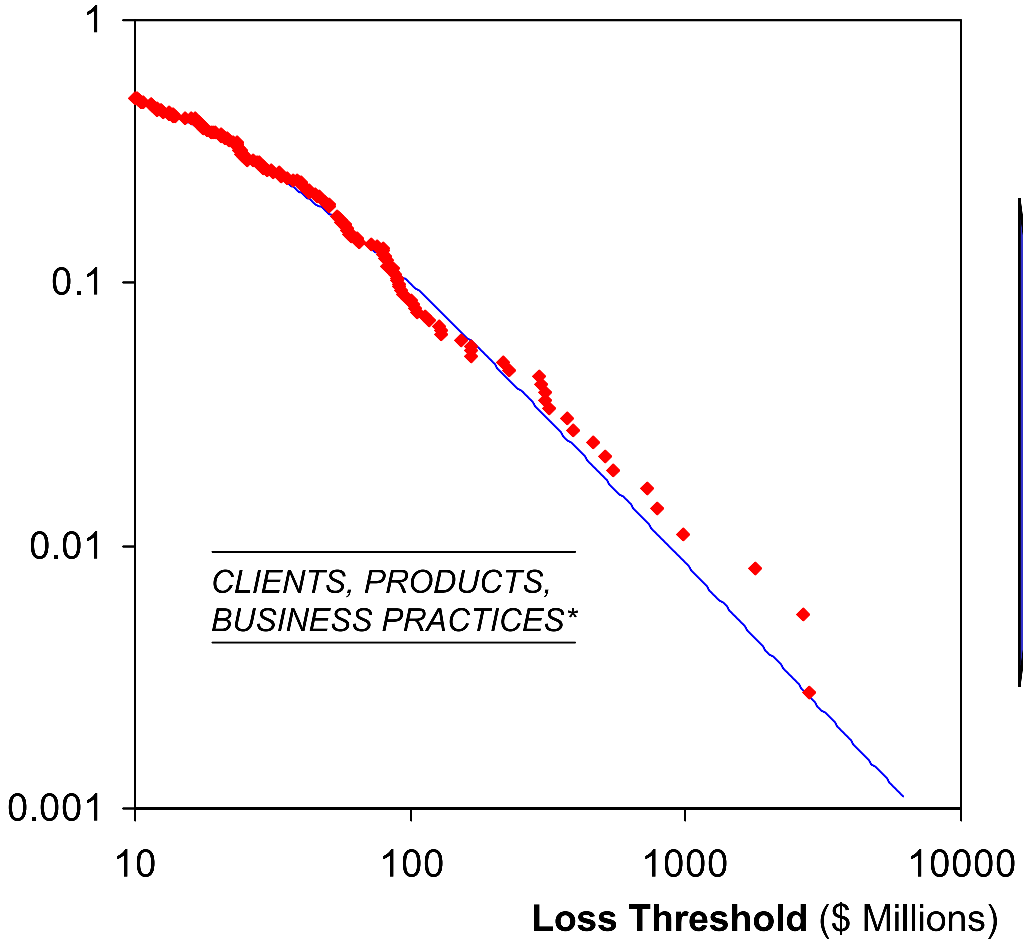
# I. Observations on Operational Risk Events

- **Operational risk is different: potential losses can be practically unbounded**
  - Observed loss amounts are not simply related to firm size
  - Losses are not capped, e.g. by exposure limits or stop loss scenarios
  - Some evidence of a deep pockets premium – e.g., lawsuits and regulatory settlements
- **Capital need is driven by the risk of infrequent but extremely large events**
  - Few firms have experienced more than one catastrophic event in one year
  - For firms that have, events had a common cause (e.g., related lawsuits)
  - "Single claim causes ruin", similar to natural catastrophes
- **Large events appear to follow a power law**
  - Loss severity distributions are fat-tailed
  - Frequency and severity appear (roughly) inversely related
- **Risks are not easily controlled in the short term**
  - No ability to "trade down" or "close positions"
  - Often significant time lags between cause and effect
  - Risks often only recognized "after the fact"

# Large Events Appear To Follow A Power Law

**Event Frequency**
Fraction of Events Exceeding each Threshold



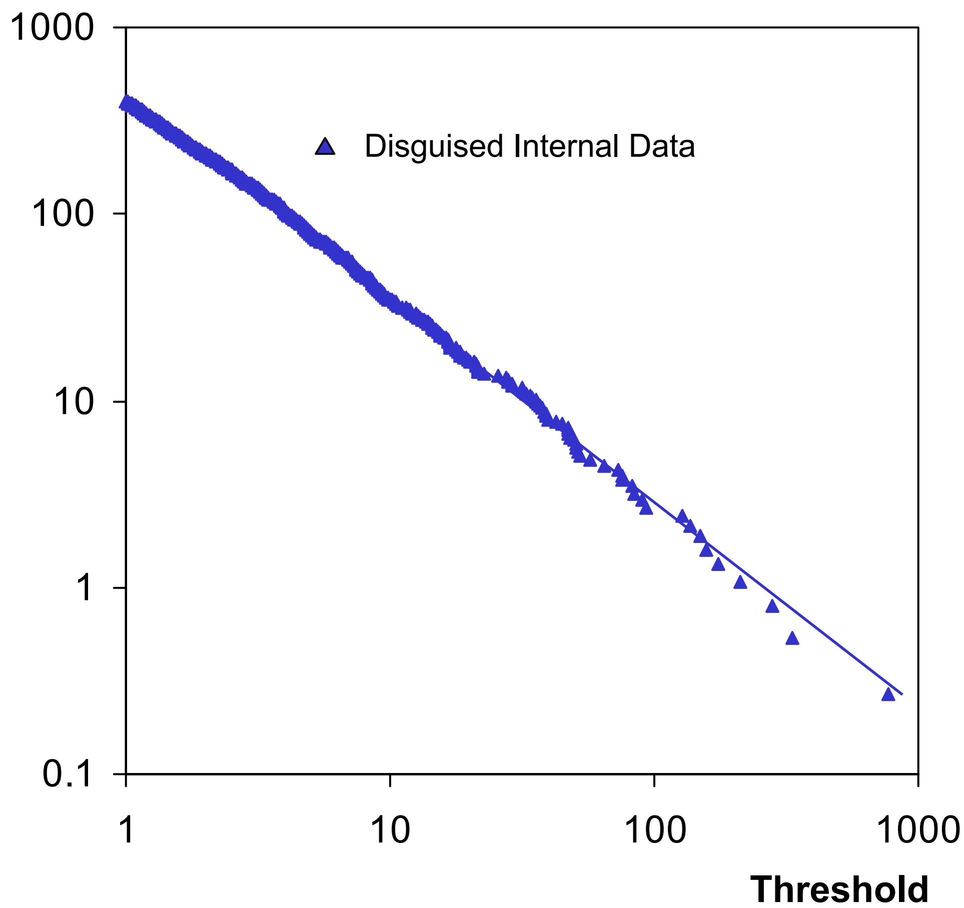

*Source: SAS® OpRisk Global Data

**Key Observations**

- **Frequency vs. severity shows quasi-linear behavior in a log-log plot**
  - $F \sim S^{-p}$
  - *p*: tail exponent
  - *t* = 1/*p:* tail parameter
- **Losses that are twice as large are roughly half as likely**
  - Tail exponent is close to 1
- **Power laws are most easily observed for large losses**
  - Smaller losses are underreported
  - EVT

# Power Laws Are Even More Striking When Reporting Biases Are Absent - Internal Loss Data

**Operational Event Frequency**
Annual Events over Threshold

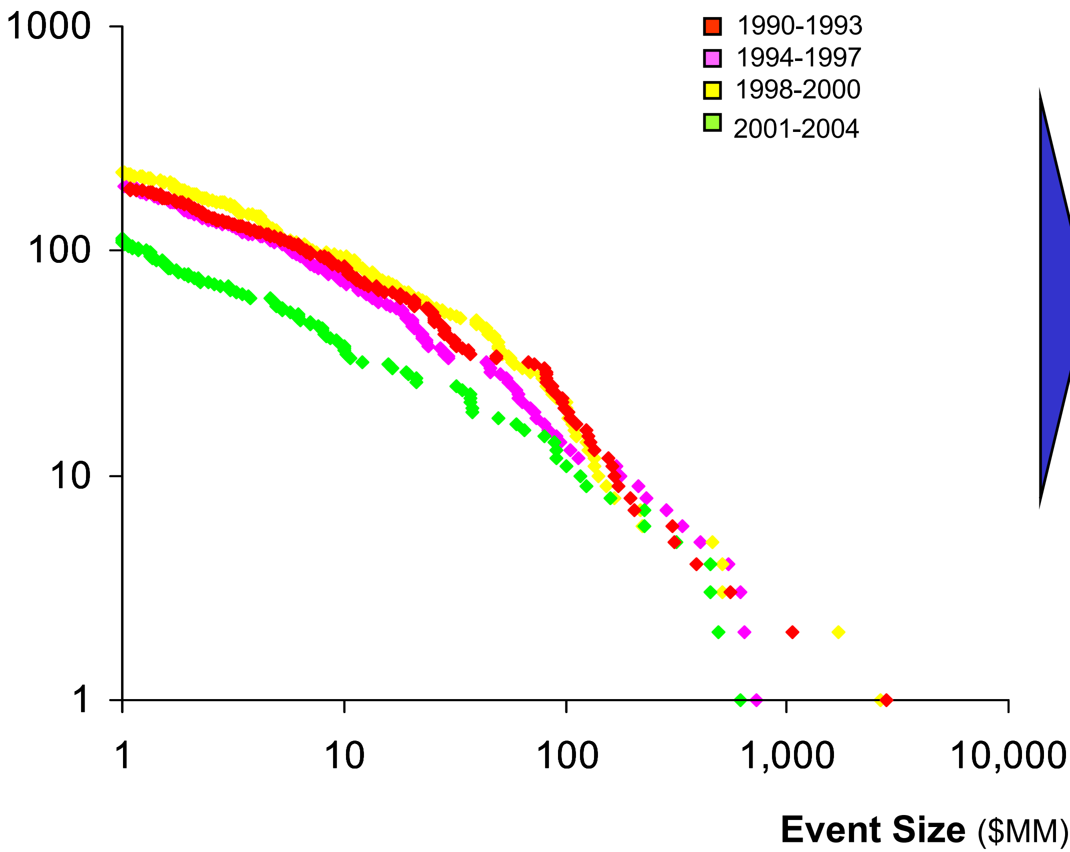



**Key Observations**

- **Almost perfect power law** behavior over three orders of magnitude in losses
- Behavior **very stable** and predictable over time
- Tail parameters for the most **fat-tailed risks** are close to, but typically below 1
- Scatter in the tail is consistent with **sampling noise.**

# Severity Distributions Appear Fairly Stable, Thus Simplifying Frequency Estimation

**Number of Events**
External Events for US Financial Institutions*




*Source: SAS® OpRisk Global Data

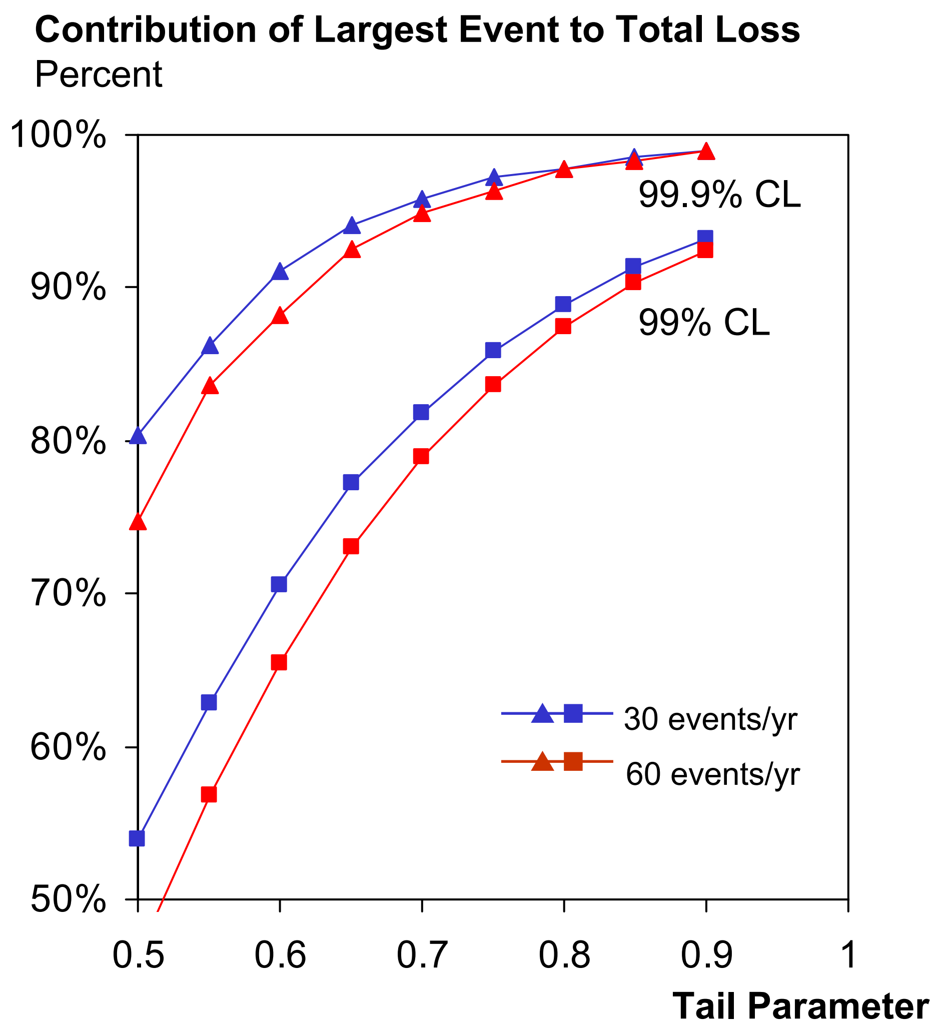
**Observations**

- Severity profiles are remarkably stable over different time periods
- Differences in the tail are fully compatible with sampling noise for rare events at or above $1B dollars
- Frequency and severity estimation can therefore be largely separated, with frequency analysis focused on the level (as opposed to the slope) of the log-log plot
- Some evidence that frequencies have increased, and that 2001-04 data are incomplete because of time lags

# II. Implications and Challenges For Op Risk Modelling

- **Fat-tailed power laws are easy to model but counter-intuitive**
  - Tail risk is dominated by the effect of **single** catastrophic losses
  - Simulation results can be approximated with simple analytical solutions (rank statistics)
  - Frequency correlations contribute little additional capital
  - Once fat-tailed risks are present, high frequency/low severity events like process errors contribute little additional capital
  - Insurance is ineffective unless it covers the largest loss events of all types
- **However, estimation errors are large**
  - Tail parameter estimates have wide error bands and are unstable to small data changes
  - Modest tail parameter changes swing large amounts of capital
  - Estimation has to be constrained in some way (e.g., Bayesian analysis, benchmarks) to produce useful, stable capital numbers
- **Some business / control environment effects may need to be captured “over the cycle”**
  - Tail parameter dependence on control environment cannot easily be derived because of lack of data
  - “Over the cycle” analysis yields a conservative tail parameter similar to “stressed LGD”

# *Tail Risk Is Dominated By Single Large Event*




**Key Observations**

- **Single largest event in 1 year** contributes over 90% of losses in the worst year.
- As the event frequency rises, the impact of the largest event falls
- As the confidence level is increased, the impact of the largest event rises
- For tail parameters above .7 and confidence levels of 99.9% and above, the **rank statistics of the largest event is an excellent approximation** for capital calculations

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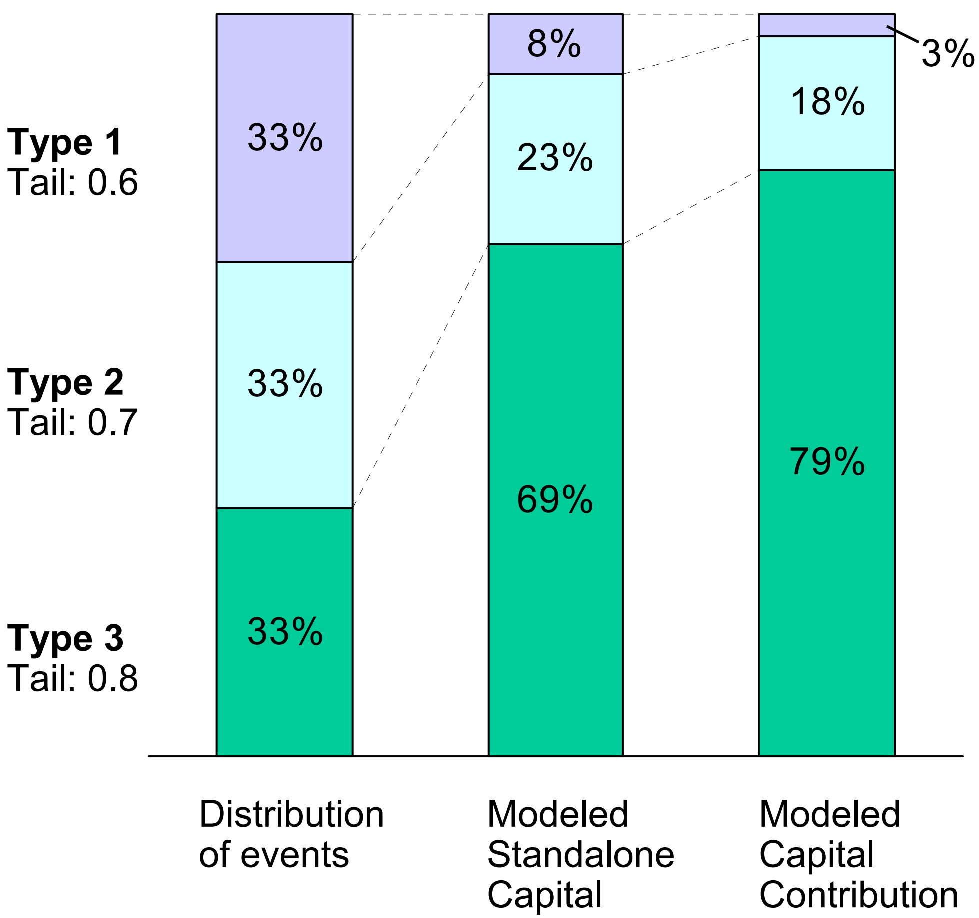
# Subdominant Event Types Contribute Little Capital

**Aggregate Loss Behavior of Three Event Types**




**Key Observations**

- Event type with the **lowest tail parameter does not contribute** significantly to total capital – less than 5% in the example shown
- Realistic fat-tailed events can be mimicked assuming **just two or three different tail parameter values**, e.g. 0.7, 0.8 and 0.85.
- Events with **tail parameter below 0.6 behave like a thin-tailed distribution** for all practical purposes

# Frequency Correlation Contributes Little Capital

**Correlation and diversification analysis can be incorporated bottom-up, at the level of frequency estimation**

- Frequencies across businesses and/or across event types can be analyzed for correlations in business as usual or stressed environments
- Resulting frequency correlations can be incorporated in capital simulations

**In practice, frequency correlations have little impact on capital estimates at high confidence levels**

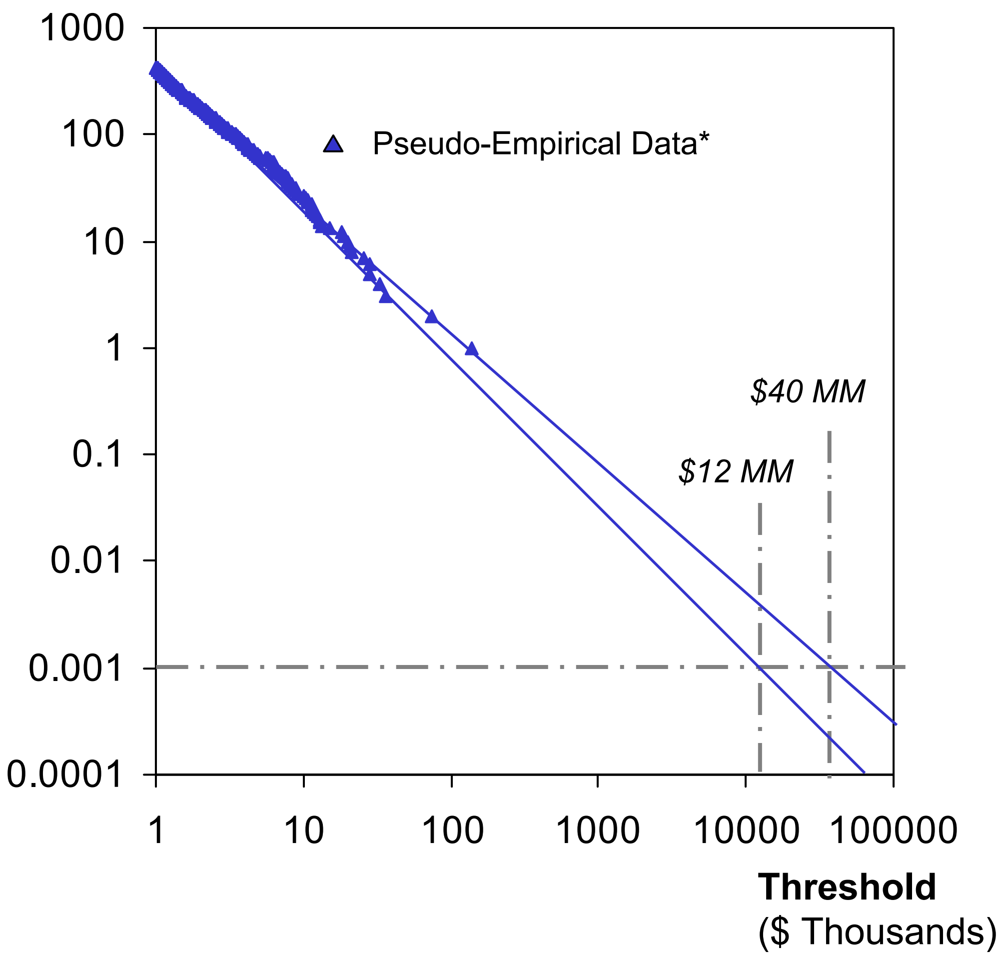
- Correlations have a significant impact on the body of the loss distribution, but very little impact on the tail
- This is because tail losses are dominated by very large single events. The likelihood of extreme events occurring simultaneously in several businesses is small in a power law environment

**Diversification therefore behaves more like an economy of scale, and is driven by the (assumed) independence in the size distribution of very large events**

- Even when frequencies are assumed perfectly correlated, resulting capital estimates show a clear economy of scale – i.e. if business size doubles, capital increases by a factor less than two.
- The resulting diversification impact can be expressed in terms of implied correlations. However, these are derived parameters in the model: they are a function of severity, frequency and confidence level.

# Capital Is Very Sensitive To Tail Parameter Choices

**Operational Event Frequency**
Annual Events over Threshold




*Simulated data similar to real internal data

**Key Observations**

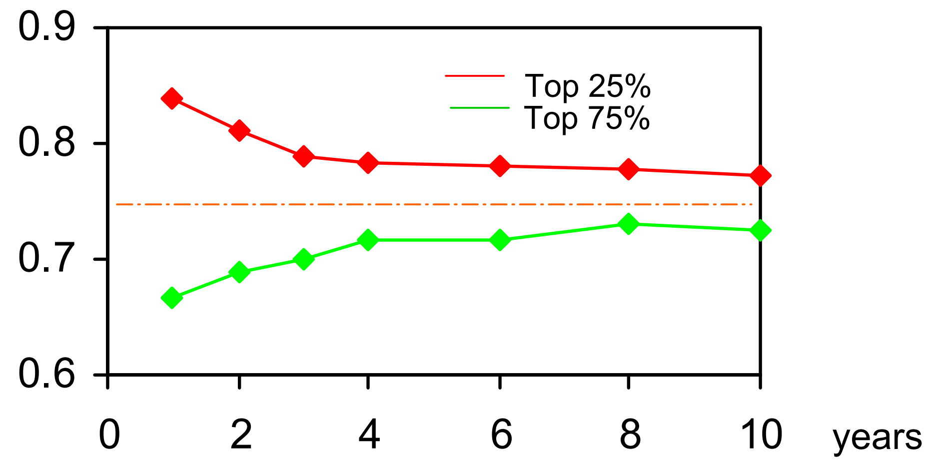
- **Capital at a high confidence level requires extrapolation** far into the tail, well beyond loss levels that are typically observed internally
- **Capital depends exponentially on the tail parameter:**
  - Capital ~ exp $\alpha$ *t*, where $\alpha$ can be 10-15
- **A small shift in tail parameter creates a large swing in capital**
  - e.g., changing t from 0.7 to 0.8 increases capital from $ 12MM to nearly $40MM

# Tail Parameter Estimation Errors Are Inherently Large Due To Data Limitations and Fat Tails

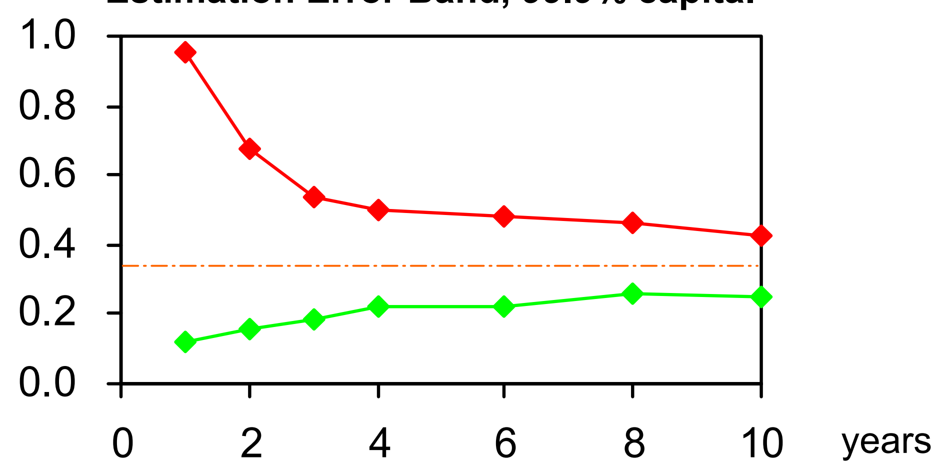
**Experiment**

- Suppose event losses over $100K follow an **exact power law**, with annual frequency 50, and tail parameter 0.75
- The resulting capital at 99.9% would be $ 334MM
- What would be the **estimation error**, if we collect between 1 and 10 years of data?

**Estimation Error Band, Tail Parameter**




**Estimation Error Band, 99.9% capital**



## III. Pragmatic Implementation In Citigroup's AMA Model

| | |
|---|---|
| **Severity Analysis** | • Severity distributions are modelled using a **wide range of distribution shapes and fitting routines**<br>• However, when all is said and done, each business line/ event type is characterized by a single **tail parameter**<br>• Tail parameters are driven by **external data on large loss events** – internal data is used to validate tail parameters against internal experience |
| **Frequency Analysis** | • Frequencies are modeled primarily from **internal loss data**<br>• Frequencies are **adjusted for scale** using extensive correlation analysis with assets, revenues and other Key Risk Indicators |
| **Scenarios** | • Base case **scenarios are derived from external data sets** that reflect our business model and customer mix<br>• Supplementary what-if scenarios can be used to adjust event rates, e.g. for **rapidly growing or newly acquired businesses** |
| **Control and Business Environment** | • Control environment effects are currently captured through **qualitative adjustment factors** that incorporate audit scores and RCSA information<br>• **Efforts are in progress** to make qualitative adjustments more fact-based and amenable to statistical testing<br>• One possible alternative is to incorporate environmental factors through KRIs that are shown to correlate with frequencies, or through **stress tests** |