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Practice of Epidemiology

Month-to-month all-cause mortality forecasting: a method allowing for changes in seasonal patterns

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Abstract

Forecasting of seasonal mortality patterns can provide useful information for planning health-care demand and capacity. Timely mortality forecasts are needed during severe winter spikes and/or pandemic waves to guide policy-making and public health decisions. In this article, we propose a flexible method for forecasting all-cause mortality in real time considering short-term changes in seasonal patterns within an epidemiologic year. All-cause mortality data have the advantage of being available with less delay than cause-specific mortality data. In this study, we use all-cause monthly death counts obtained from the national statistical offices of Denmark, France, Spain, and Sweden from epidemic seasons 2012-2013 through 2021-2022 to demonstrate the performance of the proposed approach. The method forecasts deaths 1 month ahead, based on their expected ratio to the next month. Prediction intervals are obtained via bootstrapping. The forecasts accurately predict the winter mortality peaks before the COVID-19 pandemic. Although the method predicts mortality less accurately during the first wave of the COVID-19 pandemic, it captures the aspects of later waves better than other traditional methods. The method is attractive for health researchers and governmental offices for aiding public health responses because it uses minimal input data, makes simple and intuitive assumptions, and provides accurate forecasts both during seasonal influenza epidemics and during novel virus pandemics.

Key words: short-term mortality forecasting; all-cause mortality; seasonality; public health surveillance data; mortality shocks.

Introduction

In temperate countries in the Northern Hemisphere, all-cause mortality exhibits a marked seasonality, with a winter peak driven by influenza-related mortality in the older population.[1,2] Large variations of the seasonal mortality pattern (eg, in the magnitude and timing of the winter peak) occur based on the severity and circulation of influenza, pandemics arising from novel subtypes of the influenza virus,[3] and fluctuations in temperature and humidity.[4] Addressing severe influenza seasons or pandemic outbreaks depends critically on the implementation of early public health measures, including isolation and quarantine. Accurate and timely mortality forecasts in the short term (ie, of some weeks or months) can aid public health responses by informing key preparation and mitigation efforts.[5,6]

Various types of short-term forecasts of all-cause mortality are established in the literature. The simplest way to forecast mortality is to calculate the average number of deaths or the average mortality rates over preceding years—for instance, the preceding 5 years. Modeling is commonly preferred because it extrapolates a secular trend and estimates seasonal variations. Traditional models are the Serfling model,[7-9] Serfling-Poisson regressions,[10] or time-series methods.[2,11] These models are designed to predict seasonal epidemics in the absence of mortality shocks. In the case of a shock, the forecasts are interpreted as baseline mortality (i.e., counterfactual forecasts), and excess mortality is used to quantify the severity of an influenza season,[12-15] the mortality burden of heat waves,[16,17] and the mortality burden of pandemics, such as the 1918-1919 H1N1 influenza pandemic.[8] During the COVID-19 pandemic, excess death estimates were published by media outlets and in the scientific literature,[18-20] to compare countries across time[21-24] and to evaluate the effect of policy interventions.[25]

Since excess mortality is used retrospectively, it may not be suitable for real-time mortality monitoring. The few examples of all-cause mortality forecasting in real time during severe mortality conditions are limited to the inclusion of seasonal influenza in the modeling, such as the FluMOMO model, extending the EuroMOMO model to measure excess death.[15] The limitation of these models is that they require information other than mortality, usually data collection of indicators of temperature and influenza activity provided by surveillance systems, which are often voluntary and insufficiently systematic and detailed.[26]

Examples of timely forecasting can be found in infectious disease forecasting. Compartmental models (eg, susceptible-infectious-recovered (SIR) and susceptible-exposed-infectious-susceptible (SEIR) models)[27,28] simulate scenarios of disease progression over time within a population. The aim is to anticipate the evolution of the disease and be informative on the preparation and prevention of illnesses, hospitalizations, and deaths. Infectious disease forecasting is very demanding in terms

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of information—for example, numbers of infections, recoveries, and hospitalizations. These types of data are usually available in highly specific settings (eg, hospitals and care homes (nursing homes)), leading to predictions produced on a small scale.[29-32] Furthermore, in the early stages of health shocks, testing procedures for infections and registration systems are often not in place, and limited data are available. During the COVID-19 pandemic, SEIR-type models were used for nowcasting COVID-19 spread dynamics—that is, estimating the current numbers of cases and deaths by correcting for reporting delays.[33-35]

In this paper, we propose a simple and flexible method for real-time short-term forecasting of all-cause mortality 1 month ahead—both in regular epidemic years and during pandemics of infectious diseases. Our forecasting strategy is inspired by the later/earlier method, introduced by Rizzi and Vaupel[36,37] to make counterfactual forecasts after the health shock caused by the first COVID-19 wave. Here we first introduce the later/earlier method for month-to-month all-cause mortality forecasting. We define the seasonality index as the ratio of death counts between 2 adjacent months. The expected numbers of deaths 1 month ahead are estimated on the basis of current mortality levels and recent past seasonality. The current mortality level is determined by the monthly death counts of the present epidemiologic year (epi-year), whereas the time series of ratios of death counts between adjacent months over preceding epi-years model the past seasonality. We show an application on historical forecasts of all-cause seasonal mortality from 2012 through 2022, including both non-COVID and COVID years, in Denmark, France, Spain, and Sweden. Furthermore, we compare the proposed method with alternative ones. We provide R code for full replicability of our analysis.

Methods

The method for month-to-month all-cause mortality forecasting

An epi-year is defined as July through June, covering part of 2 adjacent calendar years. The Northern Hemisphere influenza season usually starts in October and ends in May, with a seasonal mortality peak between December and March. Winter seasonality and low summer mortality make deaths in adjacent months highly positively correlated, because an increase/decrease in one month is associated with an increase/decrease in the following month. By extrapolating the relationship between the current month (earlier month) and the next month (later month), one can predict the number of deaths in the next month at any moment during the epi-year. The relationship between deaths over adjacent months can be defined by their ratio, called the later/earlier ratio.

Formally, consider the number of deaths in the ith month during an epi-year, D_i, with $i = 1, \ldots, 12$. The later/earlier ratio between the ith month and the $(i+1)$th month, denoted by υ_i, is given by

$$\upsilon_i = \frac{D_{i+1}}{D_i}. \tag{1}$$

Our aim is to forecast the deaths 1 month ahead, that is, D_{i+1}. The expected number of deaths D_{i+1} can be derived from the known deaths D_i of the ith month and the later/earlier ratio υ_i 1 month ahead. The later/earlier ratio υ_i 1 month in the future is not known. Therefore, the series of death counts for the ith month over N epi-years in the past, $\boldsymbol{D}_i = D_{i,j}$ with $j = 1, \ldots, N$, can be used to compute the series of later/earlier ratios $\boldsymbol{\upsilon}_i$. The corresponding average later/earlier ratio $\overline{\upsilon}_i$ for the ith month is

$$\overline{\upsilon}_i = E(\boldsymbol{\upsilon}_i), \tag{2}$$

that is, the average of the later/earlier ratios for N past epi-years. One can assume that the later/earlier ratio 1 month in the future equals the average month-specific later/earlier ratio of the previous years ($\upsilon_i = \overline{\upsilon}_i$). This assumption holds if the series of later/earlier ratios is stationary. The values $\boldsymbol{\upsilon}_i$, with $i = 1, \ldots, 12$, can be checked for stationarity over previous epi-years. If the series shows no trend, the number of deaths in the $(i+1)$th month can be forecast based on the deaths in the ith month and on the average ratio $\overline{\upsilon}_i$ for the ith month, according to the formula

$$\widehat{D_{i+1}} \approx \overline{\upsilon}_i \, D_i. \tag{3}$$

Illustration of the method

Let us suppose that we want to forecast the death counts 1 month ahead in 1 country (Spain) and in 2 epi-years with different seasonality (epi-years 2013-2014 and 2017-2018), as illustrated in Figure 1. In each panel, the black circles represent the observed monthly death counts during the epi-year. Below the death counts are plotted the month-specific later/earlier ratios, that is, the deaths of 1 month ahead divided by the deaths of the current month (purple squares). When there is an increase in the death counts 1 month ahead, the corresponding later/earlier ratio is greater than 1; when there is a decrease, the later/earlier ratio is lower than 1. The average later/earlier ratios are computed over the past 5 epi-years (seasons) and are represented with orange triangles in Figure 1. The average later/earlier ratios are greater than 1 from September through December and lower than 1 in the remaining months. To obtain the forecasts 1 month ahead (blue diamonds), one first tests the stationarity of the 5-year series of later/earlier ratios and then multiplies the death counts of the current month (black circles) by the corresponding average later/earlier ratio (orange triangles).

The method is suitable for forecasting mortality changes during an epi-year because (1) it assumes a seasonal mortality structure in the epi-year given by the average later/earlier ratios ($\overline{\upsilon}_i$ with $i = 1, \ldots 12$ in equation (2)) and (2) at the same time, it adjusts the level of mortality of the particular epi-year using the actual observed deaths (D_i with $i = 1, \ldots 12$ in equation (3)). This permits one to make short-term forecasts in epi-years with different mortality levels and severity of winter peaks—for example, season 2017-2018 (Figure 1A) compared with season 2013-2014 (Figure 1B) in Spain.

Prediction intervals

Prediction intervals must consider the 2 sources of variability of the forecasts. The first source comes from the uncertainty in the later/earlier ratios—that is, from the assumption that the expected later/earlier ratio 1 month ahead equals the month-specific average later/earlier ratio in the previous years. To assess how much the expected later/earlier ratio 1 month ahead might differ from its average value in previous years, we use a bootstrapping strategy. The second source comes from the observed deaths. The procedure can be described as follows.

1. Step 1—bootstrapping. Draw 10 000 simulated later/earlier ratios from the series of later/earlier ratios and substitute them in equation 2 to compute 10 000 expected deaths 1 month ahead.

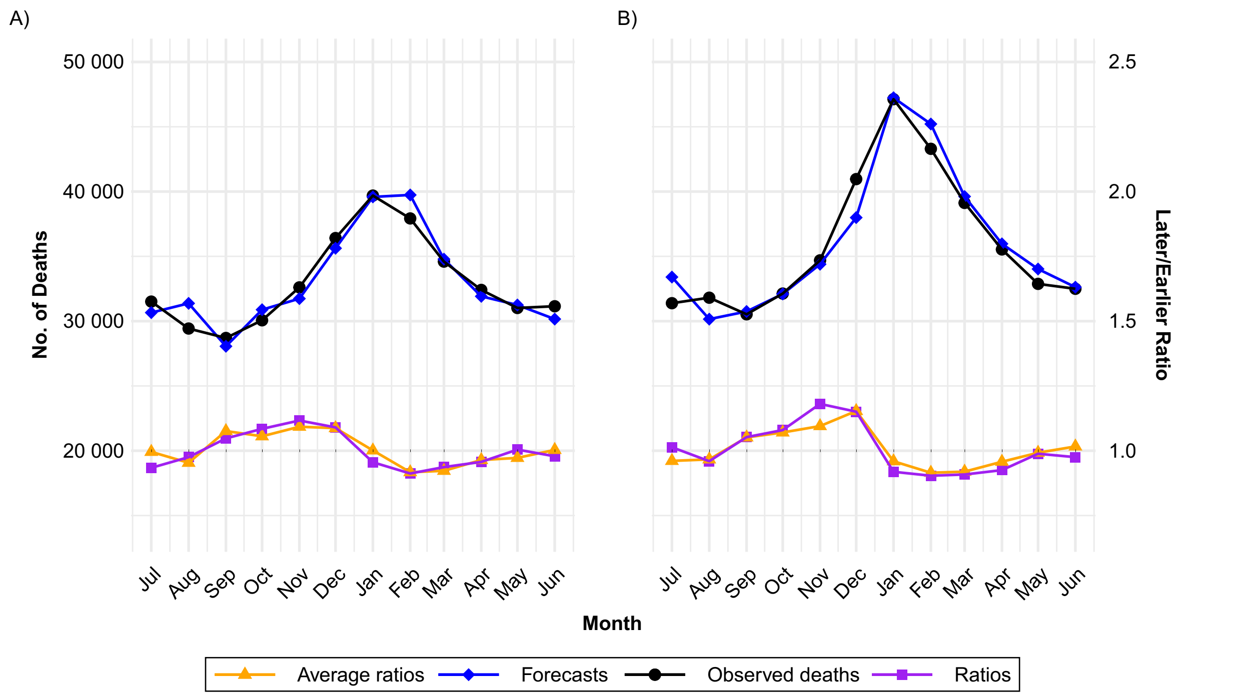

Figure 1. Illustration of the later/earlier method for Spain, 2013-2014 (A) and 2017-2018 (B). The forecast of the monthly death count (blue diamonds) is obtained using as input data the death count (black circles) of the previous month and the corresponding average later/earlier ratio (orange triangles) approximating the monthly ratio of the current year (purple squares).

2. Step 2—mapping on a distribution. Draw 10 000 death counts from a Poisson distribution with the mean equal to expected deaths 1 month ahead.
3. Step 3—computation of the prediction intervals. Compute the empirical 95% prediction intervals as the 2.5th and 97.5th percentiles of the Poisson distribution.

Data and application

Data

At the beginning of the COVID-19 pandemic, national statistical offices started publishing timely all-cause weekly and monthly mortality data series. We focused on Denmark,[38] France,[39] Spain,[40] and Sweden[41] because of the availability and high quality of data from those countries. Moreover, different population sizes allowed for a robustness check of the method. We retrieved data on monthly numbers of deaths for the total population from the individual countries' national statistical offices. Statistics Denmark and Statistics Sweden cover all deaths among those countries' residents. The Institut national de la statistique et des études économiques covers the population of metropolitan France (excluding overseas territories). The Instituto Nacional de Estadística covers all of the deaths that occur in Spain. We chose epi-year 2007-2008 as the starting point because it was the

Table 1. Average later/earlier ratios and coefficients of variation computed for all-cause mortality, by month, in Denmark, France, Spain, and Sweden for the epidemiologic years 2007-2008 through 2022-2023.

Monthly ratio	Country							
	Denmark		France		Spain		Sweden	
	Mean L/E ratio	CV, %	Mean L/E ratio	CV, %	Mean L/E ratio	CV, %	Mean L/E ratio	CV, %
υ_{July}	0.99	2.75	0.99	2.70	0.99	5.15	0.98	2.42
υ_{August}	1.01	3.02	1.02	1.65	0.96	2.61	1.03	2.13
$\upsilon_{\text{September}}$	1.02	2.80	1.07	2.64	1.06	2.38	1.03	2.29
$\upsilon_{\text{October}}$	1.03	2.34	1.03	4.60	1.07	2.16	1.03	4.02
$\upsilon_{\text{November}}$	1.09	4.43	1.08	6.13	1.08	4.91	1.10	5.16
$\upsilon_{\text{December}}$	1.04	4.10	1.08	5.35	1.14	7.50	1.05	3.54
$\upsilon_{\text{January}}$	0.99	5.96	0.98	6.97	0.95	8.70	0.97	6.01
$\upsilon_{\text{February}}$	0.97	5.18	0.95	8.15	0.95	17.30	0.97	5.04
υ_{March}	0.95	5.40	0.95	6.23	0.94	5.50	0.97	9.33
υ_{April}	0.96	4.29	0.93	7.44	0.93	11.61	0.93	4.80
υ_{May}	0.98	2.32	0.97	2.31	0.98	2.88	0.96	3.31
υ_{June}	1.00	3.29	1.01	2.89	1.01	4.60	1.01	3.74

Abbreviations: CV, coefficient of variation; L/E, later/earlier.

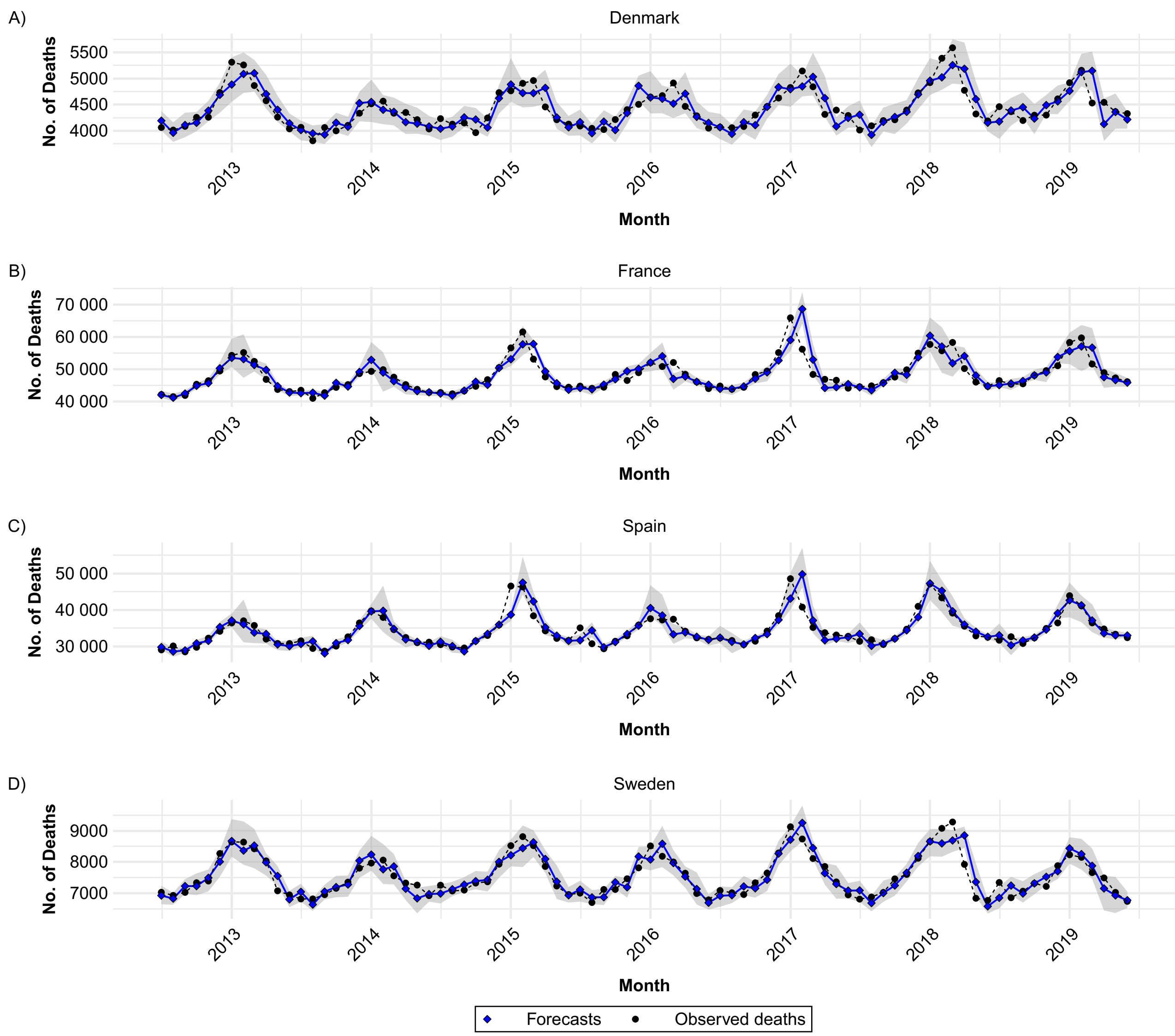

Figure 2. One-month-ahead forecasts of all-cause mortality (solid blue line with blue diamonds) derived using the later/earlier method from epidemiologic year 2012-2013 through epidemiologic year 2018-2019 in Denmark (A), France (B), Spain (C), and Sweden (D) as compared with observed death counts (dashed black line with black circles). Gray shaded areas show the 95% prediction interval obtained via a bootstrapping procedure.

first available year for Denmark. The data were available until December 2021 for Denmark, Spain, and Sweden and until July 2022 for France.

The death counts were adjusted to be comparable across months of different lengths and across leap years and nonleap years, following Nepomuceno et al.[42] We assumed the average number of days in a month in both leap and nonleap years to be 30.44 days (365.25/12). The monthly death counts were multiplied by the ratio between 30.44 and the actual number of days in each month. To adjust for any difference in the annual total number of deaths after rescaling, we distributed the difference according to the annual relative frequencies of the rescaled death counts. The relative frequencies were computed within the epidemic year, to account for the influenza season.

Testing of the method's assumptions

The later/earlier method assumes that the later/earlier ratios do not show any trend in the short term. Table 1 shows the mean values and coefficients of variation for the series of later/earlier ratios computed on the epi-years from 2007-2008 through 2022-2023 by country. The average later/earlier ratios are above 1 from September through December and below 1 from February to May. The coefficients of variation are lower than 10%, with only a few exceptions slightly larger but always lower than 20%. The series of later/earlier ratios for Denmark, France, Spain, and Sweden reveal a considerable regularity, that is, similar means by country and small coefficients of variation. Furthermore, the series are stationary (the mean and variance are constant over time) via the Ljung-Box test or the Kwiatkowski-Phillips-Schmidt-Shin test.[43] These regularities provide a simple approach for (short-term) forecasting the deaths 1 month ahead.

The first COVID-19 wave in 2020 represents an exceptional case, because the mortality shock occurred outside the window of the winter peak, and it is not safe to assume that the later/earlier ratios from March to May 2020 were the average over previous years. In Appendix S1, Figures S1-S4 show the complete series of later/earlier ratios and the departure from the average in 2019-2020 in all countries analyzed. For these months, we expected that the forecasts would not be able to predict mortality accurately.

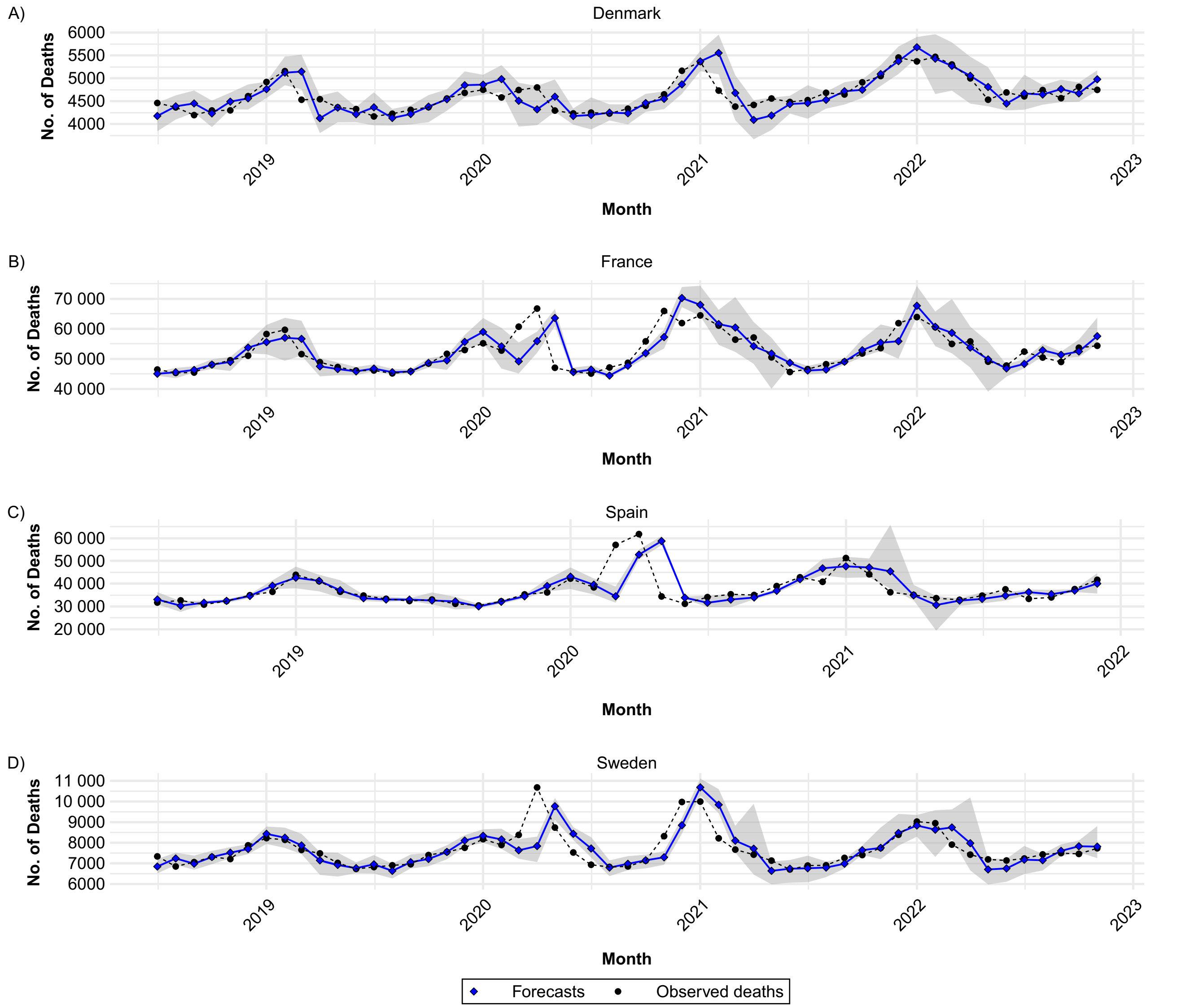

Figure 3. One-month-ahead forecasts of all-cause mortality (solid blue line with blue diamonds) derived using the later/earlier method from epidemiologic year 2018-2019 through epidemiologic year 2022-2023 in Denmark (A), France (B), Spain (C), and Sweden (D) as compared with observed death counts (dashed black line with black circles). Gray shaded areas show the 95% prediction interval obtained via a bootstrapping procedure.

Month-to-month forecasts with the later/earlier method

We applied the later/earlier method to forecast mortality 1 month ahead with a rolling window of 5 epi-years preceding the forecasting window. The summary measures for the 5-year series of later/earlier ratios for testing the method's assumptions can be found in Appendix S1 (Tables S1-S12). We forecast monthly mortality from July 2012 through November 2022 (December 2021 for Spain) based on mortality data from June 2007 through October 2022. For example, we forecast mortality in Denmark in July 2012 based on the deaths of June 2012 and the average later/earlier ratio for July/June of the preceding 5 epi-years, starting from 2007-2008. The first forecast (July 2012) used the first 5 available years of data (from 2007-2008 through 2011-2012), and the last forecast (November 2022) used the last 5 available years of data (from 2017-2018 through 2021-2022). Due to differences in years with available data by country, the years of the forecasts varied across countries. Figure 2 and Figure 3 illustrate the results for the 4 countries analyzed. To demonstrate the accuracy of the forecasts (blue diamonds), we have superimposed the observed death counts (black circles) and the 95% forecasting intervals (gray shaded areas).

The forecasts capture the seasonal trend of the data (Figure 2). For example, the method captures the higher level of winter mortality in 2012-2013 and the lower winter level in 2013-2014 in Denmark, due to different types of viruses and transmission modes. The season 2012-2013 witnessed a long period of high influenza activity dominated by the A(H3N2) strain, while influenza activity and mortality were low in the A(H1N1)-dominated 2013-2014 season.[14] A season with predominant influenza A(H3N2) has higher mortality impact than a season with predominant influenza A(H1N1) or a season with low influenza A transmission. As a second example, the method forecasts the higher seasonality peaks in the winters 2014-2015 and 2016-2017 in France and Spain. These seasons were characterized by a high activity of influenza A(H3N2) viruses, the circulation of variants of the virus, and a reduction in the effectiveness of the influenza vaccine.[13] The method provides, in a few cases, delayed forecasts corresponding to the winter peaks, which is expected due to the intrinsic variability in the

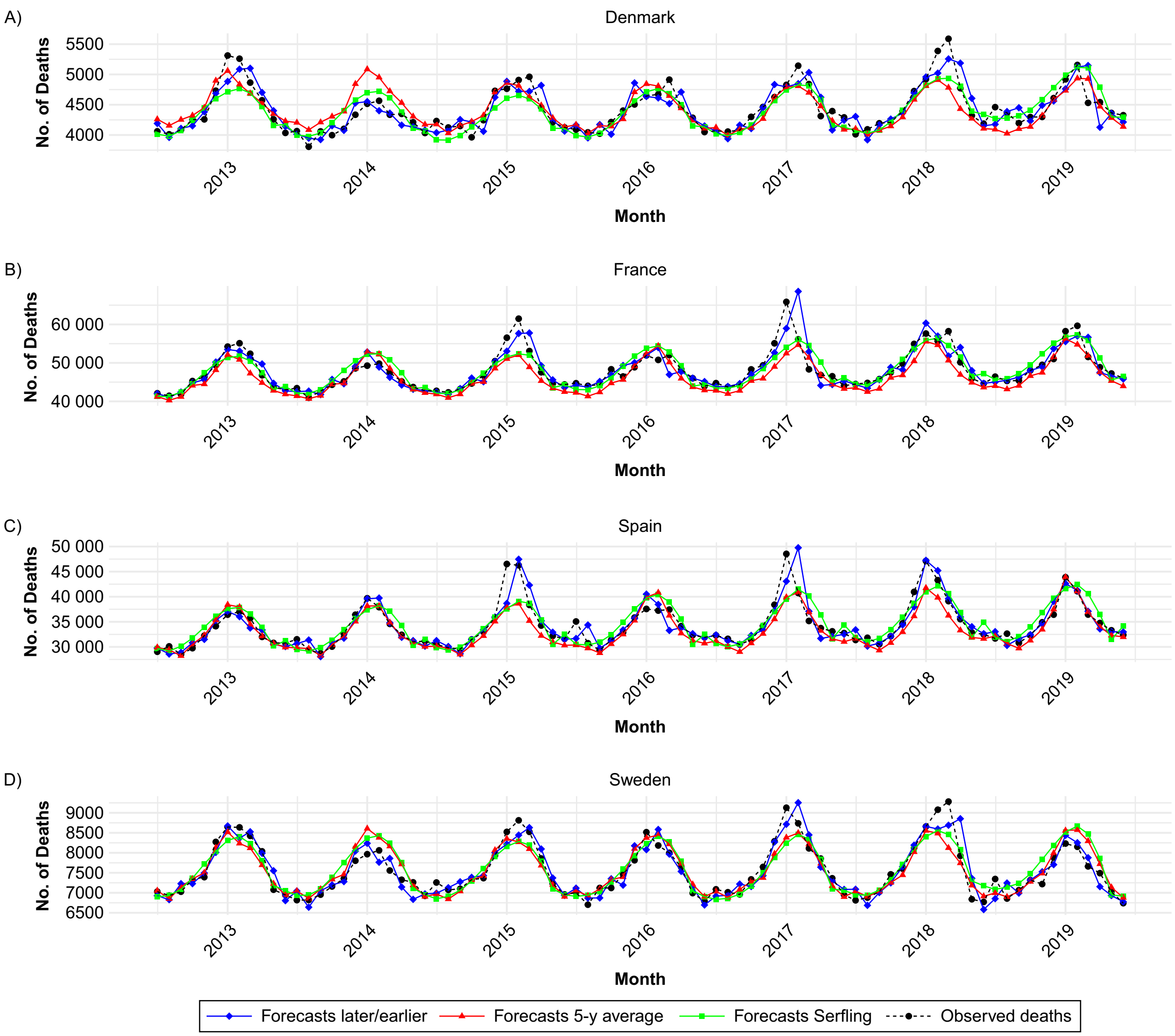

Figure 4. Observed numbers of deaths (dashed black line with black circles) and forecasts derived using the later/earlier method (solid blue line with blue diamonds), the 5-year-average method (solid red line with red triangles), and the Serfling model (solid green line with green squares) from epidemiologic year 2012-2013 through epidemiologic year 2018-2019 in Denmark (A), France (B), Spain (C), and Sweden (D).

winter peak. For instance, the mortality peak in 2016-2017 in Spain and France occurred in January. The method forecasts the mortality peak in February 2017, because it uses the average over the preceding 5 epi-years to model the seasonality, and mortality peaks before epi-year 2016-2017 occurred in February. However, the forecast in the epi-year 2017-2018 averages the change in the peak occurrence, and the winter peak is captured in January 2018, in both France and Spain.

Our forecasts reflect the synchrony of the 3 main COVID-19 waves through 2020 and 2021[44] and the different mortality burdens in the 4 countries analyzed (Figure 3). A consistent excess mortality—large in Sweden and Spain, medium in France[21-23]—was reported for the first wave (mid-February 2020 through the end of May 2020). Our monthly forecasts failed to predict the deaths in the first month of the pandemic (ie, March 2020) in France, Spain, and Sweden, because the shock occurred abruptly outside of the usual seasonal pattern and because of its magnitude. In the second wave (autumn 2020 through March 2021) and the third wave (starting in the latter half of 2021 and ongoing by the end of 2021), France experienced a toll similar to that of the first wave, whereas Spain and Sweden experienced lower tolls but lasting for many weeks.[45] In this context, the forecasts capture the level and shape of the seasonal mortality.

The forecasts fit most of the data within the 95% prediction intervals. The coverage of the 95% prediction intervals is 72.76% for all countries (82.54% for Denmark, 64.29% for France, 64.91% for Spain, and 79.37% for Sweden). Details on the coverage of the prediction intervals computed separately for pre–COVID-19 epi-years and COVID-19 epi-years is presented in Table S13. The monthly prediction intervals are not equally affected by the overall seasonality. They are wider in the winter peaks, where variability in the observed deaths is higher. Prediction intervals reflect mortality changes in preceding years. For instance, the uncertainty in the estimates for the months March through June 2021 in France is greater because of the COVID-19 wave in 2020.

Forecast evaluation

To evaluate the forecast accuracy, we compared the performance of the later/earlier method with the 5-year-average method and

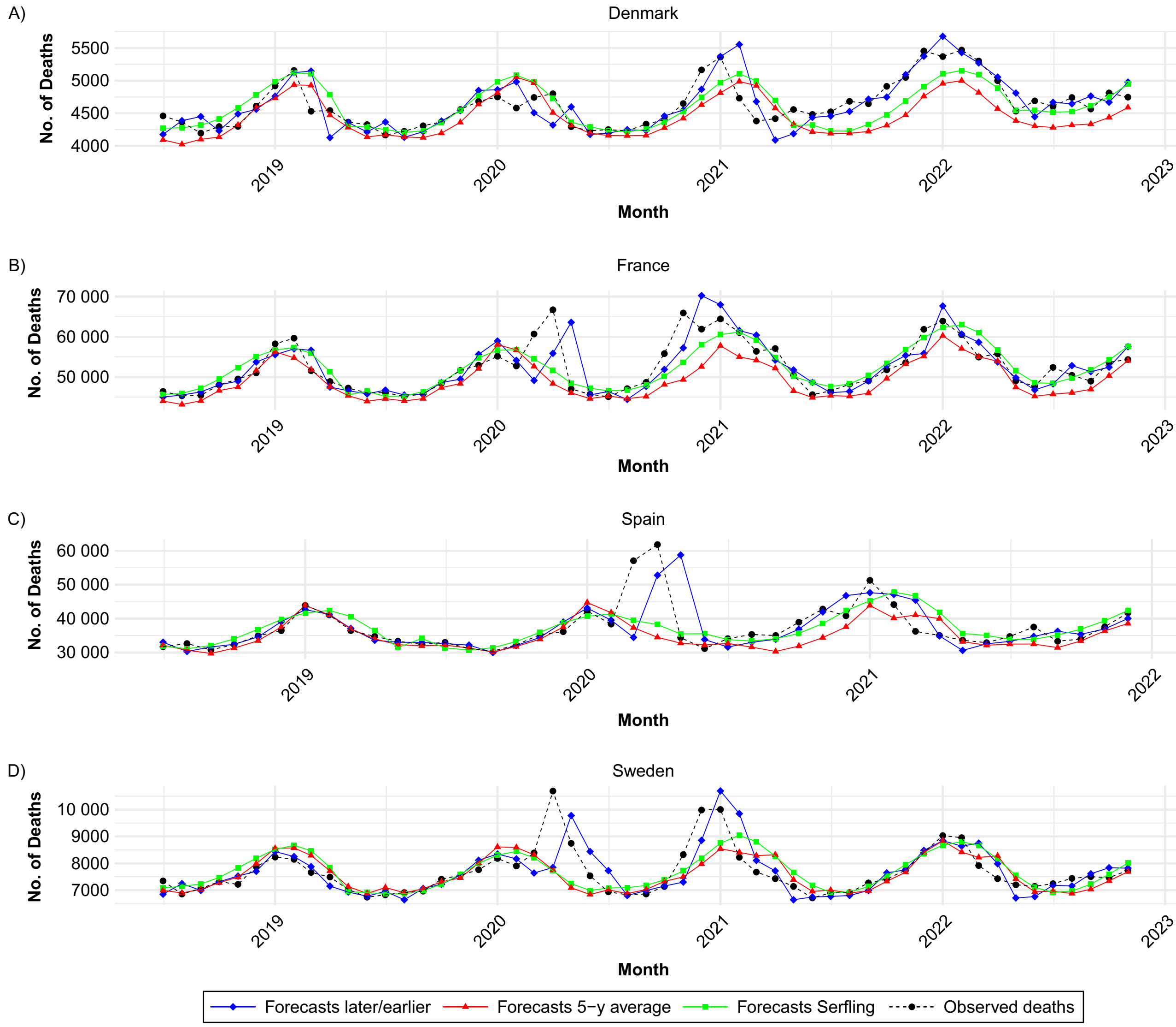

Figure 5. Observed numbers of deaths (dashed black line with black circles) and forecasts derived using the later/earlier method (solid blue line with blue diamonds), the 5-year-average method (solid red line with red triangles), and the Serfling model (solid green line with green squares) from epidemiologic year 2018-2019 through epidemiologic year 2022-2023 in Denmark (A), France (B), Spain (C), and Sweden (D).

the quasi-Poisson Serfling model (see Appendix S2). We chose these well-established methods for short-term mortality forecasting because they allow the same input data as the later/earlier method—that is, a rolling window of 5 epi-years of all-cause mortality data. Figure 4 and Figure 5 illustrate the respective monthly forecasts when each of the 3 methods is applied.

The later/earlier method better captures the interannual variability than either of the other methods (Figure 4). The coverage of the 95% prediction intervals is greater for the later/earlier method (72.76%), followed by the 5-year-average method (68.90%) and the quasi-Poisson Serfling model (56.50%). Details by country can be found in Appendix S3 (Figures S5-S8 and Tables S13 and S14). Lower winter levels of mortality (eg, in Denmark in the winter season of 2013-2014) and highest seasonality peaks (eg, in France and Spain in 2014-2015 and 2016-2017) are more accurately forecast by the later/earlier method than by the 5-year-average and quasi-Poisson Serfling methods. The delays in the forecasts in relation to specific winter peaks are observed for all 3 methods, confirming the difficulty in predicting the month of occurrence regardless of the forecasting method.

None of the methods were able to forecast the mortality shock in March and April 2020, because of the sudden sharp mortality increase beyond the regular seasonal shape (Figure 5). After the first COVID-19 wave, the later/earlier method provided better predictions of the mortality level in the 4 countries than the 5-year-average and the quasi-Poisson Serfling model, because it was more flexible in relation to the higher level of winter mortality. In 2020-2021, the seasonal peak occurred earlier than in regular endemic years (from November to January). The later/earlier method forecasts the highest mortality, albeit with 1 month of delay, unlike the 5-year-average and the quasi-Poisson Serfling model. From the final months of 2021 to the beginning of 2022, Denmark witnessed sustained excess mortality, presumably caused by the transmission of infection with the Delta variant of SARS-CoV-2. The later/earlier method turned out to be the method that forecast the highest level of mortality in Denmark in late 2021.

To evaluate the accuracy of the forecasts, we computed the root mean squared error (RMSE) and the mean absolute percentage error (MAPE) of the forecasts of the 3 methods. We chose a

Table 2. Accuracy measures (root mean squared error and mean absolute percentage error) for all-cause mortality forecasts[a] derived using the later/earlier ratio method, the 5-year-average method, and the quasi-Poisson Serfling model.

Accuracy measure and country	Mortality forecasting method		
	Later/earlier method	5-y average	Quasi-Poisson Serfling
	RMSE		
Denmark	213	236	214
France	2784	3688	2877
Spain	2262	2717	2818
Sweden	359	395	413
Total	1806	2302	2027
	MAPE		
Denmark	3.51	4.00	3.41
France	3.55	4.85	3.86
Spain	3.86	4.83	5.59
Sweden	3.22	3.14	3.82
Total	3.54	4.20	4.17

Abbreviations: MAPE, mean absolute percentage error; RMSE, root mean squared error.
[a]The forecasts were calculated for epidemiologic year 2012-2013 through epidemiologic year 2020-2021 (excluding epidemiologic year 2019-2020) for Denmark, France, Spain, Sweden, and the pooled sample.

scale-dependent measure (RMSE) and a measure based on percentage errors (MAPE) to check whether they favored different models.[46] We excluded epi-year 2019-2020 from the computation of the accuracy measures, because of the external shock that disrupted the seasonality pattern and that was not predictable by any method, and epi-year 2021-2022, for which data were available only in France. The RMSE and MAPE for the 4 countries analyzed are displayed in Table 2.

The accuracy of the methods varied across countries and indicators. When considering the RMSE, the later/earlier method proved to be more accurate than the other two methods. When considering the MAPE, the later/earlier method was the second-best method for Denmark and Sweden. On average, considering the pooled sample of the 4 countries, the later/earlier method predicted the deaths 1 month ahead more accurately according to both the RMSE and the MAPE. Using the later/earlier method instead of the 5-year average method, we decreased the RMSE by 21.55% (and the MAPE by 15.71%). Compared with the quasi-Poisson Serfling model, the later/earlier method decreased the RMSE by 10.9% (and the MAPE by 15.11%). The errors were weighted in different ways by the 2 accuracy indicators. This resulted in some differences in the measurement of the most accurate method based on RMSE or MAPE.

We performed a sensitivity analysis of the later/earlier method to the length of the time series used to train the model (Appendix S4, Table S15). The average later/earlier ratios were computed on 2-8 epi-years. Longer time series seemed preferable, although the percentage improvements were quite small. Furthermore, we computed the RMSE, MAPE, and mean absolute scaled error (MASE) for the 3 methods while distinguishing between prepandemic and COVID-19 pandemic years (Appendix S5, Tables S16 and S17). Overall, the accuracy was larger for the later/earlier method.

Discussion

In this study, we proposed a novel method for forecasting monthly all-cause mortality 1 month ahead. We applied it to 4 countries (Denmark, France, Spain, and Sweden) with different population sizes and variations in pandemic phases and death tolls during the COVID-19 pandemic (from epi-year 2012-2013 through 2021-2022). The method incorporates important features of mortality, learning from past seasonality of deaths and the current yearly variable level of mortality. This ensures a flexible structure for forecasting in normal epidemic years, during and after a major shock (eg, the COVID-19 pandemic). Compared with the well-established 5-year-average method and quasi-Poisson Serfling regression,[7-10] the later/earlier method provided better predictions in relation to the seasonal mortality peaks and competitive predictions during the pandemic waves.

The proposed method requires minimal input on monthly all-cause mortality data and minimal assumptions, differently than more sophisticated models, such as compartmental models,[27,28] which require much more information. All-cause mortality data are available in most countries with a short delay, unlike cause-specific data, which have reporting delays of up to 2 years in many countries, due to the process of coding by cause of death. They avoid bias in cause-of-death registration and issues of standardization of cause-of-death classification across countries and time. The forecasts rely on the assumption of stationarity of the series of later/earlier ratios. In our application, tests for stationarity proved that the assumption was met. If the assumption were not to hold, time-series methods could remove nonstationarity from the series of later/earlier ratios.

An innovative aspect of the method is the empirical prediction intervals estimated from the uncertainty in time series of past later/earlier ratios. This reflects the intuitive notion that a forecast is as precise as similar forecasts turned out to be in the past for that corresponding month. The approach is different from conventional parametric intervals, which rely on the suitability of parametric assumptions. The result is that the prediction intervals for our forecasts properly widen during the winter.

Some limitations have been found when forecasting mortality 1 month ahead. A delay in the forecasts was observed in correspondence of specific winter peaks due to the uncertainty in the month of occurrence of the winter peak. The delay was also observed with the other two forecasting methods considered here. Furthermore, the later/earlier method was not able to predict the first COVID-19 wave. It was able to capture the aspects of later waves better than other traditional methods (ie, the 5-year-average method and the quasi-Poisson Serfling model). The later/earlier method might be suitable for forecasting mortality in pandemic times, immediately after the initial health shock, when mortality resembles that of an influenza epidemic by circulating seasonally.

Another limitation is that the forecasts are provided only 1 month ahead. However, this is already a useful time window during a pandemic caused by a new virus, when no information on the spread of the infectious disease or cause of death is available. Information on how many people might die in the next month can support decision-makers in keeping existing measures in place, taking further actions, or, if a slowdown is forecast, relaxing the measures taken. Short-term forecasts can be used for health-care management decisions, such as hospital equipment and lodging, and by local authorities to plan mortuary capacity.

For epidemiologists, public health researchers, and demographers, the COVID-19 pandemic fostered many research questions. The question of what methods and models were best suited to monitor and predict the severity of the COVID-19 pandemic was widely discussed. The later/earlier method is a flexible forecasting method that might serve statistical offices and surveillance systems in closely monitoring mortality progression. It can be used for nonpandemic mortality and current and future pandemics. Statistical offices should continue to improve the release and timing of reliable seasonal mortality data.

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Supplementary material

Supplementary material is available at *American Journal of Epidemiology* online.

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Conflict of interest

The authors declare that they have no conflicts of interest.

Data availability

Data from national statistical offices were used in this study. The full data sets and documentation can be downloaded from Statistics Denmark, the French National Institute of Statistics and Economic Studies (INSEE), the Spanish National Statistics Institute (INE), and Statistics Sweden.

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