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Peril-based reserving – an update

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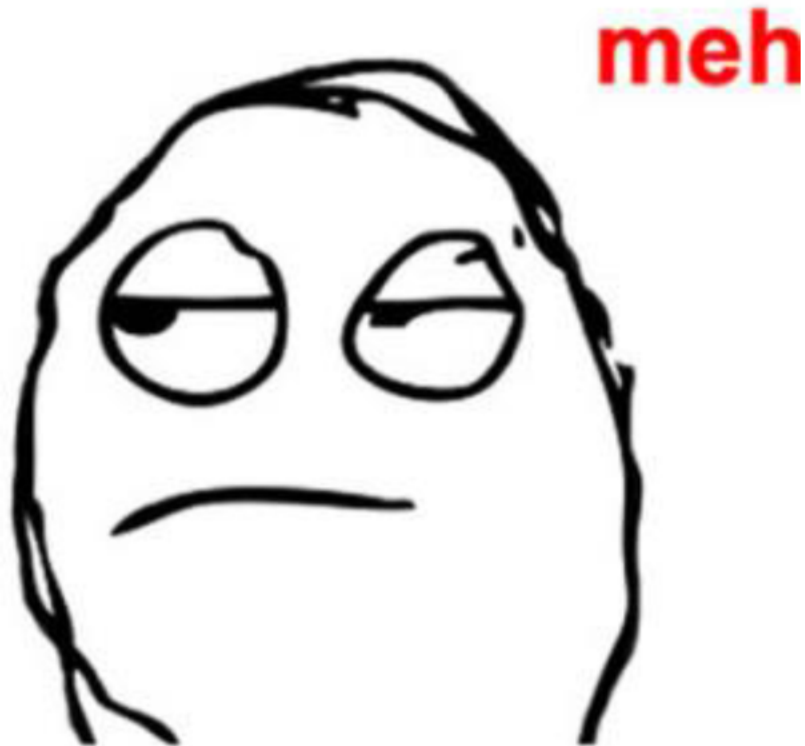
www.marcuson.co

GIRO Conference 2016

Workshop D6

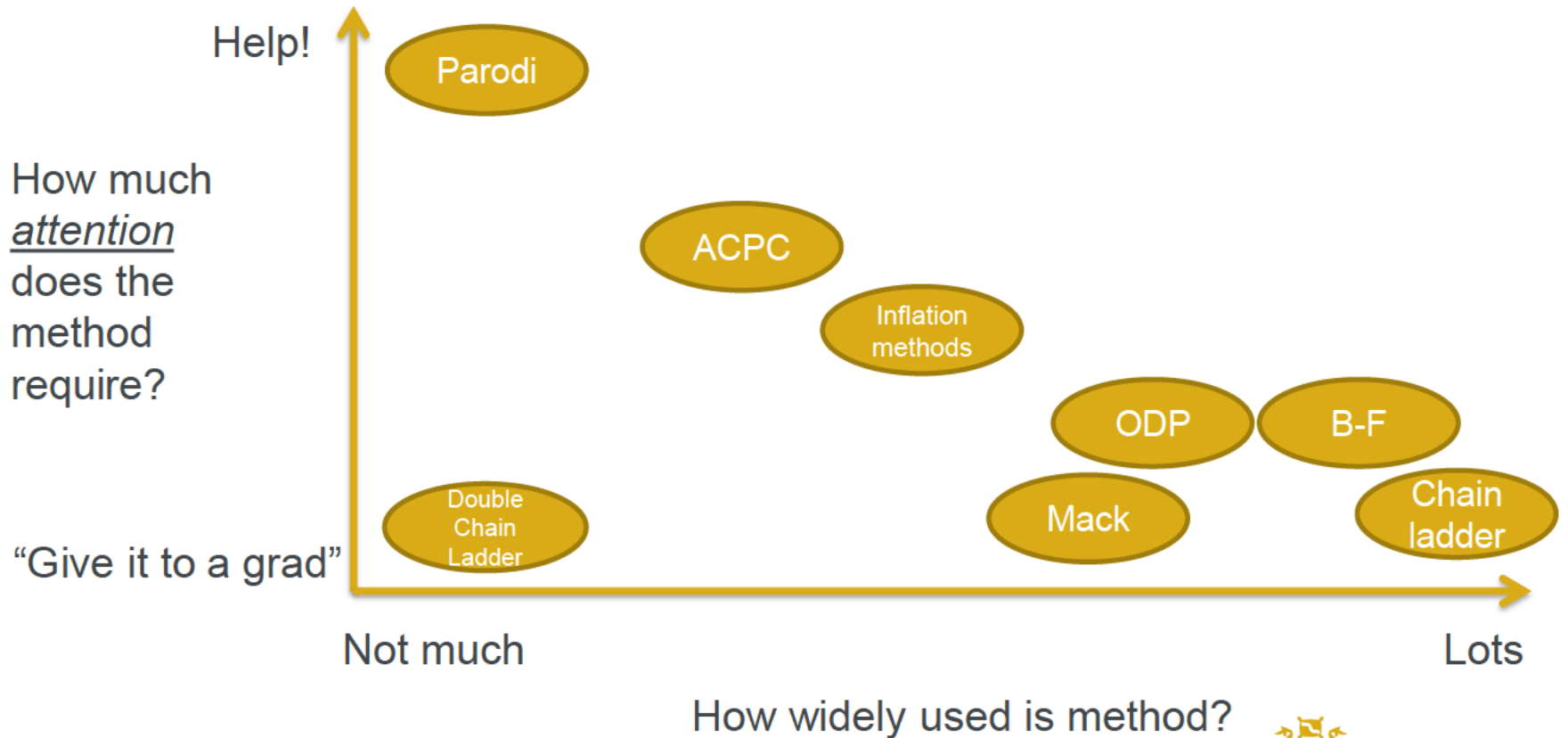
Thursday 22 September 2016, 15:45 – 16:45

Reserving – Who cares?



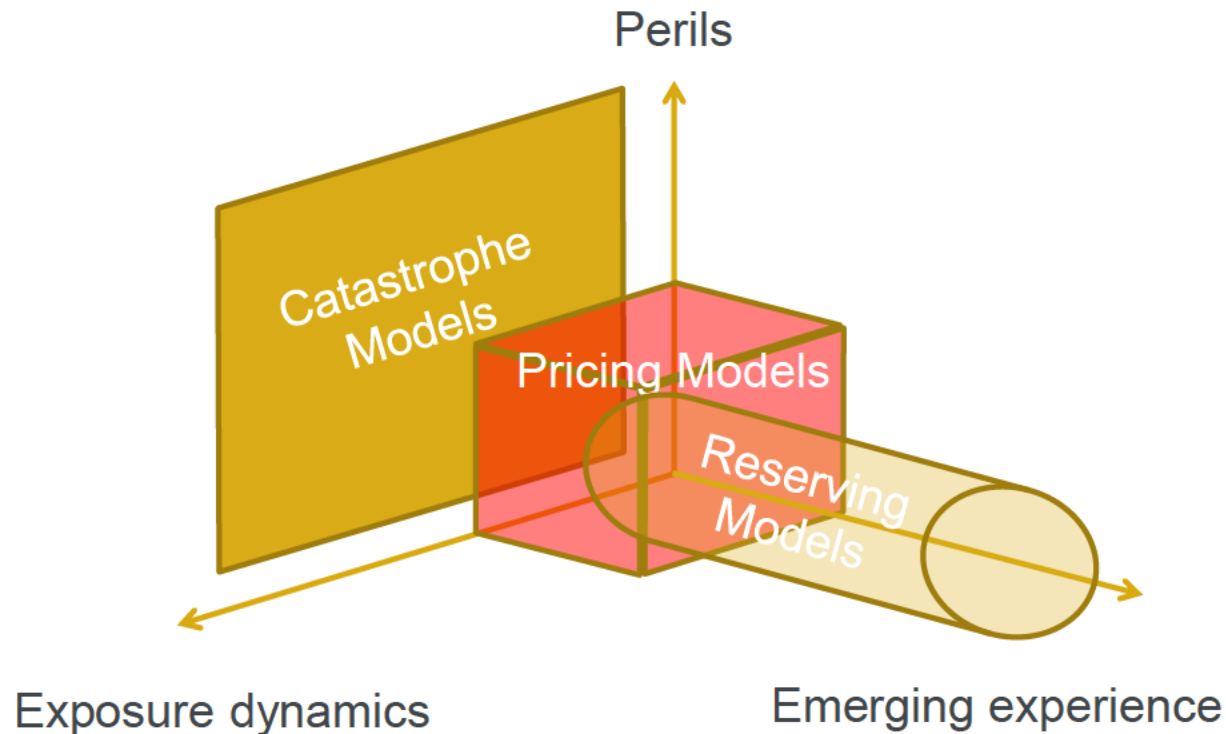
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What makes you use a method?



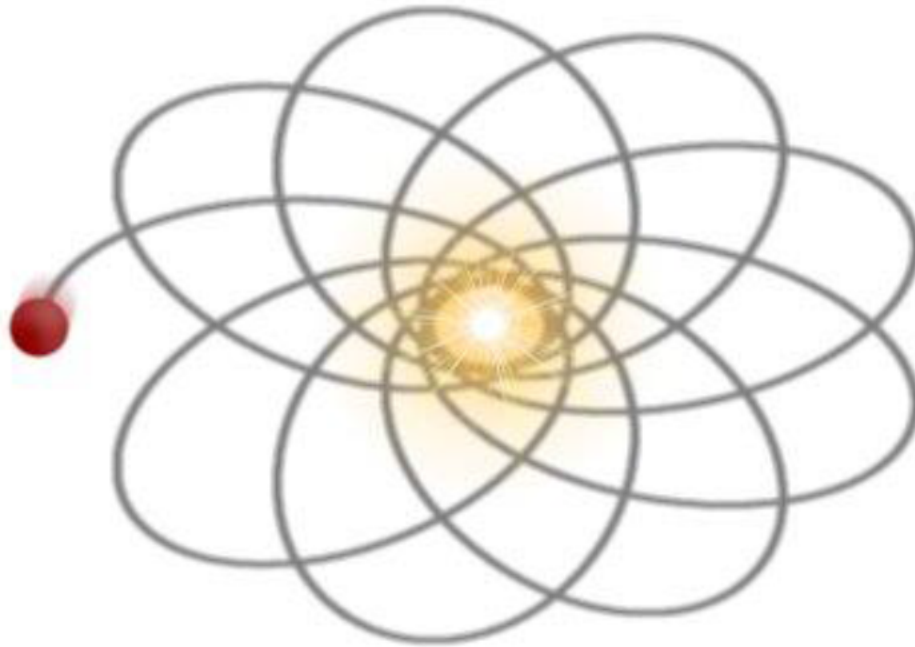
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Thinking in three dimensions



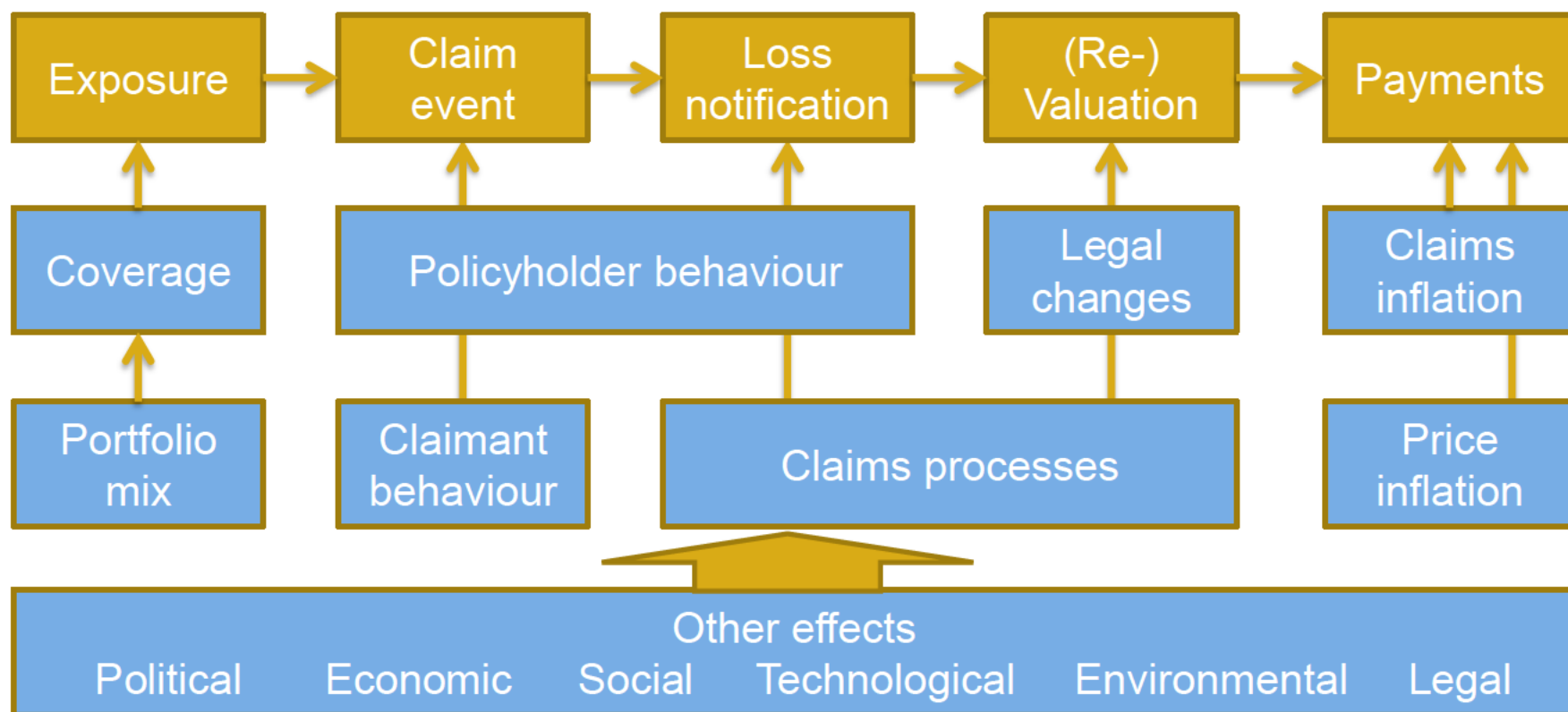
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What makes a good model?



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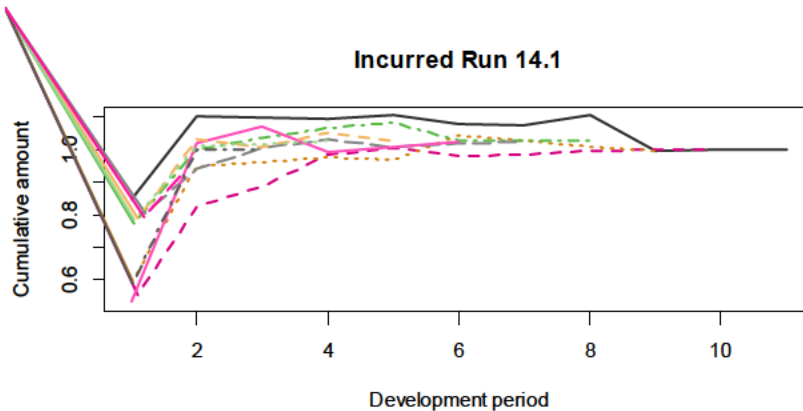
Breaking down the claims process



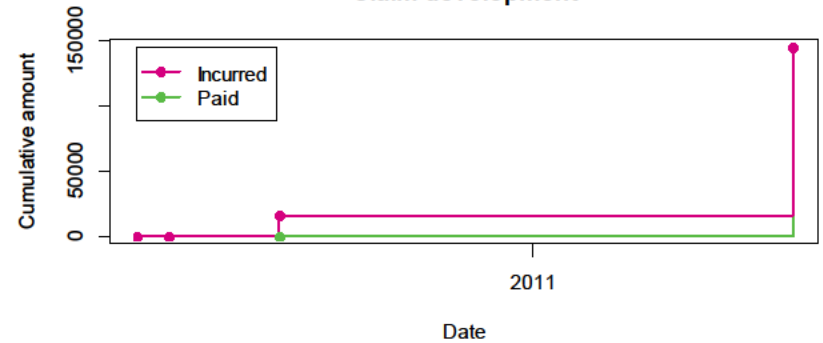
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Loss simulation – what not to do

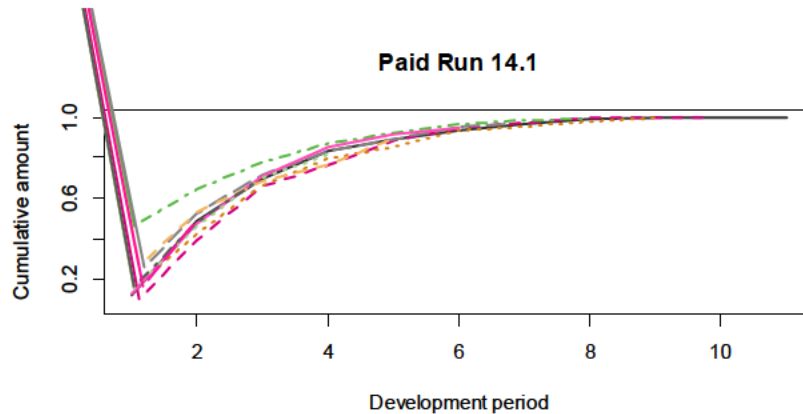
Incurred Run 14.1



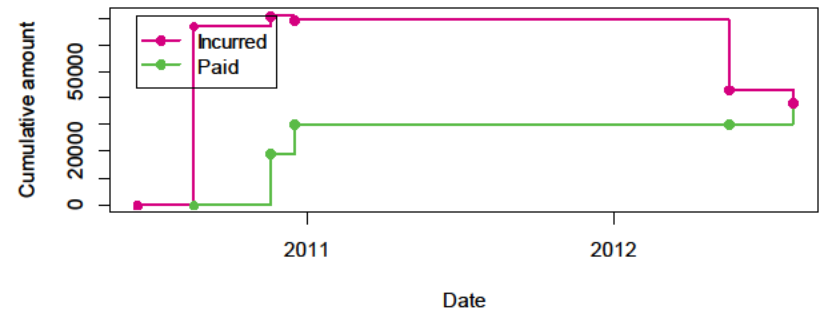
Claim development



Paid Run 14.1



Claim development



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Loss simulation – what not to do

- Complexity
- Explicit chain ladder assumptions
- Implicit assumptions

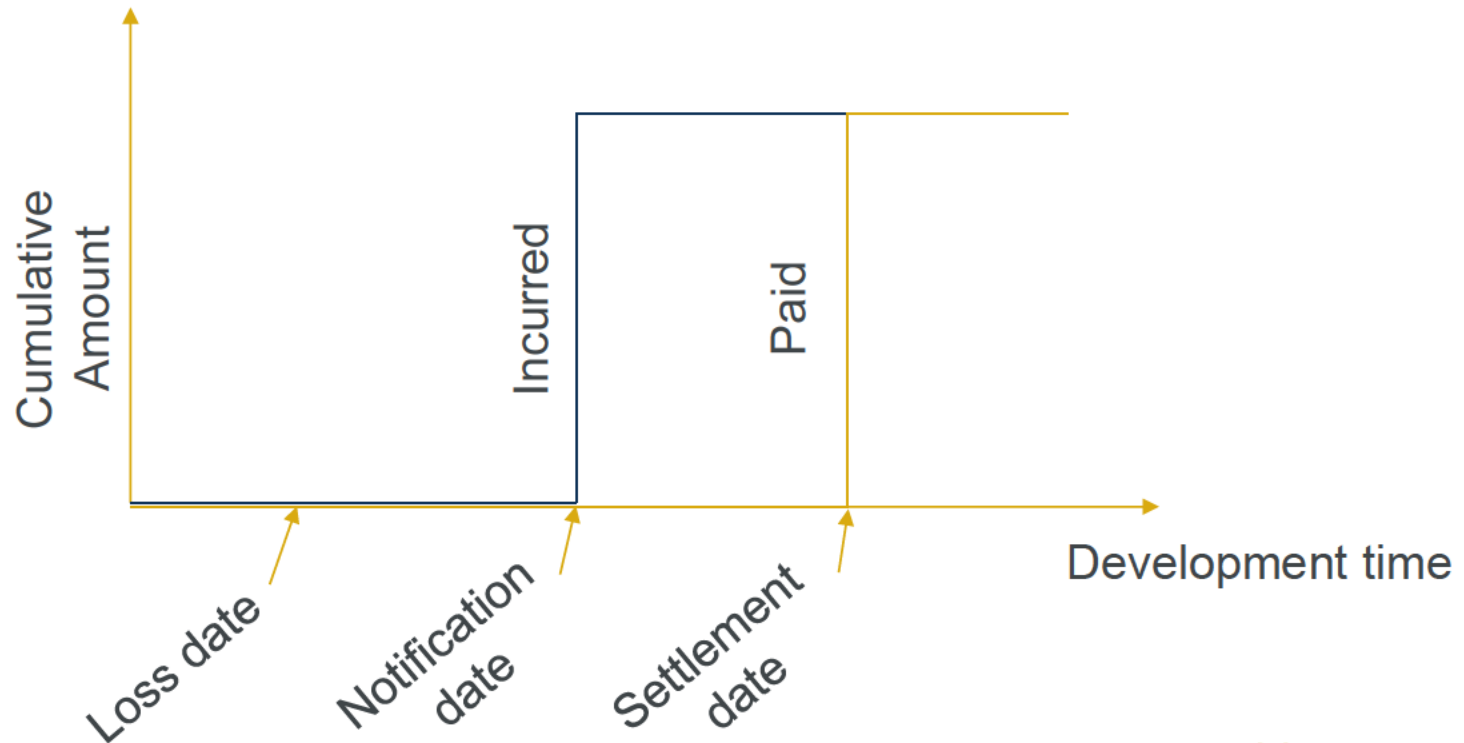


Claims simulation redux

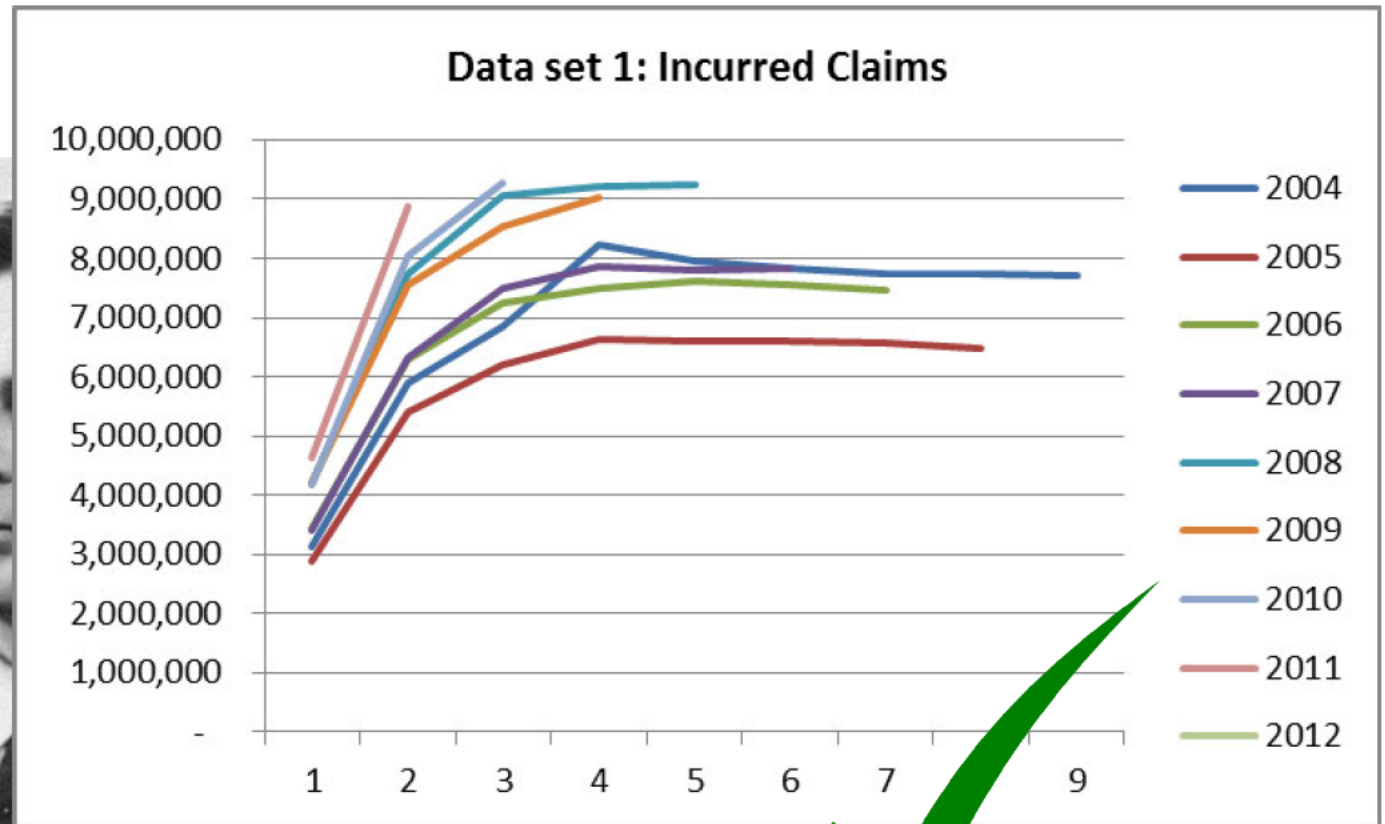
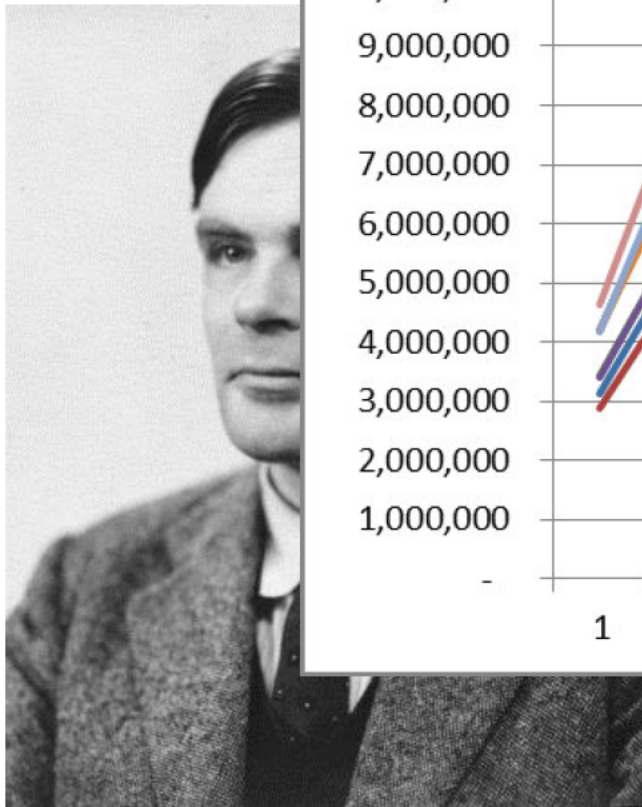
- How simple can we make our process and still get something realistic?
- Let's try stripping the process down to the following:
 - A certain number of claims happens at various points in time during the accident year
 - After a delay they are reported and we put a reserve on it
 - After a further delay each claim is settled and the file is closed



A very simple claims process...



Would it pass his test?



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Henrietta Lacks and the HeLa cell line



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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



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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



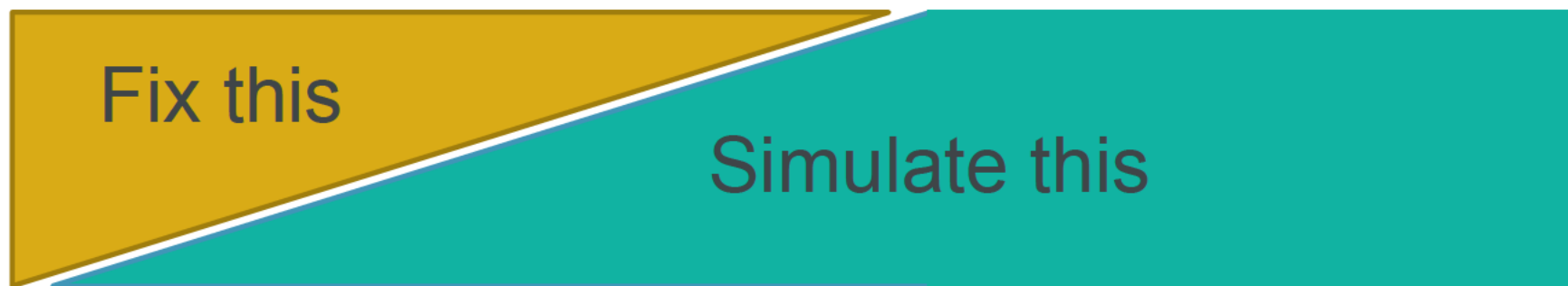
Some definitions

\wp	A particular claims generation process and parameter set.
P	A particular instance of \wp that we observe in life. Here we are able to generate thousands of P s.
R^o_P	Perfect reserve for instance P , refer to this as “ R^o ”
$E_{\wp}[R^o]$	Expected reserve across all $P \in \wp$
$SD_{\wp}[R^o]$	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:



This approach requires us to model like this:



Fixing the triangle collapses the process



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What we observe

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

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

“Model bias”

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

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

“Projection error”

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

“Coefficient of Variation” measure

Helpful to look at percentiles too



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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.



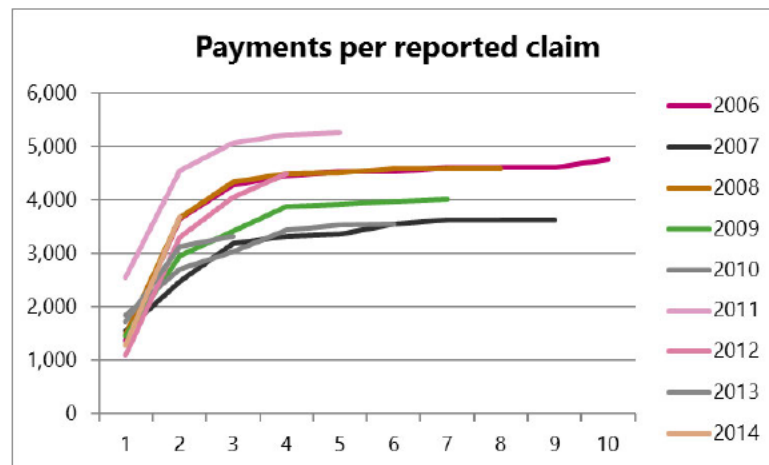
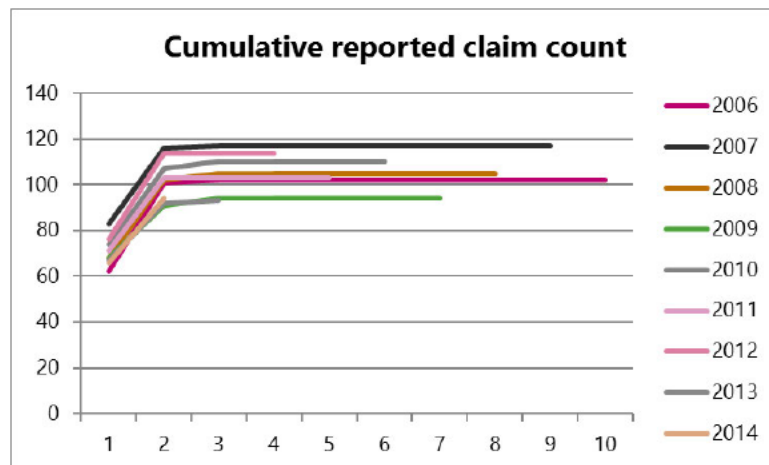
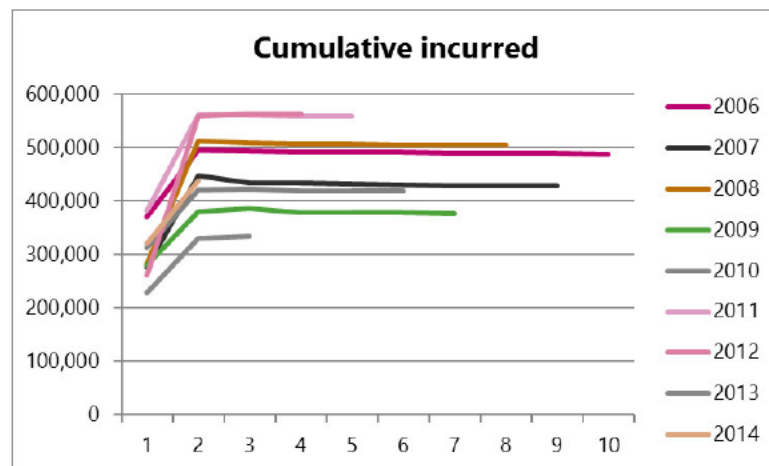
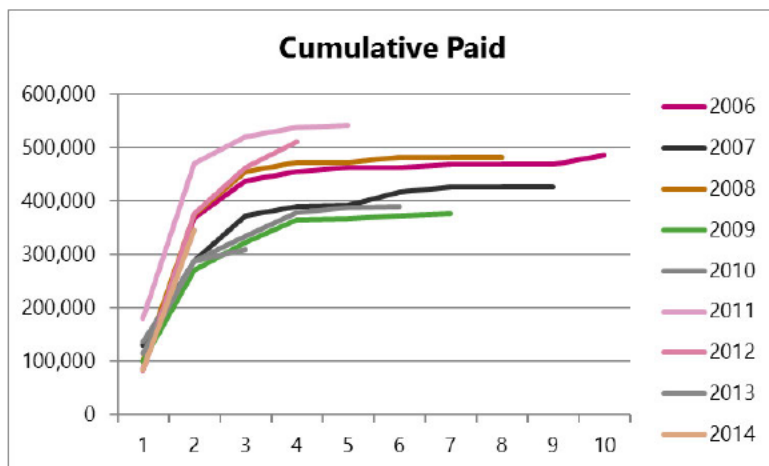


Some results

Adopting this approach enables us to quantify the performance of models

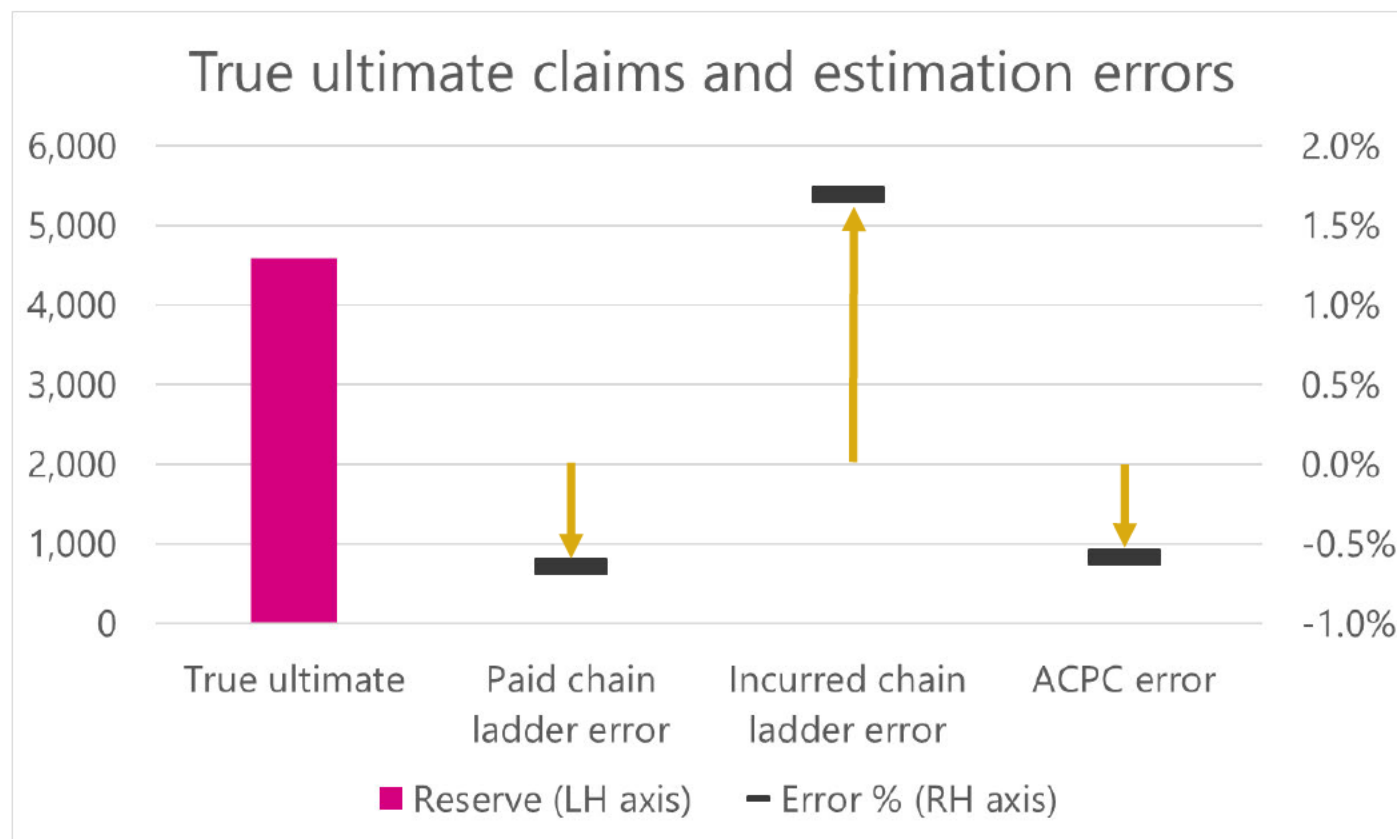
Results 1

Example summary claims triangles



Results 2

Example claims projection results



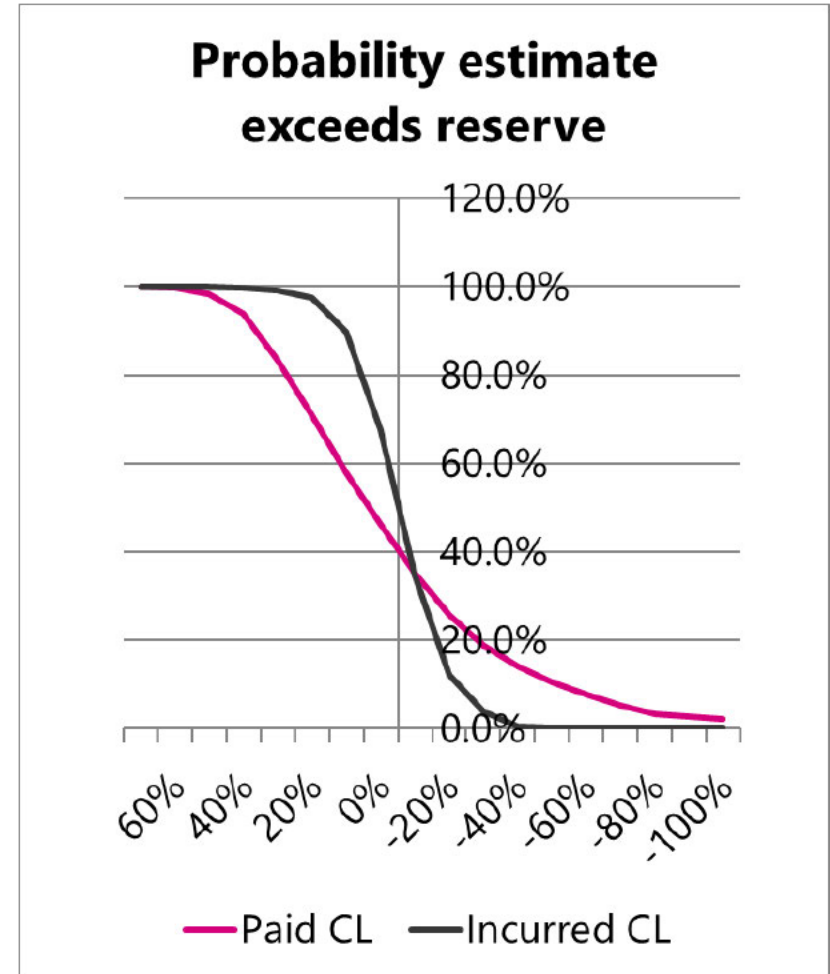
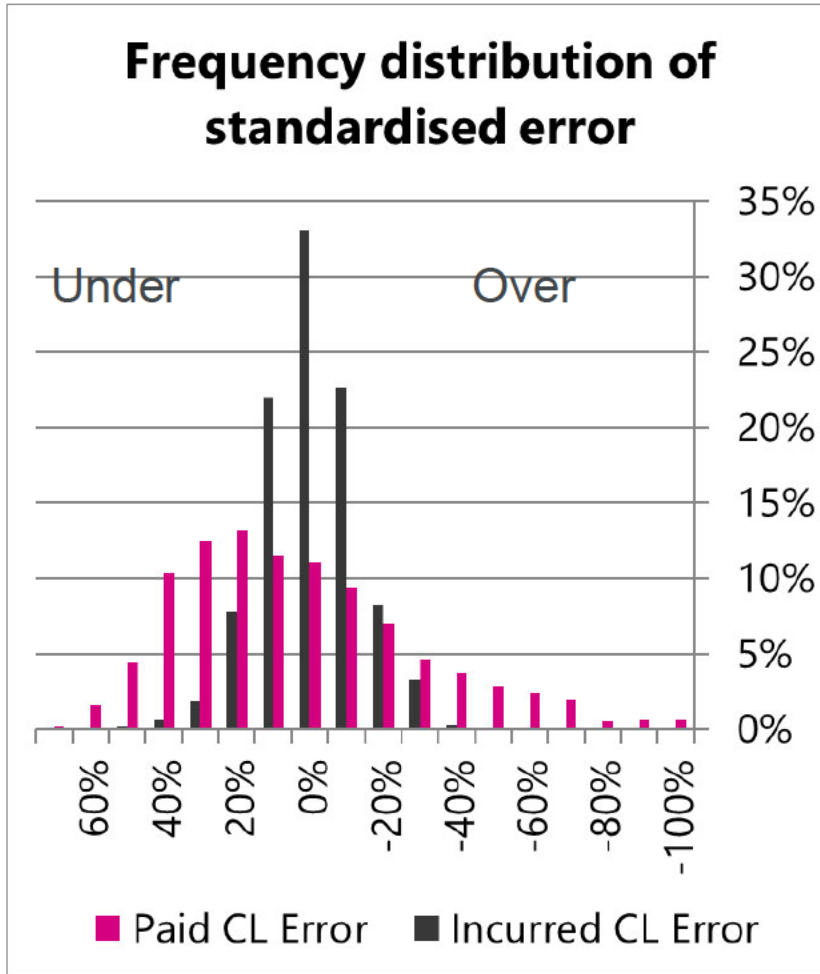
And repeat many times...



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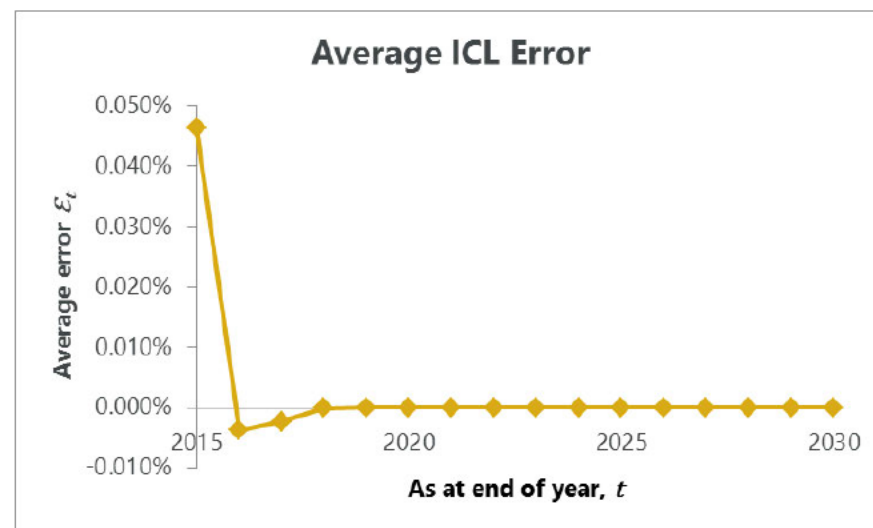
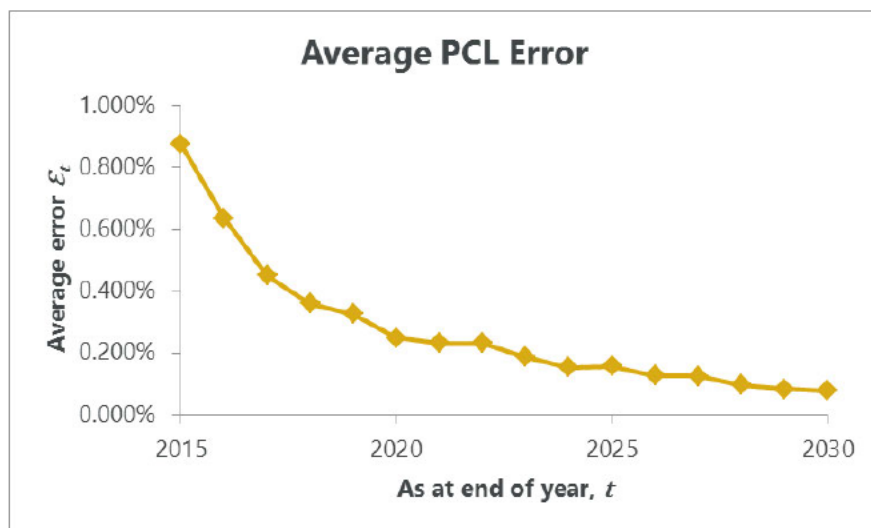
Results 3

Distribution of estimates under process



Results 4

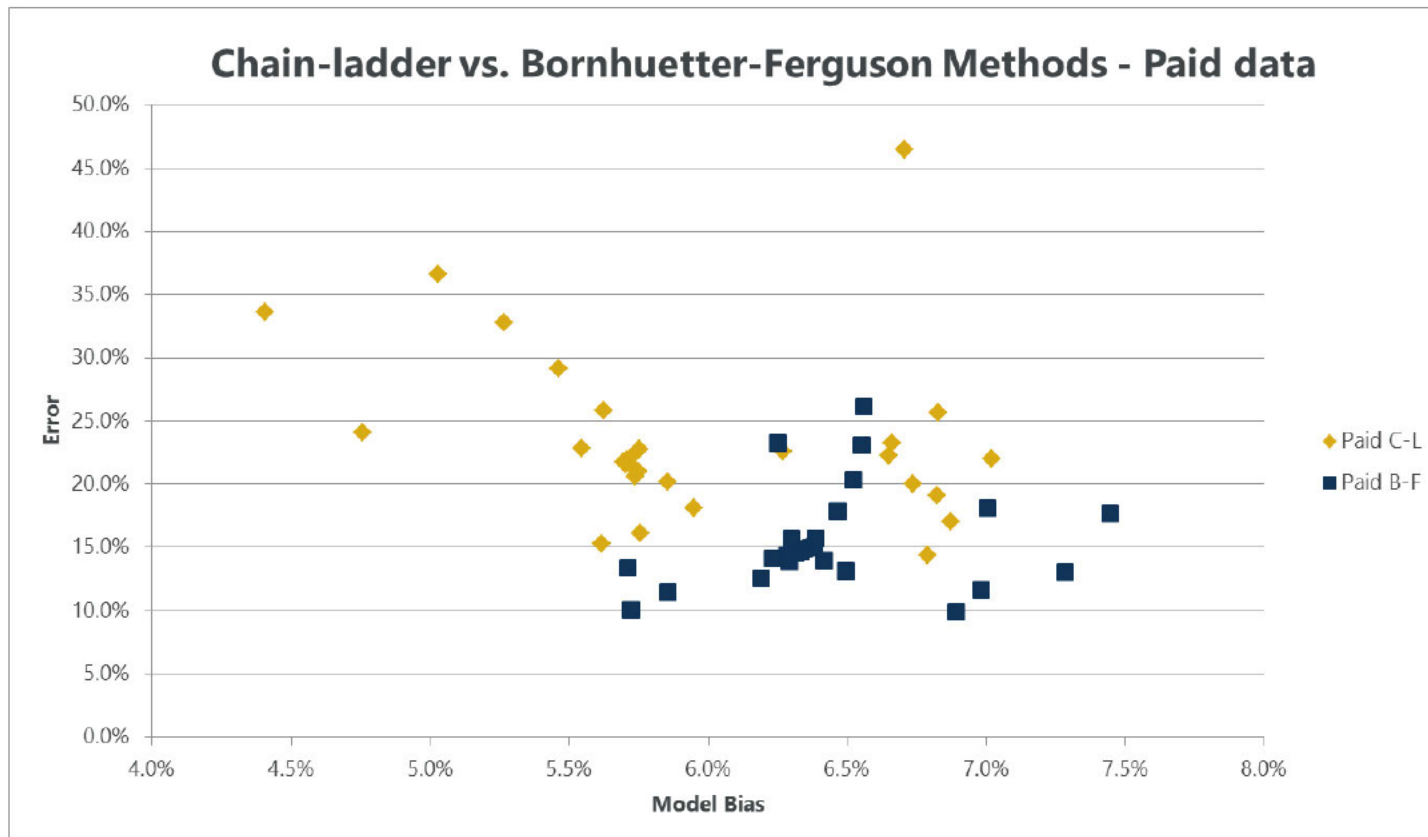
Measure speed of convergence



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Results 5 – Chain-ladder and BF models

A. Paid claims



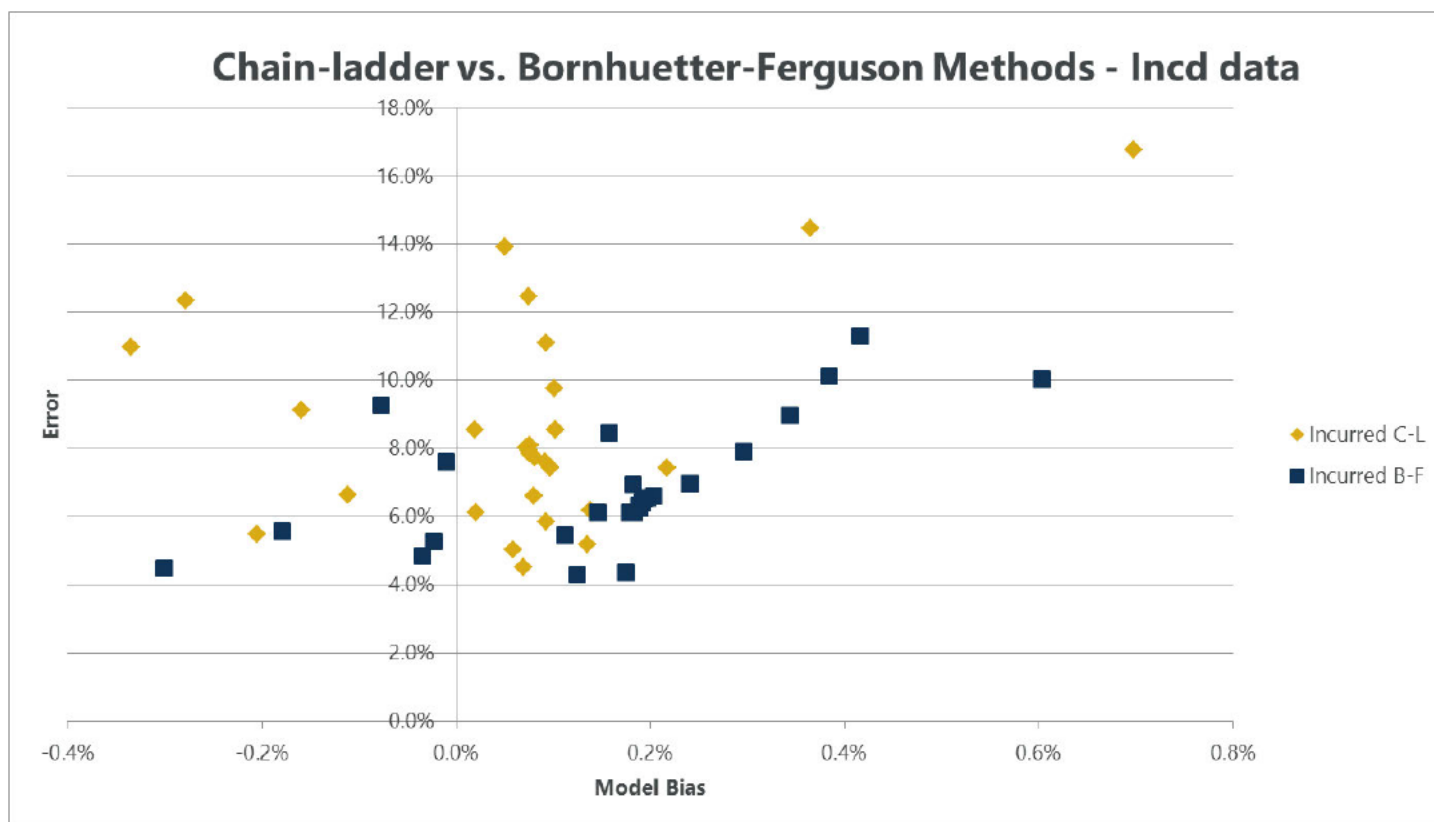
Bornhuetter Ferguson models reduce error but increase bias



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Results 5 – Chain-ladder and BF models

B. Incurred claims



Bornhuetter Ferguson models reduce error but increase bias

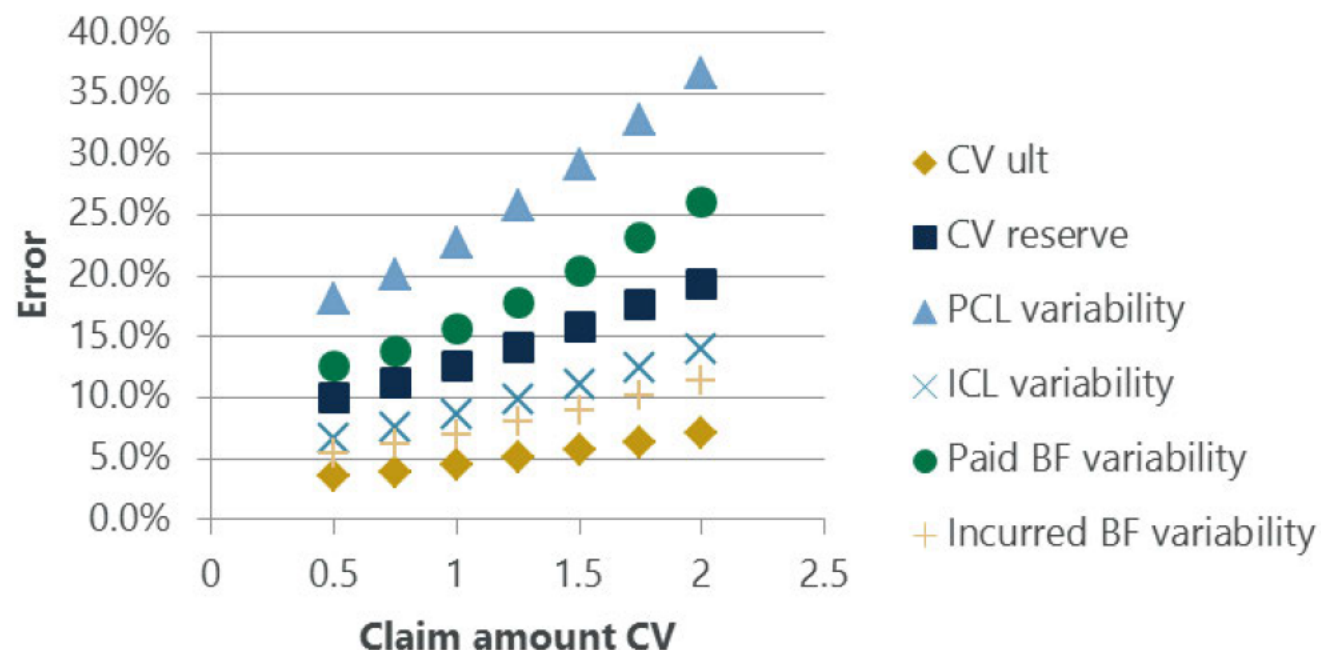


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Results 6 – Sensitivity tests

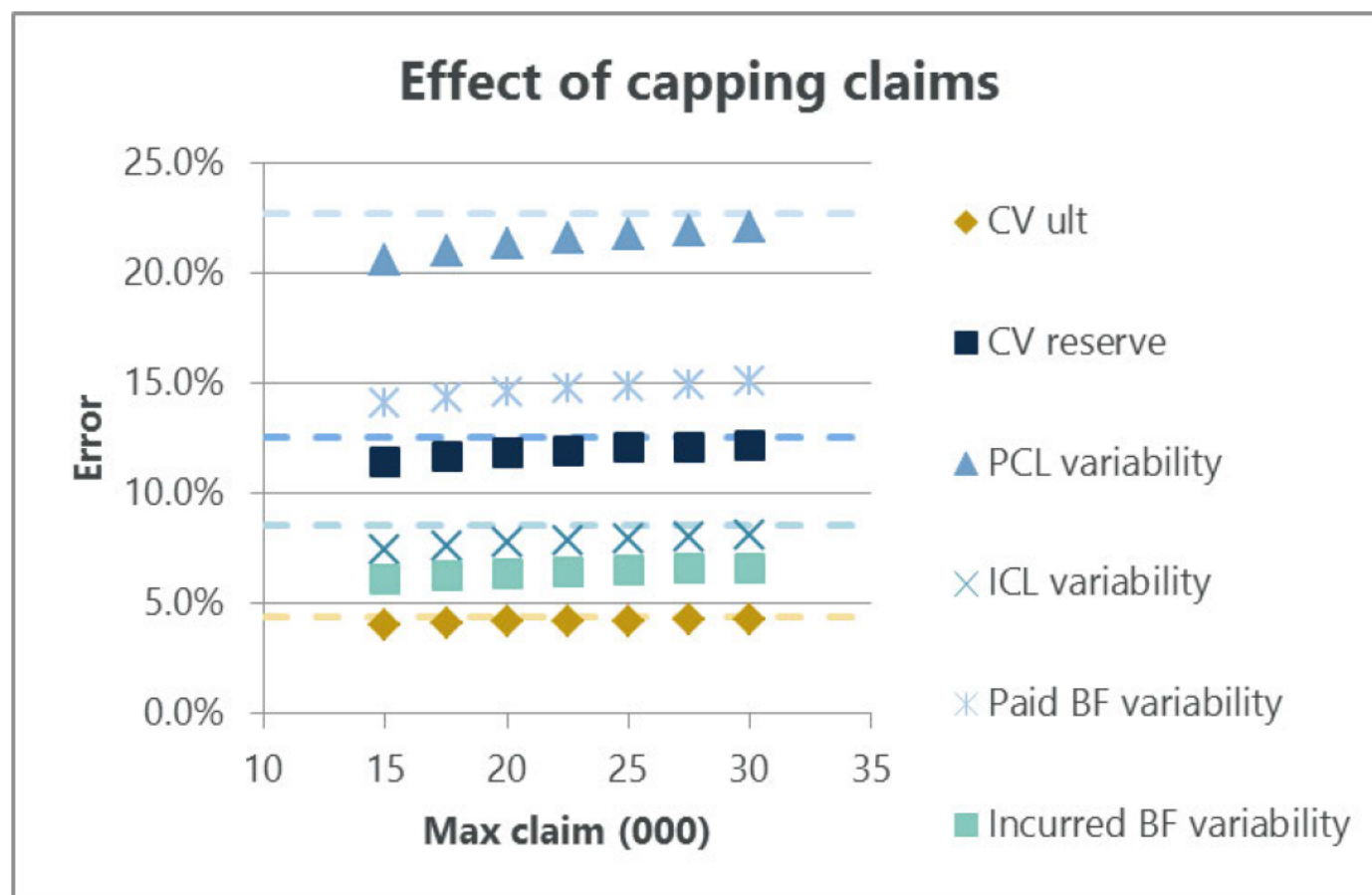
A. Claim severity

How model and process error change with claim volatility



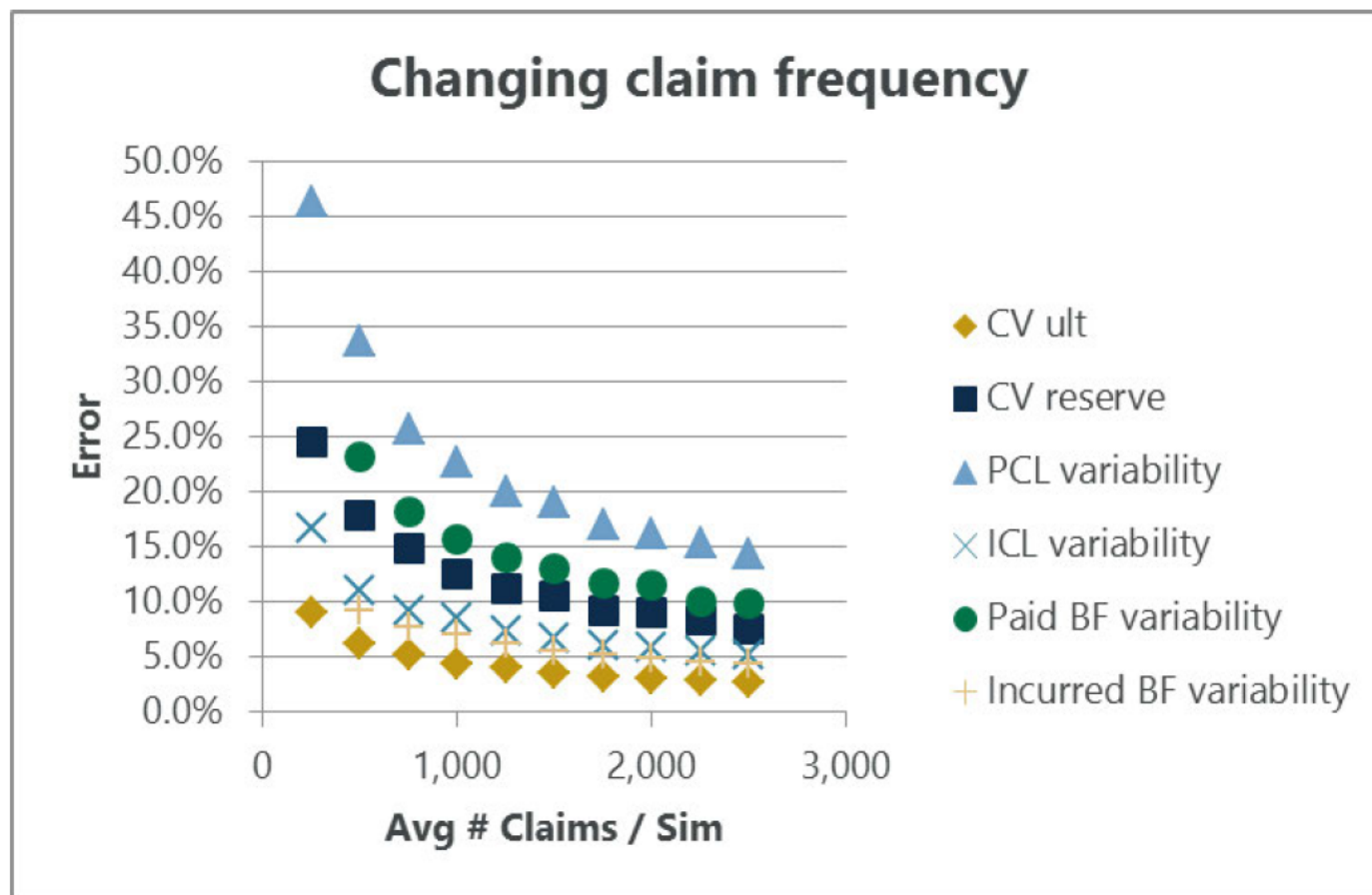
Results 6 – Sensitivity tests

B. Claim capping



Results 6 – Sensitivity tests

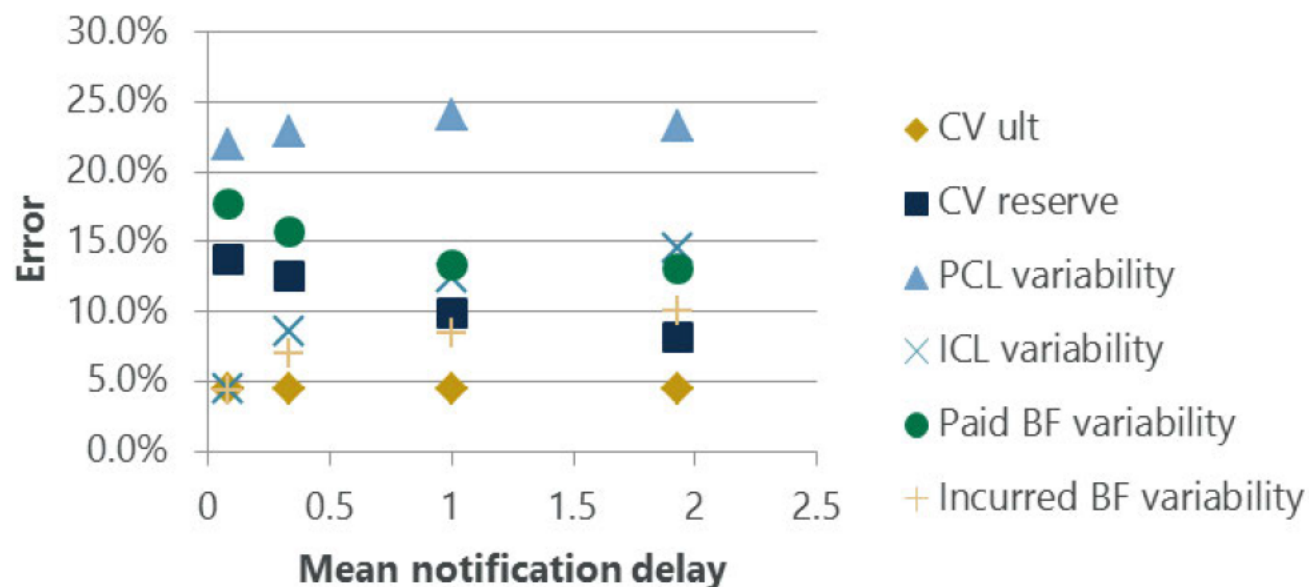
C. Claim frequency



Results 6 – Sensitivity tests

D. Notification delay

How model and process error change with 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



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Results 7 – Model robustness

Summary results

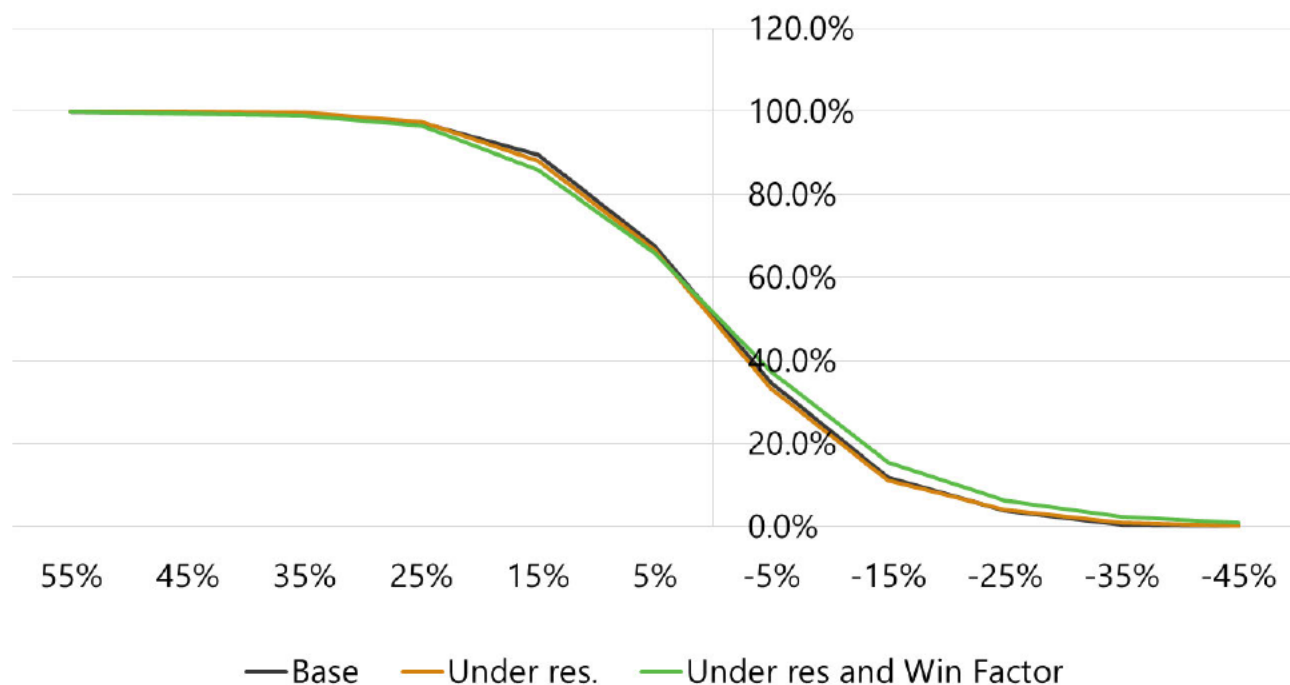
Additional feature	Model bias	Projection error	
Base model	0%	13%	No impact
Initial under-reserving	0%	14%	
Under-reserving and win factor	-1%	15%	
Weakening case estimates over time	16%	11%	Big impact



Results 7 – Model robustness

Stable features cause no problems

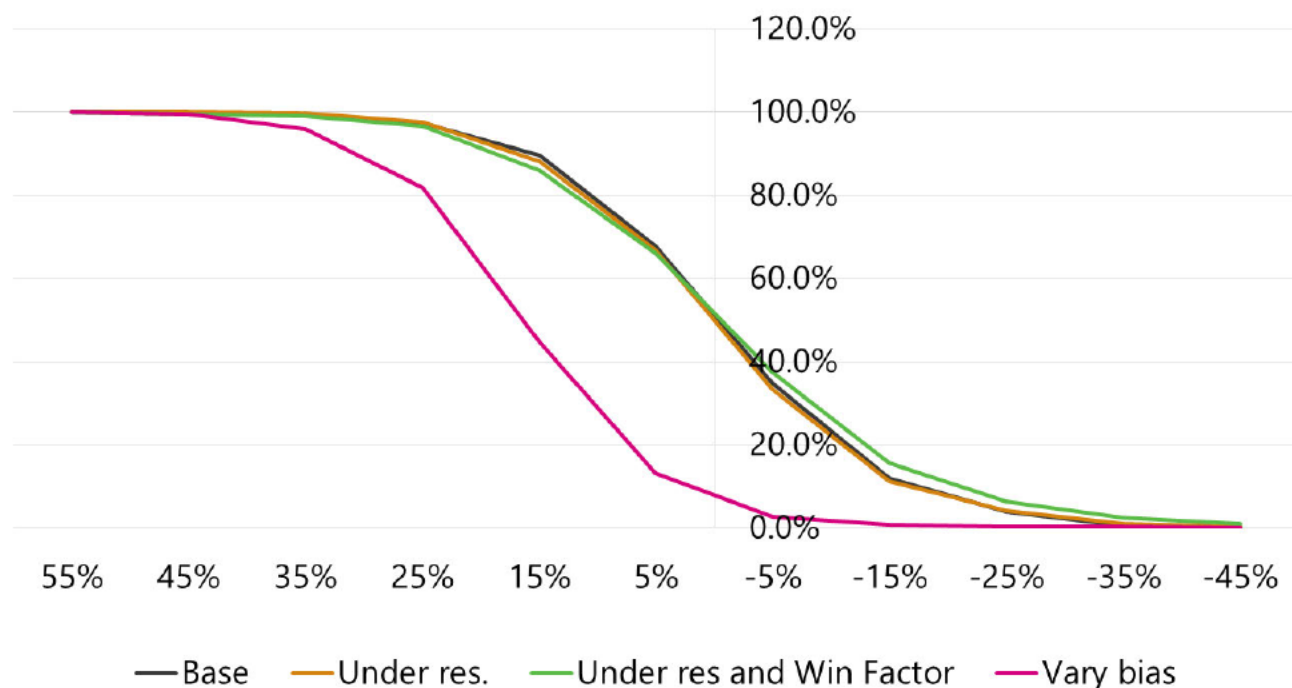
Probability estimate exceeds reserve



Results 7 – Model robustness

Model fails with non-stable process

Probability estimate exceeds reserve



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.

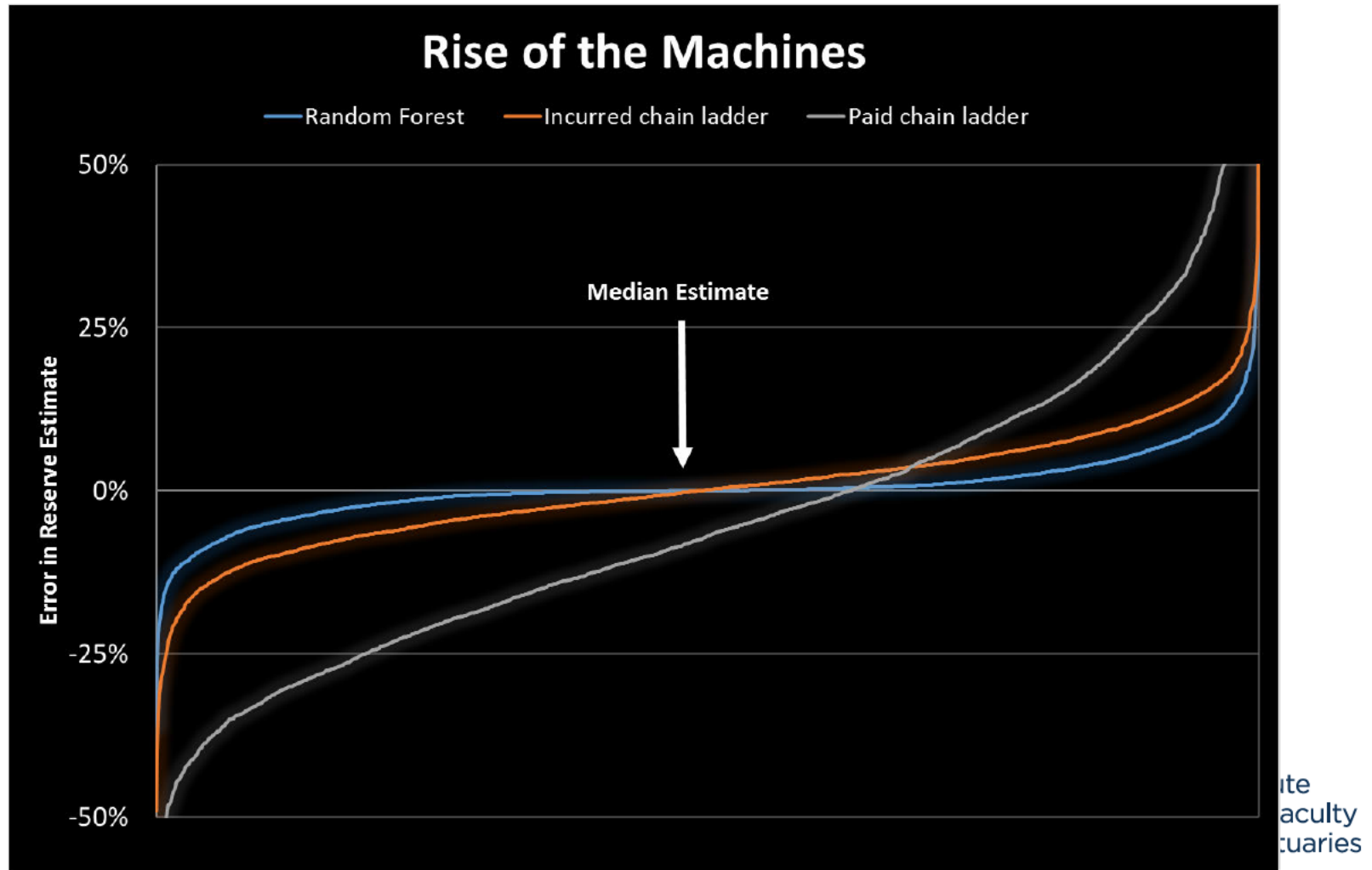


Where next?

- 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?



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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.



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