

# **PMC U.S. COVID-19 Report for September 1, 2025.**

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## **Technical Appendix**

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# Overview

The Technical Appendix outlines the various methodology used in the dashboard. Scientists, clinicians, public health officials, and community members use the dashboard and have varying familiarity with technical concepts. The dashboard and appendix are designed to be understood by community members without extensive scientific training. We provide enough detail that third parties could follow similar practices to derive their own independent estimates and have collaborated for mutual benefit with the others doing important dashboard work worldwide. Please ask questions as needed, preferably in public on social media, so that as many people as possible can benefit from hearing the answer. We have iteratively updated the dashboard periodically, and your input remains extremely valuable to the PMC. We also make periodic explainer videos when feedback suggests it would be helpful. Simply look through the older reports to see how the dashboard has evolved over time based on user input. Finally, we encourage you to use, improve, and share the images from the website broadly to increase the impact of this work. Your role providing COVID-19 outreach to others provides a vital public health service. Thank you for taking the time.

## Data Integration

The dashboard involves integrating data from the Institute for Health Metrics and Evaluation (IHME, true daily infection estimates), Biobot (wastewater transmission), and CDC (wastewater levels). Each has different timelines of existence and has varied in quality. Present cases are estimated using a composite indicator that gives 20% weight to Biobot data and 80% weight to CDC data, and the particular weights given to IHME, Biobot, and CDC have varied over time. The first step is to clean the data. We would not be able to do this as effectively if not knee-deep in the data the past 2+ years, as that allows immense opportunities to spot inconsistencies in how data are being reported and the lag between the publicly-noted date and the average actual date data were derived from. Many readers working with COVID data are familiar with the various peculiarities across different data sets. Much of the “real-time” data people think they are receiving are actually a week outdated, which is why forecasting is particularly important. In comparing data files, we noted that the lag phase has varied marginally over time in some data sets (e.g., 7-day lag versus 2-day lag, relative to stated dates) and have corrected the files accordingly. This has allowed longitudinal transmission estimates to line up closely. Then, we developed conversion multipliers to go from the metrics of one data set to another using a 20% trimmed mean. The intercorrelations among IHME, Biobot, and CDC ranged from .92 to .98 (all near perfect, as the highest possible value is 1.0), indicating that they all are getting at the same thing (construct validity). Correlations  $>.70$  would be desirable, and the  $>.90$  values indicate extremely high validity. The minor discrepancies are likely reasonable given different assumptions or geographic coverage. All three data sources were converted to a single IHME-based metric for true new daily infections. More details on the date, weights, and conversion multipliers will appear in an eventual publication; however, this should suffice to demonstrate the general methodologic approach. Overall, the intercorrelations among data sets were extremely high, near-perfect, and much more encouraging than what we would have imagined or been willing to integrate effectively.

## Case Estimation

All wastewater estimates of transmission are tied back to the IHME model’s estimate of “true” new daily infections (not merely reported or counted cases), with the intercorrelations among individual data sets of  $r=.92-.98$  (near perfect). A multiplier is used to convert wastewater values to infection estimates. The multiplier estimate varies for each day, so a measure of central tendency or typical value is used. We use a 20% trimmed mean on the daily multipliers. Regression estimates, medians, means, and varying trimmed means provide comparable estimates within  $\pm 15\%$ . Since “true” new daily infections are actually magnitudes higher than what much of the general public not monitoring wastewater tends to believe, these differences across modelers are quite negligible in terms of their implications for personal, organizational, and policy decision making. To put it more concretely, much of the public may believe there are hundreds of infections a day, while

modelers debate whether it is 0.6 or 0.8 million at a given time point. Thus, wastewater-derived estimates provide a useful tool for the public.

Two parallel lines of evidence support the validity of wastewater-derived case estimates. One, several dashboards worldwide use similar procedures, including others in the U.S. (World Health Network), Germany, Canada, Australia, and Slovenia. The latter is the only official government dashboard presently to do so. Our pre-print demonstrates a strong correspondence between the estimates of peak transmission in the U.S. during the winter 2023-24 wave and those of a high-quality testing-based surveillance study by the UKHSA as well as wastewater-derived estimates from Canada. Dozens of publications show the importance of wastewater surveillance for estimating community transmission and other metrics, which can be found through a Google Scholar search for *covid wastewater cases* and using similar terms (e.g., Hill et al., 2023, Infectious Disease Modelling; McMahan et al., 2021, Lancet Planetary Health; Shah et al., 2022, Science of the Total Environment; Varkila et al., 2023, JAMA-NO). Second, true case estimates have always been higher than reported cases. From 2021 through 2025, IHME and PMC estimates of true transmission have often approximated 25-30x those of reported infections, except during a brief interval in 2024 and the most recent two months of 2025, where hospital reporting has been allowed to lag substantially. Overall, the case estimates perform exactly as expected, and there have been no red flags to date. If there were major anomalies, the PMC model would be revised. In sum, the case estimation model has performed exceedingly well.

The model estimates the number of new daily, weekly, monthly, and annual infections (incidence, or new cases per time period) and proportion of the population actively infectious (prevalence). The incidence is tied directly to the new daily infections of the case estimation model, with additional estimates (e.g., weekly) by summing the relevant prior days. The prevalence takes the incidence, divides by the U.S. population estimate for that day, and multiplies by the average infectious window of 7 days (Hakki et al., 2022, Lancet Respiratory Medicine, "Onset and window..."). More nuanced models that attempt to account for the prior 7+ days of infections, variability in the infectious window, etc., are not of practical significance given that such factors are marginal relative to error in estimates of the population, the precise average infectious window, and real-time wastewater reports; none of these particularly matter. A common community reaction is that 7 days for the infectious window seems "too short," given known examples of people being infectious for 2 weeks, 1 month, or much longer, but those outliers stand out precisely because they are atypical (availability heuristic) and ignore the many cases where people are infectious for a limited window, asymptomatic or paucisymptomatic, and test too infrequently or with such high Ct values as to evade a positive test result.

A critical note on prevalence is that communities often struggle with percentages and decimals and prefer prevalence expressed using simple proportions using simple language: 1 in \_\_\_\_ actively infectious. This is the statistic public health organizations use to communicate to communities. Individuals prefer this statistic, especially when localized as much as possible, when communicating with family, friends, and co-workers. The news media likes this statistic, the number of new daily infections, and the projected peak new daily infections. The statistic is easily computed by taking 100 divided by the percentage actively infectious for a geographic unit (e.g.,  $100 / 0.8$  [for 0.8%] = 125, meaning 1 in 125). During state-level surges, these values often peak at the 1 in 10 or 1 in 30 range. We do not allow values to go more extreme than 1 in 20 for states with CDC-indicated "limited data" or if the state has 2 or fewer wastewater sites reporting; this has been a challenge in Louisiana, for example, where values are often corrected marginally downward retroactively, and only two sites are present. The 1 in \_\_\_\_ statistic should be emphasized in public health communication.

Extrapolating from the prevalence estimates, we also compute exposure risk estimates. Values of 1% or 1 in 100 often sound small to people, but risk adds up quickly through repeated exposures to more and more people. We provide estimates in the context of social interaction with 10, 25, 50, or 100 people. These specific values were guided by community input as useful for characterizing risk in key contexts. The risk estimates assume that each person is of average risk of infection and that nobody is testing and isolating. A few notes on these assumptions are helpful. One, sometimes clinicians or others will note that everyone stays home if ill; however, this ignores that about half of cases are asymptomatic or paucisymptomatic, people are testing much less often, and people are being pressured back to work, school, or other social situations. Two, people may note that their peers are all COVID cautious (PMC estimates are overestimates) or that the people out and

about are less cautious (PMC estimates are underestimates). Those assertions could be true, but it is difficult to know at any particular time (the “less cautious” could be more likely to get infected early in a wave, or they could be less likely to be infectious during a particular time period due to recent infection already). Overall, the PMC estimates provide good heuristic value in helping people to understand how exposure risk increases with more personal interaction. Nonetheless, it is important to note that exposure risk (being near someone infectious) does not always imply infection risk, which varies on the total time of exposure, ventilation and filtration, mask type and fit, vaccination histories, and more. High exposure risk should encourage more people to use high-quality multi-layered mitigation to avoid turning exposures into infections.

There are limitations of the case estimation model. Estimates are more precise when averaged across many wastewater collection sites and regions, and with larger populations. These are fundamental statistical rules (e.g., central limit theory, classical test theory). Each wastewater site can be thought of as having some degree of noise or error, and the more data points averaged together, the more errors can cancel out and provide a true estimate of the signal. Thus, the state-level estimates we provide should be taken with a grain of salt, especially if a particular state has fewer wastewater collection sites or has been more prone to retroactive corrections. Even in the noisier environments of smaller states with few sites and retroactive corrections (like where we are in Louisiana), the central estimate remains the best estimate and far better than non-statistical inferences (anecdote) as to transmission levels.

There are two key ways the federal government could improve transmission estimates of COVID-19 and other infectious diseases. Far too little is being invested in fundamental COVID-19 research, and large longitudinal testing-based cohort studies are needed (e.g., a nationally-representative sample of 1,000 people with weekly testing). Periodic high-quality testing-based surveillance programs for COVID-19 or other diseases allow for continuous rigorous reevaluation of wastewater models and help document the significance of the problem. Additionally, over the longer-term, we will see a greater emphasis on modeling in public health epidemiology. This is already common in some areas (e.g., cancer incidence estimates), but too often with COVID-19 and other infectious diseases, the emphasis has been on concrete outcomes that are easy to count (reported cases, hospitalizations, reported COVID-19 deaths) but presently map on poorly to the reality of true cases, Long COVID, and COVID-19 excess mortality. Public health estimates need to become more “patient-centered” or “community-centered,” and that requires modeling. It would be far more impactful if the U.S. CDC provided wastewater-derived case estimates instead of the PMC, and we encourage them to do so.

## Long COVID

The PMC model provides estimates of post-acute sequelae of COVID-19 (PASC) resulting from daily and weekly infections. We assume 5-20% of infections will result in new long-term health conditions. We use “Long COVID” – the most commonly used community term – as opposed to “PASC.” However, it should be noted that under the umbrella of PASC, we are referring to new individuals developing Long COVID, individuals with Long COVID already who develop additional health conditions, and people who do not identify with these labels but develop new conditions after infection. Minimizing estimates from people with conflicts of interest tend to provide estimates near 1%. Broad definitions that include prolonged or new symptoms regardless of impact on daily functioning tend to estimate closer to 40%. Most studies suggest 5-20% per infection, with lower estimates when emphasizing higher severity or using medical records only, and higher estimates when using broader case definitions. For example, the recent Al-Aly study noted a 3.5% estimate (Xie et al., 2024, NEJM, “Postacute Sequelae of SARS-CoV-2...”), which was likely a slight underestimate as based on medical record data on newly documented diagnoses. Wide ranges such as 5-20% are common, even in long-standing, highly studied areas, such as rates of depression among people with cancer. As noted in the prior paragraph, prospective cohort studies of SARS-CoV-2 infections and outcomes would have numerous benefits, including better tracking of Long COVID, but these are not presently funding priorities. Long COVID is a patient-centered and community-centered outcome that should be at the heart of all public health conversations about ongoing infections and warrants estimation to document the ongoing public health impact of COVID-19.

# Excess Mortality

The excess death calculations indicate the number of people in the U.S. expected to ultimately die as a result of daily or weekly infections. Excess death statistics are derived from the Swiss Re model, which we interpret to indicate 3.7-6.0% excess deaths per year in 2025 (see their publication for future years). Using death count projections from Our World in Data, this amounts to 109,000-175,000 excess deaths in 2025, 96,000-164,000 excess deaths in 2026, and 84,000-151,000 excess deaths in 2027. Our 5-year anniversary video describes that cumulative infections increase linearly, providing clear estimates of expected infections annually. To derive an oversimplified estimate of the case-fatality ratio of an infection in 2025, one could take the numbers of deaths and divide by the number of infections. However, that would assume that COVID infections in 2025 lead to deaths in 2025 (not later) or that the case-fatality ratio is identical in forthcoming years, which Swiss Re suggests is not the case. Instead, we estimate the resulting deaths from 2025 infections by assuming crudely that  $\frac{1}{2}$  of 2025 infections will result in a 2025 death,  $\frac{1}{3}$  in a 2026 death, and  $\frac{1}{6}$  in a 2027 death. This corrects the case-fatality ratio downward to account for reduced probabilities in 2026-27. The fractions ( $\frac{1}{2}$ ,  $\frac{1}{3}$ ,  $\frac{1}{6}$ ) are crude and inconsequential, in that sensitivity analyses using similar values or assuming that Swiss Re estimates for 2025 should be 10% higher and with a 10% more gradual trajectory yield similar results. With the case-fatality ratio identified with high and low estimates, one can estimate the number of resulting deaths from daily and weekly infections. This description glosses over a few details that could lead disinformation artists to misapply our case-fatality ratio to low-quality data like reported daily cases and consequently downplay COVID deaths (forgetting that the total must add up to the Swiss Re values). However, an appropriate case fatality ratio could be derived for any estimate of transmission; those that use low quality data that downplay transmission (e.g., BNO) would actually speculate a much higher (e.g.,  $>25x$ ) case fatality ratio in ways that are obviously unrealistic. One of the plausible models that estimates transmission as lightly higher (WHN) would derive a slightly lower case-fatality ratio. Across such data sets, estimates of resulting daily or weekly excess deaths would be largely the same, as such calculations are merely about parsing up the deaths that Swiss Re estimates. We made a video to walk users through these inferences, which is posted on the website, albeit for the pre-3.0 era. Overall, excess mortality estimates assume that actuaries at one of the largest reinsurers in the world can forecast excess deaths reasonably, and the PMC model merely parses out resulting deaths based on higher and lower periods of transmission.

# Forecast

The forecasting model is designed to provide a short-term projection of national SARS-CoV-2 transmission. It is designed to be nearly as simple as possible 1) to reduce the lag between incoming data and our estimates, and 2) to reduce the risk of incoming data sets changing or disappearing that could decimate more complex models that use many different data sources. The CDC provides a limited forecast using  $R_t$  values that essentially get at the extent to which emergency department (ED) visits are increasing or decreasing relative to the prior week. That is similar to the best predictor in our model, but we use additional predictor variables to better articulate the longer-term trends in transmission. This section walks readers through the basics of the model.

The model aims to predict our estimate of new daily infections, based on the composite derived from CDC, Biobot, and (previously) IHME data (see Case Estimation). The model predicts new daily infections using the following variables: the year of the ongoing pandemic, data on previous week's new daily infections (7, 14, 21, and 28 days ago), the percentage change in transmission during recent weeks (7 vs 14 days ago, 14 vs 21 days ago), the historical median for new daily infections on that date (excluding data from year 1) and recent calendar weeks (7, 14, and 21 days ago), the median historical percentage change in transmission during recent calendar weeks (0 vs 7 days, 7 vs 14 days, 14 vs 21 days), the ratio of recent changes in transmission divided by historical changes in transmission (change from 7 versus 14 days ago, versus the median change for those historical dates), the number of days since the highest observed level of transmission in the past 60 days (more days since the short-term peak forecast lower transmission), current levels relative to the max levels of the past 60 days (lower levels relative to the past 60 days forecast lower transmission), five variables

identifying the presence or absence of being within blocks of the calendar with remarkably similar patterns of transmission each year (in the summer and winter), and the proportion of states with increasing transmission at different lags (7, 14, 21, 42, and 63 days ago). More simply, one can view the model as capturing 1) the best available data on the shape of current transmission and 2) the most relevant historical data on how transmission tends to play out each year. COVID-19 is not “seasonal” in the sense of winter-only, but it is partly seasonal in terms of being affected by calendar-related patterns in behavior (holidays, air travel, school starting, time spent indoors), weather, and international waves. To explain the forecast to others who are non-scientists, simply note that the model accounts for a lot of different variables about how transmission has been changing lately and how transmission tends to follow patterns historically.

The 3.0 model was developed to better deal with summer waves and regional variation in transmission. Waves are occurring twice annually. The winter wave closely corresponds with the calendar, peaking around New Year’s Eve or shortly after, with minimal annual variation. Summer waves are more complex, varying more in timing, peak, and duration of high transmission. Several of the variables added to the model (the variables characterizing current transmission relative to the highest level in the past 60 days) especially help with summer waves, particularly avoiding overshoots (overestimating the magnitude and time until the peak) and helping to push down post-peak forecasts. We have tested many variables aimed at dealing with these issues, and they either a) do not pan out as hypothesized, or b) work well on their own but add nothing beyond our existing models. Next, variation in transmission has become slightly more regionalized based on unique patterns of vaccination, behavioral precautions, and infection in general and during the prominence of specific variants. The added variables related to the proportion of states increasing (and lags) account for additional information beyond the other variables that are all based on national levels of transmission; this improves the model overall, but it also helps with the issues of overshooting and predicting post-peak decline. Additionally, it provides a very simple metric people can understand. Specifically, if >65% of states are increasing, the peak is about 3 weeks away, and if that figure is closer to 80%, the magnitude will be higher. At a wave’s peak, about 50% of states will be increasing, 50% decreasing, so when people see 55-60% of states increasing after much higher figures, that also suggests the national peak will likely soon arrive. These are some simple shortcuts that can allow community members to explain the current outlook to others. In sum, the 3.0 model provides an improvement in general and specifically in dealing with summer waves and increasing regional variation in transmission.

The model includes 50% and 95% confidence bands. The 50% confidence band shows the typical “normal” variation, and the 95% confidence band shows what would be expected approximately 95% of the time, barring a highly atypical event, so the upper and lower bounds give a sense of so-called worst and best-case scenarios. The bands are comprised of two factors: 1) levels of error in historical data, plus 2) additional error added in that assume values of +/-10.0% for the accuracy of real-time reports (comparing real-time versus retroactively-corrected data from CDC/Biobot). Users familiar with our reports before September 2025, may notice the current intervals as slightly wider and more funnel-shaped in general. There are two reasons. One, we adjusted the real-time reporting error from 8.33% previously to 10.0% currently to account for the possibility of worsening reliability in real-time estimates, which sounds small but compounds over the forecasting duration. Two, we previously assumed that error in the real-time incoming data would apply to the most recent 4 weeks of data, but most errors tend to occur in the most recent week of reporting only. Biobot sometimes makes significant retroactive corrections to the prior 2-3 weeks, but it is not frequent. The CDC retroactive corrections generally only substantively update the most recent week’s data. In putting all of the real-time reporting error on the most recent week, it tends to suggest different forecasting scenarios (e.g., sudden spike, steep decline, increasing instead of decreasing). The CDC is making many ongoing changes to their various dashboards and is understaffed, so we will re-evaluate these assumptions periodically. The confidence bands provide useful “best case” and “worst case” scenarios under situations where the incoming CDC data are unreliable the first week posted.

There are several limitations to forecasting models, including the PMC forecasting model. One, it will perform better when current transmission follows historical patterns of what transmission waves look like and historical calendar-based patterns. The model would perform less well, for example, if there were a tri-modal (three hump) wave from March to April because that defies what waves usually look like and occurs at an atypical

time period for peak transmission. When current transmission is close to the median line of the year-over-year graph, it will perform atypically well. Two, the model only accounts for variant data, behavioral data, and weather indirectly. An underlying assumption of PMC is that simpler is better and that the over-reliance on multiple data sets will lead to catastrophic failure when one or more go down or becomes substantially delayed. Variant-level data are increasingly delayed (longer reporting lags) and of declining quality (grouping of lineages, less localized data, etc.). Walgreens' weekly positivity estimates dropped offline. The CDC recently dropped a lot of small geographic unit data, especially in their ED and hospitalization reporting. One could include data in a model from 100 different sources, but as those data become lagged, lower quality in real time, or discontinued, it creates major problems. The PMC model aims to account for all of these factors indirectly (through the general principles of mapping real-time changes in the shape of transmission, and historical patterns of transmission, where useful). This approach indirectly accounts for many factors. For example, if a BA.1-style omicron variant emerged, the model would not catch it through variant tracking, but instead by transmission picking up quickly, and extrapolating the likely wave shape accordingly. The model is agile, but it could also be better in an ideal world with commitments to ongoing improvements in data quality and reporting. Three, different modelers can agree on the forecasted pattern of transmission, while disagreeing on case estimation methods. The forecasting model is essentially divorced from or independent from the case estimation model. This means that if 10 different forecasters had vastly different estimates of historical transmission (e.g., PMC suggests winter 2024-25 peaked near 1.4 million new daily infections, but a different model has 0.7 million for the same time period), they might still have forecasts similar for *relative* changes during a particular month, despite very different estimates of how that change translates into case counts. This means that when comparing forecasts, it's important to focus on relative changes, as they will differ as to whether underlying case estimation models suggest higher or lower daily infections overall. While forecasting and case estimation models are relatively divorced in some respects, their implications are not. Imagine PMC and another model both predicting a 50% 1-month increase in transmission. PMC assumes current cases are at 500,000 new daily; the other assumes 500 cases (based on low-quality reported-only estimates). PMC would estimate 750,000 new daily infections in a month. The other would estimate 750 new daily infections. The models agree on the forecast, but disagree on the implication due to differences in underlying case estimation. One should review any forecasting data available, including that of the CDC, but apply it to the specific model with the best case estimation. These are nuanced issues that community members may find challenging.

The PMC model performs exceedingly well. Readers who recognize strengths and limitations of the model may draw qualitative inferences beyond what the analytic model describes. The benefits of understanding the minor limitations are themselves minor, given vast differences between reported cases and public understanding of the pandemic versus the reality of what case estimation, forecasting, Long COVID, and excess mortality estimates indicate.

## Heat Map

The heat map uses CDC data and levels. The color scheme (yellow to red) is emphasized in geospatial texts. The final colors were based on extensive user feedback and polling. In spring 2025, we contacted the CDC to request that they switch from a blue map to a more traditional color scheme like our map or their influenza map; they declined with a justification that appeared written by AI. Newsweek and others continue to use a color scheme similar to ours. Note that in August 2025, the CDC updated their data cleaning processes and changed how they classified quantitative levels into qualitative categories and colors; our analyses indicate that the effect has been to make transmission appear lower across the board (e.g., levels considered "High" before, now characterized as "Moderate"). Nonetheless, we use the current CDC system at this time, and simply note the discontinuity in longitudinal comparisons. The heat map is widely popular, readily understood, and should be shared widely.

# Conflicts of Interest

Dr. Hoerger and his family have no conflicts of interest, including no ownership stake or investment in any COVID-related company or product. He and his research team complete the university's annual conflict-of-interest paperwork, and he is aware of no conflicts of interest among his team. Any product recommendations, websites, promo codes, or other potential endorsements are unsolicited and will change as the evidence or available products shift over time. Dr. Hoerger intentionally avoids advertising and subscription revenue from his websites and social media accounts. Readers should be clear that many COVID minimizers generate substantial revenue from blog subscriptions and social media and website advertisements, very serious financial conflicts of interest, sometimes >\$100,000 annually. Dr. Hoerger has never accepted payment, meals, or other compensation from a pharmaceutical company, biomedical company, mask company, air purifier company, or similar organization.

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# Scientific, News Media, and Popular Coverage

- **JAMA Oncology:** <https://jamanetwork.com/journals/jamaoncology/fullarticle/2813585>
- **BMC Public Health:** <https://bmcpublihealth.biomedcentral.com/articles/10.1186/s12889-023-16787-1>
- **TODAY:** <https://www.today.com/health/news/covid-wave-2024-rcna132529>
- **Forbes:** <https://www.forbes.com/sites/judystone/2023/12/01/cdc-improves-their-covid-19-reporting-with-a-new-wastewater-dashboard>
- **Salon:** <https://www.salon.com/2023/10/19/a-lapse-in-wastewater-detection-is-worrying-scientists-about-distorted-data/>
- **The New Republic:** <https://newrepublic.com/article/177849/biden-democrats-covid-pandemic-2024>
- **Yahoo! News:** <https://news.yahoo.com/us-sees-largest-covid-wave-165811252.html>
- **Washington Post:** <https://www.washingtonpost.com/health/2024/01/12/covid-surge-january-2024/>
- **Time:** <https://time.com/6554340/covid-19-surge-2024/>
- **Stateline:** <https://stateline.org/2024/01/23/wastewater-tests-show-covid-infections-surging-but-pandemic-fatigue-limits-precautions/>
- **PRISM:** <https://prismreports.org/2024/01/29/covid-surges-senate-hearing-california/>
- **SELF Magazine:** <https://www.self.com/story/cdc-new-covid-19-isolation-guidelines>
- **TODAY:** <https://www.today.com/health/coronavirus/covid-wastewater-monitoring-rcna143158>
- **Institute for New Economic Thinking:** <https://www.ineteconomics.org/perspectives/blog/from-long-covid-odds-to-lost-iq-points-ongoing-threats-you-dont-know-about>
- **TODAY:** <https://www.today.com/health/coronavirus/states-with-highest-covid-rates-2024-rcna163403>
- **NEWSMAX:** <https://www.newsmax.com/health/health-news/covid-summer-surge/2024/07/25/id/1173945/>
- **Yahoo! News:** <https://uk.news.yahoo.com/lifestyle/covid-is-surging-here-are-8-articles-im-reading-to-stay-informed-as-a-health-editor-135558875.html>
- **People:** <https://people.com/massive-covid-spikes-in-21-states-cdc-8683478>



- **Truthout:** <https://truthout.org/articles/the-us-government-has-abandoned-us-to-endless-covid-we-can-do-better/>
- **San Francisco Chronicle:** <https://www.sfchronicle.com/health/article/mask-recommendation-covid-san-francisco-19599948.php>
- **JAMA-NO:** <https://jamanetwork.com/journals/jamanetworkopen/article-abstract/2821699>
- **MSN:** <https://www.msn.com/en-gb/health/other/masking-policies-prevalent-in-top-cancer-centers-amid-winter-covid-wave/ar-BB1qZWnr>
- **PRISM:** <https://prismreports.org/2024/08/06/covid-data-tracking-disappears/>
- **CBS:** <https://www.wlvt.com/article/news/health/new-orleans-free-home-air-filters-for-cancer-patients-covid-cases-special-kit-safe/289-5d873151-7069-478a-ab03-2260cd08c22a>
- **NBC:** <https://www.wdsu.com/article/new-orleans-cancer-covid-prevention-kit/61899479>
- **FOX:** [https://x.com/michael\\_hoerger/status/1826479530124456205](https://x.com/michael_hoerger/status/1826479530124456205)
- **OBR Oncology:** <https://www.oncologynewscentral.com/article/controversy-over-cancer-center-masking-policies-as-covid-surge-looms>
- **CNN:** <https://www.cnn.com/2024/12/31/health/covid-holiday-surge-us/index.html>
- **The Atlantic:** <https://www.theatlantic.com/health/archive/2024/12/covid-christmas-winter-wave/681133/>
- **TODAY:** <https://www.today.com/health/coronavirus/us-silent-covid-surge-holidays-2024-rcna184828>
- **USA Today:** <https://www.usatoday.com/story/news/health/2024/12/24/covid-winter-2024-cdc-data/77199841007/>
- **Case estimation model pre-print:** <https://www.researchsquare.com/article/rs-5786667/v1>
- **Frontiers in Neuroscience:** <https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2025.1498981/full>
- **TODAY:** <https://www.today.com/health/coronavirus/new-covid-variant-nb181-symptoms-rcna208189>
- **TODAY:** <https://www.today.com/health/coronavirus/covid-2025-summer-surge-rcna218754>
- **TODAY:** <https://www.today.com/health/coronavirus/stratus-covid-variant-symptoms-rcna224723>