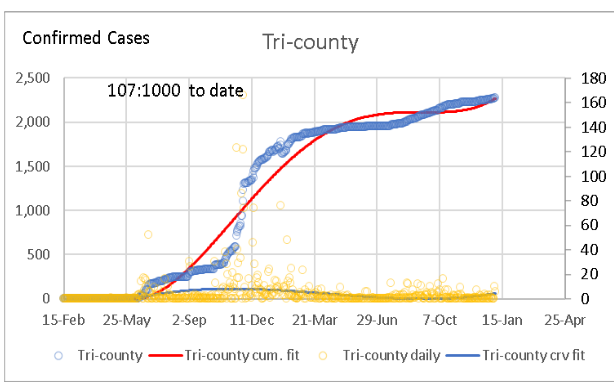
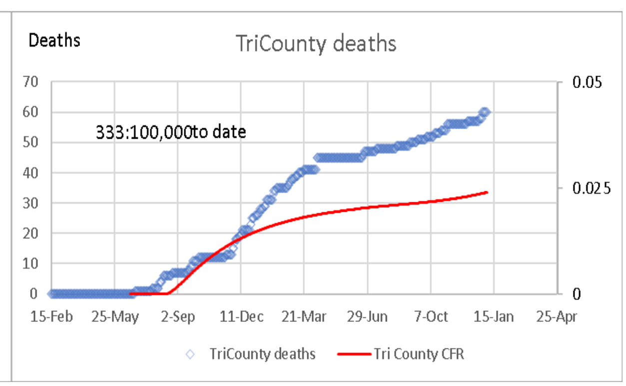
Tri-County (Brewster, Jeff Davis, and Presidio Counties) and the rest of the World, CV19

Please refer to accompanying two pdf files of graphs. The estimated number, and the related incidence relative to population, is based on maximums estimated from curve fits. These estimates are now adjusted to end of current wave, rather than end of year. They are subject to change of course, and should not be taken as precise projections, since there is no such thing. Another way to interpret them is as relative indices, that show a locale's progress relative to the others.[1]

US or Texas projections for confirmed cases scaled to Tri-County population of 18,000:

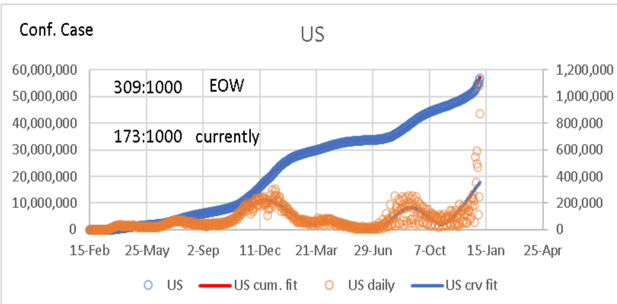
Confirmed Cases:		
max US daily	453,459	persons
equiv. max Tri-County	24.7	persons
max TX daily	162,871	persons
scaled to Tri-County	104.7	persons
max US cumulative	101,856,044	persons
equiv. max Tri-County	5556	persons
incidence	309:1000	
max TX cumulative	4,943,584	persons
scaled to Tri-County	3,178	persons
incidence	177:1000	
Tri-County (current)	107:1000	1/4/2022

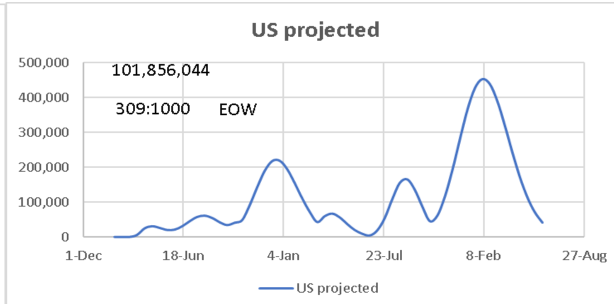




[1] Data all from publicly available Github site: https://github.com/CSSEGISandData/COVID-19

Basis of Comparison
For each curve fit, the end is extended with a gamma distribution as a rough estimate of where the last wave ends (EOW), or end of year (EOY), which ever comes first. This becomes the basis of a number per thousand or hundred thousand, in an attempt at comparison among all the locales. For example, USA:

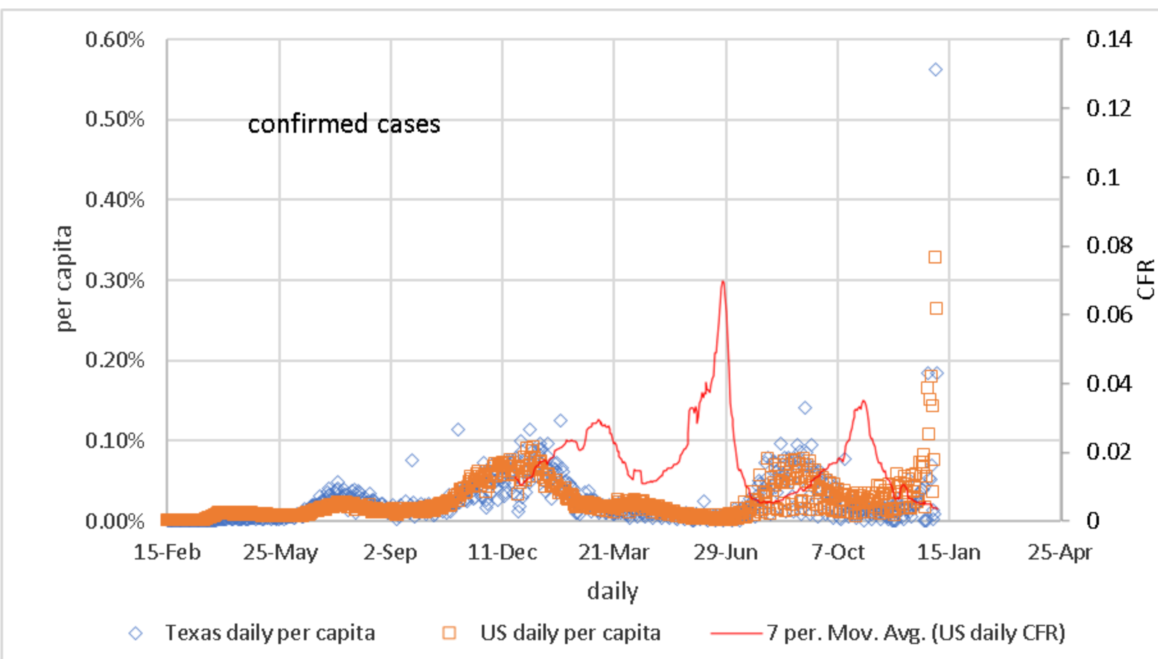




The ratio on the graph represents the total area under the daily curve, which is the total number of projected counts, divided by the locale's population. The next wave is projected as by far the biggest.

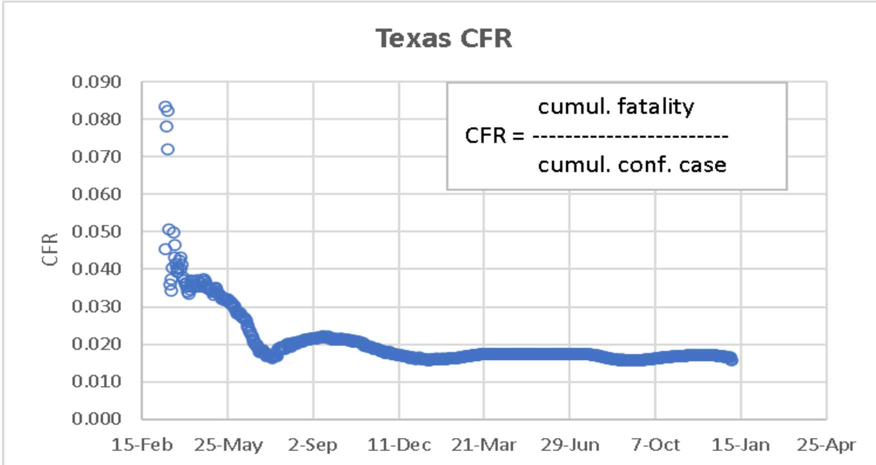
Comments

US and Texas Confirmed Cases:



Another wave, which is consistent with winter season and Omicron strain. I would guess that herd immunity doesn't really work with this virus, since it mutates so much and the immunity doesn't seem to last. So far US deaths vs. confirmed cases is favorable, so maybe this one is a lot less deadly. We hope…the 7 day rolling CFR average is as low as it has been since Summer 2020, which may be a very good sign. Notice CFR rolling average is almost 180 degrees out of phase with confirmed cases.

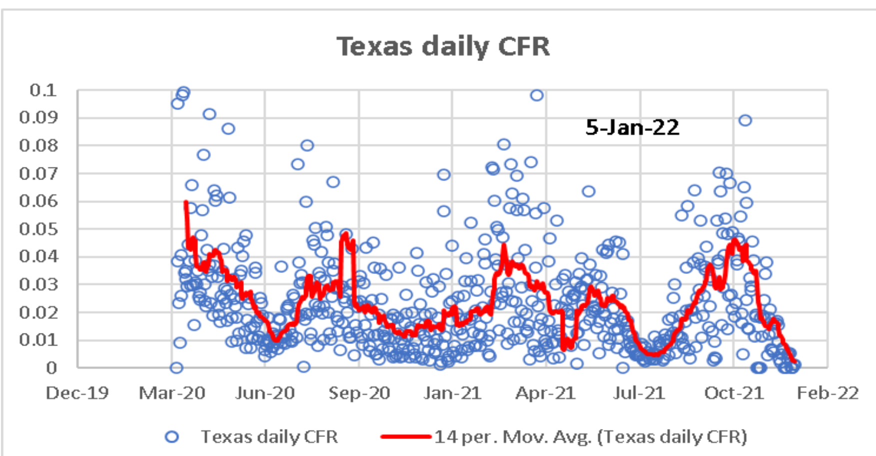
Mortality seems to have stabilized. This is an example of the confirmed case fatality ratio (CFR):



What's to be done? Your mom taught you to cover your mouth when you coughed as a act of consideration for others so you wouldn't spread germs. That is all wearing a typical cloth mask does, except more effectively than your hand (or elbow), since this virus is stronger than the usual germs.

Another good thing to do is avoid enclosed areas with low or no ventilation where there are lots of people. This would include most restaurants and bars, and probably schools, too. Or step up the air changes in such places. For example, Alpine has done some nice work on granting special use rules so restaurants can serve food outside on tables on the sidewalk. And, for better or for worse, Germany is now taking action on fresh air in buildings.[2]

A serious claim by the CDC is that 42% of the US adult population is obese, a very big comorbity with this virus. Sounds like some low hanging fruit to me; stop pushing sugary foods and drinks on the young![3]



The fact the CFR for Texas (confirmed case-fatality ratio) is pointed down is good news; hopefully it maintains that trend. It is as low as it has ever been, for once. This would be consistent with Omicron being highly transmissible, but symptoms not very serious.

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[2] https://www.bbc.co.uk/news/world-europe-54599593

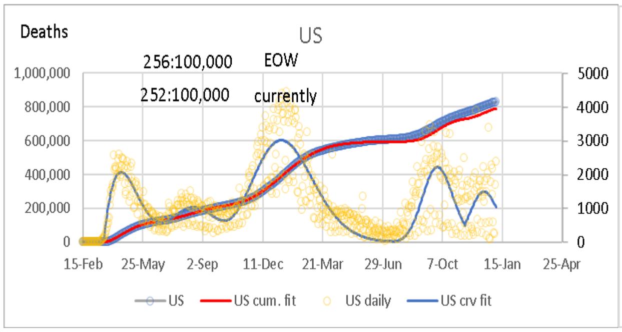
[3] https://www.cdc.gov/obesity/data/adult.html

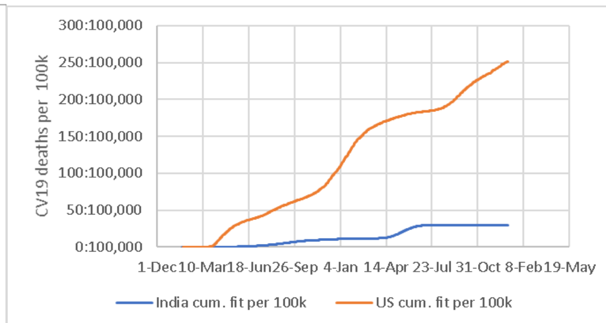
COVID-19 deaths

A point of comparison:

Around 1920, the population of the US was 105 million. It is estimated that 500,000 people in the US died from the Spanish Flu epidemic in those years. This is a death rate of around 480 per 100k. Most deaths occurred during the Fall of 1918.

The USA CV-19 death statistics are based on 7th order curve fit, combined with a last gamma distribution curve fit of US deaths that generates a cumulative maximum for the two combined (minus their overlap). See "*Experimental Page*" for a look at ratios of the curve fits, rather than the data itself:

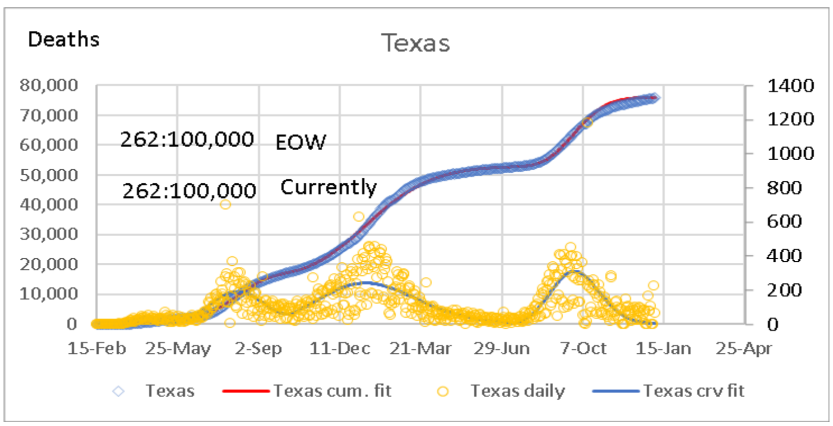




Alongside the above is the per capita plots of COVID deaths in the US and in India, included because nothing in the media would lead you to recognize this; different orders of magnitude, even! Note that a ratio of 250:100,000 is equivalent to 0.25%, less than half a percent.

Last year the Wall Street Journal published data on annual causes of death which is plotted with the USA CV-19 death statistics. The possible death value is plotted as deaths per 100,000 with WSJ data of annual averages of leading causes. CDC data also shown, for 2020, as an alternative estimate. See "*Some Graphs*" for data and plots.

Here is the current plot for Texas deaths:

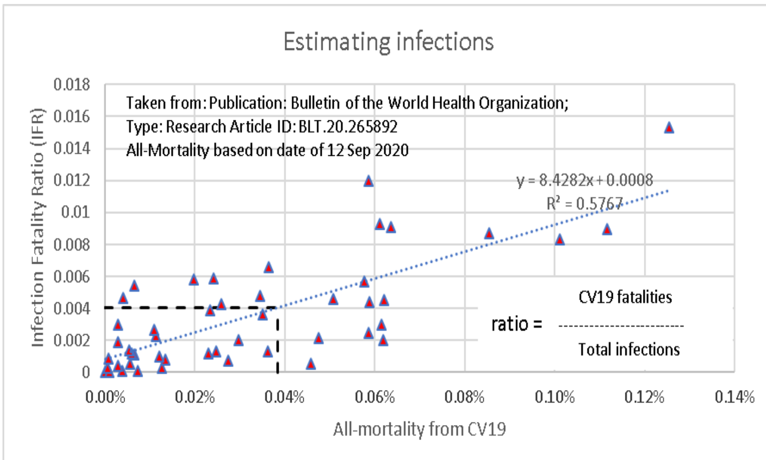


One has to wonder, is this high rate because Texans didn't stick to all the mask and lockdown rules as much as the rest, or is it just the bad nutrition and tendency to stay in poorly ventilated places that seems to be the rule here?

Estimating Actual Incidence

John Ioannidis, a well-known epidemiologist from Stanford, recently estimated CV19 infection fatality rates; for example, infection fatality rate for deaths > 50:100,000 (e.g. USA) at 0.57%.[4] See cross-plot of the data he included in the paper, to estimate actual incidence of COVID19 in the Tri-County area.

See following regression on his data, to generate an estimated IFR. For example, all-mortality for Tri-County as of 12 Sep 2020 is 0.000385 deaths per capita (7 out of 18,000 people, which has at least tripled since that date). That predicts an IFR of 0.4% ± 0.5% (based on two standard deviation of scatter in this plot, with a floor at 0%):



The IFR is defined as:

$$IFR \equiv \frac{Fatality}{Infections}$$

Likewise, the CFR is defined as

$$CFR \equiv \frac{Fatality}{Cases}$$

where *Cases* is the number of confirmed cases, known, always something less than the actual number of *Infections*, unknown. The ratio of *CFR*/*IFR* is the same as the ratio of *Infections* to *Cases*, *Fatality* cancels:

$$\frac{CFR}{IFR} = \frac{\frac{Fatality}{Cases}}{\frac{Fatality}{Infections}} = \frac{Infections}{Cases}$$

If you take the known average *daily* confirmed case incidence and apply this actual per confirmed infection factor, it results in an estimate for the actual number of infections. In this case, it's estimated at around three to five times the case incidence for Tri-County.

Another band of researchers in Colima, Mexico, took IFR estimates and applied them to the concept of using the ratio of CV19 death incidence to IFR to estimate percentage of population already infected,

[4] https://www.who.int/bulletin/online_first/BLT.20.265892.pdf
He is famous for his critique on research statistics released in 2005 which is available for free download on https://journals.plos.org. For the USA, IFR appears to be 0.34%, the weighted median from Ioannidis data.

which in turn is applied to an estimate of how close to herd immunity.[5] Let $x(t)$ be the cumulative number of CV19 deaths, N the population of a locale, and n_{inf} number of actual infections (the number that is so hard to count):

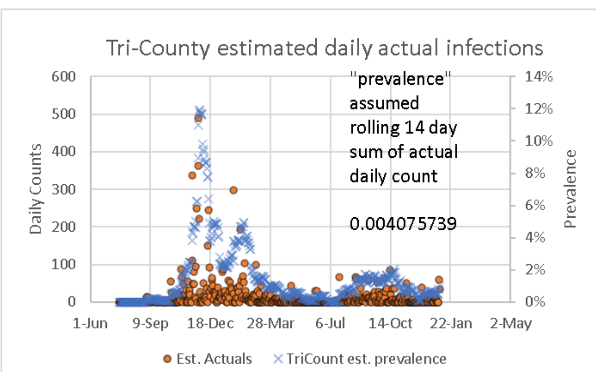
$$\frac{x(t)/N}{IFR} = \frac{x(t)/N}{x(t)/n_{\text{inf}}} \quad \text{or,} \quad a = \frac{n_{\text{inf}}}{N} = \frac{x(t)/N}{IFR}$$

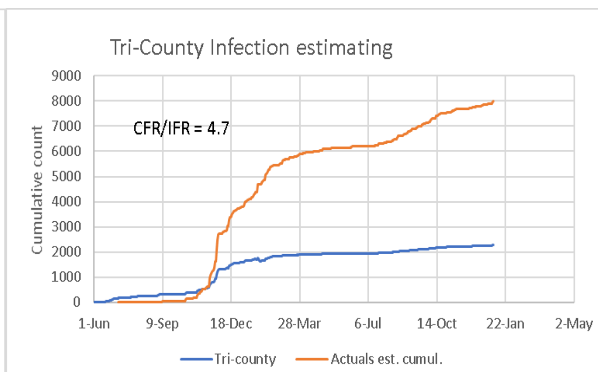
The Colima researchers took R_o to be about 5.7 for New York and New Jersey, as an example, which corresponds to γ^{-1} = 4.7 days and close to the slope of the exponential part of the early part of their CV19 growth curves, so is plausible. Graphing the Github data shows NY at R_o = 9.4 and NJ at 7.0. I ran the number of cumulative deaths to t = 03 April '21, and got $x(t)/N$ = 0.16% and 0.28%, respectively. The researchers quoted an IFR of 0.25% (from Ioannidis, again):

03 Apr 2021	New York	New Jersey	USA, eventual
Estimated infected	a = 48.4%	$a \geq$ 100%	a = 56%
Estimated not infected	$1 - a$ =51.6%	$1 - a \leq$ 0%	1 – a = 44%
Herd Imm. (1 - 1/R_o)	89.4%	85.7%	78%

For the USA, a weighted median of the 103 million people represented in Table 4 in Ioannidis' paper cited earlier comes to IFR = 0.34%, which makes the estimated infected value a = 42%, with overall CV19 mortality at the same date of 0.17%, and an R_o of 4.5. The graphs on this Github site indicate an eventual $x(t)/N$ = 0.19%, corresponding to a = 56%. (New York shown at IFR = 0.25%, New Jersey not shown on Table 4.) Obviously some places are much closer (New Jersey!) to herd immunity in the US than others.

All this is very speculative, but an example of what things have to be done to find what the actual (as opposed to confirmed) infection incidence is. Using the *CFR*/*IFR* ratio, cumulative is summed off the daily data for the Tri-County:





This is just an estimate, obviously, and the original source lists a whole bunch of caveats that go with it. Certainly, our small population size carries more uncertainty with it, too. But as you can see, having some idea of what the actual infection incidence is, when it can't be directly measured, has a whole lot of uses. There are local reports showing high incidence of COVID, but it's not showing in this Johns Hopkins data, for some reason.

[5] https://www.medrxiv.org/content/10.1101/2020.12.19.20248571v1

Masks

There's a lot of hullaballoo about masks, but it's useful to remember that the "95" rated masks, like the N95 or KN95, are rated for the most difficult particle size to trap. Above this size, it's relatively easy to make a material that will act like a seive and trap particles and still be breathable. Below this size, it's interesting that the effectiveness of the mask relies on the random kinetic motion of molecules to shove the particles *into* the material. That's how small viruses are! The viruses are on the order of 100 nanometers; the critical size most difficult to trap because it falls between the two filtration modes is about 300 nanometers. So the viruses are best trapped by kinetic motion of molecules. The N95 is rated to trap 95% of particles of 300 nanometer size, which is where the "95" designation comes from. Since this size is the hardest to trap, this implies efficacy is better than 95% for particles bigger or smaller than this critical size.[6]

However, how much virus travels in an aerosol (that is, suspended in the air by itself)? It turns out a large portion of them ride on relatively large water droplets that people cough, sneeze, or otherwise expel. The fraction traveling the one way or the other way is not well understood. An N95 is "tight" enough that it offers resistance to air flow, so if it is not fitted properly, the air you breathe will bypass the filter and it will do no good. It also will get saturated sooner or later with various particles, which increases flow resistance and increases the tendency for bypass, too. So, it must be fitted properly and changed regularly.

The cloth and surgical masks everyone wears don't offer much protection to the wearer; it's safest to consider the protection none and act accordingly. However, they do significantly impede spraying of water droplets and individual viruses in aerosols, which is their real value in protecting others *from* you, and I think that is not to be discounted, in spite of the inconvenience.

[6] Millimeter is a thousandth of a meter (mm), micrometer (or micron, or μm) is a millionth of a meter, and a nanometer is a billionth of a meter (nm). So, a nanometer is one thousandth of a micron. A human hair is measured in the micron range, for example, say from 20 μm to 200 μm; 300 nm is 0.3 μm.

Explanation of statistic used for comparative purposes:

Often the generation of confirmed cases or deaths tend to be in a gamma distribution, which is a slightly skewed bell-shaped curve. A least squares procedure is used to get the closest fit to the data. Generally, the data is provided in a *cumulative* format, so the number increases each day, until the wave is over, at which point it is at its maximum and no longer changes. This can be converted to a daily format just by finding the difference between each pair of successive days. In mathematical terms, the daily format is the time derivative of the cumulative format. In any case, the area under the daily curve is identical to the last, largest and unchanging value in the cumulative format. This is the value that is used here as a comparative statistic, on a per capita basis, for a completed curve. Each locale's "wave" has a different beginning, develops at a different rate, with a different population, so comparison of absolute values on a particular date among any given datasets doesn't tell you anything, but nonetheless that is how most of this data is usually presented to the public.

Cases are described here as incidents per thousandths; deaths are described as incidents per hundred thousandths. In this way, one can get a better feel for the relative performance of locales, as long as the current population figure is available. It's also a way to gauge one's own personal risk. Keep in mind this statistic can and will change over time, not as a direct result of increasing cases or deaths, but because of the possible change in shape of the distribution. It should be thought a qualitative measure, since it's impossible to put error bounds on it, at least in its earlier stages before the inflection point.

R_o

Basic Reproduction Rate (said as R-sub-0, or just R-0). R_o is a measure of transmissibility: $R_o < 1$, disease disappears; $R_o = 1$, it's endemic; $R_o > 1$, epidemic. R_o is mentioned a lot during this epidemic, along with flattening of curves, with not a lot of understanding or relevance. It's not even a rate, but usually defined as a ratio of two different rates. It is often referred to as "infection rate", to be confused with infectious rate and infected rate; I don't think that is a good usage. It is found in the cumulative data at the very beginning of an epidemic, when the curve is exponential. The mathematics start out pretty simple, but once you try to factor in varying immunity over time, variants through mutation, and other issues, it leads to mathematical modeling that probably doesn't tell us very much. The best prediction seems to be that we will have to get a COVID shot every year, like we do with flu. More discussion in the "*Details on R_o you may or may not be interested in*" file found elsewhere on this site.