Koninklijk Actuarieel Genootschap

PROJECTIONS LIFE TABLE AG2024

The uncertainty about when we will die,
softens the certainty that we will die.

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The subtitle 'The uncertainty about when we will die, softens the certainty that we will die' originates from the German-Austrian philosopher Emanuel Wertheimer (1846-1916).

Summary

Every two years, the Royal Dutch Actuarial Association publishes its new Projections Life Table. This Projections Life Table uses historical mortality data from the Netherlands and European countries with a similar level of prosperity. Since 2020, we have been dealing with excess mortality due to direct and indirect consequences of the covid-19 pandemic. For the publication of Projections Life Table AG2022, it was decided to base the long-term trend on European data up to and including 2019. For the short term, the expected mortality was corrected with an excess mortality term that reflected the excess mortality of the pandemic in the Netherlands. This excess mortality term is modelled separately with assumptions about the future course of this excess mortality. A similar approach has been adopted in the model for Projections Life Table AG2024. Both tables assume that excess mortality is not permanent and will eventually fade out. This means that in the short term there is a temporary effect due to covid-related mortality, but that in the longer term life expectancy returns back to the historical trend. This historical trend is based on the data up to and including 2019, so without covid effects.

Since the last publication in September 2022, two years of new mortality data have become available. Observations from this data have shown that there is still excess mortality and that this excess mortality is higher than assumed in AG2022. In the opinion of the Commissie Sterfte Onderzoek (CSO), there is no reason yet to assume that excess mortality is permanent, but the rate at which excess mortality is decreasing has been adjusted downwards. Projections Life Table AG2024 assumes that excess mortality will decrease by 25% every year, whereas in the previous publication it was assumed that excess mortality will halve every year. As in AG2022, it was decided to derive excess mortality from the mortality data in the Netherlands in the two most recent years (now 2022 and 2023). The excess mortality pattern in 2022 and 2023 differs from 2020 and 2021, the first two years of the pandemic. The CSO considers 2022 and 2023 to be the best starting point for the expected development in the coming years, because in the first covid years for example, the effects of the vaccination programs were not yet visible. The model specifications have not been changed.

With regard to the European data, which determine the long-term trend, the CSO has again chosen to use the data up to and including 2019, i.e. the mortality data before covid made its appearance. However, a limited data update for these years will apply, as the sources for mortality data have been updated retroactively.

The above changes mainly have a short-term effect. This is visible in an increase in the one-year mortality rates of females over 55 years of age in the first few projection years. For the long term, the effects are very small. Cohort life expectancy in 2025 will decrease by less than 0.1 years and the effects on pension provisions and contributions will be approximately 0.1% decrease for males and approximately 0.2% decrease for females. The effects increase with age, which means that for a pension fund with mainly retired participants, the effects are slightly larger.

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1. Consequences for mortality probabilities, life expectancy, premiums and provisions

In this chapter, Projections Life Table AG2024 is compared with historical developments, Projections Life Table AG2022 and with the latest projection by Statistics Netherlands (CBS 2023-2070).

In addition, the effect of the new projection table on life expectancy, provisions and contributions of pension funds is shown. A sample fund was used to quantify these effects.

1.1 Effects on one-year mortality probabilities

In Projections Life Table AG2024, excess mortality as a result of the covid pandemic has been projected separately for males and females aged 55 and over, as in Projections Life Table AG2022. Projections Life Table AG2022 expected excess mortality in this age group to decrease by 50% each year, for the first time in 2022. Projections Life Table AG2024 assumes that this excess mortality will decrease by 25% annually, starting in 2024. The basic model on which excess mortality is modelled has not changed. This model is based on mortality data up to and including 2019 in the selected European countries. Since excess mortality decreases annually in both Projections Life Table AG2022 and Projections Life Table AG2024, the mortality probabilities in the longer term (from around 2035) are more or less the same in both tables.

Excess mortality
Excess mortality in this sense refers to the higher mortality as a result (of both the direct and indirect effects) of covid, compared with the expected mortality from the trend model based on pre-covid data as estimated by the AG2020 model.

The figure below shows the differences compared to the basic model (data up to and including 2019) as a result of the temporary add-on, and the difference with the previous projection table. The comparison between the two projection tables therefore shows the effect on the short-term mortality probabilities and is for example insightful for the effects on term life insurance.

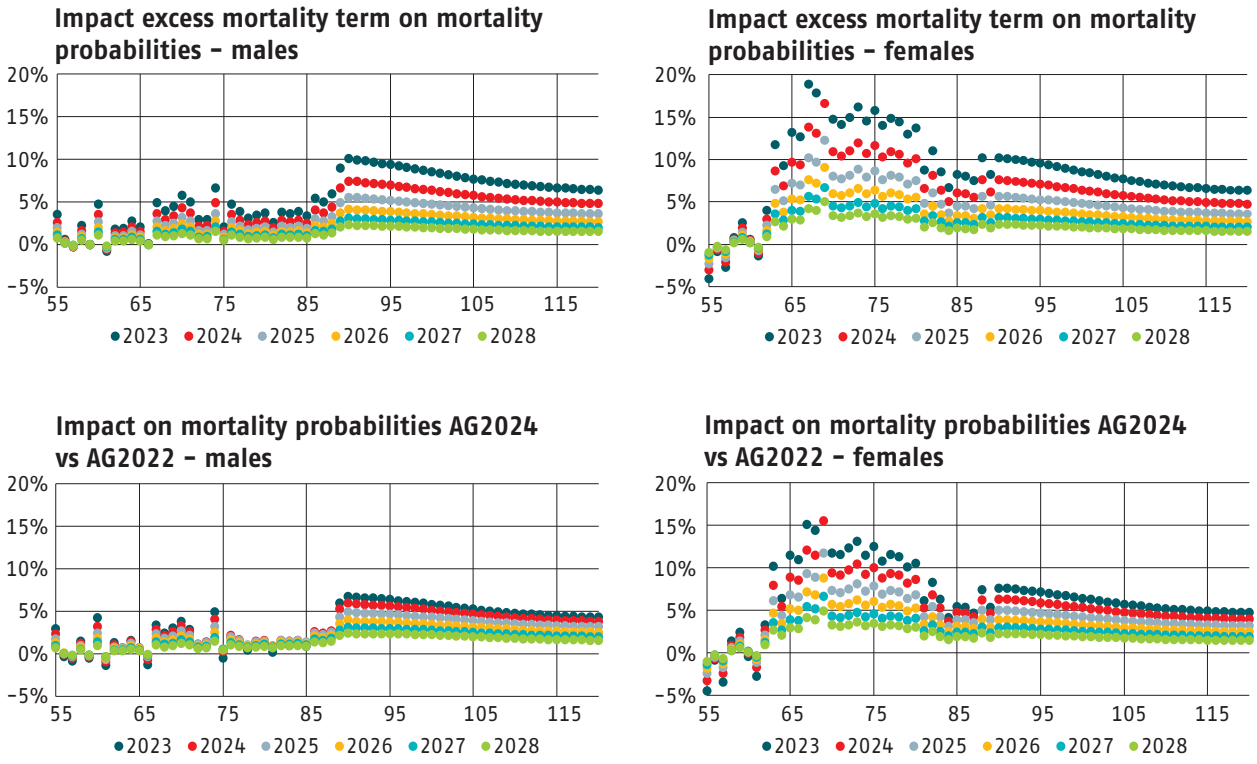

Figure 1.1 – *Differences in mortality rates for males and females with and without excess mortality modelling (top) and AG2024 compared to AG2022 (below)*

Definitions of life expectancy
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.
- **Cohortlevensverwachting**: 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.

1.2 Observations compared to AG2022 and AG2024

Figure 1.2 shows the AG2024 and AG2022 projection for period life expectancies for the years 2019 to 2025 and shows how these relate to the realised life expectancies for the years up to and including 2023. Period life expectancy is always used for this purpose, because it allows comparisons to be made of life expectancy consistent with mortality probabilities in a specific observation year.

The realised life expectancies in 2020 and 2021 are in line with AG2022, because the excess mortality factors for these years are based on data from those years. Because the excess mortality term halves annually in the AG2022 projection, a further increase in life expectancy was expected for 2022 and 2023.

However, the realisation shows that life expectancy increased less rapidly in 2022 and 2023 compared to expectations, as a result of less rapidly fading excess mortality. In retrospect, we have to conclude that the direct and indirect consequences of covid have led to higher mortality than we had previously assumed. Or to put it another way, the effect of excess mortality on life expectancy appears to be fading out slower than we had assumed in the AG2022 projection.

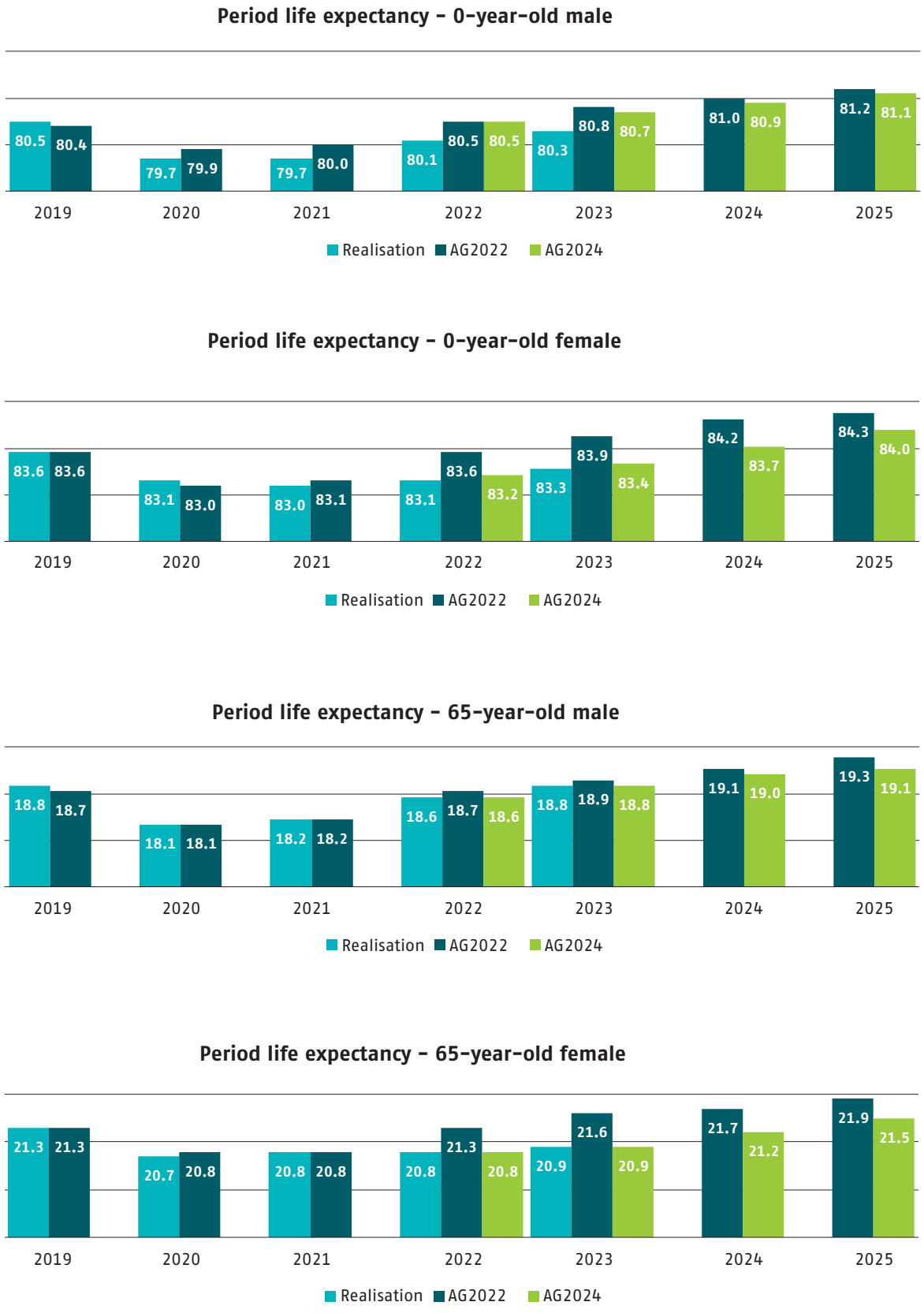

Figure 1.2 – *Period life expectancy at birth and at age 65 years for males and females*

The excess mortality factors in AG2024 are based on the realisations in 2022 and 2023. These excess mortality factors decrease less rapidly in the new projection than in AG2022, which means that life expectancy will return to the historical trend less quickly after 2023. In AG2024 for example, around 25% of the excess mortality factor remains in the fifth projection year, while in AG2022 only 3% remained in the fifth projection year. In both projections, we ultimately assume that excess mortality is not persistent. In AG2024 the excess mortality effect has virtually faded away after 17 years.

Figure 1.3 shows the development of period life expectancy at birth from 1970 to 2050. Up to and including 2023 (for the European selection up to and including 2019), realised mortality figures will be used, for the period thereafter Projections Life Table AG2024. This means that for the European selection, the effect of covid-19 related mortality is not visible in the realisation or in the (pre-covid) projection.

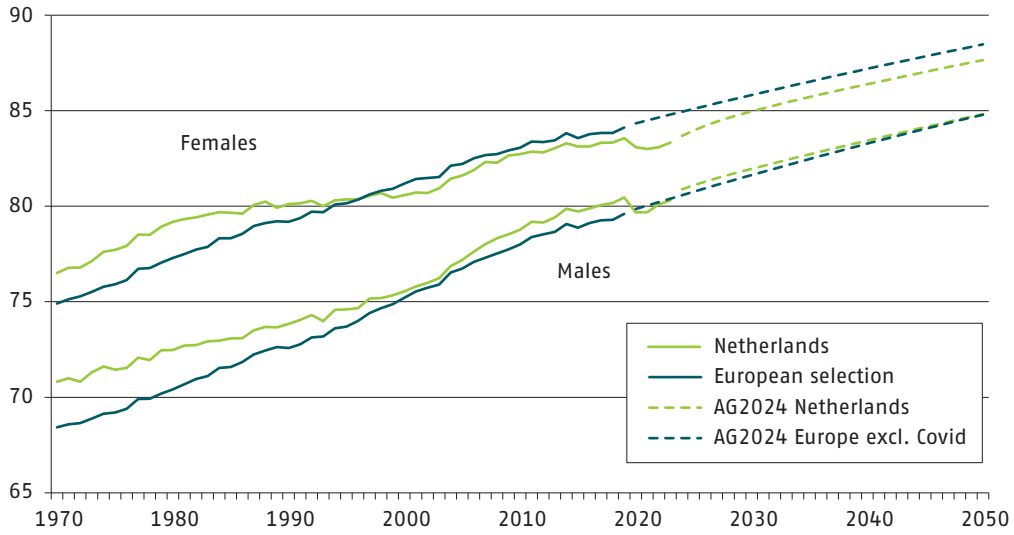

Figure 1.3 – *Period life expectancy in the Netherlands (including excess mortality term) and selected European countries (excluding excess mortality term) at birth*

Figure 1.3 shows the consequences of higher mortality in the years 2020 to 2023 in the development of life expectancy. As in the previous projections, the period life expectancy of Dutch females is below the life expectancy of females in the selected European countries. The life expectancy of Dutch males is, as before, higher than the life expectancy of males in the selected European countries. For males, this difference decreases over time, while for females the difference remains about the same.

The following figure shows the period life expectancy for 65-year-olds.

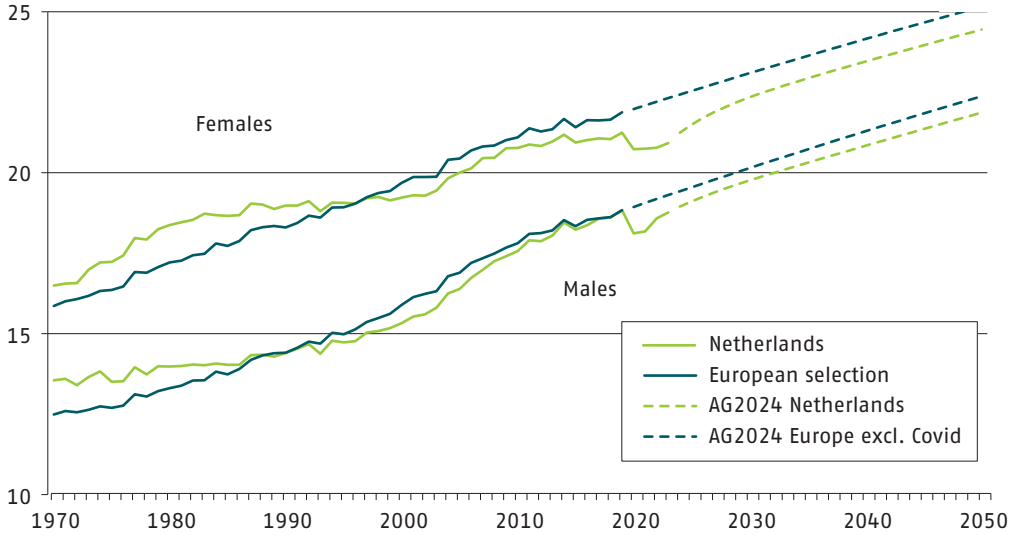

Figure 1.4 – *Period life expectancy in the Netherlands (including excess mortality term) and selected European countries (excluding excess mortality term) for a 65-year-old*

Compared to period life expectancy at birth, we see a larger effect of the higher mortality, because excess mortality mainly occurs at older ages. In the longer term we see that the period life expectancy for a 65-year-old remains below the European trend, even in years where excess mortality is expected to have disappeared.

1.3 Prognosis in perspective

Figure 1.5 compares the developments in period life expectancy at birth for AG2022, AG2024 and CBS2023-2070.

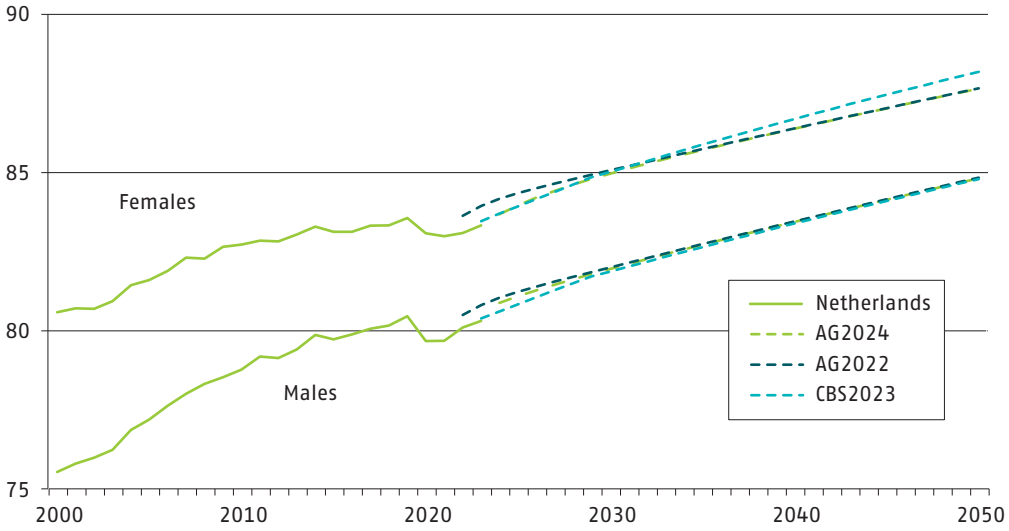

Figure 1.5 – *Development of period life expectancy at birth*

The figure shows that the AG2024 projection has been revised downwards compared to the AG2022 projection in the short term, but that there is hardly any difference between AG2022 and AG2024 in the long term. When comparing with the CBS2023 projection it can be seen that in the short term the AG2024 projection for females is in line with the projection of the CBS, but in the longer term the CBS estimates life expectancy to be higher. For males the life expectancy in Projections Life Table AG2024 is slightly higher than expected by the CBS in the short term, but there is hardly any difference in the longer term.

Table 1.1 shows the cohort life expectancies for AG2022, AG2024 and CBS2023–2070. The differences are limited.

Starting year 2025	At birth		At age 65	
Projection	**Male**	**Female**	**Male**	**Female**
AG2022	90.3	93.0	20.6	23.5
AG2024	90.2	92.9	20.6	23.4
CBS2023	not available	not available	20.7	23.3

Table 1.1 – *Cohort life expectancies for AG2022, AG2024 and CBS2023*

1.4. From AG2022 to AG2024

To show the development from AG2022 to AG2024, we distinguish three changes:

- **Update data Europe**: When Projections Life Table AG2022 was established, not all mortality data from European countries up to and including 2019 was yet available in HMD. For this reason, other sources were used for some countries at that time. In addition, HMD sometimes retroactively adjusts mortality data from previous years.
- **Update data in the Netherlands after 2019**: This update includes adjusting the years on which the excess mortality term is based (2022 and 2023 instead of 2020 and 2021).
- **Adjusting excess mortality**: In the latest adjustment, the term used to reduce excess mortality will be lowered from 50% to 25%. This means that the excess mortality term declines at a slower rate.

Table 1.2 shows the cohort life expectancy by sex for both 0-year-olds and 65-year-olds, with a quantification of the differences between AG2022 and AG2024 for starting year 2025.

Life Expectancy Cohort	At birth		At age 65	
	Male	Female	Male	Female
AG2022	**90.26**	**92.96**	**20.59**	**23.49**
Update data Europe	-0.05	-0.02	-0.02	-0.01
Update data in the Netherlands after 2019	0.00	0.00	0.00	-0.01
Adjusting excess mortality term	0.00	0.00	-0.02	-0.04
AG2024	**90.21**	**92.94**	**20.55**	**23.43**

Table 1.2 – *Effect of adjusting projection table on cohort life expectancy for a 0-year-old and a 65-year-old*

The adjustment of the projection table has marginal impact on longer-term mortality effects in cohort life expectancy. There is a slight decrease in life expectancy, which is visible in the second decimal. In the European data, the adjustments result in slightly higher mortality in the period up to and including 2019 than the data used in Projections Life Table AG2022. This leads to a slight decrease in life expectancy. The adjustment of the Dutch data has hardly any impact. The adjustments to the excess mortality term do not have a visible impact on the cohort life expectancy of a 0-year-old, but they do have a slight impact on that of a 65-year-old. This is because the excess mortality term only applies from age 55 onward and its size decreases over time and converges to zero.

Table 1.3 shows a similar quantification for period life expectancy.

Period life expectancy	At birth		At age 65	
	Male	Female	Male	Female
AG2022	**81.23**	**84.35**	**19.26**	**21.90**
Update data Europa	0.00	-0.01	0.00	-0.01
Update data in the Netherlands after 2019	-0.04	-0.14	-0.04	-0.15
Adjusting excess mortality term	-0.10	-0.24	-0.11	-0.25
AG2024	**81.09**	**83.96**	**19.11**	**21.49**

Table 1.3 – *Effect of adjusting projection table on period life expectancy for a 0-year-old and a 65-year-old*

A larger decrease is visible in period life expectancy. This is mainly because the excess mortality term remains unchanged in that calculation due to the use of mortality probabilities in the same calendar year (2025). Adjustment of the excess mortality term has the strongest effect on females.

1.5 Effects on provisions and premiums

In order to show the effects of the transition to Projections Life Table AG2024 the new projection table has been used to recalculate both the provision and the pension contributions. A model portfolio was used for this purpose.

In addition to an old-age pension (OP) starting at the age of 65, the example fund contains a deferred partner's pension and an in-payment partner's pension (PP). For the pension contribution, the standard retirement age of 68 years is used. Appendix B further explains the description of the model portfolio and the other assumptions used.

Effect	Males	Females
VPV[1] OP (65)	-0.1%	-0.2%
VPV DeferredPP	0.1%	0.1%
VPV In payment PP[2]	-0.1%	-0.1%
VPV Total	-0.1%	-0.2%
Premium	0.0%	-0.1%

Table 1.4 – *Impact on provisions and premium for sample funds of transition from AG2022 to AG2024 at the end of 2024 (difference AG2024 minus AG2022 expressed as a percentage from the value determined on the basis of AG2022). The individual percentages, as stated in the pension types OP and PP, do not add up to the percentages as stated in the total. This is because the size of the provisions of the individual types of pension is different.*

Table 1.4 shows that the transition to the new projection table only has a limited effect on the provision of lifelong pensions and the pension contributions to be paid. The adjustment is limited because the adjustment in cohort life expectancy is also limited.

Table 1.5 shows the effect on the provision for individual types of pension for different ages. In line with the impact on the provision of the sample fund, the impact of the new table is limited. As age increases, so does the effect on provision. This is because the adjustments mainly affect the short horizon in which the excess mortality term plays a role. At older ages, the remaining life expectancy is shorter and the effect on technical provision is therefore larger. Funds with higher average ages will therefore feel proportionally more of the adjustment than funds with lower average ages.

1 – Voorziening Pensioen Verplichtingen

2 – The effect on the VPV in the case of the partner's pension that has commenced relates to the sex mentioned above the column.

Effect VPV	Males		Females		Males	Females
	OP	Deferred PP	OP	Deferred PP	In payment PP	In payment PP
25	-0.1%	0.1%	0.0%	-0.3%	0.0%	0.0%
45	-0.1%	0.1%	0.0%	-0.2%	0.0%	0.0%
65	-0.1%	0.1%	-0.2%	1.1%	-0.1%	-0.2%
85	-0.9%	-0.2%	-1.0%	-0.9%	-0.9%	-1.0%

Table 1.5 – *Impact on provisions by age and sex of transition from AG2022 to AG2024 (difference AG2024 minus AG2022 expressed as a percentage of AG2022)*

The only exception where the provision increases instead of decreases is the deffered partner's pension for 65-year-old females. In the case of a deferred partner's pension, there are two opposing effects:

- The partner's pension for the surviving spouse will start earlier due to the increased mortality;
- The male receives the benefit for a shorter period of time, because the male is also expected to live shorter.

The decline in life expectancy is larger for females than for males. As a result, the male's benefit starts earlier. The benefit will also end earlier but because the decrease is smaller for males than for females, the duration of the benefit is longer than based on AG2022. This results in a limited increase in the deferred partner's pension for 65-year-old female insureds.

2

The projection model

This chapter explains which analyses have been carried out and which choices have been made to arrive at the Projections Life Table AG2024.

The model equations, which are needed to estimate the model parameters and to make projections, are provided in Appendix A.

2.1 Projections Life Table AG2022 expectations and realisation

With the Projections Life Table AG2022, the model specifications have been adjusted in response to the covid pandemic. In the years 2020 and onwards, there has been significant excess mortality. That is why it was decided not to use the data from 2020 onwards to estimate the long-term trend.

For the projection from 2022 onwards, a new term has been added to the projection according to Projections Life Table AG2020: the projection of excess mortality modelled from 2020 onwards. At that time, only two years of data was available. It was also not yet clear how the pandemic and its effects on Dutch mortality would exactly unfold. A scenario was chosen for AG2022 in which this term had a half-life of one year. Or to put it differently, it is assumed that Dutch excess mortality halves every year compared to the previous year. Under this expectation, excess mortality had more or less faded away after seven years (less than 1% of the starting level).

In the realised mortality probabilities after the release of the Projections Life Table AG2022, as explained in Figure 1.2, it can be seen that in 2022 and 2023 the decrease in excess mortality was less than expected according to AG2022. This information has been included in the model selection for AG2024.

2.2 Data for years since covid-19

Since the outbreak of the covid pandemic in 2020, there have been more deaths compared to the years before the pandemic. This is not only explained by the aging population, but also by higher observed mortality frequencies.

Figure 2.1 shows the number of deaths for Dutch people between 55 and 90 years old for the years 2018 to 2023, including the expectation based on the AG2024 model without excess mortality term. This concerns a model fit for the years 2018 and 2019 and a projection for the years 2020 to 2023. In addition, Table 2.1 presents the relative difference between the actual number of deaths (realisation) and this expectation.

The figure and table show that in the years 2018 and 2019 the difference between realisation and expectation is small, whilst for the years 2020 and onward larger differences can be observed. This indicates that the excess mortality term is not needed for the years before 2020, but it is necessary for the years after, in connection with the covid pandemic. The figure and table also show that observed mortality for males decreased slightly in the years 2022 and 2023 compared to 2020 and 2021, which can be seen from the dark blue bar graphs in the figure. The difference between expectation

and realisation has also decreased, which can be seen from the values in the table. For females however, a small increase in total mortality and excess mortality can be observed compared to 2020 and 2021.

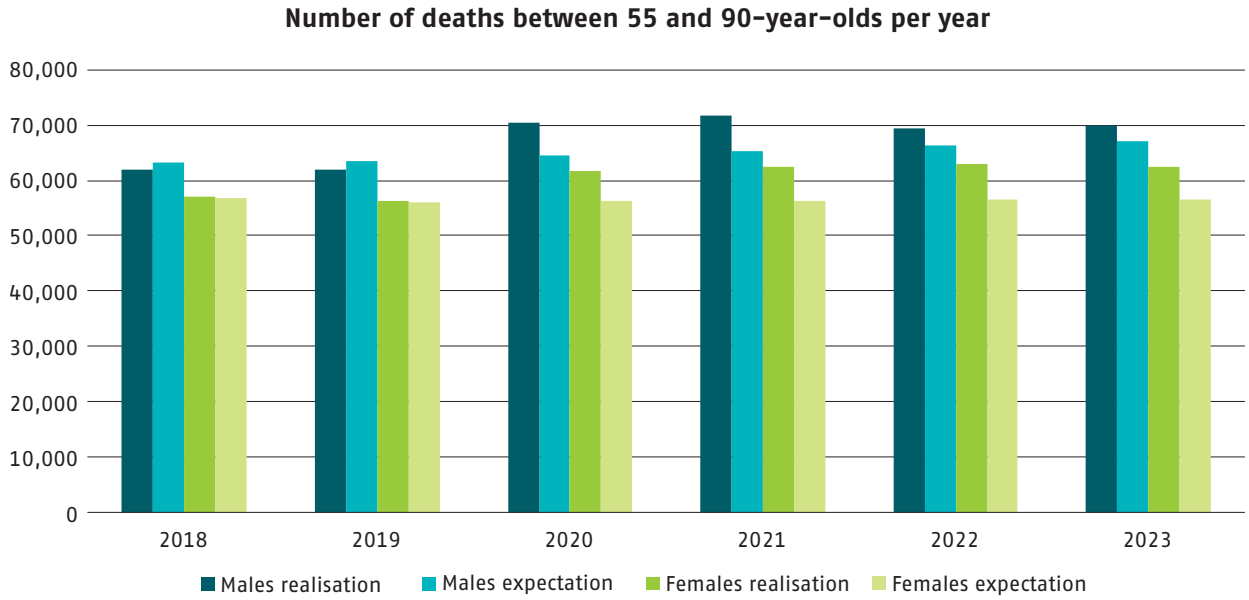

Figure 2.1 – *Number of deaths per year in the Netherlands over the years 2018-2023 for males and females aged between 55 and 90 years, including expectation based on AG2024 model excluding excess mortality term*[3]

Realisation versus Expectation		
Year	**Males**	**Females**
2018	-2%	1%
2019	-2%	1%
2020	9%	10%
2021	10%	11%
2022	5%	11%
2023	4%	11%

Table 2.1 – *Percentage deviation in realisation versus expectation of number of deaths per year, in accordance with Figure 2.1*

Figure 2.2 shows the realised mortality in the Netherlands for the years 2022 and 2023 compared to the expected mortality based on AG2024 excluding excess mortality term.

3 – Source: HMD mortality data for the years 2018-2019, weekly mortality data from Statistics Netherlands for the years 2020-2023

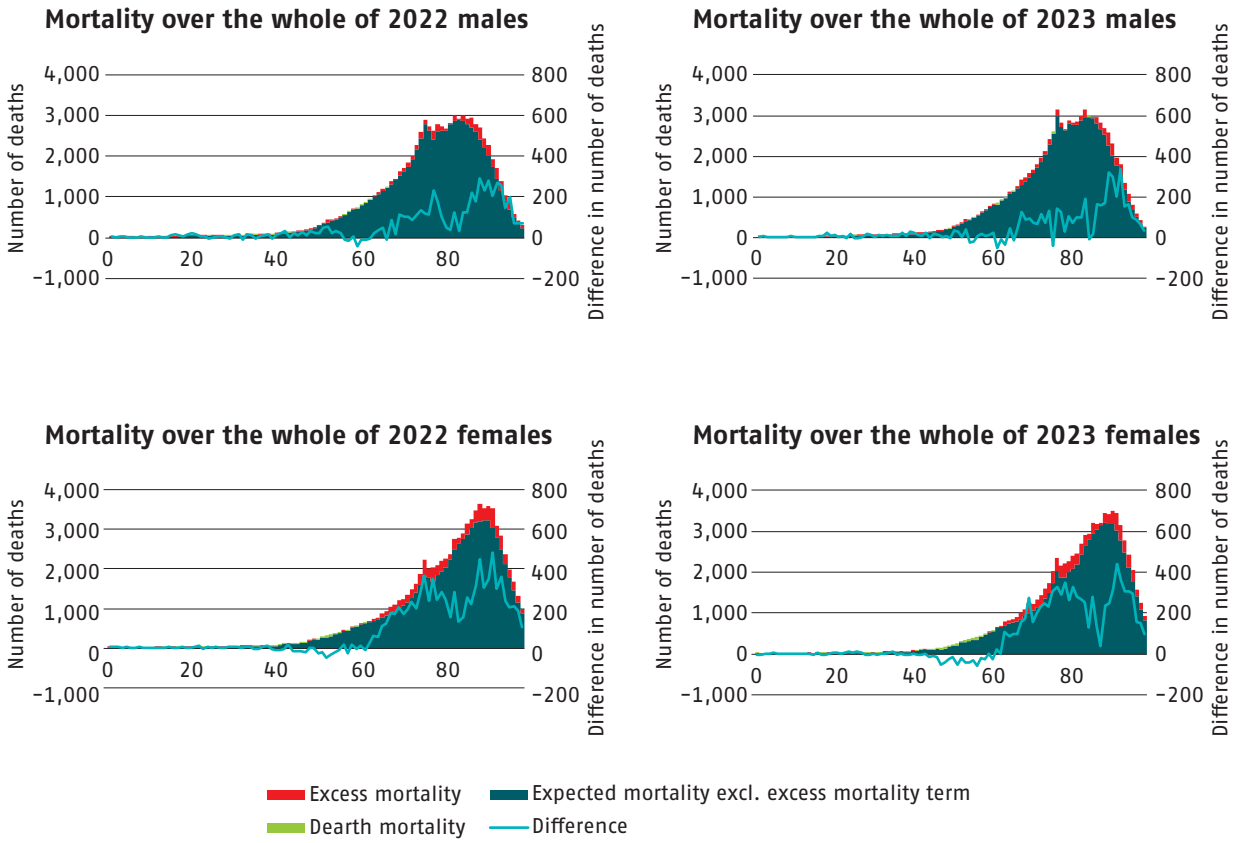

Figure 2.2 – *Number of deaths in 2022 and 2023, broken down by male and female, relative to expected mortality excluding excess mortality term. The differences between realisation and expectation excluding excess mortality are plotted on the right-hand axis.*

This figure can be interpreted as follows. The graph at the top left ("Mortality over the whole of 2022 male") shows that approximately 1,600 deaths were expected for males aged 70 years in 2022 based on the AG2024 projection excluding excess mortality term. This is shown with the green bar (left axis). Approximately 1,700 males aged 70 years old actually died in 2022, which makes the excess mortality therefore approximately 100. This is represented by the red bar (left axis) and turquoise line (right axis) in the graph.

Figure 2.2 shows that for these years the observed mortality for ages starting around 55 years and older was higher than expected (excess mortality). Excess mortality will decrease for males in 2023 compared to 2022, but for females excess mortality will remain at a stable level. For those under 55 years of age, the picture is not conclusive. For this reason and also to remain consistent with AG2022 it was decided not to use an excess mortality term for these ages.

Figure 2.3 zooms in on the mortality per week. This shows the peak moments of mortality as a result of covid-19 in the years 2020 and 2021. The influenza waves of 2017, 2018, 2022 and 2023 also appear in these graphs.

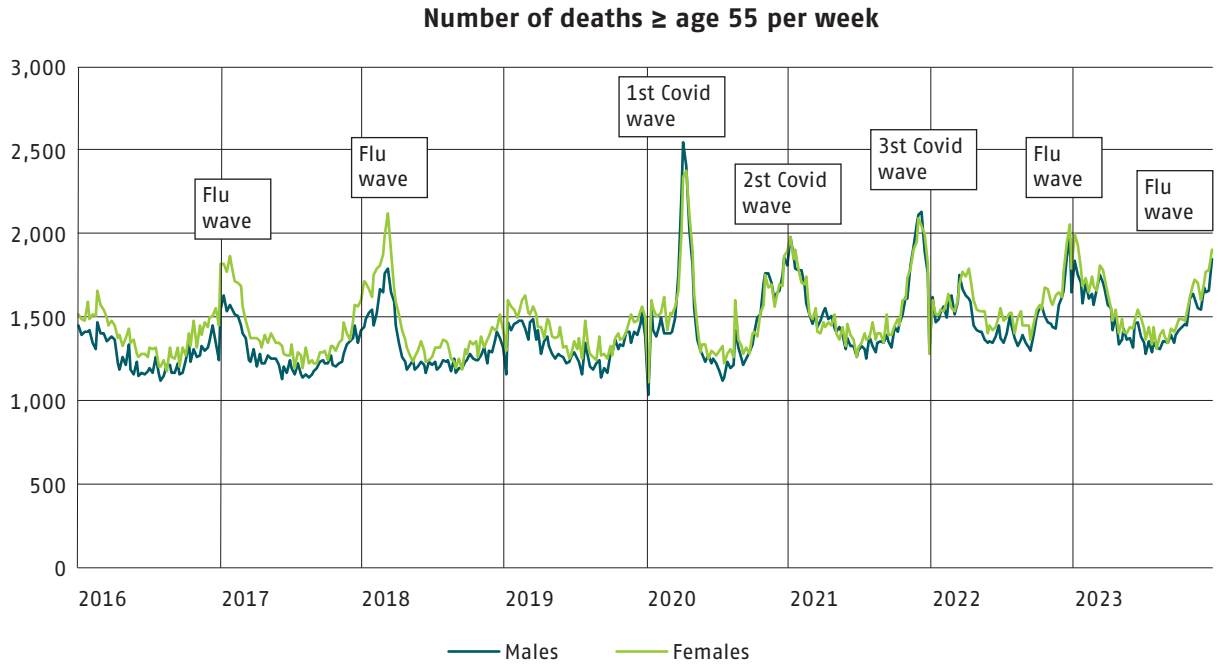

Figure 2.3 – *Number of deaths per week in the Netherlands over the years 2016-2023 for males and females aged 55 years and older, excluding broken weeks at the beginning and end of a year*[4]

Compared to these influenza waves, covid-19-related mortality appears to have led to higher peaks (first wave), which last longer (second wave) and flare up again more quickly (three waves in eighteen months). Due to the combination of these three effects, total covid-19-related mortality has been higher than influenza related mortality in earlier and later years. This also helps to explain why the total observed mortality in the years 2020 and 2021 has been higher than in the surrounding years.

The graph also shows that the influenza waves in 2022 and 2023 have been substantial and are therefore the main explanation for the observed excess mortality compared to the pre-covid projection. These influenza epidemics may have been more severe than in some other years due to the covid measures in 2020 and 2021, which prevented a large-scale spread of flu in those years. For more documentation on the flu waves in recent years, see the figures from the RIVM[5].

2.3 Examples of research performed for AG2024

For AG2024, multiple model specifications have been examined. In this section, we explain some of these.

For example, it has been examined whether the excess mortality term is still necessary. To this end, a model with similar specifications to the pre-covid AG2020 projection table was examined when using the most recent data for all countries in the country set. For European countries, the most recent available observations refer to the year 2022. Because mortality in that year was still considerably higher on average compared to the pre-covid period, this model choice does not lead to plausible results.

4 – Weekly mortality data from Statistics Netherlands (CBS)

5 – RIVM (2024). Feiten en cijfers griep. https://www.rivm.nl/griep-griepprik/feiten-en-cijfers

In addition, it was investigated whether it is possible to estimate excess mortality at the European level. This model specification also does not lead to reliable results, in particular because the timing of covid-related measures and mortality due to the different covid outbreaks differs between European countries.

The CSO also assessed whether it is possible to model the excess mortality terms on the basis of annual data, instead of using weekly data as for AG2022. Dutch mortality data for the years 2020 to 2023 were used for this purpose. This approach turns out to be feasible, however the CSO has decided to model the excess mortality terms based on weekly data. This leads to slightly different parameters than based on yearly data.

Furthermore, a model was investigated with simultaneous estimation of the parameters for the Dutch deviation from the European trend and the parameters in the excess mortality term. In the years 2020 to 2023, this option led to material differences in parameterization compared to the AG2022 model specifications. These differences complicate the extrapolation of the time series. Therefore this option has also been discarded.

2.4 Model selection AG2024

Because there is still clear excess mortality and alternative model specifications have been found either infeasible or less desirable, it was decided to maintain the AG2022 model. This means that for both the European and Dutch data, 2019 is the last data point for estimating the long-term trend.

AG2024 models the natural logarithm of the force of mortality $\mu_x^g(t)$ as:

$$\ln\left(\mu_x^g(t)\right) = A_x^g + B_x^g K_t^g + \alpha_x^g + \beta_x^g \kappa_t^g + \underset{\sim}{\mathfrak{V}}_x^g \mathfrak{X}_t^g.$$

Herein $\{A_x^g, B_x^g, \alpha_x^g, \beta_x^g, \underset{\sim}{\mathfrak{V}}_x^g\}$ are age-dependent parameters, while $\{K_t^g, \kappa_t^g, \mathfrak{X}_t^g\}$ are time-dependent quantities, for which the dynamics are given by the time series

$$\begin{aligned} K_t^g &= K_{t-1}^g + \theta^g + \epsilon_t^g, \\ \kappa_t^g &= a^g \kappa_{t-1}^g + c^g + \delta_t^g, \\ \mathfrak{X}_t^g &= \mathfrak{X}_{2023}^g \eta^{t-2023} \quad (\text{for } t \geq 2024), \end{aligned}$$

where θ^g, a^g, c^g and η are parameters and ϵ_t^g en δ_t^g are error terms, which are assumed to be independent and identically distributed (i.i.d.).

In this specification, the terms $\{A_x^g + B_x^g K_t^g\}$ represent the European pre-covid mortality intensities. The terms $\{\alpha_x^g + \beta_x^g \kappa_t^g\}$ represent the Dutch deviation from the European trend, also pre-covid. The term $\{\underset{\sim}{\mathfrak{V}}_x^g \mathfrak{X}_t^g\}$ then reflects the excess mortality since the covid pandemic.

The excess mortality, which is both directly and indirectly caused by covid, is modelled on the basis of weekly data. Because the effects of covid have been different in the past four years, the use of weekly data for 2022 and 2023 was chosen for the calibration.

Figure 2.4 shows for calibration periods 2020-2021, 2022-2023 and 2020-2023 the height of the age-dependent parameter $\mathfrak{V}_x^g$ in the excess mortality term. This figure shows that for both males and females, excess mortality by age differs between the years 2020-2021 on the one hand and the years 2022-2023 on the other. Furthermore, it appears that the parameter $\mathfrak{V}_x^g$ based on the entire period 2020-2023 is closer to the parameter $\mathfrak{V}_x^g$ from the first years, especially for males. Both the 2020-2021 calibration period and the 2020-2023 calibration period are therefore considered insufficiently representative of the most recent years 2022 and 2023, when the positive effects of vaccinations became visible and people developed more antibodies to reduce the effects of a covid-infection, or even fully prevent it.

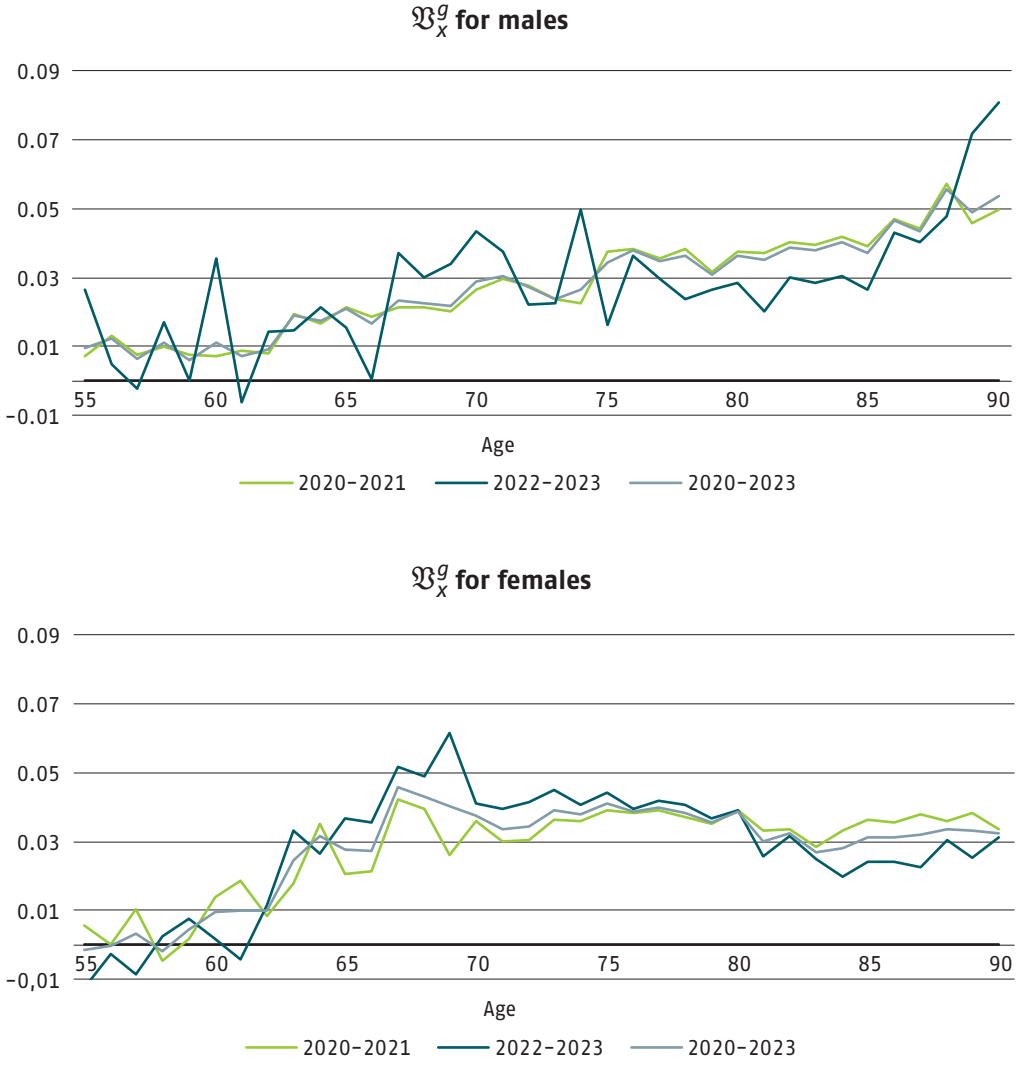

Figure 2.4 – *Course of age-dependent parameter $\mathfrak{V}_x^g$ at different calibration periods*

In order to project excess mortality, the development of this excess mortality in the future must be determined. Although four years of mortality data with excess mortality are now available, this is insufficient to make a fully data-based prognosis for the run-off. That is why, as for AG2022, the CSO makes a choice. First of all, partly as a result of

the observations made over the past two years, we distinguish three possible main scenarios:

- A **'disappearing'** scenario with $\eta \in (0,1)$[6], in which the excess mortality compared to the pre-covid period disappears at some point.
- A '**structural**' scenario with $\eta = 1$, in which the excess mortality compared to the pre-covid period does not disappear.
- A '**incidental**' scenario with $\eta = 0$, in which the excess mortality compared to the pre-covid period disappears immediately after 2023.

AG2022 assumes a 'disappearing' scenario for the projection of the excess mortality effect with a half-life equal to 1 year ($\eta = 0{,}5$).

The table below shows the development of the time-related effect in the excess mortality term ($\mathfrak{X}_t^g$) for both males and females. If this value decreases, the effect of excess mortality decreases over the years. If this excess mortality term has a value of zero, no excess mortality has been observed. For the years 2022 and 2023 it has been observed for in particular females that the actual decrease is less strong than expected based on the AG2022 projection. Based on the data from previous years, it can be seen that excess mortality among males almost halved from 2021 to 2022. In 2023, excess mortality continued to decrease, but 'only' by more than 20%. For females however, no disappearing effect of excess mortality can be seen at all.

Time effect of excess mortality term ($\mathfrak{X}_t^g$) per year and sex				
Year	**Male**	**Delta Male**	**Female**	**Delta Female**
2020	2.85		2.93	
2021	2.87	+1%	3.24	+11%
2022	1.52	-47%	3.40	+5%
2023	1.18	-22%	3.22	-5%

Table 2.2 – *Time effect excess mortality term for male and female in years 2020-2023 with the same age effect over these year. Please note that this is the reason the numbers differ from the model fit when using AG2024.*

For AG2024, the CSO still expects excess mortality to be temporary. This means that once again the 'disappearing' scenario is assumed. We base this on, among other things, the observation that the number of deaths directly related to covid-19 has decreased sharply since 2020 and 2021. Total excess mortality has already decreased for males compared to those years, but this is not yet visible for females. Although excess mortality for males decreased faster than for females in the years 2022 and 2023, we expect the decrease to be similar for males and females in the longer term. Therefore, we do not differentiate by sex in the height of the parameter η.

6 – Parameter ηdetermines the exponential course of the excess mortality term $\mathfrak{X}_t^g$

For other pandemics, such as the Spanish flu, no long-term impact on mortality has been observed as well. Therefore we maintain the assumption in AG2024 that the impact of covid on the long-term mortality projection will disappear.

Because the observed decrease in excess mortality is less strong than expected in AG2022, it was decided to adjust the parameter η upwards. AG2024 assumes η = 0,75. This means that the excess mortality term in the projection will decrease by 25% annually. The half-life of excess mortality is therefore just over 2.4 years. Excess mortality among males decreased faster on average in 2022 and 2023 than would be the case with the chosen value η = 0,75. This is the other way around for females. Please refer to the values "Delta Male" and "Delta Female" in Table 2.2.

In Figure 2.5 we show the evolution of the estimated value of $\mathfrak{X}_t^g$ based on both AG2022 and AG2024. The figure shows that the value for AG2024 decreases less quickly, due to the adjusted value for η. The starting value for 2023 was also higher than the projected value from AG2022, especially for females.

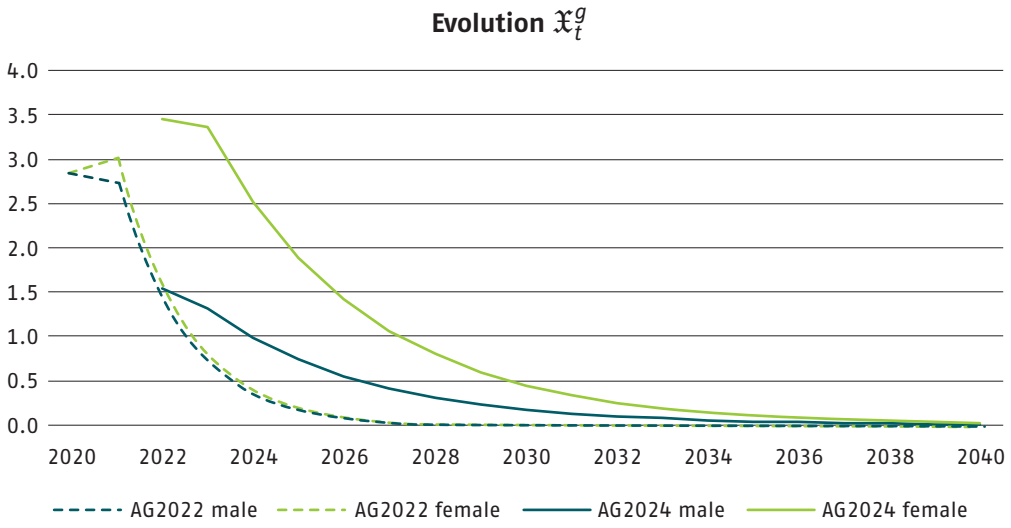

Figure 2.5 – *Evolution of the estimated time effect in the excess mortality term ($\mathfrak{X}_t^g$) for AG2022 and AG2024*

2.5 Closure method

Voor AG2024 is de sluitingsmethodiek verder onderzocht. Dit betreft de methodiek voor The closure method has been further investigated for AG2024. This concerns the methodology for determining mortality probabilities at higher ages. These probabilities are not based on the observed data but are extrapolated on the basis of lower ages.

The study did not result in any model adjustments. This means that, as for AG2022, the model parameters for AG2024 for ages 0 to 90 are based on observed data. For ages 91 to 120, the parameters and thus the mortality probabilities follow from extrapolation of the parameters based on the ages up to and including 90.

2.6 Uncertainty

The projection table presented in this publication is based on past mortality data. Developments that have been observed in the historical data are extended to the future as accurate as possible. Because the future is uncertain, the values that will be found in the coming years for the actual mortality rates in the Netherlands will deviate from the estimates that the model provides.

In general, we can distinguish four forms of uncertainty:

- Model uncertainty;
- Parameter uncertainty;
- Process uncertainty;
- Micro-longevity risk.

For a detailed description of these forms of uncertainty, and a quantification of process uncertainty (excluding excess mortality term), the CSO refers to chapter 5 of the AG2022 publication[7]. We expect this quantification to be representative of the process uncertainty excluding excess mortality term within AG2024, because the model specifications have not changed and the underlying data have hardly changed. Therefore we did not explicitly quantify the process uncertainty for AG2024.

We also did not explicitly quantify model uncertainty for AG2024. However, to give an impression of the degree of model uncertainty, we did compare the AG2024 projection table with the previous projection table and the projections of CBS. Both parameter uncertainty and micro-longevity risk have not been quantified at all. If all these forms of uncertainty are fully and coherently taken into account, the total bandwidth of possible outcomes will be larger than if only process uncertainty is considered.

At the same time, we point out that our model represents a stochastic scenario generator. Based on the fitted parameter values and the precise documentation of the model, anyone can independently generate scenarios with the model in which process uncertainty is quantified. If desired, this can be extended with alternative scenarios for the run-off of the excess mortality term and parameter uncertainty can be added. In this way, the reader get an impression of the uncertainty surrounding the Best Estimate results.

7 – Commissie Sterfte Onderzoek (2022). Projections Life Table AG2022. Living longer in uncertain times. Royal Actuarial Society

3 Data

3.1 European mortality data: selected countries

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

There is a positive correlation between prosperity and aging[8]: the higher the level of prosperity, the older an individual becomes. The selected countries are geographically coherent and in these countries there is a high level of prosperity. This set of countries was selected for the first time when Projections Life Table AG2014 was published and has not changed since then. Figure 3.1 shows the set of chosen countries underlying Projections Life Table AG2024.

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

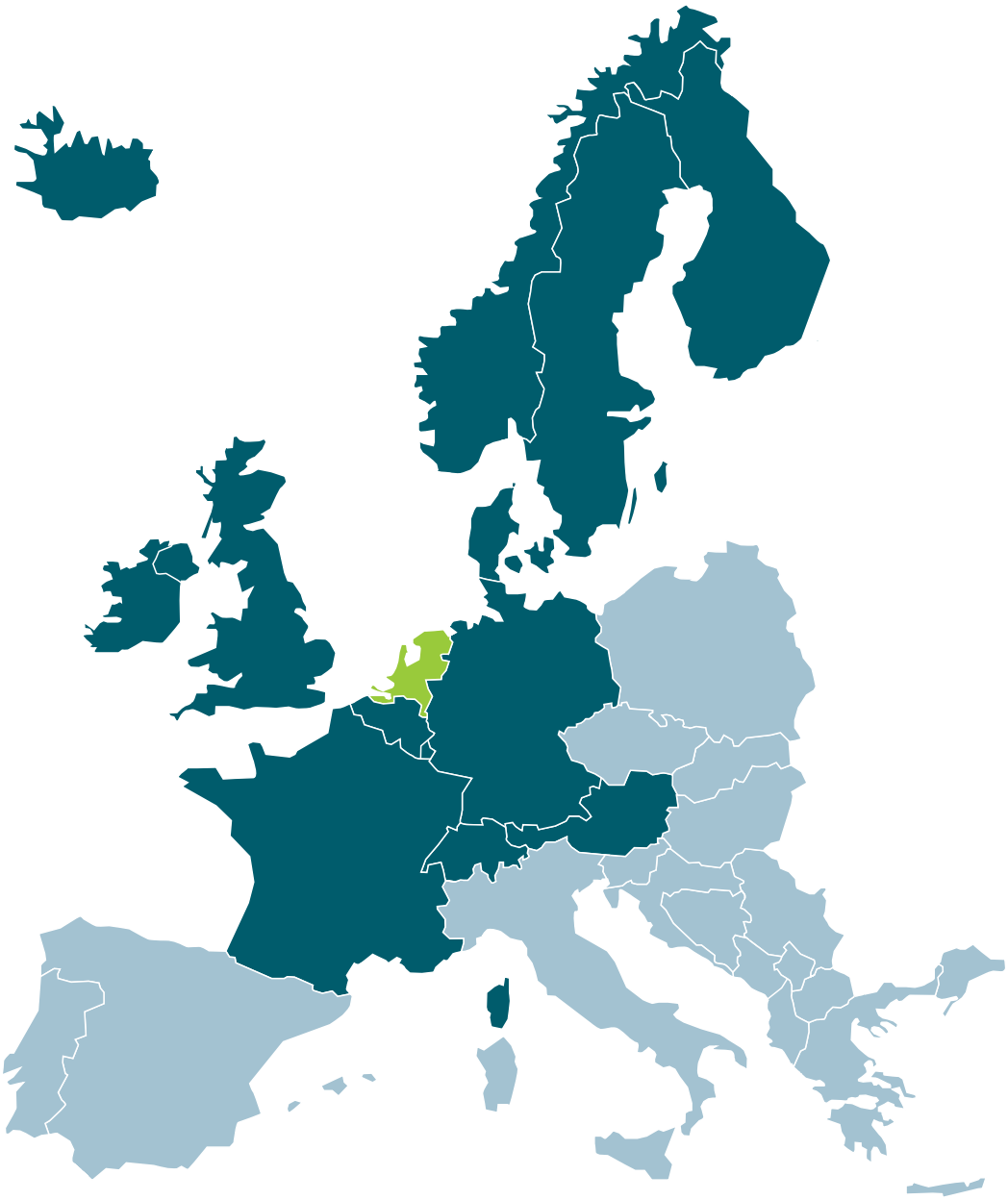

Figure 3.1 – *Selected countries in dataset Projections Life Table AG2024*

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

The data used 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.

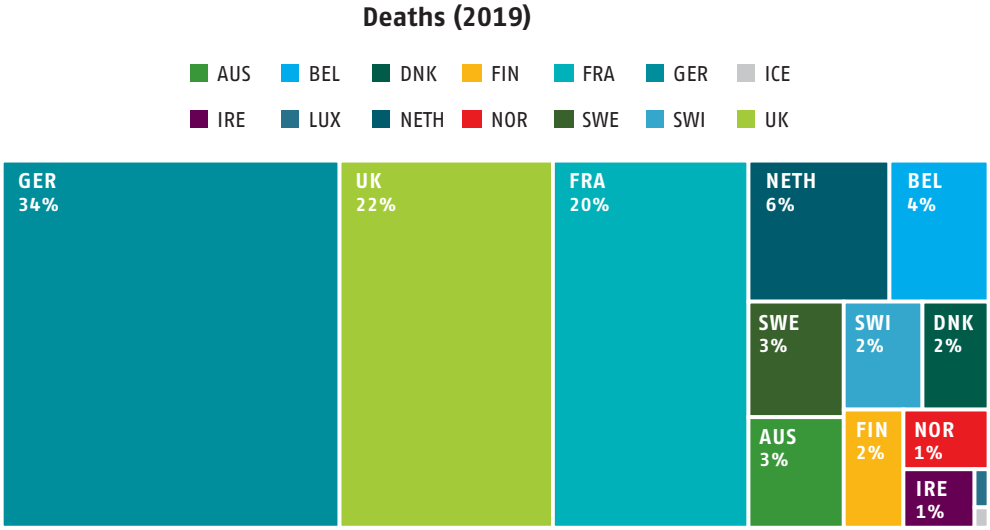

Figure 3.2 – *Distribution of deaths (males + females) in 2019 by countries*

Germany (34%), the United Kingdom (22%) and France (20%) had the highest number of deaths in 2019. The Netherlands comes next with a share of (6%).

3.2 Data range

Figure 3.3 and Figure 3.4 show the historical development of period life expectancy at birth in the Netherlands and the selected European countries since 1950. The graphs show that in the first part of this period, life expectancy in the selected countries is quite different, 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 risen less rapidly since 1970 than the average in 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 striking 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, data from 1970 to 2019 were used. Data from 1983 to 2019 were used for the Dutch deviation.

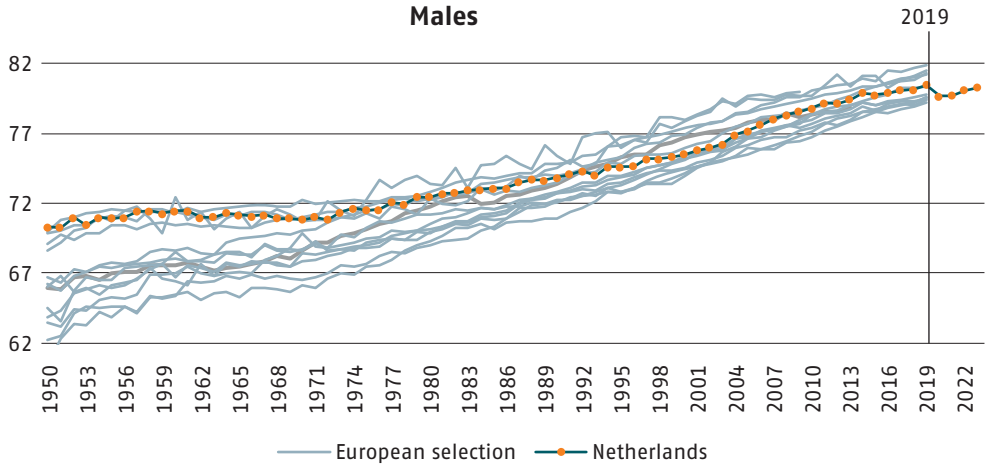

Figure 3.3 – *Period life expectancy at birth, males*

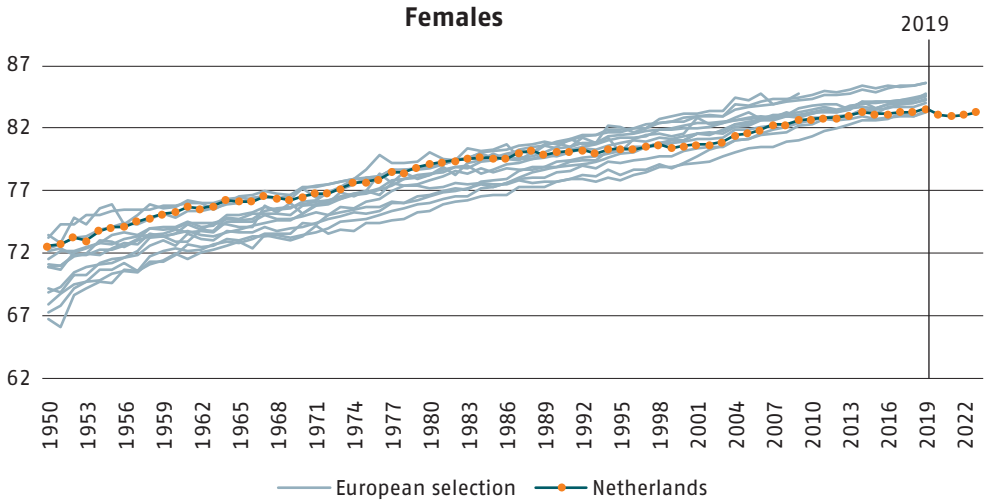

Figure 3.4 – *Period life expectancy at birth, females*

In the years since 2019, period life expectancy in the Netherlands has decreased, which is caused by the direct and indirect consequences of covid-19. In 2023, the level of period life expectancy in the Netherlands is approximately at the level of 2018.

To model the excess mortality term, we use customised data from Statistics Netherlands (CBS). This concerns data for observed mortality per week and by age and sex in the Netherlands for the years 2022 and 2023. For the same period, we used public population data 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 is further described in section 2.2.

Appendices

Appendix A
AG2024 do-it-yourself

1 Definitions

The projection table provides the 'best estimate' for the one-year mortality probabilities $q_x^g(t)$ for the sexes $g \in \{M, V\}$, for the ages $x \in X = \{0, 1, 2, .., 120\}$ and for the years $t \in T = \{2022, 2023, .., 2200\}$. The one-year mortality probability is the probability that someone who lives on January 1 of the year t and was born on January 1 of the year $t - x$ will have died on January 1 of the year $t + 1$. The model allows 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') $\mu_x^g(t)$. We assume that $\mu_{x+s_1}^g(t + s_2) = \mu_x^g(t)$ for all $0 \le s_1, s_2 < 1$. From this, it follows that

$$q_x^g(t) = 1 - e^{-\int_0^1 \mu_{x+s}^g(t+s)ds} = 1 - e^{-\mu_x^g(t)}.$$

Each dynamic model, on the basis of which the 'force of mortality' $\mu_x^g(t)$ can be predicted also provides a prognosis in terms of one-year mortality probabilities via the above equation.

2 Dynamic model

We model for $(x, t) \in X \times T$ and both sexes $g \in \{M, V\}$ the 'force of mortality' $\mu_x^g(t)$:

$$\ln\left(\mu_x^g(t)\right) = \ln\left(\mu_x^{g,\text{pre-cov}}(t)\right) + \ln\left(o_x^g(t)\right),$$

with $\mu_x^{g,\text{pre-cov}}(t)$ the pre-covid 'force of mortality' which is determined on the basis of the data up to and including 2019, and $o_x^g(t)$ as the quotient of $\mu_x^g(t)$ and $\mu_x^{g,\text{pre-cov}}(t)$, which thus represents the deviation from 2020 onwards.

We model $\ln\left(\mu_x^{g,\text{pre-cov}}(t)\right)$ according to the Li-Lee[9] model:

$$\ln\left(\mu_x^{g,\text{pre-cov}}(t)\right) = \ln\left(\mu_x^{g,\text{pre-cov,EU}}(t)\right) + \ln\left(\Delta_x^{g,\text{pre-cov}}(t)\right),$$

$$\ln\left(\mu_x^{g,\text{pre-cov,EU}}(t)\right) = A_x^g + B_x^g K_t^g,$$

$$\ln\left(\Delta_x^{g,\text{pre-cov}}(t)\right) = \alpha_x^g + \beta_x^g \kappa_t^g,$$

with $\mu_x^{g,\text{pre-cov,EU}}(t)$ the pre-covid 'force of mortality' for the reference group of Western European countries and $\Delta_x^{g,\text{pre-cov}}(t)$ the quotient of $\mu_x^{g,\text{pre-cov}}(t)$ and $\mu_x^{g,\text{pre-cov,EU}}(t)$ (i.e., the Dutch deviation versus the reference group). In these $\{A_x^g, B_x^g, \alpha_x^g, \beta_x^g\}$ are age-dependent parameters, while $\{K_t^g, \kappa_t^g\}$ are time-dependent quantities, of which dynamics are given by the time series

$$K_t^g = K_{t-1}^g + \theta^g + \epsilon_t^g,$$

$$\kappa_t^g = a^g \kappa_{t-1}^g + c^g + \delta_t^g,$$

9 – See Li and Lee (2005)

where θ^g, a^g, and c^g are parameters and ϵ_t^g and δ_t^g error terms. The stochastic vectors $Z_t = (\epsilon_t^M, \epsilon_t^V, \delta_t^M, \delta_t^V)'$ are assumed to be independent and identically distributed (i.i.d.) and have 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 $\{K_t^g\}$ and for the time series of the Dutch deviation $\{\kappa_t^g\}$ a first-order autoregressive model is assumed with a constant term.

Inspired by the Lee-Carter model, we model $o_x^g(t)$ as follows:

$$\ln\left(o_x^g(t)\right) = \mathfrak{B}_x^g \mathfrak{x}_t^g,$$

with $\{\mathfrak{B}_x^g\}$ age-dependent parameters and $\{\mathfrak{x}_t^g\}$ time-dependent quantities. The values of $\mathfrak{x}_{2022}^g$ and $\mathfrak{x}_{2023}^g$ follow from a calibrated weekly model that we will present later in this Appendix, while for $t \geq 2024$ we assume

$$\mathfrak{x}_t^g = \mathfrak{x}_{2023}^g \eta^{t-2023},$$

with a parameter η. Different values of the parameter η correspond to different scenarios for the future course of the pandemic:

- The value $\eta \in (0,1)$ corresponds to the '**disappearing**' scenario:
  the value of $\mathfrak{x}_t^g$ for $t \geq 2024$ converges to 0, so the excess mortality compared to the pre-covid period disappears, with a half-life equal to $\ln(½)/\ln(\eta)$.
  The CSO has chosen this scenario for the AG2024 projection with a value of ¾ for η and thus the half-life equals 2.4 years.
- The value $\eta = 1$ corresponds to the '**structural**' scenario:
  the value of $\mathfrak{x}_t^g$ for $t \geq 2024$ remains equal to $\mathfrak{x}_{2023}^g$, so the excess mortality compared to the pre-covid period does not disappear.
- The value $\eta = 0$ corresponds to the '**incidental**' scenario:
  the value of $\mathfrak{x}_t^g$ for $t \geq 2024$ is equal to 0, so the excess mortality compared to the pre-covid period will disappear directly after 2023.

3 'Best estimate' mortality probabilities and life expectancy

The 'best estimate' mortality probabilities are then determined via

$$q_x^g(t) = 1 - e^{-\mu_x^g(t)},$$

by filling in the equations for $\mu_x^g(t)$ the 'best estimates' of the time series K_t^g and κ_t^g. Because we identify the best estimates for future values of these time series with the most likely outcomes, they correspond to the series for K_t^g and $\kappa_t^g t$ which are obtained by filling for all future t the values $Z_t = (\epsilon_t^M, \epsilon_t^V, \delta_t^M, \delta_t^V)' = (0,0,0,0)'$. The covariance matrix C is therefore not needed to generate 'best estimates', but it is necessary to be able to perform simulations that can help to map the uncertainty surrounding the 'best estimates'.

In this way we obtain the 'best estimates' for the ages $x \in X = \{0,1,2, \ldots, 120\}$.

If we want to determine the remaining life expectancy of someone on January 1 of a year t under the assumption that this person was born on January 1 of a year $t - x$ (with $x \in X$ and $t \in T$)

and assume that someone who dies within a calendar year is on average still alive for half of that calendar year, then for that so-called *cohort life expectancy* we find:

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

Please note that according to the above formula, we "walk diagonally through the projection table". After all, the chance that the person is still alive at time $t+k$ is the product of survival chances $1 - q_{x+s}^{g}(t+s)$ for all the years s in between 0 and k where every year this person not only becomes a year older, but we also take into account a new column in the mortality table. The latter effect is not taken into account in the *period life expectancy*

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

which is based on the assumption that the mortality probabilities of time t will not change after this time. This leads to a false picture of life expectancy and although this period life expectancy is often still referred to as "the life expectancy", this is incorrect.

4 Calibration pre-covid 'force of mortality'

The parameter values for $\mu_x^{g,\text{pre-cov}}(t)$ in the above model were determined for the ages $x \in X^o = \{0, 1, \ldots, 90\}$ using the maximum likelihood method, using death counts and exposures in the Western European reference group and in the Netherlands up to and including the year 2019. The parameters for the ages $x \in \tilde{X} = \{91, 92, \ldots, 120\}$ were subsequently determined by extrapolation.

The below steps are followed separately for both sexes $g \in \{M, V\}$ to calibrate $\mu_x^{g,\text{pre-cov}}(t)$ for the ages $x \in X^o = \{0, 1, \ldots, 90\}$:

- We take the exposures $E_{x,t}^{g,EU}$ and observed death counts $D_{x,t}^{g,EU}$ for the relevant Western European countries, with $t \in T^o = \{1970, 1971, \ldots, 2019\}$. This always concerns the sum of all exposures and the sum of all deaths in the relevant countries, including The Netherlands. We assume[10] that $D_{x,t}^{g,EU}$ has a Poisson distribution with mean $E_{x,t}^{g,EU}\mu_x^{g,\text{pre-cov,EU}}(t)$ and that $\mu_x^{g,\text{pre-cov,EU}}(t) = e^{A_x^g + B_x^g K_t^g}$. The parameters A_x^g, B_x^g and K_t^g are then determined in such a way that the Poisson likelihood function for the observed deaths is as large as possible at the given exposures:

$$\max_{\{A_x^g, B_x^g, K_t^g\}} \prod_{x \in X^o} \prod_{t \in T^o} \frac{\left(E_{x,t}^{g,EU}\mu_x^{g,\text{pre-cov,EU}}(t)\right)^{D_{x,t}^{g,EU}} \exp\left(-E_{x,t}^{g,EU}\mu_x^{g,\text{pre-cov,EU}}(t)\right)}{D_{x,t}^{g,EU}!}.$$

  To achieve a unique specification of the parameters $\{A_x^g, B_x^g, K_t^g\}$, we normalize by requiring that the sum of the elements of K_t^g over $t \in T^o$ is equal to 0 and the sum of the elements of B_x^g over $x \in X^o$ is equal to 1.

- The maximum likelihood method is then applied to the Dutch data to determine α_x^g, β_x^g and κ_t^g via

10 – According to Brouhns et al. (2002)

$$\max_{\{\alpha_x^g,\,\beta_x^g,\,\kappa_t^g\}} \prod_{x\in X^o}\prod_{t\in T^*} \frac{\left(E_{x,t}^{g,NL}\mu_x^{g,\text{pre-cov}}(t)\right)^{D_{x,t}^{g,NL}} \exp\left(-E_{x,t}^{g,NL}\mu_x^{g,\text{pre-cov}}(t)\right)}{D_{x,t}^{g,NL}!},$$

with $\mu_x^{g,\text{pre-cov}}(t) = \hat{\mu}_x^{g,\text{pre-covid,EU}}(t)e^{\alpha_x^g+\beta_x^g\kappa_t^g}$, $T^* = \{1983, 1984, \dots, 2019\}$ (i.e. now from 1983), where $\hat{\mu}_x^{g,\text{pre-covid,EU}} = \exp\left(\hat{A}_x^g + \hat{B}_x^g\hat{K}_t^g\right)$. In this equation $\hat{A}_x^g, \hat{B}_x^g$ and $\hat{K}_t^g$ concern the estimates which were determined in the previous step. Again normalization is applied by the sum of elements in κ_t^g over $t \in T^*$ and β_x^g over $x \in X^o$ to be 0 and 1 respectively.

- In the third step, estimates of the time series are used $\left\{\left(\hat{K}_t^M, \hat{K}_t^V\right)' \,\middle|\, t \in T^o\right\}\{(\hat{\kappa}_t^M, \hat{\kappa}_t^V)' \mid t \in T^*\}$, as determined in the previous steps, to estimate the parameters $\Psi = (\theta^M, \theta^V, a^M, a^V, c^M, c^V)'$ and the matrix *C*. Under the assumption that the vectors $Z_t = (\epsilon_t^M, \epsilon_t^V, \delta_t^M, \delta_t^V)'$ are independent and identically distributed and have a four-dimensional normal distribution with mean $(0,0,0,0)'$ and covariance matrix *C*, we choose the estimators in such a way that the likelihood for these time series is maximized (ignoring that we are working with estimates of the 'real' underlying values for time series, not observed time series values).

  To do this, we use the equation $Y_{t+1} = X_t\Psi + Z_{t+1}$ with the following matrices for $t = 1970, \dots, 1982$

$$Y_{t+1} = \begin{bmatrix}\hat{K}_{t+1}^M - \hat{K}_t^M \\ \hat{K}_{t+1}^V - \hat{K}_t^V\end{bmatrix}, \quad X_t = \begin{bmatrix}1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0\end{bmatrix}, \quad Z_{t+1} = \begin{bmatrix}\epsilon_{t+1}^M \\ \epsilon_{t+1}^V\end{bmatrix},$$

and with the following matrices for $t = 1983, \dots, 2018$

$$Y_{t+1} = \begin{bmatrix}\hat{K}_{t+1}^M - \hat{K}_t^M \\ \hat{K}_{t+1}^V - \hat{K}_t^V \\ \hat{\kappa}_{t+1}^M \\ \hat{\kappa}_{t+1}^V\end{bmatrix}, \quad X_t = \begin{bmatrix}1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \hat{\kappa}_t^M & 0 & 1 & 0 \\ 0 & 0 & 0 & \hat{\kappa}_t^V & 0 & 1\end{bmatrix}, \quad Z_{t+1} = \begin{bmatrix}\epsilon_{t+1}^M \\ \epsilon_{t+1}^V \\ \delta_{t+1}^M \\ \delta_{t+1}^V\end{bmatrix}.$$

Subsequently, *C* and Ψ are determined by optimizing the log likelihood for the time series:

$$\arg\max_{C,\Psi} \quad -\frac{1}{2}\text{tr}\left[\tilde{C}^{-1}\sum_{t=1970}^{1982}(Y_{t+1} - X_t\Psi)(Y_{t+1} - X_t\Psi)'\right] - \frac{13}{2}\ln\left(\left|\tilde{C}\right|\right) - \frac{1}{2}(13\times 2)\ln(2\pi)$$
$$-\frac{1}{2}\text{tr}\left[C^{-1}\sum_{t=1983}^{2018}(Y_{t+1} - X_t\Psi)(Y_{t+1} - X_t\Psi)'\right] - \frac{36}{2}\ln(|C|) - \frac{1}{2}(36\times 4)\ln(2\pi).$$

Here, $\tilde{C}$ is the 2×2 submatrix consisting of the first two columns and rows of C.

5 Closure of parameter values

The parameters $\{A_x^g,\ B_x^g, \alpha_x^g, \beta_x^g\}$ for the ages $x \in \tilde{X} = \{91, 92, \ldots, 120\}$ are then determined by extrapolation as follows.

The parameters $\{B_x^g\}, x \in \tilde{X}$, are determined by linear extrapolation from $\{\ln(\hat{B}_y^g)\}$ for the ages $y \in \{80, 81, \cdots, 90\}$. We write $y_k = 80 + (k-1)$ for $k = 1, \cdots, n$ with $n = 11$. The number of ages y_k on which the regression is based is therefore $n = 11$, the mean of those ages equals $\bar{y} = \frac{1}{n}\sum_{k=1}^{n} y_k = 85$ and the sum of squared deviations is $\sum_{k=1}^{n}(y_k - \bar{y})^2 = 110$. Then we find for $x \in \tilde{X}$:

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

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

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

We then determine $\{\hat{A}_x^g\}, x \in \tilde{X}$, in such a way that in 2019 the values of the force of mortality for the Western European reference group correspond with the values according to the Kannisto closure method[11], i.e.

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

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

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

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

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

Finally, we determine $\{\hat{\beta}_x^g\}, x \in \tilde{X}$, in such a way that the Dutch pre-covid force of mortality in 2019 corresponds to the values that would follow from closure with Kannisto's method. So we solve $\hat{\beta}_x^g$ from the equation

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

11 – Kannisto (1992)

6 Simulation of the pre-covid-time series

In order to simulate scenarios for the time series $Z_t = (\epsilon_t^M, \epsilon_t^V, \delta_t^M, \delta_t^V)'$, draws from a normal distribution with mean $(0,0,0,0)'$ and covariance matrix C must be generated. This can be accomplished by multiplying a vector $\tilde{Z}_t$ of four independent standard normally distributed variables with a matrix H that meets the requirement $H' \; H = C$ so through $Z_t = H'\tilde{Z}_t$.

Therefore, in the list of parameters in the publication and the accompanying Excel spreadsheet, in addition to the covariance matrix C a Cholesky matrix H is included.

7 Dataset used for calibration over 2022 and 2023

We will now present the modelling for the years 2020 to 2023. As indicated in chapter Data, the data for years 2020 and 2021 were not used in the calibration of the excess mortality term. This means that no model fit is available for these years. The data prior to years 2022 and 2023 has been used in the calibration of the projection table and a model fit is available for these years. This model fit is described below.

We assume that there is no deviation from previous years for ages below 55. Therefore, we assume $o_x^g(t) = 1$ for ages $x \in \{0,1, \dots, 54\}$ for $t = 2022$ and $t = 2023$. For ages $x \in \{55, 56, \dots, 90\}$ we calibrate $o_x^g(t)$, whilst for the ages $x \in \tilde{X} = \{91,92, \dots, 120\}$ and for $t = 2022$ and $t = 2023$ we equalize $o_x^g(t)$ to $o_{90}^g(t)$.

The values of the parameters of $o_x^g(t)$ were determined for the ages $x \in \{55, 56, \dots, 90\}$ using an underlying model on a weekly basis. This model uses death counts per week and per individual age over the years 2016 to 2023. These data were obtained through a tailor-made data request at CBS. The number of deaths in week w of year t with age $x \in \{55,56, \dots, 90\}$ of sex $g \in \{M, V\}$ is indicated by $D_{x,w,t}^g$.

The weekly data from 2016 to 2019 are used to estimate the seasonal effect. The data from 2022 and 2023 are then used to calibrate the weekly model for those years. This also requires the exposures of 2022 and 2023 on a weekly basis. These exposures are determined via linear interpolation on the population counts $P_{m,w,t}^g$ for the population of sex g at the beginning of month m of year t[12]. For $t = 2022$ and $t = 2023$ and for $w \in W_{2022} = \{0, \cdots, 52\}$ and $w \in W_{2023} = \{0, \cdots, 52\}$ we determine:

$$E_{x,w,t}^g = \frac{N_{w,t}}{\sum_{u \in W_t} N_{u,t}} \sum_{d \in W(w,t)} \tilde{P}_{x,d,t},$$

with $W(w,t)$ representing the set of the days of week w in year t, $N_{w,t}$ the number of elements in the set $W(w,t)$, i.e. the number of days in week w of year t, and $\tilde{P}_{x,d,t}$ the estimated population of age x by day d of year t, which is obtained by interpolating linearly between the monthly data $P_{m,w,t}^g$ based on the counted number of days per week and month.

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

8 Calibration method weekly model

The following steps are followed separately to calibrate $o_x^g(t)$ for ages $x \in X^* = \{55, 56, \dots, 90\}$ for both sexes $g \in \{M, V\}$ and for the years $t = 2022$ and $t = 2023$.

We correct for the seasonal effect, which refers to the non-uniform distribution of mortality over the weeks of the year. We use the death counts of both sexes to estimate a (sexe neutral) weekly effect $\varphi_{w,t}$ which reflects how mortality during the year t is distributed over the weeks $w \in W_{2022} = \{0, \cdots, 52\}$ and $w \in W_{2023} = \{0, \cdots, 52\}$. In order to achieve this, we determine the historically observed total mortality for the week[13] $w \in \{1, \cdots, 52\}$ over the years $t \in \{2016, \cdots, 2019\}$, where we aggregate over the ages $x \in X^*$ and both sexes:

$$D_w^{tot} = \sum_{t=2016}^{2019} \sum_{g \in \{M,V\}} \sum_{x=55}^{90} D_{x,w,t}^g.$$

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 derivative in $w = 1$ and $w = 53$ match, using the Matlab routine `spcsp`. Using visual inspection, $\lambda = 0.03$ was chosen, which concerns the parameter that makes the trade-off between 'fit' and 'smoothness'. For the broken weeks $w = 0$ and $w = 53$ we assume that $\Phi(0) = \Phi(53) = \frac{\Phi(52)+\Phi(1)}{2}$. We then determine

$$\varphi_{w,t} = \frac{\Phi(w)}{\sum_{u \in W_t} \Phi(u) \cdot N_{w,t} / \sum_{u \in W_t} N_{w,t}} = \frac{\Phi(w) \cdot \sum_{u \in W_t} N_{w,t}}{\sum_{u \in W_t} \Phi(u) \cdot N_{w,t}}.$$

The maximum likelihood method is then applied to the Dutch weekly data to estimate $\mathfrak{B}_x^g, x \in X^*$ and $\mathfrak{K}_{w,t}^g, w \in W_t$ for $t = 2022$ and $t = 2023$, via

$$\max_{\left\{\mathfrak{B}_x^g, \mathfrak{K}_{w,2022}^g, \mathfrak{K}_{w,2023}^g\right\}} \prod_{x \in X^o} \prod_{t \in \{2022,2023\}} \prod_{w \in W_t} \frac{\left(E_{x,w,t}^g \mu_{x,w}^g(t)\right)^{D_{x,w,t}^g} \exp\left(-E_{x,w,t}^g \mu_{x,w}^g(t)\right)}{D_{x,w,t}^g!},$$

with $\mu_{x,w}^g(t) = \hat{\mu}_x^{g,\text{pre-covid}}(t) \varphi_{w,t} e^{\mathfrak{B}_x^g \mathfrak{K}_{w,t}^g}$ and with normalization $\sum_{x=55}^{90} \mathfrak{B}_x^g = 1$.

The next step is to determine aggregated time effects over all weeks of the year $\mathfrak{X}_t^g$ for $t = 2022$ and $t = 2023$ and the associated $\widetilde{\mathfrak{B}}_x^g, x \in X^*$.
We first determine $\widetilde{\mathfrak{X}}_t^g$ by setting for $t = 2022$ and $t = 2023$

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

By taking a logarithm on both sides, dividing by $-\hat{\mu}_x^{g,\text{pre-covid}}(t)$, taking again the logarithm and summing over the ages $x \in X^o$, using the normalization $\sum_{x=55}^{90} \widetilde{\mathfrak{B}}_x^g = 1$ we find

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

$$\tilde{\mathfrak{X}}_t^g = \sum_{x=55}^{90} \ln\left(\sum_{w\in W_t} \varphi_{w,t} \frac{N_{w,t}}{\sum_{u\in W_t} N_{u,t}} e^{\mathfrak{B}_x^g \mathfrak{K}_{w,t}^g}\right).$$

We then determine $\tilde{\mathfrak{B}}_x^g$, by setting survival over the entire years 2022 and 2023 equal to the survival over all weeks within the years 2022 and 2023:

$$\prod_{t=2022}^{2023} \exp\left(-\hat{\mu}_x^{g,\text{pre-covid}}(t) e^{\tilde{\mathfrak{B}}_x^g \tilde{\mathfrak{X}}_t^g}\right) = \prod_{t=2022}^{2023} \prod_{w\in W_t} \exp\left(-\frac{N_{w,t}}{\sum_{u\in W_t} N_{u,t}} \hat{\mu}_x^{g,\text{pre-covid}}(t) \varphi_{w,t} e^{\mathfrak{B}_x^g \mathfrak{K}_{w,t}^g}\right).$$

Rewriting gives

$$\sum_{t=2022}^{2023} \hat{\mu}_x^{g,\text{pre-covid}}(t) \sum_{w\in W_t} \frac{N_{w,t}}{\sum_{u\in W_t} N_{u,t}} \left(e^{\tilde{\mathfrak{B}}_x^g \tilde{\mathfrak{X}}_t^g} - \varphi_{w,t} e^{\mathfrak{B}_x^g \mathfrak{K}_{w,t}^g}\right) = 0.$$

This non-linear equation in $\tilde{\mathfrak{B}}_x^g$ can be solved numerically for each age $x \in X^*$ separately. Assume this gives as solutions $\tilde{\tilde{\mathfrak{B}}}_x^g$. Then we finally determine $\tilde{\mathfrak{B}}_x^g$ (in such a way that $\sum_{x=55}^{90} \tilde{\mathfrak{B}}_x^g = 1$) and $\mathfrak{X}_t^g$ through normalization

$$\tilde{\mathfrak{B}}_x^g = \tilde{\tilde{\mathfrak{B}}}_x^g \Big/ \sum_{x=55}^{90} \tilde{\tilde{\mathfrak{B}}}_x^g, \mathfrak{X}_t^g = \tilde{\mathfrak{X}}_t^g \sum_{x=55}^{90} \tilde{\tilde{\mathfrak{B}}}_x^g.$$

As a final step we state $\tilde{\mathfrak{B}}_x^g = 0 x \in \{0,1,\dots,54\}$ and we close the table via the extrapolation $\tilde{\mathfrak{B}}_x^g = \tilde{\mathfrak{B}}_{90}^g x \in \{91,92,\dots,120\}$. This implies that for the ages $o_x^g(t) = 1$ for the ages $x \in \{0,1,\dots,54\}$ and $o_x^g(t) = o_{90}^g(t)$ for the ages $x \in \tilde{X} = \{91,92,\dots,120\}$.

Appendix B
Model portfolios

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

Model portfolio provision

Two model portfolios were used to determine the effect on the provision of model portfolios. The portfolios are differentiated by sex (male and female) and have a weighted average age (according to provision) of 55 years.

The model portfolios include lifelong retirement pension (OP) and lifelong partner's pension (PP).

The table for males presents the rights that arise from male participants (i.e. including widows) and the table for females presents the rights that arise from female participants (i.e. including widowers).

	Male		
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*

	Female		
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*

Premium model portfolio

The following model portfolios have been used to determine the effect on the premium. This is based on the accrual of retirement pension and partner's pension. Table B.3 shows the accrual in any year by age.

	Male		Female	
Age	**OP (68)**	**PP (def.)**	**OP (68)**	**PP (def.)**
30	600	420	400	280
40	750	525	500	350
50	800	560	550	385
60	600	420	400	280

Table B.3 – *Accrual per type of pension for model premium portfolios*

The risk-based partner's pension is based on the future years of service (retirement at 68 – current age of participant – 1 year).

Actuarial principles

The technical provisions and premiums for these portfolios are calculated using the following assumptions:

- Survival tables: Projections Life Table AG2024 with starting year 2025
- Age corrections and/or experience mortality: none
- Actuarial interest rate: 3.0%
- Retirement age: 65 years for the provision and 68 years for the contribution
- The following applies to the deferred partner's pension:
  - Undetermined partner system until retirement age, with a partner frequency of 100%, then 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 that has commenced 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 parameters

- x the age of male participant or male partner
- y the age of female participant or female partner

Note: In the undetermined partner system, a partner of the opposite sex is used. For simplicity in the notation, the following is based on a male main insured person everywhere. For all formulas and definitions, instead of *x* (male main insured) with *y* (female partner), one can also read *y* (female main insured) with *x* (male partner).

- r the (constant) 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 a *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 that 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 an *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 in payment partner's pension for an *x*-year old participant
- CS_x^{op} one year of accrual for old-age pension for an *x*-year-old participant
- CS_x^{lpp} one year of accrual of deferred partner's pension for an *x*-year old participant

Generic formulae

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

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

- Deferred OP:

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

- Commenced OP:

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

- Commenced 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 SP per unit

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

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

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

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

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

Present value provision

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

Formulas calculations premium

- Contribution *n* year deferred retirement pension:

$$CS_x^{\text{op}} \cdot {}_n|\bar{a}_x$$

- Contribution for deferred partner's pension accrual:

$$CS_x^{\text{lpp}} \cdot \left(\tilde{a}_{x|y} + (PL - x - 1) \cdot v^{\frac{1}{2}} q_{x+t} h_{x+t+\frac{1}{2}} \bar{a}_{y+t+\frac{1}{2}}\right)$$

- Deferred partner's pension premium (risk based):

$$CS_x^{\text{lpp}} \cdot 40 \cdot v^{\frac{1}{2}} q_{x+t} h_{x+t+\frac{1}{2}} \bar{a}_{y+t+\frac{1}{2}}$$

with $$\bar{a}_{y+t+\frac{1}{2}} = v^{\frac{1}{2}}\left(1 - q_{y+t}\right)^{\frac{1}{2}} \ddot{a}_{y+t+1}$$

and $$h_{x+t+\frac{1}{2}} = h_{x+t}^{\frac{1}{2}} h_{x+t+1}^{\frac{1}{2}}$$

Appendix C
Literature and data used

Literature

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Weekly mortality data from the CBS for the years 2020-2023

Data used

HMD's databases were used to model mortality up to and including 2019 in all countries[13]. The data from HMD was downloaded on February 27, 2024. Table C.1 indicates for each geographical area which HMD version was used as input.

Country	HMD Version
Belgium	2023.11.14
Denmark	2023.03.12
Finland	2023.06.14
France	2023.09.13
Germany	2022.06.03
Iceland	2024.04.24
Ireland	2022.06.12
Luxembourg	2023.08.09
Netherlands	2023.10.06
Norway	2023.04.03
Austria	2021.03.30
Sweden	2023.04.03
United Kingdom	2023.11.28
Switzerland	2023.08.09

Table C.1 – *Data sources AG2024 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 group of Western 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 from Statistics Netherlands (CBS). This concerns data for observed mortality per week and by age in the Netherlands for the years 2022 and 2023. We also used monthly population data from CBS[14] to arrive at the exposures for those years.

The data for weekly mortality in the Netherlands in 2022 and 2023 has not been published on the AG website, as this concerns data received from CBS following a tailor-made request.

14 – http://www.mortality.org/

15 – Exposures-to-Risk (P-waarden), downloaded April 22, 2024: https://opendata.cbs.nl/#/CBS/nl/dataset/85721NED/table?ts=1716895484058

Appendix D
Committee & Working Group

The Projections Life Table AG2024 was established by the Mortality Research Committee (CSO), after extensive analyses and preparatory work by the Projections Tables 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 Committee.

Committee on Mortality Research (CSO)

The CSO consists of the following members in mid-2024:

- drs. A.Th. (Sander) Biesma AAG RC RBA, chair
- F. (Frank) van Berkum PhD
- drs. C.A.M. (Corné) van Iersel AAG CERA, secretary
- C.C.A. (Carlo) Jonk MSc AAG
- M.J.A. (Marieke) Klein MSc AAG
- drs. J. (Hans) de Mik CFA AAG, vice-chair
- J.I. (Janinke) Tol MSc AAG
- drs. J.C. (Joost) van Valkengoed
- ir. R.E.J.M. (Raymond) Waucomont AAG
- M.A. (Menno) van Wijk MSc AAG
- ir. drs. M.R. (Marco) van der Winden AAG MBA

Working Group Projection Tables

In mid-2024, the Projection Tables Working Group consists of the following members:

- C.J. (Mélanie) de Looze MSc AAG
- Ir. drs. C.C. (Carry) Mout AAG
- B. (Brian) Möllenkamp MSc
- Z.X.S. (Zeus) Paraguas MSc
- M.P.G.W. (Max) Thönissen MSc FRM
- J.I. (Janinke) Tol MSc AAG, chair
- D.L. (Dylan) van Westen MSc AAG

Advisory Board

The Advisory Board consists of the following members by mid-2024:

- Prof. Dr. B.(Bertrand) Melenberg
- Prof. Dr. Ir. M.H. (Michel) Vellekoop

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