

Benchmarking Unpaid Claim Estimates

Benchmark: A standard, or a set of standards, used as a point of reference for evaluating performance or level of quality. Benchmarks may be drawn from a firm's own experience, from the experience of other firms in the industry, or from legal requirements such as environmental regulations.

Source: businessdictionary.com

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Benchmarking Unpaid Claim Estimates

Have you ever calculated an estimate of unpaid claims?

P&C (General) Insurance, any LOB or segment

For any reason, reserves, pricing, ERM, etc.

Have you ever used a benchmark to help with your estimated unpaid claims or range of estimates?

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2 Analysis Summary	
3 Model Limitations	
4 Model Projections – Are they Unbiased?	
5 Proposed Adjustments	
6 Conclusions	
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"...study suggests that there might be environmental changes that no single model can identify."

"If this continues to hold, the actuarial profession cannot rely solely on stochastic loss reserve models to manage its reserve risk."

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Leong, Wang & Chen

"...the popular ODP bootstrap of the paid chain-ladder method is underestimating reserve risk."

"...the bootstrap model does not consider systemic risk, or, to put it another way, the risk that future trends in the claims environment – such as inflation, trends in tort reform, legislative changes, etc. – may deviate from what we saw in the past."

> Leong, Jessica (Weng Kah), Shaun Wang, and Han Chen, "Back-Testing the ODP Bootstrap of the Paid Chain-Ladder Model with Actual Historical Claims Data," CAS E-Forum, Summer 2012, 1-34.

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Gremillet & Miehe

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"...it is core to have adjustments by actuaries prior to running the stochastic methods 'automatically.' "

"Actuary in the box" dream for stochastic reserves valuation not yet happening

Gremillet, Marion, and Pierre Miehe, "Back-Testing the Reversible Jump Markov Chain Monte Carlo & further extensions," ICA 1-38 (2013).



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ltem	Meyers & Shi	Leong, Wang & Chen	Gremillet & Miehe	Shapland
Data	50 Companies	21 (MPL) to 78 (PPAL) Companies	?	1,679 Companies
Evaluations	1	11	5	9
Models	2	2	3	8
Lines of Business	1	9	4	16
Triangle Sets	50	~4,850	296	30,707

- Weighted
- Mack Bootstrap
- Paid Chain Ladder

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Analysis Details

- Beginning Data
- NAIC Schedule P 4,796 Companies (& Groups)
- Remove all triangles without 10 years of data (Paid, Incurred, etc.)
- Other data quality tests → "quality data"
- Test whether next 9 years are identical → "complete data"
- Test Data
- Total of 75,000+ LOBs with "quality data"
- 1,679 Companies with at least 1 Schedule P LOB of "complete data"
- Total of 30,707 LOBs with "complete data"
- 2,104 Companies with at least 2 Schedule P LOBs of "quality data"
- Approx. 27,000 LOBs with at least 2 for same Company

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Analysis Details

- Model Output
- Accident Year Totals (by Year & All Years Combined)
- Calendar Year Totals (by Year)
- Calendar Year Runoff Totals (by Year)
- Ultimate Loss Ratios (by Year)
- Incremental Results (by Year and Development Period)
- Diagnostic Statistics

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Analysis Details

- Model Options (Tests)
- Test 1 Defaults
 - No Tail factors (i.e., 1.000)
 - BF a priori based on hindsight L/R, No CoV
 - CC Trend = 2.5%, Decay Ratio = 90%
- Test 2 Selected Limiting of Incrementals
- Test 3 Selected Limiting & Suggested Heteroscedasticity Groups

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Model Limitations

- Model Risk
- Limited to known data
- A single model can underestimate variability
- Systemic risk
- In addition to model risk
- A shift in claims environment
- Need to Understand Assumptions

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Major Assumption

Bootstrap models (ODP & Mack) assume Chain Ladder projections are unbiased

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Model Projections Are they Unbiased?

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Leong, Wang & Chen

- Systemic Risk Distribution Method
 Multiply each simulated bootstrap result by a "systemic" factor
- Wang Transform Adjustment
- Increase the variability of the original unpaid loss distribution
- Shift the percentiles to account for bias in methods over time
- Relies on a parameter "Lambda" targeting an ideal histogram

Assumes Model Risk is Systemic! Based on Hindsight only!

Leong, Jessica (Weng Kah), Shaun Wang, and Han Chen, "Back-Testing the ODP Bootstrap of the Paid Chain-Ladder Model with Actual Historical Claims Data," CAS E-Forum, Summer 2012, 1-34.

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HDR Adjustment

- Shift distribution by multiplying unpaid claim estimates by the HDR
- Coefficient of variation unchanged
- Additive shift will not address variance
- Hindsight adjustment, but we are not advocating, just testing how much bias vs. not enough variance

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Conclusions

- Goal of Ideal Histogram Unrealized by Paid CL Bootstrap
 Both ODP Bootstrap and Mack Bootstrap
 - Confirms Other Research
- Other ODP Bootstraps Much Closer to Theoretical Ideal
- Milliman Incurred models different (Shapland Monograph)
- Bornhuetter-Ferguson and Cape Cod models
- Cyclical Bias in Reserve Distributions Paid and Incurred
- Consistent with Deterministic Projections

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Conclusions

- "Corrections" to Other ODP Models may be Unnecessary
- Addressing Model Risk is very important
- Can't "blindly" accept model results
- · Use diagnostics to assess model strengths / weaknesses
- Implications for weighting
- Still need to address systemic risks
- Guidelines (i.e., benchmarks) to Assess Results
- · Based on hindsight, but forward looking
- Correlations
- Distributions by LOB and Premium

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Claim Variability Guidelines The Way Forward



Claim Variability Guidelines Loss Development Patterns

- Back-testing output includes VWA factors for all paid data triangles
- Back-testing output includes VWA factors for simulated paid data
- Actual incurred data is part of the data set, but output for incurred simulations is not readily available
- By Schedule P Line of Business, a "distribution" of the patterns were created for both actual and simulated data

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Claim Variability Guidelines Unpaid Claim Distributions

- For each Schedule P LOB, the back-testing results contain thousands of simulated distributions for companies of all different sizes
- Regression models were used to fit the distributions by premium volume for each of the Acc Yr, Cal Yr, Cal Yr Runoff, and Loss Ratio distributions
- Fitted results were smoothed to be consistent between distribution types and to conform with statistical properties

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Claim Variability Guidelines

Unpaid Claim Distributions

- The regression model adjusts assumptions to fit statistical properties.
- For example, consider smaller vs larger number of exposures:

			Large Insurer								
Commercial Auto Liability Accident Year Guidelines (US\$ 000's)						Commercial Auto Liability Accident Year Guidelines (US\$ 000's)					
Acc Yr											CoV
2008	5,115	75.3%	17	63	369.8%	2008	40,918	75.3%	131	284	216.4%
2009	5,302	77.1%	42	112	268.7%	2009	42,415	77.1%	323	464	143.5%
2010	5,427	79.4%	95	203	213.1%	2010	43,419	79.4%	735	838	114.0%
2011	5,508	81.7%	196	308	157.3%	2011	44,064	81.7%	1,516	1,223	80.6%
2012	5,668	82.5%	404	498	123.4%	2012	45,343	82.5%	3,124	2,067	66.2%
2013	5,907	82.0%	820	737	89.9%	2013	47,256	82.0%	6,344	3,409	53.7%
2014	6,277	79.2%	1,532	1,019	66.5%	2014	50,215	79.2%	11,850	5,250	44.3%
2015	6,780	74.9%	2,719	1,640	60.3%	2015	54,236	74.9%	21,034	8,442	40.1%
2016	7,214	73.8%	4,278	2,401	56.1%	2016	57,710	73.8%	33,093	12,465	37.7%
Total	53,197	78.3%	10,102	3,654	36.2%	Total	425,576	78.3%	78,152	17,681	22.6%
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Claim Variability Guidelines Unpaid Claim Distributions

- The regression model allows for other customizations.
- · For example, consider a faster development pattern:

Average Development							Faster Development					
Commercial Auto Liability Accident Year Guidelines (US\$ 000's)						Commercial Auto Liability Accident Year Guidelines (US\$ 000's)						
Acc Yr											CoV	
2008	20,459	75.3%	66	157	238.9%	2008	20,459	75.3%	2	25	1506.9%	
2009	21,207	77.1%	162	263	161.9%	2009	21,207	77.1%	18	79	430.9%	
2010	21,709	79.4%	369	475	128.6%	2010	21,709	79.4%	69	173	249.2%	
2011	22,032	81.7%	762	700	91.9%	2011	22,032	81.7%	275	360	131.0%	
2012	22,671	82.5%	1,570	1,171	74.6%	2012	22,671	82.5%	794	721	90.8%	
2013	23,628	82.0%	3,188	1,882	59.0%	2013	23,628	82.0%	2,029	1,320	65.0%	
2014	25,108	79.2%	5,954	2,832	47.6%	2014	25,108	79.2%	4,481	2,227	49.7%	
2015	27,118	74.9%	10,568	4,556	43.1%	2015	27,118	74.9%	8,926	3,945	44.2%	
2016	28,855	73.8%	16,627	6,715	40.4%	2016	28,855	73.8%	15,589	6,351	40.7%	
Total	212,788	78.3%	39,266	9,666	24.6%	Total	212,788	78.3%	32,182	8,202	25.5%	
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Claim Variability Guidelines

Unpaid Claim Distributions

- The regression model accommodates international use.
- For example, consider a European insurer with the same development pattern:

US Insurer							European Insurer				
Commercial Auto Liability Accident Year Guidelines (US\$ 000's)						Commercial Auto Liability Accident Year Guidelines (€ 000's)					
Acc Yr			Mean	Std Dev					Mean	Std Dev	
2008	20,459	75.3%	66	157	238.9%	2008	20,459	75.3%	66	161	244.5%
2009	21,207	77.1%	162	263	161.9%	2009	21,207	77.1%	163	271	166.4%
2010	21,709	79.4%	369	475	128.6%	2010	21,709	79.4%	370	489	132.2%
2011	22,032	81.7%	762	700	91.9%	2011	22,032	81.7%	763	722	94.7%
2012	22,671	82.5%	1,570	1,171	74.6%	2012	22,671	82.5%	1,572	1,205	76.6%
2013	23,628	82.0%	3,188	1,882	59.0%	2013	23,628	82.0%	3,191	1,926	60.4%
2014	25,108	79.2%	5,954	2,832	47.6%	2014	25,108	79.2%	5,961	2,884	48.4%
2015	27,118	74.9%	10,568	4,556	43.1%	2015	27,118	74.9%	10,581	4,638	43.8%
2016	28,855	73.8%	16,627	6,715	40.4%	2016	28,855	73.8%	16,647	6,834	41.1%
Total	212,788	78.3%	39,266	9,666	24.6%	Total	212,788	78.3%	39,313	9,870	25.1%
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Claim Variability Guidelines Correlation Between Segments

- Back-testing output includes correlation statistics between all pairs of LOBs within a company (i.e., if there was more than one 'complete' LOB)
- Output includes both paid and incurred, before and after optimal hetero adjustments
- The mean and std dev (unweighted and weighted) for all specific pairs (i.e., between two specific LOBs) was measured
- Weights based on 1 minus P-Value, since the lower the P-Value the more statistically significant the correlation

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Claim Variability Guidelines

Other Potential Uses

- Calculating average durations for future cash flows
- Calculating reserve risk margins based on the expected unpaid claim runoff
- Assessing the variance parameter for a priori loss ratio assumptions in models
- Other uses which are only limited by your imagination

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