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Estimating the COVID-related Excess Deaths in 2020 Using Time-Series Analysis

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Introduction

Coronavirus disease 2019 (COVID) was identified in late 2019 and rapidly spread through the world leading to an ongoing pandemic. February 2020 saw the first U.S. deaths attributed to the pandemic. The early economic effects included a sharp fall in the U.S. stock markets, a sharp increase in the unemployment rate (and a corresponding decrease in the total employment), a sharp increase in the outstanding debt of the federal government, and a sharp deceleration in the inflation rate (see Tooze, 2021). The economic effects of the pandemic and the 2021 economic recovery have been easy to quantify, but it is remarkable that an estimate of the COVID-related death toll has not been an easy matter. The Centers for Disease Control and Prevention (CDC) reported 385,484 COVID-related deaths in 2020 (deaths with confirmed or presumed COVID, coded to ICD–10 code U07.1) (www.cdc.gov/nchs/nvss/vsrr/covid19/index.htm). According to *Our World in Data*, the cumulative confirmed U.S. COVID death toll as of December 31, 2020 was 351,999 people (ourworldindata.org/coronavirus/country/united-states). Those authors note that challenges in designating the cause of death means that the published number of deaths might be significantly different from the actual number of deaths. The cumulative U.S. death toll according to the Coronavirus Resource Center (coronavirus.jhu.edu/) on January 2, 2021, was 349,920 deaths. Issues related to an accurate death count are also evident from the "Coronavirus in the U.S.: Latest Map and Case Count" page of *The New York Times* (*New York Times*, 2020). This page includes a section that lists the reporting anomalies and methodology changes identified by their reporters. An anomaly that gained national attention was the fact that New York State's Cuomo administration failed to report thousands of COVID deaths of nursing home residents (*New York Times*, 2021). The objective of this study is to use the concepts of "abnormal" or "unexpected" (as in earnings, stock returns, trading volume, and accruals) from financial accounting research, and the time-series methodology from financial accounting and forensic accounting research, to derive an estimate of the 2020 death toll.

Leon et. al, (2020) state that a consistent measure of the pandemic's scale, across time and space, should be a priority. Objective and comparable data are crucial to determine the effectiveness of the differing national strategies used to mitigate and suppress, and thus to better prepare for the probable continuation of the epidemic into the future. They conclude that the metrics on incidence and fatality have shortcomings that make these comparisons problematic. Measuring the number of deaths beyond 2020 also should be a priority to assess the effectiveness of the vaccinations and boosters administered, and the effectiveness of social mandates (such as mask-wearing decrees and restrictions on gatherings) imposed. They add that weekly excess deaths provide the most objective and comparable way of assessing the scale of the pandemic.

The CDC define excess deaths to be the difference between the observed and the expected numbers of deaths in a time period (www.cdc.gov/nchs/nvss/vsrr/covid19/excess_deaths.htm). Beaney et. al, (2020) call this difference *excess mortality* and note that it "provides an estimate of the additional number of deaths within a given time period in a geographical region (e.g., country) compared to the number of deaths expected." They conclude that excess mortality can be useful to monitor trends within and between countries, and that it can support policymaking at the international, national, and local levels.

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An early excess deaths application involved the two outbreaks of influenza in the U.S. in 1958 and in the first three months of 1960. Eickhoff, Sherman, and Serfling (1961) used mortality data from the National Office of Vital Statistics to estimate the excess deaths from the outbreaks. Haynes (2003) used the excess deaths approach to calculate the war losses of the Soviet Union in the 1941–45 war. He interestingly noted that the excess deaths number was not a complete measure of the cost and pain of the war. The costs and pain of an event also are borne by those that lived through the period. Freitas, Gérardin, Kassar, and Donalisio (2019) found it anomalous that a major chikungunya epidemic hit Jamaica in the decade just passed with no chikungunya-associated deaths being reported. They used the monthly death rates in 2012 and 2013 to predict the monthly deaths in 2014. Their results showed an excess of 2,499 deaths in 2014, and a closer analysis of the data showed higher excess mortality rates for the months of the chikungunya epidemic and for the age groups that were most likely to be adversely affected by a viral outbreak. Phillips, Barker, and Brewer (2010) investigated whether mortality from natural causes spikes around the Christmas and New Year period. This was confirmed with an annual average of 1,628 excess deaths in the two weeks starting with Christmas in each year. They concluded that this was because of emergency room overcrowding and the fact that the facilities might be short staffed.

Woolf, Chapman, Sabo, and Zimmerman (2021) calculated the excess deaths in the U.S. from March 1, 2020, to January 2, 2021. They used a hierarchical Poisson regression model which is a specialized regression model designed for counting events over a period (see Christiansen and Morris, 1997) and selected the best fitting model using the Bayesian Information Criterion. They calculated an excess death total over the period of 522,368 people. Other death studies related to the pandemic were published in 2020 and 2021. For example, Kawashima et. al, (2021) estimated the Japanese excess all-cause deaths for each week from January 2020 to May 2020. The source of their actual death counts was the Prompt Vital Statistics report (www.mhlw.go.jp/english/database/db-hw/outline/index.html). They noted that excess death numbers were a combination of cases where (a) COVID was the primary cause of death, (b) other incorrect causes were stated as the primary cause of death, and (c) COVID-19 was not stated as the primary cause of death but it indirectly led to death from some other cause.

In their review of the statistical methods available to calculate expected death counts and the detection of infectious diseases Unkel, Farrington, and Garthwaite (2012) note that time-series methods consider the autocorrelations associated with the seasonal patterns in the data. They add that when time-series data are available over a long time period it is important to estimate both the trend and the seasonal components in the series. One of the methods used in disease surveillance is the Holt-Winters technique that allows for both trend and seasonal factors. They note that Holt-Winters has performed well when compared to other more complex methods.

The COVID-related excess death studies all use the same regression-based methodology, namely LOESS (locally estimated scatterplot smoothing) or LOWESS (locally weighted scatterplot smoothing) to get the expected values. LOESS users need to be fluent in linear regression because it is a modern modelling method that builds on the classical regression method. The *Engineering Statistics Handbook* lists several disadvantages of LOESS that includes the fact that it is computationally intensive and it does not produce a regression function that is easily represented by a mathematical model (www.itl.nist.gov/div898/handbook/pmd/section1/pmd144.htm). This study demonstrates a credible excess deaths calculation using time-series analysis.

The methods section reviews time-series forecasting using the Holt Winters approach. The data section describes the data preparation steps taken with the historical data and the descriptive statistics. The results section presents the excess death calculations using R, Excel, Minitab, and SAS. The discussion section reviews the discrepancy between the official COVID-related death numbers and the estimate made in this study, avenues for future research, and the need for accurate numbers to drive an optimal public policy response.

Methods

Time-series analysis has been used in accounting research for over 50 years and early examples include Ball and Watts (1972) and Foster (1977). Lorek (2014) provides an excellent review and a summary of time-series studies related to quarterly earnings. More recently Presley (2019) presents an excellent application of time-series analysis in an analytical procedure setting. Time-series was introduced to the forensic accounting literature in Nigrini (2006). The forensic accounting objectives were to obtain a better understanding of the revenues or expenses under consideration, and to extrapolate a past series of data points into the future followed by a comparison of the actual results (sales amounts, expenditure amounts, net income amounts) to the expected values. Significant deviations from the expected values would be a signal of a change in conditions that might be due to fraud, errors, or other anomalies. More recently Rezaee, Dorestani, and Aliabadi (2018a; 2018b) review the relevance and use of time-series analysis in forensic accounting.

In a single variable time-series analysis the data analyst has access to the historic data, which is modeled, and that model is used to forecast the future values of the series. The only input to the model is the historic data X_1, X_2, …, X_n, and the forecast is made at time n for k steps ahead to give an expected value for X_{n+k}. The Holt-Winters time-series method considers both trend and seasonality. The *trend* is the long-term change in the average level of a series over time (Hyndman and Athanasopoulos, 2021). *Seasonal* variations occur when a series is affected by seasonal factors such as the time of the year or the day of the week. A third possible pattern is a *cycle* which occurs when the historic values rise or fall in a way that is not of a fixed frequency such as the changes in economic activity due to the business cycle. The Holt-Winters method can accommodate multiplicative seasonal factors which occur when the size of the seasonal variation is proportional to the local mean in the historic data. Chatfield and Yar (1988) provide an excellent review of the Holt-Winters technique, while highly readable reviews can be found at tinyurl.com/HoltWint1, tinyurl.com/HoltWint2, and tinyurl.com/HoltWint3.

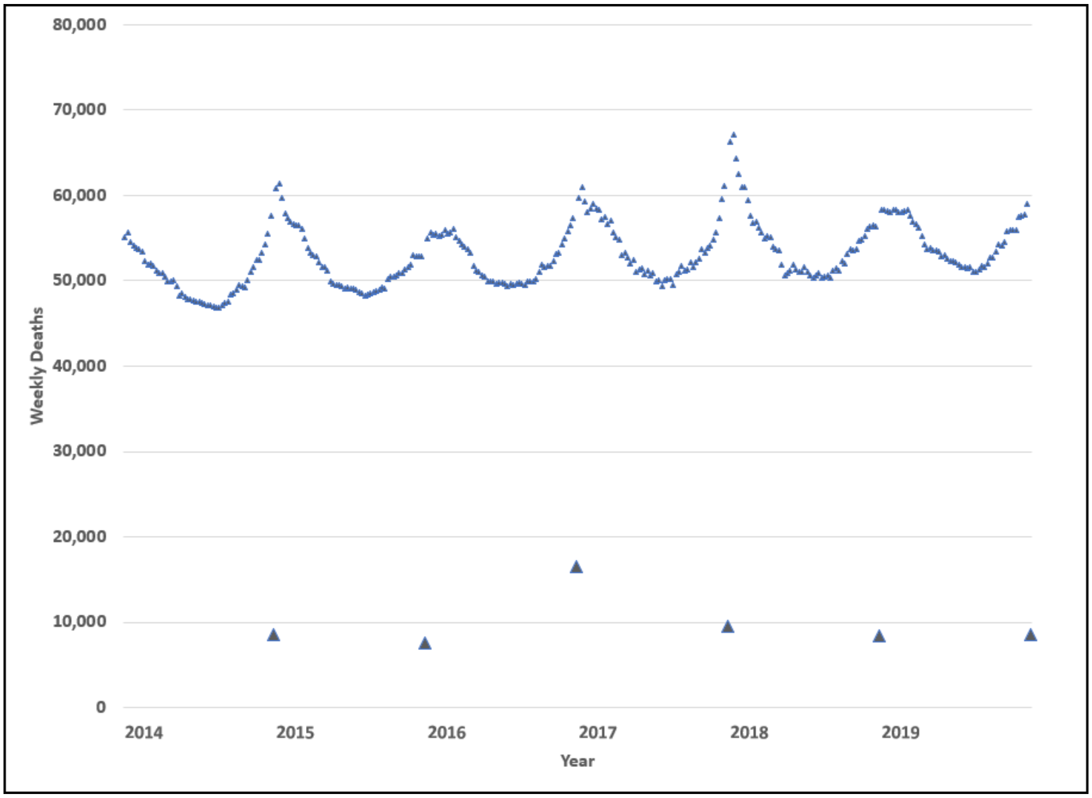
When using the Holt-Winters method users might need to provide values for the α, γ, and δ parameters that represent the "importance" or the weights that should be attributed to the local mean, the trend, and the seasonal index when calculating the forecast values. The ways to derive the optimal weights is still an open question. Fortunately, the effect of those parameters on the forecasts is most pronounced for series that are short (such as two or three years of monthly data) or that are changing in structure. Chatfield and Yar (1988) suggest that good estimates for α, γ, and δ are 0.4, 0.4, and 0.1 and they note that the Holt-Winters method will generally give reliable and robust forecasts, but that it will have difficulty in coping with unexpected features such as sudden changes in structure. The Holt-Winters method is used next to calculate the COVID-related excess deaths in 2020.

Data

The weekly death data was downloaded from the CDC's website at data.cdc.gov/NCHS/Weekly-Counts-of-Deaths-by-State-and-Select-Causes/3yf8-kanr/data. The fields used were the *Week Ending Date* and the *All Cause* field with the death counts for the weeks from 2014 to 2019 inclusive. Information about the Morbidity and Mortality Weekly Report (MWWR) can be found at ndc.services.cdc.gov/wp-content/uploads/MMWR_Week_overview.pdf. The weekly totals are all for weeks ended on a Saturday. The first entry of 54,065 deaths was for the week ending on (Saturday) January 4, 2014 which includes deaths from three days in 2013 (December 29–31). Most years have 52 Saturdays with an occasional year having 53 Saturdays.

Time-series software can generally not deal with an inconsistent seasonal length (52 weeks or 53 weeks). The data preparation steps involved starting each year in the historical series on January 1 with the "first" week of the year ending on January 7, and the 52nd week ending on December 30 (or December 29 in a leap year). This modification assumed that the number of deaths was evenly distributed over the seven days in the week (Sunday to Saturday). Any day-of-the-week variation would not affect the results in any material way. The "modified" first week in 2014 used 4/7ths of the total deaths from the week ended January 4, 2014, and 3/7ths of the total deaths from the week ended January 11, 2014. The 53rd "week" for each year used the total deaths for December 31 (the 365th day of the year) or December 30 and the 31 in a leap year. A graph of the modified data including the short 53rd week in each year is shown in Figure 1.

Figure 1: Weekly Deaths From 2014 to 2019



The markers in Figure 1 show the weekly deaths from all causes from 2014 to 2019 with a seasonal high around the start of the calendar year and a seasonal low in August. The six low points (with markers that are larger than average) are the weekly deaths for the 53rd week in each year which has only one day (December 31) except for the leap year 2016 which has two days in its 53rd week.

Figure 1 shows a seasonal pattern approximating a $y = \cos(x)$ graph with a peak in deaths in the first four weeks of each calendar year and an annual trough in August. The annual trough shows a steady upward trend over the six-year period. In contrast, the annual peaks do not increase linearly. The higher peaks in early 2015 and in early 2018 are due to the increases in the influenza-related deaths in those years. The descriptive statistics shown in Table 1 present an overview of the data, measures of central tendency, measures of the variability or the spread of the values, and an assessment of the distribution of the data in line with Nigrini (2020).

Table 1: Deaths From 2014 to 2016

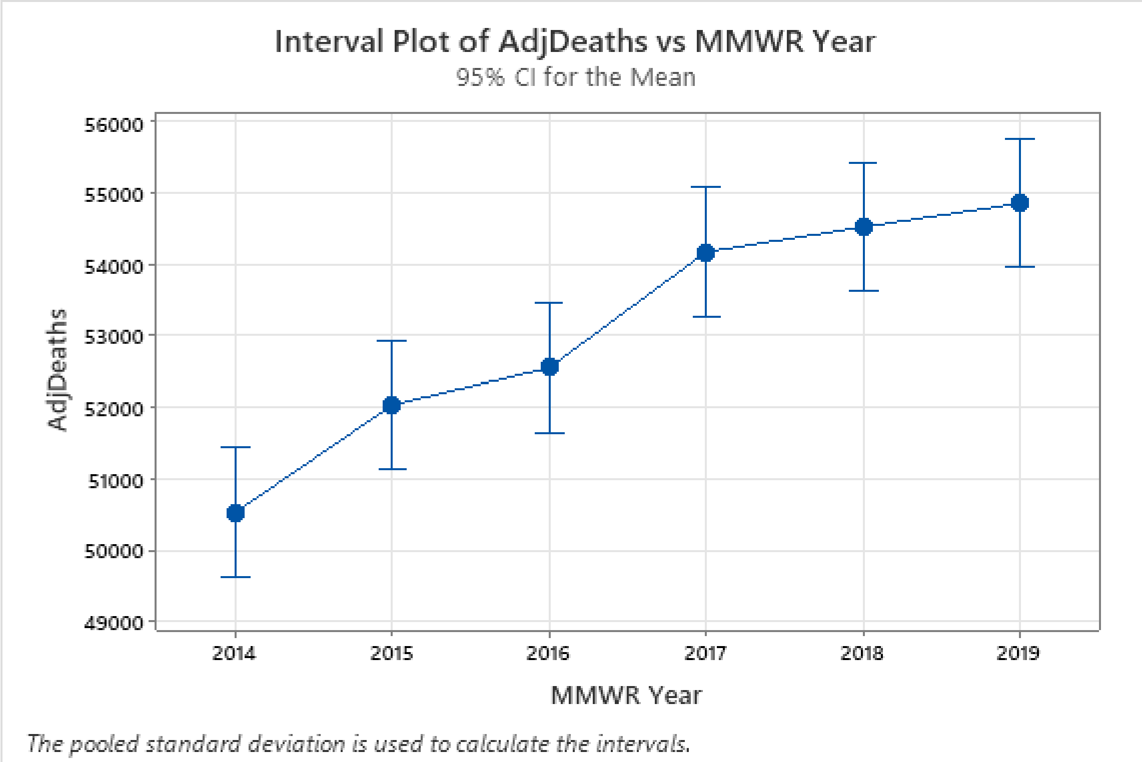
	2014	2015	2016	2017	2018	2019
Sum	2,626,762	2,712,246	2,743,634	2,813,930	2,839,211	2,855,087
Percentage increase		3.25	1.16	2.56	0.90	0.56
Number of records	53	53	53	53	53	53
Number of missing records	0	0	0	0	0	0
Mean	49,562	51,174	51,767	53,093	53,570	53,870
A significant difference between the means?	Yes, α = 0.05 (F = 3.178)					
Test used	One-Way Analysis of Variance					
Median	49,886	50,936	51,760	52,658	53,632	54,062
Mode	-	-	-	-	-	-

Minimum	8,494	7,516	16,474	9,449	8,329	8,599
Quartile 1	47,630	49,131	49,902	50.983	51,112	52,250
Quartile 3	52,330	53,033	55,012	57,048	56,251	57,598
Maximum	57,618	61,420	57,401	61,093	67,094	58,951
Range	49,124	53,904	40,927	51,644	58,764	50,352
Interquartile range	4,700	3,902	5,111	6,065	5,139	5,348
Standard deviation	6,389	7,001	5,539	6,980	7,566	6,844
A significant difference between the variances?	No, α = 0.05					
Test used	Levene's test					
Coefficient of variation (CV)	12.9	13.7	10.7	13.1	14.1	12.7
Skewness	-5.2	-4.6	-5.1	-4.7	-3.9	-5.7
Is the data normally distributed?	No, α = 0.01					
Test used	Anderson-Darling Test					

Table 1 shows the descriptive statistics of the weekly death numbers from 2014 to 2019. The statistics give a high-level overview of the data followed by measures of central tendency and measures of dispersion with the final set of measures related to the distribution of the data.

Table 1 shows that the total deaths increase by percentages that range from 0.56 percent to 3.25 percent on an annual basis. The total annual death numbers are materially influenced by the flu season. The number of records each year is 53, consisting of 52 full weeks plus the one-day or the two-day week at the end of the year. The central tendency measures, the mean and the median, are similarly sized indicating that the annual data is balanced or symmetric. There is a significant difference between the annual means as is evident from a one-way analysis of variance test. The 95 percent confidence intervals for the mean are shown in Figure 2.

Figure 2: Graphical Information Related to the Annual Means



The plot in Figure 2 shows the 95 percent confidence intervals for the annual 2014–2019 means. There is a significant difference between the means as evidenced by the fact that the upper bound for 2014 is below the lower bounds for both 2018 and 2019.

Figure 2 shows the 95 percent confidence intervals for the annual means and the lower bounds for 2018 and 2019 are higher than the upper bound for 2014, giving a significant difference in the means. It would be unusual for any two weekly periods to have the same number of deaths, making the lack of a mode for any year the expected result. That said, the raw data (using the MMWR death numbers) interestingly included duplications of 51,195, 51,046 (in the same year on June 02, 2018 and June 23, 2018), 54,074, 50,612 (in the same year on July 21, 2018 and September 01, 2018), and 51,768.

In the statistics related to dispersion, the minimum value is for the 53rd week in each year (one day for each year except for 2016). The first and third quartiles shown a steady, but uneven, upward year-on-year trend. The quartile values indicate that the center half of the distribution is stable and increasing, but the tails show some variability. The standard deviations, the interquartile ranges, and the ranges show some variability from year to year with higher ranges associated with higher standard deviations, as expected. Levene's test for equal variances fails to reject the null hypothesis of equal variances. The variability in the coefficients of variation means that the ratio of the standard deviation to the mean changes from year-to-year and hints at a somewhat unstable series of data points.

The skewness measures range from -5.7 to -3.9 and since these values fall outside of the -0.5 to 0.5 range this indicates that the data is not symmetrical. The negative values indicate that the data are skewed left. The skewness measure is, however, highly influenced by the 53rd week that has an extremely low value each year. If the skewness test is done with grossed up values for the 53rd week (explained later) the annual skewness measures range from 0.20 to 1.36. The skewness results for 2016 and 2019 shows that the data are approximately symmetric, for 2014 and 2017 are moderately skewed, and for 2015 and 2018 are highly skewed. These results make sense in the light of the flu season peaks evident in Figure 1. The Anderson-Darling Test rejects the null hypothesis that the 2014–2019 data is normally distributed.

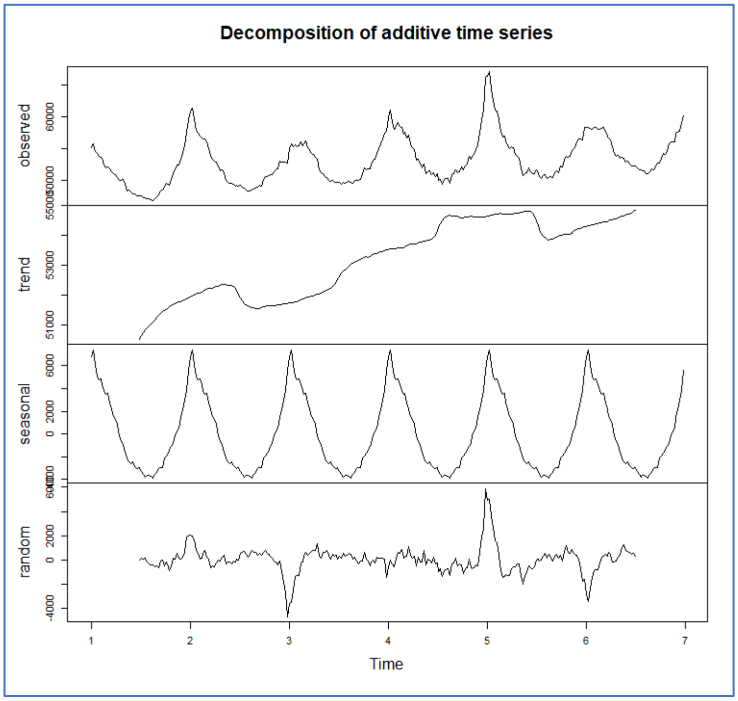
Fitting a function to the data with the short 53rd week might result in slightly less reliable forecasts. Also, 2016 was a leap year with a two-day 53rd week. The approach taken was to normalize the 53rd week by multiplying the death counts by either 7/1 or 7/2 (for the leap year) to "gross up" the 53rd week to a seven-day (normal week). The effect on the forecasts of this grossing up step would be reversed when calculating the excess deaths. The grossed up 53rd weeks were used to generate the forecasts, and the forecasts were then adjusted by grossing down the values for the 53rd week.

Results

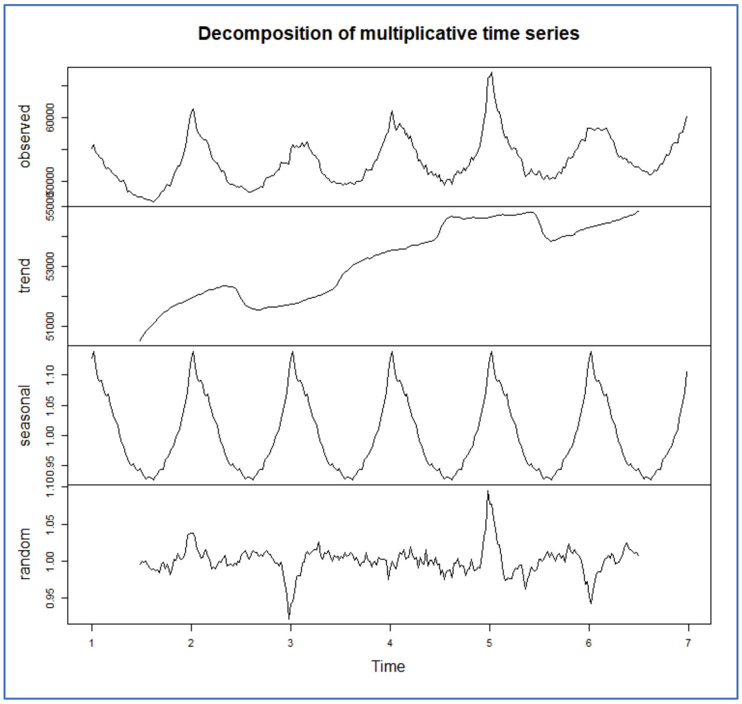
R was used for the first excess deaths estimate. R is widely used among statisticians for developing statistical software and for data analysis. The R packages used were *ggplot* and *forecast* (for a listing of the R-related time series tools see cran.r-project.org/web/views/TimeSeries.html). The first step was to decompose the historical data into its trend, seasonal, and random components (using the grossed-up counts for the 53rd week).

Figure 3: Decomposition of Time Series of Weekly Deaths

Panel A:



Panel B:



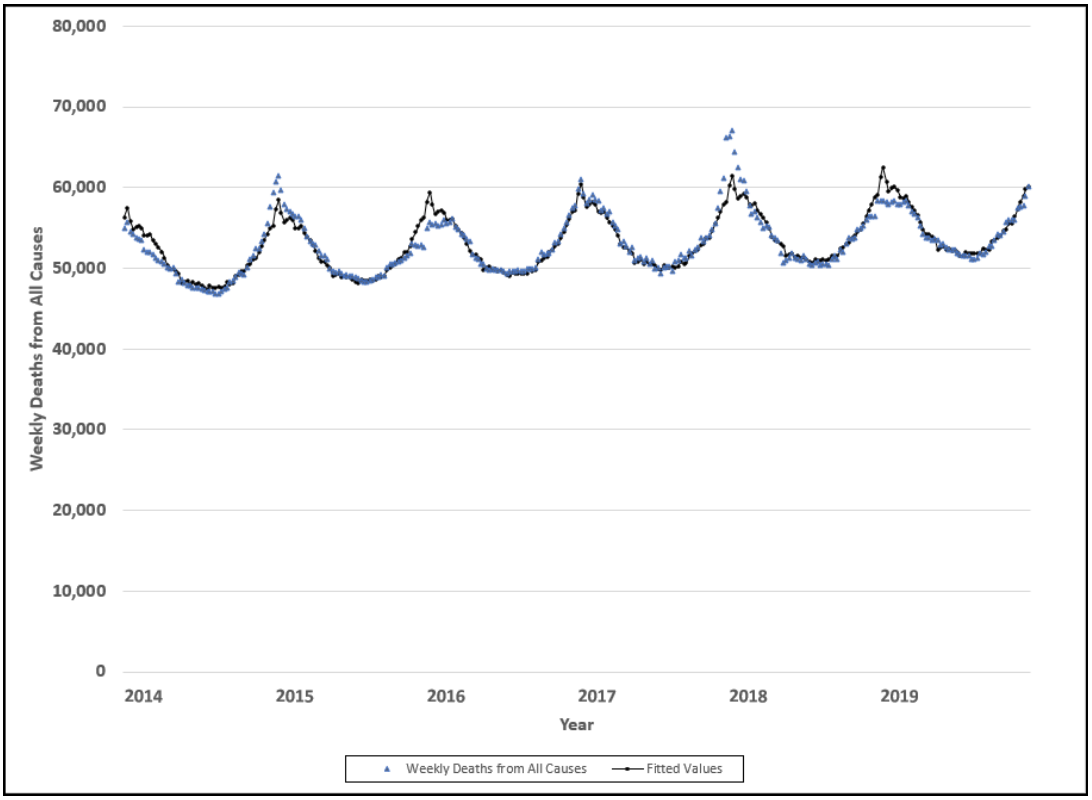
In Figure 3 Panels A and B show the observed series partitioned into its trend, its seasonal pattern, and the random component. There is no meaningful difference between the analyses that assume an additive time series in Panel A and a multiplicative time series in Panel B.

The decomposition in Panel A of Figure 3 assumes an additive trend, while the Panel B decomposition assumes a multiplicative trend. Additive decomposition is most appropriate when the magnitude of the seasonal fluctuations, or the variation around the trend-cycle, does not vary with the level of the time series. Multiplicative decomposition is most appropriate when the seasonal fluctuations are proportional to the level of the time series. The question is therefore whether the seasonal variations increase over time in line with the increase in the trend. In both Panel A and Panel B the trend (the second plot) seems to be linearly increasing rather than geometrically increasing. The two decompositions are nearly identical except for small differences in the plot of the random component (the fourth plot). The trend is highly influenced by the severity of the flu season that occurs each year in December and January. A large peak is evident in the 2014–2015 winter and an even larger peak is evident in the 2017–2018 winter. A smaller peak is evident in both the 2015–2016 winter and the 2018–2019 winter. The peaks and the plateaus are also evident in the random component graphs (the fourth plot in each case). Reliable forecasts could be created using models that assumed either an additive, or a multiplicative, seasonal decomposition. The *HoltWinters* forecast using R and the *forecast* and *ggplot* packages (see cran.r-project.org/web/packages/forecast/index.html) for 2020 was 2,799,144 deaths (after the raw forecast was adjusted by subtracting 5/7ths of the forecast for week #53 because 2020 had 52 weeks and two days). This 53rd week adjustment also was done for the other forecasts. The results are discussed after the other analyses are summarized.

The next forecast was made using Excel's **Data** tab, and in the **Forecast** group selecting **Forecast Sheet**. The steps included identifying the **Values Range** (the adjusted weekly death counts) and identifying the **Timeline Range** (an arithmetic sequence from 1 to 318). The forecast for 2020 was 2,935,288 deaths. The Mean Absolute Percentage Error was 1.27 percent which indicates that Excel was able to fit a tight function to the historic data.

In Minitab (www.minitab.com/en-us/) the forecast was made using the **Stat** tab, and in the **Time Series** group selecting **Decomposition**. The options selected were a **Seasonal length** of 53, a **Multiplicative** model type, **Trend plus seasonal** model components, fifty-three forecasts, and an index for the time variable. The results included a fitted trend equation y = 50,447 + 16.887*$WeekNumber$ where y is the weekly total deaths and *WeekNumber* is a counter from 1 to 318. The trend was positive with a weekly increase of 16.887 people. The results included the mean absolute percentage error (MAPE) and the mean absolute deviation (MAD). A graph of the fitted values is shown in Figure 4.

Figure 4: The Fitted Minitab Values



In Figure 4 the blue markers on the graph shows the weekly U.S. deaths from all causes from 2014 to 2019 with a seasonal high near the start of the calendar year and a seasonal low in the month of August. The black line with the small markers shows the fitted values using Minitab's decomposition method.

Figure 4 shows the fitted time-series values which is like the fitted line in a linear regression application. The MAPE is a goodness-of-fit measure that indicates how the historical series varies from its model-predicted level and gives users an indication of the uncertainty in the predictions. The MAPE for the data was low at 1.37 percent, suggesting a low level of uncertainty in the predictions (see www.ibm.com/docs/en/spss-modeler/18.2.0?topic=node-examining-model). The Mean Absolute Error (MAE), also referred to as the Mean Absolute Deviation (MAD), also measures the accuracy of fitted time-series values. The MAE expresses the goodness-of-fit in the same units as the data and indicates that the average absolute difference between the fitted and the actual values was 759 deaths.

SAS is a software suite for advanced analytics, business intelligence, data management, and predictive analytics. SAS includes a Holt Winters routine that is as accurate and true to the model as is reasonable to expect from the industry standard. The Proc ESM (short for "exponential smoothing models") procedure was used with the Winters model. The set of forecasts for 2020 are shown graphically in Figure 5.

Figure 5: Weekly Forecasts Using Excel, Minitab, SAS, And R

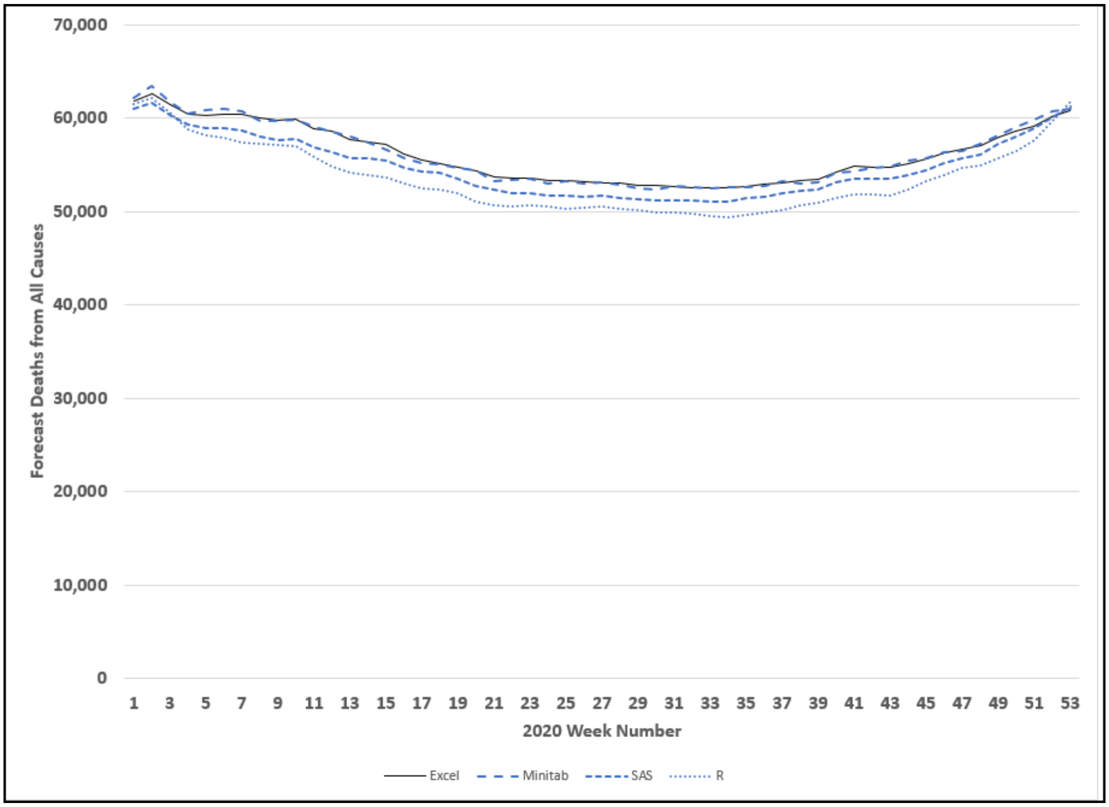


Figure 5 shows the weekly deaths forecasts for 2020 from the time-series routines in Excel, Minitab, SAS, and R.

Figure 5 shows the forecast deaths on the *y*-axis. The forecasts for Excel and Minitab (the uppermost two series) follow each other closely. The SAS forecasts are lower than the Excel and Minitab forecasts except for week 53. The R forecasts are even lower than the SAS forecasts for each week except for the first three and the last weeks of the year. The issue with the low R forecasts is that it translates to a higher excess deaths count. The excess deaths calculations are shown in Table 2.

Table 2: Time-Series Forecasts

	R	**Excel**	**Minitab**	**SAS**
Actual Deaths, 2020	3,389,095	3,389,095	3,389,095	3,389,095
Forecast Deaths, 2020	2,799,144	2,935,288	2,934,863	2,864,596
Excess Deaths, 2020	589,951	453,807	454,232	524,499
Centers for Disease Control and Prevention (CDC)	385,484	385,484	385,484	385,484
Difference	204,467	68,323	68,748	139,015
Percentage difference	53.04%	17.72%	17.83%	36.06%
MAPE		1.27%	1.37%	0.70%
MAE		720.48	759.27	381.56

Table 2 shows the R, Excel, Minitab, and SAS forecasts. The actual deaths are the CDC's numbers. The excess deaths are the excess of the actual deaths over the forecast deaths. The Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error (MAE) goodness-of-fit values also are shown.

Table 2 shows the actual deaths per the CDC (www.cdc.gov/nchs/nvss/vsrr/covid19/index.htm) and the R, Excel, Minitab, and SAS forecasts. The raw forecasts were adjusted downwards because the 53rd week in 2020 only had two days. The excess deaths are the excess of the actual deaths over the forecast numbers. The table shows the 2020 CDC death count for COVID in cases with multiple causes of death (data.cdc.gov/NCHS/Monthly-Provisional-Counts-of-Deaths-by-Select-Cau/9dzk-mvmi/data). This count (385,484) exceeds the count of 351,891 for COVID as the only underlying cause of death. The difference between the CDC number and the excess death calculation is shown as an absolute amount and as a percentage difference.

The R-based excess deaths result is higher than the other results. R has several forecasting routines that could not be used because the seasonal period was 53 and the error message "frequency too high" was often seen when trying any of the innovative options (see https://robjhyndman.com/hyndsight/longseasonality/). The creator of the package states that where there is a difference between ets() and HoltWinters(), the results from ets() are usually more reliable (https://robjhyndman.com/hyndsight/estimation2/). These factors led to the exclusion of the R forecasts from the excess deaths' calculation. Using the average forecast is supported by Clemen (1989, p. 559) who notes that "the results have been virtually unanimous: combining multiple forecasts leads to increased forecast accuracy. This has been the result whether the forecasts are judgmental or statistical, econometric or extrapolation. In many cases one can make dramatic performance improvements by simply averaging the forecasts." The excess deaths calculation is shown below:

Details	**Number of people**	**Notes**
Forecast deaths, 2020	2,911,582	Average of Excel, Minitab, and SAS
Actual deaths, 2020	3,389,095	CDC data
Excess deaths, 2020	477,513	Actual minus forecast
CDC COVID deaths	385,484	COVID-19 with or without another cause
Difference	92,029	23.87%

The calculated excess deaths in 2020 are 23.87 percent more than what was officially attributed to COVID. This number is conservative. The CDC data show that there were 24 COVID deaths in January and February 2020. For most of the first nine weeks in 2020 the actual deaths were *below* the forecast deaths. The excess deaths for the first nine weeks of 2020 amounted to -9,557 people. If we therefore recalculate the excess deaths for the COVID period only (weeks 10 to 53) the excess deaths climb to 487,070 people (26.35 percent higher than the CDC's estimate).

Conclusions

On September 16, 2021, *The Economist* noted that, "On September 11, 2001, when al-Qaeda attacked America, almost 3,000 people died. In response, the government overhauled national security and, for better or worse, struck a new balance between liberty and security. On the 20th anniversary of 9/11, roughly 3,100 people in America died because of COVID-19. Another 3,100 died on September 12 and again on September 13." This situation was the severity of the pandemic some nine months after the Food and Drug Administration gave the first emergency use authorization to the first coronavirus vaccine.

The objective of financial accounting is to provide reliable information about the reporting entity for decision making by investors, lenders, other creditors, and regulators. Management accounting produces information for managers within the organization that helps those managers to fulfill organizational objectives. Estimates are used in both disciplines and in managerial accounting some accuracy might be sacrificed for timeliness. Accurate information for public policy makers about the loss of life from COVID is many orders of magnitude more important than an organization's set of financial statements or monthly accounts. Accurate COVID death data are crucial to determining the effectiveness of the national strategies used by policy makers to mitigate and suppress, and thus to better prepare for the probable continuation of, the epidemic into the future. Measuring and reporting the number of deaths after 2020 is also important to policy makers to measure the effectiveness of the vaccinations and boosters administered, the effectiveness of social mandates such as wearing masks, and personal restrictions such as the restricted capacity of gatherings. The estimated COVID-related death toll in 2020, using time-series analysis, shows that the deaths in 2020 (January to December) were 92,029 people more than the number of deaths directly and indirectly attributed to COVID by the CDC, the agency charged with formulating a policy response to health threats. This discrepancy climbs to 101,586 people if we only consider weeks 10 to 53 in 2020. If an accounting system reported numbers that were 23.87 percent (26.85 percent understated for weeks 10 to 53 only) understated it would be deemed a failure on almost any metric, let alone a life-or-death situation.

Future research could address how the public strategies to fight the pandemic would change based on more accurate and timelier COVID-related death data. Future research also could estimate the excess deaths for 2021 once the CDC's death data is finalized. The 2021 estimate should consider the fact that the all-causes deaths in 2020 (3,389,095 people) includes some people that would have died in 2021 (and not 2020) had there not been the COVID pandemic.

The *Economist's* COVID-related mortality estimates use a machine-learning model. Some sources estimate that it would take six months of intensive study to become a machine learning engineer, and more if the person needed to upgrade their quantitative skills. In contrast, it would only take about a week to learn enough about time-series analysis to run the analyses shown in this study. It is interesting that the usual, mundane, constructs of "abnormal" or "unexpected" in accounting research, together with the time-series methodology can be used to provide information for policy decisions at the federal, state, and local levels. Time-series analysis could be used to test the information from countries where the policy makers might want to purposely understate the COVID-related loss of life.

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