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

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

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.

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

Funding Guideline Resources
Funding Guideline Resources
AGRI 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

<table>
<thead>
<tr>
<th></th>
<th>2016 Commercial Lines Carriers</th>
<th>2016 AGRiP Member Pools</th>
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</thead>
<tbody>
<tr>
<td>Loss Ratio</td>
<td>66.1%</td>
<td>73.6%</td>
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<tr>
<td>Combined Ratio</td>
<td>97.7%</td>
<td>126.5%</td>
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<tr>
<td>Operating Ratio</td>
<td>89.3%</td>
<td>113.8%</td>
</tr>
<tr>
<td>Overall Rate Change</td>
<td>-2.0%</td>
<td>N/A</td>
</tr>
<tr>
<td>Overall Contribution Change</td>
<td>N/A</td>
<td>+3.5% (includes rate &amp; exposure changes)</td>
</tr>
</tbody>
</table>

- 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)

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

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

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

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

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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

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

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

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

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<tr>
<th>Bucket</th>
<th>Exposure %</th>
<th>Premium</th>
<th>Incurred Loss</th>
<th>Loss Ratio</th>
<th>Record Count</th>
<th>Claim Count</th>
<th>Frequency</th>
<th>Severity</th>
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<td>8,123</td>
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</table>

Case Study No. 1: WC Schedule Credit/Debit

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

Case Study No. 1: Auto Liability - Rating

- 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

<table>
<thead>
<tr>
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<th>Vehicle Count</th>
<th>Vehicle %</th>
<th>Premium Incurred Loss</th>
<th>Loss Ratio</th>
<th>Claim Count</th>
<th>Frequency</th>
<th>Severity</th>
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<td>247</td>
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<td>820 and up</td>
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<td>15,674</td>
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<td>9,569,587</td>
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<td>394</td>
<td>4.117</td>
<td>3,130</td>
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Average AL Base Rate Variable supports considering ISO methodology

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### Case Study No. 1: Auto Liability - Rating

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<td>3</td>
<td>180</td>
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<tr>
<td>2014 Standard Renewal Transit Bus (9 - 20 passenger)</td>
<td>3</td>
<td>180</td>
</tr>
<tr>
<td>2014 Standard Renewal Transit Bus (over 60 passengers)</td>
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</tr>
<tr>
<td>2014 Standard Renewal School Bus (1 - 8 passenger)</td>
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<td>2014 Standard Renewal School Bus (9 - 20 passenger)</td>
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<tr>
<td>2014 Standard Renewal School Bus (over 60 passengers)</td>
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<tr>
<td>2014 Standard Renewal Emergency</td>
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<td>3.08</td>
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<tr>
<td>2014 Standard Renewal Heavy Truck</td>
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<td>2014 Standard Renewal Light Truck</td>
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<tr>
<td>2014 Standard Renewal Medium Truck</td>
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</tbody>
</table>

Average AL Base Rate Variable supports considering ISO methodology

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### Case Study No. 1: Auto Liability - Rating

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

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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 highly 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

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)

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

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
Case Study No. 2: Underwriting Predictive Analysis

Program Eligibility Guidelines
Multi-Year Agreement (MYA)
Cultural Assessments
Loss Mitigation Conditions
Contribution Assurance Program (CAP)

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

Case Study No. 2: Underwriting Predictive Analysis

CAP Program (Loss Ratio) – School Members

- 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
Case Study No. 2: Underwriting Predictive Analysis

CAP Program (Loss Ratio) – Municipal Members

• Loss ratios historically higher for participants (83%) than non-participants (71%)
• Largely driven by higher severities

Multi Year Agreement (Loss Ratio) – Municipal Members

• Significantly higher loss ratio for participants (84% vs. 45%)
• Participants have frequencies 30+% higher and severities 70+% higher

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
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

- Other Key Findings
  - 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

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

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
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

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

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<th>Average Loss Ratio</th>
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<th>Total Contribution</th>
<th>Ultimate Total Loss</th>
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<td>2</td>
<td>159.38</td>
<td>511,548</td>
</tr>
<tr>
<td>780%</td>
<td>0%</td>
<td>2</td>
<td>79.69</td>
<td>277,116</td>
</tr>
<tr>
<td>800%</td>
<td>0%</td>
<td>2</td>
<td>39.84</td>
<td>127,814</td>
</tr>
<tr>
<td>820%</td>
<td>0%</td>
<td>2</td>
<td>19.92</td>
<td>511,548</td>
</tr>
<tr>
<td>840%</td>
<td>0%</td>
<td>2</td>
<td>9.96</td>
<td>277,116</td>
</tr>
<tr>
<td>860%</td>
<td>0%</td>
<td>3</td>
<td>4.98</td>
<td>127,814</td>
</tr>
<tr>
<td>880%</td>
<td>0%</td>
<td>3</td>
<td>2.49</td>
<td>511,548</td>
</tr>
<tr>
<td>900%</td>
<td>0%</td>
<td>3</td>
<td>1.24</td>
<td>277,116</td>
</tr>
<tr>
<td>920%</td>
<td>0%</td>
<td>3</td>
<td>0.62</td>
<td>127,814</td>
</tr>
<tr>
<td>940%</td>
<td>0%</td>
<td>3</td>
<td>0.31</td>
<td>511,548</td>
</tr>
<tr>
<td>960%</td>
<td>0%</td>
<td>2</td>
<td>0.15</td>
<td>277,116</td>
</tr>
<tr>
<td>980%</td>
<td>0%</td>
<td>2</td>
<td>0.08</td>
<td>127,814</td>
</tr>
<tr>
<td>1000%</td>
<td>0%</td>
<td>2</td>
<td>0.04</td>
<td>511,548</td>
</tr>
</tbody>
</table>

Total 100.2% 312 41,107,162 41,203,015

Loss Ratio Range (1) (2) (3) (4) (5)
Case Study No. 3: Per Member Loss Ratio Analysis

P+L – Overall results allocated to members
• Results by Contribution Band
• Results are fairly evenly spread amongst size of member

<table>
<thead>
<tr>
<th>Contribution Band</th>
<th>Average Annual Losses</th>
<th>Average Number of Losses</th>
<th>Total Losses</th>
<th>Average Loss per Occurrence</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0 - $10,000</td>
<td>10,000</td>
<td>100</td>
<td>1,000</td>
<td>10</td>
</tr>
<tr>
<td>$10,001 - $20,000</td>
<td>20,000</td>
<td>200</td>
<td>4,000</td>
<td>20</td>
</tr>
<tr>
<td>$20,001 - $30,000</td>
<td>30,000</td>
<td>300</td>
<td>9,000</td>
<td>30</td>
</tr>
<tr>
<td>$30,001 - $40,000</td>
<td>40,000</td>
<td>400</td>
<td>16,000</td>
<td>40</td>
</tr>
<tr>
<td>$40,001 - $50,000</td>
<td>50,000</td>
<td>500</td>
<td>25,000</td>
<td>50</td>
</tr>
<tr>
<td>$50,001 - $60,000</td>
<td>60,000</td>
<td>600</td>
<td>36,000</td>
<td>60</td>
</tr>
<tr>
<td>$60,001 - $70,000</td>
<td>70,000</td>
<td>700</td>
<td>49,000</td>
<td>70</td>
</tr>
<tr>
<td>$70,001 and up</td>
<td>80,000</td>
<td>800</td>
<td>64,000</td>
<td>80</td>
</tr>
</tbody>
</table>

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

Per Member Analysis
• 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

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

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
Case Study No. 3: Per Member Loss Ratio

Alternative Method – Tiering

<table>
<thead>
<tr>
<th>Tier 1: Best</th>
<th>Tier 2: Average</th>
<th>Tier 3: Worst</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credible members w/calculated relativities &lt;0.95</td>
<td>Not credible. Calculated relativities from 0.95-1.05</td>
<td>Credible w/calculated relativities &gt;1.05</td>
</tr>
<tr>
<td>Factor of 0.75</td>
<td>Factor of 1.00</td>
<td>Factor of 1.25</td>
</tr>
</tbody>
</table>

*Factors applied before other Pool Modifications.

---

Case Study No. 3: Per Member Loss Ratio

Alternative Method – Tier Compared to Current Pool Mod

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

---

Case Study No. 3: Per Member Loss Ratio

Alternative Method – Potential Impact

<table>
<thead>
<tr>
<th>Tier</th>
<th>Tier 1</th>
<th>Tier 2</th>
<th>Tier 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count</td>
<td>Prop.</td>
<td>True Rate</td>
<td>Rate Neutral</td>
</tr>
<tr>
<td>1</td>
<td>54</td>
<td>6.8%</td>
<td>-7.1%</td>
</tr>
<tr>
<td>2</td>
<td>232</td>
<td>11.1%</td>
<td>-3.3%</td>
</tr>
<tr>
<td>3</td>
<td>25</td>
<td>31.9%</td>
<td>14.7%</td>
</tr>
<tr>
<td>Total</td>
<td>311</td>
<td>15.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

Contribution $13.2M $11.3M
Summary: Re-Evaluating Your Contribution Algorithm

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

What:
1. Objectives
   • Housekeeping
   • Significant Changes
2. Considerations
3. Benefits
4. Consequences

How:
1. Underwriting Predictive Analytics
2. Per Member Loss Ratio Analysis
3. Hybrid
4. Other
Thank you
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Chris.Kogut@Milliman.com