Institute for Healthcare Improvement

Out of the Crisis: Understanding Variation in COVID-19 Reported Deaths in the US Using Shewhart Control Charts

During the COVID-19 pandemic, reports of new daily cases and deaths have dominated the headlines. In areas hardest hit by the virus, citizens and their leaders anxiously await the latest daily figure. If the number of deaths increases from the prior day, the result is despair or panic; if the number of deaths decreases, the result is optimistic hope that the tide is turning. In other words, every day brings a new and seemingly meaningful story — something to which the public and leaders react and that influences decision-making about individual behaviors as well as judgments about policy. New York is a sobering example of recent oscillation in headlines. The April 6 article "Virus Toll in N.Y. Region Shows Signs of Leveling Off" suggested that "steps to control the coronaviruses' spread might be working," while a mere twelve hours later an article proclaimed that New York virus deaths had reached a new high.

We expect that the number of reported deaths — just as with anything other phenomenon that we measure — will vary with counts going up and down. Without a method to understand if the variation we experience in the number of deaths is merely randomness that we'd expect to see in any measure, we will struggle to recognize if things are improving or getting worse and to make data-driven informed decisions accordingly.

To model the trajectory of COVID-19 new reported daily deaths, we have created Shewhart control charts (graphical representations that include the mean, upper, and lower control limits). We've created charts so that within a specific geographical region, the charts can detect when the pandemic is entering a rapid growth phase and when exponential growth is ending. We hope that this analysis will be of use to subject matter experts, leaders of quality improvement, decision makers, care providers, and the general public.

The Shewhart (control) chart method and theory has been applied successfully to some of the world's most pressing problems in health care and society. Given the current realities of a global pandemic, Shewhart's charts are an invaluable tool in making sense of an increasingly complex data environment because they provide a basis for taking action. Such methods are needed to learn from daily reported COVID-19 death counts from countries, states, and other geographies.

Because the control chart method and theory are designed to distinguish between random and non-random variation, they are ideally suited to understand if the daily death counts are stable (i.e., only reflect common causes) or unstable (i.e., include special causes). The control chart method developed here — and outlined in detail below — is an advanced application of the approach that has been automated for ease of use and interpretation, though users can input their own data and create their own charts.

To improve a situation, we look at the variation in a process. A fundamental concept of the science of improvement is that variation in a measure has two potential origins: **common** causes and **special** causes. Walter Shewhart developed in 1939 this theory of variation. **Common causes** are inherent in the system over time, affecting everyone in the system and all system outcomes. **Special causes** are not part of the regular system but arise because of particular circumstances or some "special" source of variation that can be assigned to some identifiable cause. Shewhart developed the "control chart" as a tool to distinguish the random variation of common causes from the non-random variation of special causes.

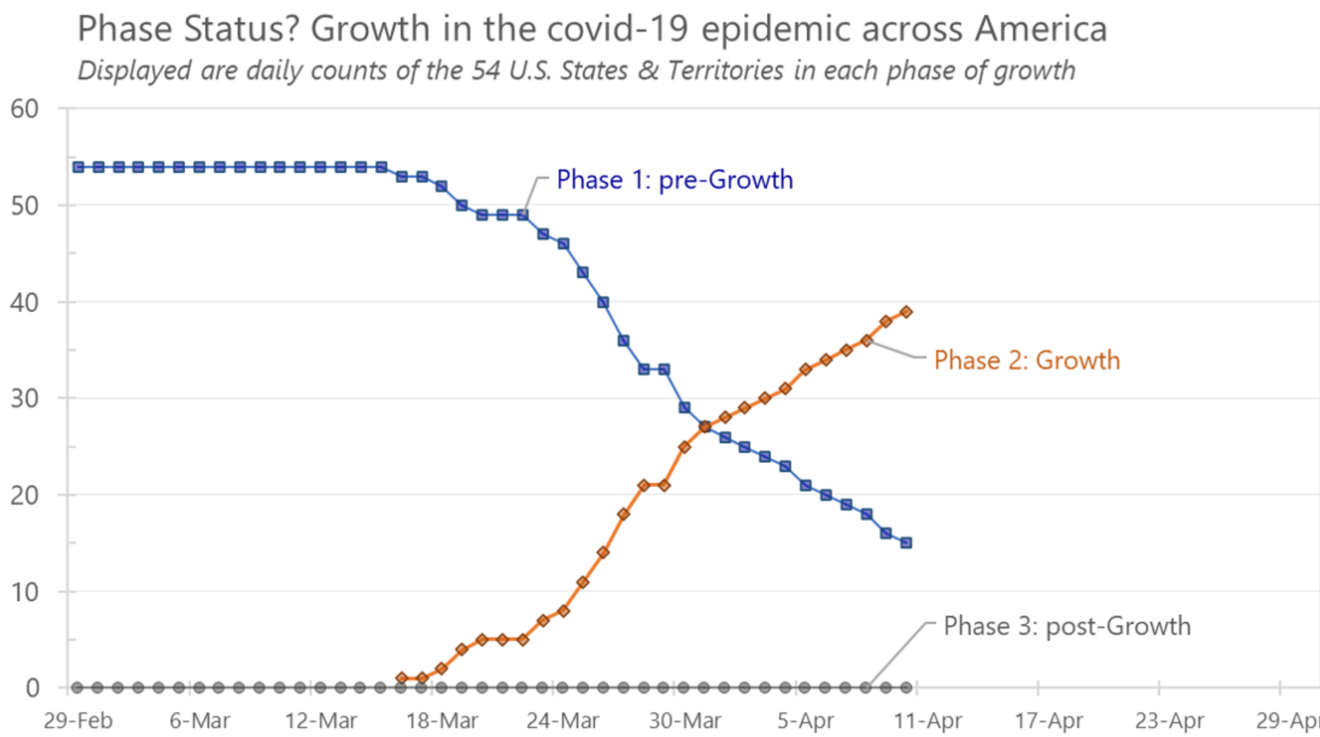
In these charts, our unit of analysis is the count of new daily reported deaths. Many high-profile news media outlets and statistical models are tracking COVID-19 cases. A problem arises when case counts data fail to convey meaningful information because of issues with underreporting and factors related to wildly variable testing and case detection across different countries and states. The use of death rates for understanding this epidemic is also challenging because of the lack of a stable denominator. The area of opportunity for detecting cases varies across communities because of variation in testing strategies and access to testing as well as the sensitivity and specificity of a new diagnostic tests. Another factor confounding death rate data is the extent of to which the health care delivery system in a region may be over capacity and/or dealing with staffing and equipment shortages.

The use of cumulative deaths in modeling this epidemic is a common approach — although studying the increasing total of deaths in an area is more likely to mask variation (and thus hinder learning) relative to tracking new daily deaths. Our method considers day-to-day variation in reported number to deaths each day to prevent us from over-responding to common cause variation in reporting errors. Our data source for these charts is updated each afternoon from *The New York Times* Github database.

Discrepancies in reported deaths are common due to under-reporting community covid-19 deaths and potential over-reporting in hospitals owing to codes used for insurance billing and reimbursement. An April 10 article in *The New York Times* describes how "paramedics are not testing those they pronounce dead for the virus, so it is almost impossible to say how many of the people were infected with it." In spite of these and other limitations associated with data quality in the reporting of COVID-19 deaths, new daily reported deaths data provide useful information to decision-makers navigating a complex pandemic landscape.

A focus on new daily reported deaths is among the distinctive contributions of our approach. Shewhart control charts offer a different way to display and learn from this type of data. Our method relies on minimal assumptions (primarily, the expected logistic increase of an epidemic) and builds on the initial data observed in an area. Our predictions consist of extending the center line (the mean) and upper- and lower-control limits and are based on the assumption of a stable system over time. We don't predict the end of exponential growth but can determine when that point has been reached.

The chart below provides a US "system view" with a summary over time of the number of states that are in each phase of exponential growth, reinforcing the point that on any given day we are dealing with different dynamics across the nation as well as changes happening within each state.

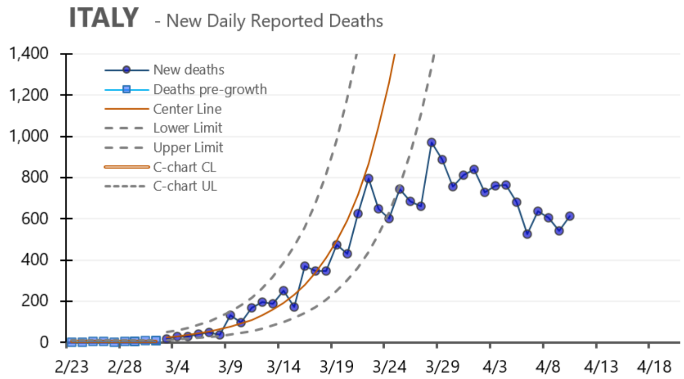


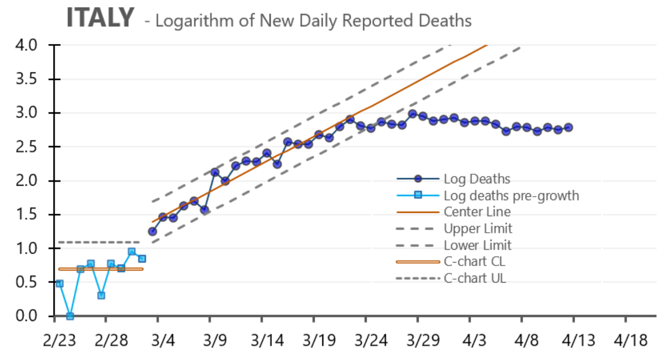
Shewhart Control Chart Methodology Used for the COVID-19 Reported Deaths in the US Control Charts

We use a C-chart for the initial pre-growth phase. After at least eight deaths have been reported and a special cause signal (above the upper limit or a shift of eight successive points above or below the center line) has emerged, we switch to a log-regression *I*-chart with slanted center line to model the growth phase. During this growth stage, we continue plotting the deaths and update the calculation of center line and limits each day (extending the center line and limits into the future). If a location is still in its growth phase after 20 days, we freeze calculation of the centerline and limits. At this time, we also extend the "frozen" limits (based on regression analysis of the 20 data points) into the future as a guide to interpret subsequent daily reported deaths plotted on the chart.

When a special cause signal below the lower limit occurs before the growth phase and has lasted for 20 days, we freeze the limits and plot the next day's observation. If this last data point also signals special cause variation, we conclude that the growth phase has ended. Then we continue to plot subsequent counts of reported deaths on the chart but do not include these values in the regression used to calculate the center line and limits that are intended to detect signals related to the trajectory of the growth phase.

The Shewhart control charts below illustrate what "completed" chart will look like on both a linear and logarithmic scale.





Details of the Combination C-chart/I-chart with log-linear regression center line

Phase 1 of the Charts (Pre-growth) – number of deaths each day are low and stable

1. Select start date as the day when the data set has first death. Plot the number of deaths each day.
2. After at least 8 total deaths have occurred, calculate the center line (CL = average of daily counts) and upper limit [UL = CL + 3* sqrt(CL)] using data from all days since the initial death. The chart is best seen on the log scale (see log-Italy chart above).
3. Continue plotting and updating the limits each day, looking for a special cause signal (a point above the UL or 8 points in a row above or below the CL). 8 consecutive points below the CL could occur at the beginning of the series. If you reach 20 days (not expected) in this phase, freeze CL and UL and extend these limits into the future.
4. When a special cause signal occurs, end the C-chart and switch to the growth chart for the 2nd phase. This last data point in the pre-growth phase will become the first data point in the second phase.

Phase 2 of the Charts (Growth) – number of deaths each day are trending higher

1. Use the data value from the last day on the C chart from Phase 1 (the point that triggered the special cause signal) as the first day on the growth chart.
2. For the first 5 days of Phase 1, just plot the daily deaths. After five data points are available in Phase 2, begin calculating a CL and limits each day. Extend the limits 7 days into the future.
3. To calculate the center line and limits, first transform the counts using log10 function (log of 0 is not defined, so 0 values will be interpreted as missing. Adding 1 to each data point in the growth phase alleviates this issue).
4. Calculate the intercept and slope (linear regression analysis) for the log10 data series. This regression line will become the center line for the I-chart base on the regression line.
5. Develop the limits for the I chart by calculating the moving range of the residuals, screen the moving ranges, then getting a revised average moving range (MRbar). Calculate upper limit for each day using (CL for day + 2.66*MRbar) and lower limit (Cl for day -2.66*MRbar).
6. Transform the center line, upper limit, and lower limit back to the original count scale using the inverse (power) transformation. Extending the CL and limits to 7 future days.
7. Plot control chart with original counts and the transformed center line and limits. (note: this chart will approximate a logistic function for the growth period of a death curve).
8. An option is to use a log scale to present this this chart (see examples of both charts above for Italy)
9. Continue to update this chart with new data each day until you reach 20 days in the growth phase. Then freeze the CL and limits and extend them seven days into the future.
10. Either a data point below the lower limit or 8 consecutive points below the center line are indications that the growth period has ended and this specific geography has reached the peak in the number of reported daily deaths (these special cause signals indicate the possibility of Phase 3, the peak or apex, may have been reached). A review of the chart is required to make this call.

11. When a special cause signal occurs freeze the limits (if not already frozen with 20 points) and plot the point for the next day. If this point also is (or is part of) a special cause signal, there is strong evidence that the growth period has ended.

Phase 3 of the Charts (at Peak or Apex) – daily reported deaths are flat or dropping

The peak phase identifies when an area has reached and/or passed the apex of mortality, after which reported deaths are expected to decline. Continue to plot the number of deaths without updating the limits for phase 1 or 2 (see Italy Chart after March 22).