SOCIETY OF ACTUARIES

2019 ANNUAL MEETING & EXHIBIT

October 27-30
Toronto, Canada

Session 084: Predictive Analytics in Group Life and Disability Experience

Predictive Modeling for Group Underwriting

SOA Annual Meeting Session 84

October 29, 2019

Milliman

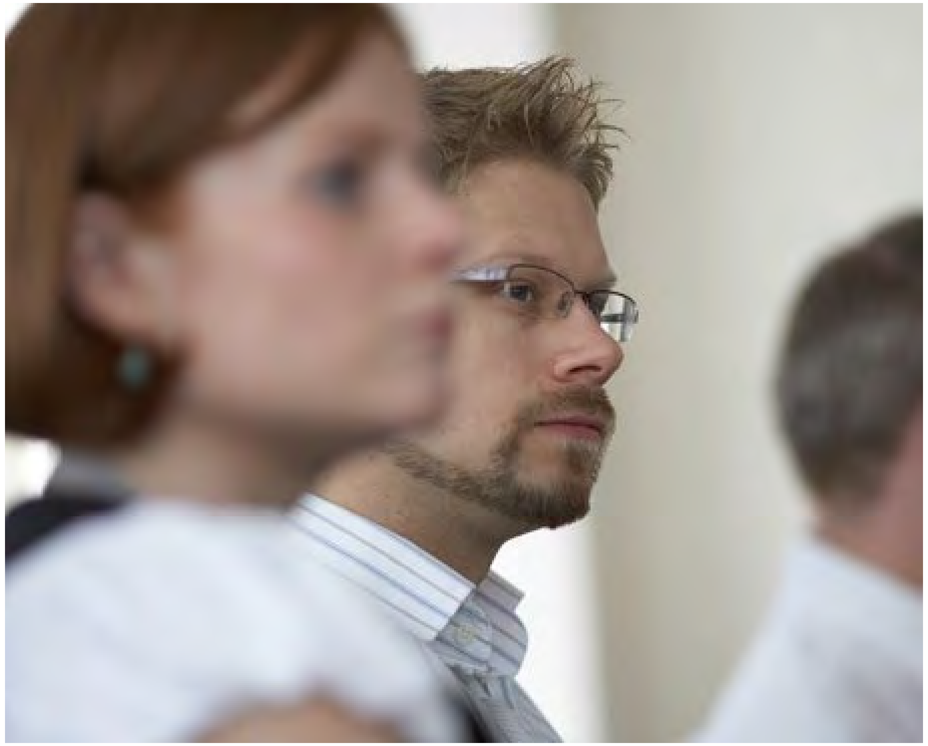
Agenda

State of Group Life/Disability Market

Predictive Model Background

De-Identified Rx Data Gathering

Case Study



Trends in the Group Market

Competition and Consolidation

- Market consolidation
- Pricing remains very competitive
- Carriers differentiating on services
- Adoption of third party data

Predictive modeling for group underwriting.

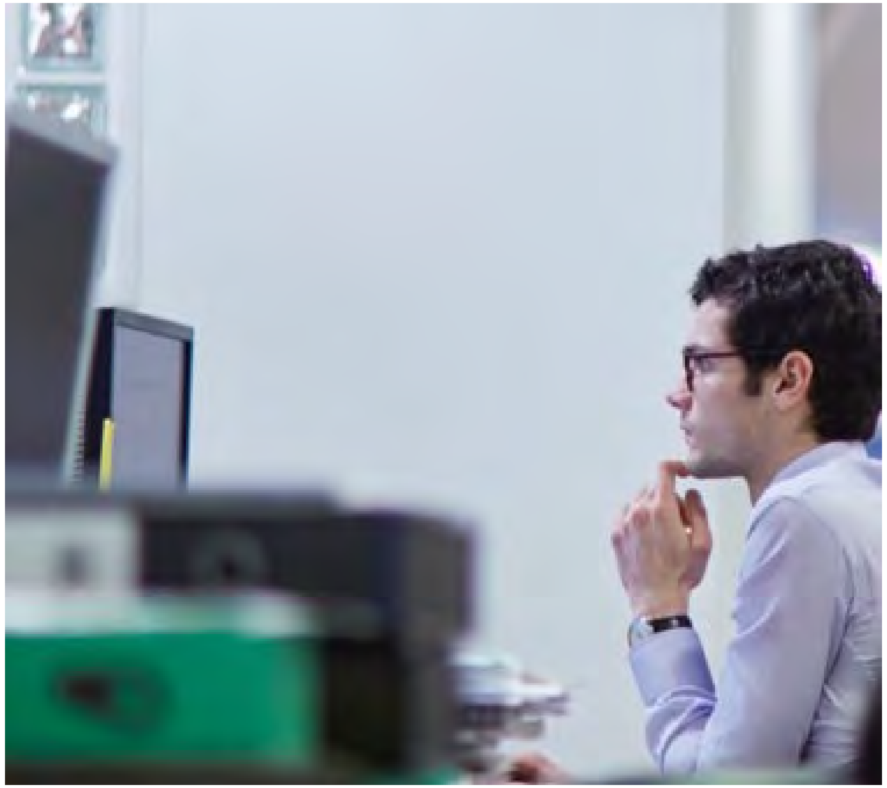
Objective	▪ Score groups at time of underwriting ▪ Better identify risk associated with group
Value	▪ Vary rates based on risk score ▪ Increase placement rate ▪ “Write the right” business ▪ Avoid “bad” blocks

How does the model work?

Calculates an individual Rx-based risk score for each member of the group

Scores are aggregated to the group level

Constructed using robust Milliman's mortality study data



The modeling data comes from large mortality studies.

2009

Milliman / RGA study

- 1M exposure years
- 2,500 deaths

2012

Milliman study

- 21M exposure years
- 45,000 deaths

2015

Milliman study

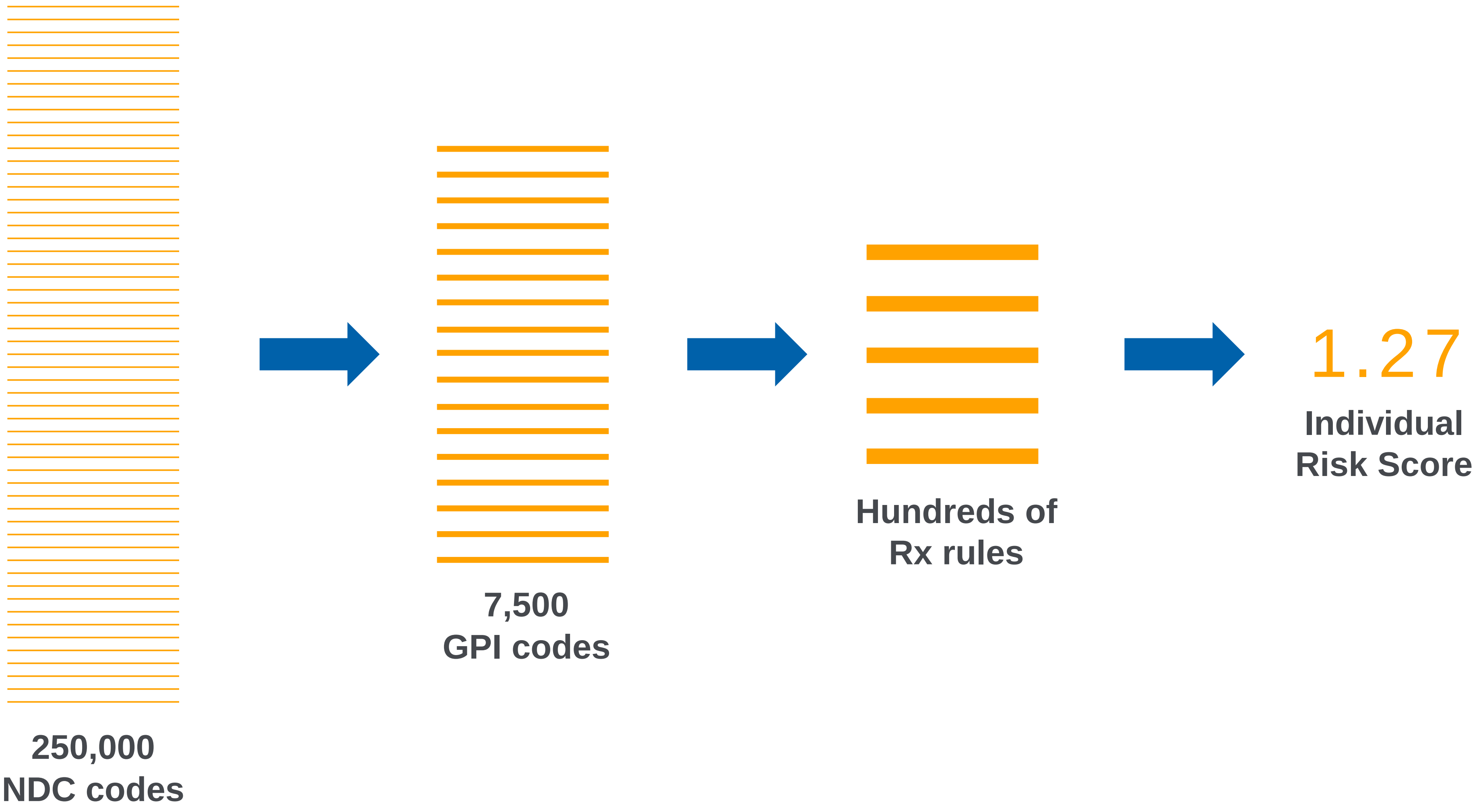
- 53M exposure years
- 231,000 deaths
- **Created predictive model used in Curv**

2017

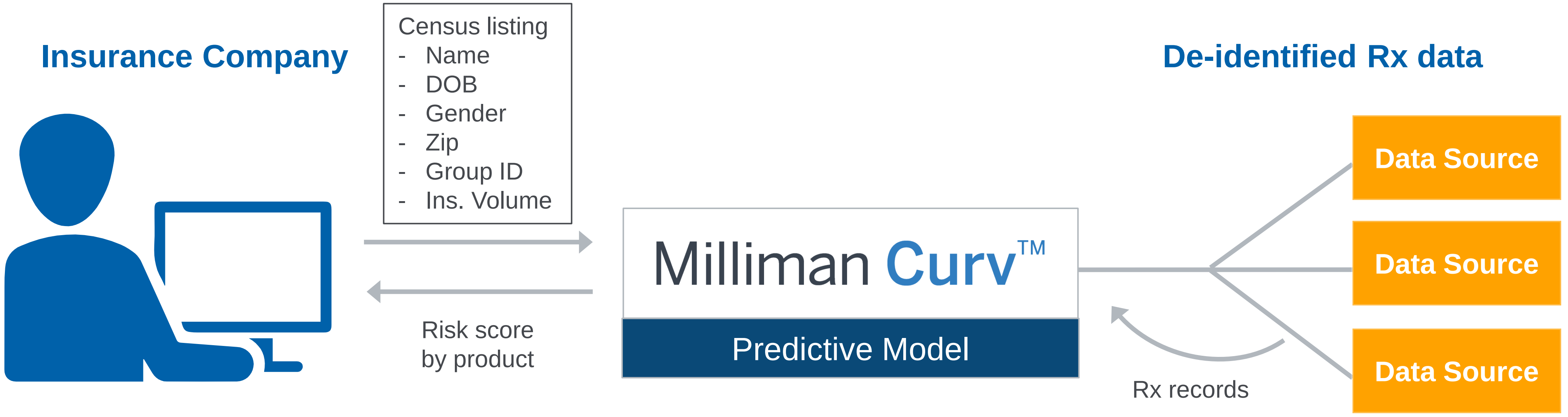
Milliman study

- 104M exposure years
- 469,000 deaths
- **New predictive model research underway**

Example of distilling information to a manageable dataset.



De-Identified Prescription Data Flow

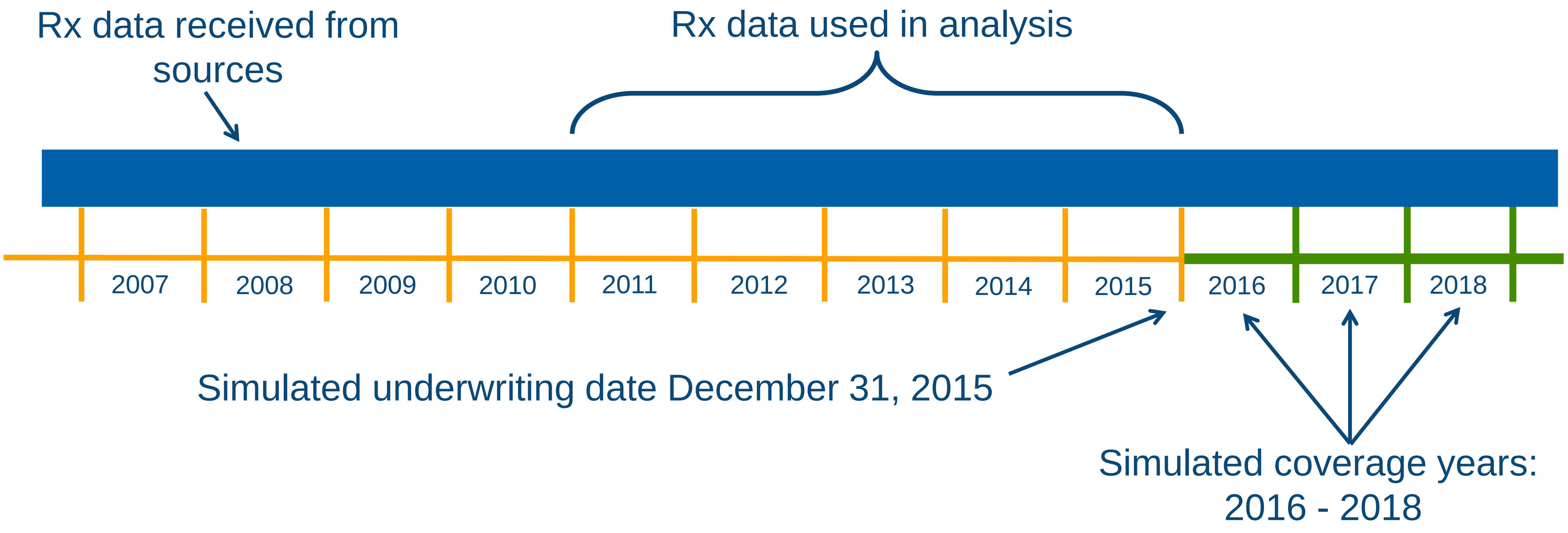


Case Study Design

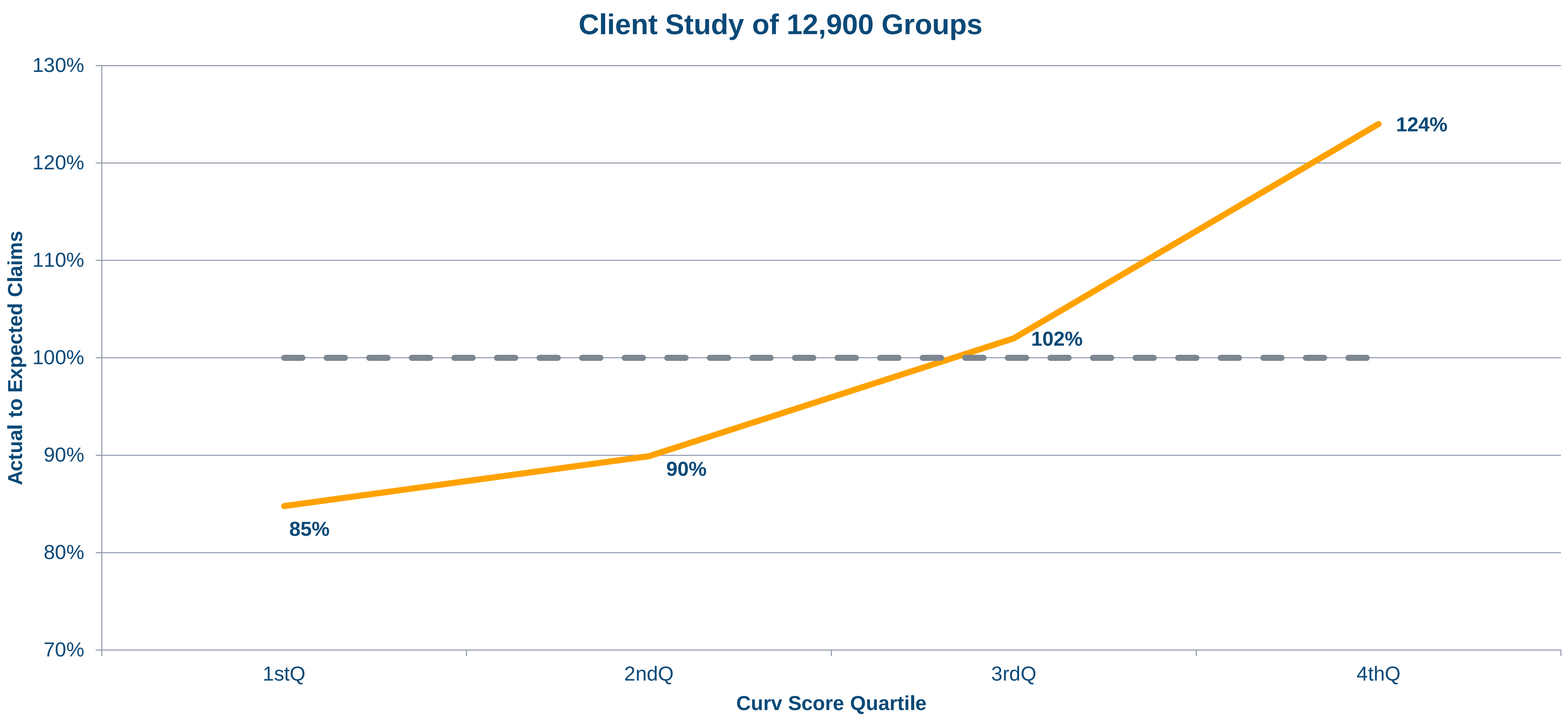
- Designed to address two key questions:
  - How effective is the risk score?
  - How do we quantify the value of using a risk score for underwriting?

Client Data	Obtain Individual Rx Histories	Group Risk Score Compared to Claims
–Point in time census –Multiple effective dates –Multiple products	–5 years of data –Rx histories scored by predictive modeling tool	–Actual-to-Expected analysis –Bidding simulation

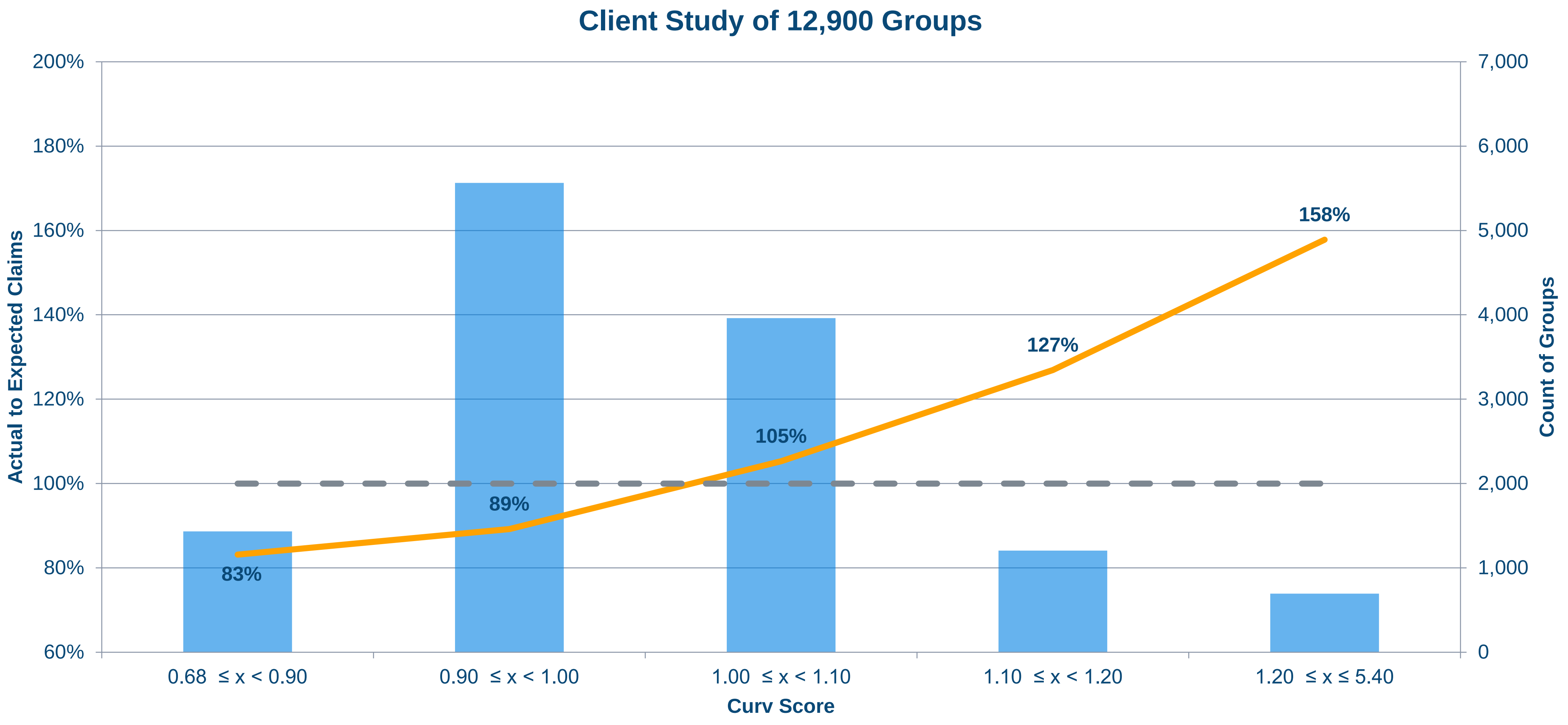
Simulating the Underwriting Process



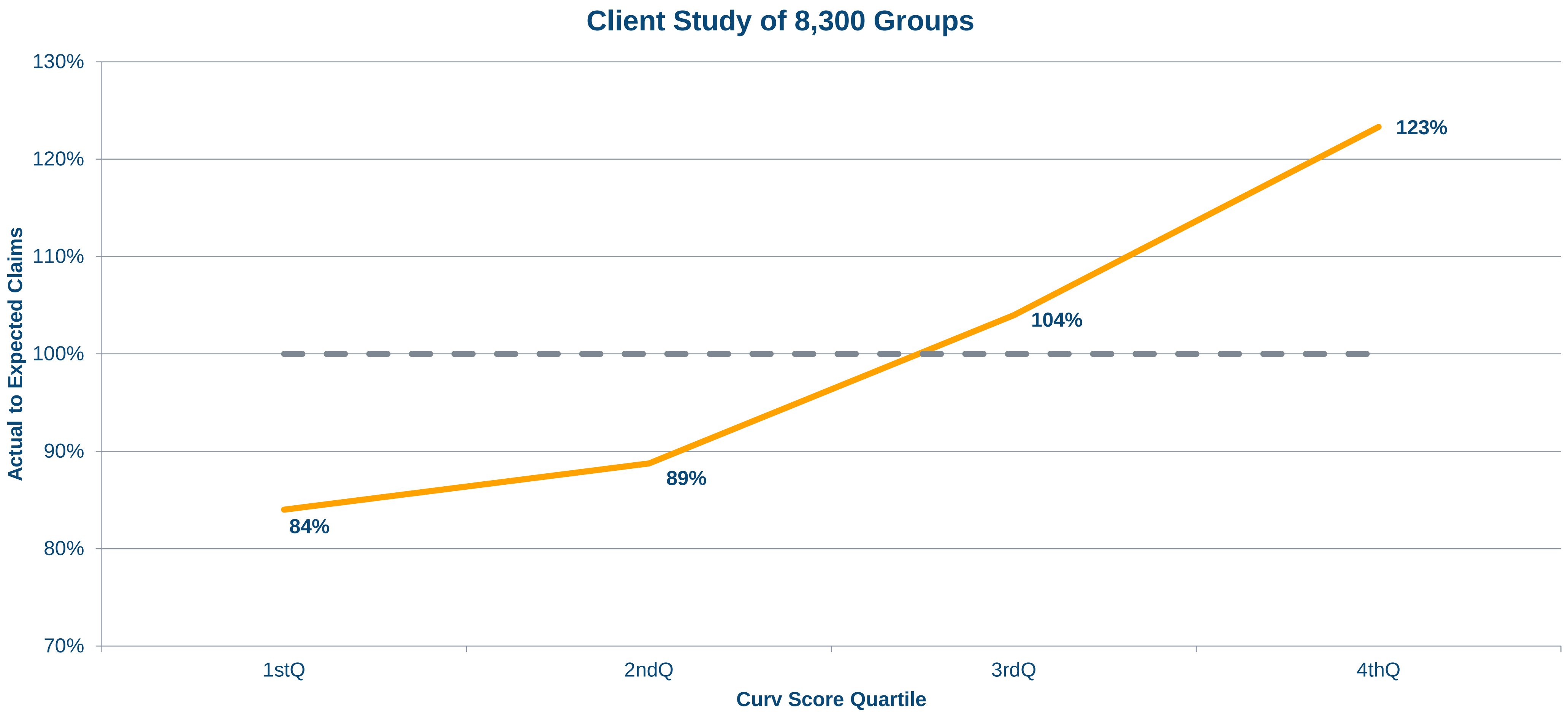
Case Study: Group Life Mortality Quartile Analysis



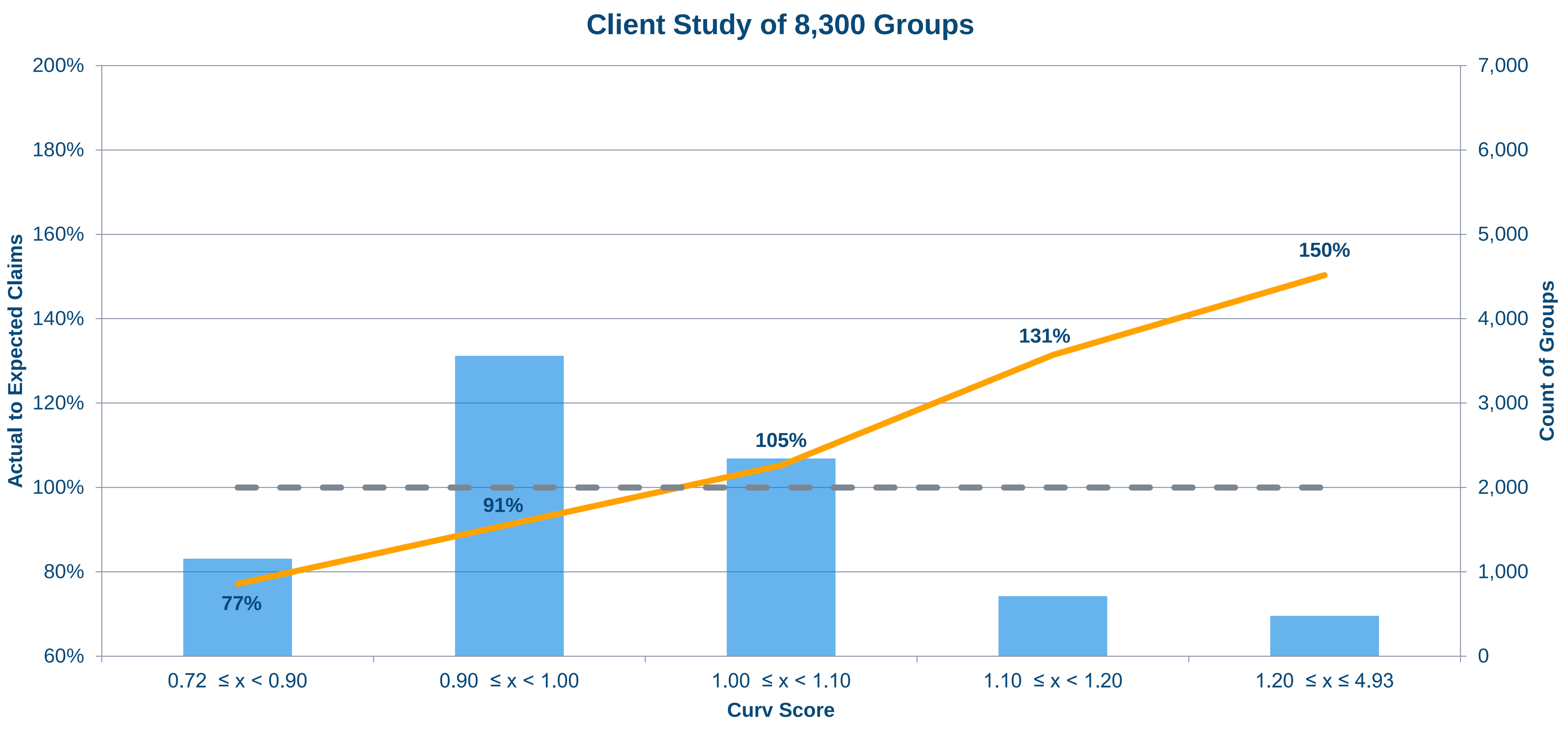
Case Study: Group Life Mortality Score Range Analysis



Case Study: Group LTD Morbidity Quartile Analysis



Case Study: Group LTD Morbidity Score Range Analysis



Bidding Simulation Example

- Idea: Simulate two insurers in a closed market
  - One player uses Curv
  - One player uses manual rate tables
  - Players ‘bid’ on groups using a fixed set of dollars (low bid wins)

- For this study
  - Each player starts with $44.6 million in premium
  - Players bid on 563 groups

Bidding Simulation Example

	Manual Method	Curv Method				Manual	Curv
Group	Gross Premium	Risk Score	Adjusted Premium	Winner	Actual Claims	Gain	Gain
1	$153,700	0.89	$137,400	Model	$0	..	$137,400
2	$4,900	1.12	$5,500	Manual	$15,000	($10,100)	..
3	$87,400	1.02	$89,500	Manual	$0	$87,400	..
4	$47,200	0.76	$35,700	Model	$133,000	..	($97,300)
.	.		.		.	.	.
..	..		..		..	..	..
Total	$44.6M		$44.6M		$34.0M	$2.8M	$6.3M

Bidding Simulation Results

- Rx risk scoring “wins” about 65% of the groups
- Rx risk scoring beats manual by $3.5M in underwriting gain

	Groups	Lives	Placed Premium	Actual Claims	Gain	Gain per $1000
Curv	363	77,517	$20,900,000	$14,643,000	$6,257,000	$299.38
Rate manual	200	56,799	$22,121,000	$19,330,000	$2,791,000	$126.17
Incremental gain per $1000 of premium					**$3,466,000**	**$173.21**

Case Study Conclusions

- Rx risk scoring is a better predictor than the traditional rating methods
  - Lift curves show that the risk score can stratify both mortality and morbidity risk
  - Bidding simulation shows positive gains using the risk score in the marketplace

- Third-party data adds valuable insights and a competitive edge

Thank you!

Predictive Analytics in Group Life and Disability

Society of Actuaries Annual Meeting

Presented by Dave Wall, FSA, MAAA

October 29, 2019

Agenda

1	Introduction
2	Group Life Example
3	Survey Results

This presentation has been prepared for general educational purposes only and does not purport to be and is not a substitute for specific professional advice. It may not be suitable for use in any other context or for any other purpose and we accept no responsibility for any such use.

In developing this presentation we relied on SOA group life experience study data.

Predictive analytics advantages – better data utilization

- Traditional techniques require data to be segregated at the granular level
- One or two variables at a time
- Ad hoc credibility methods

Age	Male	Female
50-59	M55	F55
60-69	M65	F65
70-79	M75	F75

- Predictive modeling creates an algebraic web at the granular level
- More complete use of the data results in better estimates

Age	Male	Female
50-59	M55	F55
60-69	M65	F65
70-79	M75	F75

New techniques are needed to derive the most value from historical data

- Limits of traditional analysis
  - Interactions of factors
  - Determining appropriate level of granularity
  - Changes in exposure

- Benefits of predictive analytics
  - Capture all key variables and interactions
  - Correct level of granularity (either more or less)
  - More accurate risk assessment
  - Better predictions when mix changes

Modeling Example – Group Life

Group Life Model

- **Generalized Linear Model (GLM) of group life mortality rates**
- **Built using the data from the 2016 SOA Group Life Experience Study**
- **Selected examples from development of initial model**
- **Model validation examples**

Predictive Modeling Process

Data Exploration

- Visualizing Data
- Correlation Statistics
- Distribution of Response

Make Initial Selections

- Define Training and Testing Data
- Choose Error Structure and Link Function
- Select initial model

Build Model Structure

- Include/exclude Factors
- Simplify with Groups and Curves
- Include Interactions

Validate Models

- Test for Predictiveness

Model Methodology – Group Life Mortality

- GLM using the data from the 2016 SOA group life experience study.
- We limited our analysis to ages up to age 64.
- Model mortality rates are equal to the product of a base rate and factors for each of the characteristics that were determined to be significant drivers.

The next slide shows an example of a simple model to illustrate the structure.

Simplified Example – Mortality Rate Model

- This simple example illustrates how our model is constructed
- Single variable factors for Gender, Central Age and Salary, plus an interaction between Central Age and Gender.
  - Actual model is more complex than this example

1. Base Rate
0.002

2. Gender	
Female	0.55
Male	1.00

3. Central Age	
22	0.27
27	0.21
32	0.24
37	0.30
42	0.43
47	0.64
52	1.00
57	1.53
62	2.39

4. Salary ($US 000s)	
< 25	1.12
25-49	1.00
50-74	0.77
75-99	0.66
100-149	0.51
150-249	0.41
250+	0.46

5. Central Age * Gender		
	Female	Male
22	0.45	1.00
27	0.60	1.00
32	0.82	1.00
37	0.93	1.00
42	1.03	1.00
47	1.03	1.00
52	1.00	1.00
57	0.95	1.00
62	0.95	1.00

Example Mortality Rate Calculation:

Gender:	Female
Central Age:	42
Salary:	50-74
Mortality Rate:	.002 * 0.55 * 0.43* .077 * 1.03 = .00037

Initial Mortality Rate Model

- Our initial model included factors for the following single variable factors
  - Central Age
  - Gender
  - Face Amount
  - Case Size
  - Region
  - Industry
  - Face Amount in Relation to Salary
  - Interaction between Gender and Central Age

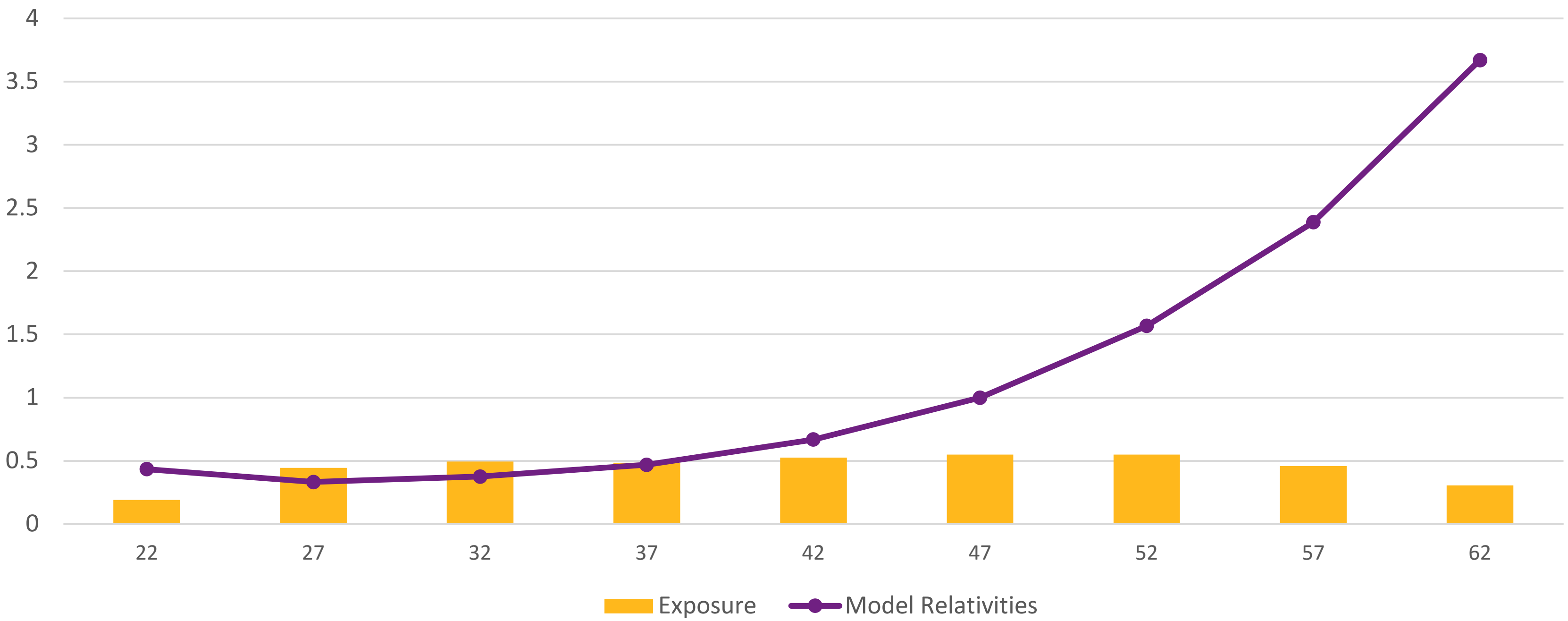
- Mortality rates are estimated by multiplying a base mortality rate times factors for each of the variables listed above

The following slides show results from the initial model

Group Life Mortality

Selected Results from Initial Model

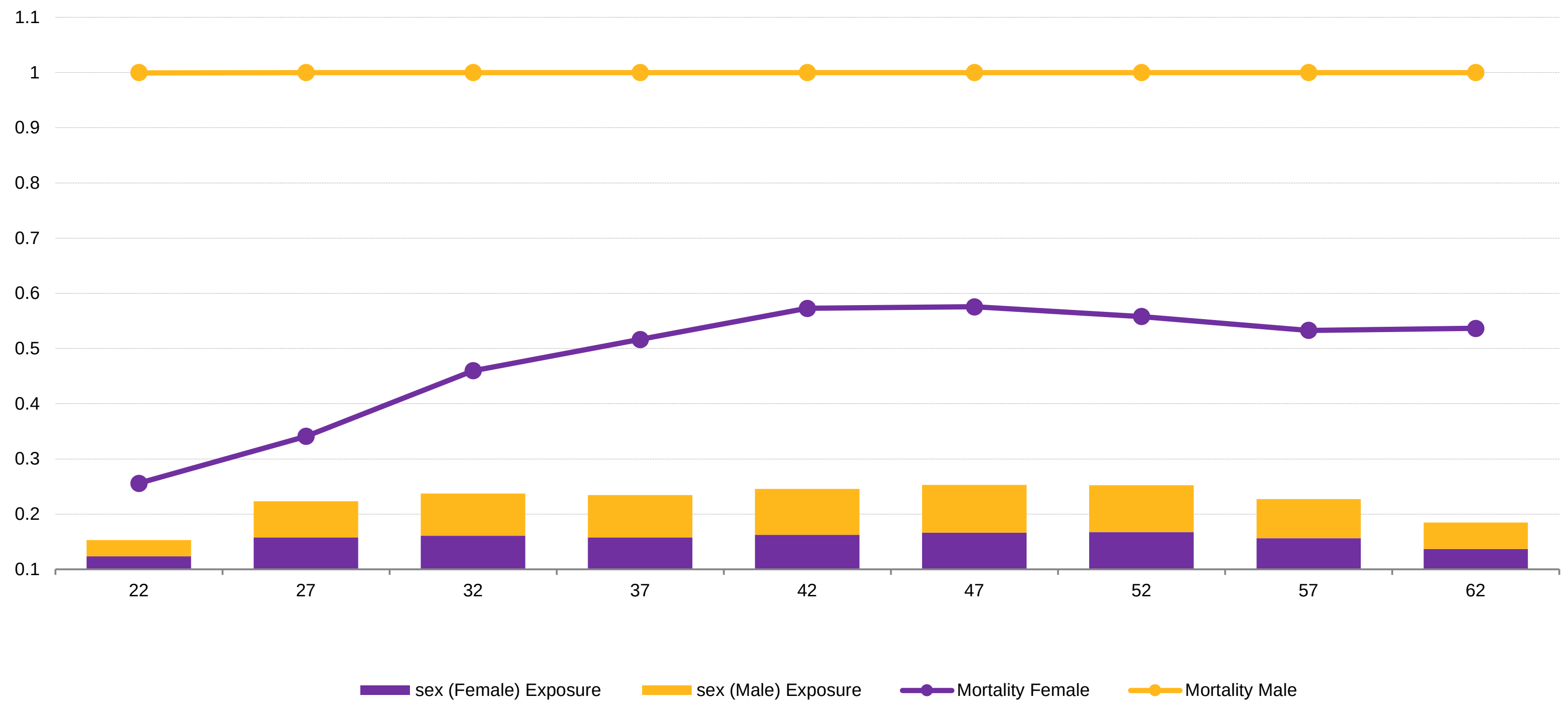
Mortality Relativities by Central Age



- Mortality relativities are shown by Central Age, with all other variables held constant
- The relativities show the effect on mortality rates of Central Age alone
- The rate for each Central Age is shown relative to the base level - here age 47.
  - As Central Age increases, mortality rates generally increase (with all other variables held constant)

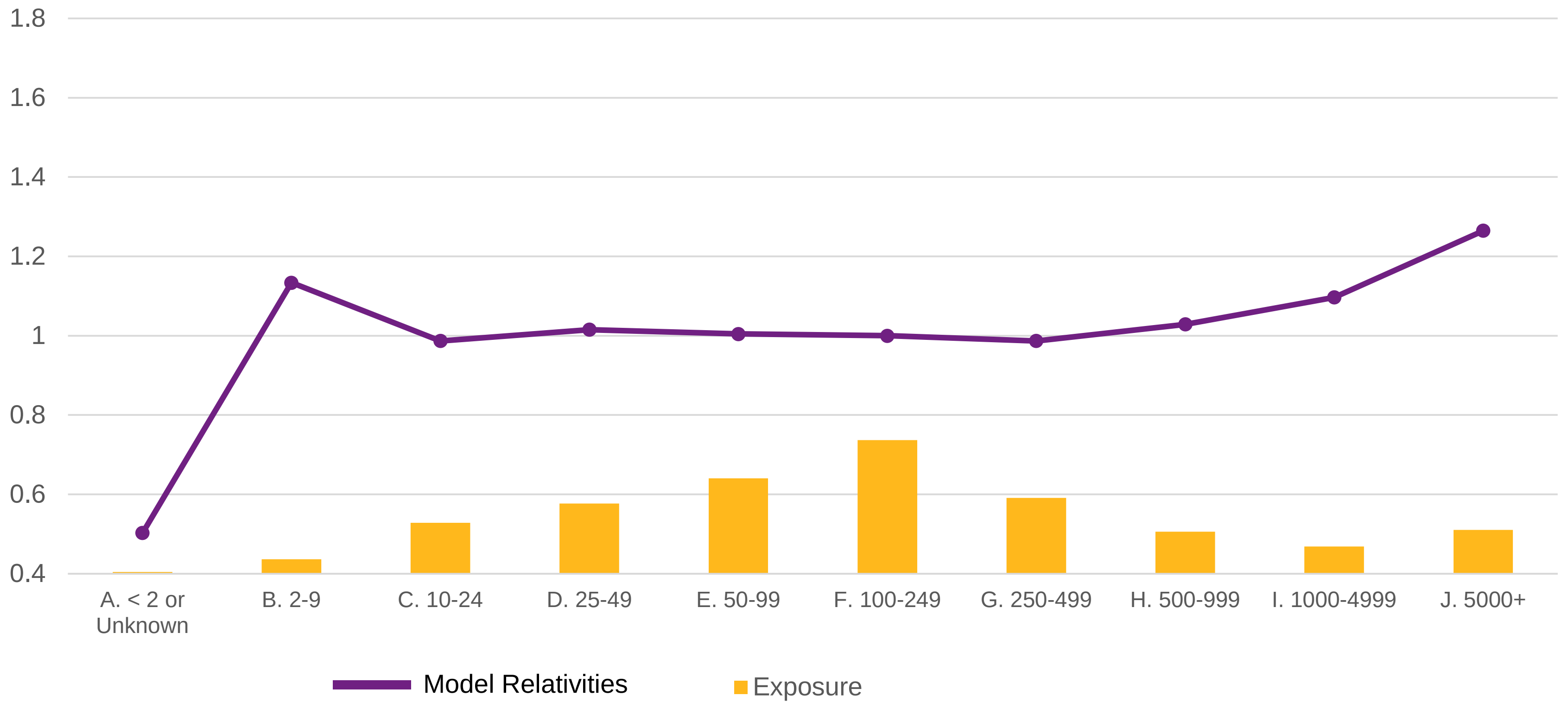
Mortality Relativities by Gender and Age

Mortality impacts shown relative to base level of Gender (Male)



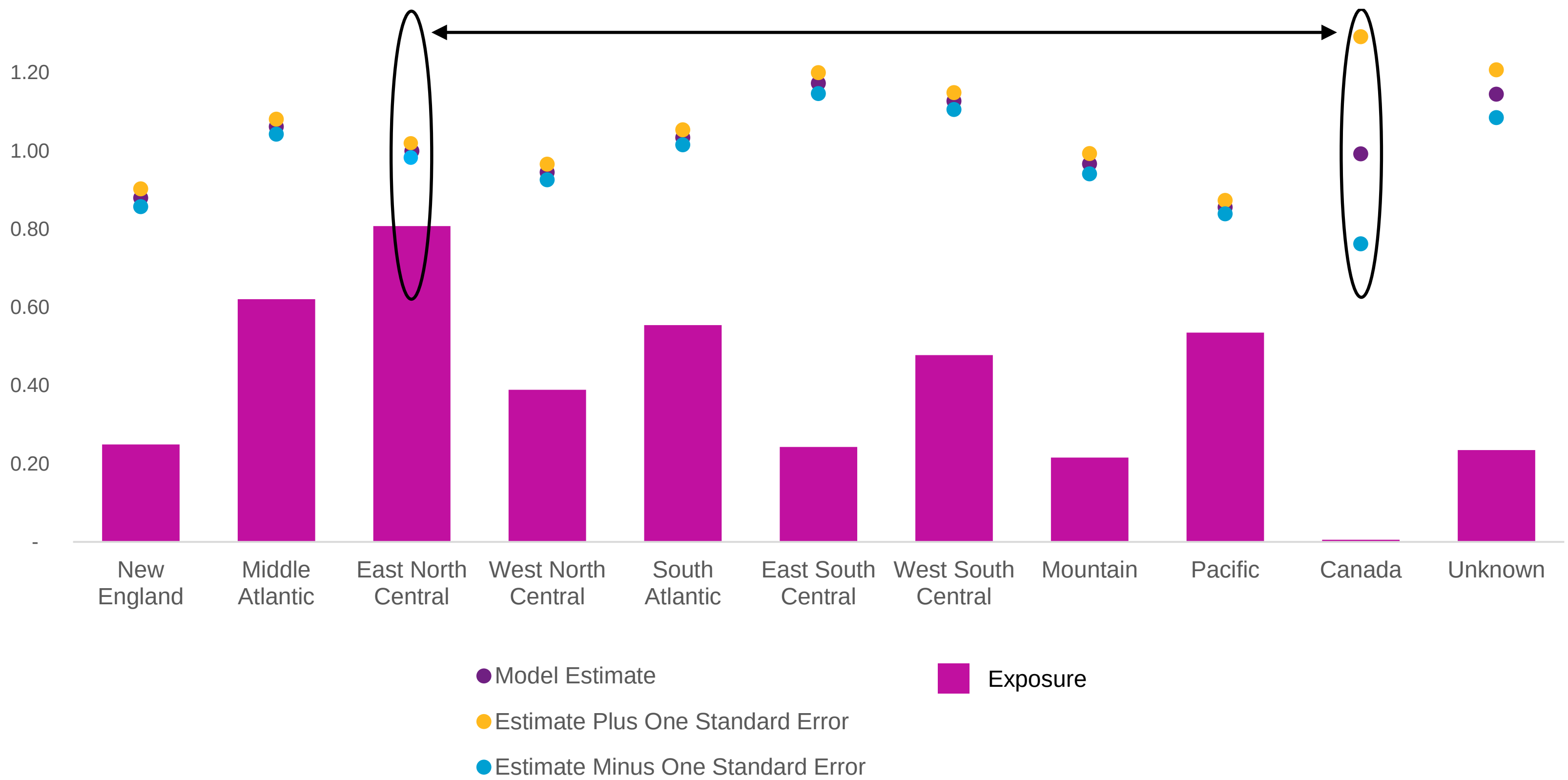
- The impact of gender on mortality declines significantly up to Central Age 47, and then increases slightly for ages 52+

Mortality Relativities by Case Size



Region - Model Relativities and Their Standard Errors

Mortality impacts shown relative to base level of Region (East North Central)

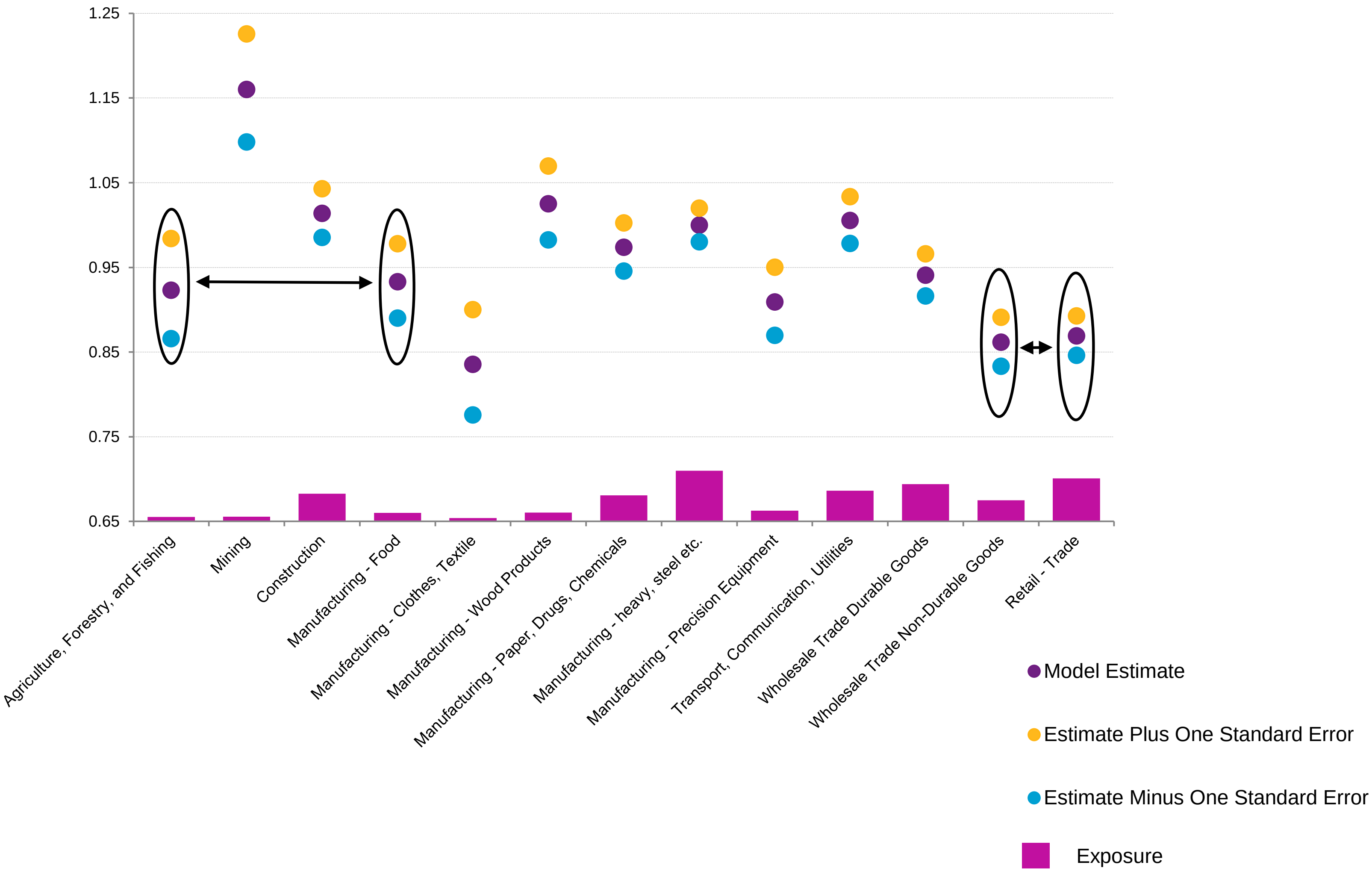


- For most regions there is a significant difference in mortality from the base level. In addition, the standard errors of the relativity estimates for most regions are small.
- For Canada the standard error of the model relativity is large
  - The model could be simplified by combining Canada with the base level (East North Central).

Industry - Model Relativities and Their Standard Errors

Grey and Blue Collar Only

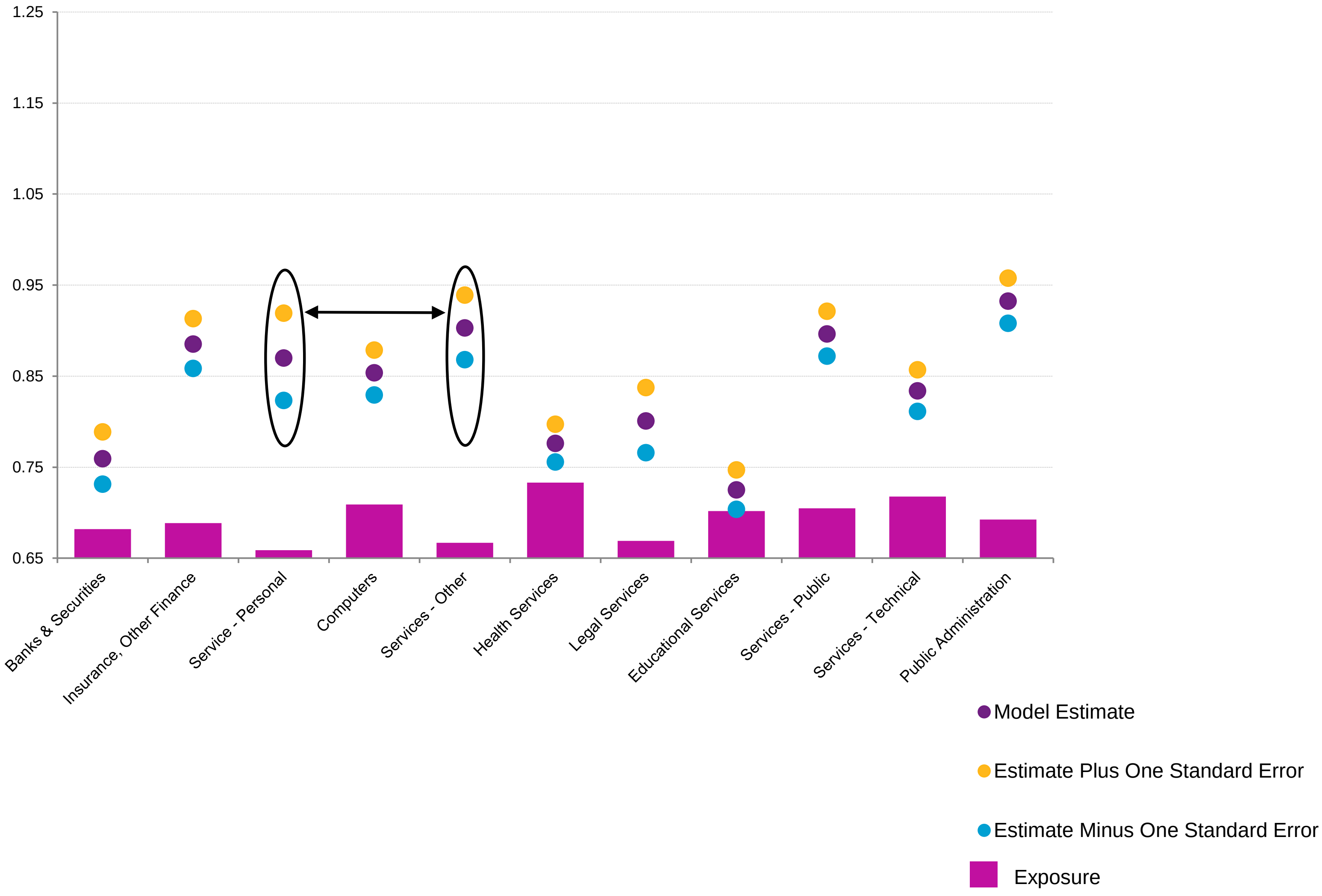
Mortality impacts shown relative to base level of Industry (Manufacturing Heavy Steel)



Industry - Model Relativities and Their Standard Errors

White Collar Only

Mortality impacts shown relative to base level of Industry (Manufacturing Heavy Steel)



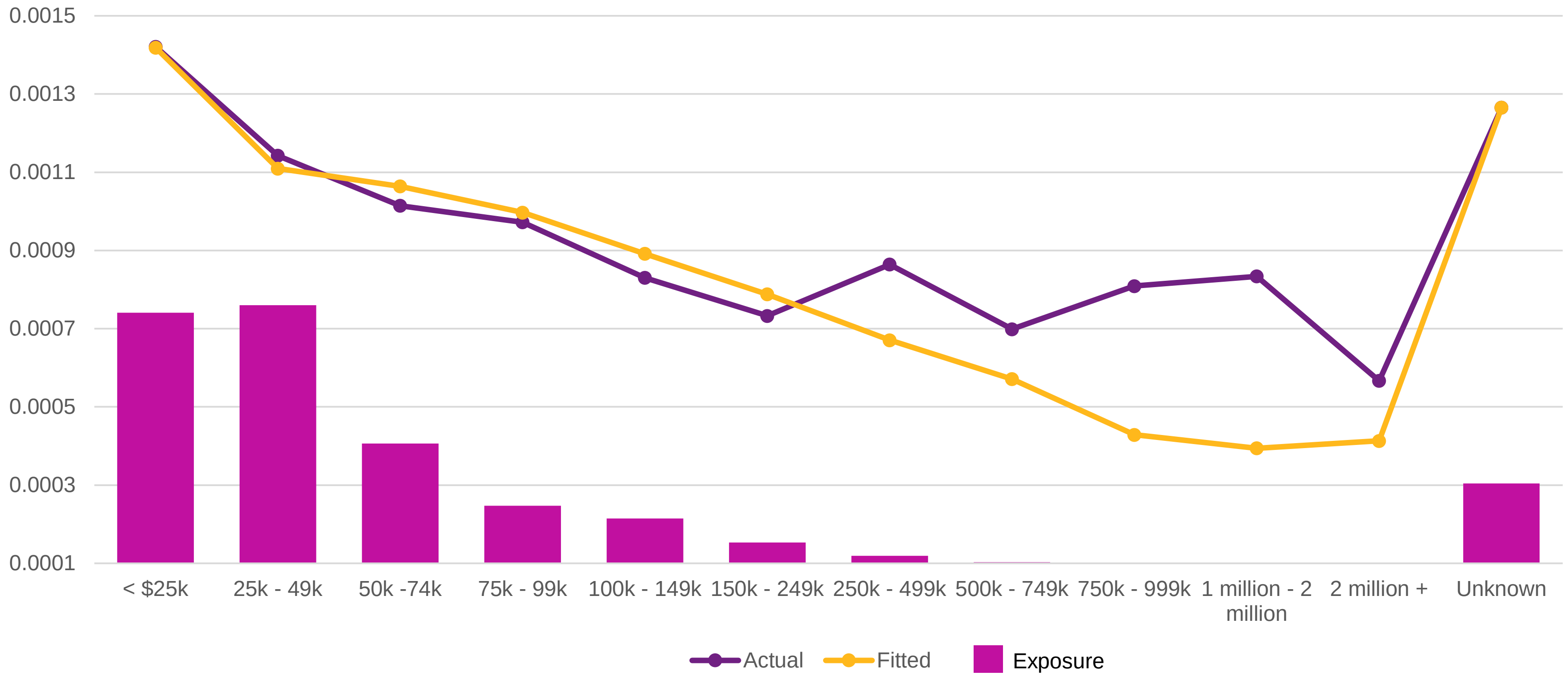
Group Life Mortality

Model Validation

Willis Towers Watson

Review of Initial Model

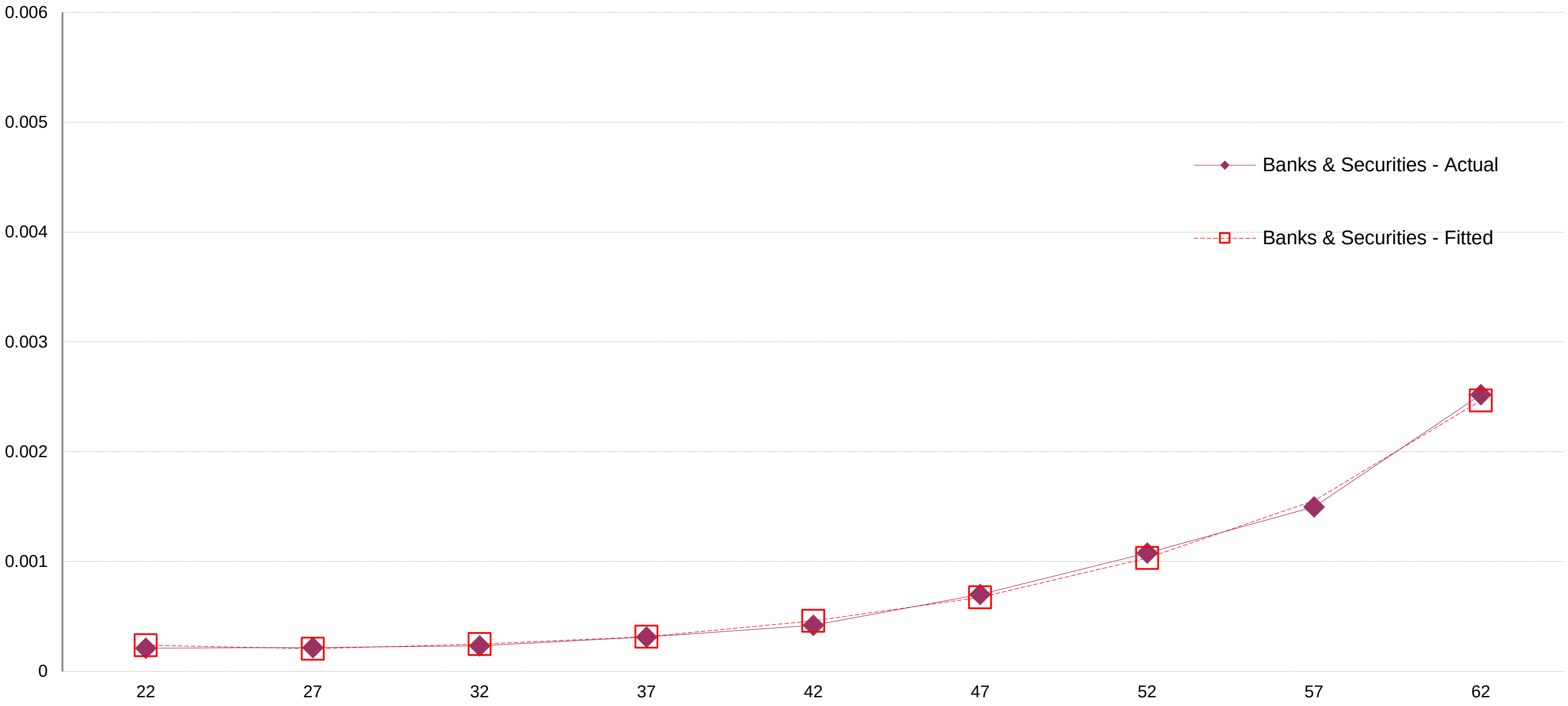
Actual and Fitted Values – Salary



- Salary is not included in the initial model.
- The initial model prediction is too high for salaries between $50k and $250k.
  - For salaries above $250k, the opposite is true. However, the results are less credible.

Review of Initial Model

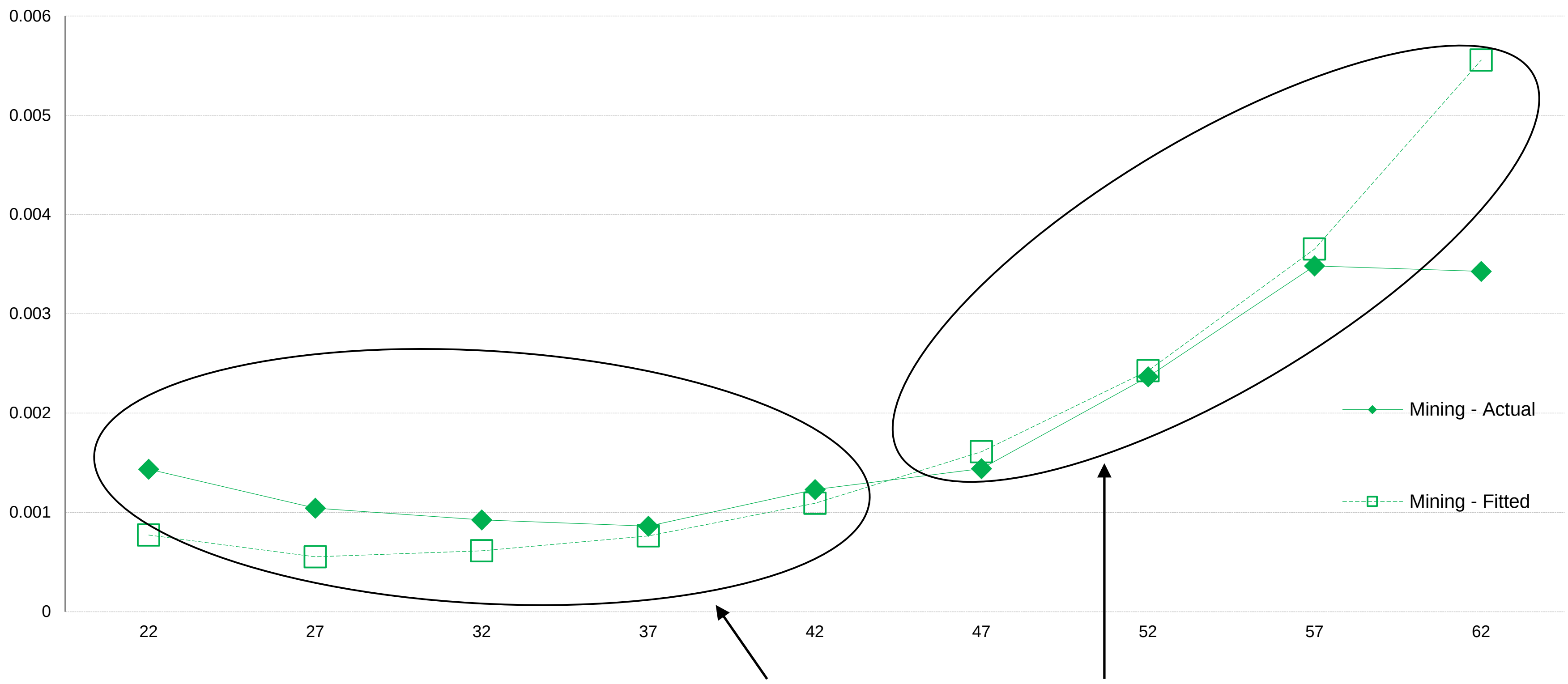
Actual and Fitted Values – Industry (Banks and Securities) & Central Age



- For the Banks & Securities industry category, the model fits the data well by age.

Review of Initial Model

Actual and Fitted Values – Industry (Mining) & Central Age

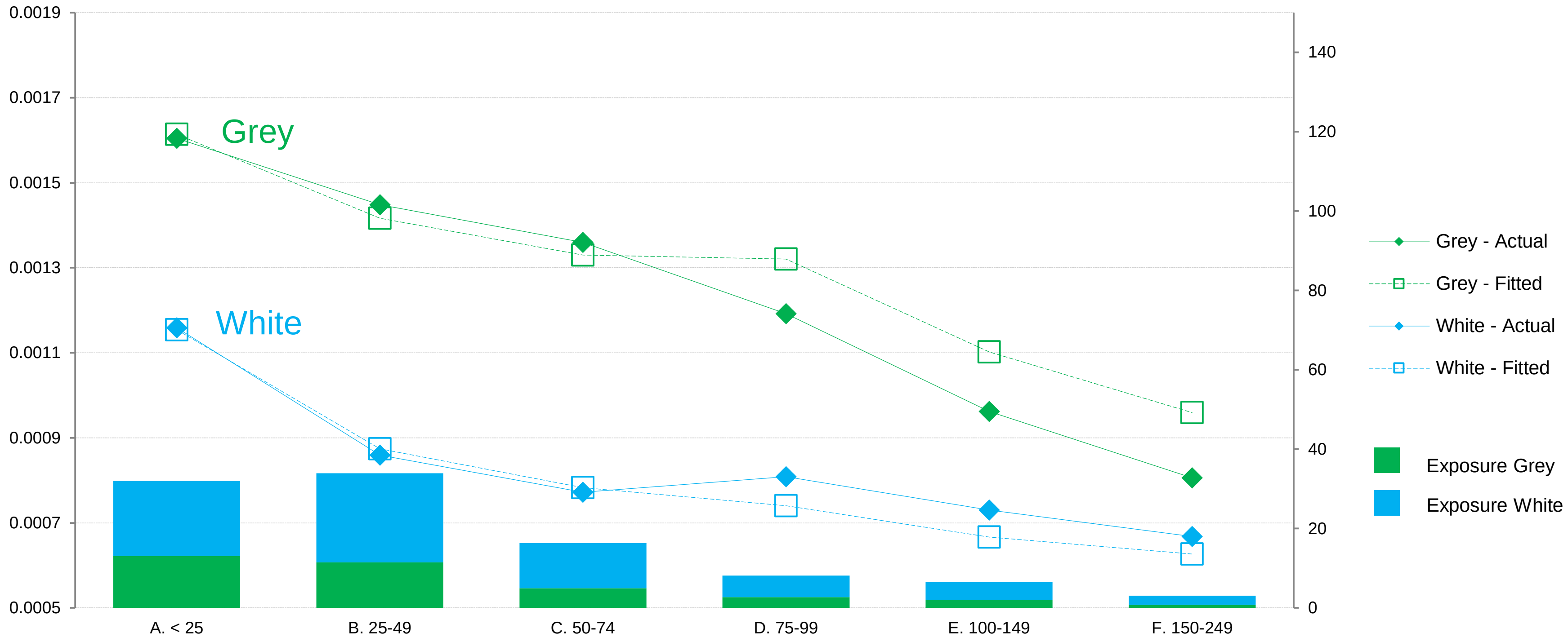


- For Mining, the model estimates are too low at younger ages and too high for ages 47+
  - Similar results are seen for Construction, and Agriculture and Forestry

- The model could be improved by including an interaction variable for Industry and Age.

Review of Initial Model

Actual and Fitted Values – Industry Collar and Salary



- The effect of Industry Collar on mortality varies by Salary
  - For Grey Collar the model estimates are too high at salaries over $75k
  - For White Collar the opposite is true

- The model could be improved by adding an interaction variable for Industry Collar and Salary.

WTW Survey Results

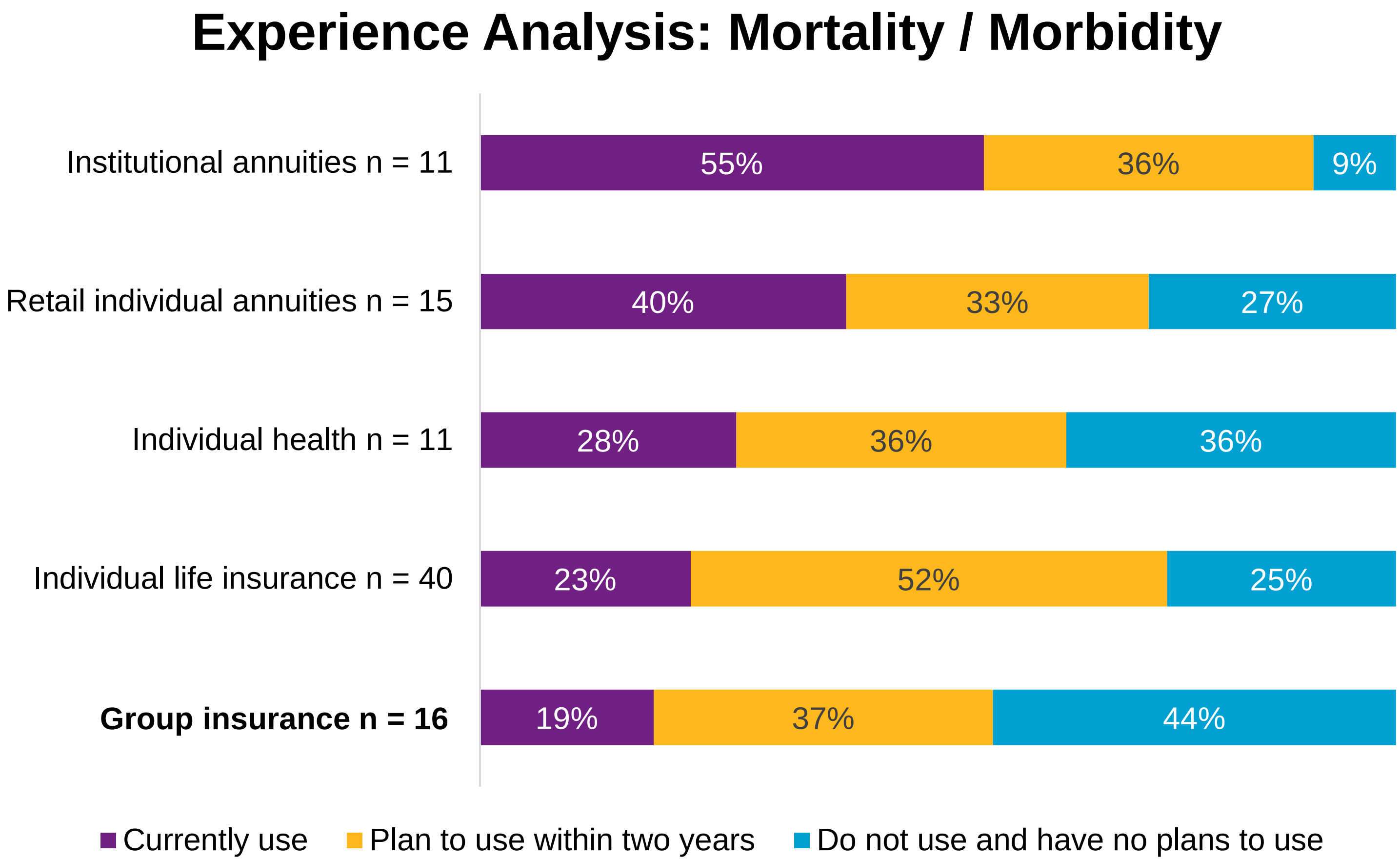
Use of Predictive Analytics

Percent of Companies Using Predictive Analytics Now vs. Within 2 Years						
Amount of Premium	Over $3 billion		$1 billion - $3 billion		less than $1 billion	
Line of Business	Now	In two years	Now	In two years	Now	In two years
Individual life insurance	70%	90%	50%	75%	53%	89%
Group insurance	71%	100%	67%	100%	23%	46%
Retail individual annuities	71%	71%	13%	38%	18%	32%
Institutional annuities	50%	83%	50%	75%	11%	33%
Individual health	40%	80%	20%	40%	15%	38%

<20%	20%-39%	40%-59%	60%-79%	80%+

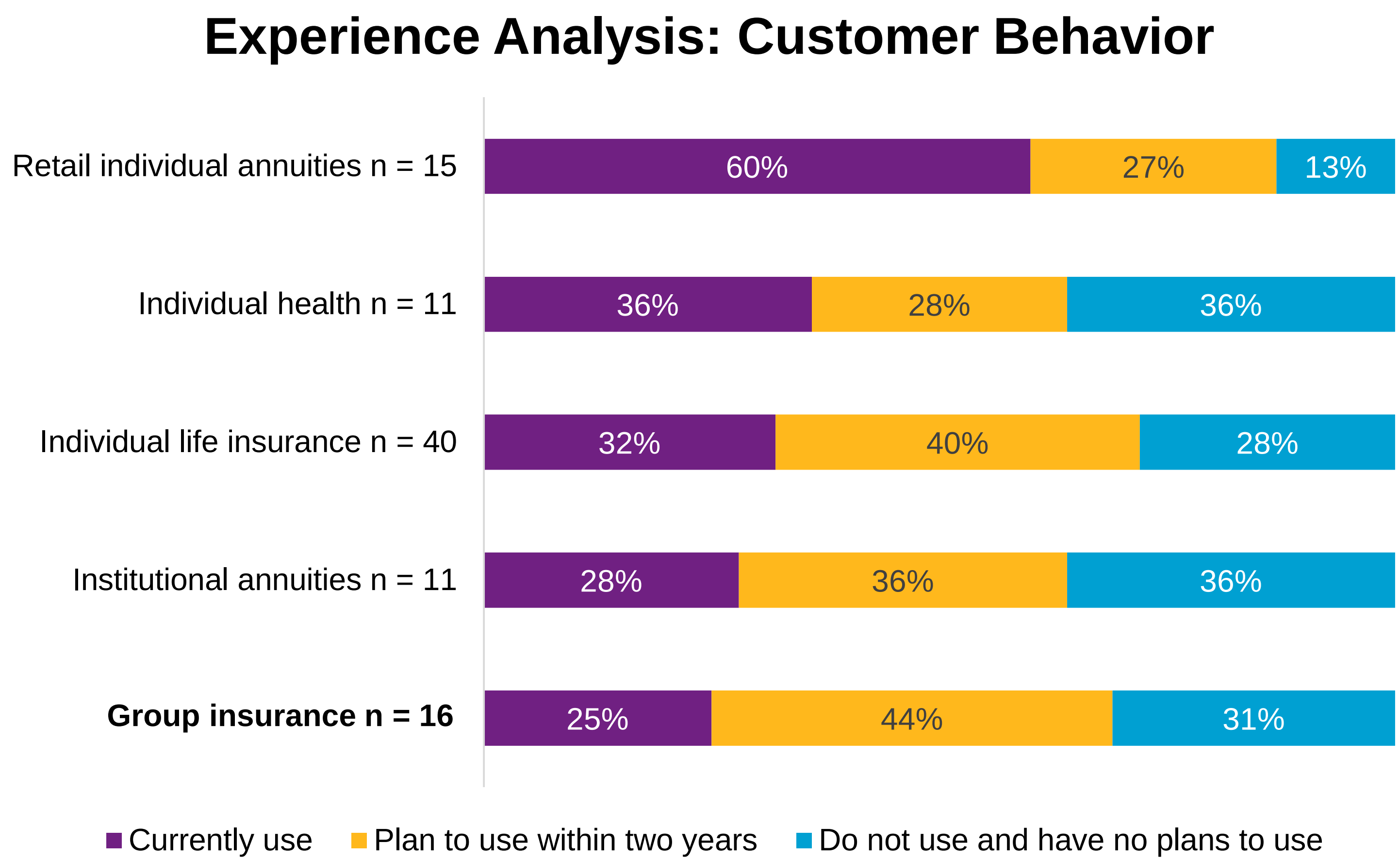
Base: Those who sell or have in-force business on the books (n varies).

Limited current use of analytics for mortality and morbidity by group carriers



Base: Those currently using or planning to use predictive analytics in at least one line of business (n varies).

Use is growing across all products



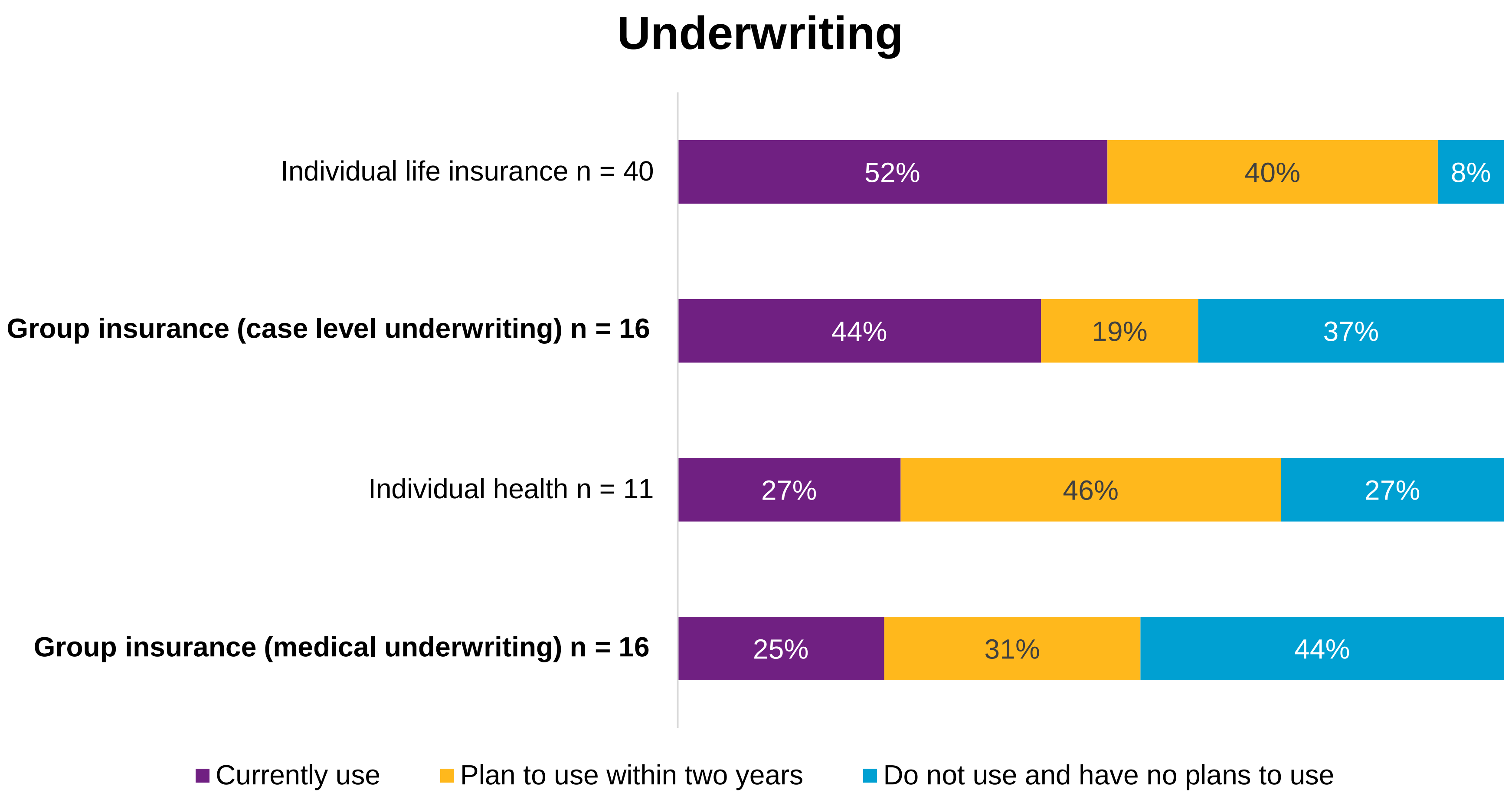
Base: Those currently using or planning to use predictive analytics in at least one line of business (n varies).

Individual Life Insurance – Accelerated Underwriting

- No one is happy with the historic approach
  - Expensive
  - Slow, many drop out
  - Invasive tests are a negative for customers

- Growing use of predictive models
  - Streamline the process
  - Fit models that predict the underwriting class
  - Use external data to replace invasive tests

Over 40% of group carriers using predictive analytics for case underwriting

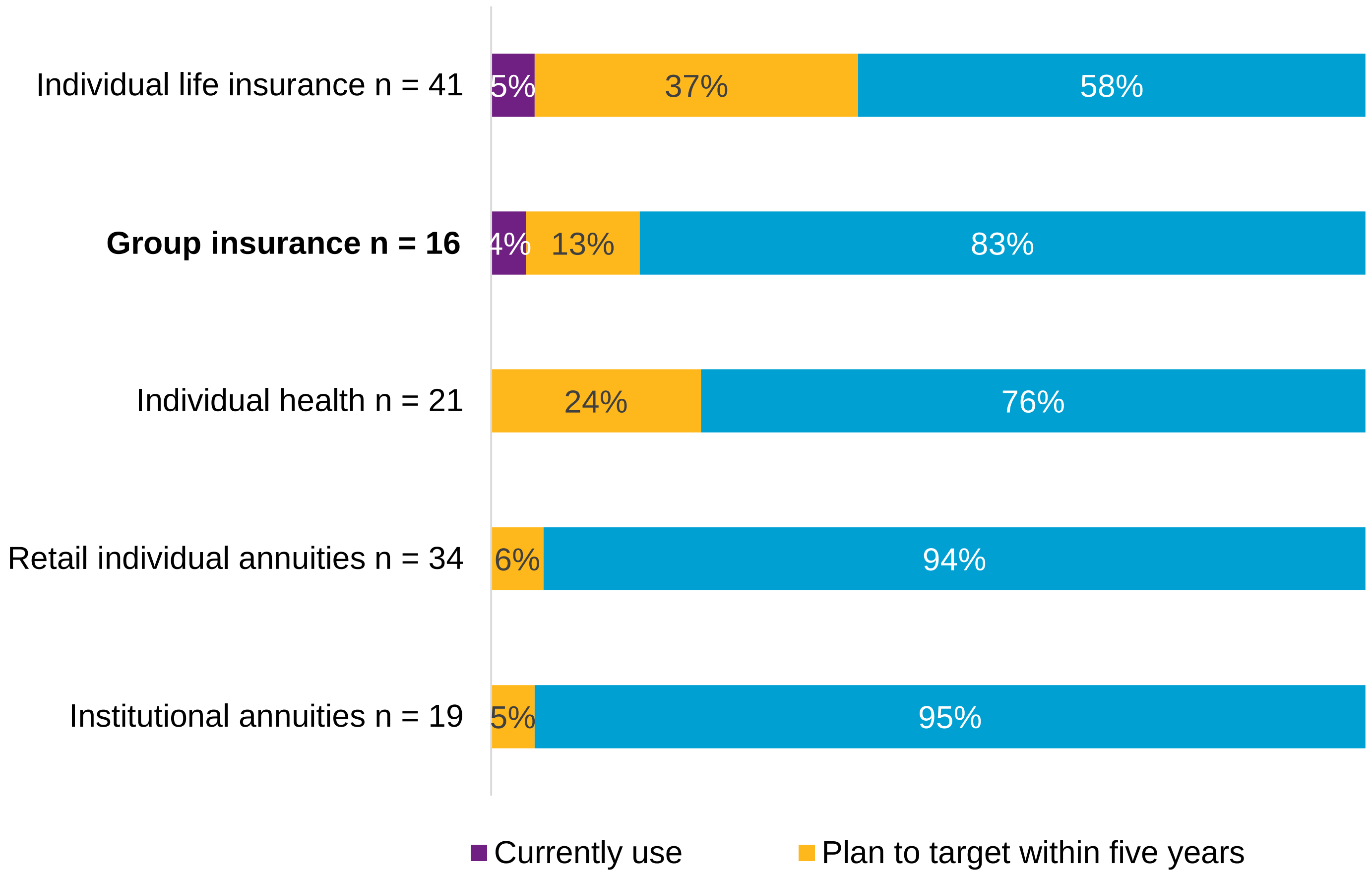


Base: Those currently using or planning to use predictive analytics in at least one line of business (n varies).

Life Insurance – Wearables

- Some life insurance companies have begun to offer discounts
- Not based on rigorous statistical models
- Potentially used more broadly once a sufficient volume of data has been collected

Limited use of wearables currently, but growth is expected



Base: Those currently using or planning to use predictive analytics in at least one line of business (n varies).

Willis Towers Watson