REINSURANCE BOOT CAMP ON PRICING TECHNIQUES:
Experience Rating

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August 14, 2019

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Agenda

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- Basic Experience Rating Method
- Experience Rating as a GLM
- Diagnostics: Telling the Story
- Credibility Weighting with Exposure

Experience Rating Method

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Steps in Experience Rating:

1. Assemble Data
2. Adjust Subject Premium to Future Level
3. Trend and Layer Losses
4. Apply Loss Development

Note: This presentation will discuss Casualty Nonproportional Treaty pricing, but the general principles may apply to other lines and products.

Experience Rating Method
Assemble Data

Premium Data:

1. Historical premium and estimate for prospective period
2. Rate/Price change history and estimate for prospective period

Loss Data:

1. Include all historical losses that would trend into the layer (rule of thumb: get all losses > half of your attachment point)
2. Split out ALAE for each loss
3. Include historical policy limits (and SIR if applicable)
4. Confirm that losses are assembled by occurrence, not by claimant
5. Loss development for excess

Experience Rating Method
Assemble Data

Key issue in assembling data is “information asymmetry” – the buyer generally knows more about the underlying risks than does the reinsurer.

Especially important if the historical experience has been adjusted to exclude discontinued operations. E.G., if we exclude losses, have we also excluded premium?

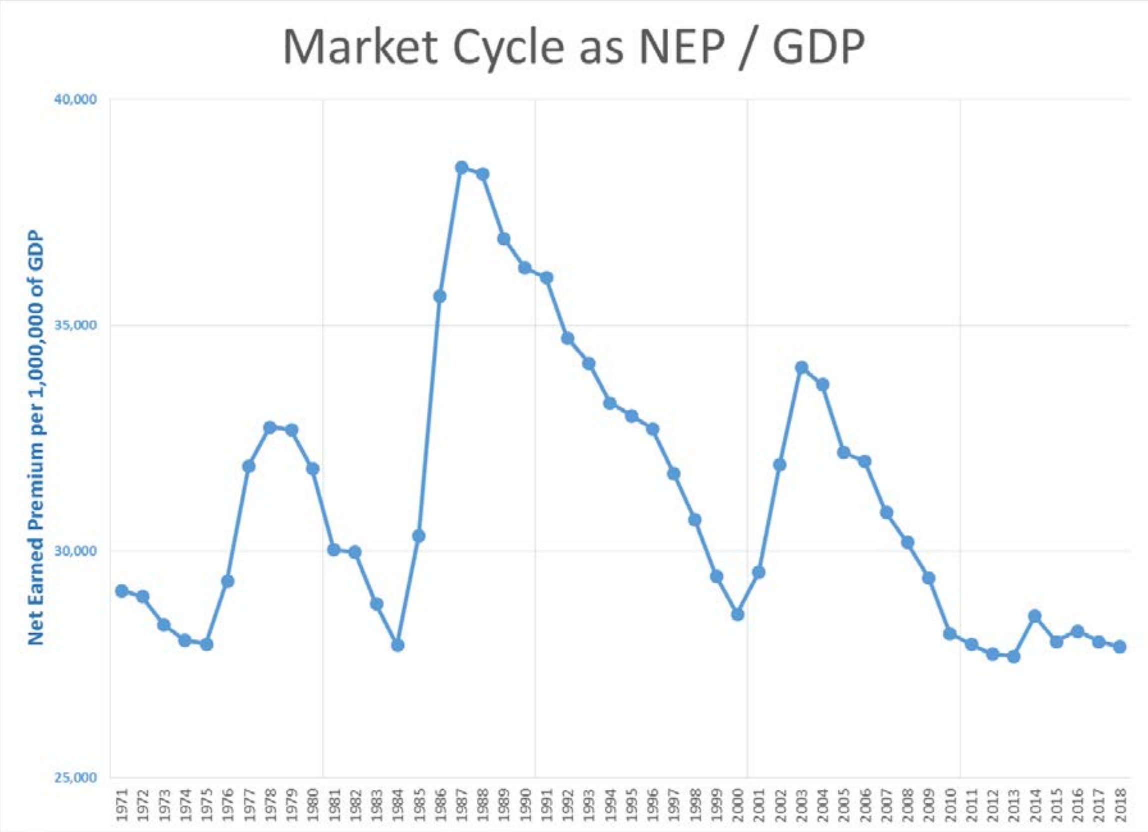
Akerlof, George A. “The Market for ‘Lemons’: Quality Uncertainty and the Market Mechanism” (1970)

http://www.utdallas.edu/~nina.baranchuk/Fin7310/papers/Akerlof1970.pdf

Selling reinsurance is a lot like buying a used car from the ceding company

Experience Rating Method

Rate Change



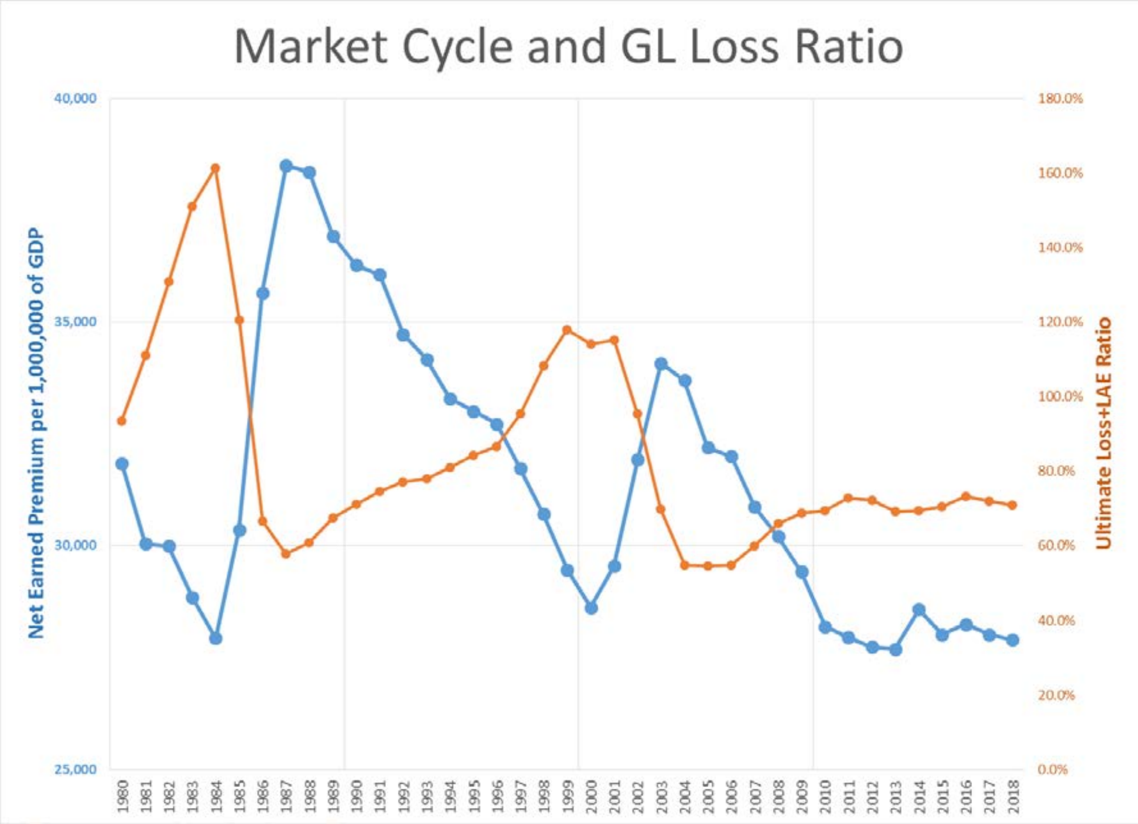
The market cycle is a critical dynamic in P&C insurance pricing.

This high-level graph shows total industry Net Earned Premium (NEP) relative to GDP as an approximate exposure base.

Source: SNL, BEA

Experience Rating Method

Rate Change

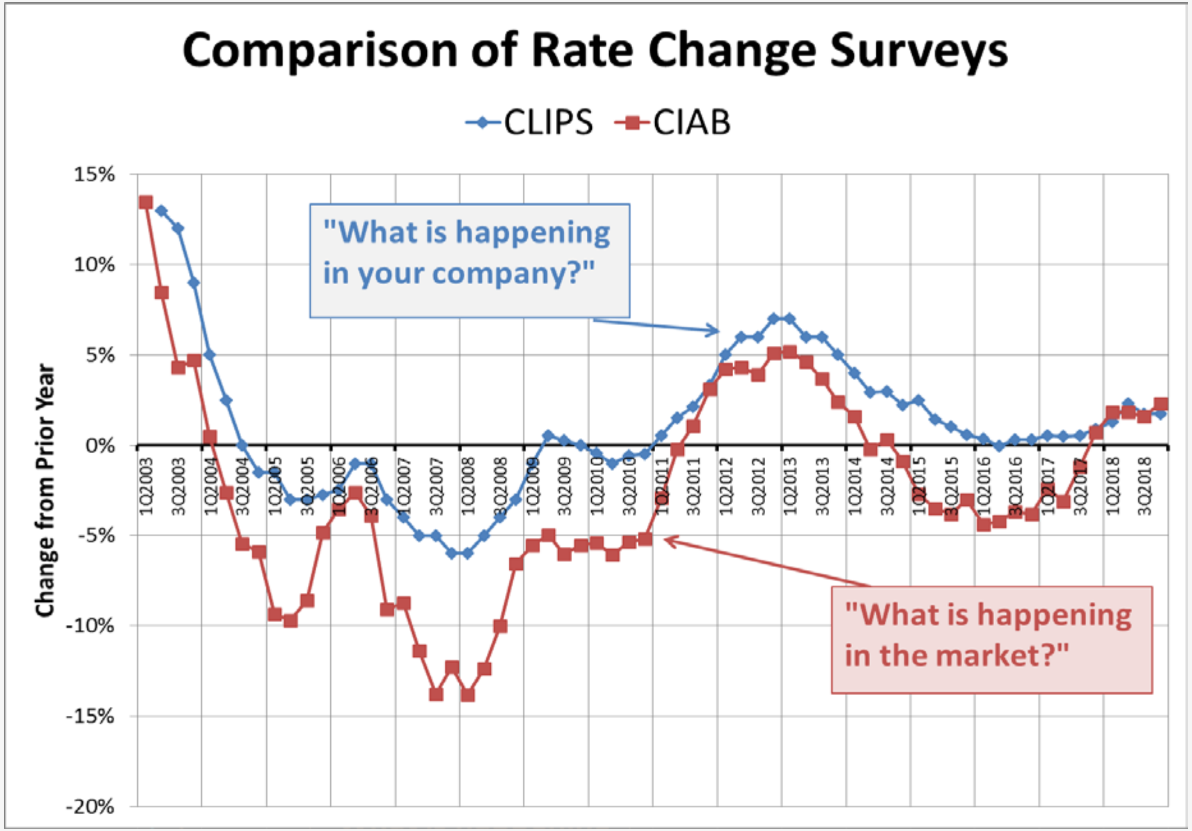


Even at a very high level, the market cycle explains much of the movement of loss ratios.

When rates increase, loss ratios decrease…

All companies are subject to this competitive pressure but they do not all have same loss ratios.

Experience Rating Method
Rate Change

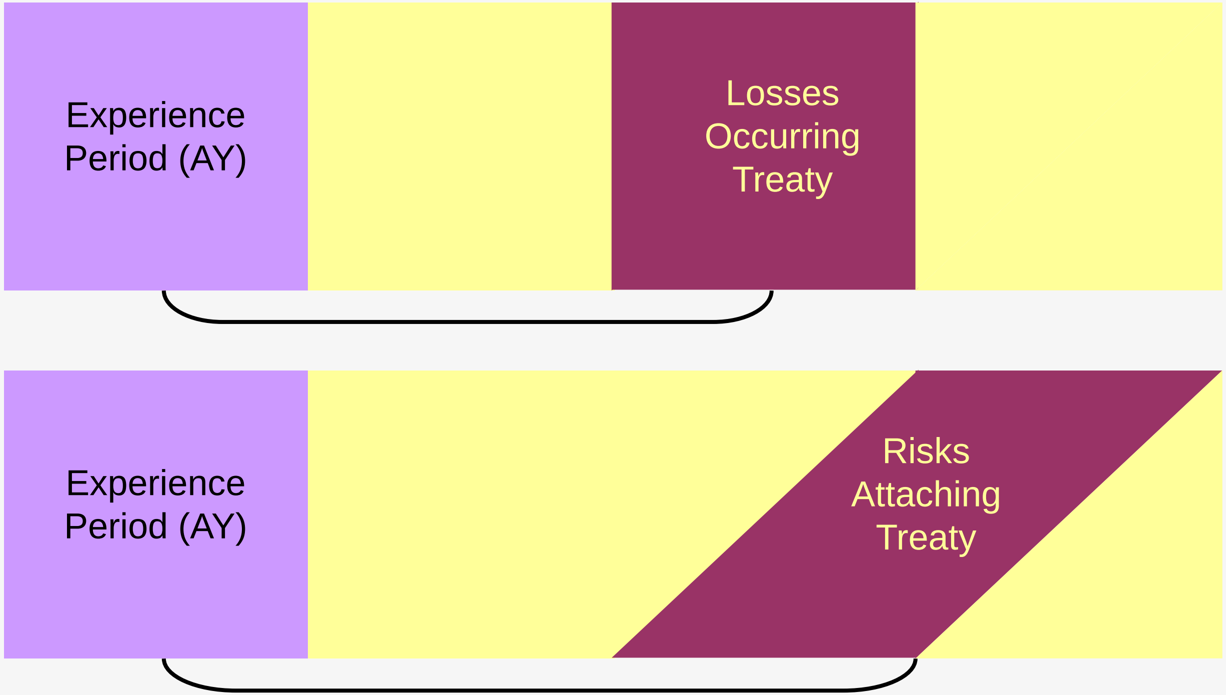


The source of rate change information may introduce bias when estimating an onlevel factor.

- Filed rates versus actual charged rates?
- Expiring/Renewal only?
- Survey Data?
- Include exposure growth?

Sources: Willis Towers Watson, CIAB

Experience Rating Method
Trending Losses



The amount of trend may be dependent upon the types of policy periods included in the data.

We want to trend from the “average” point in each period.

Experience Rating Method

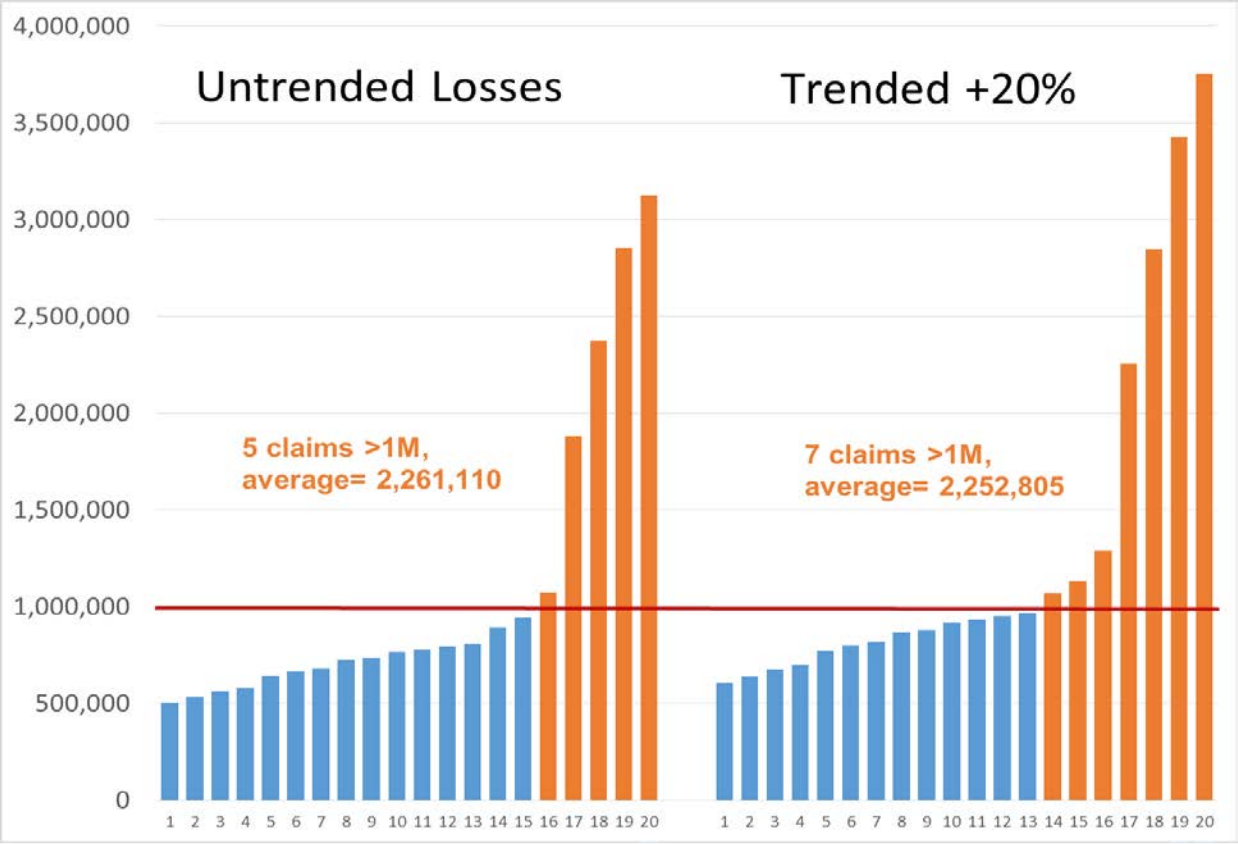
Trending Losses

Layer:	500,000	excess of	500,000
	Untrended	**Trended**	**Trend %**
Total # of Claims	100	100	
Pareto B	125,000	135,000	
Pareto Q	1.55	1.55	
Overall Severity	227,273	245,455	8.0%
Layer Counts	8.3	9.1	9.9%
Layer Severity	313,899	315,687	0.6%
Layer Loss Cost	2,590,513	2,864,008	10.6%

For excess losses, the impact of trend is seen more in the frequency than in the [conditional] severity to the layer.

Numbers for illustration only

Experience Rating Method
Trending Losses



A common error in pricing is the “Pareto problem” in which there appears to be no trend on large losses.

This example shows an example where the “true” trend is +20% but we would measure it as <0% if all we had were the losses above 1,000,000.

Don’t do this !!!

Experience Rating Method
Trending Losses

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The “Pareto Problem” for Trending:

If the size-of-loss distribution for large losses is highly skewed and approximates a single parameter Pareto, then the historical large losses do not carry sufficient information to estimate severity trend.

Trend can be estimated indirectly via frequency but this is also challenging.

Stop the madness!

Read these papers by Vytaras Brazauskas, Bruce L. Jones and Ricardas Zitikis:

“*When Inflation Causes No Increase in Claim Amounts*” (2009)

https://www.researchgate.net/publication/26843551_When_Inflation_Causes_No_Increase_in_Claim_Amounts

“*Trends in disguise*” (2015)

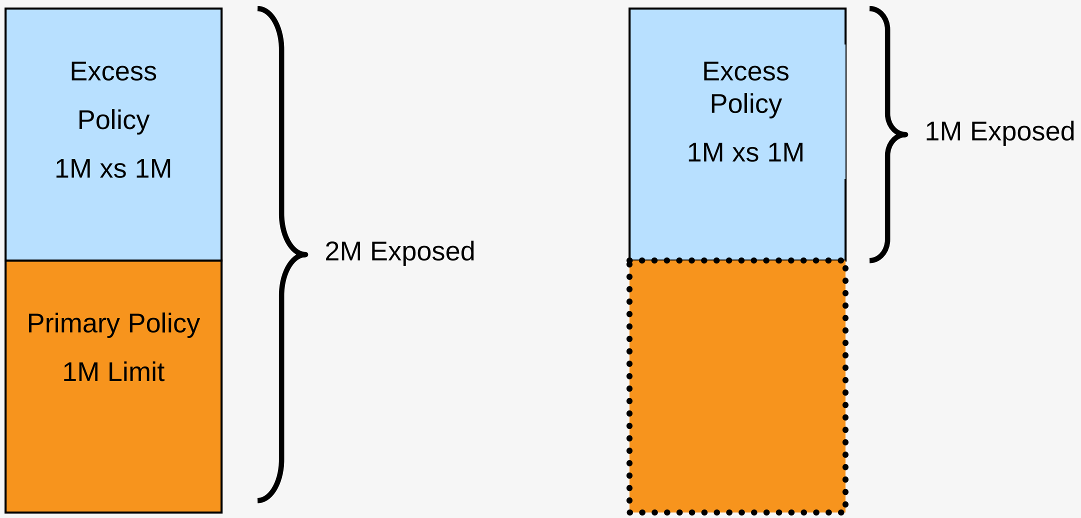
https://www.researchgate.net/publication/272247272_Trends_in_Disguise

Experience Rating Method

Trending Losses

Challenge of including excess policies:

<u>“Supported” Excess</u> **<u>“Unsupported” Excess</u>**



Experience Rating Method
Trending Losses

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Challenge of including excess policies:

We need to trend historical losses based on the full “from ground up” basis to get the trend in the excess layer.

We may still be missing losses below the unsupported excess policy that would trend into our layer. For this, we need to know the profile of limits and attachment points for the historical periods. Mata & Verheyen (2005) gives a good explanation on this.

Mata, Ana J., and Mark A. Verheyen, “An Improved Method for Experience Rating Reinsurance Treaties using Exposure Rating Techniques” (2005)

https://www.semanticscholar.org/paper/An-Improved-Method-for-Experience-Rating-Treaties-Mata-Ph./ba7197f291a90310ec96af9993f68afc50acebac

Experience Rating Method

Trending Losses

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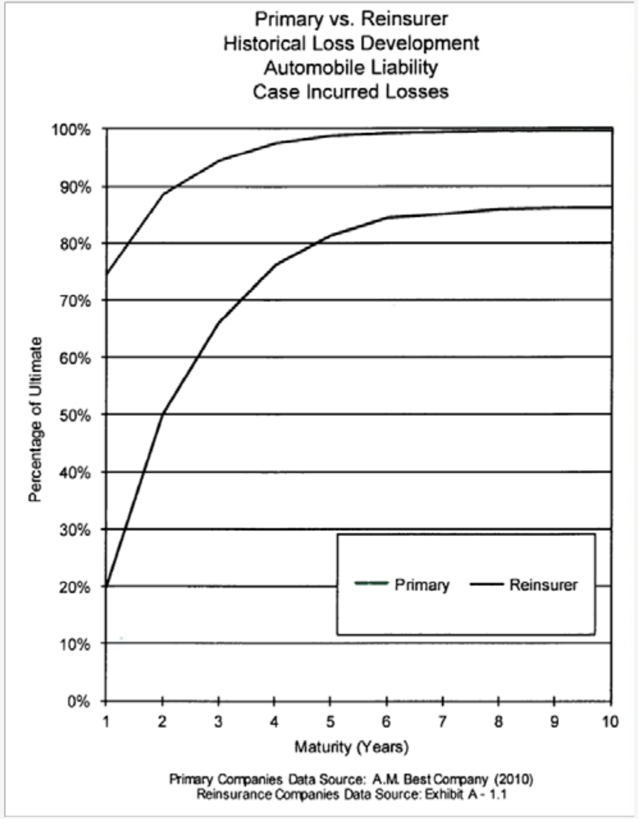
An additional challenge is social inflation, from sources such as:

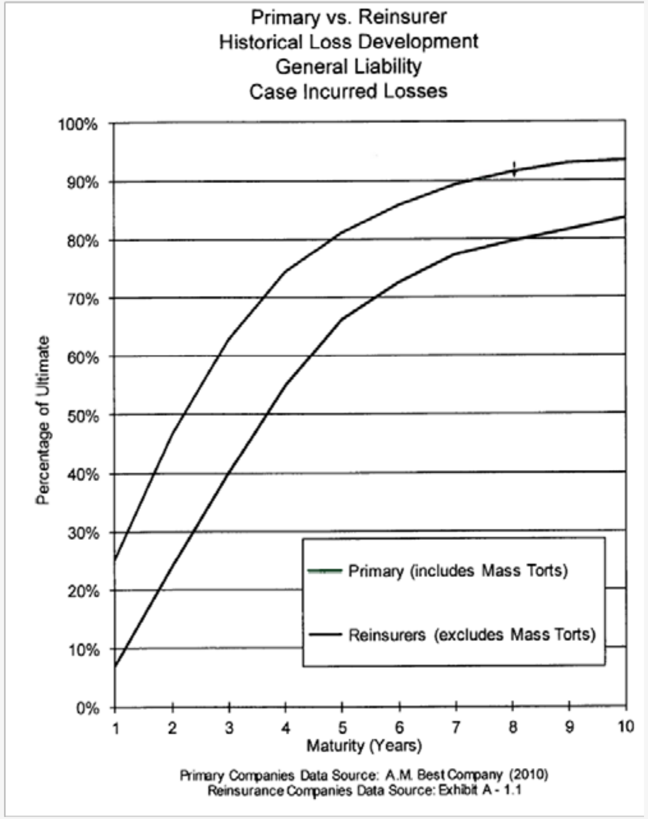
- Traumatic Brain Injuries (TBI)
- Punitive damages anchored on jury awards
- Silent Cyber
- Litigation Financing
- Social Justice and #MeToo

Emerging risks can be hard to quantify because of uncertain data sources and limited history.

Discuss with underwriting team how the reinsured portfolio may be exposed to these.

Experience Rating Method
Loss Development





Loss development for excess layers is significantly longer than for primary losses.

Source: RAA Loss Development Study 2012, via

https://www.casact.org/library/studynotes/Clark_2014.pdf

Experience Rating Method
Loss Development

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Accident Year	9	21	33	45	57	69	81
2012	837,000	3,299,000	4,698,000	6,023,000	6,551,000	7,432,000	7,880,000
2013	1,427,000	6,770,000	7,882,000	8,496,000	10,102,000	10,800,000	
2014	833,000	3,820,000	4,968,000	5,865,000	7,428,000		
2015	1,850,000	5,852,000	6,965,000	8,599,000			
2016	1,179,000	4,655,000	7,966,000				
2017	1,487,000	7,697,000					
2018	2,084,000						
2012	3.941	1.424	1.282	1.088	1.134	1.060	
2013	4.744	1.164	1.078	1.189	1.069		
2014	4.586	1.301	1.181	1.266			
2015	3.163	1.190	1.235				
2016	3.948	1.711					
2017	5.176						
Average	4.216	1.331	1.182	1.181	1.095	1.060	
LDF	10.010	2.374	1.784	1.508	1.277	1.166	1.100
	7.507	<== LDF to develop first 9 months to ultimate					

Numbers for illustration only

For loss development on the "stub period", the LDF should be consistent with the premium included.

- If premium includes only earned as of 9 months, then use lower LDF.
- If premium is for full year, then use larger LDF.

Experience Rating Method
Loss Development

Loss development is a challenge because of the volatile nature of excess losses. Some historical periods may have zero losses, so a simple LDF method may lead to biased results.

A “Cape Cod” approach includes the development with premium in the denominator of the ratio.

This allows us to include the latest immature (or “stub”) period in the experience rating.

$$ELR = \frac{\sum Loss * LDF}{\sum Premium}$$

$$ELR = \frac{\sum Loss}{\sum \frac{Premium}{LDF}}$$

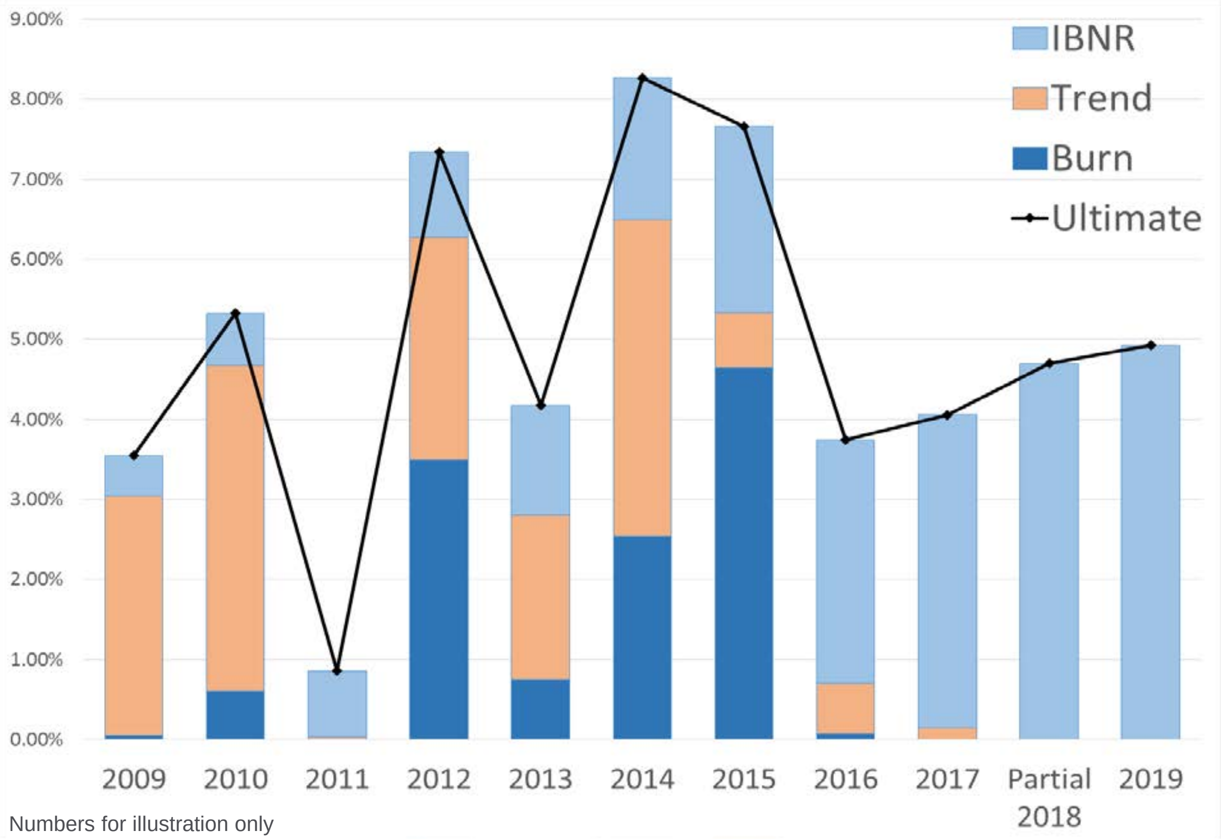
Experience Rating Method
Example

Numbers for illustration only

Pacific All Risk Insurance Company
General Liability
500,000 excess of 500,000 - Loss plus pro rata ALAE

										Cape Cod Method	
Accident Year	Historical Subject Earned Premium	Rate/Prc OnLevel Factor	Exposure Trend	Adjusted Subject Premium	LDF	Adj. Subject Premium / LDF	Layered Loss+ALAE Evaluated 9/30/2007	Trended Layered Loss+ALAE	LDF Ult. Loss Rate	Trended Ultimate Layered Loss+ALAE	Trended Ultimate Loss Rate
	(1)	(2)	(3)	(4)=(1)*(2)*(3)	(5)	(6)=(4)/(5)	(7)	(8)	(9)=(8)/(6)	(10)	(11)=(10)/(4)
2009	19,215,561	0.8497	1.2190	19,904,089	1.115	17,848,727	9,300	604,779	3.39%	705,954	3.55%
2010	18,237,944	0.9249	1.1951	20,158,836	1.151	17,513,775	122,259	942,986	5.38%	1,073,188	5.32%
2011	16,676,622	0.9740	1.1717	19,031,525	1.201	15,841,937	0	5,671	0.04%	162,677	0.85%
2012	14,924,410	1.0191	1.1487	17,470,367	1.274	13,709,805	609,711	1,096,962	8.00%	1,282,074	7.34%
2013	16,628,500	1.0076	1.1262	18,868,237	1.385	13,621,715	142,331	529,773	3.89%	788,031	4.18%
2014	17,458,606	0.9700	1.1041	18,697,037	1.566	11,942,004	475,081	1,213,582	10.16%	1,546,095	8.27%
2015	22,121,506	0.9470	1.0824	22,675,886	1.894	11,975,302	1,052,224	1,210,428	10.11%	1,737,160	7.66%
2016	24,142,794	0.9520	1.0612	24,390,168	2.614	9,330,656	18,209	171,122	1.83%	912,419	3.74%
2017	25,714,864	0.9826	1.0404	26,288,845	4.881	5,385,944	0	37,923	0.70%	1,066,858	4.06%
2018	19,810,337	1.0090	1.0200	20,388,342	22.012	926,253	0	0	0.00%	958,012	4.70%
Total	194,931,145			207,873,333		118,096,118	2,429,115	5,813,226	4.92%	10,232,467	4.92%
		Prospective Premium:		25,000,000						1,230,000	4.92%

Experience Rating Method
Example



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The oldest years in the experience period are most affected by inflation trend.

The most recent years in the experience period are most affected by loss development.

Experience Rating as a GLM

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Each year in the experience period gives us one estimate of the ELR.

$$ELR_i = \frac{E[Loss_i \cdot LDF_i]}{Premium_i}$$

We can rearrange these terms into a linear model (equivalently GLM with identity link function). Letting Y = losses reported-to-date.

$$E[Loss_i] = \left(\frac{Premium_i}{LDF_i}\right) \cdot ELR$$

$$E[Y] = X \cdot \beta$$

$$Var(Y) = \phi \cdot E[Y]^p$$

Experience Rating as a GLM

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Several examples re-casting this as GLM, with identity link and alternative variance structures. Each variance function leads to a different estimator.

GLM	**Variance**	**Best Estimator**
Overdispersed Poisson	$Var(Y) = \phi \cdot E[Y]^1$	$\widehat{ELR} = \frac{\sum Loss_i}{\sum Prem_i / LDF_i}$
Overdispersed Poisson	$Var(Y) = \phi \cdot \left(\frac{1}{LDF_i}\right) \cdot E[Y]^1$	$\widehat{ELR} = \frac{\sum Loss_i \cdot LDF_i}{\sum Prem_i}$
Gamma	$Var(Y) = \phi \cdot E[Y]^2$	$\widehat{ELR} = \frac{1}{n} \sum \frac{Loss_i \cdot LDF_i}{Prem_i}$

Experience Rating as a GLM

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For a given accident year, the different methods have different assumptions about the coefficient of variation (CV = standard deviation / mean) by development age:

LDF Method assumes:

$$CV_{12} = CV_{24} = CV_{36}$$

Cape Cod Method assumes:

$$\frac{CV_{12}}{\sqrt{LDF_{12}}} = \frac{CV_{24}}{\sqrt{LDF_{24}}} = \frac{CV_{36}}{\sqrt{LDF_{36}}}$$

which implies:

$$CV_{12} > CV_{24} > CV_{36}$$

Diagnostics – Telling the Story

Does the Experience-Rating make sense?

If we are asking for a rate increase, can we explain why?

- Graphical Display
  - Use ground-up loss ratio experience to evaluate trend and onlevel

- Comparisons
  - Prior years' Experience Rating
  - Exposure Rating

Diagnostics – Telling the Story

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Actual versus Expected Analysis

Accident Year	Evaluated 9/30/2017	LDF	Evaluated 9/30/2018	LDF	Expected Link Ratio	Expected Dvlpmnt	Actual Dvlpmnt
2009	571,093	1.103	599,683	1.077	1.024	13,787	28,590
2010	492,265	1.141	559,165	1.103	1.034	16,959	66,900
2011	319,707	1.195	219,653	1.141	1.047	15,131	-100,054
2012	1,762,534	1.277	1,831,330	1.195	1.069	120,944	68,796
2013	250,563	1.407	285,397	1.277	1.102	25,508	34,834
2014	577,569	1.633	969,391	1.407	1.161	92,772	391,822
2015	362,216	2.087	854,699	1.633	1.278	100,702	492,483
2016	333,336	3.376	712,321	2.087	1.618	205,879	378,985
2017	110,169	14.169	408,968	3.376	4.197	352,220	298,799
Total	4,779,452		6,440,607			943,902	1,661,155

Actual versus Expected checking can be very valuable to see if there have been any surprises since the last renewal.

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Even after all of the analysis, there is still uncertainty in the experience rating:

- Actual experience is volatile
- Operations of the ceding company may have changed
  - Risk profile, policy limits and attachment points
  - Claims handling
- Data quality

Credibility

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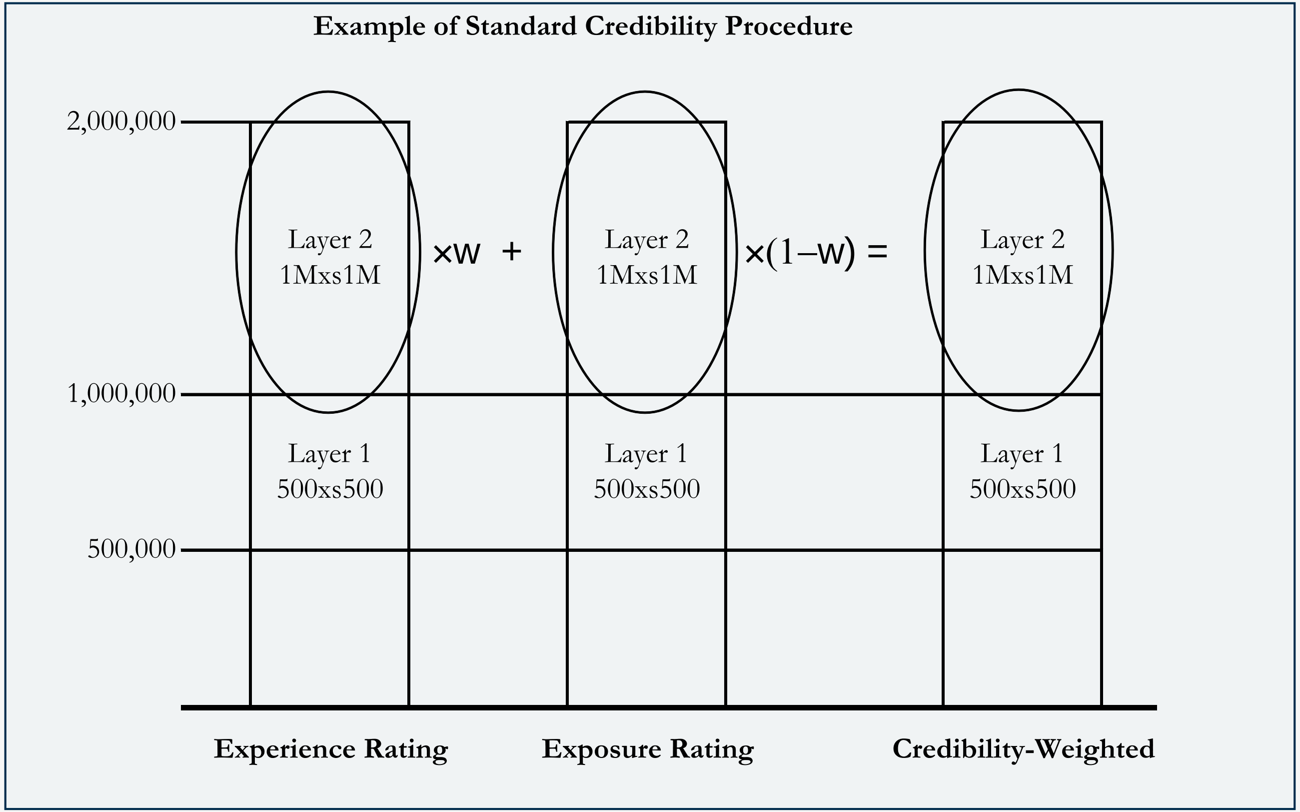

Credibility weighting of experience and exposure estimates has traditionally been applied on a layer-by-layer basis.

This approach ignores information from underlying layers.

Credibility

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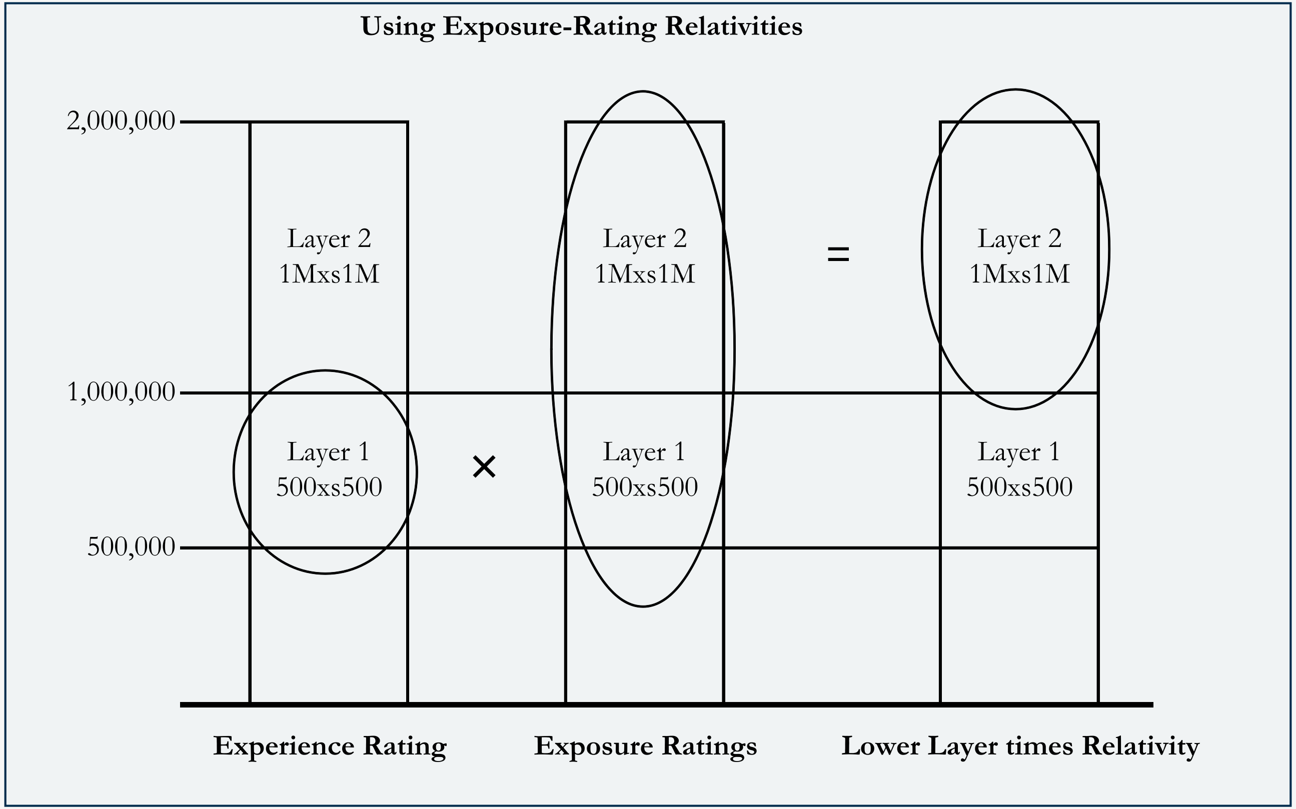

An improvement is to rely on the exposure-rating for relativities.

The "complement of credibility" for the top layer comes from the selection made on lower layers.

This also guarantees consistency of ROLs.

Credibility

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The result is a three-factor credibility formula.

$$\hat{\mu}_{cw} = w_1 \cdot \hat{\mu}_{expos\_1Mx1M}$$

$$+w_2 \cdot \hat{\mu}_{exper\_1Mx1M}$$

$$+w_3 \cdot \hat{\mu}_{exper\_500x500} \cdot \left\{\frac{\hat{\mu}_{expos\_1Mx1M}}{\hat{\mu}_{expos\_500x500}}\right\}$$

We can rearrange this expression into a recursive form:

$$\hat{\mu}_{cw} = \left(w_1 \cdot \hat{\mu}_{expos\_500x500} + w_3 \cdot \hat{\mu}_{exper\_500x500}\right) \cdot \left\{\frac{\mu_{expos\_1Mx1M}}{\mu_{expos\_500x500}}\right\}$$

$$+w_2 \cdot \hat{\mu}_{exper\_1Mx1M}$$

Where there is correlation between the estimators, we define a covariance matrix containing the covariance between every pair of estimators.

For the three variable case, we have:

$$\boldsymbol{\Sigma} = \begin{bmatrix} Var(\widehat{\mu_1}) & Cov(\widehat{\mu_1},\widehat{\mu_2}) & Cov(\widehat{\mu_1},\widehat{\mu_3}) \\ Cov(\widehat{\mu_2},\widehat{\mu_1}) & Var(\widehat{\mu_2}) & Cov(\widehat{\mu_2},\widehat{\mu_3}) \\ Cov(\widehat{\mu_3},\widehat{\mu_1}) & Cov(\widehat{\mu_3},\widehat{\mu_2}) & Var(\widehat{\mu_3}) \end{bmatrix}$$

Credibility

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The weights to be applied to the estimators are represented as a vector of numbers.

$$\overrightarrow{\boldsymbol{W}} = \langle w_1, w_2, \cdots, w_n \rangle^T$$

The “best” value for the weights, constrained so that they sum to unity, is found by matrix operations.

$$\overrightarrow{\boldsymbol{W}} = \frac{\boldsymbol{\Sigma}^{-1} \cdot \mathbf{1}_{\mathrm{n}}}{\mathbf{1}_n^T \cdot \boldsymbol{\Sigma}^{-1} \cdot \mathbf{1}_{\mathrm{n}}}$$

This is calculated by taking the inverse of the covariance matrix and then calculating each column total to the overall total.

The math is equivalent to minimum variance portfolio optimization.

Final Thought

Everything in this presentation using actuarial terminology could be “translated” for data scientists:

Actuarial Language	Data Scientist Language
Assemble Data	Data Engineering
Experience Rating	Predictive Model
Select trend, LDF, rate change	Feature Engineering
Diagnostics	Model Validation
Credibility	Regularization

Thank you!

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