Lⁱ Milliman Using Predictive Analytics to Decompose Workers' Compensation Loss Triangle Anomalies

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Overview

- Traditional Review of Loss Triangles
 - Expected-Observed Differences in Loss Reserves are often seen in Loss Triangles

- Predictive Analytics: Claim Segmentation Analysis
 - Predictive Analytics can be used to decompose Expected-Observed Differences in Loss Triangles
- Illustration based on Workers' Compensation experience



Traditional Review of Loss Triangles

Workers' Compensation Experience

Observations of Industry Data - Example

- For Discussion Purposes Only
 - Results will vary by company and line of business

- Illustration developed from Workers' Compensation losses
 - Based on Schedule P
 - Total Industry



ABC Insurance Company Workers' Compensation Data as of December 31, 2015

Cumulative Net Paid Loss & DCCE

Accident				,	Years of Dev	elopment				
<u>Year</u>	1	2	3	4	5	6	7	8	9	10
2006	5,537	11,770	15,649	17,871	19,353	20,469	21,273	22,104	22,574	22,981
2007	5,675	12,459	16,270	18,659	20,302	21,499	22,496	23,177	23,712	
2008	5,752	12,452	16,393	18,911	20,651	21,930	22,857	23,524		
2009	5,228	11,347	14,912	17,187	18,857	20,018	20,784			
2010	5,352	11,669	15,428	17,839	19,500	20,499				
2011	5,533	11,924	15,753	18,163	19,752					
2012	5,397	11,754	15,323	17,567						
2013	5,256	11,514	15,126							
2014	5,298	11,596								
2015	5,154									
Average of Last 3										
Excluding 2015 Diagonal	5,317	11,731	15,501	17,729	19,669	21,149	22,209			

Note: Data based on SNL Financial information.

ABC Insurance Company Workers' Compensation Data as of December 31, 2015

Cumulative Net Incurred Loss & DCCE

Accident				•	Years of Dev	elopment				
<u>Year</u>	1	2	3	4	5	6	7	8	9	10
2006	13,627	18,580	21,119	22,460	23,468	24,114	24,631	25,114	25,314	25,488
2007	14,058	19,596	22,087	23,643	24,573	25,271	25,830	26,146	26,350	
2008	14,076	19,679	22,369	23,924	24,910	25,485	26,053	26,400		
2009	12,628	17,752	20,189	21,599	22,459	23,148	23,505			
2010	12,864	18,260	20,835	22,205	23,129	23,594				
2011	13,248	18,659	21,118	22,562	23,418					
2012	13,073	18,379	20,651	21,161						
2013	13,014	18,299	20,355							
2014	13,201	18,293								
2015	13,037									
Average of Last 3										
Excluding 2015 Diagonal	13,096	18,446	20,868	22,122	23,499	24,635	25,505			

Note: Data based on SNL Financial information.

ABC Insurance Company Workers' Compensation Data as of December 31, 2015

Paid to Incurred Ratios

Accident				Υ	ears of Deve	elopment				
<u>Year</u>	1	2	3	4	5	6	7	8	9	10
2006	0.406	0.633	0.741	0.796	0.825	0.849	0.864	0.880	0.892	0.902
2007	0.404	0.636	0.737	0.789	0.826	0.851	0.871	0.886	0.900	
2008	0.409	0.633	0.733	0.790	0.829	0.860	0.877	0.891		
2009	0.414	0.639	0.739	0.796	0.840	0.865	0.884			
2010	0.416	0.639	0.740	0.803	0.843	0.869				
2011	0.418	0.639	0.746	0.805	0.843					
2012	0.413	0.640	0.742	0.830						
2013	0.404	0.629	0.743							
2014	0.401	0.634								
2015	0.395									



Loss Triangle Anomalies

- In this illustration, compared to the prior diagonals:
 - The paid losses in the latest diagonal are lower than the average of the three prior years
 - The incurred losses in the latest diagonal are lower than the average of the three prior years
 - The latest paid to incurred ratio is lower at 12 months



Explanation of Loss Anomalies

- How can differences in loss experience be explained to management or others?
- Have there been any changes?
 - Frequency or severity
 - Mix of business
 - Types of claims
 - Legislative
 - Medical Bill processing or distribution of services
- Predictive analytic techniques can provide guidance for explaining these differences



Predictive Analytics: Claim Segmentation Analysis

Workers' Compensation Experience

Predictive Analytics: Claim Segmentation Analysis

- Claim Segmentation Analyses common with targeting specific groups of customers ("Customer Segmentation")
 - Result from dividing a broad set of individuals or market into subgroups based on demographic, institutional, geographic, lifestyle, behavioral, or other characteristics
 - Examples from consumer purchases: banking, mobile phones, airline ticket, theater tickets, breakfast cereal, automobiles
- Challenges for Explaining Expected and Observed Differences in a Loss Triangle
 - Expected-observed differences are rarely neatly defined
 - For an evaluation, it can be difficult to detect a <u>change in the mix of claims</u>
 - For an evaluation, it is unlikely there will be a <u>uniform increase or decrease in severity</u> for all claims



Claim Segmentation Analysis for Claim Experience

- Simple illustration of a Claim Segmentation Analysis
- Illustration with claim segments tied to earlier WC loss triangle

Case study illustration of a Claim Segmentation Analysis



Predictive Analytics: Claim Segmentation Analysis

- Graph shows the process for performing a Claim Segmentation analysis to support reviews of loss-triangle experience
 - <u>Set-up</u>: Using a payer's historical experience, create the claim segments for a particular book of business at each evaluation
 - <u>Action</u>: Review the new loss triangle (observed) experience against the (expected) experience captured in the claim segmentations. Differences will identify observed-expected differences in frequency, severity, and claim distribution.



Claim Segments – Simple Illustration

- Segmentation: decision tree method that produces discrete easily understandable segments.
- Each endpoint represents a segment.
- Each segment is defined by a unique set of claim characteristics.





Claim Segments – Simple Illustration

- In this illustration, claims segments are according to total claim cost.
- Claim characteristics, payment amounts, and medical experience are used to segment claims into groups with similar total claim costs.





Claim Segments– Illustrative Example

- Analyses create mutually exclusive segments
- Claimant characteristics, payment history, and detailed medical experience are used
- 10 segments in illustration; in production, many more segments can be created
- A segment can be defined by a few factors
- A factor is not needed for every segment

		Segment								
Factor	1	2	3	4	5	6	7	8	9	10
Body Part	not multiple	not multiple			back	back			multiple	multiple
	not back				knee	knee				
					shoulder	shoulder				
Age	under 40	40+								
Medical	<= 3 med	> 3 med visits			13-24 phys ther	> 24 phys ther			> 12 med	> 12 med
	visits				visits	visits			visits	visits
					no surgery	no surgery			no surgery	surgery
									opiods	
Industry	not mfg	mfg								
	not construct	construction								
Disability Status	med only	med only			temporary	temporary			permanent	permanent
Region									high urban	
Claim Reporting									> 2 wks after	
									injury	
Claimant										Yes
attorney										



Claim Segmentation Analysis for Claim Experience

- Simple illustration of a Claim Segmentation Analysis
- Illustration with claim segments tied to earlier WC loss triangle
- Case study illustration of a Claim Segmentation Analysis



Claim Segmentation Analysis – Illustration for Decomposing Expected and Observed Differences in a Loss Triangle

- Choice of cost metric:
 - Amounts paid: total, indemnity, or medical
 - Amounts incurred: total, indemnity, or medical
- Evaluations: per timing of experience in loss triangles
 - Accident Year, Policy Year
 - 6 months, 18 months, 30 months, or other periods (or 12, 24, 36 months, etc.)
- Claim stratifications
 - Line of business
 - Coverage
 - Business units

Claim Segmentation Illustration - Observed and Expected Losses

- Table 1 presents experience for Net Paid Loss and DCCE at the Year 3 evaluation in slide 6.
 - For Accident Years 2010-2012, the average paid losses and DCCE was 15,501.
 - For Accident Year 2013, the average paid losses and DCCE was 15,126, a 2.4% decrease from the three-year average.

Accident Year	Three Prior Accident Years	Latest Accident Year	Difference
2010	15,428		
2011	15,753		
2012	15,323		
2013		15,126	
Average	15,501	15,126	-2.4%

Net Paid Loss and DCCE: Year 3 Evaluation

Claim Segmentations – Simple Illustration Using 5 Clusters

- Table presents distribution of claims and average losses for one set of clusters. Clusters are mutually exclusive.
 - Cluster 1: head concussions
 - Cluster 2: non-head, non-concussions, injured parties over 50
 - Similar descriptions for Clusters 3, 4, and 5
- Each cluster has a distribution (Column (2)) and average losses (Column (3)).
- Average loss for the book = 15,501.

Third-Report Experience: Distribution of Claims and Average Losses, by Cluster

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				CI	aim Characte	ristic	
Cluster	Percent of Claims	Average Losses	Body Part	Nature of Injury	Age	Industry	Opioid Use
1	1%	225,071	Head	Concussion			
2	10%	64,306	Not Head	Not Concussion	50 or over		
3	20%	24,115			49 or less	Transportation	
4	10%	6,769	Not Head	Not Concussion	49 or less	Not Transportation	Yes
5	59%	2,237	Not Head	Not Concussion	49 or less	Not Transportation	No
All	100%	15,501					

Claim Segmentation Analysis: Abnormal Experience Due to Claim Mix

- Table shows that lower than expected losses can be attributed to a <u>change in the mix of claims</u>.
 - Expected Losses: from preceding slide.
 - Observed Losses: average losses for each cluster are the same but there has been a change in the distribution of claims (in a manner not easily identified through summary stats).
- Observed distribution of claims indicates slight shift --
 - Away from transportation claims (compare expected 20% to observed 17.8% for Cluster 3)
 - Toward non-transportation opioid claims (compare expected 10% to observed 12.2% for Cluster 4).
- Shift produced a 2.4% decrease in observed losses (15,126) over expected losses (15,501).

	Expected	Losses	Observed Losses			
Cluster	Percent of Claims	Percent of ClaimsAverage Losses		Average Losses		
1	1%	225,071	1%	225,071		
2	10%	64,306	10%	64,306		
3	20%	24,115	17.8%	24,115		
4	10%	6,769	12.2%	6,769		
5	59%	2,237	59%	2,237		
All	100%	15,501	100%	15,126		

Lower than Expected Losses Due to a Difference in the Mix of Claims



Claim Segmentation Analysis: Abnormal Experience Due to Change in Severity

- Table shows lower than expected losses can be due to a <u>change in average severity</u> for a subset of claims.
 - Expected Losses: from earlier slide.
 - Observed Losses: indicate same mix of claims but 55% lower average losses for Cluster 4 (again, not easily identified through summary stats).
- Observed severity found a slight decrease in non-transportation opioid claims (compare expected 6,769 to observed 3,020 for Cluster 4).
- Shift produced the same 2.4% decrease in observed losses (15,126) over expected losses (15,501).

	Expected Losses		Observed Losses		
Cluster	Percent of Claims	Average Losses	Percent of Claims	Average Losses	
1	1%	225,071	1%	225,071	
2	10%	64,306	10%	64,306	
3	20%	24,115	20%	24,115	
4	10%	6,769	10%	3,020	
5	59%	2,237	59%	2,237	
All	100%	15,501	100%	15,126	

Lower than Expected Losses Due to a Change in Severity



Claim Segmentation Analysis: Summary

- Illustration showed contrasting reasons for decrease in claim costs contrasting both for the technical reasons (mix v. severity) and for the implications on claim operations (industry mix and opioid use identified characteristics v. opioid use the distinguishing characteristic)
- Table on left summarizes the change in mix of claims (decrease in Cluster 3, increase in Cluster 4).
- Table on right summarizes the change in severity (decrease in Cluster 4).

		Percent of Claims				
Cluster	Average Losses	Expected	Observed			
1	225,071	1%	1%			
2	64,306	10%	10%			
3	24,115	20%	17.8%			
4	6,769	10%	12.2%			
5	2,237	59%	59%			
All	15,501	100%	100%			

Lower	Losses	Due te	оа	Difference	in f	the	Mix	of	Claim	S
	L03303		u u				INIIA		Siaiiii	-

		Average Losses				
Cluster	Percent of Claims	Expected	Observed			
1	1%	225,071	225,071			
2	10%	64,306	64,306			
3	20%	24,115	24,115			
4	10%	6,769	3,020			
5	59%	2,237	2,237			
All	100%	15,501	15,126			

Lower than Expected Losses Due to a Change in Severity

Claim Segmentation Analysis for Claim Experience

- Simple illustration of a Claim Segmentation Analysis
- Illustration with claim segments tied to earlier WC loss triangle

Case study illustration of a Claim Segmentation Analysis



Claim Segmentation Analysis: Case Study

• **Objective**: Claim Segmentations for a WC book of business

Results:

- 41 segments
- Wide variation in payments: \$290 \$106,700
- Several variable types contributed to explanation (demographic, FROL, policy, payment trans)
- Accident Description and Adjusters Notes accounted for 50% of model results

		All Claims
Number of S	egments	41
Loss Paymer	nts	
	Maximum Segment	106,700
	Average	21,000
	Minimum Segment	290
Lift (ratio of	Average Loss Payments)	
	Maximum / Average	5.1
	Minimum / Average	0.014
	Maximum / Minimum	367
Number of P	Predictors	21
		Influence
Predictor Va	riables	on Model
	Age	
Master	Claim Status at 30 days	11%
	Wage	
	Reporting Lag	
First Report	Nature of Injury	23%
of Injury	Body Part	2370
	Cause of Accident	
Policy	Annual Premium	2%
Toncy	Premium Rate	270
Payment	Indemnity at 30 Days, Total	1/1%
Trans	Indemnity at 30 Days, Temp	1470
Accident	Low Back	
Description	Number of Body Parts	17%
Description	Number of Natures of Injury	
	Attorney Involvement	
Adjusters	Ambulance, Surgery, Hosp, MRI	33%
Notes	Multiple Body Parts Identified	5570
	Multiple Body Parts Identified	

Claim Segmentation Analysis: Case Study

- Segments were developed to cluster approximately 2-3% of the claims in each cluster.
- Segments 1-6: 13% of claims and 52% of payments.
- Segment 1 is defined by 2 variables and most of the top 6 segments are defined by 4 variables.

					Predictor Variables					
Segment	Percent of Claims	Average Loss Payment	Percent of Loss Payments	Predictor Count	Indem at 30 Days, Total	Number of Body Parts (Acc Desc)	Ambulance, Surgery, Hosp, MRI (Adjusters Notes)	Report Lag	Attorney Involved (Adjusters Notes)	Wage
Total	100%	21,000	100.0%	7.61	41	19	31	26	34	2
1	2.8%	106,700	14.1%	2	530 or more	3 or more				
2	2.0%	98,600	9.2%	4	530 or more	0 to 2	2 or more	0 to 2		
3	2.3%	87,300	9.4%	4	0 to 530	1 or more			1 or more	440 or more
4	2.1%	74,900	7.5%	4	530 or more	0 to 2	2 or more	3 or more		
5	2.1%	57,600	5.8%	4	0 to 530	1 or more			1 or more	0 to 440
6	2.2%	57,000	6.1%	3	530 or more	2	01			
1-6	13%	81,400	52%							
7 - 41	87%	11,600	48%							

Claim Segmentation Analysis: Summing Up

- <u>Cohort definitions</u>: Preceding two slides presented neatly-defined cohorts. Earlier sample results showed how the number and diversity of cohort definitions can become more complex.
- <u>Scope</u>: Number of Claim Segmentation Analyses supporting a loss triangle review will depend on the complexity and breadth of a book of business. A previous slide indicated:
 - Payment basis
 - Number of evaluations
 - Book of business stratifications
- Implementation considerations



Presentation Summary

Presentation Summary

- Traditional Review of Loss Triangles
 - Expected-Observed Differences in Losses are often seen in Loss Triangles

- Predictive Analytics: Claim Segmentation Analysis
 - Predictive Analytics can be used to decompose Expected-Observed Differences in Losses





Thank you

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