Is $R_0 < 1$ in California and New York?

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Abstract

Commonly applied metrics for tracking COVID-19, such as deaths, hospitalizations, and confirmed cases, continue to rise even in regions that have implemented shelter-in-place orders. We argue that these trends are due to reporting lags in the data, and that a more careful analysis suggests that hospitalized cases either have already peaked or will soon peak in both New York and California, and that the number of new infections likely peaked two weeks ago, around March 22nd. A preliminary analysis suggests that California cases are dropping at 29%/day while New York cases are dropping at 8%/day, but with substantial uncertainty on both estimates. Overall, we estimate that shelter-in-places dropped the per-day growth rate in both states by around 40%/day. If these numbers are correct, California could hope to re-open in late April assuming that it implements case tracking and isolation that could handle around 100 active cases at once. In contrast, New York would not be able to re-open until June or later under the status quo. However, we find evidence that the growth rate may have already been decreasing pre-lockdown, which confounds these estimates. Data on hospital demand including time-of-admission and time-of-release could substantially reduce the uncertainty on these estimates.

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1 Introduction

Among both policymakers and statistical modelers, a common belief is that the peak of the coronavirus outbreak in California and New York will not be for several more weeks (late April 2020), and we will need substantially more hospital beds than we have available today. For example, one news article states that New York needs to add 40,000 hospital beds [1]. We argue here that in fact, the number of cases has likely already peaked in both New York and California. Specifically, we will argue that:

- The number of new hospitalizations per day in New York peaked around March 29th.
- The number of total hospitalizations in New York will peak early next week (best guess April 6th), or possibly already peaked last week.
- The number of new hospitalizations per day in California peaked around March 28th.
- The number of total hospitalizations in California has already peaked on April 1st or earlier, although there might be a second one-day spike on Monday, April 6th, due to day-of-week effects.
- The number of new infections, both in California and New York, peaked some time ago (probably around March 22nd) and the number of total active infections probably reached its peak around April 1st.

These conclusions seem to contradict the apparent rise in hospitalized COVID-19 cases, as reported by the COVID Tracking Project [2] and other sources. We will explain why these counts don't reflect the true number of hospitalizations, and how other data sources that more closely match reality show that infections and hospitalizations have likely both been going down.

The basic issue is that the time series of hospital counts appears to be the number of hospitalized patients that were **reported as confirmed cases** on that day. On top of the $\sim$10-day lag from infection to hospitalization, this creates an additional lag and also makes the data more choppy due to irregular lags in test results. While undertesting in hospitals is less than in the overall population, less than 50% of California hospital patients have been designated as confirmed. The New York data also has evidence of undertesting.

Examining the California data in more detail shows that the continued increase in hospital counts is primarily "Suspected" cases being moved into the "Confirmed" category. The Suspected + Confirmed count has dropped at least since April 1st. Additionally, examining New York City syndromic surveillance data shows that ER visits for flu-like and respiratory symptoms likely peaked between March 25th and 29th.

It is difficult to estimate the post-lockdown growth rate, since hospital data are just starting to enter the exponential decay regime. Based on two indirect methods, we provide a best guess of 29%/day decay in California and 9%/day in New York.

2 Reporting Issues with Hospitalization Data

Recently, many experts (including the author) have called for looking at the number of hospitalized patients rather than confirmed case counts or deaths. The basic reasoning is that confirmed case counts are not meaningful (they mostly reflect increases in testing), while deaths have a 3-week lag and larger statistical noise. In contrast, hospital lags are only around 10 days. Since even with testing shortages most hospital patients will likely get tested, hospital numbers are a good middle ground.

Here we present evidence that the above reasoning is wrong, because most hospital patients are not tested. More specifically, even if they are tested, the delay in getting back results is long enough that the number of confirmed hospital patients may be much lower than the number of actual hospital patients.

California: For instance, based on the California Open Data Dashboard [3], these have been the counts of suspected and confirmed hospitalizations since April 1st:

Table 1: Suspected and Confirmed Hospitalizations since April 1st

	04/01	04/02	04/03	04/04	04/05	04/06	Daily % Increase
Confirmed	1855	2188	2300	2398	2509	2611	7.1
Suspected	3773	3417	3267	3187	2967	2796	-5.8
Total	5628	5606	5567	5585	5476	5407	-0.8

The confirmed hospital cases, which are what are reported in the COVID Tracking Data, have been increasing at 7.1%/day. This makes it appear that infection is continuing to spread in California. However, the growth has mostly been due to Suspected cases being moved into the Confirmed category. The total Suspected + Confirmed count has actually decreased slightly.

It is not clear if this total actually reflects the total number of COVID-19 patients in California hospitals. By some CDC classifications, "Suspected" requires that a sample has been collected and sent off to testing, so there may be additional COVID-19 patients not in this count. However, this total likely better reflects hospital demand than just the Confirmed count, and has decreased since April 1st.

New York: The New York data only reports confirmed cases according to their website [4], and did not have data on suspected cases at the time of writing. Moreover, there is evidence of lag in the New York data due to its choppiness. Below is New York data from the COVID Tracking Project.

Table 2: New York Data from the COVID Tracking Project

Date	Cumulative Hospitalizations	New Hospitalizations
Sunday, April 5th	28,092	1,709
Saturday, April 4th	26,383	2,687
Friday, April 3rd	23,696	2,879
Thursday, April 2nd	20,817	2,449
Wednesday, April 1st	18,368	2,464
Tuesday, March 31st	15,904	2,183
Monday, March 30th	13,721	1,646
Sunday, March 29th	12,075	2,021
Satuday, March 28th	10,054	1,528
Friday, March 27th	8,526	

The counts do not follow a smooth trend, even accounting for day-of-week effects. While data are always inherently noisy, comparing the New York hospital counts to Germany case counts shows a stark contrast:

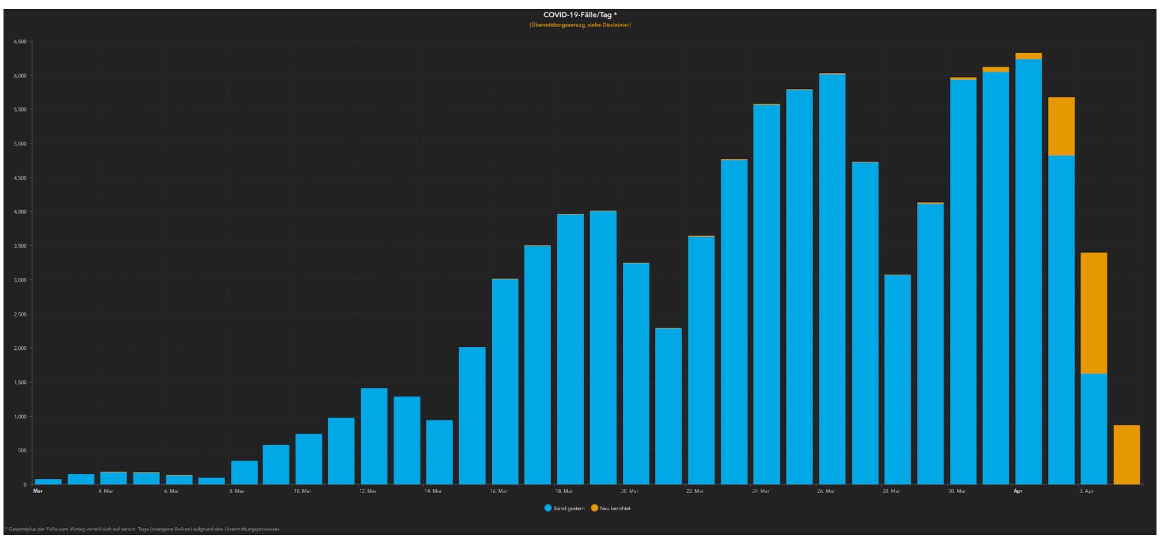

Figure 1: Germany Confirmed Cases

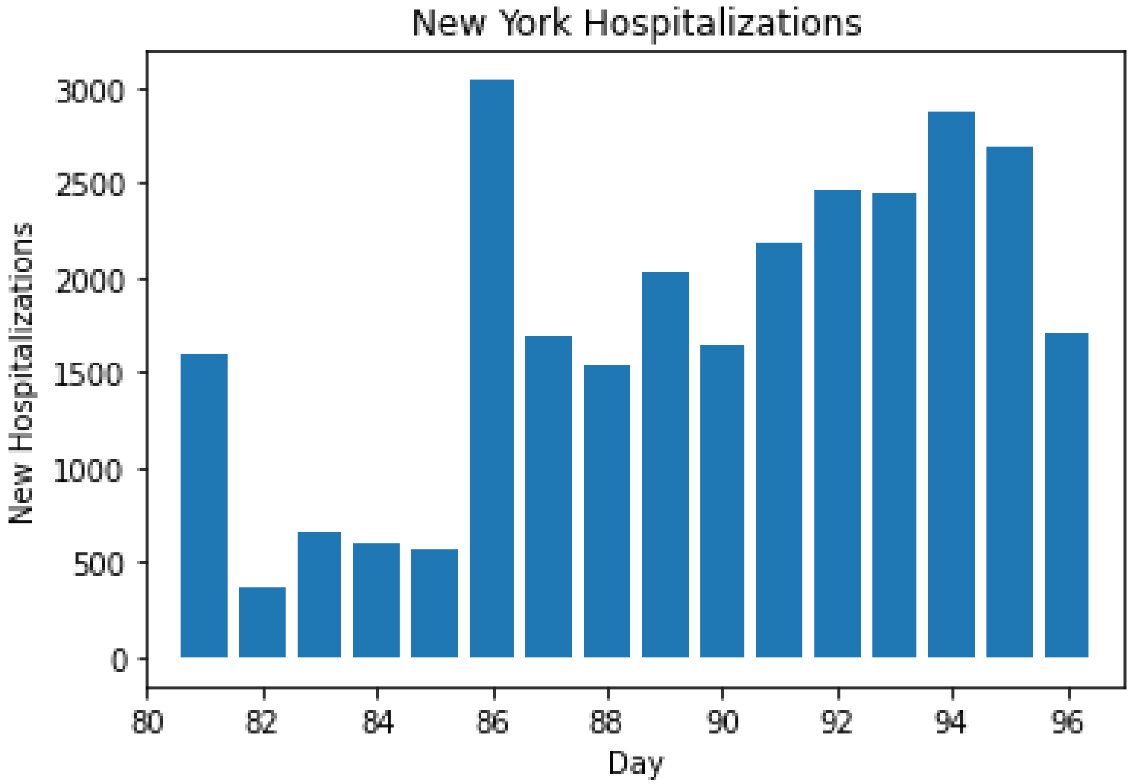

Figure 2: New York Hospitalizations

The biggest difference between the Germany data and the New York data is that the German data is backfilled: counts are computed retroactively to the date that a test was performed, rather than when the test is completed. The orange bars indicate change in data from recent backfilling. This backfilled data shows a clear trend of week-on-week growth coupled with consistent day-of-week effects. The New York data does not look like this at all.

In general, having looked at private and public data from different countries, states, and counties, my general experience is that backfilled data behaves smoothly (like the Germany data) while non-backfilled data is choppy (like the New York data). Because reporting lags are non-uniform (probably due to supply chain shortages), it is difficult to reliably estimate growth from such data. But more importantly, these lags will cause hospital and other counts to continue to "increase" even after actual hospitalizations have leveled off.

3 Estimating Date of Peak Hospitalizations

Since confirmed hospitalizations are not an accurate reflection of medical demand, we seek a different way to estimate the actual number of hospitalized COVID-19 patients in New York and California, and when these numbers peaked. We will also estimate when the number of newly admitted patients peaked; while this is not directly relevant for medical capacity, it is an early indicator that growth has leveled off.

3.1 California

We again make use of the California Open Data, looking at the total number of Suspected + Confirmed counts. Based on that data, total hospitalizations have been slowly decreasing at least since April 1st, which is the first day on which data were available. We conclude that the peak in medical demand likely has already occurred, on April 1st or earlier. However, it is possible there will be a brief second peak on Monday, April 6th, due to day-of-week effects (new hospitalizations tend to peak on Mondays).

It is harder to estimate when the peak in new hospitalizations occurred. We can say that it was probably at least a few days before April 1st. At the same time, the increase in confirmed hospital counts (which have been reported since March 28th) has had a flat or downward trend since their initial reporting, as well:

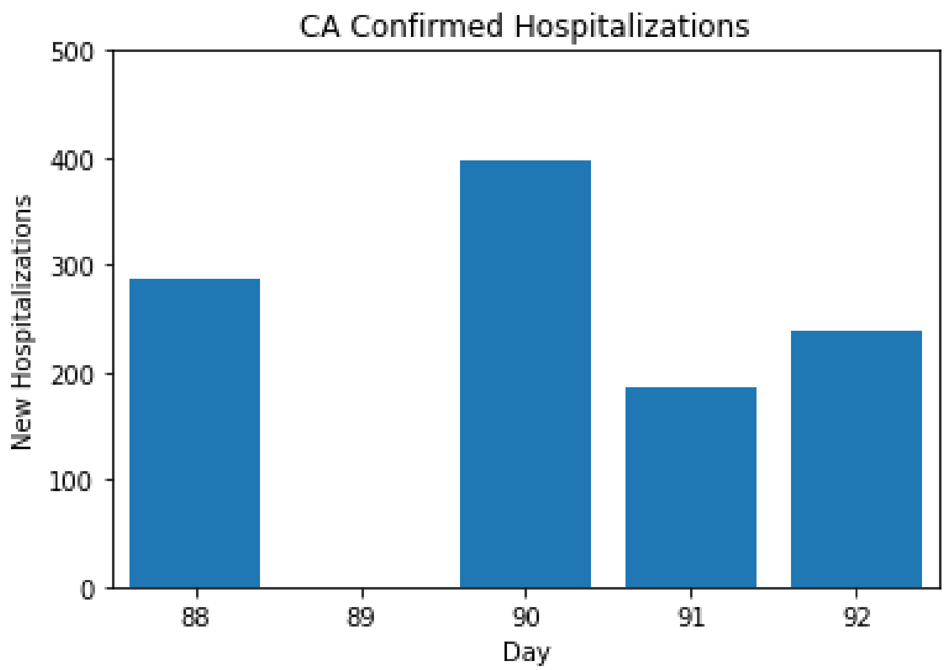

Figure 3: California Confirmed Hospitalizations

While this data suffers from lags that make it difficult to draw strong conclusions, they are consistent with new hospital counts peaking on or before March 28th.

3.2 New York

In New York, we instead make use of the Syndromic Surveillance [5] data. This allows us to determine, on a daily basis, how many patients reported to New York City emergency rooms with respiratory or flu-like symptoms. A general caveat for this data is that we do not know the relationship between ER visits and cases or hospitalizations, and it is possible that ER use has changed over time in New York City due to increased strain on the medical system.

Below are plots for respiratory symptoms:

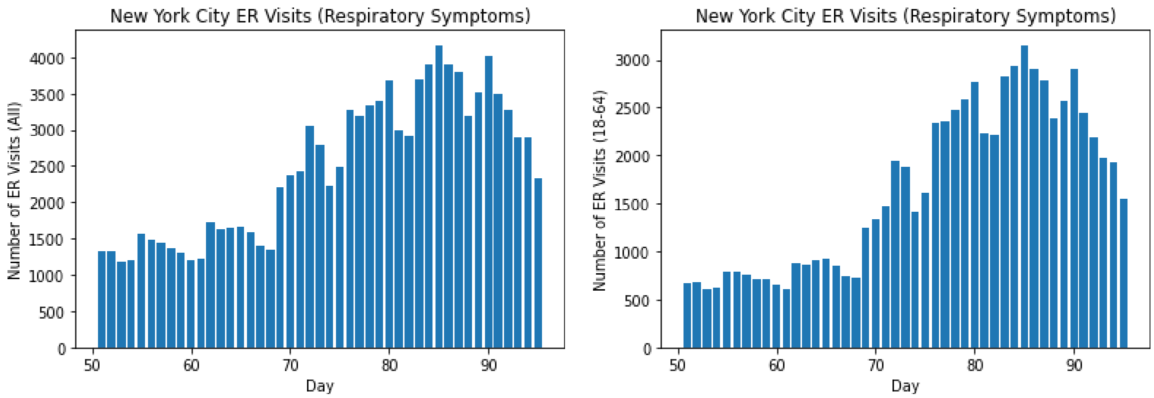

Figure 4: ER Respiratory Visits, All Age Groups (Left) and Ages 18–64 (Right)

We include both all age groups and ages 18–64. The latter data are slightly less noisy, since many non-COVID-19 respiratory cases occur in children and this removes some of that baseline. Overall, we see that there was a peak around day 85 (March 25th). There is also a peak on March 25th for flu-like symptoms. Both data also show a second peak on March 29th, likely due to a day-of-week effect.

These data suggest that ER visits due to COVID-19 peaked on March 25th. If we assume that after the lockdown, most new cases occurred due to within-household infections, then a March 25th peak is consistent with the March 20th state-wide lockdown and the widely-reported 5-day incubation time.

From various sources (see next section for details), we estimate approximately 10 days from infection to hospitalization, which perhaps corresponds to 5 days from initial ER consultation to hospitalization. This suggests the peak in new hospitalizations would have occurred around March 30th. The peak in total hospitalizations occurs slightly later—roughly when the number of new hospitalizations is smaller than it was a week ago (based on mean hospitalization duration). In the respiratory ER data this occurs on day 92 (April 1st), so we expect peak hospitalization around April 6th.

An important caveat is that an initial drop in new infections is actually possible even if the new R_0 is less than 1. In this case new infections would initially drop substantially but then increase again later. For instance, below is a possible realization of data from an SEIR model:

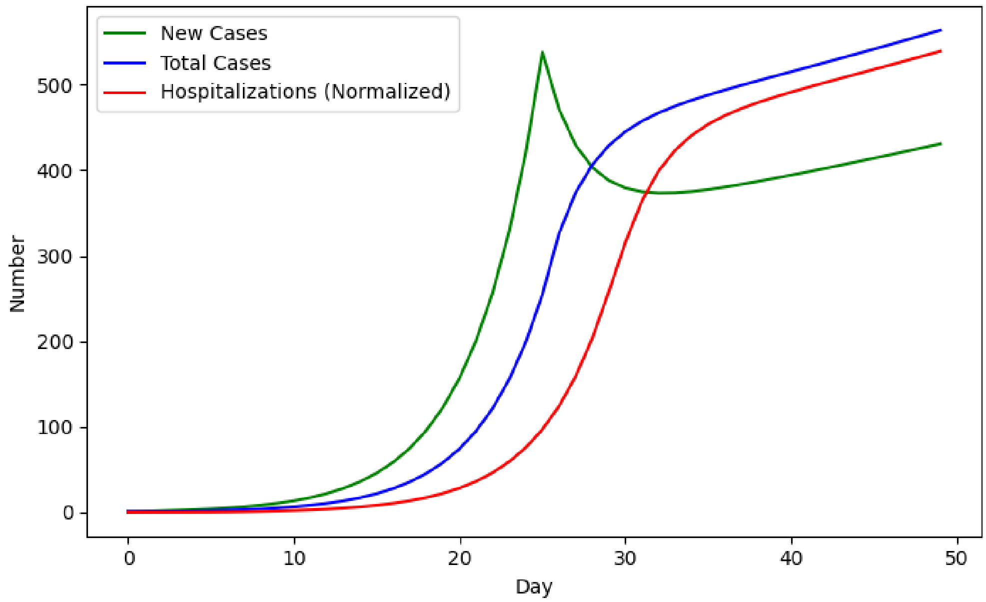

Figure 5: SEIR Model Data

In this model the growth rate per day dropped from 28% to 1%, which led new infections to initially drop but then eventually increase.

4 Preliminary Estimate of Post-Lockdown Growth Rates

It is difficult to determine what the growth rate in cases is post-lockdown, because right now the number of hospitalizations is fairly flat. This isn't because the growth rate is close to zero, but rather because the system has momentum—a hospitalized patient stays in the hospital for some time, so even if new hospitalizations drop substantially the hospital count will not immediately decrease.

Here we present two indirect ways to estimate the post-lockdown growth rate. The first uses the fact that on the day X where hospitalizations hit their peak, the number of new hospitalizations on day X equals the number of patients leaving the hospital on that day. Since most of the patients that are leaving came from the exponential growth part of the curve, and the entering patients come from the exponential decay part, we can intuitively balance these to find the ratio of the growth to decay rate. We can formalize this with a modified SEIR model that relates the growth rate, decay rate, date of lockdown, hospital lag and duration, and date of hospital peak. This relies on an assumption of a discrete change in R_0 shortly after lockdown, which we show in the next section may not be true.

The second method, which we can only apply in New York City, uses the decay in ER visits as a proxy for the decay in total cases. Due to random lags between infection and ER consultation, this decay rate may underestimate the decay rate in steady state. It is also possible that ER data is not representative of the growth and decay in cases and hospitalizations.

Based on these two methods, we estimate a decay rate of 29%/day in California and 8%/day in New York. However, there is substantial uncertainty in both estimates that could be partially eliminated using non-public hospital data on time-of-admission. In addition, we show in the next section that the growth rate may have already been decreasing prior to the lockdown, which would confound the estimates above by breaking the assumption of a discrete change.

4.1 Estimation from Hospital Peak

If we know that the hospital peak occurs on day X, then the number of new hospitalizations on day X equals the number of discharges on day X. The number of discharges is approximately the number of new cases on $X - D_H$, where D_H is (average) hospital duration. Further accounting for a lag T_H from infection to hospitalization, the number of new infections on $X - (D_H + T_H)$ would approximately equal the number of new infections on $X - T_H$. These calculations are wrong because the exponential growth in hospitalizations means that discharges are more skewed towards patients from recent days (when there were more cases). Instead of average hospital duration, we should use an exponentially weighted average that weights towards shorter durations, and similarly for average lag. We account for this below when estimating parameters.

What should the curve of new infections look like? In an SEIR model, assuming we have reached steady state exponential growth but are not near herd immunity, we expect it to increase exponentially at a rate of $1+r_{\text{grow}}$ per day, up until the time X_L of lockdown. Increase should then continue for a brief period of time T_L due to household infection post-lockdown, before leveling off and then decaying exponentially at a rate of $1 - r_{\text{decay}}$ per day. The level-off period is due to the fact that the system has momentum due to new cases staying infectious for several days or more. However, if the per-day growth and decay rates are both large, then the level-off period for new infections is negligible (less than a day for parameter regimes we consider). Therefore, we can simplify the SEIR model to exponential growth up to some day, followed by exponential decay.

If we know all of these numbers, then we would know that the growth from day $X - (D_H + T_H)$ to day $X_L + T_L$ must cancel out the decay from day $X_L + T_L$ to day $X - T_H$. Solving for this yields:

$$-log(1 - r_{\text{decay}}) = \frac{(X_L + T_L) - (X - D_H - T_H)}{(X - T_H) - (X_L + T_L)} log(1 + r_{\text{decay}})$$

A simpler way to put this is that the ratio of the log-decay rates is equal to the ratio of the days of growth to days of decay.

The quantities in this equation are only approximately known except for the date of lockdown X_L. It is therefore important to check which directions give pessimistic (slower decay) vs. optimistic (faster decay) estimates. For the hospital duration D_H, hospital lag T_H, and lockdown lag T_L, lower values gives more pessimistic estimates. In contrast, higher day X of hospital peak gives a more pessimistic estimate. Finally, slower pre-lockdown growth r_{grow} is more pessimistic.

We estimate r_{grow} from the death time series for California and New York, using the method in Yadlowsky, Shah, and Steinhardt (2020) [6]. We obtain 16.4% for California (95% CI 11.9-21.0%) and 28.2% for New York (95% CI 23.4%-33.2%).

For hospital duration, we found estimates of 10–14 days from early data in Asia ([7], [8], [9]), although informal reports from Western hospitals suggest a shorter duration and we use a conservative value of 5 days and best guess of 6.5, skewing downward to account for the exponential weighting discussed above. For hospital lag, we found onset-to-hospitalization was 7 days in early Asia data [9], but we need to add additional time for infection-to-onset. We can conservatively assume that hospital cases have a fast onset of 2.5 days, or take a best guess of 5 days based on reports of incubation time [10]. This would give conservative and best-guess estimates of 9.5 and 12, but we decrease to 8.5 and 10 based on assuming hospitalizations occur slightly sooner in the U.S. due to greater awareness and to account for the exponential weighting.

For lockdown lag, there is little data; we use 1 day as a conservative and best guess value for T_L.

Table 3

	Conservative	Best Guess
Hospital Duration, D_H	5	6.5
Hospital Lag, T_H	8.5	10
Lockdown Lag, T_L	1	1

Table 4

	Growth Rate r_{grow} (estimate / conservative)	Lockdown Date X_L	Peak Date X
California	0.151 / 0.119	79 (March 19th)	92 (April 1st)
New York	0.282 / 0.234	80 (March 20th)	97 (April 6th)

Table 5

	Growth Period (Best Guess)	Decay Period (Best Guess)	Growth Period (Conservative)	Decay Period (Conservative)
California	75.5–80 (4.5)	80–82 (2)	78.5–80 (1.5)	80–83.5 (3.5)
New York	80.5–81 (0.5)	81–87 (6)	N/A	N/A

Using the best guess numbers for California, we would need the growth from days 75.5 to 80 to cancel the decay from days 80 to 82, so decay would need to be 2.25 times as fast as growth, leading to 29%/day decay. Using conservative numbers, we would need the growth from days 78.5 to 80 to cancel out the decay on days 80 to 84.5. This leads to a much smaller decay rate of 4.7%/day. We think 29%/day is closer to the truth, but uncertainty from current estimates cannot rule out a much slower decay.

Using the best guess numbers for New York, the growth from days 80.5 to 81 would need to cancel the decay from days 81 to 87. This leads to an estimated decay of 2%/day. However, this is highly sensitive to the assumed 0.5-day growth time. If we estimate the peak in New York as April 5th instead of April 6th, we get a slightly faster 7.2%/day estimate of the decay. This is still much slower than California. The primary reason for the slower estimate is that the hospital curve in New

York seemed to take several days longer to reach its peak. With conservative instead of best-guess estimates, we cannot distinguish the decay rate from zero.

Sensitivity. Since the estimated decay rate primarily depends on the ratio of the growth period to the decay period, and these are both small integers, estimates are fairly sensitive to the exact values of these time periods and thus implicitly to the estimated parameters. Hospitals likely have data that would better estimate D_H and X fairly accurately, and also get better data on M and $T_L + T_H$. Based on these, we could better estimate the true decay rates in New York and California.

In the absence of better estimates, we could also more carefully quantify uncertainty by forming a Bayesian model, where we define prior distributions over each of the model parameters and condition on the date of the observed peak. This is one possible direction of future work.

4.2 Estimation from ER Data

Based on the New York City ER data, we can look at how quickly new ER visits are dropping. There were 19,204 upper respiratory cases in the 18–64 age range 2 weeks ago, and 15,546 last week, with a baseline number of cases around 4,000/week. Looking at the rate of decay after subtracting off the baseline, we estimate that visits are dropping around 4%/day. However, this is conservative, as some days from two weeks ago were still part of the exponential rise. If we instead only look at the fall from Saturday to Saturday, we see a drop of 44% for the week or around 8%/day.

Since ER visits have some momentum, we might continue to see the rate of drop accelerate, although it could also decelerate and then increase again if R_0 is still slightly greater than 1. To assess this, we can look at ER visits in the next week. If the decay continues at 8%/day then we would expect around 10,000 cases next week. Far fewer than this would suggest a faster rate of decay, while far more would be an early sign that total infections are still growing.

The 8%/day is consistent with our other best guess of 7.2% for New York, but both estimates have enough uncertainty that their alignment is likely a coincidence. A final caveat is that it is unclear if 4,000/week is the correct baseline to subtract, since instances of non-COVID respiratory illness have likely decreased due to the lockdown as well.

5 Do Lockdowns Work? What Measures Are Needed?

We find evidence that the March 19th shelter-in-place (California) and the March 20th lockdown (New York) both substantially decreased and reversed the growth of COVID-19. The growth rate dropped from around 28%/day to -9%/day in New York, and from 16%/day to -29%/day in California. In both cases the lockdown dropped per-day growth by around 40%/day. If this is consistent across regions, simple shelter-in-place lockdowns (closing all non-essential businesses) suffice to stop growth even in areas where the pre-lockdown growth rate is large. However, in some cases (as may be the case in New York), the rate of decrease may be undesirably low, such that it takes multiple days of lockdown to reverse one day of pre-lockdown growth. The rate of post-lockdown growth will affect how long a region needs to wait before existing a lockdown.

6 Decrease in R_0 Before Lockdown?

Finally, we provide evidence that R_0 may have been decreasing even before the New York lockdown. The suggestive evidence is mobility data from Citymapper [11]:

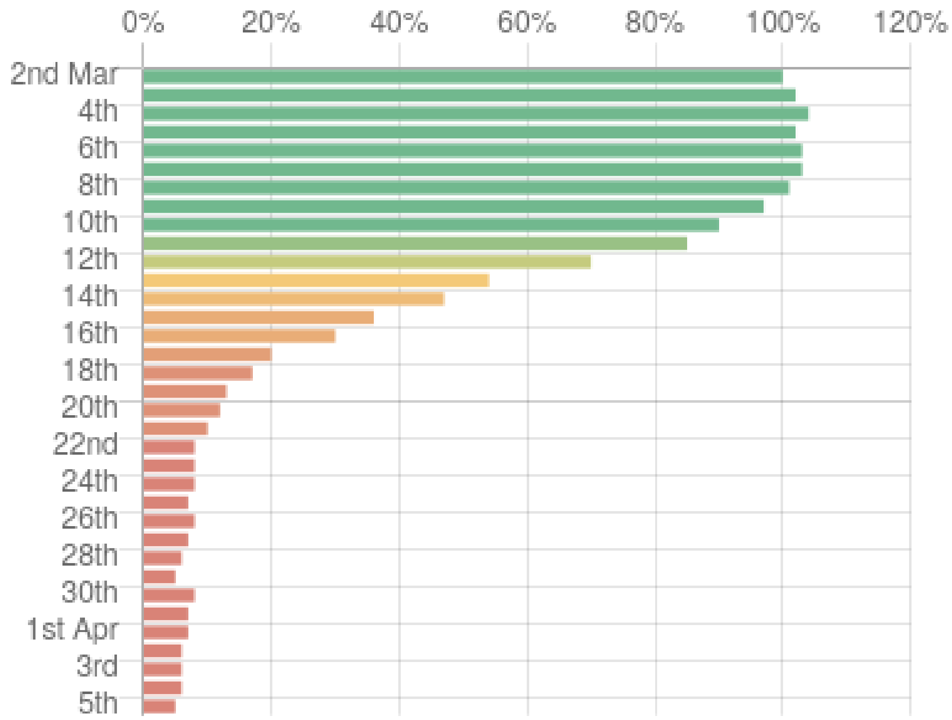

Figure 6: Citymapper Mobility Data

The New York state lockdown was on March 20th, but mobility in New York City had already dropped substantially by the 17th or earlier. At the same time, the peak in ER cases reported above occurred on March 25th. While we had previously cited a 5-day incubation time as consistent with this number, 5 days is actually somewhat short: we should expect extra time both for within-household infection to occur, and for symptoms to become severe enough to seek ER treatment. It seems more likely that there would be a 7-9 day lag from lockdown to ER peak than a 5-day lag. It is therefore possible that the peak was actually caused by the pre-lockdown decrease in mobility around March 17th.

This would be good news regarding the success of voluntary measures, but conversely it would be bad news about the current growth rate—since our calculations above were based on the time to reverse pre-lockdown growth, if that growth was slower than 28% / day, then the current decay is correspondingly slower, as well.

In an appendix, we also show that Italy's peak does not line up well with any of the official lockdown measures. A possible tenuous explanation is that the Italy peak was due to voluntary movement decrease among citizens that decreased R0. We cannot directly conclude that these measures brought the peak below 1, since they could have combined with later measures to move the peak earlier than otherwise.

7 When Might We Be Able To Restart?

In California, we estimate that as of March 22nd there were 92,000 infected individuals in California, based on 371 deaths to date on April 6th, a 16%/day growth rate, 21 days from infection to death, and a 1% case fatality rate. Assuming a decrease of 29%/day, we would hit around 30 new infections/day on April 15th. Allowing 7-10 days for those cases to be either resolved or detected, and assuming that we had a contact tracing regime in place to prevent spread from the small number of remaining cases, California could hope to re-open sometime around April 25th. However, we do not currently see large-scale efforts to contact tracing or other mitigation measures, and if California does not have these in place by April 25th it may need to wait longer to re-open.

In New York, there are substantially more cases. If our estimate of a 10%/day decrease is correct, it will also take about three times longer for the number of infections to drop by the same amount. This would not allow New York to re-open until June or later. To avoid this, New York would either need to further increase the rate of drop, or else adopt a large-scale contact tracing operation that can trace many more than the 30 infections assumed for California. Alternatively, it is possible that our estimate of New York's decay rate is too pessimistic and they would be able to re-open sooner under the status quo.

Appendix: Timeline of Interventions and Attribution

Italy

- February 21st (day 52), lockdown in 11 municipalities in Lombardy.
- March 9th (day 69), soft lockdown (6pm curfew on bars, etc.).
- March 11th (day 71), all commercial and retail businesses except those providing essential services are closed down.
- March 21st (day 81), Conte announces a further enlargement of the lockdown, shutting down all non-necessary businesses and industries.
- March 22nd (day 82), Lombardy bans all outdoor physical activity and the use of vending machines.

New deaths leveled off starting around day 80 (March 20th). This can't plausibly have been due to the March 21st lockdown, and would have been due to the order on the 9th or 11th. It also seems to be unlikely due to the February 21st order, which was at that point 28 days old. It's possible there was some ramp-up in-between days 52 and 69 that contributed, or else the level-off appeared within 10 days. These timelines don't seem consistent with any of the major measures imposed: February 21st is way too early, March 11th seems kind of too close to March 20th, and March 21st/22nd is after March 20th. My guess is that the drop is due to medical systems getting things back under control, or else they stopped reporting deaths.

New York

- March 12th (day 72), no mass gathering (500+), some school closures.
- March 15th (day 75), NYC schools closed (many schools elsewhere already closed).
- March 20th (day 80), Shelter in place.
- March 28th (day 88), non-essential construction shut down.

New York is not clearly leveling off yet, although there is some small evidence it has in the last day. If we take that optimistically to be true, then this occurred 15 days after the original shelter-in-place. On the other hand, if this is true we should have seen hospitalizations level off earlier. Looking at other data, ER visits for ILI and Respiratory symptoms reached their peak around March 25th–29th (days 85–89). This would have been 5–9 days after the shelter-in-place, or 10–14 days after New York City schools were closed. So one of these two was probably responsible for reversing growth.

California

- March 11th (day 71), no mass gatherings (1000+) in Santa Clara County.

- March 12th (day 72), Gov. Newsom bans mass gatherings (250+) state-wide.
- March 13th (day 73), school closures in many regions; Santa Clara bans gatherings of 100+.
- March 17th (day 77), shelter in place in Bay Area + Santa Cruz.
- March 19th (day 79), state-wide stay-at-home.
- March 30th (day 90), Bay Area shelter in place extended and slightly strengthened.

California state deaths don't appear to be leveling off. However, hospital numbers have gone down in absolute terms since April 2nd (day 93), and probably started to level off a few days before day 93 (let's guess day 88). This is around 9 days after the state-wide stay-at-home.

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