Estimates of excess mortality in Austria during the first three years of the COVID-19 pandemic

Authors

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Abstract

Introduction

Methods

Data sources

Reported deaths by week, 5-year age-group, and sex were obtained from the open-data repository of the official Austrian statistics office, Statistik Austria.

Model

We compared deaths reported in Austria during the first three years of the COVID-19 pandemic from 2020 to 2022 to deaths expected from pre-pandemic trends and patterns in all-cause mortality.

Excess deaths, $\delta_{y,w,a,s}$, in a given year, y, week, w, 5-year age-group, a, and sex s, were defined as the difference between reported deaths, $Y_{y,w,a,s}$ and model estimated expected deaths $E_{y,w,a,s}$.

$$\delta_{y,w,a,s} = Y_{y,w,a,s} - E_{y,w,a,s}$$

To estimate the expected number of deaths in a given week we formulated an age-structured Bayesian GAM model using R and brms. Weekly seasonality of expected deaths was modeled using a cyclic cubic spline with a knot for each week, $h(w)$. Long term trends in changes in all-cause mortality were accounted for by a thin plate spline with knots every 4 years, $g(y)$.

The model uses a negative binomial distribution for the expected number of deaths to allow for over dispersion in reported deaths, $E_{y,w,a,s} \sim \mathrm{NegBinomial}(\mu_{y,w,a,s}, \theta)$.

The predictors, $\mu_{y,w,s,x}$, were linked into the model using a log link function. The population, $N_{y,a,s}$, in each year, y, 5-year age group, a, and sex, s, was multiplied by a constant normalization factor $\gamma_{a,s}$. This normalization factor was used to improve the numerical stability of the model and was calculated for each age group and sex by dividing the mean number of deaths in the pre-pandemic period $\bar{Y}_{a,s}$ by the mean population in this age group and sex in the pre-pandemic period $\bar{N}_{a,s}$.

$$\log(\mu_{y,w,a,s}) = \beta_{a,s} \log(\gamma_{a,s} N_{y,a,s}) + g(y) + h(w)$$

The P-score is defined as the percentage difference between actual all-cause mortality and expected all-ause mortality.

$$P_{y,w,a,s} = \frac{\delta_{y,w,a,s}}{E_{y,w,a,s}}$$

Aggregate results, total weekly excess mortality, were obtained by summing over samples drawn from the posterior distribution of the model. Bayesian credible intervals were calculated using the equal-tailed method.

Code and data availability

All code is available on GitHub at github.com/fvalka/covid19-austria-excess-mortality. The data sets are available as open-data at Statistik Austria, https://data.statistik.gv.at/ and at the Austrian COVID-19 open data portal https://www.data.gv.at/en/data/austrian-covid-19-open-data-information-portal/.

Results

In total we estimate that 22521 [70% CI: 20973 - 24129, 90% CI: 19919 - 25129] excess deaths occurred in Austria during the first three years of the COVID-19 pandemic. With 6872 [70% CI: 6330 - 7392, 90% CI: 6070 - 7702] excess deaths in 2020, 7287 [70% CI: 6694 - 7883, 90% CI: 6297 - 8302] excess deaths in 2021, and 8358 [70% CI: 7663 - 9111, 90% CI: 7188 - 9500] excess deaths in 2022.

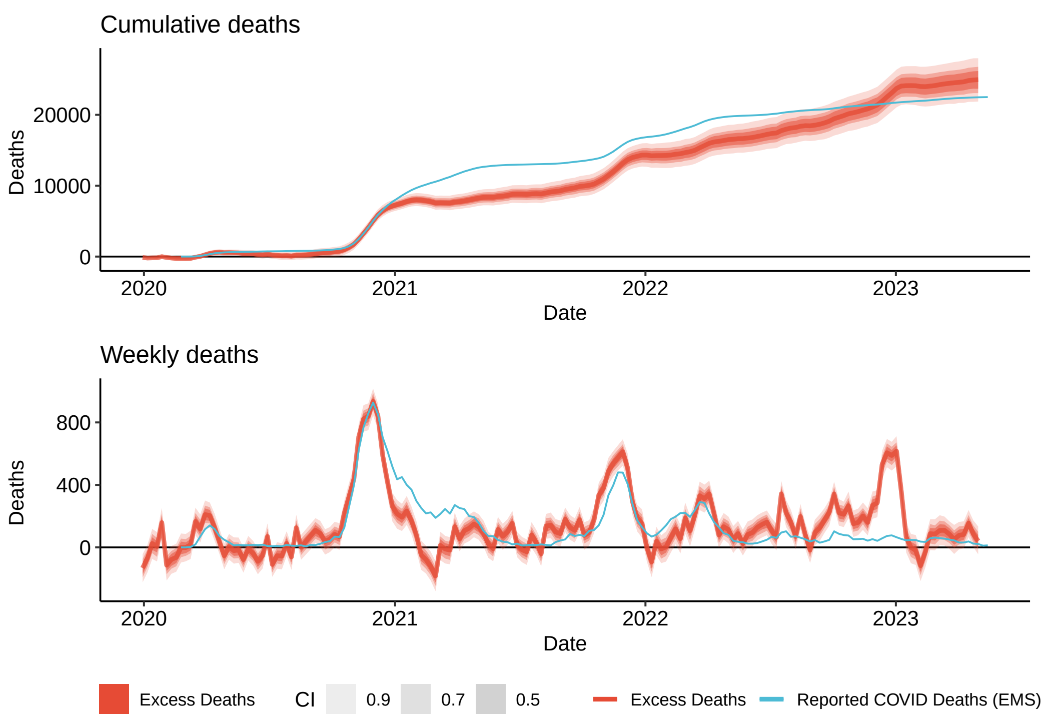

Figure 1: Model estimated cumulative and weekly deaths compared to reported COVID deaths.

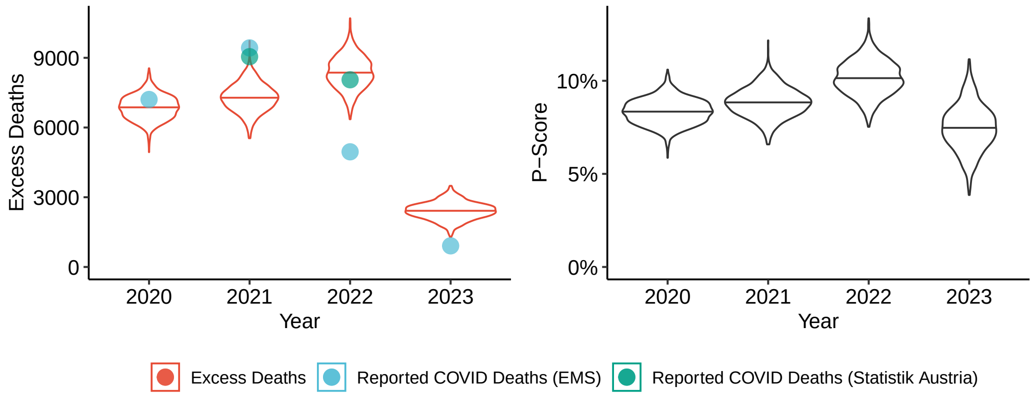

Figure 2: Posterior distributions of the yearly sums of estimated excess mortality and P-scores.

Discussion

Austria experienced excess mortality in all years of the COVID-19 pandemic with no decline in 2022. Reported COVID-19 deaths match the excess mortality in 2020, are at the upper end or slightly higher than excess mortality in 2021 and in 2022 there is a large difference between COVID deaths reported in the Austrian epidemiological surveillance system (EMS) and COVID deaths, with COVID as the primary or a secondary cause, taken from reported cause-of-death statistics from Statistik Austria.

The main strength of our method is that our model considers both changes in demography, including changes caused by excess mortality in each year of the pandemic affecting the population size in the following years, as well as long term trends in excess mortality and weekly seasonality.

References

Supplement

Long term trends and seasonality

The model contains smoothing curves for weekly seasonality $h(w)$ and yearly trends $g(y)$, which are shown in the figure. The yearly trend was fitted until 2019 and projected up to 2022.

Estimated expected mortality rates by age group and sex

The model is based upon an expected rate of deaths for each age group and sex. This estimated rate of expected deaths in the model is obtained from the estimates of the $\beta_{a,s}$ parameters multiplied with the population normalization factor $\gamma_{a,s}$.

These estimates are rates before the yearly trend and weekly seasonality are applied to them.

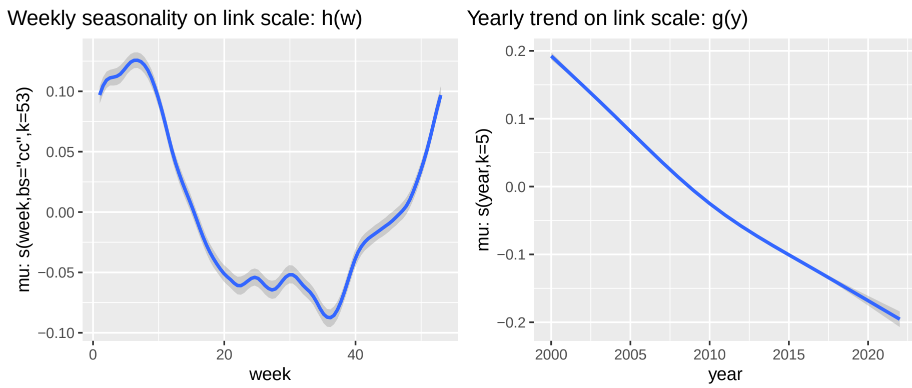

Figure 3: Supplemental figure: Model estimaed parameters for weekly seasonality cyclic cubic splines and yearly trend thin plate splines on the log-link scale.

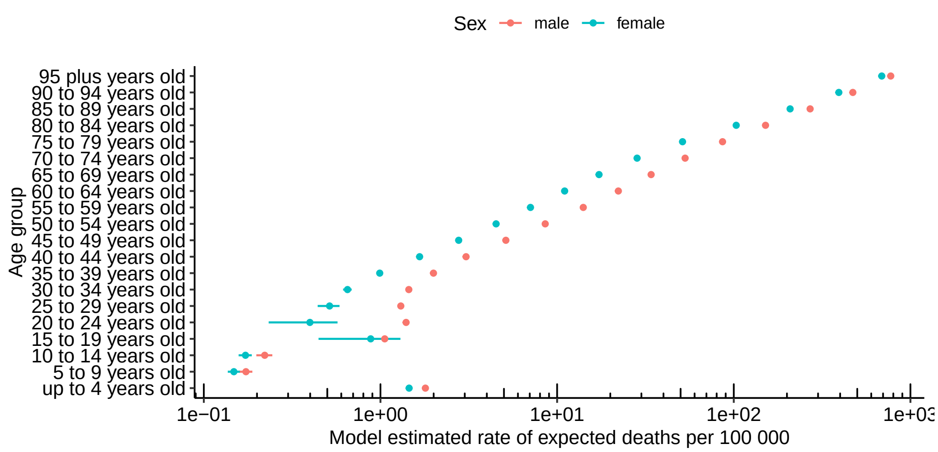

Figure 4: Supplemental figure: Estimaed mortality rates by age groups and sex, before yearly trends and weekly seasonality are applied.

Sensitivity Analysis

Model bias in pre-pandemic period

To investigate if there is any residual bias in the model for the fitted pre-pandemic years (up until 2019) we estimated the cumulative excess deaths for this period. Since we consider all patterns in all-cause mortality, including seasonality and pre-pandemic excess as the baseline this should lead to a cumulative excess from the year 2000 to 2019 of approximately 0.

Figure 5: Supplemental figure: Estimate of excess mortality in the pre-pandemic and pandemic period combined to investigate residual bias in the model after parameter estimation.

Non age-structured model

We also implemented a non age structured model similar to previously published results [WHO excess mortality ref] to investigate the effect of the age structuring in the model compared to simpler methods.

This model was also implemented as a Bayesian GAM using a negative binomial distribution and log link function. Two smoothing functions were used one cubic cylic spline for weekly seasonality, $n(w)$, and a thin plate regression spline for yearly trends, $m(y)$, which unlike the main model contain a knot for each year to account for combined changes in longer term all-cause mortality trends and shift in demographics.

The log linked estimator for this model, $\nu_{y,w}$, is defined as:

$$\log(\nu_{y,w}) = m(y) + n(w)$$

Since this model can for later years of the pandemic not consider the excess mortality which occurred during the earlier years of the pandemic we would expect the estimates based upon pre-pandemic trends to be more biased towards lower estimates for each consecutive year in the pandemic.

Using this non age-structured model we estimated a total of 20364 [70% CI: 16322 - 24345, 90% CI: 14038 - 26836] excess deaths for the years 2020 to 2022 compared to 22521 [70% CI: 20973 - 24129, 90% CI: 19919 - 25129] excess deaths from the age-structured main model.

Backtesting for a pre-pandemic estimation

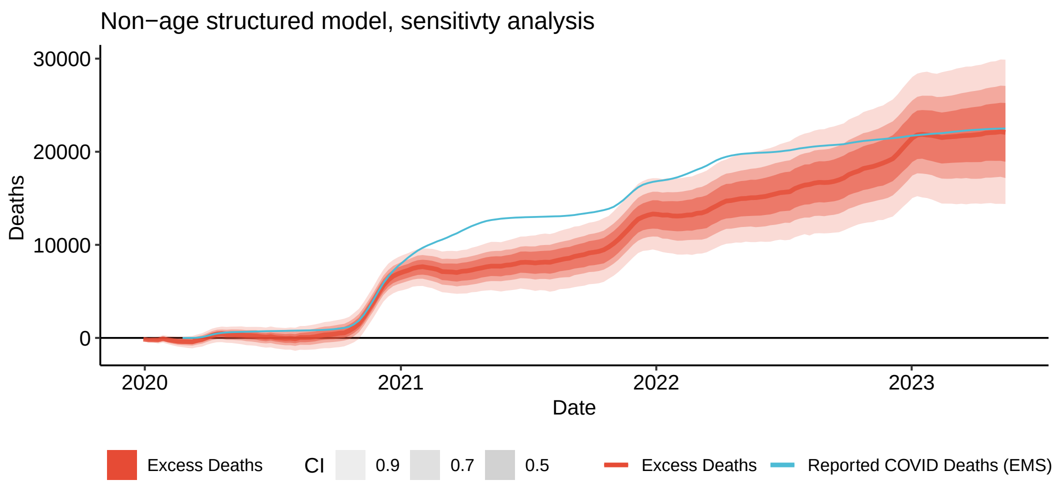

Figure 6: Supplemental figure: Estimated cumulative excess mortality from a non age structured model with weekly seasonality and yearly trend.

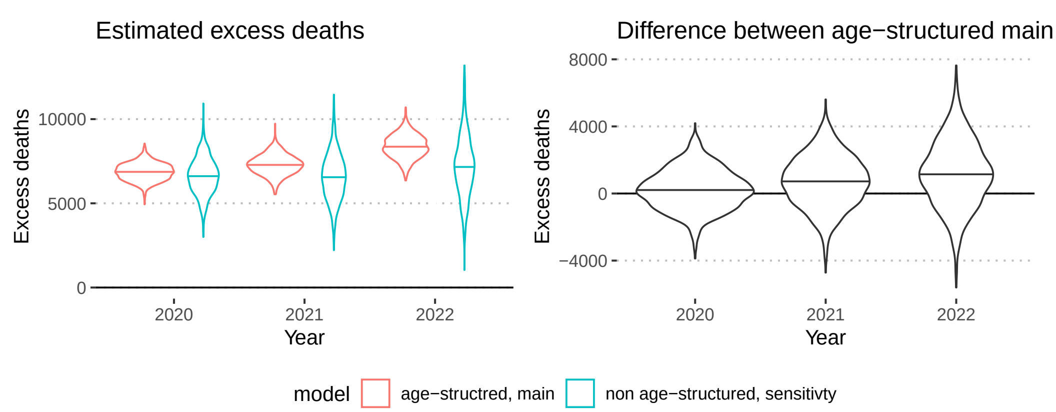

Figure 7: Supplement figure: Model estimated yearly excess model for the age-structured main model and the non-age structured sensitivty model and difference between the estimated excess deaths in both models.