Peril-based reserving – an update

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Workshop D6
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Reserving – Who cares?
What makes you use a method?

Help!

How much **attention** does the method require?

“Give it to a grad”

Not much

Lots

How widely used is method?

Parodi

ACPC

Inflation methods

ODP

B-F

Mack

Chain ladder

Double Chain Ladder
Thinking in three dimensions

Exposure dynamics  
Emerging experience

Perils

Catastrophe Models
Pricing Models
Reserving Models
What makes a good model?
Breaking down the claims process

Exposure → Claim event → Loss notification → (Re-) Valuation → Payments

Coverage → Policyholder behaviour → Legal changes → Claims inflation

Portfolio mix → Claimant behaviour → Claims processes → Price inflation

Other effects:
- Political
- Economic
- Social
- Technological
- Environmental
- Legal
Loss simulation – what not to do

In incurred runs, there should be a consistent trend over time, indicating a stable development of claims. However, in paid runs, the trend should show a decrease over time, reflecting the resolution of claims. The graphs illustrate the cumulative amount over the development period, showing how claims develop over time.

Similarly, in claim development, there should be a clear trend indicating the resolution of claims over time. The graphs show the cumulative amount of incurred and paid claims, with a clear decrease in paid claims over time.
Loss simulation – what not to do

- Complexity
- Explicit chain ladder assumptions
- Implicit assumptions
Claims simulation redux

• How simple can we make our process and still get something realistic?

• Let’s try stripping the process down to the following:
  – A certain number of claims happens at various points in time during the accident year
  – After a delay they are reported and we put a reserve on it
  – After a further delay each claim is settled and the file is closed
A very simple claims process…
Would it pass his test?
Henrietta Lacks and the HeLa cell line
### Data lines: a taxonomy - 1

- **Data set**: a published instance of transactional loss data

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Data lines: a taxonomy - 2

• Data line: a collection of data sets generated using the same generation engine and input parameters

• Accompanied by:
  – A description of its profile / characteristics
  – A parameter input file
  – Output validation

• Typically 1,000 or 10,000 data sets in a data line
Data lines: a taxonomy - 3

- Data generations: all data lines created using a common generation engine
Some definitions

\( \mathcal{P} \)  
A particular claims generation process and parameter set.

\( \mathcal{P} \)  
A particular instance of \( \mathcal{P} \) that we observe in life. Here we are able to generate thousands of Ps.

\( R^o_{\mathcal{P}} \)  
Perfect reserve for instance \( \mathcal{P} \), refer to this as “ \( R^o \) ”

\( E_{\mathcal{P}}[R^o] \)  
Expected reserve across all \( \mathcal{P} \in \mathcal{P} \)

\( SD_{\mathcal{P}}[R^o] \)  
Inherent variability in perfect reserve, the variability that arises as a result of the process

\( \mathcal{E} \)  
Our loss reserve estimation process, eg chain-ladder

\( \widehat{R}_\mathcal{E} \)  
Our reserve estimate using \( \mathcal{E} \)
What this means in practice

Most reserve approaches model like this:

Fix this

Simulate this

This approach requires us to model like this:

Simulate all of this together

Fixing the triangle collapses the process
What we observe

\[
\frac{E_\phi[R^0 - \bar{R}_\phi]}{E_\phi[R^0]} \quad \text{Expected error in reserve estimate using estimator } \phi \text{ under generation process } \phi
\]

“Model bias”

\[
\frac{SD_\phi[R^0 - \bar{R}_\phi]}{E_\phi[R^0]} \quad \text{Variability of reserve estimate using estimator } \phi \text{ under generation process } \phi
\]

“Projection error”

\[
\frac{SD_\phi[R^0 - \bar{R}_\phi]}{E_\phi[R^0 - \bar{R}_\phi]} \quad \text{“Coefficient of Variation” measure}
\]

Helpful to look at percentiles too.
Recap: What is peril-based reserving about?

• Thinking about the underlying claims process rather than an aggregate claims triangle.
• Formalising thinking in three dimensions:
  – Exposure
  – Risks
  – Time
• Testing our ideas we need some data to work with.
Some results

Adopting this approach enables us to quantify the performance of models
Results 1
Example summary claims triangles
Results 2
Example claims projection results

True ultimate claims and estimation errors

And repeat many times...
Results 3
Distribution of estimates under process

Frequency distribution of standardised error

- Paid CL Error
- Incurred CL Error

Probability estimate exceeds reserve

- Paid CL
- Incurred CL
Results 4
Measure speed of convergence

Average PCL Error

Average ICL Error

As at end of year, $t$

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Results 5 – Chain-ladder and BF models
A. Paid claims

Bornhuetter Ferguson models reduce error but increase bias
Results 5 – Chain-ladder and BF models

B. Incurred claims

Bornhuetter Ferguson models reduce error but increase bias
Results 6 – Sensitivity tests
A. Claim severity

How model and process error change with claim volatility

- CV ult
- CV reserve
- PCL variability
- ICL variability
- Paid BF variability
- Incurred BF variability
Results 6 – Sensitivity tests

B. Claim capping

Effect of capping claims

- CV ult
- CV reserve
- PCL variability
- ICL variability
- Paid BF variability
- Incurred BF variability

Max claim (000)

Error

25.0%
20.0%
15.0%
10.0%
5.0%
0.0%

10 15 20 25 30 35
Results 6 – Sensitivity tests

C. Claim frequency

Changing claim frequency

- CV ult
- CV reserve
- PCL variability
- ICL variability
- Paid BF variability
- Incurred BF variability

Error vs. Avg # Claims / Sim
Results 6 – Sensitivity tests
D. Notification delay

How model and process error change with notification delay

- CV ult
- CV reserve
- PCL variability
- ICL variability
- Paid BF variability
- Incurred BF variability

Mean notification delay vs. Error
Results 7 – Model robustness

Using our simulated loss data, we can evaluate how each of our methods performs under a range of conditions:

**Stable features**
- Initial under-reserving
- Assuming some claims settle for nil ("win factor")
- Both under-reserving and win factor

**Unstable feature**
- Weakening claims reserves over time
## Results 7 – Model robustness

Summary results

<table>
<thead>
<tr>
<th>Additional feature</th>
<th>Model bias</th>
<th>Projection error</th>
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</thead>
<tbody>
<tr>
<td>Base model</td>
<td>0%</td>
<td>13%</td>
</tr>
<tr>
<td>Initial under-reserving</td>
<td>0%</td>
<td>14%</td>
</tr>
<tr>
<td>Under-reserving and win factor</td>
<td>-1%</td>
<td>15%</td>
</tr>
<tr>
<td>Weakening case estimates over time</td>
<td>16%</td>
<td>11%</td>
</tr>
</tbody>
</table>

- **No impact**
- **Big impact**
Results 7 – Model robustness
Stable features cause no problems

Probability estimate exceeds reserve

- Base
- Under res.
- Under res and Win Factor

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Results 7 – Model robustness
Model fails with non-stable process

Probability estimate exceeds reserve

- Base
- Under res.
- Under res and Win Factor
- Vary bias

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Learning points

• Simple approach to simulating loss data behaves as we expected

• Behaviour aligns with expectations under a range of scenarios.

• Approach provides a means of evaluating new and existing reserving and reserve variability model techniques.

• And rules of thumb for practical applications.
Where next?

- Establish a set of base-line results
- Widen availability of data sets
- Refine our methodology for production and analysis of data sets
- Report on key measures and rules of thumb
- Recruiting for members of a steering group to oversee and challenge next phase of research
And the future?

Rise of the Machines

- Random Forest
- Incurred chain ladder
- Paid chain ladder

Median Estimate

Error in Reserve Estimate

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Final thoughts...

- Can a machine learning approach be used to give a better estimate than an actuary?
- Certainly it will be faster...
- How soon until human actuaries are replaced?
Expressions of individual views by members of the Institute and Faculty of Actuaries and its staff are encouraged.

The views expressed in this presentation are those of the presenter.