Milliman

AGRiP – Webinar

Resetting your Contribution Algorithm

Presented by:
Chris Kogut, FCAS, MAAA
Milliman, Inc.

May 23, 2018

Overview

Underwriting Guidelines evolve in response to:

- Change in Risk Characteristics
- Market Conditions
- Member Expectations
- Management Objectives

Overview

Reasons for changing your algorithm are often forgotten.

Forgetting carries consequences:

- Member contributions not in alignment with risk
- Underwriting by "following the formula" doesn't work

3 Goals/Topics for Today

3 Goals/Topics for Today

1. Identify situations that prompt review of your current funding allocation

3 Goals/Topics for Today

2. Understand the objectives to accomplish within your evaluation process

3 Goals/Topics for Today

3. Through this process, appreciate the:

- Considerations
- Benefits
- Consequences

Of resetting your contribution algorithm.

Milliman 7

Approach

- How do you evaluate the current funding allocation and determine the best redistribution to members?
- Learn through 3 actual Case Studies – projects done for pools

Milliman 8

Funding Guideline Resources

Milliman 9

Funding Guideline Resources

AGRiP Operations Manual

- Funding Section – 5 pages
- Actuarial studies should:
    - Review funding levels for prior losses AND
    - Assist in setting rates for future periods
- Funding should consider rates calculated at least partially on the basis of members' loss experiences

Funding Guideline Resources

Casualty Actuarial Society

- Basic Ratemaking – 423 pages
- Chapter 9 – Traditional Risk Classification

Industry Comparisons

Industry Comparisons

	2016 Commercial Lines Carriers	2016 AGRiP Member Pools
Loss Ratio	66.1%	73.6%
Combined Ratio	97.7%	126.5%
Operating Ratio	89.3%	112.8%
Overall Rate Change	-2.0%	N/A
Overall Contribution Change	N/A	+3.5% (includes rate & exposure changes)
		70,000 of 90,000 municipal entities insured through public entity pools

Industry Source: SNL

Industry Comparisons

Regulation, competition vary widely

- By state, region
- By line of coverage

Industry Comparisons

Commercial Rating Plans

- Schedule rating/Individual risk modification plans
- Difficult to compare rating plans

8 Great Reasons to Re-evaluate Your Algorithm (From Actual Case Studies)

8 Great Reasons to Re-evaluate Your Algorithm

External Influences

1. Legislative changes in state; enhanced scrutiny of operations
2. Losing a very large, good-performing member to commercial market over rate

8 Great Reasons to Re-evaluate Your Algorithm

Operational

3. Gain new members
4. Provide basis for selecting risks to participate in various credit programs
   - Validate the impact of those programs
5. Total LoB/Program contribution collected is less than actuarial indication

8 Great Reasons to Re-evaluate Your Algorithm

Due Diligence

6. Ensure members are being charged actuarially sound rates
   - A "check-up" on rating algorithm
7. Evaluate impact of various assumptions in allocating rate/credibility to member; examine impact of shock losses
8. Gain statistical support for new underwriting rules or tiering structures and/or other pricing factor improvements

6 Important Issues to Identify Before Resetting Your Contribution Algorithm

Before Resetting Your Algorithm ….

6 Important Issues to Consider

1. Objectives
2. Considerations
3. Implementation
4. Board Role
5. Consequences
6. Benefits

Before Resetting Your Algorithm: Identify Objectives

1. Housekeeping

- Create Risk Pooling Practices Agreement
- Improvements to rating algorithm
- Evaluate equity amongst members
- Eliminate program subsidies

Before Resetting Your Algorithm: Identify Objectives

2. Significant Changes

- Reconstruct the internal rating model to encompass the results of the underwriting analytics outcomes
- Design new underwriting rules or tiering structures and/or other pricing factor improvements

Before Resetting Your Algorithm: Identify Considerations

3. Considerations

- Alternatives
- Roll Out
- Implications

Before Resetting Your Algorithm: Identify Implementation

4. Implementation
- Match contributions to indications?
  - Eliminates subsidy from other programs and between members
- Change Pool rating algorithm/modifications
  - Keep current program and add ad hoc adjustments as needed
  - All new program to adjust member rate allocation
  - Hybrid

Before Resetting Your Algorithm: Identify Board Role

5. Board Role
- Use Surplus to soften positive rate change impact?
- Transition members to new program over multiple years?
- Consider price sensitivity of members
  - Varies by competitive environment
- Consider additional member services

Before Resetting Your Algorithm: Identify Consequences

Consequences
1. Large disruptions may impact member relations
   - Decide how often to reevaluate
2. Administration systems may not be sophisticated enough to implement changes
3. Members may experience large swings in contribution from year to year depending on changes implemented

Before Resetting Your Algorithm: Identify Benefits

Benefits

1. Avoid adverse selection
2. Ensure members are treated fairly
3. Comply with regulations
4. ***Be more prepared for the next disruptor***
5. ***Potentially influence member behavior to reduce losses***

Case Study No. 1: Underwriting Predictive Analysis

Case Study No. 1: Underwriting Predictive Analysis

Overview

Details of Pool A

- AL, GL, WC, etc.
- Municipalities + Schools
- Over 450 members

- Rating algorithm generally start with stationary base rates (NCCI for WC)
- Members select coverages
- Increasing use of credit programs to promote enhanced risk management across the membership

Case Study No. 1: Underwriting Predictive Analysis

Pool Goals

1. Enhance process for allocating risk costs members
2. Gain support for new underwriting rules or tiering structures and/or other pricing factor improvements
3. Provide basis for selecting risks to participate in the various credit programs AND validate the impact of those programs

Case Study No. 1: Underwriting Predictive Analysis

Achieve Goals via Following Objectives

1. Reconstruct the internal rating model to encompass the results of the underwriting analytics outcomes
2. Focus on credit programs

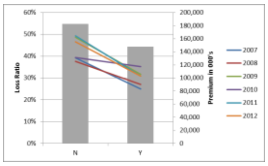
Case Study No. 1: Underwriting Predictive Analysis

Credit Programs

Risk Management Credit
Law Enforcement Credit
Auto Liability Credit
WC Schedule Credit/Debit
P&L Schedule Credit/Debit

Case Study No. 1: Risk Management Guide - Overall

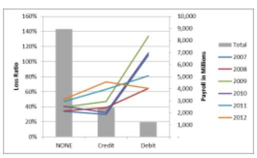
Bucket	Exposure %	Premium	Incurred Loss	Loss Ratio	Record Count	Claim Count	Frequency	Severity
N	55.27%	182,559,140	77,916,511	43%	2,302	12,207	6.687	6,383
Y	44.73%	147,727,037	45,843,724	31%	492	8,123	5.499	5,644



- RMG credit appears to differentiate good vs. bad risks when reviewing loss ratio across all lines of business

Case Study No. 1: WC Schedule Credit/Debit

Bucket	Record Count	Payroll in 000's	Payroll %	"On Level" Manual Premium	Incurred Losses as of 9/30/14	Loss Ratio	Claim Count as of 9/30/14	Frequency	Severity	Loss Cost Per Payroll in 00's	Average Premium
None	2,156	8,936,831	71%	119,438,505	48,502,809	41%	10,040	1.123	4,831	1.34	55,398
Credit	122	2,416,720	19%	25,037,113	11,463,078	46%	2,004	0.829	5,720	1.04	205,222
Debit	147	1,233,534	10%	18,697,863	17,723,821	95%	2,844	2.306	6,232	1.52	127,196



Debit better indicator of bad loss ratio than credit is of good

Case Study No. 1: Auto Liability - Rating

Predominant Territory	Predominant Vehicle Type					
Loss Ratio	Emergency	Light Truck	School Bus 60+	Other	Overall
1	19%	20%	13%	17%	16%
2	61%	57%	87%	23%	67%
3	44%	30%	91%	23%	40%
Overall	50%	37%	47%	21%	81%
Vehicle Count	Emergency	Light Truck	School Bus 60+	Other	Overall
1	4,648	5,741	16,256	1,265	27,910
2	31,331	13,309	17,830	1,885	64,355
3	16,990	14,067	1,714	1,458	34,229
Overall	52,969	33,117	35,800	4,608	126,494

Predominant Territory together with Dominant Vehicle Type provide insight into areas to consider adjustments needed to base rate consistent with ISO methodology

Case Study No. 1: Auto Liability - Rating

Bucket	Record Count	Vehicle Count	Vehicle %	Premium	Incurred Loss	Loss Ratio	Claim Count	Frequency	Severity	Loss Cost	Average Premium
0 to 367	761	35,051	27.79%	10,847,769	4,383,231	40%	675	6.222	6,494	309	14,255
367 to 394	247	18,879	14.97%	7,406,212	2,230,445	30%	333	4.496	6,698	392	29,985
394 to 398	114	14,754	11.70%	5,622,330	4,906,975	87%	305	5.425	16,088	381	49,319
398 to 442	291	14,375	11.40%	5,554,695	3,490,650	63%	390	7.021	8,950	386	19,088
442 to 456	33	12,401	9.83%	5,552,416	6,374,445	115%	673	12.121	9,472	448	168,255
456 to 820	144	15,360	12.18%	10,291,638	1,892,695	18%	434	4.217	4,361	670	71,470
820 and up	18	15,674	12.43%	9,569,587	1,233,384	13%	394	4.117	3,130	611	531,644

Average AL Base Rate Variable supports considering ISO methodology

Case Study No. 1: Auto Liability - Rating

Rate Package	Vehicle Type	Territory	Base Rate
2014 Standard Renewal	Transit Bus (1-8 passenger)	3	380
2014 Standard Renewal	Transit Bus (21-60 passenger)	3	380
2014 Standard Renewal	Transit Bus (9-20 passenger)	3	380
2014 Standard Renewal	Transit Bus (over 60 passengers)	3	380
2014 Standard Renewal	School Bus (1-8 passenger)	3	381
2014 Standard Renewal	School Bus (21-60 passenger)	3	381
2014 Standard Renewal	School Bus (9-20 passenger)	3	381
2014 Standard Renewal	School Bus (over 60 passenger)	3	381
2014 Standard Renewal	Emergency	2	408
2014 Standard Renewal	Heavy Truck	2	408
2014 Standard Renewal	Light Truck	2	408
2014 Standard Renewal	Medium Truck	2	408

Average AL Base Rate Variable supports considering ISO methodology

Case Study No. 1: Auto Liability - Rating

Loss Ratio	2007	2008	2009	2010	2011	2012	Overall
OTHER	33%	39%	71%	23%	34%	19%	36%
City	24%	75%	47%	39%	40%	46%	45%
School	71%	57%	85%	35%	27%	21%	49%
Town	123%	10%	13%	42%	48%	13%	41%
County	13%	18%	9%	163%	28%	15%	41%
Water/Sewer	11%	10%	34%	10%	20%	133%	36%
Exposure	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**Overall**
OTHER	677	765	774	798	841	906	4,761
City	6,318	6,665	6,393	6,752	6,703	6,927	39,758
School	7,208	6,197	5,937	5,697	5,805	6,215	37,059
Town	3,502	3,742	3,686	3,885	4,257	4,258	23,330
County	2,124	2,182	2,286	1,990	1,921	1,834	12,337
Water/Sewer	1,284	1,372	1,452	1,466	1,595	1,707	8,876
Frequency	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**Overall**
OTHER	0.037	0.037	0.044	0.043	0.025	0.028	0.035
City	0.026	0.027	0.031	0.024	0.026	0.022	0.026
School	0.039	0.042	0.038	0.036	0.032	0.030	0.036
Town	0.019	0.016	0.017	0.016	0.014	0.014	0.016
County	0.017	0.012	0.010	0.014	0.015	0.009	0.013
Water/Sewer	0.016	0.018	0.014	0.016	0.016	0.019	0.016

Signal to Noise Threshold > 2.000; AL overall loss ratio = 45%

Case Study No. 1:
Overall Results

1. RMG program appears to differentiate risks overall
   - Consider application on per line of business basis
2. AL and Law Enforcement programs do no differentiate risks
   - Giving away premium, may be to early to tell

Case Study No. 1:
Overall Results

3. WC Scheduled Credit/Debit program highly predictive
   - Does a better job differentiating bad risk than it does good risk
4. GL Scheduled Credit/Debit program high predictive
   - Does a good job differentiating both bad and good risk, results less stable by variable
   - Consider adjustment to E-Mod approach

Case Study No. 1:
Overall Results on Rating Variables

- Segments for all lines all members point to distinctions in member type and line of business
- Size of members (current tiering structure) does matter however it only becomes significant within the by member by line type grouping

Case Study No. 1:
Overall Results on Rating Variables

- By member by line modeled results provides size of member indicator based on exposure (not premium)
- Suggests potential refinement of tiering structure

Case Study No. 1
Results: Member = School; LOB = WC

- Size of school matters for WC: larger schools have better experience
- Segment 2 and Segment 3 have similar loss ratios but very different characteristics
  - Segment 2 is essentially one very large member; Segment 3 is made up of many smaller members

Case Study No. 1
Results: Member = School; LOB = WC

- Credit debit program seems to be applied appropriately for smaller schools
  - Loss ratios for those smaller schools which did not receive a debit is about 5pts below average
- Hazard Group D class code being reported on school policies is 7380 (Chauffeurs) which is the highest rated class code reported on about 37% of the total school WC policies

Case Study No. 1 Results:
Member = City; LOB = WC

- Larger city policies appear to perform better
  - Based on manual premium not payroll
- Of the smaller city members those with higher unemployment rates are experiencing worse loss ratios

Case Study No. 1: Considerations for Enhancement

- Data available "collectively" for each school member
  - Gather "school" level data for School members
- Liability credits and debits are recorded in "bulk"
  - Track separately according to calculation
  - Experience mod, credit/debit for each program, judgmental adjustments, etc.

Case Study No. 1: Considerations for Enhancement

- Limited information on member loyalty
  - Record member participation
  - Join, terminate, re-join; by program
- RMG questions equally weighted
  - Weight questions base on corresponding risk/losses

Case Study No. 1: Other Suggestions

- Safety inspections done for larger members
  - Perform safety procedures for smaller members
- Tiering on total policy premium
  - Develop tiers by line of business and member type
  - Consider exposure instead of premium; manual instead of annual

Case Study No. 1: Other Suggestions

- Usage of online university courses has positive impact
  - Add to RMG questionnaire
  - Expand programs
- All vehicle types rated with same base rate
  - ISO suggests various multipliers to differentiate between different vehicle types and characteristic (e.g., school buses seating capacity, truck weight, emergency vehicles)
  - Re-rate policies with ISO indications

Case Study No. 2: Underwriting Predictive Analysis

Case Study No. 2: Underwriting Predictive Analysis

Details of Pool B
- AL, GL, WC
- Municipalities + Schools
- Over 500 members

Members select coverages
- Relatively new streamlined rating program (2009)
- Industry/prior rates; experience rating; some discounts (multi-year, package)
- Features to limit swing of rating variables ("CAP" program)
- Focus on workers compensation (WC)

Milliman 52

Case Study No. 2: Underwriting Predictive Analysis

Specific Situation
- Legislative changes in state; enhanced scrutiny of operations
- Opportunity to gain many new members
- Pool Management:
  - Concerned with the allocation of risk cost amongst members and programs
  - Better selection process of risks to participate in discount programs

Milliman 53

Case Study No. 2: Underwriting Predictive Analysis

Objectives
- Identify factors that are predictive of loss; summarize School vs. Municipal members
- Support for new underwriting rules or tiering structures and/or other pricing factor improvements
- Member contributions = actuarially derived funding requirements
- Analyze the effectiveness of new rating formula
- Risk Pooling Practices Agreement

Milliman 54

Case Study No. 2: Underwriting Predictive Analysis

Program Eligibility Guidelines

Multi-Year Agreement (MYA)

Cultural Assessments

Loss Mitigation Conditions

Contribution Assurance Program (CAP)

Milliman 55

Case Study No. 2: Underwriting Predictive Analysis

Program Suggestions

Specific underwriting rules

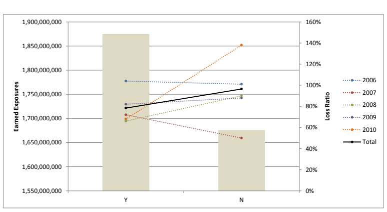
Utilize predictive modeling results

Capture data on Cultural Assessments and Loss Mitigation Conditions

Milliman 56

Case Study No. 2: Underwriting Predictive Analysis

CAP Program (Loss Ratio) – School Members



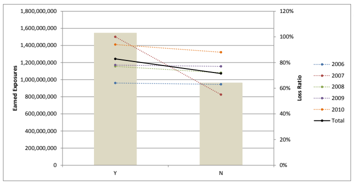
CAP Program (50% participation)

- Loss ratios historically lower for participants (78%) than for non-participants (96%); frequency is relatively stable and slightly lower for participants; severity is more volatile by year particularly for non-participants

Milliman 57

Case Study No. 2: Underwriting Predictive Analysis

CAP Program (Loss Ratio) – Municipal Members

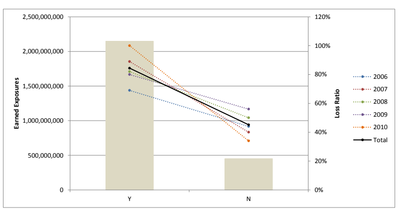


CAP Program (60% participation)
- Loss ratios historically higher for participants (83%) than non-participants (71%)
- Largely driven by higher severities

Milliman 58

Case Study No. 2: Underwriting Predictive Analysis

Multi Year Agreement (Loss Ratio) – Municipal Members



Multi-Year Agreement (83% participation)
- Significantly higher loss ratio for participants (84% vs. 45%)
- Participants have frequencies 30+% higher and severities 70+% higher

Milliman 59

Case Study No. 2: Underwriting Predictive Analysis

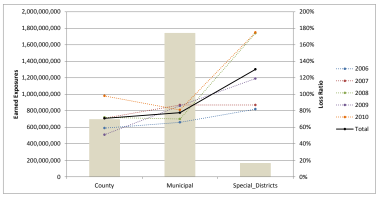
Overall Results on Rating Variables

- Segments for all lines all members point to distinctions in member type and line of business
- Territory and Representative groupings exhibiting differentials in results
- New rating algorithm shows different results (2010) from prior years; not always better in risk characterization

Milliman 60

Case Study No. 2: Underwriting Predictive Analysis

Member Type (Loss Ratio) – Municipal Members

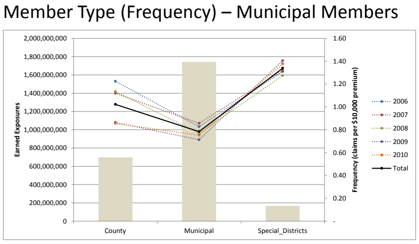


Member type (67% Municipal, 6% Special District, 27% County)

- Municipal loss ratios (78%) were generally higher than those of the Counties (71%)
- Significantly lower than the Special Districts (130%)

Case Study No. 2: Underwriting Predictive Analysis

Member Type (Frequency) – Municipal Members



Case Study No. 2: Underwriting Predictive Analysis

<u>Other Key Findings</u>

Statistics

- Class Code reporting issues
- Dominant hazard group
- Poorly performing class codes
- Tenure
- School district public data
- Alignment of exposure to losses
- Base rates

Case Study No. 3:
Per Member Loss Ratio Analysis

Milliman 64

Case Study No. 3: Per Member Loss Ratio Analysis

Overview of Pool C

- AL, GL, WC
- Municipalities
- >320 members
- All members participate in all coverages

- Rating algorithm has evolved over time
- Rates calculated in total + allocated to member
- Rate provided is “grossed” up for all modifications
- Includes discounted safety margin

Milliman 65

Case Study No. 3: Per Member Loss Ratio Analysis

Specific Situation

- Total WC contribution (after modification) is less than actuarial indication
- P+L subsidizes inadequacy in WC contribution
- Poor performing members are driving up the rate and are subsequently subsidized by better performing members
- Lost a very large good performing member to commercial market over rate

Milliman 66

Case Study No. 3: Per Member Loss Ratio Analysis

Specific Situation

Objective:

- Improve rating algorithm
- Better equity amongst members
- Eliminate program subsidy

Case Study No. 3: Per Member Loss Ratio Analysis

Overall Results

- Detailed analysis provided to management team to consider options
- Support for decision-making provided to Board
- Developed a "staged" plan to reach goal

Case Study No. 3: Per Member Loss Ratio Analysis

WC – Overall results allocated to member

- Historical experience (2012 – 2016 aggregated) for each member was compiled and loss ratios calculated
- Members negatively impacting overall experience the most were identified
  - Size of member and volatility of experience was accounted for
- Analysis highlights the shortcomings of the current approach

(1)			(2)	(3)	(4)	(5)
Loss Ratio Range			Average Loss Ratio	Number of Members	Total Contribution	Ultimate Total Loss
		0%	0%	122	2,650,520	-
0%	to	20%	6%	84	6,559,893	482,684
20%	to	40%	30%	19	3,972,387	1,284,690
40%	to	60%	50%	13	2,239,700	1,107,116
60%	to	80%	70%	10	4,005,395	2,777,122
80%	to	100%	90%	8	4,924,797	4,246,690
100%	to	120%	109%	8	4,823,400	5,149,573
120%	to	140%	127%	7	644,832	793,673
140%	to	160%	152%	7	4,635,091	7,137,568
160%	to	200%	177%	9	3,388,386	6,141,499
200%	to	400%	289%	11	1,953,572	4,476,972
400%	to	600%	501%	7	749,683	3,633,211
600%	to	1000%	843%	3	335,407	1,784,330
1000%	to	1500%	1171%	2	166,631	1,487,225
1500%	to	3000%	2352%	2	57,470	700,663
		Total	100.2%	312	41,107,162	41,203,015

Case Study No. 3: Per Member Loss Ratio Analysis

<u>P+L – Overall results allocated to member</u>

- Results by Contribution Band
- Results are fairly evenly spread amongst size of member

Property & Liability
Ultimate Loss Ratio by Contribution Band
2012-2016

(1)			(2)	(3)	(4)	(5)
Average Annual Contribution Range			Average Loss Ratio	Number of Members	Total Contribution	Ultimate Total Loss
1	to	2,000	3%	42	241,182	9,425
2,000	to	5,000	5%	27	448,673	26,236
5,000	to	7,500	89%	15	488,003	493,186
7,500	to	10,000	56%	11	479,717	299,403
10,000	to	12,500	41%	15	853,811	434,805
12,500	to	15,000	29%	15	1,043,663	386,361
15,000	to	20,000	25%	30	2,650,488	718,638
20,000	to	25,000	71%	38	4,234,911	3,359,227
25,000	to	30,000	18%	34	4,689,828	959,649
30,000	to	35,000	31%	22	3,533,082	1,297,782
35,000	to	40,000	20%	14	2,647,428	512,483
40,000	to	50,000	46%	15	3,337,895	1,974,482
50,000	to	75,000	55%	16	4,706,139	3,025,387
75,000	to	100,000	57%	15	6,554,635	4,361,723
100,000	to	250,000	33%	21	15,714,791	6,006,653
250,000	to	500,000	24%	7	12,139,239	3,446,813
500,000	to	750,000	47%	1	3,016,211	1,347,138
		Total	42.9%	338	66,779,698	28,659,392

Case Study No. 3: Per Member Loss Ratio Analysis

- WC experience has been significantly worse than P&L
- Members typically have poor experience in either WC, or P&L, but not both
  - Only 7 members have 5 year loss ratios greater than 100% for both programs
- In general, severity (average size of loss), not frequency (number of claims) is the driving force between poor experience

Case Study No. 3: Per Member Loss Ratio Analysis

<u>Per Member Analysis</u>

- Allocate contributions to individual members using actuarial approach (not rating algorithm) to reflect historical experience
- Four allocation methods:
  - 2 experience periods with 2 loss limits
    - 5 years and 7 years
    - Losses limited to $500,000 (current retention) per occurrence and losses limited to $100,000 per occurrence
      - Excess losses were loaded back in after determining member distribution

Case Study No. 3: Per Member Loss Ratio Analysis

Per Member Analysis
- For each allocation approach:
  - Relativities per member were calculated ("actuarial mod")
  - Rates per member were calculated based on funding study
  - 5 year experience period with losses limited to $100,000 was used for comparison to current contribution for each member

Milliman 73

Case Study No. 3: Per Member Loss Ratio

Analysis: Actuarial Modification (Per Member Relativities) Compared to Current Pool Modification

Relativity < 1.0 (262 members, 52% of total contribution)
- Average payroll: $0.5M

- 40 members with current Pool modification > 1.0
- 201 members with current Pool modification < 1.0
- 21 members currently at minimum premium

Milliman 74

Case Study No. 3: Per Member Loss Ratio

Analysis: Actuarial Modification (Per Member Relativities) Compared to Current Pool Modification

Relativity > 1.0 (49 members, 48% of total contribution)
- Average payroll: $1.6M

- 29 members with current Pool modification > 1.0
- 20 members with current Pool modification < 1.0

Milliman 75

Case Study No. 3: Per Member Loss Ratio

Alternative Method – Tiering

Tier 1: Best	Tier 2: Average	Tier 3: Worst
Credible members w/calculated relativities <0.95	Not credible. Calculated relativities from 0.95-1.05	Credible w/calculated relativities >1.05
Factor of 0.75	Factor of 1.00	Factor of 1.25

*Factors applied before other Pool Modifications

Case Study No. 3: Per Member Loss Ratio

Alternative Method – Tier Compared to Current Pool Mod

Tier	Tier 1: 25% (54 members; 36% of total contribution)	Tier 2: No Debit/Credit (232 members; 22% total contribution)	Tier 3:25% Debit (25 members; 42% total contribution)
Average Payroll	$1.68M	$0.2M	$2.73M
Members w/current Mod >1.0	4	52	13
Members w/current Mod <0.75	29	NA	NA
Members w/current Mod 0.75-1.0	21	NA	NA
Members w/current Mod <0.95	NA	159	NA
Members at min premium	NA	21	NA

Case Study No. 3: Per Member Loss Ratio

Alternative Method – Potential Impact

Tier	Count	Average True Rate Change	Average Rate Neutral Change
1	54	6.8%	-7.1%
2	232	11.1%	-3.3%
3	25	31.9%	14.7%
Total	311	15.0%	0.0%
Contribution		$13.2M	$11.3M

Tier	Proposed Factor	Average Current Mod
1	-25%	-25.4%
2	0	-10.3%
3	25%	-4.0%
Total		-14.9%

Summary: Re-Evaluating Your Contribution Algorithm

Why:

1. External Influences
2. Operational Considerations
3. Due Diligence

Summary: Re-Evaluating Your Contribution Algorithm

What:

1. Objectives
   - Housekeeping
   - Significant Changes
2. Considerations
3. Benefits
4. Consequences

Summary: Re-Evaluating Your Contribution Algorithm

How:

1. Underwriting Predictive Analytics
2. Per Member Loss Ratio Analysis
3. Hybrid
4. Other

Milliman
IT TAKES VISION

Thank you

Chris Kogut, FCAS, MAAA
Chris.Kogut@Milliman.com