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Short-term forecasts of expected deaths

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We introduce a method for making short-term mortality forecasts of a few months, illustrating it by estimating how many deaths might have happened if some major shock had not occurred. We apply the method to assess excess mortality from March to June 2020 in Denmark and Sweden as a result of the first wave of the coronavirus pandemic; associated policy interventions; and behavioral, healthcare, social, and economic changes. We chose to compare Denmark and Sweden because reliable data were available and because the two countries are similar but chose different responses to COVID-19: Denmark imposed a rather severe lockdown; Sweden did not. We make forecasts by age and sex to predict expected deaths if COVID-19 had not struck. Subtracting these forecasts from observed deaths gives the excess death count. Excess deaths were lower in Denmark than Sweden during the first wave of the pandemic. The later/earlier ratio we propose for shortcasting is easy to understand, requires less data than more elaborate approaches, and may be useful in many countries in making both predictions about the future and the past to study the impact on mortality of coronavirus and other epidemics. In the application to Denmark and Sweden, prediction intervals are narrower and bias is less than when forecasts are based on averages of the last 5 y, as is often done. More generally, later/earlier ratios may prove useful in short-term forecasting of illnesses and births as well as economic and other activity that varies seasonally or periodically.

short-term forecasting | mortality forecasting | excess deaths | coronavirus pandemic | Denmark and Sweden

Suppose a period, perhaps 1 y long or somewhat shorter, can be divided into two segments. Consider a population, perhaps specified by sex and age category, e.g., women 65 through 74 y old. Let D be the number of deaths in the period. Let D^- be the death count in the earlier segment and let D^+ be death count in the later segment, such that $D = D^- - D^+$. Let π be the proportion of deaths in the later segment:

$$\pi = \frac{D^+}{D} = \frac{D^+}{D^- + D^+}. \quad [1]$$

It follows that $D^+ = \pi D$ and $D^- = (1 - \pi)D$. Hence, the later/earlier ratio, denoted by υ (upsilon), is given by:

$$\upsilon = \frac{D^+}{D^-} = \frac{\pi}{1 - \pi}. \quad [2]$$

Suppose values of υ over time periods are stationary, showing no trend. Assessing whether a time series is stationary is a major topic in statistical and economic analysis (1). Whether $\upsilon(t)$ can be viewed as showing no trend can be checked (2, 3). Let $\bar{\upsilon}$ be the average value. If $\upsilon(t)$ is stationary, then a forecast of D^+ for the current period is

$$D^+ \approx \bar{\upsilon} D^-. \quad [3]$$

The time period could be a calendar year. In the Northern Hemisphere, however, the accuracy of a short-term mortality forecast might be greater if the time period were an epiyear (epidemic year) starting in July and ending in late June. If in addition to a winter peak of mortality, there is also a summer peak, then nonsummer forecasts might be more accurate if the time period studied began, say, in early October and ended, perhaps, in late April.

Deaths might be observed in an earlier segment of the period, say up through January 31, and a forecast might be needed for the later segment after February 1. This task might be called shortcasting imminent deaths, with shortcasting being a neologism for short-term forecasting. Statisticians, economists, epidemiologists, and others have developed powerful approaches to shortcasting, especially when seasonal fluctuations are important (4). This article focuses on a method that has the advantage of simplicity and that yields relevant estimates of excess deaths due to the COVID pandemic.

In medium-term and long-term mortality forecasting, predictions are made about age-specific death rates and age-specific population sizes; these values are used to derive death counts (5–7). Such forecasts usually pertain to the future. There is growing interest in forecasting mortality in the past using earlier data, in part because alternative forecasting methods can be evaluated by how well they predict what actually happened (8).

For the short-term forecasting considered here, it may be possible, using Eq. **3**, to forecast deaths in the later segment of a time period based on deaths in the earlier segment of the period. The later segment could be in the past, as in the example stressed below about deaths between March and June 2020. Alternatively, the later segment could be in the future, with the prediction concerning something that has not yet been observed. Death counts often show trends over time because of changes in population age structure and changes in age-specific mortality. Hence, it is problematic to forecast death counts based on

Significance

We introduce a simple but powerful method for analyzing mortality after a major shock. We apply the method to show, more conclusively than up to now, that Denmark, which imposed a lockdown during the first wave of the coronavirus pandemic, suffered considerably lower risks of death than Sweden, which did not impose a lockdown. Our method makes short-term forecasts of the number of deaths that would have occurred if the coronavirus pandemic or other health catastrophe had not occurred. By subtracting the forecast counts from actual death counts, excess mortality can be estimated. This can be done by age, sex, and other characteristics. The method can also be used for other kinds of short-term forecasting.

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averages of death counts in previous years. In some circumstances, however, later/earlier ratios may be fairly constant. This would permit a remarkably simple approach to mortality shortcasting.

Application

In both Denmark and Sweden, the first coronavirus death occurred in week 11 of 2020, which began on March 9. Changes in behavior, such as washing hands more frequently and keeping

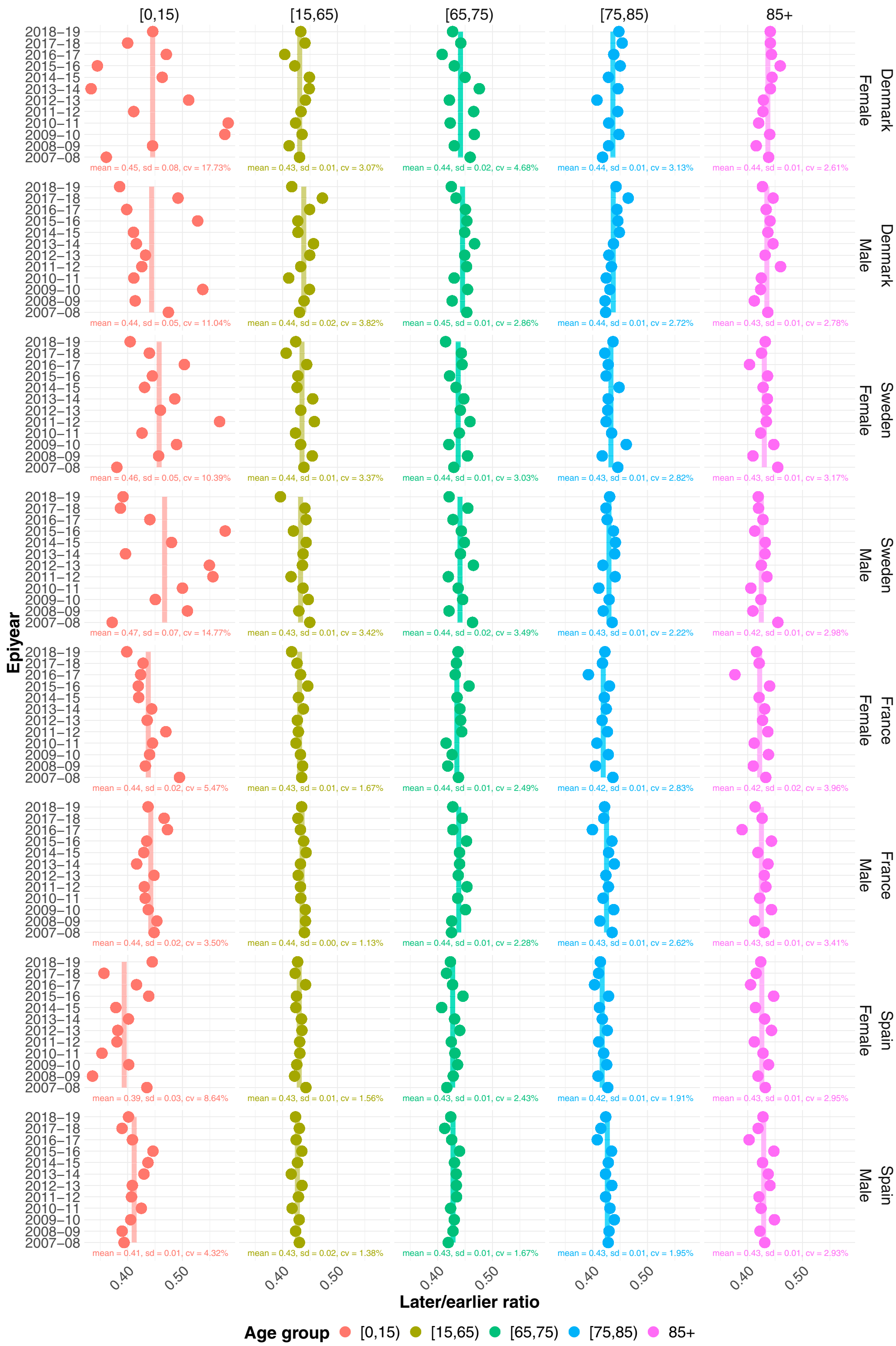

Fig. 1. Ratios between deaths in the later and earlier segments of epiyears 2007–2008 through 2018–2019 for Danish, Swedish, French, and Spanish females and males in five age groups (colored dots) and corresponding average ratios over epiyears (colored lines). The data for France are for the total national population, labeled FRATNP in the data source, Short Term Mortality Fluctuations data series, Human Mortality Database (9).

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distance from others, started about this time in both countries, and Denmark mandated the first official restrictions on social interactions. Denmark and Sweden are ideal for comparing the impacts of these alternative policies because in other respects they are similar, with mutually understandable languages, intertwined histories, related cultures, and comparable political systems: They are two neighbors that keep a close eye on each other.

Eq. **3** can be used to estimate expected deaths from week 11 through week 26 at the end of June if COVID-19 had not struck, based on data from week 27, which started on July 1, 2019, through week 10 in 2020. To estimate the average later/earlier ratio $\bar{\upsilon}$, we used readily available data (9) on weekly death counts in Denmark and Sweden for five age categories (0 to 14, 15 to 64, 65 to 74, 75 to 84, and 85+) and 12 epiyears (2007–2008, 2008–2009, ..., 2018–2019). The time series of the 12 later/earlier ratios by country and sex were found stationary through the augmented Dickey–Fuller test (2) and the Kwiatkowski–Phillips–Schmidt–Shin test (3). To check whether later/earlier ratios might also be fairly constant in other countries, we also present data on France and Spain from the same data source. The data pertain to International Organization for Standardization (ISO) weeks, which are widely used by governments and organizations for budget years (10). Each week's year is the Gregorian year in which the first Thursday falls. All weeks start with Monday. Hence, the first week of the year always includes January 4. The five age categories limited the scope of our analysis but yielded useful findings. Because so few deaths occur between ages 0 and 15, stochastic fluctuations were larger for this category than the other categories. The category 15 to 64 is broad but, because relatively few deaths occur at these ages, this was not a major problem.

Fig. 1 shows the later/earlier ratios for Danish, Swedish, French, and Spanish females and males from epiyear 2007–2008 through 2018–2019 for the five age categories, which are denoted by five colors. The average values of the later/earlier ratios, marked by vertical lines, for the five age categories, two sexes, and four countries range from 0.39 to 0.47. For three-quarters of the 40 later/earlier ratios, the average value was either 0.43 or 0.44.

Variation in the youngest category, which included few deaths, was greater than in the other categories but only modestly greater. For ages above 15, SDs were mostly 0.01, with a couple of cases of 0.02. Coefficients of variation were, except for children, between 0.01 and 0.05.

Why are the SDs and the coefficients of variation as small as they are? That is, why are death counts in the earlier segment of an epiyear so closely associated with death counts in the later segment? This merits close examination. The severity of influenza mortality earlier in an epiyear may predict the severity later in the year. Severe weather conditions before March may be correlated with severe conditions in March through June. Deeper understanding of the close link between death counts in the earlier and later segments might further improve the sophisticated time-series models that have been developed to study seasonal patterns of mortality, including the impact of influenza epidemics (11–16).

Using the average later/earlier ratios in Fig. 1, we applied Eq. **3** to estimate the expected number of deaths (in the absence of the coronavirus pandemic) by sex and age for Denmark and Sweden from week 11 through week 26 in 2020. We then calculated excess deaths by subtracting the expected number of deaths from the reported number of deaths. Table 1 summarizes the results about observed, expected, excess, and COVID deaths for the entire populations of Denmark and Sweden. Table 2 breaks observed, expected, and excess deaths down by age and sex.

Consider the total observed (16,663), expected (16,146) and excess (16,663 − 16,146 = 517) deaths in Denmark shown in Table 1. The observed deaths were 3.1% higher than the expected deaths. The coronavirus pandemic—and the various policy interventions and behavioral, social, economic, health, and health-care changes resulting from it—increased Danish mortality by 517 deaths, a modest 1/30th more than we predict would have occurred if COVID-19 had not struck.

Sweden is different. Death counts were considerably higher—32,172 observed deaths, 25,927 expected deaths, yielding 6,245 excess deaths. The Swedish population is 60% larger than the Danish population and expected deaths were also 60% higher. To compare the two populations, the key statistic is that excess deaths accounted for 19.4% —almost a fifth—of observed deaths in Sweden but only 3.1% in Denmark. If Sweden had been as successful as Denmark in averting excess deaths, Sweden would have lost about 5,200 fewer lives, given by 32,172 × (0.194 − 0.031) = 5,242.

Estimation of the deaths that would have occurred in the absence of the coronavirus pandemic depends on Eq. **3**, which hinges on the assumption that the later/earlier ratio in epiyear 2019–2020 equals the average of the later/earlier ratio in previous years. This might not be true. Our estimates of expected deaths and, hence, excess deaths are thus uncertain. The probability distribution of expected deaths is not known and a mathematical formula for it cannot be readily derived. A statistical strategy known as bootstrapping can, however, be used to assess how much the actual later/earlier ratio in epiyear 2019–2020, which is unknown, might differ from its average value in previous years (17, 18).

We applied this statistical technique, using the 12 y of data from epiyears 2008–2009 through 2018–2019 by age group, country, and sex. From the 12 later/earlier ratios, we randomly drew one, with replacement. We multiplied the ratio by the observed number of deaths in the first part of epiyear 2019–2020 to get the expected number of deaths in the second part of epiyear 2019–2020. We assumed that death counts followed a Poisson distribution defined by the expected number of deaths (19). We randomly chose a death count from the Poisson distribution. We repeated this 100,000 times to approximate the distribution of expected number of deaths. From this distribution, we derived empirical percentiles for excess deaths. The resulting prediction intervals reflect considerable uncertainty but are reassuringly narrow, ranging from roughly 15,000 to 17,000 deaths for Denmark and roughly 24,000 to 28,000 deaths for Sweden. This is consistent with the variation in later/earlier ratios shown in Fig. 1.

We also used the bootstrapping approach to estimate uncertainty about how many excess deaths would have occurred in Sweden if instead of a 19.4% excess death rate, the Swedish rate had been at the Danish level of 3.1%. As noted above, our estimate is that Sweden would have lost about 5,200 fewer lives: The 95% prediction interval ranges from 3,620 to 6,135. This indicates that different policies and conditions in Sweden resulted in thousands of extra deaths.

The width of the prediction intervals for excess deaths given in Table 1 equals the width of the prediction intervals for expected deaths, because excess and expected deaths differ by a known quantity, namely, the number of observed deaths. For instance, the width of the prediction interval for expected and for excess deaths in Sweden is 3538 = 27730 – 24192 = 7980 – 4442. Since excess deaths are only a fraction of expected deaths, the relative width of prediction intervals is greater for excess deaths. The absolute uncertainty is the same, but the relative uncertainty is much greater. Because the main interest is in excess deaths, it is reassuring that the lower and upper bounds for excess deaths allow some major conclusions to be drawn: 1) excess deaths in Denmark probably were greater than zero but less than 2,000, 2) excess deaths in Sweden were probably between 4,000 and 8,000, and 3) excess deaths as a proportion of observed deaths were considerably lower in Denmark than in Sweden (because the

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Table 1. Deaths in week 11 through week 26 in Denmark and Sweden

	Denmark			Sweden		
	Lower PI		Upper PI	Lower PI		Upper PI
Observed deaths		16,663			32,172	
Expected deaths	14,955	16,146	17,362	24,192	25,927	27,730
Excess deaths	−699	517	1,708	4,442	6,245	7,980
Excess/observed deaths, %	−4.2	3.1	10.2	13.8	19.4	24.8
COVID deaths		604			5,447	

The lower and upper values give the 95% prediction interval (PI).

upper bound of excess deaths as a proportion of observed deaths for Denmark, 10.2%, is less than the lower bound, 13.8%, for Sweden).

As shown in Table 1, in Denmark excess deaths were slightly less than reported COVID deaths, whereas in Sweden excess deaths exceeded reported COVID deaths. It is difficult to rigorously determine whether a death was due to COVID-19 or some other, perhaps preexisting, condition. Deaths in hospital might be classified more often as due to COVID-19 than deaths out of hospital. Furthermore, policy interventions; behavioral changes; and altered economic, social, health, and hospital conditions may have led to the net loss of lives from causes other than the coronavirus. A further complication is that some of those who died from COVID-19 might otherwise have died before the end of June from some other cause. Such deaths would increase the number of COVID deaths but not the number of excess deaths.

In Denmark, there were 517 excess deaths and 604 COVID deaths. In Sweden, the 6,245 excess deaths exceeded the 5,447 COVID deaths by almost 800 cases. Excess deaths exceeded COVID deaths by 15% in Sweden while excess deaths were 14% less than COVID deaths in Denmark. In Sweden, either COVID deaths were underreported or lives were lost on balance from other causes as a result of the turmoil resulting from the coronavirus pandemic. In Denmark, policy interventions and behavioral and other changes reduced mortality from other causes by more than the mortality from COVID-19. This merits deeper analysis.

Using the statistics in Table 2, the excess mortality in Denmark and in Sweden can be broken down by age and sex. In Denmark, more than half of the lives lost were for people aged 75 through 84, and a further third were lost among people above 85. Excess deaths of females were roughly comparable to excess deaths for males, except for people between 15 and 64: In this broad category, our estimate is that 47 women's lives were lost, and 90 men's lives were saved. Close to half of all excess deaths among women and fully three-fifths of excess deaths among men occurred in the decade of age between 75 and 85.

The age and sex breakdowns of excess deaths in Sweden are rather different. Half of the excess deaths occurred after age 85, while a third occurred between 75 and 84. Except at the highest ages, the toll of excess mortality was higher for men than for women. For females, however, many extra deaths occurred after age 85: These accounted for 60% of all extra deaths at ages 85+. For males, ages 75 to 84 and 85+ were about equally important and together accounted for three-quarters of all excess male mortality.

The female excess deaths in Sweden after age 85 were 25% higher than the expected number. In Denmark, in contrast, female excess deaths age 85+ were only 2% higher than expected. If in Sweden the pandemic-related mortality of women at the oldest ages had been kept to the Danish levels, then 1,392 lives would have been saved, half of the total of 2,784 Swedish excess deaths for women. This discrepancy may be a result of differences between Sweden and Denmark in how care and housing

Table 2. Observed, expected, and excess deaths in later segment (week 11 through week 26) of epiyear 2019–2020 by age group, sex, and country

Age		Denmark female	Denmark male	Sweden female	Sweden male
0 to 14	Observed deaths	29	55	55	78
	Expected deaths	33	52	53	65
	Excess deaths	−4	3	2	13
	95% prediction interval	−21 to 10	−17 to 19	−17 to 19	−12 to 35
15 to 64	Observed deaths	868	1,359	1,088	1,954
	Expected deaths	821	1,449	1,100	1,536
	Excess deaths	47	−90	−12	418
	95% prediction interval	−26 to 124	−229 to 32	−108 to 86	321 to 568
65 to 74	Observed deaths	1,302	1,986	1,883	2,924
	Expected deaths	1,301	1,958	1,763	2,437
	Excess deaths	1	28	120	487
	95% prediction interval	−135 to 126	−100 to 170	−7 to 252	304 to 662
75 to 84	Observed deaths	2,427	2,830	4,360	5,409
	Expected deaths	2,252	2,637	3,410	4,161
	Excess deaths	175	193	950	1,248
	95% prediction interval	30 to 357	−1 to 346	694 to 1,129	1,050 to 1,473
85+	Observed deaths	3,494	2,313	8,613	5,808
	Expected deaths	3,433	2,210	6,889	4,513
	Excess deaths	61	103	1,724	1,295
	95% prediction interval	−147 to 272	−53 to 252	1,280 to 2,203	937 to 1,553

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for the elderly are organized, coupled with a less successful Swedish strategy of shielding the elderly.

Some of the estimates and lower bounds of excess deaths in Table 2 are negative. Negative values imply the saving of lives. Other values for ages up to age 75 are positive but fairly close to zero relative to the much larger tolls of excess deaths after age 75. Analyzing why some lives may have been saved and relatively few lives were lost before age 75 would shed light not only on the pandemic itself but also on the impact of the social, economic, and healthcare changes that accompanied the pandemic.

Perspectives

This note presents an approach to shortcasting, with a policy-relevant application. Much more research is warranted. Publication of the concept and example may spur discussion and elaboration. Research comparing the accuracy and bias of alternative shortcasting methods is needed. The average later/earlier strategy proposed here has the advantage of simplicity, but it is unlikely to prove to be the most accurate and least biased way to forecast excess deaths during the first wave of the COVID pandemic or in other applications if more detailed data are available.

Preliminary comparisons with studies using more detailed data and sophisticated methods suggest that the average later/earlier strategy does not yield radically different estimates of excess deaths (20). This is reassuring, as are the results presented below that the later/earlier approach is superior to the equally simple 5-y-average method that has been and is being widely employed. Time-series methods that use more information, e.g., about levels and patterns of weekly death counts, about correlations among countries and regions, and about covariates such as temperature, may well give more precise forecasts (11, 21–23). Use of the average later/earlier ratio, however, may be of value when it is advantageous to use a method that requires little statistical information, is easy to explain, and yields serviceably narrow prediction intervals.

The application of the method to excess deaths from March to June 2020 is highly relevant but narrow. Estimates of excess deaths after June 2020 are of urgent interest, but a different method has to be used. The method would have yielded useful forecasts of deaths in Denmark, Sweden, France, and Spain and perhaps other countries from March to June of earlier years—not forecasts if some unique shock had not happened, but ordinary forecasts based on observed deaths in July of the previous year through February. Hence, in the future, the method might be of value in predicting deaths in some period, say January through April, based on deaths in a prior period, say September through December, supplementing the elaborate methods developed by influenza epidemiologists. To explore this, later/earlier ratios for various time periods could be studied. Shortcasting imminent deaths by age, sex, and perhaps other characteristics is of interest to pension companies, health-care systems, nursing homes, churches, funeral parlors, tax authorities, and other organizations.

Meteorologists make short-term forecasts of temperature, rainfall, and flooding risks. Economists make short-term forecasts of various kinds of economic activity, from rates of international growth, interest, and unemployment to the sales of particular products by specific manufacturers in small regions. Epidemiologists have developed sophisticated methods for forecasting weekly influenza infections and deaths in a flu season based on data early in the season (24, 25). Many of these shortcasts have strong seasonal or periodic components. Eq. **3** might also be used for various kinds of shortcasting, such as forecasting the incidence of heart attacks, the number of births, or sales of a product—provided the later/earlier ratio over some duration is approximately constant over time.

Sometimes what is of interest is not a forecast of the future but a forecast of what would have happened in the absence of a shock. Those who like to second-guess history ask: suppose Hannibal vanquished Rome, suppose Napoleon won the battle of Waterloo, suppose Lee was victorious at Gettysburg? Individuals occasionally ask themselves—what might have happened if I had done something different? In this article, we make forecasts to estimate excess deaths: Excess deaths are actual deaths minus expected deaths if a major shock had not occurred. We hypothesize that the range of applications is much broader than this and includes forecasts of the future as well as of the past and forecasts of different kinds of stationary time series that show seasonality. Whether this is true remains to be shown. Indeed, whether our analysis of excess deaths in Denmark and Sweden can be usefully extended to other countries and regions remains to be shown, although the data for France and Spain encourage some optimism.

Careful attention should be devoted to how accurate and unbiased the use of the average later/earlier ratio in Eq. **3** is in short-term forecasting compared with alternative strategies, including SARIMA models (11) and Serfling regression (22). These alternative approaches are often used to forecast weekly deaths. To use a later/earlier forecast to estimate weekly deaths in the later period, a method is needed to decompose the total into weekly levels. One strategy is to modify the method for killing off cohorts that are not extinct (26).

Of particular current interest is estimation of total excess deaths from the coronavirus in March through June 2020. Expected deaths over the first wave of the pandemic commonly have been estimated by taking the average of deaths in the past five corresponding periods (27, 28). Like the later/earlier ratio approach, this method requires modest statistical information and is easy to explain. As indicated in Fig. 2, for Danish and Swedish men and women as well as for French and Spanish men and women, numbers of deaths vary considerably across epiyears, but the number in the second segment of the year tend to be correlated with the number in the first segment. Hence, using information about deaths in the first segment can improve forecasts of deaths in the second segment. This is the basic advantage of using average later/earlier ratios rather than average death counts.

The slopes $\bar{\upsilon}$, the average later/earlier ratio, of the regression lines $D^{+}(t) = \bar{\upsilon}\, D^{-}(t)$ are remarkably similar across population and sex: 0.436 for Danish females, 0.439 for Danish males, 0.432 for Swedish females, 0.431 for Swedish males, 0.423 for French females, 0.430 for French males, 0.423 for Spanish females, and 0.427 for Spanish males.

When comparing two alternative models, the criterion is often goodness of fit adjusted for the number of parameters. For example, the goodness of fit of the regression lines in Fig. 2 might be assessed by the sum of the squares of the deviations of the points from the lines. In evaluating forecasting strategies, however, prediction error and prediction bias are preferred over goodness of fit because models that fit well can yield poor predictions (29). Prediction error and bias can be estimated by analysis of forecasts of the past. Data up to some time are used to forecast to some later time in the past. The forecast can then be compared with the known actual outcome.

The advantage of using later/earlier ratios rather than 5-y averages is revealed by prediction errors estimated by this method of historical forecasts. In Table 3, the standard measure of prediction error, the square root of the mean of squared errors (RMSE), is shown for the later/earlier method and for the 5-y-average method for males and females in five age categories in Denmark and Sweden.

In only 1 of the 20 cases is the RMSE smaller for the 5-y-average approach. At the ages when most excess deaths occurred, 75 to 84 and 85+, the average RMSE for the 5-y-average method was 70% higher than the value for the later/earlier strategy. RMSE is commonly used in forecasting research as a

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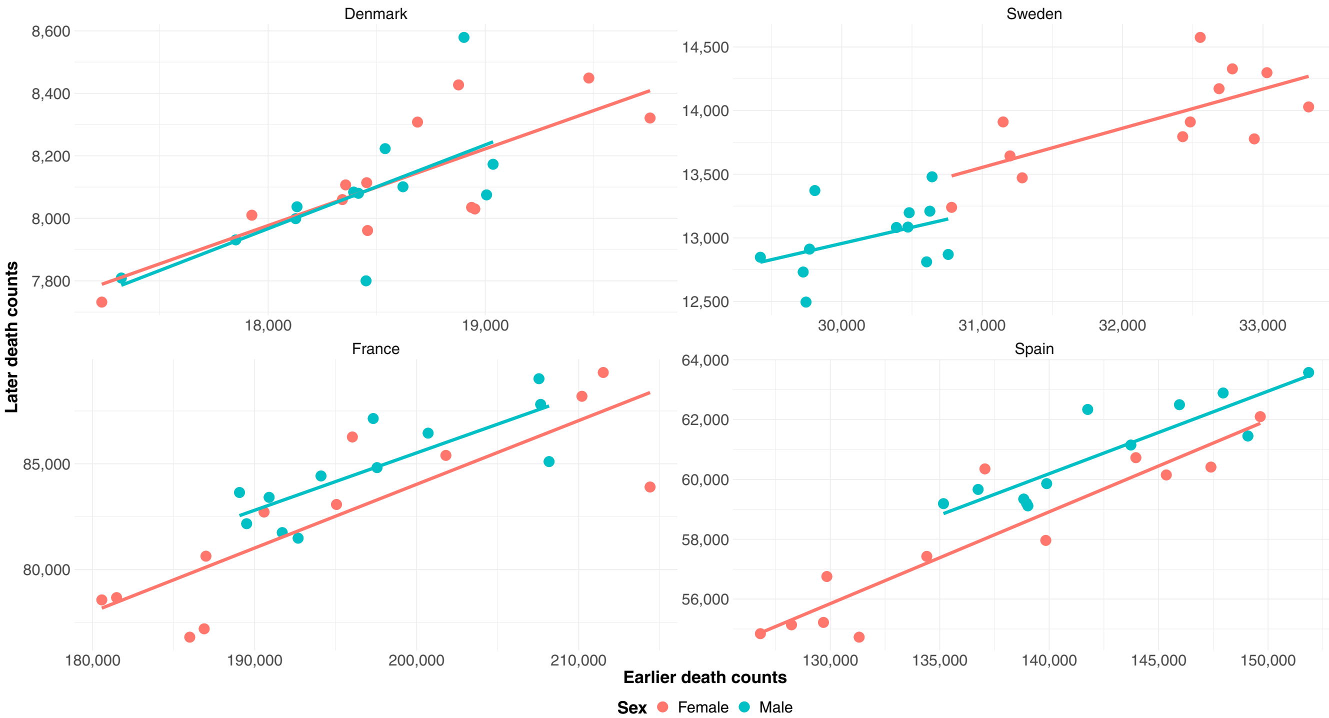

Fig. 2. Deaths in the later vs. earlier segments of epiyears 2007–2008 through 2018–2019 for Danish and Swedish females and males. The slopes of the regression lines equal the values of $\bar{\upsilon}$, the average later/earlier ratio.

measure of how close predictions are to actual values, and that is the way we are using it here rather than as a property of an estimator. It is worth noting, however, that since the RMSE of the 5-y-average method is 70% higher at older ages than the RMSE for the later/earlier approach, prediction intervals will be about 70% wider, making it more problematic to draw conclusions.

Forecasting methods are also judged on whether they tend to be biased, systematically underpredicting or overpredicting. In our comparisons of the later/earlier approach and the 5-y-average method for males and females in Denmark and Sweden for five age categories, the mean percentage error (MPE) using the later/earlier approach was −1.44% compared to −2.65% resulting from the 5-year-average method. We also computed the absolute percentage error (MAPE), which yielded a value of 4.7% for the later/earlier approach, considerably closer to zero than the value of 7.7% for the 5-y-average method.

Our prediction intervals are narrow enough and the bias is small enough to let us reach conclusions about excess deaths in Denmark vs. Sweden, in males vs. females, and in various age groups. A goal of future research should be to further reduce uncertainties in forecasts of expected deaths.

In Denmark and Sweden, various data registries include extensive information about individuals, including detailed data about health care and health status as well as information about education, occupation, place of residence, living arrangements, and much else. Information is also available on the environment, such as daily outdoor temperature and pollution levels. Much is known and more details are being added every year. Perhaps application of machine learning to these data will yield reliable predictions of when a person might die. If so, simple, aggregate methods such as the one proposed in this article may eventually be superseded by complicated algorithms using detailed individual data. Until now, however, this vision is far from operational. In the interim, barebone approaches such as use of later/earlier ratios might yield serviceably accurate forecasts and be more intuitively understandable than data-intensive machine learning.

Later/earlier ratios can be applied to the data available in Denmark, Sweden, and other countries on broad characteristics of individuals who died in some period. In this article, we focused on two characteristics—sex and age. It is known whether a deceased person 1) lived in a rural or urban area; 2) was living alone, cohabiting with a few others, or living institutionally; 3) was childless or had one, two, or more children; 4) was born in Denmark, in a country in the Near East or Africa, or elsewhere; 5) was working, a student, unemployed, or retired; 6) had a few

Table 3. Accuracy measures: RMSE observed vs. fitted with the later/earlier ratio method and with the 5-y-average method both applied to the previous 5 y of data, by age group, sex, and country for epiyears 2012–2013 through 2018–2019

	Denmark female		Denmark male		Sweden female		Sweden male	
Age	RMSE later/ earlier	RMSE 5-y average	RMSE later/ earlier	RMSE 5-y average	RMSE later/ earlier	RMSE 5-y average	RMSE later/ earlier	RMSE 5-y average
0 to 14	8	8	6	9	4	9	13	15
15 to 64	41	93	69	157	41	111	69	186
65 to 74	73	43	70	76	56	118	90	176
75 to 84	79	125	70	162	66	150	93	125
85+	99	132	44	145	220	236	82	180

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years or many years of education; 7) was in the lower or upper range of an affluence index; 8) had no, a couple, or several chronic conditions; and many other characteristics. Later/earlier ratios could be applied to determine expected deaths (and, hence, excess deaths) for people classified into subpopulations according to one or more of these characteristics. What proportion, for instance, of observed deaths were excess deaths (i.e., observed minus expected) among males above 65 living alone in Copenhagen?

Up until now, it is not possible, except for some people on their death beds, to accurately forecast when a person might die. Yet it is possible to estimate how many people in a population will die the next day, week, month, or year. It is not possible to pinpoint the date of the death of an individual or the cause of death, because the cause has immediate, proximate, underlying, and earlier-life components and hinges not only on an individual's personal characteristics but also on availability and excellence of medical care, air quality, family and social networks, and many other factors (30). It is, however, feasible—and this is a remarkable achievement of demography—to forecast death counts by age and sex in a population in the short term and, with decreasing accuracy, in the medium and long term (31). Furthermore, informative forecasts can be made of how many deaths would have occurred if some major change in mortality conditions had not happened. Such shortcasting is highly relevant in the time of COVID-19.

Data Availability. All study data are included in the article and/or supporting information. Previously published data were used for this work (https://www.mortality.org).

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1. C. Chatfield, *The Analysis of Time Series* (Chapman & Hall/CRC, ed. 6, 2004).
2. D. A. Dickey, W. A. Fuller, Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* **74**, 427–431 (1979).
3. D. Kwiatkowski, P. C. Phillips, P. Schmidt, Y. Shin, Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *J. Econom.* **54**, 159–178 (1992).
4. C. Beaumont, Short-term forecasting: An introduction to the box-jenkins approach. *J. Oper. Res. Soc.* **34**, 1017–1018 (1983).
5. H. Booth, L. Tickle, Mortality modelling and forecasting: A review of methods. *Ann. Actuarial Sci.* **3**, 3–43 (2008).
6. I. D. Currie, M. Durban, P. H. Eilers, Smoothing and forecasting mortality rates. *Stat. Model.* **4**, 279–298 (2004).
7. R. D. Lee, L. R. Carter, Modeling and forecasting US mortality. *J. Am. Stat. Assoc.* **87**, 659–671 (1992).
8. M.-P. Bergeron Boucher, S. Kjærgaard, J. Oeppen, J. W. Vaupel, The impact of the choice of life table statistics when forecasting mortality. *Demogr. Res.* **41**, 1235–1268 (2019).
9. Human Mortality Database, Short-term Mortality Fluctuations (STMF) data series. Human Mortality Database. University of California, Berkeley (USA), and Max Planck Institute for Demographic Research (Germany) (2021). Available at https://www.mortality.org/. Accessed 16 December 2020.
10. International Organization for Standardization 8601-1:2019. Date and Time – Representations for Information Interchange – Part 1: Basic Rules. https://www.iso.org/standard/81801.html. Accessed 6 October 2020.
11. G. E. P. Box, G. M. Jenkins, G. C. Reinsel, G. M. Ljung, *Time Series Analysis: Forecasting and Control* (Wiley Series in Probability and Statistics, ed. 5, 2015).
12. J. Nielsen, A. Mazick, S. Glismann, K. Mølbak, Excess mortality related to seasonal influenza and extreme temperatures in Denmark, 1994-2010. *BMC Infect. Dis.* **11**, 350 (2011).
13. B. Nunes, I. Natário, M. L. Carvalho, Time series methods for obtaining excess mortality attributable to influenza epidemics. *Stat. Methods Med. Res.* **20**, 331–345 (2011).
14. P. H. C. Eilers, J. Gampe, B. D. Marx, R. Rau, Modulation models for seasonal time series and incidence tables. *Stat. Med.* **27**, 3430–3441 (2008).
15. J. D. Healy, Excess winter mortality in Europe: A cross country analysis identifying key risk factors. *J. Epidemiol. Community Health* **57**, 784–789 (2003).
16. J. P. Mackenbach, A. E. Kunst, C. W. Looman, Seasonal variation in mortality in The Netherlands. *J. Epidemiol. Community Health* **46**, 261–265 (1992).
17. B. Efron, R. J. Tibshirani, *An Introduction to the Bootstrap* (Chapman and Hall/CRC, 1994).
18. T. J. DiCiccio, B. Efron, Bootstrap confidence intervals. *Stat. Sci.* **11**, 189–228 (1996).
19. N. Keiding, Statistical inference in the lexis diagram. *Philos. Trans. Phys. Sci. Eng.* **332**, 487–509 (1990).
20. V. Kontis *et al*., Magnitude, demographics and dynamics of the effect of the first wave of the COVID-19 pandemic on all-cause mortality in 21 industrialized countries. *Nat. Med.* **26**, 1919–1928 (2020).
21. T. J. Hastie, R. J. Tibshirani, *Generalized Additive Models* (Chapman & Hall/CRC, 1990).
22. R. E. Serfling, Methods for current statistical analysis of excess pneumonia-influenza deaths. *Public Health Rep.* **78**, 494–506 (1963).
23. J. Nielsen, T. G. Krause, K. Mølbak, Influenza-associated mortality determined from all-cause mortality, Denmark 2010/11-2016/17: The FluMOMO model. *Influenza Other Respir. Viruses* **12**, 591–604 (2018).
24. B. J. Cowling, I. O. Wong, L. M. Ho, S. Riley, G. M. Leung, Methods for monitoring influenza surveillance data. *Int. J. Epidemiol.* **35**, 1314–1321 (2006).
25. C. Viboud, P.-Y. Boëlle, F. Carrat, A.-J. Valleron, A. Flahault, Prediction of the spread of influenza epidemics by the method of analogues. *Am. J. Epidemiol.* **158**, 996–1006 (2003).
26. Rizzi, S., Kjærgaard S., Bergeron Boucher M.-P., Camarda, C.G., Lindahl-Jacobsen R., Vaupel J.W. (2021). Killing off cohorts: Forecasting mortality of non-extinct cohorts with the penalized composite link model. *Int. J. Forecast.* **37**, 95–104.
27. P. Michelozzi *et al*., Temporal dynamics in total excess mortality and COVID-19 deaths in Italian cities. *BMC Public Health* **20**, 1238 (2020).
28. D. Morgan, J. Ino, G. Di Paolantonio, F. Murtin, Excess mortality: Measuring the direct and indirect impact of COVID-19. OECD Health Working Papers, No. 122 (OECD Publishing, Paris), https://doi.org/10.1787/c5dc0c50-en (2020). Accessed 1 December 2020.
29. M.-P. Bergeron Boucher *et al*., "Alternative forecasts of Danish life expectancy" in *Developments in Demographic Forecasting*, S. Mazzuco, N. Keilman, Eds. ((Springer, Springer Series on Demographic Methods and Population Analysis, Bind, 2020), 49, pp. 131–151.
30. M. Wensink, R. G. Westendorp, A. Baudisch, The causal pie model: An epidemiological method applied to evolutionary biology and ecology. *Ecol. Evol.* **4**, 1924–1930 (2014).
31. J. W. Vaupel, F. Villavicencio, M. P. Bergeron-Boucher, Demographic perspectives on the rise of longevity. *Proc. Natl. Acad. Sci. U.S.A.* **118**, e2019536118 (2021).

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