



ACTUARIAL SOCIETY
S O U T H A F R I C A

EXPANDING YOUR RESERVING TOOLKIT

15 August 2024

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AGENDA



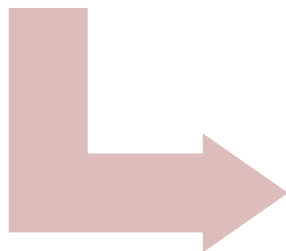
1. Introduction
 2. Global Reserving Landscape
 3. Reserving in the South African Landscape
 4. Practical Constraints - Data
 5. Expanding your reserving toolkit
 - ☐ *Projected Case Estimate Method*
 - ☐ *Munich Chain Ladder Method*
 - ☐ *Alternative BF Creditability Weights*
 - ☐ *Trend Adjustments*
 6. Conclusion and Discussion
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INTRODUCTION



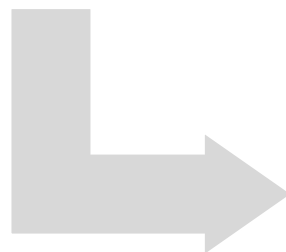
Global Reserving Landscape

- So much research, innovation, variety, suggestions and demand to change



Uncertainties and problems

- Clear problems with traditional methods, but we face difficulty implementing more robust solutions



How do we navigate this in SA market?

- Still heavily relying on traditional methods

Global Reserving Landscape



Factors influencing reserving processes

- Increased need to **adapt** to change, uncertainty and emerging trends
 - Increased reporting **frequency** and level of **sophistication** required
 - **Competitive** push to respond to **technological** advances, e.g. GenAI
 - **SaaS** products becoming available for Actuaries
 - Actuaries delving into **data science** and **ML**, challenging traditional modelling mindsets
 - Management and governance require **proactivity** and not reactivity
-

Global Reserving Landscape



Responding to inflation in the UK general insurance market



Claims inflation — technical challenge and decision-making uncertainty

- Claims inflation **impacts all general insurers** — but not in the same way
- The PRA has **identified a range of areas** across modelling, capital management and governance that require further consideration by firms
- It is critical to carefully **challenge assumptions** about the impact of claims inflation on reserving, capital, risk modelling, pricing and business planning — both for existing and future exposures
- The first step is identifying the **drivers of claims inflation** for an individual firm, which will be different from the headline inflation rate and vary by geography and product line
- Firms cannot necessarily rely on historical data and **should assess existing modelling techniques** to determine if they can still be relied on
- There needs to be a **holistic view of inflation**, bringing together claims, reserving, capital modelling and underwriting/pricing functions as well as feeding into the business planning cycle

Global Reserving Landscape



Reserving practices continue to change

Influenced by

.. technology

.. big data

.. regulatory requirements

Need to understand uncertainty in models

Time and opportunity to broaden our roles and evolve reserving techniques

Guess the year

Reserving practices are expected to continue to change, as the influences of technology, big data and regulatory requirements continue to evolve. Actuaries can have significant role, although it requires collaboration with other professions and being aware of technology and new techniques. Technology developments should be embraced but core actuarial skills and insight are a key actuarial strength.

There remains a need to understand the uncertainty in models, be able to provide insights, and design of data and models. There is likely to be opportunities for actuaries to focus more on the application of expert judgement than mechanics and potentially work with more diverse teams. Actuaries, with professional and ongoing training are well placed to be key advisers to the many stakeholders.

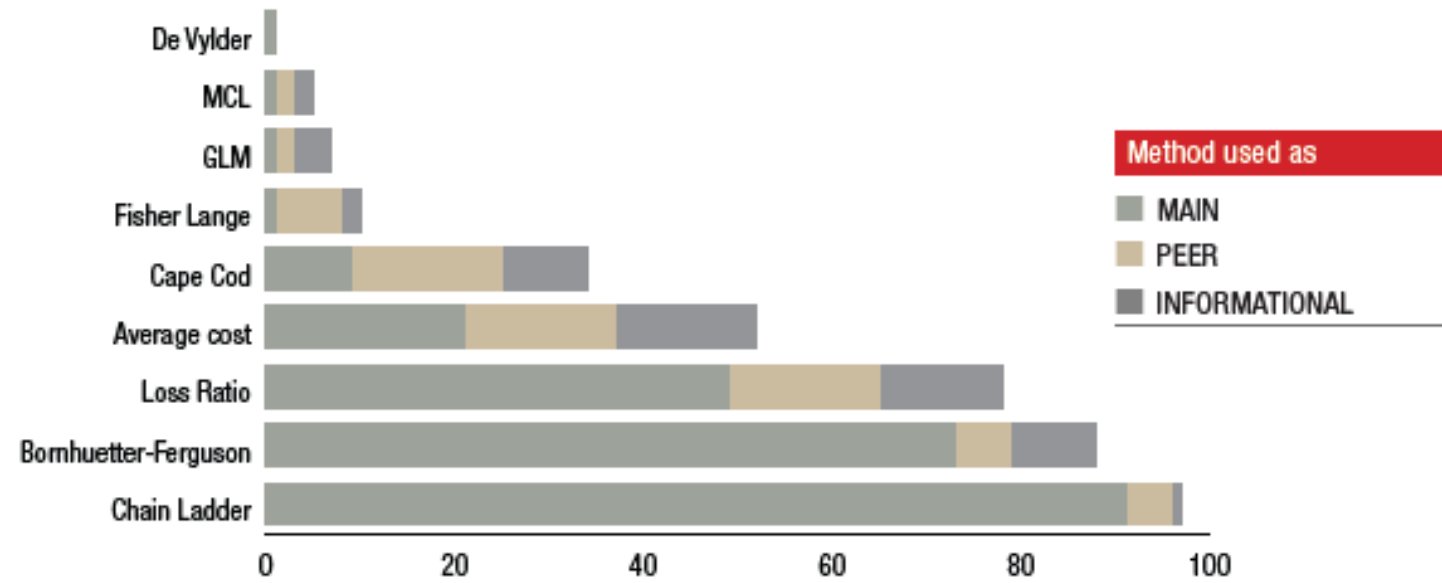
The view across our global professional is these represent exciting times for our profession, the opportunity to broaden our roles, and continue to evolve the reserving techniques and support to our industry.

2016



Global results MOST USED METHODS

Main deterministic methods used



Reserving in the South African Landscape



Standard claims: triangle-based technologies 2016

	Main method	Peer method	Informational	Unused
Percentage	10%	0%	5%	86%
Loss ratio	5%	24%	14%	57%
Chain ladder	74%	0%	17%	9%
Bornhuetter-Ferguson	32%	23%	18%	27%
Cape Cod	9%	5%	0%	86%
Average cost	14%	5%	29%	52%
De Vylder	0%	0%	0%	100%
Fisher-Lange	0%	0%	0%	100%
GLM	0%	0%	0%	100%
Munich Chain Ladder	0%	0%	0%	100%

Reserving in the South African Landscape



Adjustments / misc.

Past inflation	Not treated	86%	Year per year	14%	Other modalities	0%
Future inflation	Not treated	87%	Flat assumption	13%	Other modalities	0%
Discounting	Not treated	57%	Dvt patterns-based	26%	Other modalities	17%
Discount type	Yield curve	75%	Flat rate	25%	Other modalities	0%
Development patterns	Chain ladder/paid	91%	Other	5%	Other modalities	5%
Diversification effect	Not calculated	96%	Correlation matrix	4%	Other modalities	0%
Large claims	Treated separately	48%	Treated jointly	43%	Other modalities	9%
Reinsurance / retrocession	Projection of net triangles	43%	N/A	26%	Other modalities	30%
Subrogations	Projection of net triangles	48%	Not calculated	17%	Other modalities	35%
Ibnr contract allocation	Not allocated	65%	Individual claims reserving	17%	Other modalities	17%
Equalization reserve (local)	No eq. reserve	83%	Calculated	17%	Other modalities	0%
Risk Margin	Projected	64%	Percentage	18%	Other modalities	18%
Ibnyr and Ibner diff.?	No	83%	Yes	17%	Other modalities	0%

Reserving in the South African Landscape



Key developments



Covid 19



Adverse weather conditions



KZN Riots



High inflation, rise in interest rates and volatile markets



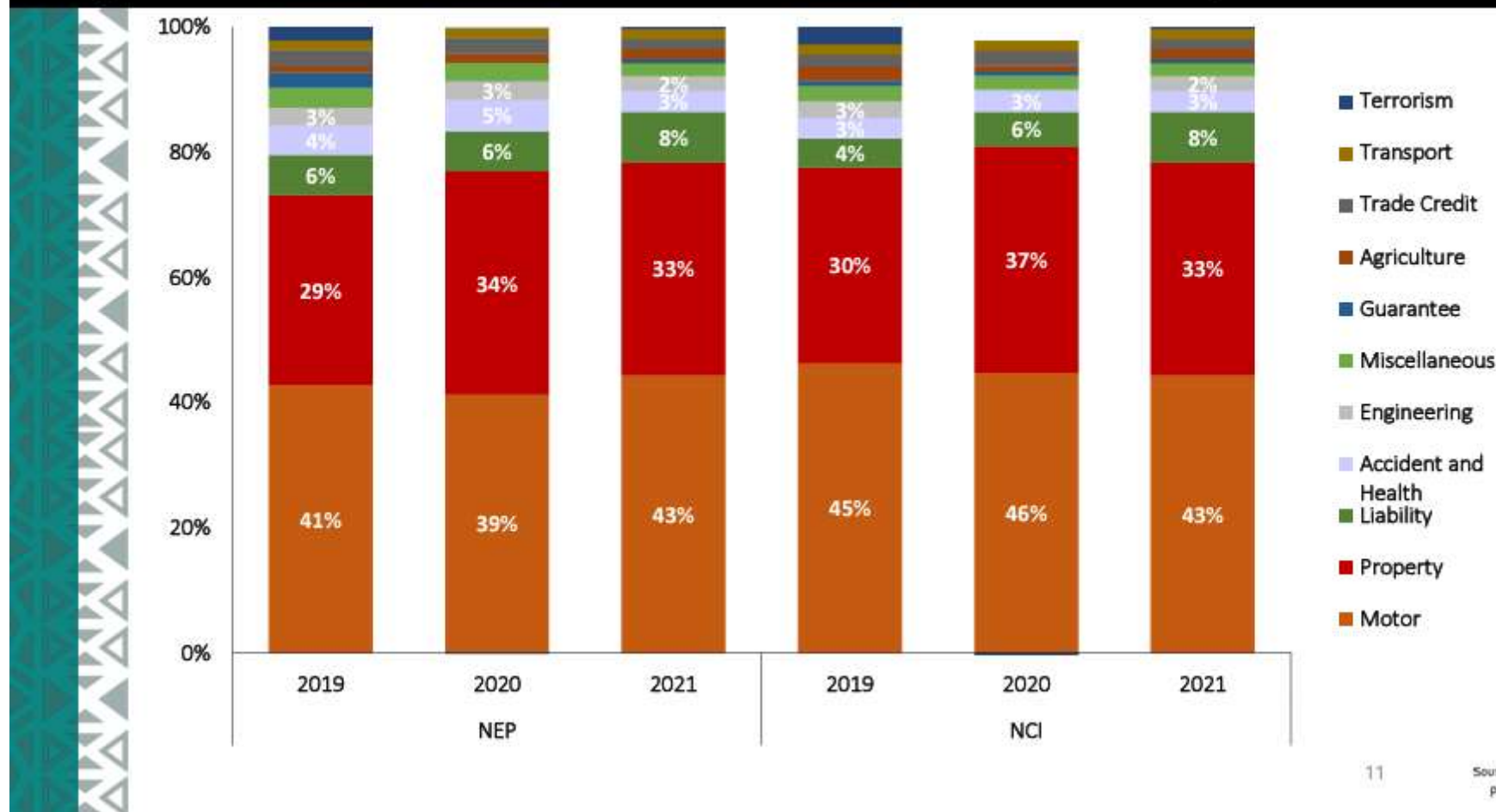
Loadshedding



Reserving in the South African Landscape



Key Financial Indicators – Premium and Claims by Line of Business





Addressing practical constraints

Addressing Practical Constraints



Improving level of information in data

1. Alternatives to bordereaux
 2. Aggregated / monthly claim positions vs transactional claims data
 3. Increase frequency of preparing claims datasets – ideally available on demand
 4. Add data points – finalised dates, activity periods
 5. Expand triangles available in reserving process
 - case estimates, closed numbers, open numbers, reported numbers, active numbers
 6. Need to set goals (roadmap)
-



Expanding your reserving toolkit –



– a few practical ways

Projected Case Estimate Method



Method Description

The Projected Case Estimate (PCE) method calculates the **development** of **case estimates** and **payments** on these case estimates, producing lower triangles of both payments and case estimates.

Selections required for each development period:

- Paid to Outstanding (PO) factors
- Case Estimate Development (CED) factors

$$PO_{i,t} = \frac{P_{i,t}}{CE_{i,t-1}}$$

$$CED_{i,t} = \frac{P_{i,t} + CE_{i,t}}{CE_{i,t-1}}$$

Projected Case Estimate Method



Assumptions

The PCE method assumes **consistency** over time for:

- The approach to case estimation
- The claims reporting patterns
- The payment patterns
- The mix of claims
- Inflation and currency trends

If the approach to case estimation has not been consistent over time, any changes need to be allowed for, e.g. by segmenting the triangle or on-levelling the data.

Projected Case Estimate Method



Method Description

Suitable:

- older origin periods for which case estimates are more accurate (or at least stable)

Less suitable:

- recent origin periods
 - portfolios with a high proportion of IBNR claims
 - volatile case estimates
-

Projected Case Estimate Method



Calculations

1. **Calculate** $PO_{i,t}$ and $CED_{i,t}$

(Paid to outstanding factor and case estimate development factor)

$$PO_{i,t} = \frac{P_{i,t}}{CE_{i,t-1}}$$

$$CED_{i,t} = \frac{P_{i,t} + CE_{i,t}}{CE_{i,t-1}}$$

2. Make **selections** for PO_t and CED_t

3. **Project** future $P_{i,t}$ and $CE_{i,t}$

(Incremental payments and closing case estimate position)

$$P_{i,t} = CE_{i,t-1} \times PO_t$$

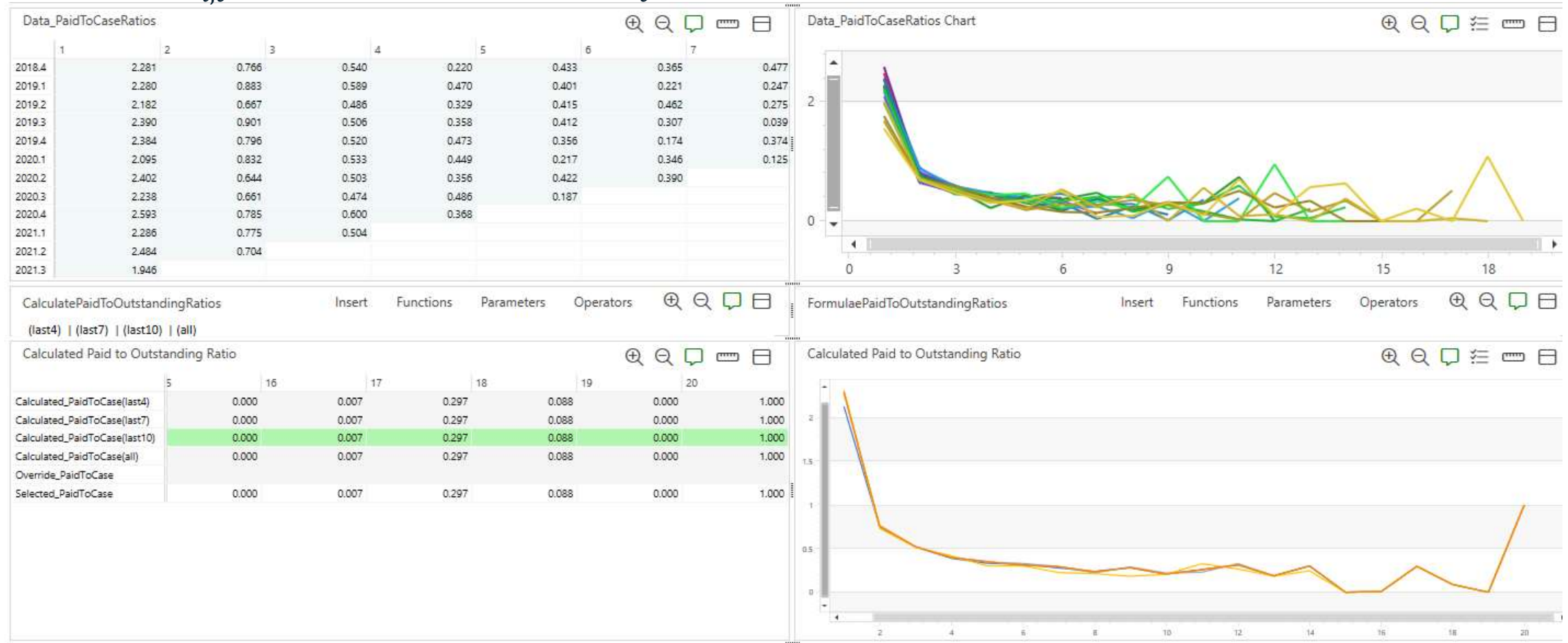
$$CE_{i,t} = CE_{i,t-1} \times (CED_t - PO_t)$$

Projected Case Estimate Method



Paid to Case Estimate Ratios

Calculate $PO_{i,t}$ and make selections for PO_t

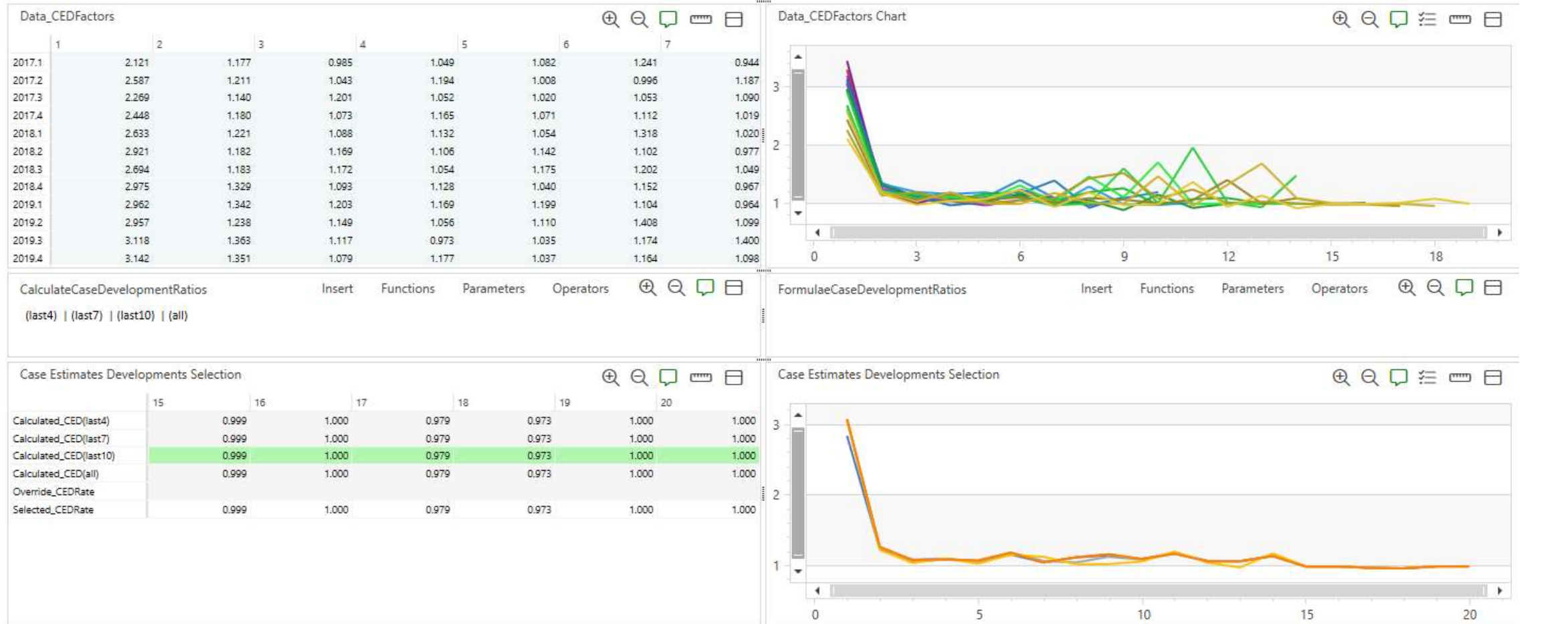


Projected Case Estimate Method



Case Estimate Development Factors

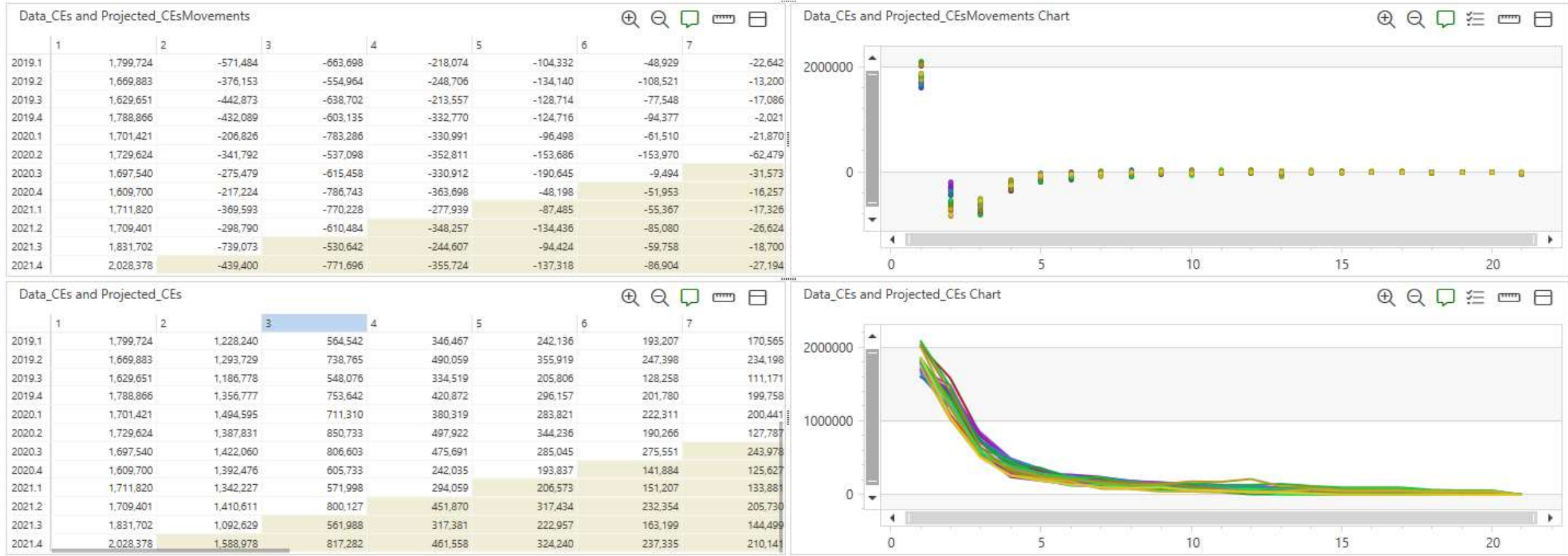
Calculate $CED_{i,t}$ and make selections for CED_t



Projected Case Estimate Method



Projected Case Estimates

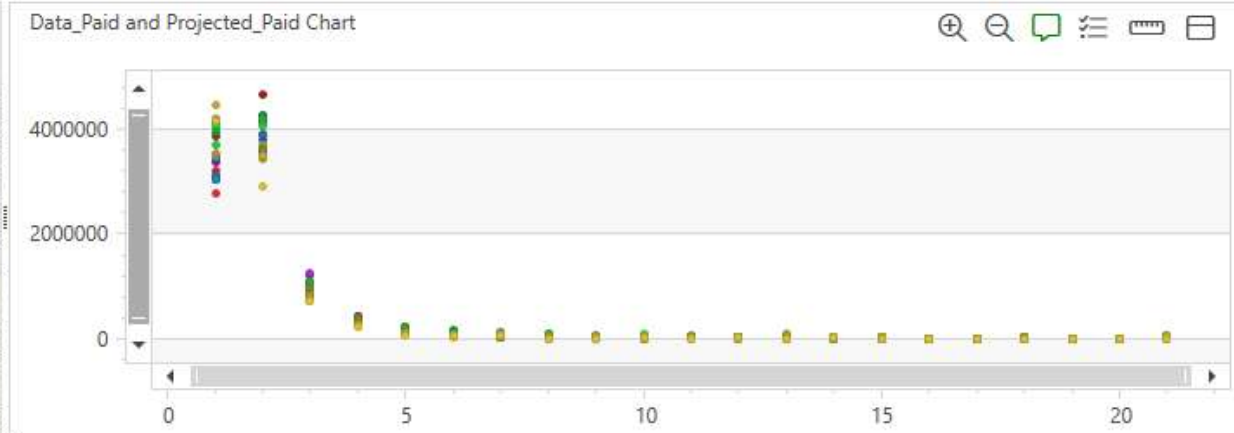


Projected Case Estimate Method

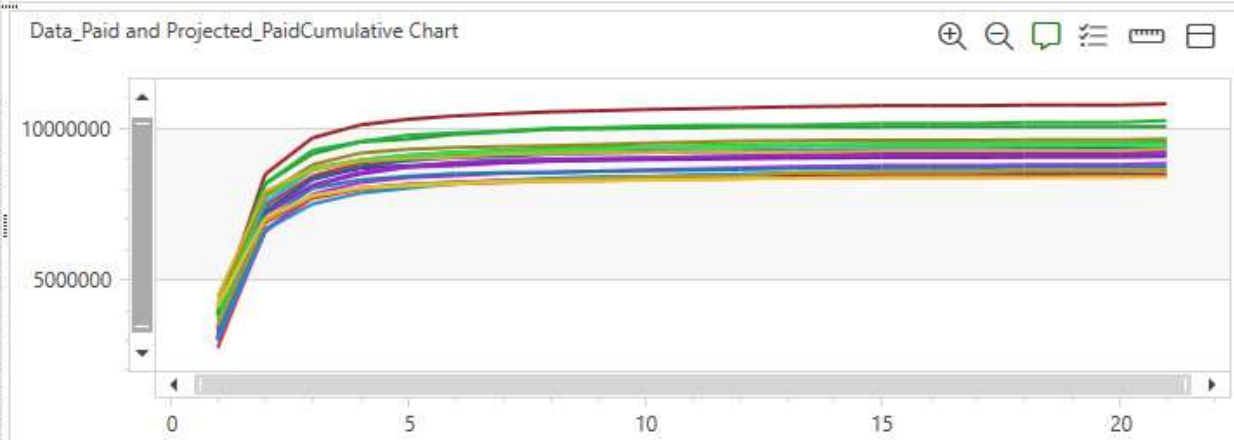


Projected Payments

Data_Paid and Projected_Paid							
	1	2	3	4	5	6	7
2019.1		3,470,736	4,103,324	1,084,100	332,767	162,947	96,998
2019.2		3,033,957	3,643,497	862,674	359,066	161,380	147,559
2019.3		3,095,428	3,894,893	1,069,378	277,498	119,804	84,846
2019.4		3,035,841	4,264,380	1,079,617	392,186	199,129	105,287
2020.1		3,053,923	3,565,049	1,243,439	379,439	170,832	61,538
2020.2		3,113,371	4,155,040	893,362	427,725	177,191	145,368
2020.3		3,404,225	3,799,185	939,673	382,507	231,062	53,421
2020.4		3,087,078	4,174,621	1,093,322	363,585	89,134	68,039
2021.1		2,777,210	3,913,393	1,040,611	288,405	117,041	72,509
2021.2		3,221,841	4,246,604	993,081	418,251	179,853	111,422
2021.3		3,364,688	3,564,061	832,630	293,769	126,324	78,260
2021.4		3,856,052	4,657,862	1,210,869	427,219	183,709	113,811



Data_Paid and Projected_PaidCumulative							
	1	2	3	4	5	6	7
2019.1		3,470,736	7,574,060	8,658,160	8,990,926	9,153,873	9,250,871
2019.2		3,033,957	6,677,454	7,540,128	7,899,194	8,060,574	8,208,133
2019.3		3,095,428	6,990,321	8,059,699	8,337,198	8,457,002	8,541,848
2019.4		3,035,841	7,300,222	8,379,838	8,772,025	8,971,154	9,076,440
2020.1		3,053,923	6,618,972	7,862,410	8,241,849	8,412,682	8,474,220
2020.2		3,113,371	7,268,412	8,161,774	8,589,499	8,766,691	8,912,059
2020.3		3,404,225	7,203,410	8,143,082	8,525,590	8,756,652	8,810,073
2020.4		3,087,078	7,261,699	8,355,021	8,718,606	8,807,740	8,875,779
2021.1		2,777,210	6,690,603	7,731,214	8,019,619	8,136,661	8,209,170
2021.2		3,221,841	7,468,445	8,461,526	8,879,777	9,059,631	9,171,053
2021.3		3,364,688	6,928,749	7,761,379	8,055,148	8,181,472	8,259,732
2021.4		3,856,052	8,513,915	9,724,784	10,152,003	10,335,712	10,449,523



Munich Chain Ladder Method



Method Description

“A reserving method that reduces the gap between IBNR projections based on paid losses and IBNR projections based on incurred losses.”

- Gerhard Quarg and Thomas Mack

[illegible]

Munich Chain Ladder Method



Calculations

- Development factors – incurred and paid
- Paid to incurred and incurred to paid ratios
- Residuals for all of the above
- Relationship between residuals (λ)

Using these residuals and the relationship between them, the method iteratively calculates future claim development factors to arrive at a lower triangle of paid and incurred claims.

Munich Chain Ladder Method



Example

Taken from the original MCL paper by Quarg and Mack (2008). Further details on the method can be found in this paper.

Paid Losses

Year	1	2	3	4	5	6	7
1	576	1804	1970	2024	2074	2102	2131
2	866	1948	2162	2232	2284	2348	
3	1412	3758	4252	4416	4494		
4	2286	5292	5724	5850			
5	1868	3778	4648				
6	1442	4010					
7	2044						

Incurred Losses

Year	1	2	3	4	5	6	7
1	978	2104	2134	2144	2174	2182	2174
2	1844	2552	2466	2480	2508	2454	
3	2904	4354	4698	4600	4644		
4	3502	5958	6070	6142			
5	2812	4882	4852				
6	2642	4406					
7	5022						

Munich Chain Ladder Method



Example

Paid Development Factors

Year	1	2	3	4	5	6
1	3.13	1.092	1.027	1.025	1.014	1.014
2	2.25	1.11	1.032	1.023	1.028	
3	2.66	1.131	1.039	1.018		
4	2.31	1.082	1.022			
5	2.02	1.23				
6	2.78					

Incurred Development Factors

Year	1	2	3	4	5	6
1	2.151	1.014	1.00	1.014	1.00	1.00
2	1.384	0.966	1.006	1.011	0.978	
3	1.50	1.079	0.979	1.01		
4	1.70	1.019	1.012			
5	1.736	0.994				
6	1.668					

Incurred to Paid Ratio

Year	1	2	3	4	5	6	7
1	1.70	1.166	1.083	1.059	1.048	1.038	1.02
2	2.13	1.31	1.141	1.111	1.10	1.045	
3	2.06	1.159	1.10	1.042	1.033		
4	1.53	1.126	1.06	1.05			
5	1.51	1.292	1.044				
6	1.83	1.10					
7	2.46						

Paid to Incurred Ratio

Year	1	2	3	4	5	6	7
1	0.589	0.857	0.923	0.944	0.954	0.963	0.98
2	0.47	0.763	0.877	0.9	0.911	0.957	
3	0.486	0.863	0.905	0.96	0.968		
4	0.653	0.888	0.943	0.952			
5	0.664	0.774	0.958				
6	0.546	0.91					
7	0.407						

Munich Chain Ladder Method



Example

Summary Stats of paid development factors, weighted by paid losses

Weighted Average	2.437	1.131	1.029	1.021	1.021	1.014
Std dev (weighted)	13.456	3.666	0.482	0.210	0.479	0.100

Summary Stats of incurred to paid ratios, weighted by paid losses

Weighted Average	1.878	1.178	1.078	1.058	1.054	1.042	1.020
Std dev (weighted)	14.943	4.990	2.167	1.619	1.791	0.237	

Summary Stats of incurred development factors, weighted by incurred losses

Weighted Average	1.652	1.019	1.000	1.011	0.990	0.996
Std dev (weighted)	9.727	2.545	1.004	0.120	0.860	0.100

Summary Stats of paid to incurred ratios, weighted by incurred losses

Weighted Average	0.533	0.849	0.928	0.945	0.949	0.960	0.980
Std dev (weighted)	5.711	3.819	1.918	1.461	1.637	0.221	

For $j = 1 \dots J - 2$, $K = \{P, I\}$

$$f_j^K = \frac{\sum_{n=1}^{J-j} C_{n,j+1}^K}{\sum_{n=1}^{J-j} C_{n,j}^K}$$

$$\hat{\sigma}^P(j) = \sqrt{\frac{1}{J-j-1} \sum_{n=1}^{J-j} P_{n,j} \left(\frac{P_{n,j+1}}{P_{n,j}} - \hat{f}_j^P \right)^2}$$

$$\hat{\sigma}^I(j) = \sqrt{\frac{1}{J-j-1} \sum_{n=1}^{J-j} I_{n,j} \left(\frac{I_{n,j+1}}{I_{n,j}} - \hat{f}_j^I \right)^2}$$

$$\hat{q}(j) = \frac{\sum_{n=1}^{J-j+1} P_{n,j}}{\sum_{n=1}^{J-j+1} I_{n,j}} \quad \text{and} \quad \hat{q}_{Inv}(j) = \frac{\sum_{n=1}^{J-j+1} I_{n,j}}{\sum_{n=1}^{J-j+1} P_{n,j}}$$

and

$$\hat{\sigma}^Q(j) = \sqrt{\frac{1}{J-j} \sum_{n=1}^{J-j+1} I_{n,j} (Q_{n,j} - \hat{q}(j))^2}$$

$$\hat{\sigma}^{Q_{Inv}}(j) = \sqrt{\frac{1}{J-j} \sum_{n=1}^{J-j+1} P_{n,j} (Q_{n,j}^{-1} - \hat{q}_{Inv}(j))^2}$$

Munich Chain Ladder Method



Residuals

Residuals of paid development factors

Year	1	2	3	4	5	6
1	1.24	-0.45	-0.18	0.85	-0.72	0
2	-0.41	-0.26	0.29	0.57	0.69	
3	0.628	0.00	1.25	-0.98		
4	-0.43	-0.98	-1.15			
5	-1.33	1.66				
6	0.971					

Residuals of incurred development factors

Year	1	2	3	4	5	6
1	1.61	-0.08	0.22	1.13	0.73	0
2	-1.18	-1.04	0.29	0.1	-0.68	
3	-0.85	1.57	-1.42	-0.84		
4	0.3	0.00	0.93			
5	0.46	-0.68				
6	0.08					

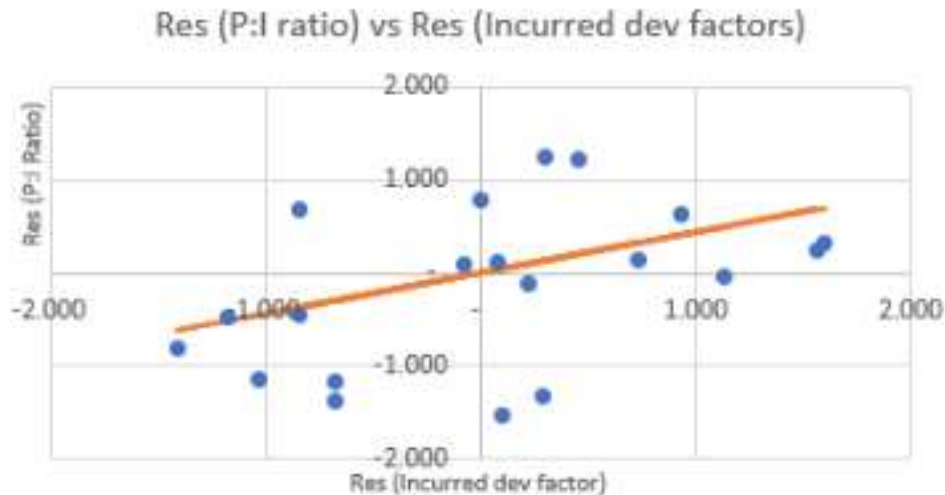
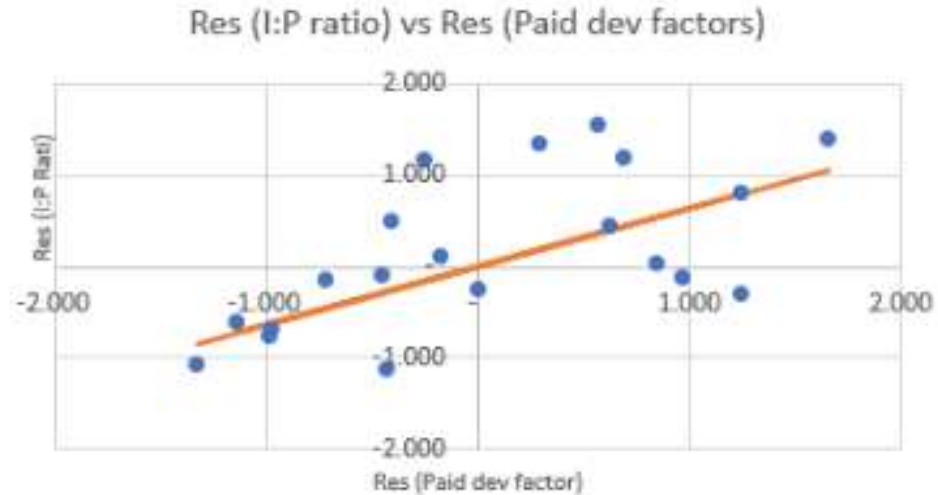
Residuals of incurred:paid ratio

Year	1	2	3	4	5	6
1	-0.29	-0.1	0.11	0.03	-0.14	-0.72
2	0.496	1.17	1.34	1.55	1.19	0.69
3	0.45	-0.24	0.81	-0.68	-0.75	
4	-1.11	-0.76	-0.61	-0.39		
5	-1.08	1.41	-1.08			
6	-0.12	-1.01				
7	1.753					

Residuals of paid:incurred ratio

Year	1	2	3	4	5	6
1	0.31	0.1	-0.11	-0.03	0.14	0.73
2	-0.47	-1.13	-1.32	-1.54	-1.18	-0.69
3	-0.44	0.25	-0.8	0.69	0.77	
4	1.25	0.8	0.63	0.4		
5	1.22	-1.37	1.1			
6	0.12	1.06				
7	-1.56					

Munich Chain Ladder Method



Lambda values

Paid Lambda = 0.636

Incurred Lambda = 0.436

$$\widehat{\lambda}^P = \frac{\sum_A \widehat{\text{Res}}(Q_{i,j}^{-1}) \widehat{\text{Res}}(F_{i,j}^P)}{\sum_A \widehat{\text{Res}}(Q_{i,j}^{-1})^2}$$

$$\widehat{\lambda}^I = \frac{\sum_A \widehat{\text{Res}}(Q_{i,j}) \widehat{\text{Res}}(F_{i,j}^I)}{\sum_A \widehat{\text{Res}}(Q_{i,j})^2}$$

Relationship:

Residual of paid dev factor (i, j → j+1)

= paid lambda * residual of incurred to paid ratio (i, j)

Residual of incurred dev factor (i, j → j+1)

= incurred lambda * residual of paid to incurred ratio (i, j)

Munich Chain Ladder Method



Example

Paid Losses

Year	1	2	3	4	5	6	7
1	576	1804	1970	2024	2074	2102	2131
2	866	1948	2162	2232	2284	2348	2383
3	1412	3758	4252	4416	4494	4573	4597
4	2286	5292	5724	5850	5967	6081	6119
5	1868	3778	4648	4762	4848	4923	4938
6	1442	4010	4388	4493	4574	4643	4656
7	2044	5659	6944	7177	7330	7485	7549

Incurred Losses

Year	1	2	3	4	5	6	7
1	978	2104	2134	2144	2174	2182	2174
2	1844	2552	2466	2480	2508	2454	2444
3	2904	4354	4698	4600	4644	4618	4629
4	3502	5958	6070	6142	6212	6167	6176
5	2812	4882	4852	4885	4944	4931	4950
6	2642	4406	4567	4601	4657	4646	4665
7	5022	7828	7687	7644	7727	7650	7650

Paid Development Factors

Year	1	2	3	4	5	6
1	3.132	1.092	1.027	1.025	1.014	1.014
2	2.249	1.110	1.032	1.023	1.028	1.015
3	2.661	1.131	1.039	1.018	1.018	1.005
4	2.315	1.082	1.022	1.020	1.019	1.006
5	2.022	1.230	1.025	1.018	1.015	1.003
6	2.781	1.094	1.024	1.018	1.015	1.003
7	2.769	1.227	1.033	1.021	1.021	1.008

Incurred Development Factors

Year	1	2	3	4	5	6
1	2.151	1.014	1.005	1.014	1.004	0.996
2	1.384	0.966	1.006	1.011	0.978	0.996
3	1.499	1.079	0.979	1.010	0.994	1.002
4	1.701	1.019	1.012	1.011	0.993	1.001
5	1.736	0.994	1.007	1.012	0.997	1.004
6	1.668	1.036	1.007	1.012	0.998	1.004
7	1.559	0.982	0.994	1.011	0.990	1.000

Incurred to Paid Ratio

Year	1	2	3	4	5	6	7
1	1.698	1.166	1.083	1.059	1.048	1.038	1.020
2	2.129	1.310	1.141	1.111	1.098	1.045	1.026
3	2.057	1.159	1.105	1.042	1.033	1.010	1.007
4	1.532	1.126	1.060	1.050	1.041	1.014	1.009
5	1.505	1.292	1.044	1.026	1.020	1.002	1.003
6	1.832	1.099	1.041	1.024	1.018	1.001	1.002
7	2.457	1.383	1.107	1.065	1.054	1.022	1.013

Paid to Incurred Ratio

Year	1	2	3	4	5	6	7
1	0.589	0.857	0.923	0.944	0.954	0.963	0.980
2	0.470	0.763	0.877	0.900	0.911	0.957	0.975
3	0.486	0.863	0.905	0.960	0.968	0.990	0.993
4	0.653	0.888	0.943	0.952	0.961	0.986	0.991
5	0.664	0.774	0.958	0.975	0.981	0.998	0.997
6	0.546	0.910	0.961	0.977	0.982	0.999	0.998
7	0.407	0.723	0.903	0.939	0.949	0.978	0.987

Munich Chain Ladder Method



Results Comparison – Basic CL vs Munich CL

“A reserving method that reduces the gap between IBNR projections based on paid losses and IBNR projections based on incurred losses.”

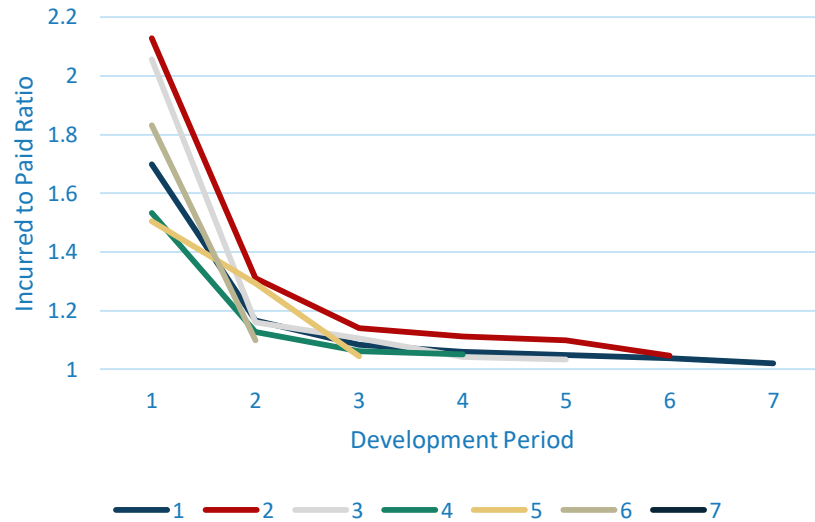
- Gerhard Quarg and Thomas Mack

Year	Paid		Incurred	
	Ultimate CL	Ultimate MCL	Ultimate CL	Ultimate MCL
1	2,131	2,131	2,174	2,174
2	2,380	2,383	2,445	2,444
3	4,652	4,597	4,582	4,629
4	6,182	6,119	6,126	6,176
5	5,056	4,938	4,839	4,950
6	4,934	4,656	4,476	4,665
7	6,128	7,549	8,429	7,650
Total	31,463	32,372	33,071	32,688

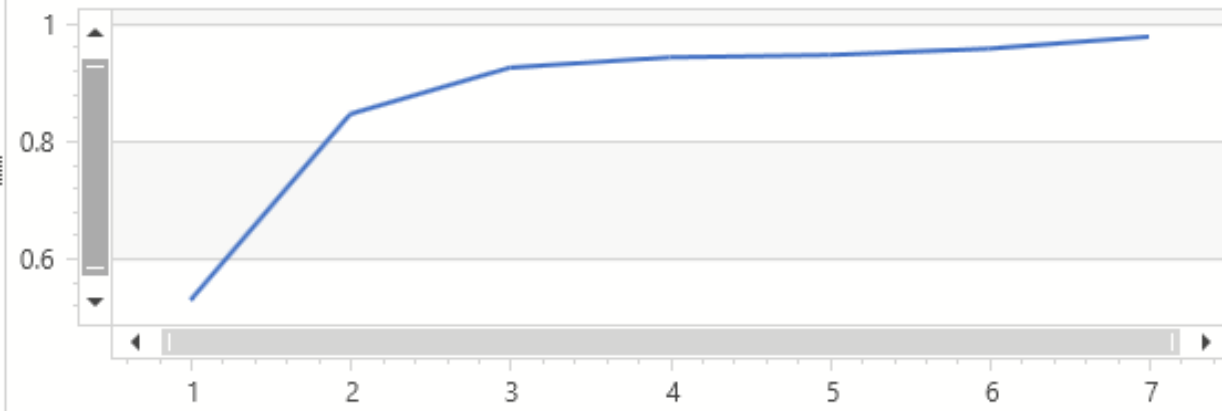
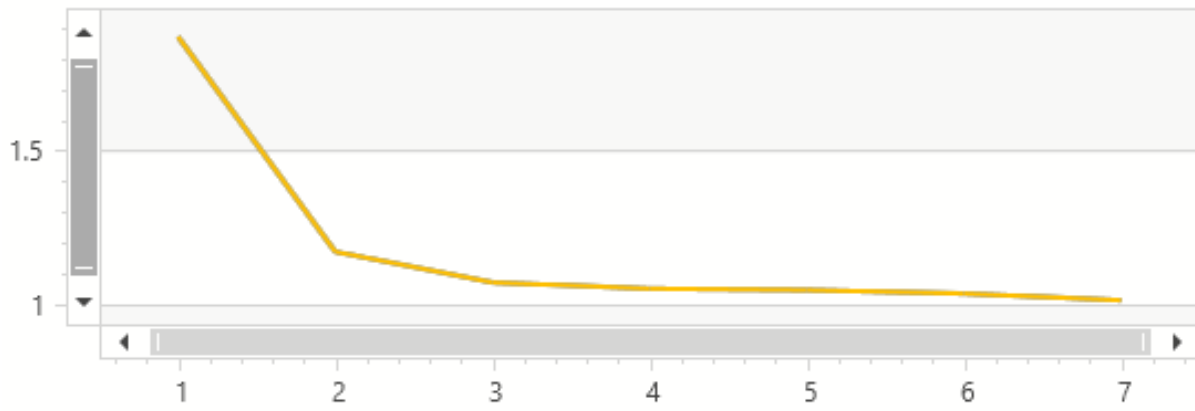
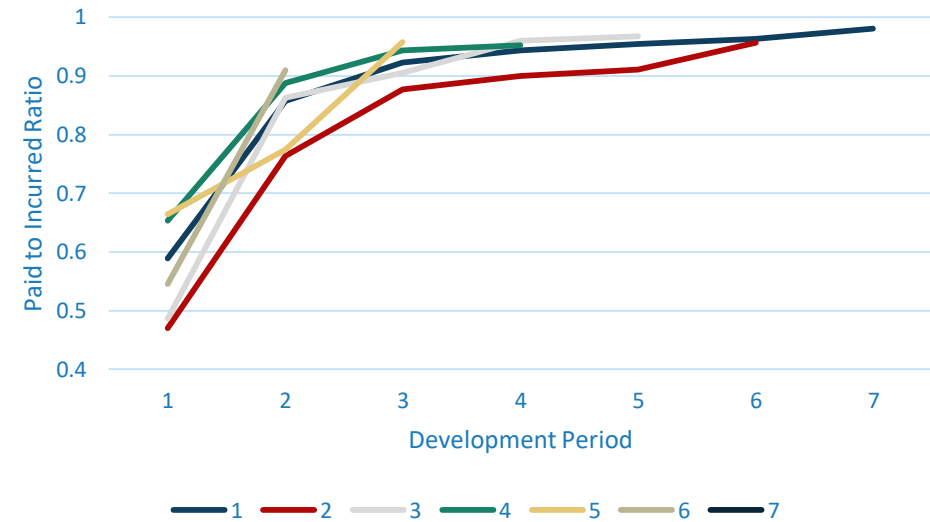
Munich Chain Ladder Method



Incurred to Paid ratios per origin year



Paid to Incurred ratios per origin year



Munich Chain Ladder Method



Advantages

Closes the gap between IBNR projected on paid vs incurred basis

Allows for **correlation** between paid and incurred data

Takes **variance** of paid and incurred claims into account

Residuals are calculated which can be used in a **Bootstrap**

Insights gained on **speed of development** of paid vs incurred claims relative to average speed

Limitations

Assumes **past** claims development pattern is reflective of **future** development patterns

- If claims triangles are not inflation-adjusted, implicitly assumes weighted average of **past** inflation is reflective of expected **future** inflation

- Development of latest claims of the first origin period will be as dictated by the **tail factor**

- Assumes a **linear relationship** between the residuals of the paid development factor and the residuals of the I:P ratio

- Assumes a **linear relationship** between the residuals of the incurred development factor and the residuals of the P:I ratio

Alternative BF Credibility Weights



Gluck (1998) proposed that the weights used in the Standard BF method might not be the most optimal, especially when:

- The LDF is less than 1.0
- The LDF is close to 1.0 when a large portion of incurred consists of case estimates

Solutions:

- Use Paid CL pattern for credibility weights
- Rework the credibility weights by taking the absolute value of pattern increments

$$L = D \frac{1}{LDF} + A \left[1 - \frac{1}{LDF} \right]$$

where

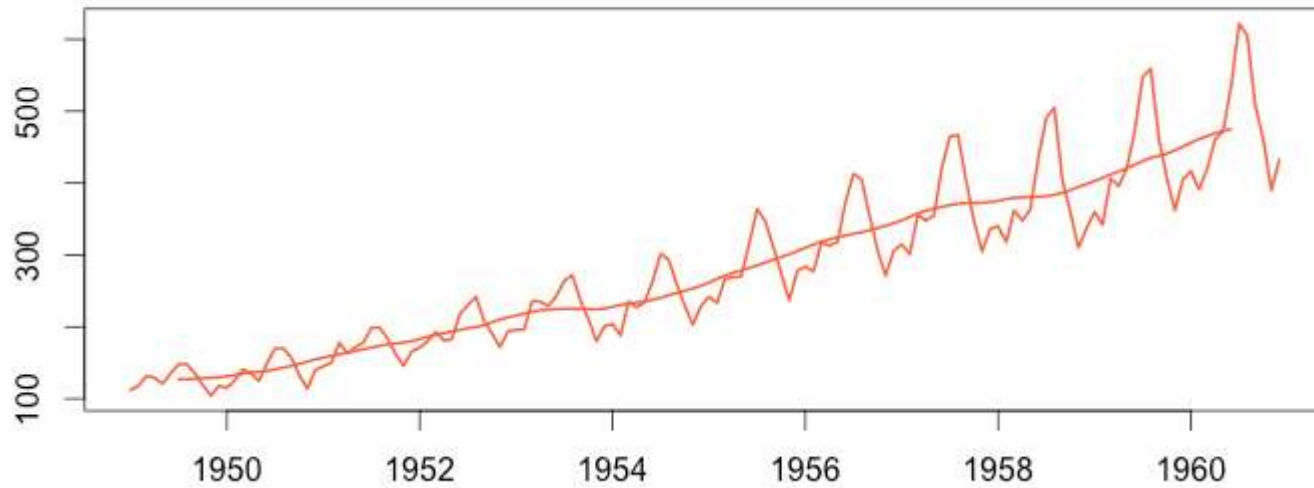
L	=	estimated ultimate loss
D	=	loss development estimate
A	=	expected loss estimate
LDF	=	loss development factor.

Balancing Development and Trend in Loss Reserve Analyses (Gluck, Spencer, 1998)

Trend Adjustments

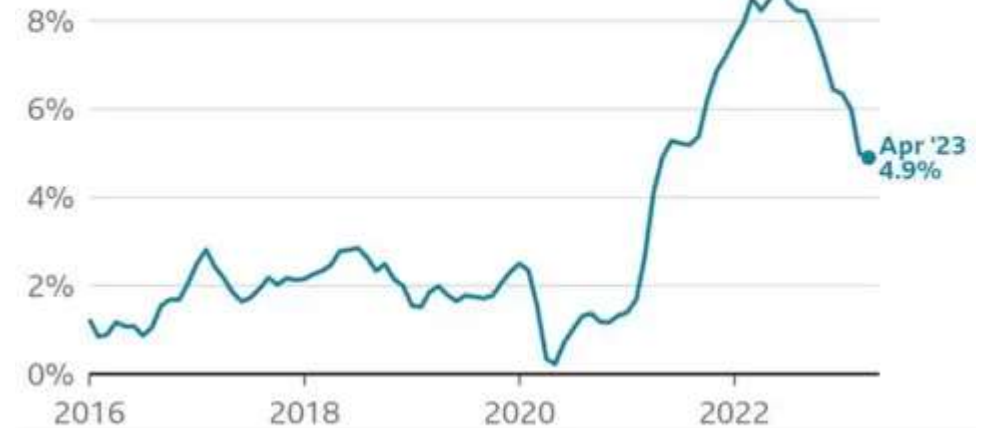


Seasonality



US inflation at 4.9%

Consumer Price Index for all urban consumers,
% change from a year ago



Source: US Bureau of Labor Statistics

BBC

Trend Adjustments



What else can you adjust your claims history for?

- Changes in mix of business
 - Changes in T's and C's
 - Changes in average policy length
 - Distortions in data
 - Changes in Claims Handling
 - Changes in case reserve policy
 - Allowance for re-underwriting
 - External Environment Impacts
 - “actuarial judgement”
-

Trend Adjustments



Methodology Example

1. Split trend analysis in Frequency and Severity
(combine at the end to arrive at an ultimate claim projection)
 2. Adjust Frequency (Numbers / Exposure) for:
 - Changes in risk mix of business -> divide historic data with risk adjustment factors
 - Seasonality
 - > Calculate average frequency by quarter/month for last couple of periods
 - > Investigate for trends
 - > Set assumption about seasonality trend (adjustment factor per quarter)
 - > Historic data with risk adjustment factors
 3. Fit a curve through adjusted frequency (e.g. log-linear regression fit)
 4. Calculate final frequency by multiplying extrapolated curve by Risk Mix and Seasonality factors
-

Trend Adjustments



Methodology Example

5. Repeat process for Severity.

Adjust for:

- Changes in risk mix of business
- Seasonality
- Inflation

6. Multiply final frequency x exposure x severity

- Can be used as Ultimate
 - Can be used as APriori in BF
-

CONCLUSION AND DISCUSSION



These methods give additional insights and provide benefits even if not used to set reserves directly.

E.g.

- identifying trends which may otherwise be overlooked
- breaking down drivers
- support assumption setting
- provide more narrative

Relevant to the SA market (predominantly short tail)

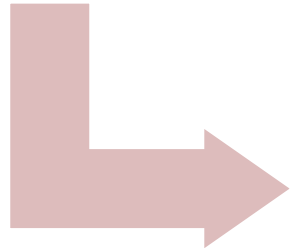
Realistic to implement given constraints

CONCLUSION AND DISCUSSION



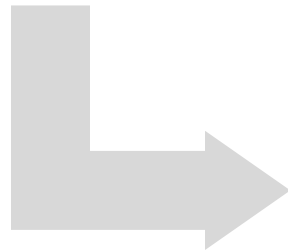
Global
Reserving
Landscape

So much research, innovation, variety,
suggestions and demand to change



Uncertainties
and problems

Clear problems with traditional methods, but
we face difficulty implementing more robust
solutions



How do we
navigate this
in SA market?

Still heavily relying on
traditional methods



Questions?

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