Joining Up Op Risk Modelling and Management

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IT TAKES VISION

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The “Problem”

**Modelling** typically avoids “how” and directly assesses “what”

**Managing** typically more interested in “how” and in a different “what” to the modellers
Loss Models – Approaches

① Scenario

Estimate an “extreme” outcome
Loss Models – Approaches

Fit Curve

Make an assumption about the shape of the loss curve and fit by estimating points on the curve (e.g. mode/tail)
Loss Models – Approaches

Probability

Aggregate Annual Loss

③ Whole Curve

Produce an estimate of the whole curve
Typical Modelling

\[ \rho = \begin{pmatrix} 1 & \cdots & \rho_{1m} \\ \vdots & \ddots & \vdots \\ \rho_{n1} & \cdots & 1 \end{pmatrix} \]

or

\[ c_{v,r} (X_1, \ldots, X_n) \]
“Expert Input”

We have calibrated our model with past loss data and it says that there is a 10% chance of losses exceeding £4m and a 5% chance of losses exceeding £6m. What do you think Dave?

No idea. We have never had a loss that big. We added some new controls last month so maybe we should reduce the figures a bit. How about £3m & £5m?
Scenario Overload But Incomplete

These are lots of different variations we thought of for how loss type X could happen

...but so are these that we didn’t think of!

They are actually specific examples contributing to the aggregate loss of type X
Modelling The Past
Operational Risk

Path to the future

Past

Small events occur all the time

Interacting to create emergent outcomes...

which interact to produce further outcomes

Present

Some of which trigger risk events...

leading to a cascade of different consequences

Future
Implementation

Engage experts to describe operational activity and its impact on company goals

Analyse narrative to form a “minimally complex” understanding of the operational “system”

Determine set of operational risk dimensions to be modelled, which cover profile

Each dimension is discussed with experts, summarised to a “minimally complex” form and modelled using a causal model.
Maintenance

During ORSA, consider whether any changes are required to operational dimensions being modelled.

Periodically validate with experts that no material operational changes have occurred and use management information to confirm model calibrations.

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“If the data was lost by a partner there would be contractual issues to resolve which would strain the relationship and there would be damages to claim. This could cause a loss of confidence in the partner themselves..”
Cognitive Analysis

- Identify unfinished explanations more clearly
- Produce a “minimally complex” summary
- Find the most important elements of the “system”
- Nodes which lead to multiple highly connected nodes
- Ultimately connected to many nodes
- Immediately connected to many nodes
Bayesian Network Models

Aggregate scenario outcome
Contributing outcomes
Scenario dynamics

Source: Milliman, using AgenaRisk™
Data Loss Example

The image shows a hierarchical diagram illustrating various data loss scenarios, each with associated risk factors and impact assessments. The diagram is structured with nodes representing different aspects of data loss, such as reconciliation costs, human error, and physical access security, among others. Each node is connected by branches indicating the relationship and impact of these factors on overall data loss. The diagram includes statistical data and percentages to quantify the risks and impacts.
Data Loss Example

\[ P(I) = P(I|L)P(L) + P(I|A)P(A) + P(I|H)P(H) \]
\[ = 0.01 \times 0.1 + 0.05 \times 0.85 + 0.1 \times 0.05 \]
\[ = 0.0485 \]
Estimating Outcomes

Bayesian Network is taking estimates of outcomes relating to a particular “state” of the scenario components and then “mixing” them to create an aggregated view.

If servicing quality meets expectations I think policy payments are more or less zero

If servicing quality does not meet expectations I think policy payments are still mostly zero but there is more chance of higher amounts
Uses

“What if” scenarios can be used to explore the outcomes associated with particular sets of initial conditions.

“Reverse stress” – particularly useful for determining multivariate scenarios of moderate stress which lead to a highly adverse aggregate outcome.

Projections for operational risk outcomes can be achieved by entering estimates for future conditions.

Models can be used in business case preparation and decision-making by highlighting the impact of proposed actions on multiple objectives.
Reverse Stress
Recovering Scenarios

Travel Disruption

Pandemic

Reverse Stress

Civil Unrest
Real Features

The transition from A to B will be sudden not smooth
### Asking/Answering Questions

<table>
<thead>
<tr>
<th>Factor</th>
<th>Potential to Make Tail Worse</th>
<th>Potential to Make Tail Better</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adequacy of external modeling and results</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Accuracy of model fit</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Representation of assumptions</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Analysis of valuation methodology and trend</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Adequacy of annual price trend</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Appropriateness of pricing methodology</td>
<td>High</td>
<td>Low</td>
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<tr>
<td>Appropriateness of sensitivity analysis</td>
<td>High</td>
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<tr>
<td>Appropriateness of flexibility data</td>
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<td>Appropriateness of valuation</td>
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<tr>
<td>Appropriateness of technical skills</td>
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<tr>
<td>Systems errors</td>
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<td>Low</td>
</tr>
<tr>
<td>Availability of competent staff</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Quality of data</td>
<td>High</td>
<td>Low</td>
</tr>
</tbody>
</table>

*Biggest potential to make tail worse*

*Biggest potential to make tail better*
Projecting Op Risk
Correlation from cause

\[ \rho = \begin{pmatrix}
1 & 0.83825 & 0 & 0.8438 & 0 & 0.00005 \\
0 & 1 & 0.809371 & 0 & 0.000006 & 0.000000 \\
0.83825 & 0.809371 & 1 & 0.813145 & 0.000000 & 0.000000 \\
0 & 0.8438 & 0.813145 & 1 & 0.000000 & 0.000000 \\
0.00005 & 0.000006 & 0.000000 & 0.000000 & 1
\end{pmatrix} \]
Other Applications

- Policyholder behaviours can be modelled using this approach to provide dynamic assumption setting
- Dependency assumptions can be validated from first principles
- Integration of soft and hard outcomes to assist with risk appetite assessment
- Development of monitoring frameworks for emerging risks using Bayesian learning process
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