

LEVERAGING RISK MANAGEMENT DATA TO DRIVE INSIGHT AND SAVINGS

Mary Daly, FCAS, MAAA

Oliver Wyman Actuarial Consulting

AGENDA

Why?

Risk Management Applications

Examples of Applications

Call to Action

Q&A

1

WHY SHOULD YOU CARE?

EXAMPLES FROM OTHER INDUSTRIES

Leveraging Data to Drive Solutions

Industry

Problem

Data Application

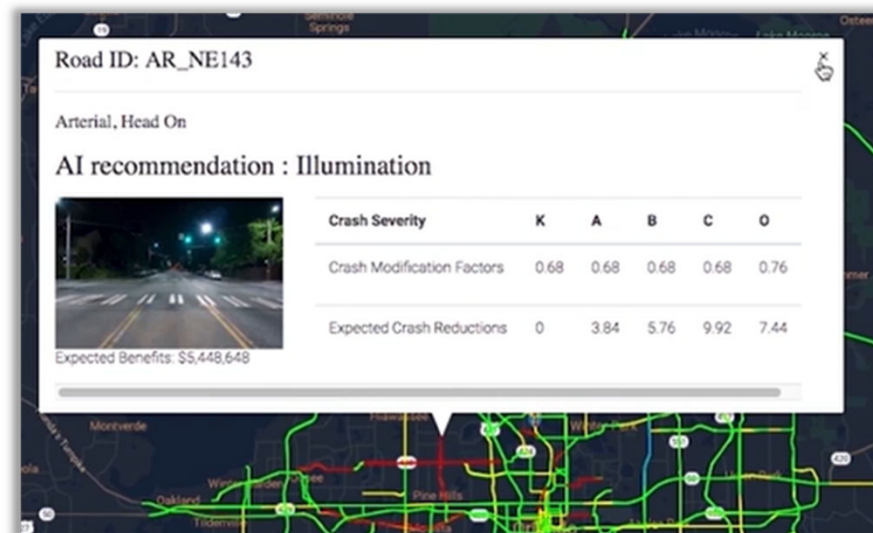
Solution/Impacts

Department of
Transportation

Increasing number of fatalities/serious injuries on
roadways

Data Visualization
Predictive Analytics
Artificial Intelligence

Develop optimal solution to hazardous
conditions;
Inform key stakeholders to enable them to
reduce/prevent risk of injury.



INVEST IN TECHNOLOGY

Relevance to today's business environment

Technology can make your business more transparent, more flexible, and more efficient

“...the first reason to prioritize digital transformation ahead of or during a downturn is that **improved analytics can help management better understand** the business, how the recession is affecting it, and where there's potential for operational improvements.

...The second reason is that digital technology can help cut costs. Companies should prioritize “self-funding” transformation **projects that pay off quickly, such as automating tasks or adopting data-driven decision making**.

...The third reason is that IT investments make companies more agile and therefore **better able to handle the uncertainty and rapid change** that come with a recession.”

2

RISK MANAGEMENT APPLICATIONS

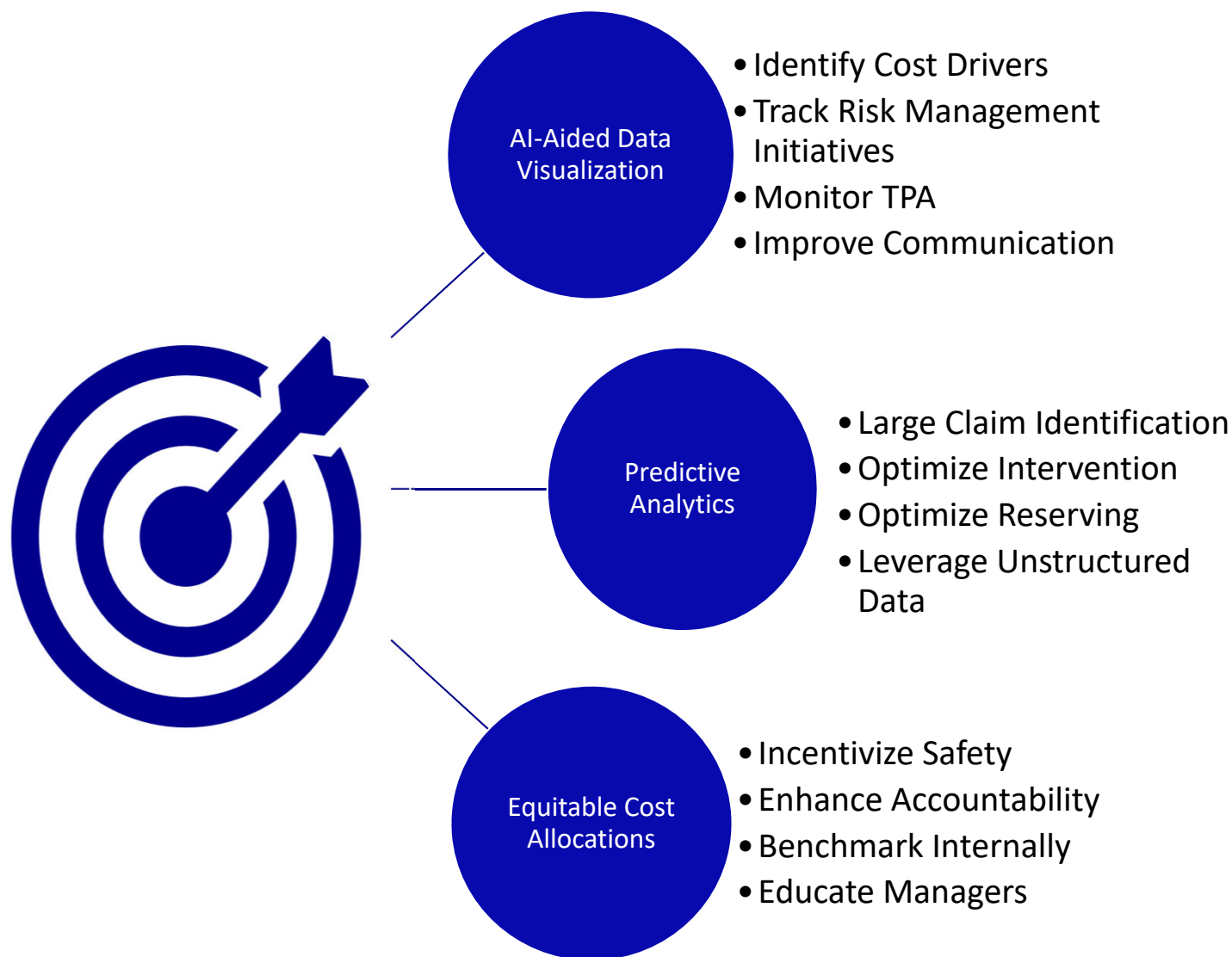
LEVERAGING RISK MANAGEMENT DATA

Common Uses of Risk Management Data



LEVERAGING RISK MANAGEMENT DATA

Elevated State

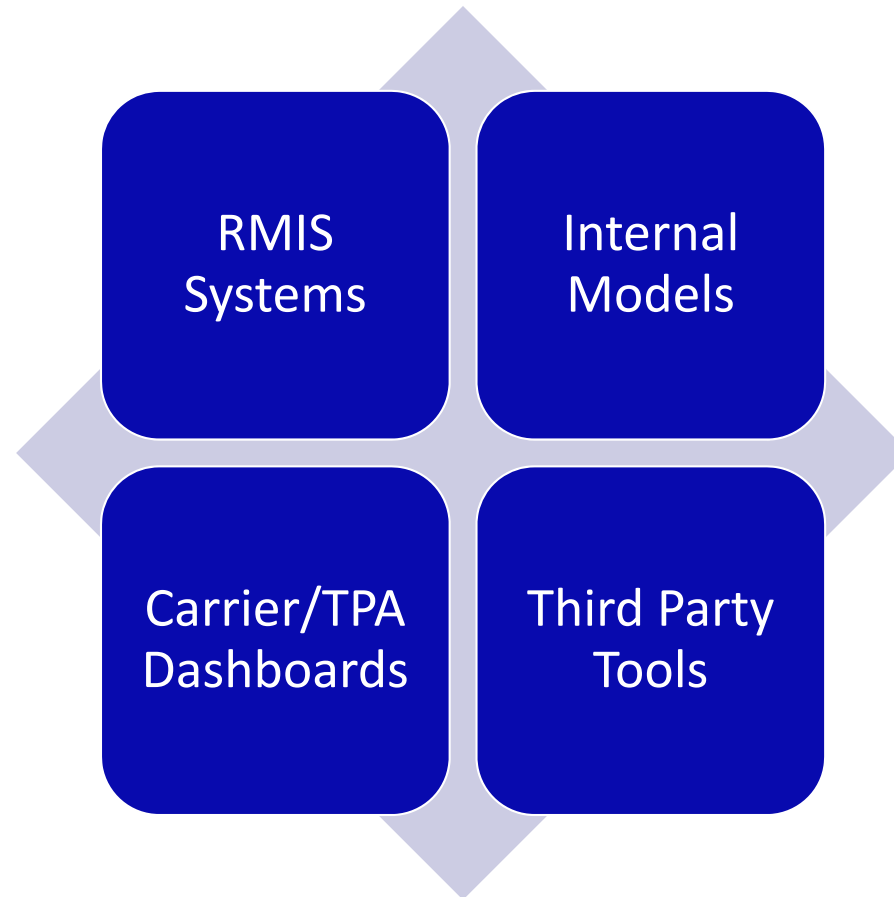


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EXAMPLES OF APPLICATIONS

Data Visualization

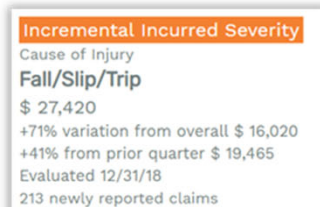
Examples/Types



Data Visualization

Demonstration

Client's actuary leveraged historical loss runs, exposure information and AI to automatically alert user to problematic trends:



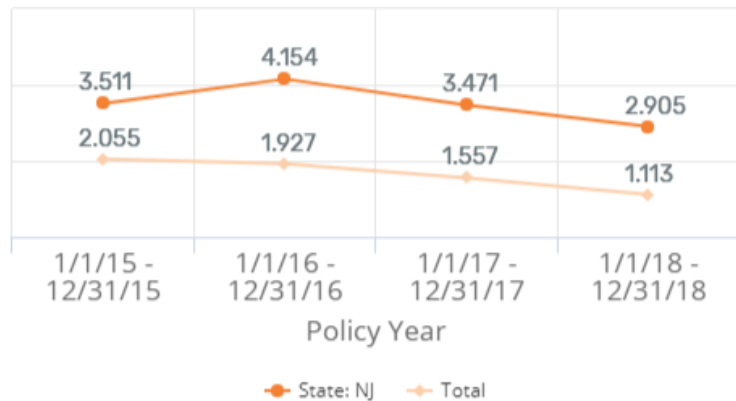
Data Visualization

Demonstration

Incurred Loss Rate

Total Incurred / Exposure x 100

Current Evaluation; Coverage: WC Exposures Pro-rated to Maturity.

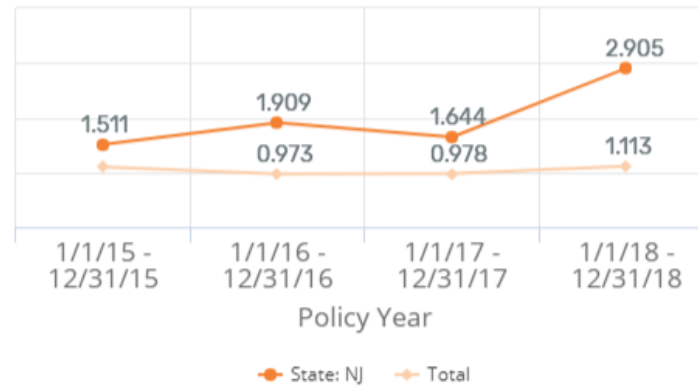


vs.

Incurred Loss Rate

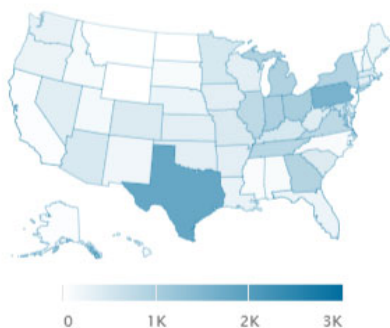
Total Incurred / Exposure x 100

12 Months Maturity; Coverage: WC Exposures Pro-rated to Maturity.



Reported Counts

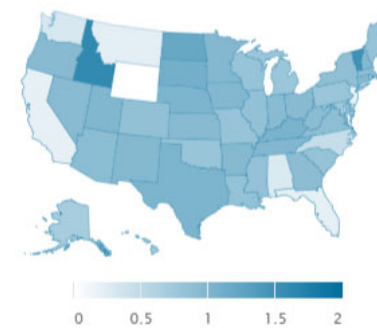
12 Months Maturity; Coverage: WC



Reported Frequency

Reported Counts / Exposure x 1,000,000

12 Months Maturity; Coverage: WC



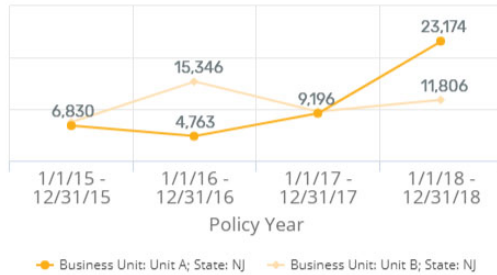
vs.

Data Visualization

Demonstration

Paid Severity

Total Paid / Count of Closed Claims
12 Months Maturity; Coverage: WC



Paid Severity

Total Paid / Counts of Closed Claims
12 Months Maturity; Coverage: WC; Business Unit: Unit B; State: NJ

Cause of Injury	Accident Year				
	2014	2015	2016	2017	2018
Burn	1,775	2,152		551	
Caught In	1,616	4,286	1,330	5,217	119,160
Struck	4,228	4,955	19,482	4,898	4,237
All Other	1,816	1,305	24,631	1,075	733
Cut	1,734	350	171	374	1,435
Fall/Slip/Trip	14,579	14,522	16,750	12,233	12,969
Motor Vehicle		4,755	7,349	1,476	2,720
Strain	11,567	8,126	16,227	12,316	15,138

Coverage: WC; Business Unit: Unit B; State: NJ; Cause of Injury: Caught In
Show 15 entries

Prior values as-of 9/30/2018

Search:

Claim Number	Business Unit	Location	State	Loss Date	Total Paid	Total Incurred	Prior Total Paid	Prior Total Incurred	Case Reserve	Total Paid Change	Total Incurred Change
NJ20180619104159	Unit B	Location 172	NJ	6/19/2018	\$60,973	\$142,091	\$17,920	\$126,347	\$81,119	\$43,053	\$15,744
NJ200504071336	Unit B	Location 516	NJ	4/7/2005	\$920,934	\$1,425,209	\$913,459	\$1,425,209	\$504,275	\$7,476	\$0
NJ2017081646044	Unit B	Location 1	NJ	8/16/2017	\$13,712	\$13,712	\$9,063	\$16,791	\$0	\$4,650	-\$3,079
NJ20060919110528	Unit B	Location 516	NJ	9/19/2006	\$693,742	\$874,248	\$690,690	\$874,248	\$180,506	\$3,052	\$0

PREDICTIVE ANALYTICS

What is it?

WHAT IS PREDICTIVE ANALYTICS?

REGRESSION ANALYSIS

NEURAL NETWORKS

DECISION TREES

CLASSIFICATION ANALYSIS



BY DEFINITION:

Predictive analytics encompasses a variety of statistical techniques from predictive modeling, machine learning, and data mining that analyze current and historical facts to make predictions about future or otherwise unknown events.

PREDICTIVE ANALYTICS

Leveraging Data



Claim / Incident Information

- | | |
|---|-----------------------------|
| - Geography | - Accident / Adjuster Notes |
| - Report Lag | - Weather |
| - Body Part | - Surveillance Info |
| - Nature of Injury | - Witness Info |
| - Cause of Loss | - Department of Occurrence |
| - Attorney Representation | |
| - Initial Treatment (First Aid / Ambulance) | |



Medical Information

- | | |
|-----------------------|----------------------|
| - Diagnoses (ICD) | - Hospitalization |
| - Procedures (CPT) | - Specialist Visits |
| - Prescriptions (NDC) | - Restrictions |
| - Rehabilitation | - Medical Management |
| - Physical Therapy | |



External Data

- | |
|--|
| - Industry Claims Data |
| - Census Demographic Data (crime rates, income, etc) |
| - Weather Data |
| - Lawyer Density |

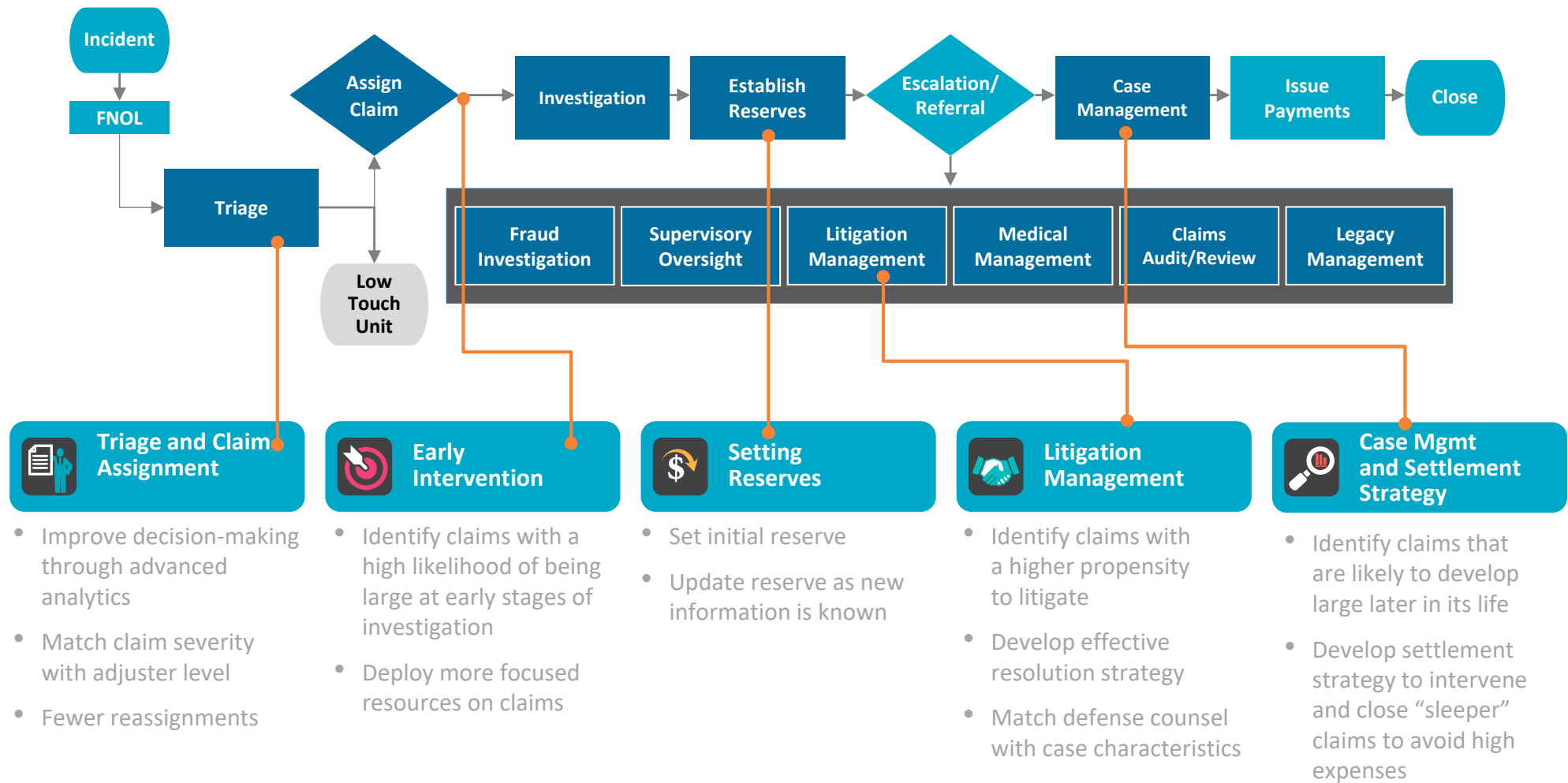


Claimant Information

- | |
|------------------|
| - Geography |
| - Age |
| - Sex |
| - Marital Status |
| - Tenure |

PREDICTIVE ANALYTICS

APPLICATIONS – CLAIM CYCLE



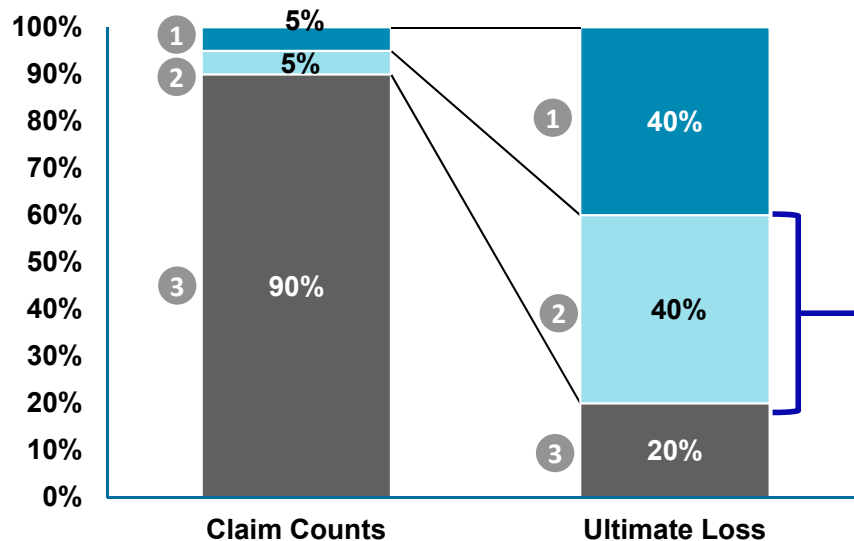
Predictive Analytics

Sleeper Claim Example

Three Types of Claims

- 1 Known Large Claims
- 2 “Sleeper” Claims – Start Small, End Large
- 3 Known Small Claims

Distribution of Worker’s Compensation Claims



Primary Focus of “Sleeper” Model

2 “Sleeper” Claims

- High cost claims under-reserved early on.
- Sleeper claims only represent ~ 5% of claim counts, however...
- ~ 40% of workers’ compensation cost is associated with sleeper claims.
- Expected to contribute \$4 million to annual ultimate losses for a client with a \$10 million loss estimate.

\$4MM

Sleeper claims per year

50-75%

Sleeper claims identified

10–20%

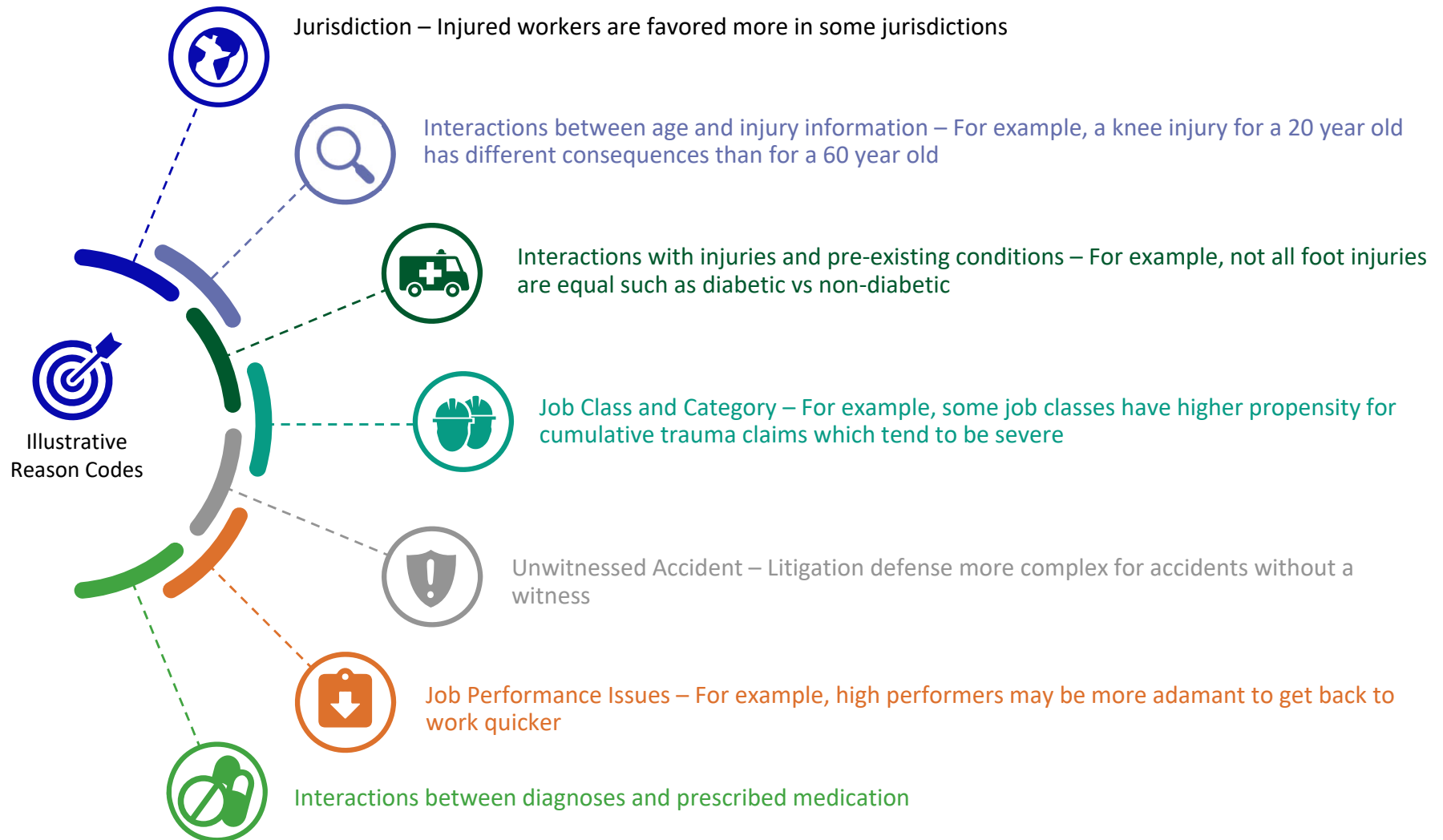
Approx. savings per claim

**\$200k-
\$600k
annual
savings**

Predictive Analytics

Driving Insights

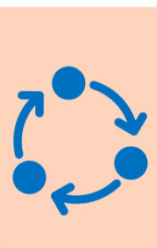
UNDERSTAND WHAT'S DRIVING A CLAIM'S SEVERITY / RISK



PREDICTIVE ANALYTICS

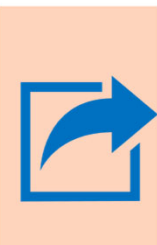
Translating Results into Actions

Models should act as a safety net. If a claim's score does not match current actions, the strategy should be adjusted.



Each claim given a new score *daily*, which leads to defined action

- New information vs. claim review every 60-90 days
- Ex: FNOL may not indicate co-morbidity, prescriptions



Scores pushed to choice of:

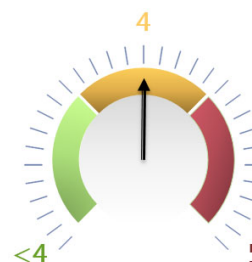
- RMIS system
- TPA dashboard
- Email notifications
- Customized webpage

Risk Score ILLUSTRATIVE Guidelines:



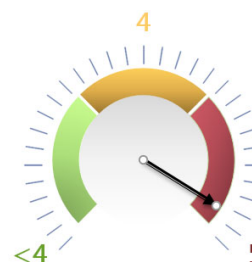
Risk Score of "< 4"

- 70% lowest risk claims
- Follow current procedure
- Likely assigned to junior adjuster
- Likely lower priority for monitoring



Risk Score of "4"

- Next 20% highest risk claims
- Assigned to senior adjuster
- Nurse case management applied
- Carefully monitored



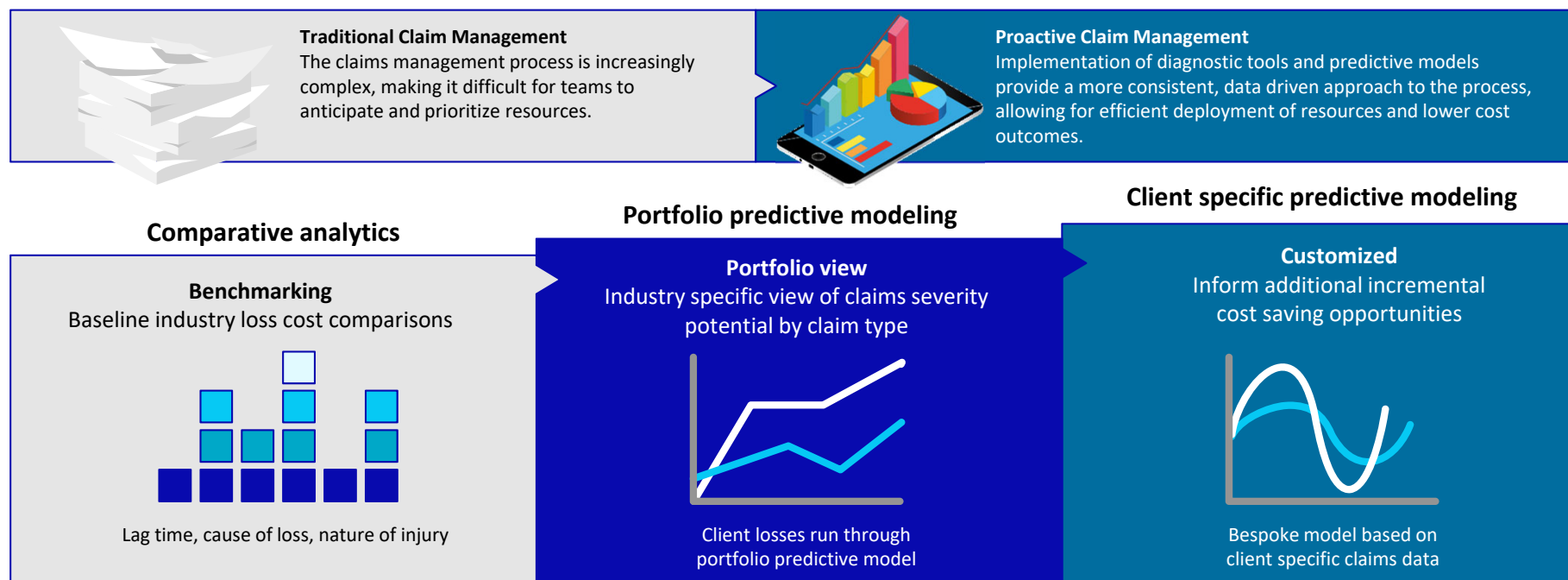
Risk Score of "5"

- Top 10% highest risk claims
- Assigned to most senior adjusters
- Swift and aggressive investigation
- Nurse case management applied

Use data visualization to track performance

PREDICTIVE ANALYTICS

Importance of a Tailored Approach



Custom tailored models offer tremendous advantages over readily available portfolio models through...

- Tailoring to client data structures
- Tailoring to client needs
- Tailoring to client risk profiles
- Tailoring to client workflows
- Advanced Modelling Techniques
- Text Mining
- External Data (Census Demographics, Weather, etc)
- Providing transparency

COST ALLOCATIONS

What and why

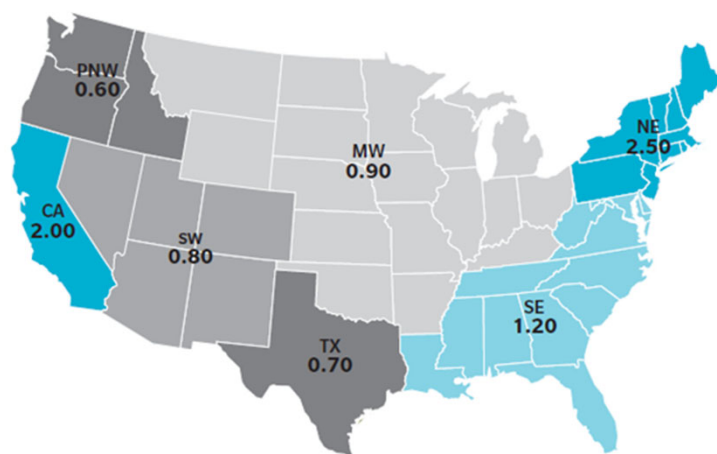
An allocation is a means of assigning total amounts to individual cost centers, business units or locations

What can be allocated:

- Retained unpaid claim estimates
- Prospective year retained loss forecasts
- Commercial insurance premiums
- Other associated program costs

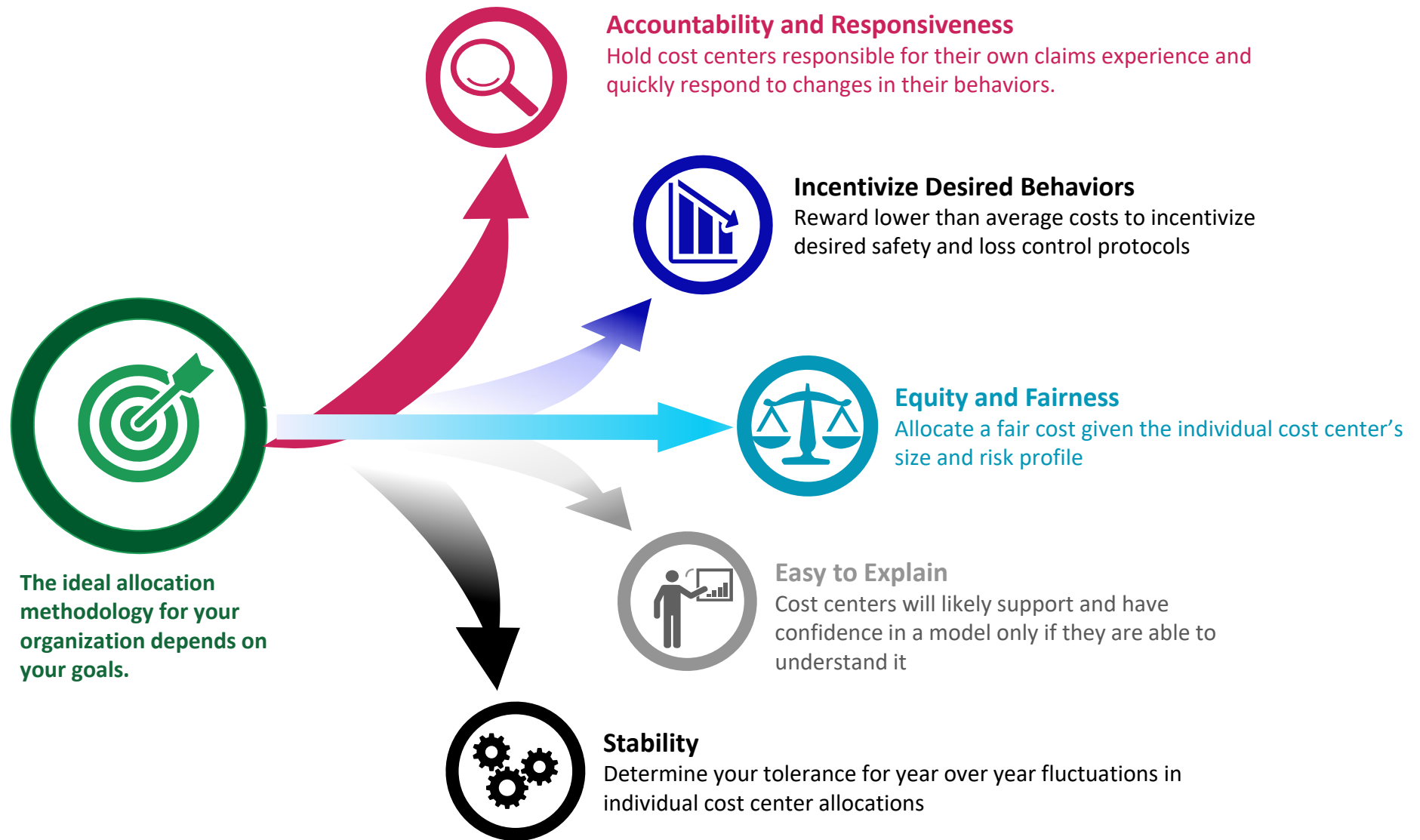
Benefits of allocations:

- Equitable distribution of costs
- Financial incentives to reduce losses
- Division/location leader accountability
- Benchmark individual experience versus total



COST ALLOCATIONS

Goals drive the design



COST ALLOCATIONS

Potential data and design elements

Potential Data

- Losses
 - Paid
 - Incurred
- Claim Counts
 - Consider lost-time, excluding nuisance, etc.
- Exposures
 - Payroll, sales, vehicle counts, etc.
 - May include risk adjustments
- Industry Benchmarks
 - Expected loss rates
 - Commercial premium quotes
- Non-insurance data
 - Safety statistics
 - Safety or satisfaction scores

Design Elements

- Experience Period
 - Number of years of historical losses to include
 - Potential to exclude immature periods
- Caps on Individual Claims
 - To moderate the impact of a severe loss on an individual cost center
- Credibility
 - Allows model to be more responsive to actual experience of larger cost centers and less responsive for smaller cost centers with volatile experience
- Limitations on Year Over Year Changes
 - Limitation on percentage change in an individual cost center's allocation rate from year to year for an element of stability

COST ALLOCATIONS

Illustration

ABC Restaurant Group retains \$1 million per occurrence for its workers compensation program. The projected retained losses for policy year 2019 (\$7.8 million) need to be allocated between ABC's three divisions for budgeting purposes.

Option 1: Allocate the forecasted losses based on projected payroll by division.

Division	2019 Payroll (\$Millions)	% of Total	2019 Loss Projection
Div 1	300	51%	4,000,000
Div 2	60	10%	800,000
Div 3	225	38%	3,000,000
Total	585	100%	7,800,000

Pro: Simple to calculate and explain

Con: Doesn't reflect differences in loss rates by division

Option 2: Allocate the forecasted losses based on benchmark losses by division.

Division	Benchmark Loss Rate	Expected Ultimate Loss	% of Total	2019 Loss Projection
Div 1	0.70	2,091,153	25%	1,978,190
Div 2	1.15	687,269	8%	650,143
Div 3	2.43	5,466,993	66%	5,171,667
Total		8,245,415	100%	7,800,000

Pro: Reflects exposures and expected differences in loss rates by division

Con: Doesn't reflect actual loss experience by division

COST ALLOCATIONS

Illustration

Option 3: Allocate the forecasted losses based on experience-modified benchmark losses by division.

Division	5 Year Actual Reported (\$1Mill)	5 Year Benchmark Reported (\$1Mill)	Experience Modification Factor	2019 Expected Ultimate Loss	2019 Modified Expected Ultimate Loss	% of Total	2019 Loss Projection
Div 1	8,042,851	7,651,456	1.05	2,091,153	2,198,122	28%	2,189,319
Div 2	1,884,598	1,548,926	1.22	687,269	836,209	11%	832,860
Div 3	16,664,141	18,991,480	0.88	5,466,993	4,797,032	61%	4,777,821
Total	26,591,590	28,191,862	0.94	8,245,415	7,831,363	100%	7,800,000

A review of more detailed data for Division 2 suggests potential model adjustments to consider.

Policy Year	Reported Loss (\$1Mill)	Experience Modification Factor (\$1Mill)	Reported Loss (\$250k)	Experience Modification Factor (\$250k)
2014	124,309	0.47	124,309	0.50
2015	1,179,567	3.91	329,567	1.15
2016	96,596	0.29	96,596	0.30
2017	169,737	0.48	169,737	0.50
2018	314,389	1.06	314,389	1.10
5 Yr Total	1,884,598	1.22	1,034,598	0.70
3 Yr Total	580,722	0.59	580,722	0.61

Division 2 experienced two large (over \$250k) claims in policy year 2015. As a result, the indicated experience modification factor varies significantly depending on the selected experience period and per-claim limitation.

COST ALLOCATIONS

Illustration

Experience Period: longer period is more stable; shorter period is more responsive

Credibility: for smaller divisions, indicated experience modification factor can be tempered using credibility

Division	5 Year Actual Reported (\$250k)	5 Year Benchmark Reported (\$250k)	Experience Modification Factor	2019 Expected Ultimate Loss	2019 Modified Expected Ultimate Loss	% of Total	2019 Loss Projection	2019 Allocated Rate
Div 1	7,742,851	6,917,898	1.12	2,091,153	2,340,521	30%	2,371,717	0.79
Div 2	1,034,598	1,482,467	0.70	687,269	479,638	6%	486,031	0.81
Div 3	16,229,141	18,191,542	0.89	5,466,993	4,877,245	63%	4,942,252	2.20
Total	25,006,590	26,591,907	0.94	8,245,415	7,697,404	100%	7,800,000	1.33

Individual Claim Limits: lower limits mitigate the impact of severe losses

Rate Caps: caps on year over year changes in allocation rates are another option to add stability to the model

4

WHAT CAN YOU DO?

NEXT STEPS

1. Maximize use of data visualization process. Ask yourself whether your process involves:
 - Artificial Intelligence/automation for ease of use
 - Proper year-over-year comparisons
 - The ability to monitor your TPA
 - Easy communication with key stakeholders
2. Incorporate predictive analytics into risk management process:
 - Use analytics to identify issues and determine optimal responses.
 - Think through your claim process – what could be improved?
 - Communicate with stakeholders to understand what is possible.
 - Track progress of action using data visualization.
3. Re-think your allocation; considerations include:
 - Accountability, responsiveness, sensitivity
 - Does your allocation incite desirable behavior?
 - How equitable is your process?
 - Can your process be explained simply?

5

QUESTIONS?

THANK YOU!



Mary Daly, FCAS, MAAA

Oliver Wyman Actuarial Consulting, Inc.

Mary.Daly@oliverwyman.com

(213) 346-5639

APPENDIX

SOURCES

➤ **Examples from Other Industries:**

- <https://www.transportation.gov/solve4safety/challenge>
- <http://www.govtech.com/analytics/Real-Time-Data-Analytics-Aims-to-Reduce-Traffic-Fatalities.html>

➤ **Invest in Technology:**

- <https://hbr.org/2019/05/how-to-survive-a-recession-and-thrive-afterward>