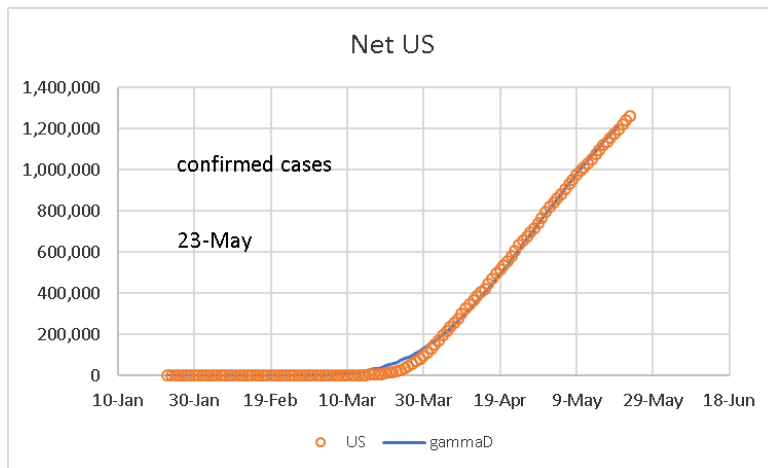
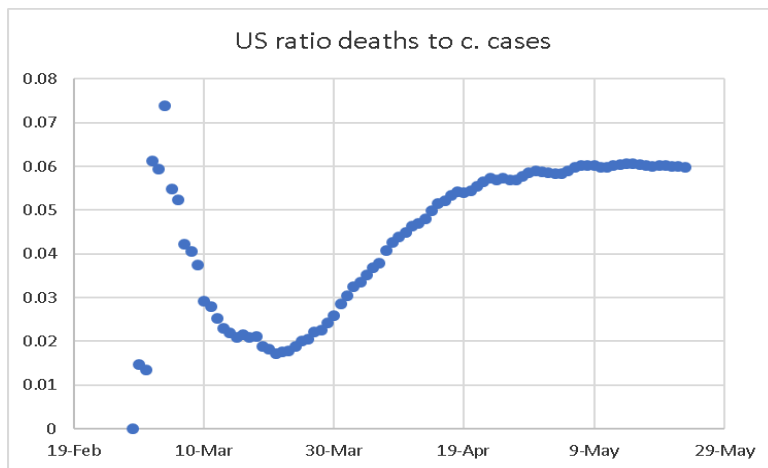


As of 24 May 2020, the US Covid-19 epidemic looks like this, cumulative:¹



The ratio of deaths to confirmed cases looks like this:



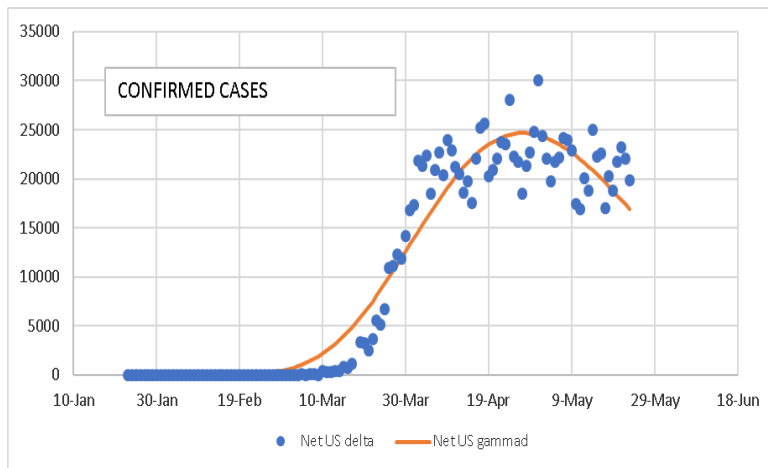
So, it appears that 6% of confirmed cases die, which proves this is no common flu.²

The distribution of this data could be applied locally, assuming the US case applies to the local situation. It makes sense to subtract out New York City confirmed cases, the urban extreme (and about 23% of total US cases), to arrive at a more applicable distribution, although still predominantly urban. Since here in the Big Bend we live more spread out, and don't crowd together on rapid transit, our "wave" is probably something less than the NET US (that is, US confirmed cases minus NYC). It also probably lags in time the urban populations by quite a bit. But since an epidemic is nothing but a deadly diffusion phenomenon, sooner or later it reaches its equilibrium, no matter what we do (save a vaccine).

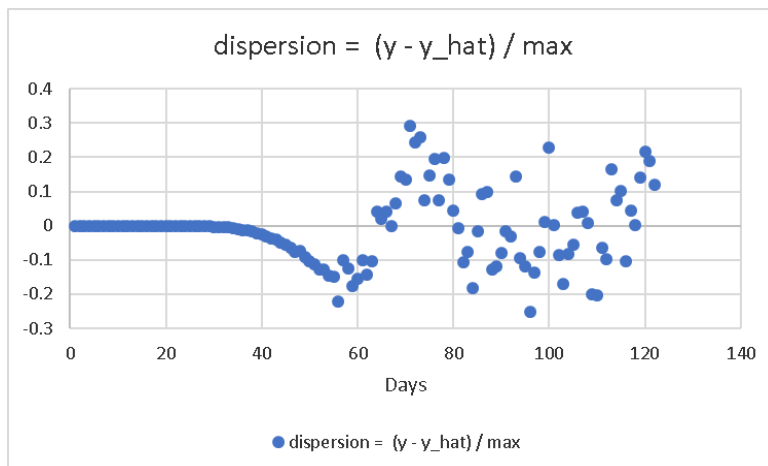
¹ <https://github.com/CSSEGISandData/COVID-19>

² A lot of useless discussion on actual vs. confirmed cases occurs, in my opinion, in order to minimize the deadliness of this virus. Why would you try to minimize the deadliness of something that is so obviously deadly?

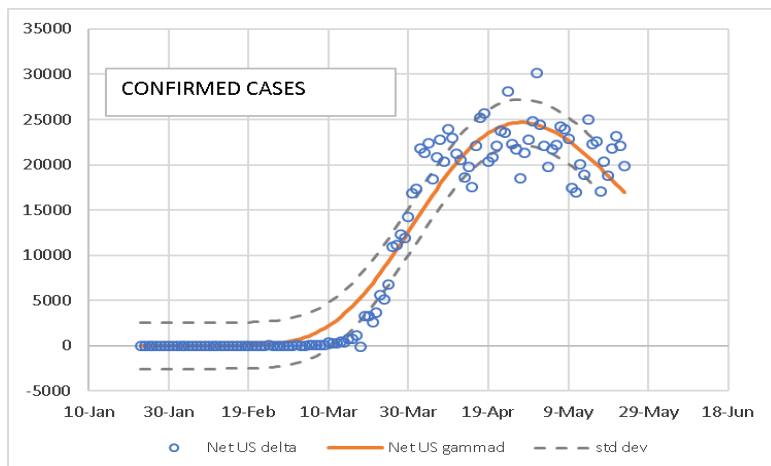
NET US appears like this, on a *daily* basis, not cumulative:



The curve fit is a gamma distribution, often used to characterize disease, population growth, and epidemics. A measure of dispersion is the standard deviation of $(y - y_{\hat{}}) / y_{\hat{\max}}$. y is data recorded (in this case, the difference between each pair of successive values on the previously shown cumulative data), $y_{\hat{}}$ (pronounced *wye hat*) is the value at each date of the gamma distributed curve fit, and $y_{\hat{\max}}$ is the maximum value of the gamma distributed curve fit. The dispersion looks like this (below) and gives an idea of the goodness of fit of the data around the gamma distribution. R^2 is another, and is equal to 0.907.

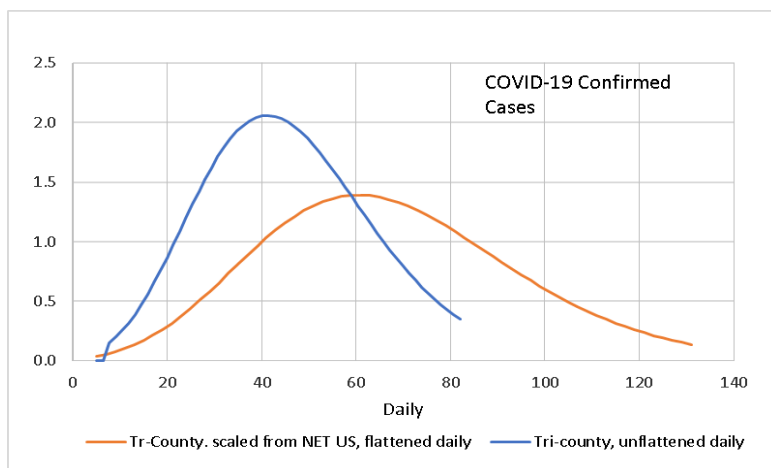


The standard deviation of the dispersion values (0.103) can be used to construct a 1 standard deviation boundary around the curve fit:

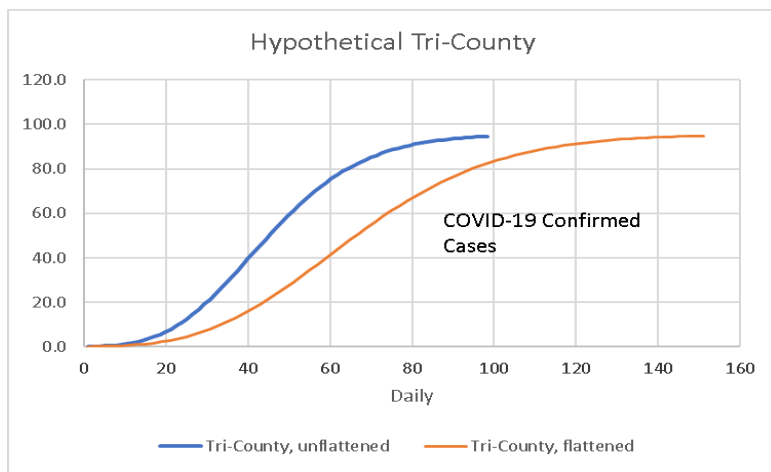


This data is for a population of 320 million (US population less NYC's), but why not scale it to a Tri-County population of 16,000, in order to have a better idea of what to expect here? You certainly wouldn't expect the Tri-County would be *worse* than this.

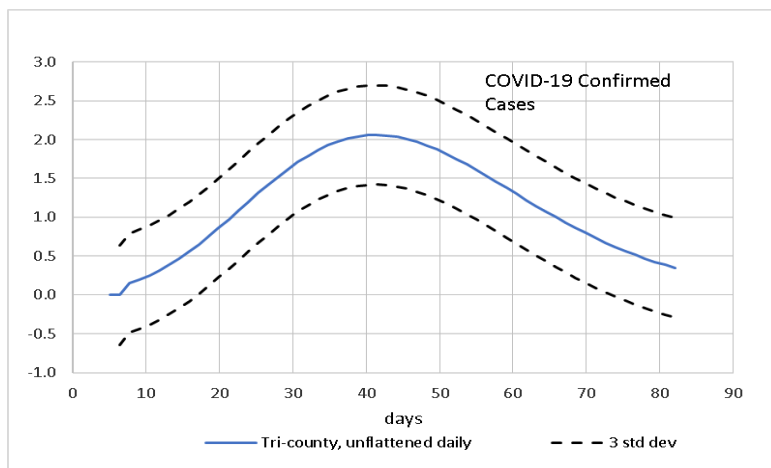
First, assume the above data represents a *flattened* curve—that is, all the restrictive measures that were put in place succeeded in lengthening its duration and reducing its peak (but not changing the total number of infections, the area under the curve). This was the original explanation given for the restrictive measures, to alleviate the burden on the medical facilities, and it makes sense. It can be scaled by a simple population ratio to fit the Tri-County area. The resulting curve can also have its time scale compressed, to simulate an unflattened curve, presumably what would happen here without the restrictions. This is compressed by a factor 1.5. Here is what that looks like:



The area under each curve is the same, there is no change in total cases. It's also worth looking at the cumulative version of this distribution, to see what the time compression does to it. Notice it doesn't change the final, cumulative value, which is equivalent to 5 in 1,000 being a confirmed case.³



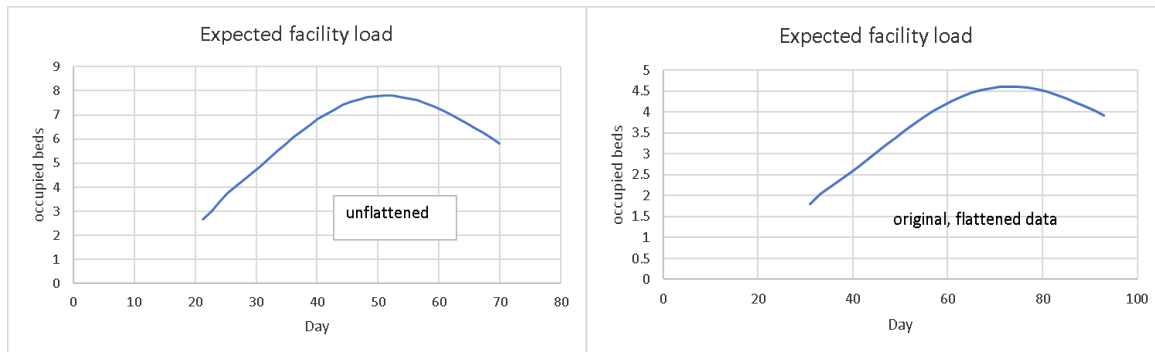
Secondly, taking the unflattened curve (blue), and applying the dispersion factor previously created, we can apply a three standard deviation upper bound—this could be a conservative design criteria to use for county-supplied COVID-19 treatment centers, to avoid sending any virus suffers to the regional hospital. Three standard deviations should take care of 95% of the possibilities. The county could provide something less than this, and still do a lot of good, of course.



On first glance, it appears that *three* confirmed cases are what to expect for the maximum daily cases in the Tri-County during a virus wave. But, there will already be cases ongoing, with an average length of 14 days. A rolling sum of the two (new cases, plus cases lasting 14 days) can be constructed.

³ If one assumes the Tri-County is a sample of the US NET population, scaling it this way will likely increase its dispersion, since that is the nature of small samples. The rolling sum probably smooths that out enough that it is not significant, but that is not rigorously addressed here.

To find the impact on medical care one needs to apply a 20% factor to the confirmed case estimate, since only about 10 to 20% of confirmed cases require medical care or hospitalization:



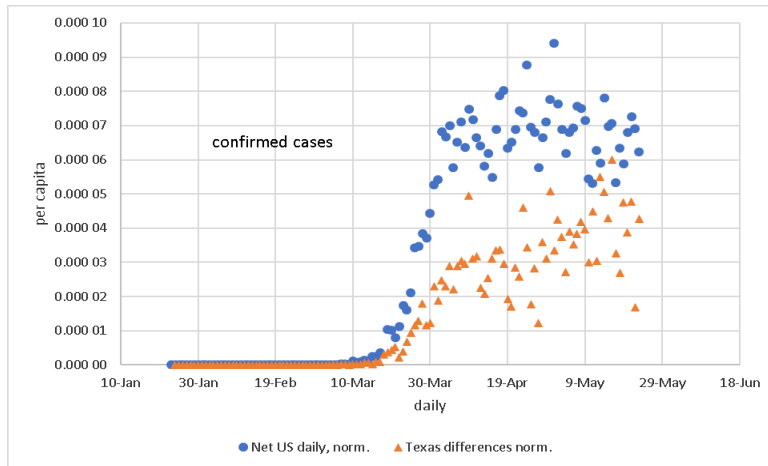
This peaks at 8, or about 3 beds per county, or to be apportioned by each counties' respective populations. A similar calculation can be done for the flattened curve case, where the expected facility load is 5, or about two beds per county.

Either case is one that the regional hospital could probably handle, or each county could undertake on their own, with separate medical facilities. It's worth reviewing the spread of both SARS-Covid-1 and SARS-Covid-2 (the current one) to see the key role of hospitals in initially *spreading* the disease, a good reason to *not* use the hospital if possible. Looked at this way, with life and economic restrictions, it would require two beds per county, while unrestricted liberty and economics costs three beds per county, for a net cost of one bed per county to preserve personal and economic liberty.

Remember, the area under the curve is the *same* in either flattened or unflattened case, which implies shutting everyone in *doesn't* reduce total cases. That was the original rationale, as was promoted when restrictions were introduced nation-wide. The restrictions were to help avoid inundating health facilities. Recently there are claims found in the news media and made by politicians that lockdowns save lives, but there is no direct evidence of it, and logically, it doesn't hold water. It may defer virus infections, and it certainly can have a benefit for relieving medical facilities of their load, which surely saves lives, but that's not a direct effect on the epidemic itself, and leads to the question of what other more effective and less damaging actions can we take to reduce the threat. We surely will have a second, and maybe a third wave, and it's not clear if we can survive any more lockdowns.

Postscript

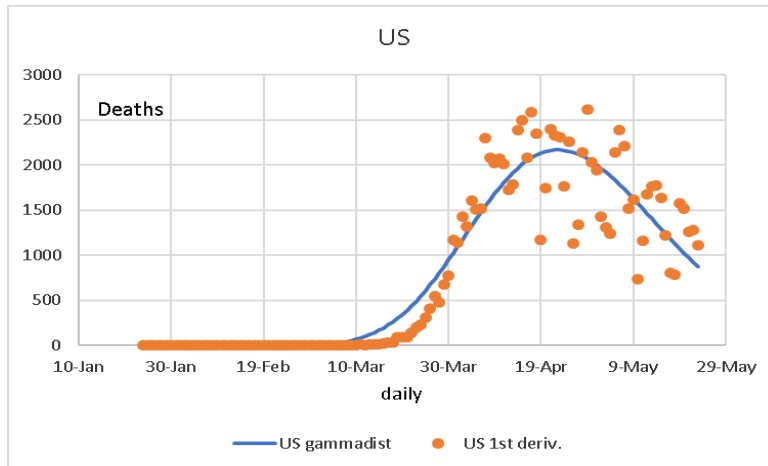
If Texas and the NET USA data are plotted as daily data concurrently, on a per capita basis, here is what you see:



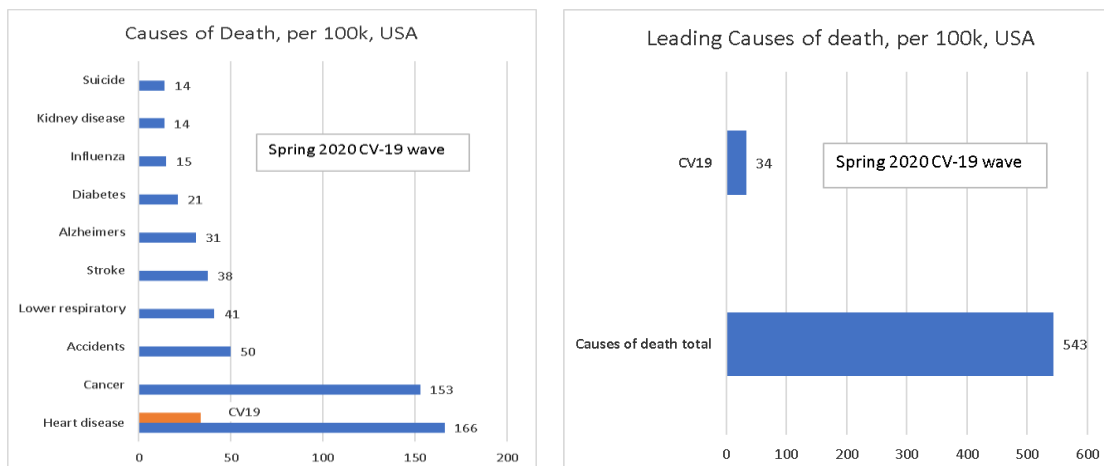
It appears Texas lags the NET USA a little, but even more significantly, the per capita basis looks about a third to half of the NET USA. Texas would probably be a better dataset to scale the Tri-County from, since we're in Texas. But USA is more complete. Also, USA represents a more conservative assumption.

P.S.S.

Anyone who maintains this epidemic is not a serious issue is being foolish. A few weeks ago the Wall Street Journal published data in the form of a chart that I have taken the data from and plotted with the USA CV-19 death statistics. The USA CV-19 death statistic is based on a gamma distribution curve fit of USA deaths that generates a cumulative maximum for the wave.



This distribution predicts 110,000 deaths, once this particular wave is over. We may get one or two more waves this year. This value is plotted with deaths per 100,000 from the WSJ data.



It's right up there with major killers. It's not clear where dying from old age fits in here, though. I suspect it would deduct from all these more or less equally, so the relative size remains unchanged.

NYC appears to suffer 250 deaths per 100,000 in this wave, while Texas only has 7 per 100,000. That is an estimate based on the maximums predicted by their respective gamma distributed curve fits. It's something to keep in mind when considering the desperation found in NYC and the northeast United States; they have every reason to be desperate.