Koninklijk Actuarieel Genootschap

PROJECTIONS LIFE TABLE AG2026

In the end, it's not about the number of years in your life – it's the life during those years.

Table of Contents

The subtitle reads: In the end, it's not about the number of years in your life – it's the life during those years. Even the attribution of a quote can be uncertain – let alone the projection of human lifespan. This statement is often attributed to Abraham Lincoln, but is most likely an example of quote laundering, linking appealing statements to prominent individuals without a verifiable source.

Summary

Every two years, the Royal Dutch Actuarial Association publishes its new Projections Life Table which provides insights into the future development of Dutch life expectancy. The Projections Life Table is used in particular by financial institutions that offer life insurance and pension products to their customers. A good estimate is important in order for these institutions to reserve appropriately in order to meet future benefits. The Projections Life Table can also be used to determine purchasing factors for pension benefits.

The projections are built using historical mortality data from the Netherlands and European countries with similar prosperity. Since 2020, mortality data has shown excess mortality, partly due to direct and indirect consequences of the COVID-19 pandemic. For the publications of Projections Life Table AG2022 and AG2024, it was decided to base the long-term trend on the European data up to and including 2019 before the appearance of COVID-19. The mortality that followed from this pre-covid projection was corrected with an excess mortality term that reflected excess mortality in the Netherlands. This excess mortality term was modelled separately with assumptions about the future course of excess mortality. A similar approach has been chosen in the model for Projections Life Table AG2026.

With regard to the European data underlying the pre-COVID projection in Projections Life Table AG2026, a data update for the years up to and including 2019 applies, because the source data (Human Mortality Database) have been updated retroactively. Furthermore, the pre-covid model specification has been adjusted on one point. In order to improve the reconciliation of the projection with the mortality observations in the years before 2020, it was decided to change the method used to determine the starting point of the pre-COVID projection. The prognosis now starts from mortality probabilities derived directly from observed mortality. This adjustment of the starting point will eventually converge to the pre-covid projection without this adjustment.

Since the last publication in September 2024, two additional years of new mortality data for the Dutch population have become available. These data show that excess mortality is still present, more so for females than for males, and that this excess mortality is higher than what was assumed two years ago. To estimate excess mortality in Projections Life Table AG2026 the years since 2022 were examined, similarly as in AG2024. This effectively means that the years 2024 and 2025 have been added to the data. In addition, in the Projections Life Table AG2026, the excess mortality terms are applied to all ages, whereas in AG2024 this was only the case for ages 55 and upwards. This adjustment does justice to the observed excess mortality at lower ages.

In AG2024, the excess mortality was assumed to decrease by about 25% per year. As a result of the current mortality developments, combined with an evaluation of various scenarios, the CSO has decided to adjust the future development of excess mortality. In contrast to previous publications, where it was assumed that excess mortality will eventually fade out completely, the Projections Life Table AG2026 assumes that 25% of excess mortality is permanent and also that it will take a longer time to reach this level by reducing the run-off factor of excess mortality from 25% to 5%.

These changes affect both mortality rates in the short term and the development of life expectancy in the medium to long term. Life expectancy is still rising, but less rapidly than expected in the AG2024 prognosis. If we compare the projection of AG2024 with that of AG2026, the cohort life expectancy decreases by about 4 months for someone born in 2027. This applies to both males and females. The cohort life expectancy at age 65 decreases by 3 months for males and 7 months for females. As a result of these new life projections, an average purchasing factor for pension and partner's pension around retirement age decreases by about 1.0% for males and 1.5% for females. The provision of an average pension portfolio decreases by about 0.9% for males and 1.4% for females.

1

Results of the new projection table

This chapter explains the changes from Projections Life Table AG2024 (hereinafter: AG2024) to Projections Life Table AG2026 (hereinafter: AG2026). The impact of the new projection table is shown on one-year mortality probabilities, life expectancy, and on provisions and contributions for an average pension portfolio. AG2026 is also compared with historical developments, AG2024 and the most recent projection from Statistics Netherlands (CBS2025-2070).

1.1 Changes from AG2024 to AG2026

In order to determine AG2026, several changes have been made compared to AG2024. The projections model broadly consists of the pre-covid projection, based on mortality data up to and including 2019, and the excess mortality modelling. Changes have been made to both components; the model and the data used.

The projection model and the technical changes from AG2024 to AG2026 are explained in detail in Chapter 2. The changes from AG2024 to AG2026 are broadly as follows.

1. **Pre-covid projection**
   a. **Update data Europe**: The European data in the HMD are regularly updated retroactively. AG2026 was determined using the updated mortality data from the HMD for the selected European countries for the period 1970 to 2019.
   b. **Model change starting point prognosis**: For certain age groups, the alignment between mortality probabilities as fitted by the model and recent observations was not as good as desired. The CSO therefore decided to start the pre-covid projection in 2019 from a starting point derived from observed mortality. Subsequently, the adjustment of this starting point is given less and less weight in the projection so that, after 25 years, the pre-covid projection is again assumed without adjustment of the starting point.

Excess mortality
Excess mortality as a result of (the direct and indirect consequences of) COVID-19 refers to higher mortality compared to the expected mortality according to the trend estimated on the basis of data from before the COVID-19 pandemic (up to and including 2019).

2. **Excess mortality modelling**
   a. **Update on excess mortality terms**: The years 2024 and 2025 have been added to the excess mortality terms, so now data is used from the period 2022 to 2025. In addition, excess mortality terms have also been introduced for the ages below 55 years because substantial excess mortality is observed at younger ages. Up to and including age 40, a flat parameter per sex is used in order to limit volatility due to the low number of (mortality) observations for these ages.
   b. **Adjustment of the development of excess mortality**: The future development of excess mortality has been changed from completely fading out with a run-off factor of 25% per year to an alternative scenario with a permanent excess mortality of 25% and a run-off factor that is reduced to 5% per year of the non-permanent part of the excess mortality.

Due to the adjustments to the pre-covid projection, projected mortality probabilities connect better with recent observations, for all age groups. Through amending the excess mortality scenario, the CSO captures the probability of different scenarios and recent developments in observed mortality after 2019.

1.2 Development of life expectancy

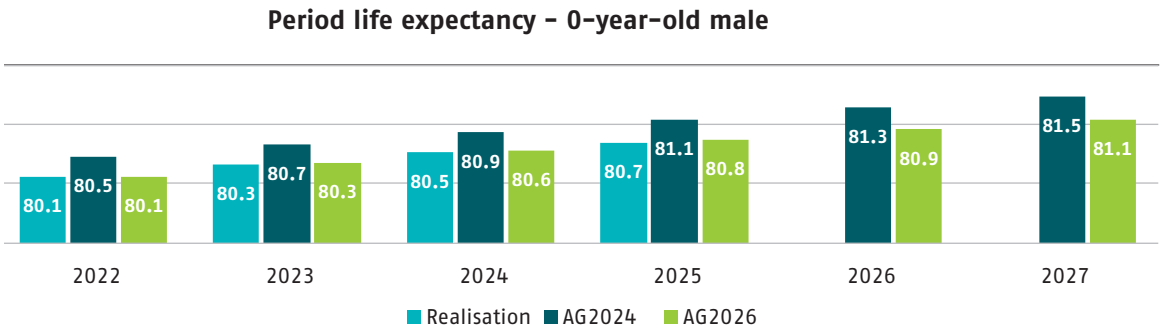
Life Expectancy Definitions
In this publication, a distinction is made between two types of life expectancy:

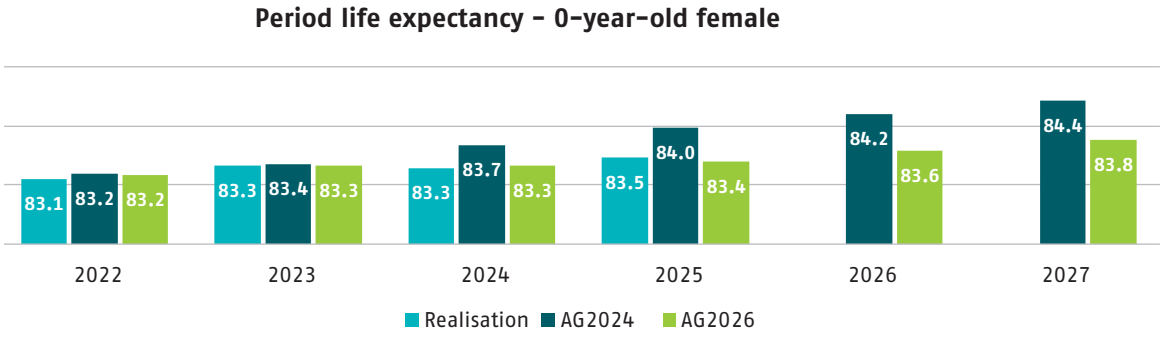
- **Period life expectancy**: this is based on mortality probabilities in one calendar year and therefore does not take into account any further change in mortality probabilities in the future.
- **Cohort life expectancy**: this takes into account expected future mortality developments. When cohort life expectancy at birth is calculated, the mortality probabilities of a now 0-year-old, a projected probability for a 1-year-old in 1 year, a projected probability for a 2-year-old in 2 years and so on are needed. Cohort life expectancy is therefore based on the expected developments in mortality probabilities in successive calendar years.

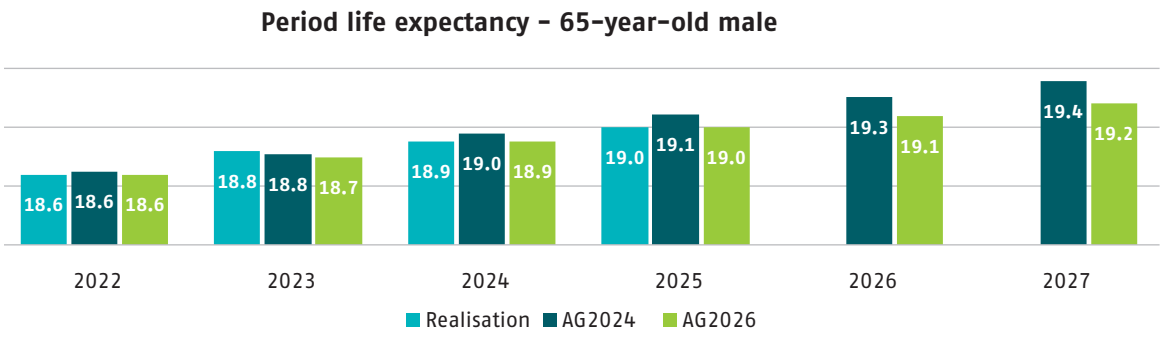
Period life expectancy is often used to compare developments over time, but cannot be used to estimate how long people are expected to live.

Cohort life expectancy is higher than period life expectancy when mortality probabilities are expected to decrease and indicates how old people can become when expected future mortality developments are taken into account.

Figure 1.1 shows the AG2026 and AG2024 projections of the period life expectancies for the years 2022 to 2027 and also shows how they relate to realised life expectancies for the years up to and including 2025. Period life expectancy is always used for this purpose, because it allows comparisons to be made with the realized life expectancies in a specific observation year.







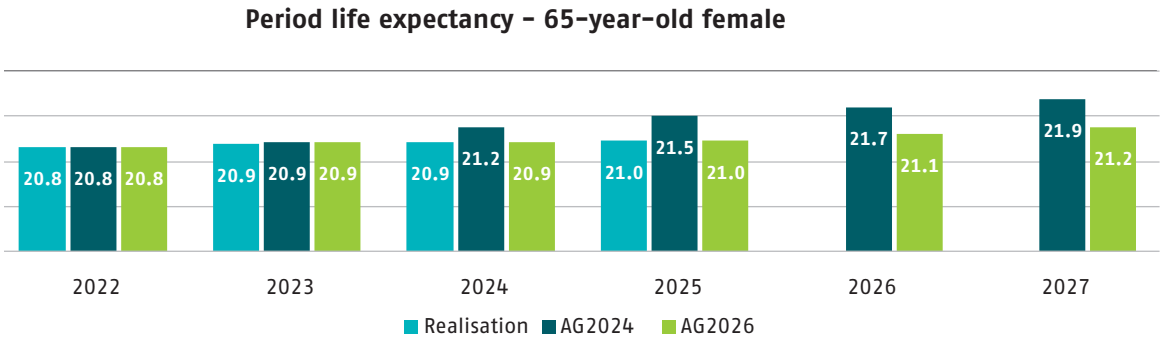


Figure 1.1 – *Period life expectancy at birth and at age 65 for males and females.*

The realised life expectancies for 65-year-olds in 2022 and 2023 are in line with the results of AG2024, because in AG2024 the excess mortality terms for ages 55 and above were based on data from those years. For 0-year-olds, the alignment between the life expectancy of AG2026 and the realisation has been improved by modelling excess mortality terms for the ages under 55.

As the excess mortality terms in the AG2024 projection increased by 25% per year, a faster increase in life expectancy was expected for 2024 and beyond. However, the realisation shows that in 2024 and 2025, life expectancy is lower than expected in the AG2024 projection. The effect of excess mortality on life expectancy appears to fade out slower, not at all or not completely, compared to the expectations in the AG2024 projections. Therefore, the future development of excess mortality has been adjusted. As a result, life expectancy in the AG2026 projections increases at a slower pace than in the AG2024 projections.

1.3 Effects on mortality probabilities

This section presents the effects of the changes on mortality probabilities, specifically looking at the one-year mortality probabilities. This impact also provides an indication of the effect of the projections on provisions and benefits for term life and funeral insurance. Figure 1.2 shows the impact of AG2026 on mortality probabilities compared to AG2024.

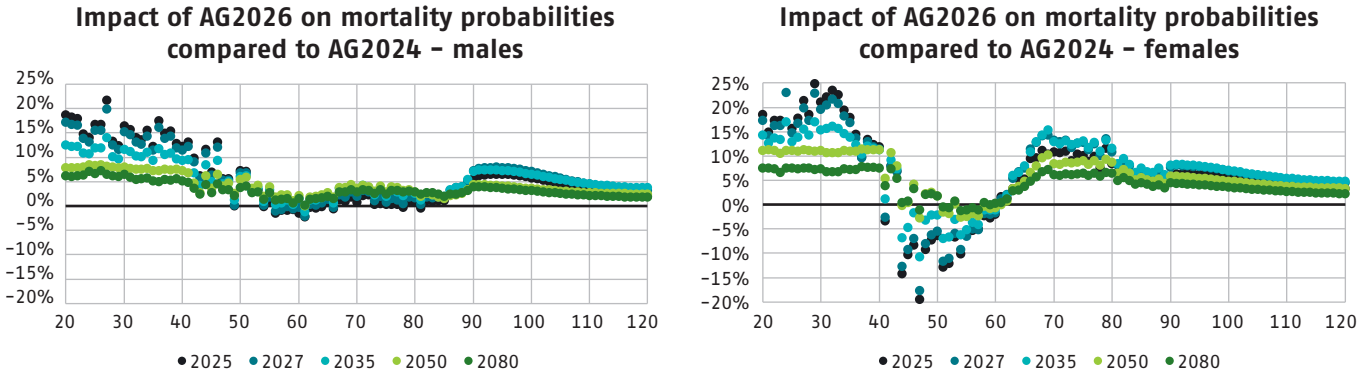


Figure 1.2 *– Differences in mortality rates for males and females AG2026 compared to AG2024.*

From AG2024 to AG2026, the mortality rates among males will increase for almost all ages, mainly due to adjustments in excess mortality modelling. Between the ages of 50 and 90, the increase is limited. For females, the mortality rates under the age of 40 and over the age of 60 are rising. This increase is mainly due to adjustments in the excess mortality modelling. Between the ages of 40 and 60, it is striking that the mortality rates among females have predominantly decreased. This is because the starting point of the pre-covid projection has been adjusted and also caused by the lower-than-expected mortality within this group. Because the excess mortality terms fade out slower and not completely, the mortality rates for both sexes will also increase further in the future.

In the remainder of this section, the effects of each step are shown in relation to the previous step in order to explain the results in more detail.

Step 1a: Update data Europe

The first step is the update of the European data up to and including 2019. The following figure shows the impact of this on mortality probabilities compared to AG2024.

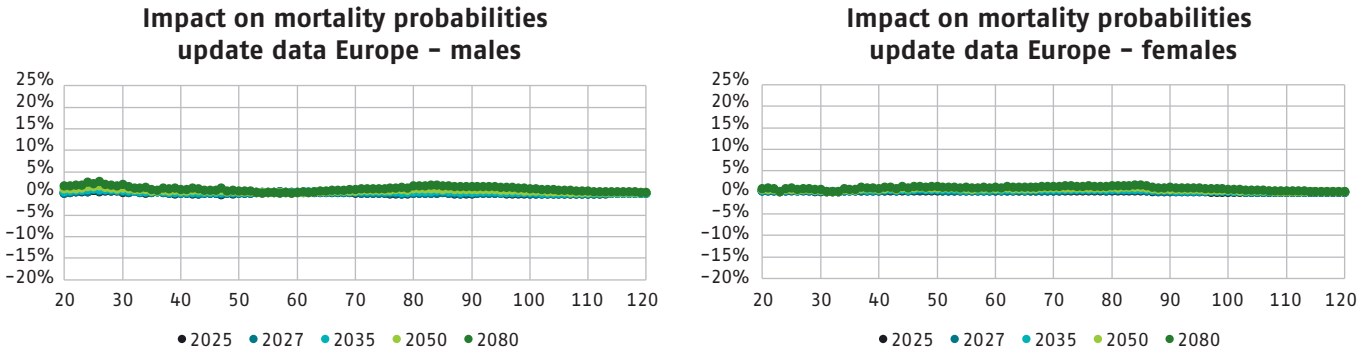


Figure 1.3-1a *– Differences in mortality probabilities for males and females due to update data from Europe (step 1a).*

The update of the European data slightly impacts the long-term trend. Therefore, mortality rates increase structurally, especially in the medium to long term, which reduces cohort life expectancy at birth (see section 1.3).

Step 1b: Model change starting point projection

In order to better align the pre-covid model with the observed mortality in the last few years up to and including 2019, the starting point has been adjusted. The following figure shows the impact of this change on mortality probabilities compared to step 1a.

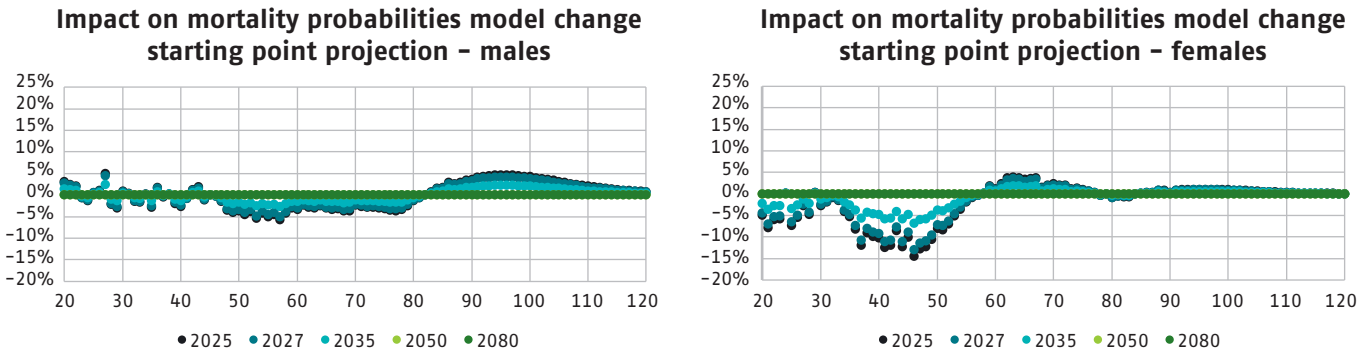


Figure 1.3-1b *– Differences in mortality probabilities for males and females due to model change in starting point of prognosis (step 1b).*

In particular, the mortality rates of females around the age of 40 to 50 have been reduced in the short term as a result of this model change. We see a slight decrease in mortality rates for males around the age of 50 to 80 years. At older ages, mortality rates have risen slightly, especially among males, but also among females. Due to the return in 25 years to the pre-covid projection without adjusting the starting point, this change has no impact on mortality probabilities further into the future.

Step 2a: Update excess mortality terms

The next step is to update the excess mortality terms. Next to adding the data for the years 2024 and 2025 to the data on which the excess mortality terms are based, the excess mortality terms are now being expanded to include ages under 55 years. The following figure shows the impact of these changes in excess mortality terms on mortality probabilities compared to step 1b.

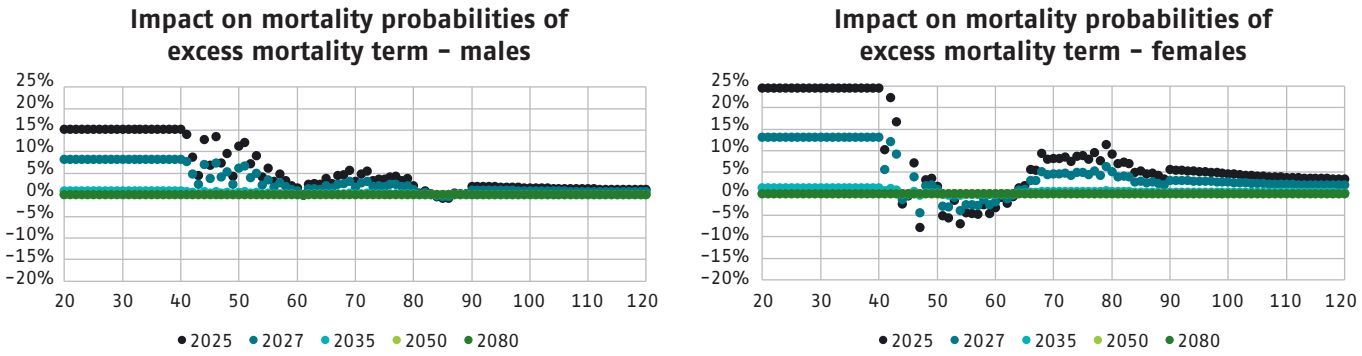


Figure 1.3-2a *– Differences in mortality probabilities for males and females due to update of excess mortality terms (step 2a).*

Up to and including age 40, it is assumed that relative excess mortality is constant per sex. From age 41 up to and including age 90, the relative excess mortality is determined to be age- and sex-dependent. The impact of excess mortality on ages over 90 years decreases with age. This is because at those ages, the mortality probabilities are closer to 1 and the excess mortality term therefore has less influence. The update of the excess mortality terms will lead to an increase in mortality rates for most ages, with the exception of females around the age of 50 to 60. A decrease can be observed in that group, because for those ages mortality slightly lower than expected compared to the pre-covid projection (after changing the starting point of the model).

Step 2b: Adjustment of the development of excess mortality

In AG2024, it was assumed that excess mortality would eventually fully disappear. In AG2026, it is assumed that part of the excess mortality (25%) is permanent. It is also assumed that the fading part of this excess mortality will do so at a pace which is more slowly, namely from 25% to 5% per year. The following figure shows the impact of this change on the mortality probabilities compared to step 2a.

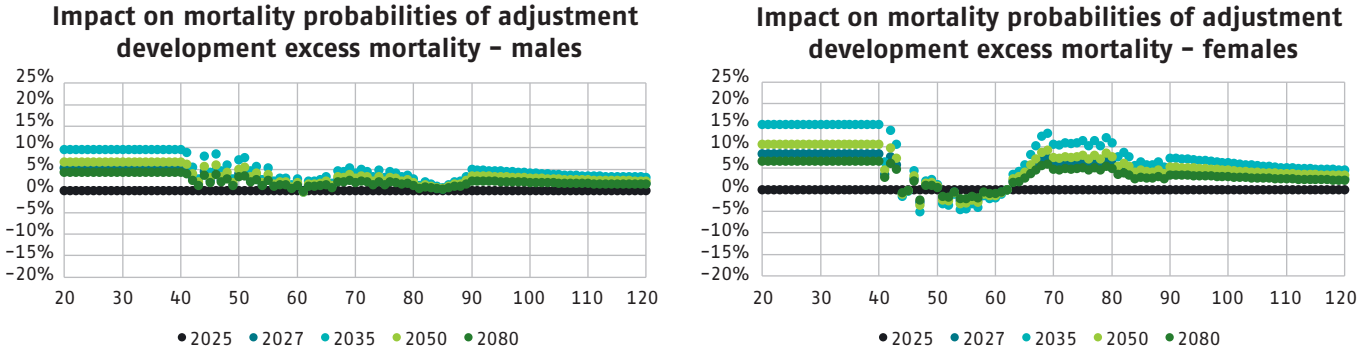


Figure 1.3-2b *– Differences in mortality probabilities for males and females due to adjustment for the development of excess mortality (step 2b).*

In 2025, the mortality probabilities will be the same as in the previous step because only the extension of the excess mortality terms will be adjusted in this step. The slower fade-out of excess mortality in combination with a lasting effect means that the mortality probabilities for most ages increase and remain structurally at a higher level compared to the previous step and therefore also compared to AG2024. Exceptions to this are the ages where a lower-than-expected mortality has been observed (ages 40 to 60 years for females).

1.4 Effects on cohort and period life expectancy

In order to quantify the impact of the changes on the life expectancy from AG2024 to AG2026 as mentioned in section 1.1, the effect was determined for each step. Table 1.1 and Table 1.2 show the impact of the changes on cohort life expectancy and period life expectancy for both 0-year and 65-year-old males and females, respectively, for the starting year 2027.

Cohort life expectancy	At birth		At age 65	
	Male	Female	Male	Female
AG2024	**90.42**	**93.15**	**20.79**	**23.67**
1a. Update data Europe	-0.13	-0.10	-0.05	-0.05
1b. Model change starting point projection	-0.06	-0.02	+0.06	-0.03
2a. Update of excess mortality terms	-0.02	-0.03	-0.02	-0.02
2b. Adjustment of the development of excess mortality	-0.15	-0.23	-0.20	-0.49
AG2026	**90.07**	**92.77**	**20.57**	**23.08**

***Table 1.1** – Effect of adjusting projection table on cohort life expectancy for 0-year and 65-year-old. The sum of the opening position plus the impact of the changes does not always exactly match the final position due to rounding differences.*

Period life expectancy	At birth		At age 65	
	Male	Female	Male	Female
AG2024	**81.46**	**84.42**	**19.39**	**21.89**
1a. Update data Europe	-0.01	-0.03	+0.00	-0.02
1b. Model change starting point projection	+0.04	+0.01	+0.04	-0.04
2a. Update of excess mortality terms	-0.20	-0.30	-0.09	-0.25
2b. Adjustment of the development of excess mortality	-0.20	-0.36	-0.13	-0.33
AG2026	**81.08**	**83.75**	**19.21**	**21.25**

***Table 1.2** – Effect of adjusting the projection table on period life expectancy for a 0-year and a 65-year-old. The sum of the opening position plus the impact of the changes does not always exactly match the final position due to rounding differences.*

The adjustments In the European data result in slightly higher mortality frequencies in the period up to and including 2019. The changes have mainly taken place in the most recent years, which cause adjustments to the long-term trend. This leads to a decrease in mortality probabilities in the longer term and thus to a decrease in cohort life expectancy, while little impact is visible in period life expectancy.

Adjusting the starting point has limited impact on life expectancy, due to various causes. The change mainly impacts lower ages, where the number of deaths is low and therefore an adjustment has a limited impact on life expectancy. Furthermore, there are different effects over the ages. For females, mortality decreases to about 60 years and then rises. For males, mortality decreases up to the age of 80 and then rises. These effects partly compensate each other. Lastly, the impact of the adjustment of the starting point will fade out in 25 years, which means that after 25 years there will no longer be any difference.

The update of the excess mortality terms has a limited impact on cohort life expectancy, because excess mortality continues to fade out completely in this step. In period life expectancy, the impact is clearly visible in a negative adjustment for both males and females. This is caused by the fact that higher excess mortality has been observed in the years 2024 and 2025 that have been added, compared to the AG2024 projection. This is reflected in the life expectancies in Figure 1.1. The downward impact for females is greater than for males because in recent years there has been more excess mortality among females at older ages than among males.

The impact of the adjustment of the excess mortality terms and the development towards the future becomes visible in the cohort life expectancy in the last step. The application of a scenario with 25% permanent excess mortality and the adjustment of the fade-out factor of the non-permanent part of the excess mortality from 25% per year to 5% per year will result in higher mortality probabilities in the longer term. Therefore, adjusting the development of excess mortality has a downward effect on cohort life expectancy. Here again, the impact is greater for females than for males due to the higher excess mortality among females. Period life expectancy is also lower due to the slower fading out of excess mortality. Recall that the AG2024 projections expected that part of the excess mortality would disappear by 2027.

1.5 Effects on provision for pension portfolio

In order to show the effects on provisions of the transition from AG2024 to AG2026, the impact of the transition to the new projection table has been calculated on the provision of an average pension portfolio.

In addition to an old-age pension (OP) starting at the age of 65, the average portfolio includes a deferred partner's pension and an in-payment partner's pension (PP). Appendix B explains the description of the model portfolio and the other assumptions used.

Table 1.3 shows the effects of the transition from AG2024 to AG2026 on provisions of the average pension portfolio.

Effect	Males	Females
VPV OP (65)	-0.9%	-1.8%
VPV Deferred PP	-1.1%	+2.5%
VPV In-payment PP[1]	-0.9%	-0.5%
VPV total	**-0.9%**	**-1.4%**

Table 1.3 *– Impact on Provision for pension liabilities (VPV) against 3% actuarial interest rate for pension portfolio of the transition from AG2024 to AG2026 (difference AG2026 minus AG2024 expressed as a percentage from the value determined on the basis of AG2024). The average of the separate percentages that are mentioned for the pension types OP and PP does not equal to the total because the contributions of the individual forms of pension to the total are different.*

The transition from AG2024 to AG2026 reduces the total provision of an average pension portfolio.

- The impact on the provision of lifelong old-age pension (OP) at retirement age 65 is larger for females than for males, because the average (cohort) life expectancy for females, especially among 65-year-olds, has reduced more than for males.

- Because the decrease life expectancy is higher for females than for males, an opposite effect is visible on the provision for deferred partner's pension (deferred PP). Due to the decrease in life expectancy among males, the partner's pension on a female's life starts earlier. However, the impact of the earlier termination of the benefit due to the lower life expectancy of females is larger and this results in a reduction of the provision for a deferred partner's pension where a male is the main insured person. When the main insured person is a female, the effect is reversed.

- The impact on the in-payment partner's pension (in-payment PP) is larger for males than for females because widows (column 'Males') have a larger decrease in life expectancy than the widowers (column 'Females'). This is a similar movement as for an old-age pension.

1.6 Effects on purchasing factors

Table 1.4 shows the effect of the transition to the new projections on purchasing factors for old-age pension (or partner's pension), deferred partner's pension and the total impact on the in-payment pension plus 70% latent partner's pension. This impact gives an indication of the effect in case of a collective benefit payment institution under the new pension system.

1 – The effect on the VPV for an in-payment partner's pension relates to widows in the column 'Males' and widowers in the column 'Females'.

A lower purchasing factor indicates that a higher amount of pension can be purchased for every euro of capital. Normally a participant purchases either old-age pension or old-age pension with a deferred partner's pension, if the participant has a partner. The old-age pension column is also applicable to the relative's surviving in-payment partner's pension. The table shows the impact on ages 50 to 90.

Age	Males			Females		
	In-payment OP	Deferred PP	In-payment OP + 70% deferred PP	In-payment OP	Deferred PP	In-payment OP + 70% deferred PP
50	-0.4%	-0.0%	-0.4%	-0.5%	+0.6%	-0.4%
55	-0.5%	-0.6%	-0.5%	-0.8%	+2.5%	-0.7%
60	-0.6%	-1.2%	-0.7%	-1.3%	+4.8%	-1.0%
65	-0.7%	-1.8%	-0.9%	-1.9%	+6.7%	-1.4%
70	-0.9%	-2.7%	-1.2%	-2.4%	+6.3%	-1.8%
75	-1.0%	-3.4%	-1.6%	-2.9%	+4.4%	-2.3%
80	-1.6%	-3.7%	-2.2%	-3.3%	+0.5%	-3.0%
85	-3.1%	-3.4%	-3.2%	-4.1%	-4.2%	-4.1%
90	-5.8%	-3.3%	-5.0%	-5.7%	-6.3%	-5.8%

Table 1.4 *– Impact on Single-premium factors by age and sex of transition from AG2024 to AG2026 (difference AG2026 minus AG2024 expressed as a percentage of AG2024).*

The effect of the new projections table on an average purchasing factor for old-age and partner's pensions around retirement age is approximately -1.0% for males and -1.5% for females. The decline in purchasing factors is the result of the downward adjustment of life expectancy for both males and females. This decrease increases as age increases, because both males from about 80 years and females from about 65 years have the largest increase in mortality rates, see also Figure 1.2.

1.7 Projection in perspective

Figure 1.4 shows the development of period life expectancy at birth from 1970 to 2050 for the Netherlands and the selected European countries. Realised values are shown up to and including 2019 for the European selection and up to and including 2025 for the Netherlands. This means that the effect of excess mortality in recent years is not visible for the European selection. From 2020 onwards, the figure shows the pre-covid projection that follows directly from the Li-Lee model (without adjustment of the starting point) for both the European selection and the Netherlands. The AG2026 projection is visible from 2026 onwards.

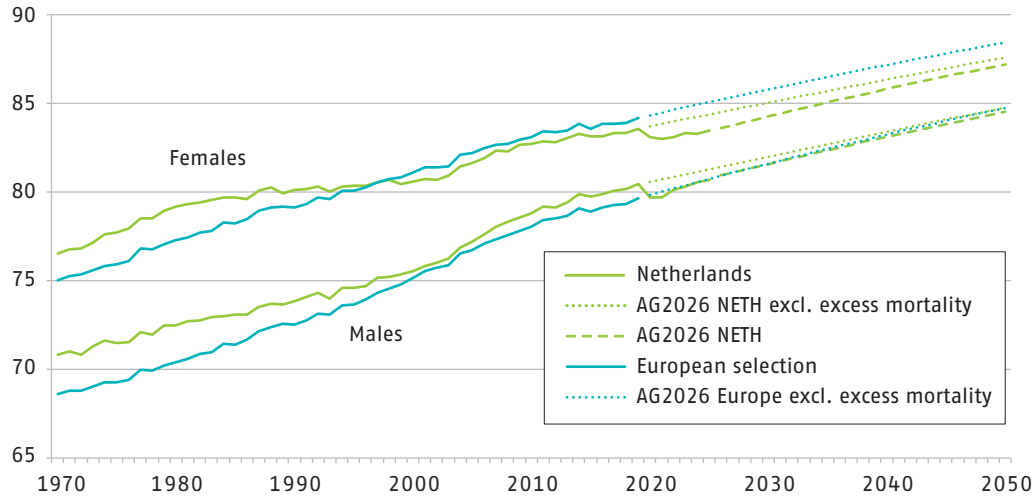


Figure 1.4 *– Period life expectancy at birth according to AG2026 projection and the pre-covid projection of the Netherlands and selected European countries.*

The consequences of the higher mortality in the years 2020 to 2025 are visible in the development of life expectancy in the Netherlands. Period life expectancy in 2025 is close to the level from before the start of the COVID-19 pandemic in 2020 (slightly lower for females, slightly higher for males). The difference between the pre-COVID projection (AG2026 excl. excess mortality) and the AG2026 projection including excess mortality is larger for females than for males. Part of the excess mortality is assumed to be persistent, which means that, contrary to previous projections, the AG2026 projection including excess mortality no longer fully converges to the pre-covid projection.

As in the previous projections, the pre-Covid prognosis of the period life expectancy of Dutch females is lower than that of females in the selected European countries. The pre-covid prognosis of the period life expectancy of Dutch males is, as before, higher than that of males in the selected European countries.

Figure 1.5 shows the impact of the excess mortality terms on the pre-covid projection of mortality probabilities in AG2026.

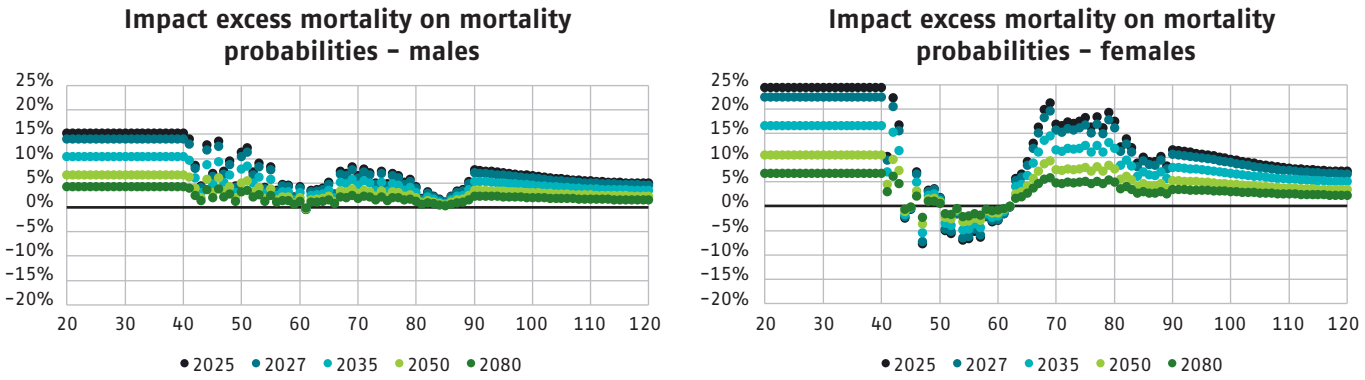


Figure 1.5 *– Impact of excess mortality terms on pre-covid projection of mortality probabilities in AG2026.*

For both males and females, the AG2026 projection includes substantial excess mortality in most age groups. It is remarkable that there is lower-than-expected mortality among females for ages around 50 to 60. For ages over 60 years, excess mortality in the AG2026 projection is higher for females than for males.

Figure 1.6 compares the developments in period life expectancy at birth for AG2024, AG2026 and CBS2025-2070.

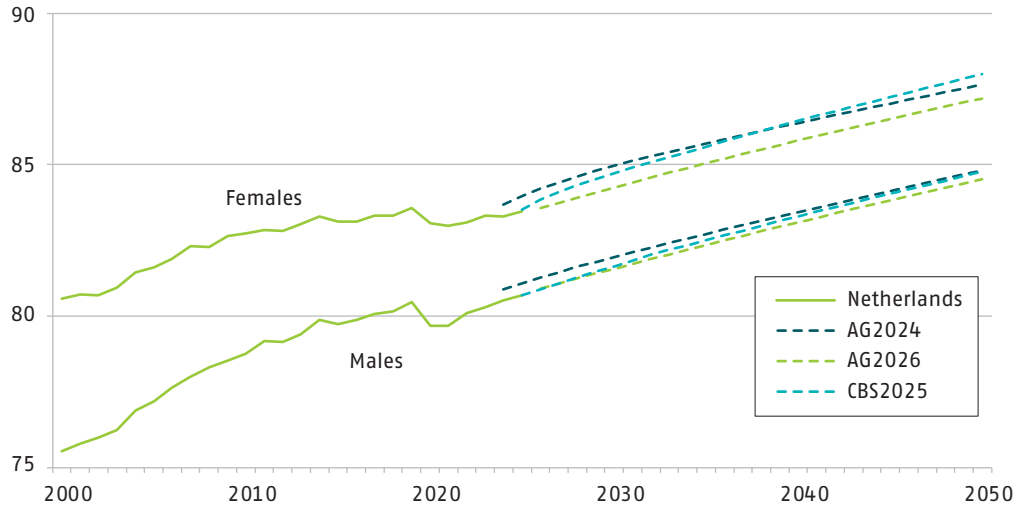


***Figure 1.6** – Development of period life expectancy at birth.*

It is clearly visible that the AG2026 projection has been revised downwards compared to the AG2024 projection, for both the short term and the long term. Compared to the CBS2025 projection, it can be seen that CBS estimates life expectancy to be higher for both males and females. For females, the difference is greater than for males. For males, the difference is small, especially in the short term.

Table 1.5 shows the (remaining) cohort life expectancies for AG2024, AG2026 and CBS2025-2070 (65-year-olds only).

Starting year 2027	At birth		At age 65	
Projection	**Males**	**Females**	**Males**	**Females**
AG2024	90.4	93.1	20.8	23.7
AG2026	90.1	92.8	20.6	23.1
CBS2025			20.9	23.4

***Table 1.5** – (Remaining) cohort life expectancies for AG2024, AG2026 and CBS2025. Life expectancies at birth are not available for CBS2025.*

The differences in cohort life expectancy between CBS2025 and AG2026 at age 65 are 0.3 years for both males and females.

Figure 1.7 shows the expected age of death of Dutch males and females in 2027 by age, given that they have already reached the age which is depicted on the x-axis. The results for both AG2024 and AG2026 are shown.

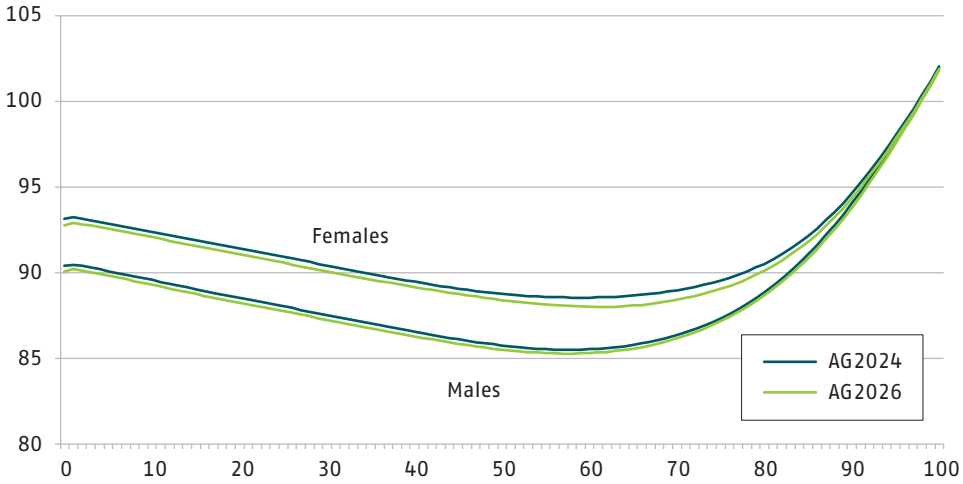


Figure 1.7 *– Expected age of death (y-axis) by age (x-axis) for Dutch males and females in 2027 in AG2024 and AG2026.*

This life expectancy first decreases until the age of about 60 years and then increases. Two effects play a role here. Someone who is older has already survived for a certain period, which increases life expectancy with age. In addition, someone who is younger will benefit more from expected future mortality improvements. It is here again visible that the decrease in cohort life expectancy in 2027 will be greater for females than for males.

2

The projection model

This chapter first discusses the model criteria which are used by the CSO to determine the Projections Life Table AG2026. It then explains developments since the COVID-19 pandemic, both from a Dutch and a European perspective, and explains the various analyses that have been carried out but which have not led to changes in the model.

We then discuss the model choices that lead to the AG2026 projection, including the model changes that have been incorporated into this new projection: adjustment to the starting point of the projection and adjustments to the excess mortality terms. The model equations that are needed to estimate the model parameters and to reconstruct the projection are described in Appendix A.

2.1 Model criteria

The CSO has drafted model criteria in advance. These have been taken into account when choosing and calibrating the Projections Life Table AG2026. These criteria are:

1. **Plausible and explainable outcomes** – the outcomes of the model are plausible and explainable. This means, for example, that there are no negative mortality probabilities (and the probabilities vary between 0 and 1) and that outcomes are sufficiently stable.
2. **Transparent and sufficiently reproducible model** – the design and working of the model are transparent and sufficiently reproducible for a quantitatively trained person on the basis of the technical model description in the publication.
3. **Connection with historical data** – the model should have the best possible fit on the historical data, with a focus on the age range that is most important for the sector.
4. **Quantification of uncertainty** – the model allows users to quantify certain types of uncertainty and thereby generate confidence intervals.

The CSO strives for a balance between complexity (including the number of parameters) and the predictive power. This means that extra complexity is only added if it provides sufficient added value in the outcomes and projections of the model.

2.2 Developments in mortality since the COVID-19 pandemic

The previous projection table, AG2024, is based on a pre-covid projection that has been adjusted for excess mortality that was still observed after the pandemic. It has been investigated to what extent mortality rates have returned to the level expected before the pandemic or whether there is still excess mortality. This research was carried out for both the Netherlands and selected European countries.

2.2.1 Mortality developments in the Netherlands since 2020

Since the outbreak of the COVID-19 pandemic in 2020, there have been more deaths compared to previous years. Figure 2.1 shows the observed and expected deaths on a weekly basis for the entire Dutch population.

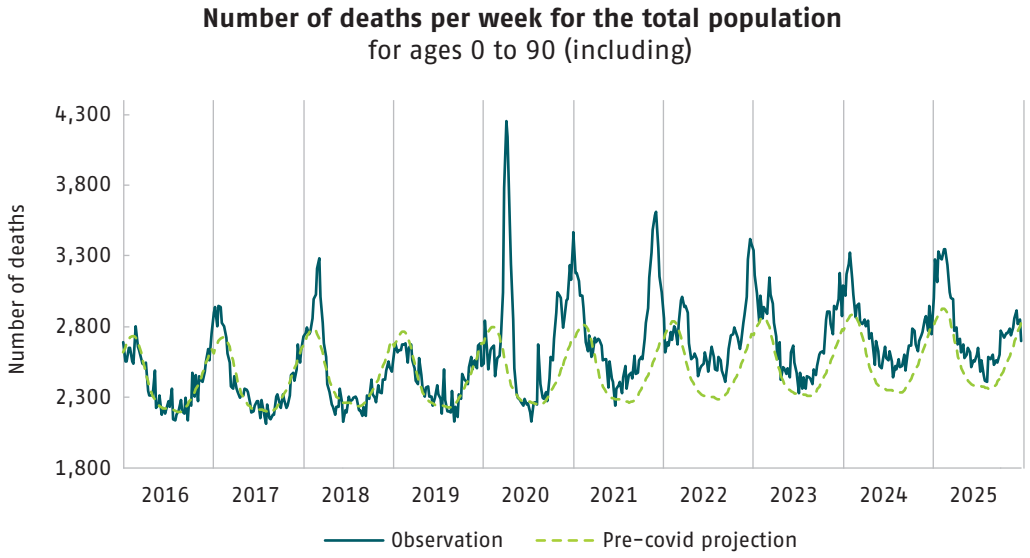


Figure 2.1 *– Number of deaths in the Dutch population per week during the years 2016–2025 for ages 0 to 90. Source: CBS tailor-made file for weekly mortality.*

Especially in the years 2020 and 2021, we see large peaks due to the pandemic; in the following years the peaks are mainly due influenza. The higher numbers are partly explained by the aging population. A more important cause of the higher numbers is the increased mortality after the pandemic, which is confirmed by the fact that observations have been consistently above the pre-covid projection since 2020.

Figure 2.2 shows the number of deaths for Dutch people for the years 2018 to 2025, including the expectation based on AG2026 without excess mortality term. The projections for the years 2018 and 2019 are based on the model estimate, and for the years 2020 to 2025 on the pre-covid projections. Table 2.1 shows the percentage differences between the actual number and the expected number of deaths.

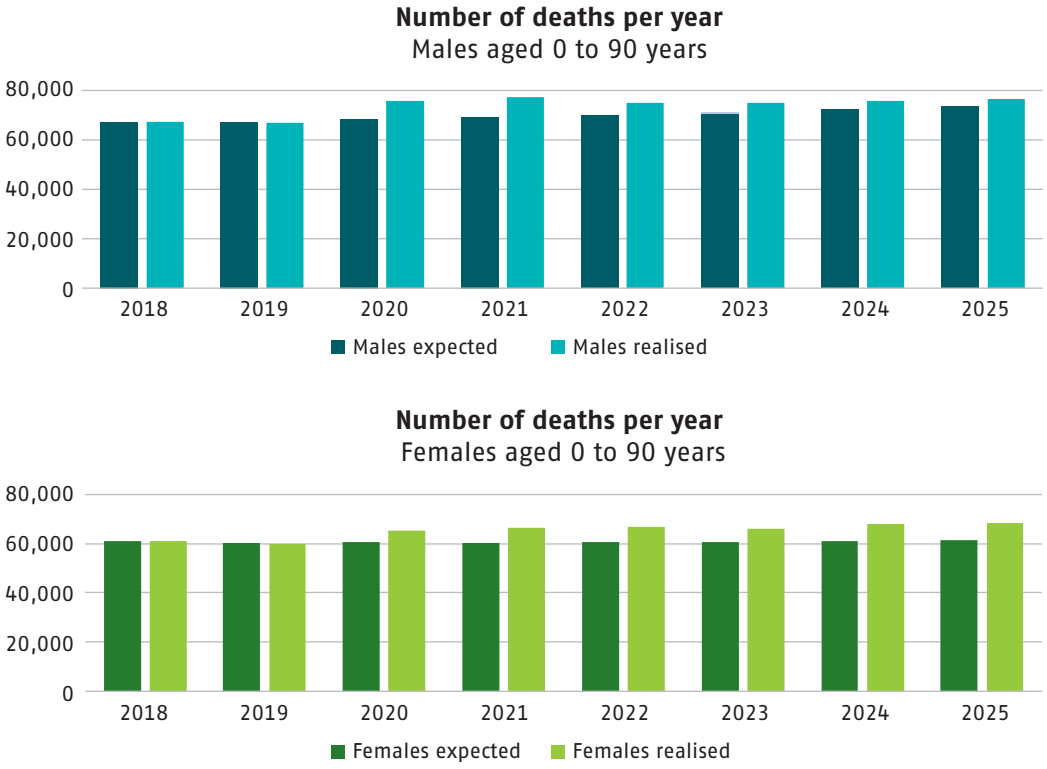


Figure 2.2 *– Number of deaths per year in the Netherlands over the years 2018-2025 for males and females aged 0 to 90 years, including expectation based on AG2026 excluding excess mortality term (pre-covid projection).*

Realisation vs. Expectation (%)		
Year	**Males**	**Females**
2018	0.2%	0.0%
2019	-0.3%	-0.2%
2020	10.8%	8.1%
2021	11.9%	9.8%
2022	7.0%	10.1%
2023	5.7%	8.9%
2024	4.7%	11.0%
2025	4.2%	11.2%

Table 2.1 *– Percentage deviation from realisation to expectation in number of deaths per year for the ages 0 to 90 years, corresponding to Figure 2.2.*

The figure and the table show that in the years 2018 and 2019 the difference between realisation and expectation is small, while from 2020 onwards larger differences are observed. The need for the excess mortality term in the projection model has therefore arisen since the COVID-19 pandemic. After the initial peak in 2020 and 2021, excess mortality has decreased for males: in 2022, excess mortality is much lower and has since then also been declining. For females, excess mortality shows a different pattern: excess mortality is still around 11% and does not yet appear to be structurally declining.

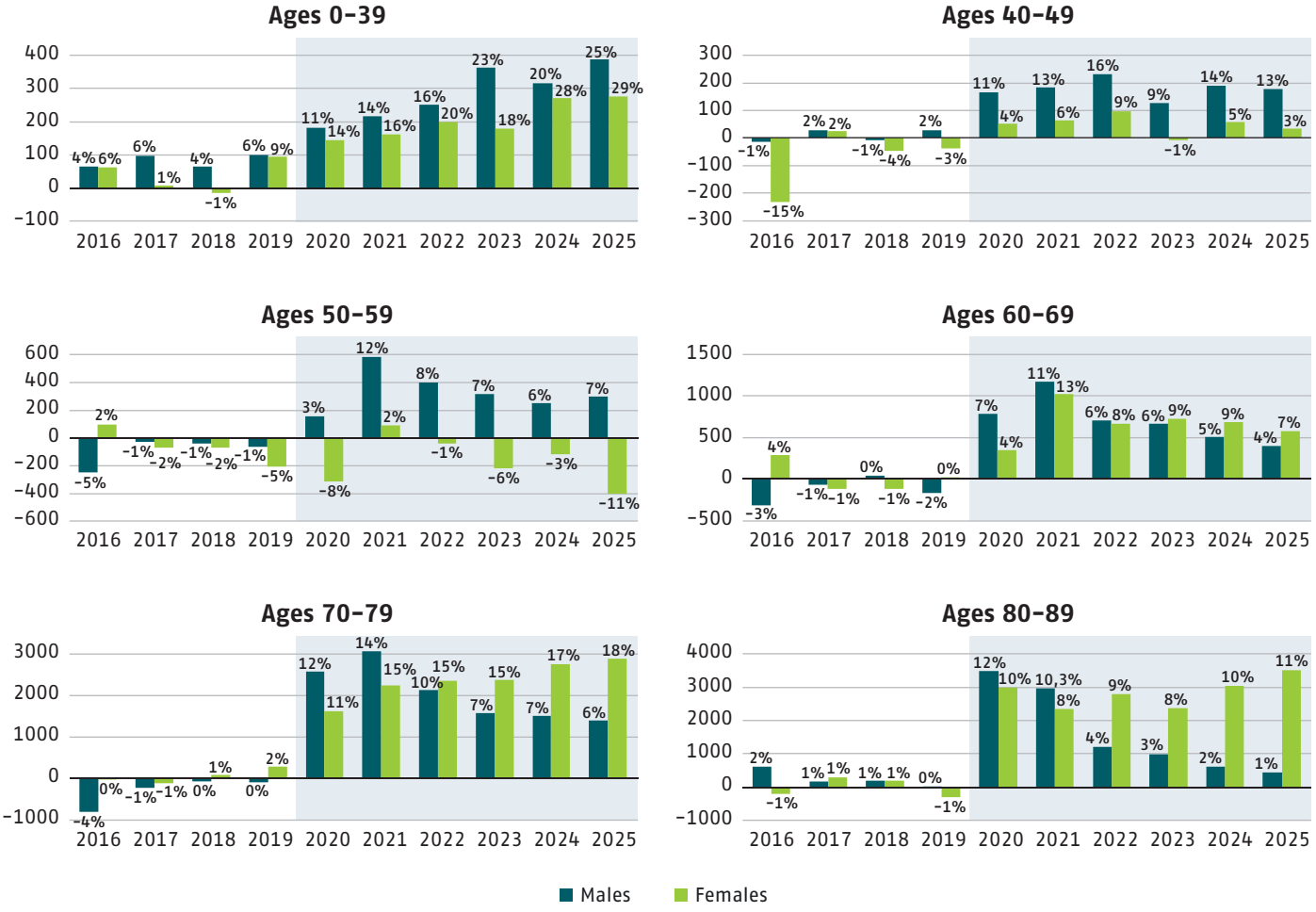


Figure 2.3 *– Absolute and relative excess mortality compared to the AG2026 pre-covid projection (i.e. excluding Excess mortality term).*

Figure 2.3 shows the absolute (y-axis) and the relative (labels) excess mortality per age group since the year 2020. Excess mortality appears to be high for the ages 0-39, but these are relatively small numbers for this large age group. For ages 50-59, males and females show a different picture: there is excess mortality for males, while mortality is lower than expected for females. For all age groups from 60 years old, observed mortality since 2020 has been higher than expected for both males and females.

2.2.2 Mortality developments in Europe since 2020

In Dutch mortality data from recent years, we still see excess mortality compared to the pre-covid projections. We observe that excess mortality among females has hardly decreased after the pandemic, but partly among males.

It was investigated whether increased mortality in recent years is specific to the Netherlands or whether this also applies to other, large European countries (France, Germany and the United Kingdom). For each country and sex, a projection has been made for 2020 to 2023 based on data from 2003 to 2019. Subsequently, the mortality observations from 2020 to 2023 were compared with this projection in order to quantify excess mortality and to be able to compare different countries.

The analyses show that in other European countries, as in the Netherlands, there is still excess mortality compared to the pre-covid expectation. Excess mortality compared to the pre-covid expectation in the Netherlands is comparable to the other European countries studied. However, excess mortality shows a different pattern between countries over the years and between age groups.

Since mortality rates in the countries studied are not yet at a comparable level to pre-covid and we are therefore still observing excess mortality, we continue to opt for an excess mortality term for AG2026 in addition to the long-term trend estimated based on the pre-covid period up to and including 2019. For the excess mortality term, we look at the years since 2022, as we did for AG2024. The excess mortality term has been estimated anew due to the update of the model specification and the availability of new mortality data for the years 2024 and 2025.

2.3 Analyses carried out after the publication of AG2024

Analysis to improve general model fit. The CSO has determined that the Li-Lee model as used in AG2024 for the pre-covid projection does not lead to a good alignment with the observations for all ages. If the model fit is not good in recent years, this leads to an incorrect starting point of the prognosis and also has an impact on the excess mortality modelling. Therefore, several studies have been conducted on improving model fit:

- **A cohort effect**: The Pearson residues were analysed to determine whether any factors are missing from the model. This analysis shows that a cohort effect can be observed in Europe. However, in the Dutch dataset, the relevance of a cohort effect is less significant. Adding a cohort effect makes the estimation routine substantially more complex, while there is no clear need for the Netherlands.
- **Alternative model structures**: the current pre-covid model is based on the Lee Carter model, which has been applied to both European data and to the Dutch deviation from the European trend. Alternative model structures have been considered for the Dutch deviation, including the Cairns–Blake–Dowd variations. Changing the model structure does not generally lead to a major improvement in the in-sample fit, but it does introduce (material) challenges around the projection of the time series.

Since both studies did not result in model modifications that substantially improve model fit without significantly increasing the complexity of the model, the CSO chose not to change this part of the model specification.

Analysis by calibration period. The starting point of the calibration has been determined for some time at 1970 for Europe and 1983 for the Netherlands. For Europe, developments have been stable for decades until 2020 and the starting point of 1970 therefore still seems suitable for the model without taking into account the excess mortality term. For the Netherlands, developments are less stable. Therefore, it was investigated whether adjusting the starting point of the Netherlands offers advantages, for example through better in-sample fit and better alignment between observations and model fit in recent years.

After analyses carried out, we conclude that the use of shorter calibration periods introduces new challenges: the Dutch deviation is then no longer stationary, allowing Dutch mortality to diverge from European mortality. In addition, the age effects show a lot of volatility at short calibration periods. Longer calibration periods lead to a fit which becomes worse (also for recent years). It was therefore decided to keep the starting point of calibration for the Netherlands at 1983.

2.4 Model changes from AG2024 to AG2026

The Projections Life Table AG2026 is largely based on the model used for the previous projection. However, two important changes have been made:

- **The pre-covid projection has been adjusted.** For specific age groups, the model's alignment with recent observations was not as good as preferred. It was therefore decided to start the pre-covid projection from a starting point that is directly derived from observed mortality. Subsequently, the projection converges to the pre-covid projection that follows directly from the Li-Lee model (without adjustment of the starting point), because we still find that projection more appropriate in the long term.
- **The excess mortality modelling has been adjusted.** The adjustment of the starting point of the projection has led to new insights into excess mortality. This excess mortality also appears to be relevant at lower ages. It was therefore decided to calibrate the excess mortality terms for all ages up to and including 90 years in the model. In addition, the most recent data points lead to new insights into the future development of excess mortality terms. It was decided to let excess mortality fade out more slowly and no longer fully.

The sections below first discuss the pre-covid projection. After that, the model changes are then briefly explained; the full description is included in Appendix A.

2.4.1 Pre-covid prognosis in accordance with Li-Lee

To model the long-term mortality trend, as in AG2024, the structure of Li-Lee (2005) is used with a Poisson assumption for the observed number of deaths:

$$D^s_{t,x} \sim \text{Poisson}(E^s_{t,x} \times \mu^s_{t,x}) \ ,$$

with

$$\ln \mu^s_{t,x} = A^s_x + B^s_x K^s_t + \alpha^s_x + \beta^s_x \kappa^s_t \ ,$$

where $\{A^s_x, B^s_x, \alpha^s_x, \beta^s_x\}$ are age effects and $\{K^s_t, \kappa^s_t\}$ period effects. The term $A^s_x + B^s_x K^s_t$ refers to the log of the mortality intensity for the European dataset, and the term $\alpha^s_x + \beta^s_x \kappa^s_t$ refers to the deviation of the Netherlands from the European reference group (including the Netherlands).

The period effects are projected using time series models:

$$K^s_t = K^s_{t-1} + \Theta^s + \varepsilon^s_t$$
$$\kappa^s_t = a^s \cdot \kappa^s_{t-1} + c^s + \delta^s_t \ ,$$

where $\{\Theta^s, a^s, c^s\}$ are parameters of the time series models. The vector $z_t = \{\varepsilon^M_t, \varepsilon^F_t, \delta^M_t, \delta^F_t\}$ contains the error terms that are assumed to follow a multivariate normal distribution with expectation 0 and covariance matrix Σ; the vector z_t is assumed to be independently and identically distributed (i.i.d.).

The above model is estimated on mortality data for the ages 0 to 90 and the years 1970 to 2019 for the group of European countries and 1983 to 2019 for the Netherlands. Mortality probabilities for ages higher than 90 years are obtained by extrapolating the age parameters to those higher ages.

2.4.2 Adjustment of starting point pre-covid projection

Since the introduction of AG2014, the (pre-covid) projection starts from the model fit that is determined by the calibrated parameters. Further inspection shows that the model fit (hereafter referred to as projection A) in recent years does not match the observations for females aged 30 to 55 years in particular, as visualized for a 46-year-old woman in Figure 2.4.[2]

2 – Figure 2.4 shows that for females 46 years of age, the model fit is higher than recent observations, causing the mortality projection to start and remain too high. For other age-sex combinations, this pattern can be the other way around and this pattern can also change over time.

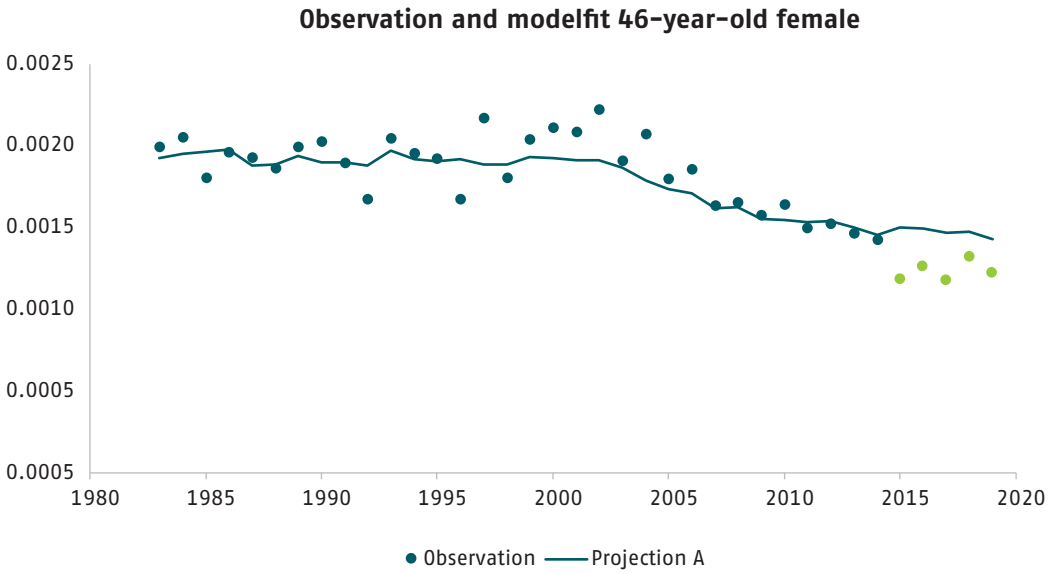


Figure 2.4 *– Observed and fitted mortality probabilities for a 46-year-old woman. The green observations are used to determine the adjusted starting point.*

In order to improve the alignment between the starting point of the projection and the recent observations, it has been decided to change the method used to determine the starting point of the pre-covid projection. The following principles underpin the model change that has been implemented for this point:

- Recent observations contain relevant information to determine an appropriate level for the starting point of the projection.
- By taking the average over several years and ages, a stable starting point is obtained.
- The projection that follows from the Li-Lee model provides relevant information about the long-term mortality trend and the corresponding level; In the long term, the projection should therefore converge to this projection.

These principles have led to the following adjustments to the model:

1. The existing model shows a prognosis A (with corresponding mortality probabilities $q_{t,x}^{s,A}$) – the blue line in Figure 2.5.
2. An alternative starting point of the projection is defined by averaging recent observations. The observed mortality is averaged over the years 2015 to 2019 (observations marked ingreen in Figure 2.5) and over the surrounding ages (three ages).
3. The alternative starting point is combined with the mortality improvements from the existing projection, leading to a projection B – green line in Figure 2.5.
4. The final projection is constructed by converging from projection B to projection A over a period of 25 years – light blue line in Figure 2.5.

Step 1 was explained earlier in the publication; Steps 2 to 4 are explained in more detail below. In addition, the steps are visualized in Figure 2.5.

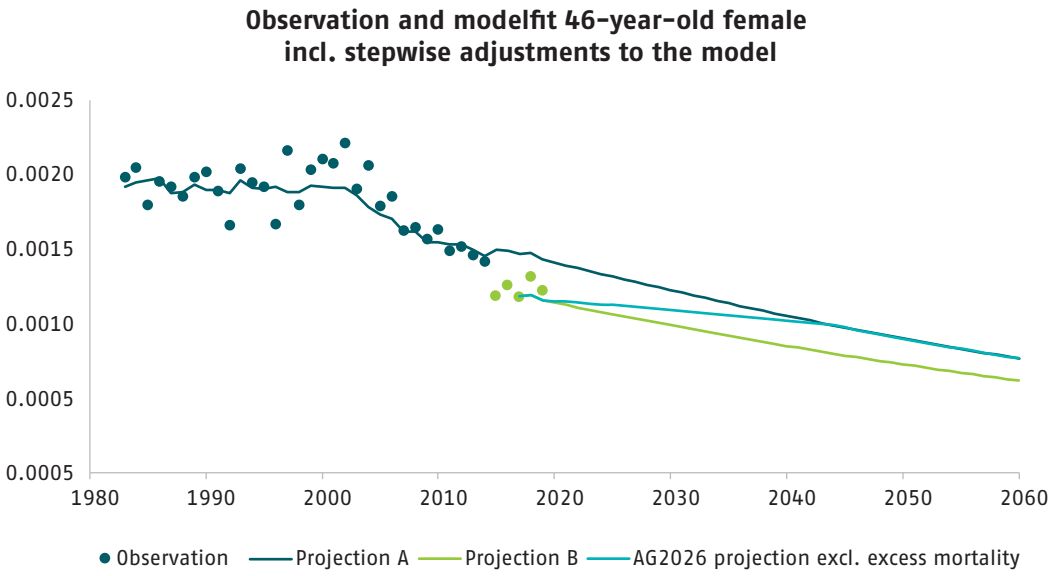


Figure 2.5 *– Visualization of the adjustment in the starting point of the projection in AG2026 compared to AG2024 excluding excess mortality term, where the green observations are used to determine the adjusted starting point.*

Determining the alternative starting point projection

Under the assumption that mortality intensity is constant per age and calendar year ($\mu_{t+u,x+v} := \mu_{t,x}$ for $0 \leq u, v < 0$), it holds the observed mortality frequency, $m^s_{t,x} = d^s_{t,x} / E^s_{t,x}$, is the maximum likelihood estimator for mortality intensity $\mu^s_{t,x}$. Furthermore, the mortality intensity for the most relevant ages increases log-linearly with age.

The starting point of the projection is therefore determined as the average of the observed log mortality frequencies. Define t_T as the most recent observation year and d as the number of years over which the average is calculated. The adjusted starting point of the projection is then defined via:

$$\overline{\ln \mu^s_{t_{\text{ref}},x}} := \overline{\ln m^s_{t_{\text{ref}},x}} =$$

$$\begin{cases} \frac{1}{d} \times \sum_{t=t_T-d+1}^{t_T} \ln m^s_{t_{\text{ref}},x}\,, & \text{for } x \in \{0,1\} \\ \frac{1}{3} \times \frac{1}{d} \times \sum_{u=x-1}^{x+1} \sum_{t=t_T-d+1}^{t_T} \ln m^s_{t_{\text{ref}},x}\,, & \text{for } x \in \{2,3,\ldots,90\}\,, \end{cases}$$

where t_{ref} is the reference year for which $\overline{\ln m^s_{t_{\text{ref}},x}}$ is considered representative and this is equal to the midpoint of the calendar years which are used. For ages 0 and 1, ages are not averaged because of the different level of mortality at age 0. For ages 2 to 90, the surrounding ages are averaged to increase the robustness of the projection. The average mortality intensity is obtained by taking the exponent:

$$\bar{\mu}^s_{t_{\text{ref}},x} = \exp\left(\overline{\ln \mu^s_{t_{\text{ref}},x}}\right) \qquad \text{for } x \in \{0,\ldots,90\}\,.$$

For AG2026, the value $d = 5$, has been chosen, which means that the average is calculated over the last five years and that 2017 is the reference year for the pre-covid projection.

For ages higher than 90, the Kannisto closure method is applied to the mortality intensity as defined for the reference year. In other words, mortality intensity is determined for ages $x \in \{91,\ldots,120\}$ by extrapolating $\bar{\mu}^{s}_{x,t_{\text{ref}}}$ log-linearly, based on the trend which is observed for the ages $x \in \{80,\ldots,90\}$.

Determining alternative projection
The mortality improvements that follow from the Li-Lee model are the starting point for the projection that starts from the alternative starting point. The mortality improvements are defined through the relationship:

$$\mu_{t,x} = \mu_{t-1,x} \cdot \exp(-r_{t,x}) \ ,$$

or

$$r_{t,x} = -\ln\left(\frac{\mu_{t,x}}{\mu_{t-1,x}}\right) = \ln(\mu_{t-1,x}) - \ln(\mu_{t,x})$$

$$= B_x\,(K_{t-1} - K_t) + \beta_x\,(\kappa_{t-1} - \kappa_t) \ .$$

This last equation shows why it is logical to determine the mortality improvements at the level of the mortality intensities. The mortality improvements are determined for the ages $x = 0,\ldots,120$ and for the years $t = t_T - d + 1,\ldots,t_T,\ldots,t_T + h$ (derived from $\hat{\mu}^{s,A}_{t,x} = -\ln(1 - \hat{q}^{s,A}_{t,x})$, which leads to mortality improvements $\hat{r}^{s}_{t,x}$. Mortality improvements are therefore determined for some historical years as well as for future years.

The starting point for constructing the various projections is that the mortality improvements are applied as they are derived from the model. When $t_{ref} = 2017$, then two mortality improvements are first applied which have been fitted to the observed data after which the projected mortality improvements are applied from 2019 onwards. Thus, the projection based on an adjusted starting point is defined as:

$$\mu^{s,B}_{t_{\text{ref}}+h,x} = \bar{\mu}^{s}_{t_{\text{ref}},x} \cdot \exp\left(-\sum_{j=1}^{h} \hat{r}^{s}_{t_{\text{ref}}+j,x}\right)$$

The corresponding mortality probabilities are then determined via the known relationship:

$$q^{s,B}_{t,x} = 1 - \exp(-\mu^{s,B}_{t,x}).$$

Determining the final pre-covid projection
Two projections are now available:

- $q^{s,A}_{t,x}$: the projection that follows directly from the Li-Lee model
- $q^{s,B}_{t,x}$: the projection that starts from a modified starting point

The final pre-covid projection starts in the projection with an adjusted starting point (projection B) and converges to the projection that immediately follows the Li-Lee model (projection A):

$$q^{s,\text{pre-cov}}_{2019+h.x} = \left(1 - \frac{\min(h,c)}{c}\right) \times q^{s,B}_{2019+h.x} + \frac{\min(h,c)}{c} \times q^{s,A}_{2019+h.x} \ .$$

For AG2026, the CSO has chosen the value $c = 25$. A smaller value of c leads to faster convergence, but in some cases can lead to non-plausible mortality projections as visualized in the figure below. The value $c = 25$ leads to plausible mortality projections at all ages and is expected to be robust for future data updates.

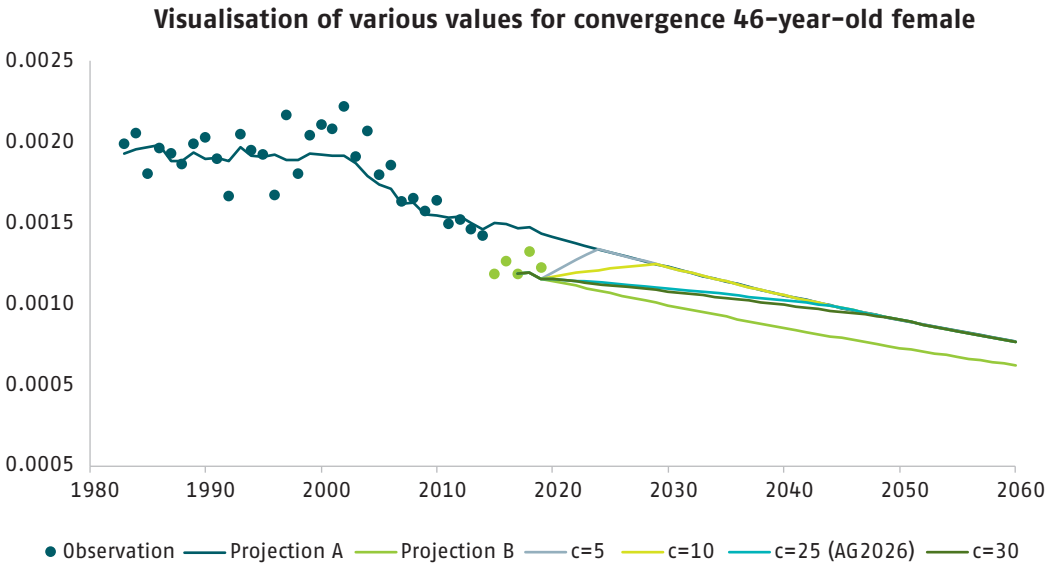


Figure 2.6 *– Visualization of the application of different convergence values between projection A and projection B for a 46-year-old woman.*

2.4.3 Adjustment of excess mortality modelling

To incorporate the observed excess mortality into the projection, an excess mortality term has been added to a variant of the Li-Lee model on a weekly basis *w*, since AG2022:

$$\ln \mu^{s}_{t,w,x} = \ln \mu^{s,C}_{t,w,x} + \ln \Phi^{s}_{t,w} + \ln o^{s}_{t,w,x} \ ,$$

where $\Phi^{s}_{t,w}$ is an observed seasonal effect and the excess mortality term is defined as

$$\ln o^{s}_{t,w,x} = \mathfrak{V}^{s}_{x} \cdot \mathfrak{K}^{s}_{t,w} \, .$$

The structure of the excess mortality term is comparable to the Lee-Carter model and can therefore be estimated in a similar way. For projection purposes, the parameters $\mathfrak{V}^{s}_{x}$ and $\mathfrak{K}^{s}_{t,w}$ are transformed into excess mortality parameters on an annual basis.

The adjustment of the starting point of the projection leads to larger and smaller adjustments in the mortality projection in the short term. This subsequently has an impact on the quantification of excess mortality because the expected mortality has

changed. In addition, data points for 2024 and 2025 provide new insights into the further course of excess mortality. This has led to the following adjustments in the excess mortality modelling:

- Age range is extended to ages 0-90.
- The future development changes from a 'disappearing' scenario to a 'new normal' scenario with persistent excess mortality.

These changes are explained in more detail below.

Adjustment of age range for excess mortality parameters
Adjusting the starting point of the projection leads to new insights into the level of excess mortality. Figure 2.7 shows the estimated parameters for ages 0-90 (calibrated for 2022-2025) based on the new pre-covid projection.

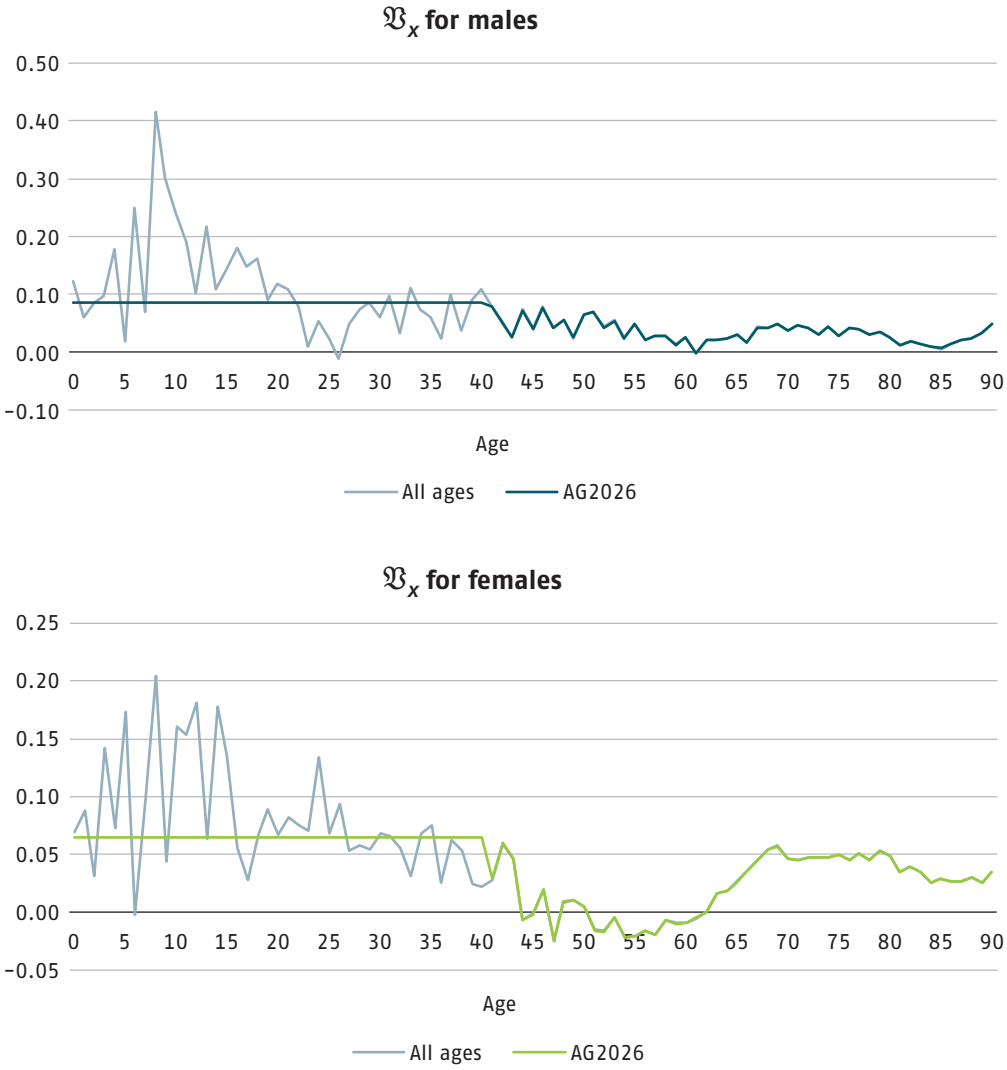


***Figure 2.7** – Estimated excess mortality age parameter $\mathfrak{V}_x$ for ages 0-90 calibrated for 2022-2025 with an age-dependent parameter for all ages (in grey) and a constant factor for ages 0 to year 40 as chosen for AG2026 (in green).*

The grey line shows the estimates when an age-dependent parameter is estimated for all ages. For the lower ages, the estimated parameters are volatile over the ages, but materially larger than zero. Therefore, the CSO has chosen to expand the age range to ages 0 to 90 (instead of 55 to 90 in AG2024). To counteract volatility at low ages, it was decided to use an age-independent parameter for ages 0 to 40, differently for males and females.

Adjustment of scenario for future development

Six years have now already passed since the outbreak of COVID-19. The number of covid-related deaths has fallen to less than 1% of the total number of deaths by 2025. Nevertheless, we are still observing materially higher mortality in the Netherlands than expected in comparison with the adjusted pre-covid projection. This raises the question whether the disappearing scenario is still the most likely scenario.

Although in AG2024 it was assumed that excess mortality would decrease by about 25% per year, Table 2.1 shows that excess mortality is decreasing slower. For males, excess mortality decreases by about 10% annually and the 'disappearing' scenario still seems suitable for males. Excess mortality does not seem to be decreasing for females, making the scenario 'persistent' more realistic for females. The 'new normal' scenario lies between these two scenarios: a scenario in which excess mortality does decrease, but part of the excess mortality is assumed to be permanent.

The CSO has opted for this 'new normal' scenario in which 25% of the excess mortality observed in 2025 is assumed to be permanent. The substantiation for this is as follows. If only the Dutch population is considered, an equal weighting of the 'disappearing' scenario for males and the 'structural' scenario for females leads to the calculation of 50% excess mortality in the long term. The observation that excess mortality is still decreasing also in Europe leads the CSO to assign more weight to the disappearing scenario, leading to a 75% weight for the 'disappearing' scenario and a 25% weight for the 'structural' scenario. The rate at which excess mortality is decreasing has been adjusted downwards to a 5% decrease per year. This is an average of approximately 10% decrease for males and approximately 0% decrease for females:[3]

$$\begin{aligned}\mathfrak{X}_{2025+h} &= \eta^h \cdot \mathfrak{X}_{2025} + (1 - \eta^h) \cdot \mathfrak{X}_{\infty} \\ &= 0.95^h \cdot \mathfrak{X}_{2025} + (1 - 0.95^h) \cdot 0.25\mathfrak{X}_{2025} \\ &= 0.95^h \cdot 0.75\mathfrak{X}_{2025} + 0.25\mathfrak{X}_{2025}\end{aligned}$$

The CSO has considered sex-specific projections, but did not find any valid reasons why Dutch females would differ from Dutch males or European males or females in the future. This is why the same approach has been chosen for both males and females.

The resulting projection of the effects of excess mortality period is shown in Figure 2.8, together with the projection of the excess mortality period effects as they were included in AG2024.

3 – See Van Berkum et al. (2025) for more scenarios that can be shaped within this framework.

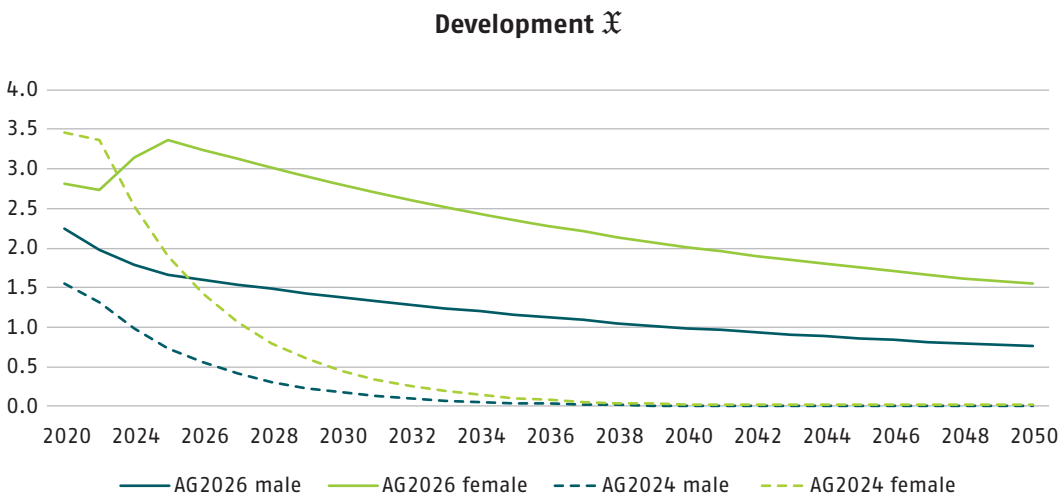


Figure 2.8 *– Development of the estimated time effect of the excess mortality term for AG2024 and AG2026. The parameters for AG2026 shown in this graph differ from the published values to enhance comparability between AG2024 and AG2026. The parameters shown here for AG2026 are only based on 55 years and older, because otherwise the starting values are not comparable due to normalization.*

3 Data

3.1 European mortality data: selected countries

The projection model uses not only Dutch mortality data, but also mortality data from a number of European countries. The country set (see Figure 3.1), which is used (besides the Netherlands) consists of Belgium, Denmark, Germany, Finland, France, Ireland, Iceland, Luxembourg, Norway, Austria, Sweden, Switzerland and the United Kingdom.

There is a positive correlation between prosperity and ageing[4]: a higher level of prosperity generally goes hand in hand with a higher average life expectancy. The selected countries are geographically coherent and these countries exhibit a high level of prosperity. The country set was selected for the first time when AG2014 was published and has not changed since. Figure 3.1 shows the set of selected countries which have been used for AG2026.

4 – Niu G., Melenberg B. (2014). *Trends in mortality decrease and economic growth*. Demography 51(5):1755–1773.

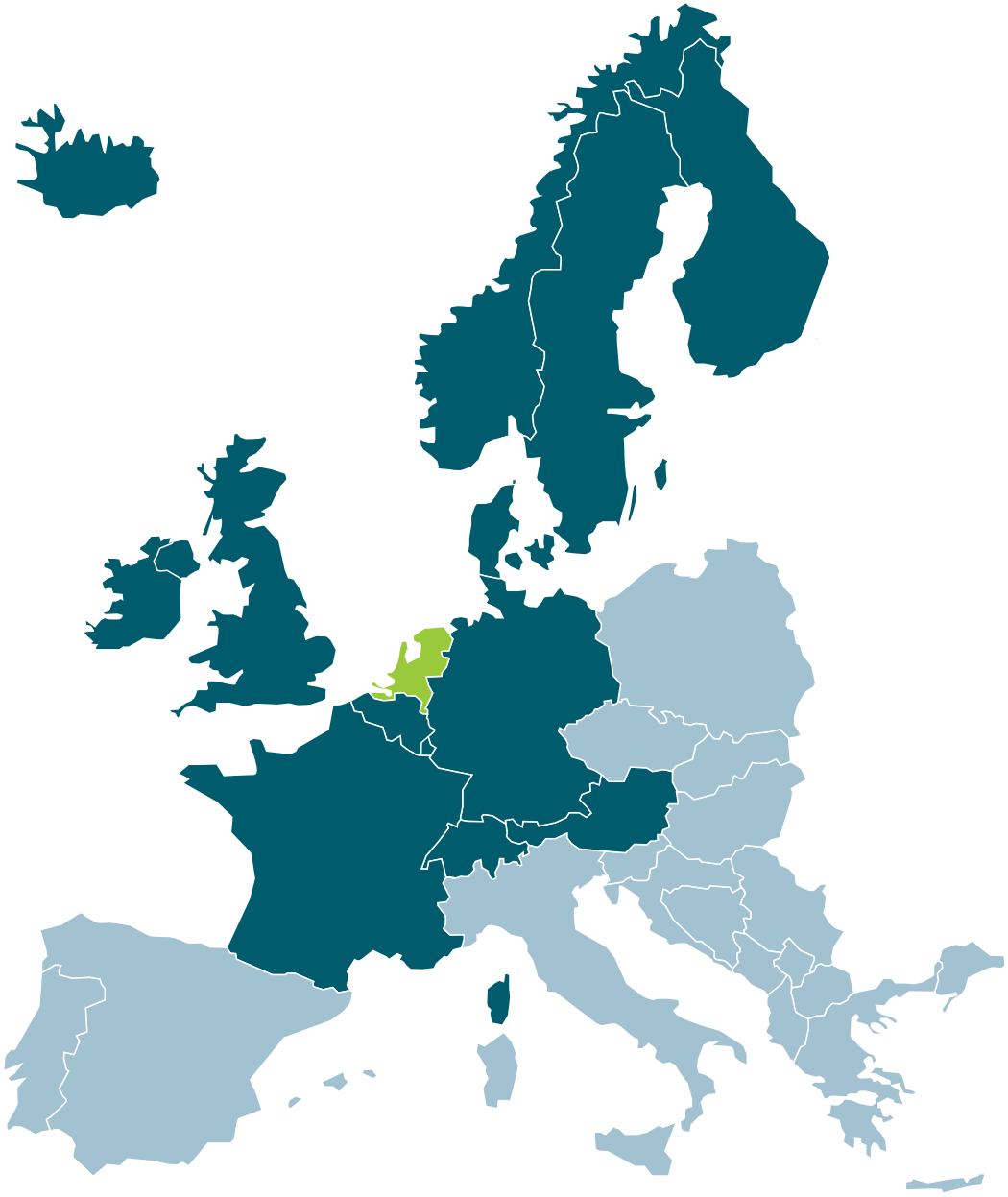


Figure 3.1 *– Selected countries in dataset projection model AG2026.*

The Human Mortality Database (HMD) was used for the data up to and including 2019. For the Dutch data from 2020 onwards, both public and customised tables from Statistics Netherlands (CBS) were used. An explanation of the data used can be found in Appendix C.

The used data contains a total of almost 120 million deaths. Figure 3.2 shows for the year 2019 how these deaths are distributed across the different countries.

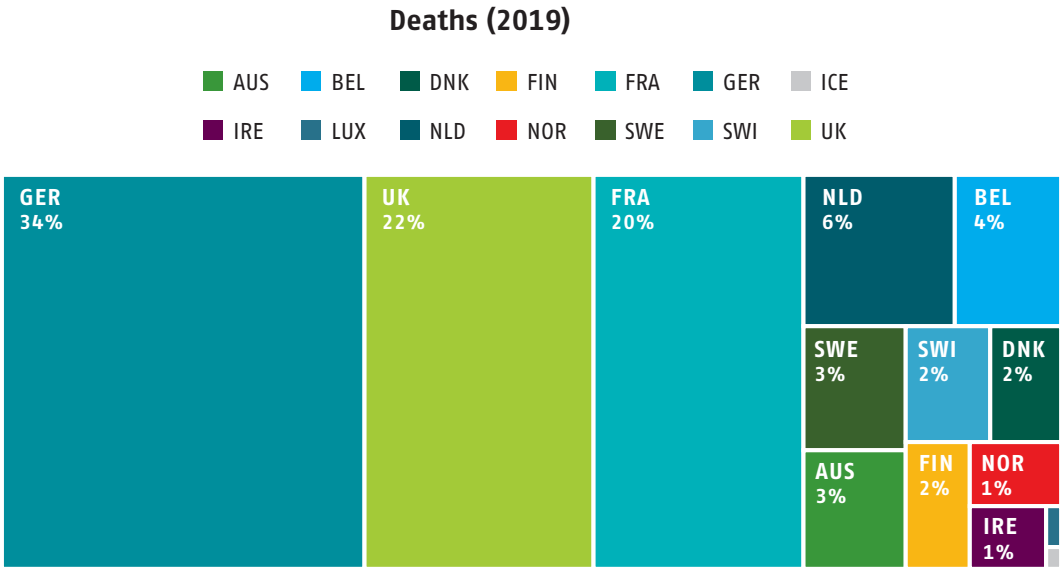


Figure 3.2 *– Distribution of deaths (males + females) in 2019 by country. Germany (34%), the United Kingdom (22%) and France (20%) had the highest number of deaths in 2019. The Netherlands follows with a share of (6%).*

3.2 Data range

Figure 3.3 and Figure 3.4 show the historical development since 1950 of the period life expectancy at birth for the countries in the country set, where the Netherlands is highlighted.

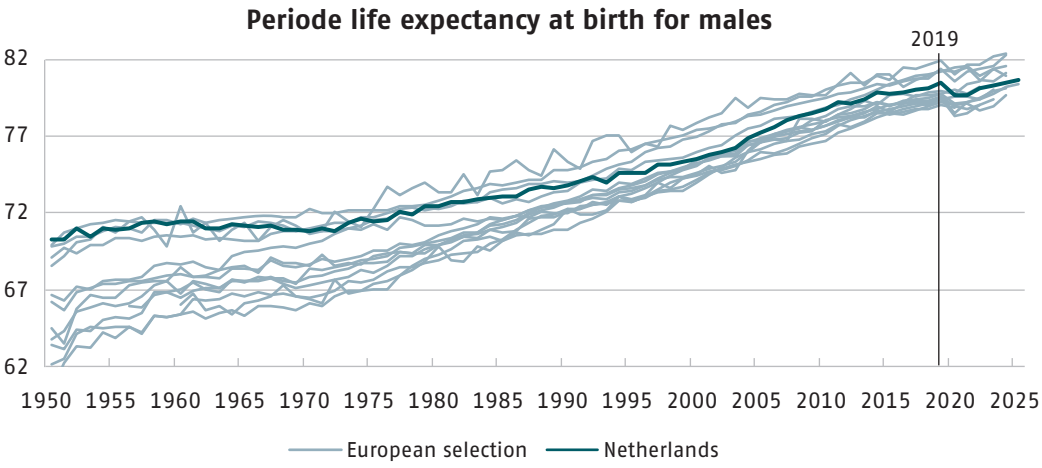


Figure 3.3 *– Historical development of period life expectancy at birth for males.*

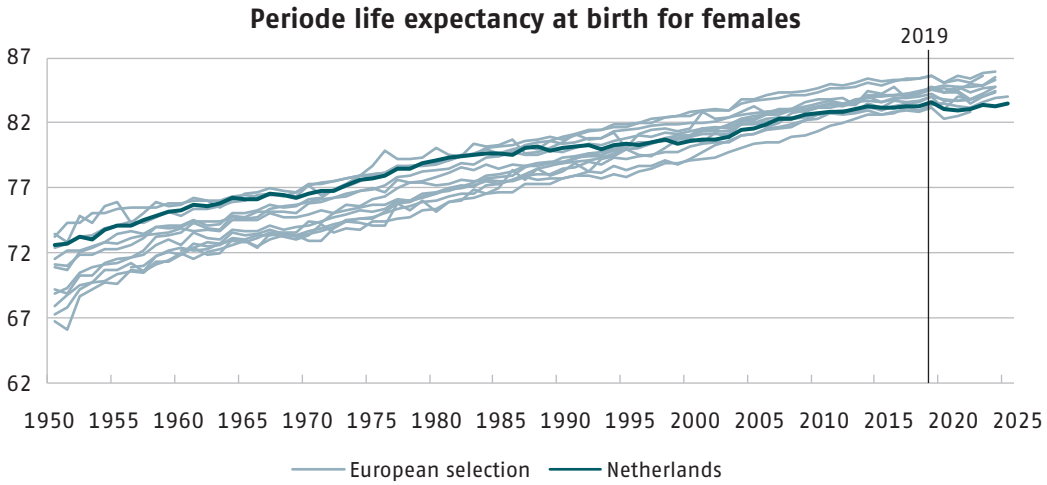


***Figure 3.4** – Historical development of period life expectancy at birth for females.*

The graphs show that in the first part of this timespan, life expectancies in the selected countries vary considerably, especially for males. From 1970 onwards, a similar trend can be seen in the development of life expectancy of both males and females in the various European countries.

In addition, the graphs show that life expectancy in the Netherlands has increased at a slower pace since 1970 than the average of the selected European countries. This has been particularly the case for females, since the early 1980s. The difference between Dutch and European females is even more remarkable when looking at the underlying mortality probabilities.

The above observations form the basis for the chosen data range. To estimate the European part of the model, of which the Netherlands is a part, the data from 1970 to 2019 are used. For the Dutch deviation, data from 1983 to 2019 are used.

In the years after 2019, period life expectancy decreased, which was caused by the direct and indirect consequences of COVID-19. Period life expectancy in 2025 in the Netherlands is close to the level before the start of the COVID-19 pandemic in 2020 (slightly lower for females, slightly higher for males).

In order to model the excess mortality term, we use customised data from Statistics Netherlands. This concerns data for observed mortality per week, and by age and sex in the Netherlands for the years 2022 to 2025. For the same period, we used publicly available population sizes per month, and by age and sex from CBS to arrive at the exposures for those years. The data used for the excess mortality term are further described in paragraph 2.2.

Appendices

Appendix A
AG2026 model description

A.1 Definitions

The projection table provides the 'best estimate' for the one-year mortality probabilities $q_{x,t}^s$ for the sexes $s \in \{M, F\}$, for the ages $x \in X = \{0, 1, 2, .., 120\}$ and for the years $t \in T = \{2022, \ldots, 2025, .., 2200\}$. The one-year mortality probability is the probability that someone who is alive on 1 January of the year t and was born on 1 January of the year $t - x$, will have died on 1 January of the year $t + 1$. The model enables the user to create a projection for the years after 2200 as well.

The mortality probabilities are not directly modelled; Instead, we specify the corresponding force of mortality (or hazard rate) $\mu_{x,t}^s$. We assume that $\mu_{x+u,t+v}^s = \mu_{x,t}^s$ for all $0 \leq u, v < 1$. From this assumption, it follows that

$$q_{x,t}^s = 1 - e^{-\int_0^1 \mu_{x+u,t+u}^s du} = 1 - e^{-\mu_{x,t}^s}.$$

Each dynamic model, on the basis of which the mortality intensity $\mu_{x,t}^s$ can be predicted, also provides a prognosis in terms of one-year mortality probabilities via the above presented equation.

A.2 Global description of selected dynamic model

We model all $(x, t) \in X \times T$ for both sexes $s \in \{M, F\}$ the mortality intensity $\mu_{x,t}^s$:

$$\ln\left(\mu_{x,t}^s\right) = \ln\left(\mu_{x,t}^{s,\text{pre-cov}}\right) + \ln\left(o_{x,t}^s\right),$$

with the pre-covid mortality intensity $\mu_{x,t}^{s,\text{pre-cov}}$ determined using the data up to and including 2019, and $o_{x,t}^s$ the quotient of $\mu_{x,t}^s$ and $\mu_{x,t}^{s,\text{pre-cov}}$, which thus represents the deviation from 2022 onwards. This deviation represents the excess mortality observed in the mortality figures after the COVID-19 pandemic.

Pre-covid prognosis. The projection of the pre-covid mortality intensity $\mu_{x,t}^{s,\text{pre-cov}}$ is established as follows. First, the Li-Lee[5] model is calibrated to historical mortality data (the emphasis ˜ refers to a mortality intensity which is calibrated to observed data):

$$\begin{aligned}
\ln\left(\tilde{\mu}_{x,t}^{s,\text{pre-cov}}\right) &= \ln\left(\tilde{\mu}_{x,t}^{s,\text{pre-cov,EU}}\right) + \ln\left(\tilde{\Delta}_{x,t}^{s,\text{pre-cov}}\right), \\
\ln\left(\tilde{\mu}_{x,t}^{s,\text{pre-cov,EU}}\right) &= A_x^s + B_x^s K_t^s, \\
\ln\left(\tilde{\Delta}_{x,t}^{s,\text{pre-cov}}\right) &= \alpha_x^s + \beta_x^s \kappa_t^s,
\end{aligned}$$

with the $\tilde{\mu}_{x,t}^{s,\text{pre-cov,EU}}$ as the pre-covid mortality intensity for the reference group of Western European countries and $\tilde{\Delta}_{x,t}^{s,\text{pre-cov}}$ the quotient of $\tilde{\mu}_{x,t}^{s,\text{pre-cov}}$ and $\tilde{\mu}_{x,t}^{s,\text{pre-cov,EU}}$ (i.e. the deviation of the Dutch population compared to the reference group). In this equation $\{A_x^s, B_x^s, \alpha_x^s, \beta_x^s\}$ are age-dependent parameters, while $\{K_t^s, \kappa_t^s\}$ are time-dependent quantities, whose dynamics are given by the time series

5 – See Li and Lee (2005)

$$K_t^s = K_{t-1}^s + \theta^s + \epsilon_t^s,$$
$$\kappa_t^s = a^s \kappa_{t-1}^s + c^s + \delta_t^s,$$

where θ^s, a^s and c^s are parameters and ϵ_t^s and δ_t^s are error terms. The stochastic vectors $Z_t = (\epsilon_t^M, \epsilon_t^F, \delta_t^M, \delta_t^F)'$ are assumed to be independently and identically distributed (i.i.d.) and to follow a four-dimensional normal distribution with mean $(0,0,0,0)'$ and a given 4×4 covariance matrix *C*. This means that a 'random walk with drift' is assumed for the time series of the reference group $\{K_t^s\}$, and a first order autoregressive model with a constant term for the time series of the deviation of the Dutch population compared to the reference group.

The time series K_t^s and κ_t^s are projected based on the time series parameters θ^s and a^s. By combining these time series with the age parameters, we get a mortality projection $\tilde{\mu}_{x,t}^{s,\text{pre-cov}}$ for $t > 2019$ that follows from the model.

The starting point of the projection is adjusted, because the model does not fully align with recent observations for all ages. The starting point of the projection is determined by averaging recent observations and applying the mortality improvements from the model forecast to this adjusted starting point. This leads to a projection with an adjusted starting point, $\breve{\mu}_{x,t}^{s,\text{pre-cov}}$. The mortality intensities are transformed into mortality probabilities through the known relationship. The final pre-covid projection 1) starts in the projection with an adjusted starting point of the prognosis, and 2) converges to the forecast that follows directly from the calibrated model:

$$q_{x,t}^{s,\text{pre-cov}} = w_t \cdot \breve{q}_{x,t}^{s,\text{pre-cov}} + (1 - w_t) \cdot \tilde{q}_{x,t}^{s,pre-cov},$$

where w_t represent the weights that determine the rate of convergence. In paragraph A.3.8 we describe in more detail how that convergence occurs.

Adjustment for excess mortality. We model the excess mortality term $o_{x,t}^s$, inspired by the Lee-Carter model, as follows:

$$\ln\left(o_{x,t}^s\right) = \widetilde{\mathfrak{B}}_x^s \mathfrak{K}_t^s,$$

with $\{\widetilde{\mathfrak{B}}_x^s\}$ as age-dependent parameters and $\{\mathfrak{K}_t^s\}$ as time-dependent quantities. The values of $\mathfrak{K}_t^s$ for $t = 2022, \ldots, 2025$ follow from a calibrated weekly model that we will discuss later in this Appendix, while for $t > 2025$ we assume

$$\mathfrak{K}_{2025+h}^s = \eta^h \cdot \mathfrak{K}_{2025}^s + \left(1 - \eta^h\right) \cdot \mathfrak{K}_\infty^s,$$

with η as a parameter and $\mathfrak{K}_\infty^s$ as the level to which the excess mortality period effect converges. Different values of the parameters η and $\mathfrak{K}_\infty^s$ correspond to different scenarios for the future course of the pandemic:

- The values $\eta \in (0,1)$ and $\mathfrak{K}_\infty^s = 0$ correspond to the '**disappearing**' scenario: the value of $\mathfrak{K}_t^s$ for $t > 2025$ converges to 0, so the excess mortality compared to the pre-covid period disappears with a half-life period equal to $\ln(½)/\ln(\eta)$.

- The value $\eta = 1$ ($\mathfrak{X}^s_\infty$ is not relevant) corresponds to the '**structural**' scenario: the value of $\mathfrak{X}^s_t$ for $t > 2025$ remains equal $\mathfrak{X}^s_{2025}$, so the excess mortality compared to the pre-covid period does not disappear.

- The values $\eta \in (0,1)$ and $\mathfrak{X}^s_\infty \neq 0$ correspond to the scenario '**new normal'**: the value of $\mathfrak{X}^s_t$ for $t > 2025$ converges to the limit value $\mathfrak{X}^s_\infty$. In the long term, the force of mortality will be increased by a factor $\exp(\mathfrak{B}^s_x \mathfrak{X}^s_\infty)$, if $\mathfrak{X}^s_\infty > 0$.
  The CSO has chosen this scenario for the AG2026 projection with the value 0.95 for η and $\mathfrak{X}^s_\infty = 0.25 \cdot \mathfrak{X}^s_{2025}$, which means that in the long term a quarter of the excess mortality observed in 2025 will be included in the mortality projection. The value $\eta = 0.95$ implies a half-life of 13.5 years.

A.3 Detailed description of pre-covid projection

The creation of the pre-covid projection is described below. First, the data is introduced. This is followed by the description of the Li-Lee model, closure of the parameter values, estimation of the time series parameters, and an explanation of how the most likely projection is constructed. These elements are comparable to AG2024. This is followed by an explanation of how to derive an adjusted starting point from the projection and how this is combined with the most likely projection to get to a new pre-covid forecast.

A.3.1 Definition of input data

For the calibration of the pre-covid model, we use the following input data:

- d_{xtsc}: the observed number of deaths at age $x \in \mathcal{X}^o = \{x_1, \dots, x_X\} = \{0, \dots, 90\}$ in calendar year $t \in \mathcal{T}^{EU} = \{t_1^{EU}, \dots, t_T^{EU}\} = \{1970, \dots, 2019\}$ for sex $s \in \mathcal{S} = \{M, F\}$ in country $c \in \mathcal{C} = \{\text{NLD}, \text{BEL}, \dots\}$.

- E_{xtsc}: the exposure-to-risk at age $x \in X^o$ in calendar year $t \in \mathcal{T}^{EU}$ for sex $s \in \mathcal{S}$ in country $c \in \mathcal{C}$.

- $d_{xt}^{\text{EU},s} = \sum_c d_{xtsc}$: the observed number of deaths at age $x \in X^o$ in calendar year $t \in \mathcal{T}^{EU}$ for sex $s \in \mathcal{S}$ in the European Reference Group (including the Netherlands).

- $E_{xt}^{\text{EU},s} = \sum_c E_{xtsc}$: the exposure-to-risk at age $x \in X^o$ in calendar year $t \in \mathcal{T}^{EU}$ for sex $s \in \mathcal{S}$ in the European reference group (including the Netherlands).

- $d_{xt}^{\text{NLD},s} = d_{xts,c=\text{NLD}}$: the observed number of deaths at age $x \in X^o$ in calendar year $t \in \mathcal{T}^{NLD} = \{t_1^{NLD}, \dots, t_T^{NLD}\} = \{1983, \dots, 2019\}$ for sex $s \in \mathcal{S}$ in the Netherlands.

- $E_{xt}^{\text{NLD},s} = E_{xts,c=\text{NLD}}$: the exposure-to-risk by age $x \in X^o$ in calendar year $t \in \mathcal{T}^{NLD}$ for sex $s \in \mathcal{S}$ in the Netherlands.

Note that different calibration periods are used for Europe and the Netherlands.

A.3.2 The mortality model

Given the input data, the mortality model is estimated in two steps:

1. We estimate the Lee-Carter model on European data (separately for males and females):

$$D_{xt}^{EU,s} \sim \text{Poisson}\left(E_{xt}^{EU,s} \cdot \mu_{xt}^{EU,s}\right) \qquad \text{with} \qquad \ln \mu_{xt}^{EU,s} = A_x^s + B_x^s K_t^s.$$

   After estimating this model, we have obtained parameter estimates $\hat{A}_x^s$, $\hat{B}_x^s$ and $\hat{K}_t^s$ for $x \in \mathcal{X}^o$ and $t \in \mathcal{T}^{EU}$.

2. Given the parameter estimates for Europe, the same model is estimated for the Netherlands:

$$D_{xt}^{NLD,s} \sim \text{Poisson}\left(E_{xt}^{NLD,s} \cdot \mu_{xt}^{NLD,s}\right) \quad \text{with} \quad \ln \mu_{xt}^{NLD,s} = \ln \hat{\mu}_{xt}^{EU,s} + \alpha_x^s + \beta_x^s \kappa_t^s, \qquad \text{Equation (1)}$$

   where $\ln \hat{\mu}_{xt}^{EU,s}$ is the fitted mortality intensity for Europe from the previous step. After estimating this model, we have obtained parameter estimates $\hat{\alpha}_x^s$, $\hat{\beta}_x^s$ and $\hat{\kappa}_t^s$ or $\in \mathcal{X}^o$ and $t \in \mathcal{T}^{NLD}$.

The log-likelihood is optimised for both Europe and the Netherlands. We specify these for the European dataset, it is similar for the Dutch dataset :

$$\log \mathcal{L} \propto \sum_{t=t_1^{EU}}^{t_T^{EU}} \sum_{x=x_1}^{x_X} \left\{ d_{xt}^{EU,s} \cdot \log\left(E_{xt}^{EU,s} \cdot \mu_{xt}^{EU,s}\right) - E_{xt}^{EU,s} \cdot \mu_{xt}^{EU,s} \right\},$$

where $\mu_{xt}^{EU,s}$ is specified as a function of the parameters A_x^s, B_x^s and K_t^s that are to be estimated. To identify the parameters, we apply the following parameter restrictions: $\sum_x B_x = 1$, $\sum_t K_t = 0$, $\sum_x \beta_x = 1$ and $\sum_t \kappa_t = 0$.

A.3.3 Closure of the parameters

Next, the parameters $\{A_x^s, B_x^s, \alpha_x^s, \beta_x^s\}$ for the ages $x \in \tilde{X} = \{91,92,\dots,120\}$ are determined via extrapolation as follows. The parameters $\{B_x^s\}$, $x \in \tilde{X}$, are determined by linear extrapolation of $\left\{\ln\left(\hat{B}_y^s\right)\right\}$ for the ages $y \in \{80,81,\dots,90\}$. We write $y_k = 80 + (k-1)$ for $k = 1,\cdots,n$ with $n = 11$. The regression will therefore be based on the number of ages $n = 11$, the average of those ages equals $\bar{y} = \frac{1}{n}\sum_{k=1}^n y_k = 85$ and the sum of squares of the deviation is $\sum_{k=1}^n (y_k - \bar{y})^2 = 110$. Then we find for $x \in \tilde{X}$:

$$\hat{B}_x^s = \exp\left(\sum_{k=1}^n w_k(x) \ln\left(\hat{B}_k^s\right)\right),$$

where the regression weights $w_k(x)$ are given by

$$w_k(x) = \frac{1}{n} + \frac{(y_k - \bar{y})(x - \bar{y})}{\sum_{j=1}^n \left(y_j - \bar{y}\right)^2} = \frac{1}{11} + \frac{(y_k - 85)(x - 85)}{110}.$$

We then determine $\{\hat{A}_x^s\}, x \in \tilde{X}$, in such a way that in 2019 the values of the force of mortality for the Western European reference group match with the values according to the Kannisto closure of parameter values methodology[6], i.e.

$$\exp(\hat{A}_x^s + \hat{B}_x^s \hat{K}_{2019}^s) = L\left(\sum_{k=1}^{n} w_k(x) L^{-1}\left(\exp\left(\hat{A}_{y_k}^s + \hat{B}_{y_k}^s \hat{K}_{2019}^s\right)\right)\right)$$

with respectively L and L^{-1} the logistic and inverse logistic functions

$$L(x) = \frac{1}{1+e^{-x}} \quad , \quad L^{-1}(x) = \ln\left(\frac{x}{1-x}\right).$$

The parameters $\{\alpha_x^s\}, x \in \tilde{X}$, are determined by linear extrapolation of $\hat{\alpha}_{90}^s$ to $\hat{\alpha}_{120}^s = 0$, so

$$\hat{\alpha}_x^s = \hat{\alpha}_{90}^s \cdot \frac{120-x}{120-90}, x \in \tilde{X}.$$

Finally, we determine $\{\hat{\beta}_x^s\}, x \in \tilde{X}$, in such a way that the Dutch pre-covid mortality intensity in 2019 matches with the values that would follow from closure of the parameter values using Kannisto's methodology. In other words, we solve $\hat{\beta}_x^s$from the equation:

$$\exp\left(\hat{A}_x^s + \hat{B}_x^s \hat{K}_{2019}^s + \hat{\alpha}_x^s + \hat{\beta}_x^s \hat{\kappa}_{2019}^s\right) = L\left(\sum_{k=1}^{n} w_k(x) L^{-1}\left(\exp\left(\hat{A}_{y_k}^s + \hat{B}_{y_k}^s \hat{K}_{2019}^s + \hat{\alpha}_{y_k}^s + \hat{\beta}_{y_k}^s \hat{\kappa}_{2019}^s\right)\right)\right).$$

A.3.4 The time series model

When all parameters of the mortality model have been estimated, the time series model is calibrated. For the European time effects, a random walk with drift is assumed, and for the Dutch deviation, an AR(1) process with the following constant term:

$$\begin{aligned} K_t^s &= K_{t-1}^s + \theta^s + \varepsilon_t^s \\ \kappa_t^s &= c^s + a^s \kappa_{t-1}^s + \eta_t^s \end{aligned} \qquad \text{Equation (2)}$$

where we assume that $(\varepsilon_t^M, \varepsilon_t^F, \eta_t^M, \eta_t^F)$ is multivariate normally distributed with a mean vector equal to $\mathbf{0}_4$ and covariance matrix C. This can be rewritten to:

$$Y_{t+1} = X_t \Psi + Z_t,$$

with

$$\begin{cases} Y_{t+1} = \begin{bmatrix} K_{t+1}^M - K_t^M \\ K_{t+1}^F - K_t^F \end{bmatrix}, \quad X_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad \text{and} \quad Z_t = \begin{bmatrix} \varepsilon_t^M \\ \varepsilon_t^F \end{bmatrix} & \text{for} \quad t = t_1^{EU}, \ldots t_1^{NL} - 1 \\ Y_{t+1} = \begin{bmatrix} K_{t+1}^M - K_t^M \\ K_{t+1}^F - K_t^F \\ \kappa_{t+1}^M \\ \kappa_{t+1}^F \end{bmatrix}, \quad X_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \kappa_t^M & 0 & 1 & 0 \\ 0 & 0 & 0 & \kappa_t^F & 0 & 1 \end{bmatrix}, \quad \text{and} \quad Z_t = \begin{bmatrix} \varepsilon_t^M \\ \varepsilon_t^F \\ \eta_t^M \\ \eta_t^F \end{bmatrix} & \text{for} \quad t = t_1^{NL}, \ldots t_T^{NL} - 1, \end{cases}$$

and $\Psi = (\theta^M, \theta^F, a^M, a^F, c^M, c^F)$.

6 – Kannisto (1992)

The parameters of this time series model are estimated through optimising the corresponding log likelihood:

$$\log \mathcal{L} = \sum_{t=t_1^{EU}}^{t_1^{NL}-1} \left\{ -\frac{1}{2}(Y_{t+1} - X_t\Psi)^T \tilde{C}^{-1}(Y_{t+1} - X_t\Psi) \right\} - \frac{t_1^{NL} - t_1^{EU}}{2} \ln\left(|\tilde{C}|\right) - \frac{t_1^{NL} - t_1^{EU}}{2} 2\ln(2\pi)$$
$$+ \sum_{t=t_1^{NL}}^{t_T^{NL}-1} \left\{ -\frac{1}{2}(Y_{t+1} - X_t\Psi)^T C^{-1}(Y_{t+1} - X_t\Psi) \right\} - \frac{t_T^{NL} - t_1^{NL}}{2} \ln(|C|) - \frac{t_T^{NL} - t_1^{NL}}{2} 2\ln(2\pi).$$

In the above equation $\tilde{C}$ is the 2 x 2 submatrix consisting of the first two columns and rows of C.

A.3.5 Most likely projection of mortality probabilities

After the age parameters have been extrapolated to the high ages and the time series model has been estimated, the mortality intensity can be projected for all ages. We obtain the most likely projections of the period effects by putting the error terms in Equation (2) to 0. When we combine these most-likely projections of the period effects with the extrapolated age effects in Equation (1), then we get the most-likely projections of the mortality intensity $\hat{\mu}_{xt}^{s,\text{pre-cov}}$. Subsequently, we obtain the most likely projections of mortality probabilities through the transformation $\hat{q}_{xt}^{s,\text{pre-cov}} = 1 - \exp\left(-\hat{\mu}_{xt}^{s,\text{pre-cov}}\right)$.

A.3.6 Adjustment of starting point projection

As mentioned above, the starting point of the projection based on the model fit does not align closely with the recent observations for all ages. To improve alignment between the projection and recent observations, we determine the starting point of the projection by averaging recent observations. We average mortality observations at the level of the log of the mortality intensity, i.e. at $\ln \mu_{xt}^s$. There are no observed mortality intensities, so we use the observed mortality frequency, $m_{xt}^s = d_{xt}^{NLD,s} / E_{xt}^{NLD,s}$ as an estimator for the mortality intensities.

If $t_{\max}$ is the last observed year and the last d years are used for averaging, then for ages 0 to 90 we estimate the average log mortality intensity as

$$\overline{\ln \mu_{x,t_{\text{ref}}}^s} = \overline{\ln m_{x,t_{\text{ref}}}^s} = \frac{1}{d} \times \sum_{t=t_{\max}-d+1}^{t_{\max}} \ln m_{xt}^s, \qquad \text{for} \quad x \in \{0,1\}$$
$$\overline{\ln \mu_{x,t_{\text{ref}}}^s} = \frac{1}{3} \times \frac{1}{d} \times \sum_{u=x-1}^{x+1} \sum_{t=t_{\max}-d+1}^{t_{\max}} \ln m_{ut}^s, \qquad \text{for} \quad x \in \{2,3,\ldots,90\}$$

where t_{ref} is the reference year for which $\overline{\ln \mu_{x,t_{\text{ref}}}^s}$ is considered to be representative; this is equal to the midpoint of the calendar years that are used. For ages 0 and 1, we do not average over the ages because of the different levels of mortality at age 0. For ages 2 to 90, we average over the surrounding ages to increase the robustness of the projection. We obtain the average mortality intensity by taking the exponent:

$$\breve{\mu}_{x,t_{\text{ref}}}^{s,\text{pre-cov}} = \exp\left(\overline{\ln \mu_{x,t_{\text{ref}}}^s}\right) \qquad \text{for} \quad x \in \{0,\ldots,90\}.$$

The CSO has chosen for the value $d = 5$, as this value strikes the right balance between using enough years for robustness, but not so many years which would make the starting point too far away from $t_{\max}$. Combined with $t_{\max} = 2019$, this value of d leads to $t_{\text{ref}} = 2017$.

For ages above 90, we apply the Kannisto methodology for closure of parameter values on the mortality intensity as defined for the reference year. In other words, the mortality intensity is determined for ages $x \in \{91, \ldots, 120\}$ by log-linear extrapolation of $\breve{\mu}^{s}_{x,t_{\text{ref}}}$, based on trend that is observed for the ages $x \in \{80, \ldots, 90\}$.

A.3.7 Projection from an alternative starting point

The starting point for all projections is the mortality improvements as they follow from the pre-covid projection from the existing model as described in section A.3.5. We define the mortality improvements through the connection:

$$\mu_{x,t} = \mu_{x,t-1} \cdot \exp\left(-r_{x,t}\right), \qquad \text{Equation (3)}$$

or

$$\begin{aligned} r_{x,t} &= -\ln\left(\frac{\mu_{x,t}}{\mu_{x,t-1}}\right) = \ln\left(\mu_{x,t-1}\right) - \ln\left(\mu_{x,t}\right) \\ &= B_x(K_{t-1} - K_t) + \beta_x(\kappa_{t-1} - \kappa_t). \end{aligned} \qquad \text{Equation (4)}$$

The result from Equation (4) shows why, from a modelling point of view, it is natural to determine mortality improvements at the level of mortality intensities. In practice, we use the result from Equation (3)[7], and with this we obtain mortality improvements $\hat{r}^{s}_{x,t}$ for all ages $x = 0, \ldots, 120$, and for all years $t = t_{\text{max}} - d + 1, \ldots, t_{\text{max}}, \ldots, t_{\text{max}} + h)$ (i.e. derived from the previously defined $\hat{\mu}^{s}_{xt}$). We therefore also use the model results to determine the fitted mortality improvements for some historical years.

The basic principle for constructing the various projections is that we apply the mortality improvements as they result from the model. When $t_{\text{ref}} = 2017$, we first apply two mortality improvements that are fitted on the data, and from 2019 onwards we apply projected mortality improvements.

Therefore, the projection based on an adjusted starting point is defined as:

$$\breve{\mu}^{s,\text{pre-cov}}_{x,t_{\text{ref}}+h} = \breve{\mu}^{s,\text{pre-cov}}_{x,t_{\text{ref}}} \cdot \exp\left(-\sum_{j=1}^{h} \hat{r}^{s}_{x,t_{\text{ref}}+j}\right)$$

We determine the corresponding mortality probabilities with the known connection $\breve{q}^{s,\text{pre-cov}}_{x,t} = 1 - \exp\left(-\breve{\mu}^{s,\text{pre-c}}_{x,t}\right)$.

A.3.8 Convergence between projections

The previous sections have now provided two mortality projections:

- $\hat{q}^{s,\text{pre-cov}}_{x,t}$: the projection following the Li-Lee model.
- $\breve{q}^{s,\text{pre-cov}}_{x,t}$: the projection based on the adjusted starting point in combination with the mortality improvements from the Li-Lee model.

7 – An alternative is to determine the mortality improvements at the level of the mortality probabilities. We expect that there will be no material difference between the two approaches.

The final pre-covid mortality projection that is used for AG2026 is presented as $q_{x,t}^{s,\mathrm{pr}}$, and we determine this by starting from the adjusted projection $\breve{q}_{x,t}^{s,\mathrm{pre-c}}$, and linearly converging to the projection in accordance with the Li-Lee model, $\hat{q}_{x,t}^{s,\mathrm{pre-cov}}$. The pre-covid projection starts after the year 2019 and convergence takes place in c year:

$$q_{x,2019+h}^{s,\mathrm{pre-cov}} = \left(1 - \frac{\min(h,c)}{c}\right) \cdot \breve{q}_{x,2019+}^{s,\mathrm{pre-cov}} + \frac{\min(h,c)}{c} \cdot \hat{q}_{x,2019+}^{s,\mathrm{pre-c}}$$

The CSO has chosen for the value $c = 25$. This value leads to plausible projections for all ages and is also robust for data updates.

A.4 Detailed description of excess mortality modelling

A.4.1 Dataset used for the years 2022-2025

We now present the modelling for the years 2020 to 2025. As indicated in the chapter Data, the data for the years 2020 and 2021 are not used in the calibration of the excess mortality term. This means that no model fit is available for these years. The data for the years 2022 to 2025 have been used in the calibration of the projection, and a model fit is available for these years. This is described in detail below.

We calibrate the term $o_{x,t}^s = \exp\left(\widetilde{\mathfrak{B}}_x^s \mathfrak{K}_t^s\right)$ for the ages $x \in \mathcal{X}^{\mathrm{o}} = \{0, \dots, 90\}$ for $t \in \mathcal{T}^a = \{2022, \dots, 2025\}$. For ages $x \in \tilde{X} = \{91, 92, \dots, 120\}$ and for $t \in \mathcal{T}^a$ we set $o_{x,t}^s$ equal to $o_{90,t}^s$.

For the ages $x \in \mathcal{X}^{\mathrm{o}}$ the parameter values of $o_{x,t}^s$ are determined using the same model on a weekly basis as was used for AG2022 and AG2024. However, the age range has been expanded from ages 55 to 90 to ages 0 to 90 where the age effect $\widetilde{\mathfrak{B}}_x$ is assumed to be constant for the ages $x \in \{0, \dots, 40\}$. For the calibration of the weekly model, mortality observations are used per week, per individual age and per sex over the years 2016 to 2025. These data were obtained through a tailor-made data request to the CBS. The number of deaths in week w of year t with age $x \in \mathcal{X}^{\mathrm{o}}$ of sex $s \in \mathcal{S}$ is indicated by $d_{x,w,t}^s$.

The weekly data from 2016 to 2019 are used to estimate the seasonal effect. The data from 2022 to 2025 are then used to calibrate the weekly model for those years. This also requires the exposures from 2022 to 2025 on a weekly basis. These exposures are determined by applying linear interpolation on the population sizes $P_{m,t}^s$ for the population of sex s at the beginning of month m of year t.[8] Using this, we determine for $t \in \mathcal{T}^a$ and for $w \in \mathcal{W}_t = \{w_1, \dots, w_t\}$ (the set of weeks in year t):[9]

$$E_{x,w,t}^s = \frac{N_{w,t}}{365\frac{1}{4}} \cdot \frac{\sum_{d \in \mathcal{D}_{w,t}} \tilde{P}_{x,d,t}^s}{N_{w,t}}$$

with $\mathcal{D}_{w,t}$ the collection of days of week w in year t, $N_{w,t}$ the number of elements in the collection $\mathcal{D}_{w,t}$, or in other words the number of days in week w of year t and $\tilde{P}_{x,d,t}^s$ the estimated population size of sex s, age x on day d of year t, which is obtained by linearly interpolating between the month data $P_{m,t}^s$ on the basis of the counted number of days per week and month.

8 – See https://opendata.cbs.nl/#/CBS/nl/dataset/85721NED/table?ts=1716895484058

9 – W_{2022} = {0,...,52}, W_{2023} = {0,...,52}, W_{2024} = {1,...,53} and W_{2025} = {1,...,53}.

A.4.2 Methodology for weekly model calibration

To calibrate $o_{x,t}^{s}$, for ages $x \in X^{o} = \{0, \dots, 90\}$ for both sexes $s \in \mathcal{S}$, the following steps are taken separately for years $t \in \mathcal{T}^{a} = \{2022, \dots, 2025\}$.

We adjust for the seasonal effects, which indicates the use of a non-uniform distribution of mortality over the weeks of the year. We use the mortality rates of both sexes to estimate a (sex-independent) weekly effect $\varphi_{w,t}$ that reflects how mortality is distributed over the weeks $w \in \mathcal{W}_t$ for $t \in \mathcal{T}^{a}$ during the year t. In order to achieve this, we determine the historically observed total mortality for the weeks[10] $w \in \{1, \cdots, 52\}$ over the years $t \in \{2016, \cdots, 2019\}$, where we aggregate over the ages $x \in \{55, \dots, 90\}$[11] and both sexes:

$$d_{w}^{tot} = \sum_{t=201}^{2019} \sum_{s \in \mathcal{S}} \sum_{x=55}^{90} d_{x,w,t}^{s}.$$

We estimate a cyclic cubic spline Φ, which minimizes

$$\lambda \sum_{w=1}^{53} \left(\frac{d_{w}^{tot}}{\sum_{w} d_{w}^{tot}} - \Phi(w) \right)^{2} + (1 - \lambda) \int_{1}^{53} \left(\Phi''(w) \right)^{2} dw$$

with $d_{53}^{tot} = d_{1}^{tot}$, under the condition that $\Phi''(w)$ is piecewise linear and continuous and the function values and first and second derivatives in $w = 1$ and $w = 53$ match, using the Matlab routine spcsp. On the basis of visual inspection, the parameter $\lambda = 0.03$ is chosen. This parameter governs the trade-off between 'fit' and 'smoothness'. For broken weeks $w = 0$ and $w = 53$ we assume that $\Phi(0) = \Phi(53) = \frac{\Phi(52) + \Phi(1)}{2}$. We then determine

$$\varphi_{w,t} = \frac{\Phi(w)}{\sum_{u \in \mathcal{W}_t} \Phi(u) \cdot N_{u,t} \,/\, \sum_{u \in \mathcal{W}_t} N_{u,t}} = \frac{\Phi(w) \cdot \sum_{u \in \mathcal{W}_t} N_{u,t}}{\sum_{u \in \mathcal{W}_t} \Phi(u) \cdot N_{u,t}},$$

in such a way that the number of days-weighted average seasonal effect is equal to 1.

The maximum likelihood method is then applied to the Dutch weekly data to estimate $\mathfrak{B}_{x}^{s}$ for $x \in X^{0}$ and $\mathfrak{K}_{w,t}^{s}$ for $w \in \mathcal{W}_t$ and $t \in \mathcal{T}^{a}$ using

$$\max_{\{\mathfrak{B}_{x}^{s}, \mathfrak{K}_{w,t}^{s}\}} \prod_{x \in X^{o}} \prod_{t \in \mathcal{T}^{a}} \prod_{w \in \mathcal{W}_t} \frac{\left(E_{x,w,t}^{s} \mu_{x,w,t}^{s} \right)^{d_{x,w,t}^{s}} \exp\left(-E_{x,w,t}^{s} \mu_{x,w,t}^{s} \right)}{d_{x,w,t}^{s}!},$$

with $\mu_{x,w,t}^{s} = \mu_{x,t}^{s,\text{pre-covid}} \cdot \varphi_{w,t} \cdot \exp\left(\mathfrak{B}_{x}^{s} \mathfrak{K}_{w,t}^{s} \right)$, with the restriction $\mathfrak{B}_{x}^{s} := \mathfrak{B}_{0/40}^{s}$ for $x \in \{0, \dots, 40\}$ and with normalization $\sum_{x=0}^{90} \mathfrak{B}_{x}^{s} = 1$.
Note that the weekly data for ages $x \in \{0, \dots, 40\}$ are therefore fully used to estimate the parameter $\mathfrak{B}_{0/40}^{s}$.

10 – There are broken weeks in the dataset for $w = 0$ and $w = 53$. However, we do not include them in the estimation of the seasonal effect. Week 1 and week 52 can also be broken; We don't take this into account when determining the values of D_{w}^{tot}, but the spline that we use will slightly correct for this.

11 – We use the same ages as those used in AG2022 and AG2024 to determine the seasonal effect; In fact, we use the same seasonal effect. Sensitivity analyses on the use of the seasonal effect show limited impact on the excess mortality parameters as long as ages 55-90 are used to calibrate the seasonal effect and the seasonal effect is applied to those ages.

The next step is to determine the aggregated time effects for all weeks of the year $\mathfrak{X}_t^s$ for $t \in \mathcal{T}^a$ and the associated $\widetilde{\mathfrak{B}}_x^s$ for $x \in X^o$.

We first determine $\widetilde{\mathfrak{X}}_t^s$ by determining for every year $t \in \mathcal{T}^a$ that the annual survival rate should be equal to the product of the weekly survival rates for that year:

$$\exp\left(-\mu_{x,t}^{s,\text{pre-covid}} \cdot \exp\left(\widetilde{\mathfrak{B}}_x^s \widetilde{\mathfrak{X}}_t^s\right)\right) = \prod_{w \in \mathcal{W}_t} \exp\left(-\frac{N_{w,t}}{\sum_{u \in \mathcal{W}_t} N_{u,t}} \hat{\mu}_{x,t}^{s,\text{pre-covid}} \cdot \varphi_{w,t} \cdot \exp\left(\mathfrak{B}_x^s \mathfrak{K}_{w,t}^s\right)\right).$$

By taking a logarithm on both sides, dividing by $-\hat{\mu}_{x,t}^{s,\text{pre-covid}}$, taking the logarithm again and summing over the ages $x \in X^o$, using the normalization $\sum_{x=0}^{90} \widetilde{\mathfrak{B}}_x^s = 1$, we find

$$\widetilde{\mathfrak{X}}_t^s = \sum_{x=0}^{90} \ln\left(\sum_{w \in \mathcal{W}_t} \varphi_{w,t} \cdot \frac{N_{w,t}}{\sum_{u \in \mathcal{W}_t} N_{u,t}} \cdot \exp\left(\mathfrak{B}_x^s \mathfrak{K}_{w,t}^s\right)\right).$$

We then determine $\widetilde{\mathfrak{B}}_x^s$ by making survival over the entire years 2022 to 2025 equal to the survival over all weeks within the years 2022 to 2025:

$$\prod_{t=2022}^{2025} \exp\left(-\hat{\mu}_{x,t}^{s,\text{pre-covid}} \cdot \exp\left(\widetilde{\mathfrak{B}}_x^s \widetilde{\mathfrak{X}}_t^s\right)\right) = \prod_{t=2022}^{2025} \prod_{w \in \mathcal{W}_t} \exp\left(-\frac{N_{w,t}}{\sum_{u \in \mathcal{W}_t} N_{u,t}} \hat{\mu}_{x,t}^{s,\text{pre-covi}} \cdot \varphi_{w,t} \cdot \exp\left(\mathfrak{B}_x^s \mathfrak{K}_{w,t}^s\right)\right).$$

Rewriting gives

$$\sum_{t=2022}^{2025} \hat{\mu}_{x,t}^{s,\text{pre-covid}} \sum_{w \in \mathcal{W}_t} \frac{N_{w,t}}{\sum_{u \in \mathcal{W}_t} N_{u,t}} \left(\exp\left(\widetilde{\mathfrak{B}}_x^s \widetilde{\mathfrak{X}}_t^s\right) - \varphi_{w,t} \cdot \exp\left(\mathfrak{B}_x^s \mathfrak{K}_{w,t}^s\right)\right) = 0.$$

This non-linear equation in $\widetilde{\mathfrak{B}}_x^s$ can be solved numerically separately for each age $x \in X^o$. Assume this gives $\widetilde{\widetilde{\mathfrak{B}}}_x^s$ as solutions. Then lastly, we determine $\widetilde{\mathfrak{B}}_x^s$ (in such a way that $\sum_{x=0}^{90} \widetilde{\mathfrak{B}}_x^s = 1$) and $\mathfrak{X}_t^s$ via standardization

$$\widetilde{\mathfrak{B}}_x^s = \widetilde{\widetilde{\mathfrak{B}}}_x^s \Big/ \sum_{x=0}^{90} \widetilde{\widetilde{\mathfrak{B}}}_x^s, \quad \text{en} \quad \mathfrak{X}_t^s = \widetilde{\mathfrak{X}}_t^s \sum_{x=0}^{90} \widetilde{\widetilde{\mathfrak{B}}}_x^s.$$

As a final step, we close the table through extrapolation $\widetilde{\mathfrak{B}}_x^s = \widetilde{\mathfrak{B}}_{90}^s$, $x \in \tilde{X} = \{91,92,\ldots,120\}$. This implies that $o_{x,t}^s = o_{90,t}^s$ for the ages $x \in \tilde{X}$.
Note after the transformation from weekly to annual effects, the age parameters $\mathfrak{B}_x^s$ are no longer exactly the same for $x \in \{0,..,40\}$, but show a very stable course, which would not have been the case without the restriction $\mathfrak{B}_x^s := \mathfrak{B}_{0/40}^s$.

A.5 Further use of the results

The results of the model can be used more broadly than just projecting mortality probabilities. Two applications are described below: the calculation of cohort and period life expectancies, and the construction of stochastic projections for mortality probabilities.

A.5.1 Cohort and period life expectancy

If we want to determine the remaining life expectancy of someone on 1 January of the year t under the assumption that this person was born on 1 January of the year $t - x$ (with $x \in X$ and $t \in T$) and if we assume that someone who dies within a calendar year is still alive for an average of half of that calendar year, then we find for that so-called cohort life expectancy:

$$e_{x,t}^{s,\text{coh}} = \frac{1}{2} + \sum_{k=0}^{\infty} \prod_{j=0}^{k} \left(1 - q_{x+j,t+j}^{s}\right).$$

Note that according to the above formula, we "walk diagonally through the projection table". After all, the probability that the person is still alive at that time $t + k$ is the product of survival probabilities $1 - q_{x+j,t+j}^{s}$ for all the years j between 0 and k where every year the person not only grows a year older, but we also enter a new column in the mortality table. This latter effect is not included in period life expectancy

$$e_{x,t}^{s,\text{per}} = \frac{1}{2} + \sum_{k=0}^{\infty} \prod_{j=0}^{k} \left(1 - q_{x+j,t}^{s}\right),$$

which is based on the assumption that the mortality probabilities will no longer change after this point in time t. This leads to a wrong view on the life expectancy, and although this period life expectancy is often still referred to as "life expectancy", this is incorrect. The (remaining) cohort life expectancy is an expectation of the remaining lifespan of real people, whereas the period life expectancy is a statistic to summarize mortality probabilities over different ages in one number.

A.5.2 Times series simulation

In order to simulate scenarios for the times series $Z_t = (\epsilon_t^M, \epsilon_t^F, \delta_t^M, \delta_t^F)'$, random draws from a normal distribution with mean $(0,0,0,0)'$ and covariance matrix C must be generated. This can be done by multiplying a vector $\tilde{Z}_t$ with four independent standard normally distributed variables with a matrix H which satisfies $H'H = C$, or in other words $H'\tilde{Z}_t$. Therefore, next to the covariance matrix C, also a Cholesky-matrix H is included in the list of parameters in the publication as well as the accompanying spreadsheet.

Appendix B
Model Portfolios

This appendix explains the model portfolio and actuarial principles on the basis of which the percentage effects on the provisions have been determined. The formulas of the actuarial factors are also provided.

Model portfolio provision

A file with males and females has been used to determine the effect on the provision of the model portfolio. These have a (provision-weighted) average age of approximately 55 years.

The model portfolio includes lifelong retirement pension (OP) and lifelong partner's pension (PP).

The table for males represents the rights that arise from male participants (i.e. including the widows of deceased males at the starting date of the partner's pension), and for females it represents the rights that arise from female participants (i.e. including the widowers of deceased females at the starting date of the partner's pension).

	Males		
Age	**OP (65)**	**PP (def.)**	**PP (in paym.)**
30	1,500	1,050	-
40	8,500	5,950	1,000
50	15,000	10,500	2,000
60	15,000	10,500	2,000
70	8,500	5,100	500
80	3,500	1,750	150
90	500	200	-

Table B.1 – *Accrued rights by type of pension for the male model portfolio*

	Females		
Age	**OP (65)**	**PP (def.)**	**PP (in paym.)**
30	2,500	1,750	-
40	7,500	5,250	100
50	12,500	8,750	250
60	10,000	7,000	250
70	7,500	2,250	100
80	5,000	1,000	-
90	1,000	100	-

Table B.2 – *Acquired rights by type of pension for the female model portfolio*

Actuarial Principles

The provisions for this model portfolio are calculated using the following assumptions:

- Survival Tables: Projection Table AG2026 starting year 2027.
- Age corrections and/or experiential mortality: none.
- Actuarial interest rate: 3.0%.
- Retirement age: 65 years.
- For the deferred partner's pension, the following applies:
  - Undetermined partner system until retirement age, with a partner frequency of 100%, after that based on the determined partner system.
  - An age difference between male and female of 3 years (male older than female).
  - The sex of the partner is not the same as the sex of the main insured.
- The single premium rates for the retirement pension and the partner's pension are determined by taking the average of a 'prenumerando' benefit and a 'postnumerando' benefit.

Actuarial factors

The following formulas have been used to determine the actuarial factors.

Definition of parameters

- x the age of the participant
- y the age of the partner

Note: In the indefinite partner system, calculations are made with a partner of the opposite sex.

- r the (fixed) interest rate
- q_x the mortality probability of an *x*-year-old person
- p_x the survival probability of a *x*-year-old person, with $p_x = 1-q_x$
- ${}_tp_x$ the probability that an *x*-year-old person will live for at least another *t* years
- ${}_t\tilde{p}_x$ the probability that a participant will have died after *t* year and there is a partner who is entitled to a partner's pension at that time
- h_x the partner frequency for an *x*-year old participant
- ${}_th_x$ the probability that a *x*-year-old participant will still be married in *t* years
- PL the retirement age (65 years for provisions, 68 years for contributions)
- U_x^{op} the annual old-age pension payment for an *x*-year-old participant
- U_x^{lpp} the annual payment of a deferred partner's pension for an *x*-year-old participant
- U_x^{ipp} the annual payment of an in-payment partner's pension for an *x*-year-old participant
- CS_x^{op} one year of accrual for an old-age pension for an *x*-year-old participant
- CS_x^{lpp} one year of accrual for a deferred partner's pension for an *x*-year-old participant

Generic formulas

- $v = (1+r)^{-1}$ The one-year discount factor
- ${}_tp_x = \prod_{j=0}^{t-1} p_{x+j}$ The *t*-year survival rate for a *x*-year old person

Annuity factors for deferred and commenced retirement pension (OP) and commenced partner's pension (PP) per unit

- Deferred OP:

$$ {}_n|\bar{a}_x = \frac{1}{2}\left(\sum_{t=n+1}^{\infty} {}_tp_x \cdot v^t + \sum_{t=n}^{\infty} {}_tp_x \cdot v^t \right) $$

- In-payment OP:

$$ \bar{a}_x = \frac{1}{2}\left(\sum_{t=1}^{\infty} {}_tp_x \cdot v^t + \sum_{t=0}^{\infty} {}_tp_x \cdot v^t \right) $$

- In-payment PP:

$$ \bar{a}_y = \frac{1}{2}\left(\sum_{t=1}^{\infty} {}_tp_y \cdot v^t + \sum_{t=0}^{\infty} {}_tp_y \cdot v^t \right) $$

Annuity factors for deferred PP per unit

$$ \tilde{a}_{x/y} = \sum_{t=0}^{\infty} v^t \cdot {}_t\tilde{p}_x $$

with

$$ {}_0\tilde{p}_x = 0 $$

$$ {}_t\tilde{p}_x = {}_{t-1}\tilde{p}_x \cdot \left(1 - q_{y+t-1}\right) + {}_{t-1}p_x \cdot q_{x+t-1} \cdot h_{x+t-\frac{1}{2}} \cdot \sqrt{1 - q_{y+t-1}} $$

$$ h_{x+t-\frac{1}{2}} = \begin{cases} 1 & \text{voor } x+t \leq PL \\ {}_{x+t-\frac{1}{2}-PL}p_{y+PL-x} & x+t > PL \end{cases} $$

$$ {}_{\frac{1}{2}}p_{y,t} = \sqrt{1 - q_{y,t}} $$

Discounted provision

- Provision for a *n*-year deferred retirement pension: $U_x^{\text{op}} \cdot {}_n|\bar{a}_x$
- Provision for an immediate in-payment old-age pension: $U_x^{\text{op}} \cdot \bar{a}_x$
- Provision for a deferred partner's pension: $U_x^{\text{lpp}} \cdot \tilde{a}_{x/y}$
- Provision for an in-payment partner's pension: $U_y^{\text{ipp}} \cdot \bar{a}_y$

Formulas for calculations of purchasing factors

- Purchase factor for an immediate payment: $\bar{a}_x$
- Purchase factor for a deferred partner's pension: $\tilde{a}_{x/y}$

Appendix C
Literature and data used

Literature

Niu, G., & Melenberg, B. (2014). Trends in mortality decrease and economic growth. Demography, 51(5), 1755-1773.

Committee for Mortality Research (2024). Projections Life table AG2024. Royal Dutch Actuarial Society.

Kannisto, V. (1994). Development of oldest-old mortality, 1950-1990: Evidence from 28 developed countries (Vol. 1). University Press of Southern Denmark.

Li, N., & Lee, R. D. (2005). Coherent mortality forecasts for a group of populations: An extension of the Lee-Carter method. Demography, 42(3), 575-594.

van Berkum, F., Melenberg, B., & Vellekoop, M. (2025). Estimating the impact of COVID-19 on mortality using granular data. Insurance: Mathematics and Economics, 121, 144-156.

Weekly mortality data from CBS for the years 2020-2025

Data used

HMD databases were used to model mortality up to and including 2019 in all countries[12]. The data from HMD was downloaded on March 17, 2026. Table C.1 indicates which HMD version has been used as input for each geographical area.

Country	HMD version
Belgium	2025.10.21
Denmark	2025.03.26
Finland	2025.06.02
France	2025.07.14
Germany	2022.06.03
Iceland	2025.04.25
Ireland	2025.01.23
Luxembourg	2026.01.15
The Netherlands	2025.09.16
Norway	2025.09.09
Austria	2024.12.12
Sweden	2025.05.29
United Kingdom	2025.02.03
Switzerland	2025.09.26

Table C.1 *– Data sources AG2026 for observation years up to and including 2019.*

The dataset used up to and including 2019, in the form of death counts and exposures for both the Netherlands and the selected European countries, can be found on the AG website.

When modelling the additional model component for COVID-19, we used data compiled following a tailor-made request to the Statistics Netherlands. This concerns data for observed death counts per week and by age in the Netherlands for the years 2016 to 2025. We also used population data per month from CBS[13] to arrive at the exposures for those years.

The data for weekly mortality in the Netherlands in 2016 to 2025 has not been published on the AG website, as this concerns data received from CBS following a tailor-made request to the CBS on behalf of the AG.

12 – http://www.mortality.org/
13 – Population sizes (P-values), downloaded on March 17, 2026:
https://opendata.cbs.nl/#/CBS/nl/dataset/85721NED/table?ts=1716895484058

Appendix D
Committee, Working Group and Advisory Board

Projections Life Table AG2026 was adopted by the Mortality Research Committee, after extensive analyses and preparatory work by the Projections Life Table Working Group. All calculations of the working group have been independently validated to ensure the quality of the results. In addition, the Advisory Board assisted the Mortality Research Committee.

The committee, the working group and the advisory board will consist of the following members by mid-2026.

Mortality Research Committee (CSO)

F. (Frank) van Berkum PhD
drs. A.Th. (Sander) Biesma AAG RC RBA, chairman
C.C.A. (Carlo) Jonk MSc AAG
M.J.A. (Marieke) Klein MSc AAG
J. (Hans) de Mik CFA AAG, vice-chairman
J.I. (Janinke) Tol MSc AAG
R.E.J.M. (Raymond) Waucomont AAG
M.R. (Marco) van der Winden AAG MBA

Working Group Projection Tables

J.M.H.H. (Joyce) Delsing MSc AAG
L.M. (Lisa) Foppen MSc AAG
D. (Dave) 't Hart - MSc AAG
C.J. (Mélanie) de Looze MSc AAG
ir. drs. C.C. (Carry) Mout AAG
B. (Brian) Möllenkamp MSc
Z.X.S. (Zeus) Paraguas MSc
F.C. (Frank) Tesselaar MSc
M.P.G.W. (Max) Thönissen MSc FRM AAG, chairman

Advisory Board

Prof. B. (Bertrand) Melenberg
Prof. M.H. (Michel) Vellekoop

Koninklijk Actuarieel Genootschap

PROJECTIONS LIFE TABLE AG2026

Publication

Royal Dutch Actuarial Association
Groenewoudsedijk 80
3528 BK Utrecht
telephone 31-(0)30-686 61 50
website www.actuarieelgenootschap.nl

Design

Stahl Ontwerp

Print

De Mediagraaf