A Quantum Leap in Benchmarking Unpaid Claims

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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Benchmarking Unpaid Claim Estimates

Outline

1	Background
2	Analysis Summary
3	Model Limitations
4	Model Projections – Are they Unbiased?
5	Proposed Adjustments
6	Conclusions
7	Claim Variability Benchmarks

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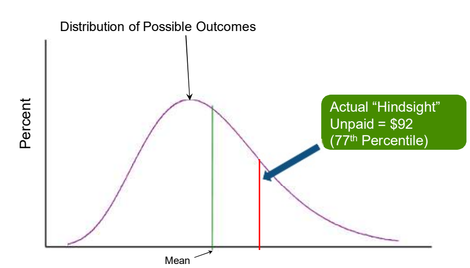
Background

Hindsight Analysis

Hypothetical Unpaid Claim Distribution



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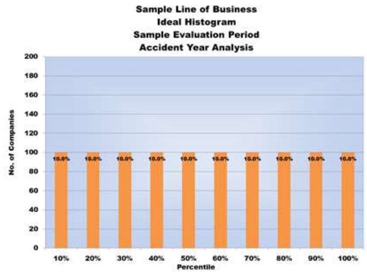
If Model is Correct…



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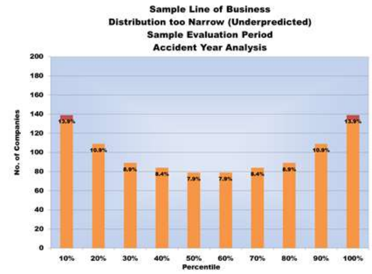
If Model Underestimates Distribution…



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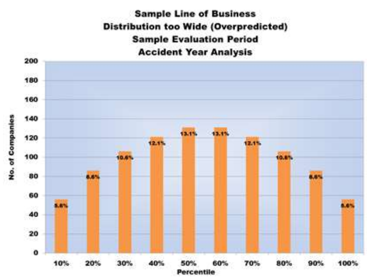
If Model Overestimates Distribution…



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Background

Prior Research

Meyers & Shi

"…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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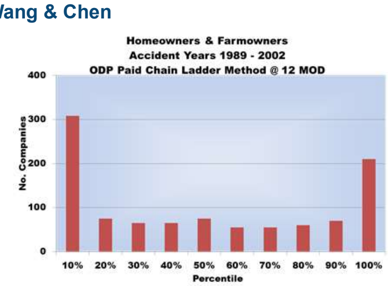
Leong, Wang & Chen



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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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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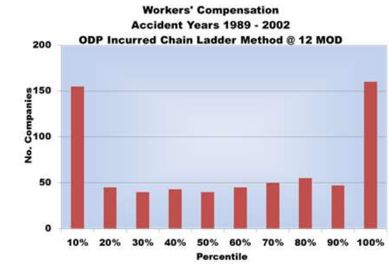
Leong, Wang & Chen



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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Leong, Wang & Chen

"…it appears that the incurred bootstrap model is also underestimating the risk of falling in these extreme percentiles."

Note: This is not the same incurred ODP bootstrap model as described in the Shapland Monograph.

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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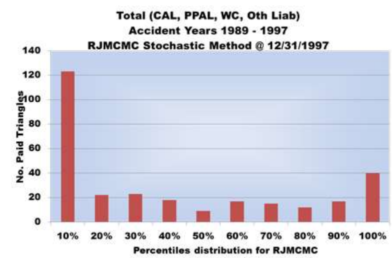
Gremillet & Miehe



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

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Gremillet & Miehe

"…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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Analysis Summary

Comparison of Analyses

Item	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

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Analysis Details

- **ODP Bootstrap**
  - Paid Chain Ladder
  - Incurred Chain Ladder
  - Paid Bornhuetter-Ferguson
  - Incurred Bornhuetter-Ferguson
  - Paid Cape Cod
  - Incurred Cape Cod
  - 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 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?

Comparison of Tests

Test 1

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Comparison of Tests

Test 2

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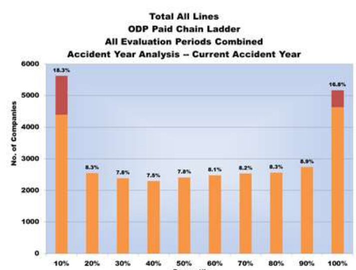
Comparison of Tests

Test 3



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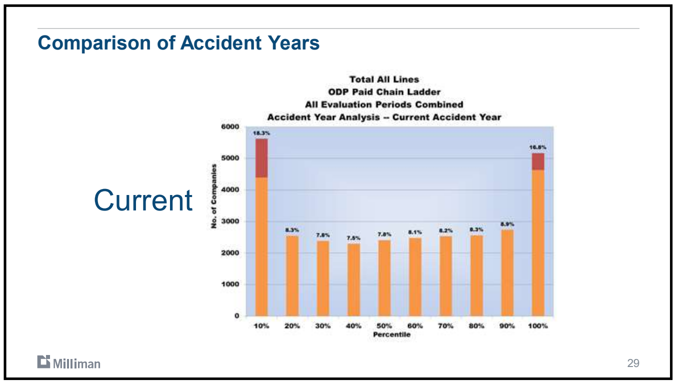
Comparison of Accident Years
Total All Lines
ODP Paid Chain Ladder
All Evaluation Periods Combined
Accident Year Analysis – Current Accident Year
Current
No. of Companies
Percentile
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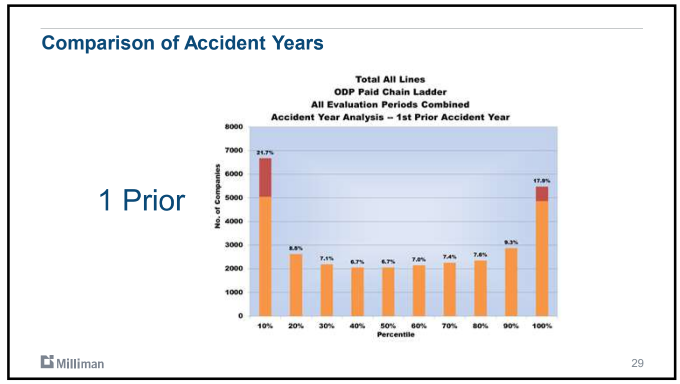
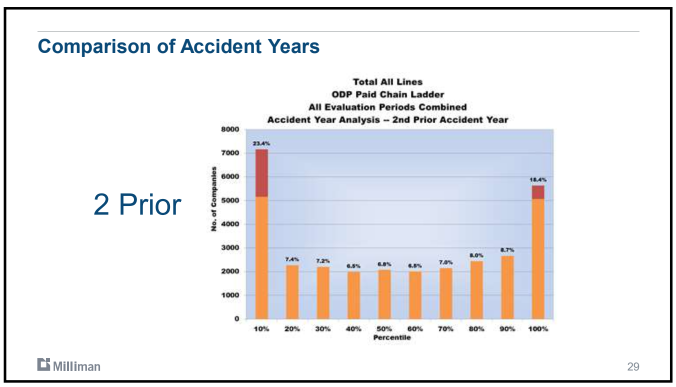
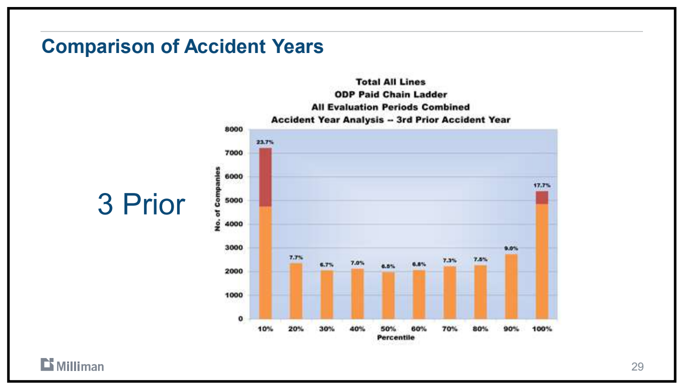
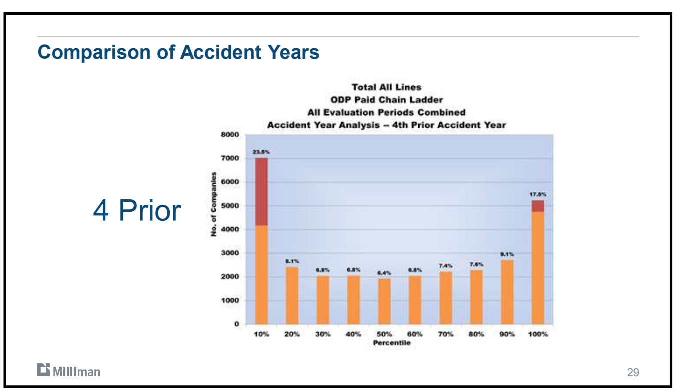
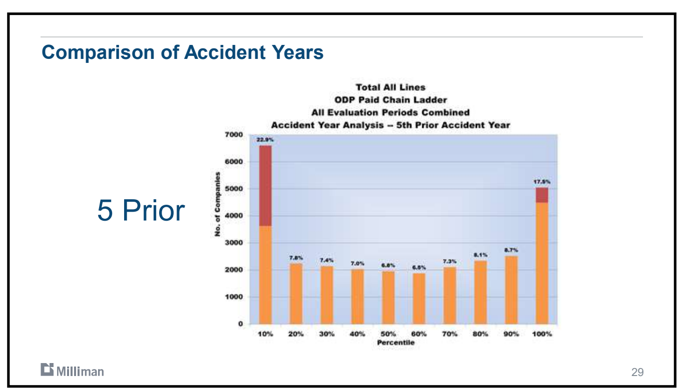
29


Comparison of Accident Years
Total All Lines
ODP Paid Chain Ladder
All Evaluation Periods Combined
Accident Year Analysis – 1st Prior Accident Year
1 Prior
No. of Companies
Percentile
Milliman
29


Comparison of Accident Years
Total All Lines
ODP Paid Chain Ladder
All Evaluation Periods Combined
Accident Year Analysis – 2nd Prior Accident Year
2 Prior
No. of Companies
Percentile
Milliman
29


Comparison of Accident Years
Total All Lines
ODP Paid Chain Ladder
All Evaluation Periods Combined
Accident Year Analysis – 3rd Prior Accident Year
3 Prior
No. of Companies
Percentile
Milliman
29


Comparison of Accident Years
Total All Lines
ODP Paid Chain Ladder
All Evaluation Periods Combined
Accident Year Analysis – 4th Prior Accident Year
4 Prior
No. of Companies
Percentile
Milliman
29


Comparison of Accident Years
Total All Lines
ODP Paid Chain Ladder
All Evaluation Periods Combined
Accident Year Analysis – 5th Prior Accident Year
5 Prior
No. of Companies
Percentile
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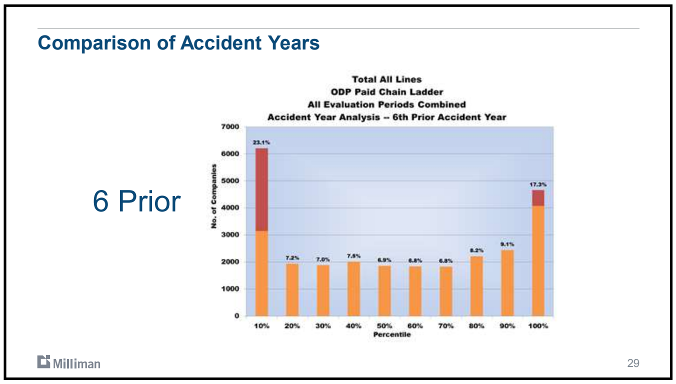
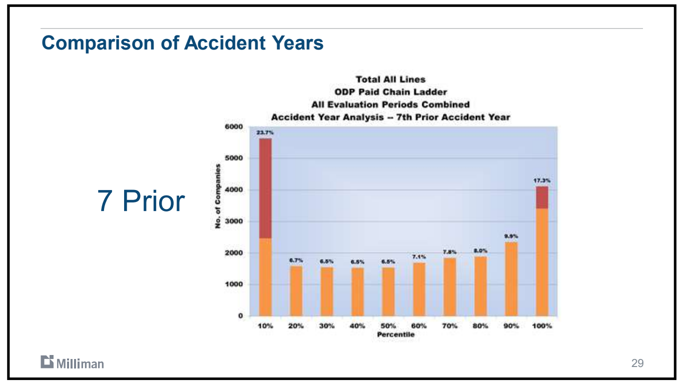
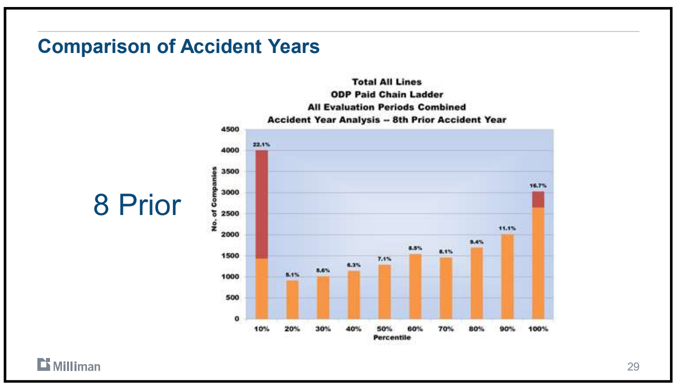
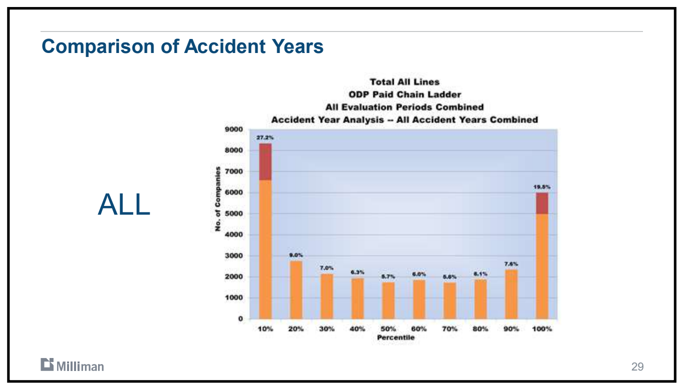
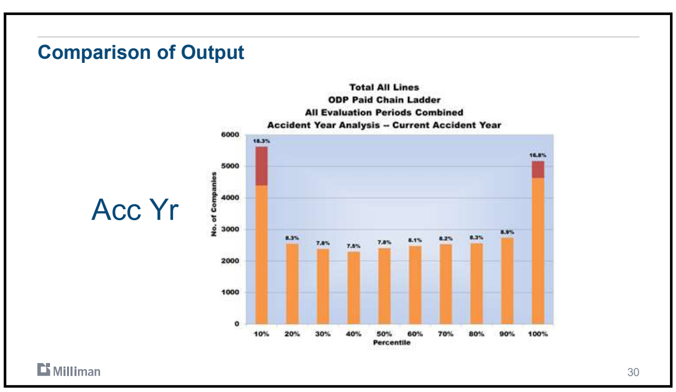
A Quantum Leap in Benchmarking Unpaid Claims

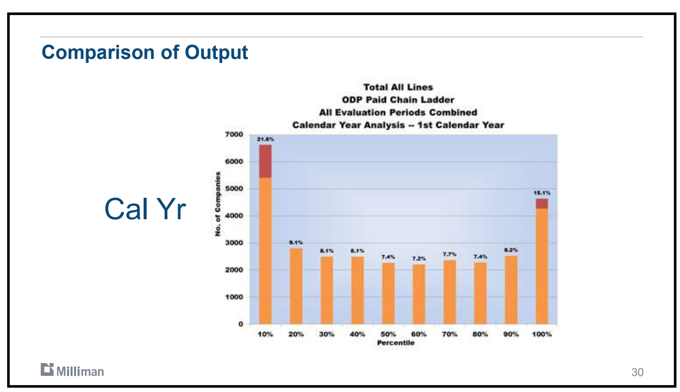






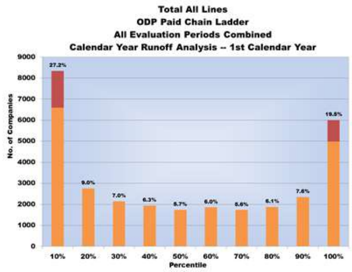






Comparison of Output

Cal Yr Runoff



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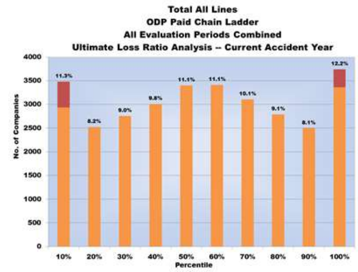
Comparison of Output

Ult L/R



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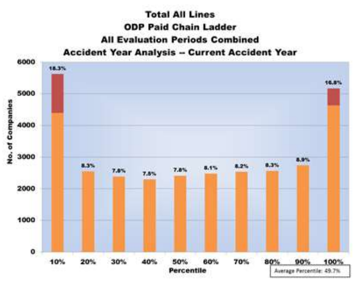
Comparison of Evaluation Years

ALL



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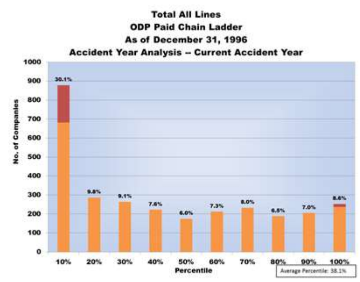
Comparison of Evaluation Years

1996



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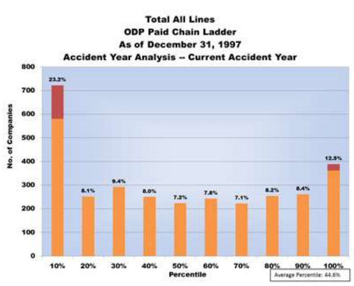
Comparison of Evaluation Years

1997



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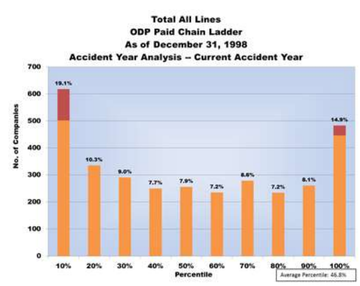
Comparison of Evaluation Years

1998



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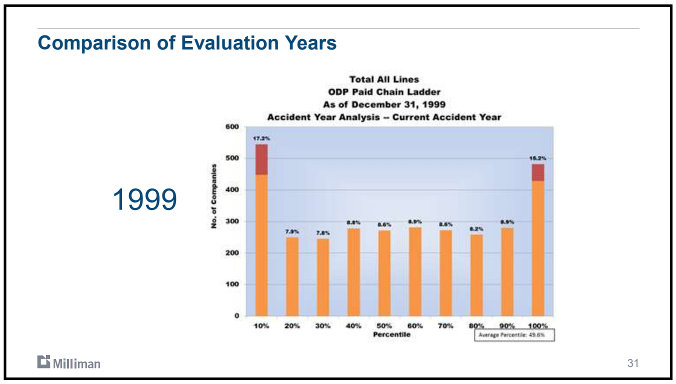
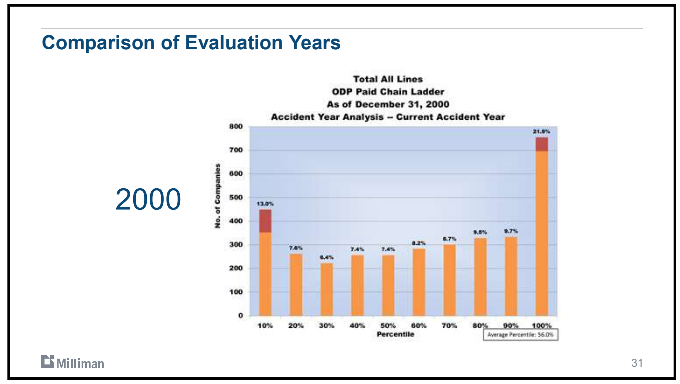

Comparison of Evaluation Years
Total All Lines
ODP Paid Chain Ladder
As of December 31, 1999
Accident Year Analysis – Current Accident Year
1999
No. of Companies
Percentile
Milliman
31


Comparison of Evaluation Years
Total All Lines
ODP Paid Chain Ladder
As of December 31, 2000
Accident Year Analysis – Current Accident Year
2000
No. of Companies
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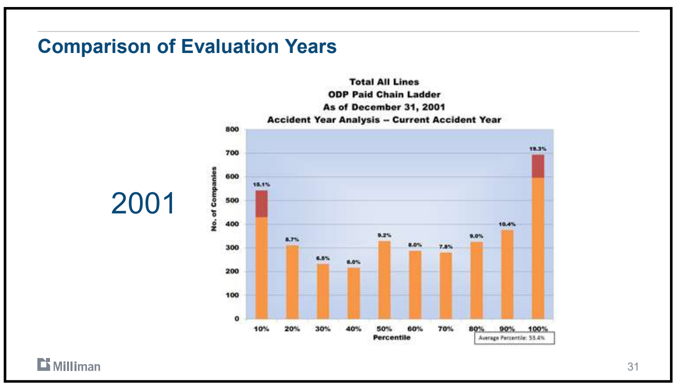
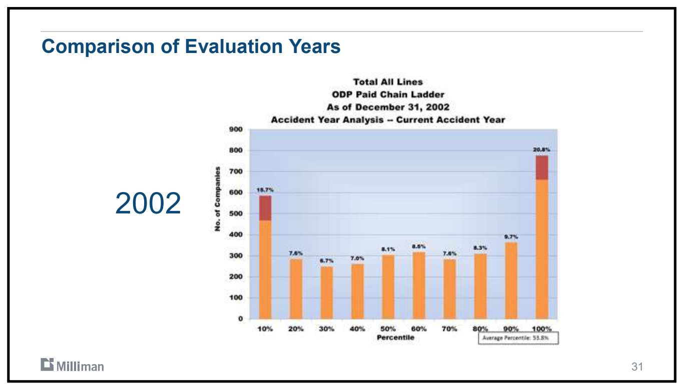
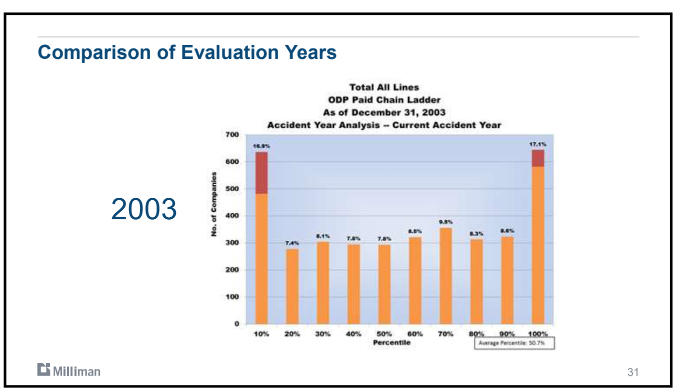
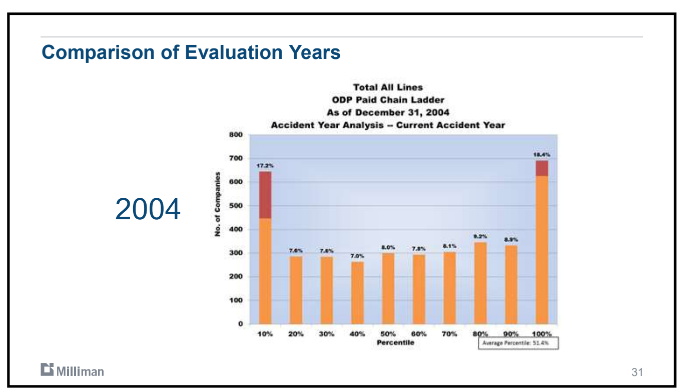
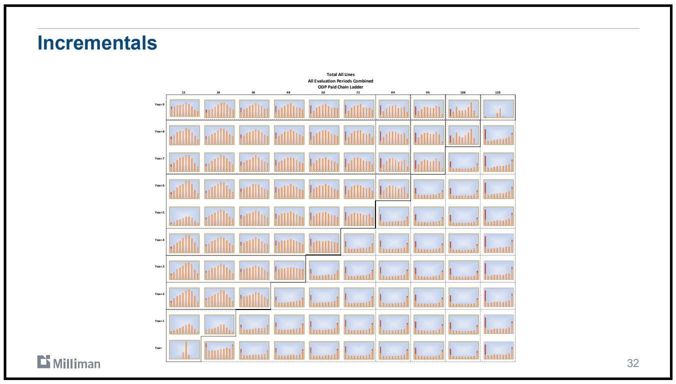
31


Comparison of Evaluation Years
Total All Lines
ODP Paid Chain Ladder
As of December 31, 2001
Accident Year Analysis – Current Accident Year
2001
No. of Companies
Percentile
Milliman
31


Comparison of Evaluation Years
Total All Lines
ODP Paid Chain Ladder
As of December 31, 2002
Accident Year Analysis – Current Accident Year
2002
No. of Companies
Percentile
Milliman
31


Comparison of Evaluation Years
Total All Lines
ODP Paid Chain Ladder
As of December 31, 2003
Accident Year Analysis – Current Accident Year
2003
No. of Companies
Percentile
Milliman
31


Comparison of Evaluation Years
Total All Lines
ODP Paid Chain Ladder
As of December 31, 2004
Accident Year Analysis – Current Accident Year
2004
No. of Companies
Percentile
Milliman
31


Incrementals
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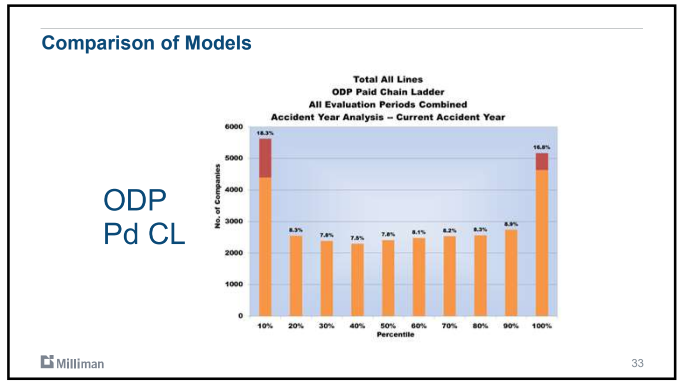
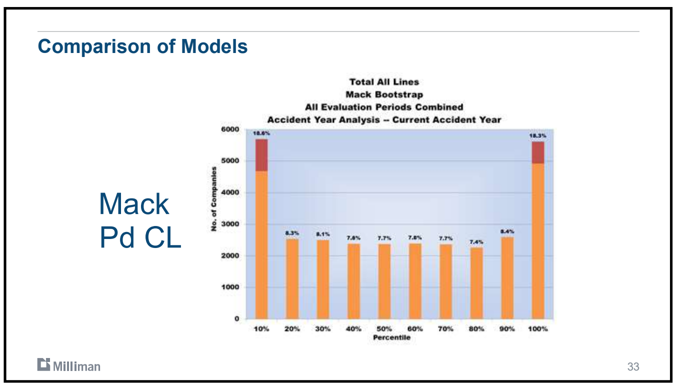

Comparison of Models
ODP
Pd CL
Total All Lines
ODP Paid Chain Ladder
All Evaluation Periods Combined
Accident Year Analysis – Current Accident Year
No. of Companies
Percentile
Milliman
33


Comparison of Models
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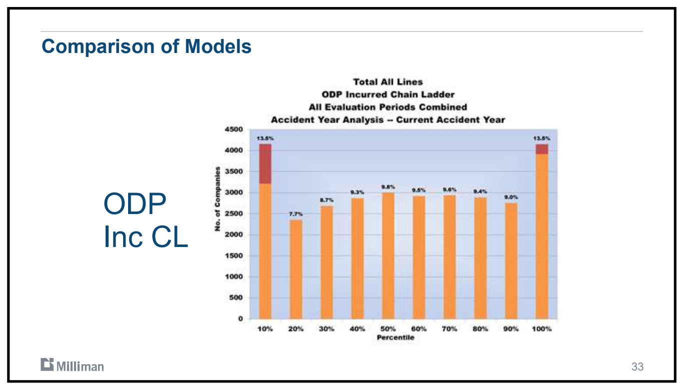
Pd CL
Total All Lines
Mack Bootstrap
All Evaluation Periods Combined
Accident Year Analysis – Current Accident Year
No. of Companies
Percentile
Milliman
33


Comparison of Models
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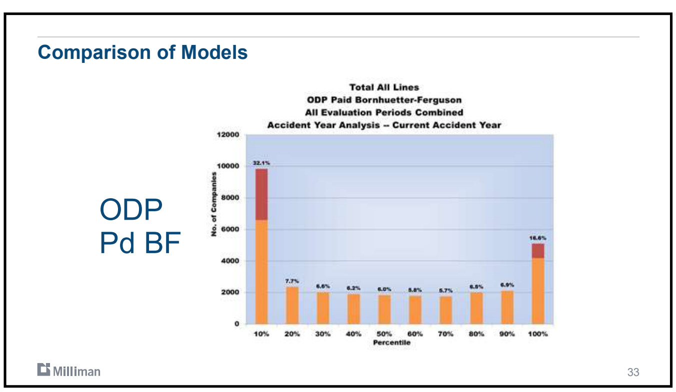
Total All Lines
ODP Incurred Chain Ladder
All Evaluation Periods Combined
Accident Year Analysis – Current Accident Year
No. of Companies
Percentile
Milliman
33


Comparison of Models
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Pd BF
Total All Lines
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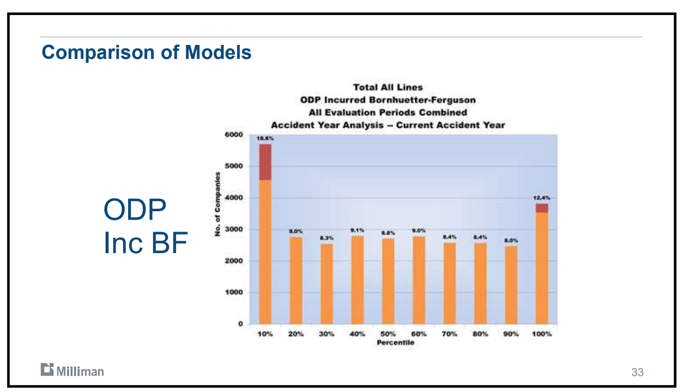
All Evaluation Periods Combined
Accident Year Analysis – Current Accident Year
No. of Companies
Percentile
Milliman
33


Comparison of Models
ODP
Inc BF
Total All Lines
ODP Incurred Bornhuetter-Ferguson
All Evaluation Periods Combined
Accident Year Analysis – Current Accident Year
No. of Companies
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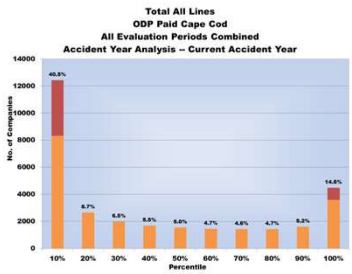
Milliman
33

Comparison of Models

ODP
Pd CC



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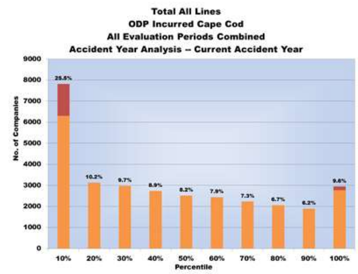
Comparison of Models

ODP
Inc CC



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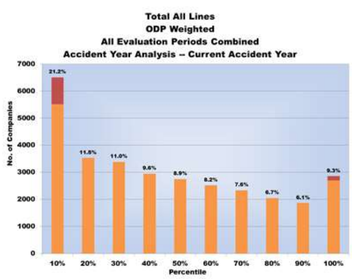
Comparison of Models

ODP
Wgtd



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Proposed Adjustments

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," Variance 8-2: 182-202.

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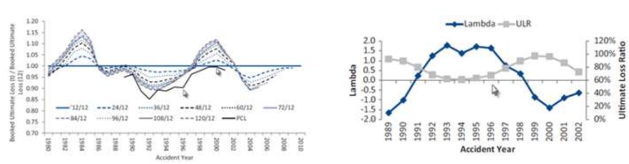
Leong, Wang & Chen



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," Variance 8-2: 182-202.

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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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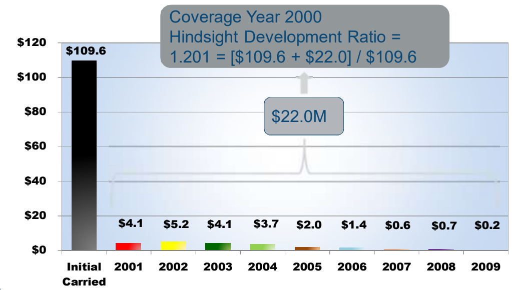
Example – Coverage Year 2000 ($B)



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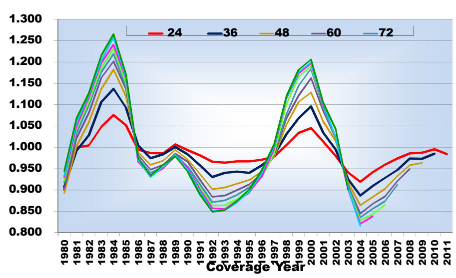
HDR by Evaluation Month



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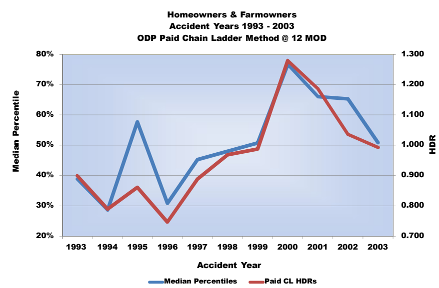
HDRs vs. Median Percentiles



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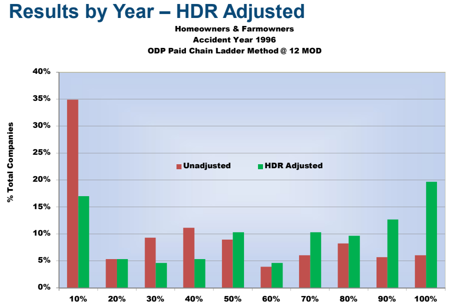
Results by Year – HDR Adjusted



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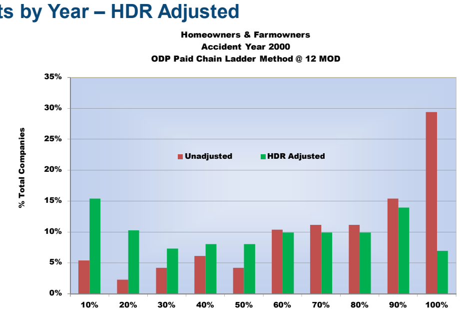
Results by Year – HDR Adjusted



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Conclusions

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**
  - 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
  - Including Correlations
- **Distributions by LOB and Premium**

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Claim Variability Benchmarks

A Quantum Leap in Benchmarking

Claim Variability Benchmarks

Types of Benchmarks

1. Loss Development Patterns
2. Unpaid Claim Distributions
3. Correlation Between Segments

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Claim Variability Benchmarks

Loss Development Patterns

- Common LDF benchmarks are “static” – one size fits all
- Back-testing includes VWA factors for all actual & simulated paid data triangles, by Schedule P Line of Business
- A “distribution” of the patterns were created for both actual and simulated data
- This allows for “dynamic” benchmarks – patterns are better tailored to your data
- You can also create a benchmark for your range of point estimates

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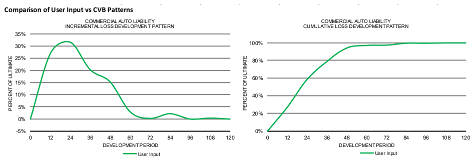
Claim Variability Benchmarks
Loss Development Patterns



Development Age:	12	24	36	48	60	72	84	96	108	120
User Input Pattern:	27.2%	58.8%	79.0%	94.3%	97.1%	97.4%	99.6%	99.6%	100.0%	100.0%

- As an example of how you might use this information, suppose you are analyzing Commercial Auto data and have selected the following LDF pattern.

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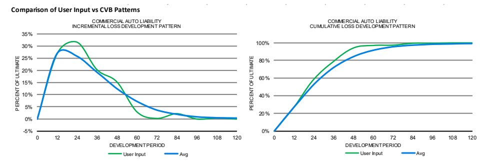
Claim Variability Benchmarks
Loss Development Patterns



Development Age:	12	24	36	48	60	72	84	96	108	120
User Input Pattern:	27.2%	58.8%	79.0%	94.3%	97.1%	97.4%	99.6%	99.6%	100.0%	100.0%
CVB Average Pattern:	26.9%	52.6%	71.8%	84.3%	91.5%	95.2%	97.2%	98.1%	98.7%	99.1%

- A typical benchmark is based on an overall average pattern, which may or may not provide a reasonable fit.

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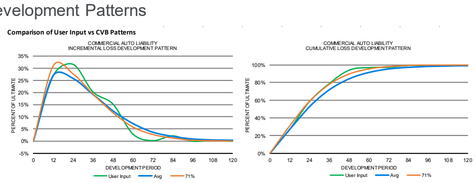
Claim Variability Benchmarks
Loss Development Patterns



Development Age:		12	24	36	48	60	72	84	96	108	120
User Input Pattern:		27.2%	58.8%	79.0%	94.3%	97.1%	97.4%	99.6%	99.6%	100.0%	100.0%
CVB Average Pattern:		26.9%	52.6%	71.8%	84.3%	91.5%	95.2%	97.2%	98.1%	98.7%	99.1%
Best Fit:	71%	56%	71%	74%	90%	84%	60%	74%	66%	78%	76%
CVB:	71%	31.1%	58.8%	78.0%	89.7%	95.5%	98.2%	99.4%	99.8%	99.9%	100.0%

- But using average patterns from thousands of companies, you can search percentiles for a better fit.

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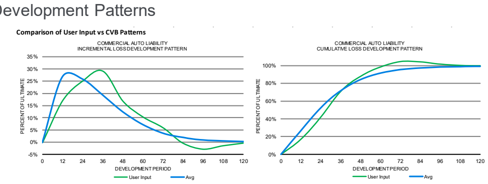
Claim Variability Benchmarks
Loss Development Patterns



Development Age:		12	24	36	48	60	72	84	96	108	120
User Input Pattern:		17.0%	42.0%	71.2%	88.1%	98.5%	104.5%	104.2%	101.5%	100.1%	99.8%
CVB Average Pattern:		26.9%	52.6%	71.8%	84.3%	91.5%	95.2%	97.2%	98.1%	98.7%	99.1%
Best Fit:	46%	13%	18%	46%	63%	92%	99%	99%	99%	97%	59%

"Slower" Development

"Faster" Development

- While a single percentile can often provide a better fit than the overall average, you might find that your pattern is slower than average in early periods and faster in later periods. Or vice versa.

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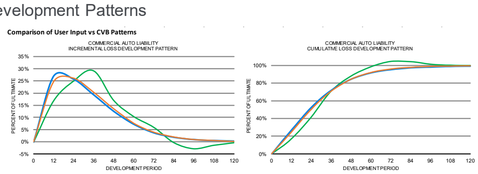
Claim Variability Benchmarks
Loss Development Patterns



Development Age:		12	24	36	48	60	72	84	96	108	120
User Input Pattern:		17.0%	42.0%	71.2%	88.1%	98.5%	104.5%	104.2%	101.5%	100.1%	99.8%
CVB Average Pattern:		26.9%	52.6%	71.8%	84.3%	91.5%	95.2%	97.2%	98.1%	98.7%	99.1%
Best Fit:	46%	13%	18%	46%	63%	92%	99%	99%	99%	97%	59%
CVB:	46%	24.8%	50.8%	71.1%	84.5%	92.2%	96.1%	98.0%	99.0%	99.5%	99.6%

- In this example, a single percentile is better than the average, but only marginally better.

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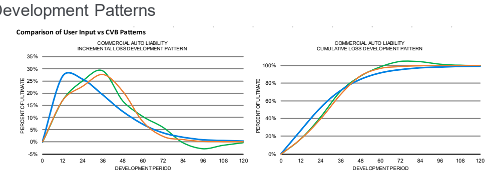
Claim Variability Benchmarks
Loss Development Patterns



Development Age:		12	24	36	48	60	72	84	96	108	120
User Input Pattern:		17.0%	42.0%	71.2%	88.1%	98.5%	104.5%	104.2%	101.5%	100.1%	99.8%
CVB Average Pattern:		26.9%	52.6%	71.8%	84.3%	91.5%	95.2%	97.2%	98.1%	98.7%	99.1%
Best Fit:	46%	13%	18%	46%	63%	92%	99%	99%	99%	97%	59%
CVB:	Blended	17.0%	39.8%	67.5%	88.4%	96.7%	98.9%	99.8%	99.9%	100.0%	100.0%

- But, by blending percentiles you can create an even more customized benchmark pattern.

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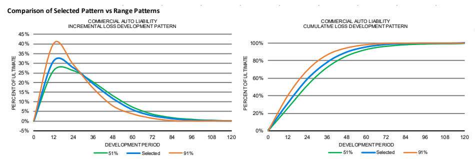
Claim Variability Benchmarks
Loss Development Patterns



Development Age:		12	24	36	48	60	72	84	96	108	120
Selected Pattern:		31.1%	58.8%	78.0%	89.7%	95.5%	98.2%	99.5%	99.8%	99.9%	100.0%
Lower:	51%	26.0%	52.2%	72.4%	85.6%	92.9%	96.6%	98.3%	99.2%	99.6%	99.7%
Upper:	91%	40.2%	69.5%	86.6%	94.6%	98.3%	99.8%	100.0%	100.0%	100.0%	100.0%

- To develop a range, you could calculate new unpaid claim estimates by selecting development patterns +/- X% from the best fit.

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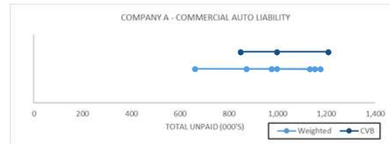
Claim Variability Benchmarks
Loss Development Patterns



- The range from the selected benchmark patterns can then be compared to the estimates from a traditional range.

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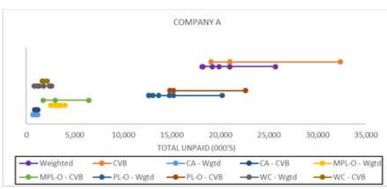
Claim Variability Benchmarks
Loss Development Patterns



- The ranges for each segment can be combined into a range for the entire company.

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Claim Variability Benchmarks
Types of Benchmarks

1 Loss Development Patterns

2 **Unpaid Claim Distributions**

3 Correlation Between Segments

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Claim Variability Benchmarks
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 – e.g., less exposure = more risk
- Algorithm allows for a variety of customizations – e.g., development patterns
- Underestimation of unpaid claim distributions can impact required capital, reinsurance, pricing, risk margins, etc.
- Overestimation is also problematic – e.g., capital does not match risk appetite

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Claim Variability Benchmarks
Unpaid Claim Distributions

- Variance Adjustment Factors are used to correct for back-testing results
- Separate variance adjustments factors for Loss Ratio distributions
- For example, this is the Acc Yr adjustment for Commercial Auto
- “Fitted” results still appear to under-estimate, but this is reserve cycle affect

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Claim Variability Benchmarks

Unpaid Claim Distributions

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

Small

Sample Line of Business (Using CA) Accident Year Guidelines (000's)					
Acc Yr	Premium	L/R	Mean	Std Dev	CoV
2010	5,115	75.3%	50	127	255.3%
2011	5,302	77.1%	76	157	204.9%
2012	5,427	79.4%	121	229	189.3%
2013	5,508	81.7%	215	322	149.8%
2014	5,668	82.5%	398	495	124.4%
2015	5,907	82.0%	762	708	92.9%
2016	6,277	79.2%	1,405	966	68.7%
2017	6,780	74.9%	2,410	1,523	63.2%
2018	7,214	73.8%	3,893	2,264	58.2%
Total	58,127	77.9%	9,330	3,490	37.4%

Large

Sample Line of Business (Using CA) Accident Year Guidelines (000's)					
Acc Yr	Premium	L/R	Mean	Std Dev	CoV
2010	51,148	75.3%	497	991	199.6%
2011	53,018	77.1%	764	1,015	132.8%
2012	54,273	79.4%	1,212	1,312	108.3%
2013	55,080	81.7%	2,150	1,662	77.3%
2014	56,679	82.5%	3,976	2,558	64.3%
2015	59,070	82.0%	7,625	4,029	52.8%
2016	62,769	79.2%	14,048	6,152	43.8%
2017	67,796	74.9%	24,097	9,580	39.8%
2018	72,138	73.8%	38,929	14,503	37.3%
Total	581,269	77.9%	93,297	20,803	22.3%

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Claim Variability Benchmarks

Unpaid Claim Distributions

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

Slower

Sample Line of Business (Using CA) Accident Year Guidelines (000's)					
Acc Yr	Premium	L/R	Mean	Std Dev	CoV
2010	20,459	75.3%	199	415	208.7%
2011	21,207	77.1%	306	442	144.7%
2012	21,709	79.4%	485	590	121.7%
2013	22,032	81.7%	860	768	89.4%
2014	22,671	82.5%	1,590	1,183	74.4%
2015	23,628	82.0%	3,050	1,815	59.5%
2016	25,108	79.2%	5,619	2,695	48.0%
2017	27,118	74.9%	9,639	4,210	43.7%
2018	28,855	73.8%	15,572	6,345	40.7%
Total	232,508	77.9%	37,319	9,264	24.8%

Faster

Sample Line of Business (Using CA) Accident Year Guidelines (000's)					
Acc Yr	Premium	L/R	Mean	Std Dev	CoV
2010	20,459	75.3%	61	147	242.9%
2011	21,207	77.1%	87	168	193.3%
2012	21,709	79.4%	152	258	169.5%
2013	22,032	81.7%	376	431	114.7%
2014	22,671	82.5%	895	780	87.1%
2015	23,628	82.0%	2,046	1,328	64.9%
2016	25,108	79.2%	4,421	2,203	49.8%
2017	27,118	74.9%	8,415	3,754	44.6%
2018	28,855	73.8%	14,680	6,033	41.1%
Total	232,508	77.9%	31,132	7,985	25.6%

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Claim Variability Benchmarks

Unpaid Claim Distributions

- The regression model includes four different types of results:

Acc Yr

Sample Line of Business (Using CA) Accident Year Guidelines (000's)					
Acc Yr	Premium	L/R	Mean	Std Dev	CoV
2010	20,459	75.3%	199	415	208.7%
2011	21,207	77.1%	306	442	144.7%
2012	21,709	79.4%	485	590	121.7%
2013	22,032	81.7%	860	768	89.4%
2014	22,671	82.5%	1,590	1,183	74.4%
2015	23,628	82.0%	3,050	1,815	59.5%
2016	25,108	79.2%	5,619	2,695	48.0%
2017	27,118	74.9%	9,639	4,210	43.7%
2018	28,855	73.8%	15,572	6,345	40.7%
Total	232,508	77.9%	37,319	9,264	24.8%

Cal Yr

Sample Line of Business (Using CA) Calendar Year Guidelines (000's)					
Cal Yr	Total Premium	Wgt. Avg. L/R	Mean	Std Dev	CoV
2019	232,508	77.9%	14,631	4,402	30.1%
2020	212,788	78.3%	9,629	3,441	35.7%
2021	192,329	78.6%	5,749	2,544	44.3%
2022	171,122	78.8%	3,204	1,905	59.5%
2023	149,412	78.7%	1,728	1,292	74.7%
2024	127,380	78.2%	970	958	98.8%
2025	104,709	77.2%	570	755	132.4%
2026	81,081	75.9%	382	562	147.0%
2027	55,973	74.3%	456	929	204.0%
Total			37,319	9,264	24.8%

Cal Yr Runoff

Sample Line of Business (Using CA) Calendar Year Runoff Guidelines (000's)					
Cal Yr End	Total Premium	Wgt. Avg. L/R	Mean	Std Dev	CoV
2018	232,508	77.9%	37,319	9,264	24.8%
2019	212,788	78.3%	22,687	6,688	29.5%
2020	192,329	78.6%	13,058	4,774	36.6%
2021	171,122	78.8%	7,310	3,418	46.8%
2022	149,412	78.7%	4,106	2,407	58.6%
2023	127,380	78.2%	2,378	1,775	74.7%
2024	104,709	77.2%	1,408	1,376	97.7%
2025	81,081	75.9%	838	1,034	123.4%
2026	55,973	74.3%	456	929	204.0%

Loss Ratio

Sample Line of Business (Using CA) Loss Ratio Guidelines (000's)				
Acc Yr	Premium	Mean	Std Dev	CoV
2010	20,459	75.3%	10.7%	14.2%
2011	21,207	77.1%	11.4%	14.8%
2012	21,709	79.4%	12.2%	15.3%
2013	22,032	81.7%	12.1%	14.9%
2014	22,671	82.5%	13.7%	16.6%
2015	23,628	82.0%	13.5%	16.4%
2016	25,108	79.2%	13.6%	17.2%
2017	27,118	74.9%	13.8%	18.4%
2018	28,855	73.8%	15.4%	20.9%

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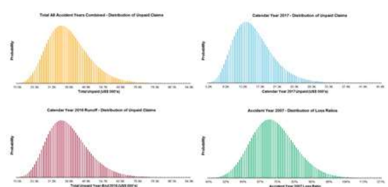
Claim Variability Benchmarks

Unpaid Claim Distributions

- In Excel, these are easy to graph:

Acc Yr

Cal Yr



Cal Yr Runoff

Loss Ratio

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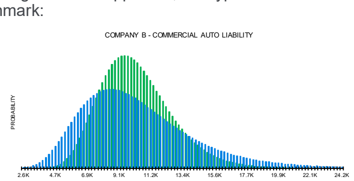
Claim Variability Benchmarks

Unpaid Claim Distributions

- Compared to “single” model approach, the typical estimate has less variance than the benchmark:



	Mean	Std Dev	CoV	75.0%	90.0%	95.0%	99.5%
ODP Pd CL Results	10,428	2,473	23.7%	11,881	13,694	14,909	18,536
CVB	10,428	3,878	37.2%	12,460	15,502	17,668	24,700

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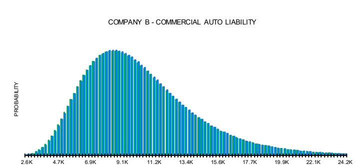
Claim Variability Benchmarks

Unpaid Claim Distributions

- Compared to “multiple” model approach, the typical estimate closer to the benchmark:



	Mean	Std Dev	CoV	75.0%	90.0%	95.0%	99.5%
Model Results*	10,428	3,911	37.5%	12,471	15,543	17,733	24,859
CVB	10,428	3,878	37.2%	12,460	15,502	17,668	24,700

** Model Results based on weighting of 4 different models.*

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Claim Variability Benchmarks
Types of Benchmarks

1. Loss Development Patterns
2. Unpaid Claim Distributions
3. **Correlation Between Segments**

Claim Variability Benchmarks
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
- Industry benchmarks have long been needed

Claim Variability Benchmarks
Correlation Between Segments

- For example, consider the weighted results for 4 LOBs using 1996 data:

Means

COMPANY A Model Correlation	CA	MPL-O	PL-O	WC
CA	100%	34.1%	-17.4%	46.6%
MPL-O	34.1%	100%	-19.4%	29.9%
PL-O	-17.4%	-19.4%	100%	10.5%
WC	46.6%	29.9%	10.5%	100%

Means

COMPANY A CVB Correlation - Means	CA	MPL-O	PL-O	WC
CA	100%	15.8%	12.0%	14.1%
MPL-O	15.8%	100%	10.3%	-3.4%
PL-O	12.0%	10.3%	100%	11.6%
WC	14.1%	-3.4%	11.6%	100%

Standard Deviations

COMPANY A CVB Correlation - Std Dev	CA	MPL-O	PL-O	WC
CA		21.9%	24.7%	27.6%
MPL-O	21.9%		20.2%	21.5%
PL-O	24.7%	20.2%		24.6%
WC	27.6%	21.5%	24.6%	

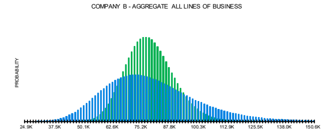
Modeled Correlation

Correlation Benchmarks

Claim Variability Benchmarks
Correlation Between Segments

- Consistent with individual segments, aggregates using a "single" model approach tend to be narrower than benchmarks:

COMPANY B - AGGREGATE ALL LINES OF BUSINESS



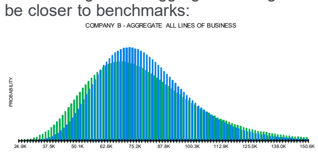
	Mean	Std Dev	CoV	75.0%	90.0%	95.0%	99.5%
ODP Pd CL Results*	80,159	10,504	13.1%	86,792	93,946	98,507	111,231
CVB	80,159	20,222	25.2%	91,900	106,857	116,949	147,377
TVaR Estimates							
ODP Pd CL Results*				94,017	100,081	104,153	116,002
CVB				107,420	120,852	130,320	159,855
Capital Required							
ODP Pd CL Results*				13,858	19,922	23,994	35,843
CVB				27,261	40,693	50,161	79,696

** Using only the ODP Bootstrap model for Paid data for each LOB.*

Claim Variability Benchmarks
Correlation Between Segments

- Consistent with individual segments, aggregates using a "multiple" model approach tend to be closer to benchmarks:

COMPANY B - AGGREGATE ALL LINES OF BUSINESS

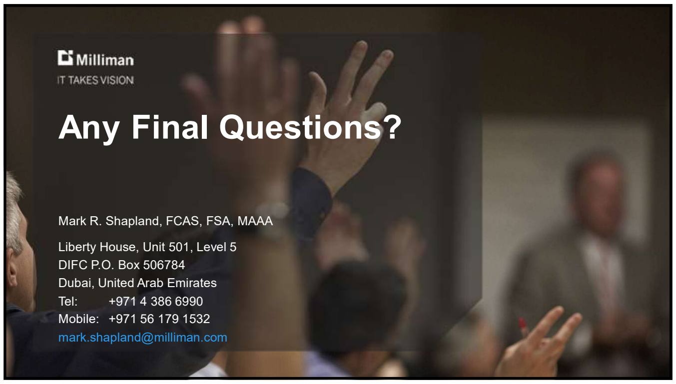


	Mean	Std Dev	CoV	75.0%	90.0%	95.0%	99.5%
Model Results*	80,159	24,749	30.9%	93,879	112,752	125,815	166,623
CVB	80,159	20,222	25.2%	91,900	106,857	116,949	147,377
TVaR Estimates							
Model Results*				113,720	131,133	143,675	184,053
CVB				107,420	120,852	130,320	159,855
Capital Required							
Model Results*				33,561	50,974	63,516	103,894
CVB				27,261	40,693	50,161	79,696

** Model Results based on weighting of 4 different models for each LOB.*

Claim Variability Benchmarks
Other Potential Uses

- Calculating average durations for future cash flows
- Calculating reserve risk margins based on the expected unpaid claim runoff – e.g., Solvency II or IFRS-17
- Assessing the variance parameter for a priori loss ratio assumptions in models
- Creating back-testing benchmarks for ERM thresholds
- Other uses which are only limited by your imagination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