Mortality and Longevity

U.S. Individual Life Mortality Improvement Analysis

MAY | 2024

SOA Research INSTITUTE

U.S. Individual Life Mortality Improvement Analysis

AUTHORS SOA Individual Life Experience Committee

Mortality Improvement Analysis Subgroup

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Executive Summary

This study was developed by the Mortality Improvement Analysis Subgroup of the Society of Actuaries (SOA) Research Institute's Individual Life Experience Committee (ILEC). The purpose of this study is to present a methodology for estimating mortality improvement factors based on data from insured lives.

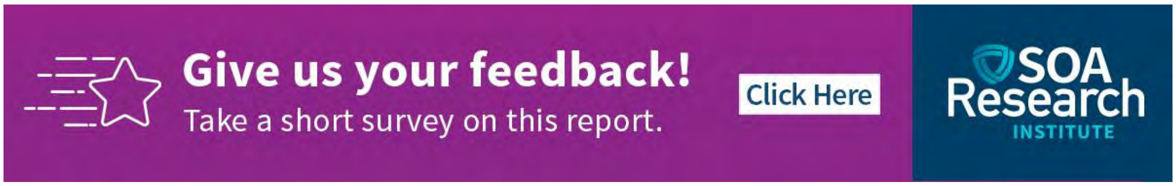
The methodology as laid out in this report is not meant to produce a proposed set of mortality improvement factors for any specific purpose. The release of the methodology and thinking around its development is intended to solicit comments from other actuaries and suggestions for further refinements.

Below is a summary of the methodology and findings:

- Insured policy data was extracted from a summary file compiled by the SOA Research Institute. The data was collected by the New York State Department of Financial Services, the Kansas Insurance Department, and the National Association of Insurance Commissioners (NAIC) based on requirements prescribed in Section 20 of the NAIC valuation manual.
- The data covered calendar observation years 2009 through 2019. During this period the number of companies varied substantially. Additionally, the mix of business changed. For example, as smaller policies terminated, the average size of new policies increased. Underwriting processes changed and new preferred class structures were offered. These changes in mix of business made it difficult to distinguish the true biometric mortality improvement from noise in the data caused by the changes in mix of business. For this reason, U.S. general population data has been relied on for estimating insured lives mortality improvement – recognizing that relying on general population data introduces an inherent error cause by differences in the population bases.
- To address the insured data concerns, a predictive modeling approach was suggested. The purpose of the predictive models was to identify the key non-biometric variables in the data impacting mortality results. A set of predictive models was developed which both confirmed the hypothesis of the group regarding key factors impacting mortality and also revealed the importance of insurance plan and its interdependence on face amount and risk class. The model was useful in not just identifying the relation of these variables to mortality results but also the interrelationships between them. The five variables identified are:
    - Face Amount Band
    - Risk Class
    - Plan Type
    - Issue Era
    - Duration
- For each of these five variables, normalization factors were developed to force the distribution of the data by the selected key factor to be consistent across each of the observation years with a selected reference distribution, thus "normalizing" for the effect of that key variable in the mortality improvement results.
- Mortality improvement factors were developed based on both the unadjusted and normalized data.
- For reference, mortality improvement factors derived from this exercise were compared to the U.S. general population socioeconomic deciles developed as part of the Society of Actuaries report, *Mortality by Socioeconomic Category in the United States* . The mortality improvement factors normalized for risk class and face amount distributions showed patterns that are consistent with the level and pattern of those of

the sixth socioeconomic decile (where the tenth decile is the most favorable / highest-ranked socioeconomic decile).

- An accompanying Excel workbook allows the user to examine the result of normalizing data by selecting observation years, a key variable for normalization, and which subgroups of the key variable to include. It also allows the user to create results based on face amount as well as policy count, and to compare calculated mortality improvement factors to those based on socioeconomic deciles of the general population.



Section 1: Purpose of Study

It is currently difficult to determine historical mortality improvement factors to apply to insured policies using available industry data directly. So instead, factors based on general population data, which may or may not be applicable to insured populations, are commonly used. The impediment to developing mortality improvement factors based on insured lives has been the lack of a sufficient quantity of data that is consistent across observation years. Although pursuant to VM20, data has been collected by regulators on a mandatory basis since 2009, the data continues to lack consistency for two reasons. First, the population of companies contributing to the data has varied over the years. Second, observed mortality improvement factors can be distorted by changes in the mix of business. For example, over time, older policies with smaller face amounts and simple risk class structures have terminated, while newer policies have been issued with larger face amounts and more granular risk class structures.

The purpose of this study is to present a methodology that may be useful in estimating mortality improvement factors based on data from insured lives. This study is not meant to produce a proposed set of mortality improvement factors for any specific purpose.

An Excel workbook that accompanies this study allows the user to examine mortality improvement factors as developed by application of this methodology. The user can select observation years, any one of five key variables for normalizing the mix of data, and which subgroups of the key variables to include. It also allows the user to examine results based on face amount or policy count, and to compare calculated mortality improvement factors to population-based factors and to the most recent historical mortality improvement factors published on the SOA website on an annual basis in accordance with VM20. The SOA published factors are currently determined based on an estimate using U.S. general population data. Information about the Excel workbook can be found in Appendix E.

Section 2: Data Statistics

The data used for this analysis was the 2009-2019 individual life mortality experience data submitted to New York, Kansas, and NAIC, under the requirements of Principal-Based Reserving and VM51. It is summarized below.

TABLE 2.0.1

SUMMARY OF 2009-2019 INDIVIDUAL LIFE MORTALITY EXPERIENCE DATA

Data Dimension	Statistic
Observation Period	2009-2019
Number of Companies	Between 48 and 107 companies, depending on the observation year
Number of Death Claims	5,785,461
Exposed Lives	593,515,845
Underwriting Status	Only fully underwritten
Risk Classes	Substandard and Rated policies excluded
Joint Life Policies	Joint life policies excluded
Issue Years	1901 to 2019
Issue Ages	All
Attained Ages	All

Section 3: Methodology

3.1 CHALLENGES

The methodology described in this report attempts to isolate the biometric component of mortality improvement. There are four significant challenges to determining the biometric component of mortality improvement for insured policies.

1. Consistent mix of Data: The first challenge is the difficulty of obtaining data that is consistent across multiple observation years. Differences over time in the mix of data regarding average face amount, risk classification, target market, and insurance plan can distort observed insured mortality improvement results, obscuring the biometric component.
2. Credibility of data for determining mortality improvement: The second challenge is the difficulty of obtaining data that is sufficiently credible to produce meaningful results. Reaching a desired level of credibility for a mortality improvement factor requires significantly more data than for an observed mortality rate (qx) or an actual to expected (A/E) mortality ratio. This is because the credibility of a mortality improvement factor is based on the volatility of two dynamic cohorts, whereas the credibility of qx or A/E are based on a single dynamic cohort.
3. Identifying key non-biometric factors impacting changes in mortality results over time: The third challenge is identifying those independent variables that most materially impact the observed mortality improvement factors, thereby obscuring the biometric component.
4. The fourth challenge is determining whether the observed mortality improvement factors, after normalization for non-biometric impacts, are reasonable with respect to expectations regarding the underlying insured population.

3.2 PROCESS

The purpose of this study is to attempt to isolate, to the greatest extent possible, the true individual life insured biometric mortality improvement, by removing the impact of non-biometric factors such as changes in the mix of business.

The following five key variables were hypothesized to have a potentially significant impact on mortality results for the insured population.

- **Face Amount Band:** Less than 25K, 25K-99K, 100K-249K, 250K-499K, 500K-999K, 1000K-4999K, 5000K+
- **Risk Class ID*[1]:** NA, NB, NC, ND, SA, SB, UU
- **Plan Type:** Perm, Term, UL, ULSG, VL, VLSG, Other
- **Issue Era:** Pre 1980, 1980-1989, 1990-1999, 2000-2009, 2010-2014, 2015-2019
- **Duration:** 1, 2-3, 4-5, 6-10, 11-20, 21-25, 26 plus

The significance of these five variables was confirmed using a predictive model. Of the five, face amount band, risk class, and insurance plan were found to be the most influential drivers of mortality relative to the SOA 2015 VBT tables. A summary of the learnings of the predictive model are discussed in Appendix A.

[1] Regarding Risk Class ID: The SOA data file contains 16 distinct risk classes. Risk classes with similar Actual to Expected ratios based on face amount were combined into the seven shown in the Risk ID Assignment table in Appendix D.

The normalization process consisted of applying factors that would adjust the mix of business for one of the five key variables so that it is the same in every observation year. The factors vary by observation year, sex, and the selected key variable. For example, table 3.2.1 shows the normalization factors that would be applied to 2009 experience when adjusting by the key variable face amount band.

Table 3.2.1

SAMPLE CALCULATION OF NORMALIZATION FACTORS (BASED ON FACE AMOUNT)

Sex	Face Amount Band	Distribution 2009 to 2019 Combined (D_{ALL})	Distribution 2009 Observation Year (D_{2009})	2009 Normalization Factors (D_{ALL}/D_{2009})
F	Less than 25K	26.95%	32.27%	83.5%
F	25K-99K	26.64%	28.75%	92.7%
F	100K-249K	22.69%	20.88%	108.7%
F	250K-499K	13.39%	11.08%	120.8%
F	500K-999K	7.17%	5.16%	138.9%
F	1000K-4999K	3.06%	1.82%	168.2%
F	5000K+	0.09%	0.04%	238.7%
F	**Total**	**100.00%**	**100.00%**	
M	Less than 25K	25.84%	27.51%	93.9%
M	25K-99K	23.26%	26.41%	88.1%
M	100K-249K	20.26%	20.18%	100.4%
M	250K-499K	13.42%	12.31%	109.0%
M	500K-999K	9.89%	8.29%	119.3%
M	1000K-4999K	7.07%	5.16%	136.8%
M	5000K+	0.26%	0.13%	197.9%
M	**Total**	**100.00%**	**100.00%**	

Experience data, consisting of the number of death claims and exposed policies, was initially summarized from the SOA data file at the level of sex, observation year, and the key variable (in this example face amount band) to create the normalization factors. A second summary of the SOA data was produced which included attained age in addition to sex, observation year, and the key variable. This summary file will be referred to as the "raw experience data".

The normalization factors were then applied to the raw experience data to create the "normalized experience data". Both the raw experience data and the normalized experience data was then summarized to the level of sex, observation year, and attained age. At this point mortality rates were calculated. To improve smoothness, the mortality rate for each attained age was calculated based on data for the surrounding nine individual ages. For example, the mortality for attained age 55 was calculated using death claims for attained ages 51 to 59 divided by exposures for those ages. For both the raw and normalized data, we then calculated the mortality improvement factors by sex and attained age for observation years 2010 to 2019, and then calculated the algebraic average over the ten-year period.

To provide a point of comparison, mortality improvement factors were also calculated based on population data for the same period. The population data was extracted from the study, *Mortality by Socioeconomic Category in the*

United States Study[2]. A summary description from this study is included in Appendix B. As the title indicates, this study provides an estimate of mortality results for each of ten socioeconomic deciles and in total for the U.S. general population. Mortality improvement factors derived from this study, were then compared to normalized levels of mortality improvement determined by the method described above.

In the following tables, results of the normalization process are compared to socioeconomic decile six -- where decile one is the least favorable / lowest-ranked socioeconomic decile, and decile ten is the most favorable / highest-ranked socioeconomic decile. Decile six was chosen because it tracks well against the calculated normalized mortality improvement factors.

3.3 ADDRESSING THE CHALLENGES

For purposes of analysis, mortality improvement factors that vary by sex and attained age are calculated. The methodology employed in this study to address the challenges outlined above is to normalize observed mortality experience such that the impact of changes caused by non-biometric factors are neutralized, thereby isolating the biometric component. This is accomplished by developing normalization factors for the five key independent variables identified: class, face amount, issue era, insurance product, and duration. Using these factors, the experience data is modified such that the percentage of exposure for each subsegment remains constant across all observation years. This addresses the first of the challenges described above, obtaining data that is consistent across multiple observation years.

To address the second challenge, obtaining data that is sufficiently credible to produce meaningful results, there are limited avenues to pursue, other than to make maximum use of the data that we have available.

- The current insured dataset includes eleven observation years. For this analysis, the entire dataset is used, without applying any filters.
- To further enhance the credibility of the data, mortality improvement factors are developed based on sex and attained age. Results can be examined by other variables such as smoker status, face amount, or issue era, but subdividing or filtering the data would rapidly degrade the credibility.
- For this analysis, mortality improvement factors are based on policy count rather than face amount. This is to eliminate the volatility caused by variations in face amounts.
- Finally, to improve smoothness, mortality ratios for both the insured data and the population data based on aggregate death claims and exposure for the nine attained ages around the age of interest, x. Age x results are based on aggregated results for attained age x-4 to attained age x+4. For example, the mortality rate for attained age 55 would be based on the combined death claims and exposed lives for ages 51 to 59. In addition to improving smoothness, by increasing the amount of data used for each rate by nine, the credibility is increased by a factor of three.

To address the third challenge, a predictive model was developed by Philip Adams (a member of the Individual Life Experience Committee MI Subgroup) to identify independent variables that have the most significant impact on the observed mortality rate.

[2] https://www.soa.org/resources/research-reports/2020/us-mort-rate-socioeconomic/ by Magali Barbieri, Ph.D., University of California-Berkeley

To address the fourth challenge, determining the reasonability of the calculated mortality improvement factors, results were compared to mortality improvement factors calculated based on population data. [3]

[3] https://www.soa.org/resources/research-reports/2020/us-mort-rate-socioeconomic/ by Magali Barbieri, Ph.D., University of California-Berkeley

Section 4: Results

In this section mortality improvement results based on the application of the outlined methodology are examined. For each of the key variables defined by the predictive modeling exercise, raw insured mortality improvement results are compared to both the normalized insured results and the Decile 6 results from the U.S. general population.

4.1 MORTALITY IMPROVEMENT FACTORS NORMALIZED BY FACE AMOUNT BAND

After normalization for the key variable face amount band, the adjusted Mortality improvement factors track reasonably well by pattern and level with the Decile 6 general population rates, particularly for the female insureds.

Figure 4.1.1
FEMALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY FACE AMOUNT)

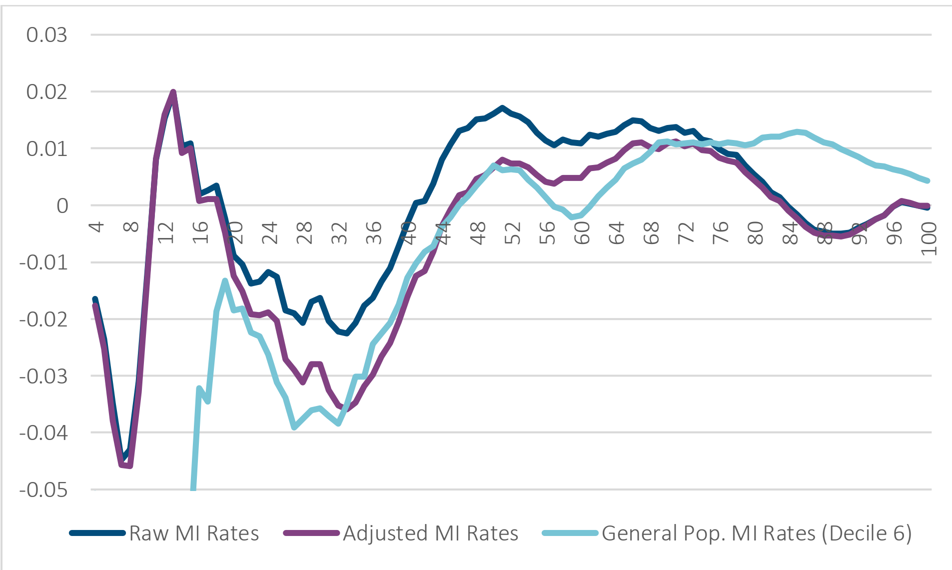
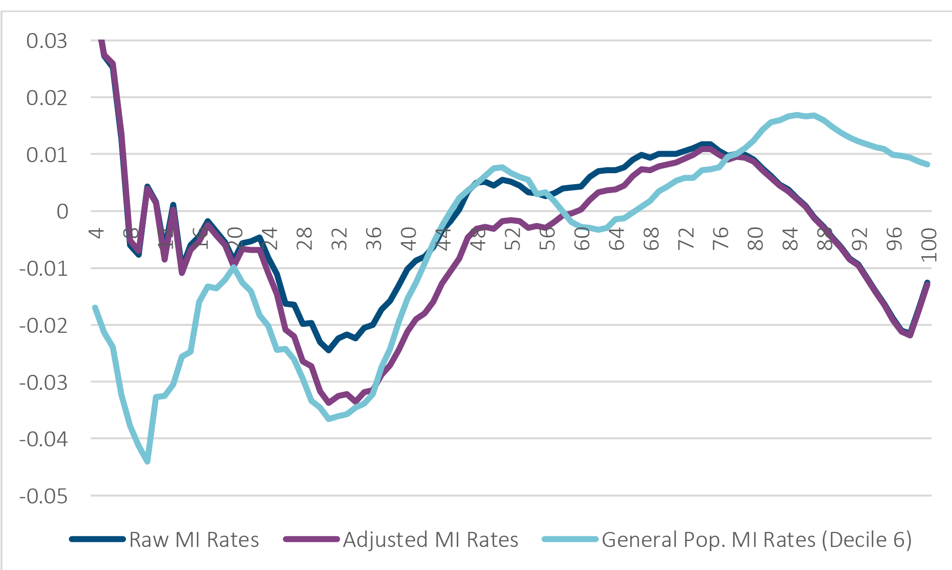


Figure 4.1.2
MALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY FACE AMOUNT)



4.2 MORTALITY IMPROVEMENT FACTORS NORMALIZED BY RISK CLASS

Results normalized for risk class are similar to those normalized for face amount band.

Figure 4.2.1

FEMALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY RISK CLASS)

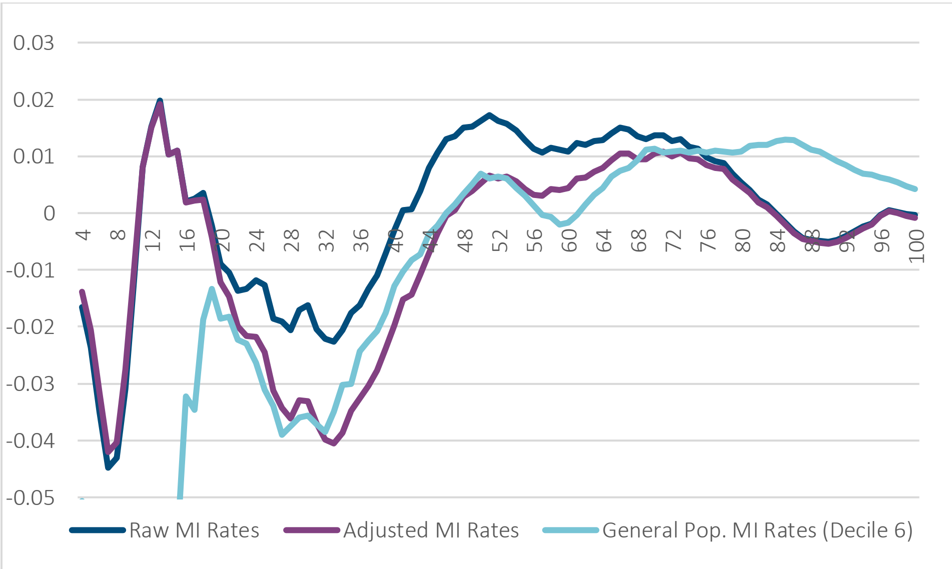
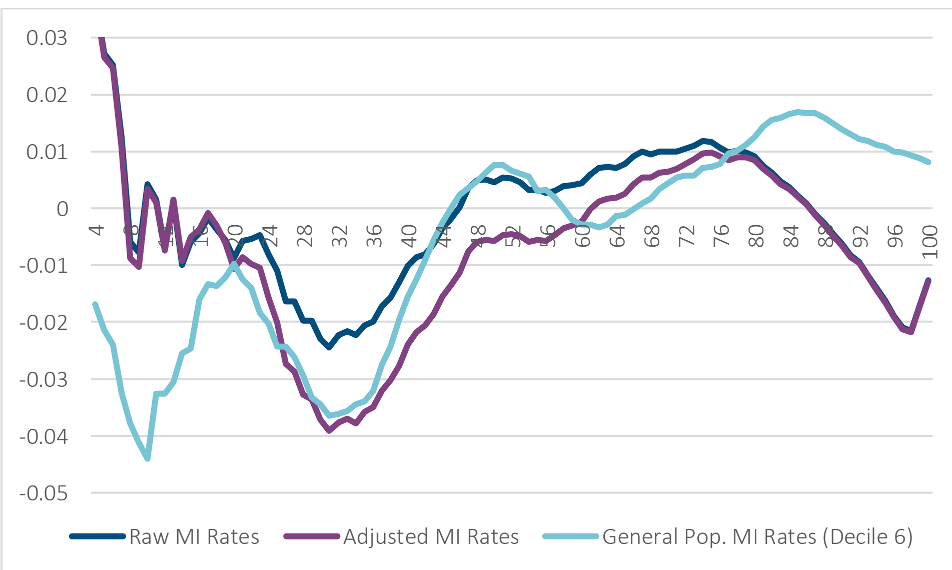


Figure 4.2.2

MALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY RISK CLASS)



4.3 MORTALITY IMPROVEMENT FACTORS NORMALIZED BY INSURANCE PLAN

Figure 4.3.1

FEMALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY INSURANCE PLAN)

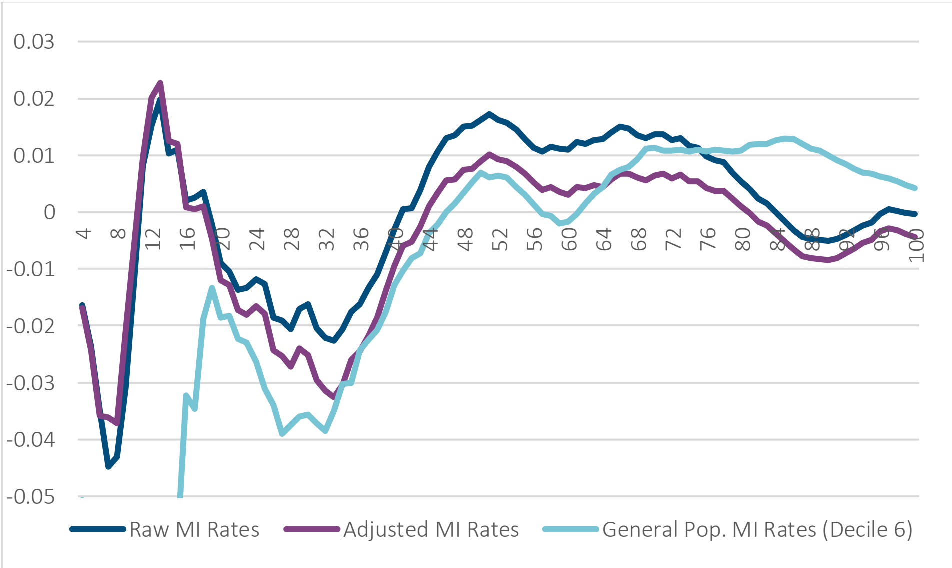
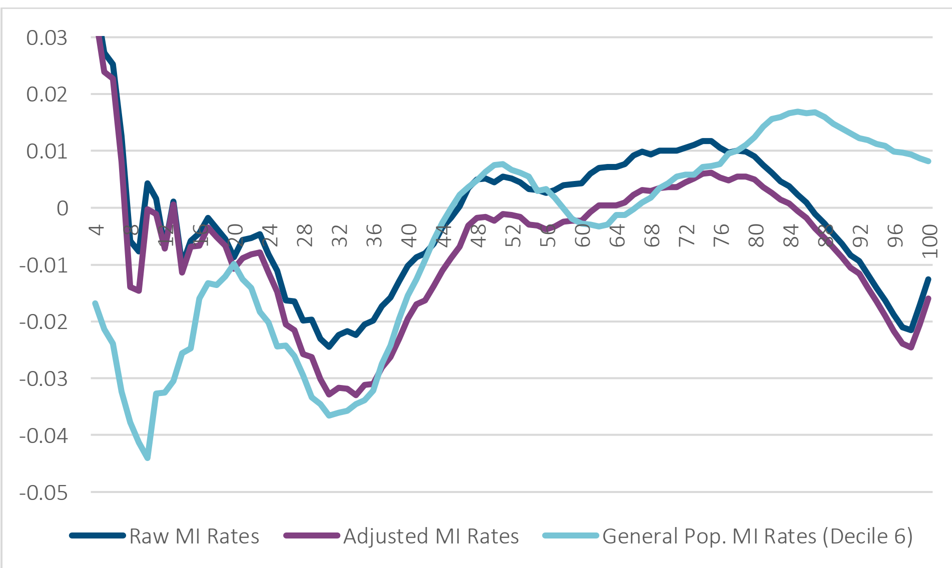


Figure 4.3.2

MALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY INSURANCE PLAN)



4.4 MORTALITY IMPROVEMENT FACTORS NORMALIZED BY DURATION GROUP

Results normalized by duration and by issue year show a pattern of stronger mortality improvement for the general population decile than for the insured normalized and unadjusted results.

Figure 4.4.1

FEMALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY DURATION GROUP)

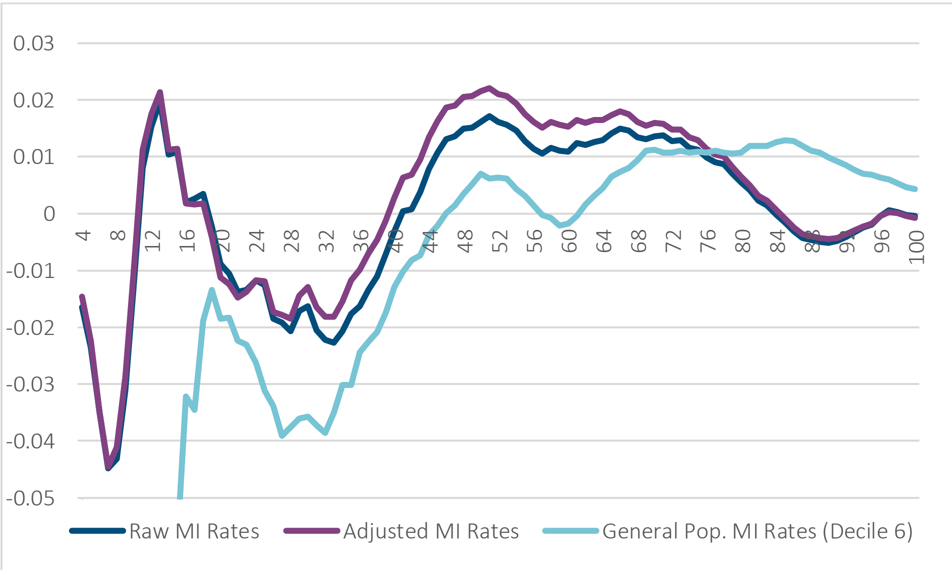
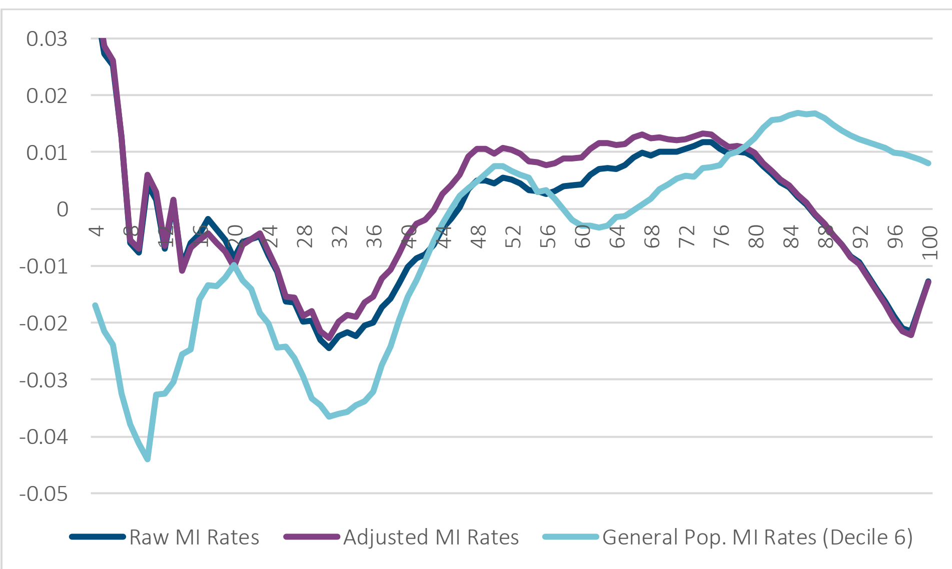


Figure 4.4.2

MALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY DURATION GROUP)



4.5 MORTALITY IMPROVEMENT FACTORS NORMALIZED BY ISSUE YEAR GROUP

Figure 4.5.1

FEMALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY ISSUE YEAR GROUP)

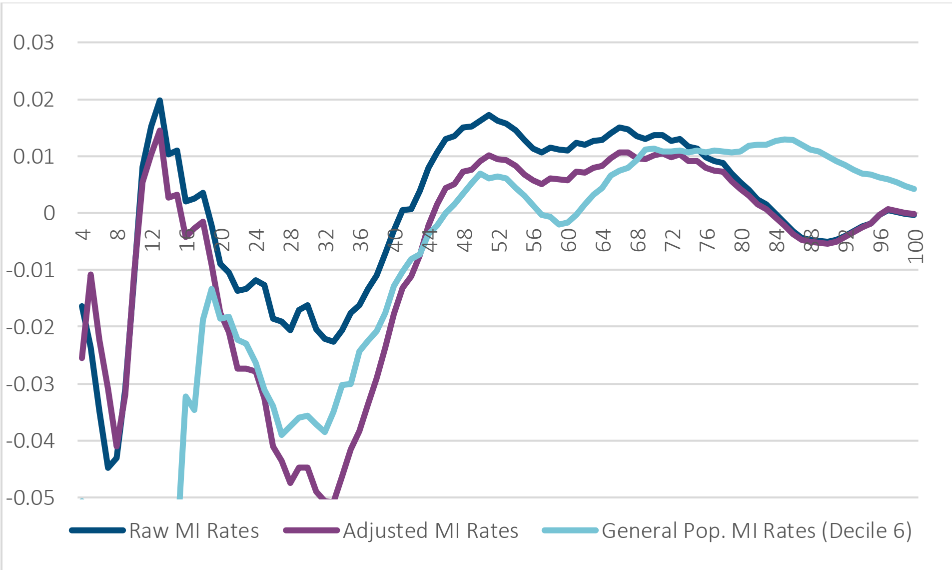
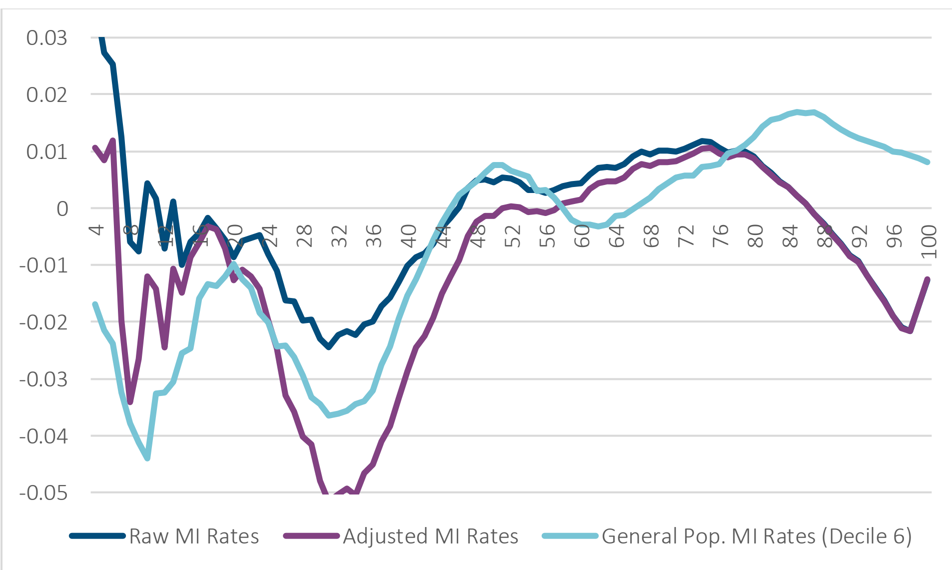


Figure 4.5.2

MALE MORTALITY IMPROVEMENT FACTORS (NORMALIZED BY ISSUE YEAR GROUP)



4.6 COMPARISON TO 2023 VM20 HISTORIC MORTALITY IMPROVEMENT FACTORS

In charts 4.6.1 and 4.6.2 the historical mortality improvement rates implied by the insured data (and normalized for face amount band changes over time) are compared to the 2023 VM20 Historic Mortality improvement factors. Note that the SOA VM20 scale appears consistent with the normalized insured factors with the exception of attained ages under 40 and over 80 for both males and females. For more information regarding the development of the 2023 VM20 HMI factors, please see Appendix C.

Figure 4.6.1

FEMALE MI RATES (NORMALIZED BY FACE AMOUNT) WITH 2023 VM20 HMI RATES

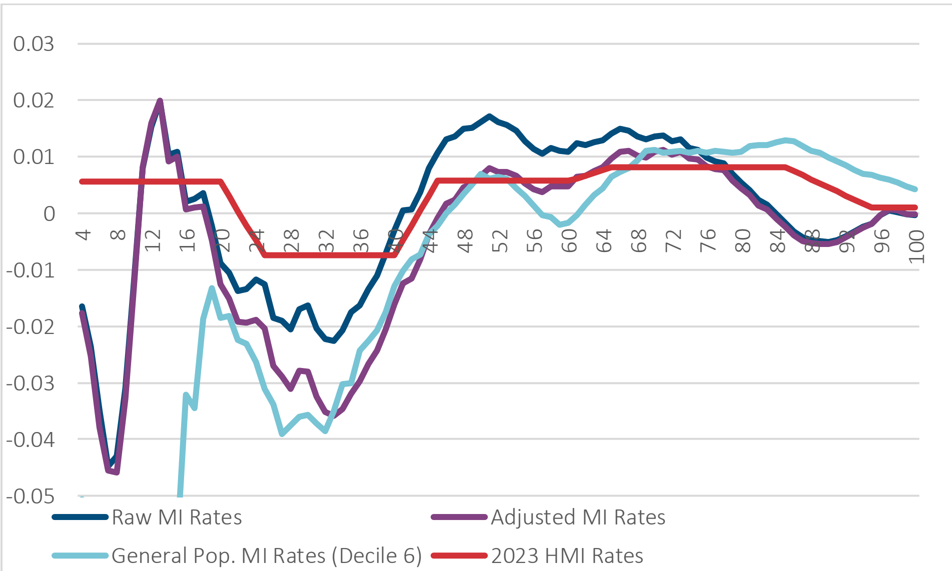
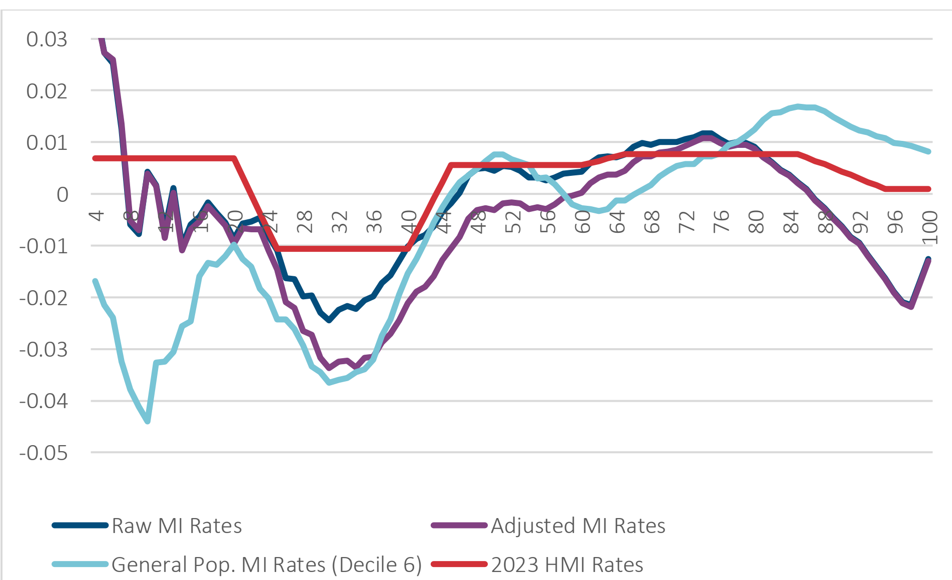


Figure 4.6.2

MALE MI RATES (NORMALIZED BY FACE AMOUNT) WITH 2023 VM20 HMI RATES



Section 5: Limitations and Potential Improvements

As stated earlier, this study is not meant to produce a proposed set of mortality improvement factors for any specific purpose. Hopefully, other actuaries can use this study as a starting point and add further refinements.

This section addresses some weaknesses and areas for potential improvement of the approach discussed in this report.

1. Age of data: In this study we used data for observation years 2009 through 2019. Some actuaries may prefer to use data for a shorter period covering recent years. Our decision to use all eleven years of data is rooted in the fact that a tremendous amount of data is required to approach full credibility for mortality improvement.
2. Normalization process: The normalization process applied for this analysis is relatively crude. The normalization factors are applied across all attained ages within the cohort defined by sex, observation year, and subsegment of the selected key variable (e.g., face amount band). Some actuaries may decide to develop more granular normalization factors. Attempts were made to develop normalization factors based on two key variables, but the resulting MI factors did not line up well with any particular socio-economic decile.
3. Reference mix: The normalization factors are developed to force the mix of business for a particular observation year to a reference mix based on the entire 11 years covered by the study (2009-2019). Depending on the intended purpose, an actuary may choose to create a reference mix that reflects a more recent period or even a projected future mix of business.
4. Actuarial judgment: To create mortality improvement factors applicable to a given purpose, the actuary needs to apply judgment. For example, one would need to assess whether the results seem reasonable, how the data should be filtered, how the results should be smoothed, and whether margins need to be applied. Also, for developing future mortality improvement factors, the actuary will need to place bets on the future; for example, does the actuary believe that the mortality trends for young insureds will remain unchanged, improve, or degrade.
5. Granularity: In this study, mortality improvement factors were developed by sex and attained age only. This is consistent with the way that VM20 mortality improvement assumptions are currently produced and allows the results to be compared to general population mortality improvement factors. Some actuaries may feel that mortality improvement factors should vary by other criteria such as smoker status, issue year, or insurance plan.
6. Impact of COVID-19: The data used for this study ends with observation year 2019, which is the most recent available. It is unknown how mortality experience for the COVID period would affect the results.

The reader is highly advised to independently analyze industry data as well as other data and resources. An Excel analysis tool was published in conjunction with this report to allow users to perform independent analysis.

Section 6: Implications for Other Studies

One of the learnings from this study is that, for some purposes, it may not be sufficient to project mortality trends using only a biometric mortality improvement assumption. A second assumption regarding the changing mix of business may also be advisable. For example, a newly built mortality table may quickly become obsolete if the mix of business assumption reflects the average of past years rather than a projection of the future.

This may not be a consideration for valuation purposes if future issues of new business are not being assumed. Also, over time the mix of business industry insured data may become less volatile as the population of companies contributing data to VM20 becomes more stable.

Section 7: Reliance and Limitations

No assessment has been made concerning the applicability of this experience to other purposes. In developing this report, the SOA relied upon data and information supplied by company contributors via MIB and NAIC, as the Statistical Agents for VM51. For each contributor this information includes, but is not limited to, the data submission for mortality experience and the responses to follow-up questions.

The results in this report are technical in nature and are dependent on certain assumptions and methods. No party should rely upon these results without a thorough understanding of those assumptions and methods. Such an understanding may require consultation with qualified professionals. This report should be distributed and reviewed only in its entirety.

Section 8: Acknowledgments

The SOA Research Institute's deepest gratitude goes to the Subgroup for their diligent work to design the study, analyze the results, and draft and peer review this report for accuracy and relevance.

Subgroup members:

Phillip Adams, FSA, CERA, MAAA (Predictive Model)

Mark Rosa, ASA (Mortality Improvement Analysis Tool)

Reviewers:

At The Society of Actuaries Research Institute:

Korrel Crawford, Senior Research Administrator,

Kate Eubank, FSA, MAAA, Senior Experience Studies Actuary

Cynthia MacDonald, FSA, MAAA, Senior Director, Experience Studies

Pete Miller, ASA, MAAA, Experience Studies Actuary

At LIMRA:

Marianne Purushotham, FSA, MAAA, Corporate Vice President, LIMRA Research Data Services

At Right Brain Data:

Craig A. Rolling, PhD, Data Science Consultant

At The American Academy of Actuaries:

Anshita Dogra, FSA, MAAA, CERA, MS

At Purdue University:

Lucas Embrey, Actuarial Student

Appendix A: Mortality Predictive Model

This study discusses some of the challenges of estimating mortality trend factors. These include:

1. The short window over which mortality trends would be calibrated, in this case experience years 2009-2019, and
2. The highly heterogeneous nature of the underlying data, including but not limited to
    a. The impact of exogenous trends, such as diverging health outcomes by socioeconomic status and the opioid epidemic,
    b. Changes in underwriting standards and methods, including the implementation of accelerated underwriting and the removal of fluid testing at lower face amounts,
    c. The increasing granularity of underwriting segmentation, and
    d. The change in composition of contributing companies over time.

There is nothing today which can be done about the first item. However, it is possible to mitigate the impact of the second item using predictive modeling. The basic idea is to develop a predictive model which adjusts the baseline expected claims to control for relevant variables whose shifts over time may obscure the true mortality trend. For example, the spread of mortality by underwriting class may be stable over time. However, the underlying prevalence of underwriting risk classes may shift over time. This would induce a nominal mortality trend as the weighted average of mortality shifts along with the shifts in prevalence. However, this would distort estimation of the true trend.

To assist with the analysis of trend, a predictive model was developed which lifts the baseline of analysis away from the 2015 VBT. The data underlying the modeling was the ILEC data restricted to 2011 to 2017. The workflow from the forthcoming ILEC predictive analytics framework was applied to develop the models. This workflow has two components: an exploratory component which uses boosted decision trees to discover the most influential variables, and a modeling component which applies elastic net GLMs to develop mortality factors. All analysis was against the 2015 VBT as a baseline.

While all variables exhibited some impact in various regions of the data, the interrelationships within and among face amount, insurance plan, and underwriting risk class were the most common and influential throughout the analysis. The analysis further resulted in the creation of elastic net models for each of the following subsets:

1. Insurance plan Term, excluding post-level, with face amounts 100,000 and greater
2. Insurance plan Term, excluding post-level, with face amounts less than 100,000
3. Insurance plan Term, post-level only
4. Insurance plan Perm with unknown smoker status
5. Insurance plans other than Perm or Term, and Insurance Plan Perm with known smoker status

The choice of subdividing the data in this fashion was driven partly by knowledge of known impacts (e.g., separating post-level term data from the rest of the term data) and by checking goodness-of-fit for models as they are being developed. A unified model for term policies excluding post-level term data showed poor fit for smaller face amounts. This suggests that higher orders of interaction may have been necessary. Instead, the term data were subdivided for the sake of retaining reasonable explainability. The subset of the data for unknown smoker Perm policies was modeled separately due to its sheer size; with over 2 million claims and heavy weighting to older ages, it dwarfed the rest of the non-term data and distorted the model’s fit.

The mortality factors that we get from the models are attached to the data used to build the models and define a new expected basis. Consider the following table:

		Actual-to-Table	
Calendar Year	Death Count	2015 VBT	Predictive Models
2011	563,694	98.3%	103.5%
2012	537,286	96.5%	102.8%
2013	554,199	93.8%	99.9%
2014	560,393	92.6%	99.3%
2015	565,853	92.3%	99.9%
2016	552,127	90.1%	98.5%
2017	558,579	89.4%	98.1%
Overall	**3,892,131**	**92.8%**	**100.0%**

The unweighted trend (computed using LOGEST in Excel) for mortality against the 2015 VBT is -1.5% per annum. The same value for the predictive models is -0.9% per annum. This suggests that roughly 40% of the nominal mean trend over those seven years was due to shifts in predictors other than calendar year itself.

Included here is a compiled Quarto document on the development and analysis of the predictive models. The sources can be found at https://www.github.com/pladams/ILEC_MI.

The Mortality Predictive Model is located at https://www.soa.org/globalassets/assets/files/resources/research-report/2024/mort-improvement-predictive-models.zip.

Appendix B: Summary of Mortality by Socioeconomic Category in the United States Study

Barbieri, Ph.D., Magali. *Mortality by Socioeconomic Category in the United States*, soa.org, 2020, https://www.soa.org/resources/research-reports/2020/us-mort-rate-socioeconomic/

This SOA-sponsored research report presents mortality analysis and rate estimates for the United States by year from 1982 through 2019, separately by socioeconomic quintile and decile. Details on the development of the estimates are summarized in the report. The life tables by socioeconomic category are available for download, and some of the results are presented in online graphs and maps, and a data summary report.

The results were produced by combining data from three sources:

- county-level mortality data from processed National Center for Health Statistics data
- socioeconomic data extracted from the United States Decennial Census
- socioeconomic data extracted from the American Community Survey

Separately for each year of data, a Socioeconomic Index Score was computed for each county. The Socioeconomic Index Scores, in turn, were used to group counties into deciles, with each decile holding 10% of the total U.S. population. Mortality rates were then estimated for each decile. In addition, a parallel analysis was performed using quintiles rather than deciles.
This web page, the associated report and the online data visualizations were initially released by the SOA in November 2020, using mortality data from the CDC-Wonder database. To address constraints in the CDC-Wonder data, the socioeconomic mortality analysis was repeated in December 2020, using a restricted dataset from the National Centers for Health Statistics with data back to 1982 and covering ages up to 110+.
This report updates the December 2020 version and relies on a different way to allocate all U.S. counties into deciles/quintiles. Changes to the methodology from the December 2020 report are:

1. One more year of mortality data (2019) was incorporated in the analysis.
2. The variables used to determine the Socioeconomic Index Scores were modified as follows:
    I. Instead of the percentage of the population aged 25 and over with at least a high school education, the percentage of the population aged 25 and over with at least 4 years of college education was used to account for the rise in education over the past forty years.
    II. Instead of the raw median household income, the median household income in each county was adjusted by the median housing cost at the state level to account for variations in standards of living across the country.
3. Instead of recalculating the county Socioeconomic Index Scores for each year when data are available as in the previous report, the score is fixed to the year 2000, keeping the grouping of counties into the socioeconomic deciles/quintiles the same over the whole study period (1982-2019).

Rather than presenting the new results alongside the December 2020 results (both the report, Excel data files and the data visualizations) were removed from the website, and replaced with an updated report and visualizations that reflect the new data.

Additionally, the mortality by socioeconomic category data is used in the Society of Actuaries Research Institute's Mortality Improvement Model (MIM-2021). The current version is MIM-2021-v4. The data is updated annually to extend the series by another year. With each annual iteration, historical data may change to reflect new U.S.

population estimates. Since mortality at the older ages is estimated using a combination of methods[4], mortality generally for ages 80 and over may also change from prior data versions. Therefore, the decile 6 population data shown in this report and used in the accompanying Excel spreadsheet may be inconsistent with the decile 6 population data used in MIM-2021-v4. Work is underway to integrate the Excel spreadsheet produced through this study into the MIM-2021 framework.

[4] Barbieri, Magali, *The Impact of COVID-19 on the Socioeconomic Differential in Mortality in the United States,* 2024, https://www.soa.org/resources/research-reports/2023/mortality-improvement-model/, p.7

Appendix C: VM20 2023 Mortality Improvement Assumptions

American Academy of Actuaries' Life Work Group and the Society of Actuaries' Mortality and Longevity Oversight Advisory Council. *Individual Life Insurance Mortality Improvement Scale – for Use with AG38/VM20 – 2023*, soa.org, 2023, https://www.soa.org/resources/research-reports/2023/ind-life-mort-imp-scale/

DESCRIPTION

The Mortality Improvement subgroup of the American Academy of Actuaries' Work Group and the Society of Actuaries' Mortality and Longevity Oversight Advisory Council released a recommendation for a set of improvement factors that vary by gender and attained age to be used in conjunction with the 2008 Valuation Basic table or the 2015 Valuation Basic table for AG-38 purposes. This recommendation has been adopted by the NAIC's Life Actuarial Task Force.

Under 'Materials', find the report that describes the mortality improvement scale and its intended use and the spreadsheet that contains the final version of the mortality improvement factors for year-end 2023.

APPLICABILITY OF IMPROVEMENT SCALE

These improvement scales represent a view of reasonable historical and future mortality improvement factors for to be used in conjunction with AG 38 and VM20 for year-end 2023 valuation. These improvement scales are not intended to be employed as a standard for any other purpose. For US statutory reserves under VM20 or AG38 using the 2008 Valuation Basic Table (2008 VBT) or the 2015 Valuation Basic Table (2015 VBT), the HMI and FMI scales discussed herein are applicable. For statutory reserves using the 2008 Limited Underwriting tables, the HMI and FMI mortality improvement assumptions are zero.

Appendix D: Risk ID Assignment

Table D1 illustrates how 16 risk classes included in the SOA file were consolidated into seven groups. The seven groups are referred to as Risk ID subgroups in the study. Risk classes were grouped based on actual to expected mortality ratios.

Table D1
RISK ID ASSIGNMENT

Smoker Status	Preferred Indicator	Number of Pfd Classes	Preferred Class	Risk ID	A/E Amt	Amount Exposed	Death Claim Amount	ExpDth Amt VBT2015
NS	0	NA	NA	NC	100%	16,934,451,064,213	83,827,602,670	83,473,802,377
NS	1	2	1	NB	81%	12,821,836,770,714	27,480,518,989	33,794,984,526
NS	1	2	2	ND	117%	7,360,823,378,818	32,353,352,564	27,637,862,045
NS	1	3	1	NA	66%	16,422,655,730,388	16,122,501,836	24,417,820,414
NS	1	3	2	NA	73%	10,296,647,621,708	23,473,526,814	32,019,593,070
NS	1	3	3	NC	99%	10,439,453,020,147	39,045,223,947	39,262,849,762
NS	1	4	1	NA	64%	22,794,693,092,637	16,527,199,360	25,849,535,808
NS	1	4	2	NA	77%	10,210,310,233,034	12,705,108,396	16,546,394,474
NS	1	4	3	NB	94%	6,477,227,338,460	8,920,667,806	9,518,019,137
NS	1	4	4	NC	112%	5,171,207,767,983	9,545,938,615	8,554,163,960
NS		U	U	NC	84%	63,289,505,190	90,988,064	108,518,063
S	0	NA	NA	SB	111%	2,054,685,948,330	19,655,841,722	17,740,366,783
S	1	2	1	SA	81%	1,746,216,258,513	4,854,945,920	6,030,960,078
S	1	2	2	SB	104%	1,018,788,663,990	4,605,937,617	4,437,718,611
S		U	U	SB	116%	3,028,783,152	37,281,432	32,182,850
U	0	NA	NA	UU	101%	4,714,437,570,669	43,873,609,711	43,229,063,755
Total	Total	Total	Total	Total	92%	128,529,752,747,947	343,120,245,463	372,653,835,715
				NA	70%	59,724,306,677,767	68,828,336,406	98,833,343,767
				NB	84%	19,299,064,109,174	36,401,186,795	43,313,003,663
				NC	101%	32,608,401,357,532	132,509,753,296	131,399,334,163
				ND	117%	7,360,823,378,818	32,353,352,564	27,637,862,045
				SA	81%	1,746,216,258,513	4,854,945,920	6,030,960,078
				SB	109%	3,076,503,395,472	24,299,060,771	22,210,268,244
				UU	101%	4,714,437,570,669	43,873,609,711	43,229,063,755
				Total	92%	128,529,752,747,947	343,120,245,463	372,653,835,715

Appendix E: Accompanying Excel Workbook

The accompanying Excel workbook enables the user to generate adjusted mortality improvement factors by normalizing on any one of these five key variables.

- **Face Amount Band:** Less than 25K, 25K-99K, 100K-249K, 250K-499K, 500K-999K, 1000K-4999K, 5000K+
- **Risk Class ID*[5]:** NA, NB, NC, ND, SA, SB, UU
- **Plan Type:** Perm, Term, UL, ULSG, VL, VLSG, Other
- **Issue Era:** Pre 1980, 1980-89, 1990-99, 2000-09, 2010-14, 2015-19
- **Duration:** 1, 2-3, 4-5, 6-10, 11-20, 21-25, 26 plus

The workbook allows the user to select:

- Experience Years
- Reference Years
- The key variable for normalizing the mix of data
- Subgroups of the key variable to include
- Face Amount or Policy Count basis
- Mortality improvement factors for a particular socio-economic decile of the general population.

The Excel workbook can be found at https://www.soa.org/globalassets/assets/files/resources/research-report/2024/mort-improvement-analysis-tool.xlsx.

The SQL code used to summarize the data can be found at https://www.soa.org/globalassets/assets/files/resources/research-report/2024/mort-improvement-summary-sql-code.docx.

[5] Regarding Risk Class ID: The SOA data file contains 16 distinct risk classes. Risk classes with similar Actual to Expected ratios based on face amount were combined into the seven shown in the Risk ID Assignment table in Appendix D.

References

Barbieri, Ph.D., Magali. *Mortality by Socioeconomic Category in the United States*, soa.org, 2020, https://www.soa.org/resources/research-reports/2020/us-mort-rate-socioeconomic/

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Society of Actuaries Research Institute
8770 W Bryn Mawr Ave, Suite 1000
Chicago, IL 60631
www.SOA.org