Koninklijk Actuarieel Genootschap

PROJECTIONS LIFE TABLE AG2022

Living longer in uncertain times

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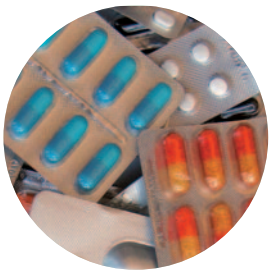

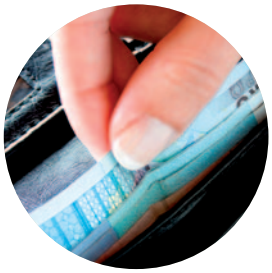


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Preface

Every two years The Royal Dutch Actuarial Association (Koninklijk Actuarieel Genootschap or 'AG') publishes its new projections table for Dutch life expectancy. Since the AG2014 publication a stochastic model is used, so that in addition to the well-known 'best estimate' mortality probabilities to set provisions and contribution levels, one can also allow for the uncertainty in mortality probabilities. Over the course of ten years the model was improved every two years and before you now lies the publication of Projections Life Table AG2022 (in short AG2022). Life expectations has often made the headlines in 2020 and 2021 because of COVID-19. This has prompted the AG Mortality Research Committee (Commissie Sterfte Onderzoek or 'CSO') in 2021 to issue an intermediate publication on the possible effects of COVID-19 on life expectancy. The most prominent conclusions were that much is still uncertain and that we can only read into the tea leaves to predict the long-term effects of COVID-19. Even now there is only a limited picture of these. There are however developments that give hope, such as a high vaccination coverage and a milder omicron variant.

CSO and the Projection Life Tables Working Group have investigated and considered a number of potential COVID-19 scenarios. Over two years COVID-19 dominated the news: many contaminations, many hospitalisations, postponed care and many more deaths. The current reality raises the question what the long-term effect of COVID-19 will be and how to include this effect in the mortality probability forecast and long-term life expectancy. In this publication we will elaborate extensively on the COVID-19 modelling approach and the view of the committee.

This publication gives an update of the projections table. The CSO and working group not only considered the potential effects of COVID-19. Other research was also done, improving the model in some areas. The committee and working group have heeded the questions from within the profession that were raised at earlier publication events and deep dive sessions. Not every line of research has led to a model adjustment. It is however true to say that a minor adjustment in the model or a model parameter could lead to substantial changes in provisions and contribution levels.

As ever, the AG Boards extends its gratitude to the committee and the working group for their unremitting commitment to achieve the best possible life expectancy forecast. Clearly, given the exceptional circumstances in the past two years, the AG is happy with the thoroughness of the research and the timely publication of this projections table.

Justification

Monitoring the development of mortality in the Netherlands and developing projections of this has traditionally been an important task of the Royal Dutch Actuarial Association (AG). An expression of this is the long series of period and projections life tables the Association has published biennially since 2010. In addition to mortality projections, the current stochastic model, in use since AG2014, also represents the uncertainty thereof. In recent years much research was performed, and the model has been improved further, yielding a more robust model.

To develop this mortality forecast, the Association combines expertise from the scientific world and the pensions and insurance industry. The AG model is transparent and almost exclusively uses data from the public domain[1]. On the basis of the model documentation and the data used, the model can be copied, and the results reproduced. The Association has developed this model for the entire sector, thereby contributing to uniformity in the market.

1 – Covid-19 factors are an exception, as customised data obtained from CBS was used.

Mortality Research Committee

The committee consists of members with an academic background, members from the pensions and insurance sector with a technical background and members from these sectors with a managerial background. Mid 2022, the Mortality Research Committee consists of the following members:

B.L. de Boer AAG, chair
drs. C.A.M. van Iersel AAG CERA, secretary
M.J.A. Klein MSc AAG
prof. dr. B. Melenberg
drs. J. de Mik CFA AAG
drs. E.J. Slagter FRM
prof. dr. ir. M.H. Vellekoop, vicechair
ir. R.E.J.M. Waucomont AAG
M.A. van Wijk MSc AAG
ir. drs. M.R. van der Winden AAG MBA

AG Projections Life Tables Working Group

The Mortality Research Committee set up the Projections Life Tables Working Group with the task of supporting the Committee in the development of projection tables. Mid 2022, the Working Group consists of the following members:

F. van Berkum PhD, chair
F.J. Cuijpers MSc AAG
ir. drs. J.H. Tornij
J.I. Tol MSc AAG
W. van Wel MSc AAG
K. Wittekoek MSc

The AG Projections Life Tables Working Group has performed various supporting analyses to achieve the AG2022 forecast. All calculations were independently validated to ensure the quality of the results.

Summary

With the publication of the Projections Life Table AG2022 the Royal Dutch Actuarial Association presents an assessment of the expected development of survival rates and life expectancy in the Netherlands. The result is a forecast of mortality probabilities per age for each future year for males and females. Projections Life Table AG2022 replaces Projections Life Table AG2020.

This projection model is relevant to, among others, pension funds and life insurance companies. The projection model can be used for the determination of the provisions held by pension funds and insurers, considering fund or portfolio specific mortality experience if desired. Pension benefits depend on the survival of a participant or spouse. Appraising these benefits requires an estimation of their future mortality rates.

The conclusion is that life expectancy is expected to keep rising, at a pace even slightly faster than anticipated based on Life Table AG2020. This means that provisions and contributions will go up compared to Life Table AG2020.

Exceptional years: 2020 and 2021

The past two years are a special period, because since the beginning of 2020 the corona virus circulates. This has impacted many areas and higher mortality made COVID-19 an important topic for the CSO in the development of AG2022.

At the time of publication of AG2020 (September of 2020) the first corona wave was dying out. After the publication multiple waves followed. The first intermediate publication in July 2021 did not lead to any adjustment of the projection table in view of the prevailing uncertainty about how COVID-19 would develop.

In this biennial publication much attention is paid to effects of COVID-19, but in addition some other issues were investigated:

- The **country criterion** was revisited;
- The **closing method** of the projection table was evaluated and adjusted.

Country criterion

The projection model uses not only Dutch mortality data, but also mortality data from a selection of European countries. These are countries that, as is the Netherlands, are above average in prosperity. For the AG2022 publication, the decision was made to use the same set of countries used in previous publications. In previous publications an above average gross domestic product (GDP) was used as the country selection criterion. The current numbers lead to the same selection of countries, but if in years to come other countries meet the above average GDP criterion, this will not automatically lead to a different selection of countries. Evidently, we will continue to monitor developments in European countries.

Closure method

Because for higher ages not enough observations are available to reliably model survival probabilities, a so-called closure mechanism is used. With AG2014 the Kannisto closure method was introduced to close for higher ages in each projection year. This application of the method was studied further, also in light of signals received from some users of the publication. In the projections, mortality probabilities decline over time. Our application of the Kannisto closure method as of AG2014 however has the mortality rates rising for ages around 100 and over, with life expectancy converging to a limit (which is known in advance). As a consequence of this the uncertainty in the projections declines with the duration of the projection. Our research has yielded a new closure method that shows mortality improvements for higher ages too.

Impact COVID-19 in 2020 and 2021

COVID-19 mainly impacted ages 55 and over, sparing lower ages. Unabridged application of the AG2020 model to data from the COVID-19 years means that the time effect parameters determine the impact of COVID-19, while the age effect parameters hardly change. This would lead to a significant excess mortality for lower ages in the projections, while the observations for ages up to around 55 do not justify this.

The CSO has decided to adapt the Projection Model AG2022 to the new reality. At the time of writing this report, the prevailing views on COVID-19 are as follows:

- The impact of COVID-19 may continue for some time.
- The severity of the symptoms has declined (since the ascent of the omicron variant).
- The high vaccination density curtails the number of infections and the severity of the infections.

As a result of these developments the COVID-19 virus has become less lethal since the start of the pandemic.

Much uncertainty remains regarding COVID-19 and its impact on life expectancy and there are many questions that we are as yet unable to answer accurately:

- What new variants will emerge and what is the severity of these variants' symptoms?
- Has the impact of COVID-19 on hospital occupancy also impacted (i.e., delayed) the treatment of other conditions causing a higher expected death count?
- To what degree are COVID-19 and influenza mortality correlated? In 2020 no flu epidemic occurred, thanks in part to the measures such as social distancing and wearing face masks.
- To what extent will we experience enhanced resilience?
- Will contracting COVID-19 or not impact the course of other condition in the (mid to) long term?

Projection Model AG2022 – impact excess mortality due to COVID-19 in 2020 and 2021

AG2020 model with EU2019 update

For modelling, the original AG2020 model was used until January 1st, 2020, while the period as of January 1st, 2020 was modelled separately. The original Projection Model AG2020 is re-estimated after adding European data of the year 2019 (the last year without COVID-19) and updates of all other data points, where applicable)[2]. These data were not yet available at the construction of the AG2020 projections table. Adding and updating the data leads to a rise in life expectancy compared to the original Projections Life Table AG2020, because mortality in Europe in 2019 was below the expected values.

Impact COVID-19: excess mortality 2020 and 2021

The data for the COVID-19 years is used to model excess mortality 2020 and 2021. Projection Model AG2020 features a European factor and a factor that quantifies the Dutch deviation from European mortality. For the excess mortality, only Dutch data is considered. There are several reasons for this.

- The approach to COVID-19 differs between European countries. The differences cause a higher or indeed lower impact of COVID-19 in the countries around us.
- At the European level we have mortality data on a weekly basis that is not age specific, only deaths in five-year age classes. For the Netherlands we do have age specific data.

2 – Incidentally adjustments are made retro-actively to mortality data in particular. These adjustments are in general minor and therefore have little impact on the results. Hence, in the remainder of this publication we speak only of adding European data for the year 2019, implying any retroactive updates to both Dutch and European data in case of adjustments in the data or data sources.

The COVID-19 effect is estimated on the basis of weekly Dutch CBS mortality data over 2020 and 2021, by age and sex. By adjusting the data for seasonality – more people die in winter than in summer- the excess mortality effect can be determined as a time effect (for 2020 and 2021) that, combined with the age effect, yields a surcharge on the estimated mortality. This age dependent excess mortality has a totally different shape than the age effects from the AG2020 model: in the AG2022 model only higher ages show a distinct age effect and the age effect for ages below 55 is set to zero. This is consistent with observed mortality in 2020 and 2021, which presents very little excess mortality due to COVID-19 for this age group. Through this modelling approach the mortality probability projections for ages under 55 are not impacted by COVID-19.

Expected development of COVID-19 life expectancy impact

In view of the uncertainty around the impact of COVID-19, a number of likely future scenarios has been analysed and considered. Based on current information, the Committee has selected one specific scenario, in which the impact of COVID-19 on survival rates disappears over time. COVID-19 may still be a life-threatening disease, but the Committee expects little or no lasting effect on long term life expectancy. This implies that in the model the impact of COVID-19 on life expectancy disappears after several years and we revert to the situation of the pre COVID-19 period. The half-life used is 1 year, so that after every year only half of the COVID-19 impact remains, compared to the previous year.

Summary of model adjustments

The adjustments to model and data are:

a. Adding European 2019 data to Projection Model AG2020;
b. Improvement of the closure method;
c. Adding a temporary COVID-19 effect for ages 55 and up based on excess mortality in 2020 and 2021.

Effects on cohort life expectancy, provisions and contributions

The table below presents the effects of the new projections table and shows that life expectancy at birth increases for men and women: for men with 0.5 years and for women with 0.9 years. The remaining life expectancy at age 65 goes up 0.2 years for both men and women.

Cohort life expectancy in 2023	At birth		Age 65	
	Male	Female	Male	Female
AG2020	89.5	91.9	20.2	23.1
Addition of EU2019	0.2	0.3	0.1	0.1
Closure method	0.3	0.6	0.1	0.1
COVID-19-effect	0.0	0.0	0.0	0.0
AG2022	90.0	92.8	20.4	23.3

Table of remaining cohort life expectancy in 2023

The rise is mainly caused by adding the 2019 data point for Europe and adjustment of the closure method.

The impact of adding a temporary COVID-19 effect is next to zero. In chapter 4 the results are explained further.

The conclusion is that life expectancy is expected to continue to rise and even at a slightly faster rate than was expected before on the basis of Projections Life Table AG2020.

The table below shows the change in the provision for an average pension fund (average age 55) at a 3% and 1% interest rate.

Effect provision average fund	**3% interest rate**		**1% interest rate**	
	Male	**Female**	**Male**	**Female**
Addition of EU2019	0.4%	0.4%	0.5%	0.5%
Closure method	0.2%	0.3%	0.4%	0.5%
COVID	0.0%	0.0%	0.0%	0.0%
Total	**0.6%**	**0.7%**	**0.9%**	**1.0%**

For an average pension fund the provisions increase by around 0.7% at a 3% interest rate. The increments are a few tenths of a percent higher at 1% interest rate.

The effect on contributions exceeds the effect on provisions. At 3% interest rate the increase for an average fund is 0.6% to 1.1%, depending on the survivor's pension cover. At 1% interest rate the increase is 1% to 1.5%.

1

COVID-19 and the impact on the mortality table

1.1 Data points used in Projection Model AG2020

In the previous publication (Projections Life Table AG2020) the following survival data was used:

- **The Netherlands** up to and including 2019;
- **Europe** up to and including 2018.

These are the data known at that time. The corona virus has introduced a new cause of death, starting early 2020. During the period when there were no protective measures to prevent infections or to mitigate the effects after contamination, the corona virus caused a significant excess mortality in certain age categories, attributable in part to COVID-19 and in part to indirect consequences of COVID-19.

The mortality data used for Projections Life Table AG2020 did not include any excess mortality related to COVID-19. The Projections Life Table AG2020 publication did show initial sensitivity analyses for the effects of COVID-19 based on the excess mortality data of the first half of 2020. At that time the decision was taken not to adjust the projections table.

Mid 2021 the CSO performed an intermediate analysis. For this analysis the excess mortality relative to the AG2020 projection model's 'best estimate' was modelled as an additional term that we calibrated to the weekly data available at that time (i.e., all weeks of 2020 and the first 10 weeks of 2021). The committee concluded from this analysis that an intermediate update was not necessary[3].

3 – Commissie Sterfte Onderzoek, 2021. *AG2020 en de impact van de COVID-19-pandemie: Over- en ondersterfte sinds januari 2020.* Koninklijk Actuarieel Genootschap

1.2 Adding new data: excess mortality not evenly spread across all ages

For Projections Life Table AG2022 more data are available. The data points that would normally be added for a projection in 2022 (year data Europe 2019 and 2020 and Netherlands 2020 and 2021) have, with the exception of Europe 2019, been impacted by COVID-19 related excess mortality. The pandemic has altered the pattern in the mortality data for 2020 and 2021. The excess mortality in 2020 and 2021 occurred mainly in higher ages. In chapter 2 this is illustrated in graph 2.3.

1.3 Projection Model AG2020 cannot be used without adjustments

Projection Model AG2020, which projects trends from the past into the future, cannot be used as is for the mortality data for 2020 and 2021, in view of the age specific consequences of COVID-19.

The AG2020 projection model forecasts mortality rates using two elements: the age dependent factors (A, Alpha, B and Beta parameters) and a projection of the development of time effects aggregated over age groups (K and Kappa time series).

Without adjustments the AG2020 projection model will place the 2020 and 2021 excess mortality almost exclusively in the K and Kappa time series, as the age-dependent parameters (A, Alpha, B and Beta parameters) hardly change after adding the years 2020 and 2021, if at all. This is because these two years have limited impact compared to the dozens of earlier years of data. This means that in the unadjusted model the excess mortality is attributed to all ages according to the pre-COVID age effects, rendering a higher predicted mortality for all ages compared to the AG2020 projections. Ages below 55 also show higher mortality, although excess mortality hardly occurs in these age groups. Higher ages present a higher mortality, but less so than is to be expected based on the observations in 2020 and 2021. Clearly, modelled mortality does not match what we observe in the 2020 and 2021 data.

1.4 Projection Model AG2020: excess mortality in the Netherlands modelled separately

We opted for a model that models excess mortality starting in 2020 in the Netherlands separately. This applies to excess mortality relative to expected mortality based on the trend estimated on the basis of pre-corona data (in the AG2020 projection model). This excess mortality is for the most part, albeit not fully, caused directly or indirectly by COVID-19. When calibrating the model in 2020, the European 2019 data was not yet available to us. It is now. Therefore, the AG2020 projection model was recalibrated, including the European data for 2019.

We have only two years of data to quantify excess mortality in 2020 and 2021. To mitigate this, we first used a model with weekly data. Subsequently, the weekly results were aggregated to annual effects for males and females.

We have looked into the possibility of modelling excess mortality in Europe and the Dutch deviation separately. However, we elected to model Dutch excess mortality only, because:

- Waves of COVID-19 infections did not occur simultaneously across Europe.
- Measures against COVID-19 varied, both in terms of lockdowns and in vaccine roll outs.
- In Europe weekly mortality data is only available in 5-year age group, whereas Dutch data is available for each age.

And so, the separate "Excess mortality 20-21" term is an additional element in the projection model.

1.5 Which excess mortality scenario is the most suitable?

For the forecast as from 2022 an additional element was added to the projections from the AG2020 model (recalibrated after inclusion of European 2019 data): the projection of excess mortality, modelled from 2020 onwards. As only two years of data are available to us, it is uncertain whether the development of excess mortality in those years also represents the development in the future. Therefore, we need to select the scenario that we consider the most likely at the time of writing of this publication. Based on scientific literature and experts' statements on COVID-19[4] the CSO has defined a number of scenarios. These scenarios represent expected excess mortality development. Excess mortality is defined relative to mortality as forecast in the AG2020 model, recalibrated to include European 2019 data).

1. **Structural**: Excess mortality as observed is structural, in other words mortality in 2020 and 2021 is indicative of mortality in years to come.
2. **One off**: Excess mortality is incidental and will not occur in years to come (not even in 2022). The forecast will in this case more or less match the pre-corona forecasts.
3. **Fade out**: The impact of COVID-19 will decline and eventually disappear.
4. **New normal**: The impact of COVID-19 will decline, but not disappear altogether. Excess mortality will stabilise to a fixed level.
5. **Growing**: In the (mid to) long term excess mortality will increase over the level in 2020 and 2021. This increase could be caused by a more deadly variant, postponed care, damage to the immune system and/or postponed mortality due to long COVID.
6. **Reintroduction**: Following a short-term decline, excess mortality will after a few years revert to the level of 2020-2021.
7. **Boosted immunity**: the weaker members of the population having died from COVID-19, the coming years will see lower mortality and/or COVID-19 has boosted the immune system, as a result of which influenza will also be less lethal in years to come. This creates an enduring effect on mortality rates.

4 – Stoeldraijer, L., de Regt, S., & van Duin, C. (2021, 12 16). Retrieved from CBS - Kernprognose 2021-2070: *Bevolkingsgroei trekt weer aan: https://www.cbs.nl/nl-nl/longread/statistische-trends/2021/kernprognose-2021-2070-bevolkingsgroei-trekt-weer-aan?onepage = true#c-3--Bijgestelde-veronderstellingen-en-resultaten-voor-geboorte--sterfte-en-migratie*;
– Woolnough, K., Dr Ivanovic, B., Kramer, S., & Busenhart, J. (2007). *Pandemic influenza: A 21st century model for mortality shocks.* Swiss Reinsurance Company;
– Wetenschappelijke Raad voor het Regeringsbeleid. (2021). *Navigeren en anticiperen in onzekere tijden*. Den Haag: KNAW

We have considered, discussed, and evaluated the impact of each of these seven scenarios. In addition, we have assessed which scenario we would consider most likely and what parameters would best describe the future. Clearly, how COVID-19 will develop over the coming years and what its impact on the survival rates of the Dutch population, is extremely uncertain.

As a committee we opted for the 'Fade out' scenario. In our opinion at this moment, it is most likely that COVID-19 is or soon will be endemic. We expect COVID-19 to precipitate increased mortality in the Netherlands (relative to the AG2020 model's 'best estimate'), but vaccines and other measures will curb excess mortality, so that the impact will be less than in 2020 and 2021 and excess mortality will eventually disappear.

CBS[5] makes a similar choice and in the base forecast 2021-2070 reports to have opted for a scenario in which COVID ceases to impact mortality as of 2023.

1.6 Parameters in the 'Fade out' scenario

How fast does the excess mortality fade and after how long is the effect of COVID-19 no longer present? These questions are not easy to answer on the basis of the current information. We have not found any literature or statements from experts that we can use to estimate the speed at which the impact of a virus disappears. The 'Fade out' scenario is implemented with an exponential decline with a one-year half-life. Based on this assumption, the impact of COVID-19 in the upcoming years is limited (which is consistent with the articles mentioned in subscript[4]) and is all but gone after 2026.

The impact on cohort life expectancy and the provisions of longevity products using a one-year half-life is quite limited. For risk products, risk insurance in particular, the effect is more prominent. An alternative, but similar choice of half-life in the 'Fade out' scenario will not lead to much higher or lower life expectancy and provisions for longevity products.

5 – Stoeldraijer, L., de Regt, S., & van Duin, C. (2021, 12 16). Retrieved from CBS - *Kernprognose 2021-2070: Bevolkingsgroei trekt weer aan: https://www.cbs.nl/nl-nl/longread/statistische-trends/2021/kernprognose-2021-2070-bevolkingsgroei-trekt-weer-aan?onepage = true#c-3--Bijgestelde-veronderstellingen-en-resultaten-voor-geboorte--sterfte-en-migratie*

2 Data

2.1 Data Netherlands and Europe are input for the projections model AG2022

To set the Projections Life Table AG2022, the following data was used:

1. Annual Dutch and European mortality data for 1970 to 2019;
2. Weekly Dutch mortality data for 2020 and 2021.

The reason for continuing to use mortality data from countries with a prosperity comparable to that of the Netherlands is twofold. Firstly, there is a positive correlation between prosperity and longevity. Also, the period life expectancy in these countries has shown a similar upward trend for decades now, as demonstrated in graphs 2.1 and 2.2.

We assume that the long-term increase of life expectancy in the Netherlands can be forecast more accurately and more robustly when using a wider European population. Adding European mortality data raises the number of observations from just over 0.1 million deaths annually in the Netherlands to over 2.6 million annual deaths in the selected European countries.

The COVID-19 pandemic has led to higher mortality in the Netherlands and in the selected European countries in 2020 and 2021. This deviant mortality pattern led to a model adjustment as discussed in the chapter 1. This model adjustment called for different data than was used to date. For the years 2020 and 2021 weekly Dutch mortality data per age was used.

2.2 European mortality data: selected countries

The projection model used not only Dutch mortality data, but also mortality data from several European countries. The set of countries used was first selected for the publication of Projections Life Model AG2014 and has not been changed since. This group of countries will be used again for publications to come, unless developments occur that warrant a different selection to be made.

Prosperity and ageing are positively correlated[6]: the higher the level of prosperity, the older people get. When selecting the countries at the time, Gross Domestic Product (GDP) was the measure of prosperity and countries were selected that had a (sustained) above average per capita GDP. The Netherlands, along with the selected countries, is a country where prosperity is at a high level.

The selection of countries consists, besides the Netherlands, of Belgium, Denmark, Germany, Finland, France, Ireland, Iceland, Luxemburg, Norway, Austria, the UK, Sweden and Switzerland.

As time progresses, other countries may also exceed the above average GDP threshold, or countries may drop below it. As mortality data from the selected countries is used from 1970 onwards, the fact that a country would currently show an above average prosperity, while in the past it did not, is not sufficient reason to add that country to the set. Equally it would not be right to remove mortality data from a country from the data set as soon as this country presents a lower GDP, while it did have an above average GDP in the past. The set of countries (see Figure 2.1) provides a solid basis in the historical timeframe used. Therefore, the current set of countries will continue to be used, unless major development cause us to decide otherwise. As it happens, applying the country criterion at present would not change AG2022, because the criterion would allow no new countries in, nor would it exclude a country from the selection.

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

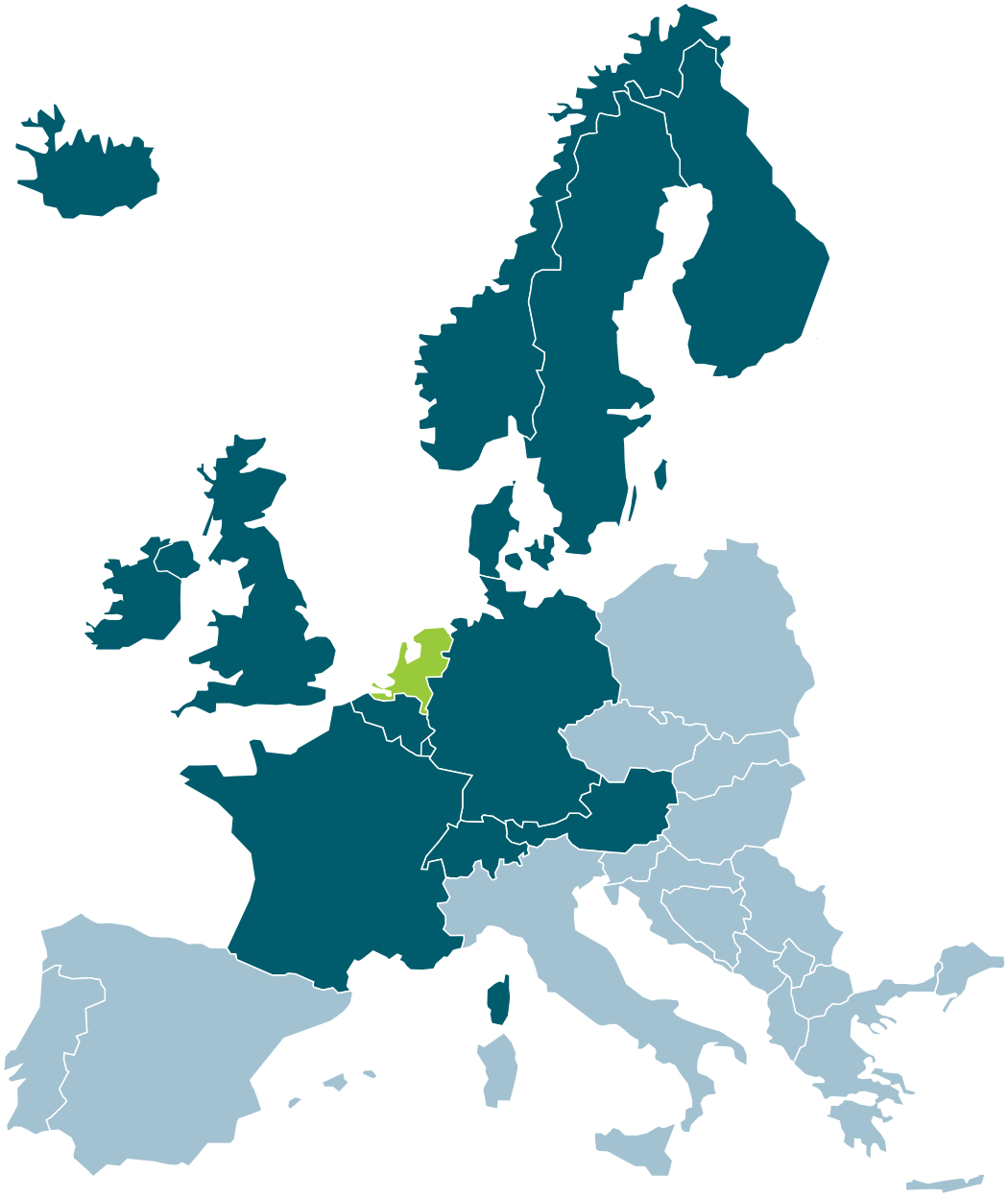
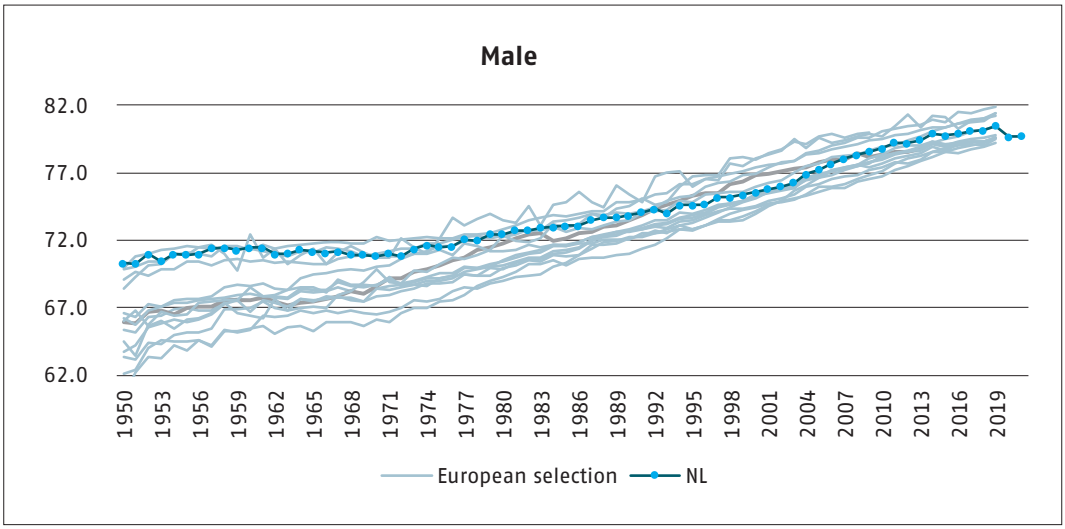


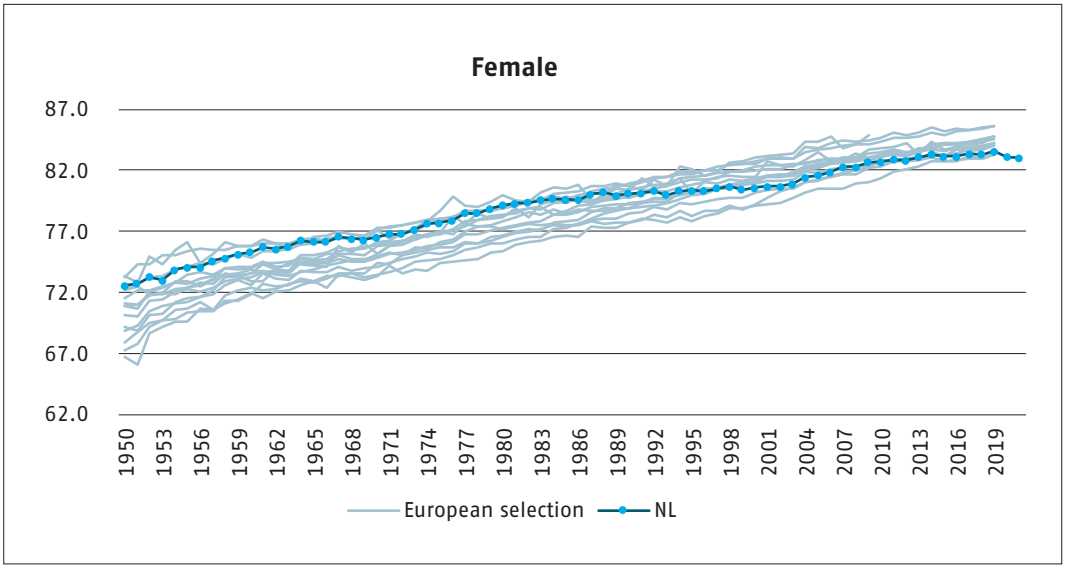
Figure 2.1 shows the group of selected countries underlying the AG2022 projection model.

2.3 Data range

Graphs 2.1 and 2.2 show the historical development of period life expectancy at birth in the Netherlands and the selected European countries as from 1950. The graphs demonstrate that in the first part of this period life expectancies in the selected countries are quite far apart, for males in particular. From 1970 onwards a steady trend is visible in the life expectancies of both males and females. To estimate the European section of the model, in which the Netherlands is also represented, data from 1970 up to and including 2019 is used. For the Dutch deviation, data from 1983 through 2019 is used.



Graph 2.1 – Period life expectancy at birth, male



Graph 2.2 – Period life expectancy at birth, female

Graphs 2.1 and 2.2 show, that life expectancy in the Netherlands has gone up less than the average over the selected European countries. This applies in particular to women, from the early 1980's onwards. The difference between Dutch and European women is even more noticeable when looking at the underlying mortality probabilities. For this reason, as with AG2020, the Dutch deviation from the European mortality trend is modelled from the year 1983.

In the years 2020 and 2021 period life expectancy in the Netherlands is down from the year 2019, which is caused by COVID-19.

2.4 Data for COVID-19 years

Mortality in the years 2020 and 2021 deviated from previous years as a consequence of the COVID pandemic. Graph 2.3 shows that the numbers of deaths in the Netherlands in the years 2020 and 2021 are much higher than in previous years.

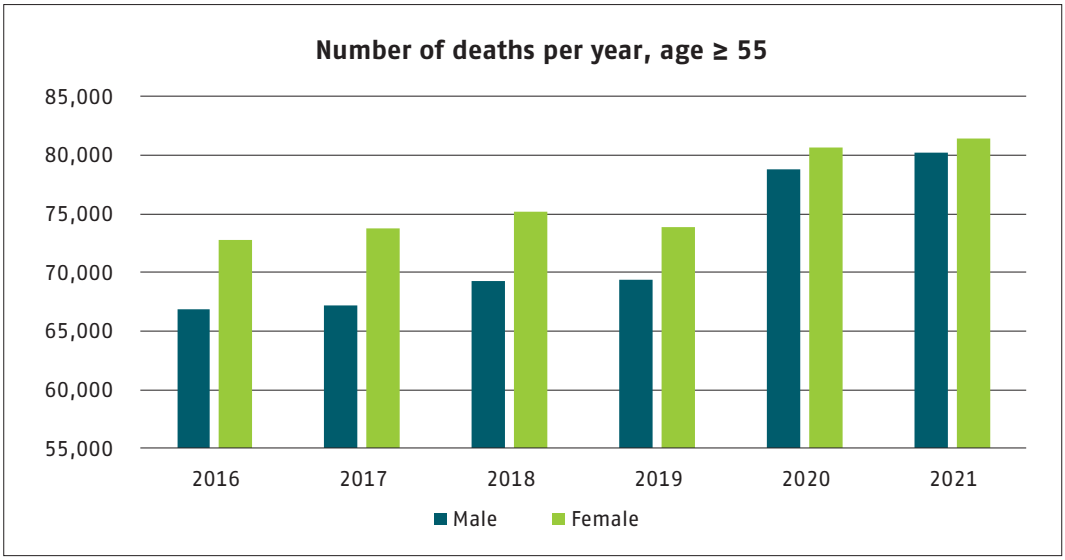
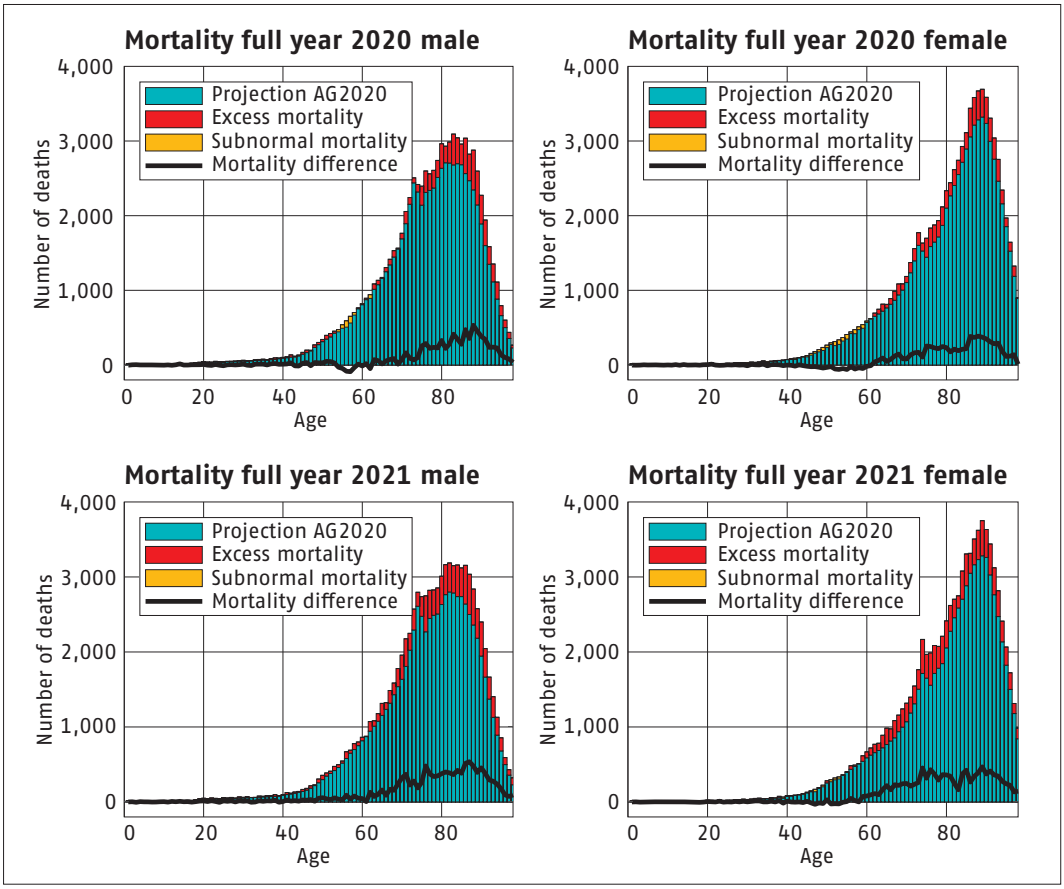


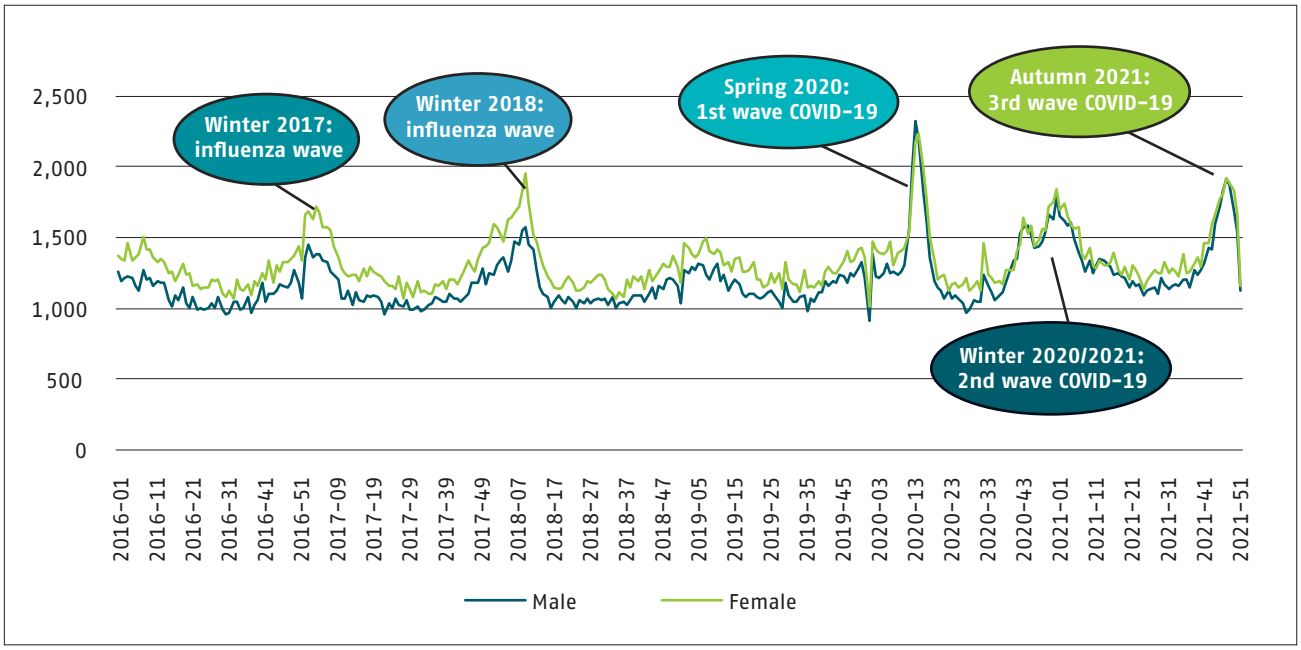
Figure 2.2 – number of deaths per year in the Netherlands 2016-2021 for males and females. Source: weekly mortality data from CBS

In figure 2.3 we present the incurred mortality in the Netherlands in the years 2020 and 2021 compared to the expected mortality according to Projections Life Table AG2020. This shows that for both years and both sexes observed mortality exceeded expected values from around age 55 up (excess mortality). It also shows that excess mortality was higher for men than for women and higher in 2021 than in 2020. For ages below 55 hardly any differences are seen.



Figures 2.3 – number of deaths in 2020 and 2021, male and female relative to the AG2020 forecast

The figures 2.3 show that mortality in 2020 and 2021 was higher than in previous years and higher than projected in Projections Life Table AG2020. Graph 2.3 focuses on week-by-week mortality. It features the mortality spikes caused by COVID-19 in recent years. It also shows the waves of influenza in 2017 and 2018. Compared to these flu waves COVID-19 related deaths give higher spikes (first wave) and more sustained spikes (second wave), which flare up quicker (three waves in a one-and-a-half-year timespan). These three effects have caused the COVID-19 related mortality to be higher than flu mortality in earlier years, which helps to explain that the total observed mortality was higher than expected.



Graph 2.3 – number of deaths per week in the Netherlands 2016-2021 for males and females, excluding incomplete weeks at the start and the end of a year. Source: weekly mortality data from CBS

2.5 Data sources: Human Mortality Database, Eurostat, CBS and statistical sources in the UK

The data was obtained from the Human Mortality Database (HMD), supplemented with data from Eurostat for years and countries missing in HMD. For the UK the dataset was augmented with data from local statistics agencies for the year 2019, because this information is no longer available in Eurostat (see Appendix D).

The Dutch data for observation years up to and including 2019 was also taken from HMD. Mortality in 2020 and 2021 on a weekly basis was obtained from CBS through a customised query. Regular CBS data was used for the population size in the Netherlands in 2020 and 2021.

The information from these sources is regularly supplemented and sometimes also adjusted retroactively. The data set used (with the exception of the customised data), in the shape of mortality frequencies and exposures for both the Netherlands and the group of selected Western European countries can be found on the AG website and totals almost 120 million deaths. Figure 2.4 shows how, for the year 2019, these deaths are spread across the various countries.

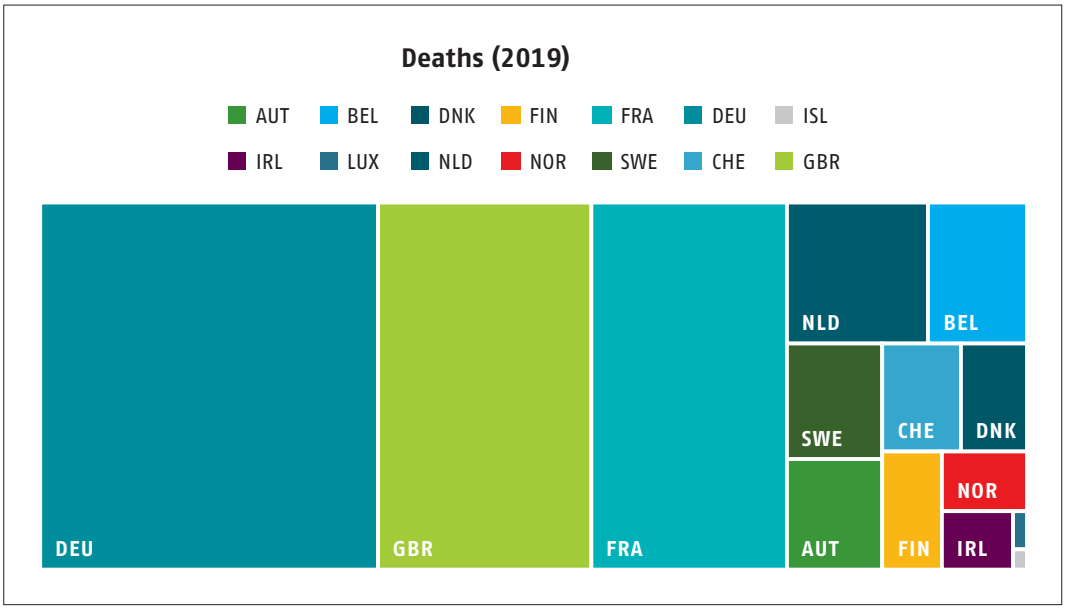


Figure 2.4 – Spread of deaths (male plus female) in 2019 by country

The weekly mortality data for the Netherlands in 2020 and 2021 was not published on the AG website, as this is a customised CBS query.

3

The projection model

In 2020 and 2021 some age categories presented a considerable excess mortality, attributable partly to COVID-19 and partly to indirect consequences of COVID-19. The committee therefore decided to adapt the AG2020 estimation method for AG2022. This chapter first discusses the starting points for this adjustment. Then the new estimation method is explained. The model equations needed to estimate the model's parameters and to make projections, are in Appendix A. This chapter finishes with the adjustment of the closure method.

3.1 Excess mortality as a direct and an indirect result of COVID-19

Assumptions

For AG2022 we estimate the direct and indirect impact of the COVID-19 pandemic on the survival rates as of 2020, to include this in the forecast as from 2022. We compare observed mortality in the years 2020 and 2021 to expected mortality based on data before 2020, to gain an insight into the impact of the COVID-19 pandemic.

To do this, we first analyse excess and subnormal mortality in 2020 and 2021 at week level. Then we transform the model results at week level to year level. To quantify excess mortality from 2020 per week, we must also determine how the annual (2020 and 2021) mortality forecast is distributed across the weeks within these years. The distribution is not uniform: on average there are more deaths during the cold winter months and less during the summer. This seasonal effect must be modelled if we want to determine the impact of COVID-19. We use a data set provided by CBS, which represents historical weekly Dutch mortality by sex and single age.

The excess or subnormal mortality in 2020 and 2021 strongly depends on age. As it stands, it has been established globally that the currently known variants of the virus share the property of increasing the risk of dying only for the elderly. Younger people can fall seriously ill and have long lasting symptoms, but death of persons below 55 as a result of an infection hardly ever occurs. Hence, we describe the effect of COVID-19 on mortality probabilities in terms of an *additional age effect* and an *additional time effect*. By doing so, we opt to represent the effect of COVID in a structure that is similar to that of the models for European and Dutch mortality intensities that are used to describe pre-pandemic mortality in AG2020.

Following this choice, the procedure to attain a forecast of future survival rates in the Netherlands consists of the following three steps:

1. An estimate of the **mortality intensities by age at the start of 2020**, based on pre-pandemic data sets. This regards an update after adding European 2019 data to the AG2020 parameter values A_x^g, α_x^g, B_x^g and β_x^g which descibe the age effects for ages x and the time series K_t^g and κ_t^g which describe the development over time (for year t and sex g).

2. An estimate of the **increase or decrease of those mortality intensities by age over all weeks in 2020 and 2021**. This is first expressed in a new age effect $\mathfrak{V}_x^g$ and new time series at week level $\mathfrak{K}_{w,\,2020}^g$ and $\mathfrak{K}_{w,\,2021}^g$ for all weeks w in the years 2020 and 2021. These age and week effects are then transformed into year effects $\mathfrak{X}_{2020}^g$ and $\mathfrak{X}_{2021}^g$, with ancillary age effects at annual level.

3. The final forecast combines the **projection of the existing time series** K_t^g and κ_t^g (the future run off of the European trend and of the Dutch deviation from that trend) with the **projection of the new time series at annual level** $\mathfrak{X}_t^g$ (the future run off of the effects of the pandemic).

Each of these elements is discussed below. We will consistently estimate the age parameters for ages up to and including 90. For higher ages we use a closure method. This differs from the closure method used for AG2020 and earlier models. The new closure method will be discussed at the end of this chapter.

Estimation of mortality intensities at the beginning of the pandemic

To create a 'best estimate' of the mortality probabilities at the beginning of 2020, we use the same estimation procedure as in AG2020. We do have a larger data set, because European 2019 is now available. Also, the data for some countries was updated with new values from the Human Mortality Database.

The method used to derive updates to the AG2020 parameters at the start of the pandemic using new European data is added for reference in Appendix A. This method does not differ from the approach for AG2020, and the assumptions remain unchanged. Men and women again have their own mortality probabilities and development thereof, and the developments in the Netherlands and the rest of Europe are jointly modelled. Potential dependencies between processes are described by correlations which are part of the calibration. And as before the parameters are calculated with a maximum likelihood method, that provides a distinction between observed mortality frequencies and the underlying mortality probabilities, by explicitly modelling the difference ('measurement noise').

For ages x (until 90), years t after 1983 and sexes g the maximum likelihood estimation yields estimated results for the following **pre-COVID mortality intensities** for Europe and the Netherlands:

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

The mortality intensities are built from the same combinations of age dependent factors and time series as before. Projection of time series for $t \geq 2020$ is done by fitting a random walk with drift and a first order auto regressive process with one constant to the extended data set[7]:

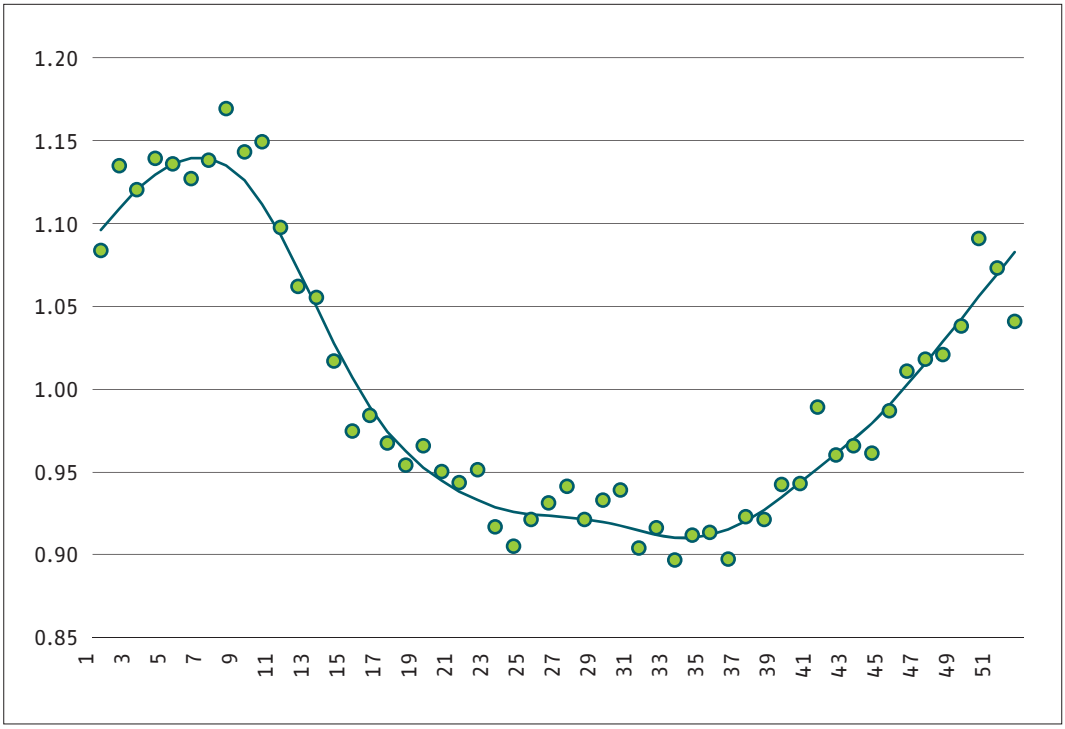
$$K_t^g = K_{t-1}^g + \theta^g + \epsilon_t^g$$
$$\kappa_t^g = a^g \kappa_{t-1}^g + c^g + \delta_t^g.$$

As in AG2020, 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 4x4 covariance matrix C.

7 – Commissie Sterfte Onderzoek, 2020. *Prognosetafel 2020*. Koninklijk Actuarieel Genootschap.

Estimation of the increase and decrease of mortality intensities in 2020 and 2021

Because for 2020 and 2021 weekly data instead of annual data is analysed initially, we first determine the seasonal effect to allow for the fact that mortality is not spread uniformly across the weeks in a year. We do this by averaging the mortality per week in the Netherlands over the years 2016 through 2019, for both sexes and over all relevant ages (between 55 and 90). A 'cyclic cubic spline' was fitted to the values for the historical average weekly mortality derived in this way. The fit is normalised for both 2020 and 2021, setting the average effect over all weeks (week 1 to 53 in 2020 and week 0 to 52 in 2021) to 1. The estimated effects $\phi_{w,2020}$ and $\phi_{w,2021}$ are shown in Graph 3.1. A distinct seasonal pattern emerges here, with mortality being higher on average in winter months than in the summer.



Graph 3.1 – Seasonal patterns in mortality 2016–2019

Estimation of the excess and subnormal mortality per week in 2020 and 2021

To describe the deviation in mortality in 2020 and 2021 relative to what is expected on the basis of data before 2020, we introduce a new time effect $\mathfrak{V}_x^g$ and new (week-based) timeseries $\mathfrak{K}_{w,2020}^g$ for 2020 and $\mathfrak{K}_{w,2021}^g$ for 2021. We add the product of this age effect and the time series to the logarhythm of the mortality intensities for these years. The seasonal effect determined earlier is also added. This turns the new weekly mortality intensities on a logarhythmic scale into the sum of three factors: the pre-pandemic estimate for a given year (a model AG2020 update with datapoints until 2019), a seasonal effect for a given week and a new factor representing the impact of the altered circumstances since the pandemic:

$$\ln\left(\mu_{x,w}^g(t)\right) = \ln\left(\mu_x^{g,\text{pre-covid}}(t)\right) + \ln\left(\phi_{w,t}\right) + \mathfrak{V}_x^g \mathfrak{K}_{w,t}^g .$$

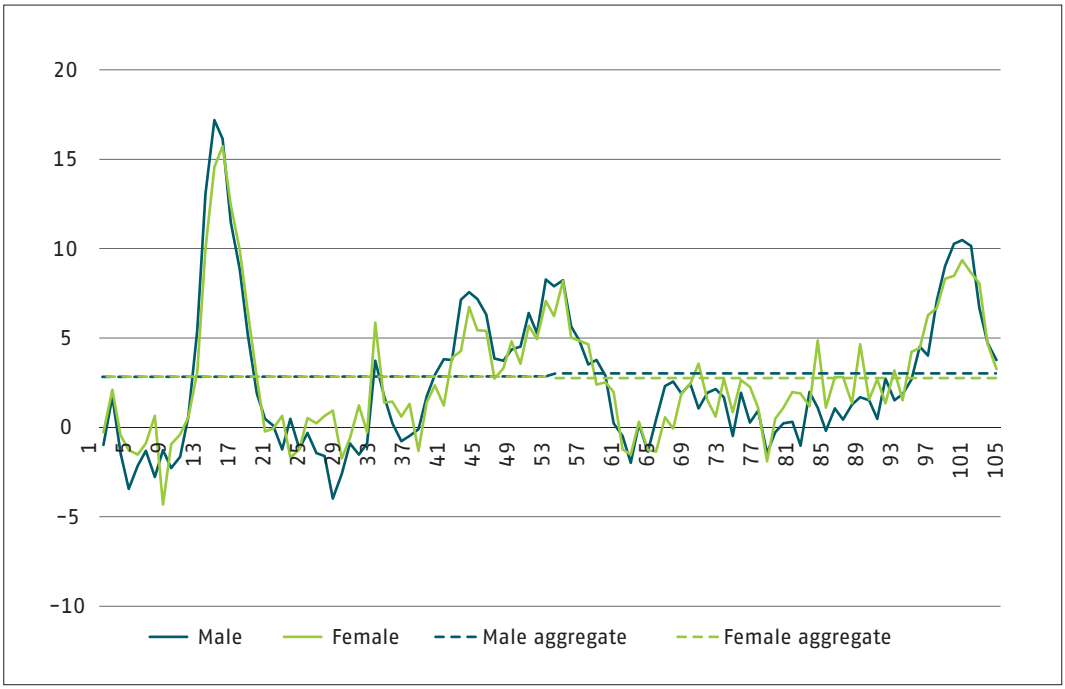
Number of deaths per week and by age, $D^g_{x,w,2020}$ and $D^g_{x,w,2021}$, stem from the dataset provided by CBS. The exposures per week and by age, $E^g_{x,w,2020}$ and $E^g_{x,w,2021}$, were determined by applying linear interpolation to Dutch population levels at the beginning of each month during 2020 and 2021.

This completes the data required to estimate the factors representing excess and subnormal mortality by week in 2020 and 2021. To do this, we maximise the likelihood associated with the specification

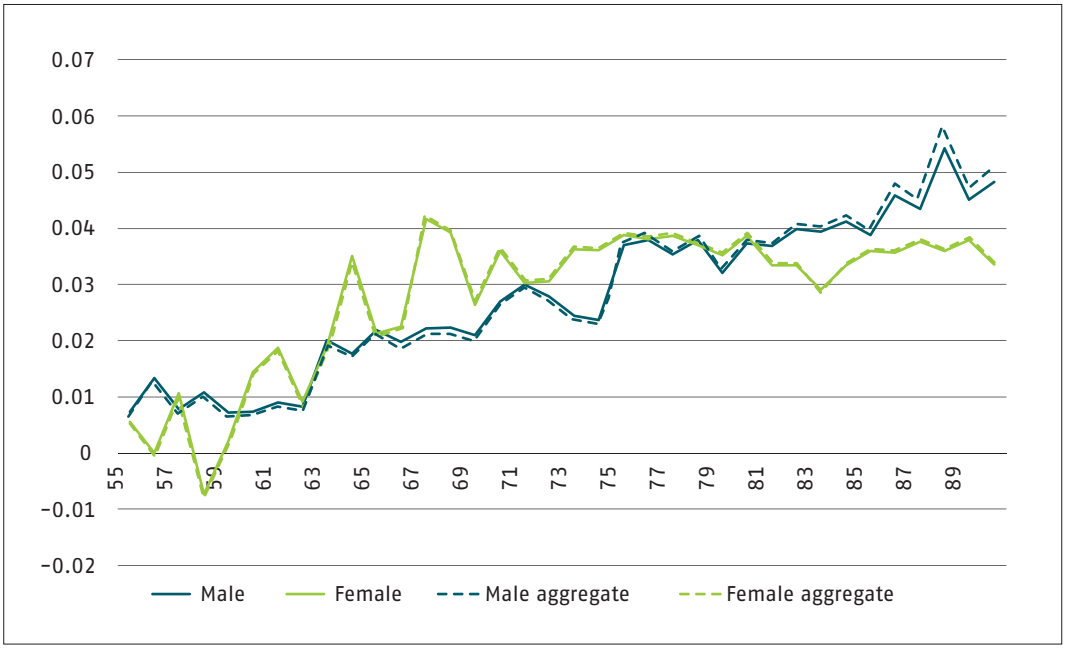
$$D^g_{x,w,t} \sim \text{Poisson}\left(E^g_{x,w,t}\,\mu^g_{x,w}(t)\right), \quad \mu^g_{x,w}(t) = \mu_x^{g,\text{pre-covid}}(t)\phi_{w,t}\exp\left(\mathfrak{V}^g_x\mathfrak{K}^g_{w,t}\right),$$

for all ages x between 55 and 90, years t equalling 2020 and 2021, all weeks w in these years and both sexes g. The choice to only look at these ages is prompted by the exceptionally small effects for ages below 55 and the relatively large uncertainty in the estimations for ages over 90. For this reason, the values of $\mathfrak{V}^g_x$ are set to zero for all ages below 55 and kept constant for ages over 90. We maximise the likelihood only for the parameters $\mathfrak{V}^g_x$ and $\mathfrak{K}^g_{w,t}$. The other parameters were not re-estimated but fixed to the values obtained earlier. For normalisation we use $\sum_{x=55}^{90}\mathfrak{V}^g_x = 1$.

These assumptions are reflected in the graphs below, showing the development of the new weekly time series $\mathfrak{K}^g_{w,2020}$ and $\mathfrak{K}^g_{w,2021}$ and the values of the new age effects $\mathfrak{V}^g_x$. The time series show the impact through time aggregated over all ages. The picture is consistent with a succession of different waves of infections, but periods of slightly subnormal mortality are also visible, even after adjustment for seasonal effects. In the development per age (graph 3.3) we see that the direct and indirect impact of the pandemic on mortality is particularly severe at higher ages. This supports the choice to model separate age dependent factors in the model as from 2020: the shifts in mortality probabilities in the years 2020 and 2021 cannot be adequately captured in the model by using existing age effects and only adding a shock to the time series (K^g_t and κ^g_t). This would generate a COVID-19 impact for younger ages comparable to or even higher than for the elderly.



Graph 3.2 – Time series COVID-19 factor. Covid-19 factor in the weeks of 2020 and 2021 aggregated to an annual level with the number of weeks since January 1st, 2020, on the x-axis. Note that the dotted lines for the aggregated values for males and females in 2020 are hardly distinguishable.



Graph 3.3 – Age effect COVID-19 factor

To generate a forecast with annually changing mortality probabilities, we aggregate the values for the weeks in 2020 and in 2021 to a single value that captures the effects for a whole year. These values $\mathfrak{X}^g_{2020}$ and $\mathfrak{X}^g_{2021}$ are included in graph 3.2 as horizontal lines. The are determined so, that the survival probabilities over the full years 2020 and 2021 exactly match the product of the survival probabilities per week in each of the

years. Details and exact assumptions made during the calculations can be found in Appendix A. The final **annual forecast** then becomes (with $\tilde{\mathfrak{B}}_x^g$ for the resulting annual age effect):

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

This forecast is made for the ages $x = 0,1,\cdots,90$, where $\tilde{\mathfrak{B}}_x^g = 0$ for all ages below 55 and normalisation is done by $\sum_{x=55}^{90} \tilde{\mathfrak{B}}_x^g = 1$.

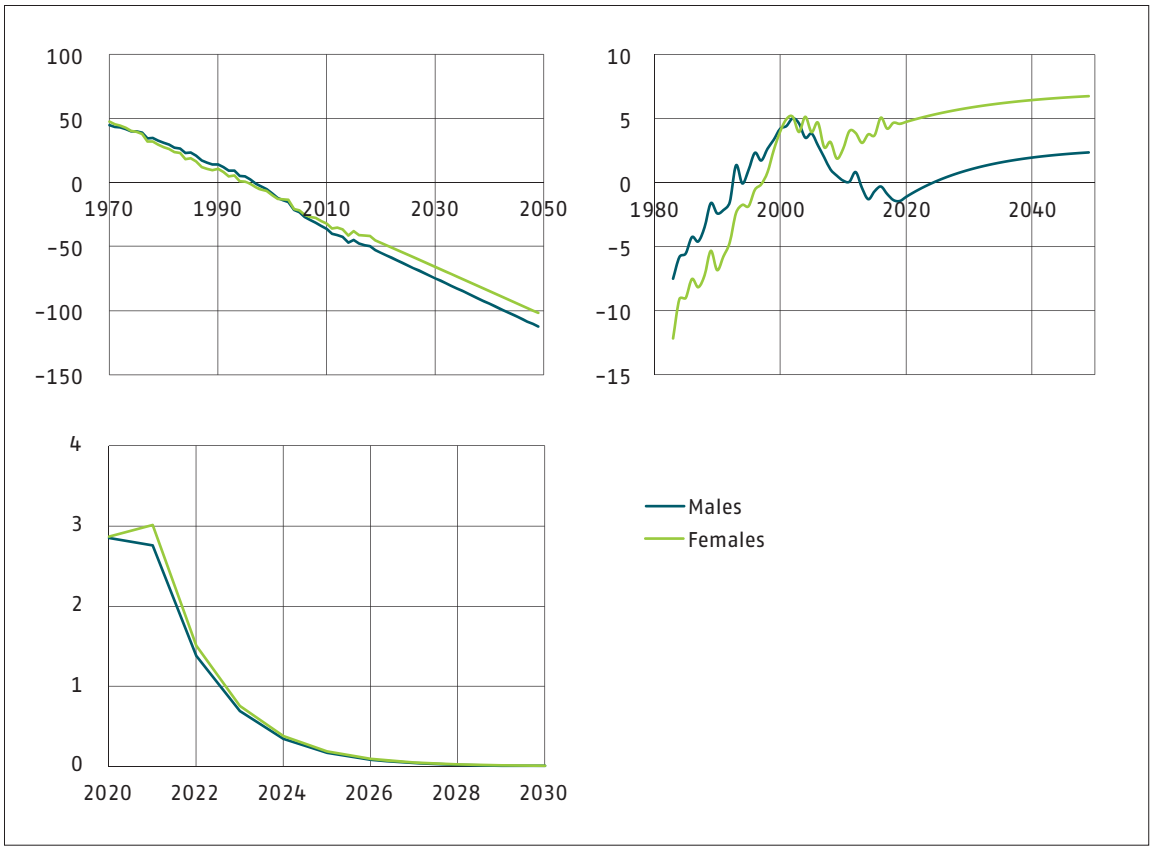
Forecast for future years

Given the parameter value estimates θ^g, a^g, c^g and covariance matrix C, we can now apply the equations given before to initial values K_{2020}^g and κ_{2020}^g to determine the development of the time series K_t^g and κ_t^g for $t \geq 2020$ including the projection years 2022 and after. To set values of the new time series $\mathfrak{X}_t^g$ for $t \geq 2022$ an assumption is required about the future development of the pandemic.

As CSO we have decided to decrease the impact of the deviation from the pre-pandemic estimations in 2020 and 2021 exponentially to zero as from 2021. This means that

$$\mathfrak{X}_t^g = \mathfrak{X}_{2021}^g \, \eta^{t-2021}, \; t \geq 2022,$$

With $\eta = ½$, which implies that the half-life of the impact equals one year. This assumption determines the 'best estimates' for all future values of the time series in the model.



Graphs 3.4 – Parameters AG2022: Time series and projections

In chapters to come the new survival probabilities and period and cohort life expectancies that the model produces are discussed, as are the effects on the levels of contributions and provisions. But first, we explain the new closure method which is used to supplement the parameter values for ages until 90, as calculated with the procedure described above, with parameter values for higher ages.

3.2 New closure method

In AG2020 and earlier projections life tables starting at AG2014 the closure method of Kannisto[8] (in short hereafter: Kannisto) was used to calculate mortality probabilities for high ages. Further research was performed, after receiving signals from some users of the publication. Two undesirable properties of this closure method came to the fore:

1. Not all ages show improved mortality over time. For higher ages mortality rises monotonously to a positive and limit value that is known with certainty. At the same time, mortality improvement is modelled for ages below about 100: there, mortality probabilities decrease monotonously to zero. As a result, life expectancy also converges to a limit value known with certainty.
2. Because of the limit values known with certainty, uncertainty decreases (smaller confidence intervals) over time, while we expect increasing uncertainty (wider confidence intervals).

We deem both the life expectancy limit value known with certainty and the decreasing uncertainty in life expectancy to be undesirable consequences of this application of Kannisto. Therefore, a new closure method was developed for Projections Life Table AG2022.

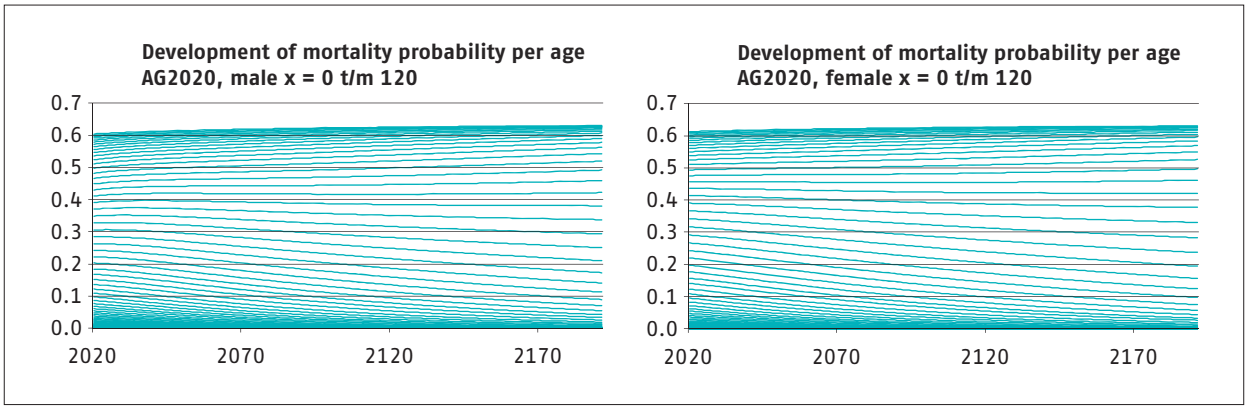
We first explain why the combination of the AG2020 model and this Kannisto application leads to the undesirable properties listed above. Then we describe the new closure method and show that the undesirable properties do not occur here.

Kannisto by projection year: illustration of the problem

According to AG2020 (and earlier projections life tables) the mortality probability at very high ages rises over time and converges to a limit value.

The lines in the following graphs signify the future ('best estimate') development of the mortality probability per age over time. For each age there is one line. Lower lines refer to lower ages, starting with 0. The higher lines represent higher ages ending at 120.

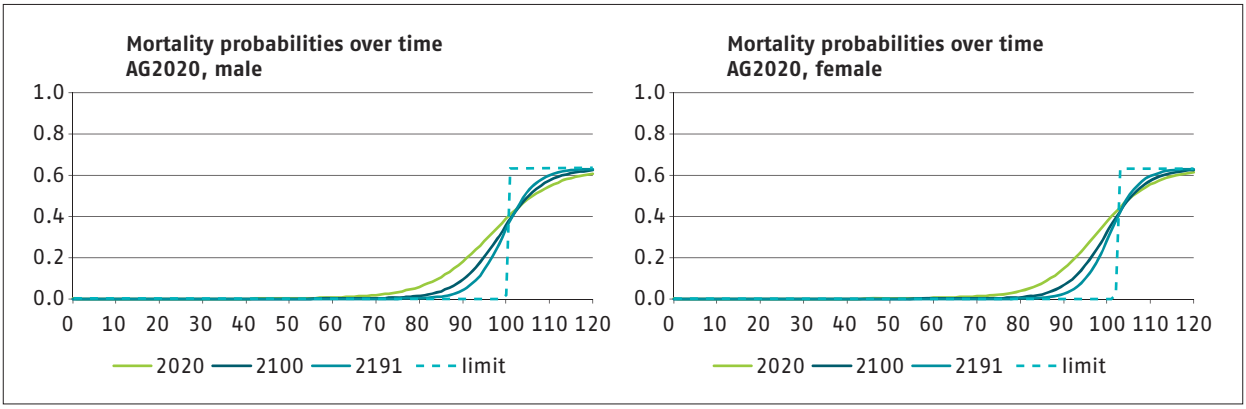
8 – V. Kannisto. (1992). *Development of the oldest – old mortality, 1950–1980: evidence from 28 developed countries.* Odense University Press.



Graphs 3.5 – Mortality probability per age over time (line) under Kannisto

For the ages 0 to 90 the mortality probability per age as modelled with Projection Model AG2020 decreases over time and converges to zero. For the ages 91 to 120 this is not always the case: from a certain age the mortality probabilities per age as extrapolated with Kannisto increase over time and converge to a non-zero limit.

The graphs 3.5 do not clearly show from what age the decrease turns into an increase. This is better demonstrated by looking at the development of mortality probabilities across the ages for a number of projection years in the following graphs (3.6).



Graphs 3.6 – Mortality probability per age (line) for progressive projection years

There is a tipping point at a certain age. Below this age, the mortality probability by age decreases over time (mortality improves), while above this age the mortality probability by age increases over time (mortality deteriorates). In the limit (dotted line) the mortality probability is 0 below the tipping point and above it $1 - e^{-1}$ (for a technical explanation of the limit value see Appendix B). The convergence of mortality probabilities to $1 - e^{-1}$ accellerates as time passes.

As a result of this, life expectancy converges to a limit known in advance and the confidence intervals around the life expectancy decrease, when normally uncertainty increases over time. These unwanted properties are illustrated in the remainder of this chapter by comparing to the new closure method.

We stress that these unwanted properties arise because we apply Kannisto *per projection year*, in other words an out-of-sample application of Kannisto. There is no objection to an in-sample application of Kannisto. As seen later, the new closure method indeed uses that.

New closure method

We have studied some alternative closure methods and opted for the method described below.

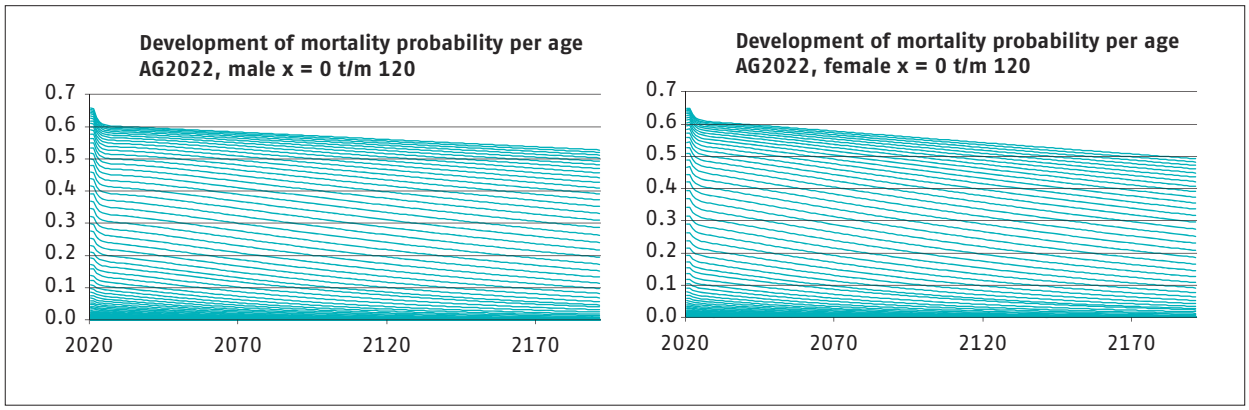
Under the old closure method, we apply Kannisto to extrapolate, by projection year, the *mortality* probabilities for ages 80 through 90 to ages 91 through 120. In the new method we extrapolate age dependent *parameter values* of the model. We do this as follows:

- First extrapolate B_x^g; then determine A_x^g by applying Kannisto to European data.
  - B_x^g is extrapolated by *linear* extrapolation of $\ln(B_x^g)$.
  - A_x^g is determined by applying the Kannisto extrapolation to European data from the latest sample period 2019.
- First extrapolate α_x^g; then determine β_x^g by applying Kannisto to the extrapolation of the Netherlands (= Europe + Dutch deviation) minus Kannisto applied to European data.
  - α_x^g takes *linear* extrapolation to $\alpha_{120}^g = 0$.
  - β_x^g is determined by applying Kannisto to data from the latest sample period.
- •Assume that the age dependent parameter for the COVID term is constant from age 90 upwards.
  - $\mathfrak{V}_x^g = \mathfrak{V}_{90}^g$, $x \geq 91$

In Appendix A the closure of the parameter values is explained in more detail. In the remainder of this chapter the consequences of the closure are illustrated graphically.

Desirable properties of the new closure method

In this paragraph we demonstrate that the unwanted properties as observed in the application of Kannisto by projection year do not occur with the new closure method. With this new method the development of one year mortality probabilities in Projections Life Table AG2022 looks as follows:

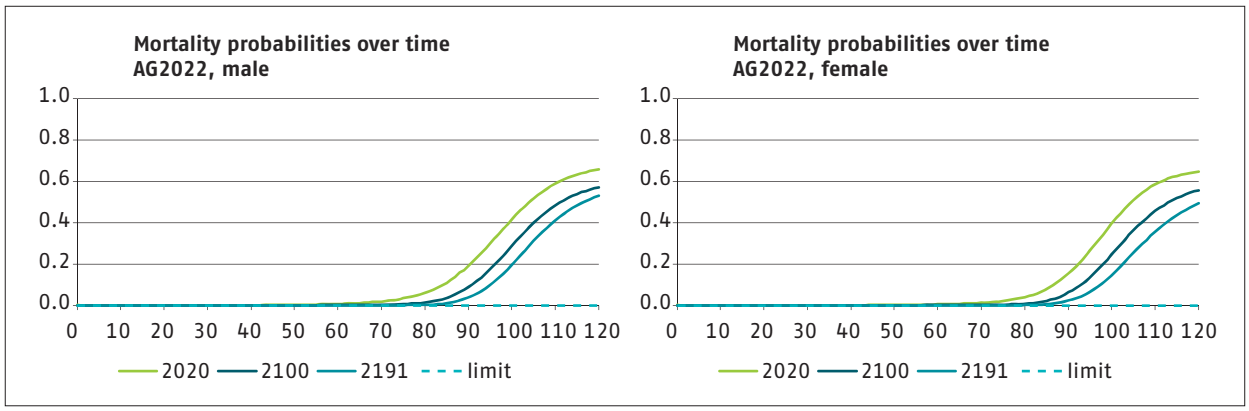


Graphs 3.7 – Mortality probability per age (line) over time with the new closure method

Now the mortality probability per age decreases over time for higher ages too. The new closure method impacts the calculations of cohort life expectancy, provisions or contributions for lower ages as well, because these calculations will now use lower mortality rates at higher ages.

Please note that mortality in the initial years of the projection has increased for higher ages in particular. This is the result of the COVID-19 modelling. This effect is strongest in 2020 and 2021 and disappears in later years.

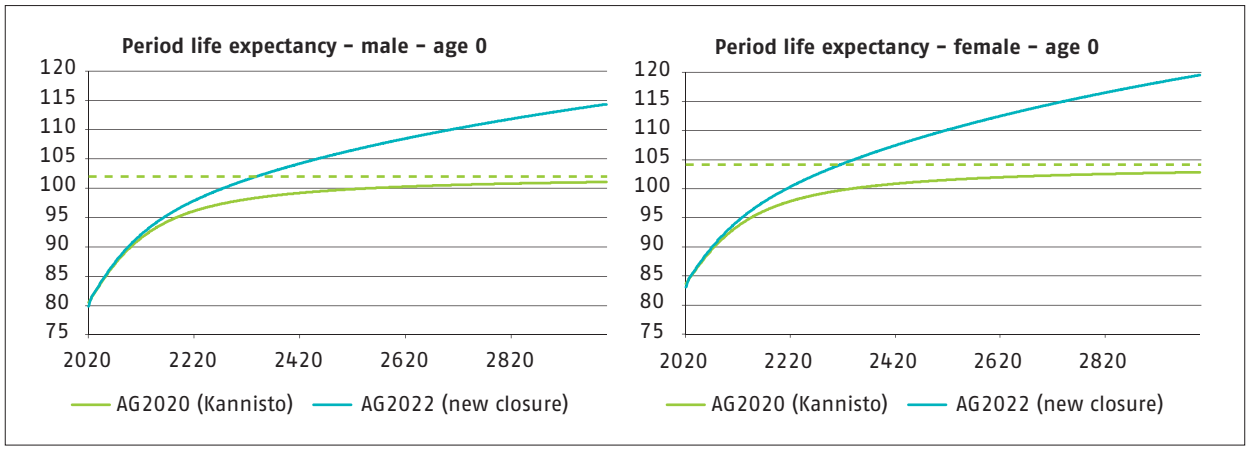
There no longer exists a tipping point at any age when we look at the development of the mortality probability across the ages for a selection of projection years:



Graphs 3.8 – Mortality probability by age (line) for selected projection years

For all ages the mortality probability decreases over time.

Graph 3.9 shows the period life expectancy at birth under the old and new closure methods[9]:

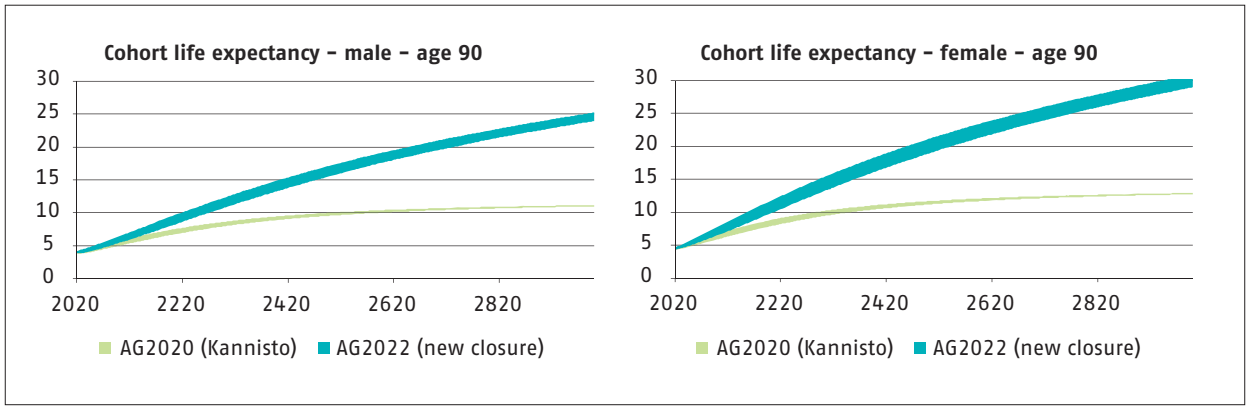


Graphs 3.9 – Period life expectancy at birth under AG2020 (Kannisto per projection year) versus AG2022 (new closure)

9 – We publish mortality probabilities to age 120. In practice, mortality probabilities for higher ages are set equal to the level at age 120. However, the mortality probability for these higher ages can also be set according to the new closure method. For this illustration we no longer cut off at age 120. That is, we look at the model instead of the published table.

When applying Kannisto per projection year there is a well-defined limit for life expectancy which is known in advance: we know the limit value to which the mortality probabilities converge (see Appendix A). With the new closure method life expectancy no longer converges to a limit.

Next, we look at confidence intervals. We zoom in on the ages directly impacted by the new closure method (ages above 90):



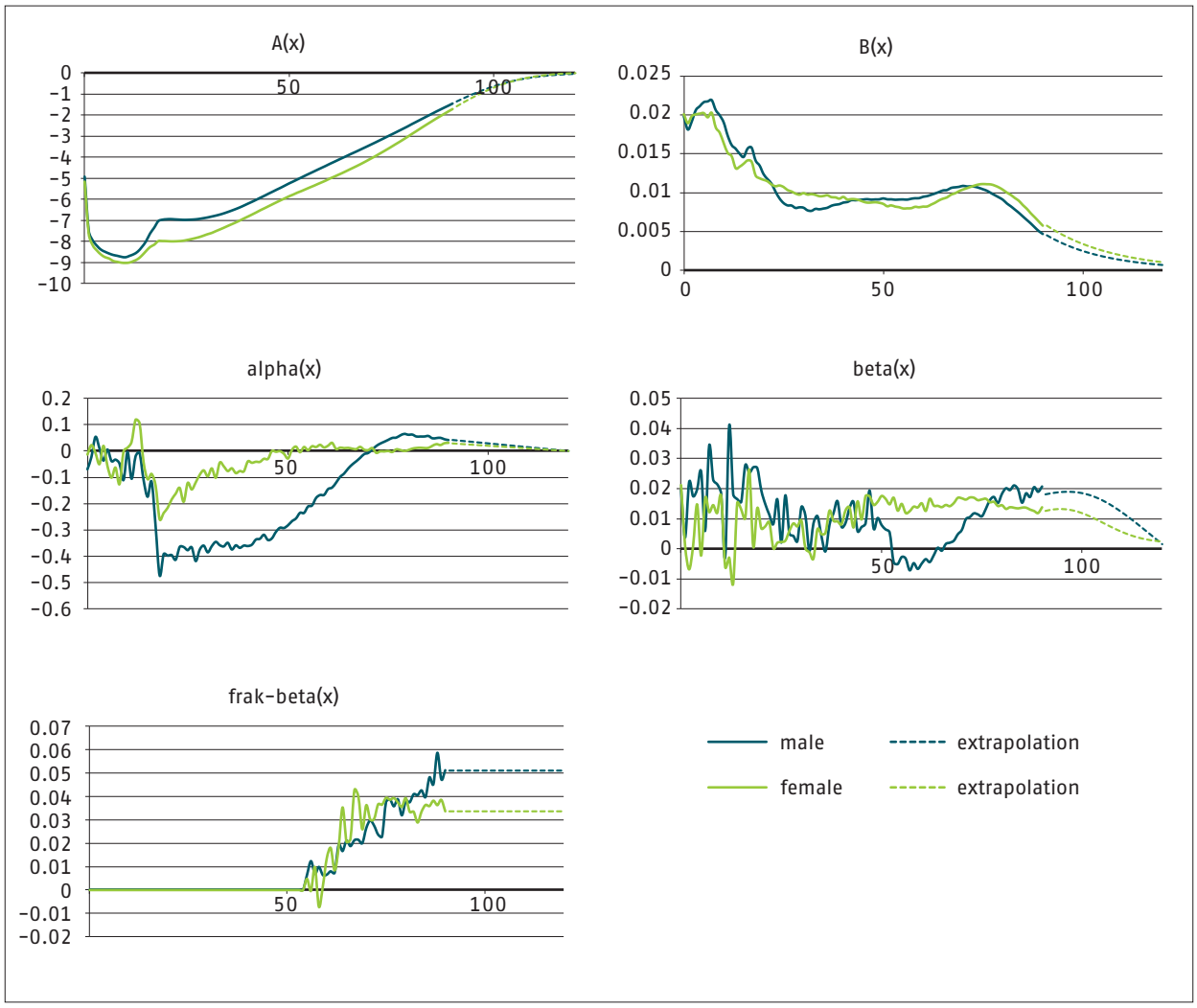
Graphs 3.10 – Cohort life expectancy under Kannisto versus new closure (inculding confidence interval)

The graphs 3.10 show that under the new closure methods the confidence intervals do not decrease.

We conclude that the new closure method lacks the unwanted properties we see when applying Kannisto per projection year: there is no longer a tipping point age, so for all ages mortality probabilities decrease over time and life expectancy does not have a limit known with certainty and this prevents confidence intervals from narrowing over time.

3.3 Parameter values derived for age effects

In the following graphs 3.11 we show the age effects, including the age effects for over 90s, resulting from the Li-Lee model, COVID-19 modelling and the new closure method. The continuous segments of the curves are the estimated values for ages until 90, the dashed segments show the extrapolations. These age effects are constant over time.



Graphs 3.11 – Age effect parameters

4

Consequences for life expectancy, provisions, contributions and retirement age

This chapter presents the results of Projections Life Table AG2022. The results are compared to those of Projections Life Table AG2020. For a number of example funds the effect on the level of the provisions is evaluated. With the aid of these example funds it is possible to assess the impact for other pension funds. In addition, the Projections Life Table AG2022 is discussed against the backdrop of historical developments and compared to the latest forecast by Statistics Netherlands (CBS 2021-2070).

4.1 Definitions of life expectancy

A classic definition of life expectancy is the so-called period life expectancy. This period life expectancy is based on mortality probabilities in a certain period, such as one calendar year, and assumes that mortality probabilities will be constant in the future. This definition is commonly used to compare developments over time but must never be used to estimate how long people are expected to live.

There is, however, a second definition, cohort life expectancy, which does take on board expected mortality developments. When calculating cohort life expectancy at birth, mortality probabilities are required for a new-born, a one-year-old a year from now, a two-year-old two years from now and so on. In cohort life expectancy, for probabilities you need in one- and two-years' time, you use mortality probabilities projected one and two years into the future. So, cohort life expectancy is based on expected developments in mortality probabilities. To evaluate cohort life expectancy, you need a forward projection of mortality probabilities.

In case of an expected decrease in mortality probabilities, cohort life expectancy is therefore higher than period life expectancy and signifies how old people may get, when allowing for future mortality development.

4.2 Observations with respect to AG2020

Tables 4.1 and 4.2 give the AG2020 and AG2020 forecast of period life expectancies for the years 2019 through 2025 and, for the years 2019, 2020 and 2021, show how these relate to the observed life expectancies. In this case, period life expectancy is used, as this can be used to compare life expectancies in a given observation year.

	Male			Female		
	Realised	**AG2020**	**AG2022**	**Realised**	**AG2020**	**AG2022**
2019	80.5	80.4	80.4	83.6	83.6	83.6
2020	79.7	80.5	79.9	83.1	83.7	83.0
2021	79.7	80.7	80.0	83.0	83.8	83.1
2022		80.8	80.5		83.9	83.6
2023		80.9	80.8		84.1	83.9
2024		81.1	81.0		84.2	84.2
2025		81.2	81.2		84.3	84.3

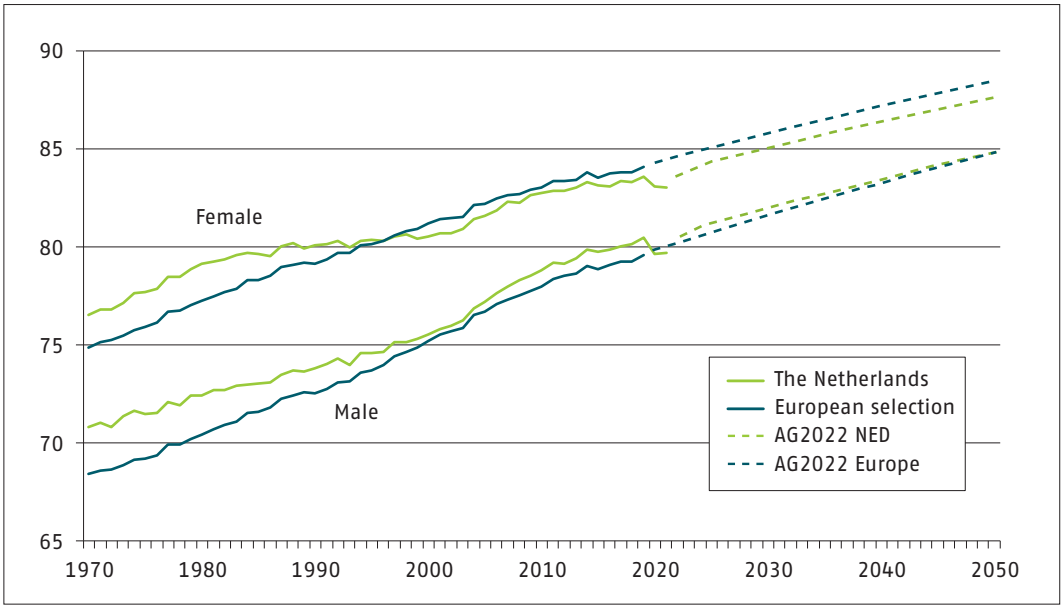
Table 4.1 – Period life expectancy at birth

	Male			Female		
	Realised	AG2020	AG2022	Realised	AG2020	AG2022
2019	18.8	18.7	18.7	21.3	21.3	21.3
2020	18.1	18.8	18.1	20.7	21.4	20.8
2021	18.2	18.9	18.2	20.8	21.5	20.8
2022		19.0	18.7		21.6	21.3
2023		19.1	18.9		21.7	21.6
2024		19.2	19.1		21.8	21.7
2025		19.3	19.3		21.9	21.9

Table 4.2 – Period life expectancy at age 65

The realised life expectancies in 2020 are below expectations based on the AG2020 forecast. This is caused by the COVID-19 pandemic in these years. The AG2022 forecast matches lower life expectancy in 2021 through the introduction of COVID-factors. Because these COVID factors are assumed to decrease exponentially, the lower life expectancy is temporary in nature. In 2025 period life expectancy, based on AG2022, is back to a level comparable to the previous forecast AG2020.

In graph 4.1 the development of period life expectancy at birth is given for the period up to 2050. Up to 2021 (for the European selection up to 2019), the graph is based on realised mortality, for the period thereafter it is the AG2022 forecast. This means that for the European selection the effect of COVID is visible in neither the realisation nor the forecast (a pre-COVID forecast).



Graph 4.1 – Period life expectancy Netherlands (including COVID term) and selected European countries (excluding COVID term)

In graph 4.1 the decline in life expectancy in 2020 and 2021, caused by COVID-19, is visible in the Dutch observations. Period life expectancy for Dutch women is, as in previous forecasts, below the same quantity in selected European countries. Life expectancy of Dutch men is, as before, above life expectancy of men in the selected European countries. For men the difference diminishes over time, while for women it remains roughly the same.

4.3 From AG2020 to AG2022

To further clarify the differences between the old and the new projections tables, both mortality probabilities and cohort life expectancy are used. The differences between AG2020 and AG2022 are explained by three components:

a. Adding European 2019 data to projection model AG2020.
b. Improving the closure method.
c. Adding a temporary COVID effect based on excess mortality in 2020 and 2021 for ages 55 and over.

Adding European 2019 data to projection model AG2020

The starting point of the AG2020 forecast is determined by the calibrated parameters for the year 2019, based on Dutch observations up to 2019 and European observation up to 2018. The time series parameter for Europe 2019 in AG2020 is determined by means of an extrapolation of the historical trend over the period from 1970 to 2018, starting from the 2018 parameter value. This historical trend is also applied in the forecast for the European selection.

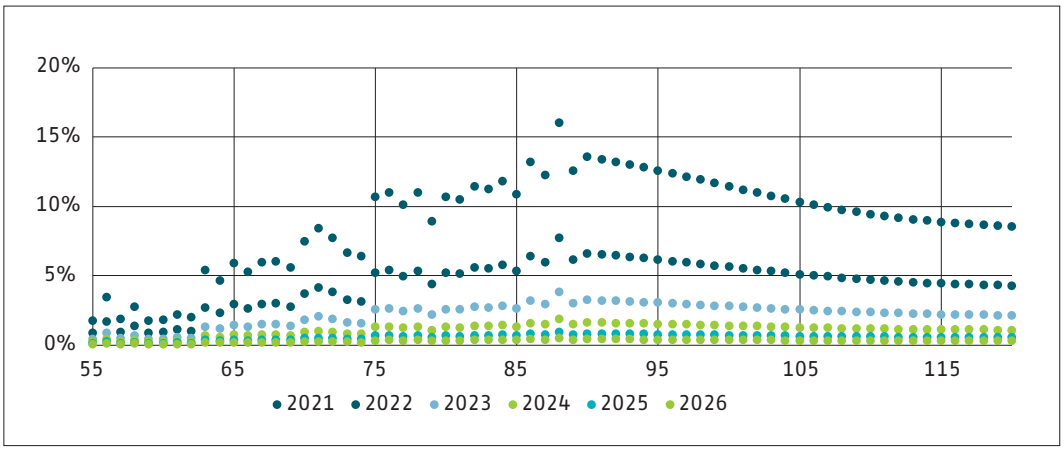
Only for Europe data from 2019 was added and these show that mortality probabilities have improved since 2018 more than was expected on the basis of the historical trend determined in 2018. This causes an increase in future mortality improvement and in life expectancy.

Improvement of the closure method

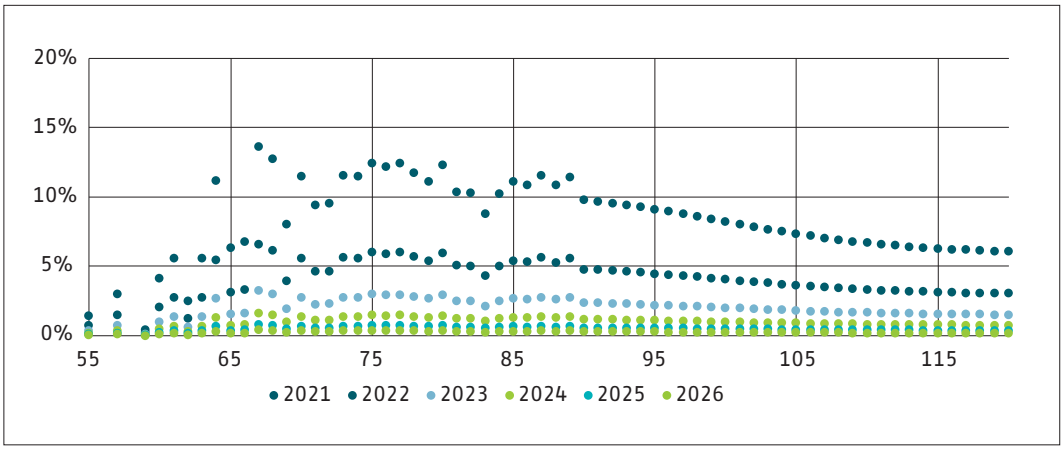
Mortality probabilities for ages over 90 change in the new forecast as a result of the improvement in the closure method. This causes decreased mortality probabilities relative to the rates following from the old closure method. Mortality rates for ages up to 90 are not affected by the new closure method.

Temporary COVID effect

The temporary COVID effect affects the forecast for ages from 55 upwards. Graphs 4.2 and 4.3 show how this effect impacts the forecast.



Graph 4.2 – Impact temporary relative surcharge mortality probability males becasue of COVID



Graph 4.3 – Impact temporary relative surcharge mortality probability females becasue of COVID

In the AG2022 forecast it is assumed that the COVID effect fades exponentially, assuming an annual halving onwards from 2021. In 2021 the mortality rate of a 65-year-old male came out around 6 per cent higher than expected (pre COVID). In the forecast the expectation is that in 2022 the mortality probability of a 65-year-old male is still around 3 percent higher than expected. In projection year 2026 the COVID effect according to the selected method will have diminished strongly, setting the average surcharge on the mortality probabilities for ages 55 and over at around 0.3 per cent. In subsequent years this further converges to zero.

Development of cohort life expectancy

Cohort life expectancy includes all future mortality developments. This paragraph gives a step-by-step breakdown of the impact of the components described before on cohort life expectancies for starting year 2023.

Table 4.3 shows that life expectancy at birth for both men and women goes up: for men with around 0.5 years and for women with around 0.9 years. The remaining life expectancy for a 65-year-old goes up by approximately 0.1 years for men and 0.2 for women.

Cohort life expectancy in 2023	At birth		At age 65	
	Male	Female	Male	Female
AG2020	89.47	91.88	20.24	23.07
Adding EU2019	0.21	0.29	0.08	0.13
Closure method	0.36	0.59	0.04	0.08
COVID	0.00	0.00	-0.01	-0.01
AG2022	90.04	92.76	20.35	23.27

Table 4.3 – Cohort life expectancy in 2023

Adding the 2019 datapoint for Europe partly explains the increase. Because observed European mortality has decrease more than was expected on the basis of the historical trend determined in 2018, life expectancy goes up. The adjustment of the closure method mainly impacts ages under 65 to a substantial degree. With the new closure method mortality probabilities for ages over 90 are lower than in the previous forecast. This affects the cohort life expectancy of people younger than 90 too. The effect is more severe for women than for men, because women on average live to a higher age and are therefore more likely to reach an age over 90.

The 'Fade out' scenario that was selected for COVID-19 generates a temporarily higher mortality probability for ages 55 and up, which decreases exponentially over time. In the selected starting year 2023 this additional mortality has halved twice already (i.e., to a quarter of the excess mortality modelled in 2021) and it will further halve in each of the years after. This means the impact on the cohort life expectancy of a 65-year-old in 2023 is almost nil.

Table 4.4 lists the future cohort life expectancies for starting years 2023, 2048 and 2073.

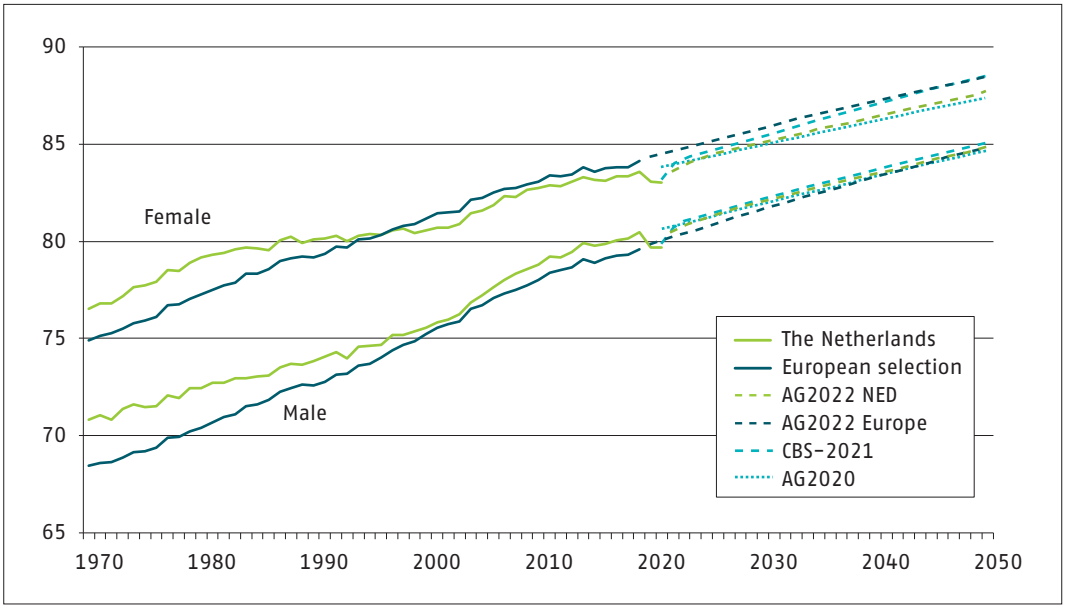
Starting year	At birth			At age 65		
	Male	Female	Difference	Male	Female	Difference
2023	90.0	92.8	2.8	20.4	23.3	2.9
2048	92.5	95.1	2.6	23.1	25.9	2.8
2073	94.5	97.0	2.5	25.5	28.1	2.6

Table 4.4 – Future cohort life expectancy based on AG2022

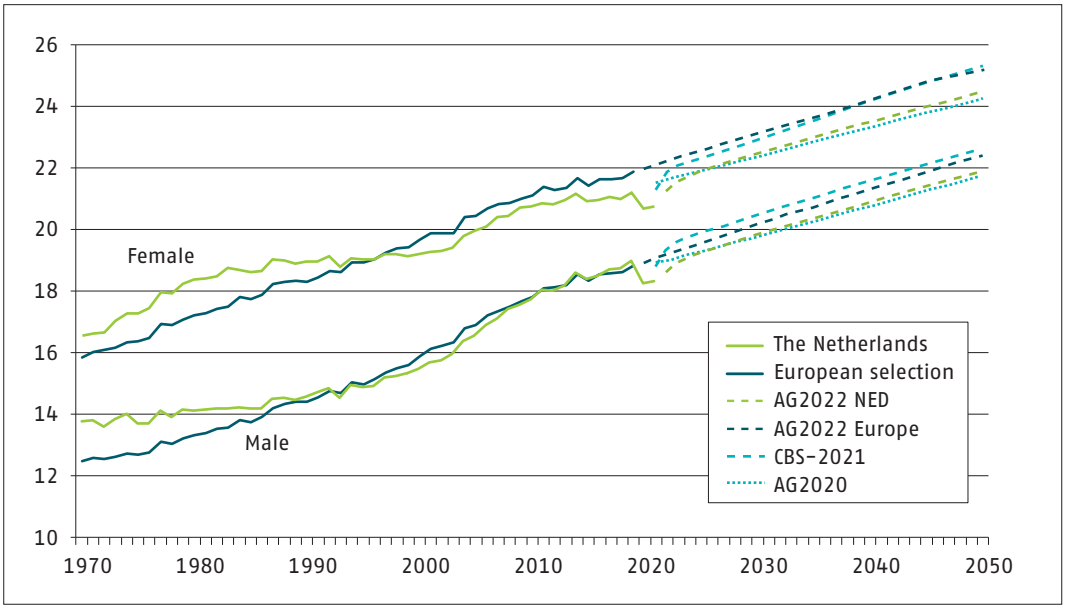
These figures show that according to the forecast life expectancy will continue to rise, slightly faster for men than for women. The difference in life expectancy between men and women will therefore decrease.

4.4 Forecast in perspective

Graph 4.4 compares the development of period life expectancy at birth for AG2020, AG2022 and CBS2021-2070. It shows that the AG2022 forecast was adjust upwards for the long term, bringing it closer to the CBS forecast. The trend of the AG2022 forecast for Dutch men converges to the male trend in the forecast for selected European countries, while for women the difference remains roughly the same.



Graph 4.4 – Development of period life expectancy at birth



Graph 4.5 – Development of period life expectancy at age 65

Graph 4.5 shows the development of period life expectancy at age 65. For men and women, it shows that the AG2022 forecast is initially below the AG2020 forecast due to the inclusion of excess mortality from COVID in the first few years. In later years the slight upward adjustment from adding European 2019 data and adjusting the closure method becomes apparent.

Table 4.5 lists the cohort life expectancies for AG2020, AG2022 and CBS2021–2070. The differences in cohort life expectancy at age 65 with CBS2021–2070 are lower for AG2022 than they were for AG2020.

Starting year 2023	At birth		At age 65	
Forecast	**Male**	**Female**	**Male**	**Female**
AG2020	89.5	91.9	20.2	23.1
AG2022	90.0	92.8	20.4	23.3
CBS2021	not available	not available	20.8	23.4

Table 4.5 – Cohort life expectancy for AG2020, AG2022 and CBS2021

Table 4.5 also shows that the difference in life expectancy at birth between men and women has increased since AG2020.

4.5 Link between life expectancy at age 65 and 1st and 2nd tier retirement age

The Raising of the State Pension Retirement Age and Standard Pension Retirement Age Act (Wet Verhoging AOW- en Pensioenrichtleeftijd) links the first tier (State pension) retirement age and the standard retirement age in the second tier (employers' pension schemes) to the development of period life expectancy.

The development of the State Pension retirement age and the standard retirement age using the latest views based on Projections Life Table AG2022 is summarised in graph 4.6. However, the actual adjustment of the State Pension age is linked to the CBS estimates, so the values shown are to be considered indicative.

Graph 4.6 – Fictitious development of State Pension retirement age and standard pension age based on AG2022

Raising the State Pension retirement age

Raising the State Pension age is done in three-month steps. The adjustments depend on the level of the average remaining period life expectancy at age 65, as estimated by CBS.

The Amendment of State Pension retirement age linking Act stipulates that the adjustments to the State Pension age after 2025 are based on 2/3rds of the expected rise in remaining life expectancy at age 65. Because the State Pension age is adjusted in 3-month steps, a minimum increase of 4.5 months in remaining life expectancy is required for a further adjustment (considering the 2/3^{rds} calculation).

For 2026 and 2027 it has already been decided that based on the CBS estimates the State Pension retirement age will not go up.

According to Projections Life Table AG2022 the State Pension retirement age will not move to 67 years and 3 months before 2029, because only then will the remaining life expectancy have increased by 4.5 months from the reference value of 20.64, laid down in law. Table 4.6 shows when the State Pension retirement age is expected to have increased by a full year. Projections Life Table AG2022 sets the raise of retirement age at a later moment than CBS.

Expected State Pension retirement age	CBS2021	AG2022
68	2038	2040
69	2051	2055
70	2067	2071
71	Not available	2089

Table 4.6 – Years when State Pension retirement age is expected to go up by a full year according to the latest CBS and AG forecasts

Raising the Standard retirement age

The raising of the standard retirement age (in one-year steps) in the second tier is based on the same formula as for the State Pension retirement age. By law however, expected increases in life expectance are to be anticipated sooner: it is to be based on the remaining life expectancy of a 65-year-old that is expected to occur ten years after the calendar year of the adjustment. An adjustment to the standard retirement age must be published at least one year before it is implemented. For instance, an adjustment of the standard retirement age in 2024 must be published before January 1st, 2023. This will be based on the remaining life expectancy of a 65-year-old in 2034.

The standard retirement age is expected to reach 69 only around the year 2045.

4.6 Effects on provisions

To plot the effects of Projections Life Table AG2022 on the technical provisions of pension portfolios six fictitious example funds have been constructed. Three of the funds have male participants and three have female participants. For both sexes a young, an old and an average fund has been constructed. An additional model portfolio was designed to assess the impact om pension contributions. See Appendix C for a description of the model portfolios.

Besides an old age pension (OAP) the example funds contain a deferred survivor's pension (SP) and a survivor's pension in payment. For male portfolios spouses receiving survivor's benefits are assumed to be females. For female portfolios the opposite applies. Further applicable assumptions are listed in Appendix C.

The model portfolios have a weighted (by provision) average age of 45 (young), 55 (average) and 65 (old). The effects are shown for interest rates 3 and 1%.

Effect technical provision	**Males**			**Females**		
3% interest rate	**Young**	**Average**	**Old**	**Young**	**Average**	**Old**
OAP (65)	0.7%	0.6%	0.3%	0.9%	0.7%	0.6%
Deferred SP	0.9%	0.8%	1.0%	0.2%	0.3%	0.4%
SP in payment *	0.5%	0.4%	0.5%	0.3%	0.3%	0.3%
Total	**0.7%**	**0.6%**	**0.5%**	**0.9%**	**0.7%**	**0.6%**
1% interest rate	**Young**	**Average**	**Old**	**Young**	**Average**	**Old**
OAP (65)	1.0%	0.8%	0.5%	1.3%	1.1%	0.9%
Deferred SP	1.7%	1.4%	1.4%	0.8%	0.8%	0.7%
SP in payment *	0.7%	0.7%	0.7%	0.5%	0.5%	0.4%
Total	**1.2%**	**0.9%**	**0.7%**	**1.3%**	**1.0%**	**0.8%**

Table 4.7 – Impact on model portfolio provisions of a transition from AG2018 to AG2020 (difference AG2020 minus AG2018 expressed as percentage of AG2018). The separate percentages as listed for OAP and SP do not add up to the percentages in the total lines. This is caused by the difference in the provisions for the separate benefits.

* The effect on the provisions of survivor's pensions in payment refer to the sex of the surviving partner.

As table 4.7 demonstrates, the adjustment is larger for women than for men. This shows in the higher impacts on women's old age pensions than on men's. A related effect shows in the deferred survivor's pensions, where the provision for men increases more than for women due to the stronger decline in mortality for the female partners after the death of a male participant in comparison with male partners of female participants.

Table 4.7 shows that the impact on technical provisions is substantial. For an average fund the provisions at 3% interest go up by around 0.6 to 0.7 per cent. The impact across the model funds varies, in terms of total technical provisions, between 0.5 and 0.7 per cent for men and 0.6 to 0.9 per cent for women. At 1% interest the lower interest rate causes a larger impact than at 3%.

The impact on pension scheme contributions for the model portfolio is listed in table 4.8.

Effect pension contributions	3% interest rate		1% interest rate	
	Males	Females	Males	Females
OAP (68)	0.9%	1.1%	1.1%	1.5%
OAP + 70% deferred SP accrual	0.8%	1.0%	1.2%	1.4%
OAP + 70% deferred SP risk	0.6%	1.0%	1.0%	1.4%

Table 4.8 – Impact on model portfolio contributions of a transition from AG2020 to AG2022 (difference AG2022 minus AG2020 expressed as a percentage of AG2020)

The impact on contributions exceeds the impact on provisions due to a longer average projection horizon and shows an increase of contributions of 0.6 to 1.1 percent at 3% interest rate and an increase of 1.0 to 1.5 percent at 1% interest rate. These effects are relative to the contribution itself. If contributions are, e.g., 25%, the effect corresponds to 0.3 percentage points of contribution.

In table 4.9 the impact on technical provisions from AG2020 to AG2022 for an average portfolio is broken down into three steps, at 3% and 1% interest rates.

Effect Technical provision Average fund	3% interest rate		1% interest rate	
	Males	Females	Males	Females
Adding European 2019 data	0.4%	0.4%	0.5%	0.5%
Closure methode	0.2%	0.3%	0.4%	0.5%
COVID	0.0%	0.0%	0.0%	0.0%
Total	**0.6%**	**0.7%**	**0.9%**	**1.0%**

Table 4.9 – Impact on technical provision for average model portfolio

It shows that more than half the increase is explained by the addition of European 2019 data and the remainder by the adjustment of the closure method. The impact of COVID-19, in terms of effect on provisions, is zero.

Table 4.10 shows the effect on technical provisions for each of the benefits separately at various ages. Consistent with the impact on the provisions for the model funds, the impact of the new table on OAP is more severe at lower ages.

Effect Technical provision	Males		Females		Males	Females
3% interest rate	OAP	Deferred SP	OAP	Deferred SP	SP in payment*	SP in payment*
25	1.0%	1.2%	1.4%	0.2%	0.2%	0.3%
45	0.8%	0.8%	1.0%	0.2%	0.3%	0.4%
65	0.4%	0.9%	0.5%	0.5%	0.4%	0.5%
85	-0.2%	1.6%	0.4%	-0.1%	-0.2%	0.4%
1% interest rate	OAP	Deferred SP	OAP	Deferred SP	SP in payment*	SP in payment*
25	1.4%	2.5%	1.9%	1.3%	0.4%	0.6%
45	1.0%	1.6%	1.3%	0.8%	0.5%	0.7%
65	0.5%	1.3%	0.7%	0.7%	0.5%	0.7%
85	-0.2%	1.7%	0.5%	-0.0%	-0.2%	0.5%

Table 4.10 – Impact on technical provision by age and sex from AG2020 to AG2022 (difference AG2022 minus AG2020 expressed as a percentage of AG2020)

* The effect on provision for survivor's pension in payment refers to the sex stated in the header of the column.

5 Uncertainty

The projection model AG2022 presented in this publication is based on mortality data from the past. Developments observed in the historical data, are projected into the future as best we can. The future being uncertain, values obtained for actual mortality in the Netherlands in the next few years will deviate from the best possible estimations we can give at this moment. The CSO chooses to also partly explore this uncertainty.

5.1 Types of uncertainty

In general, we can distinguish four types of uncertainty:

- **Model uncertainty**
- **Parameter uncertainty**
- **Process uncertainty and**
- **Micro-longevity risk.**

For the confidence intervals presented later in this chapter, the CSO chose to **only model process uncertainty**, based on Projections Life Table AG2022 without the COVID term. Model uncertainty is not modelled explicitly; there is a comparison of Projections Life Table AG2022 with some alternative projections to give an impression of the scale of model uncertainty. Parameter uncertainty and micro-longevity have been disregarded completely. Taking all these types of uncertainty into account fully and in conjunction would widen the confidence intervals considerably. The confidence intervals presented are therefore a lower boundary of the actual uncertainty.

At the same time, we would point out that our model represents a stochastic scenario generator. The AG2022 model is therefore a *starting point*, not an end point for modelling and quantifying uncertainty. Reproducability and minute documentation ensure that anyone can use the model (with or without COVID factors) to add their own scenarios to those generated by the AG2022 model for process uncertainty.

Model uncertainty

As any other model, the AG2022 projection model is a simplified representation of reality. This means that we cannot with certainty state that the chosen model in actual fact provides a correct specification of future mortality developments.

In scientific literature methods are known to formalise this model uncertainty. Including model uncertainty would require the specification of a class of alternative models. The CSO decided not to model this explicitly.

The results of alternative projections tables (AG2020 and CBS2021) and the results of alternative COVID scenarios included later in this chapter do provide an indication of the level of model uncertainty. However, this by no means covers the full extent of model uncertainty; there is, after all, a myriad of alternative model specifications. Moreover, these alternative model specifications have not been studied in conjunction with the other types of uncertainty (parameter uncertainty, process uncertainty and micro-longevity risk). The actual uncertainty around future mortality development will therefore be considerably higher.

Parameter uncertainty

The parameters in the AG2022 projection model are estimated from observed deaths, that comprise a limited sample. This implies that there is also uncertainty in the parameter estimates in the projection model. As a matter of fact, the distinction between parameter and model uncertainty is somewhat arbitrary. Parameter uncertainty

quantifies specific model uncertainty (within the model class of choice), whereas model uncertainty can sometimes be classified as parameter uncertainty through an appropriate choice of parameters.

There is scientific literature that indicates the standard way to quantify parameter risk for some implementations of the Lee-Carter of Li-Lee models[10]. This literature does not yet suit the AG2022 model.

Parameter risk can be charted by way of bootstrapping. This is a statistical method based on a so-called resampling technique, in which for a given set of parameters a large number of possible deaths from the connected Poisson distribution are simulated. For each of these samples we then determine what parameters would be found if that particular sample were used to calibrate the model. This provides an insight into the uncertainty in the parameter values found. After all, if we find roughly the same parameters for all possible samples, the impact of the sample on the parameters is small. If, on the other hand, we see a lot of variation in the parameters generated in this way, parameter uncertainty is large.

Because our parameters are based on many observations from multiple years from both the Netherlands and in the rest of Europe, the estimation is less uncertain than if only a smaller population had been used. Although it would be desirable to study the effect of using a sample, the CSO has decided not to include this in the confidence intervals shown later in this chapter. Were this risk to be included, the confidence intervals would be considerably wider.

Process uncertainty

The model equations in Appendix A not only invite one to work with a fixed forecast table. Actuaries can use them to generate scenarios through simulation. This yields a collection of possible futures paths of mortality probabilities, similar to scenarios that are generated for, e.g., future interest curves and investment yields. These scenarios can then be used to generate distributions for (future) life expectancy/portfolio values and more. This uncertainty (*given* the model specification and *given* the parameter estimates) is called *process uncertainty*.

Besides this uncertainty in the projected time series there is another form of process uncertainty, i.e., uncertainty in the mortality observations. In the estimations of the Li-Lee model we explicitly account for the fact that we cannot accurately observe mortality probabilities; we only have observed mortality frequencies at our disposal. This implies a certain "measurement noise". This is also called Poisson noise because of the distribution that we assume for the number of deaths observed. This Poisson noise has no significance in determining the uncertainty in life expectancy and is therefore not included in the confidence intervals presented later in this chapter.

10 – Liu, Q., Ling, C., Li, D. & Peng, L. (2019). *Bias-Corrected Inference for a Modified Lee-Carter Mortality Model*. Astin Bulletin, 49, 433-455 en Liu, Q., Ling, C. & Peng, L. (2019). *Statistical Inference for Lee-Carter Mortality Model and Corresponding Forecasts*. North American Actuarial Journal, 23, 335-363.

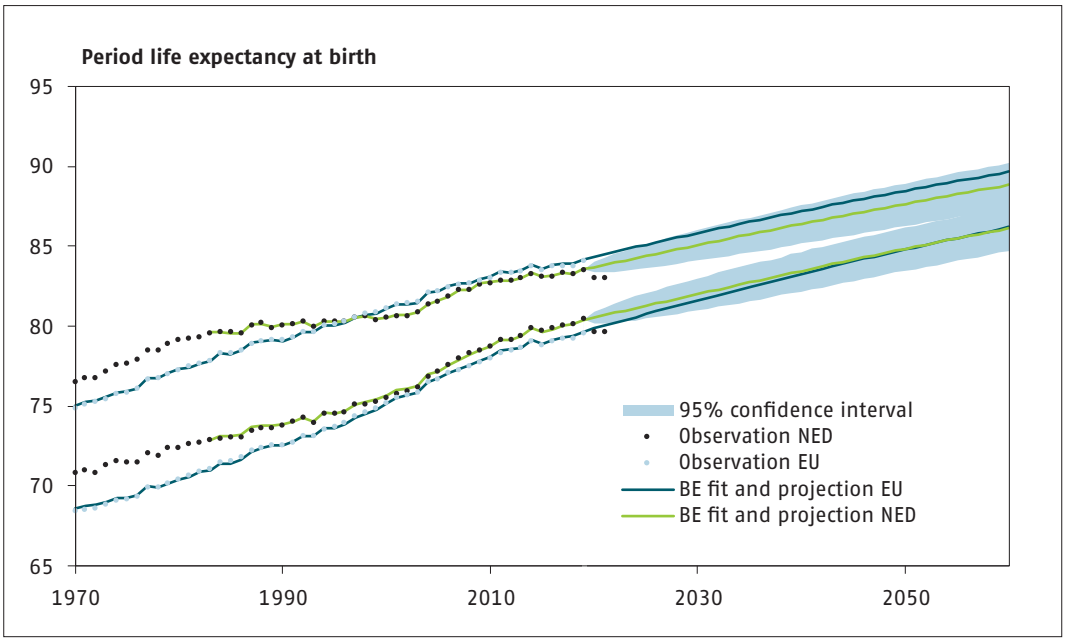
Micro-longevity risk

Even if there is no uncertainty with regard to the model, the parameters, the process and the resulting mortality probabilities, there is still uncertainty caused by micro-longevity risk. After all, no uncertainty in mortality probabilities does not mean that there is no uncertainty about the actual time of death of a single individual. Knowing the *expected* age of death does of course not imply that the moment of death of an individual is fixed. Contrary to the types of uncertainty mentioned before, which tend to affect all participants in a similar way, micro-longevity is a non-systemic risk that is diversifiable if stochastic independence between the individuals in the sample exists and the sample size is sufficiently large (similar to tossing a coin). For this reason, this risk is not included in the confidence intervals presented later in this chapter.

5.2 Simulations for life expectancy

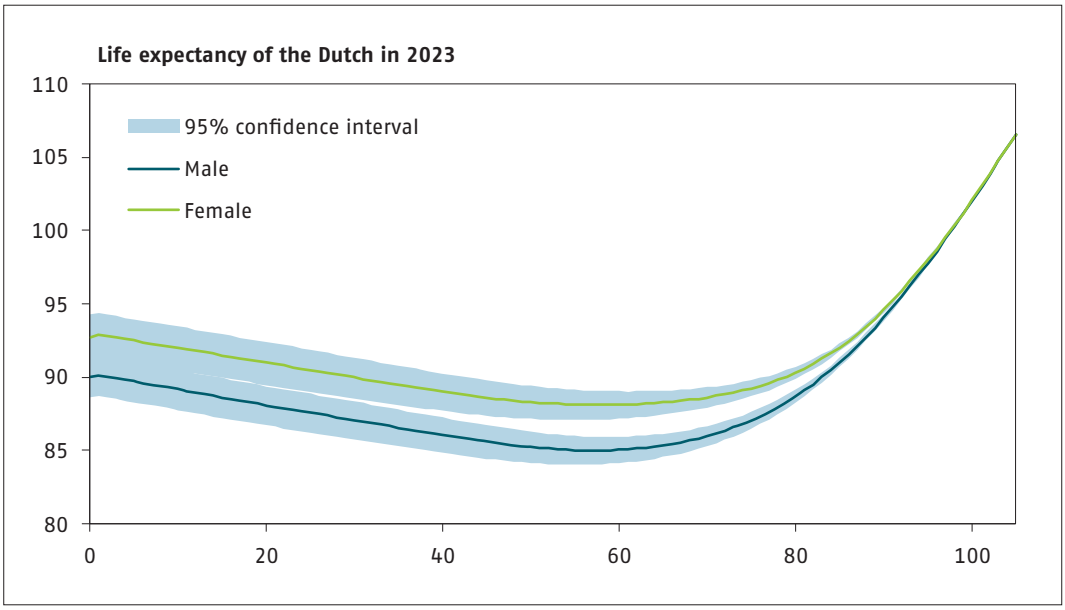
The best estimate mortality probabilities can be obtained by assuming that future mortality develops as specified in Appendix A, with all noise terms set to zero. It is also possible to generate stochastic scenarios from this specification: by sampling correlated noise terms $\epsilon_t^M, \epsilon_t^V, \delta_t^M, \delta_t^V$ from a multivariate normal distribution, time series K_t^g and κ_t^g and, from that, hazard rates $\mu_x^g(t)$ and mortality probabilities $q_x^g(t)$ can be simulated. Based on this a confidence interval around life expectancy can be determined for the whole horizon.

The 95% confidence interval up to 2060 for men and women is represented in graph 5.1. As expected, the graph shows that the uncertainty in the forecast of period life expectancy grows as the projections extend into the future. Also note that the observed mortality in the COVID years 2020 and 2021 are outside of the confidence interval; after all, the confidence interval only shows process uncertainty for the AG2022 forecast table without COVID term and as the COVID term is a deterministic component of the AG2022 model, this can be seen as parameter/model uncertainty.



Graph 5.1 – Confidence interval around the best estimate of period life expectancy for Dutch men and women

Graph 5.2 shows the process uncertainty in the cohort life expectancy per age of Dutch men and women in 2023. This graph demonstrates that process uncertainty decreases with the rising of age. This is due to the number of years estimated decreasing as age progresses. Also, it shows that life expectancy first decreases until an age of around 60 and then increases again. Two effects play a part here. An older person has already survived a period of time, so life expectancy will rise as age progresses. On the other hand, a younger person will benefit more from future mortality improvements.

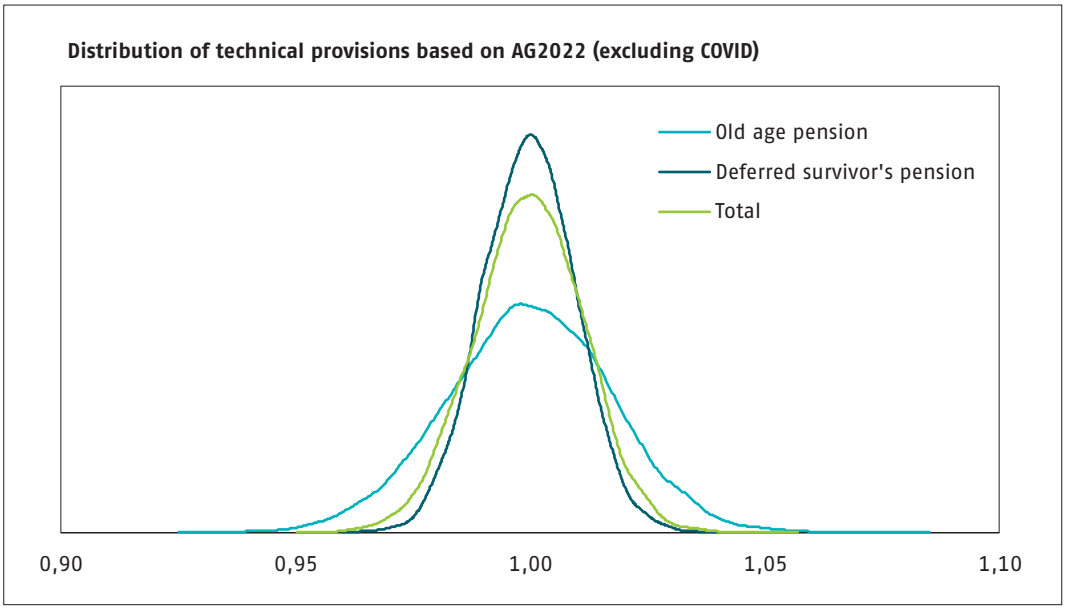


Graph 5.2 – Confidence interval around the best estimate cohort life expectancy for Dutch men and women in 2023

Please note that the confidence intervals shown only include uncertainty in future mortality probabilities and do not regard a single individual. As mortality probabilities for (e.g.) a 90-year-old changes very little over time, we observe hardly any difference in their expected age at death when simulating all kinds of scenarios with our model. But this does not mean that the time of death of a 90-year-old individual is already fixed. Little uncertainty in mortality probabilities over a certain age does not imply little uncertainty about the actual time of death of an individual.

5.3 Simulations for provisions

For every scenario of mortality rates described in paragraph 5.2 the value of the provisions can be established. Combining all scenarios results in a distribution of provision values. Graph 5.3 shows the distribution of simulated values for OAP, SP and the combination of both relative to the best estimate after simulating 10,000 such scenarios. This concerns the model portfolio for men with average age structure and 3% interest rate. The distribution that comes from the simulation strongly resembles a normal distribution. Please note that the distributions presented are not entirely smooth because of the inherent simulation uncertainty with 10,000 simulations.



Graph 5.3 – Distribution of simulation results for technical provisions (3% interest rate) for model portfolio males average age structure relative to the best estimate

Tables 5.1 and 5.2 present the average and 95%, 97.5% and 99.5% quantiles of the technical provisions at 3% and 1% interest rates. These use the average model portfolios for men and women at a flat 3% and 1% interest rate. The results are expressed as percentages of best estimate values.

Simulation results technical provisions (relative to the best estimate)						
3% interest rate	**Males**			**Females**		
	OAP	**SP**	**OAP+SP**	**OAP**	**SP**	**OAP+SP**
Standard deviation	1.7%	1.0%	1.2%	1.5%	2.2%	0.6%
Quantiles						
50%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
95%	102.8%	101.6%	101.8%	102.5%	103.6%	102.0%
97.5%	103.3%	101.9%	102.2%	103.0%	104.4%	102.5%
99.5%	104.5%	102.6%	102.9%	103.8%	105.8%	103.1%

Table 5.1 – Simulation results technical provisions at 3% interest rate for model portfolios (average age structure)

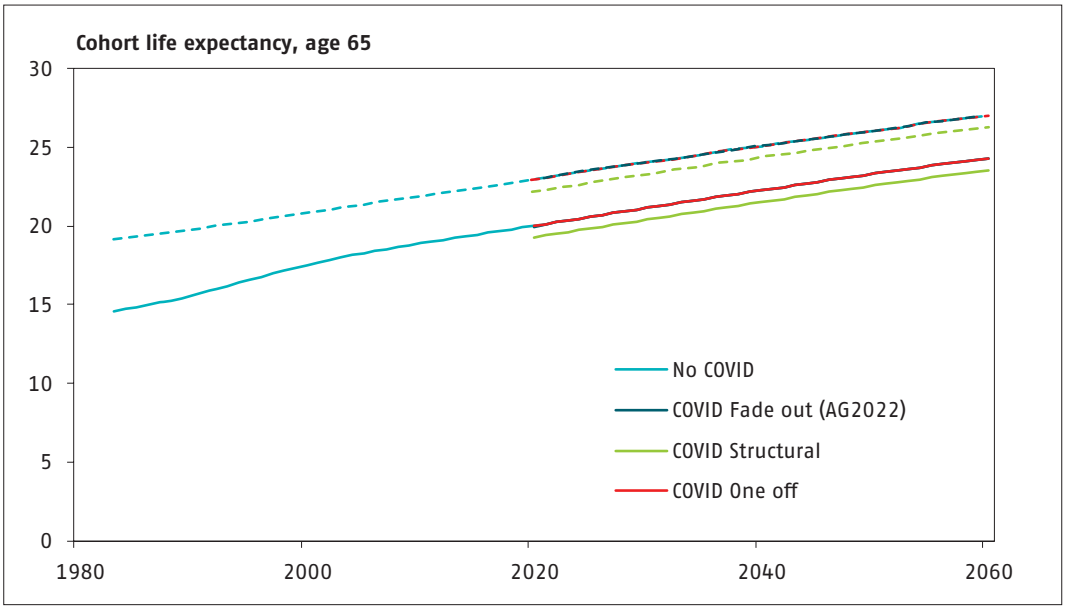
Results simulation technical provisions (relative to the best estimate)						
1% interest rate	**Males**			**Females**		
	OAP	**SP**	**OAP+SP**	**OAP**	**SP**	**OAP+SP**
Standard deviation	2.1%	1.2%	1.5%	1.9%	2.3%	1.6%
Quantiles						
50%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
95%	103.4%	102.0%	102.4%	103.1%	104.0%	102.6%
97.5%	104.1%	102.4%	102.9%	103.7%	104.7%	103.1%
99.5%	105.5%	103.2%	103.8%	104.7%	106.1%	104.0%

Table 5.2 – Simulation results technical provisions at 3% interest rate for model portfolios (average age structure)

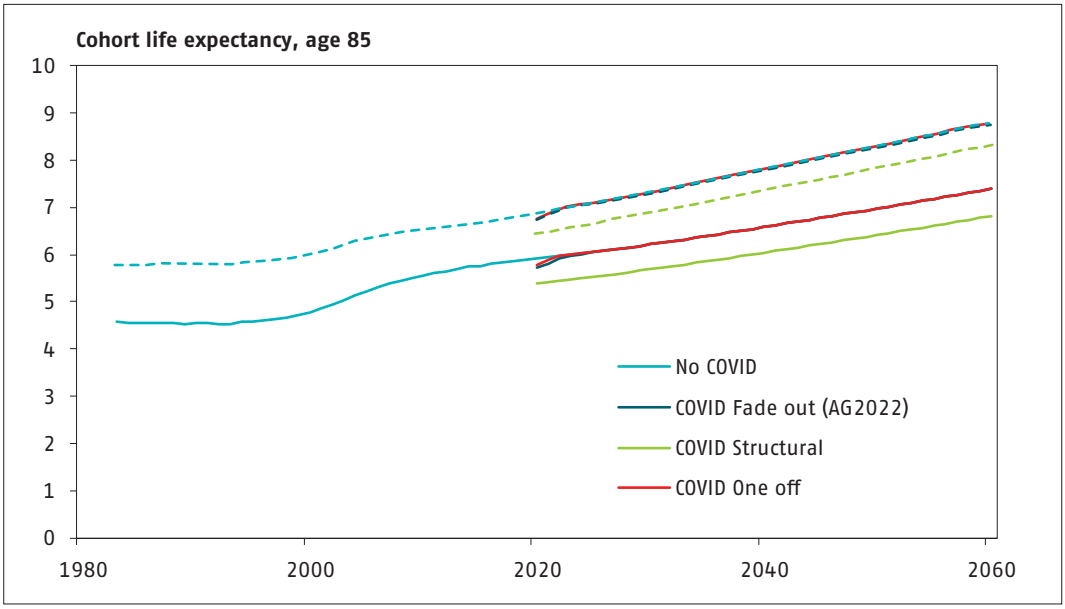
As the tables above show, the spread for old age pension is higher than for the combined OAP and SP. This is because with a combination of old age and survivor's pensions there is a combination of longevity and mortality risks. Also shown is, that the spread in old age pension for women is smaller than for men. Although both kappa processes for women are in themselves more volatile than for men (also after multiplication with beta), the Dutch deviation for women is negatively correlated to the European trend. Hence, contrary to men, a shock in the European trend for women is generally compensated in part by an opposite effect in the Dutch deviation. For men, a shock in the European trend is amplified by an effect in the Dutch deviation in the same direction. In addition, it shows that the spread in old age pension (stand-alone or combined) for women is smaller than in survivor's pensions of female participants (i.e., including widowers), but for men the opposite occurs. This can be explained by the fact that uncertainty decreases as age progresses (as shown in graph 5.2), combined with the fact that male partners are assumed to be three years older than female participants, and vice versa. Finally, a lower rate of interest leads to a wider spread on the results.

5.4 Alternative COVID scenarios

To get an impression of the scale of model uncertainty the (cohort) life expectancy of the AG 2022 forecast table was compared to (cohort) life expectancy according to a number of alternative COVID scenarios ('Structural', 'Fade out' and 'One off'). Graph 5.4 shows that a 65-year-old man in 2023 according to the AG2022 forecast is expected to live about 20 years and a 65-year-old woman about 23 years. According to the alternative COVID scenarios this remaining life expectance ranges from 19.6 to 20.4 years for men and from 22.5 to 23.3 years for women. This implies a bandwidth of 0.7 to 0.8 years. Graph 5.5 shows a slightly smaller bandwidth for an 85-year-old man/woman (+/- 0.4 to 0.5), although relative to the remaining life expectancy (6 to 7 years) this is actually bigger. We would point out that the size of the bandwidth is almost exclusively driven by the 'structural' COVID scenario; the other COVID scenarios ('One off' and no COVID) hardly differ from the 'Fade out' COVID scenario (AG2022).



Graph 5.4 – Remaining cohort life expectancy of a 65-year-old man (continuous lines) and a 65-year-old woman (dashed lines) for alternative COVID scenarios



Graph 5.5 – Remaining cohort life expectancy of an 85-year-old man (continuous lines) and an 85-year-old woman (dashed lines) for alternative COVID scenarios

We stress again that we do not claim to have quantified the full model risk with these results; there is, after all, a whole range of alternative model specifications. The results of alternative projections shown in the previous chapter (AG2020 and CBS2021) are examples of this. The actual model uncertainty will therefore be substantially larger.

Appendices

Appendix A
AG2022 diy section

1 Definitions

The projections table shows the best estimate for one-year mortality probabilities $q_x^g(t)$ for sexes $g \in \{M, V\}$, ages $x \in X = \{0, 1, 2, .., 120\}$ and years $t \in T = \{2020, 2021, .., 2191\}$. The one-year mortality probability is the likelihood that a person alive at 1 January of year t and born on 1 January of year $t - x$ will have died before 1 January of year $t + 1$. The model also facilitates users to make a forecast for years after 2191.

The mortality probabilities are not modelled directly; instead, we specify the corresponding force of mortality (or hazard rate) $\mu_x(t)$. We assume that $\mu_{x+s}(t+s) = \mu_x(t)$ for all 0 ≤ s < 1. It follows, that

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

Any model that forecasts the 'force of mortality' $\mu_x^g(t)$ also provides forecasts in terms of one-year mortality probabilities via the above equation.

2 Dynamic model

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

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

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

We model $\ln\left(\mu_x^{g,\text{pre-cov}}(t)\right)$ using the Li-Lee[11] 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' fort he 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 $\mu_x^{g,\text{pre-cov,EU}}(t)$ (that is, the Dutch deviation relative to the reference group). Here $\{A_x^g, B_x^g, \alpha_x^g, \beta_x^g\}$ are age-dependent parameters, whereas $\{K_t^g, \kappa_t^g\}$ are time-dependent quantities, the dynamics of which are defined by the time series

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

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

11 – Li, N. and Lee, R. (2005). *Coherent Mortality Forecasts for a Group of Populations: An Extension of the Lee-Carter Method.* Demography 42(3), pp. 575-594.

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

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

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

with $\{\widetilde{\mathfrak{B}}_x^g\}$ age-dependent parameters and $\{\mathfrak{K}_t^g\}$ time-dependent quantities. The values of $\mathfrak{K}_{2020}^g$ and $\mathfrak{K}_{2021}^g$ follow from a calibrated weekly model that we will discuss later in this Appendix, while for $t \geq 2022$ we assume

$$\mathfrak{K}_t^g = \mathfrak{K}_{2021}^g \eta^{t-2021},$$

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

- $\eta \in (0,1)$ correspond to the scenario "**Fade out**":
  the values of $\mathfrak{K}_t^g$ for $t \geq 2022$ converge to 0, so the excess mortality over the pre-COVID period fades out, with a half-life equal to $\ln(½)/\ln(\eta)$.
  The CSO opted for this scenario in the AG2022 forecast with η equal to 0.5, thereby setting the half-life to 1 year.
- $\eta = 1$ corresponds to the scenario '**structural**':
  the values of $\mathfrak{K}_t^g$ for $t \geq 2022$ remain $\mathfrak{K}_{2021}^g$, so the excess mortality over the pre-COVID period does not disappear.
- $\eta = 0$ corresponds to the scenario "**one-**off":
  the values of $\mathfrak{K}_t^g$ for $t \geq 2022$ are equal to 0, so the excess mortality over the pre-COVID period disappears immediately after 2021.

3 Best estimates for mortality probabilities and life expectancies

Best estimates mortality probabilities are then determined by

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

by entering best estimates of the time series K_t^g and κ_t^g into the equations for $\mu_x^g(t)$. Because we identify the *best estimate* future values of the time series as the *most likely* results, these will match the series for K_t^g and κ_t^g obtained by entering $Z_t = (\epsilon_t^M, \epsilon_t^V, \delta_t^M, \delta_t^V)' = (0,0,0,0)'$ for every future t. The covariance matrix C is not required to generate best estimates but is required to perform simulations that can serve to analyse the uncertainty around the best estimates.

This gives us the best estimates for the ages $x \in X = \{0,1,2, \ldots, 120\}$. Where a mortality probability for an age beyond 120 is required, this is assumed to be equal to the value for age 120.

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

assume that, on average, a person who dies in any calendar year is alive for half of that calendar year, then we will find for that person the so-called *cohort life expectancy*:

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

Please note that with the formula above we move diagonally across the table of projections. The probability that that person is alive at time $t + k$ is the product of survival probabilities $1 - q_{x+s}^{g}(t+s)$ for each year s between 0 and k, with the person not only ageing a year, but also moving to a new column in the mortality table. This effect is not included 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 suggests that mortality probabilities at time t will not change after that moment. This creates a false image of life expectancy and while this period life expectancy is often denoted as 'the life expectancy', this is incorrect.

4 Data set used for pre-COVID calibration

The parameter values $\mu_x^{g,\mathrm{pre-cov}}(t)$ in the model above for ages $x \in X^o = \{0,1,\ldots,90\}$ were determined with the maximum likelihood method, using mortality data and exposures from the Western European reference group and from the Netherlands up to and including 2019. The parameters for ages $x \in \tilde{X} = \{91,92,\ldots,120\}$ were subsequently derived by extrapolation. In this paragraph we leave out the sex and EU/NL suffixes in the notation.

Appendix D lists the exact data sources. The data from the Human Mortality Database (HMD) has been supplemented with some data from the Eurostat database (EUROS) and data from local statistics agencies in the UK. These databases contain the required death frequencies by sex, but not the exposures. These can, however, be derived from other quantities that are given:

- $P_{x,t}$: the population at 1 January of year t aged between x and $x + 1$
- $C_{x,t}$: the number of people that have died within year t, who would have been between x and $x + 1$ years old on 31 December of year t.

Conversion to exposures is done using the method laid down in the HMP protocol[12] . For $x > 0$ this gives:

$$E_{x,t} = \frac{1}{2}\left(P_{x,t} + P_{x,t+1}\right)\frac{1}{6} + \left(\frac{1}{2}C_{x,t} - \frac{1}{2}C_{x+1,t}\right),$$

and for $x = 0$:

$$E_{0,t} = \frac{1}{2}\left(P_{0,t} + P_{0,t+1}\right) + \frac{1}{6}\left(C_{0,t} - \frac{1}{2}C_{1,t}\right).$$

12 – HMD (2019). *Methods Protocol for the Human Mortality Database.* https://www.mortality.org/File/GetDocument/Public/Docs/MethodsProtocolV6.pdf

5 Calibration pre-COVID force of mortality

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

- We take the exposures $E_{x,t}^{g,EU}$ and observed deaths $D_{x,t}^{g,EU}$ for the relevant Western European countries, with $t \in T^o = \{1970,1971,\ldots,2019\}$. It is always the sum of all exposures and the sum of all deaths in the included countries, including the Netherlands. We assume (as in Brouhns et al. 2002) 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 andn K_t^g are the determined so, that the Poisson likelihood function fort he observed deaths is as large as possible for the exposures provided:

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

  To obtain a unique specification of the parameters $\{A_x^g,\ B_x^g,\ K_t^g\}$ we normalise by requiring that the sum of the elements of K_t^g over $t \in T^o$ equals 0 and the sum of all elements of B_x^g over $x \in X^o$ equals 1.

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

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

  with $\mu_x^{g,\text{pre-cov}}(t) = \hat{\mu}_x^{g,\text{pre-covid,EU}}(t)e^{\alpha_x^g + \beta_x^g\kappa_t^g}$, $T^* = \{1983,1984,\ldots,2019\}$ (from 1983 this time), where $\hat{\mu}_x^{g,\text{pre-covid,EU}} = \exp\left(\hat{A}_x^g + \hat{B}_x^g\hat{K}_t^g\right)$. Here, $\hat{A}_x^g, \hat{B}_x^g$ en $\hat{K}_t^g$ are the estimations obtained in the previous step. Again, normalisation is done by setting sums of the elements κ_t^g over $t \in T^*$ and β_x^g over $x \in X^o$ to 0 and 1 respectively.

- In the third step the estimations of the time series $\left\{\left(\hat{K}_t^M, \hat{K}_t^V\right)' \,\middle|\, t \in T^o\right\}$ and $\{(\hat{\kappa}_t^M, \hat{\kappa}_t^V)' \,|\, t \in T^*\}$, as defined in the previous steps, to estimate parameters $\Psi = (\theta^M, \theta^V, a^M, a^V, c^M, c^V)'$ and matrix C. Assuming 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 select the estimators for Ψ and C so, that the likelihood for these time series is maximized (ignoring the fact that we are using estimations of the actual underlying time series values and not the observed time series values).

  We do this by using the equation $Y_{t+1} = X_t\Psi + Z_{t+1}$ with the following matrices for $t = 1970,\ldots,1982$

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

And the following matrices for $t = 1983, \ldots, 2018$

$$Y_{t+1} = \begin{bmatrix} \widehat{K}^M_{t+1} - \widehat{K}^M_t \\ \widehat{K}^V_{t+1} - \widehat{K}^V_t \\ \hat{\kappa}^M_{t+1} \\ \hat{\kappa}^V_{t+1} \end{bmatrix}, \quad X_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \hat{\kappa}^M_t & 0 & 1 & 0 \\ 0 & 0 & 0 & \hat{\kappa}^V_t & 0 & 1 \end{bmatrix}, \quad Z_{t+1} = \begin{bmatrix} \epsilon^M_{t+1} \\ \epsilon^V_{t+1} \\ \delta^M_{t+1} \\ \delta^V_{t+1} \end{bmatrix}.$$

Next, C and Ψ are determined by optimising the log likelihood for the time series:

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

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

6 Closure of the parameter values

Next, the parameters $\{A^g_x,\ B^g_x, \alpha^g_x, \beta^g_x\}$ for the ages $x \in \tilde{X} = \{91,92, \ldots, 120\}$ are determined via extrapolation as follows.

The parameters $\{B^g_x\}, x \in \tilde{X}$, are obtained by linear extrapolation of $\{\ln(\hat{B}^g_y)\}$ for the ages $y \in \{80,81, \cdots, 90\}$. We write $y_k = 80 + (k-1)$ for $k = 1, \cdots, n$ with $n = 11$. So, the number of ages upon which the regression is based, is $n = 11$, the average of these ages is $\bar{y} = \frac{1}{n}\sum_{k=1}^n y_k = 85$ and de square sum of the deviation is $\sum_{k=1}^n (y_k - \bar{y})^2 = 110$. We then find for $x \in \tilde{X}$:

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

In which the regression weights $w_k(x)$ are given by

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

Next, we set $\{\hat{A}^g_x\}, x \in \tilde{X}$, so, that in 2019 the values of the force of mortality for the Western European reference group match the values according to Kannisto's closure method, that is

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

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

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

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 set $\{\hat{\beta}_x^g\}, x \in \tilde{X}$, so, that the Dutch pre-COVID force of mortality in 2019 matches the values that would follow from closure by using Kannisto's method. That means, we solve $\hat{\beta}_x^g$ from the equation

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

7 Simulation of the pre-COVID time series

To be able to simulate scenarios for the time series $Z_t = (\epsilon_t^M, \epsilon_t^V, \delta_t^M, \delta_t^V)'$, samples must be generated from a normal distribution with mean $(0,0,0,0)'$ and covariance matrix *C*. This can be done by multiplying a vector $\tilde{Z}_t$ with four independent standard normally distributed variables with a matrix H that meets $H'H = C$, so by $Z_t = H'\tilde{Z}_t$. Therefore, the list of parameters in the publication and in the accompanying Excel spreadsheet include not only the covariance matrix C, but also a Cholesky matrix H.

8 Data set used for the calibration over 2020 and 2021

We now discuss the modelling fort he years 2020 and 2021. For ages below 55 we assume that there is no divergence from previous years. So, we assume $o_x^g(t) = 1$ for the ages $x \in \{0,1, \ldots,54\}$ for $t = 2020$ and $t = 2021$. For the ages $x \in \{55,56, \ldots,90\}$ we calibrate $o_x^g(t)$, while for the ages $x \in \tilde{X} = \{91,92, \ldots,120\}$, for both $t = 2020$ and $t = 2021$, we set $o_x^g(t)$ equal to $o_{90}^g(t)$.
The parameter values of $o_x^g(t)$ for the ages $x \in \{55,56, \ldots,90\}$ were determined with the aid of an underlying weekly model, which uses weekly mortality data per individual age from the years 2016 to 2021. These data were obtained by a customised inquiry from CBS. The number of deaths in week w of year t at age $x \in \{55,56, \ldots,90\}$ with sex $g \in \{M, V\}$ is denoted $D_{x,w,t}^g$.

The weekly data from 2016 to 2019 are used to estimate the seasonal effect. The data from 2020 and 2021 are the used to calibrate the weekly model for those years. This also requires knowing the exposures in 2020 and 2021 on a weekly basis. These exposures are determined by linear interpolation of the population levels $P_{m,w,t}^g$ for the population of sex g at the start of month m in year t.[13] With this we determine for $t = 2020$ and $t = 2021$ and for $w \in W_{2020} = \{1, \cdots,53\}$ and $w \in W_{2021} = \{0, \cdots,52\}$:

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

with $W(w,t)$ the set of days in week w in year t, $N_{w,t}$ the number of elements in 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 at day d of

13 – https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83482NED/table?dl=61916.

year t, obtained by linear extrapolation between the monthly data $P^g_{m,w,t}$ based on the counted numbers of days per week and per month.

9 Calibration method weekly model

The following steps are processed separately for ages $x \in X^* = \{55,56, \ldots ,90\}$ for both sexes $g \in \{M, V\}$ and for the years $t = 2020$ and $t = 2021$ to calibrate $o^g_x(t)$ v.
We adjust for the seasonal effect, which constitutes the non-uniform distribution of mortality over the weeks of a year. We use numbers of deaths of both sexes to estimate an (age-independent) weekly effect $\varphi_{w,t}$ that represents how mortality within year t is distributed across the weeks $w \in W_{2020} = \{1, \cdots ,53\}$ and $w \in W_{2021} = \{0, \cdots ,52\}$. For this we determine the historically observed mortality for the weeks[14] $w \in \{1, \cdots ,52\}$ over the years $t \in \{2016, \cdots ,2019\}$, where we sum over the ages $x \in X^*$ and over both sexes:

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

We estimate a cyclical cubic spline Φ, that minimises

$$\lambda \sum_{w=1}^{53} \left(D^{tot}_w - \Phi(w)\right)^2 + (1-\lambda) \int_1^{53} \left(\Phi''(w)\right)^2 dw$$

with $D^{tot}_{53} = D^{tot}_1$, under the secondary condition that $\Phi''(w)$ is one-by-one lineair and continuous and the function values and first and second derivatives match in $w = 1$ and $w = 53$, utilising the Matlab routine `spcsp`. On the basis of visual inspection $\lambda = 0{,}03$ was chosen as the parameter that balances “fit” and “smoothness”. For the broken weeks $w = 0$ and $w = 53$ we assume that $\Phi(0) = \Phi(1)$ and $\Phi(53) = \Phi(52)$. We then set

$$\varphi_{w,2020} = \frac{\Phi(w)}{\frac{1}{53}\sum_{u=1}^{53}\Phi(u)}, w \in W_{2020}, \qquad \varphi_{w,2021} = \frac{\Phi(w)}{\frac{1}{53}\sum_{u=0}^{52}\Phi(u)}, w \in W_{2021}.$$

Subsequently, the maximum likelihood method is applied to the Dutch weekly data to estimate $\mathfrak{B}^g_x, x \in X^*$ en $\mathfrak{K}^g_{w,t}, w \in W_t$, for $t = 2020, 2021$, via

$$\max_{\left\{\mathfrak{B}^g_x,\, \mathfrak{K}^g_{w,2020},\mathfrak{K}^g_{w,2021}\right\}} \prod_{x\in X^o} \prod_{t\in\{2020,2021\}} \prod_{w\in W_t} \frac{\left(E^g_{x,w,t}\mu^g_{x,w}(t)\right)^{D^g_{x,w,t}} \exp\left(-E^g_{x,w,t}\mu^g_{x,w}(t)\right)}{D^g_{x,w,t}!},$$

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

14 – There are broken weeks in the dataset for $w = 0$ and $w = 53$ but these are not included in the estimation of the seasonal effect. Weeks 1 and 52 may also be broken; we do not take this into account in the determination of the D^{tot}_w-waarden, but the spline we use will somewhat compensate for this.

The next step is to determine time effects $\mathfrak{X}_t^g$ aggregated over all weeks in the year $t = 2020, 2021$, and matching $\widetilde{\mathfrak{B}}_x^g$, $x \in X^*$.
We first determine $\widetilde{\mathfrak{X}}_t^g$ and $\widetilde{\mathfrak{B}}_x^g$ by assuming for $t = 2020, 2021$

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

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

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

We then determine $\widetilde{\mathfrak{B}}_x^g$ by setting survival over the complete years 2020 and 2021 equal to survival over all weeks of 2020 and 2021:

$$\prod_{t=2020}^{2021} \exp\left(-\hat{\mu}_x^{g,\text{pre-covid}}(t) e^{\widetilde{\mathfrak{B}}_x^g \widetilde{\mathfrak{X}}_t^g}\right) = \prod_{t=2020}^{2021} \prod_{w \in W_t} \exp\left(-\frac{N_{w,t}}{\sum_{u \in W_t} N_{u,t}} \hat{\mu}_x^{g,\text{pre-covid}}(t) \varphi_{w,t} e^{\mathfrak{B}_x^g \mathfrak{K}_{w,t}^g}\right).$$

Re-writing yields:

$$\sum_{t=2020}^{2021} \hat{\mu}_x^{g,\text{pre-covid}}(t) \sum_{w \in W_t} \frac{N_{w,t}}{\sum_{u \in W_t} N_{u,t}} \left(e^{\widetilde{\mathfrak{B}}_x^g \widetilde{\mathfrak{X}}_t^g} - \varphi_{w,t} e^{\mathfrak{B}_x^g \mathfrak{K}_{w,t}^g}\right) = 0.$$

This non-linear equation in $\widetilde{\mathfrak{B}}_x^g$ can be numerically solved for each age $x \in X^*$. If we suppose that the solutions are $\widetilde{\widetilde{\mathfrak{B}}}_x^g$, we then, to conclude, set $\widetilde{\mathfrak{B}}_x^g$ (allowing for $\sum_{x=55}^{90} \widetilde{\mathfrak{B}}_x^g = 1$) and $\mathfrak{X}_t^g$ via normalisation

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

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

Appendix B
Mortality probability limit value by projection year under Kannisto

In this paragraph we provide the technical background why applying Kannisto's closure method per projection year forces life expectancy to converge to a predetermined limit value and the confidence intervals around life expectancy to decrease over time. A calculation of the tipping point for AG2020 is also included. For this we focus on the limit of the mortality probabilities per age over time.

First, we will show that the AG model in the long term resembles a standard Lee-Carter (LC) model. Then we clarify the above problem for a standard LC model, making it clear also, that the tipping point for a standard LC model is one specific age. For the AG model the tipping point moves over time because of the Dutch deviation, which causes the tipping point age to rise.

Description of the Kannisto method
First, we provide a short description of Kannisto (see the AG2020 publication). This method is used to derive calculate one-year mortality probabilities $q_{x,t}^g = 1 - e^{-\mu_{x,t}^g}$ for ages 91-120 from the one-year mortality probabilities for ages 80-90. For an age $x \in \{91, \cdots, 120\}$, $\mu_{x,t}^g$ is determined by

- $\mu_{x,t}^g = L\left(\sum_{k=80}^{90} w_k(x)\, L^{-1}\left(\mu_{k,t}^g\right)\right)$,

with $L(z) = 1/(1+e^{-z})$ and $L^{-1}(z) = -\ln\left(\frac{1}{z} - 1\right) = \ln(z) - \ln(1-z)$.

Kannisto in the long term
We start from projections $\ln\left(\hat{\mu}_{x,T+t}^g\right)$. These projections look as follows:

- $\ln\left(\hat{\mu}_{x,T+t}^g\right) = \left(\alpha_x^g + \beta_x^g \hat{\kappa}_{T+t}^g\right) + \left(A_x^g + B_x^g\left(K_T^g + \theta^g \times t\right)\right)$.

We can rewrite this as:

- $\ln\left(\hat{\mu}_{x,T+t}^g\right) = \left(\frac{\left(\alpha_x^g + \beta_x^g \hat{\kappa}_{T+t}^g\right) + A_x^g}{K_T^g + \theta^g \times t} + B_x^g\right) \times \left(K_T^g + \theta^g \times t\right)$.

In case of *coherence*, that is if $\left|\hat{\kappa}_{T+t}^g\right| \leq Bound$, it follows from this formula that the AG model will start to behave like a Lee-Cartel model, with the results determined by $B_x^g \times \left(K_T^g + \theta^g \times t\right)$. This means that the long-term results of the AG model for the higher ages will resemble Lee-Carter combined with Kannisto. This is further elaborated below.

In the inverse function $L^{-1}(z)$ we substitute $z = \hat{\mu}_{x,T+t}^g$ for the projected hazard rates. For

$z = e^y$ (with $z = e^{\ln(z)}$, i.e. $y = \ln(z) = \ln\left(\hat{\mu}_{x,T+t}^g\right)$) we get:

- $L^{-1}(e^y) = \ln(e^y) - \ln(1-e^y) = y - \ln(1-e^y)$.

So, if y assumes very negative values, then approximately $\ln(1-e^y) \approx \ln(1-0) = 0$ and we get $L^{-1}(e^y) \approx y$ as a good (and ever improving) approximation for $L^{-1}(e^y)$.

In our case, looking at future timeframes $T+t$, $y = \ln(z) = \ln\left(\hat{\mu}^g_{x,T+t}\right)$ is given by

- $\ln\left(\hat{\mu}^g_{k,T+t}\right) = \left(\alpha^g_k + \beta^g_k \hat{\kappa}^g_{T+t}\right) + \left(A^g_k + B^g_k \hat{K}^g_{T+t}\right)$,

with $80 \leq k \leq 90$. For future periods $\ln\left(\hat{\mu}^g_{k,T+t}\right)$ get ever more negative and (as explained above) is ultimately completely dominated by $B^g_k \hat{K}^g_{T+t}$.

So, for ages $x \in \{91, \cdots, 120\}$ we ultimately find

- $\hat{\mu}^g_{x,T+t} = L\left(\sum_{k=80}^{90} w_k(x)\, L^{-1}\left(\mu^g_{k,T+t}\right)\right) \approx L\left(\sum_{k=80}^{90} w_k(x)\, B^g_k \hat{K}^g_{T+t}\right)$.

For the function $L(z) = 1/(1+e^{-z})$ (a distribution) it holds that:

- $\lim_{z\to-\infty} L(z) = 0$ and $\lim_{z\to+\infty} L(z) = 1$.

So, using these properties of the function $L(\cdot)$, it holds that if $\hat{K}^g_{T+t} \to -\infty$,

- If $\sum_{k=80}^{90} w_k(x)\, B^g_k > 0$, then $L\left(\sum_{k=80}^{90} w_k(x)\, B^g_k \hat{K}^g_{T+t}\right) \to 0$.
- If $\sum_{k=80}^{90} w_k(x)\, B^g_k < 0$, then $L\left(\sum_{k=80}^{90} w_k(x)\, B^g_k \hat{K}^g_{T+t}\right) \to 1$.

The values $\sum_{k=80}^{90} w_k(x)\, B^g_k$ are fixed. For AG2020 we find:

- For men $\sum_{k=80}^{90} w_k(x)\, B^g_k$ turn out to be positive for $x \in \{91, \cdots, 100\}$ and negative for $x \in \{101, \cdots, 120\}$.
- For women $\sum_{k=80}^{90} w_k(x)\, B^g_k$ is positive for $x \in \{91, \cdots, 102\}$ and negative for $x \in \{103, \cdots, 120\}$.

So, $\hat{q}^g_{x,T+t} = 1 - e^{-\hat{\mu}^g_{x,T+t}}$ we find:

- For men, if $x \in \{91, \cdots, 100\}$, then $\hat{q}^g_{x,T+t} \to 0$; if $x \in \{101, \cdots, 120\}$, then $\hat{q}^g_{x,T+t} \to 1 - e^{-1} \approx 0.6321$.
- For women, if $x \in \{91, \cdots, 102\}$ then $\hat{q}^g_{x,T+t} \to 0$; if $x \in \{103, \cdots, 120\}$, then $\hat{q}^g_{x,T+t} \to 1 - e^{-1} \approx 0.6321$.

Appendix C
Model portfolios

This appendix explains what model portfolios and actuarial assumptions were used to calculate the percentage effects on the factors, technical provisions and contributions. Also, the formulae of the actuarial factors are listed.

Model portfolios technical provisions

To evaluate the effect on the technical provisions of model portfolios six model portfolios were used. The portfolios differ in sex (male and female) and average age (young, average and old). The model portfolios have a weighted (by provision) average age of 45 (young), 55 (average) and 65 (old).

The model portfolios contain the benefits lifelong old age pension and lifelong survivor's pension.

Listed under male are the benefits accrued by male participants (including widows) and under females the benefits accrued by female participants (including widowers).

	Males young			Males average			Males old		
Age	OAP (65)	SP (def.)	SP (i.p.)	OAP (65)	SP (def.)	SP (i.p.)	OAP (65)	SP (def.)	SP (i.p.)
30	15,000	10,500	-	1,500	1,050	-	500	350	-
40	25,000	17,500	150	8,500	5,950	1,000	3,000	2,100	-
50	10,000	7,000	450	15,000	10,500	2,000	7,000	4,900	200
60	7,500	5,250	450	15,000	10,500	2,000	15,000	10,500	5,000
70	3,500	2,100	600	8,500	5,100	500	15,000	9,000	10,000
80	1,500	750	-	3,500	1,750	150	15,000	7,500	5,000
90	-	-	-	500	200	-	10,000	4,000	2,000

Table C.1 – Accrued rights per type of benefit for model portfolio males

	Females young			Females average			Females old		
Age	OAP (65)	SP (def.)	SP (i.p.)	OAP (65)	SP (def.)	SP (i.p.)	OAP (65)	SP (def.)	SP (i.p.)
30	7,500	5,250	50	2,500	1,750	-	750	525	-
40	20,000	14,000	150	7,500	5,250	100	1,000	700	-
50	15,000	10,500	250	12,500	8,750	250	5,000	3,500	250
60	5,000	3,500	50	10,000	7,000	250	10,000	7,000	500
70	1,000	600	-	7,500	2,250	100	12,500	3,750	1,000
80	-	-	-	5,000	1,000	-	10,000	2,000	500
90	-	-	-	1,000	100	-	5,000	500	250

Table C.2 – Accrued rights per type of benefit for model portfolio females

Model portfolio contribution level

For the effect on contribution levels a single model portfolio was used. Table C.3 lists the accrual by age in any year.

	Males		Females	
	OAP (68)	SP (def.)	OAP (68)	SP (def.)
30	600	420	400	280
40	750	525	500	350
50	800	560	550	385
60	600	420	400	280

Table C.3 – Rights accrual per type of benefit for model portfolio contribution levels

For the survivor's pension risk premium 40 years of service are assumed (in service at age 28, retirement at age 68). For schemes with old age pension and risk only survivor's pension this means assuming 40 service years for all participants. For funds with survivor's pension accrual, the survivor's pension risk premium is based on future service years (68 minus current participant age minus 1).

Actuarial assumptions

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

- Life tables: Projections Life Table AG2022, starting year 2023;
- Age corrections and/or experience mortality: none;
- Interest rate: 1% and 3%;
- Retirement age: 65 for provisions and 68 for premiums;
- For deferred survivor's pensions the following applies:
  - Undefined-partner system prior to retirement age with a 100% partner frequency, defined-partner system after that;
  - 3 years age difference between man and woman (man older than woman)
  - Different sexes for participant and partner;
- Lump sum rates for old age pension and survivor's pension in payment are set by taking the average of in advance and in arrears payments.

Actuarial factors

The formulae below define the actuarial factors.

Definition parameters

- x the age of a male participant or male spouse
- y the age of a female participant or female spouse

Note: In the undefined-partner system a spouse of the other sex is assumed. For notational simplicity a male participant is taken in all formulae below. For all formulae and definitions instead of *x* (male participant) with *y* (female spouse), one can also read *y* (female participant) with *x* (male spouse).

- r the (flat) rate of interest
- q_x the mortality probability of a person aged x
- p_x the survival probability of a person aged x, with $p_x = 1-q_x$
- ${}_tp_x$ the probability of a person aged x will survive at least t years
- ${}_t\tilde{p}_x$ the probability of a participant being deceased after t years, leaving a partner eligible for survivor's benefit
- h_x the partner frequency for a participant aged x
- ${}_th_{\underline{x}}$ the probability of a participant aged x still being married after t years
- PL the retirement age (65 for technical provisions, 68 for contributions)
- U_x^{op} the annual benefit old age pension for a participant aged x
- U_x^{lpp} the annual benefit deferred survivor's pension for a participant aged x
- U_x^{ipp} the annual benefit survivor's pension in payment for a participant aged x
- CS_x^{op} one year's accrual of old age pension for a participant aged x
- CS_x^{lpp} one year's accrual of deferred survivor's pension for a participant aged x

Generic formulae

- $v = (1+r)^{-1}$ the discount rate
- ${}_tp_x = \prod_{j=0}^{t-1} p_{x+j}$ the t-year survival probability for a person aged x

Annuity factors for deferred and in-payment old age pension (OAP) and in-payment survivor's pension (SP) per unit

- Deferred OAP:

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

- OAP in payment:

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

- SP in payment:

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

Annuity factor 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 technical provision

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

Formulae for calculation of contributions

- Contribution for old age pension deferred *n* years:

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

- Contribution for accrual of deferred survivor's pension:

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

- Risk premium deferred survivor's pension:

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

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 D
Data used and Literature

This report makes use of data as was available in the Eurostat, CBS (Statline) and HMD databases mid-April 2022. Additional customised data was obtained from CBS, while for the UK we have also used data from local statistical agencies.

1) Eurostat data (data t/m 2019):
   Exposures to Risk (demo_pjan), downloaded on Apri 23rd, 2022:
   http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=demo_pjan&lang=en
   Observed Deaths (demo_mager en demo_magec), downloaded on Apri 23rd, 2022:
   http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=demo_mager&lang=en
   http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=demo_magec&lang=en

2) HMD-database:
   http://www.mortality.org/

3) CBS week-by-week deaths in the Netherlands for 2020 and 2021; custom query

4) CBS (Statline) data for population size in the Netherlands in 2020 and 2021:
   Exposures-to-Risk (P values), downloaded on April 22nd, 2022:
   https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83482NED/table?dl=61916

5) Deaths in the UK in 2019 were retrieved from aggregate data as available on the websites of ONS (England & Wales), NRS (Scotland) and NISRA (Northern Ireland):
   a. England & Wales: ONS table 4 and table 5:
      https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/datasets/deathsregisteredinenglandandwalesseriesdrreferencetables
   b. Scotland: NRS table DT.03:
      https://www.nrscotland.gov.uk/statistics-and-data/statistics/statistics-by-theme/vital-events/deaths/deaths-time-series-data
   c. Northern Ireland: Deaths by age 1955 – 2020 from NISRA:
      https://www.nisra.gov.uk/publications/death-statistics

   To deduce exposures in the UK we use the mid-year population estimates on the ONS website:
   d. https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland

   These data were also downloaded on April 23rd, 2022.

Table D.1 lists by geographical area and year what data source was used as input for the AG2022 model.

GEO	2013 to 2017	2018	2019	HMD-version
Austria	HMD	HMD	HMD	2021.03.30
Belgium	HMD	HMD	HMD	2021.09.25
Denmark	HMD	HMD	HMD	2022.03.22
Finland	HMD	HMD	HMD	2021.08.02
France (metropolitan)	HMD	HMD	HMD	2022.04.11
Germany (until 1990 former territory of the FRG)	HMD	***EUROS***	***EUROS***	2018.12.17
Iceland	HMD	HMD	***EUROS***	2020.04.02
Ireland	HMD	***EUROS***	***EUROS***	2019.10.01
Luxembourg	HMD	HMD	HMD	2022.01.21
Netherlands	HMD	HMD	HMD	2021.03.31
Norway	HMD	HMD	HMD	2021.04.15
Sweden	HMD	HMD	HMD	2021.09.29
Switzerland	HMD	HMD	HMD	2021.10.28
United Kingdom	HMD	HMD	***ONS***	2020.07.11

Table D.1 – data sources AG2022 for observation year from 2013 onwards

For the modelling of the additional COVID-19 model component we have used customised data from CBS. This regards observed mortality by age in the Netherlands for the years 2020 and 2021. Also, we have used the most recent CBS population data to derive exposures for 2020 and 2021.

Literature

Brouhns, N., Denuit, M. and Vermunt, J.K. (2002). *A Poisson log-bilinear regression approach to the construction of projected lifetables.* Insurance: Mathematics and Economics 31(3), pp. 373-393.

Commissie Sterfte Onderzoek. (2021). *AG2020 en de impact van de COVID-19-pandemie: Over- en ondersterfte sinds januari 2020.* Koninklijk Actuarieel Genootschap.

HMD (2019). *Methods Protocol for the Human Mortality Database.* https://www.mortality.org/File/GetDocument/Public/Docs/MethodsProtocolV6.pdf

Kannisto, V. (1992). *Development of the oldest – old mortality, 1950-1980: evidence from 28 developed countries.* Odense University Press.

Li, N. and Lee, R. (2005). *Coherent Mortality Forecasts for a Group of Populations: An Extension of the Lee-Carter Method*. Demography 42(3), pp. 575-594.

Liu, Q., Ling, C., Li, D. & Peng, L. (2019). *Bias-Corrected Inference for a Modified Lee-Carter Mortality Model*. Astin Bulletin, 49, 433-455.

Liu, Q., Ling, C., & Peng, L. (2019). *Statistical Inference for Lee-Carter Mortality Model and Corresponding Forecasts*. North American Actuarial Journal, 23, 335-363.

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

Stoeldraijer, L., de Regt, S., & van Duin, C. (2021, 12 16). Retrieved from CBS - Kernprognose 2021-2070: *Bevolkingsgroei trekt weer aan*: https://www.cbs.nl/nl-nl/longread/statistische-trends/2021/kernprognose-2021-2070-bevolkingsgroei-trekt-weer-aan?onepage = true#c-3--Bijgestelde-veronderstellingen-en-resultaten-voor-geboorte--sterfte-en-migratie

Wetenschappelijke Raad voor het Regeringsbeleid. (2021). *Navigeren en anticiperen in onzekere tijden*. Den Haag: KNAW.

Woolnough, K., Dr Ivanovic, B., Kramer, S., & Busenhart, J. (2007). *Pandemic influenza: A 21st century model for mortality shocks*. Swiss Reinsurance Company.

Appendix E
Glossary

Best estimate
In this publication: the most likely value for a quantity subject to chance, such as a mortality probability, the value of a product or portfolio etc.

Cohort life expectancy
Life expectancy based on a projections life table allowing for expected future mortality developments in the following calendar years. To calculate cohort life expectancy at birth, mortality probabilities are needed for a new-born today, a 1-year-old in one year's time, a 2-year-old in two years' time and so on.

Eurostat database
The database of Eurostat (the European Union's bureau of statistics) offers a wide range of data, for use by governments, companies, the education sector, journalists and the broader public.

Excess mortality
Excess mortality as a result of (the direct and indirect effects of) COVID-19 refers to the increased mortality relative to the expected mortality based on the trend estimated on the basis of data from before the corona era (based on the AG2020 projections model).

Human Mortality Database (HMD)
International database containing population and mortality data from over 40 countries worldwide.

Period life expectancy
Life expectancy based on mortality probabilities in an observation year. This expectancy assumes that mortality probabilities are stationary over time. Thus, period life expectancy does not allow for expected future developments in mortality. This definition is often used to compare developments in time but must not be used to estimate the expected longevity of individuals.

Projections life table
Mortality table in which mortality rates are given for each future year. This offers the possibility to calculate a remaining life expectancy for every age and every (future) starting year.

Standard retirement age
The assumed age at which payment of a (deferred) life-long old age pension will commence.

Statline
The public database of Statistics Netherlands (CBS). It provides statistics on economics, the Dutch population and our society.

Stochastic model
Model in which future mortality probabilities are not fixed but are defined by means of probability distributions.

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