<u>Supplementary material</u>

This Supplementary Material describes the methods we used to estimate excess deaths. We combined accepted demographic methods for forecasting mortality with accepted epidemiological methods for estimating seasonal fluctuations. We strengthened these methods a bit by some modest, uncontroversial improvements. The methods we used are state of the art, given the data and time we had. We plan, over the next three years, to develop and test more accurate methods, taking advantage of additional data from Denmark and other countries and of advances in demographic and statistical methods. It will never be possible to precisely calculate how many deaths would have occurred if the corona pandemic did not strike. Future estimates will be more reliable than the ones we currently can make. We think our estimates are serviceable accurate given the pressing need for better information to inform decision making.

Statistical Approach: The statistical analysis consisted of three main steps. We forecast mortality and population by age groups on a weekly basis. This provided a baseline mortality level of what would have been expected had the Covid-19 pandemic not occurred. Subsequently we subtracted the observed deaths that happened in week 11 through week 25 from the baseline to get estimates of lives saved/lost during the pandemic in Denmark.

Annual forecasts of death and population counts by age and sex in Denmark

We forecast death rates and population sizes by age and sex using historical data from 1970 to 2019 Denmark. To estimate the number of infants, we forecast fertility in 2020 but this was of minor importance because few babies died from Covid19 or were saved by policies to confront it. We assumed no in or out migration, because the low levels of migration in 2020 would have only a minor impact on the sizes of the populations at the older ages most affected by Covid19. This method mirrors the standard projection approach known as the cohort-component method (CCM) for population projections (*1*). The method has a longstanding tradition in demography and is notably used by the UN for their population projections (*2*) since it provides a flexible and powerful approach. An important advantage of the method is its consideration of the age-specific population structure and its influence on death counts, which is very relevant for the study of mortality during the Covid-19 pandemic (*3*). Mortality and fertility used in the analysis were forecast using powerful approaches described below and then fed to the model.

Annual forecasts of mortality and fertility

Female mortality was forecast using a Compositional Data Analysis approach developed by Oeppen (2008) (*4*) with data from 1970-2019 for Denmark available from the Human Mortality Database (HMD) (*5*). Compositional data is defined as a set of values that sum up to a fixed constant. Therefore, this method relies on the property that deaths from the life table sum up to the radix, often 1 or 100%. This method has gained recent attention and its advantages compared to other approaches have been discussed elsewhere (*6*).

Male mortality was forecast implementing the coherent forecasts based on compositional data analysis developed by Bergeron-Boucher et al. (2017) (*7*), where male mortality is forecast coherently with female trends. This approach has several advantages. For example, it allows to preserve coherence between subpopulations (e.g. males and females), it acknowledges covariance between components and explains a large proportion of the observed variability, and allows the rate of mortality improvement to change over time

Fertility rates were forecast using a Lee-Carter model (*8*) fitted over the period 1990-2019 with publicly available data from the Human Fertility Database (*9*) and Statistics Denmark (*10*). The Lee-Carter model is a well-known extrapolative approach that uses linear extrapolations of the logarithms of age-specific fertility rates to forecast fertility using principal component techniques such as Singular Value Decomposition.

Deaths occurring at ages 105+ were redistributed using a penalized composite link model for ungrouping (*11*) and aggregated in a last age interval 105+. Additionally, to estimate weekly exposures by sex and age, we used standard spline interpolation techniques to estimate population counts by week from the annual projections (*12*).

Estimation of weekly expected death counts by age and sex in Denmark for 2020 using the Serfling Poisson with offsets model

The examination of all-cause mortality is an important tool to define the nature and extent of excess mortality due to Covid-19, to identify those groups at higher risk of death, and to estimate the potential benefit (lives saved) from multiple interventions during the pandemic. Extending the standard Serfling model (*13, 14*) by assuming Poisson distributed death counts (*15*) and taking into account changes in population exposed to risk of dying as offset by age, we estimated weekly death counts by age and sex (see Eq. 1). Offset is the variable that is used to denote the exposure period in the Poisson regression: it enables change from counts to rates or vice versa. This strategy allowed us to model death rates and their change over time, and subsequently derive death counts multiplying the rates by the projected population at risk. The model is trained with data prior to Covid-19 outbreak, starting at week 1 of 2008 up to week 10 of 2020. Pandemic-free predictions start at week 11 and end at week 24. The model structure is defined as follows:

$$\log(E(Y_t)/\theta_t) = \alpha + \beta t + \gamma_2 \sin\left(\frac{2\pi t}{52}\right) + \gamma_3 \cos\left(\frac{2\pi t}{52}\right) + \gamma_4 \sin\left(\frac{2\pi t}{26}\right) + \gamma_5 \cos\left(\frac{2\pi t}{26}\right) + \epsilon_t, \text{Eq. } 1$$

where Y_t are the number of deaths at week t, t is the long-term trend, seasonality is expressed as 2 sine waves (or 2 Fourier terms) of 1 year and half year periods (15), and θ represents the population offset. Parameters were estimated via iteratively reweighted least squares. The model was fitted controlling for sex and 20-year age groups simultaneously.

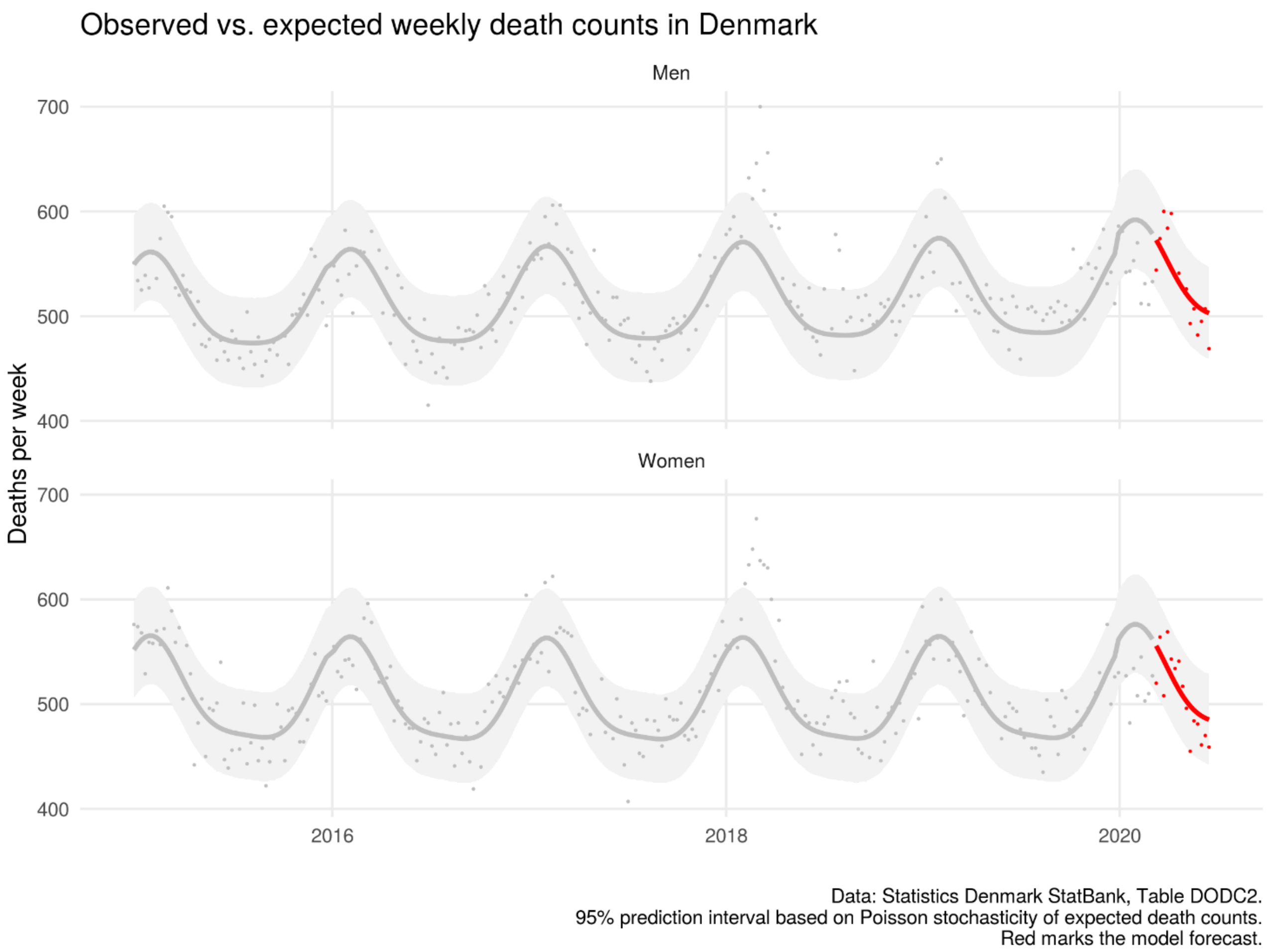
The predictive intervals around weekly expected death counts, excess deaths and cumulative excess deaths were derived from 1,000 draws from a Poisson distribution with a rate parameter equal to $E(Y_t)$, given fixed parameters of the Serfling model and fixed exposures. Including uncertainty around the parameter estimates of the regression model will further increase the width of the predictive intervals.

Figures 1 shows how the model fitted to data for Denmark. The solid lines refer to estimates derived from the model. Grey lines refer to the training dataset and solid red lines are predictions for week

11 onwards. The points are the observed deaths in a given week. These results represent the baseline from which we subtract the observed deaths during the pandemic.

The analyses were carried out using the R software (*16*). All the data we used is publicly available and our results are fully reproducible from the code and data provided.

Figure 1 Weekly estimates predicted by model Eq. 1 and observed deaths in Sweden and Denmark.



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