

Peril-based reserving – an update

Alex Marcuson, Marcuson Consulting Ltd www.marcuson.co

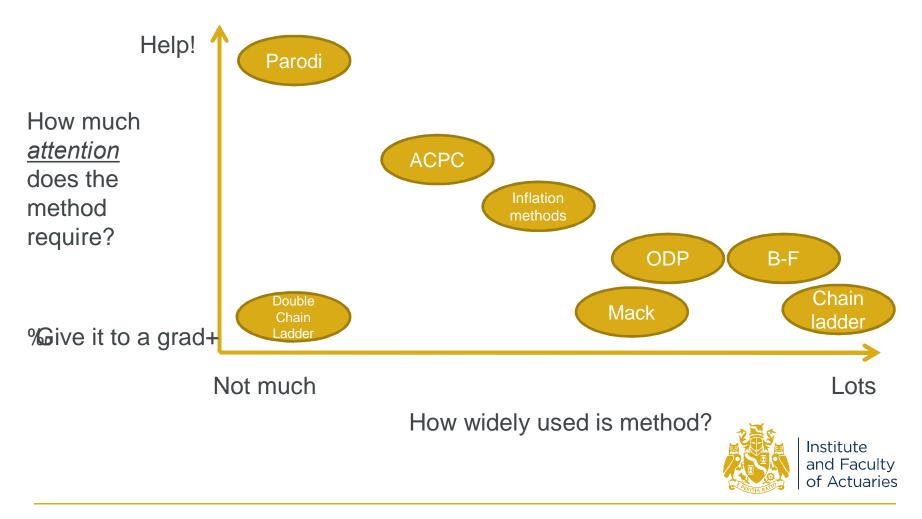
GIRO Conference 2016 Workshop D6 Thursday 22 September 2016, 15:45 . 16:45

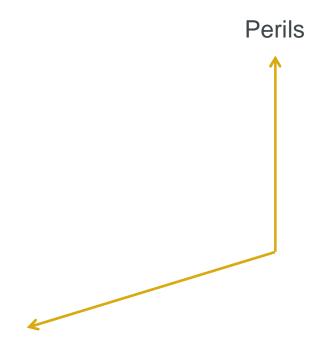
Reserving – Who cares?





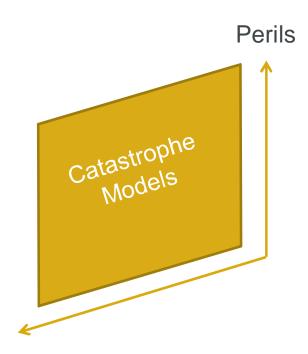
What makes you use a method?





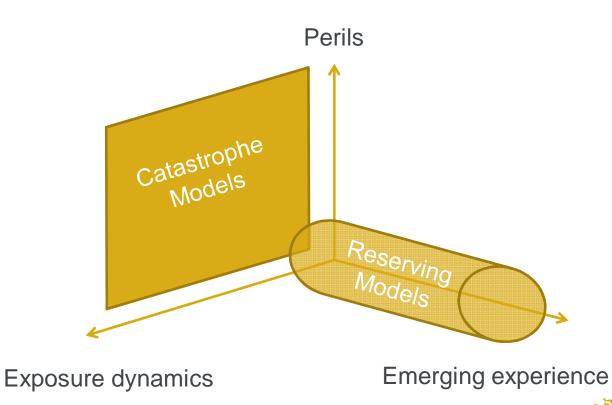
Exposure dynamics



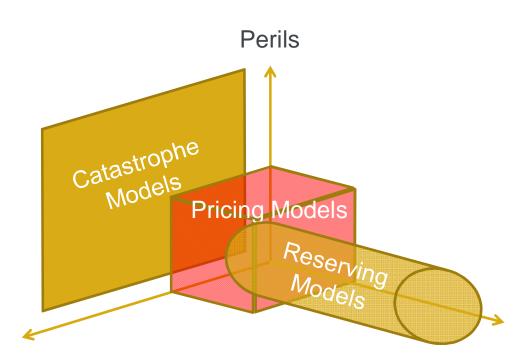


Exposure dynamics







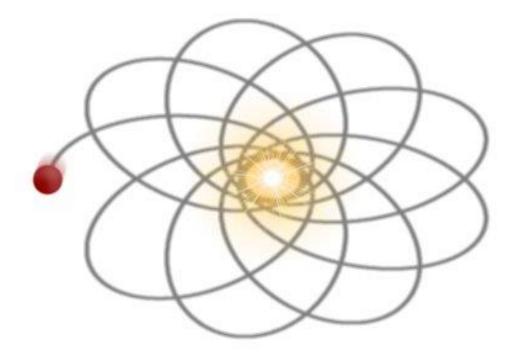


Exposure dynamics

Emerging experience

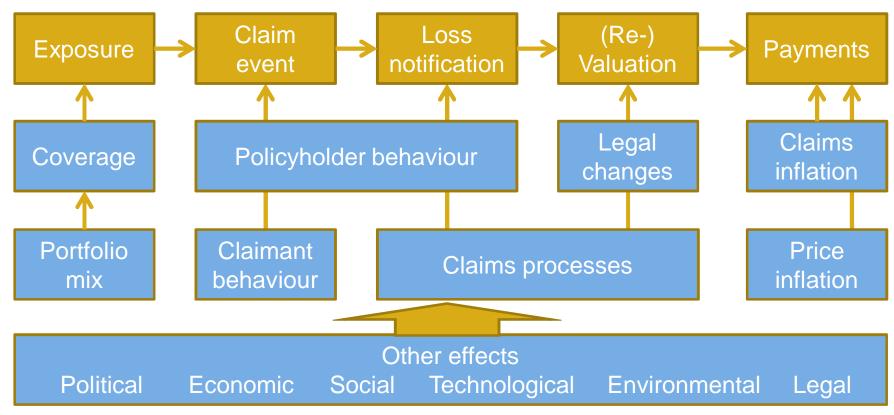


What makes a good model?



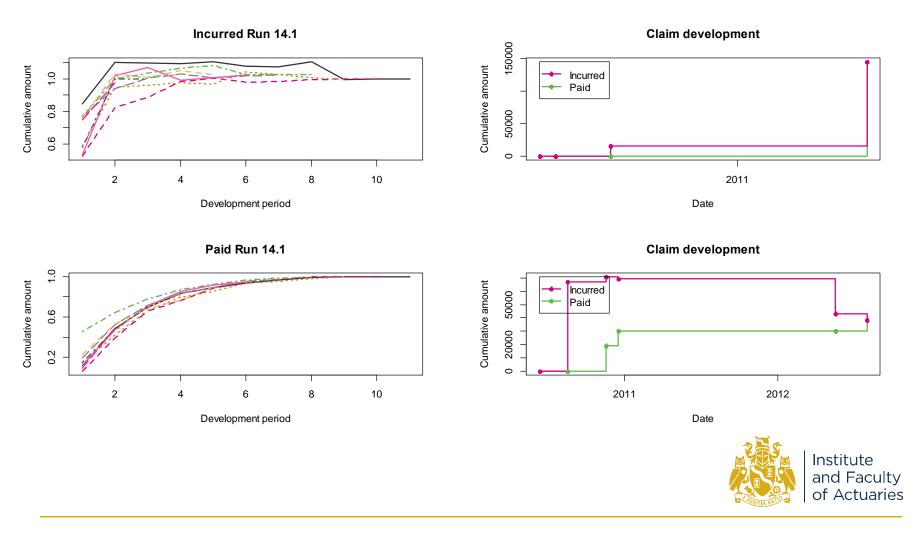


Breaking down the claims process





Loss simulation – what not to do



Loss simulation – what not to do

- Complexity
- Explicit chain ladder assumptions
- Implicit assumptions



Claims simulation redux

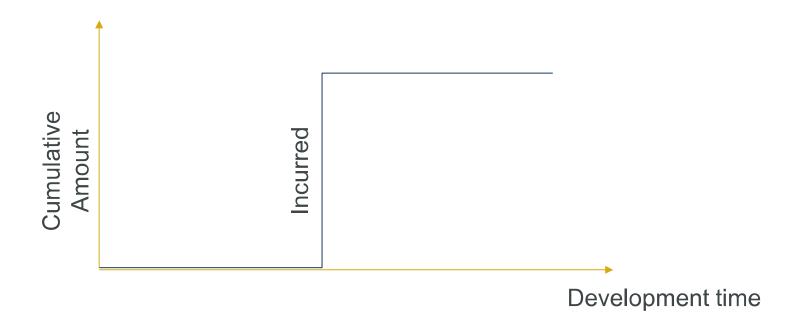
 How simple can we make our process and still get something realistic?

- 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

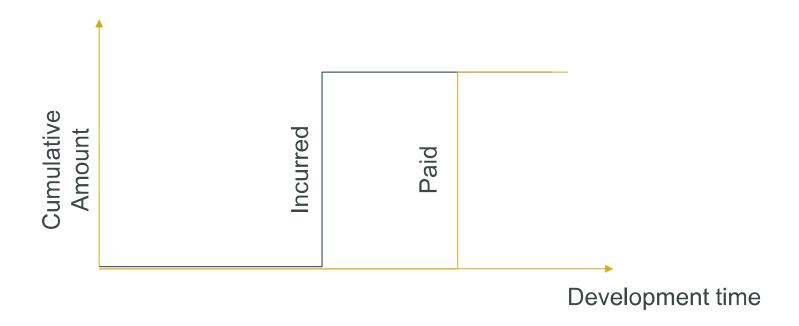




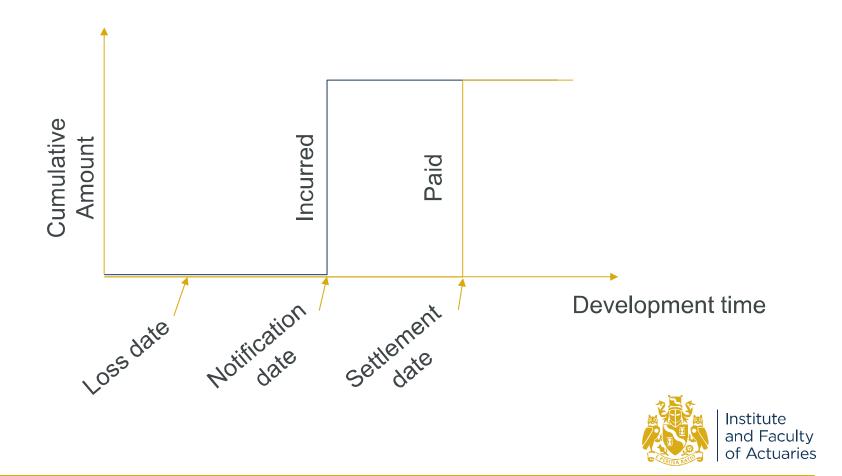


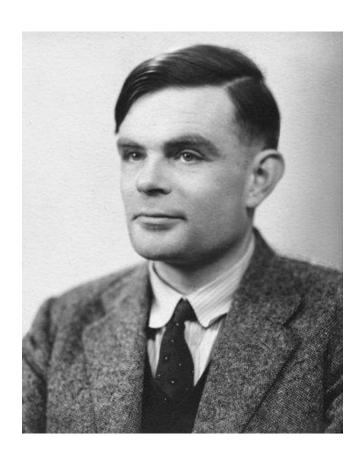




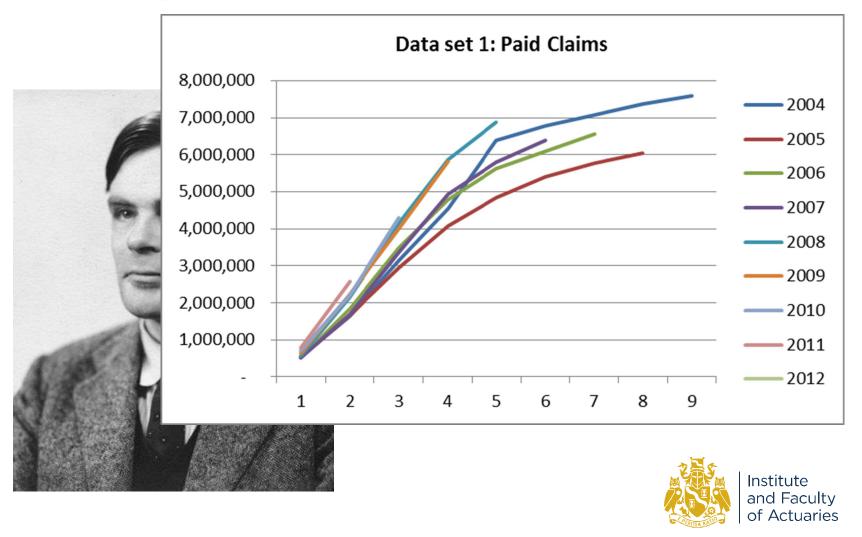


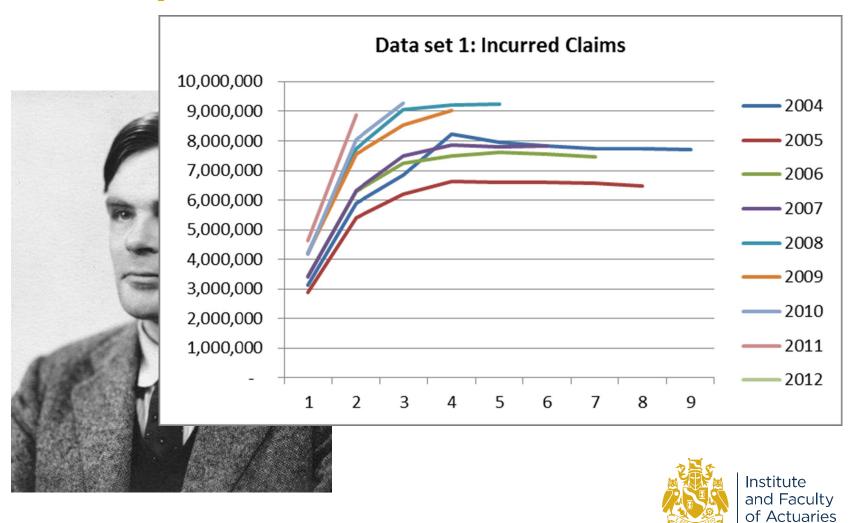


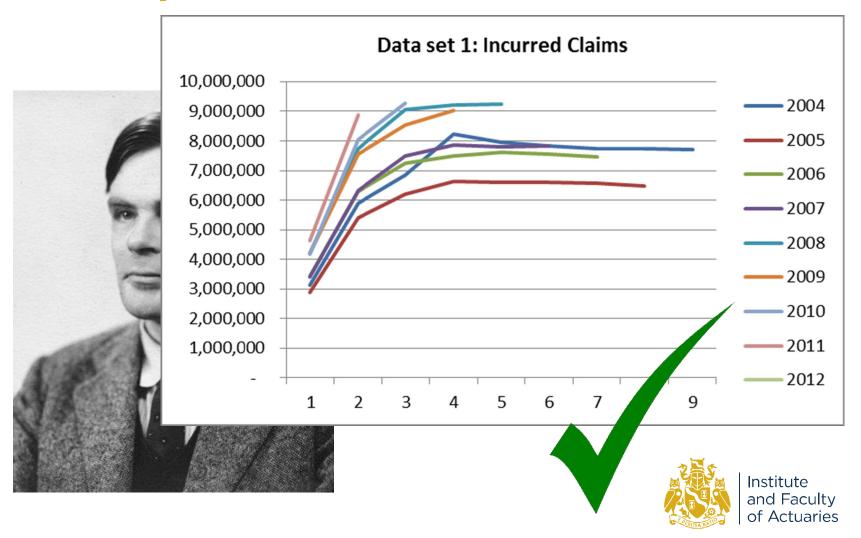












Henrietta Lacks and the HeLa cell line





Data lines: a taxonomy - 1

Data set: a published instance of transactional loss data

	Acc_Yr	Dev_Yr	Cal_Yr	Claim.no	policytype	claimtype	Acc_Date	Transaction.date	Open_Cla	Closed_Cl	Incurred	Paid
1	2006	1	2006	1	1	1	28/07/2006	04/08/2006	1	0	4434.653	0
2	2006	2	2007	1	1	1	28/07/2006	23/02/2007	0	0	1168.6	2869.797
3	2006	2	2007	1	1	1	28/07/2006	28/07/2007	0	1	211.6391	2945.096
4	2006	1	2006	2	1	1	06/04/2006	13/04/2006	1	0	1435.956	0
5	2006	1	2006	2	1	1	06/04/2006	31/08/2006	0	0	2362.533	1584.567
6	2006	1	2006	2	1	1	06/04/2006	23/10/2006	0	1	492.2458	2706.167
7	2006	1	2006	3	1	1	25/12/2006	29/12/2006	1	0	2729.804	0
8	2006	2	2007	3	1	1	25/12/2006	30/08/2007	0	0	670.7003	0
9	2006	3	2008	3	1	1	25/12/2006	25/07/2008	0	1	1393.593	4794.098
10	2006	1	2006	4	1	1	03/09/2006	07/09/2006	1	0	3397.113	0
11	2006	1	2006	4	1	1	03/09/2006	21/10/2006	0	0	905.2508	0
12	2006	2	2007	4	1	1	03/09/2006	02/08/2007	0	1	247.1809	4549.545



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 / charactaristics
 - 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

89	A particular claims generation process and parameter set.							
Р	A particular instance of \wp that we observe in life. Here we are able to generate thousands of Ps.							
R^o_{P}	Perfect reserve for instance P, refer to this as " \mathbb{R}^o "							
$E_{\wp}[R^o]$	Expected reserve across all P ∈ ℘							
$SD_{\wp}[R^o]$	Inherent variability in perfect reserve, the variability that arises as a result of the process							
3	Our loss reserve estimation process, eg chain-ladder							
$\widehat{R_{\mathcal{E}}}$	Our reserve estimate using E Institute and Faculty of Actuaries							

Most reserve approaches model like this:

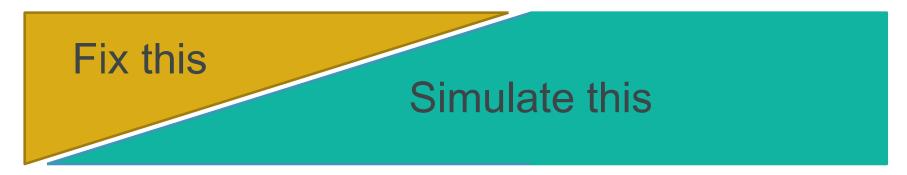


Most reserve approaches model like this:



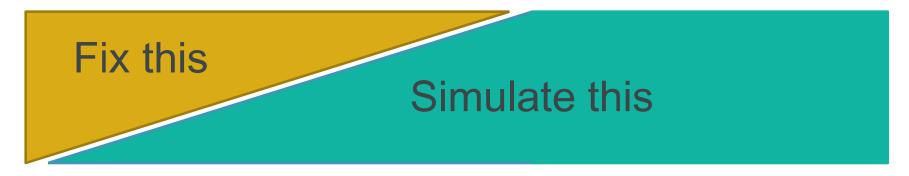


Most reserve approaches model like this:





Most reserve approaches model like this:



This approach requires us to model like this:



Most reserve approaches model like this:



This approach requires us to model like this:

Simulate all of this together



Most reserve approaches model like this:



This approach requires us to model like this:

Simulate all of this together



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

$$\frac{E_{\wp}[R^o - \widehat{R_{\varepsilon}}]}{E_{\wp}[R^o]}$$

Expected error in reserve estimate using estimator \mathcal{E} under generation process \wp

"Model bias"

$$\frac{SD_{\wp}\big[R^o-\widehat{R_{\mathcal{E}}}\big]}{E_{\wp}\big[R^o\big]}$$

Variability of reserve estimate using estimator \mathcal{E} under generation process \wp

"Projection error"

$$\frac{SD_{\wp}\big[R^o - \widehat{R_{\varepsilon}}\big]}{E_{\wp}\big[R^o - \widehat{R_{\varepsilon}}\big]}$$

"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.



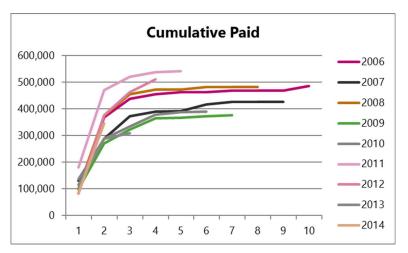


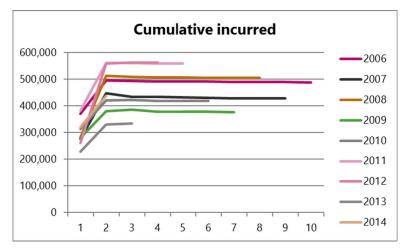
Some results

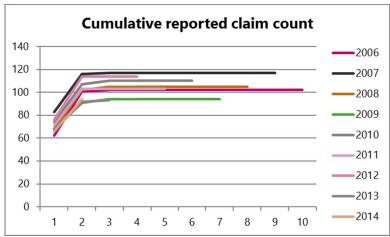
Adopting this approach enables us to quantify the performance of models

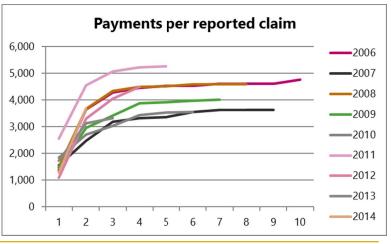
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Results 1 Example summary claims triangles

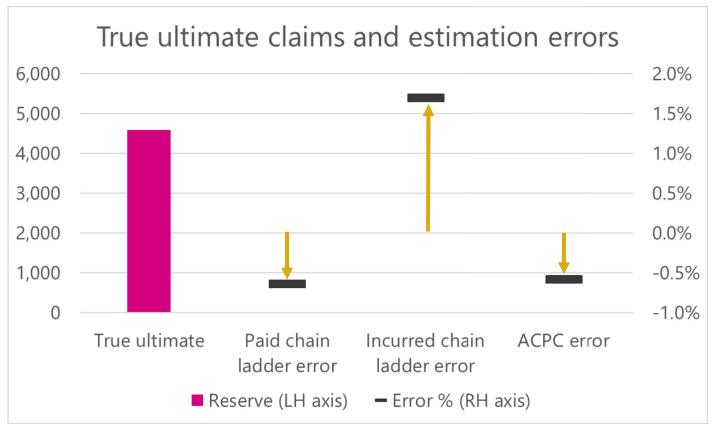








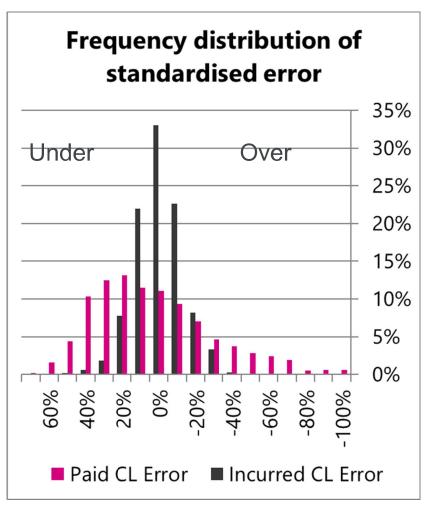
Results 2 Example claims projection results

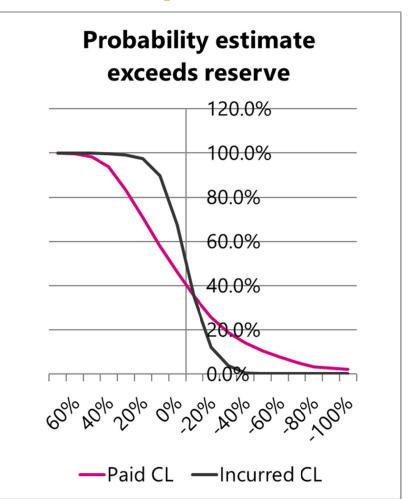


And repeat many times...

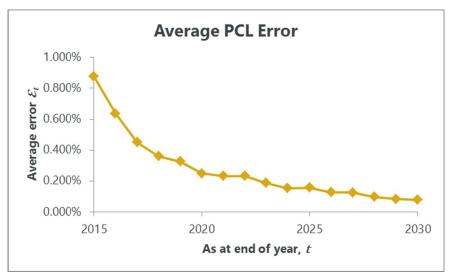


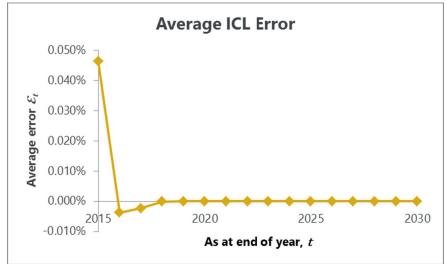
Results 3 Distribution of estimates under process





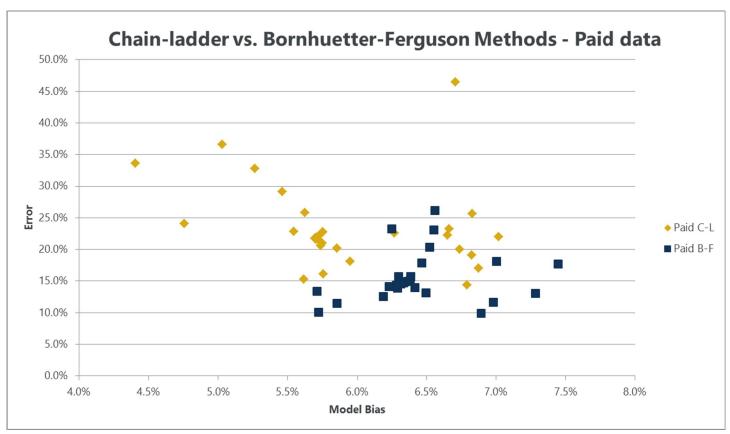
Results 4 Measure speed of convergence







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

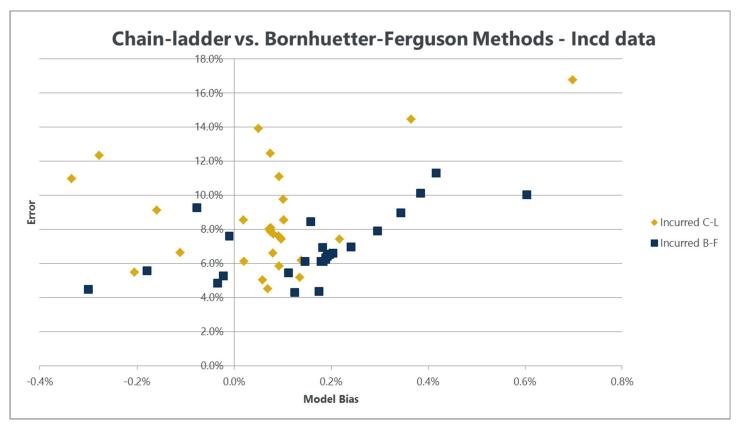


Bornhuetter Ferguson models reduce error but increase bias



Results 5 – Chain-ladder and BF models

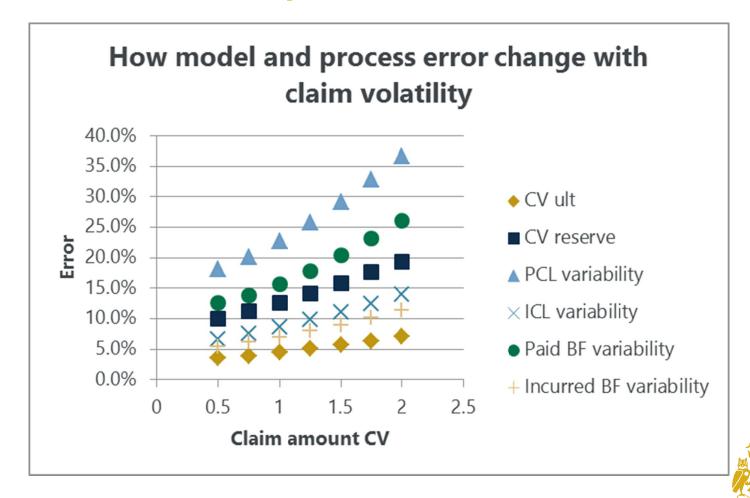
B. Incurred claims



Bornhuetter Ferguson models reduce error but increase bias



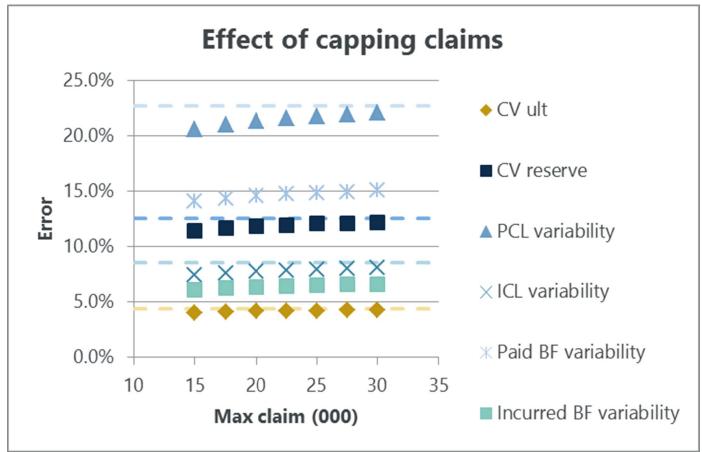
A. Claim severity



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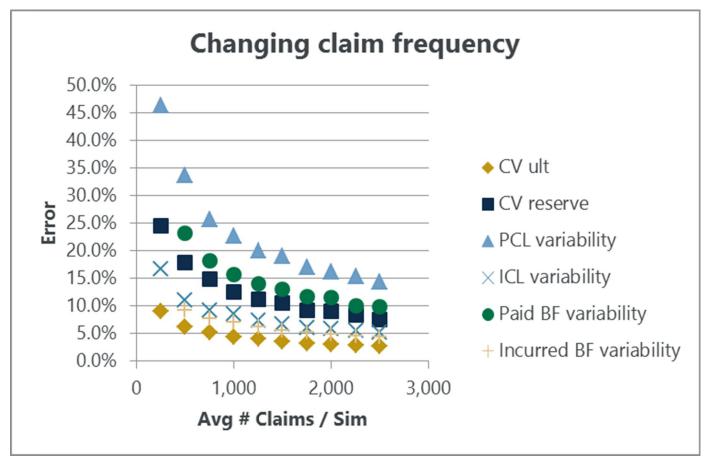
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B. Claim capping



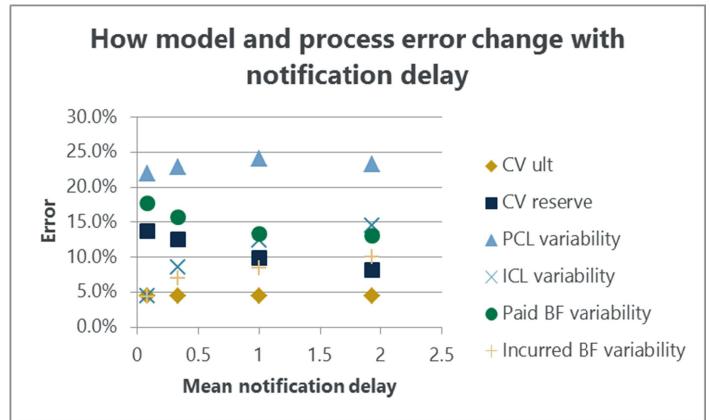


C. Claim frequency





D. Notification delay





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

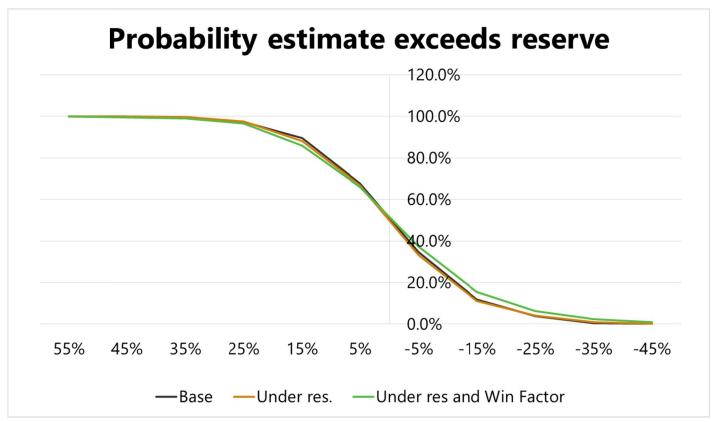


Results 7 – Model robustness Summary results

Additional feature	Model bias	Projection error	
Base model	0%	13%	
Initial under-reserving	0%	14%	No impact
Under-reserving and win factor	-1%	15%	No impact
Weakening case estimates over time	16%	11%	Big impact

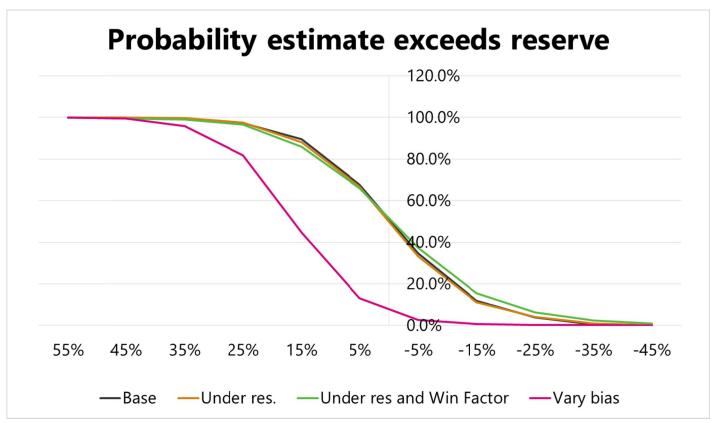


Results 7 – Model robustness Stable features cause no problems





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





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.

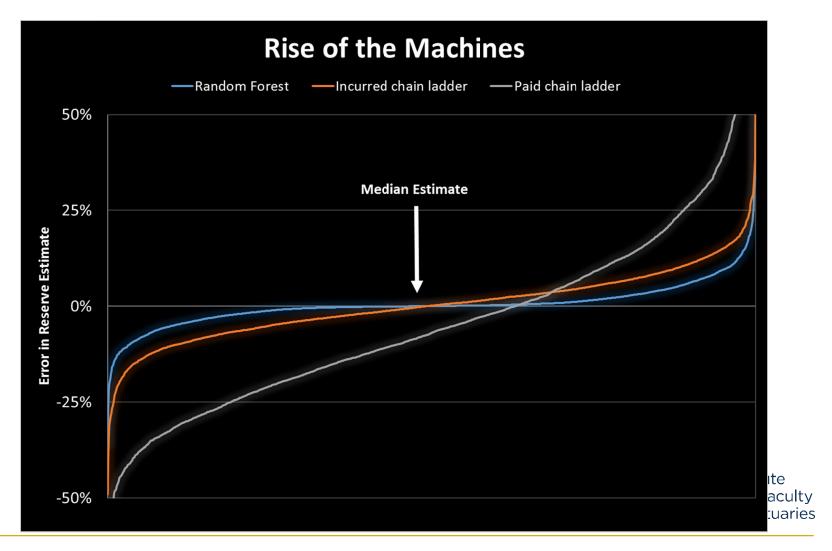


Where next?

- 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?



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?



Questions

Comments

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.

