Report

Canadian Mortality Table Construction Alternative Methods

Generalized Additive Model and Neural Network Model

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1. INTRODUCTION

1.1. Purpose of this Report

This report documents our application of alternative methods to construct a new mortality table based on the same 2009-2019 industry data used by Bob Howard in the construction of the CIA2014 Table.

In this report, we cover the use of the Generalized Additive Model (GAM), a more widely used alternative method, and Neural Network Model (NNM), a more recent and less widely used method. We demonstrate the advantages and disadvantages of each method over traditional methods such as the Whittaker-Henderson method used for the construction of the CIA2014 Table.

We refer the reader to the report from Mr. Howard (Howard Report) for further details on the underlying data and the adjustments made to the data. We used the final data modified and used in the construction of the CIA2014 Table by Mr. Howard as our training data for the alternative methods. The expression *training data* is explained later on.

Using the results of the GAM2014 Table and the NNM2014 Table, we assess the tables (a) from a numeric standpoint, (b) based on actual to expected (A/E) ratios, and (c) by visualization (the use of charts). We also assess the CIA2014 Table using the same approach. Since the latter is not the core of our alternative methods, we address the assessment of the CIA2014 Table in Appendix A of this report. While this part of the report is an appendix, it should not be overlooked. Appendix A contains relevant information in comparison to the GAM2014 Table and the NNM2014 Table which the reader may find interesting.

1.2. Intended Users and Third-Party Users

The work underlying this report including our findings was commissioned by the Canadian Institute of Actuaries (CIA) with respect to the Canadian Mortality Table Construction Research Project and overseen by a Project Oversight Group (POG). Eckler and QED are responsible to the CIA for this work and associated material. However, it can be made available by the CIA to any third party outside of the organization (including free public access), with the understanding that both Eckler and QED are not responsible to any such third party for any content of this report, interpretation, use, and associated material such as spreadsheets. We would, however, be pleased to answer any questions.

1.3. Use in Whole or in Parts

The entire report must be distributed rather than any excerpt thereof. All parts of this report are integral to understanding and explaining its contents. No part may be taken out of context, used or relied upon without reference to the report as a whole.

1.4. Reliances

We have relied on life insurance companies' data as modified and provided to us by Bob Howard. Our final products, the GAM2014 Table and the NNM2014 Table, as well as related material including spreadsheets and the RShiny web site, depend on the integrity of that data. If the data was subsequently found to contain material errors that may render our products defective, then both Eckler and QED, independently or together, cannot be found liable for such deficiencies. However, we did examine the data for reasonableness and did not find any cause for concern.

1.5. Limitations

Note that the alternative tables, GAM2014 and NNM2014, should not be considered as alternative choices to the CIA2014 Table. The CIA2014 Table remains the official mortality table provided by the CIA to replace older tables such as the CIA8692 Table and the CIA9704 Table. Eckler and QED do not opine on whether the alternative tables are superior or not to the CIA2014 Table; any opinions in that respect would be irrelevant.

The GAM2014 Table and the NNM2014 Table were constructed using alternative methods in order to explore unfamiliar methods for the construction of future mortality tables. It is only exploratory work at this stage; more research and testing need to be done in order to fully adapt these techniques for the construction of mortality tables. So, although the GAM2014 Table and particularly the NNM2014 Table compare well against the CIA2014 Table, we should avoid jumping to the conclusion that these alternative methods are without flaws. The selection of predictors as well as factors applied to them remain a subjective choice. Putting less constraints on these variables, namely fewer variables and less precise coefficients, may cause the final rates to deviate from the observed data, while putting more constraints, namely more variables and more precise coefficients, may result in overfitting the data.

2. MOTIVATION FOR ALTERNATIVE METHODS

The application of alternative methods does not imply that the traditional construction method used by Mr. Howard is inadequate or lacking in any way. Instead, the application of alternative methods is performed to explore and demonstrate these methods in order to determine if they offer improvements over traditional methods in ways that would benefit the users of the CIA2014 Table.

The approach used in constructing the CIA2014 Table relies on the Whittaker-Henderson (WH) graduation technique. This technique is simple to apply and is effective when correctly implemented. Its main limitation is that it does not provide a model with which further investigations can be performed. That is, one only receives a set of static graduated tables and not a model to determine graduated tables depending on different inputs. With a dynamic model like the ones used for the GAM2014 Table or the NNM2014 Table, were able to derive future tables for calendar years 2020 to 2024.

One question that may arise is why we have specifically chosen a Generalized Additive Model (GAM) and a Neural Network Model (NNM) as our alternative methods. There is no "one size fits all" approach to modelling problems, and the choice of model often comes down to a balance of interpretability and predictability.

The alternative methods presented in this report provide a model that can be used for further investigations. This includes projecting future, unseen tables, as well as directly modelling uncertainty of the constructed tables. In addition, the methods considered allow greater flexibility in modelling the mortality rates which will be demonstrated in each section.

On the one hand, we have GLMs (a GAM is a GLM) which offer very high interpretability depending on the model structure, but often this interpretability is at the cost of predictability as a simplified linear model structure needs to be adopted. As soon as one starts introducing measures to improve the fit in a GLM, one slowly begins to lose interpretability. On the other hand, NNMs have been shown to offer superior predictive ability to GLMs and GAMs in several tasks. However, unless specific modifications are made, they are very difficult to interpret. In fact, NNMs are often simply GLMs, with highly non-linear and complex transformations and interactions applied to the features.

Initially, we intended to only apply the NNM to the problem, as recent research had demonstrated that NNMs are particularly good at predicting mortality. Thus, the choice was simply driven by curiosity and the desire to push the boundaries of actuarial work. We included the GAM as a middle ground between traditional methods such as WH graduation and cutting-edge approaches like the

NNM. Our thought was that most actuaries, and more specifically those working in the life insurance area, would be familiar with WH, but that the vast majority would be very unfamiliar with deep learning, the neural network model, and generally artificial intelligence (AI). Further, almost none would have applied them to mortality modelling. The GAM was then included as a middle ground between the familiar and unfamiliar, as we expect that some actuaries would be familiar with GLMs and GAMs, especially those with some experience in property and casualty, but would not have applied them to mortality modelling.

3. ASSESSING THE PERFORMANCE OF MODELS

Given that the methods used in this report are non-traditional and stem from machine learning, it is worth reviewing the approaches taken to assess the performance of the models for those readers who are not familiar with them.

We include an assessment of the CIA2014 Table in Appendix A for comparison purposes. Comparison between the various tables should be done with caution. For the CIA2014 Table, a select period of 20 years was chosen and a separate graduation performed by section (select, ultimate, younger ages, older ages). Also, the fitting was not performed with prediction as an objective, so there are no in-sample versus out-sample comparisons to make. Therefore, we include the assessment for the total data set split into select and ultimate rates. We provide comparison figures for each alternative method.

3.1. In-Sample and Out-Sample Metrics

Given that we have the additional objective of projecting mortality into unseen periods, for example 2020 to 2024, it is necessary to ensure that the methods chosen not only fit well to the data they are trained on, but that they also generalize well to unseen data. To assess this, we split the data into a *training data set* and a *testing data set*. The training data set is used to fit the model and assess in-sample performance, whereas the testing data is used to assess out-sample performance, that is the ability of the model to generalize to unseen data. Given that projecting mortality forward in time is one of the primary objectives, we define the training data as all data from 2009 to 2016. The testing data is then all data from the years 2017 to 2019 inclusive. For each of the metrics below, we can assess both in-sample and out-sample performance. Note that the final model used to construct the final set of mortality tables is retrained on all available data, namely 2009 to 2019, which produces the GAM2014 Table and the NNM2014 Table. This final model is used when assessing select and ultimate performance as a comparison against the CIA2014 graduated rates.

3.2. Poisson deviance

The alternative methods applied are modelled as Poisson distributed count variables, therefore a natural metric to assess performance is the Poisson deviance which has the following formula:

$$D = 2 \times \sum_{i=1}^{n} [y_i \times Log(\frac{y_i}{\mu_i}) - (y_i - \mu_I)]$$

where:

- y_i is the actual death amount for policy i, and
- $\boldsymbol{\mu_i}$ is the predicted death amount for policy i.

In this report, we have taken the average Poisson deviance in the face amount and divided by 1000 to give the mean Poisson Deviance per 1000 exposure amount. **A lower number is better, and the Poisson deviance penalizes large errors more than smaller ones.**

3.3. Kolmogorov–Smirnov

The Kolmogorov–Smirnov (KS) test is a test of the equality of two distributions. Roughly speaking, it works by comparing the distance between the cumulative distribution functions of two samples. The statistic provided in this report is the p-value of the resulting test statistic. The closer the p-value is to 1.0, the closer the two distributions are. Essentially, think of it as a correlation measure. **A number towards 1.0 implies a good correlation whereas a number towards 0.0 implies a poor correlation.**

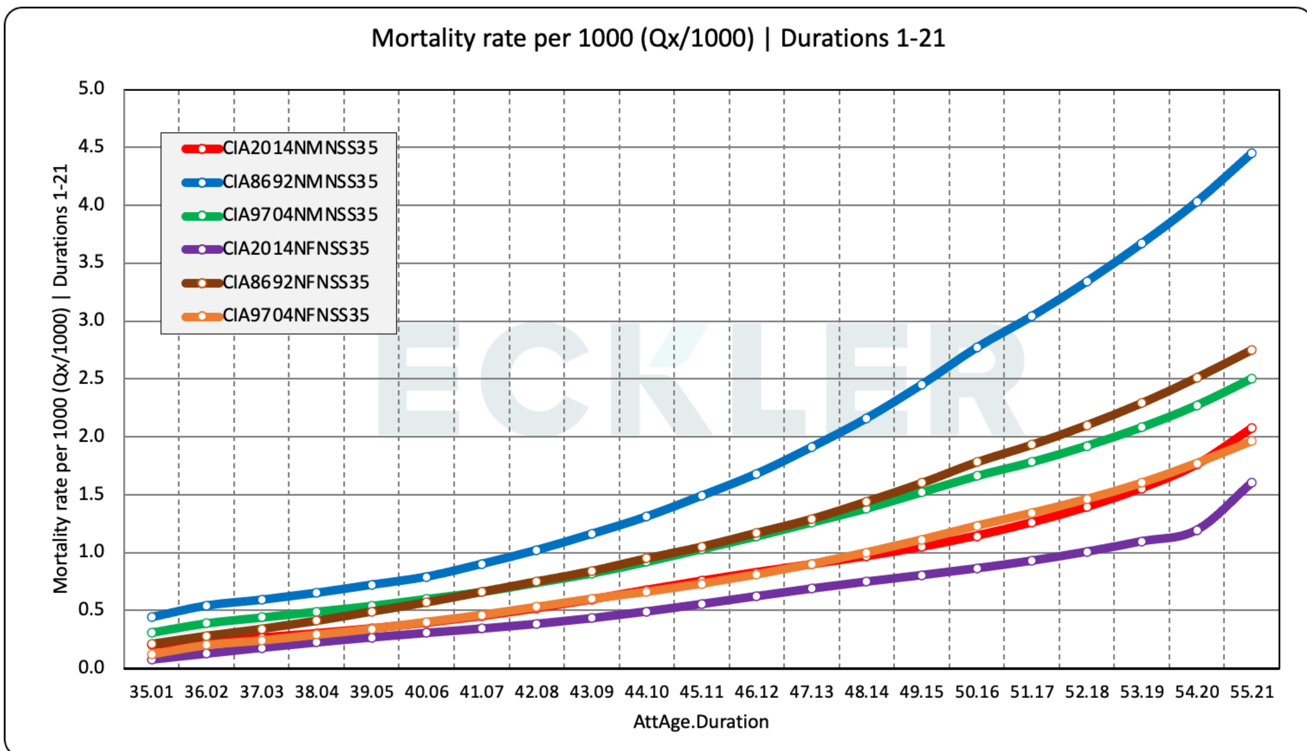
3.4. Actual-to-Expected Ratios

In addition to the statistical metrics above, we also include the more traditional actual-to-expected (A/E) ratios. An A/E ratio of 100.0% indicates that the actual death amounts are within 0.1% of the expected death amounts.

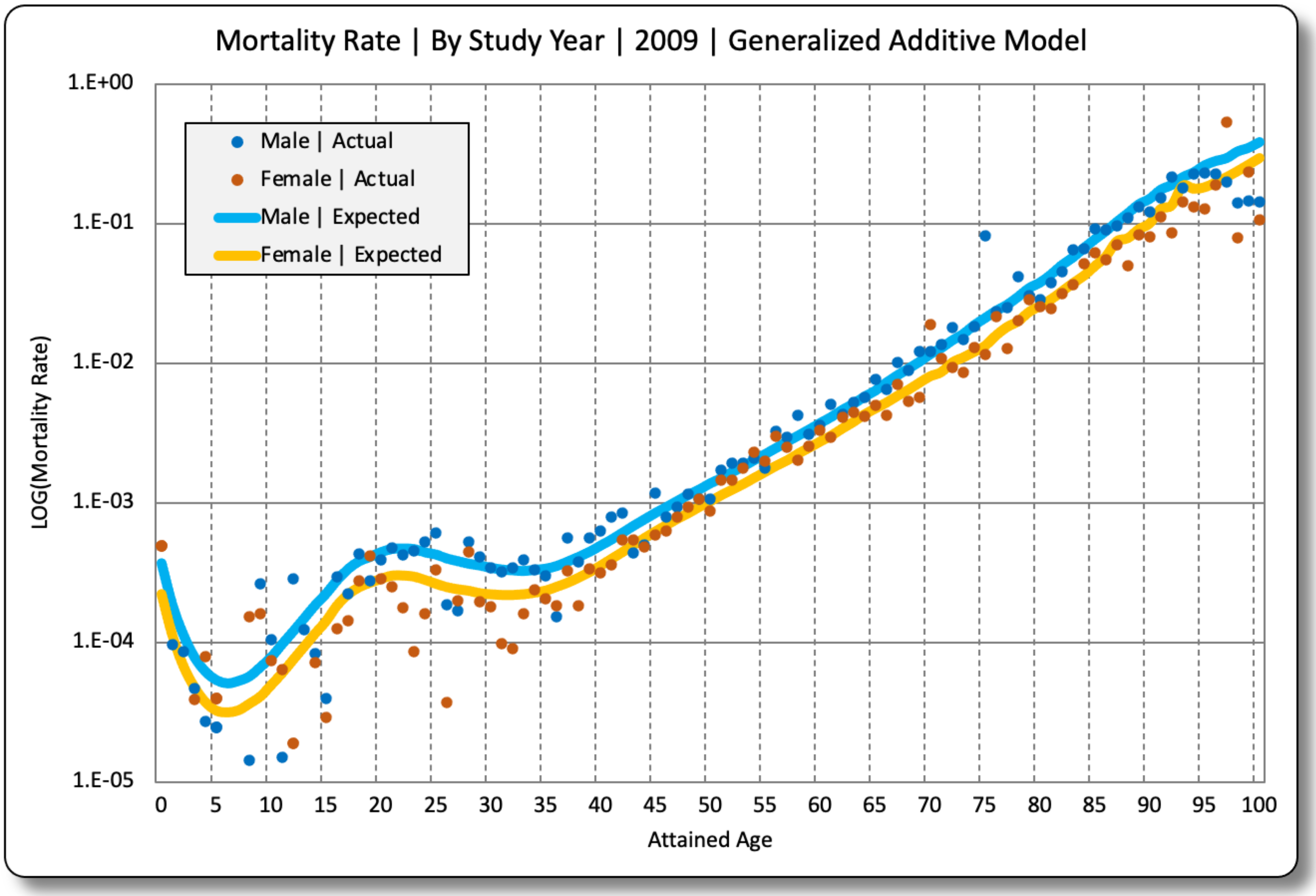
3.5. Visual Assessment

Numerical assessments provide an objective one-dimensional measure of the goodness of fit, but it is necessary to visually examine the fit of the models as the test statistics can still report good results even where the visual fit is not ideal. We provide numerous charts that examine the fit for each method from various perspectives. Furthermore, we make extensive use of visual assessment charts.

Several of the visualization charts provided in this report may seem unfamiliar at first glance as they are presented in a manner that is not commonly used. For example, one would normally expect mortality curves to be presented as per the figure below where a specific issue age is chosen and the mortality by duration thereafter is provided. Further, each individual segmentation of data is normally provided. The following chart shows the comparison of the CIA9704 Table to other tables, issue age 35, for MNS, MSM, MAG, FNS, FSM, and FAG, for duration 1 to 21.

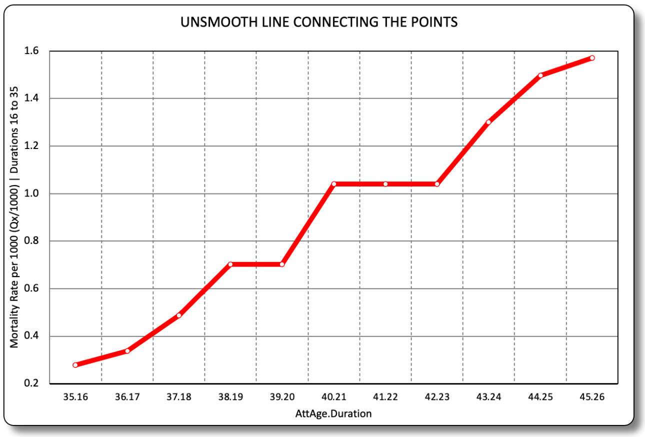


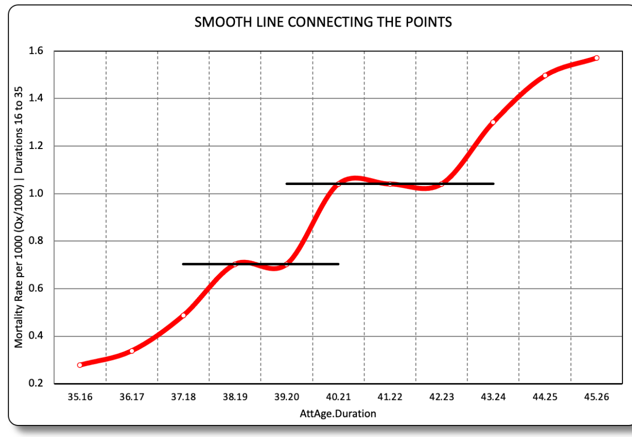
When comparing actual experience to expected experience, this becomes more difficult due to the volatility of the actual underlying data. Further, for the models used in this report, there are hundreds of curves fitted, which would make a comparison by every issue age and duration infeasible. To capture the maximum amount of information and reduce the volatility of the actual data, we present the results aggregated across unseen dimensions. For example, in the next chart, the unseen dimensions are smoking status and duration. Meaning, we have summed up the exposure and death data across smoke status and duration and derived the curve below by dividing the aggregate death amounts by the aggregate exposure amounts. This provides us with a clearer actual curve (albeit still showing some volatility), and a clear comparison of the expected curve.



We believe this approach provides a clearer direct comparison of the mortality tables provided in this report to the actual data and is a natural visual assessment considering that the models presented in this report are exposure based.

When we present our charts, we smooth the lines that connect the points as opposed to joining each point by a straight line. A smooth line provides a more evident pattern rather than a jagged line. This has an apparent flaw in that if the points to be joined suddenly change pattern, then the smooth line may increase above the points and then decrease, as in the following examples:





However, this behaviour also helps identify the points where the pattern changes.

3.6. Other Measures of Performance for Dimension/Model Selection

Other measures could have been used, such as the Akaike information criterion (AIC) or confidence interval. AIC is used to compare the fit of different regression models. However, it does not determine if the model is a good fit or not as it is used to compare models. As the focus was more on predictive accuracy, more reliance was placed on metrics that measure predictive ability and are more widely used in the machine learning literature.

3.7. Other Considerations

Our base data is the mortality experience from various companies from 2009 to 2019, inclusive. Although somewhat homogeneous, the data is not always homogeneous across companies and years, or at times within a company. The observed data is therefore imperfect and applying a graduation without extrapolating on what the data should have been if it were homogeneous would, by default, result in an imperfect table.

The experience study is by definition the benchmark. However, that does not necessary mean that the end result has to perfectly fit the experience. The most obvious example here is the sex inversion for smokers at old ages found in the CIA2014 Table. The table fits the experience, but the alternative methods do not. Another obvious example is where the CIA2014 Table shows flat mortality rates at extreme older ages and then jumps to 1.00 at attained age 115. This is obviously theoretical because we simply do not have data to support the exact rates. However, the alternative methods can logically derive these rates because they are models. While this does not necessarily make the rates more appropriate, it simply provides an alternative way to derive the rates reasonably.

3.8. Amount versus Count

The alternative methods have been based on face amount as the weighting factor, and not policy count. This was chosen to match what was used for the CIA2014 Table. Using policy count as the weighting factor would have resulted in different tables, however, we have not explored this approach in our work.

An alternative approach might be to use policy count as the weighting factor but to include in the model a face amount band as one of the factors. This might result in a more accurate table that would also reflect the size of the policy, but it would create a larger set of individual tables. For instance, if we were to use broad face amount bands, say four, the number of tables would be multiplied by four

In an early draft of the tables, we had derived mortality tables by year, duration, smoker status, sex, issue age, and size band. But at some point, we decided to forego policy size in order to keep the number of tables manageable. The advantage of using GAMs and NNMs is that additional variables, like face amount band, can be used while retaining all the data. So with a model using four bands for instance, all four bands will contribute to, or influence, the curve by attained ages or by policy year.

However, in our opinion, using face amount as the weighting factor at this time is the best compromise. Technically, the process is the same as using policy count. It is simply that the count is composed of large numbers. Maybe in a future table construction, this could be added if a GAM or NNM approach is used.

3.9. Select Period

In theory, the select period has to be different by issue age, gender and especially smoking status. In other words, it is not reasonable to assume that the underwriting process would result in exactly the same number of years of reduced mortality for all ages, gender and smoking status. For instance, if the lives being underwritten were in perfect health to begin with, one has to assume that the underwriting process would add nothing in the selection of healthier lives. That would imply that young female non-smoker lives would have a near-zero select period. At the other extreme, doing underwriting on older male smokers' lives should result in a significant select period.

Forcing a select period of 15 (prior tables) or 20 years (the CIA2014 Table) creates a burden on the construction of the table, by definition. It is chosen by necessity, perhaps because traditional graduation methods have been used in the past.

With the alternative methods, we have chosen not to impose such a burden on the tables. This allows for a more natural progression of mortality rates by attained age. In the early stages of construction of the CIA2014 table, one of the challenges Mr. Howard had faced was the discontinuity of mortality rates for young ages from duration 20 (last select duration) to the ultimate period (duration 21). As Mr. Howard clearly explained, the ultimate period is not duration 21 but is made up of many durations, hence the jump, which is more obvious for certain ages than others. The alternative methods simply do not face this challenge.

It is challenging to analyze the selective effect on mortality when there is no set select period. However, we can make an attempt to do this by analyzing what is the characteristics of the select period of the CIA2014 Table. If we take the absolute value of the ratios of the rate for duration 21 for an issue [x] over the rate for duration 20 for an issue [x+1], minus 1, we obtain the percentage difference between an ultimate rate and the last previous select rate for the same attained age:

$$\% \ Diff = ABS[\ (Q_{[x]+21}/Q_{[x+1]+20}) - 1\ ]$$

This percentage difference varies significantly by class, with higher percentages for the non-smoker group and much lower percentages for the smoker group, as the following table shows:

(Q[x]+21/Q[x+1]+20) - 1				
ISSUE AGE	MALE N-S	MALE SMK	FEMALE N-S	FEMALE SMK
020	0.4%	3.0%	14.6%	3.7%
025	7.4%	5.8%	19.5%	4.5%
030	7.1%	5.5%	20.1%	3.4%
035	7.9%	4.9%	19.5%	0.7%
040	10.4%	6.0%	17.6%	1.7%
045	11.6%	3.1%	15.0%	1.5%
050	11.0%	2.6%	13.5%	2.1%
055	10.9%	2.1%	13.4%	1.7%
060	11.9%	1.7%	12.5%	2.7%
065	11.9%	2.0%	12.9%	6.3%
070	11.9%	1.3%	9.7%	7.2%
075	11.6%	1.0%	7.4%	5.1%
080	10.9%	1.0%	7.2%	5.1%
085	7.1%	0.7%	5.1%	5.4%
Minimum 20-89	0.4%	0.7%	5.1%	0.7%
Maximum 20-89	12.8%	6.0%	20.3%	7.5%

Our first thought was to apply these percentages to the alternative tables and calculate the number of *select* years. However, by design, the alternative tables provide a smooth transition from any attained age to the next. The traditional approach of using a select period creates an abrupt change from duration 20 to the ultimate period. As pointed out previously, there is no real duration 21 rate. So, using the above percentages will not be a valid comparison.

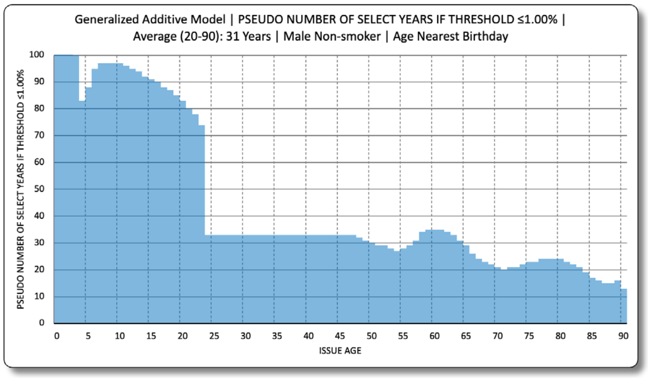
The first series of charts on the following pages show the number of *select* years if the threshold percentage is set at 1%. The second series shows the same measure based on a 2% threshold. It shows that the number of *select* years decreases rapidly as we increase the threshold. As long as the ratio is below that threshold, we consider it to be the select period. So, the formula for the GAM2014 Table and the NNM2014 Table becomes:

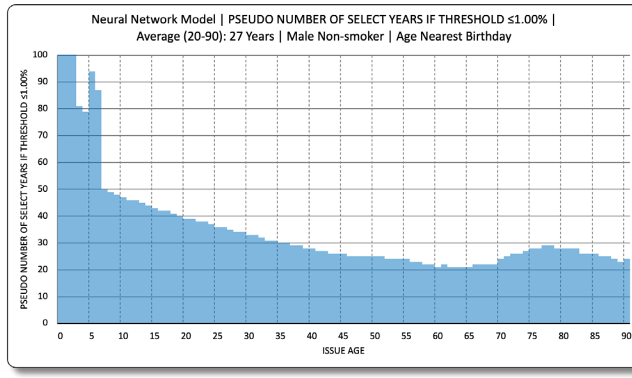
$$\% \ Diff = ABS[\ (Q_{[x]+t+1}/Q_{[x+1]+t}) - 1\ ]$$

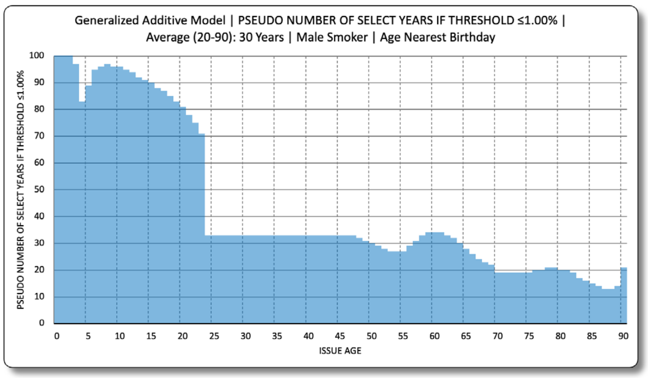
Once the threshold is exceeded, **t** is equal to the *implied select period*.

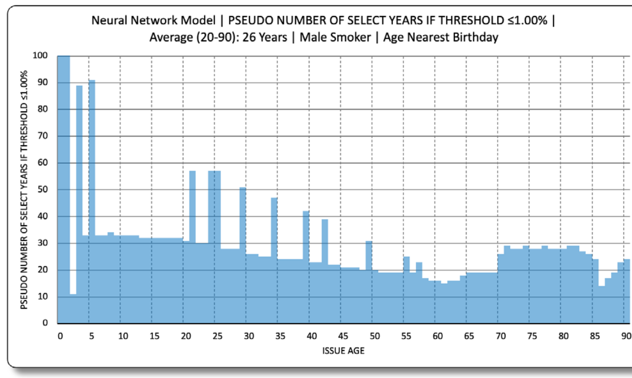
Interestingly enough, using a threshold of 2%, the average number of *select* years is between 16 and 20 for issue ages 20 to 90. In fact, under the NNM2014 Table, the average for the male non-smoker group is 20 years, starting at 27 for issue age 20, grading down to 14 for issue age 60, grading up to 25 for issue age 80, and finally grading down to 23 for issue age 90.

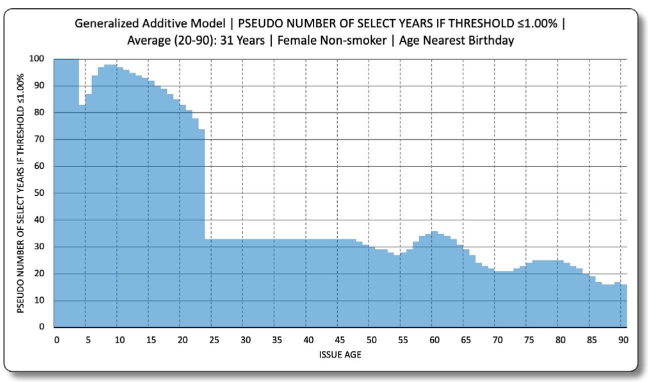
Number of select years if threshold ≤ 1%

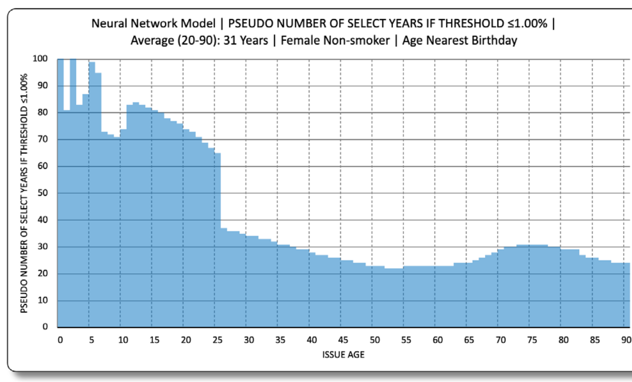


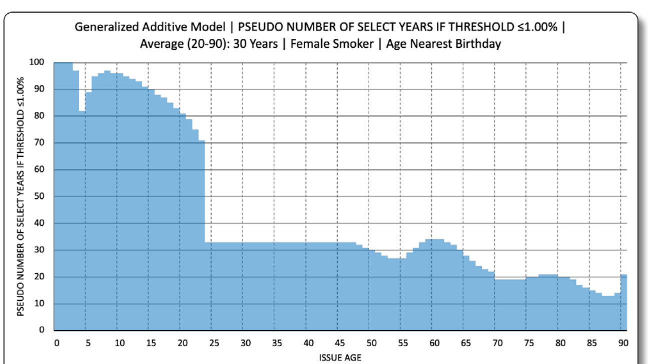


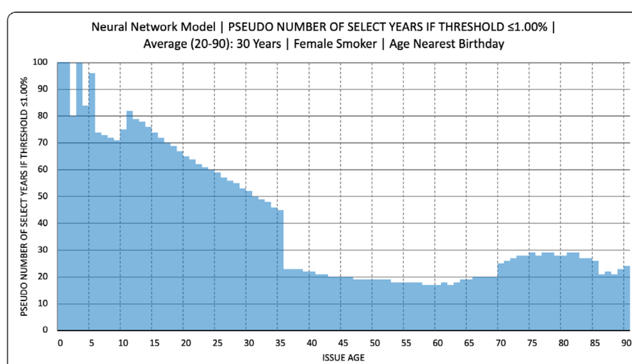












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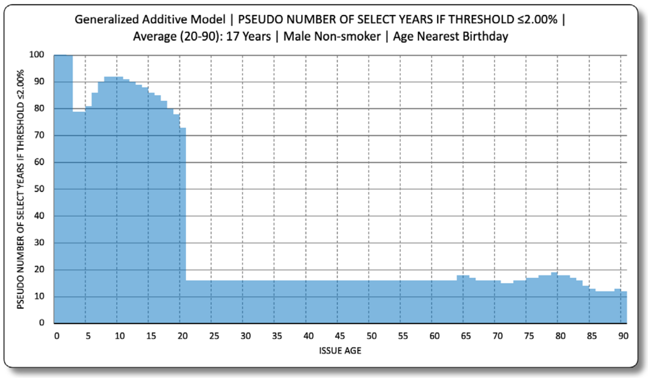
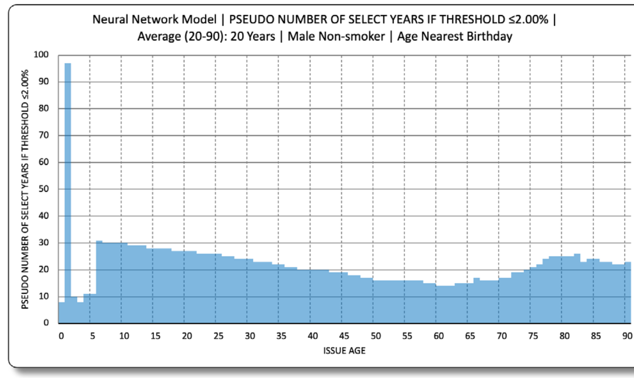
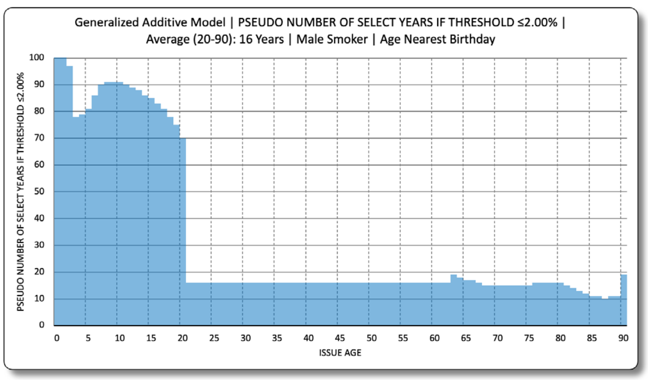
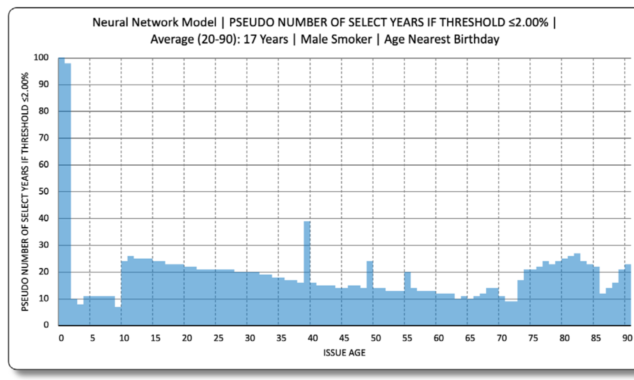
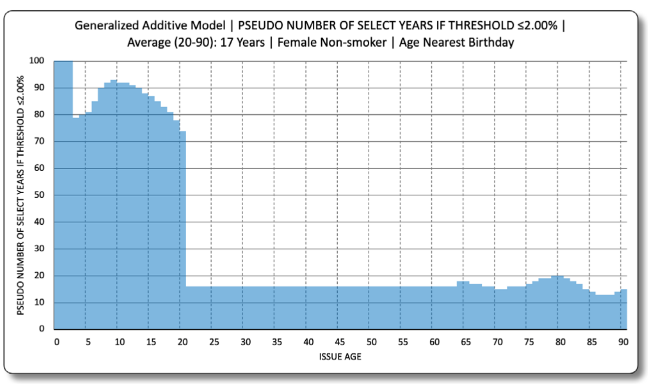
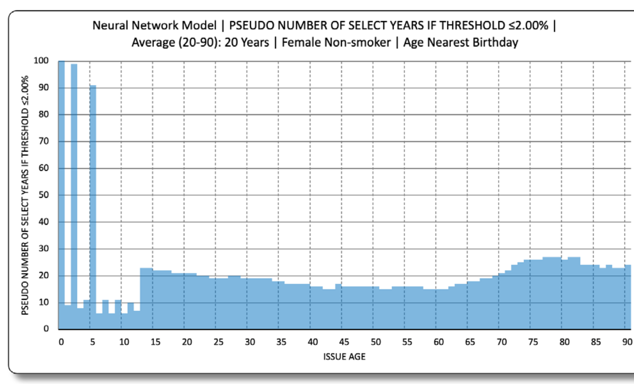


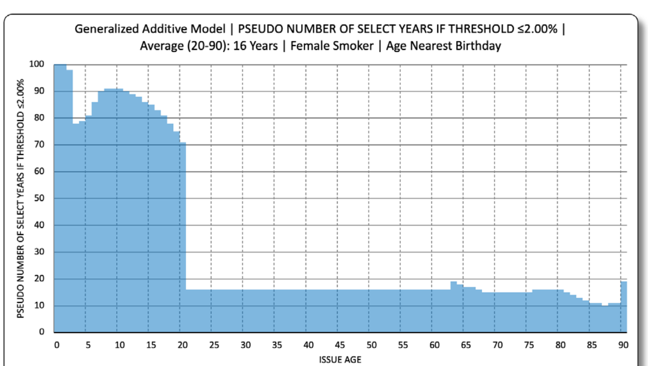


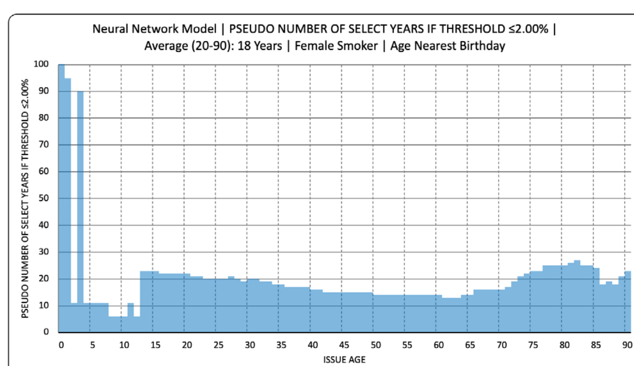












4. GENERALIZED ADDITIVE MODELS

4.1. What is a Generalized Linear Model (GLM)?

To understand a GAM, we first describe a Generalized Linear Model (GLM). GLMs take the following form:

$$g(y_i) = \beta_0 + \beta_1 \cdot x_{i1} + \beta_2 \cdot x_{i2} + \ldots + \beta_p \cdot x_{ip} + \epsilon_i$$

where:

- y_i, i ε [0, 1, …, n], is the response variable
- x_{ij}, j ε [0, 1, …, p], are the predictors,
- β_j are the coefficients for predictor j,
- *g(.)* is the link function, and
- ε_i is the error following a distribution from the exponential dispersion family.

The two key extensions of GLMs over linear models are (1) they allow the response variable error to be specified by any distribution from the exponential dispersion family and (2) that we can specify a link function that describes the relationship between the mean of the distribution and the predictors.

In other words, the response variable (mortality rate) is expressed as a linear function or a linear combination of all the predictors observed variables (gender, smoking status, issue age, duration, attained age, year of observation). The underlying relationship between the response and the predictors is linear, that is the relationship is in the form of a straight line.

4.2. What is a Generalized Additive Model (GAM)?

A GAM extends a GLM by providing a basis for some of the predictors that allows them to be *transformed* in such a way to fit the data more closely. A GAM is specified as follows:

$$g(y_i) = \beta_0 + f_1 \cdot x_{i1} + f_2 \cdot x_{i2} + \ldots + f_p \cdot x_{ip} + \epsilon$$

where:

- f_j provides the basis for predictor x_j.

GAMs are chosen as an alternative method as GLMs are widely used for frequency modelling in non-life insurance and life insurance, and the extension to a GAM allows complex relationships in the data to be accurately modelled. GAMs also provide a high level of interpretability through the coefficients which can provide additional insight. Further, one has significant freedom in specifying the model structure and what predictive variables can be included.

In other words, a GAM permits the model to learn non-linear features.

4.3. Model Form

For constructing mortality tables, we have opted for the following model[1]:

$$Log(d_i) = Year_i + IssueAge_i + Sex_i * Smoke_i * AttAge_i + f_{AttAge} + f_{PolYear} + Log(e_i) + \epsilon_i$$

Where:

- $Year_i$ is the experience year, i.e., 2009, 2010, …, 2019,
- d_i is the death amount for policy i,
- " ∗ " signifies to include interaction effect between variables and variables themselves,
- f_{AttAge} and $f_{PolYear}$ are spline bases fitted to AttdAge and PolYear respectively,
- e_i is the exposure, and
- ε_i is Poisson distributed.

The features are as described in Appendix B. Note that $Log(e_i)$ has a constant coefficient of 1.

The main elements of the model are the spline bases fitted to AttdAge and PolYear. These terms are the most significant and explain most of the variance in $\boldsymbol{d_i}$. Note that having PolYear included

[1] Coefficients have been omitted for conciseness.

allows for the modelling of selection periods. The addition of Smoke and Sex terms interacting with AttdAge allows the model to learn differentiating features between genders and smoker status. This further allows the generation of separate tables per gender and smoking status. Finally, the addition of the Year term allows the model to learn mortality trends over time which can also be used to determine mortality improvements, as well as project mortality into unseen periods.

The feature set is chosen to minimize predictive error. That is, subsets of features are fitted and used to predict mortality and the subset of features with the lowest out-sample Poisson deviance is chosen. The subset of features shown above exhibited the lowest out-sample Poisson deviance.

One may question the choice of a Poisson error term when modelling amounts. It is more natural that a Poisson error term is used to model the frequency of counts, rather than amounts. There are numerous distributional assumptions that can be made about the distribution of the response variable, and each come with their own advantages and disadvantages. The choice of Poisson is simply one of them. Alternative choices could be made, such as a Tweedie model, which may be more fitting for modelling death amounts. Poisson was also chosen based on the underlying research. A binomial is an adequate alternative. Amounts were chosen to capture the size element.

4.4. Results

The results presented in this section are based on the constructed GAM2014 Table using the combined actual experience data 2009–2019. To be clear, it does not include any results from projected tables for the years 2020 to 2024. This is the case throughout this report unless specifically indicated.

4.4.1. Numeric Assessment | In-Sample and Out-Sample

Generalized Additive Model | Numeric Assessment		
	In-Sample	Out-Sample
Poisson Deviance	93.52	118.57
Kolmogorov-Smirnov	0.98	0.73

In terms of Poisson deviance (lower is better), the fit shows minor deterioration to out-of-sample data indicating relatively strong generalization ability. Considering the KS metric (closer to 1.00 is better), we see the statistic is very strong on the in-sample data, with slight deterioration on the out-sample data.

4.4.2. Select and Ultimate Periods

Generalized Additive Model | Numeric Assessment		
	Select	Ultimate
Poisson Deviance	186.64	47.59
Kolmogorov-Smirnov	0.81	0.93

When comparing to the CIA2014 Select and Ultimate tables, the GAM2014 Table performs in line with the CIA2014 Table on both the select and ultimate data using the Poisson deviance. Using the KS metric, the GAM2014 Table performs much better than the CIA2014 on the select data, but slightly worse on the ultimate data.

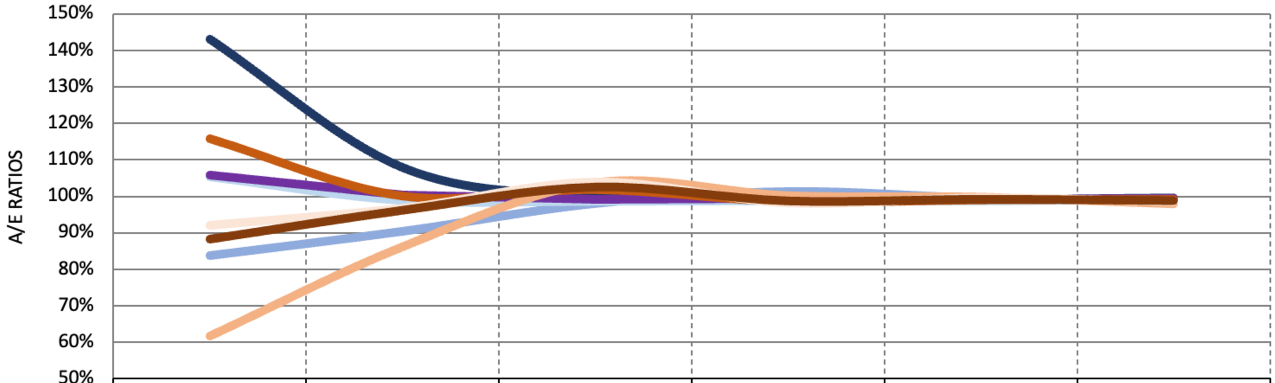
For more details on the assessment of the CIA2014 Table, please see Appendix A. For a more detailed comparison between the GAM2014 Table and the CIA2014 Table, please see Appendix C. In particular, for a comparison of the Poisson Deviant and the Kolmogorov-Smirnov metric, see section C.7 of Appendix C.

4.4.3. A/E Ratios

The charts and tables below show the A/E ratios for each risk class and various issue age groups, aggregated across all years of experience. The Actual (A) represents the actual death claims as provided by the companies and modified by Mr. Howard. The Expected (E) represents the expected death claims as calculated using the GAM2014 rates.

For issue ages past 20, the ratios are very close to 100.0%. Issue ages 0 to 19 do show large variations, especially with respect to non-smokers and smokers across both genders. The amount of data in these subsets is very low due to non-smoker or smoker status, and the predicted table only differentiates between smoking status after age 16. Looking across issue ages 25 to 80, where most of the exposure data lies, the ratios are all within 1% except for male unknown. Considering all issue ages 0 to 90, all rates are within 2% with the exception of the female smoker group.

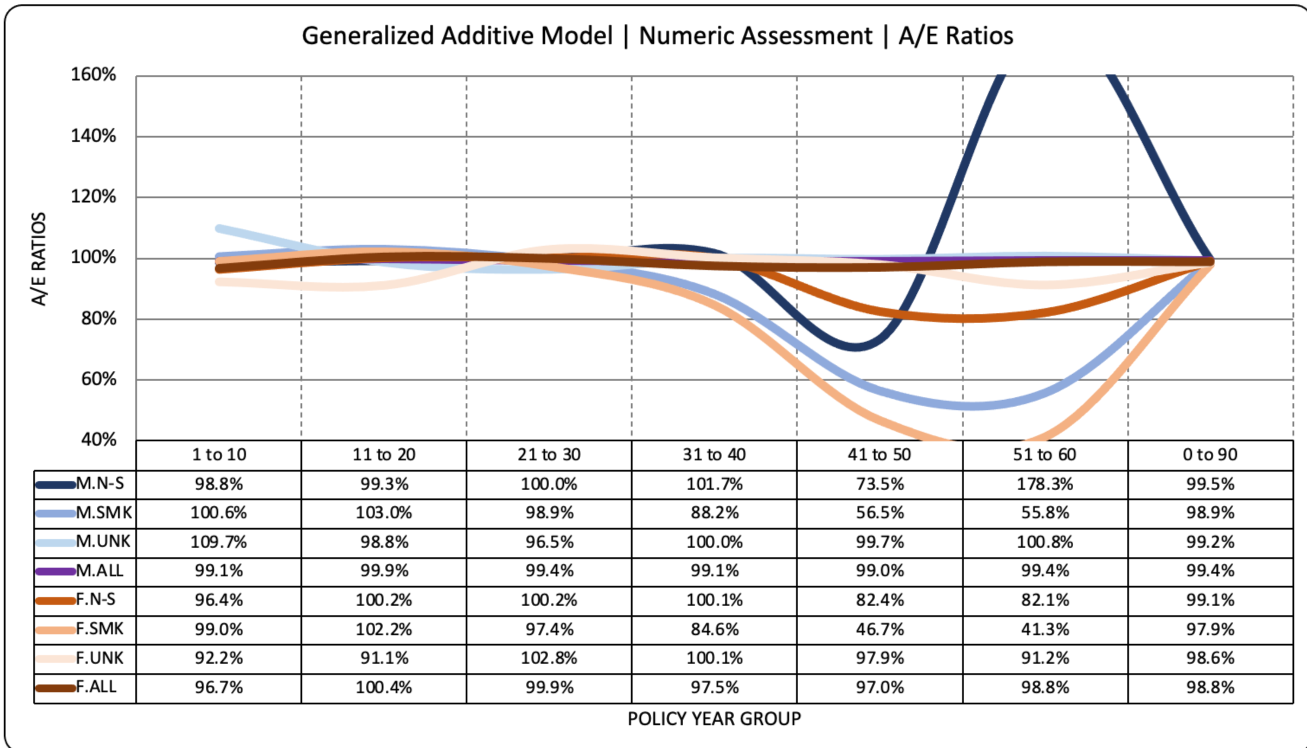
Generalized Additive Model | Numeric Assessment | A/E Ratios



	0 to 19	20 to 29	30 to 39	40 to 70	25 to 80	0 to 90
M.N-S	143.1%	107.9%	99.9%	99.0%	99.1%	99.5%
M.SMK	83.8%	90.5%	98.1%	101.3%	99.5%	98.9%
M.UNK	105.3%	98.8%	98.6%	98.8%	98.7%	99.2%
M.ALL	105.8%	100.4%	99.2%	99.3%	99.1%	99.4%
F.N-S	115.7%	100.0%	101.8%	98.5%	99.0%	99.1%
F.SMK	61.6%	86.2%	103.7%	100.2%	99.8%	97.9%
F.UNK	92.1%	96.8%	104.0%	98.2%	99.6%	98.6%
F.ALL	88.3%	96.2%	102.5%	98.7%	99.2%	98.8%

ISSUE AGE GROUP

The following chart and table show the A/E ratios again, but this time for various policy years. The A/E ratios are very close to 100% until policy year 40. After 40 years, the performance begins to deteriorate considerably due to the volatility in the actual data and the increasingly sparse amount of data.



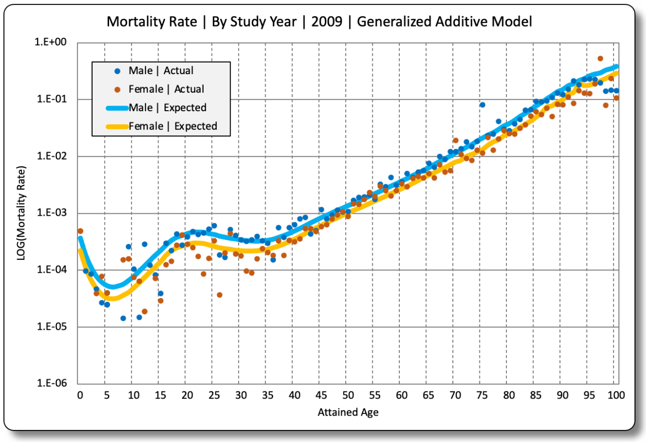
	1 to 10	11 to 20	21 to 30	31 to 40	41 to 50	51 to 60	0 to 90
M.N-S	98.8%	99.3%	100.0%	101.7%	73.5%	178.3%	99.5%
M.SMK	100.6%	103.0%	98.9%	88.2%	56.5%	55.8%	98.9%
M.UNK	109.7%	98.8%	96.5%	100.0%	99.7%	100.8%	99.2%
M.ALL	99.1%	99.9%	99.4%	99.1%	99.0%	99.4%	99.4%
F.N-S	96.4%	100.2%	100.2%	100.1%	82.4%	82.1%	99.1%
F.SMK	99.0%	102.2%	97.4%	84.6%	46.7%	41.3%	97.9%
F.UNK	92.2%	91.1%	102.8%	100.1%	97.9%	91.2%	98.6%
F.ALL	96.7%	100.4%	99.9%	97.5%	97.0%	98.8%	98.8%

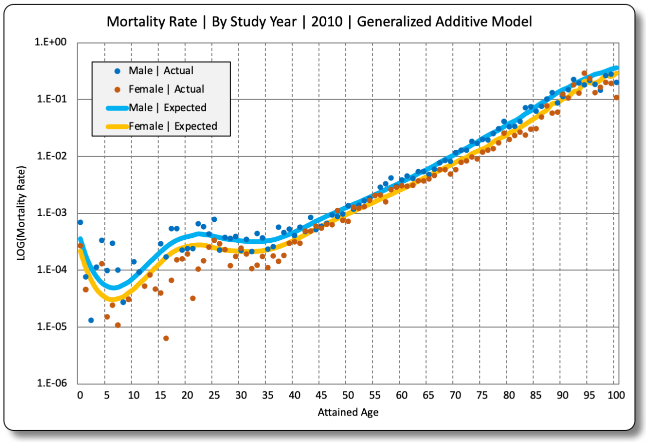
4.4.4. Visual Assessment

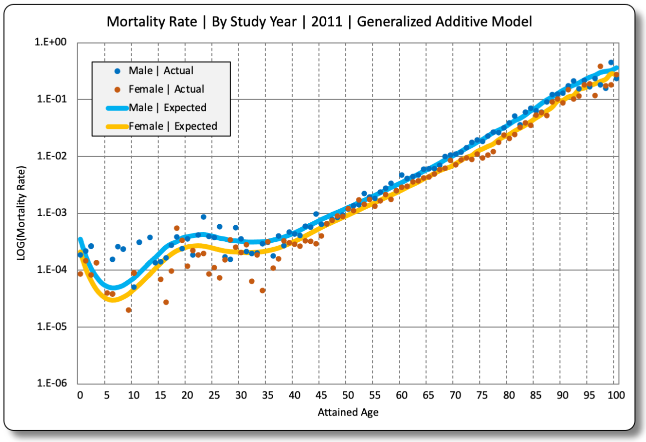
The following charts show the aggregated mortality curves for both males and females by year. The GAM has managed to fit the overall trend of the mortality curve including the hump around ages 20.

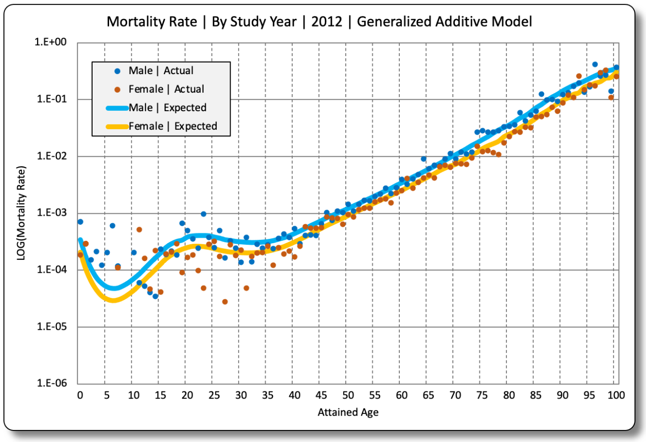
In the following charts, the x-axis is AttdAge (attained age). AttdAge of 0 is duration 1. AttdAge 1 is both duration 1 (for issue age 1) and duration 2 (for issues age 0), and so on. It is therefore an aggregated plot across all durations and issue ages to show the fit across the entire data set. This is achieved by aggregating the death and exposure amounts and then deriving the mortality curve by attained age.

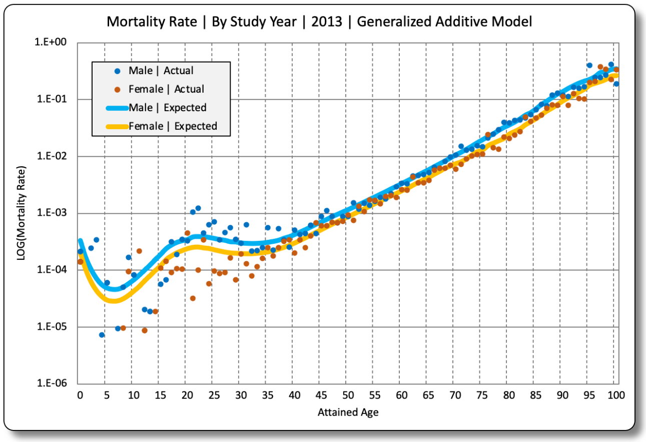
Mortality, actual versus expected, males and females, 2009–2019, aggregated across other fields, for the GAM

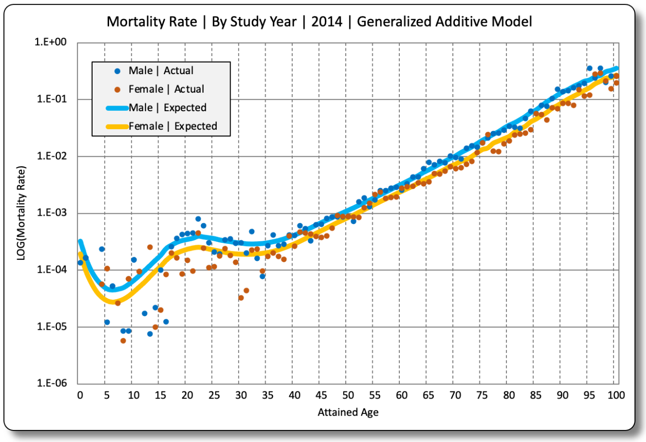




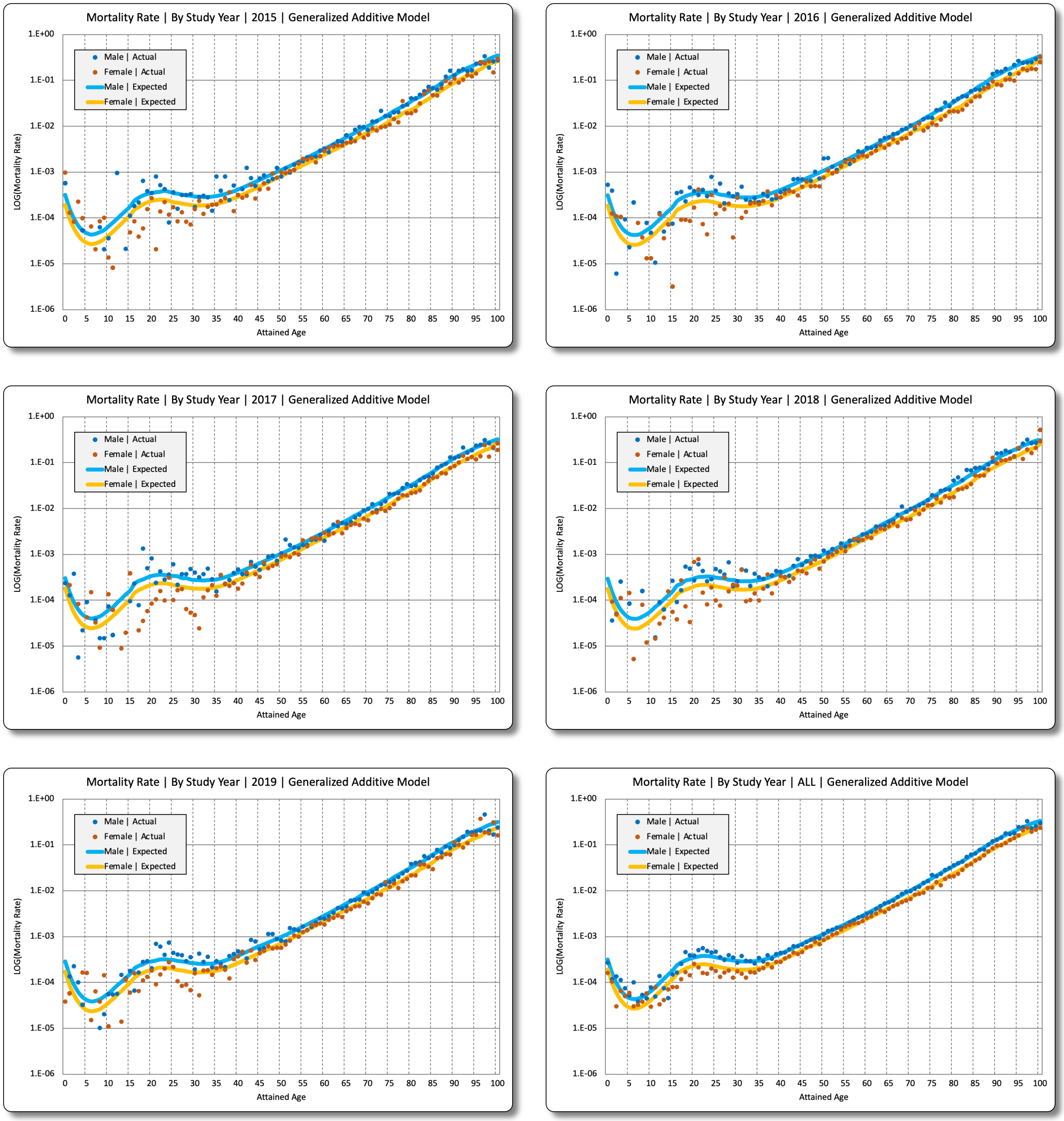






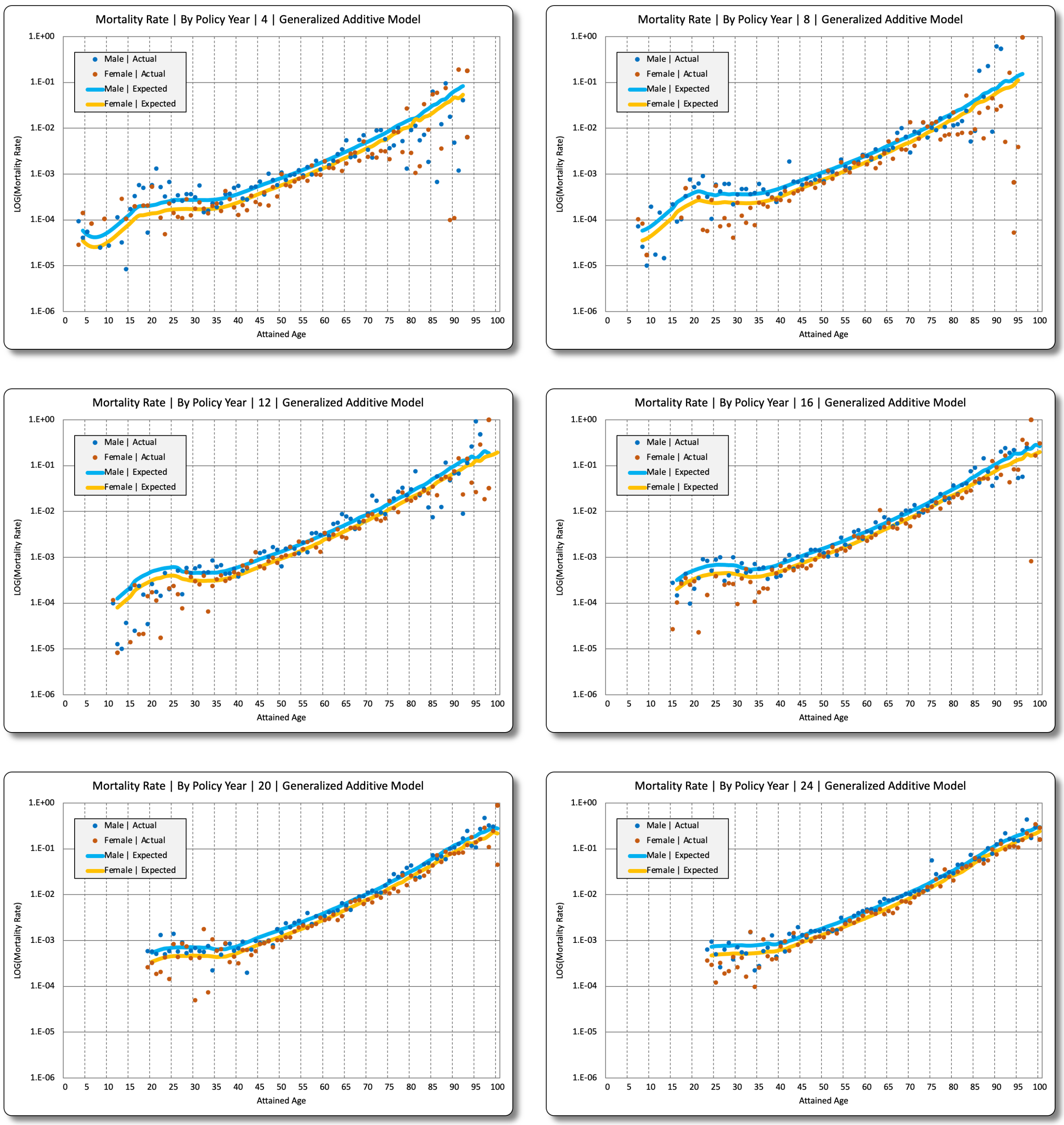


Mortality, actual versus expected, males and females, 2009–2019, aggregated across other fields, for the GAM



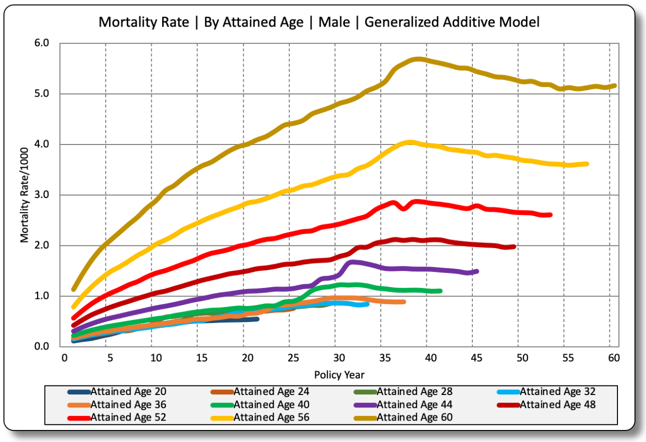
The following charts show the mortality curves for increments of four policy years. A clear increasing trend of mortality rates can be observed, specifically when comparing policy year 4 to policy year 24.

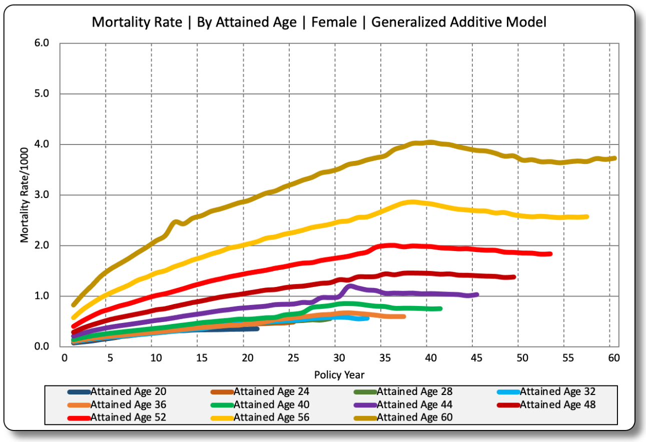
Mortality, actual versus expected, by sex, policy years 4–24 in increments of four, aggregated across other fields, for the GAM



The next charts explicitly show mortality by policy year for ages 20 to 60 in increments of four. We can see that mortality worsens across all ages until around policy year 40, where it stabilizes thereafter.

Mortality by policy year by gender, attained ages 20–60 in increments of four, aggregated across other fields, for the GAM

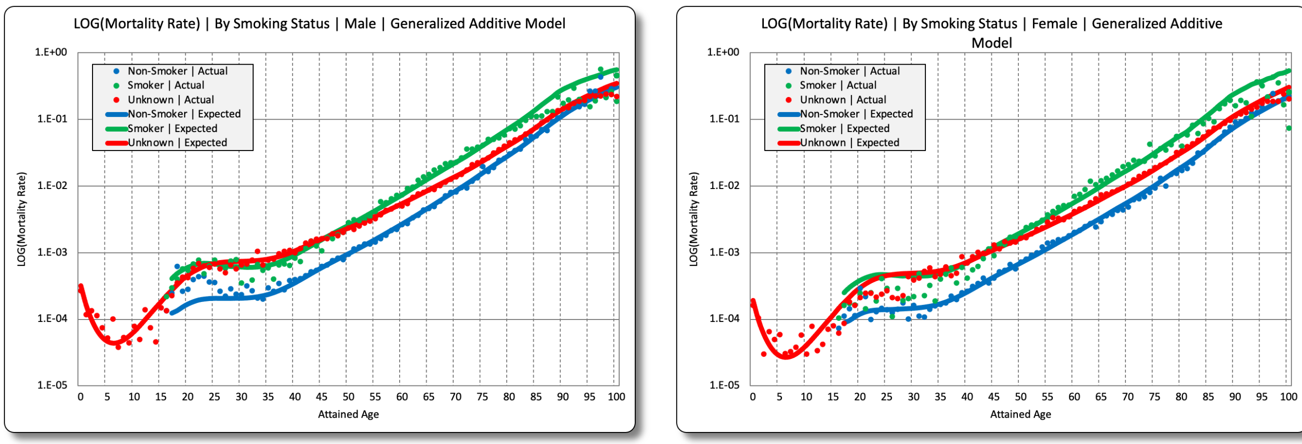




In the visual inspections above, we can see clearly that the GAM2014 Table has approximated the trend in mortality well, albeit missing some finer details in the younger ages. Note that the curve decreases in the later ages, most evident for the topmost curve, age 60. This is counterintuitive and suggests overfitting. When constructing the GAM2014 Table, splines are created based on policy year with no consideration of the exposure and hence there is a possibility that the lack of data in the advanced ages is leading to overfitting. This can be rectified by adjusting the spline basis to first allow for the amount of data across policy years and restricting their sensitivity in the later ages.

The next charts show how the model has differentiated between smokers and non-smokers in both genders, showing slightly higher mortality for smokers, with unknown status between smokers and non-smokers. We note that the fit is not strong in the older ages, particularly for female smokers and unknown smokers.

Mortality, actual versus expected, males and females, smoker status, aggregated across other fields, for the GAM



5. NEURAL NETWORK MODELS | DEEP LEARNING

5.1. What is a Neural Network Model (Deep Learning)?

Richman (2021a)[2] describes deep learning as the modern approach of designing and fitting neural network architectures. Further, Richman (2021a) notes that neural network models can be seen as generalizations of GLMs where multiple intermediate layers, Z^l, learn representations of the data to be used as features in a GLM to make predictions. More precisely, a feed-forward fully connected[3] neural network model with ***L*** intermediate layers is defined as follows:

$$
\begin{aligned}
Z^1 &= \sigma_0\,(c_0 + B'_0\,X)\\
Z^2 &= \sigma_1\,(c_1 + B'_1\,Z^1)\\
Z^3 &= \sigma_2\,(c_2 + B'_2\,Z^2)\\
&\;\;\vdots\\
Z^L &= \sigma_{L-1}\,(c_{L-1} + B'_{L-1}\,Z^{L-1})\\
y &= \sigma_L\,(c_L + B'_L\,Z^L)
\end{aligned}
$$

[2] Richman, Ronald, Mind the Gap - Safely Incorporating Deep Learning Models into the Actuarial Toolkit (April 2, 2021). Available at SSRN: https://ssrn.com/abstract=3857693 or http://dx.doi.org/10.2139/ssrn.3857693. A copy is provided with the present report.

[3] Feed-forward describes the flow of information in a neural network in that no information is sent *backward* or *cycled* through the network. i.e., information moves strictly forward. Other forms of neural network models exist which do cycle information, such as recurrent neural networks, however they are not used and hence are not further discussed. Fully connected means that all nodes are connected in some way to all other nodes in the network.

where:

- $l \in \{1, 2, 3, \ldots, L\}$ is the number of intermediate layers;
- Z^l are intermediate layers;
- B_l are weight matrices (analogous to coefficients in a GLM);
- c_l are intercepts;
- σ_l are activation functions that can be non-linear; and
- y is the response.

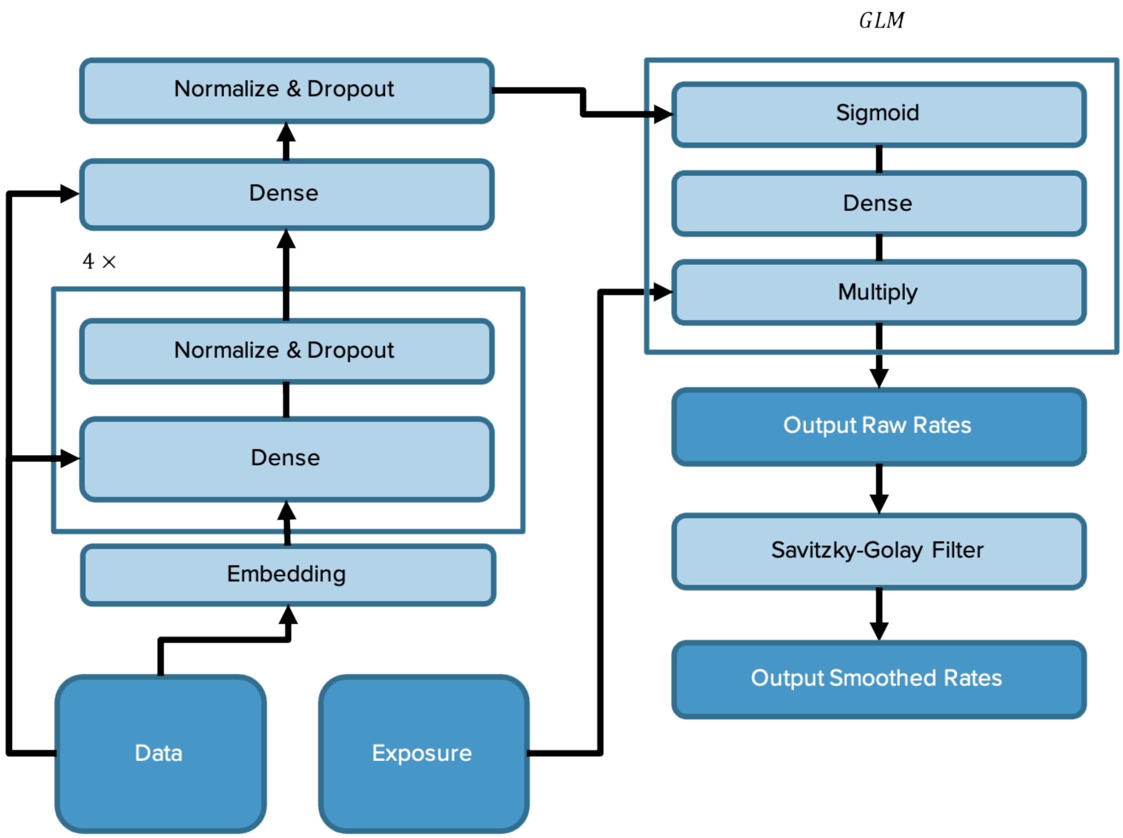
The intermediate layers, Z^l, form complex representations of the input data, which we can think of as engineered features that will be used in the final layer to predict y. This final layer is thus a GAM with input features Z^L. The choice of activation function in intermediate layers is mainly to constrain the information to a small domain as neural network models perform better when all numerical components are close to 0 (i.e., in the range [-1, 1]). The selection of the final activation function, σ_L, is related to the prediction problem at hand, and since the final layer forms a GLM, a natural choice is the inverse of the link function of an equivalent GLM. Finally, a neural network model is considered deep (and hence performing deep learning) when L is at least 3.

5.2. Model Form

When constructing deep neural network models the choice of architecture is the main consideration. Richman (2021) demonstrates an architecture that performs well for forecasting mortality; however, the main limitation is that it does not produce smooth predictions of mortality rates. To address this, we applied a Savitzky-Golay filter to the raw rates to achieve smoothed rates. The in-sample and out-sample numeric performance results considered below are using the un-smoothed rates. It is expected that smoothing will degrade performance immaterially. Analysis of the results for the smoothed rates over the select and ultimate split shows performance is still extremely strong.

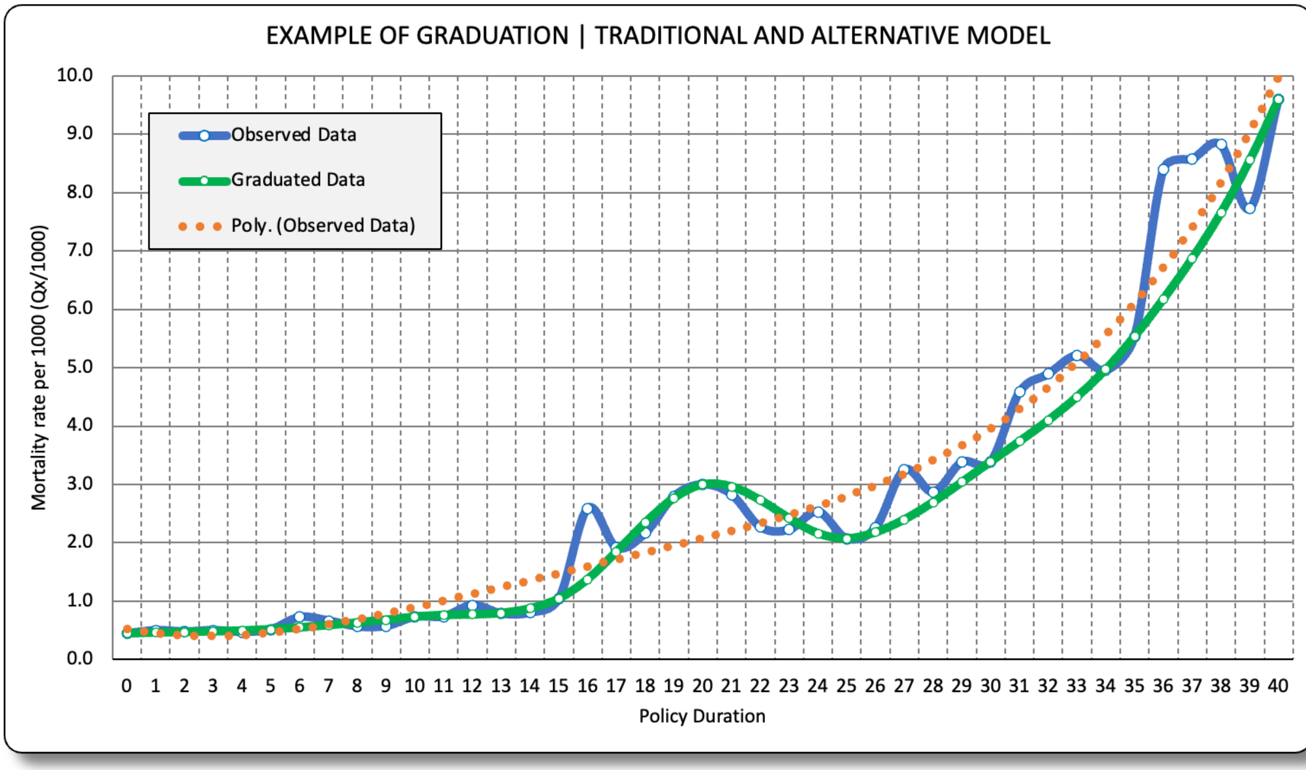
This architecture is described in the diagram below:

Neural Network Model (NNM) architecture



We have included smoothness as a reasonability check on the final rates. Some may disagree, arguing that rates from one duration to the next or one age to the next do not necessarily have to be smooth. The lack of smoothness would reflect more actual deviations from the expected and may be more inherent in traditional graduation methods where the principal objective is to reflect the experience. The use of GAM and NNM implies that the end results must be smooth since the rates are generated through a model. Although the model is influenced by the actual data, its objective is not necessarily to reflect all unusual behaviours. An example of that is again the older female smoker group having higher mortality than the corresponding male smoker group.

Let us assume the following very simple example to illustrate. The blue line in the chart below represents the observed data. The green line represents the graduated data. Let us further assume that our expectation is that mortality rates will increase by duration, which is true in most cases, except in certain cases around age 20–30 and particularly for the male group.



The observed data in the following chart show that the rate increases at duration 16, then decreases at duration 17. It further increases at duration 18, 19, and 20. Then, it follows an up and down movement, but overall following an upward trend, as expected. The green line, which is the graduated one, attempts to create a smooth transition from one duration to the next, but also tries to fit the data. In doing so, the rate increases rapidly at durations 16 to 20, where it starts to decrease to duration 25, before increasing again. This may reflect a more traditional graduation method.

The modelled rate (Poly. (Observed Data)) attempts to follow the general pattern of the observed rates. However, it knows that rates are not supposed to quickly increase or decrease and therefore the model iterates to smooth the final rates.

This example is an over-simplification, and the numbers are fictitious just to illustrate the point. In reality, depending on the predictor variables used and their coefficient or weight, the modelled rates may be smooth to reflect an expected mortality trend or made to overfit if desired and be closer to the observed data, much like that shown with the green line.

5.3. Results

The results presented in this section are based on the constructed NNM2014 Table using the combined actual experience data 2009–2019. To be clear, it does not include any results from projected tables for the years 2020 to 2024. This is the case throughout this report, unless specifically indicated.

5.3.1. Numeric Assessment | In-Sample and Out-Sample

Neural Network Model | Numeric Assessment		
	In-Sample *	Out-Sample *
Poisson Deviance	91.21	117.52
Kolmogorov-Smirnov	1.00	0.90

* : un-smoothed rates

In terms of Poisson deviance, the fit shows slight deterioration to out-of-sample data indicating strong generalization ability. Considering the KS metric, we see the statistic is extremely strong, indicating that the data likely come from the same distribution, or in other words, the distributions of the data are likely equivalent. This holds true for out-of-sample data, where there is slight deterioration.

5.3.2. Select and Ultimate Periods

Neural Network Model | Numeric Assessment		
	Select	Ultimate
Poisson Deviance	185.24	47.33
Kolmogorov-Smirnov	0.99	0.95

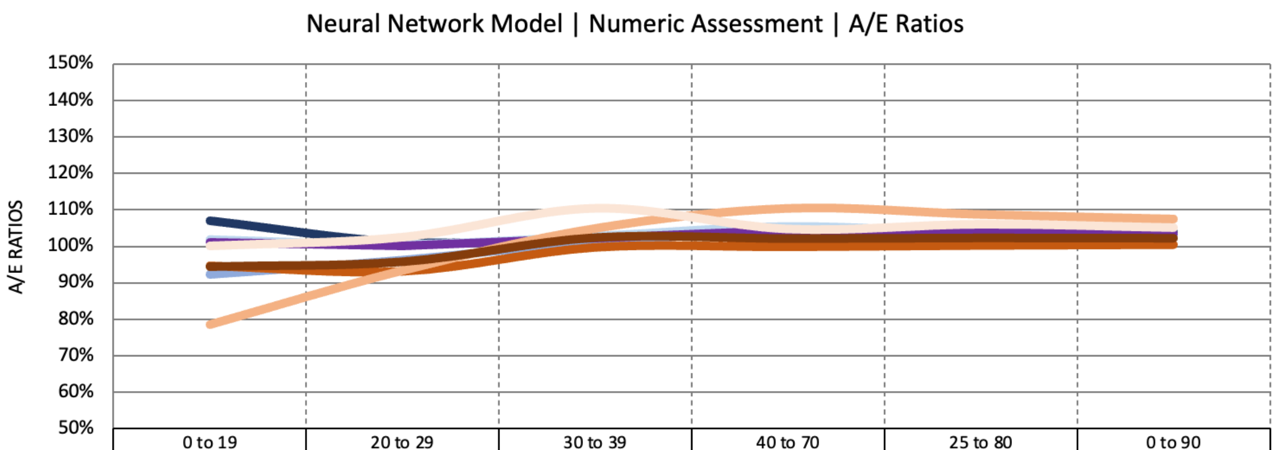
When comparing to the CIA2014 Select and Ultimate tables, the NNM outperforms on select data, and slightly underperforms on the ultimate data. The KS metric performs very well on both the select data and the ultimate data, exceeding the GAM and performing slightly worse than CIA2014 on the ultimate data.

For more details on the assessment of the CIA2014 Table, please see Appendix A. For a more detailed comparison between the NNM2014 Table and the CIA2014 Table, please see Appendix C. In particular, for a comparison of the Poisson Deviant and the Kolmogorov-Smirnov metric, see section C.7 of Appendix C.

5.3.3. A/E Ratios

The charts and tables below show the A/E ratios for each risk class and for various issue age groups, aggregated across all years of experience. The Actual (A) represents the actual death claims as provided by the companies and modified by Mr. Howard. The Expected (E) represents the expected death claims as calculated using the NNM2014 rates.

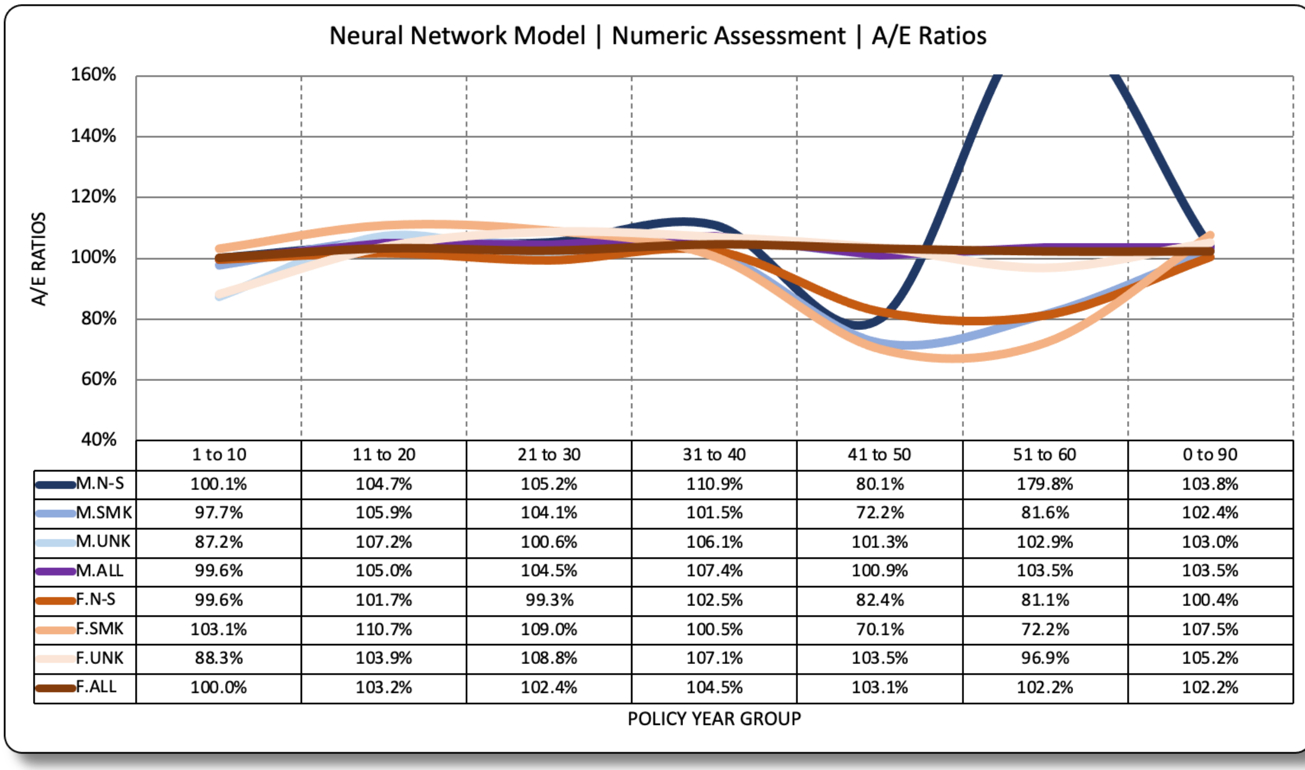
Compared to the ratios under the GAM2014, the ratios under the NNM2014 are more stable, albeit slightly biased to above 100.0%. In the younger issue ages, performance is overall close to actual. At the older issue ages, the NNM is slightly under the actual rates, specifically for females.



	0 to 19	20 to 29	30 to 39	40 to 70	25 to 80	0 to 90
M.N-S	107.0%	101.1%	102.3%	104.4%	103.8%	103.8%
M.SMK	92.3%	96.2%	101.3%	104.0%	102.8%	102.4%
M.UNK	101.8%	100.4%	102.8%	105.5%	103.7%	103.0%
M.ALL	101.1%	100.1%	102.2%	104.5%	103.6%	103.5%
F.N-S	94.6%	93.1%	99.7%	99.8%	100.2%	100.4%
F.SMK	78.6%	93.4%	104.9%	110.4%	108.8%	107.5%
F.UNK	100.2%	102.6%	110.5%	104.8%	106.1%	105.2%
F.ALL	94.3%	95.7%	102.4%	102.1%	102.3%	102.2%

ISSUE AGE GROUP

The following chart and table show the A/E ratios again, but this time for various policy years. The A/E ratios are showing a much better fit than the GAM in the later policy years despite the sparse data, albeit still showing some deviation from 100%. Notably, the male non-smokers in policy years older than 51 shows a high level of variation. It is noted that there was a particularly large claim for male non-smokers in the advanced ages, which is driving the ratio higher.

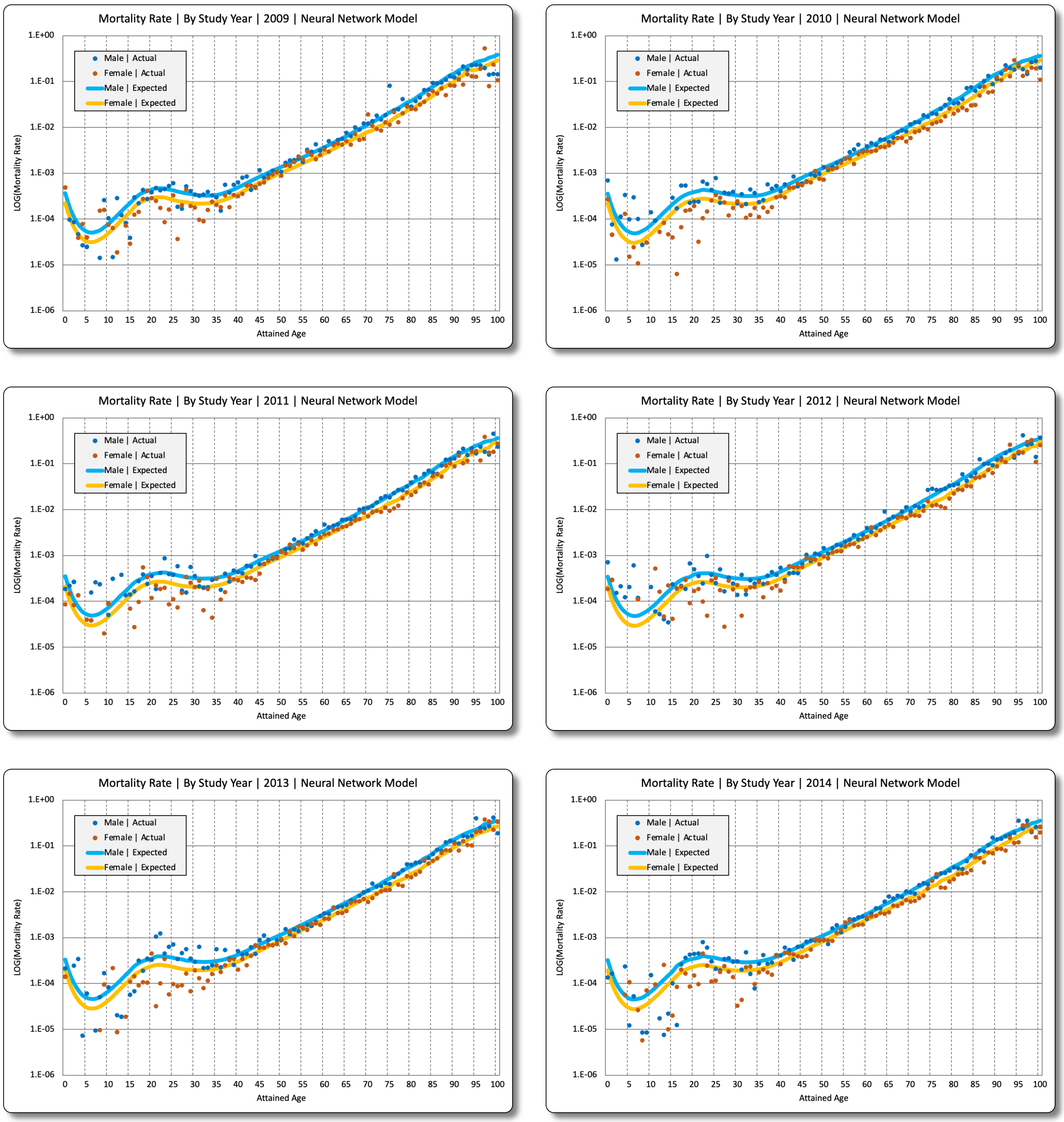


	1 to 10	11 to 20	21 to 30	31 to 40	41 to 50	51 to 60	0 to 90
M.N-S	100.1%	104.7%	105.2%	110.9%	80.1%	179.8%	103.8%
M.SMK	97.7%	105.9%	104.1%	101.5%	72.2%	81.6%	102.4%
M.UNK	87.2%	107.2%	100.6%	106.1%	101.3%	102.9%	103.0%
M.ALL	99.6%	105.0%	104.5%	107.4%	100.9%	103.5%	103.5%
F.N-S	99.6%	101.7%	99.3%	102.5%	82.4%	81.1%	100.4%
F.SMK	103.1%	110.7%	109.0%	100.5%	70.1%	72.2%	107.5%
F.UNK	88.3%	103.9%	108.8%	107.1%	103.5%	96.9%	105.2%
F.ALL	100.0%	103.2%	102.4%	104.5%	103.1%	102.2%	102.2%

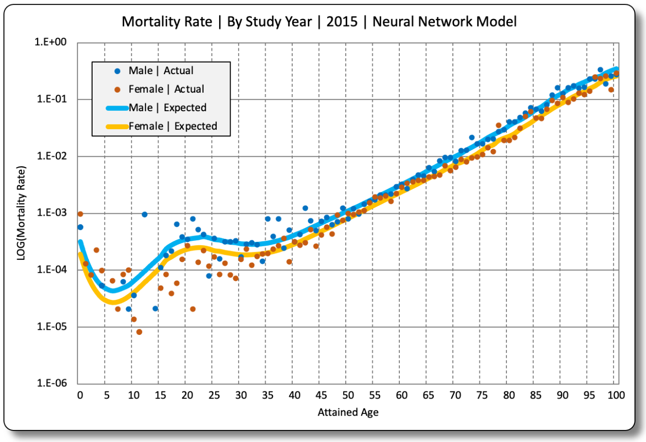
5.3.4. Visual Assessment

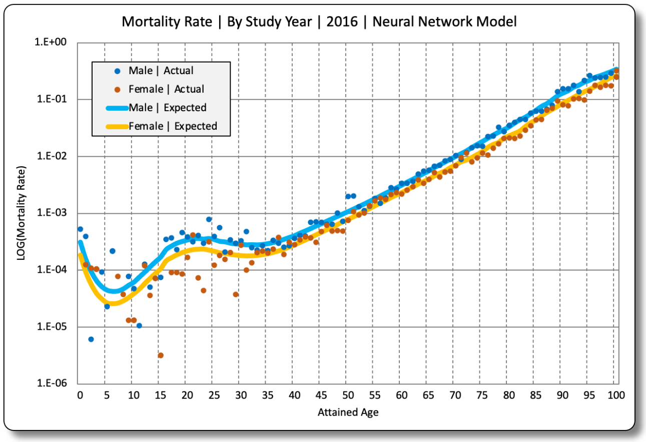
The following chart show the aggregated mortality curves for both male and female by year. The NNM has managed to fit the overall trend of the mortality curve, as well as the intricacies of younger ages.

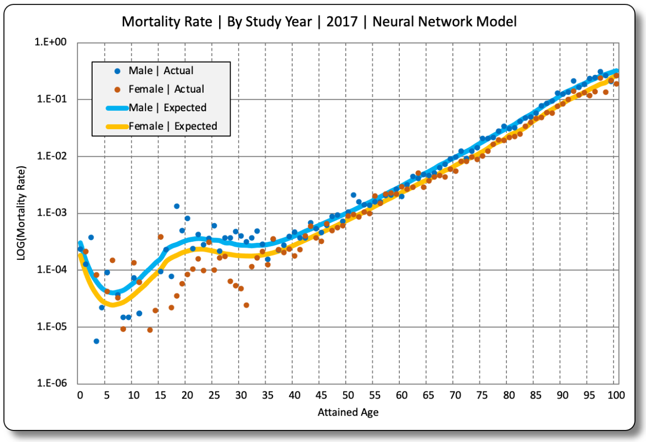
Mortality, actual versus expected, males and females, 2009–2019, aggregated across other fields, for the NNM

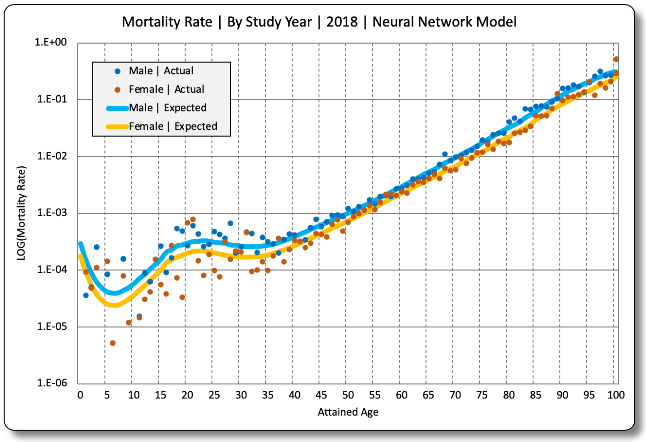


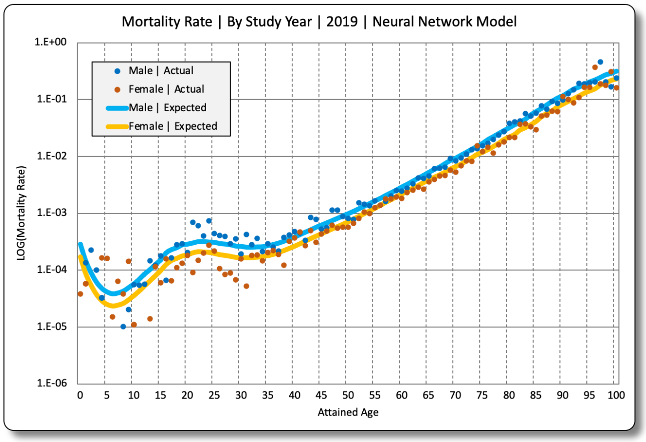
Mortality, actual versus expected, males and females, 2009–2019, aggregated across other fields, for the NNM

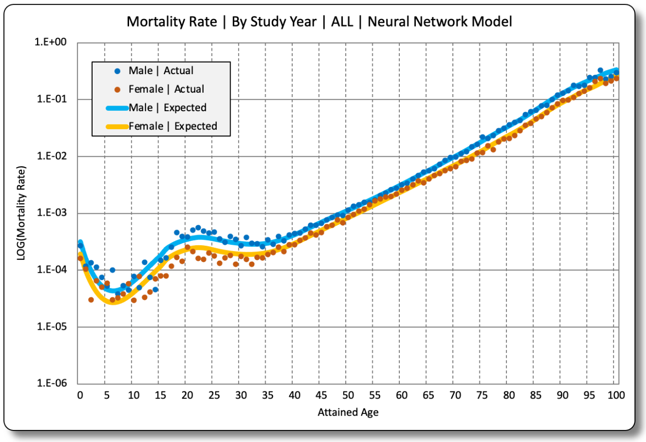






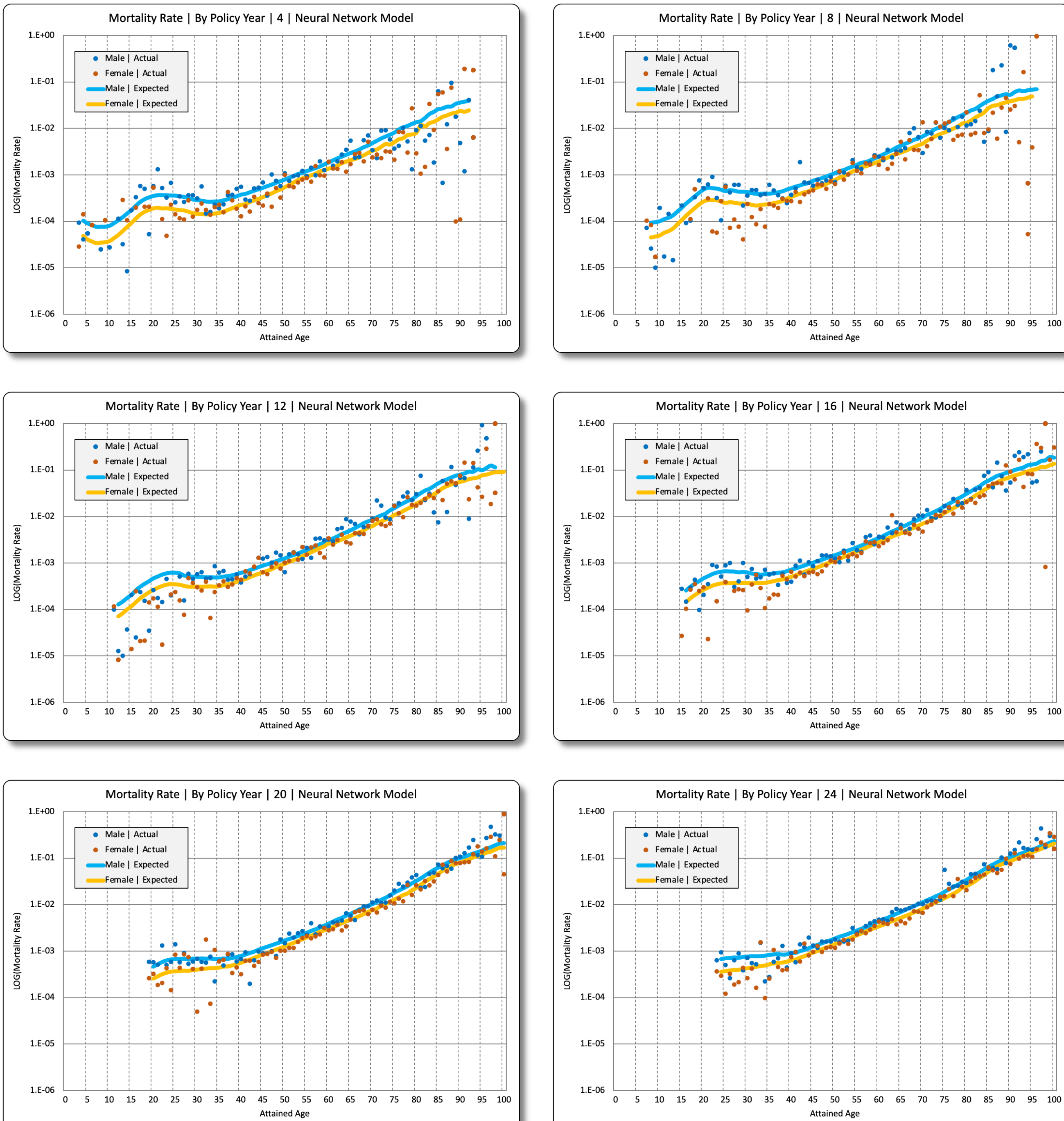






The following charts show the mortality curves for increments of four policy years. Again, the NNM has learned a clear trend of selection over time.

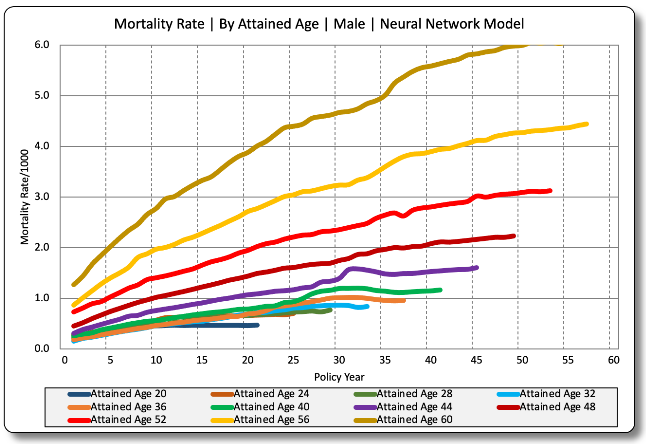
Mortality, actual versus expected, by sex, policy years 4–24 in increments of four, aggregated across other fields, for the NNM

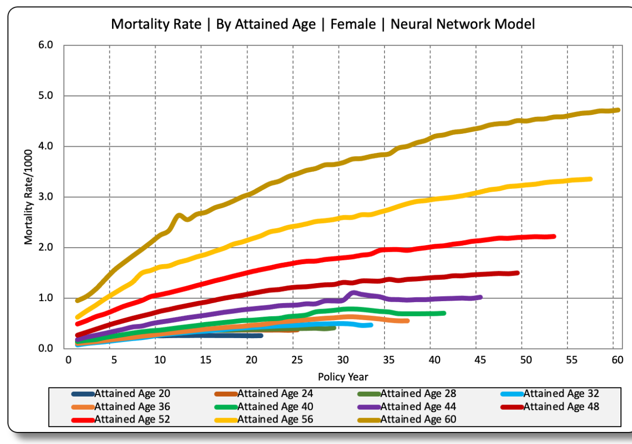


The following charts explicitly show mortality by policy year this time for the NNM2014 Table. We can see that mortality worsens across all ages, showing the select effect to continue for at least 60 years. The advantage of the NNM approach is that the user of the tables can choose their own select period, and then the ultimate rates can be derived from the remainder of the policy years.

Note that the overfitting observed in the GAM2014 Table is not present here. However, overfitting is still a risk and a possible improvement in future is to regularize the fit over policy years to restrain the model and reduce any possible overfitting.

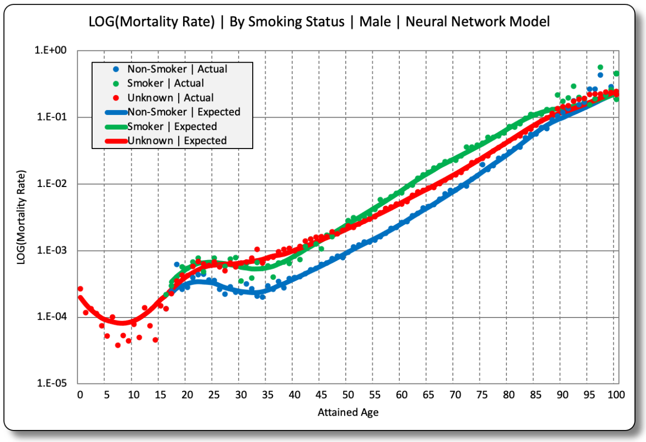
Mortality by policy year by gender, attained ages 20–60 in increments of four, aggregated across other fields, for the NNM

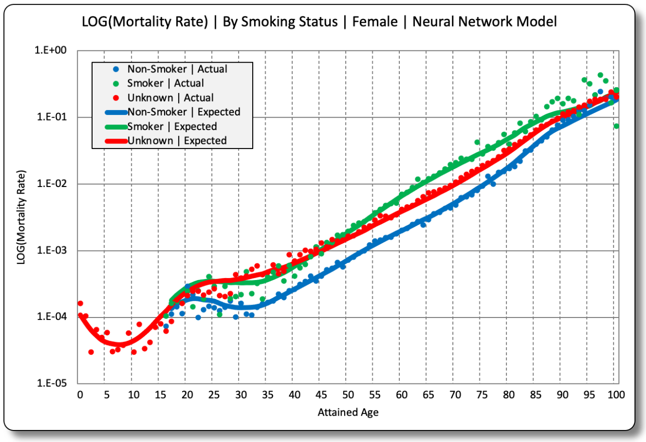




Compared to the GAM2014 Table, the NNM2014 Table is much more sensitive to changing mortality by age. This is more evident in the next charts which show how the model has differentiated between smoker and non-smoker in both genders, showing slightly higher mortality for smokers, and in fact slightly different curve shapes for smokers versus non-smokers, most notably for females. Examining the unknown curve, we also see how for some ages the mortality of unknown smokers is worse than that of known smokers.

Mortality, actual versus expected, males and females, smoker status, aggregated across other fields, for the NNM





6. NNM2014 versus GAM2014

6.1. Performance

The NNM2014 Table performs better than the GAM2014 Table. The GAM2014 Table has limitations in that there is a non-fixed but linear relationship between various classes. The NNM2014 Table eliminates this limitation so it fits the experience better. The NNM2014 Table in effect avoids an overfit in situations where the experience is not in line with the predictive model. We can think of it this way: *the model starts with the experience, iterates to generate the variables to create the rates, examine the fit, iterates new variables, and does it again*. If the experience does not fit some points (A) but fits most points (B), then the points (A) are dismissed. We should recall the CIA2014 Table with the female smoker age 85–90 group where the mortality *is traditionally not supposed* to exceed that of the male smoker group. But since the data show that it does, the WH method kept this characteristic, and the decision was made not to change it manually. GAM and NNM try to model the rates through variables and coefficients. If the variables are calibrated to produce all rates and generally (or typically) male rates are higher than female rates, it will then avoid this situation for the older female smoker rates. In terms of A/E, the NNM is worse than the GAM. The NNM is slightly more biased than the GAM and this leads to the results looking worse overall. However, it has a better overall fit and offers superior predictive ability per the other metrics.

6.2. Choice of Variables

One member of the POG asked if it would be possible to compare the fit with and without each variable, or by selecting only a few variables. For instance, one could compare the model results with all chosen variables versus the revised model results excluding the duration variable. This may provide some insight as to which variable is more important than another.

Although this may help us understand what is actually happening in the models, it would be a lot of work to perform and also to report in the appropriate manner. And if we were to exclude a variable which otherwise is considered crucial, say the issue age, then the model might just spin out of control. Excluding the observed calendar year may work because the only difference between calendar years is, *in theory*, the implied mortality improvement.

But here is an interesting question: what if there is really no intrinsic mortality improvement but in fact (say for Canada) the improvement is a result of global warming whereby winters are less severe over time? What if it is linked to changes in eating habits overall (everyone is more educated on the issue today than 20 years ago)? So, if we were to reach a stable climate or the pinnacle of eating habits, would mortality improvement stop?

Many other example can be found, including the COVID-19 pandemic. Although mortality increased temporarily in most countries due to the pandemic, it has decreased in some countries because of lockdowns. If, as a result of a pandemic scare, people travel less and less, would that contribute to mortality improvement overall due to the reduced number of accidental deaths?

So, it may just be that the passage of time is not the real reason for mortality improvement. We simply observe the correlation, which in fact, may not exist at all. Maybe the real variables to add to the model is a global warming index and a general population health index.

7. MORTALITY IMPROVEMENT

7.1. Implied Mortality Improvement

With the Neural Network Model technique, we are able to generate tables by calendar year. The table for calendar years 2009 to 2019 are meant to reflect the actual experience of these calendar years, while 2020 to 2024 were projected using the model. There is therefore an implied mortality improvement or deterioration from one table to the next.

The charts on the following page show the implied annual mortality improvement for various underwriting classes and issue ages, for each of the alternative methods. The calculation is a simple one:

$$^{Annual}MI_{[x+t]} = 1 - ({}^{2019}Rate_{[x+t]}/{}^{2009}Rate_{[x+t]})^{0.10}$$

where:

- $[x+t]$ is the attained age for issue age x at duration t;
- $MI_{[x+t]}$ is the mortality improvement for attained age x+t;
- ${}^{2019}Rate_{[x+t]}$ is the mortality rate for attained age x+t, in the 2019 table; and
- ${}^{2009}Rate_{[x+t]}$ is the mortality rate for attained age x+t, in the 2009 table.

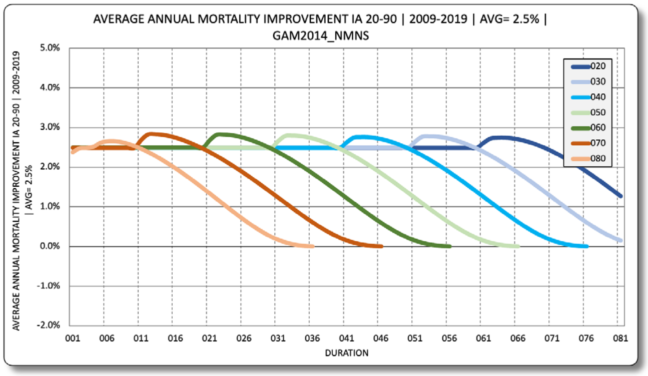
For the GAM, the mortality improvement is the same for all ages, gender and smoking status (2.5%). However, there is an out-of-model adjustment that trends the mortality improvement towards 0 at age 115.

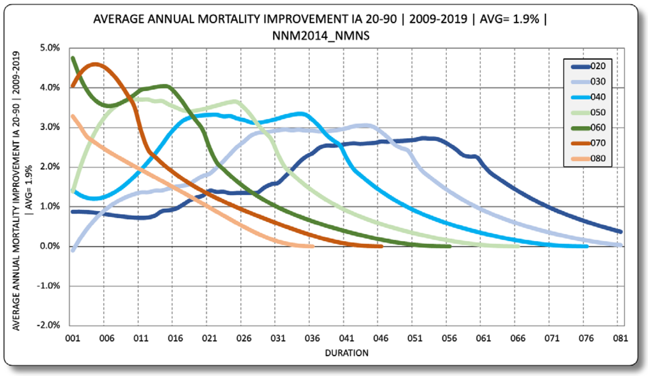
We have also added the weighted average annual rate for issue ages 20 to 90 at all attained ages. The weighted used were the exposure for the issue age and duration, aggregated over all exposure years 2009 to 2019. Although this is a single number and it could not of course be applied as an actual mortality improvement rate for actuarial calculations, it provides a certain measure of comparability between the overall methods and underwriting classes.

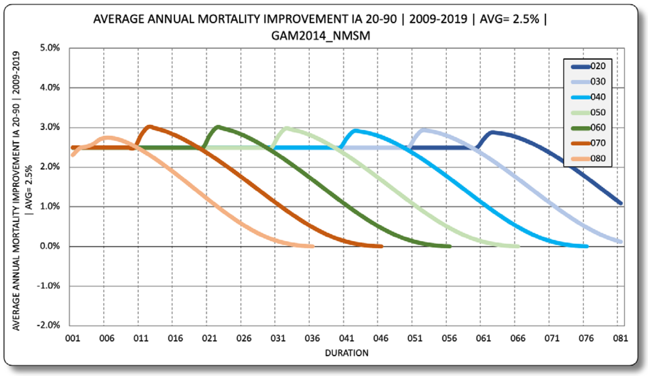
The following observations can be made:

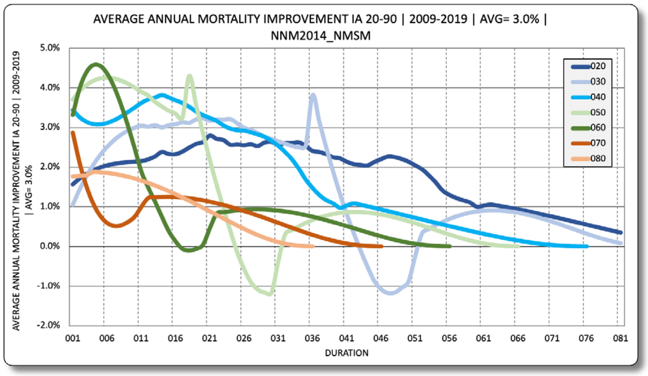
- Overall, the GAM2014 Table shows slightly higher mortality improvement (MI) rates than those under the NNM2014 Table.
- The MI rates under the GAM2014 Table are very close to each other and they certainly have the same pattern.
- The NNM2014 Table has a closer fit than the GAM2014 Table. We also see that the MI rates for male smokers are generally slightly higher than for female smokers. We have seen this empirical evidence for some time.
- Under the NNM2014 Table, and using the weighted average as the yardstick, the smoker MI rates are higher than the non-smoker ones, and especially for male, 3.0% versus 1.9%, and for female 2.5% versus 1.9%.

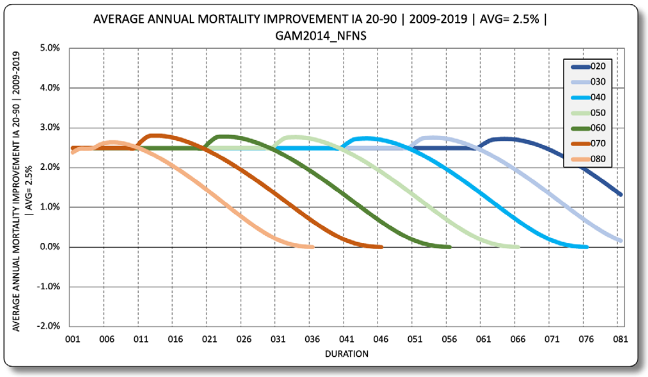
Implied Annual Mortality Improvement Rates 2009–2019

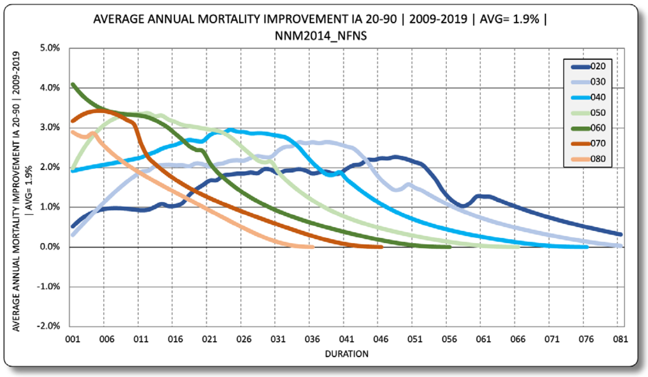


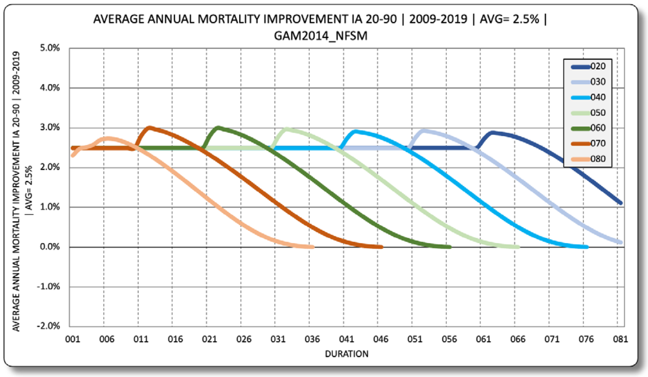


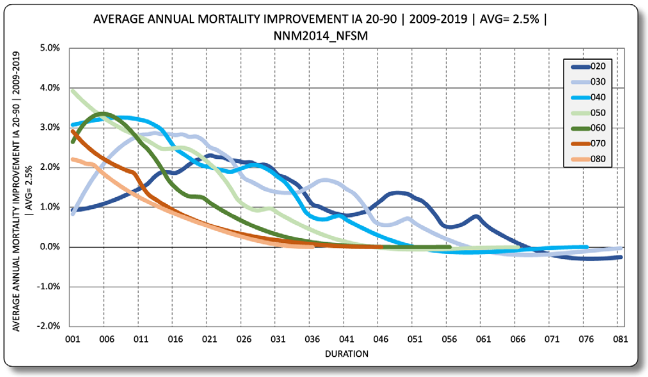












8. CONCLUSIONS

8.1. Viability of Mortality Graduation using Alternate Methods

In this report, we have used one widely adopted alternative method, the Generalized Additive Model (GAM), a more widely used alternative method, and, to our knowledge, one never before adopted method, the Neural Network Model (NNM) to build mortality tables based on mortality experience data. We believe, considering the results presented in this report, that these alternative methods can certainly be used successfully to derive mortality tables that are accurate and offer several advantages over traditional methods, such as the Whittaker-Henderson method.

The alternative methods offer several advantages which we detail below.

8.2. Advantages and Disadvantages of Alternate Methods over Traditional Graduation Methods

8.2.1. Predictive Ability

The first advantage offered by the alternative methods is that of predictive ability. The traditional method used to graduate mortality tables, such as the Whittaker-Henderson method, is not able to predict to unseen data as it simply fits a curve to observed data. Both alternative methods used in this report can predict future unseen mortality through the weights and biases estimated by the modelling approaches used. In fact, we have demonstrated the ability of these models to predict unseen future data by deriving mortality rates on observed data from 2009 until 2016, and then assessing predictive performance on the remaining years, 2017 to 2019. We have shown that both methods are able to predict well, with the NNM2014 table outperforming the GAM2014 table.

8.2.2. Richer Relationships between Predictors

The second advantage is that we can model much richer relationships between predictors, and we are less limited by missing data. One of the key reasons for using a 15-year or 20-year select period is that it becomes difficult to use longer select periods due to a lack of credible data. Both alternative methods learn a parametric representation of the data that allows them to reliably, or at least reasonably, extrapolate where data is sparse. Thus, we can have practically an unlimited select period, and model each issue age individually, with relative ease. This is the primary reason why the alternative methods outperform the traditional methods.

In addition, having no set select period removes the issues created by having one. It may also remove the underwriting differences observed at given ages or amounts. The select period also would vary by company since it reflects their own underwriting practices. Perhaps in future table construction, a much longer select period should be set, maybe 40–60 years, but using an NNM approach.

8.2.3. Easier to Derive and Update

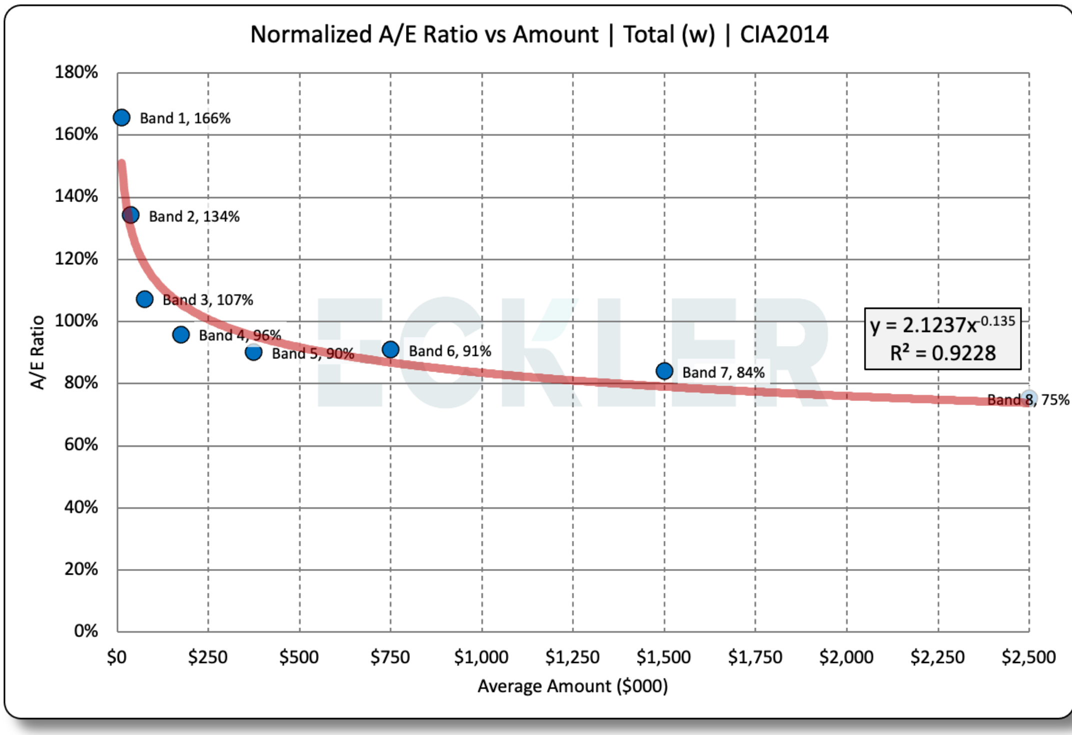
The advantages stretch further than prediction and unlimited select periods. We believe that the alternate tables are also easier to derive despite their additional modelling complexity and will allow for much more frequent analysis and updates of mortality experience if the data is readily available. In particular, due to the nature of the NNM, the rates can be updated incrementally each year as new data is provided. The neural network can remember the general shape of the mortality curve, and then use the updated data to make minor adjustments for emerging mortality experience, without needing to completely rebuild the model from the ground up.

The CIA produces A/E ratios with each additional passing year using updated experience from companies. Using an alternative method like the NNM for instance would permit the actual mortality table to be reliably updated without much additional effort.

8.2.4. More Granular Levels of Detail

Although not fully demonstrated in this report, both the GAM and NNM can extend to much more granular levels of detail. In an early draft of the tables, we had derived mortality tables by year, duration, smoker status, sex, issue age, and size band. We decided against including size band as this led to the report and analysis being unnecessarily complicated. However, one can see that such abilities can be of use.

Even without complicating the models, extensions can be added to a particular final table to complete it and to add new features. For example, with respect to size, we can show the relationship between mortality and policy size using the empirical experience behind the CIA2014 Table. The following was derived on a combined basis, namely male and female, non-smoker, smoker, and unknown:



So, the above fitting power curve, % Table = 2.1237•(FACE/1000)$^{-0.135}$, can be used to derive the percentage of the table assumption for any number of band sizes. The correlation factor of 0.9228 is high enough to be reliable. A logarithmic curve would also work, % Table = -0.152•LN(FACE/1000) + 1.878, but the correlation factor is inferior at 0.8683.

The table below is an example where the average size within a band could be used or the lower end of the band as an additional margin, using the power curve illustrated above:

% Table = 2.1237•(FACE/1000)$^{-0.1350}$				
Band | Low	Band | High	Average	% Table (Avg)	% Table (Low)
$10,000	$24,999	$17,000	145.0%	155.0%
$25,000	$49,999	$37,000	130.0%	140.0%
$50,000	$99,999	$75,000	120.0%	125.0%
$100,000	$249,999	$175,000	105.0%	115.0%
$250,000	$499,999	$375,000	95.0%	100.0%
$500,000	$999,999	$750,000	85.0%	90.0%
$1,000,000	$2,499,999	$1,750,000	75.0%	85.0%
$2,500,000	$4,999,999	$3,750,000	70.0%	75.0%
$5,000,000	$9,999,999	$7,500,000	65.0%	65.0%
$10,000,000	$10,000,000	$10,000,000	60.0%	60.0%

8.2.5. Additional Ability for Insight

Although NNMs are often criticized as being *black box* models that are difficult to interpret, there is active research on improving their *explainability*. The powerful feature representation learning ability of NNMs allows them to uncover many relationships between the features and mortality, providing additional insight into what is impacting mortality and how. This can be used to develop a richer understanding of what factors may be affecting population mortality. Current research shows that the interpretability benefits of generalized linear models can be combined with the superior predictive power of NNMs to uncover both linear and nonlinear effects on mortality. Those interested in a deeper discussion are referred to Richman (2021a)[4], Richman (2021b)[5], and Richman (2021b)[6].

8.2.6. Overfitting

The added power of these alternative methods introduces an increased risk of overfitting. Overfitting occurs when a model fits too closely to the data and thus is unable to generalize and hence has limited predictive power. This can be particularly troublesome when subsets of the data exhibit irregularities that are not expected to repeat, thus leading the model to create in incorrect representation of the data. Overfitting is not unique to the GAM or NNM, but their additional non-linearity exacerbates overfitting if it is not handled correctly. Evidence of overfitting is seen in the GAM2014 Table where the mortality rate by policy year decreases in the late ages, which is not expected. There are methods to minimize and handle overfitting, and some effort has been made in this work. However, care must still be taken when using these tables as there is the risk that of overfitting, and further improvements to reduce overfitting could be made.

When examining this type of work, it is useful to assume extreme situations. Imagine that we have two models, one using five variables and another one using 10 variables. The model using 10 variables will have a tendency to overfit the data because we have more variables to consider the differences between the data set. Using another extreme, if a model used one variable, overfitting would be virtually impossible. But of course, it will have a near zero correlation with the data. So, the number of variables as well as which variables are important. We all know intuitively that

[4] Richman, Ronald, Mind the Gap - Safely Incorporating Deep Learning Models into the Actuarial Toolkit (April 2, 2021). Available at SSRN: https://ssrn.com/abstract=3857693 or http://dx.doi.org/10.2139/ssrn.3857693. A copy is provided with the present report.
[5] Richman, Ronald and Wüthrich, Mario V., LocalGLMnet: interpretable deep learning for tabular data (July 26, 2021). Available at arXiv: https://arxiv.org/abs/2107.11059v1. A copy is provided with the present report.
[6] Richman, Ronald, AI in Actuarial Science, The State of the Art | ASTIN Webinar. Available at: https://www.youtube.com/watch?v=X0zYnkAopmQ.

gender, smoking, age, and duration (attained age, policy year) are a must. We have added calendar year. As we mentioned earlier, maybe a global warming index and a general population health index could replace calendar year. And as stated in the introduction, putting fewer constraints on these variables may cause the final rates to deviate from the observed data, while putting more constraints may result in overfitting the data.

8.2.7. Judgment or Adjustments Needed

There are still judgment or adjustments needed while using the NNM and GAM. This is particularly the case where there is less data as the formula may predict strange rates. The traditional methods try to reproduce the actual data while the alternative methods try to interpret what the actual data are indicating. The sex inversion for older smoker rates for instance is such a situation. Another situation is where the rates converge smoothly to 1.00 at the extreme old ages under the alternative methods while the rates are relatively flat under the traditional methods.

8.3. Concluding Remarks

We hope that this report provides an interesting and exciting view into the application of non-traditional methods to constructing mortality tables. We believe that the NNM2014 Table is the first ever fully constructed mortality table using a NNM. If the CIA chooses to adopt the NNM2014 Table as an alternate table for practical use or for education and training purposes, we believe that it will be the first ever NNM derived mortality table adopted for industry use. This would certainly be considered forward looking for the profession.

Although we believe both alternate tables could be used, we recommend the NNM2014 Table as it offers superior predictive accuracy and much richer non-linear relationships between different smoker and sex statuses. For instance, in all modern and recent life insurance mortality studies, the relationship between smoker and non-smoker mortality has long been observed as a non-linear one. At the younger ages, the SM/NS ratio may be 1.50, increasing to 2.50–2.75 at around ages 55–60, then decreasing towards 1.00 at the very old ages. Because of the linear nature of GAMs, this relationship is linear for most attained ages. For MNS, the ratio is 2.50 at age 20 decreasing in a linear fashion to 2.35 at age 90, and then to 1.00 at age 115. So, although the overall fit might be fine, the result certainly would not be acceptable or at least not as expected.

Finally, one may ask whether using such alternative methods and particularly one based on NNMs, is practical. Although our results clearly show a positive outcome in using these methods, they are new in the construction of mortality tables. As such, they are not time tested, even if the results are positive. NNMs are also more difficult to understand and program than Whittaker-Henderson graduation models. However, we will encourage the CIA to explore such techniques through additional research and education.

In addition to this report, we have also built an R Shiny dashboard that allows actuaries to interact with the tables directly in a dynamic environment. The dashboard can be accessed here.

8.4. Tables Offered in Excel

We will also provide the various tables in Excel format for easy comparison. This will include the following:

- the CIA8692 Table (12): ANB/ALB x M/F x NS/SM/AG;
- the CIA9704 Table (12): ANB/ALB x M/F x NS/SM/AG;
- the new CIA2014 Table (16): ANB/ALB x M/F x NS/SM/AG/UN;
- the GAM2014 Table (136): ANB x M/F x NS/SM/AG/UN x 17 years (2009 to 2024, plus combined 2009–2019); and
- the NNM2014 Table (136): ANB x M/F x NS/SM/AG/UN x 17 years (2009 to 2024, plus combined 2009–2019).

User friendly input to generate comparative charts will also be provided to facilitate comparisons.

A. ASSESSMENT OF THE CIA2014 TABLE

This appendix includes an assessment of the CIA2014 Table in line with that performed for the alternative methods above for comparison. Note that the comparison is not direct as the data used is slightly different. For the CIA2014 Table, a select period of 20 years was chosen and a separate graduation performed for each. Also, the fitting was not performed with prediction as an objective, so there are no in-sample versus out-sample comparisons to make. Therefore, we include the assessment for the total data set split into select and ultimate rates. We provide comparison figures for each alternative method.

A.1. Numeric Assessment | Select and Ultimate Periods

CIA2014 Table | Numeric Assessment		
	Select	Ultimate
Poisson Deviance	187.42	47.23
Kolmogorov-Smirnov	0.27	1.00

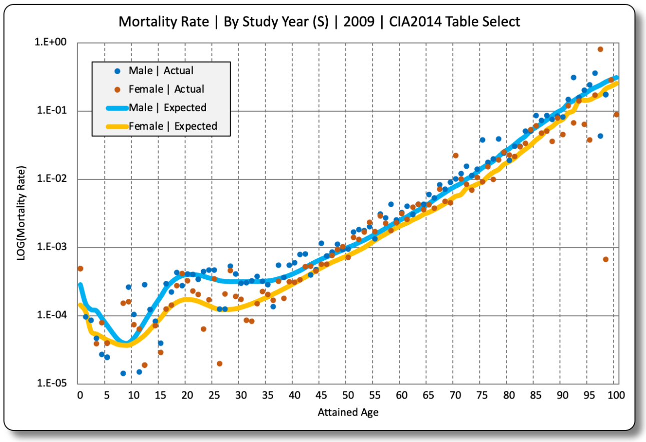
The graduated CIA2014 Table performs comparatively well with the alternative methods in terms of Poisson deviance on the select data and on the ultimate data. Looking at the KS metric, the select data shows weak similarity between distributions, performing worse than both the GAM2014 and the NNM2014. For the ultimate rates, the KS statistic shows very strong similarity, and performing slightly better than both the GAM2014 and the NNM2014.

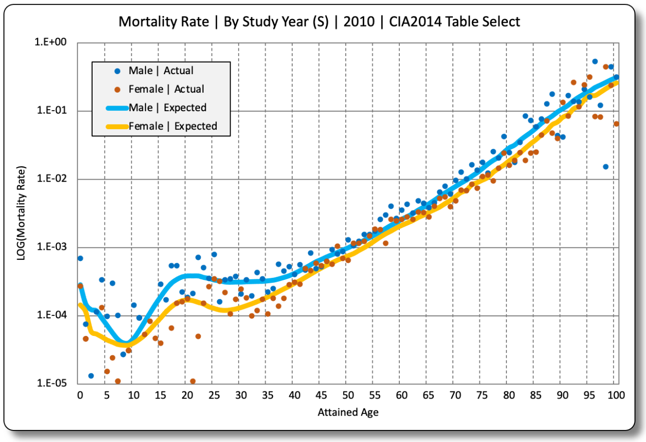
A.2. Visual Assessment

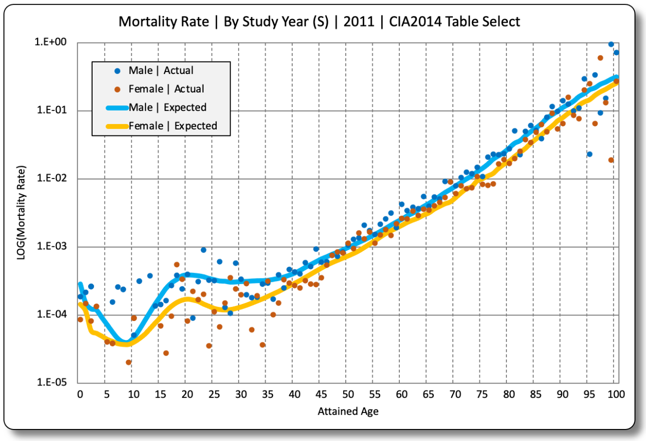
A.2.1. Select Period

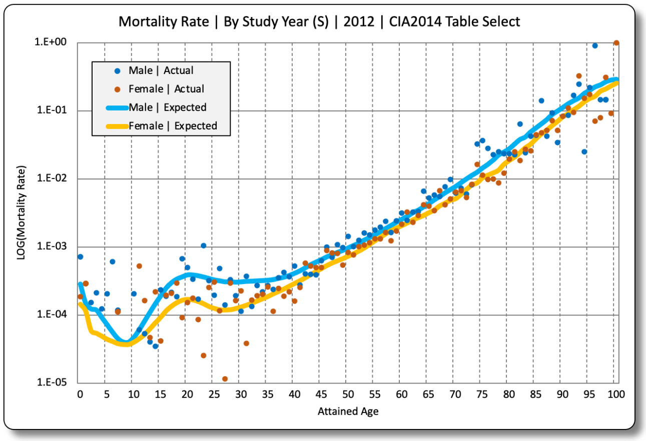
The following charts show a strong fit visual to the underlying data even across years, which the tables were not designed to do. We do note slight underestimating of mortality in the earlier years, however the figures were not adjusted for mortality trends.

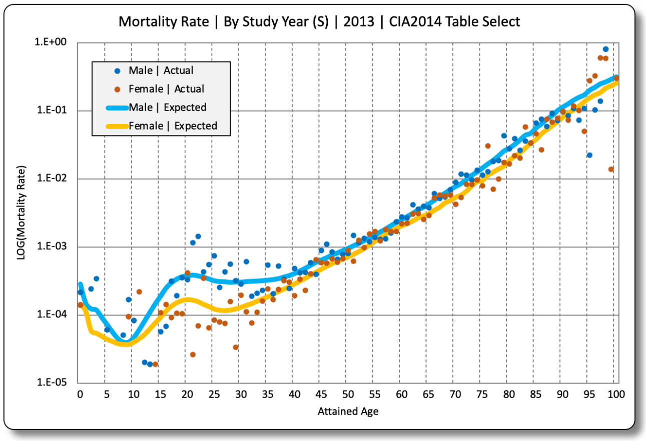
Mortality, actual versus expected, males and females, 2009–2019, aggregated across other fields, for the CIA2014 Select

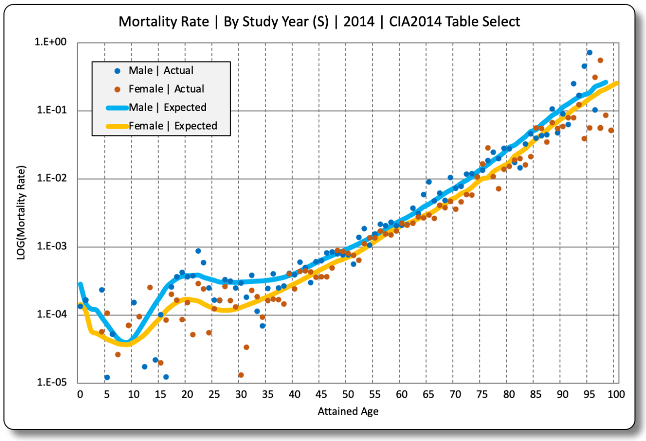




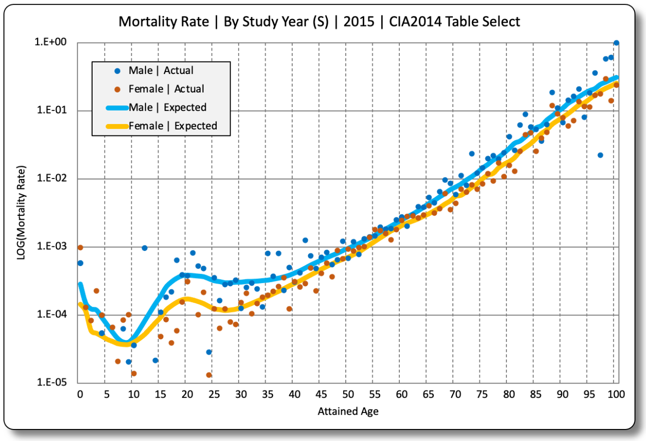


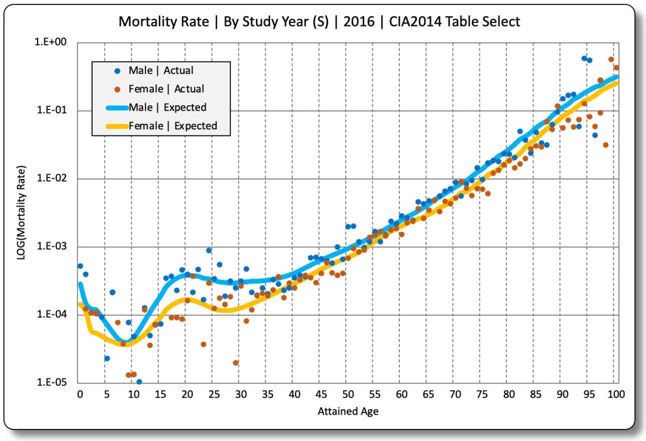


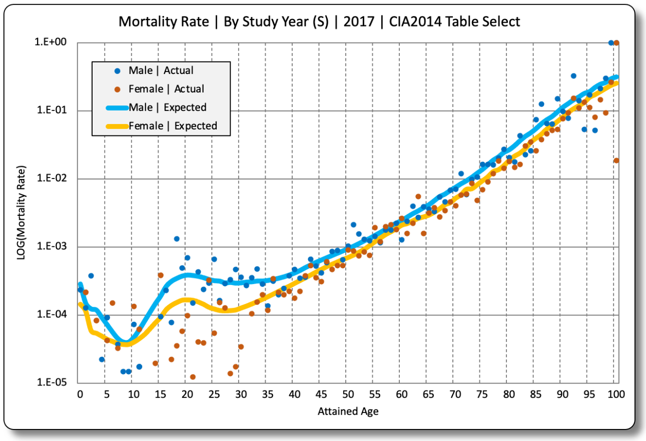


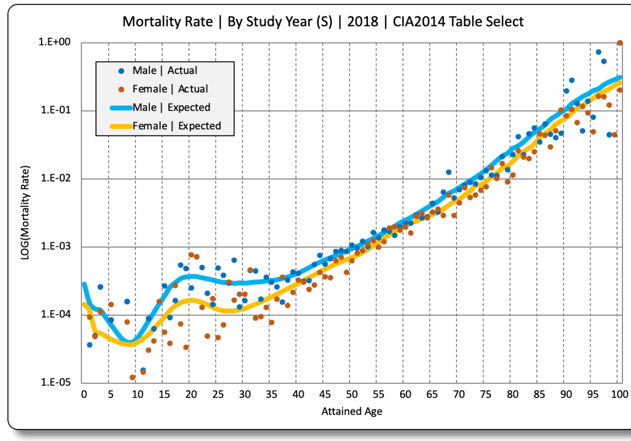


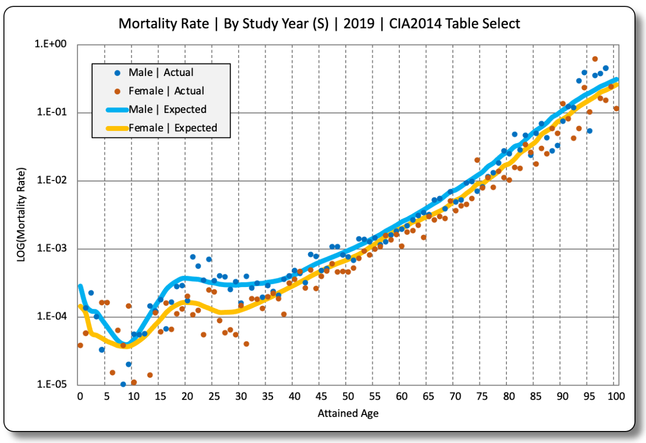
Mortality, actual versus expected, males and females, 2009–2019, aggregated across other fields, for the CIA2014 Select

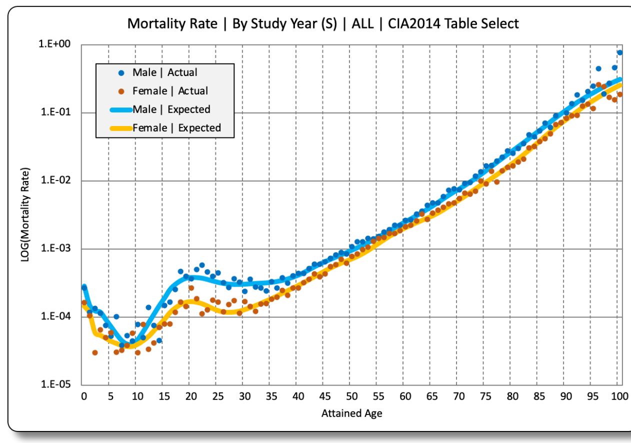






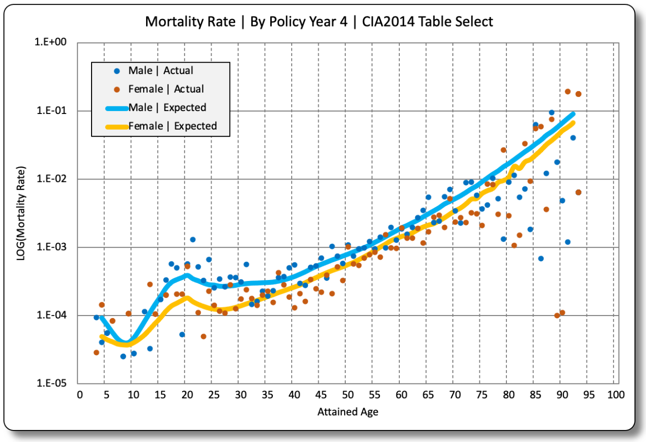


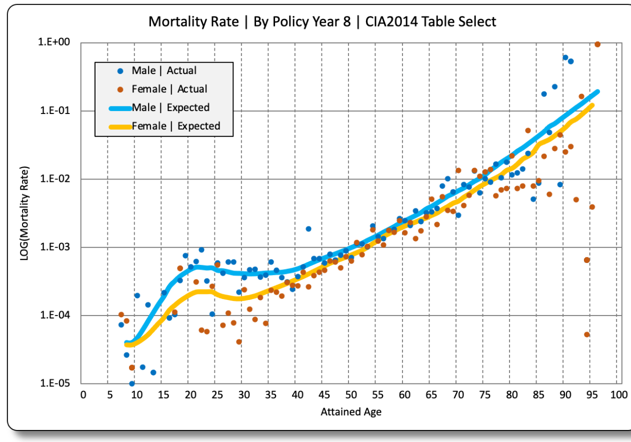


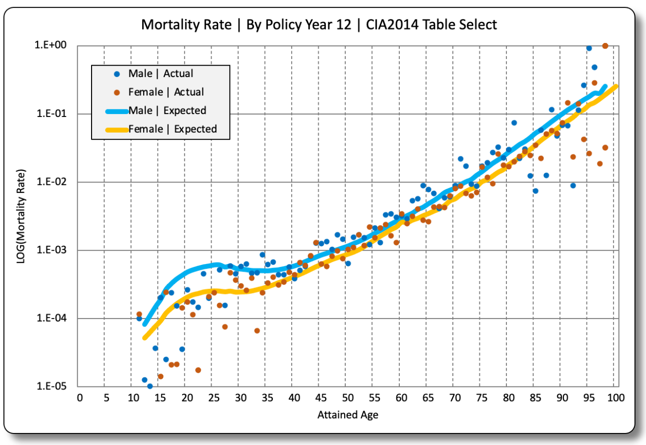


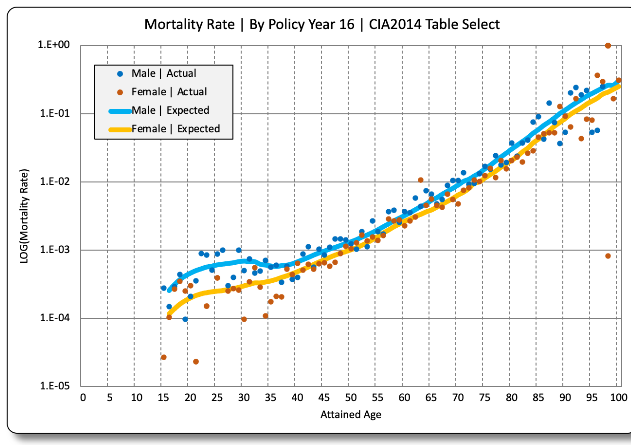
Looking at the fit by policy year, again, the CIA2014 Table fit well all throughout, as shown in the following charts.

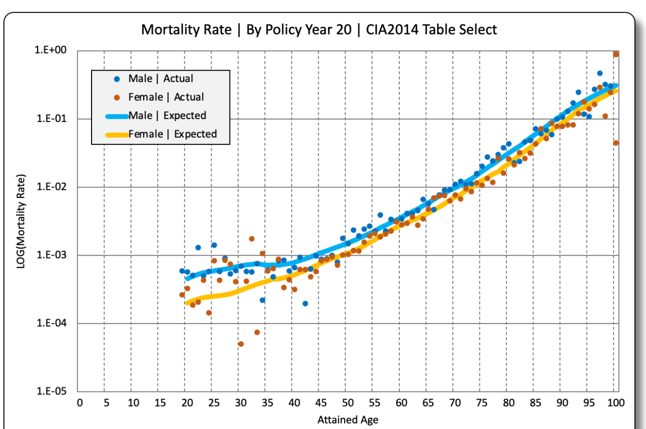
Mortality, actual versus expected, by sex, policy years 4–20 in increments of four, aggregated across other fields, for CIA2014 Select





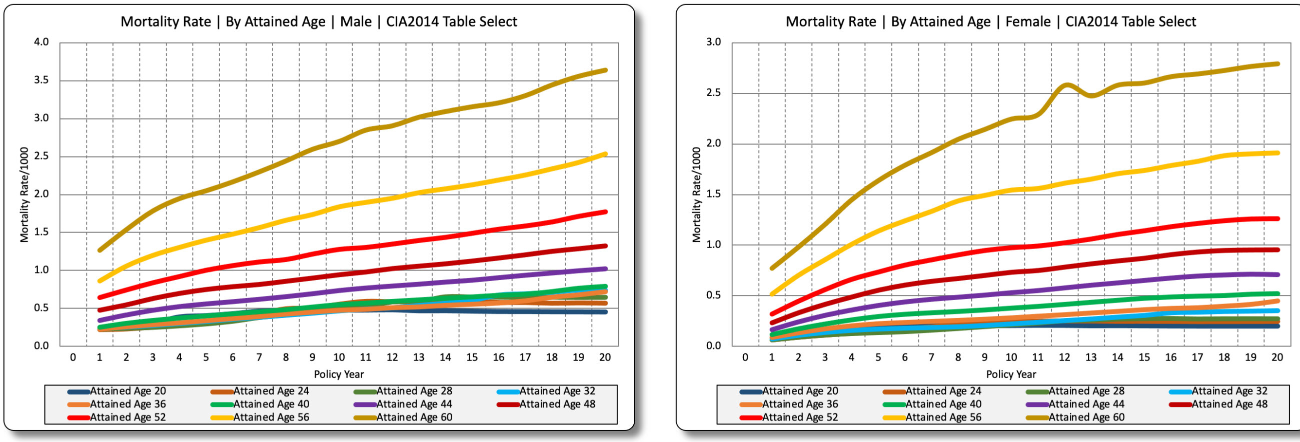






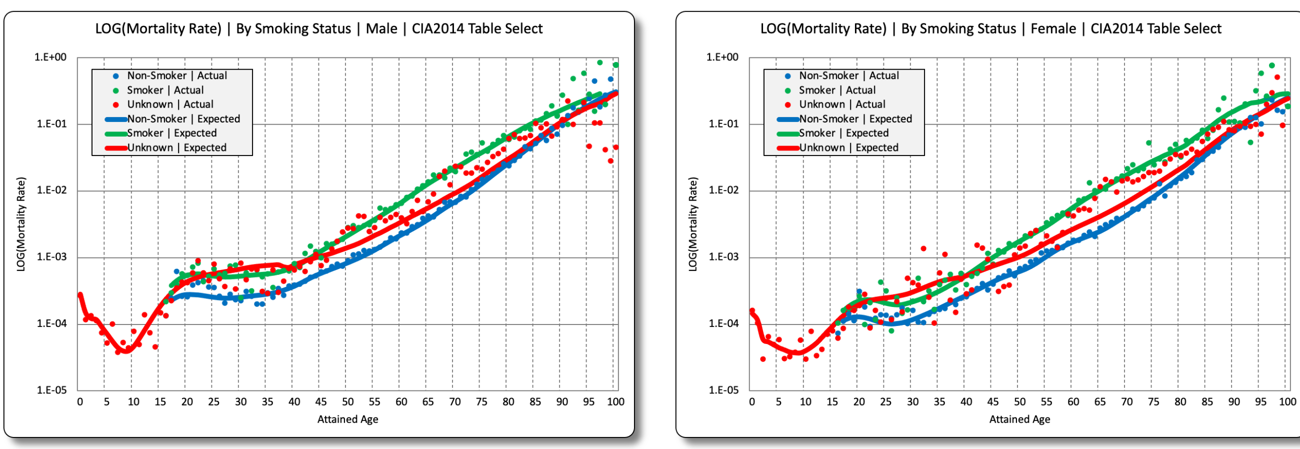
The following charts show that mortality slowly deteriorates throughout the select period in a smooth fashion.

Mortality by policy year by gender, attained ages 20–60 in increments of four, aggregated across other fields, for CIA2014 Select



Finally, considering gender and smoker status, we see from the following charts that the CIA2014 Table fails to fit well to unknown smoker status, but fit the other statuses well. It should be remembered that the CIA2014 Table did not produce explicit select rates for smoker status unknown because of lack of credible data. Select rates of *smoking all* were used for smoking unknown.

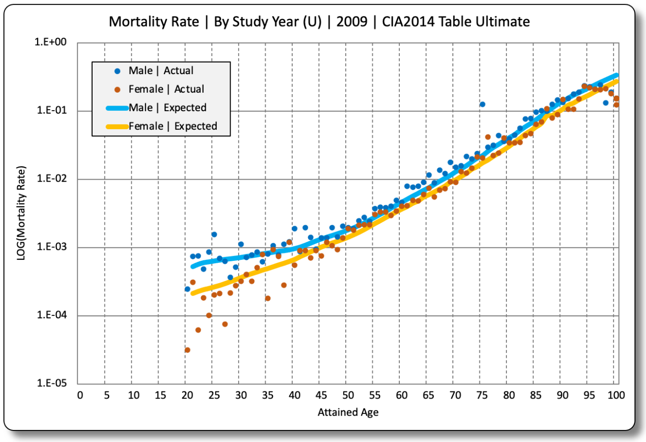
Mortality, actual versus expected, males and females, smoker status, aggregated across other fields, for CIA2014 Select

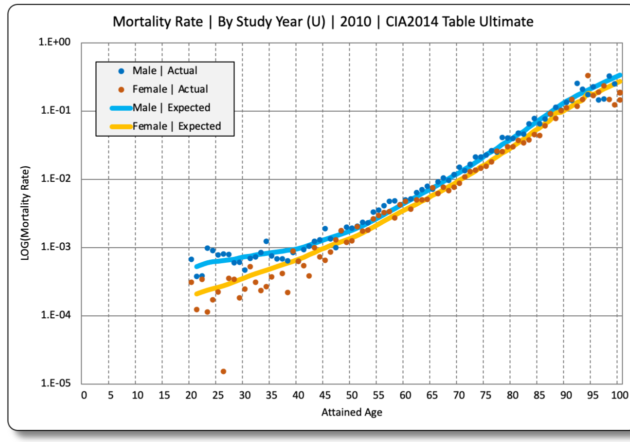


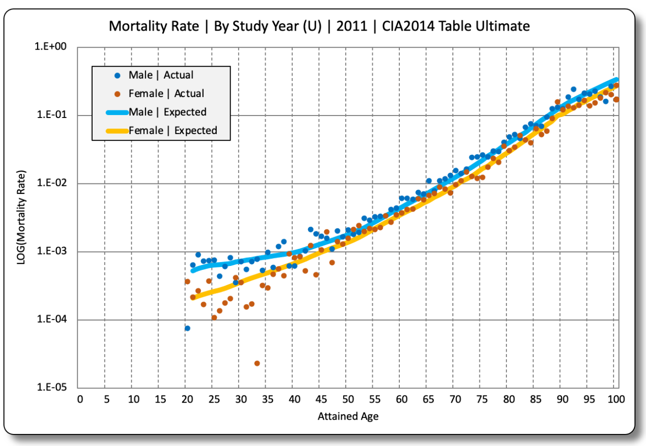
A.2.2. Ultimate Period

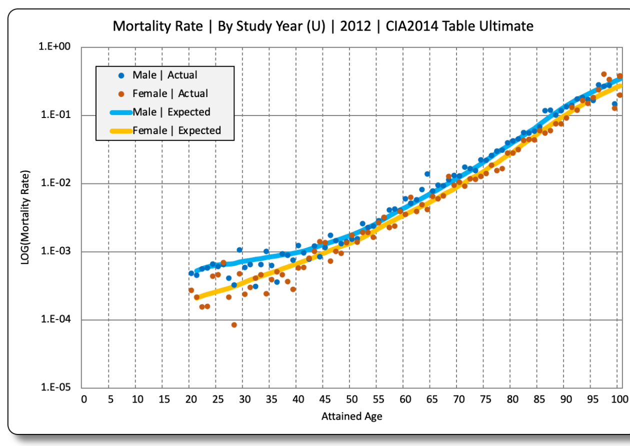
The following charts show a strong fit to the ultimate data, even across years.

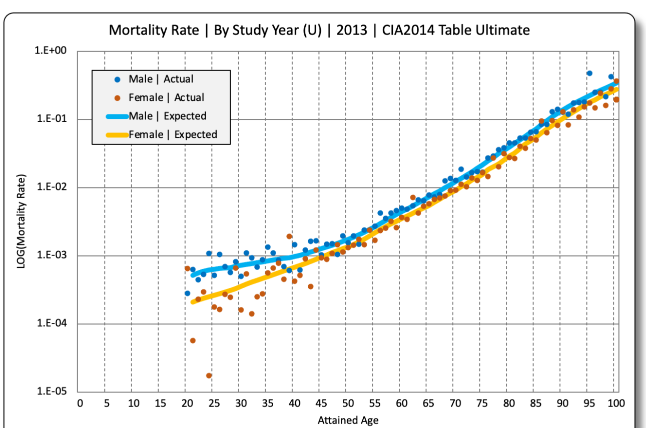
Mortality, actual versus expected, males and females, 2009–2019, aggregated across other fields, for the CIA2014 Ultimate

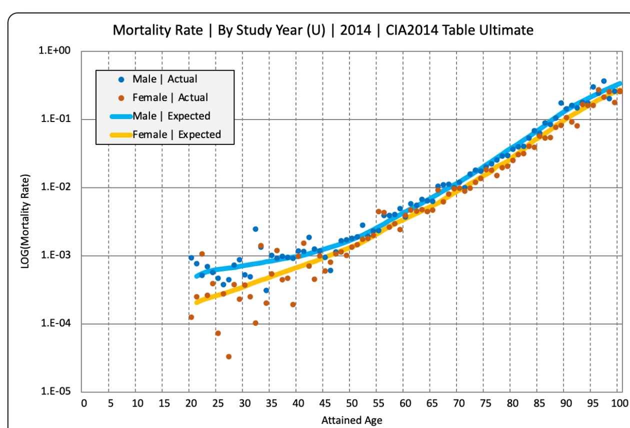




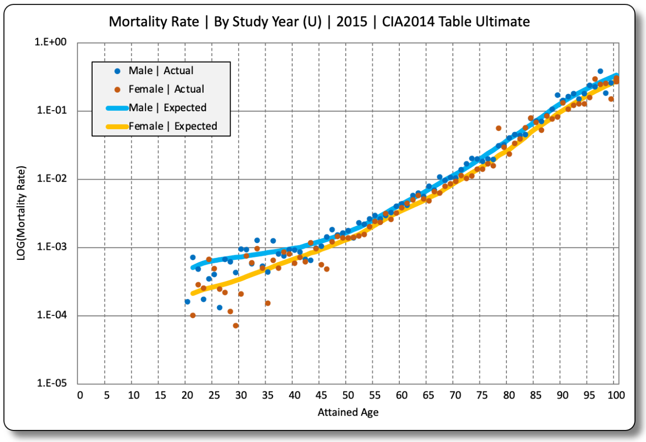


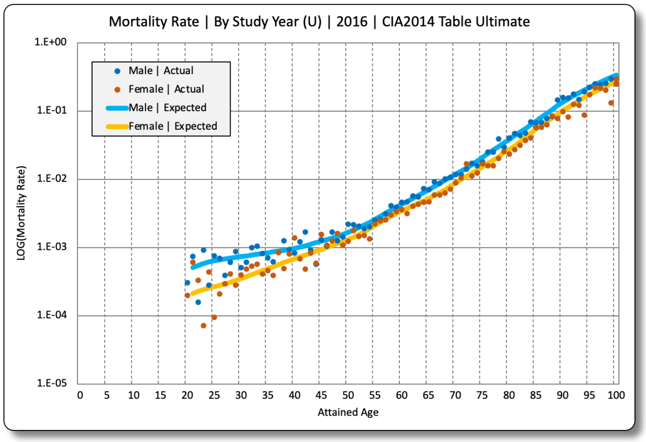


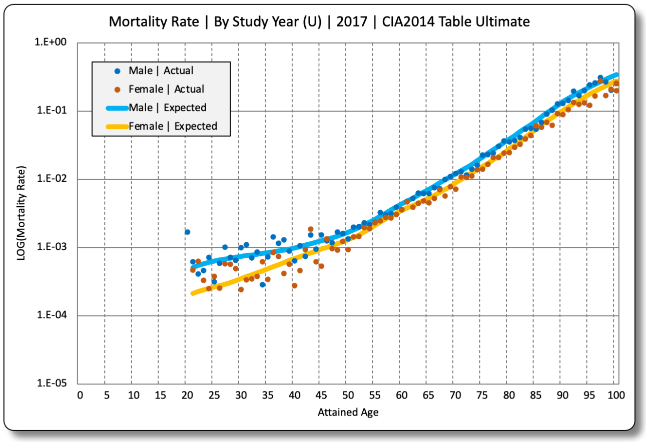


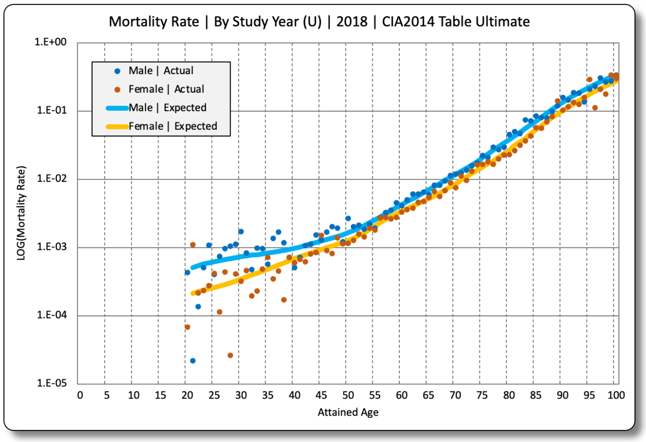


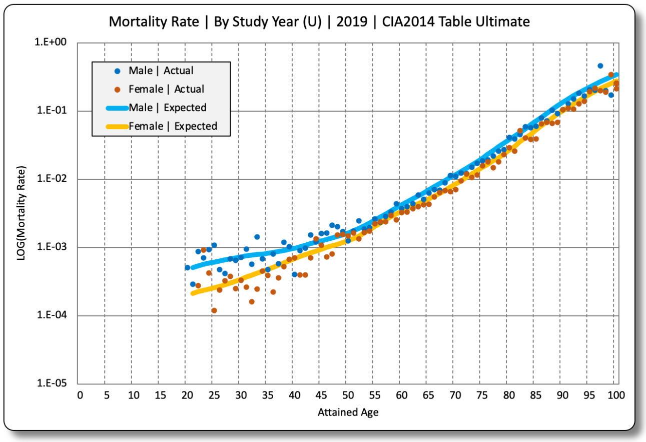
Mortality, actual versus expected, males and females, 2009–2019, aggregated across other fields, for the CIA2014 Ultimate

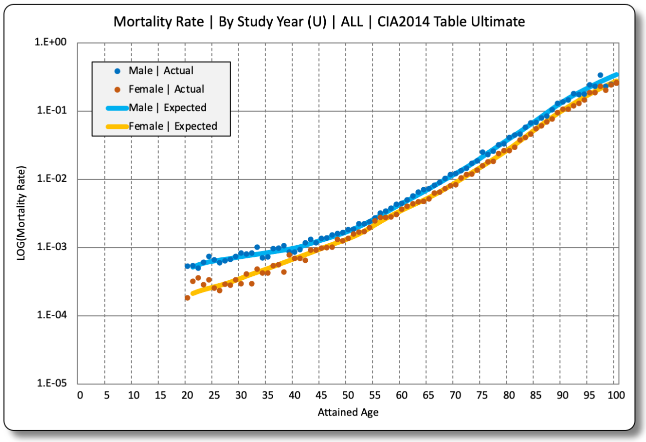






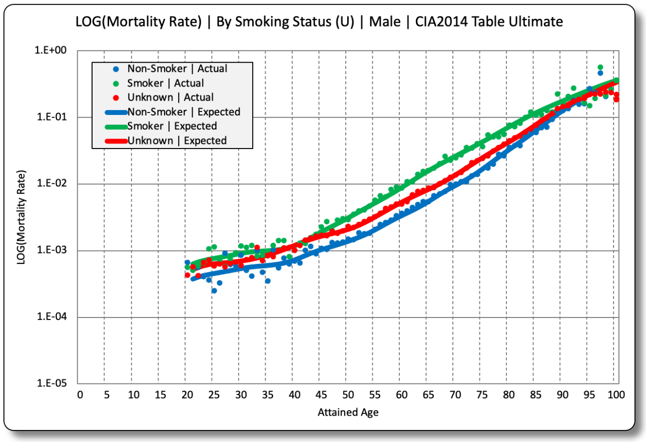


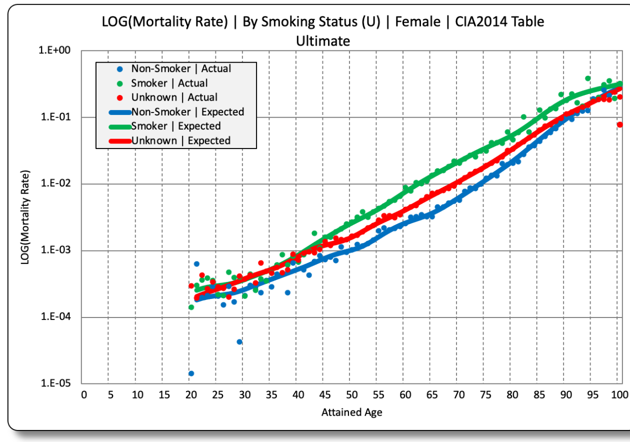




Finally, considering gender and smoker status, we see that the CIA2014 Ultimate tables continue to fit strongly, showing a much better fit to unknown status, as evidenced in the following charts.

Mortality, actual versus expected, males and females, smoker status, aggregated across other fields, for CIA2014 Ultimate





B. SUMMARY OF THE PREDICTORS USED IN THE ALTERNATIVE METHODS

This appendix includes a summary of the predictors used for the methods demonstrated in this report. Some descriptions are taken from the Howard Report detailing the graduation of the CIA2014 Table entitled "*CIA2014: A mortality table constructed from the CIA individual insurance data of policy years 2009–2019*". The following terms are defined:

Predictor	Description
Year	The calendar year from which the experience is derived.
IssueAge	The age at which the policy was issued.
PolYear	The year of experience relative to policy inception. For example, PolYear 2 refers to the second year of experience since policy inception.
AttdAge	IssueAge + PolYear – 1.
Sex	Sex of the insured under the policy, male or female.
Smoke	Smoker status of the insured under the policy, Smoker, Non-Smoker, Aggregate, or Unknown.

C. GAM REGRESSION RESULTS

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                 DthAmt   No. Observations:               184064
Model:                         GLMGam   Df Residuals:                184026.00
Model Family:                 Poisson   Df Model:                        37.00
Link Function:                    log   Scale:                          1.0000
Method:                         PIRLS   Log-Likelihood:            -8.6077e+09
Date:                Wed, 05 Jan 2022   Deviance:                   1.7214e+10
Time:                        13:21:22   Pearson chi2:                 3.20e+10
No. Iterations:                    13
Covariance Type:            nonrobust
=====================================================================================================
                                      coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------------------
Intercept                          45.5713      0.006   7020.137      0.000      45.559      45.584
C(Sex)[T.2]                        -0.6506      0.000  -4160.335      0.000      -0.651      -0.650
C(Smoke)[T.2]                      -0.9830      0.000  -9368.669      0.000      -0.983      -0.983
C(Smoke)[T.3]                      -0.3852      0.000  -2579.659      0.000      -0.386      -0.385
C(Sex)[T.2]:C(Smoke)[T.2]           0.3730      0.000   2124.427      0.000       0.373       0.373
C(Sex)[T.2]:C(Smoke)[T.3]           0.1902      0.000    790.738      0.000       0.190       0.191
Year                               -0.0263   3.21e-06  -8202.798      0.000      -0.026      -0.026
IssueAge                           -0.0199   1.11e-05  -1789.103      0.000      -0.020      -0.020
AttdAge                             0.0658   1.36e-05   4846.475      0.000       0.066       0.066
C(Sex)[T.2]:AttdAge                 0.0057   2.45e-06   2326.155      0.000       0.006       0.006
C(Smoke)[T.2]:AttdAge               0.0012   1.68e-06    731.259      0.000       0.001       0.001
C(Smoke)[T.3]:AttdAge              -0.0036   2.19e-06  -1663.495      0.000      -0.004      -0.004
C(Sex)[T.2]:C(Smoke)[T.2]:AttdAge  -0.0066   2.72e-06  -2425.935      0.000      -0.007      -0.007
C(Sex)[T.2]:C(Smoke)[T.3]:AttdAge  -0.0032   3.43e-06   -941.104      0.000      -0.003      -0.003
AttdAge_s0                         -5.5797      0.002  -3388.897      0.000      -5.583      -5.576
AttdAge_s1                         -1.5561      0.001  -1589.387      0.000      -1.558      -1.554
AttdAge_s2                         -0.9920      0.001  -1187.500      0.000      -0.994      -0.990
AttdAge_s3                         -2.6754      0.000  -6265.888      0.000      -2.676      -2.675
AttdAge_s4                         -1.8028      0.000  -5928.005      0.000      -1.803      -1.802
AttdAge_s5                         -1.7399      0.000  -7864.269      0.000      -1.740      -1.740
AttdAge_s6                         -1.3178      0.000  -7182.186      0.000      -1.318      -1.317
AttdAge_s7                         -1.1086      0.000  -8026.001      0.000      -1.109      -1.108
AttdAge_s8                         -0.7248      0.000  -6256.447      0.000      -0.725      -0.725
AttdAge_s9                         -0.5407      0.000  -5318.657      0.000      -0.541      -0.540
AttdAge_s10                        -0.0245      0.000   -226.377      0.000      -0.025      -0.024
AttdAge_s11                         0.0270      0.000    205.278      0.000       0.027       0.027
AttdAge_s12                         1.0136      0.000   5054.449      0.000       1.013       1.014
AttdAge_s13                         0.8528      0.000   3072.646      0.000       0.852       0.853
AttdAge_s14                         1.3907      0.000   3878.185      0.000       1.390       1.391
AttdAge_s15                         1.3638      0.000   3463.124      0.000       1.363       1.365
AttdAge_s16                         1.1548      0.000   3560.137      0.000       1.154       1.155
PolYear_s0                          0.4533      0.000   4227.094      0.000       0.453       0.453
PolYear_s1                          0.6357      0.000   5679.504      0.000       0.635       0.636
PolYear_s2                          0.9983      0.000   6252.107      0.000       0.998       0.999
PolYear_s3                          0.5675      0.000   2073.547      0.000       0.567       0.568
PolYear_s4                          1.1125      0.000   2459.366      0.000       1.112       1.113
PolYear_s5                         -1.1628      0.001  -1218.202      0.000      -1.165      -1.161
PolYear_s6                          1.8209      0.001   1966.658      0.000       1.819       1.823
PolYear_s7                         -4.2736      0.003  -1557.265      0.000      -4.279      -4.268
PolYear_s8                          2.3777      0.003    749.839      0.000       2.372       2.384
=====================================================================================================
```

"**T.X**" refers to the category or level for the variable. So, for Sex, **T.2** refers to female, the base level being male. For Smoke, **T.2** is non-smoker, and **T.3** is unknown, the base level being smoker. "**sX**" refers to the spline basis. A spline basis is fit to AttdAge and PolYear, each "s" represents a different spline along the domain of the variable. So **AttdAge_s0** roughly relates to the early attained ages, around 0-5, **AttnAge_s1** is roughly 6-10, etc.

D. COMPARISON OF THE CIA2014, GAM2014 AND NNM2014 TABLES

Because the objective of the alternative methods was to provide different methodologies to derive a new mortality table based on the same 2009–2019 industry data used by Bob Howard in the construction of the CIA2014 Table, it is inevitable that actuaries will be interested in comparing the results from the three tables. In other words, how do the GAM2014 Table and the NNM2014 Table compare to the CIA2014 Table.

In this appendix, we present a number of visualizations of this comparison. We usually use the CIA2014 Table as the basis of the comparison.

Although presenting a comparison is essential to satisfy this curiosity, it is important to remember that the CIA2014 Table is a 20-year select table, while both the GAM2014 Table and NNM2014 Table effectively have a select period to age 114 (at age 115, the rates are the same at 1000/1000). And although the rates for the ultimate attained ages for the GAM2014 Table and NNM2014 Table get closer to each other by issue age at the same attained age, they are never exactly the same. For this comparison, we decided to use issue age 35 in most comparisons because the exposure at attained age 35 to 70 is in the highest range.

Another important distinction, all else being the same, is that the CIA2014 Table was *normalized* to the same common date, January 1, 2014, using the CIA mortality improvements scale MI2017 while both the GAM2014 Table and the NNM2014 Table summed up the experience from all years based on exposure, 2009 to 2019. So, essentially, these tables use a weighted average, which is in fact an alternative approach.

The key to quickly identifying the mortality curve displayed is a 14-character term such as **CIA2014NMNSS35**; CIA2014 followed by:

- **N**: nearest birthday | **L**: last birthday
- **M**: male | **F**: female
- **NS**: non-smoker | **SM**: smoker | **AG**: aggregate **UN**: unknown
- **S**: select | **U**: ultimate
- **XX**: issue age or attained age depending on the selection

The curves are presented in red for the CIA2014 Table, in blue for the GAM2014 Table, and in green for the NNM2014 Table. To make the comparison for all ages at once, we also include a logarithmic scale of the rates per 1000.

Some general observations:

(1) Generally speaking, the GAM2014 Table is slightly higher than the NNM2014 Table for male and female non-smoker groups, and the NNM2014 Table also slightly higher than the CIA2014 Table. The relationship is similar for male smokers, except that the gap between the GAM2014 Table and the NNM2014 Table is increased. For female smokers, the NNM2014 Table generally shows lower rates.

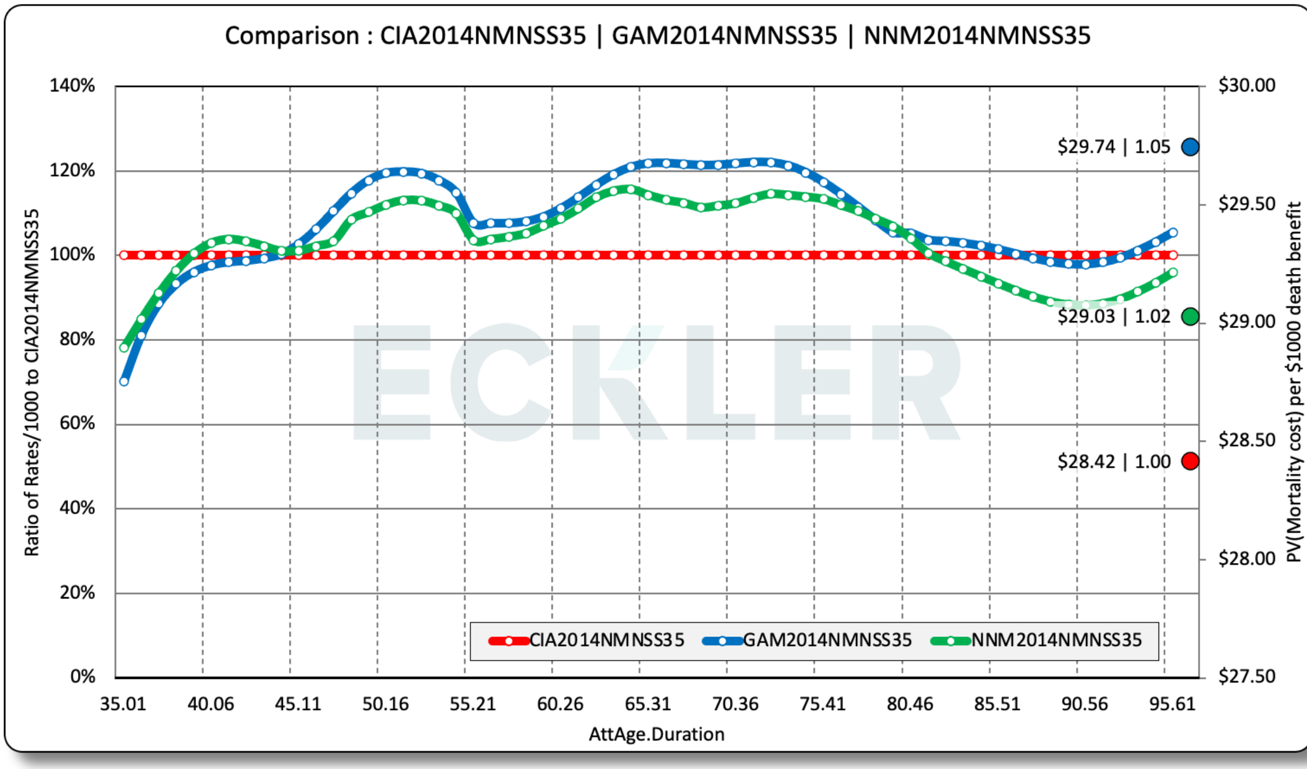
(2) It is interesting to observe that for attained ages 95 to 115, the rates for the GAM2014 Table and the NNM2014 Table female non-smokers almost exactly overwrite each other.

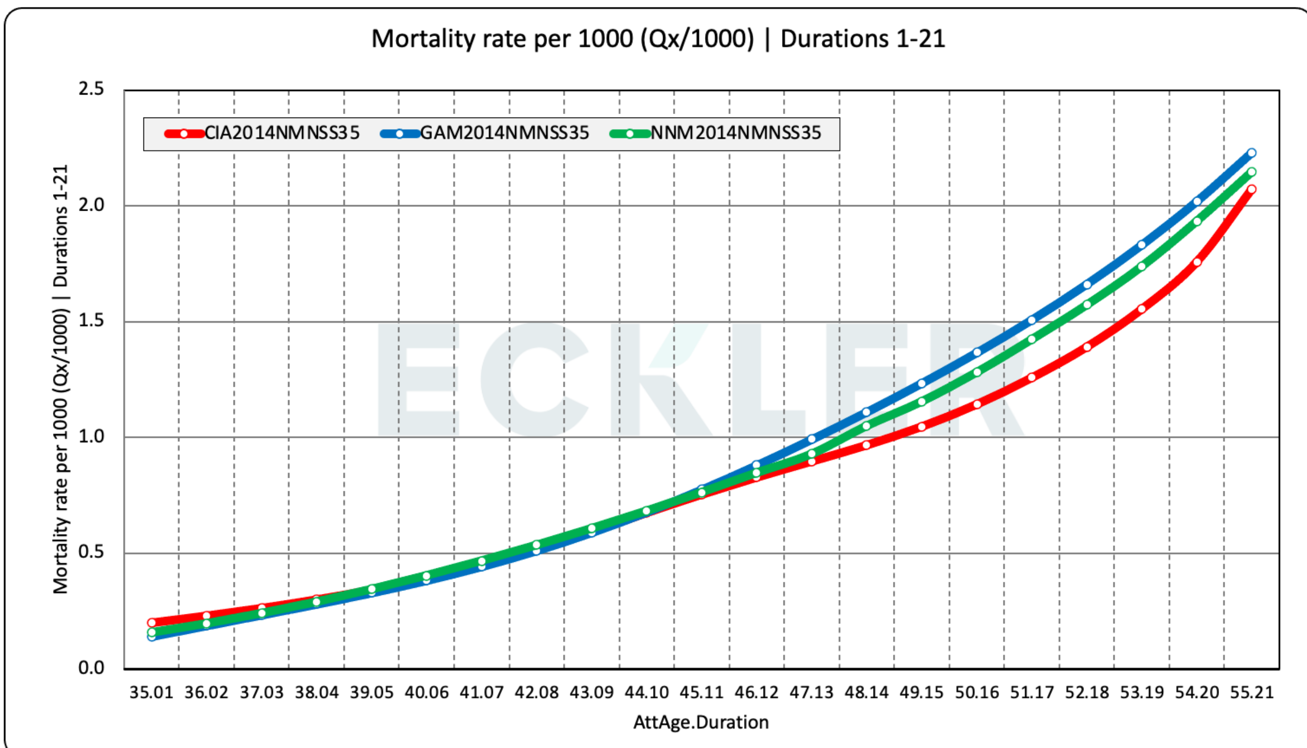
(3) Both the GAM2014 Table and the NNM2014 Table merge smoothly at the very old ages from their respective rates to a mortality rate of 1.00 at age 115.

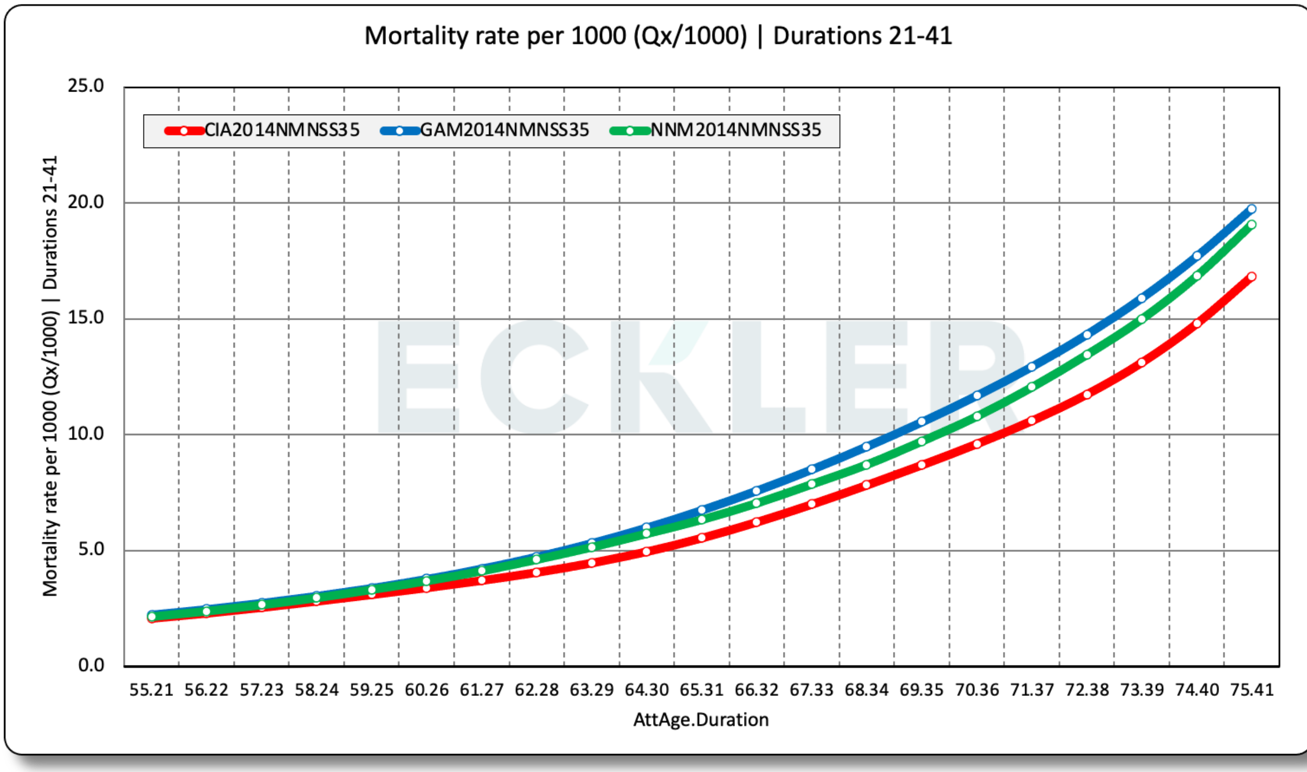
(4) Comparing the non-smoker, smoker, aggregate, and unknown rates within each table and by gender highlight some of the particularities of the various tables. The CIA2014 Table shows erratic relationship between the male smoker and unknown classes versus the non-smoker class, and even more erratic for the female class. The GAM2014 Table shows generally a linear relationship which is by design due to the *linear* model. The NNM2014 Table shows a very smooth relationship as well as a more expected one as compared to the CIA2014 Table.

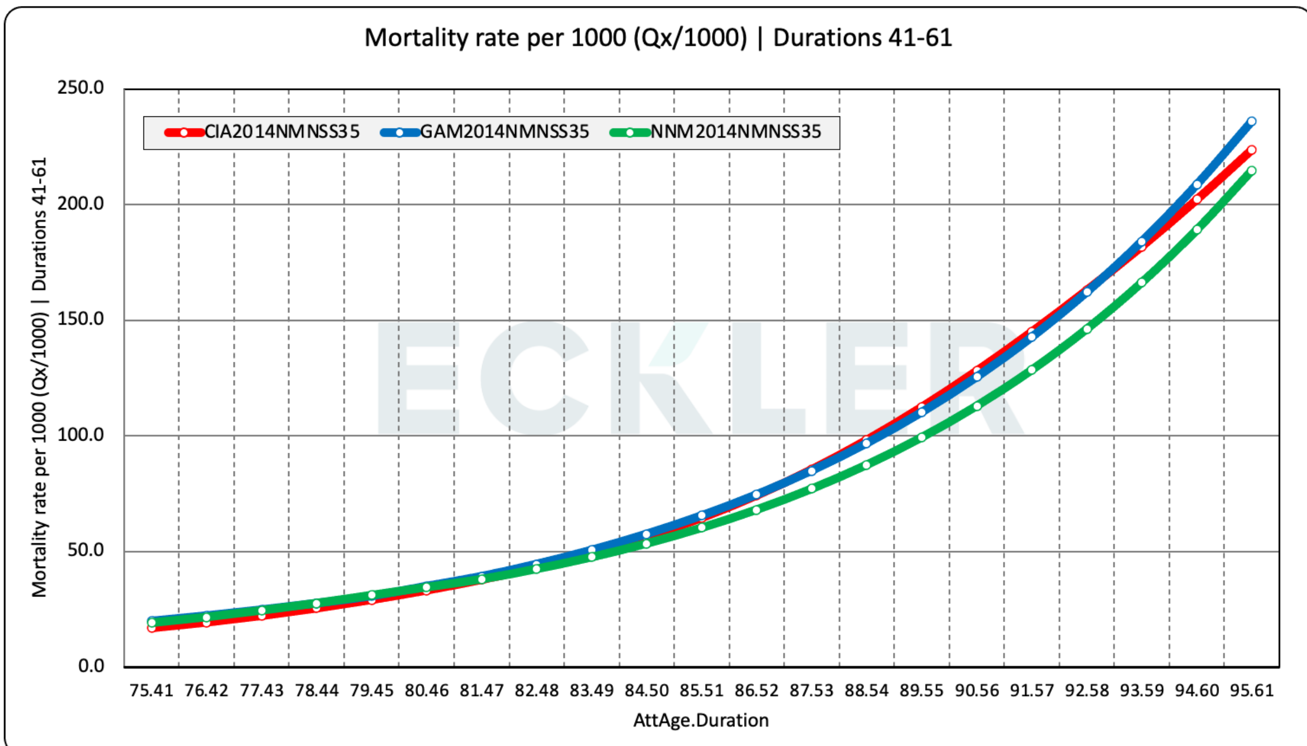
The scale on the right side indicates a proxy for a single premium (SP) estimating the cost impact of the mortality protection. We assume a reasonable declining lapse rate tables and a flat discount rate of 4%. This is by no means an absolute and useful value. It is simply a means for a relative comparison between the tables. The dollar value is the calculated figure while the second number is the ratio to the dollar value for the CIA2014 Table.

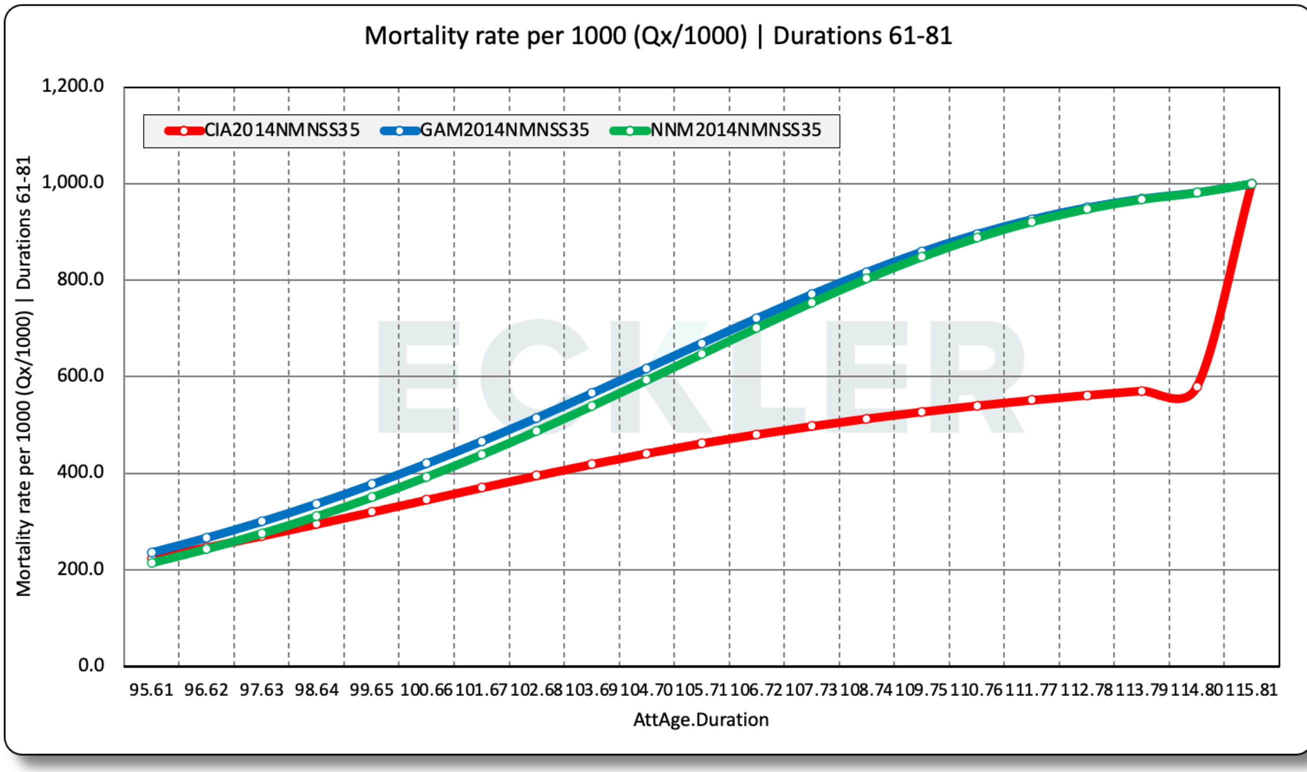
D.1. Male Non-Smokers

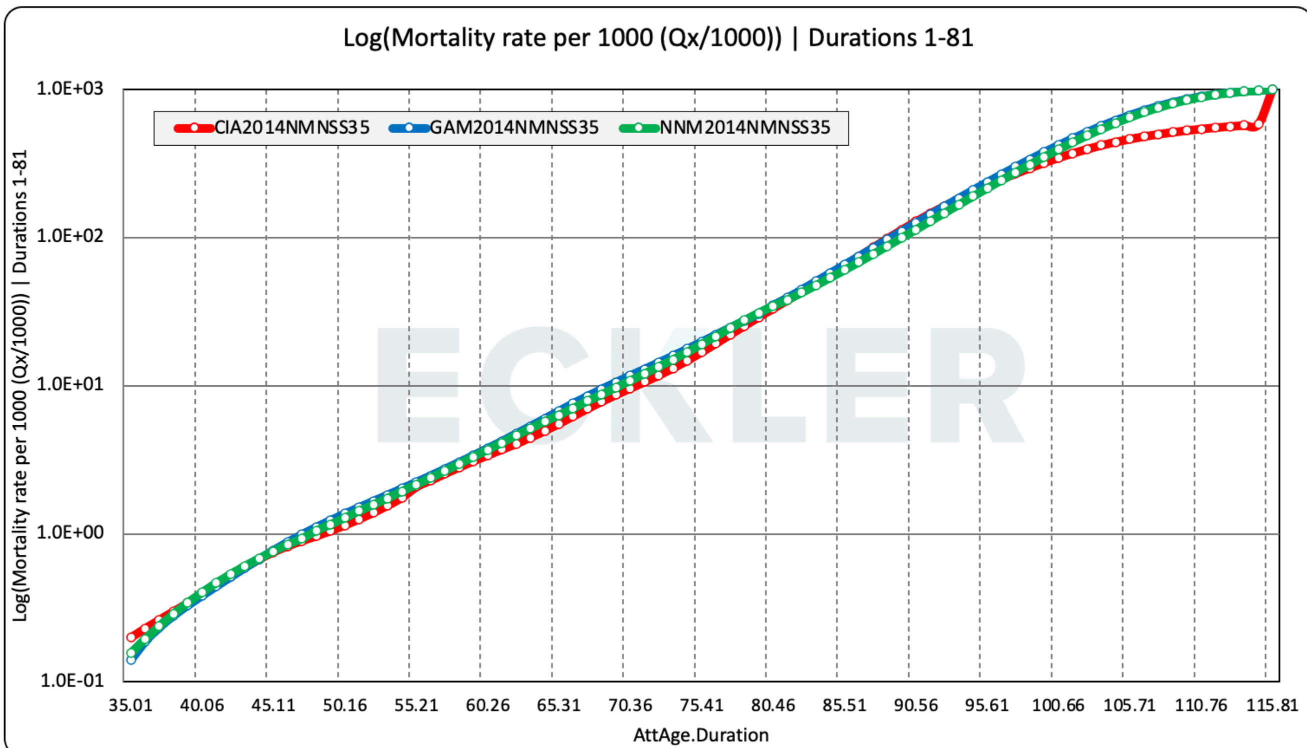




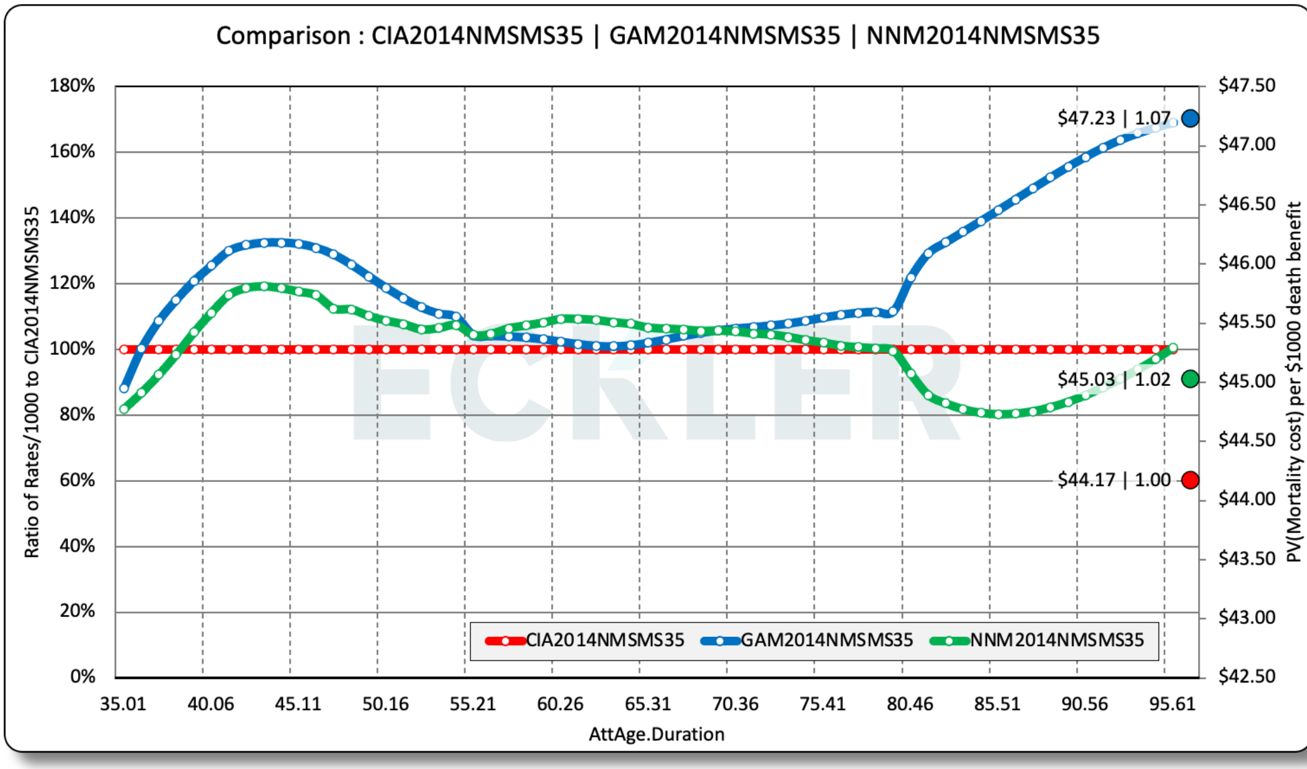

Mortality rate per 1000 (Qx/1000) | Durations 21-41
CIA2014NMNSS35
GAM2014NMNSS35
NNM2014NMNSS35
Mortality rate per 1000 (Qx/1000) | Durations 21-41
25.0
20.0
15.0
10.0
5.0
0.0
55.21 56.22 57.23 58.24 59.25 60.26 61.27 62.28 63.29 64.30 65.31 66.32 67.33 68.34 69.35 70.36 71.37 72.38 73.39 74.40 75.41
AttAge.Duration
ECKLER

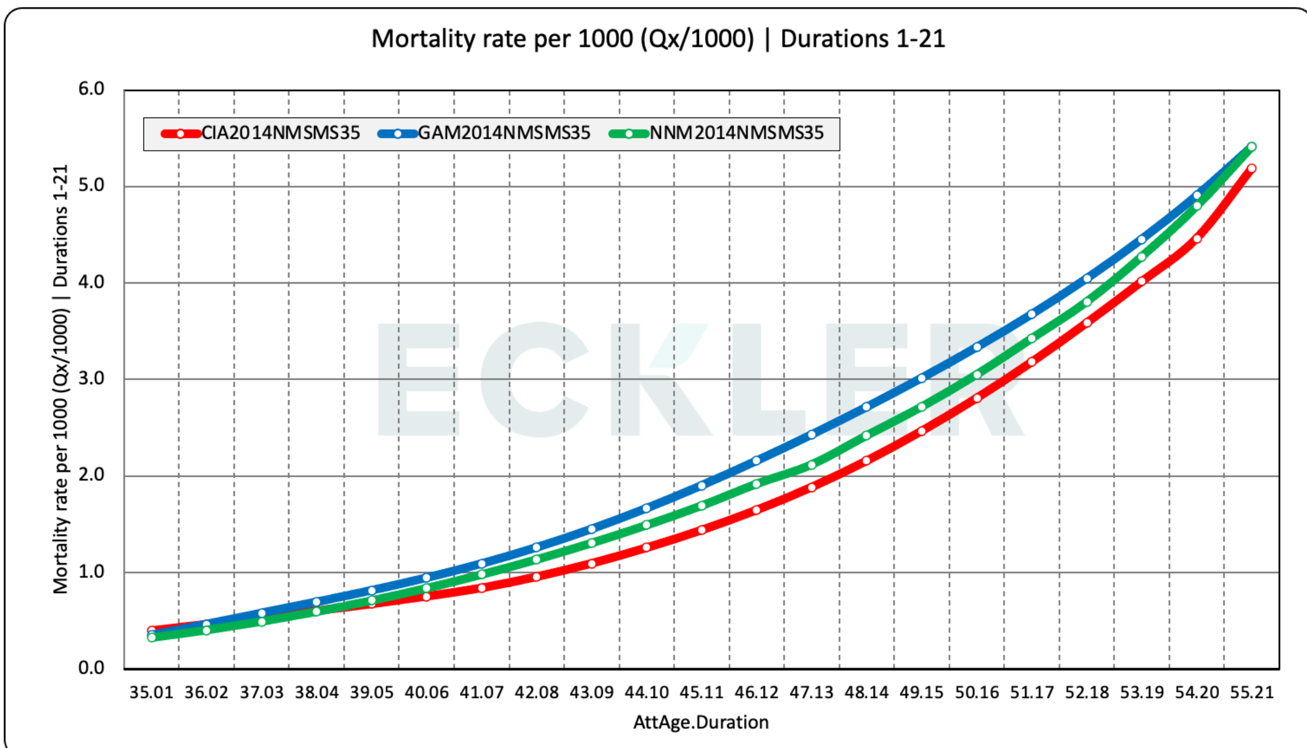

Mortality rate per 1000 (Qx/1000) | Durations 41-61
CIA2014NMNSS35
GAM2014NMNSS35
NNM2014NMNSS35
Mortality rate per 1000 (Qx/1000) | Durations 41-61
250.0
200.0
150.0
100.0
50.0
0.0
75.41 76.42 77.43 78.44 79.45 80.46 81.47 82.48 83.49 84.50 85.51 86.52 87.53 88.54 89.55 90.56 91.57 92.58 93.59 94.60 95.61
AttAge.Duration
ECKLER

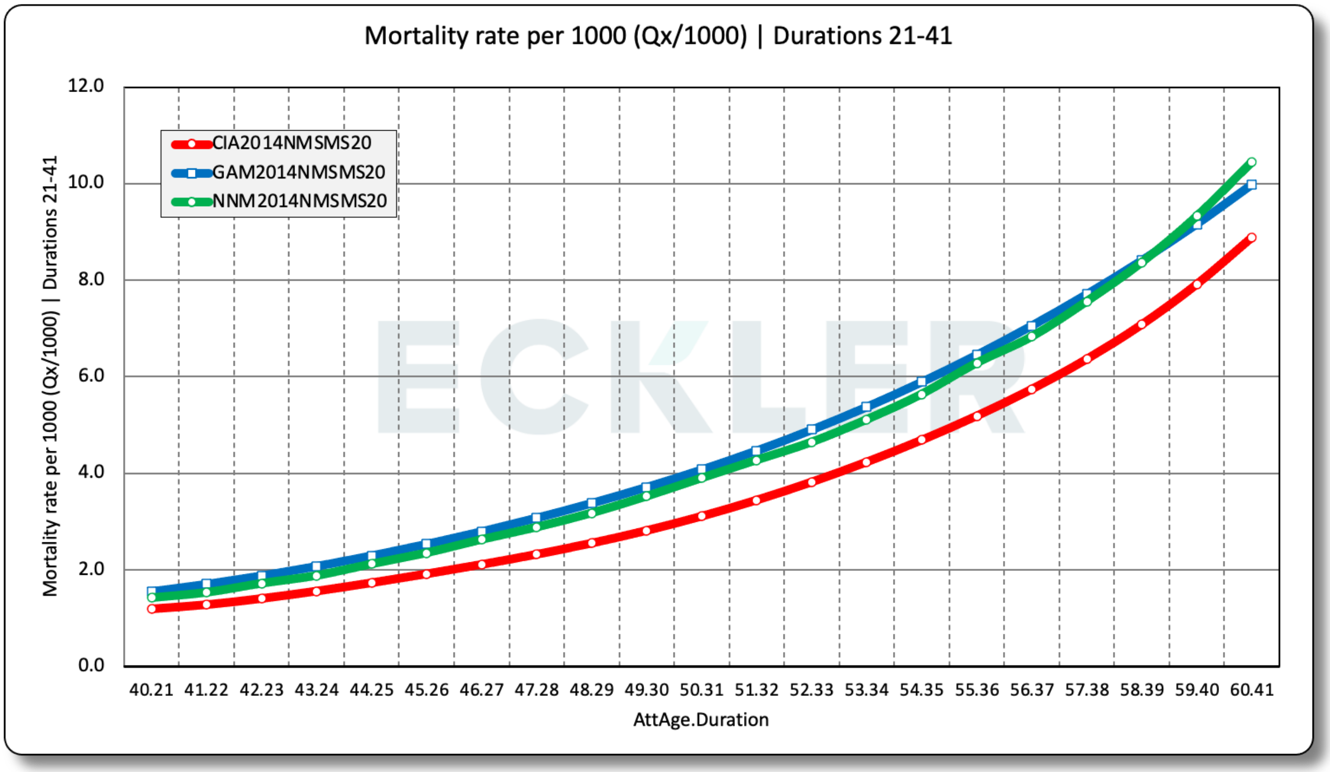

Mortality rate per 1000 (Qx/1000) | Durations 61-81
CIA2014NMNSS35
GAM2014NMNSS35
NNM2014NMNSS35
Mortality rate per 1000 (Qx/1000) | Durations 61-81
1,200.0
1,000.0
800.0
600.0
400.0
200.0
0.0
95.61 96.62 97.63 98.64 99.65 100.66 101.67 102.68 103.69 104.70 105.71 106.72 107.73 108.74 109.75 110.76 111.77 112.78 113.79 114.80 115.81
AttAge.Duration

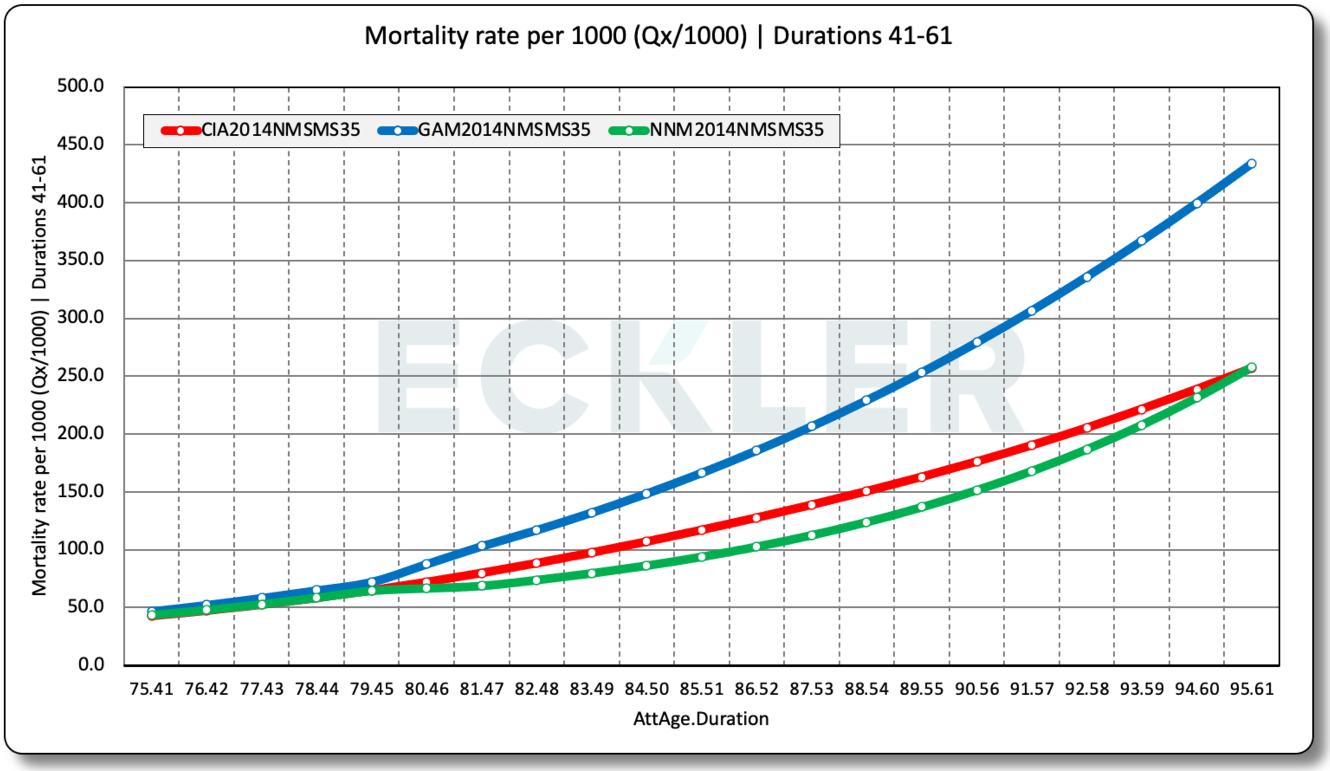

Log(Mortality rate per 1000 (Qx/1000)) | Durations 1-81
CIA2014NMNSS35
GAM2014NMNSS35
NNM2014NMNSS35
Log(Mortality rate per 1000 (Qx/1000)) | Durations 1-81
1.0E+03
1.0E+02
1.0E+01
1.0E+00
1.0E-01
35.01 40.06 45.11 50.16 55.21 60.26 65.31 70.36 75.41 80.46 85.51 90.56 95.61 100.66 105.71 110.76 115.81
AttAge.Duration

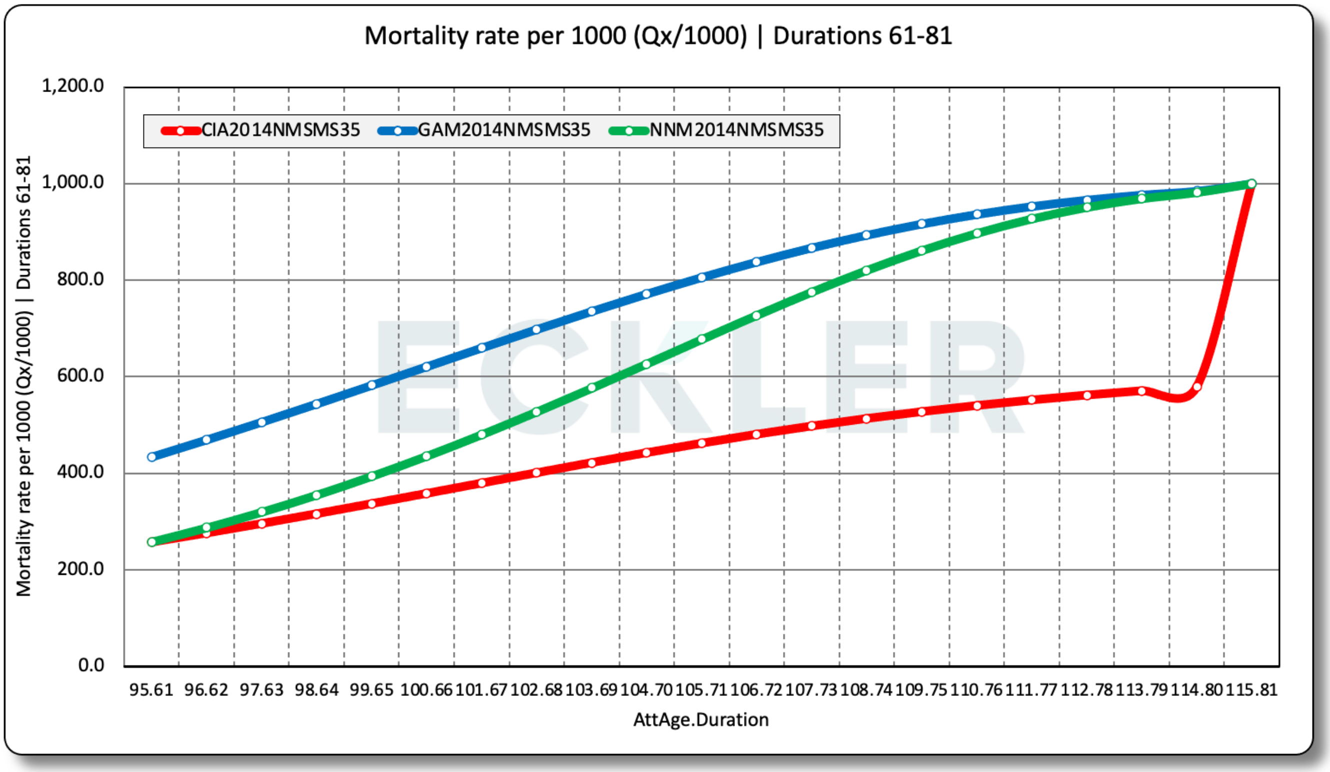
D.2. Male Smokers

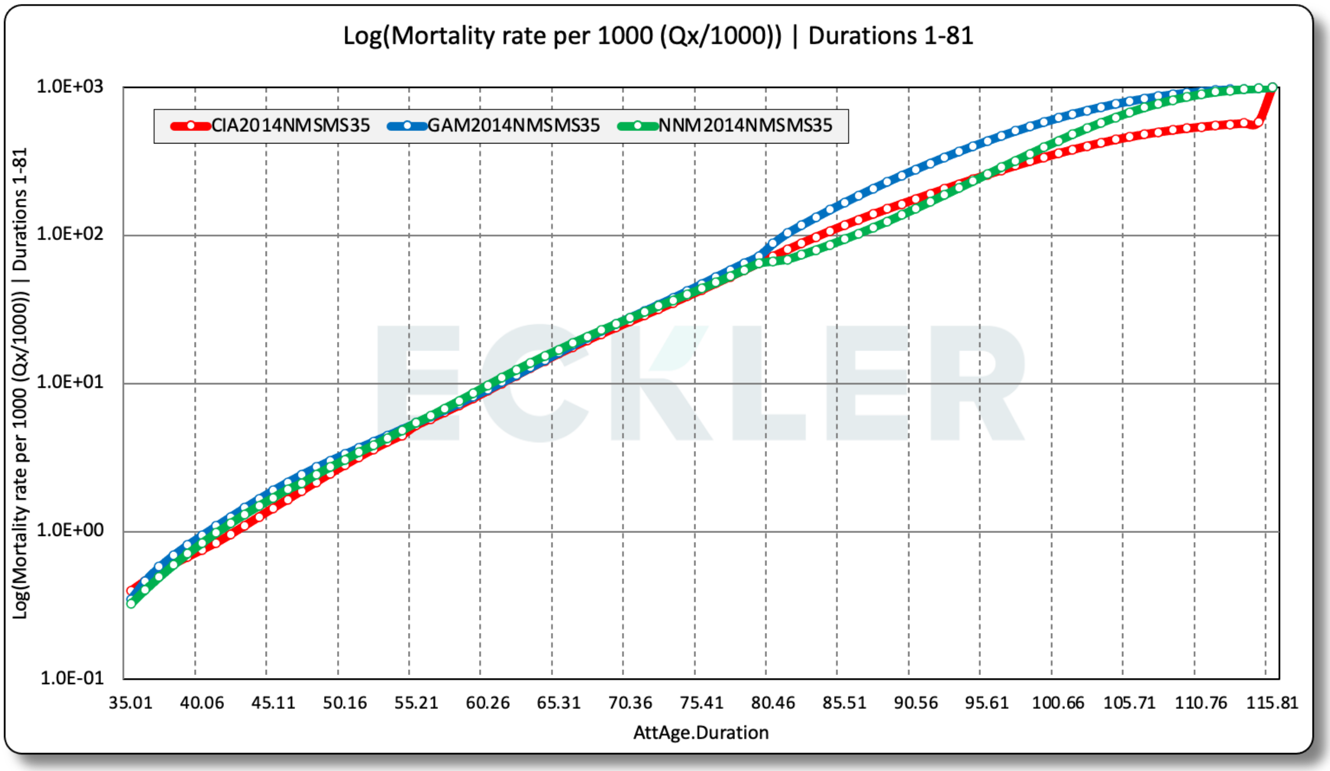




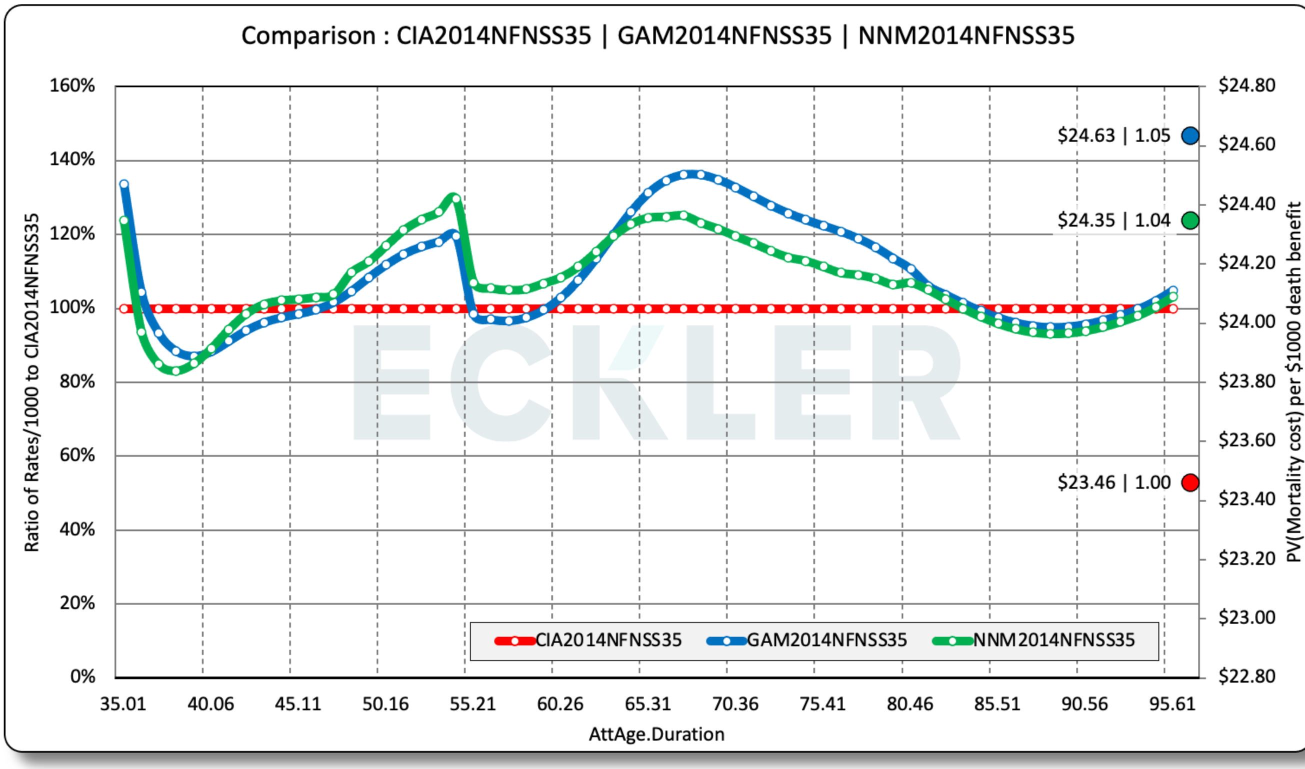

Mortality rate per 1000 (Qx/1000) | Durations 21-41
Mortality rate per 1000 (Qx/1000) | Durations 21-41
CIA2014NMSMS20
GAM2014NMSMS20
NNM2014NMSMS20
12.0
10.0
8.0
6.0
4.0
2.0
0.0
40.21 41.22 42.23 43.24 44.25 45.26 46.27 47.28 48.29 49.30 50.31 51.32 52.33 53.34 54.35 55.36 56.37 57.38 58.39 59.40 60.41
AttAge.Duration

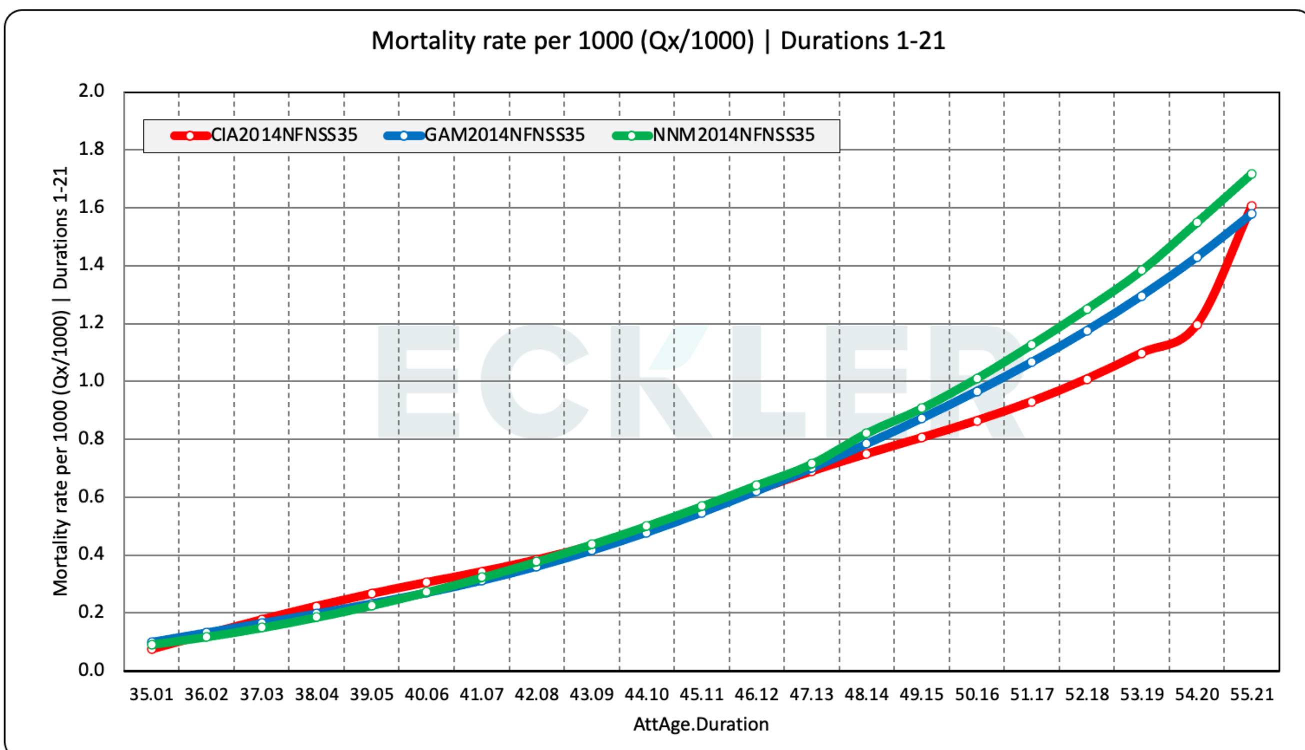

Mortality rate per 1000 (Qx/1000) | Durations 41-61
Mortality rate per 1000 (Qx/1000) | Durations 41-61
CIA2014NMSMS35
GAM2014NMSMS35
NNM2014NMSMS35
500.0
450.0
400.0
350.0
300.0
250.0
200.0
150.0
100.0
50.0
0.0
75.41 76.42 77.43 78.44 79.45 80.46 81.47 82.48 83.49 84.50 85.51 86.52 87.53 88.54 89.55 90.56 91.57 92.58 93.59 94.60 95.61
AttAge.Duration

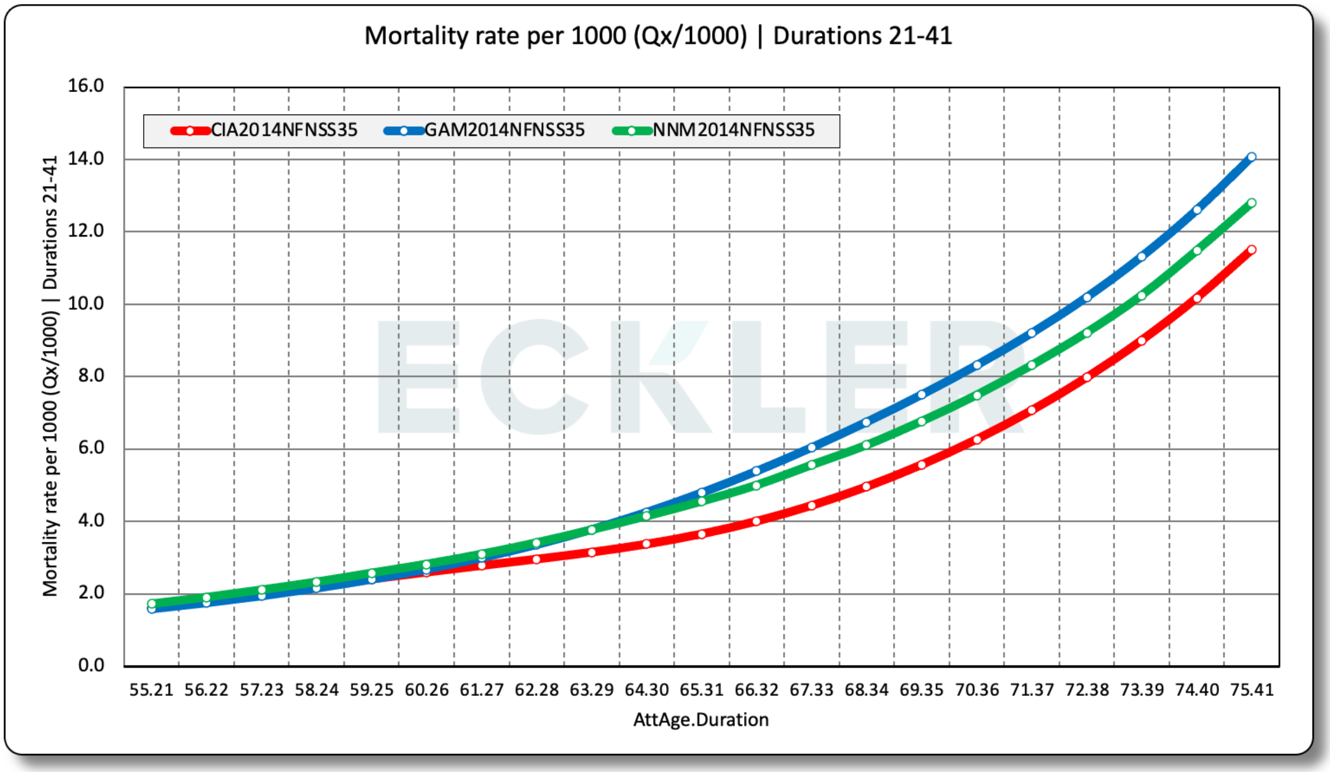

Mortality rate per 1000 (Qx/1000) | Durations 61-81
CIA2014NMSMS35
GAM2014NMSMS35
NNM2014NMSMS35
Mortality rate per 1000 (Qx/1000) | Durations 61-81
1,200.0
1,000.0
800.0
600.0
400.0
200.0
0.0
95.61 96.62 97.63 98.64 99.65 100.66 101.67 102.68 103.69 104.70 105.71 106.72 107.73 108.74 109.75 110.76 111.77 112.78 113.79 114.80 115.81
AttAge.Duration

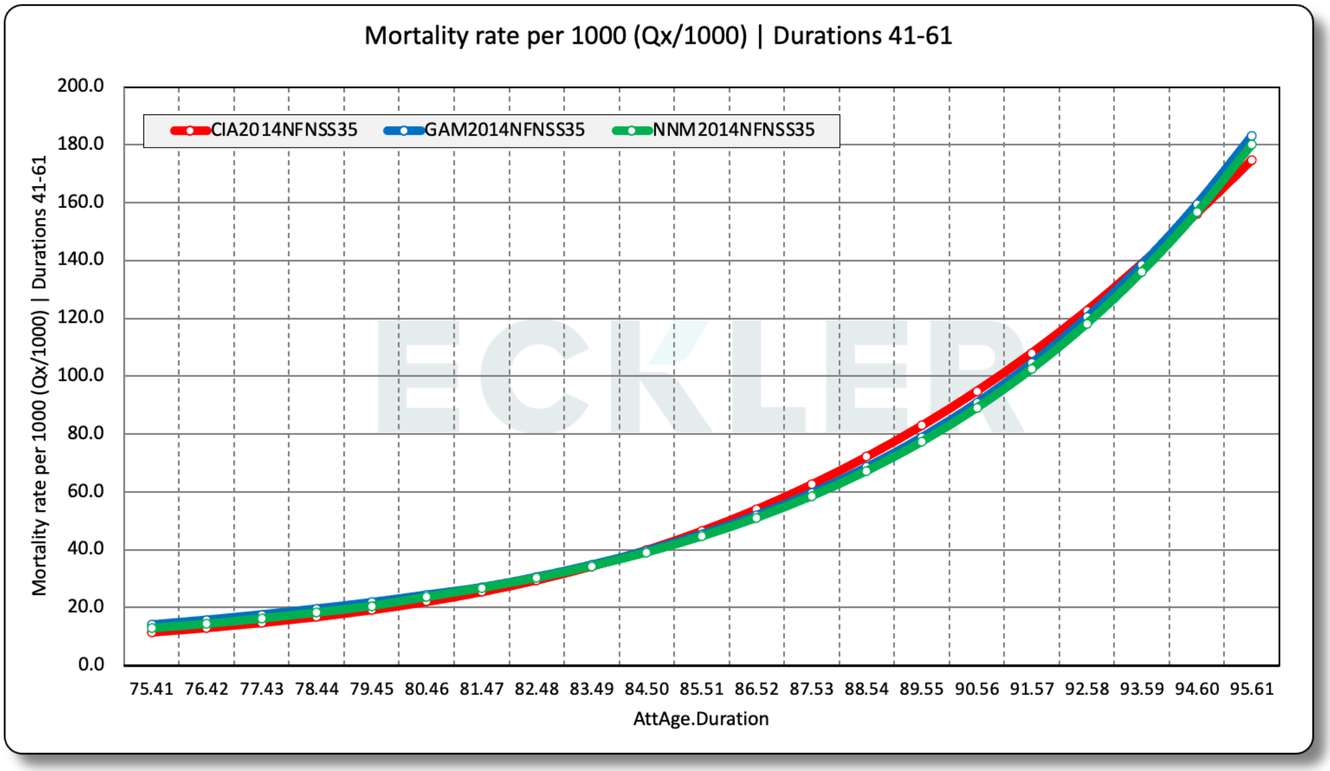

Log(Mortality rate per 1000 (Qx/1000)) | Durations 1-81
CIA2014NMSMS35
GAM2014NMSMS35
NNM2014NMSMS35
Log(Mortality rate per 1000 (Qx/1000)) | Durations 1-81
1.0E+03
1.0E+02
1.0E+01
1.0E+00
1.0E-01
35.01 40.06 45.11 50.16 55.21 60.26 65.31 70.36 75.41 80.46 85.51 90.56 95.61 100.66 105.71 110.76 115.81
AttAge.Duration

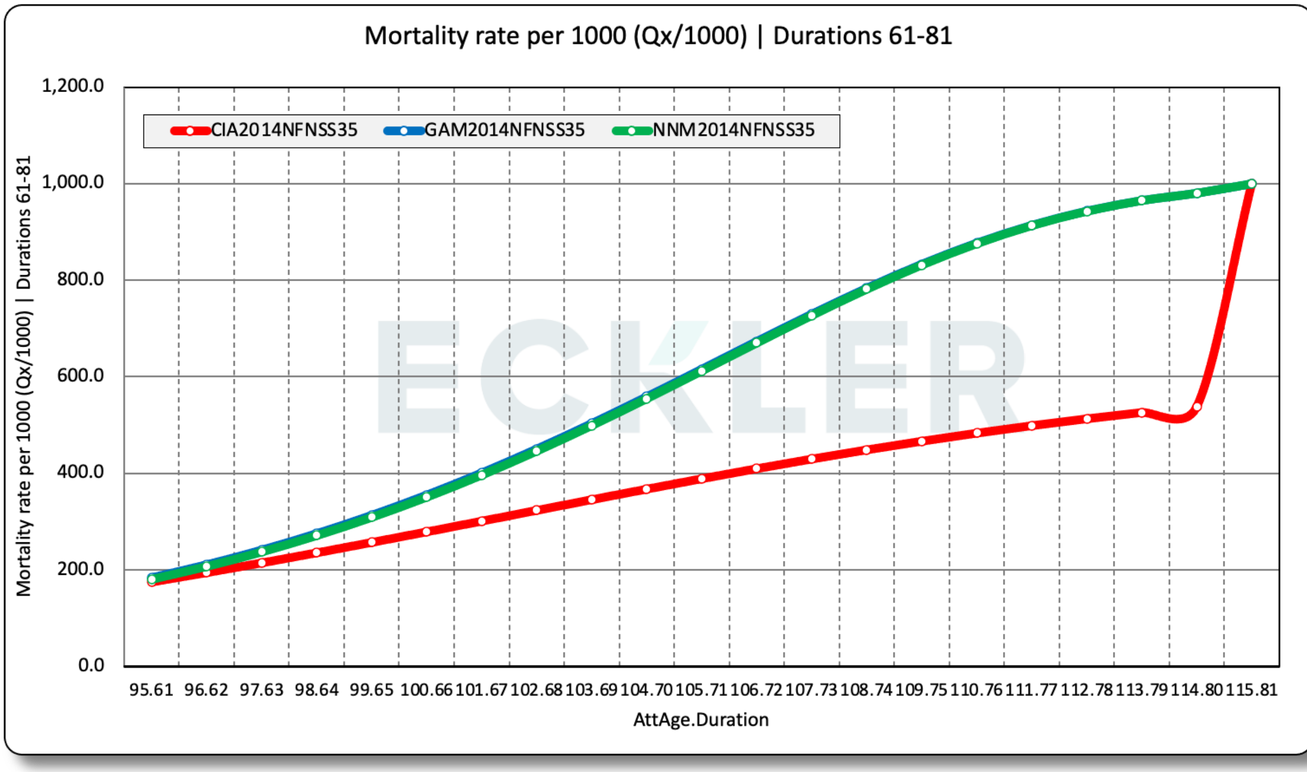
D.3. Female Non-Smokers

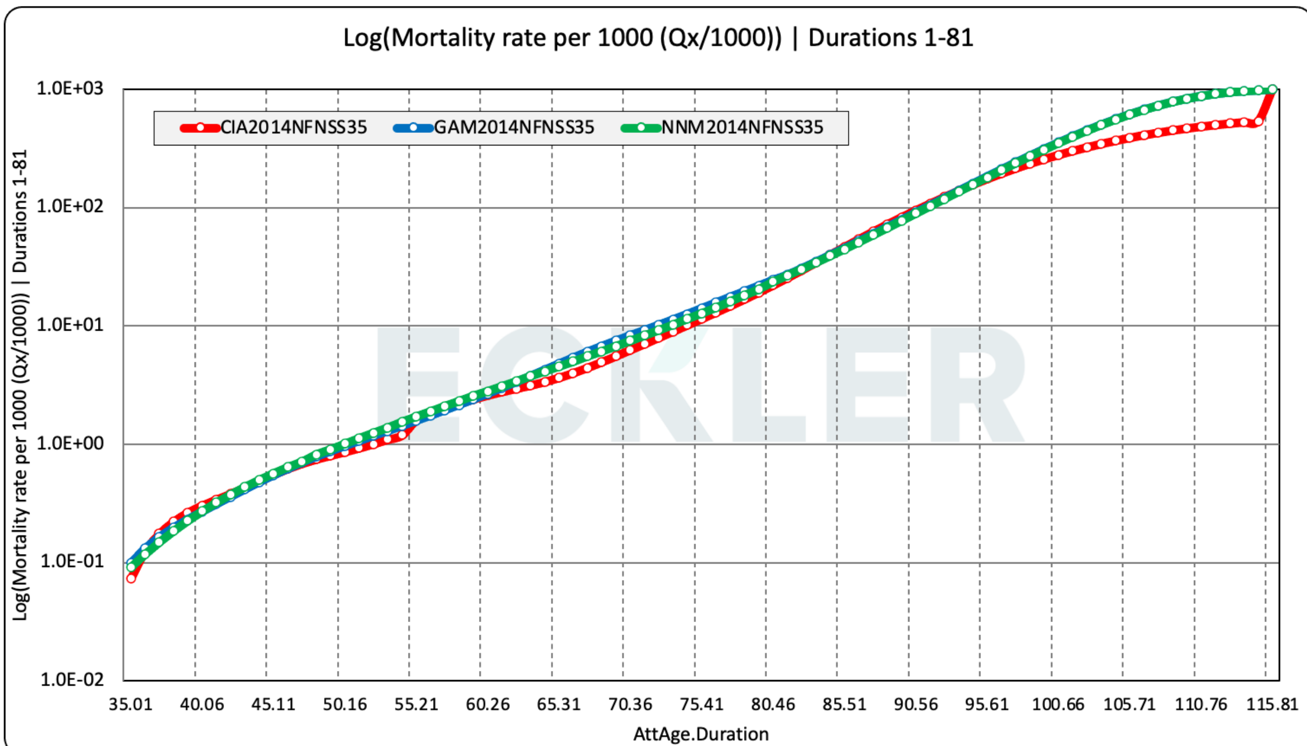




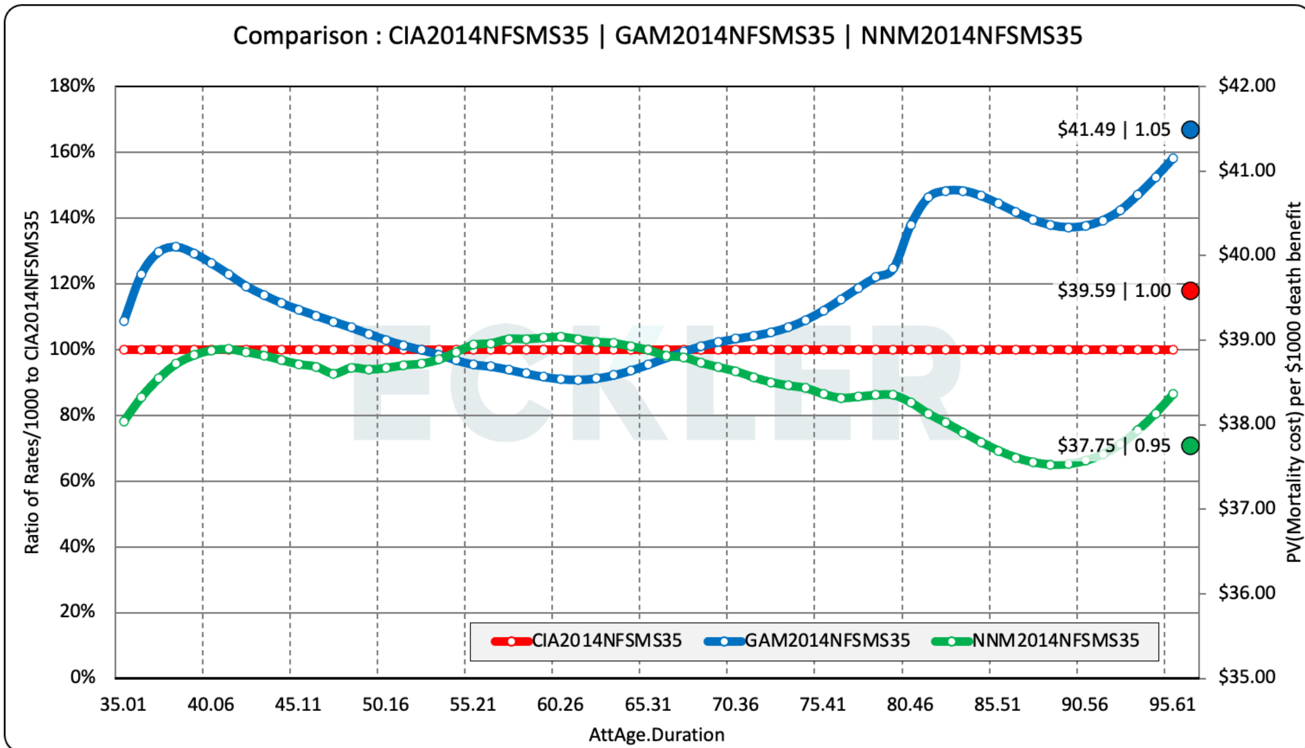

Mortality rate per 1000 (Qx/1000) | Durations 21-41
CIA2014NFNSS35
GAM2014NFNSS35
NNM2014NFNSS35
Mortality rate per 1000 (Qx/1000) | Durations 21-41
16.0
14.0
12.0
10.0
8.0
6.0
4.0
2.0
0.0
55.21 56.22 57.23 58.24 59.25 60.26 61.27 62.28 63.29 64.30 65.31 66.32 67.33 68.34 69.35 70.36 71.37 72.38 73.39 74.40 75.41
AttAge.Duration
ECKLER

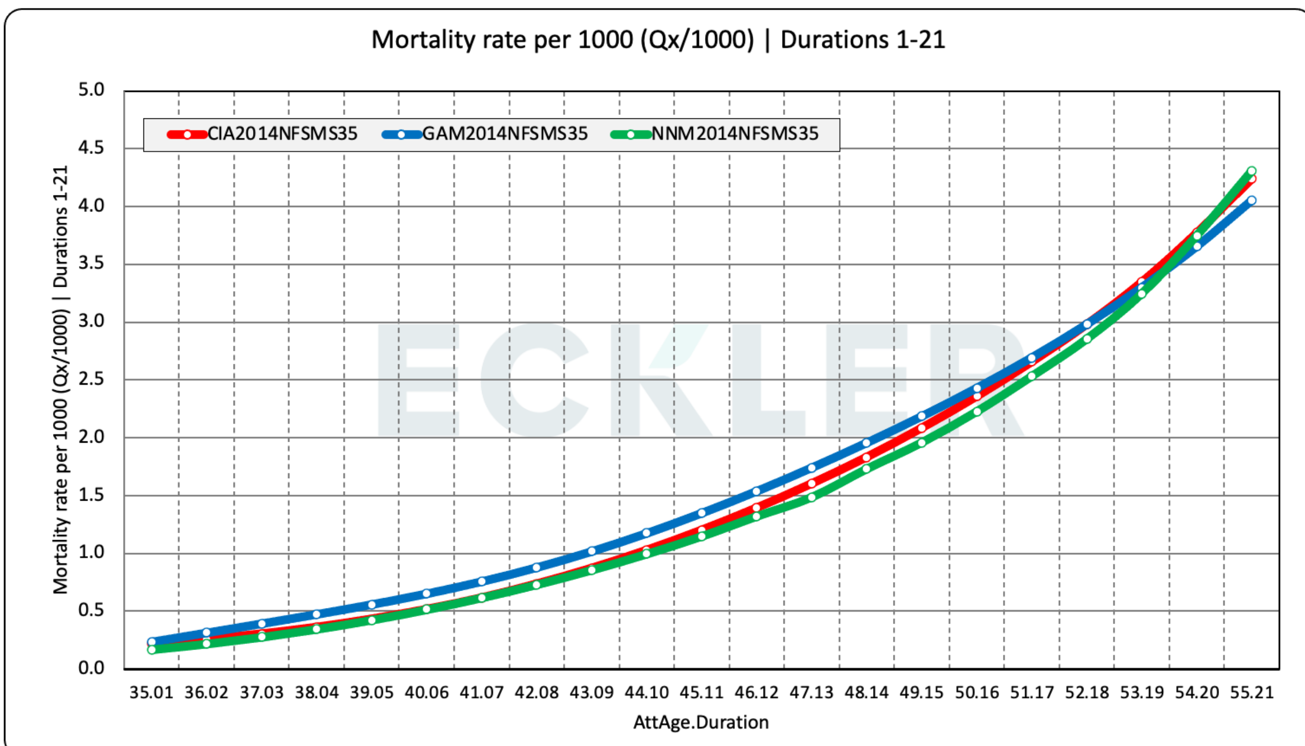

Mortality rate per 1000 (Qx/1000) | Durations 41-61
CIA2014NFNSS35
GAM2014NFNSS35
NNM2014NFNSS35
Mortality rate per 1000 (Qx/1000) | Durations 41-61
200.0
180.0
160.0
140.0
120.0
100.0
80.0
60.0
40.0
20.0
0.0
75.41 76.42 77.43 78.44 79.45 80.46 81.47 82.48 83.49 84.50 85.51 86.52 87.53 88.54 89.55 90.56 91.57 92.58 93.59 94.60 95.61
AttAge.Duration
ECKLER

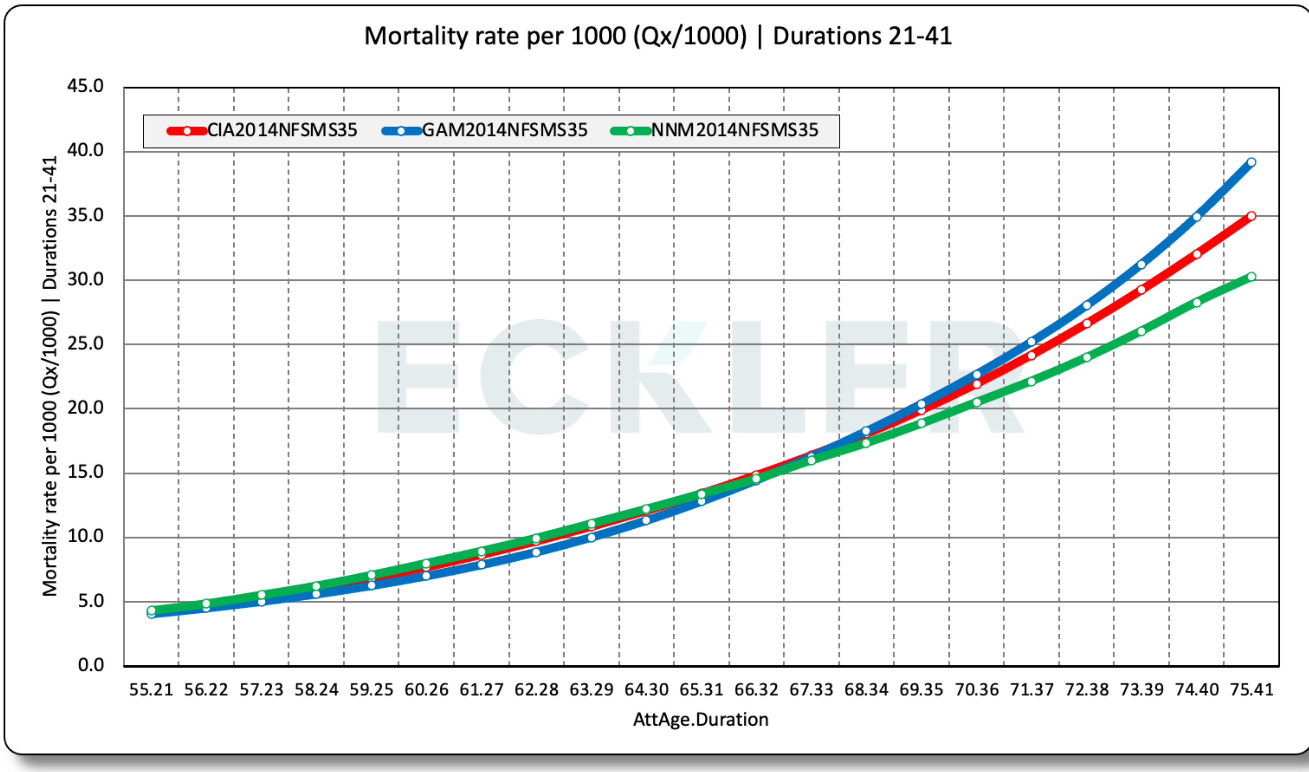

Mortality rate per 1000 (Qx/1000) | Durations 61-81
CIA2014NFNSS35
GAM2014NFNSS35
NNM2014NFNSS35
Mortality rate per 1000 (Qx/1000) | Durations 61-81
1,200.0
1,000.0
800.0
600.0
400.0
200.0
0.0
95.61 96.62 97.63 98.64 99.65 100.66 101.67 102.68 103.69 104.70 105.71 106.72 107.73 108.74 109.75 110.76 111.77 112.78 113.79 114.80 115.81
AttAge.Duration

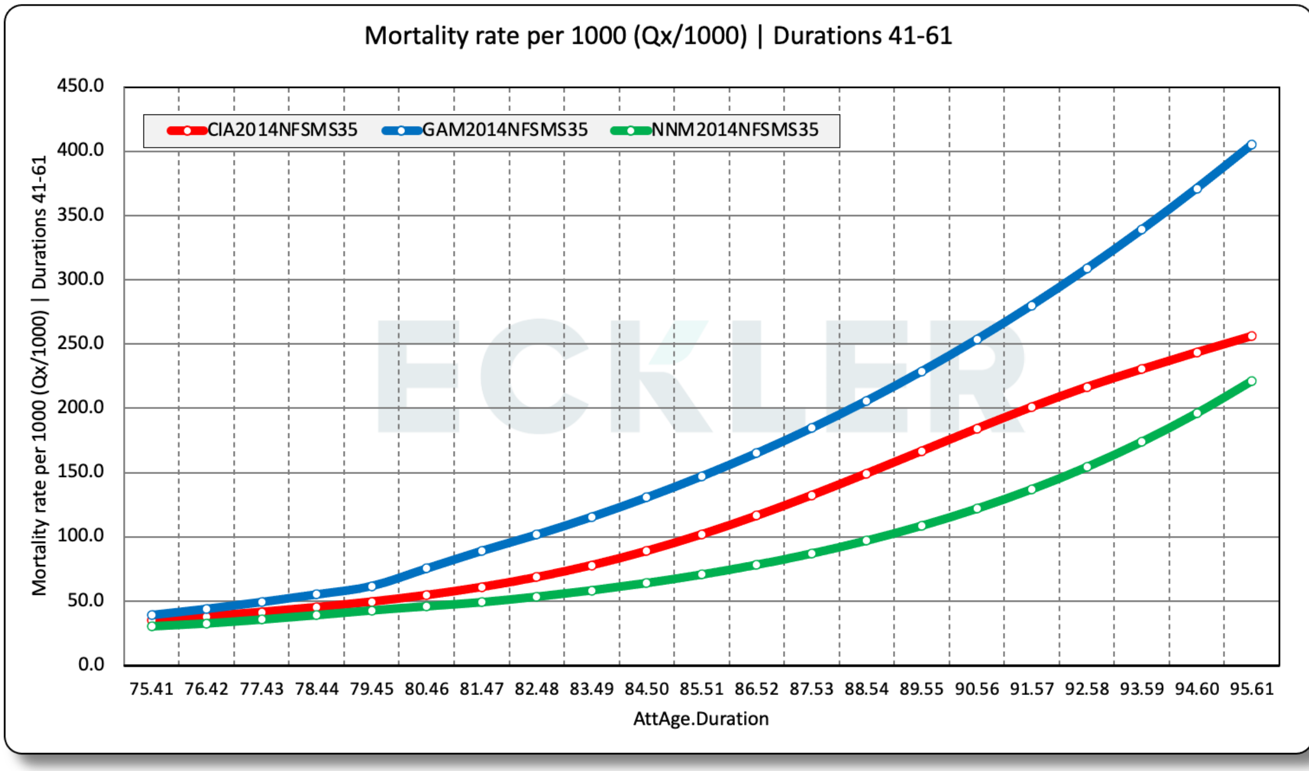

Log(Mortality rate per 1000 (Qx/1000)) | Durations 1-81
CIA2014NFNSS35
GAM2014NFNSS35
NNM2014NFNSS35
Log(Mortality rate per 1000 (Qx/1000)) | Durations 1-81
1.0E+03
1.0E+02
1.0E+01
1.0E+00
1.0E-01
1.0E-02
35.01 40.06 45.11 50.16 55.21 60.26 65.31 70.36 75.41 80.46 85.51 90.56 95.61 100.66 105.71 110.76 115.81
AttAge.Duration

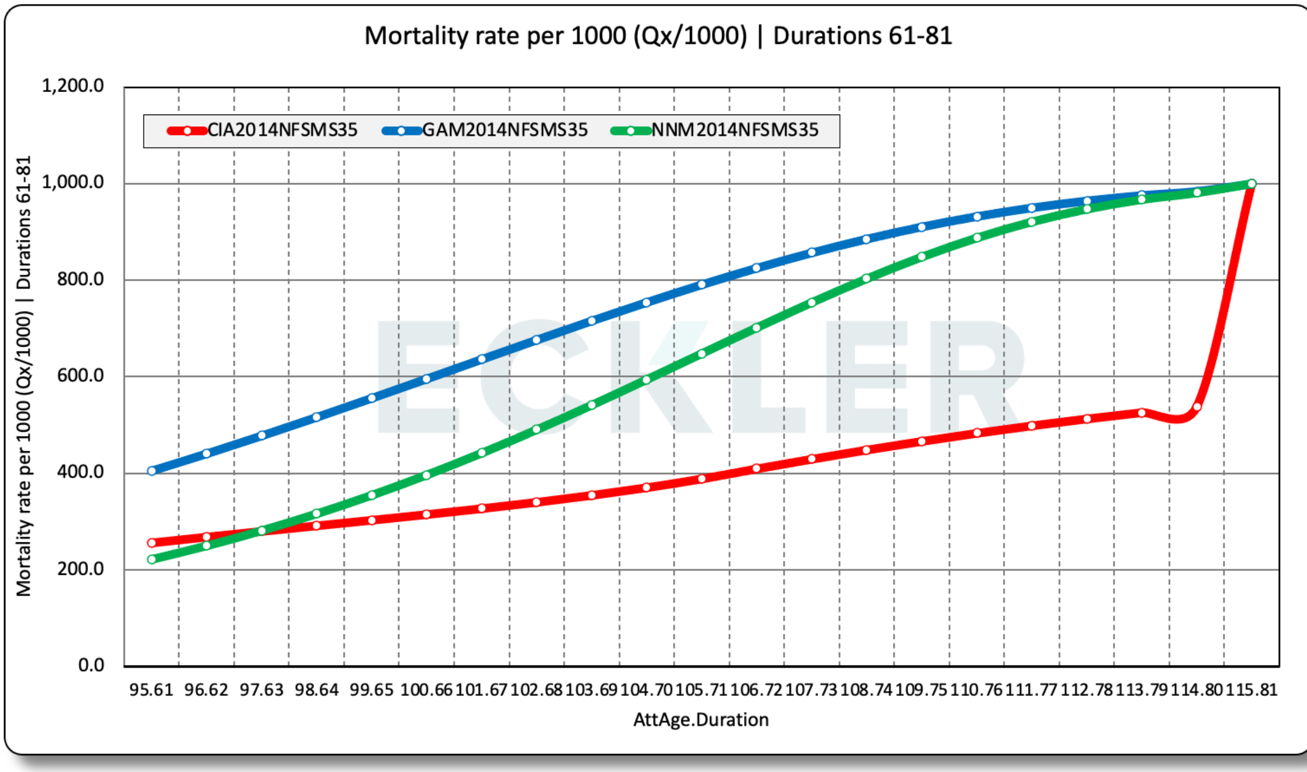
D.4. Female Smokers

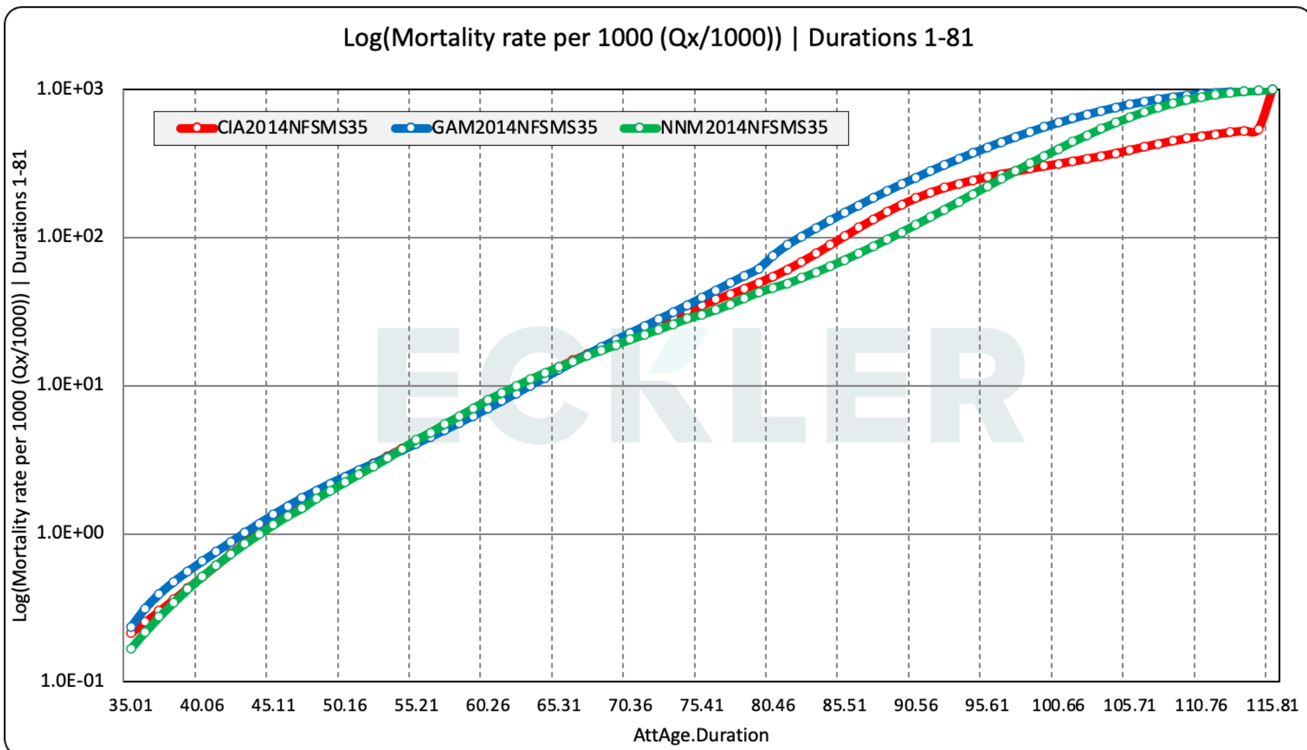





Mortality rate per 1000 (Qx/1000) | Durations 21-41
CIA2014NFSMS35
GAM2014NFSMS35
NNM2014NFSMS35
Mortality rate per 1000 (Qx/1000) | Durations 21-41
45.0
40.0
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
55.21 56.22 57.23 58.24 59.25 60.26 61.27 62.28 63.29 64.30 65.31 66.32 67.33 68.34 69.35 70.36 71.37 72.38 73.39 74.40 75.41
AttAge.Duration

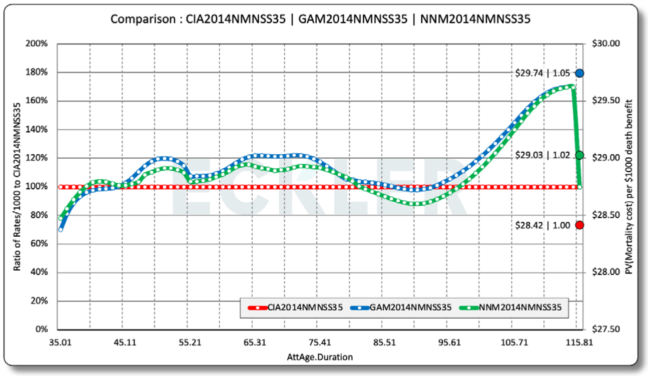

Mortality rate per 1000 (Qx/1000) | Durations 41-61
CIA2014NFSMS35
GAM2014NFSMS35
NNM2014NFSMS35
Mortality rate per 1000 (Qx/1000) | Durations 41-61
450.0
400.0
350.0
300.0
250.0
200.0
150.0
100.0
50.0
0.0
75.41 76.42 77.43 78.44 79.45 80.46 81.47 82.48 83.49 84.50 85.51 86.52 87.53 88.54 89.55 90.56 91.57 92.58 93.59 94.60 95.61
AttAge.Duration


Mortality rate per 1000 (Qx/1000) | Durations 61-81
CIA2014NFSMS35
GAM2014NFSMS35
NNM2014NFSMS35
Mortality rate per 1000 (Qx/1000) | Durations 61-81
1,200.0
1,000.0
800.0
600.0
400.0
200.0
0.0
95.61 96.62 97.63 98.64 99.65 100.66 101.67 102.68 103.69 104.70 105.71 106.72 107.73 108.74 109.75 110.76 111.77 112.78 113.79 114.80 115.81
AttAge.Duration

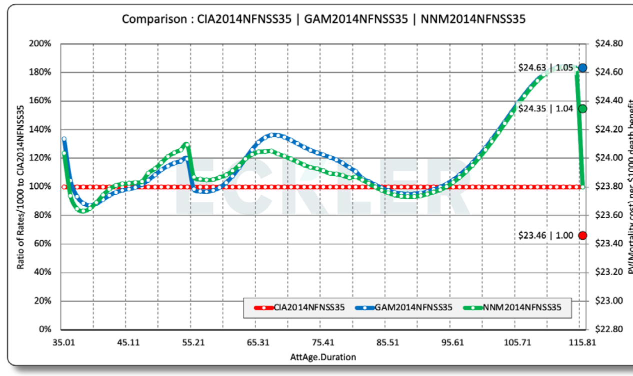

Log(Mortality rate per 1000 (Qx/1000)) | Durations 1-81
CIA2014NFSMS35
GAM2014NFSMS35
NNM2014NFSMS35
Log(Mortality rate per 1000 (Qx/1000)) | Durations 1-81
1.0E+03
1.0E+02
1.0E+01
1.0E+00
1.0E-01
35.01 40.06 45.11 50.16 55.21 60.26 65.31 70.36 75.41 80.46 85.51 90.56 95.61 100.66 105.71 110.76 115.81
AttAge.Duration

D.5. All Classes

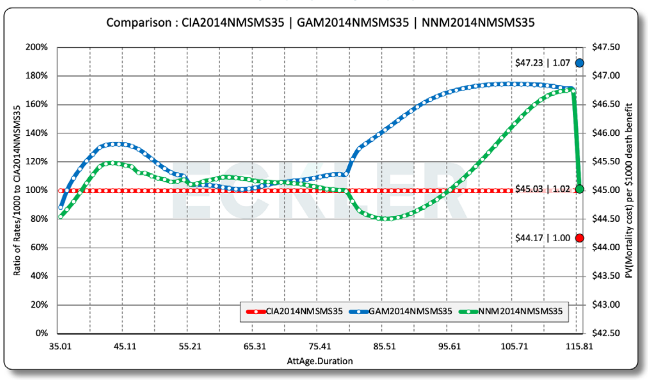
Male Non-Smokers



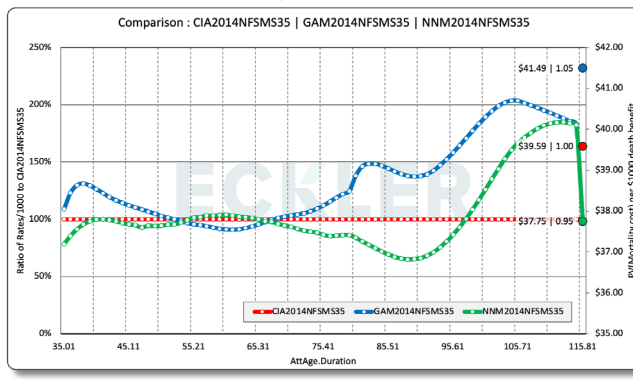
Female Non-Smokers



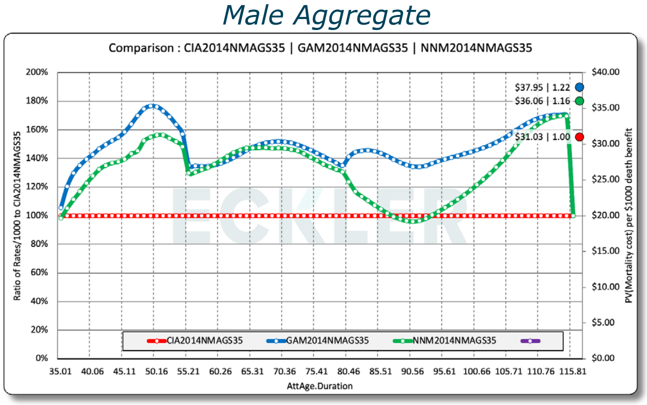
Male Smokers



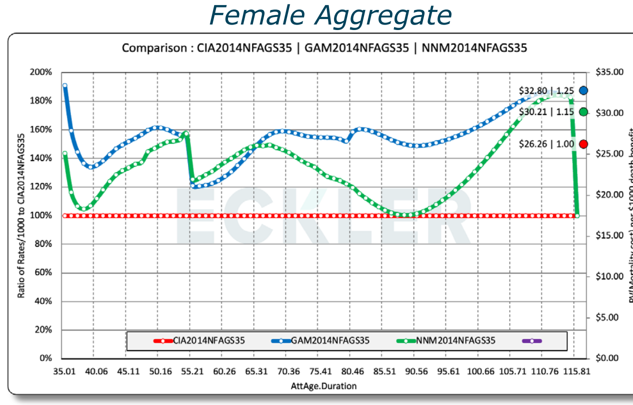
Female Smokers



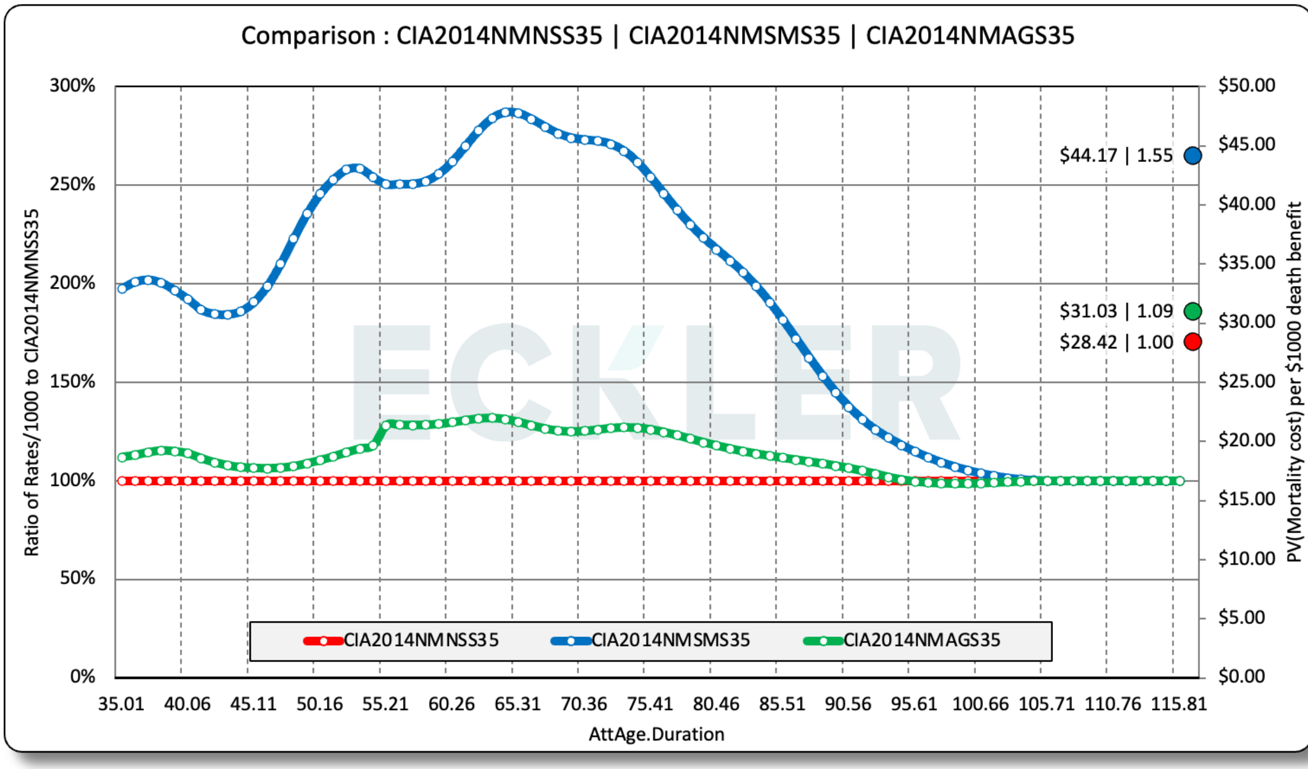
Male Aggregate

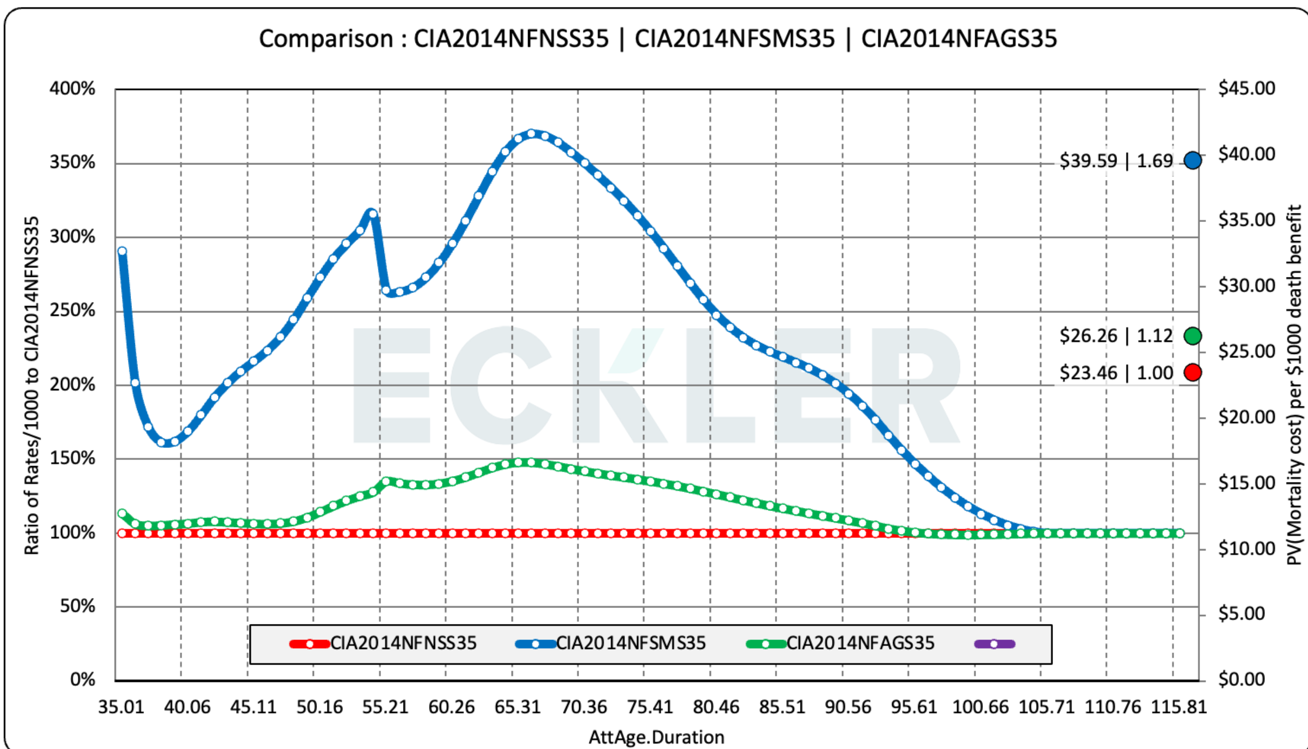


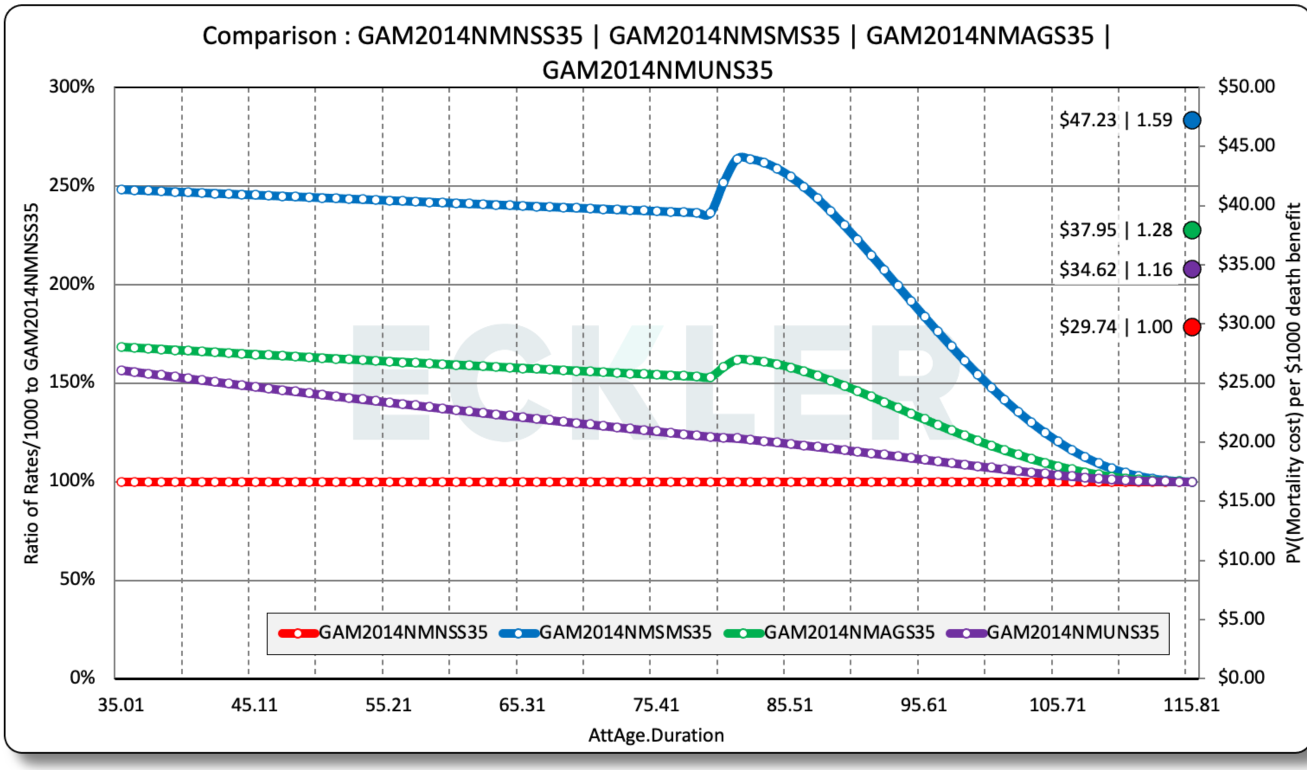
Female Aggregate

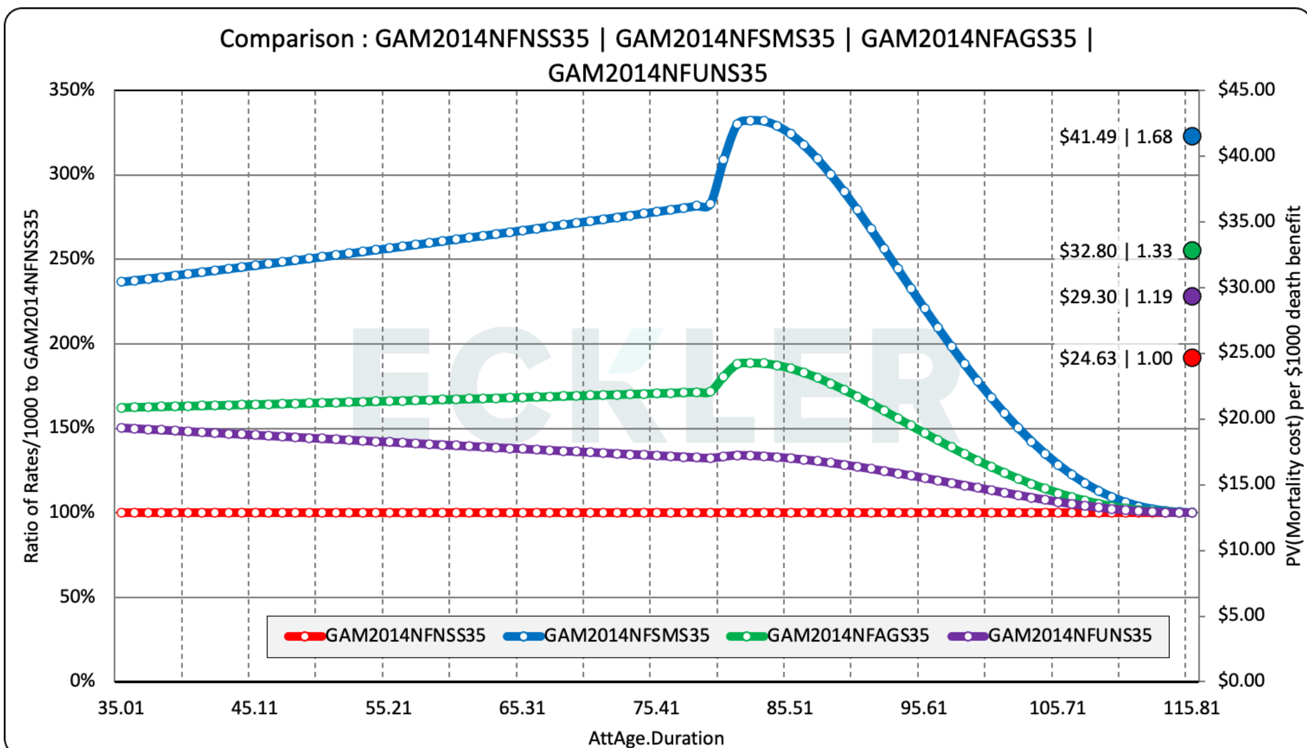


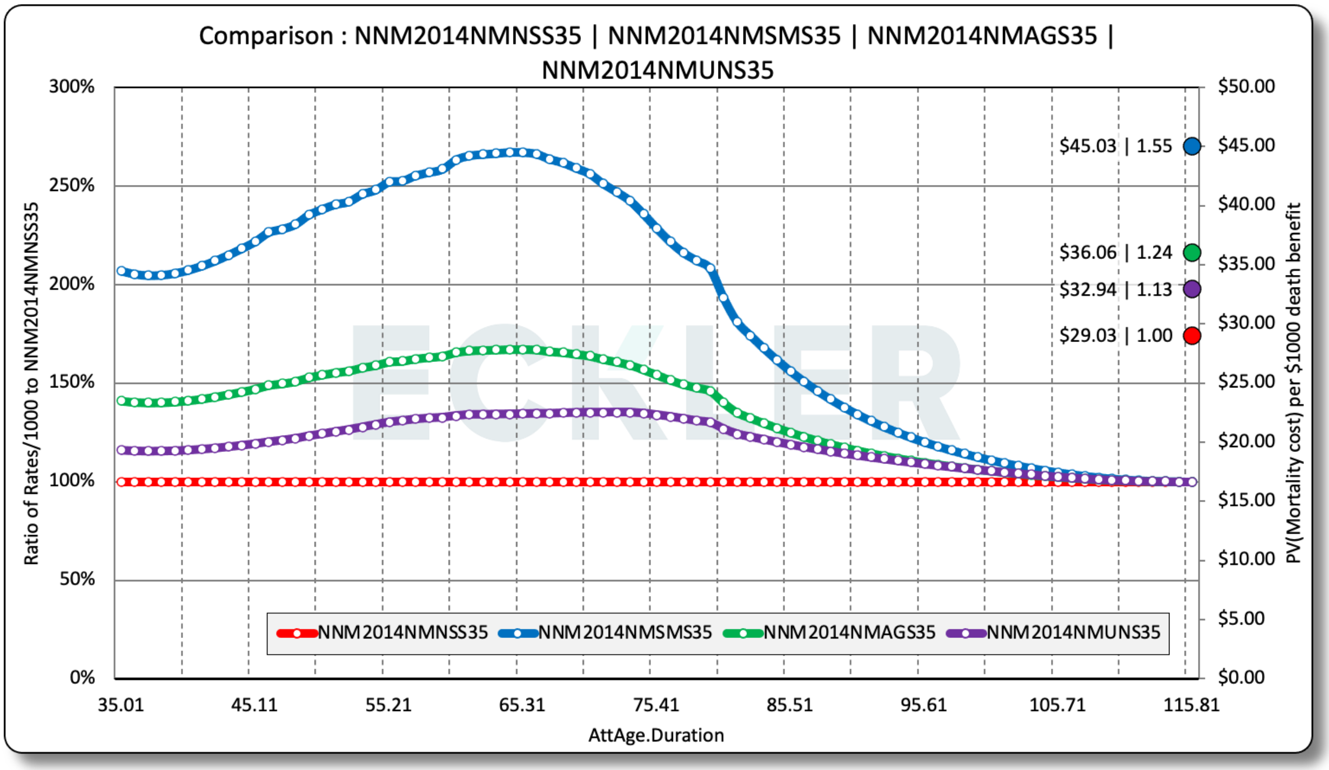
D.6. Comparison Across Classes

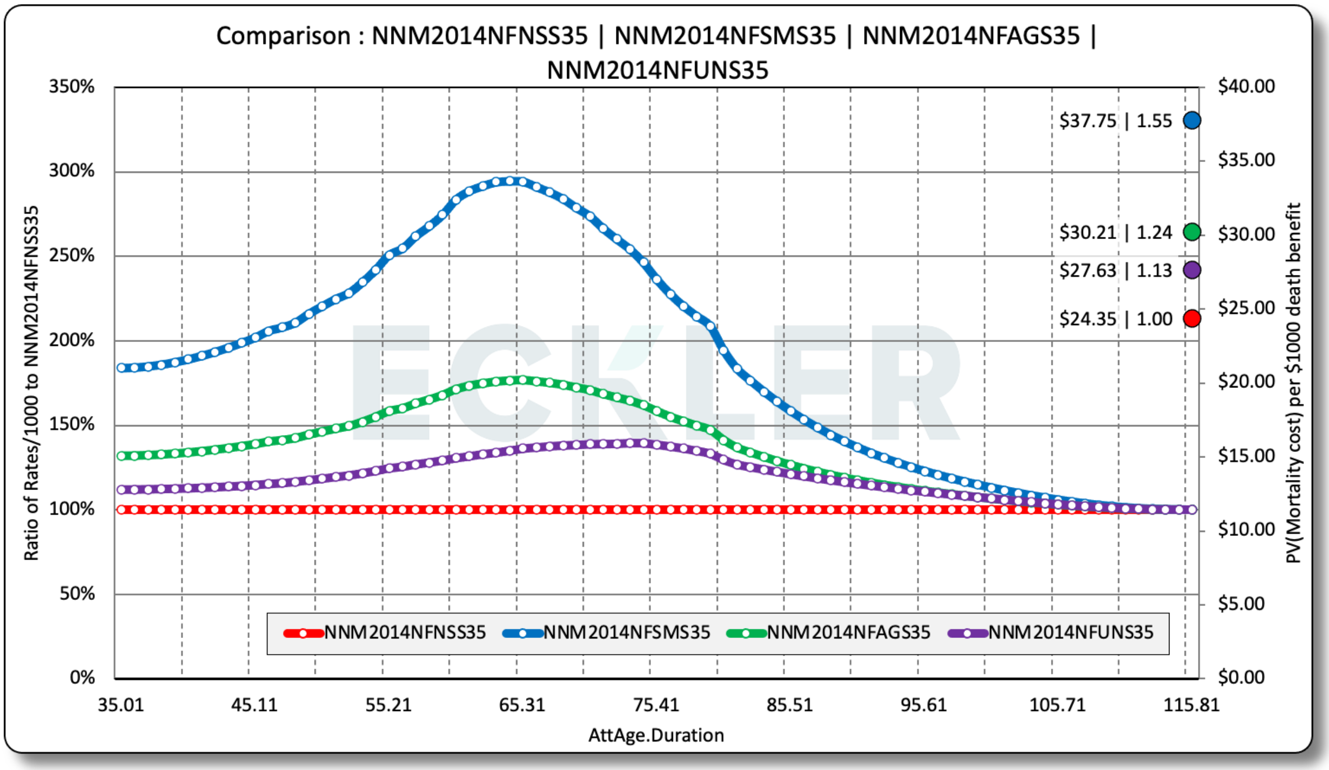




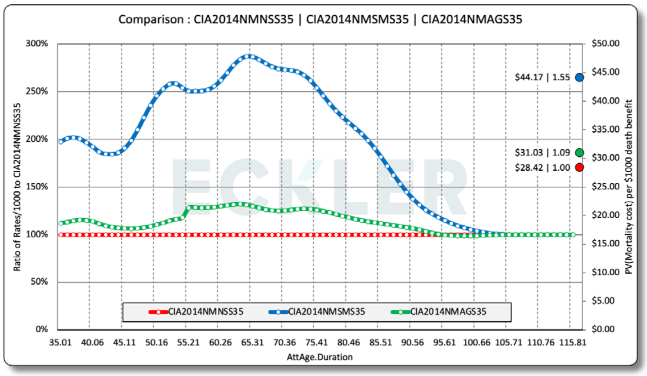

Comparison : GAM2014NMNSS35 | GAM2014NMSMS35 | GAM2014NMAGS35 | GAM2014NMUNS35
Ratio of Rates/1000 to GAM2014NMNSS35
PV(Mortality cost) per $1000 death benefit
$47.23 | 1.59
$37.95 | 1.28
$34.62 | 1.16
$29.74 | 1.00
GAM2014NMNSS35
GAM2014NMSMS35
GAM2014NMAGS35
GAM2014NMUNS35
AttAge.Duration
300%
250%
200%
150%
100%
50%
0%
$50.00
$45.00
$40.00
$35.00
$30.00
$25.00
$20.00
$15.00
$10.00
$5.00
$0.00
35.01
45.11
55.21
65.31
75.41
85.51
95.61
105.71
115.81


Comparison : GAM2014NFNSS35 | GAM2014NFSMS35 | GAM2014NFAGS35 | GAM2014NFUNS35
Ratio of Rates/1000 to GAM2014NFNSS35
PV(Mortality cost) per $1000 death benefit
$41.49 | 1.68
$32.80 | 1.33
$29.30 | 1.19
$24.63 | 1.00
GAM2014NFNSS35
GAM2014NFSMS35
GAM2014NFAGS35
GAM2014NFUNS35
AttAge.Duration
350%
300%
250%
200%
150%
100%
50%
0%
$45.00
$40.00
$35.00
$30.00
$25.00
$20.00
$15.00
$10.00
$5.00
$0.00
35.01
45.11
55.21
65.31
75.41
85.51
95.61
105.71
115.81

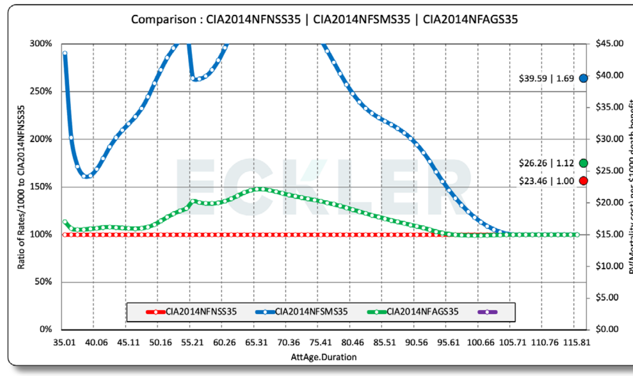

Comparison : NNM2014NMNSS35 | NNM2014NMSMS35 | NNM2014NMAGS35 | NNM2014NMUNS35
Ratio of Rates/1000 to NNM2014NMNSS35
PV(Mortality cost) per $1000 death benefit
AttAge.Duration
$45.03 | 1.55
$36.06 | 1.24
$32.94 | 1.13
$29.03 | 1.00
NNM2014NMNSS35
NNM2014NMSMS35
NNM2014NMAGS35
NNM2014NMUNS35


Comparison : NNM2014NFNSS35 | NNM2014NFSMS35 | NNM2014NFAGS35 | NNM2014NFUNS35
Ratio of Rates/1000 to NNM2014NFNSS35
PV(Mortality cost) per $1000 death benefit
AttAge.Duration
$37.75 | 1.55
$30.21 | 1.24
$27.63 | 1.13
$24.35 | 1.00
NNM2014NFNSS35
NNM2014NFSMS35
NNM2014NFAGS35
NNM2014NFUNS35

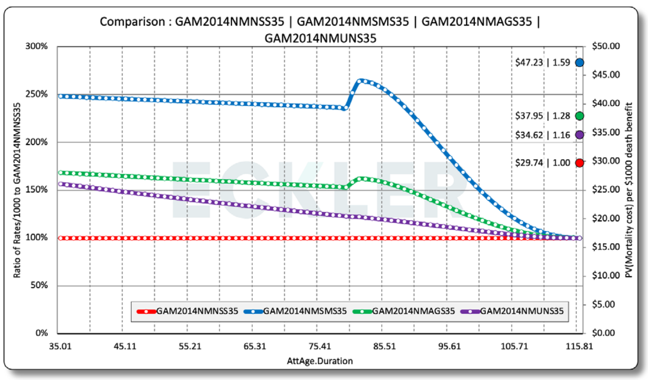
CIA2014 Males



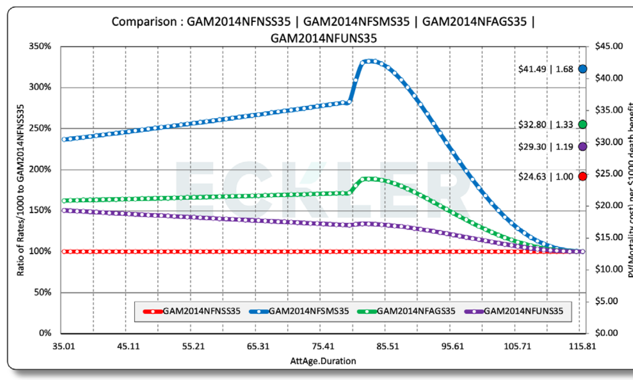
CIA2014 Females



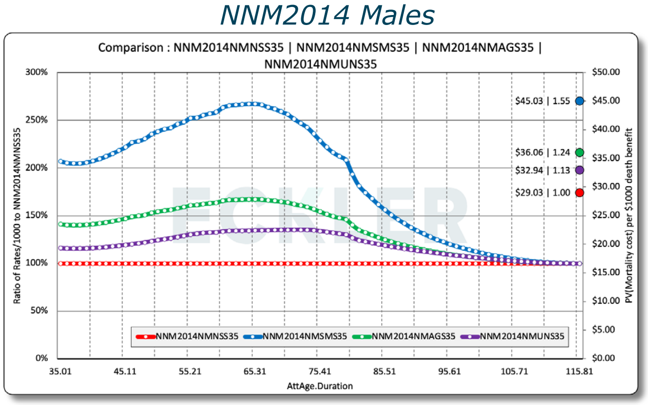
GAM2014 Males



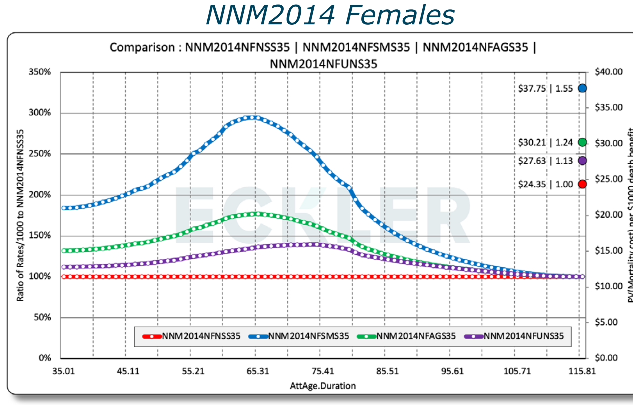
GAM2014 Females



NNM2014 Males

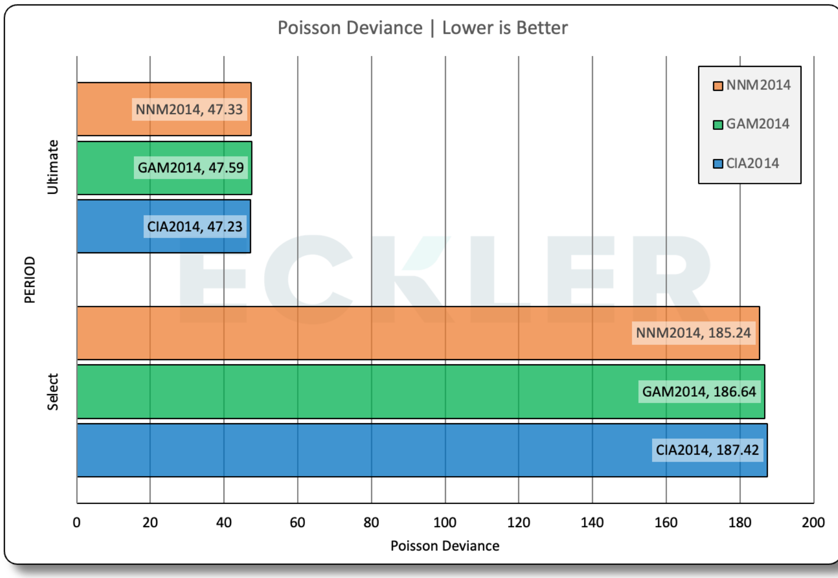


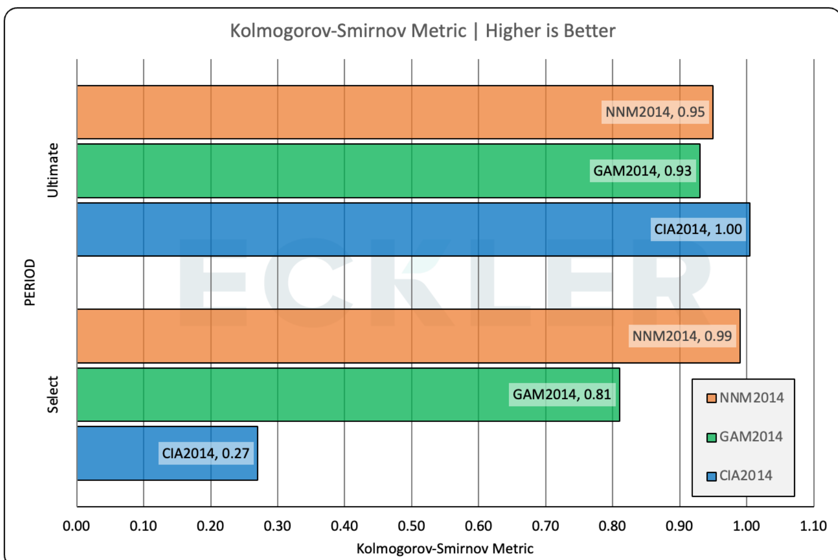
NNM2014 Females



D.7. Poisson deviance and Kolmogorov–Smirnov Metric

The following charts show the comparison between the three tables of the Poisson deviance and the KS Metric:





One explanation for the poorer performance of the CIA2014 Table on the select period is that the table does not differentiate by year, so there will be a poor fit by year.

For the ultimate period, our initial expectation was for the fit to be poorer under the alternative methods, owing to the CIA2014 ultimate period not differentiating by duration and year. We do see that the CIA2014 performs slightly better than the alternative methods. This could be due to the added dimensions of complexity introduced by the alternative methods leading to more variance in prediction. However, in our opinion, the difference in performance on the ultimate rates is not significant, particularly between CIA2014 and the NNM2014.

E. EXTRACT OF THE CIA2014 TABLE

E.1. Age Nearest Birthday | Male Non-Smokers

	MORTALITY RATES PER 1000 | CIA2014 | Male Non-smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.285	0.072	0.047	0.191	0.346	0.457	0.541	0.603	0.730	3.391	33.123	344.883	1000.000
005	0.072	0.047	0.191	0.346	0.457	0.541	0.603	0.730	1.043	5.538	64.464	461.928	0.000
010	0.047	0.191	0.346	0.457	0.541	0.603	0.730	1.043	1.394	9.602	128.035	540.058	0.000
015	0.191	0.346	0.457	0.541	0.603	0.730	1.043	1.394	2.072	16.833	223.658	1000.000	0.000
020	0.204	0.321	0.445	0.515	0.730	1.043	1.394	2.072	3.391	33.123	344.883	0.000	0.000
025	0.193	0.291	0.437	0.603	1.043	1.394	2.072	3.391	5.538	64.464	461.928	0.000	0.000
030	0.202	0.320	0.527	0.860	1.394	2.072	3.391	5.538	9.602	128.035	540.058	0.000	0.000
035	0.200	0.391	0.754	1.143	2.072	3.391	5.538	9.602	16.833	223.658	1000.000	0.000	0.000
040	0.229	0.578	1.007	1.699	3.391	5.538	9.602	16.833	33.123	344.883	0.000	0.000	0.000
045	0.331	0.814	1.537	2.779	5.538	9.602	16.833	33.123	64.464	461.928	0.000	0.000	0.000
050	0.489	1.201	2.523	4.569	9.602	16.833	33.123	64.464	128.035	540.058	0.000	0.000	0.000
055	0.701	1.971	4.209	8.041	16.833	33.123	64.464	128.035	223.658	1000.000	0.000	0.000	0.000
060	1.142	3.296	7.312	14.282	33.123	64.464	128.035	223.658	344.883	0.000	0.000	0.000	0.000
065	1.834	5.732	12.855	28.784	64.464	128.035	223.658	344.883	461.928	0.000	0.000	0.000	0.000
070	3.260	9.970	25.080	56.889	128.035	223.658	344.883	461.928	540.058	0.000	0.000	0.000	0.000
075	5.776	19.689	48.366	113.438	223.658	344.883	461.928	540.058	1000.000	0.000	0.000	0.000	0.000
080	11.404	38.360	96.103	199.045	344.883	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000
085	22.042	78.477	178.838	312.725	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	46.036	159.301	337.020	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

E.2. Age Nearest Birthday | Male Smokers

	MORTALITY RATES PER 1000 | CIA2014 | Male Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.285	0.072	0.047	0.191	0.579	0.765	0.905	0.995	1.183	8.885	71.985	357.794	1000.000
005	0.072	0.047	0.191	0.579	0.765	0.905	0.995	1.183	1.910	15.859	117.003	461.928	0.000
010	0.047	0.191	0.579	0.765	0.905	0.995	1.183	1.910	3.106	26.210	176.001	540.058	0.000
015	0.191	0.579	0.765	0.905	0.995	1.183	1.910	3.106	5.186	42.733	256.655	1000.000	0.000
020	0.351	0.592	0.766	0.887	1.183	1.910	3.106	5.186	8.885	71.985	357.794	0.000	0.000
025	0.355	0.584	0.760	1.064	1.910	3.106	5.186	8.885	15.859	117.003	461.928	0.000	0.000
030	0.394	0.628	0.899	1.718	3.106	5.186	8.885	15.859	26.210	176.001	540.058	0.000	0.000
035	0.395	0.751	1.438	2.806	5.186	8.885	15.859	26.210	42.733	256.655	1000.000	0.000	0.000
040	0.467	1.225	2.344	4.717	8.885	15.859	26.210	42.733	71.985	357.794	0.000	0.000	0.000
045	0.815	2.031	3.975	8.174	15.859	26.210	42.733	71.985	117.003	461.928	0.000	0.000	0.000
050	1.387	3.414	6.955	14.664	26.210	42.733	71.985	117.003	176.001	540.058	0.000	0.000	0.000
055	2.257	5.954	12.771	24.378	42.733	71.985	117.003	176.001	256.655	1000.000	0.000	0.000	0.000
060	3.769	10.658	21.394	40.003	71.985	117.003	176.001	256.655	357.794	0.000	0.000	0.000	0.000
065	6.835	17.749	35.429	67.675	117.003	176.001	256.655	357.794	461.928	0.000	0.000	0.000	0.000
070	11.377	28.882	60.046	110.585	176.001	256.655	357.794	461.928	540.058	0.000	0.000	0.000	0.000
075	18.796	48.581	97.530	166.587	256.655	357.794	461.928	540.058	1000.000	0.000	0.000	0.000	0.000
080	31.767	78.979	146.941	243.196	357.794	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000
085	52.586	121.840	219.143	341.276	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	79.918	204.266	357.794	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

E.3. Age Nearest Birthday | Male Aggregate

	MORTALITY RATES PER 1000 | CIA2014 | Male Aggregate | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.285	0.072	0.047	0.191	0.444	0.587	0.694	0.805	0.967	4.395	39.015	340.621	1000.000
005	0.072	0.047	0.191	0.444	0.587	0.694	0.805	0.967	1.283	7.186	71.930	461.928	0.000
010	0.047	0.191	0.444	0.587	0.694	0.805	0.967	1.283	1.719	12.023	136.204	540.058	0.000
015	0.191	0.444	0.587	0.694	0.805	0.967	1.283	1.719	2.656	21.210	222.751	1000.000	0.000
020	0.251	0.387	0.529	0.661	0.967	1.283	1.719	2.656	4.395	39.015	340.621	0.000	0.000
025	0.226	0.324	0.500	0.711	1.283	1.719	2.656	4.395	7.186	71.930	461.928	0.000	0.000
030	0.229	0.366	0.599	0.945	1.719	2.656	4.395	7.186	12.023	136.204	540.058	0.000	0.000
035	0.224	0.445	0.803	1.262	2.656	4.395	7.186	12.023	21.210	222.751	1000.000	0.000	0.000
040	0.255	0.625	1.080	1.946	4.395	7.186	12.023	21.210	39.015	340.621	0.000	0.000	0.000
045	0.361	0.895	1.717	3.209	7.186	12.023	21.210	39.015	71.930	461.928	0.000	0.000	0.000
050	0.549	1.347	2.832	5.281	12.023	21.210	39.015	71.930	136.204	540.058	0.000	0.000	0.000
055	0.795	2.200	4.744	8.998	21.210	39.015	71.930	136.204	222.751	1000.000	0.000	0.000	0.000
060	1.275	3.647	7.972	16.139	39.015	71.930	136.204	222.751	340.621	0.000	0.000	0.000	0.000
065	2.039	6.122	14.196	30.734	71.930	136.204	222.751	340.621	461.928	0.000	0.000	0.000	0.000
070	3.511	10.706	26.080	58.194	136.204	222.751	340.621	461.928	540.058	0.000	0.000	0.000	0.000
075	6.293	19.850	47.824	111.295	222.751	340.621	461.928	540.058	1000.000	0.000	0.000	0.000	0.000
080	11.633	36.739	90.907	183.353	340.621	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000
085	21.196	72.230	160.632	288.916	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	42.500	139.170	302.628	461.928	540.058	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

E.4. Age Nearest Birthday | Female Non-Smokers

	MORTALITY RATES PER 1000 | CIA2014 | Female Non-smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.144	0.044	0.040	0.093	0.167	0.212	0.261	0.372	0.526	2.596	22.055	278.525	1000.000
005	0.044	0.040	0.093	0.167	0.212	0.261	0.372	0.526	0.771	3.651	46.482	388.555	0.000
010	0.040	0.093	0.167	0.212	0.261	0.372	0.526	0.771	1.017	6.265	94.819	483.037	0.000
015	0.093	0.167	0.212	0.261	0.372	0.526	0.771	1.017	1.605	11.499	174.589	1000.000	0.000
020	0.079	0.149	0.214	0.333	0.526	0.771	1.017	1.605	2.596	22.055	278.525	0.000	0.000
025	0.055	0.149	0.261	0.445	0.771	1.017	1.605	2.596	3.651	46.482	388.555	0.000	0.000
030	0.062	0.212	0.372	0.651	1.017	1.605	2.596	3.651	6.265	94.819	483.037	0.000	0.000
035	0.074	0.305	0.555	0.864	1.605	2.596	3.651	6.265	11.499	174.589	1000.000	0.000	0.000
040	0.106	0.449	0.761	1.360	2.596	3.651	6.265	11.499	22.055	278.525	0.000	0.000	0.000
045	0.159	0.618	1.242	2.208	3.651	6.265	11.499	22.055	46.482	388.555	0.000	0.000	0.000
050	0.226	0.999	2.021	3.125	6.265	11.499	22.055	46.482	94.819	483.037	0.000	0.000	0.000
055	0.386	1.590	2.805	5.324	11.499	22.055	46.482	94.819	174.589	1000.000	0.000	0.000	0.000
060	0.630	2.242	4.752	9.877	22.055	46.482	94.819	174.589	278.525	0.000	0.000	0.000	0.000
065	0.914	3.816	8.524	19.110	46.482	94.819	174.589	278.525	388.555	0.000	0.000	0.000	0.000
070	1.519	6.787	15.881	40.848	94.819	174.589	278.525	388.555	483.037	0.000	0.000	0.000	0.000
075	2.647	12.554	32.262	84.187	174.589	278.525	388.555	483.037	1000.000	0.000	0.000	0.000	0.000
080	4.940	26.094	64.950	152.568	278.525	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000
085	10.445	55.943	126.086	250.849	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	24.878	123.996	261.833	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

E.5. Age Nearest Birthday | Female Smokers

	MORTALITY RATES PER 1000 | CIA2014 | Female Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.144	0.044	0.040	0.093	0.236	0.300	0.370	0.533	0.869	7.683	54.623	314.799	1000.000
005	0.044	0.040	0.093	0.236	0.300	0.370	0.533	0.869	1.550	13.394	101.828	388.555	0.000
010	0.040	0.093	0.236	0.300	0.370	0.533	0.869	1.550	2.624	21.938	184.126	483.037	0.000
015	0.093	0.236	0.300	0.370	0.533	0.869	1.550	2.624	4.242	34.972	256.077	1000.000	0.000
020	0.134	0.215	0.310	0.472	0.869	1.550	2.624	4.242	7.683	54.623	314.799	0.000	0.000
025	0.123	0.223	0.413	0.775	1.550	2.624	4.242	7.683	13.394	101.828	388.555	0.000	0.000
030	0.152	0.322	0.675	1.389	2.624	4.242	7.683	13.394	21.938	184.126	483.037	0.000	0.000
035	0.215	0.515	1.201	2.358	4.242	7.683	13.394	21.938	34.972	256.077	1000.000	0.000	0.000
040	0.321	0.917	2.028	3.828	7.683	13.394	21.938	34.972	54.623	314.799	0.000	0.000	0.000
045	0.528	1.587	3.285	7.000	13.394	21.938	34.972	54.623	101.828	388.555	0.000	0.000	0.000
050	0.869	2.584	5.952	12.153	21.938	34.972	54.623	101.828	184.126	483.037	0.000	0.000	0.000
055	1.459	4.792	10.545	19.705	34.972	54.623	101.828	184.126	256.077	1000.000	0.000	0.000	0.000
060	2.939	8.346	17.368	30.872	54.623	101.828	184.126	256.077	314.799	0.000	0.000	0.000	0.000
065	5.356	13.968	27.471	47.502	101.828	184.126	256.077	314.799	388.555	0.000	0.000	0.000	0.000
070	9.079	22.697	43.932	89.094	184.126	256.077	314.799	388.555	483.037	0.000	0.000	0.000	0.000
075	14.920	35.259	82.366	163.606	256.077	314.799	388.555	483.037	1000.000	0.000	0.000	0.000	0.000
080	23.545	64.884	148.531	230.232	314.799	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000
085	41.562	123.379	219.154	290.272	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	75.922	194.052	314.799	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

E.6. Age Nearest Birthday | Female Aggregate

	MORTALITY RATES PER 1000 | CIA2014 | Female Aggregate | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.144	0.044	0.040	0.093	0.198	0.251	0.310	0.456	0.675	3.510	27.841	275.846	1000.000
005	0.044	0.040	0.093	0.198	0.251	0.310	0.456	0.675	0.969	5.394	54.242	388.555	0.000
010	0.040	0.093	0.198	0.251	0.310	0.456	0.675	0.969	1.336	8.882	102.940	483.037	0.000
015	0.093	0.198	0.251	0.310	0.456	0.675	0.969	1.336	2.167	15.523	175.516	1000.000	0.000
020	0.089	0.164	0.231	0.376	0.675	0.969	1.336	2.167	3.510	27.841	275.846	0.000	0.000
025	0.058	0.149	0.272	0.497	0.969	1.336	2.167	3.510	5.394	54.242	388.555	0.000	0.000
030	0.066	0.218	0.405	0.714	1.336	2.167	3.510	5.394	8.882	102.940	483.037	0.000	0.000
035	0.084	0.325	0.591	0.988	2.167	3.510	5.394	8.882	15.523	175.516	1000.000	0.000	0.000
040	0.119	0.473	0.839	1.598	3.510	5.394	8.882	15.523	27.841	275.846	0.000	0.000	0.000
045	0.168	0.680	1.395	2.608	5.394	8.882	15.523	27.841	54.242	388.555	0.000	0.000	0.000
050	0.244	1.123	2.268	4.024	8.882	15.523	27.841	54.242	102.940	483.037	0.000	0.000	0.000
055	0.421	1.789	3.454	6.583	15.523	27.841	54.242	102.940	175.516	1000.000	0.000	0.000	0.000
060	0.698	2.721	5.679	11.635	27.841	54.242	102.940	175.516	275.846	0.000	0.000	0.000	0.000
065	1.087	4.478	9.792	21.203	54.242	102.940	175.516	275.846	388.555	0.000	0.000	0.000	0.000
070	1.721	7.709	17.472	42.593	102.940	175.516	275.846	388.555	483.037	0.000	0.000	0.000	0.000
075	2.873	13.464	33.545	83.168	175.516	275.846	388.555	483.037	1000.000	0.000	0.000	0.000	0.000
080	5.059	25.984	63.733	142.102	275.846	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000
085	9.893	52.164	115.836	233.373	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	22.000	108.234	233.794	388.555	483.037	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

F. EXTRACT OF THE GAM2014 TABLE

F.1. Age Nearest Birthday | Male Non-Smokers

	MORTALITY RATES PER 1000 | Generalized Additive Model | Observation Period: ALL | Male Non-Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.327	0.057	0.087	0.251	0.314	0.451	0.499	0.554	0.734	3.874	21.063	338.683	1000.000
005	0.028	0.066	0.213	0.295	0.424	0.462	0.533	0.751	1.133	6.416	37.610	563.812	0.000
010	0.033	0.162	0.251	0.398	0.435	0.494	0.723	1.158	1.696	10.714	81.329	865.443	0.000
015	0.081	0.191	0.338	0.408	0.464	0.669	1.115	1.733	2.601	18.508	192.509	1000.000	0.000
020	0.095	0.257	0.347	0.436	0.629	1.032	1.670	2.658	4.135	33.291	399.965	0.000	0.000
025	0.128	0.264	0.370	0.591	0.971	1.545	2.561	4.226	6.848	64.527	668.936	0.000	0.000
030	0.131	0.282	0.502	0.912	1.453	2.371	4.072	6.999	11.437	126.338	896.139	0.000	0.000
035	0.140	0.382	0.774	1.365	2.229	3.769	6.743	11.688	19.755	235.915	1000.000	0.000	0.000
040	0.190	0.589	1.159	2.095	3.544	6.242	11.261	20.189	35.998	420.486	0.000	0.000	0.000
045	0.293	0.882	1.778	3.330	5.870	10.424	19.451	36.667	68.452	676.658	0.000	0.000	0.000
050	0.439	1.352	2.826	5.515	9.802	18.005	36.008	70.612	136.024	900.641	0.000	0.000	0.000
055	0.674	2.150	4.681	9.210	16.931	34.230	70.208	137.058	255.597	1000.000	0.000	0.000	0.000
060	1.071	3.560	7.817	15.908	32.106	66.338	131.232	247.692	435.780	0.000	0.000	0.000	0.000
065	1.774	5.946	13.502	29.451	61.057	122.706	235.556	421.843	672.023	0.000	0.000	0.000	0.000
070	2.963	10.270	25.298	56.148	116.192	227.316	412.976	665.477	894.247	0.000	0.000	0.000	0.000
075	5.118	19.280	49.017	108.453	219.141	405.345	660.384	892.759	1000.000	0.000	0.000	0.000	0.000
080	10.662	36.532	92.645	199.673	384.548	644.936	887.897	1000.000	0.000	0.000	0.000	0.000	0.000
085	19.007	70.755	172.739	355.410	622.829	880.835	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	35.335	138.528	326.016	604.443	875.802	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

F.2. Age Nearest Birthday | Male Smokers

	MORTALITY RATES PER 1000 | Generalized Additive Model | Observation Period: ALL | Male Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.327	0.057	0.087	0.251	0.793	1.131	1.246	1.374	1.812	9.347	52.511	512.284	1000.000
005	0.028	0.066	0.213	0.745	1.064	1.154	1.324	1.852	2.780	15.393	93.889	702.321	0.000
010	0.033	0.162	0.633	0.999	1.085	1.225	1.785	2.841	4.138	25.561	184.825	912.367	0.000
015	0.081	0.481	0.848	1.019	1.152	1.652	2.737	4.229	6.311	43.905	362.720	1000.000	0.000
020	0.240	0.645	0.865	1.083	1.553	2.533	4.074	6.450	9.977	83.105	596.723	0.000	0.000
025	0.322	0.658	0.919	1.460	2.382	3.771	6.214	10.197	16.430	164.443	804.812	0.000	0.000
030	0.328	0.699	1.239	2.238	3.546	5.752	9.824	16.792	27.284	281.087	936.716	0.000	0.000
035	0.348	0.942	1.900	3.332	5.409	9.094	16.178	27.884	46.864	433.606	1000.000	0.000	0.000
040	0.470	1.445	2.828	5.082	8.551	14.975	26.864	47.894	90.398	621.971	0.000	0.000	0.000
045	0.720	2.151	4.313	8.035	14.082	24.868	46.143	92.382	174.559	812.447	0.000	0.000	0.000
050	1.072	3.281	6.819	13.231	23.384	42.714	91.474	180.760	301.856	940.327	0.000	0.000	0.000
055	1.635	5.187	11.230	21.972	40.165	87.570	180.250	303.585	464.344	1000.000	0.000	0.000	0.000
060	2.585	8.542	18.648	37.739	82.122	170.362	290.926	450.806	637.761	0.000	0.000	0.000	0.000
065	4.257	14.185	32.030	75.159	156.732	272.561	430.392	620.171	806.039	0.000	0.000	0.000	0.000
070	7.069	24.364	64.990	144.526	258.146	415.481	607.811	799.050	934.527	0.000	0.000	0.000	0.000
075	12.141	47.799	125.973	244.613	407.435	604.535	798.521	934.629	1000.000	0.000	0.000	0.000	0.000
080	23.925	91.563	213.028	381.174	586.420	789.723	932.524	1000.000	0.000	0.000	0.000	0.000	0.000
085	40.446	165.754	341.517	558.817	776.242	929.319	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	82.418	284.569	528.472	765.779	927.763	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

F.3. Age Nearest Birthday | Male Aggregate

	MORTALITY RATES PER 1000 | Generalized Additive Model | Observation Period: ALL | Male Aggregate | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.327	0.057	0.087	0.251	0.548	0.776	0.850	0.932	1.222	6.169	33.131	404.679	1000.000
005	0.028	0.066	0.213	0.514	0.730	0.787	0.897	1.249	1.864	10.108	58.813	616.762	0.000
010	0.033	0.162	0.437	0.686	0.740	0.831	1.203	1.905	2.759	16.703	120.061	883.615	0.000
015	0.081	0.332	0.582	0.695	0.781	1.114	1.835	2.820	4.187	28.551	256.626	1000.000	0.000
020	0.166	0.443	0.590	0.734	1.047	1.699	2.717	4.279	6.585	52.375	475.221	0.000	0.000
025	0.221	0.449	0.623	0.984	1.597	2.515	4.122	6.730	10.789	101.973	721.766	0.000	0.000
030	0.224	0.474	0.835	1.501	2.365	3.816	6.483	11.027	17.828	184.382	912.044	0.000	0.000
035	0.236	0.635	1.274	2.222	3.588	6.002	10.623	18.220	30.476	310.647	1000.000	0.000	0.000
040	0.317	0.969	1.886	3.371	5.644	9.834	17.554	31.146	56.818	497.634	0.000	0.000	0.000
045	0.483	1.435	2.861	5.303	9.247	16.250	30.007	57.972	108.218	729.498	0.000	0.000	0.000
050	0.715	2.177	4.500	8.689	15.280	27.777	57.179	111.856	198.277	916.238	0.000	0.000	0.000
055	1.085	3.423	7.374	14.357	26.120	54.562	111.381	199.567	334.727	1000.000	0.000	0.000	0.000
060	1.706	5.609	12.185	24.542	51.172	105.252	191.160	324.659	513.390	0.000	0.000	0.000	0.000
065	2.795	9.269	20.829	46.879	96.852	178.946	309.387	498.047	724.305	0.000	0.000	0.000	0.000
070	4.619	15.844	40.405	89.191	169.484	298.680	487.929	717.669	910.130	0.000	0.000	0.000	0.000
075	7.896	30.208	77.784	159.433	290.321	481.724	714.201	909.227	1000.000	0.000	0.000	0.000	0.000
080	15.830	57.181	137.577	267.975	461.587	701.098	905.387	1000.000	0.000	0.000	0.000	0.000	0.000
085	27.332	106.107	235.892	432.566	682.012	899.755	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	52.866	192.819	402.357	666.396	896.016	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

F.4. Age Nearest Birthday | Male Unknown

	MORTALITY RATES PER 1000 | Generalized Additive Model | Observation Period: ALL | Male Unknown | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.327	0.057	0.087	0.251	0.535	0.746	0.804	0.867	1.119	5.286	25.818	363.071	1000.000
005	0.028	0.066	0.213	0.503	0.702	0.744	0.835	1.144	1.679	8.515	44.941	584.154	0.000
010	0.033	0.162	0.427	0.659	0.700	0.773	1.102	1.716	2.445	13.832	94.029	873.036	0.000
015	0.081	0.324	0.559	0.658	0.727	1.020	1.653	2.499	3.648	23.242	214.649	1000.000	0.000
020	0.162	0.426	0.558	0.683	0.959	1.530	2.407	3.728	5.642	40.730	428.975	0.000	0.000
025	0.212	0.425	0.580	0.901	1.439	2.228	3.592	5.766	9.089	76.950	691.551	0.000	0.000
030	0.212	0.441	0.765	1.352	2.095	3.325	5.555	9.289	14.765	145.722	903.277	0.000	0.000
035	0.220	0.582	1.148	1.969	3.127	5.142	8.949	15.089	24.808	262.419	1000.000	0.000	0.000
040	0.290	0.873	1.671	2.938	4.835	8.284	14.537	25.354	44.057	450.445	0.000	0.000	0.000
045	0.435	1.271	2.493	4.543	7.790	13.457	24.427	44.866	81.643	699.389	0.000	0.000	0.000
050	0.633	1.897	3.856	7.319	12.654	22.611	44.056	84.197	156.953	907.747	0.000	0.000	0.000
055	0.945	2.933	6.212	11.890	21.262	41.886	83.684	158.057	284.240	1000.000	0.000	0.000	0.000
060	1.462	4.725	10.091	19.978	39.287	79.056	151.322	275.479	466.628	0.000	0.000	0.000	0.000
065	2.355	7.676	16.956	36.026	72.766	141.572	262.211	452.128	694.854	0.000	0.000	0.000	0.000
070	3.825	12.898	30.926	66.901	134.115	253.242	443.002	688.480	901.617	0.000	0.000	0.000	0.000
075	6.427	23.545	58.362	125.232	244.386	435.293	683.697	900.293	1000.000	0.000	0.000	0.000	0.000
080	12.904	43.450	107.059	223.079	413.794	668.636	895.740	1000.000	0.000	0.000	0.000	0.000	0.000
085	22.545	81.810	193.421	383.470	646.964	889.111	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	40.845	155.361	352.582	628.968	884.483	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

F.5. Age Nearest Birthday | Female Non-Smokers

	MORTALITY RATES PER 1000 | Generalized Additive Model | Observation Period: ALL | Female Non-Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.196	0.035	0.054	0.159	0.221	0.317	0.351	0.390	0.518	2.748	14.770	284.265	1000.000
005	0.017	0.041	0.135	0.207	0.298	0.325	0.376	0.529	0.800	4.557	26.242	511.990	0.000
010	0.020	0.102	0.176	0.280	0.306	0.348	0.510	0.818	1.199	7.620	58.503	844.811	0.000
015	0.051	0.134	0.237	0.287	0.327	0.472	0.788	1.226	1.842	13.180	148.221	1000.000	0.000
020	0.067	0.181	0.244	0.307	0.444	0.729	1.181	1.883	2.933	23.362	336.461	0.000	0.000
025	0.090	0.186	0.261	0.417	0.686	1.093	1.814	2.997	4.864	44.718	614.772	0.000	0.000
030	0.092	0.198	0.354	0.644	1.028	1.679	2.888	4.971	8.133	91.516	877.909	0.000	0.000
035	0.099	0.269	0.547	0.966	1.579	2.673	4.789	8.312	14.068	183.140	1000.000	0.000	0.000
040	0.134	0.416	0.820	1.484	2.514	4.433	8.008	14.378	25.220	354.764	0.000	0.000	0.000
045	0.207	0.624	1.259	2.362	4.169	7.413	13.852	25.667	47.436	622.266	0.000	0.000	0.000
050	0.311	0.958	2.004	3.917	6.971	12.822	25.146	48.871	98.577	882.723	0.000	0.000	0.000
055	0.477	1.525	3.324	6.550	12.057	23.854	48.548	99.417	199.120	1000.000	0.000	0.000	0.000
060	0.760	2.529	5.559	11.329	22.370	45.862	95.187	192.918	369.071	0.000	0.000	0.000	0.000
065	1.260	4.228	9.615	20.530	42.201	88.936	183.247	356.745	618.374	0.000	0.000	0.000	0.000
070	2.107	7.314	17.596	38.754	84.201	176.831	349.137	612.097	876.091	0.000	0.000	0.000	0.000
075	3.645	13.592	33.937	78.267	169.471	340.911	605.532	873.901	1000.000	0.000	0.000	0.000	0.000
080	7.720	25.570	66.483	152.984	320.617	588.115	867.807	1000.000	0.000	0.000	0.000	0.000	0.000
085	13.968	50.498	130.677	292.704	563.449	858.956	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	25.266	103.333	264.951	542.204	852.007	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

F.6. Age Nearest Birthday | Female Smokers

	MORTALITY RATES PER 1000 | Generalized Additive Model | Observation Period: ALL | Female Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.196	0.035	0.054	0.159	0.491	0.719	0.815	0.923	1.251	7.194	45.082	490.726	1000.000
005	0.017	0.041	0.135	0.461	0.676	0.754	0.889	1.278	1.971	12.175	82.774	687.920	0.000
010	0.020	0.102	0.392	0.636	0.709	0.823	1.232	2.015	3.016	20.777	167.443	907.901	0.000
015	0.051	0.298	0.539	0.666	0.774	1.140	1.941	3.082	4.727	36.673	337.900	1000.000	0.000
020	0.148	0.410	0.565	0.727	1.072	1.797	2.969	4.831	7.679	71.414	571.851	0.000	0.000
025	0.204	0.430	0.617	1.007	1.690	2.749	4.654	7.848	12.996	145.195	789.849	0.000	0.000
030	0.214	0.469	0.855	1.588	2.585	4.308	7.561	13.282	22.177	255.242	932.563	0.000	0.000
035	0.234	0.650	1.347	2.429	4.051	6.999	12.796	22.665	39.144	404.909	1000.000	0.000	0.000
040	0.324	1.025	2.061	3.807	6.582	11.845	21.836	40.005	77.664	596.650	0.000	0.000	0.000
045	0.511	1.568	3.231	6.184	11.138	20.213	38.542	79.378	154.091	797.485	0.000	0.000	0.000
050	0.781	2.457	5.249	10.465	19.007	35.678	78.607	159.590	274.068	936.202	0.000	0.000	0.000
055	1.225	3.992	8.882	17.859	33.549	75.255	159.185	275.751	433.887	1000.000	0.000	0.000	0.000
060	1.990	6.756	15.157	31.523	70.580	150.487	264.251	421.140	612.133	0.000	0.000	0.000	0.000
065	3.367	11.530	26.754	64.620	138.462	247.461	401.766	594.800	791.009	0.000	0.000	0.000	0.000
070	5.746	20.351	55.918	127.717	234.307	387.615	582.590	783.863	930.250	0.000	0.000	0.000	0.000
075	10.142	41.066	111.280	221.942	379.935	579.234	783.195	930.308	1000.000	0.000	0.000	0.000	0.000
080	20.673	80.833	193.175	355.122	561.381	774.167	928.101	1000.000	0.000	0.000	0.000	0.000	0.000
085	35.597	150.255	317.886	534.417	760.479	924.777	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	74.709	264.895	505.338	750.183	923.235	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

F.7. Age Nearest Birthday | Female Aggregate

	MORTALITY RATES PER 1000 | Generalized Additive Model | Observation Period: ALL | Female Aggregate | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.196	0.035	0.054	0.159	0.353	0.509	0.567	0.633	0.846	4.595	26.515	366.011	1000.000
005	0.017	0.041	0.135	0.331	0.478	0.525	0.610	0.864	1.313	7.671	47.887	582.893	0.000
010	0.020	0.102	0.281	0.449	0.494	0.565	0.833	1.342	1.981	12.916	100.248	870.794	0.000
015	0.051	0.214	0.381	0.464	0.531	0.771	1.293	2.024	3.061	22.500	221.935	1000.000	0.000
020	0.107	0.290	0.394	0.499	0.725	1.197	1.950	3.128	4.904	41.959	430.143	0.000	0.000
025	0.145	0.300	0.423	0.681	1.126	1.805	3.014	5.012	8.188	83.031	686.302	0.000	0.000
030	0.149	0.322	0.578	1.058	1.697	2.790	4.829	8.368	13.786	154.407	900.596	0.000	0.000
035	0.160	0.440	0.898	1.595	2.623	4.470	8.062	14.089	24.016	269.634	1000.000	0.000	0.000
040	0.219	0.683	1.354	2.465	4.203	7.463	13.574	24.544	45.497	451.161	0.000	0.000	0.000
045	0.340	1.030	2.092	3.950	7.017	12.565	23.647	46.419	88.103	693.911	0.000	0.000	0.000
050	0.513	1.591	3.352	6.594	11.816	21.889	45.770	91.059	166.032	904.961	0.000	0.000	0.000
055	0.793	2.550	5.596	11.102	20.583	43.659	90.679	167.198	290.900	1000.000	0.000	0.000	0.000
060	1.271	4.257	9.422	19.340	40.946	85.699	160.159	282.104	466.206	0.000	0.000	0.000	0.000
065	2.121	7.167	16.414	37.523	78.857	149.854	268.617	451.834	689.050	0.000	0.000	0.000	0.000
070	3.572	12.486	32.344	72.614	141.894	259.215	442.436	682.462	898.644	0.000	0.000	0.000	0.000
075	6.222	24.229	63.368	133.349	251.480	435.883	678.151	897.354	1000.000	0.000	0.000	0.000	0.000
080	12.818	46.670	114.910	231.412	416.147	663.900	892.825	1000.000	0.000	0.000	0.000	0.000	0.000
085	22.485	88.521	202.923	388.087	643.365	886.207	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	44.122	165.312	359.330	626.309	881.482	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

F.8. Age Nearest Birthday | Female Unknown

	MORTALITY RATES PER 1000 | Generalized Additive Model | Observation Period: ALL | Female Unknown | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.196	0.035	0.054	0.159	0.346	0.490	0.536	0.586	0.768	3.842	19.691	323.042	1000.000
005	0.017	0.041	0.135	0.325	0.461	0.496	0.565	0.785	1.169	6.280	34.646	548.770	0.000
010	0.020	0.102	0.276	0.433	0.467	0.523	0.756	1.194	1.726	10.351	74.798	859.669	0.000
015	0.051	0.210	0.367	0.438	0.492	0.700	1.151	1.764	2.614	17.646	179.683	1000.000	0.000
020	0.105	0.279	0.372	0.462	0.658	1.065	1.700	2.671	4.101	31.100	382.117	0.000	0.000
025	0.139	0.283	0.392	0.618	1.002	1.574	2.574	4.191	6.704	59.181	654.283	0.000	0.000
030	0.141	0.298	0.525	0.941	1.480	2.382	4.038	6.851	11.048	116.465	891.316	0.000	0.000
035	0.149	0.399	0.799	1.390	2.240	3.738	6.600	11.292	18.835	220.853	1000.000	0.000	0.000
040	0.199	0.608	1.180	2.105	3.515	6.110	10.879	19.250	33.607	402.070	0.000	0.000	0.000
045	0.303	0.898	1.786	3.303	5.745	10.070	18.546	34.213	62.782	661.980	0.000	0.000	0.000
050	0.447	1.359	2.803	5.398	9.469	17.168	33.556	64.714	125.451	895.959	0.000	0.000	0.000
055	0.677	2.132	4.582	8.897	16.143	31.868	64.303	126.425	239.692	1000.000	0.000	0.000	0.000
060	1.063	3.485	7.551	15.168	29.889	60.747	121.039	232.255	417.413	0.000	0.000	0.000	0.000
065	1.737	5.744	12.873	27.419	55.907	113.165	220.839	403.957	657.766	0.000	0.000	0.000	0.000
070	2.862	9.792	23.519	51.372	107.174	213.198	395.581	651.428	889.591	0.000	0.000	0.000	0.000
075	4.880	18.030	44.888	99.838	205.034	387.505	645.725	887.854	1000.000	0.000	0.000	0.000	0.000
080	10.060	33.607	85.071	186.130	366.444	629.418	882.567	1000.000	0.000	0.000	0.000	0.000	0.000
085	17.888	64.809	160.205	337.140	606.166	874.889	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	32.389	127.707	307.702	586.541	869.204	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

G. EXTRACT OF THE NNM2014 TABLE

G.1. Age Nearest Birthday | Male Non-Smokers

	MORTALITY RATES PER 1000 | Neural Network Model | Observation Period: ALL | Male Non-Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.210	0.100	0.102	0.210	0.407	0.592	0.640	0.795	1.021	5.166	29.207	376.409	1000.000
005	0.080	0.090	0.206	0.398	0.565	0.596	0.732	0.956	1.416	7.232	51.741	620.076	0.000
010	0.058	0.190	0.387	0.531	0.543	0.658	0.878	1.327	2.043	11.005	100.242	879.921	0.000
015	0.126	0.379	0.487	0.488	0.581	0.793	1.225	1.909	2.939	19.070	199.035	1000.000	0.000
020	0.247	0.374	0.427	0.504	0.707	1.114	1.765	2.759	4.396	33.734	379.038	0.000	0.000
025	0.247	0.303	0.418	0.621	0.997	1.611	2.570	4.188	6.811	58.565	640.210	0.000	0.000
030	0.157	0.298	0.529	0.883	1.448	2.367	3.954	6.602	11.006	111.378	886.725	0.000	0.000
035	0.156	0.403	0.762	1.281	2.147	3.688	6.332	10.789	19.081	214.636	1000.000	0.000	0.000
040	0.226	0.567	1.105	1.912	3.383	5.995	10.473	18.736	34.257	395.382	0.000	0.000	0.000
045	0.328	0.851	1.661	3.036	5.586	10.044	18.230	33.810	60.473	651.121	0.000	0.000	0.000
050	0.588	1.281	2.642	5.098	9.482	17.539	33.112	60.133	114.613	889.582	0.000	0.000	0.000
055	0.726	2.048	4.485	8.737	16.632	32.112	59.381	114.152	218.600	1000.000	0.000	0.000	0.000
060	1.164	3.424	7.656	15.474	30.711	58.063	112.894	217.474	398.054	0.000	0.000	0.000	0.000
065	1.744	5.777	13.756	28.646	55.829	110.445	214.840	395.528	650.536	0.000	0.000	0.000	0.000
070	3.147	10.058	24.917	51.764	105.921	209.884	390.688	647.145	888.111	0.000	0.000	0.000	0.000
075	5.441	18.020	44.085	95.757	196.758	375.982	635.723	884.398	1000.000	0.000	0.000	0.000	0.000
080	8.951	30.807	75.005	166.162	337.921	603.589	873.357	1000.000	0.000	0.000	0.000	0.000	0.000
085	15.049	44.947	114.444	264.154	532.699	846.529	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	22.884	56.708	153.133	391.253	778.530	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

G.2. Age Nearest Birthday | Male Smokers

	MORTALITY RATES PER 1000 | Neural Network Model | Observation Period: ALL | Male Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.210	0.100	0.102	0.210	0.596	0.953	1.129	1.380	1.802	10.791	51.198	424.126	1000.000
005	0.080	0.090	0.206	0.575	0.917	1.080	1.322	1.761	2.683	15.986	75.977	647.028	0.000
010	0.058	0.190	0.555	0.863	1.000	1.224	1.678	2.616	4.214	24.981	129.975	888.548	0.000
015	0.126	0.553	0.796	0.902	1.098	1.559	2.502	4.077	6.479	39.509	234.213	1000.000	0.000
020	0.382	0.647	0.792	0.955	1.414	2.345	3.897	6.283	10.445	60.582	415.509	0.000	0.000
025	0.465	0.600	0.800	1.253	2.150	3.669	6.058	10.287	17.262	88.503	667.888	0.000	0.000
030	0.298	0.588	1.078	1.930	3.386	5.778	10.056	17.395	27.186	148.029	895.819	0.000	0.000
035	0.323	0.835	1.691	3.051	5.412	9.712	16.914	27.647	43.624	257.846	1000.000	0.000	0.000
040	0.524	1.314	2.677	4.948	9.209	16.468	27.262	42.925	66.680	441.683	0.000	0.000	0.000
045	0.802	2.130	4.397	8.514	15.773	26.586	41.882	66.195	96.092	686.060	0.000	0.000	0.000
050	1.547	3.509	7.615	14.943	25.428	40.727	65.617	96.404	158.062	900.813	0.000	0.000	0.000
055	2.299	6.171	13.549	24.050	39.682	64.944	96.224	158.647	270.777	1000.000	0.000	0.000	0.000
060	3.766	11.236	21.695	38.177	63.893	95.327	158.264	271.051	452.960	0.000	0.000	0.000	0.000
065	6.439	17.600	35.598	61.350	93.014	156.575	270.211	452.994	692.032	0.000	0.000	0.000	0.000
070	11.488	27.910	55.751	88.017	153.128	268.817	453.609	693.446	902.624	0.000	0.000	0.000	0.000
075	16.634	47.306	80.067	140.002	249.955	431.881	676.865	897.309	1000.000	0.000	0.000	0.000	0.000
080	26.859	64.679	115.753	215.140	390.712	644.187	886.540	1000.000	0.000	0.000	0.000	0.000	0.000
085	41.539	73.546	145.888	296.941	558.798	855.412	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	37.311	98.179	236.915	502.412	833.692	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

G.3. Age Nearest Birthday | Male Aggregate

	MORTALITY RATES PER 1000 | Neural Network Model | Observation Period: ALL | Male Aggregate | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.210	0.100	0.102	0.210	0.479	0.731	0.831	1.025	1.332	7.439	38.595	398.740	1000.000
005	0.080	0.090	0.206	0.465	0.700	0.783	0.963	1.275	1.922	10.781	62.582	634.054	0.000
010	0.058	0.190	0.451	0.658	0.718	0.878	1.193	1.840	2.914	16.762	114.372	884.614	0.000
015	0.126	0.446	0.605	0.646	0.780	1.093	1.731	2.777	4.369	27.776	216.623	1000.000	0.000
020	0.301	0.479	0.566	0.676	0.981	1.599	2.615	4.181	6.838	45.441	398.000	0.000	0.000
025	0.333	0.416	0.563	0.865	1.449	2.428	3.975	6.647	11.019	72.070	654.733	0.000	0.000
030	0.212	0.408	0.739	1.290	2.212	3.736	6.410	10.928	17.653	128.451	891.486	0.000	0.000
035	0.220	0.568	1.121	1.974	3.451	6.107	10.584	17.671	29.415	235.500	1000.000	0.000	0.000
040	0.340	0.854	1.717	3.118	5.714	10.197	17.331	28.975	48.196	418.116	0.000	0.000	0.000
045	0.511	1.346	2.741	5.219	9.665	16.807	28.298	47.768	76.249	668.370	0.000	0.000	0.000
050	0.959	2.157	4.613	9.018	16.013	27.440	47.122	76.160	134.369	895.134	0.000	0.000	0.000
055	1.335	3.680	8.080	14.995	26.445	46.220	75.618	134.318	242.885	1000.000	0.000	0.000	0.000
060	2.199	6.482	13.381	25.090	44.893	74.443	133.421	242.378	424.173	0.000	0.000	0.000	0.000
065	3.550	10.575	22.942	42.571	72.155	131.301	240.553	422.825	670.604	0.000	0.000	0.000	0.000
070	6.440	17.512	37.991	67.664	127.234	237.166	420.426	669.394	895.159	0.000	0.000	0.000	0.000
075	10.061	30.118	59.695	115.867	221.966	403.374	656.398	890.994	1000.000	0.000	0.000	0.000	0.000
080	16.298	45.252	93.473	189.676	364.485	624.735	880.379	1000.000	0.000	0.000	0.000	0.000	0.000
085	26.222	57.558	129.162	280.526	546.489	851.419	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	29.014	73.917	188.086	438.374	802.346	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

G.4. Age Nearest Birthday | Male Unknown

	MORTALITY RATES PER 1000 | Neural Network Model | Observation Period: ALL | Male Unknown | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.210	0.100	0.102	0.210	0.435	0.650	0.723	0.901	1.172	6.361	35.381	395.686	1000.000
005	0.080	0.090	0.206	0.423	0.618	0.673	0.834	1.108	1.667	9.126	60.028	635.059	0.000
010	0.058	0.190	0.411	0.579	0.611	0.751	1.024	1.578	2.485	14.301	112.900	885.374	0.000
015	0.126	0.407	0.533	0.547	0.660	0.927	1.467	2.344	3.687	24.748	216.622	1000.000	0.000
020	0.273	0.416	0.478	0.569	0.823	1.338	2.184	3.500	5.672	42.007	399.452	0.000	0.000
025	0.285	0.344	0.471	0.720	1.198	2.004	3.295	5.465	8.984	69.142	656.101	0.000	0.000
030	0.179	0.339	0.611	1.056	1.803	3.062	5.220	8.785	14.766	125.946	891.914	0.000	0.000
035	0.181	0.467	0.909	1.591	2.794	4.920	8.505	14.577	25.540	234.018	1000.000	0.000	0.000
040	0.271	0.680	1.370	2.493	4.550	8.128	14.258	25.265	43.652	417.284	0.000	0.000	0.000
045	0.404	1.056	2.167	4.105	7.637	13.790	24.782	43.299	72.183	667.929	0.000	0.000	0.000
050	0.741	1.683	3.583	7.014	13.130	24.053	42.637	71.943	130.431	895.007	0.000	0.000	0.000
055	0.981	2.820	6.206	12.197	23.021	41.605	71.251	130.154	239.278	1000.000	0.000	0.000	0.000
060	1.667	4.787	10.793	21.618	40.075	69.940	129.106	238.610	421.507	0.000	0.000	0.000	0.000
065	2.469	8.348	19.471	37.719	67.621	126.883	236.610	419.953	669.245	0.000	0.000	0.000	0.000
070	4.686	14.566	33.305	63.211	122.654	232.797	416.981	667.590	894.743	0.000	0.000	0.000	0.000
075	8.107	25.027	54.933	111.842	219.184	402.260	656.606	891.273	1000.000	0.000	0.000	0.000	0.000
080	13.084	40.270	89.661	187.726	364.822	626.428	881.240	1000.000	0.000	0.000	0.000	0.000	0.000
085	22.079	54.179	127.153	280.482	547.969	852.317	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	26.847	66.863	174.209	421.456	794.816	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

G.5. Age Nearest Birthday | Female Non-Smokers

	MORTALITY RATES PER 1000 | Neural Network Model | Observation Period: ALL | Female Non-Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.114	0.048	0.054	0.120	0.245	0.338	0.369	0.476	0.636	3.983	17.187	304.361	1000.000
005	0.033	0.044	0.115	0.246	0.338	0.363	0.463	0.621	0.944	5.376	32.403	559.175	0.000
010	0.024	0.104	0.239	0.326	0.346	0.438	0.595	0.910	1.468	7.829	68.884	859.168	0.000
015	0.066	0.221	0.298	0.317	0.400	0.559	0.865	1.388	2.237	12.373	152.441	1000.000	0.000
020	0.138	0.212	0.270	0.348	0.513	0.812	1.305	2.103	3.353	21.301	323.003	0.000	0.000
025	0.134	0.175	0.278	0.457	0.750	1.217	1.976	3.172	4.984	40.937	596.243	0.000	0.000
030	0.089	0.185	0.378	0.676	1.121	1.850	2.994	4.776	7.708	85.615	873.198	0.000	0.000
035	0.092	0.272	0.569	1.010	1.717	2.814	4.547	7.486	12.794	180.133	1000.000	0.000	0.000
040	0.139	0.395	0.860	1.566	2.623	4.302	7.213	12.598	23.870	356.892	0.000	0.000	0.000
045	0.205	0.622	1.363	2.402	4.039	6.902	12.288	23.866	46.423	621.738	0.000	0.000	0.000
050	0.376	1.024	2.093	3.730	6.542	11.868	23.555	46.554	94.195	880.124	0.000	0.000	0.000
055	0.513	1.543	3.256	6.068	11.327	22.919	46.086	93.973	189.805	1000.000	0.000	0.000	0.000
060	0.842	2.296	5.256	10.580	21.888	44.918	92.619	188.235	362.728	0.000	0.000	0.000	0.000
065	1.070	3.866	9.156	20.170	42.734	89.815	184.652	358.670	620.168	0.000	0.000	0.000	0.000
070	1.950	6.277	16.872	38.604	84.363	177.495	350.369	613.421	876.615	0.000	0.000	0.000	0.000
075	3.412	11.168	30.738	72.531	160.223	328.650	594.656	870.039	1000.000	0.000	0.000	0.000	0.000
080	5.395	19.716	52.601	126.899	281.938	550.338	853.425	1000.000	0.000	0.000	0.000	0.000	0.000
085	9.577	29.649	81.679	208.293	468.994	818.869	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	15.630	38.599	113.310	327.986	740.149	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

G.6. Age Nearest Birthday | Female Smokers

	MORTALITY RATES PER 1000 | Neural Network Model | Observation Period: ALL | Female Smoker | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.114	0.048	0.054	0.120	0.301	0.461	0.586	0.791	1.102	8.179	31.933	367.771	1000.000
005	0.033	0.044	0.115	0.298	0.455	0.572	0.777	1.107	1.749	11.659	52.838	607.400	0.000
010	0.024	0.104	0.291	0.437	0.541	0.738	1.081	1.752	2.974	17.107	97.981	875.311	0.000
015	0.066	0.279	0.406	0.496	0.673	1.024	1.709	2.931	5.107	25.652	194.274	1000.000	0.000
020	0.187	0.311	0.431	0.586	0.938	1.624	2.831	4.992	8.390	39.036	372.620	0.000	0.000
025	0.217	0.306	0.475	0.831	1.501	2.679	4.825	8.321	12.965	64.267	635.417	0.000	0.000
030	0.150	0.329	0.696	1.346	2.477	4.601	8.200	13.239	19.826	117.229	885.588	0.000	0.000
035	0.168	0.514	1.148	2.227	4.306	7.983	13.381	20.498	30.247	221.345	1000.000	0.000	0.000
040	0.288	0.838	1.913	3.930	7.624	13.302	20.963	31.347	47.950	403.976	0.000	0.000	0.000
045	0.462	1.419	3.447	7.077	12.923	21.078	32.080	49.637	76.242	659.916	0.000	0.000	0.000
050	0.906	2.657	6.265	12.169	20.704	32.278	50.696	78.259	134.130	893.363	0.000	0.000	0.000
055	1.504	4.864	10.854	19.653	31.817	50.948	79.376	136.595	243.272	1000.000	0.000	0.000	0.000
060	2.801	8.163	17.478	30.528	50.172	79.308	137.700	245.831	426.573	0.000	0.000	0.000	0.000
065	4.012	13.581	27.594	47.849	77.597	137.167	246.818	428.874	674.846	0.000	0.000	0.000	0.000
070	7.400	19.952	42.105	72.667	133.998	246.012	430.366	677.073	897.638	0.000	0.000	0.000	0.000
075	11.204	31.561	62.594	120.492	228.757	411.636	663.142	893.246	1000.000	0.000	0.000	0.000	0.000
080	16.549	46.486	95.352	192.500	368.174	628.042	881.561	1000.000	0.000	0.000	0.000	0.000	0.000
085	28.699	56.405	121.899	265.675	529.188	844.057	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	27.317	73.306	190.541	445.303	807.259	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

G.7. Age Nearest Birthday | Female Aggregate

	MORTALITY RATES PER 1000 | Neural Network Model | Observation Period: ALL | Female Aggregate | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.114	0.048	0.054	0.120	0.265	0.383	0.451	0.596	0.818	5.638	23.419	333.516	1000.000
005	0.033	0.044	0.115	0.264	0.380	0.441	0.582	0.809	1.262	7.866	41.400	582.913	0.000
010	0.024	0.104	0.258	0.367	0.419	0.550	0.781	1.240	2.069	11.602	82.362	867.377	0.000
015	0.066	0.242	0.338	0.383	0.502	0.736	1.193	1.998	3.378	17.957	172.349	1000.000	0.000
020	0.157	0.250	0.331	0.437	0.674	1.125	1.902	3.243	5.341	28.944	347.328	0.000	0.000
025	0.167	0.225	0.352	0.598	1.037	1.785	3.093	5.198	8.177	51.453	616.043	0.000	0.000
030	0.112	0.240	0.498	0.931	1.644	2.922	5.031	8.146	12.676	100.525	879.620	0.000	0.000
035	0.121	0.364	0.789	1.478	2.721	4.824	8.041	12.793	20.257	200.287	1000.000	0.000	0.000
040	0.196	0.564	1.264	2.479	4.557	7.836	12.787	20.583	34.384	380.500	0.000	0.000	0.000
045	0.304	0.929	2.167	4.203	7.506	12.613	20.669	35.063	59.849	641.170	0.000	0.000	0.000
050	0.581	1.655	3.697	7.009	12.216	20.456	35.274	60.741	112.748	886.885	0.000	0.000	0.000
055	0.895	2.817	6.200	11.485	19.889	34.937	60.894	113.640	215.282	1000.000	0.000	0.000	0.000
060	1.597	4.556	10.109	18.856	33.929	60.136	113.299	215.483	393.688	0.000	0.000	0.000	0.000
065	2.193	7.709	16.737	31.864	58.080	111.392	213.806	392.362	646.892	0.000	0.000	0.000	0.000
070	4.094	11.851	27.436	53.509	106.762	209.187	388.131	643.984	886.824	0.000	0.000	0.000	0.000
075	6.555	19.544	44.485	94.037	191.862	367.854	627.629	881.354	1000.000	0.000	0.000	0.000	0.000
080	9.915	30.941	71.368	156.671	322.092	587.295	867.007	1000.000	0.000	0.000	0.000	0.000	0.000
085	17.290	41.282	100.335	236.181	499.193	831.766	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	20.658	53.000	145.443	377.641	769.190	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

G.8. Age Nearest Birthday | Female Unknown

	MORTALITY RATES PER 1000 | Neural Network Model | Observation Period: ALL | Female Unknown | Age Nearest Birthday												
	DURATION												
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	0.114	0.048	0.054	0.120	0.249	0.350	0.396	0.520	0.716	4.754	21.137	328.415	1000.000
005	0.033	0.044	0.115	0.249	0.349	0.388	0.505	0.699	1.095	6.563	38.959	582.163	0.000
010	0.024	0.104	0.244	0.338	0.369	0.475	0.668	1.058	1.764	9.869	80.222	867.651	0.000
015	0.066	0.228	0.311	0.338	0.433	0.624	1.004	1.675	2.789	15.846	170.332	1000.000	0.000
020	0.146	0.227	0.291	0.377	0.570	0.937	1.571	2.635	4.282	26.495	346.361	0.000	0.000
025	0.150	0.194	0.303	0.506	0.860	1.458	2.478	4.099	6.582	49.155	616.470	0.000	0.000
030	0.098	0.205	0.421	0.772	1.334	2.315	3.898	6.424	10.493	98.733	880.073	0.000	0.000
035	0.102	0.307	0.652	1.196	2.139	3.675	6.194	10.396	17.730	199.383	1000.000	0.000	0.000
040	0.161	0.459	1.020	1.941	3.424	5.904	10.184	17.803	31.333	380.634	0.000	0.000	0.000
045	0.245	0.744	1.691	3.129	5.556	9.858	17.640	31.688	56.881	641.856	0.000	0.000	0.000
050	0.461	1.285	2.732	5.127	9.401	17.221	31.570	57.411	109.920	887.168	0.000	0.000	0.000
055	0.670	2.042	4.491	8.735	16.524	30.945	57.220	110.351	212.770	1000.000	0.000	0.000	0.000
060	1.148	3.209	7.593	15.458	29.727	56.183	109.578	212.382	391.762	0.000	0.000	0.000	0.000
065	1.499	5.678	13.461	27.572	53.909	107.194	209.947	389.543	645.663	0.000	0.000	0.000	0.000
070	2.931	9.322	23.332	49.254	101.924	204.054	383.659	641.459	886.218	0.000	0.000	0.000	0.000
075	5.048	15.903	40.121	89.087	186.605	363.276	625.089	880.778	1000.000	0.000	0.000	0.000	0.000
080	7.801	26.620	66.151	150.614	316.164	583.505	866.034	1000.000	0.000	0.000	0.000	0.000	0.000
085	13.594	37.792	97.426	234.575	499.398	832.373	1000.000	0.000	0.000	0.000	0.000	0.000	0.000
090	19.027	47.095	132.478	359.633	760.160	1000.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

H. EXTRACT OF THE EXPOSURE BY ISSUE AGE AND DURATION

H.1. Age Nearest Birthday | Male Non-Smokers

	TOTAL EXPOSURE FACE AMOUNT | ALL YEARS | Male Non-Smoker | Age Nearest Birthday										
EXPOSURE	DURATION										
IssueAge	001	006	011	016	021	026	031	036	041	061	081
000					719,311,176	428,544,702	178,490,303	30,667,478	225,959	2,000	
005				177,814,676	174,378,276	92,879,879	32,464,731	5,282,160	108,384	2,000	
010			145,692,226	175,646,688	168,986,307	97,307,695	37,626,815	5,287,489	30,000		
015		380,686,762	313,452,065	298,838,450	260,234,450	180,753,030	75,398,996	6,504,265	198,815		
020	2,673,597,997	1,608,793,602	1,083,233,184	933,921,014	813,001,941	659,918,286	341,180,421	51,623,005	804,392		
025	8,805,583,201	5,111,520,532	2,771,815,650	2,053,330,263	1,950,496,894	1,743,445,904	924,825,130	130,868,178	2,109,556	1,150	
030	21,026,075,603	13,504,573,531	6,445,914,029	4,323,004,732	3,540,737,637	2,929,716,858	1,280,004,130	163,899,155	1,942,460	1,000	
035	29,684,685,044	20,276,907,583	9,289,176,408	5,742,029,401	3,779,686,254	2,737,511,372	1,037,652,866	135,891,052	1,723,787		
040	29,194,221,036	21,603,695,232	9,227,642,441	5,456,803,861	3,131,584,831	1,975,198,967	699,133,819	93,695,375	1,011,078		
045	23,997,984,615	17,488,416,766	6,413,024,668	3,722,568,425	1,994,741,097	1,234,553,806	399,017,737	58,027,204	1,445,950		
050	18,136,915,902	13,169,416,619	3,869,180,983	2,188,043,076	1,289,740,412	696,381,265	222,949,587	33,143,139	486,736		
055	11,008,255,567	7,018,446,813	1,743,868,497	1,088,470,341	638,919,158	418,329,210	124,057,968	16,195,340	201,518		
060	5,115,624,038	3,146,806,606	832,061,108	552,120,817	435,537,268	263,720,856	47,378,261	2,283,482			
065	2,334,922,772	1,272,852,624	469,897,788	444,082,431	343,388,229	122,002,594	12,210,812	206,192			
070	565,358,240	282,793,937	121,085,948	117,739,100	67,488,653	16,208,467	1,011,736				
075	108,462,070	86,110,403	47,723,544	26,343,308	9,248,472	371,250					
080	23,209,191	16,566,809	8,101,017	3,606,502	321,688						
085	2,279,192	4,072,746	2,572,557	200,000							
090	237,422	50,000									
7,574,621,998,178	744,217,806,901	510,520,855,911	208,788,343,182	133,200,695,720	91,714,441,909	64,703,943,193	25,871,232,402	3,544,497,593	43,437,146	78,623	0

H.2. Age Nearest Birthday | Male Smokers

	TOTAL EXPOSURE FACE AMOUNT | ALL YEARS | Male Smoker | Age Nearest Birthday										
EXPOSURE	DURATION										
IssueAge	001	006	011	016	021	026	031	036	041	061	081
000					805,257,731	682,163,323	382,796,302	41,324,378	2,342,945	176,840	
005				189,821,763	143,013,726	148,153,732	89,490,681	5,103,872	205,971	57,862	
010			256,834,323	178,744,272	139,710,457	121,496,877	74,268,845	3,406,807	149,778	38,512	7,000
015		178,823,647	193,979,437	196,466,983	120,369,751	88,854,349	31,177,205	3,659,387	286,512	94,127	3,860
020	432,272,173	300,690,915	233,385,049	205,681,490	136,976,372	99,225,455	56,611,658	13,896,810	2,108,213	234,658	2,150
025	1,681,856,649	963,557,967	490,275,259	358,186,804	338,460,805	326,301,899	186,290,978	33,025,734	1,963,372	290,270	
030	3,494,444,891	2,000,416,817	806,574,652	590,728,205	555,650,721	494,214,474	236,589,517	36,442,256	1,423,042	78,622	
035	4,121,913,402	2,344,096,052	956,319,963	695,183,471	532,130,935	402,658,895	167,341,391	22,824,236	828,745	21,956	
040	3,205,490,891	2,150,191,717	820,767,936	566,498,271	376,485,911	255,481,988	99,723,235	16,998,869	1,935,869		
045	2,223,802,726	1,463,831,604	489,294,495	321,498,064	197,649,134	138,742,843	55,323,183	8,677,314	273,852		
050	1,520,835,177	947,915,813	306,263,264	190,021,330	110,162,751	64,712,628	24,730,485	5,404,597	90,132		
055	731,471,580	361,056,096	92,826,200	68,643,329	50,546,035	25,585,479	9,110,370	1,503,762	19,018		
060	247,594,898	107,458,376	44,271,137	29,572,848	24,217,974	9,213,099	1,850,935	176,875	1,184		
065	68,048,525	35,664,262	21,355,897	19,951,960	17,658,013	3,630,377	590,812	28,323			
070	20,565,681	5,120,024	4,106,750	4,381,245	1,243,867	139,091	27,938				
075	1,823,031	901,122	635,748	147,797	26,175	1,000					
080	392,509	365,570	405,000	10,000							
085	25,000										
090											
924,092,596,978	87,056,217,874	54,074,085,006	23,712,142,327	18,598,181,340	15,081,501,008	12,105,623,203	5,877,933,198	801,137,040	50,665,071	4,583,251	21,181

H.3. Age Nearest Birthday | Male Aggregate

	TOTAL EXPOSURE FACE AMOUNT | ALL YEARS | Male Aggregate | Age Nearest Birthday										
EXPOSURE	DURATION										
IssueAge	001	006	011	016	021	026	031	036	041	061	081
000	4,820,942,769	3,030,650,603	2,424,907,593	2,634,080,163	2,887,883,067	2,245,605,343	1,326,224,994	677,954,127	398,007,696	138,348,183	801,776
005	1,427,201,394	817,007,255	639,324,730	578,951,212	576,072,378	434,075,986	231,749,351	80,660,705	39,526,891	10,006,966	328,501
010	1,275,087,886	778,341,785	609,898,037	516,763,661	460,786,732	358,160,118	190,358,933	60,673,499	31,338,239	10,473,565	637,970
015	1,500,040,526	973,612,625	779,005,669	641,777,767	512,408,670	370,705,405	189,480,993	76,622,254	50,091,115	18,885,361	734,267
020	3,116,149,344	1,927,603,143	1,336,967,822	1,153,997,321	1,013,643,559	897,768,357	621,885,789	343,938,221	259,339,508	44,177,444	654,273
025	10,487,902,250	6,075,543,588	3,263,553,998	2,414,915,905	2,443,755,101	2,538,409,320	1,663,893,925	605,588,454	305,615,420	46,788,688	
030	24,520,788,366	15,505,335,789	7,252,605,706	4,917,761,825	4,287,157,515	3,946,233,842	2,052,639,793	511,213,157	170,156,578	20,593,135	
035	33,806,906,223	22,621,124,517	10,245,630,869	6,440,511,336	4,454,910,319	3,549,397,066	1,617,225,057	382,781,866	107,975,800	5,948,707	
040	32,399,917,967	23,753,997,947	10,048,519,878	6,028,227,836	3,621,431,480	2,524,060,359	1,082,151,119	261,050,512	84,477,949	1,066,317	
045	26,222,086,566	18,952,422,686	6,902,541,550	4,047,969,857	2,256,536,083	1,521,846,112	611,619,469	157,295,672	37,322,884		
050	19,658,017,026	14,117,528,914	4,175,643,149	2,381,406,083	1,435,246,401	839,517,677	336,887,087	91,425,155	13,596,521		
055	11,740,066,591	7,379,741,231	1,837,123,715	1,158,934,278	708,300,087	489,690,733	179,035,618	32,539,520	2,098,273		
060	5,363,390,729	3,254,415,272	876,930,884	583,209,751	472,543,907	295,450,135	64,681,548	4,730,868	146,270		
065	2,404,161,992	1,309,730,526	492,309,992	465,697,027	369,230,546	135,678,669	16,327,935	581,237			
070	586,154,318	288,084,390	125,315,205	122,541,863	70,642,095	17,623,658	1,331,947				
075	110,537,086	87,067,640	48,390,804	26,526,659	9,349,977	379,687					
080	23,693,782	16,962,751	8,513,785	3,616,502	370,197						
085	2,317,453	4,080,158	2,576,260	254,574							
090	240,276	50,000									
9,071,261,284,373	860,671,764,957	580,190,055,796	242,402,629,652	158,645,100,637	116,490,465,301	92,100,253,715	46,107,220,569	13,952,152,281	5,999,055,974	982,913,980	10,421,965

H.4. Age Nearest Birthday | Male Unknown

	TOTAL EXPOSURE FACE AMOUNT | ALL YEARS | Male Unknown | Age Nearest Birthday										
EXPOSURE	DURATION										
IssueAge	001	006	011	016	021	026	031	036	041	061	081
000	4,820,942,769	3,030,650,603	2,424,907,593	2,634,080,163	1,363,314,161	1,134,897,318	764,938,389	605,962,271	395,438,791	138,169,343	801,776
005	1,427,201,394	817,007,255	639,324,730	211,314,773	258,680,376	193,042,376	109,793,939	70,274,672	39,212,536	9,947,104	328,501
010	1,275,087,886	778,341,785	207,371,488	162,372,700	152,089,968	139,355,546	78,463,273	51,979,202	31,158,461	10,435,053	630,970
015	1,500,040,526	414,102,216	271,574,167	146,472,334	131,804,470	101,098,026	82,904,792	66,458,602	49,605,788	18,791,234	730,407
020	10,279,175	18,118,626	20,349,588	14,394,817	63,665,246	138,624,615	224,093,710	278,418,406	256,426,903	43,942,786	652,123
025	462,401	465,089	1,463,089	3,398,838	154,797,403	468,661,516	552,777,818	441,694,541	301,542,492	46,497,268	
030	267,872	345,442	117,025	4,028,888	190,769,158	522,302,511	536,046,146	310,871,745	166,791,076	20,513,513	
035	307,777	120,882	134,498	3,298,463	143,093,130	409,226,799	412,230,800	224,066,578	105,423,268	5,926,751	
040	206,040	110,998	109,502	4,925,705	113,360,738	293,379,403	283,294,065	150,356,269	81,531,002	1,066,317	
045	299,225	174,316	222,387	3,903,369	64,145,852	148,549,463	157,278,550	90,591,154	35,603,082		
050	265,947	196,483	198,901	3,341,677	35,343,237	78,423,783	89,207,014	52,877,419	13,019,653		
055	339,444	238,322	429,018	1,820,609	18,834,893	45,776,044	45,867,281	14,840,418	1,877,737		
060	171,794	150,290	598,639	1,516,086	12,788,665	22,516,179	15,452,352	2,270,510	145,086		
065	1,190,696	1,213,640	1,056,307	1,662,635	8,184,305	10,045,698	3,526,311	346,722			
070	230,397	170,430	122,507	421,518	1,909,575	1,276,100	292,273				
075	251,986	56,116	31,512	35,554	75,330	7,437					
080	92,082	30,373	7,768		48,509						
085	13,261	7,412	3,703	54,574							
090	2,854										
572,546,689,217	29,397,740,182	15,595,114,878	9,902,144,143	6,846,223,576	9,694,522,385	15,290,687,319	14,358,054,969	9,606,517,647	5,904,953,757	978,252,107	10,400,784

H.5. Age Nearest Birthday | Female Non-Smokers

	TOTAL EXPOSURE FACE AMOUNT | ALL YEARS | Female Non-Smoker | Age Nearest Birthday									
EXPOSURE	DURATION										
IssueAge	001	006	011	016	021	026	031	036	041	061	081
000					765,198,717	442,496,616	182,828,879	29,205,059	435,206	3,000	
005				169,979,164	155,435,125	85,942,995	35,356,136	5,499,151	25,000		
010			126,976,456	180,383,999	162,037,138	88,043,785	32,445,330	4,805,874	57,006		
015		370,554,268	271,570,465	273,365,851	238,033,855	156,480,363	63,693,683	5,093,318	181,028		
020	2,637,080,091	1,485,812,333	1,041,002,746	896,724,627	794,321,336	601,655,418	275,512,105	32,078,078	558,138		
025	10,649,044,247	6,519,838,185	3,317,672,389	2,184,713,077	1,805,577,839	1,416,257,693	620,198,429	66,328,282	498,851		
030	21,465,188,222	13,484,011,401	6,097,500,411	3,530,822,967	2,432,648,501	1,753,313,526	680,054,445	70,464,657	329,113	500	
035	24,234,978,318	15,713,944,063	6,820,566,658	3,850,166,244	2,244,603,718	1,420,532,539	461,656,995	53,667,724	252,803		
040	19,858,772,183	13,679,323,450	5,722,243,260	3,152,512,177	1,647,743,773	877,315,430	266,303,041	28,533,749	116,338		
045	14,437,783,419	9,658,839,226	3,563,407,591	1,956,948,586	996,666,981	509,727,444	132,385,868	15,665,471	21,612		
050	9,424,661,827	6,067,430,847	2,059,273,597	1,193,506,399	570,812,061	253,130,623	70,092,285	8,242,017	463,261		
055	5,063,726,106	2,977,857,213	961,870,120	617,869,813	357,389,454	168,989,800	40,277,849	3,783,911			
060	2,233,728,379	1,306,490,818	529,123,997	403,664,586	277,266,196	140,574,439	22,911,073	1,585,815			
065	1,202,407,581	692,548,478	409,685,806	316,200,561	231,150,741	86,795,171	7,372,908	142,162			
070	395,905,530	279,649,491	251,691,596	215,816,429	98,742,253	25,932,343	547,747				
075	162,307,040	132,626,569	106,328,582	73,148,660	22,061,792	1,977,831					
080	59,076,180	65,620,015	41,011,806	13,368,211	1,927,613						
085	5,197,179	7,508,647	7,016,877	3,573,074							
090	45,000										
5,288,416,668,676	551,099,856,424	356,552,358,614	154,339,927,861	93,649,857,636	61,045,613,603	38,163,079,143	13,709,767,458	1,470,829,114	9,449,458	22,100	0

H.6. Age Nearest Birthday | Female Smokers

	TOTAL EXPOSURE FACE AMOUNT | ALL YEARS | Female Smoker | Age Nearest Birthday									
EXPOSURE	DURATION										
IssueAge	001	006	011	016	021	026	031	036	041	061	081
000					794,565,625	675,934,481	379,989,044	29,207,311	873,599	146,762	
005				180,610,651	133,889,150	146,067,902	91,128,808	4,087,965	203,721	25,000	275
010			257,616,855	155,377,497	129,329,422	115,271,682	69,625,884	3,172,563	97,092	12,000	3,000
015		153,604,497	179,154,080	144,453,640	108,792,733	74,580,025	27,052,657	1,918,921	146,844	19,512	1,000
020	249,651,239	216,965,983	164,281,436	170,246,013	154,180,039	132,678,755	70,025,440	11,333,597	1,093,742	77,330	740
025	1,040,780,302	697,913,908	391,997,912	320,677,861	331,660,187	307,861,469	160,936,118	18,934,355	1,032,694	45,092	
030	1,566,134,709	1,013,819,800	488,170,088	413,215,533	409,746,729	353,333,504	156,766,311	15,210,276	446,518	26,561	
035	1,508,165,719	960,903,087	504,216,220	440,864,706	362,122,955	254,013,951	83,086,852	7,669,070	274,920	8,000	
040	1,177,001,305	875,207,575	403,738,340	328,637,528	218,072,262	136,147,712	48,327,235	5,889,137	296,070	1,500	
045	852,294,966	691,584,485	286,030,056	207,360,238	130,431,516	72,514,944	22,232,824	3,814,727	177,225		
050	693,802,741	487,152,697	152,487,637	109,907,412	72,006,328	34,349,711	12,681,513	1,823,638	106,323		
055	396,326,141	201,003,157	66,731,642	53,156,075	39,918,099	20,993,827	7,894,581	751,376	8,500		
060	147,693,437	85,444,015	42,855,764	32,553,028	24,359,198	11,180,619	1,771,240	283,733	3,500		
065	55,463,288	31,786,260	19,343,354	19,713,204	14,398,260	4,724,818	1,190,919	39,885			
070	22,487,154	9,970,486	11,623,817	7,547,344	3,627,725	551,690	21,686				
075	6,458,807	6,760,876	2,447,010	875,148	267,195	26,937					
080	11,998,638	3,810,071	557,443	122,501							
085	135,000	37,872	2,000,000								
090	42,263										
538,067,855,688	38,290,238,112	27,497,471,770	15,413,539,984	13,950,708,220	11,989,063,040	9,373,081,912	4,436,226,133	414,867,388	18,531,991	1,290,883	15,337

H.7. Age Nearest Birthday | Female Aggregate

	TOTAL FACE AMOUNT EXPOSURE | Observation Period: ALL | Female Aggregate | Age Nearest Birthday											
EXPOSURE	DURATION											
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	4,697,765,645	3,020,366,272	2,508,558,060	2,773,307,232	3,013,152,997	2,288,178,810	1,235,249,564	510,774,255	250,935,247	46,857,646	560,144		
005	1,471,055,744	878,772,043	713,683,625	565,838,128	549,161,337	429,257,063	224,880,796	62,245,047	24,654,806	2,376,546	115,492		
010	1,230,850,265	736,529,754	607,823,558	517,307,513	452,564,896	344,864,587	167,428,340	41,713,611	14,890,462	1,576,920	354,100		
015	1,388,668,470	952,457,520	677,253,197	530,697,268	459,633,369	315,836,551	147,915,087	40,332,839	16,976,896	2,653,001	259,348		
020	2,896,989,000	1,721,399,337	1,227,786,279	1,079,567,326	1,012,268,554	866,037,965	521,153,044	201,127,341	105,904,306	7,316,944	171,544		
025	11,690,133,958	7,218,111,522	3,710,212,848	2,508,417,746	2,267,527,188	2,081,152,607	1,124,805,722	258,781,612	69,469,506	3,585,198			
030	23,031,906,895	14,498,039,975	6,585,792,492	3,946,970,445	2,956,928,902	2,425,446,515	1,129,956,297	211,988,295	42,631,119	2,017,498			
035	25,743,559,236	16,674,954,468	7,324,831,342	4,295,033,064	2,699,011,528	1,889,882,862	735,941,962	141,926,214	27,192,319	1,108,700			
040	21,036,091,009	14,554,683,112	6,126,105,040	3,485,427,417	1,921,203,976	1,141,196,167	425,758,033	84,731,361	22,019,498	266,583			
045	15,290,323,779	10,350,504,649	3,849,560,198	2,168,792,075	1,159,448,522	647,411,265	215,210,482	51,428,637	14,847,112				
050	10,118,697,077	6,554,844,549	2,211,931,605	1,306,212,874	662,529,042	325,414,789	117,692,542	28,556,737	7,653,288				
055	5,460,690,082	3,179,036,226	1,028,770,594	673,152,961	409,342,946	213,927,291	68,626,567	13,078,000	2,032,088				
060	2,381,621,510	1,392,080,296	572,127,382	439,126,925	312,438,057	166,401,034	33,016,694	4,409,507	335,018				
065	1,258,174,764	724,546,140	429,270,730	338,178,603	253,821,513	100,321,198	11,795,698	653,192					
070	418,659,050	289,651,539	263,518,193	224,442,115	104,556,074	27,801,874	640,946						
075	168,814,519	139,412,704	108,869,229	74,426,299	23,021,904	2,123,542							
080	71,559,645	69,452,331	41,613,290	13,764,051	2,026,767								
085	5,341,327	7,550,520	9,016,877	3,573,074									
090	66,086	704											
6,262,139,407,722	618,549,144,824	399,907,651,664	180,061,756,739	114,648,576,518	81,622,500,967	58,800,549,906	26,855,689,395	6,519,052,650	2,101,966,247	170,892,821	4,648,984	0	0

H.8. Age Nearest Birthday | Female Unknown

	TOTAL FACE AMOUNT EXPOSURE | Observation Period: ALL | Female Unknown | Age Nearest Birthday											
EXPOSURE	DURATION											
ISSUE AGE	001	006	011	016	021	026	031	036	041	061	081	101	116
000	4,697,765,645	3,020,366,272	2,508,558,060	2,773,307,232	1,453,388,654	1,169,747,713	672,431,641	452,361,885	249,626,441	46,707,884	560,144		
005	1,471,055,744	878,772,043	713,683,625	215,248,314	259,837,062	197,246,166	98,395,852	52,657,931	24,426,085	2,351,546	115,217		
010	1,230,850,265	736,529,754	223,230,247	181,546,017	161,198,336	141,549,121	65,357,127	33,735,174	14,736,364	1,564,920	351,100		
015	1,388,668,470	428,298,755	226,528,652	112,877,777	112,806,781	84,776,162	57,168,747	33,320,600	16,649,024	2,633,489	258,348		
020	10,257,670	18,621,021	22,502,096	12,596,686	63,767,178	131,703,793	175,615,499	157,715,666	104,252,426	7,239,614	170,804		
025	309,410	359,429	542,547	3,026,808	130,289,163	357,033,446	343,671,174	173,518,974	67,937,961	3,540,106			
030	583,964	208,774	121,993	2,931,945	114,533,672	318,799,485	293,135,541	126,313,362	41,855,488	1,990,437			
035	415,200	107,318	48,464	4,002,114	92,284,855	215,336,371	191,198,114	80,589,419	26,664,596	1,100,700			
040	317,521	152,087	123,441	4,277,712	55,387,941	127,733,024	111,127,756	50,308,475	21,607,089	265,083			
045	245,393	80,937	122,551	4,483,251	32,350,025	65,168,877	60,591,790	31,948,439	14,648,274				
050	232,508	261,005	170,371	2,799,063	19,710,653	37,934,456	34,918,743	18,491,082	7,083,705				
055	637,834	175,857	168,833	2,127,072	12,035,393	23,943,663	20,454,138	8,542,713	2,023,588				
060	199,695	145,462	147,621	2,909,312	10,812,663	14,645,976	8,334,381	2,539,959	331,518				
065	303,895	211,401	241,570	2,264,838	8,272,513	8,801,208	3,231,871	471,145					
070	266,366	31,562	202,780	1,078,343	2,186,096	1,317,841	71,513						
075	48,671	25,259	93,637	402,491	692,917	118,774							
080	484,828	22,246	44,042	273,339	99,154								
085	9,148	4,001											
090	11,086	704											
435,654,938,148	29,159,092,551	15,857,821,281	10,308,288,894	7,048,010,662	8,587,824,325	11,264,388,851	8,709,695,804	4,633,356,148	2,073,984,798	169,579,838	4,633,647	0	0

I. ACKNOWLEDGEMENTS

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