Quantifying operational risk in life insurance companies

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Context

- GIRO working party on quantifying operational risk in general insurance companies
  - Michael Tripp (chair), Helen Bradley, Russell Devitt, George Orros, Gregory Overton, Louise Pryor, Richard Shaw
- Report at GIRO followed by paper at Institute sessional meeting
- Very little that was specific to general insurance companies

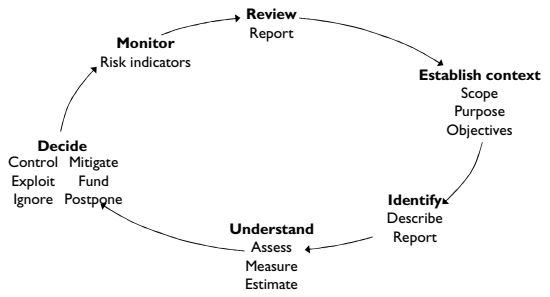
Paper includes

- Case study
- Risk management framework
- Stress and scenario testing
- Frequency and severity analysis (including EVT)
- Causal modelling and Bayesian methods
- DFA and overall risk modelling
- Pitfalls and consideration of soft issues
- Reporting and pulling the threads together

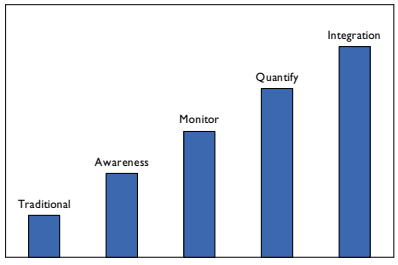
Outline

- Risk management framework
- Causal analysis
- EVT for operational risk
- Risk indicators
- Data and other pitfalls
- Conclusions

A basic risk management control cycle



Evolution of operational risk practices



Leaping ahead?

- Don't run before you can walk
  - Awareness: realise the need for explicit management of operational risk
  - Monitor: effective risk reporting, risk indicators with escalation triggers
  - Quantify: loss database, quantitative targets, analysis techniques
  - Integration: correlations between risk indicators, compensation linked to risk adjusted returns
- Integration may not be an appropriate long term goal

Classifying risk

- Often difficult to assign a loss to a risk category
- Eg, is reputational risk a form of operational risk?
  - Systems failure → poor customer service → poor reputation → lower sales — Operational risk
  - Strategic decision → failure → poor reputation → lower sales — Core business risk
- Eg, bad underwriting strategy or poor implementation of good strategy

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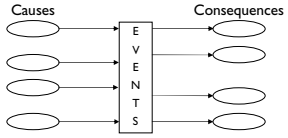
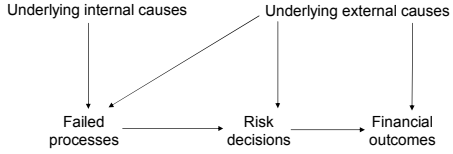
Cause and consequence

- Analyse risk by cause and consequence
- A single consequence may have more than one cause
- A single cause may have many consequences



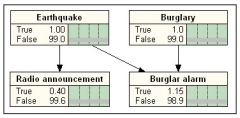
Causal risk mapping

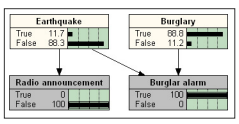
- Analyse known losses to learn about risks
  - Document causal chain and make it explicit
  - Look at the effect of the outcome



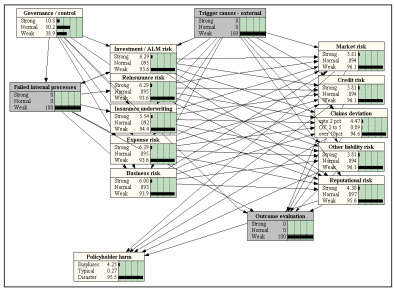
Bayesian modelling

- Use conditional probabilities
- Either earthquake or burglary may make alarm go off
  - 1.15% chance of hearing alarm
- What if alarm but no radio?
  - 88.3% chance of burglary





Simple Bayesian model



Results from Bayesian model

Failed internal processes	External trigger causes	Outcome evaluation	Individual risks	Prob(p'holder harm=disaster)
Weak	-	-	-	68.9%
Weak	Weak	-	-	92.0%
Weak	Strong	-	-	43.8%
Weak	-	Weak	-	83.6%
Weak	-	Strong	-	35.6%
Weak	Weak	Weak	-	95.5%
Weak	-	-	Weak	99.8%

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Modelling operational risk

- Traditional frequency and severity analysis
  - Fit distributions to historical loss data
  - Frequency: Poisson, negative binomial, binomial
  - Severity: Lognormal, weibull, gamma
- May want to modify historical data first
  - Known changes in controls and procedures may affect future numbers of losses
- Curve fitting
  - Maximum likelihood, other goodness of fit
  - Criteria may depend on which is the important part of the curve

Skew distributions

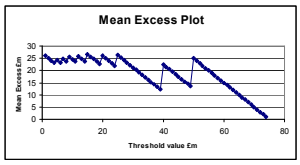
- Some operational losses have extremely skew distributions
- Low frequency, high impact means little data available
- Traditional statistical methods emphasise the area around the mean of the distribution
- Extreme value theory (EVT) concentrates on tails
  - Pick a threshold
  - Use generalised pareto distribution to determine severity given that it exceeds threshold

EVT

- Cumulative distribution function $1-\lambda(1+\xi(x-u)/\sigma)^{-1/\xi}$
  - u is threshold (large)
  - $\lambda = \Pr(X>=u)$
  - ξ, σ shape and scale parameters
- First determine threshold u
- Then fit ξ and σ
- Have distribution for losses above u in size
- Use normal curve fitting for smaller losses, scale so that distributions meet smoothly

Determining threshold

- Plot mean excess above threshold against threshold
- Becomes linear at u
- λ is number of losses above threshold divided by total number of losses



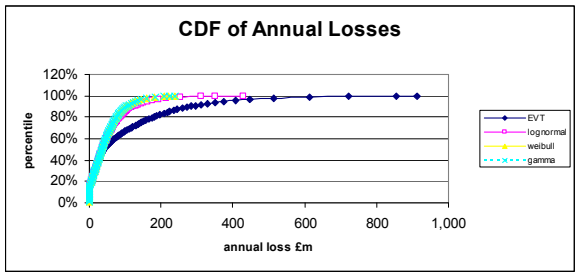
Shape and scale parameters

- Maximise log likelihood function for
  $-\log\sigma - (1/\xi + 1)\sum\log(1+\xi(x_i-u)/\sigma$
  for i=1 to r (number of observations larger than u)

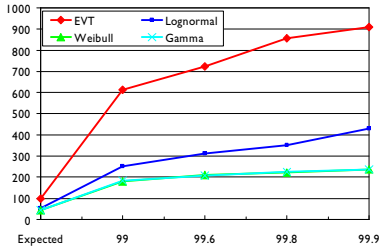
Comparison

- Used poisson for loss frequency
- Compared EVT, lognormal, weibull, gamma for loss amount

Fitted distributions



Percentile comparison



Comments

- Large variation in results at higher percentiles
  - Tails have very different shapes
  - Small number of large losses
- Choice of threshold not always obvious
  - Especially with small data set
  - Linearity may be a matter of interpretation
- EVT gave less extreme results at less extreme percentiles
- Gamma worse fit than weibull or lognormal

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Risk indicators

- Help with qualitative assessment of risk
  - Can indicate that subjective assessments should be updated
- Can be used even if there have been no losses so far
- Help gauge effectiveness of systems and controls
- Tie in with management incentives (and penalties)
- Can only be used within a more general risk management framework

- Risk indicators should be
  - Easy to calculate
  - Predictive (leading rather than lagging)
  - And so based on causal analysis
- Categories
  - Exposure-related
  - Loss-related
  - Cause-related

Exposure-related

- Typically measure the throughput of processes with the potential for operational failure
- Don't pick up changes in loss rate or size
- Examples
  - Number of claims handled
  - Sales volume
  - Sizes of outsourcing contracts
  - Numbers of IT projects under way
  - Percentage of business given to each supplier

Loss-related

- Measure outcomes, so lagging
- Examples
  - Number of customer complaints
  - Budget overruns

Cause-related

- Measure factors identified as drivers (so leading)
- Difficult to identify
- More complex than others
- Examples
  - Number of unresolved "severe" internal audit issues
  - Staff turnover
  - Training hours (or £) per staff member
  - Number of un(der)trained staff members
  - Number of different desktop computer configurations in use
  - Hours of paid overtime per staff member

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Data collection

- Accuracy of quantitative results depends on
  - Appropriateness of model
  - Availability of data
- Need to understand the connection between causes and consequences
- Data collection driven by needs of models
  - Or models driven by available data?
- Need losses and exposure

Loss database

- Events
  - Date incurred, reported
  - Development of loss amount
  - Cause (consistent with firm-wide risk matrix)
  - Consequence (how the loss manifested)
- Losses due to more than one cause
  - Split amounts between causes, or whole amount to each
- Near misses
- Blame-free procedures
  - Avoid underreporting

Exposure

- Often no commonly agreed measures
- May be able to use some of the data collected for risk indicators
- May be able to use data used for activity-based costing
  - In general, exposure data likely to encounter all the same problems as activity-based costing

Double counting

- Some operational risk probably already modelled implicitly
- Don't model it explicitly too!

Conclusions

- Don't run before you can walk
  - Start with identifying, assessing, understanding, controls...
  - Statistical techniques come later
- Operational risk management should be driven by value creation
- How important is operational risk compared to other risks?
  - But much that is currently considered insurance risk has its root cause in poor operational practices