Mortality Improvement Model, MIM-2021-v4

OCTOBER | 2023
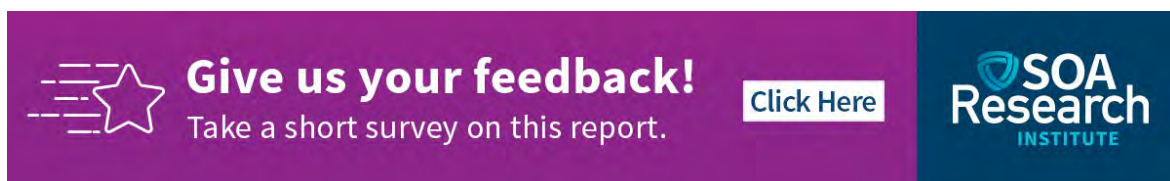
Mortality Improvement Model, MIM-2021-v4

AUTHOR	MIM Advisory Group	**SPONSOR**	Mortality and Longevity Strategic Research Program Steering Committee

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Executive Summary

As an aid to practitioners who project mortality improvement (MI), the Society of Actuaries (SOA) Research Institute released MIM-2021 with its two simultaneously released Excel-based tools in April 2021. When it was released, the MIM Advisory Group (Advisory Group) anticipated updating MIM-2021 and associated tools at least annually. There have been two updates. The first update, MIM-2021-v2 Application Tool, was released in October 2021. MIM-2021-v3[1] Application Tool was released a year later and included:

- A more straightforward user interface and a high-level process schematic, both designed to facilitate the entry of model parameters.
- Addition of a preselected parameter set designed as a possible starting point for individual life insurance and individual annuity practitioners.
- Expansion of the feature introduced in MIM-2021-v2[2] that allows the user to adjust mortality for COVID-19 and other reasons.

Historical Social Security Administration (SSA) and National Center for Health Statistics (NCHS) based population mortality tables that currently underpin MIM-2021 do not reflect COVID-19. Therefore MIM-2021-v3 Application Tool data covers the historical period only through 2019. For MIM-2021-v4, the Application Tool will be the same as MIM-2021-v3 with the exception of changing the individual life insurance and individual/group annuity preselected historical NCHS decile dataset for mortality improvement projection.

- SOA's Mortality and Longevity Strategic Research Program Steering Committee (MLPSC) commissioned a study to examine mortality changes across the 2020 to 2021 period, including the impact of COVID and other causes of death, such as opioids, on the NCHS socioeconomic subpopulations used in the Application Tool. The study was recently completed; the Advisory Group is now examining its results to determine if future changes to MIM including the addition of more recent data are appropriate.

- The Retirement Plans Experience Committee (RPEC) has analyzed the 2020 and 2021 SSA mortality data. RPEC does not believe it would be appropriate to incorporate, without adjustment, the substantially higher rates of mortality experience from 2020 and 2021 into the graduation and projection models used to forecast future mortality. Therefore, RPEC elected to not release a new MI scale for 2023.[3]

  Consistent with the prior version, running the MIM-2021-v4 Application Tool using the SSA mortality tables and other RPEC parameters can be used to replicate the MP-2021 and O2-2021 MI scales. Users can also optionally input mortality loads by age and sex on a select basis through 2027 and an ultimate basis for

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[1] SOA Research Institute (2022), Mortality Improvement Model, MIM-2021-v3, https://www.soa.org/4a9b13/globalassets/assets/files/resources/research-report/2022/mim-2021-v3-report.pdf
[2] SOA Research Institute (2021), Developing a Consistent Framework for Mortality Improvement: MIM-2021-v2, https://www.soa.org/4a9d42/globalassets/assets/files/resources/research-report/2021/2021-mim-consistent-framework-v2.pdf
[3] SOA Research Institute (2023), RPEC 2023 Monthly Improvement Update, https://www.soa.org/resources/research-reports/2023/rpec-mort-improvement-update/

2028 and later. This functionality enables practitioners to model their selected assumption for the effects of the pandemic on mortality.

To help pension and other practitioners in selecting the mortality load assumption, RPEC has issued the 2023 Mortality Improvement Update[4]. Information in the report are population excess mortality statistics, considerations for selecting mortality loads, and summaries of sources for COVID-19's impact on future mortality.

In addition, the MIM-2021-v4 Data Analysis Tool has been enhanced over the prior version to include SSA data through 2021. The more current data could be useful to all practitioners for mortality load assumption development.

This MIM-2021-v4 Report includes four key sections:

- Section 1 contains more information for life practitioners on how to use the MIM-2021-v4 Application Tool.

- Section 2 explains the preselected parameter sets for life and annuity practitioners used in the MIM-2021-v4 Application Tool.

- Section 3 illustrates how key MIM-2021 input assumptions in the MIM-2021-v4 Application Tool affect life expectancies and the impact on various insurance/annuity products.

- Section 4 describes certain anticipated future MIM-2021 updates and enhancements.

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[4] SOA Research Institute (2023), RPEC 2023 Monthly Improvement Update, https://www.soa.org/resources/research-reports/2023/rpec-mort-improvement-update/
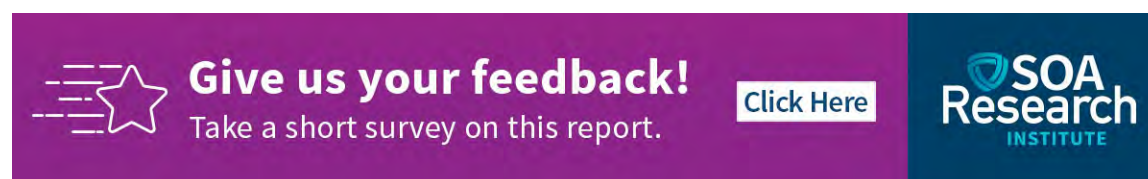
Section 1: Considerations for Life Actuaries Who Use the Mortality Improvement Model

1.1 OVERVIEW

Mindful of the need to maintain the Mortality Improvement Model (MIM) and to ensure that its dataset remains relevant, the SOA's Mortality and Longevity Strategic Research Program Steering Committee (MLPSC) commissioned a study to examine mortality changes across the 2020 to 2022 period, including the impact of COVID-19 and other causes of death which have become more prevalent, such as opioids. The study was recently completed; the MIM Advisory Group (Advisory Group) is now examining its results to determine if future changes to MIM are appropriate. In the meantime, practitioners should keep in mind that the model's underlying data does not yet reflect mortality experience from 2020 onwards.

Because the Advisory Group is still examining 2020 to 2022 mortality data, this document offers no specific guidance with respect to modeling the effects of COVID-19. Instead, the focus of this document is general MIM modeling concepts that may be helpful to life actuaries, as well as actuaries in other practice areas. It is assumed that practitioners already have a basic understanding of MIM, as provided by its user guide. This document provides additional details for model users who already have a basic understanding of MIM. The following topics are covered:

- A brief review of MIM's datasets.
- Selection of specific data deciles or quintiles to develop a mortality projection scale.
- Use of the selected data to develop a set of initial mortality improvement rates that reflect recent experience.
- Use of the data and professional judgement to develop a set of medium and/or long-term improvement rates.
- Interpolation between the initial improvement rates and the medium/long-term rates.

1.2 A DESCRIPTION OF MIM'S DATASETS

Practitioners may select either of two datasets as a source for estimating improvement rates: (1) national-level mortality rate data from the Social Security Administration (SSA) or (2) mortality rate data segmented by socioeconomic decile, developed from National Center for Health Statistics (NCHS) death counts combined with exposure counts and socioeconomic data obtained from the U.S. Census and the American Community Survey. For the sake of convenience, this report refers to the second dataset simply as "NCHS" data, even though it was developed by combining information from several data sources.

Relative to the SSA data, the NCHS data offers the following advantage: it is segmented into socioeconomic deciles, providing practitioners with the flexibility to select an individual decile or combinations of two or more deciles as the basis for estimating mortality improvement rates. A parallel NCHS dataset is provided that is segmented into quintiles rather than deciles. MIM offers the flexibility to use either of these datasets.

Note that some of this document's graphs present quintile (rather than decile) data to help make the graphs easier to read. Had the decile data been used instead, the graphs would have been cluttered, making them harder to interpret.

As explained in the user guide, MIM's socioeconomic deciles and quintiles are based on county-level data rather than individual or household-level data. The highest decile in MIM corresponds to those U.S. counties that, socioeconomically, rank in the top 10% of all counties. Even the wealthiest counties have a heterogenous mix of households from across the socioeconomic spectrum and, consequently, the socioeconomic differences captured in the NCHS dataset are less pronounced than would appear in an individual-level or household-level dataset.

Nevertheless, the NCHS data reveals striking differences in mortality rates and rates of mortality improvement as a function of county-level socioeconomic ranking:

Figure 1

NCHS MORTALITY RATES FOR FEMALES BY AGE AND SOCIOECONOMIC QUINTILE,
AS A PERCENT OF NATIONAL-LEVEL AGE-SPECIFIC NCHS FEMALE MORTALITY RATES
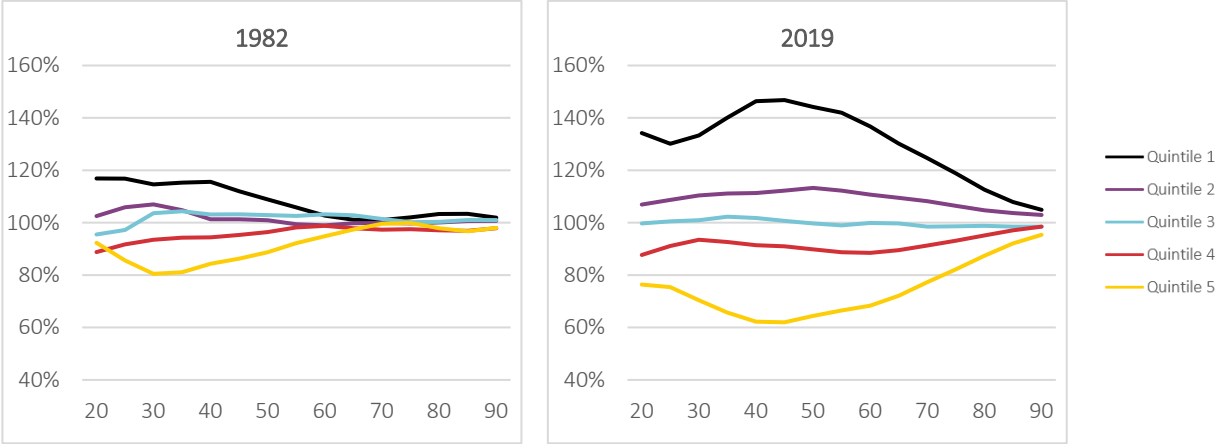
Female mortality rates are used for illustration purposes. Male mortality rates follow similar patterns.

In 1982, clear differences in mortality rates existed across the quintiles, as illustrated in Figure 1. For example, at age 50 the mortality rate for quintile 5 -- the highest socioeconomic quintile -- was about 90% of the national-level mortality rate for age 50; in contrast, the mortality rate for quintile 1 was nearly 110% of the national-level rate. Over time, the mortality gaps across socioeconomic quintiles have become more pronounced across all ages. Looking again at age 50, the quintile 5 mortality rate using 2019 data is just 64% of the national-level rate, while the corresponding quintile 1 mortality rate is 144% of the national-level rate.

The increasing "spread" of mortality rates depicted in Figure 1 stems from significant differences in the rates of historical mortality improvement as a function of socioeconomic ranking: the higher the ranking of the quintile or decile, the greater the historical rate of mortality improvement, as illustrated in Figure 2:

Figure 2

ANNUALIZED RATES OF FEMALE MORTALITY IMPROVEMENT ACROSS THE 1982 TO 2019 PERIOD,
BY AGE AND SOCIOECONOMIC QUINTILE
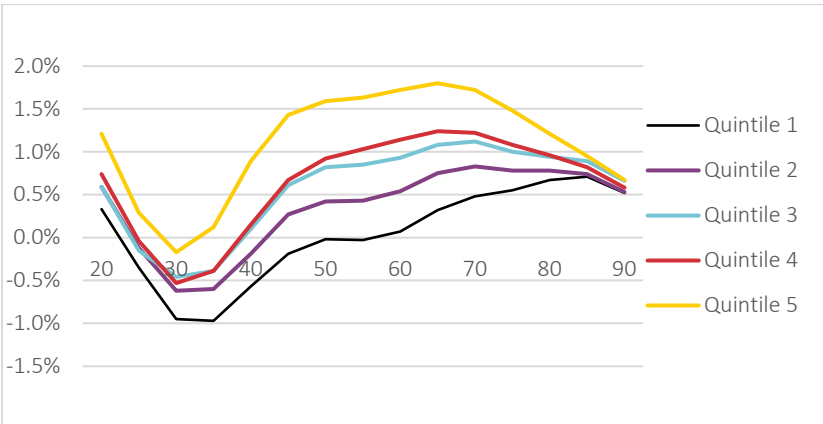
Female mortality improvement rates are used for illustration purposes. Male improvement rates follow similar patterns.
A positive value indicates that the mortality rate is improving (declining) across time, while a negative value
 indicates that the mortality rate is deteriorating (increasing).

Figure 2 reveals a strong relationship between socioeconomic quintile and the annualized rate of mortality improvement: the higher the ranking of the quintile, the greater the rate of mortality improvement[5]. Note that a positive value indicates that the mortality rate is improving (declining) across time, while a negative value indicates that the mortality rate is deteriorating (increasing).

MIM contains four variants of the NCHS data, reflecting two options for ranking counties by socioeconomic level and two options for smoothing historical mortality rates:

Table 1
THE FOUR VARIANTS OF NCHS DATA INCLUDED IN MIM

	Ranking of Counties	Whittaker-Henderson Smoothing Process Applied to Raw Mortality Rate
1	Static	Order-2
2	Static	Order-3
3	Dynamic	Order-2
4	Dynamic	Order-3

The segmentation of the NCHS data into quantiles involves the ranking of counties using socioeconomic data. Two options were used to rank counties: (1) a static approach in which counties were ranked using socioeconomic data drawn from the year 2000 Census, and (2) a dynamic approach in which counties were re-ranked in 1990 and 2000 using the decadal Census and re-ranked in each year from 2005 onwards using the American Community Survey. Each of these two options was run separately, resulting in parallel datasets that contain similar (but not identical) mortality rates by socioeconomic quantile.

Although the NCHS dataset captures data for over 300 million lives, it is nevertheless necessary to smooth the raw mortality rate data prior to calculating improvement rates. Smoothing "irons out" bumps in the data that could potentially interfere with the process of estimating mortality trends. As indicated in Table 1, MIM provides practitioners with two smoothing options – "Order-2" and "Order-3" – that refer to the degree of the finite difference operators used in the smoothness components of the two-dimensional Whittaker-Henderson objective function. Relative to the order-3 model, the order-2 model tends to yield greater year-over-year stability in mortality improvement rates. However, order-2 methodology will likely be less sensitive to emerging changes in U.S. mortality patterns and generally produces a weaker fit when compared to ungraduated historical mortality improvement rates.

When estimating average annualized improvement rates across a long period (roughly, greater than 15 years), the four variants of NCHS data (see Table 1) generally produce similar results. However, the shorter the period of analysis, the greater the potential differences in improvement rate estimates across the four variants of the NCHS data. Importantly, MIM's "jumping off point" – discussed subsequently in this report – is typically estimated across a short time interval, and, consequently, the choice of dataset may have a material impact on the estimated improvement rates, as illustrated in Figure 3.

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[5] Each age-specific annualized improvement rate was calculated as follows: 1 – [(mortality rate in 2019) / (mortality rate in 1982)] ^ (1/37). The exponent of "37" is equal to the number of years captured in the data.

Figure 3
AGE-SPECIFIC RATES OF MORTALITY IMPROVEMENT FROM 2016 TO 2017 FOR DECILE 10,
FOR EACH OF THE FOUR VARIANTS OF MIM'S DATA
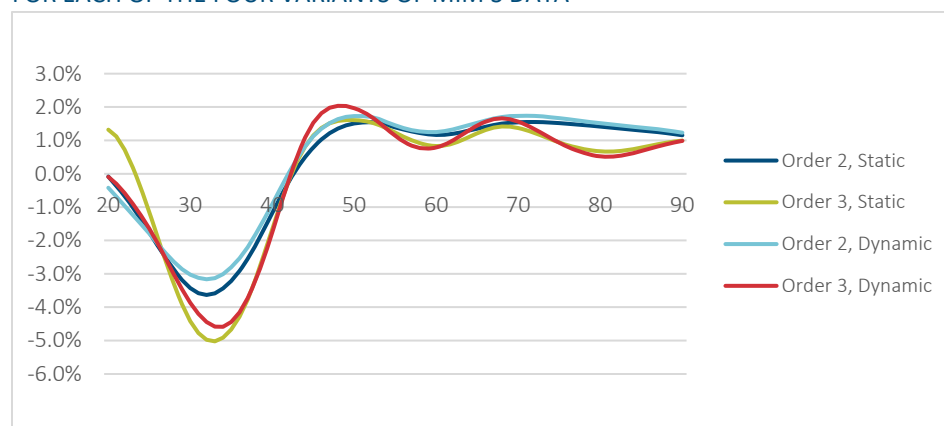
Female mortality improvement rates are used for illustration purposes. Male improvement rates follow similar patterns. "Order" refers to the degree of smoothing. "Static" indicates that counties were ranked only once by socioeconomic level, while "dynamic" indicates that they were re-ranked with every new Census or American Community Survey.

The results shown in Figure 3 were computed across a one-year time interval[6], from 2016 to 2017. While the four dataset variants show the same basic patterns by age, the results are not identical. There is no "best" variant among these four. Each variant offers a valid estimate of mortality trends.

By default, MIM uses the dataset with statically ranked counties and order-3 smoothing. However, this option is not hardwired into the model, and practitioners are encouraged to examine results generated using the other three data variants.

1.3 OPERATING MIM: CONSIDERATIONS FOR SELECTION OF QUINTILES OR DECILES

Practitioners who elect to use the NCHS data must select either the entire national-level dataset, a single decile or quintile, or a combination of deciles or quintiles. This discussion focuses on the selection of deciles, but practitioners who prefer to work with the quintile data are free to do so. Selection of deciles is accomplished by entering percentages that sum to 100% in range "E23:N23" in the model's interface. For example, to use the 10th (highest) decile, a user would place the full 100% weight in cell N23.

For an insurance product that caters primarily to middle and high-income individuals and households, it is likely that the weighting approach should focus on the higher deciles. Practitioners should keep in mind that the NCHS dataset is segmented not by individuals' socioeconomic status, but rather by counties' status, and that even the most affluent counties contain a heterogenous socioeconomic mix of individuals. This fact supports an even heavier weighting on the upper decile(s) for practitioners who wish to examine mortality trends at the high-end of the socioeconomic spectrum.

Some practitioners approach the selection of deciles using the following logic: they compare decile-level NCHS mortality rates against an industry table (or their own experience) that is appropriate for the block of business that

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[6] Although the time interval is a single year (from 2016 to 2017), the underlying mortality rate data has been smoothed across both age and year. Because the data has been smoothed across time, each year of smoothed data reflects information that spans multiple years. Roughly, the smoothed 2016 and 2017 data captures mortality data from years 2010 through 2019.

they wish to evaluate. Based on this comparison, they select the MIM decile(s) that most closely resembles the industry table.

For example, in Figure 4, NCHS mortality rates for deciles 1, 5, and 10 are compared against the ultimate 2015 Valuation Basic "Unismoker" Table (the other 7 deciles are omitted to avoid cluttering the graph). Because the Valuation Basic Table (VBT) experience is drawn from the period from 2002 through 2009, the comparison uses NCHS mortality rates for the year 2006, which falls roughly at the center of the 2002-to-2009 period.

The comparison depicted in Figure 4 reveals that decile 10 provides the closest match to the VBT. This finding, in turn, provides some empirical support for selecting decile 10 (for this case study) as the data source for estimating rates of mortality improvement.

Figure 4
2006 NCHS MORTALITY RATES FOR DECILES 1, 5, AND 10,
DIVIDED BY MORTALITY RATES FROM THE 2015 UNISMOKER ULTIMATE VALUATION BASIC TABLE
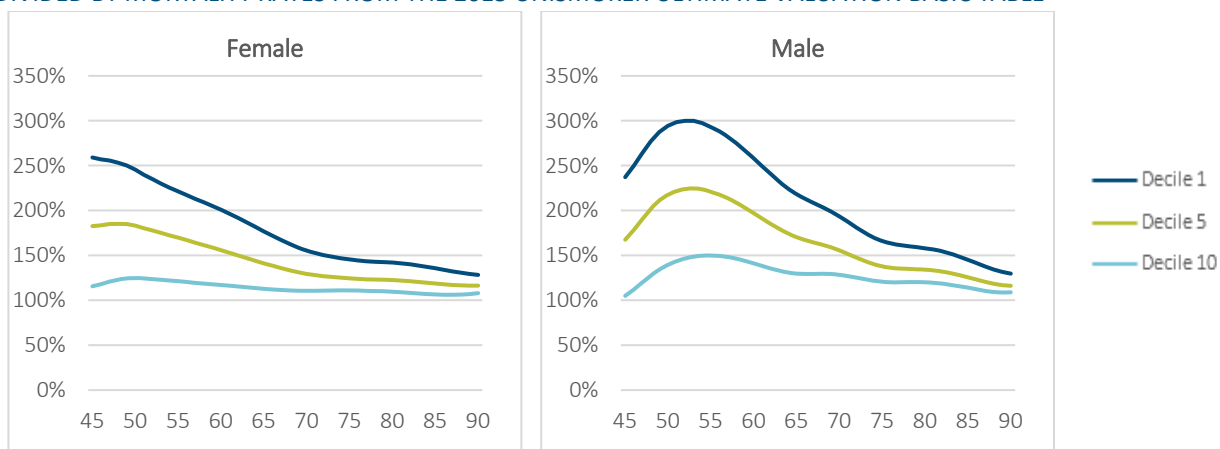
These results are based on the order-3 statically ranked NCHS dataset. To avoid cluttering the graphs, only 3 of the 10 deciles are shown.

While decile 10 provides the best match to VBT compared to other deciles in the example just provided, for most ages the decile 10 mortality rates are significantly greater than the corresponding VBT rates. This is not entirely surprising given that MIM's socioeconomic segmentation is based on county-level data rather than individual-level data, and even the most affluent counties contain a diverse socioeconomic mixture of individuals and households. Decile 10 mortality rates may exceed the rates in many industry tables. Given this fact, and given that MIM's data suggests a positive correlation between mortality improvement rates and socioeconomic status, some practitioners may believe it is appropriate to implement an upward adjustment to the improvement rates estimated from decile 10 data. MIM permits this type of manual adjustment, but the data's limitations make it difficult to devise a data-driven method for performing such an adjustment. Therefore, the Advisory Group suggests that practitioners use professional judgement to determine the magnitude of any adjustments.

The example presented in Figure 4 uses unismoker VBT mortality rates that reflect data both for nonsmokers and smokers. Some practitioners may wish to decompose the analysis, separately comparing non-smoker and smoker VBT tables against MIM's data, as in Figure 5:

Figure 5

2006 NCHS FEMALE MORTALITY RATES FOR DECILES 1, 5, AND 10,
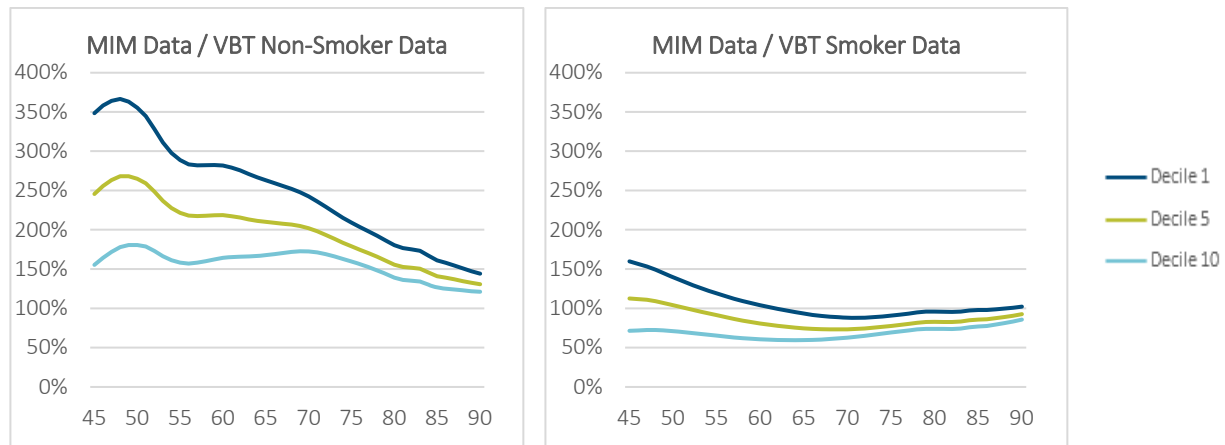DIVIDED BY MORTALITY RATES FROM THE 2015 VALUATION SMOKER-DISTINCT BASIC TABLES

These results are based on the order-3 statically ranked NCHS dataset. To avoid cluttering the graphs, only 3 of 10 deciles are shown.

Based on Figure 5, decile 10 provides the best match for the non-smoker data. For smokers, decile 1 is the best match across most ages.

At the risk of stating the obvious, smokers are not concentrated solely in counties at the least affluent socioeconomic level; rather, both smokers and non-smokers are distributed across all counties. Therefore, the approach outlined in Figure 5 is a creative use of MIM's data that is a mix of art and science. It is plausible that smokers living in affluent counties have experienced significantly higher rates of mortality improvement compared to smokers living in socioeconomically weak counties.

Unfortunately, industry (i.e., policyholder) data generally lacks the number of lives needed to produce credible mortality improvement rate estimates. For this reason, MIM uses NCHS and SSA data that provide enough lives from which credible mortality improvement rate estimates can be developed, but which are based on the general population rather than the insured population and do not capture policyholder characteristics such as smoker versus non-smoker, or other risk classification differences. Consequently, the Advisory Group suggests that practitioners use professional judgement when using MIM's general population data to draw inferences about rates of mortality improvement in the insured population. These inferences are likely to vary by risk class – for example, the selected deciles (or quintiles) may vary by risk class, as well as any manual adjustments to the jumping-off point.

1.4 OPERATING MIM: CONSIDERATIONS FOR DEFINING THE "JUMPING OFF POINT"

After selecting a dataset -- such as the 10th decile of the statically ranked order-3 NCHS data -- the next step is to select a "jumping off year" and to generate the model's "jumping off point" (JOP) which consists of a set of age/sex specific improvement rates calculated from historical data. The JOP serves as a springboard from which MIM launches its forward projection. For example, if the jumping off year is set to 2017, then mortality improvement rates for 2017 will be determined from historical mortality data, while improvement rates for 2018 and beyond will be determined by interpolating between the JOP and medium and/or long-range improvement rate assumptions specified by the practitioner.

As explained in the user guide, the JOP improvement rates are calculated from historical data by pressing the "Calculate" button in Step 4c, and the results are displayed in columns AL and AM.

By default, the JOP year in MIM-2021-v4 is defined as 2017, and the improvement rates associated with this year are determined by comparing smoothed mortality rates in 2017 against the corresponding rates in 2016. This is a

short time interval because the intended purpose of the JOP is to capture recent mortality trends, as opposed to trends that existed in decades past and which may have little bearing on the present.

Figure 6 compares long-term annualized rates of historical mortality improvement -- computed across the 37-year period from 1982 to 2019 -- against recent rates of mortality improvement computed across the period from 2016 to 2017. Unlike the long-term improvement rates which exhibit an unambiguous positive correlation with socioeconomic quintile, the short-term results present a more complicated picture. Between the ages of 45 and 75, mortality improvement is positively correlated with socioeconomic quintile. But for ages 30 to 45, and above 75, the relationship reverses such that improvement rates are negatively correlated with socioeconomic quintile. For ages 20 to 30, the pattern is inconsistent. In addition, the short-term improvement rates for ages below 45 show mortality deterioration. For age 30, for example, the improvement rates for quintiles 3, 4, and 5 are between negative 4% and negative 5%.

Figure 6
A COMPARISON OF ANNUALIZED RATES OF FEMALE MORTALITY IMPROVEMENT
COMPUTED ACROSS TWO DIFFERENT PERIODS, BY AGE AND SOCIOECONOMIC QUINTILE
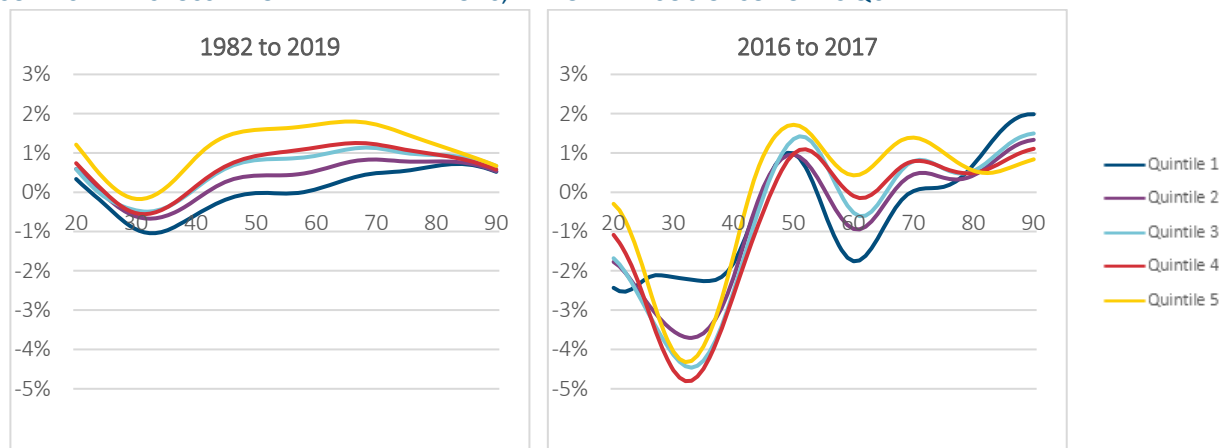
Female mortality improvement rates are used for illustration purposes. Male improvement rates follow similar patterns. Mortality rates are calculated using the NCHS statically ranked order-3 dataset (the 2nd row of Table 1).

While the short-term rates present a more complex picture compared to the long-term rates (which display an unambiguous positive correlation with socioeconomic ranking), they can nevertheless be viewed as unbiased estimates of recent mortality improvement (and deterioration) trends. However, the shorter the historical period across which the JOP mortality improvement rates are estimated, the greater the uncertainty associated with the estimates[7].

The uncertainty of mortality improvement rate estimates is a complicated subject that will be dealt with in a separate report to be released in 2024. Briefly, estimating a rate of change of a mortality rate (q_x) across time is more challenging than estimating q_x for a particular year. To estimate a mortality improvement rate from historical data, one must compare q_x estimates across time. Each annual q_x estimate must be highly robust to produce a robust mortality improvement rate estimate. Robust estimates of recent improvement rates are needed to create a statistically reliable starting point for forward projections. The Advisory Group suggests that practitioners keep in mind three key points with respect to the credibility of mortality improvement rate estimates:

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[7] It is important to distinguish between estimates of recent historical mortality improvement rates versus projections of future improvement rates. Here, the discussion is focused on the recent past as opposed to the future.

- The greater the number of lives in a dataset, the greater the credibility (i.e., the tighter the confidence interval of the mortality improvement rate estimate).

- The greater the number of years included in the analysis, the tighter the confidence interval -- but subject to the constraint that only recent data is relevant for predicting the near-term future.

- The greater the mortality rate, the lower the uncertainty – that is, for a given level of exposure, it is easier to estimate mortality improvement rates for older ages than it is for younger ages.

In sum, it is difficult to quantify the uncertainty associated with mortality improvement rate estimates. For MIM's jumping off point – which uses a short historical period as its basis for estimation – rough estimates of uncertainty are presented in Table 2. These estimates assume that the sole source of uncertainty is the random nature of the mortality process (each life is assumed to be an independent Bernoulli trial).

Table 2
HALF OF THE WIDTH OF 90% CONFIDENCE INTERVALS FOR MIM'S MORTALITY IMPROVEMENT RATE ESTIMATES FOR THE "JUMPING OFF POINT"

Age	National-Level	Quintile-Level	Decile-Level
20	0.37%	0.83%	1.17%
30	0.34%	0.77%	1.08%
40	0.26%	0.59%	0.84%
50	0.17%	0.37%	0.52%
60	0.10%	0.23%	0.33%
70	0.08%	0.17%	0.24%
80	0.08%	0.17%	0.24%
90	0.08%	0.17%	0.24%

These estimates assume that the sole source of uncertainty is the random nature of the mortality process, with each life assumed to be an independent Bernoulli trial. Each value in the table is half of the width of the associated 90% confidence interval. The lower bound of the confidence interval is obtained by subtracting the value in the table from the estimated improvement rate, and the upper bound is obtained by adding the value to the estimated improvement rate.

Suppose, for example, that the estimated improvement rate for the 10th socioeconomic decile at age 70 is 1.0%. Then according to Table 2, the 90% confidence interval would have an upper bound of 1.0% plus 0.24%, and a lower bound of 1.0% minus 0.24%. Thus, there is a 90% chance that the actual rate of improvement falls between 0.76% and 1.24%, and a 10% chance that it falls outside of this range. At the quintile level, confidence is greater – and the confidence interval is tighter -- because each quintile contains twice the lives of a decile. Similarly, confidence at the national level is greater than for individual quintiles or deciles.

Confidence intervals for MIM's mortality improvement rate estimates are significantly wider -- and credibility is lower -- for younger ages compared to older ages. All else equal, the lower the mortality rate, the greater the challenge of estimating the rate of mortality improvement.

1.5 OPERATING MIM: CONSIDERATIONS FOR MANUAL ADJUSTMENTS TO THE JUMPING OFF POINT

The purpose of MIM's jumping off point (JOP) is to capture recent historical mortality improvement trends which are used as a springboard for launching a forward projection. As described in the last section of this report, it is challenging to estimate recent mortality improvement rates (hereafter referred to simply as "improvement rates), and the estimates are therefore subject to some degree of uncertainty. When reviewing the JOP's mortality improvement rates prior to running a forward projection, the Advisory Group suggests that practitioners keep the following key points in mind:

- The credibility of MIM's improvement rates is weakest for ages below 40.
- The credibility of MIM's improvement rates is weakest for decile-level estimates, and strongest for national-level estimates.

The Advisory Group suggests that practitioners be particularly vigilant when running individual deciles or quintiles. The JOP improvement rates produced by MIM – reflecting the dataset and deciles/quintiles specified by the model user -- should be carefully examined, particularly at ages under 40. Practitioners should exercise professional judgement, assessing the reasonableness of the JOP improvement rates. Some practitioners may wish to manually adjust any JOP improvement rates (which vary by age and sex) which they believe to be unreasonable with respect to the block of business they are evaluating.

Consider a scenario in which a practitioner has selected decile 10 data from the statically ranked order-3 dataset, and is using a JOP year of 2017. The associated improvement rates are presented in Figure 7.

Figure 7
"JUMPING OFF POINT" IMPROVEMENT RATES USING DECILE 10 NCHS DATA
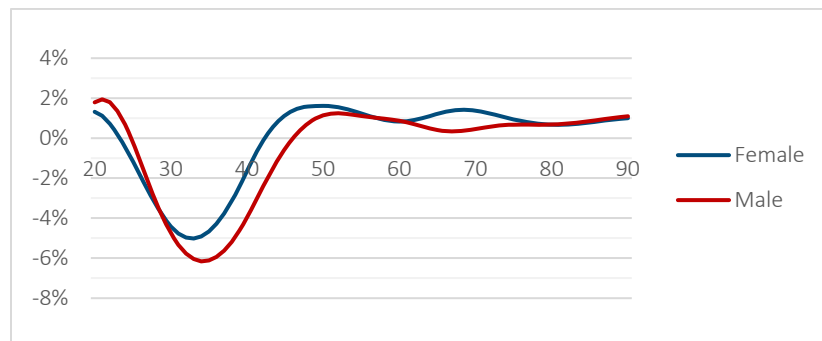
Computed using the NCHS statically ranked order-3 dataset (the 2nd row of Table 1).
The jumping-off year is set at 2017, and the improvement rates are computed across the 2016-to-2017 period.

The negative improvement rates from age 25 to 45 are particularly striking. While these rates can be viewed as unbiased estimates that reflect MIM's historical data, credibility is relatively low in this age range. Therefore, a practitioner may wish to examine their own data to assess whether it also suggests negative mortality improvement (or deterioration) at young ages[8]. After careful consideration, a practitioner may wish to tweak the JOP by making manual adjustments to the improvement rates. For example, a practitioner may decide to manually adjust the JOP rates at young ages such that none dip below 2%, as depicted in Figure 8.

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[8] When using data from an individual insurer to estimate improvement rates, practitioners should be mindful the credibility of improvement rate estimates is inversely correlated with the square root of the number of covered lives. Each of MIM's deciles reflects about 32 million lives. If a practitioner's dataset covers only 2 million lives, then the associated confidence intervals for improvement rates will be 4 times as wide as those generated from MIM's decile data: 4 = (32 million / 2 million) ^ 0.5. An option for addressing this issue is to make the simplifying assumption that mortality improvement is constant across age groups, such as age 10 through 19, 20 through 29, etc. Grouping age cohorts together for the purpose of assessing improvement rates may facilitate credible improvement rate estimates.

Figure 8

"JUMPING OFF POINT" IMPROVEMENT RATES USING DECILE 10 NCHS DATA,
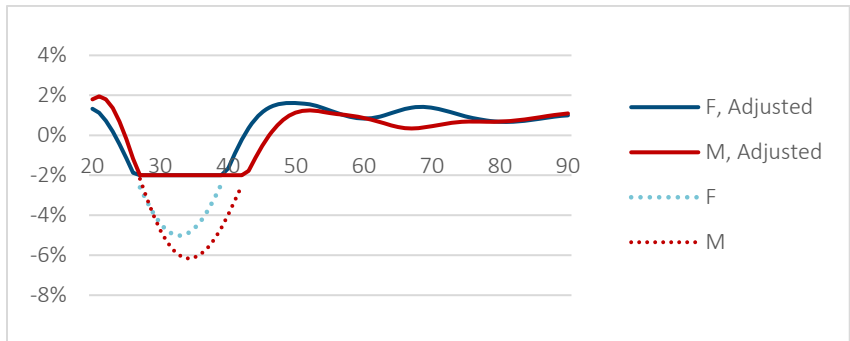**WITH MANUAL ADJUSTMENT TO PREVENT VALUES BELOW NEGATIVE 2%**

Computed using the NCHS statically ranked order-3 dataset (the 2nd row of Table 1).
The jumping-off year is set at 2017, and the improvement rates are computed across the 2016-to-2017 period.

Via MIM's interface, manual adjustments can be accomplished by modifying the JOP improvement rates in columns AL and AM. Recall that these values are calculated from historical data when the "Calculate" button in Step 4C is pressed. After the model populates columns AL and AM, a user may adjust any cell(s) at their discretion.

1.6 OPERATING MIM: CONSIDERATIONS FOR SETTING MID-TERM OR LONG-TERM ASSUMPTIONS

To move forward in time, MIM interpolates between the jumping off point (JOP) -- which reflects improvement rate trends estimated from recent data -- and medium and/or long-term rates that can be determined by empirical analysis and/or professional judgment. When developing medium/long-term rates, a logical starting point is to examine historical average improvement rates computed across a lengthy period, such as the full extent of MIM's data from 1982 through 2019. It may also be helpful to examine other lengthy periods, such as from 2000 to 2019. In Figure 9, improvement rates estimated from recent experience (2016 to 2017) are compared against rates computed across two overlapping historical periods (2000 to 2019 and 1982 to 2019):

Figure 9

"JUMPING OFF POINT" IMPROVEMENT RATES FOR FEMALES, COMPARED TO LONG-TERM AVERAGE RATES
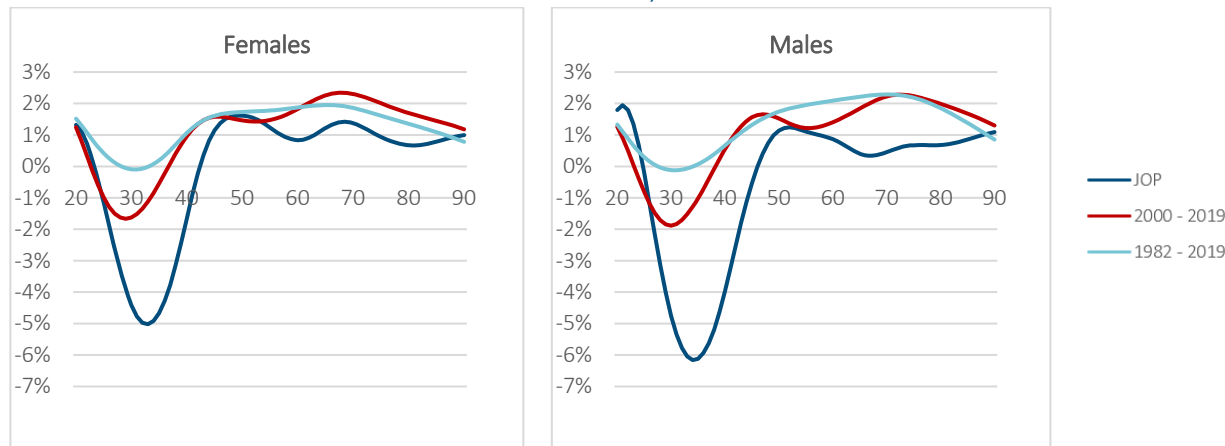
These results were computed using the decile 10 NCHS data from the order-3 statically ranked dataset.

Figure 9 reveals that for this case study, improvement rates estimated from recent experience are significantly lower than rates estimated across longer historical periods. Given this finding, a practitioner might reason that improvement rates are likely to increase across time, and wish to build an increase into MIM's forward projection. There are many approaches that might be used for developing medium or long-term improvement rates, including

relying solely on professional judgement. Alternatively, a practitioner may wish to take a data-driven approach. One data-driven option is to set long-term future rates equal to their long-term historical geometric averages[9] computed across the full extent of MIM's data, from 1982 to 2019. This can be accomplished via the following steps:

- In MIM's interface, set cell AC17 equal to "2". This indicates the practitioner's intention to use historical data to calculate improvement rates for time points "B" and/or "D". This example assumes that MIM is operated in basic interpolation model, and, consequently, time point "D" is immaterial[10].

- In cell AG27 and AH27, enter the starting and ending years of the historical period that the practitioner wishes to use to calculate historical average improvement rates. To use the full extent of MIM's data, enter "1982" in cell AG27 and "2019" in cell AH27.

- At the top of step 4c, press the "Calculate" button. The resulting long-term average improvement rates will appear in columns AN and AO (correspondingly, the "jumping off" rates that reflect recent experience will appear in columns AL and AM).

Columns AL and AM are the age-sex specific improvement rates for the jumping off point, and columns AN and AO are the age-sex specific improvement rates for time point B. At the practitioner's discretion, manual adjustments may be made to any of these rates.

1.7 OPERATING MIM: CONSIDERATIONS FOR INTERPOLATION BETWEEN POINTS "A" AND "B"

To generate a projection scale, MIM interpolates between the jumping off point (JOP) improvement rates in columns AL and AM and the rates for time point "B" in columns AN and AO. As described in the user guide, various user-specified parameters control the interpolation process between points "A" and "B":

1. The length of time across which MIM interpolates from "A" to "B" is controlled by the parameters in the range R27:S28. These parameters can be used to either lengthen or shorten the A-to-B time period.

2. MIM interpolates both horizontally (by age) and/or diagonally (by cohort). MIM performs each of these two interpolation approaches separately, and then computes the weighted average of the results. The parameter in cell Q38 specifies the weight placed on the cohort interpolation, with the remaining weight placed on the horizontal projection.

3. Cubic splines are used to interpolate between points A and B. By default, the initial slope of the cubic splines is set to zero using the parameters in cells Y30:Y31. With this constraint, the rate-of-change of the improvement rates is quite slow during the first couple of years of a projection. However, practitioners are free to change the slope constraints in Y30:Y31. Relaxing these constraints leads to a faster rate-of-change of projected improvement rates in the first few years after time point A[11].

To illustrate the impact of the cohort weight parameter in cell Q38, it is helpful to compare a projection in which this parameter is set to 0% against a projection in which the parameter has been shifted to 100%. For this case study,

---

[9] Suppose that the mortality rate for 60-year-old females was 1.00% in 1982, and that this rate dropped to 0.50% by 2019. The geometric average improvement rate would be calculated as follows: 1 - (0.50% / 1.00%) ^ (1/37) = 1.86%.

[10] As explained in the user guide, MIM can be operated using either "basic" or "advanced" interpolation mode. Using basic interpolation, MIM interpolates between the jumping off point (referred to as time point "A") and a mid-term or long-term set of assumptions, referred to as point "B". Using advanced interpolation, two additional time points are included: C and D. MIM assumes that improvement rates remain constant between points B and C, and change linearly across time between points C and D.

[11] To develop an understanding of the effects of the slope constraints, it is useful to run the model once with the initial slopes constrained to zero, and a second time with slope constraints fully relaxed. The results of the two runs can then be compared to each other.

the MP-2021 parameter settings were loaded by setting cell B17 to "1" and then pressing the step 1 button. Next, cell Q38 was set to "0%". MIM was run using these parameters, a heat map was produced and saved, and then the process was repeated with cell Q38 set to 100%. The heat maps for these two projections are compared in Figure 10.
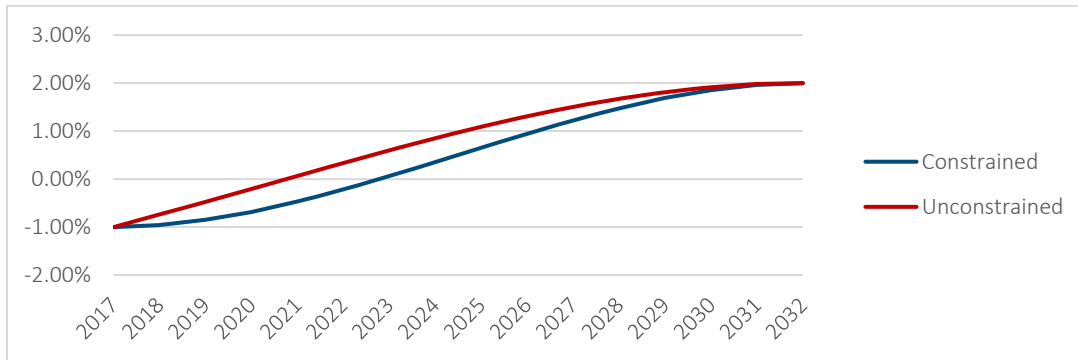
Figure 10

ILLUSTRATION OF THE IMPACT OF CHANGES TO THE COHORT INTERPOLATION WEIGHT PARAMETER
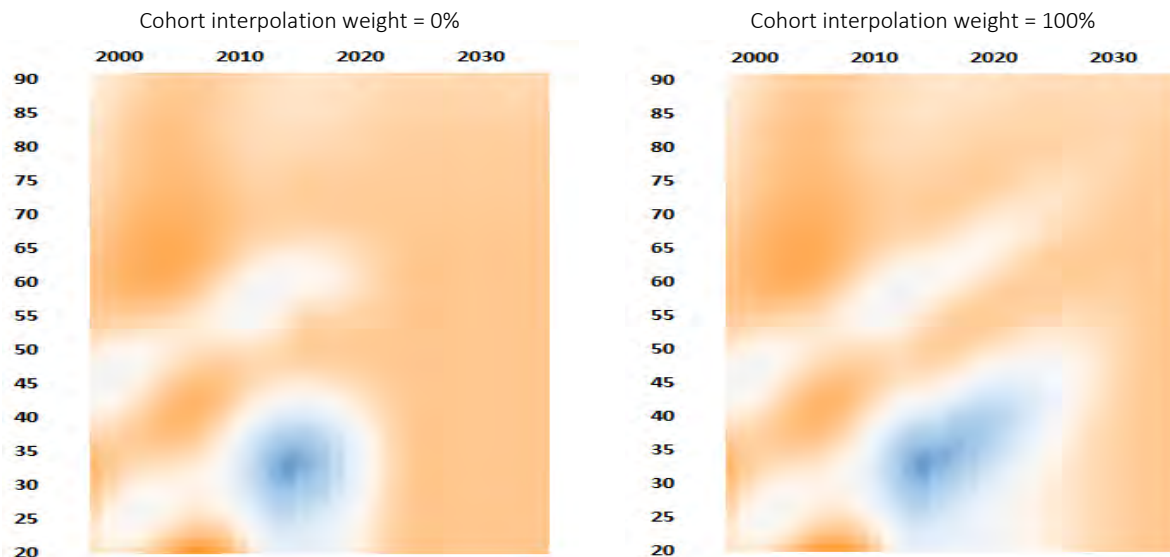
These results are for females and were computed using the parameters for the MP-2021 projection scale, with sensitivity testing performed on the cohort weight parameter. Historical data runs through 2017, and the projection begins in 2018. Blue indicates negative mortality improvement, white indicates no mortality improvement, and red indicates positive mortality improvement.

When the cohort weight parameter is set to zero, the forward projection from 2018 onwards exhibits a horizontal pattern. When the parameter is set to 100%, the pattern exhibits a diagonal pattern, tracing the path of cohorts as they age across time. If the parameter were set to 50%, the resulting improvement rates would be the average of the two scenarios depicted in Figure 10. Note that some cohort-level improvement is evident in the historical data that runs from 2000 through 2017, as evidenced by diagonal color patterns.

To illustrate the potential impact of the slope constraint parameters in cells Y30:Y31, it is helpful to consider a stylized example that focuses on a single age cohort, and which uses age-based interpolation (cell Q38 set to 0%). Assume the following values for this hypothetical cohort: (a) an initial improvement rate of negative 1%, estimated from recent data; (b) an initial improvement rate slope of positive 0.25%, estimated from recent data; (c) an assumed long-term improvement rate of positive 2%, and (d) a projection period of 15 years from time point "A" to "B". Using these assumptions, Figure 11 compares the effects of constraining the initial slope to be 0% and using the actual slope (obtained from data) of 0.25%:

Figure 11

IMPROVEMENT RATE PROJECTION WITH CONSTRAINED VERSUS UNCONSTRAINED INITIAL SLOPES

Time points A and B are assumed to be 2017 and 2032, respectively. MIM uses cubic spline interpolation between these two points.

As expected, Figure 11 reveals that improvement rates change at a faster initial pace when the constraint on the initial slope is removed. There is no "right" or "best" choice with respect to using constrained versus unconstrained initial slopes. Practitioners must exercise professional judgement in making this choice.

Section 2: Individual Life and Annuity Preselected Parameter Sets

Since the release of MIM-2021-v3, a preselected set of parameters to provide a reasonable starting point for the development and exploration of MI projection scales for individual life insurance and individual/group annuity products has been included in the Application Tool. With a click of a single button, practitioners may select a starting set of parameters that are populated directly into the spreadsheet.

Whereas RPEC uses the Social Security Administration (SSA) historical dataset for its MI projections, the preselected parameter set for individual life insurance and individual/group annuity MI projections is based on the National Center for Health Statistics (NCHS) decile datasets. In the MIM-2021-v3 Application Tool, the Advisory Group selected 50% each of NCHS deciles 6 and 7 historical datasets. Based on additional research and analysis comparing the mortality of the NCHS decile datasets to 2015 VBT mortality, summarized in Section 1, in MIM-2021-v4, the preselected parameter set for individual life insurance and individual/group annuity MI projections is 100% of NCHS decile 10.

The choice of these historical datasets is an appropriate starting point for further review and modification. The Advisory Group encourages practitioners, when using the preselected parameter set for MI projections, to examine the projection results via the heat map and the dynamic graph. These visualization features simplify the review process and are helpful for fine-tuning assumption parameters to reflect applicable individual company target market, experience, underwriting strategies, products, risk classes and any other factors unique to their company or personal future expectations.

Consistent with the prior version, the structure of the MIM-2021-v4 Application Tool is based on the user selecting (1) the dataset of historical MI rates, (2) the long-term MI rate structure and (3) the interpolation options to fill in the intervening MI rates between historical MI and long-term MI rates. MIM provides the user with two interpolation options:

- Basic Interpolation (Figure 12; left side)—a family of cubic polynomials between points A and B.

- Advanced Interpolation (Figure 12; right side)—a family of cubic polynomials between points A and B, followed by an optional period of flat MI rates between points B and C, then linear convergence to the appropriate long-term MI rate between points C and D.

Figure 12
TWO INTERPOLATION OPTIONS
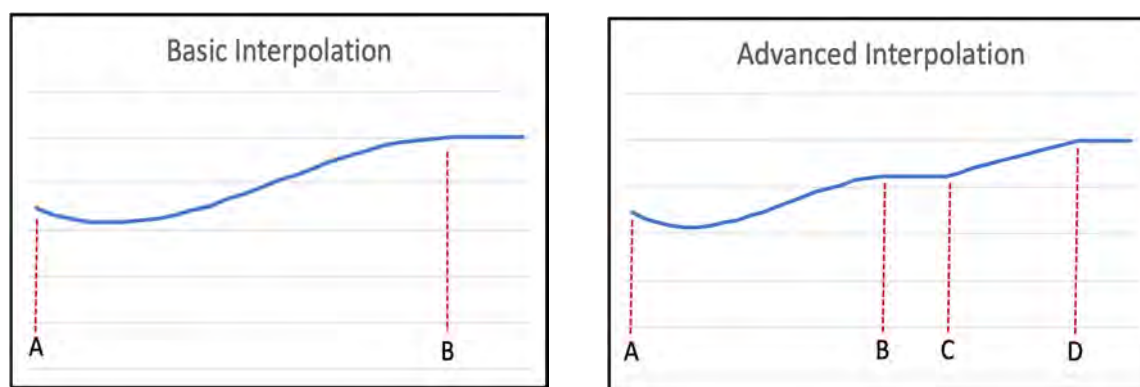
The Advisory Group anticipated that individual life insurance and individual/group annuity practitioners might prefer to have the additional flexibility offered by the Advanced Interpolation structure. Users must always select the

historical MI rates at point A, and so the preselected parameters for Option 3 relate to assumed intermediate- and long-term mortality improvement parameters at points B and D. Table 1 shows the preselected MI assumptions for these two points introduced in MIM-2021-v3 and used in the MIM-2021-v4 Application Tool. Linear interpolation is used to calculate MI rates between age 35 and age 55, age 75 and age 85, age 85 and age 95, and age 95 and age 115.

Table 3
PRESELECTED MI ASSUMPTIONS RELATED TO POINTS B AND D FOR THE INDIVIDUAL LIFE INSURANCE AND INDIVIDUAL/GROUP ANNUITY OPTION

Male and Female Attained Age	MI Rate
17–35*	0.8
55	1.0
75	1.0
85	0.8
95	0.3
115	0.0

*The MIM-2021-v4 Application Tool's lowest age is 17.

The Advisory Group recognizes that the Advanced Interpolation structure is not required when the assumed sets of intermediate- and long-term MI rates are the same; the same results can be achieved using the Basic Interpolation structure. The Advisory Group, however, thought it would be helpful to present the preselected parameters for the individual life insurance and individual/group annuity option using the Advanced Interpolation framework, anticipating that practitioners would find it helpful when reviewing and modifying parameters for such applications.

The Advisory Group also recognizes that recent changes in reported U.S. mortality experience have deviated from the above assumptions at point B for certain age groups. Significant deterioration or slowdown in rates of improvement has occurred at many ages through age 65, especially at ages through 45, and then again between about ages 57 and 65. Thus, careful analysis by age group is warranted, especially if mortality at those ages is particularly important in the application that the practitioner is assessing. Although differing by age, this deterioration or slowdown in mortality improvement has been due to several major reasons, including:

- Drug overdoses;
- Cardiovascular disease;
- Accidents and firearm related deaths; and
- Diabetes.

Other than the historical mortality database and the intermediate- and long-term MI assumptions, the preselected parameters for the individual life insurance and individual/group annuity option are the same as those selected by RPEC for use in the MP-2021 scale:

- Whittaker-Henderson smoothing of historical mortality data: Order 3.
- Number of years into the future when MI rates are assumed to remain constant: Horizontal = 10; Diagonal = 20.
- Blending of horizontal and diagonal projects: 50%/50%.
- Starting years for MI values and slopes at point A: 2016–2017.
- Restriction on the absolute value of the MI slopes at point A: 0.0%.

Users who are interested in the rationale for these assumptions are directed to previous RPEC reports, particularly the MP-2016[12] and MP-2018[13] reports.

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[12] Society of Actuaries (2016), Mortality Improvement Scale MP-2016, https://www.soa.org/4937da/globalassets/assets/files/research/exp-study/mortality-improvement-scale-mp-2016.pdf.
[13] Society of Actuaries (2018), Mortality Improvement Scale MP-2018, https://www.soa.org/49964f/globalassets/assets/files/resources/experience-studies/2018/mortality-improvement-scale-mp-2018.pdf.

Section 3: Longevity Mortality Improvement Sensitivities

This section examines the relationship between the base mortality table and MI assumptions and their impact. Base mortality tables can be customized to the population represented by the pension plan or the group annuity in-force block of business to be assessed or valued. However, determining the appropriate mortality improvement assumption applicable to the population being assessed is more subjective.

There are several model variables that can affect the impact of the future of longevity improvement and life expectancy. MIM uses the concept of a short-term rate of improvement converging to a long- term rate of improvement over a convergence period.

To show the impact of various sensitivities, a standard base mortality table (Amounts Weighted PRI-2012) was used. MP-2021 served as the base improvement assumption at ages 45, 55, 65, and 75. For each age, a life expectancy was calculated as a baseline. To then test sensitivity of changes in life expectancy input, each key variable was arbitrarily shocked. The shocks were as follows:

- Increase/decrease to long-term rate of improvement by 1.0%
- Increase/decrease to short-term rate of improvement by 0.5%
- Increase/decrease of convergence period to long term rate of 5 years.
- Increase/decrease of 5 years to the age at which the long-term rate begins its piecewise linear grade-down to 0%.

Appendix shows the results on life expectancy impact by age of each shock. The greatest impact is the shock on the long-term rate of improvement. A combined effect of all four increase shocks shows a life expectancy effect of over 3 years at the younger ages. In the case of a 45-year-old male, using a 5% interest rate, the valuation is impacted by approximately 10% using a standard pension base mortality table.

More research is required to determine impacts by socioeconomic class, income level, work collar and other key variables. However, it is very clear that model assumptions for future mortality improvement have a significant impact on life expectancy.

Section 4: Future Updates and Enhancements

This section outlines anticipated future updates and enhancements to the MIM-2021 Application Tool. Users of MIM-2021 are encouraged to provide their feedback and additional ideas to research@soa.org.

1. **Added functionality to adjust SSA and NCHS datasets if pension plan or insured/annuity cohort data suggest better (or worse) historical mortality.** This issue requires additional analysis and research. It will remain an issue for future consideration.

2. **More insight/research on differences between SSA and NCHS datasets and when to use one or the other.** After subsequent consideration of the data available, RPEC concluded that the rationale for using the historical data furnished by SSA for mortality improvement projections from the Scale MP-2021 Report still applies.

   These differences represent an important issue. The Advisory Group, along with a separate SOA Research Institute project, are working to provide more analysis in this area.

3. **Analysis to determine whether some loosening of the two-year step-back at the jumping-off point is appropriate.** This issue requires additional analysis and research. It will remain an issue for future consideration.

4. **Study of how to create projection MI scales for select and ultimate mortality periods and different risk classifications (e.g., smoker and nonsmoker, preferred and standard).** This issue requires additional analysis and research. It will remain an issue for future consideration.

5. **More insight and research on required credibility size for user-supplied historical insured or pensioner data for mortality improvement projections.** This issue requires additional analysis and research. It will remain an issue for future consideration.

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Section 5: Acknowledgments

The Society of Actuaries Research Institute would like to thank the MIM Advisory Group for their support, guidance, direction and feedback throughout the project.

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Appendix A: Results on Life Expectancy Impact by Age of Each Shock

The following are the assumptions used in the analysis:

1. The base mortality table for the sensitivities is PRI-2021 Total Dataset Amount Weighted.

2. The baseline improvement used for the sensitivities is Mortality Improvement Scale MP-2021.

3. As of date for life expectancy was 1/1/2022

4. For LTR we increased or decreased every rate up or down by the shock before age 63 and then grade to 0 at the same percentage to preserve shaping of the grading period.

5. For STR we increased or decreased every rate up and down by the shock except ages greater than 114 where they are 0.

Table 4
INCREASED LIFE EXPECTANCY SENSITIVITIES FOR AGES 45-75

Sex	Age	Baseline Scenario	Long Term Rate		Short Term Rate		Convergence Period between LTR and STR		Age at which LTR Starts to Grade to 0		Combined Scenario*	LE Increase
			+100bps	Delta	+50bps	Delta	+5 Years	Delta	-5 Years	Delta		
Female	45	41.98	43.70	1.72	42.35	0.38	42.13	0.15	42.43	0.46	45.19	3.22
Male	45	39.16	40.94	1.78	39.55	0.39	39.40	0.24	39.56	0.41	42.48	3.32
Female	55	31.76	32.90	1.14	32.12	0.36	31.90	0.14	32.09	0.34	34.15	2.39
Male	55	29.3	30.43	1.14	29.66	0.36	29.48	0.18	29.59	0.30	31.68	2.38
Female	65	22.53	23.17	0.64	22.85	0.32	22.63	0.10	22.76	0.23	24.12	1.59
Male	65	20.55	21.16	0.61	20.86	0.31	20.68	0.13	20.75	0.20	22.08	1.53
Female	75	14.10	14.36	0.26	14.36	0.26	14.14	0.05	14.22	0.12	14.98	0.88
Male	75	12.66	12.90	0.24	12.91	0.24	12.71	0.04	12.76	0.10	13.47	0.80
*Combined Scenario refers to a shock combining all scenarios.												

Table 5
DECREASED LIFE EXPECTANCY SENSITIVITIES FOR AGES 45-75

		Baseline Scenario	Long Term Rate		Short Term Rate		Convergence Period between LTR and STR		Age at which LTR Starts to Grade to 0		Combined Scenario*	LE Increase
Sex	Age		-100bps	Delta	-50bps	Delta	+5 Years	Delta	-5 Years	Delta		
Female	45	41.98	40.22	-1.75	41.60	-0.37	41.81	-0.16	41.52	-0.46	39.66	-2.31
Male	45	39.16	37.37	-1.79	38.77	-0.39	38.90	-0.25	38.74	-0.42	36.72	-2.43
Female	55	31.76	30.62	-1.14	31.40	-0.36	31.62	-0.14	31.42	-0.33	30.13	-1.63
Male	55	29.3	28.18	-1.12	28.94	-0.36	29.12	-0.18	28.99	-0.30	27.66	-1.64
Female	65	22.53	21.91	-0.62	22.22	-0.31	22.44	-0.09	22.32	-0.22	21.52	-1.01
Male	65	20.55	19.96	-0.59	20.24	-0.31	20.43	-0.12	20.35	-0.20	19.56	-0.99
Female	75	14.10	13.84	-0.26	13.84	-0.25	14.07	-0.03	14.00	-0.10	13.56	-0.54
Male	75	12.66	12.43	-0.23	12.42	-0.24	12.64	-0.03	12.57	-0.09	12.17	-0.49
*Combined Scenario refers to a shock combining all scenarios.												

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