2019 Individual Life Insurance Mortality Experience Report

Exhibit 1 - Evaluation of Differences between NAIC and MIB ILEC Datasets using Predictive Analytics Approaches

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Mortality and Longevity

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Section 1: Introduction and Summary

The Individual Life Experience Committee (ILEC) evaluated the data quality of the 2018-2019 experience data received from the NAIC. Since this was the first time that we received data from the NAIC as the new statistical agent, we wanted to know whether and to what extent the newer data was consistent with or diverged from the prior data.

This document summarizes the results of the working group charged with testing whether and how AI/machine learning/statistical methods could answer these questions. There were two major quantities to assess: the distribution of exposures and mortality outcomes.

For assessing the distribution of exposures, we chose to apply vine copula modeling. A technical appendix describes what they are, how they work, and how we arrived at our findings. Differences in the details of the copula structures across experience years were deemed as evidence of differences in the exposures across experience years. At the same time, persistent and stable similarities in the copula models across experience years were deemed as evidence of similarities in the exposures across experience years.

For assessing mortality outcomes, we applied gradient-boosted machines to detect interactions of data sources (i.e., NAIC or MIB) with other variables. The main output from this approach was the table of two-way feature importance, from which we manually explored the mortality to find and illustrate interactions.

1.1 KEY FINDINGS FROM EXPOSURE MODELING

Vine copula models separate the modeling of univariate marginal distributions from the dependencies which tie them together.

Overall, there do not appear to be unexpected differences between the MIB and NAIC datasets from an exposure perspective. By count and by amount, while there are some shifts in marginal distributions of exposures, the interdependencies of the exposures either changed very little or changed in ways that are expected.

Drift was observed in the marginal distributions by observation year.

1. By count, there was an increase (+1.5%) in juvenile exposures with associated increases in exposures for Perm, unismoke, and lower face amounts. The “Other” category of insurance plan was also significant (0% to 2% of exposures).
2. By amount, there was an increase in Term (+1%-1.5%) and its associated variables of higher face amounts, age basis ANB, and preferred class structures (3- and 4-class non-smokers).

On the other hand, the dependency structures over time tended to be stable.

1. The by-count copulas were almost identical across experience years, with one important exception. The NAIC devoted significant efforts to correcting preferred class information for lower face amounts. This emerged in the 2019 copula as a multi-way dependency among preferred class, smoker status, sex, face amount band, and insurance plan.

2. By amount, the copulas were not identical to the by-count copulas. However, they tended to be like the by-count copula models. Some key differences include:
    a. Whereas Sex was independent of all other variables in the first copula level of the by-count model, it developed a dependency with face amount band in the by-amount model.
    b. For the by-count copula models, the fitted copulas tended to be those with meaningful tail dependency features. However, the Gaussian copula occasionally appeared in the by-amount copulas, suggesting weaker to no tail dependencies in some situations. For example, the association of Smoker_Status and SOA_Post_Lvl_Ind in the two-way by-amount copulas is Gaussian which have no tail dependencies. In the by-count model, the two variables connect eventually though BB7 copulas which carry tail dependencies. This suggests that there may be additional unmodeled face amount dependencies that are being obscured by the banding of the face amount variable.
3. In both by-count and by-amount cases, much of the dependency was modeled via two-way interactions, and those tended to be as expected.
    a. SOA_Post_Lvl_Ind and Insurance_Plan were occasionally interchangeable, where SOA_Post_Lvl_Ind could be viewed as a simplified “term” versus “whole of life” split.
    b. Term plans tended to be associated with higher face amounts, earlier durations, ANB age basis, and 3- and 4-class non-smoker preferred systems. Conversely, Perm tended to be associated with lower face amounts, later durations, unismoke and 2-class non-smoker preferred systems, and ALB age basis.

1.2 KEY FINDINGS FROM MORTALITY MODELING

The gradient boosted machine models tended to show weak interactions between the source of the data and other variables. Since these models can be sensitive to differences lacking in credibility, each of the interactions must be inspected manually.

The credible interactions included:

1. Attained Age
    a. Starting at attained age 70, mortality differs significantly by source for Term with unknown level term period (mostly ART on level death benefit term)
    b. Starting at attained age 70, mortality and exposure differ for Term that is not level term (decreasing benefit term)
2. Duration: For Perm, durations 1 and 2 are lower in the NAIC data
3. Face Amount Band
    a. For UL and ULSG in face amounts < 10K, mortality is much higher in the NAIC data
    b. For Term between $10,000 and $99,999 in the Unknown Level Term subgroup, mortality is much lower in the NAIC data
    c. For Term between $10,000 and $49,999 in the Within Level Term subgroup, mortality is somewhat lower in the NAIC data
    d. For VLSG with face amount below $25,000, mortality is higher in the NAIC data
4. Underwriting: For face amounts under $100,000 in Term within level term, the spread across preferred classes of A/E ratios by count and by amount for 4-class systems has narrowed. However, this finding is of modest credibility.
5. Term Length: Within the level term period, there was a reduction in the A/E by Amount for 25-year term

Section 2: Data

The data used for the copula analysis was the dataset released to the committee by the SOA on April 29, 2024. The data were extracted, filtered, and adjusted as follows:

1. Fields included
    a. Sex
    b. Smoker_Status
    c. Insurance_Plan
    d. Face_Amount_Band
    e. Issue_Age
    f. Duration
    g. Age_Ind
    h. SOA_Antp_Lvl_TP
    i. SOA_Guar_Lvl_TP
    j. SOA_Post_Lvl_Ind
    k. Number_of_Pfd_Classes
    l. Preferred_Class
    m. Policies_Exposed
    n. Death_Count
    o. Amount_Exposed
    p. Death_Claim_Amount
2. Data were limited to experience years 2016-2019
3. Data were grouped on fields a-l, and summarized on fields m-p
4. If any of Preferred_Class or Number_of_Pfd_Classes were NA, they were set to U
5. Smoker statuses other than U prior to 1981 issue years were set to U
6. Data were broken into three segments: 2016-2017, 2018, 2019
7. Issue ages were grouped into quinquennial ages from 25-105, and the rest were grouped into 0-17 and 18-24
8. Durations were grouped as follows: 1, 2, 3, 4-5, 6-10, 11-15, 16-20, 21-25, 26-30, 31-40, 41+

Note that Issue Year is not included in the copula analysis. Issue year, duration, and experience year are almost rigidly correlated. In this situation, once two are entered into the model, the third no longer contributes meaningfully to the analysis.

The data used for the mortality analysis were the same source without modifications. Filtering was performed as needed to zero on subsets of the data (e.g., Term other than post-level term).

Section 3: Mortality Differences

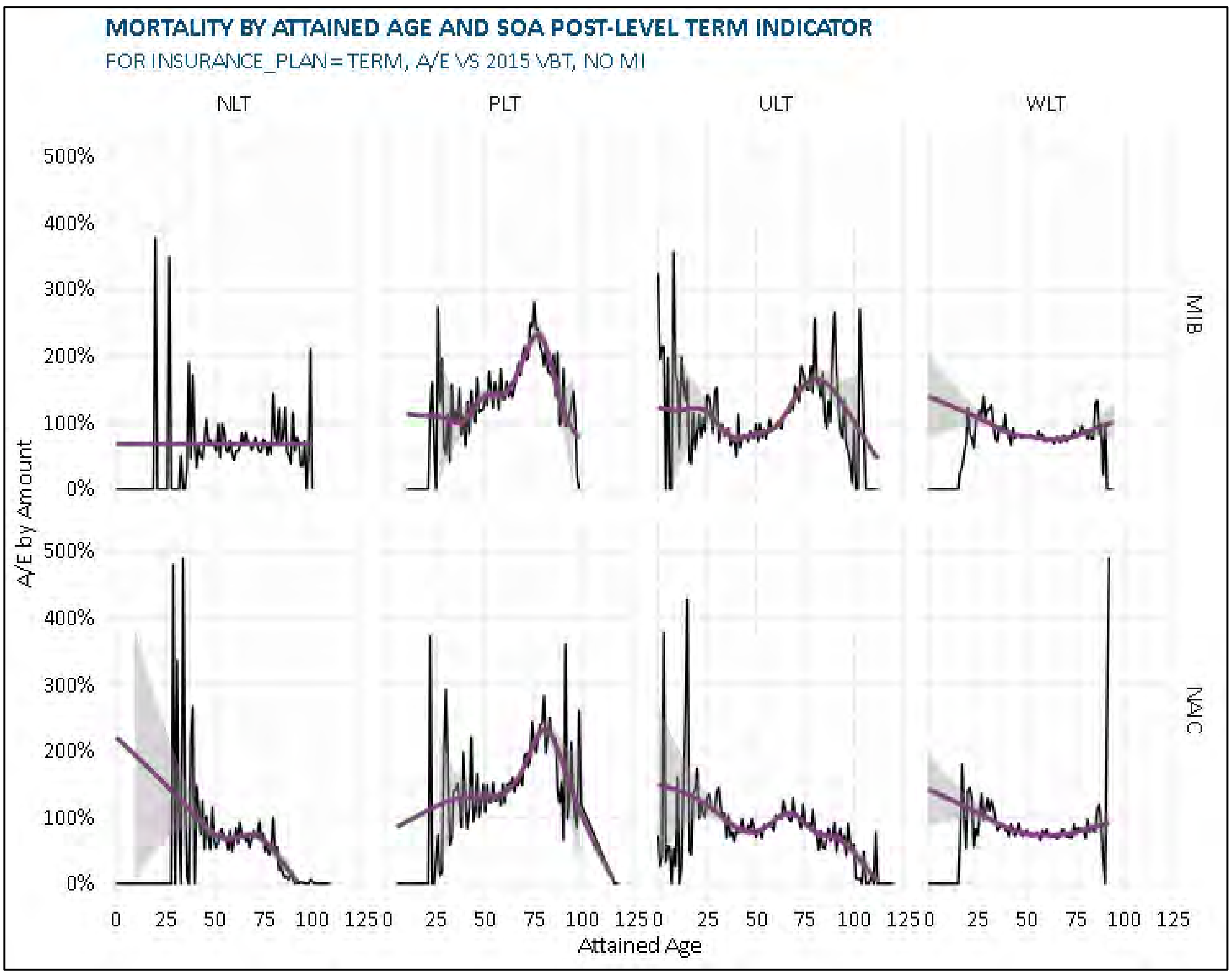
3.1 METHODOLOGY

Once data were extracted into a Python environment, XGBoost models were built. These models are Poisson models, which use the target of the A/E by Amount against the 2015 VBT and baseline of the 2015 VBT expected claims. Details of the model fitting can be found in the included Jupyter notebook.

3.2 SUMMARY OF SIGNIFICANT FINDINGS

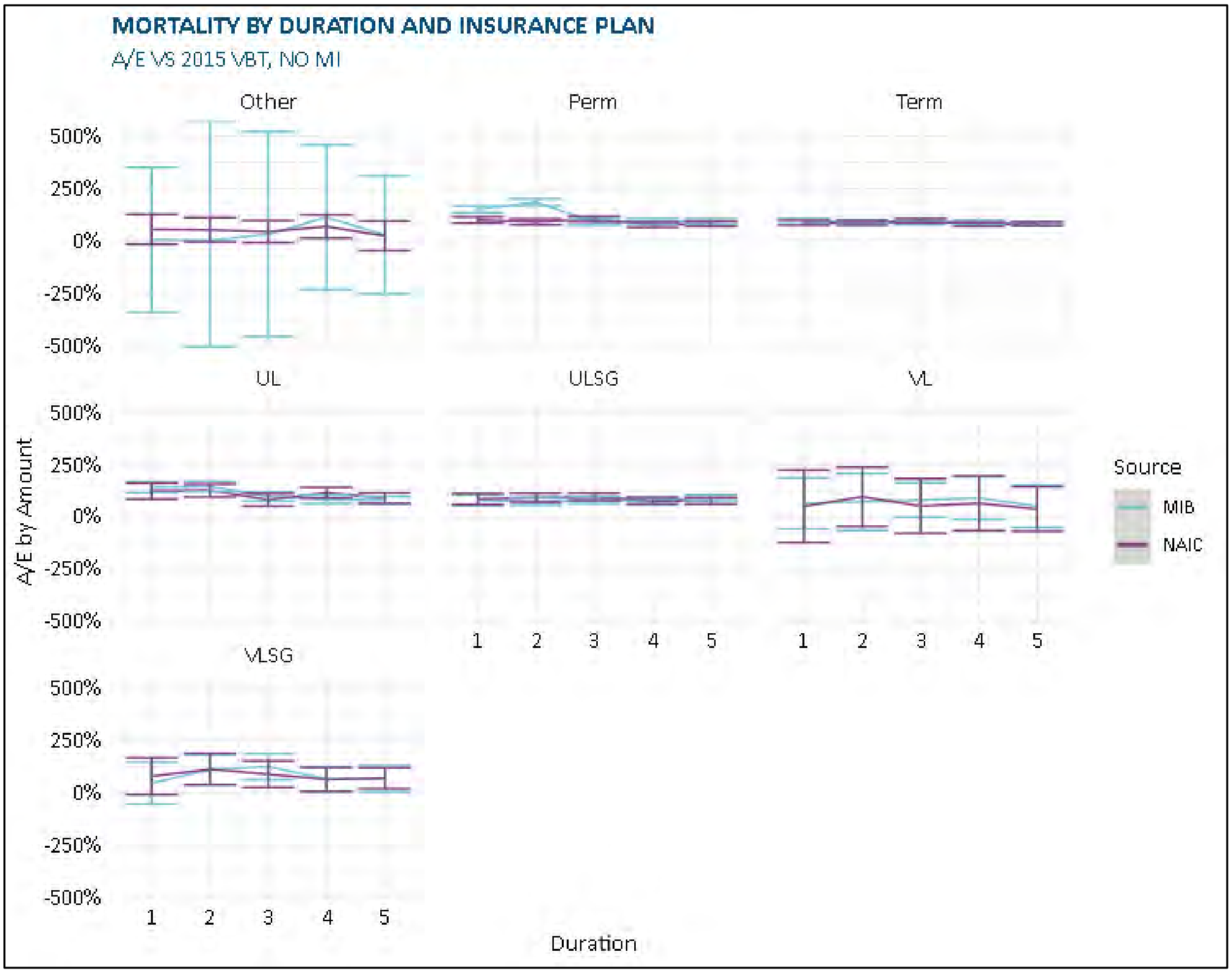
3.2.1 ATTAINED AGE

In the plot below, it can be seen that NLT (which is decreasing benefit term in the 2018-2019 dataset) and ULT (which is mostly ART on level term) exhibited different mortality slopes. This difference was obvious at attained ages 70+. A GAM was fit and plotted to each series to aid the eye in finding patterns.



3.2.2 DURATION

For Perm, the GBM detected that duration 1 and 2 claims were significantly higher in MIB than in NAIC. The plot below compares the early duration experience for all insurance plans. The confidence interval is the 95% confidence interval about the observed A/E ratio, where the standard error is 2.5 times the Poisson standard error for the A/E by count. The Poisson standard error for the A/E by count is assumed to be the reciprocal square root of the claim count. The 2.5 factor is based on one author's experience.

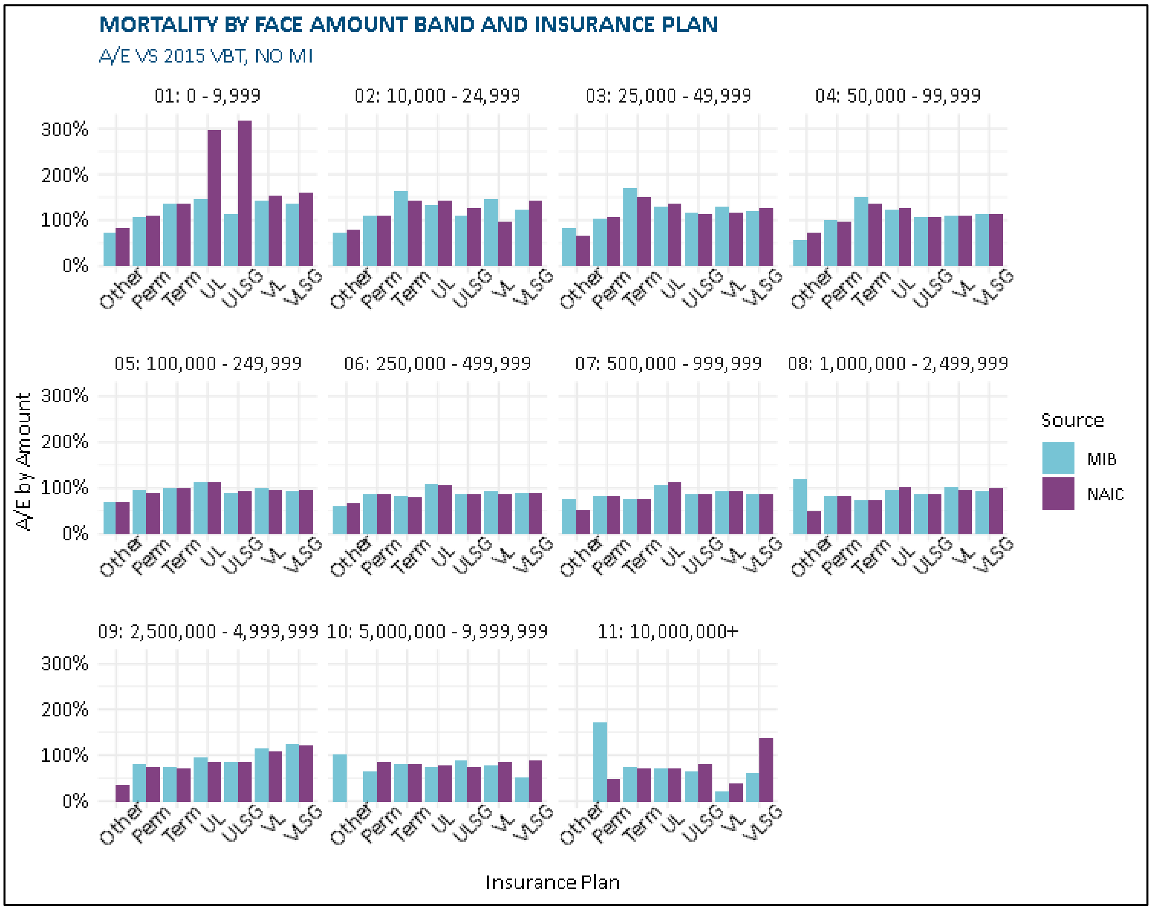


Experience by Early Duration, Perm Only				
	MIB		NAIC	
Duration	Death Count	A/E by Amount	Death Count	A/E by Amount
1	961	149.7%	1,141	98.7%
2	919	183.0%	1,225	89.6%
3	1,005	89.0%	1,462	102.8%
4	1,430	93.1%	1,567	76.6%
5	1,405	91.9%	1,681	80.2%

The table above is for early duration Perm. The reduction in mortality is almost fully credible and appears to be due to NAIC data quality improvement efforts.

3.2.3 FACE AMOUNT BAND

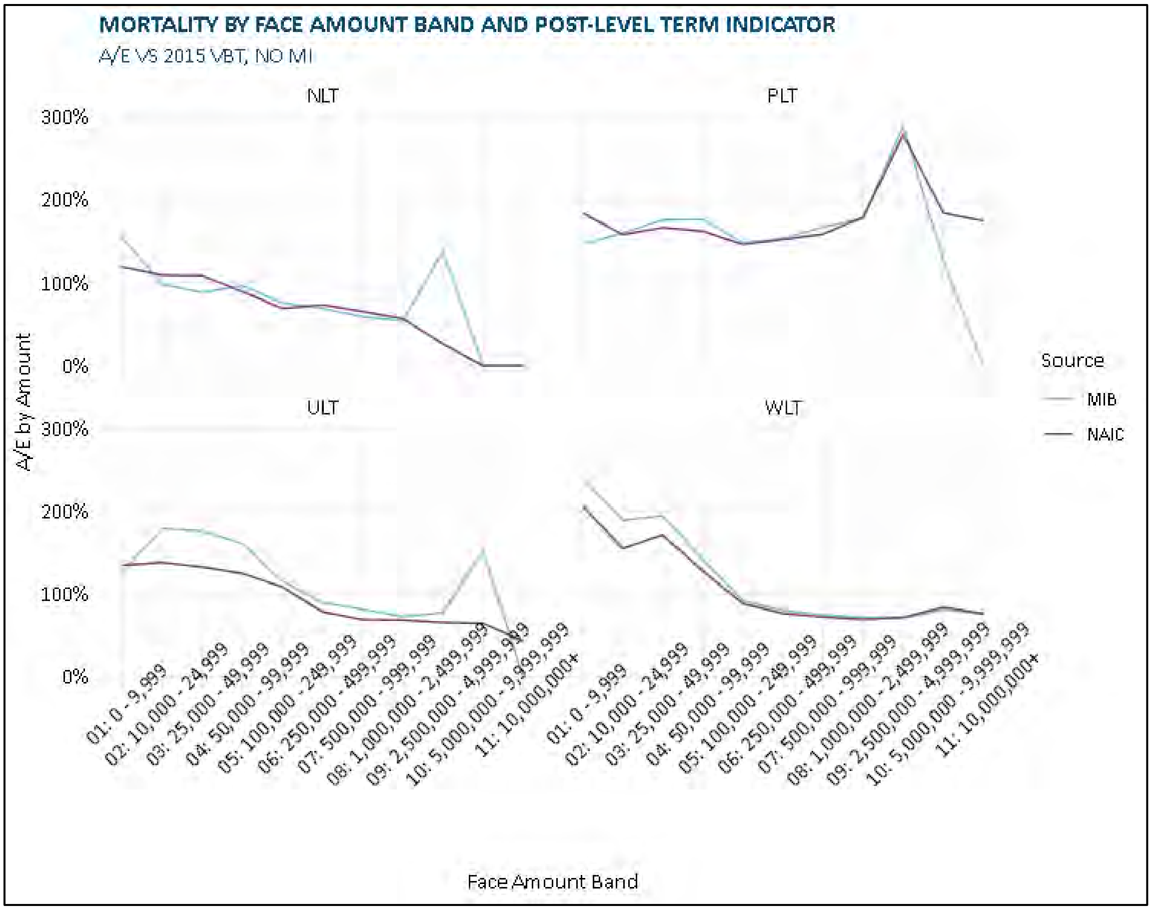
There is a very prominent increase in mortality in the NAIC data for the smallest face amounts for UL and ULSG.



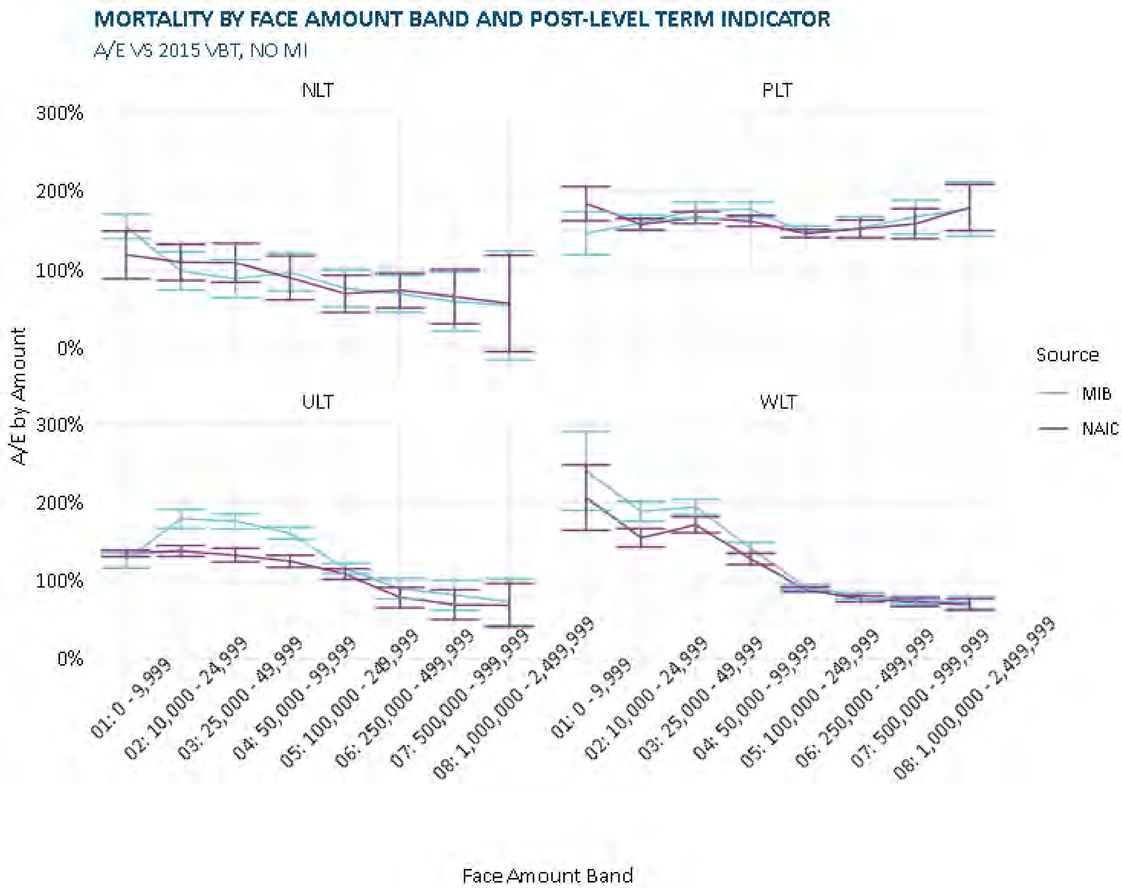
Experience by Insurance Plan Under 10,000				
	MIB		NAIC	
Insurance Plan	Death Count	A/E by Amount	Death Count	A/E by Amount
Other	178	72.8%	35,498	82.6%
Perm	441,149	107.8%	520,018	110.1%
Term	3,865	138.2%	17,030	137.1%
UL	2,612	145.7%	2,433	295.7%
ULSG	57	114.2%	81	315.8%
VL	488	144.7%	465	151.9%
VLSG	275	137.6%	527	158.9%

While the ULSG increase is not credible, the UL increase is.

Within the unknown level term subgroup of Term for face amounts $10,000 to $99,999, NAIC mortality is substantially lower. Within level term, for face amounts $10,000 to $99,999, NAIC mortality is somewhat lower.



Confidence intervals are omitted for clarity here, as the error bars for face amounts $2.5 million and greater overwhelm the scale. The spikes at those face amounts are not credible.



MORTALITY BY FACE AMOUNT BAND AND POST-LEVEL TERM INDICATOR
A/E VS 2015 VBT, NO MI
NLT
PLT
ULT
WLT
300%
200%
100%
0%
A/E by Amount
Source
MIB
NAIC
01: 0 - 9,999
02: 10,000 - 24,999
03: 25,000 - 49,999
04: 50,000 - 99,999
05: 100,000 - 249,999
06: 250,000 - 499,999
07: 500,000 - 999,999
08: 1,000,000 - 2,499,999
Face Amount Band

Experience by Term SOA Post-Level Indicator, Under $250,000				
	MIB		NAIC	
	Death Count	A/E by Amount	Death Count	A/E by Amount
NLT				
01: 0 - 9,999	991	155.1%	256	119.0%
02: 10,000 - 24,999	396	98.3%	451	109.4%
03: 25,000 - 49,999	406	88.5%	387	108.7%
04: 50,000 - 99,999	405	96.9%	308	89.5%
05: 100,000 - 249,999	441	75.9%	419	69.1%
PLT				
01: 0 - 9,999	318	146.5%	507	184.5%
02: 10,000 - 24,999	2,447	160.0%	4,577	158.2%
03: 25,000 - 49,999	2,141	176.1%	4,432	166.6%
04: 50,000 - 99,999	2,492	176.9%	5,084	162.4%
05: 100,000 - 249,999	4,095	148.2%	7,957	146.2%
ULT				
01: 0 - 9,999	2,462	125.8%	16,129	134.9%
02: 10,000 - 24,999	1,634	179.2%	5,177	138.0%
03: 25,000 - 49,999	2,621	176.0%	3,249	132.7%
04: 50,000 - 99,999	4,106	160.9%	3,889	124.9%
05: 100,000 - 249,999	5,174	115.5%	5,522	108.5%
WLT				
01: 0 - 9,999	94	240.6%	138	206.4%
02: 10,000 - 24,999	1,484	188.9%	1,682	154.9%
03: 25,000 - 49,999	2,676	194.3%	2,363	171.6%
04: 50,000 - 99,999	4,864	141.6%	4,291	127.9%
05: 100,000 - 249,999	23,274	92.0%	23,364	88.7%

3.2.4 UNDERWRITING

The GBM appears to have homed in on notable changes in mortality for Term, within the level term period, with face amounts under $100,000. The notable changes are highlighted in the following table. Within 2-class non-smoker preferred systems, mortality and claim count both declined. Within 4-class non-smoker preferred systems, mortality and claims counts declined, with the additional change that the spread of preferred class mortality in the NAIC data narrowed.

Experience for Term, within Level Term Period, Under $100,000						
Smoker Status	Number of Pfd Classes	Preferred Class	MIB		NAIC	
			Death Count	A/E by Amount	Death Count	A/E by Amount
NS	2	1	49	91.0%	39	72.6%
		2	4,115	205.4%	3,279	162.7%
	3	1	41	72.4%	52	68.7%
		2	154	118.8%	306	85.1%
		3	524	134.1%	515	145.9%
	4	1	124	67.4%	145	67.7%
		2	267	94.7%	252	84.6%
		3	124	108.6%	124	95.7%
		4	426	144.7%	326	129.6%
	NA		897	164.2%	655	148.2%
	U				322	216.0%
S	2	1	190	99.5%	167	95.0%
		2	375	143.2%	288	120.1%
	NA		1,631	155.9%	1,544	143.0%
	U				58	198.0%
U			201	138.5%	402	156.4%

3.2.5 TERM LENGTH

We noted a downward shift in mortality for term within the level term period having a 25-year anticipated level term period. Although it has modest credibility compared to other term lengths, the reduction in mortality is more than would be expected from calendar year trend alone.

Experience By Term Length Within Level Term Period				
Anticipated Term Length	MIB		NAIC	
	Death Count	A/E by Amount	Death Count	A/E by Amount
5	44	92%	7	62%
10	9,318	83%	8,940	83%
15	9,520	78%	8,236	74%
20	32,793	76%	34,645	74%
25	1,853	89%	2,057	75%
30	5,796	80%	6,883	75%
40			0	0%

Section 4: Exposure Differences

4.1 SUMMARY OF DIFFERENCES

After assessing the vine copula models, we feel confident in asserting the following statements:

1. As measured by policies exposed, the dependencies among variables from year to year are quite similar, with the most prominent difference between the MIB and NAIC sources being the remediation of small face amount preferred information undertaken by the NAIC.
2. As measured by amount exposed, the dependencies among variables from year to year are close to those of the by-count analysis, except that the calibrated copulas are often of a different type and potentially even spurious due to the exaggeration of amount-based weights.
3. The vine copula model, which explicitly includes Source, failed to detect a qualitatively meaningful interaction with Source and other variables. While this generally reinforces the previous points, this vine copula model only weakly detected the NAIC's remediation efforts. This suggests that the simplifying assumption as described above may have difficulty holding for relationships in the data where such relationships are contained in relatively small subsets of the data. Stratifying on other predictors or including regression capabilities in the vine models might improve the detection power of the methods.
4. All of this is despite the changes observed in the marginal distributions of each variable.

Overall, this analysis provides strong (though not absolute) evidence that the quality of the data received from the NAIC is as good as or better than what was received from MIB, and that except where noted, the exposures in the NAIC data are similar to what was observed in the MIB data in recent years.

4.2 METHODOLOGY

Vine copula models were fit to the data as described above in the Data section. Technical details of the analysis are included in the HTML file.

The analysis viewed the exposure distributions as probability distributions, both by count and by amount. Vine copulas were chosen over other methods due to their explainability and computational tractability. Other artificial intelligence (AI) methods would not have been explainable and may not have been computationally tractable. Traditional methods of manually exploring the data were deemed too laborious given the extremely large number of combinations to check.

This analysis considered copula models stratified by experience year, with models for each of experience years 2019, 2018, and the combination of 2016 and 2017. Further, within each year group, models were separately fit by count and amount. Each copula model produced a family of best-fit dependency graphs and their associated best-fit copulas. The analysis illustrates the results of these models and discusses salient points at each level. Also included is a brief discussion of changes in the univariate marginal distributions.

Stratifying the models into three experience years made it challenging to tell whether and to what extent experience year interacted with other variables. It was inferred by comparing the three models. However, we also fit a vine copula model against all the data, where the experience years are grouped into “MIB” for experience years 2016-2017 and “NAIC” for 2018-2019.

To understand differences, we looked for differences in the dependency graphs and associated copulas. The degree to which they differed across experience years, if at all, was used to indicate the degree to which the underlying exposures differed across experience years.

4.3 SUMMARY OF SIGNIFICANT FINDINGS

4.3.1 CHANGES IN MARGINAL DISTRIBUTIONS

Noteworthy changes from 2016-2017 to 2018 and 2019 in the marginal distributions included:

1. Sex: Slight shift toward females (+0.5%)
2. Smoker Status: Slight shift toward unismoke (+3-3.5%)
3. Insurance Plan: 0.5-1% shift within plans, with notable increase in "Other" category
4. Face Amount Band: 1-3% increase in face amounts < $25,000, offset by decreases in face amounts $50,000+
5. Issue Age: +1.5% for juvenile ages
6. Duration: Decreases in durations 6-15 (-0.5%) and increases in durations 31-40 (+1.5-2%)
7. Age Indicator: ALB increase of 2-2.5%
8. SOA Anticipated Term Period: Unknown category increased 2.3%
9. SOA Guaranteed Term Period: Unknown category increased 2.3%
10. SOA Post-Level Indicator: 1.8% increase in "Unknown Level Term," 0.8-0.9% increase in "Post-Level Term," fluctuations in "Within Level Term"
11. Number of Preferred Classes: 1.1-1.8% increase in U category
12. Preferred Class: 1.1-1.8% increase in U category, 1.5% decline in category 1

Compared to the view by count, shifts were muted by amount. Noteworthy changes from 2016-2017 to 2018 and 2019 in the marginal distributions included:

1. Sex: Slight shift toward females (+0.5%)
2. Smoker Status: Slight shift toward unismoke (+0.5)
3. Insurance Plan: Small, steady shift to Term (+1.5%) and ULSG (+1.2%)
4. Face Amount Band: Increase in average face amounts, with $1 million+ face amount bands increasing and the others declining
5. Duration: Increases in durations 11+, with decreases in durations 1-10. Durations 6-10 had the largest decrease (-2.9%), and durations 16-20 had the largest increase (+3.1%)
6. Age Indicator: +1.5% shift toward ANB
7. SOA Anticipated Term Period: Unknown category increased 1.7%, 20-year term increased 0.8%
8. SOA Guaranteed Term Period: Unknown category increased 1.7%, 20-year term increased 0.8%
9. SOA Post-Level Indicator: 1.1% increase in "Unknown Level Term," 0.5% increase in "Post Level Term"
10. Number of Preferred Classes: 1.3% decline in U category, 0.9% increase in 4-class, 1.2% increase in 3-class, 0.5% decline in 2-class

4.3.2 CHANGES IN DEPENDENCY STRUCTURE

For this document, we only include changes in the dependency structure of the data. For further details, including a discussion of dependencies that did not change over time, see the included file.

The sole noteworthy change occurred in the interdependencies among insurance plan, face amount, and preferred class information.

Among the 2-class non-smoker systems with face amounts under $50,000, there was a shift in the ULSG preferred mix.

Policies Exposed as Percent of 2-class NS Preferred System and Insurance Plan					
		Policies Exposed		Amount Exposed	
Insurance Plan	Preferred Class	MIB	NAIC	MIB	NAIC
Other	1	0.0%	22.7%	0.0%	44.1%
	2	100.0%	77.3%	100.0%	55.9%
Perm	1	27.6%	23.8%	33.9%	52.6%
	2	72.4%	76.2%	66.1%	47.4%
Term	1	5.2%	6.0%	5.5%	6.6%
	2	94.8%	94.0%	94.5%	93.4%
UL	1	16.1%	15.9%	18.9%	19.6%
	2	83.9%	84.1%	81.1%	80.4%
ULSG	1	36.7%	13.6%	36.7%	14.3%
	2	63.3%	86.4%	63.3%	85.7%
VL	1	29.9%	27.9%	29.4%	29.7%
	2	70.1%	72.1%	70.6%	70.3%
VLSG	1	5.2%	5.7%	6.0%	36.7%
	2	94.8%	94.3%	94.0%	63.3%

Among the 3-class non-smoker systems with face amounts under $50,000, shifts were more widespread. Movements were pronounced in Term and VLSG.

Policies Exposed as Percent of 3-class NS Preferred System and Insurance Plan					
		Policies Exposed		Amount Exposed	
Insurance Plan	Preferred Class	MIB	NAIC	MIB	NAIC
Other	1	8.9%	16.5%	8.8%	21.0%
	2	21.8%	25.8%	21.8%	23.9%
	3	69.4%	57.7%	69.3%	55.1%
Perm	1	1.2%	1.5%	1.5%	23.7%
	2	1.7%	2.4%	2.4%	14.3%
	3	97.1%	96.2%	96.1%	62.1%
Term	1	8.6%	5.0%	9.6%	9.2%
	2	5.5%	47.1%	6.0%	26.4%
	3	85.9%	47.9%	84.4%	64.4%
UL	1	7.1%	5.8%	8.1%	7.1%
	2	22.7%	15.0%	23.0%	16.0%
	3	70.2%	79.2%	68.9%	76.9%
ULSG	1	4.6%	10.5%	4.8%	10.8%
	2	12.5%	24.4%	13.0%	28.8%
	3	82.9%	65.1%	82.1%	60.4%
VL	1	0.8%	0.7%	0.8%	1.1%
	2	11.5%	9.8%	11.3%	10.6%
	3	87.7%	89.5%	87.9%	88.4%
VLSG	1	5.0%	7.2%	5.6%	42.7%
	2	20.5%	13.4%	20.7%	18.1%
	3	74.5%	79.4%	73.6%	39.2%

Among the 4-class non-smoker systems with face amounts under $50,000, there were pronounced movements in Perm, Term, VL, and VLSG.

Policies Exposed as Percent of 4-class NS Preferred System and Insurance Plan					
		Policies Exposed		Amount Exposed	
Insurance Plan	Preferred Class	MIB	NAIC	MIB	NAIC
Other	1		52.7%		32.5%
	2		19.9%		15.0%
	3		8.5%		6.9%
	4		18.8%		45.6%
Perm	1	9.1%	3.5%	8.5%	14.7%
	2	11.6%	5.6%	11.5%	15.2%
	3	1.2%	0.6%	0.5%	6.6%
	4	78.1%	90.3%	79.5%	63.5%
Term	1	9.5%	16.3%	7.6%	16.2%
	2	6.3%	8.3%	5.9%	11.4%
	3	3.1%	3.6%	3.0%	6.8%
	4	81.0%	71.8%	83.5%	65.6%
UL	1	0.9%	1.4%	0.7%	1.1%
	2	6.9%	6.2%	6.0%	5.3%
	3	0.8%	1.1%	0.7%	1.0%
	4	91.5%	91.3%	92.5%	92.5%
ULSG	1	23.4%	29.9%	23.3%	29.3%
	2	22.5%	16.3%	22.3%	16.6%
	3	12.4%	9.8%	12.3%	9.8%
	4	41.6%	44.0%	42.1%	44.4%
VL	1	2.2%	25.7%	1.5%	21.4%
	2	7.9%	11.3%	5.6%	12.5%
	3	0.0%	12.2%	0.0%	16.5%
	4	90.0%	50.8%	92.9%	49.6%
VLSG	1	3.1%	31.0%	3.7%	27.2%
	2	5.5%	10.7%	6.8%	11.8%
	3	3.1%	7.5%	2.9%	13.2%
	4	88.3%	50.8%	86.6%	47.8%

Shifts in distribution were broad-based among the 2-class smoker systems with face amounts under $50,000.

Policies Exposed as Percent of 2-class SM Preferred System and Insurance Plan					
		Policies Exposed		Amount Exposed	
Insurance Plan	Preferred Class	MIB	NAIC	MIB	NAIC
Other	1	44.3%	33.0%	47.3%	34.9%
	2	55.7%	67.0%	52.7%	65.1%
Perm	1	33.4%	17.7%	39.2%	35.6%
	2	66.6%	82.3%	60.8%	64.4%
Term	1	15.7%	16.4%	16.8%	35.7%
	2	84.3%	83.6%	83.2%	64.3%
UL	1	11.2%	7.4%	12.6%	8.3%
	2	88.8%	92.6%	87.4%	91.7%
ULSG	1	27.6%	24.3%	28.9%	24.9%
	2	72.4%	75.7%	71.1%	75.1%
VL	1	16.3%	6.7%	16.5%	9.7%
	2	83.7%	93.3%	83.5%	90.3%
VLSG	1	9.1%	6.6%	11.3%	23.6%
	2	90.9%	93.4%	88.7%	76.4%

Above $50,000, shifts were not as widespread. Among 2-class non-smoker systems, only VL showed a notable shift.

Policies Exposed as Percent of 2-class NS Preferred System and Insurance Plan					
		Policies Exposed		Amount Exposed	
Insurance Plan	Preferred Class	MIB	NAIC	MIB	NAIC
Other	1	55.0%	62.6%	62.0%	68.6%
	2	45.0%	37.4%	38.0%	31.4%
Perm	1	75.0%	73.9%	78.0%	77.8%
	2	25.0%	26.1%	22.0%	22.2%
Term	1	46.0%	44.8%	60.3%	60.1%
	2	54.0%	55.2%	39.7%	39.9%
UL	1	55.2%	53.2%	65.2%	63.5%
	2	44.8%	46.8%	34.8%	36.5%
ULSG	1	61.6%	58.9%	64.2%	64.0%
	2	38.4%	41.1%	35.8%	36.0%
VL	1	61.5%	54.7%	67.4%	61.6%
	2	38.5%	45.3%	32.6%	38.4%
VLSG	1	64.7%	62.5%	70.0%	70.0%
	2	35.3%	37.5%	30.0%	30.0%

Moving to 3-class non-smoker systems, only the Other category contained shifts in the mix of preferred class distribution.

Policies Exposed as Percent of 3-class NS Preferred System and Insurance Plan					
		Policies Exposed		Amount Exposed	
Insurance Plan	Preferred Class	MIB	NAIC	MIB	NAIC
Other	1	36.1%	63.0%	41.3%	61.3%
	2	29.1%	22.8%	25.9%	27.6%
	3	34.8%	14.2%	32.8%	11.1%
Perm	1	47.2%	47.1%	52.2%	53.4%
	2	22.3%	20.8%	23.2%	21.6%
	3	30.5%	32.1%	24.6%	25.0%
Term	1	41.9%	41.5%	47.4%	47.6%
	2	26.1%	26.9%	26.4%	27.1%
	3	32.0%	31.6%	26.2%	25.3%
UL	1	36.2%	35.2%	36.7%	35.1%
	2	25.8%	26.1%	29.3%	30.8%
	3	38.0%	38.7%	34.0%	34.1%
ULSG	1	33.2%	34.7%	38.0%	40.0%
	2	27.3%	27.2%	29.9%	28.9%
	3	39.5%	38.0%	32.0%	31.2%
VL	1	36.9%	35.9%	41.7%	40.1%
	2	27.7%	27.1%	31.0%	31.1%
	3	35.4%	36.9%	27.3%	28.8%
VLSG	1	40.6%	38.5%	42.6%	41.5%
	2	29.0%	27.7%	30.8%	30.2%
	3	30.5%	33.8%	26.6%	28.2%

For 4-class systems having face amounts $50,000 or greater, both UL and VL experienced shifts.

Policies Exposed as Percent of 4-class NS Preferred System and Insurance Plan					
		Policies Exposed		Amount Exposed	
Insurance Plan	Preferred Class	MIB	NAIC	MIB	NAIC
Other	1	31.7%	27.7%	34.0%	45.5%
	2	30.3%	15.1%	30.2%	19.6%
	3	10.7%	7.2%	9.7%	7.4%
	4	27.3%	49.9%	26.2%	27.5%
Perm	1	34.8%	31.7%	37.1%	32.2%
	2	23.3%	21.8%	23.1%	25.0%
	3	12.9%	13.1%	14.0%	13.4%
	4	29.1%	33.5%	25.9%	29.4%
Term	1	47.3%	47.1%	51.7%	51.7%
	2	22.7%	22.0%	22.2%	21.8%
	3	15.9%	15.8%	14.8%	14.6%
	4	14.1%	15.1%	11.2%	11.9%
UL	1	32.1%	18.1%	39.8%	31.4%
	2	18.1%	16.7%	16.4%	22.0%
	3	18.9%	9.4%	20.0%	13.0%
	4	31.0%	55.8%	23.8%	33.6%
ULSG	1	48.8%	43.5%	51.0%	47.5%
	2	20.3%	22.9%	22.4%	24.3%
	3	13.1%	14.9%	11.9%	13.5%
	4	17.8%	18.7%	14.6%	14.7%
VL	1	50.0%	43.0%	49.5%	48.5%
	2	14.8%	17.8%	16.1%	17.6%
	3	16.5%	14.8%	16.3%	14.7%
	4	18.7%	24.5%	18.1%	19.1%
VLSG	1	49.5%	49.9%	51.8%	50.6%
	2	21.6%	20.5%	21.5%	22.8%
	3	14.8%	16.3%	13.4%	14.4%
	4	14.1%	13.3%	13.3%	12.2%

For 2-class smoker systems with face amounts $50,000 and greater, several insurance plans saw shifts in their distributions by count, but not by amount.

Policies Exposed as Percent of 2-class SM Preferred System and Insurance Plan					
		Policies Exposed		Amount Exposed	
Insurance Plan	Preferred Class	MIB	NAIC	MIB	NAIC
Other	1	56.8%	44.2%	60.1%	59.6%
	2	43.2%	55.8%	39.9%	40.4%
Perm	1	66.4%	58.5%	67.0%	60.7%
	2	33.6%	41.5%	33.0%	39.3%
Term	1	61.5%	59.5%	65.3%	63.5%
	2	38.5%	40.5%	34.7%	36.5%
UL	1	42.5%	38.4%	50.4%	48.7%
	2	57.5%	61.6%	49.6%	51.3%
ULSG	1	58.2%	48.4%	60.9%	50.8%
	2	41.8%	51.6%	39.1%	49.2%
VL	1	52.6%	49.5%	58.1%	54.8%
	2	47.4%	50.5%	41.9%	45.2%
VLSG	1	58.3%	51.1%	61.3%	54.3%
	2	41.7%	48.9%	38.7%	45.7%

4.4 MINOR ADDITIONAL DIFFERENCE BETWEEN SOURCES

In 2019, a dependency emerged between insurance plan and SOA post-level term indicator, depending on face amount band. Digging into the data, the prevalence of ULT (unknown level term which is mostly ART on level term) for face amounts under $50,000 increased from approximately 45-46% of this subset in the MIB data to approximately 71-72% in the NAIC data.

Section 5: Conclusion

Overall, the NAIC data were nearly identical to what was received in prior years. As of the April 29, 2024 release, it appeared that most differences were due to the NAIC's efforts to improve data quality among the reporting companies.

The gradient-boosted machine approach to exploring mortality differences has been useful in homing in on data quality issues and highlighting differences between sources. Since it tended to be sensitive to variation in outcomes, it led the analyst quickly to where differences in mortality resided. In prior iterations of the data, the gradient-boosted machine approach was able to diagnose anomalous mortality due to paid-up additions and due to simplified issue business that a company had included in error.

The vine copula-based approach was useful to compare distributions across experience years. The main challenges in using vine copulas were their relative newness as a tool for mortality data analysis and their complexity. Outputs of the model required patience to interpret. However, that patience was rewarded. It provided analysis which reinforced confidence that the quality of the new data source is the same as or better than that of the prior data source.

Section 6: Acknowledgments

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Pete Miller, ASA, MAAA, Experience Studies Actuary

Appendix

EXPOSURE MODELING

See HTML file DistributionalChanges.html

MORTALITY MODELING WITH GRADIENT-BOOSTED MACHINES

In this section, you will find instructions on how to reproduce the analysis using gradient-boosted machines. The instructions assume that you are comfortable with setting up, running, and interpreting XGBoost models in your environment.

1. Load the dataset.
2. In addition to the main dataset, you will also carry out the analysis on the following subsets:
    a. Insurance Plan == "Term"
    b. Insurance Plan == "Term" and Post-Level-Term Indicator == "PLT"
    c. Insurance Plan == "Perm"
3. Select only the following columns:
    a. Observation_Year
    b. Sex
    c. Smoker_Status
    d. Insurance_Plan
    e. Face_Amount_Band
    f. Attained_Age
    g. Duration
    h. SOA_Guar_Lvl_TP
    i. SOA_Post_Lvl_Ind
    j. Number_of_Pfd_Classes
    k. Preferred_Class
    l. Policies_Exposed
    m. Death_Count
    n. Amount_Exposed
    o. Death_Claim_Amount
    p. ExpDth_Cnt_VBT2015
    q. ExpDth_Amt_VBT2015
4. Filter out rows with 0 exposures, whether by policies exposed or by amount exposed.
5. Create or change columns as follows:
    a. Concatenate the columns Smoker_Status, Preferred_Class, and Number_of_Pfd_Classes to form the column "UW." For example, "NS/1/4" is non-smoker, preferred class 1, with number of preferred classes 4.
    b. Group Duration into a new Dur_Grp variable into groups: 1, 2, 3, 4-5, 6-10, 11-15, 16-20, 20-30, 31+.
    c. Group Attained_Age into a new AA_Grp variable into groups: quinquennially from ages 25-99, plus groups 0-17, 18-24, and 100+ for the rest.
    d. Create a Data_Source variable defined as "NAIC" for Observation_Year of 2018 and later, "MIB" otherwise.
    e. Ensure all columns other than purely numeric columns are of categorical type.

   f. Add a Noise variable. We used a random permutation of the numerical representation of the Sex variable.

6. Summarize the dataset by grouping on Observation_Year, Sex, Insurance_Plan, UW, Face_Amount_Band, Dur_Grp, AA_Grp, and SOA_Guar_Lvl_TP (if appropriate) on summing on Policies_Exposed, Death_Count, ExpDth_Cnt_VBT2015, Amount_Exposed, Death_Claim_Amount, and ExpDth_Amt_VBT2015.
7. Calculate and append the A/E ratios for count and amount.
8. Train with XGBoost:
   a. Split the data into features X and target Y. Convert categorical features into dummy/indicator variables as appropriate.
   b. The features are grouping variables in step 6.
   c. The target is A/E by amount.
   d. The weight is ExpDth_Amt_VBT2015.
   e. Split the data into train/test datasets.
   f. Apply XGBoost per your environment's instructions, including properly specifying cross validation using the train and test datasets.
   g. The following parameters were used:
      i. max_depth: 6
      ii. learning_rate: 1
      iii. n_estimators: 100
      iv. objective: "count:poisson"
      v. colsample_bytree = 0.8
      vi. subsample: 0.8
      vii. gamma: 0
      viii. random_state: 42
      ix. alpha: 0.1
      x. eval_metric: "rmse"
9. Obtain feature importance and interaction scores. Since these only suggest the existence of interactions, the next step is to examine the data for interactions between Data_Source and the indicated variable in the interaction score chart.

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