When and How Should Government Officials Lift Social Distancing Orders in Los Angeles

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Introduction

In the following series of experiments, I will first tune the parameters so that they match Los Angeles conditions. Then I will explore the effects of lifting social distancing after it's been in effect starting at day 20. I compare gradual lifting of social distance order with abrupt end, and the time in which it might be best to do so. This is important because as the pandemic progresses, government officials are pressured by economic factors, including job loss and loss of healthcare access, income loss, business closures, etc. to find the earliest, yet safest time to lift the social distancing orders.

Note: Function definitions can be found at the end of the report

Baseline simulation for Los Angeles

Hospitalization rates in Los Angeles changed from 1/100 to 1.5/100

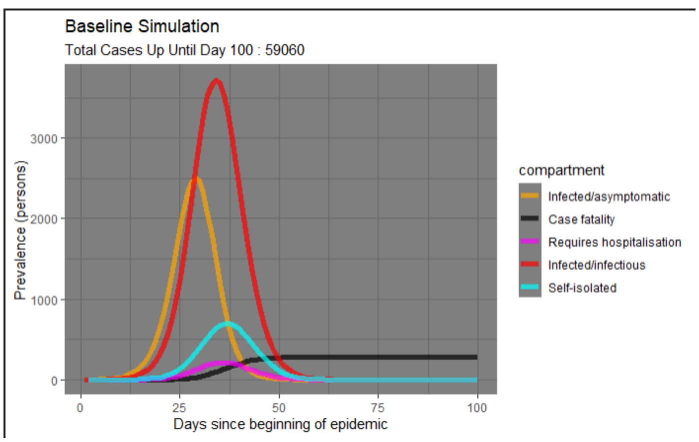
The original estimations for hospitalization rate calculate a rate of 1/100. According to the documentation:

> "A default rate of 1% per day with an average illness duration of about 10 days means a bit less than 10% of cases will require hospitalisation, which seems about right (but can be tweaked, of course)."

However, looking at figures from the LA Department of Health, we can see that 1,433 people have been hospitalized up until now, this is out of reported 9,420 tested cases in LA county. That is, 15% of cases in Los Angeles, have been hospitalized also in Los Angeles. Of course, this figure is not exact, as the total cases are uncounted, and only about 90% of hospital are reporting. Further, there is a nonnegligible number of cases which might not be tested and might have required hospitalization but stayed at home regardless. At any rate, 15% seems like a more realistic figure for Los Angeles.

Baseline exposure rates in Los Angeles changed from an average of 10

Population density in Australia is roughly 3.1 people per square kilometer. In Los Angeles it is roughly 2,910 people per square kilometer. Therefore, exposure rates from S to E should be increased, just based on the mere number of people each person sees per day regardless of whether they are in the E or S compartment. This will be manipulated later on.



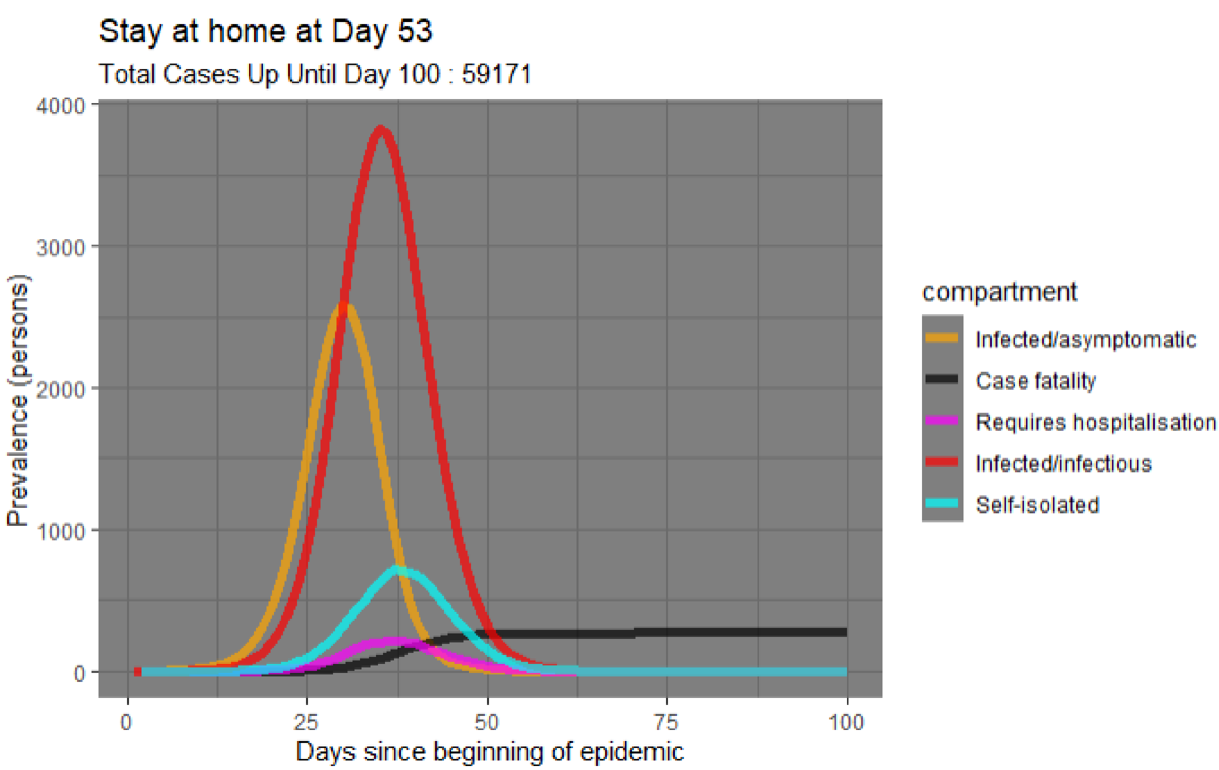
Experiment 1: Increased social distancing

Finding day 1 date to increase social distancing after 'stay at home' ordinance

The LA times reports that the first reported case in California occured on January 26th, in LAX. It is of course impossible to know whether this was the actual first case, but it will be the closest estimate. If Jan. 26th is the first day, then the stay at home ordinance, which happened on March 19th would be day 53.

Experiment 1a: Increased social distancing starting at 53 (stay at home order)

```
social_distance_day53 <- function(t) {
  ifelse(t < 53, 13, ifelse(t <= 70, 10 - (t - 53) * (10 - 5)/15, 5))
}

stay53 <- simulate(ncores = 4,
                   act.rate.i = social_distance_day53(1:366),
                   act.rate.e = social_distance_day53(1:366))
plot_sims(stay53,100,
          sim_title ="Stay at home at Day 53",
          day_stats = 100)
```

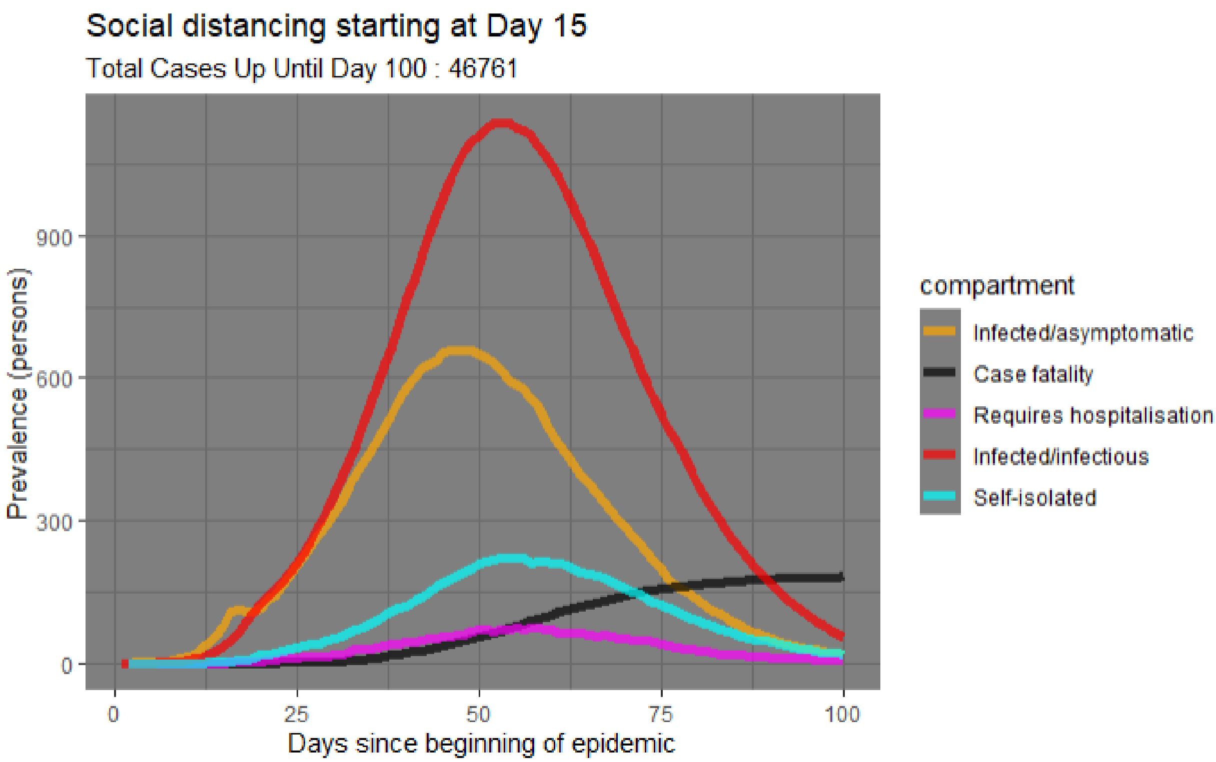


Results If we estimate January 26th as day number 1, the stay at home order was enacted on day 53. Thus, act rates had to decrease starting then. Extrapolating further April 14th would be day 79.

As we can see by the results, model estimates the pandemic as being much shorter than it has actually turned out to be. Therefore, stay at home order at day 53 turns out to be too late in this model, and thus yields small benefits. In the next study, the start of the stay at home order will be decreased to day 15.

Experiment 1b: Social distancing at day 15

```
social_distance_day15 <- function(t)ifelse(t <= 15, 13, 5)

day15 <- simulate(ncores = 4,
                  act.rate.i = social_distance_day15(1:366),
                  act.rate.e = social_distance_day15(1:366))

plot_sims(day15,100,
          sim_title ="Social distancing starting at Day 15",
          day_stats = 100)
```

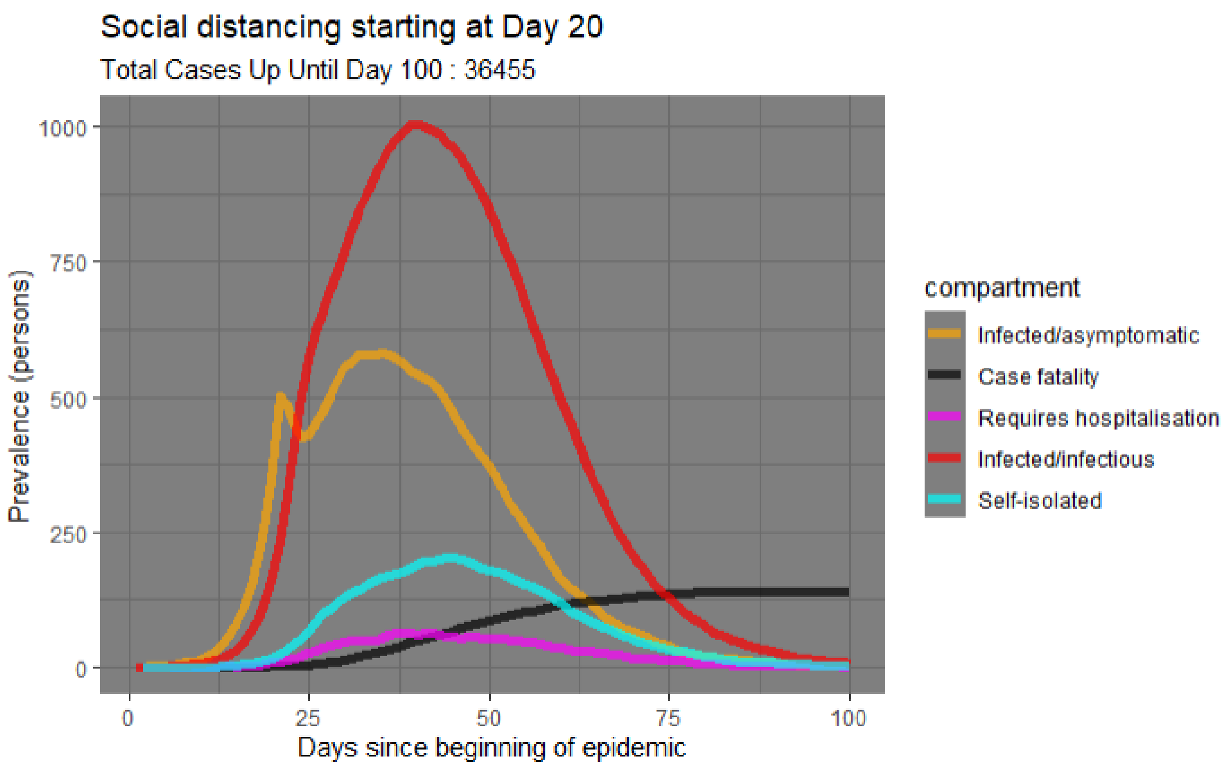


Results As we can see from these results, enacting a stay order earlier, is much more effective for total number of cases, and for the length of time the pandemic takes to peak. It is also worth nothing, that enacting strict stay at home orders, where suddenly act rates are much lower, creates a small mode, in the distribution of infected asymptomatic rates. Suggesting that social distancing measures are effective (albeit less effective) even if enacted later.

In the next condition I will compare enacting social distancing slightly later, towards the peak of the pandemic.

Experiment 1c: Social distancing at day 20

```
social_distance_day20 <- function(t)ifelse(t <= 20, 13, 5)

day20 <- simulate(ncores = 4,
                  act.rate.i = social_distance_day20(1:366),
                  act.rate.e = social_distance_day20(1:366))

plot_sims(day20,100,
          sim_title ="Social distancing starting at Day 20",
          day_stats = 100)
```



Results Comparing social distancing starting at day 15 vs day 20, we can see that the overall numbers and peaks are higher if social distancing is enacted on day 20, rather than 15.

Interestingly, the infected distribution seems to "correct" itself in such a way that when social distancing is enacted, the number of infected/asymptomatic people does not continue to increase and the distribution thus gains a small mode and beomes positively skewed.

This further suggests that social distancing orders that are enacted later, can still be very effective, but that the sooner the order is enacted, the more effective it will be, especially with diseases such as COVID-19 which spreads quickly.

Experiment 2: How to End Social Distancing

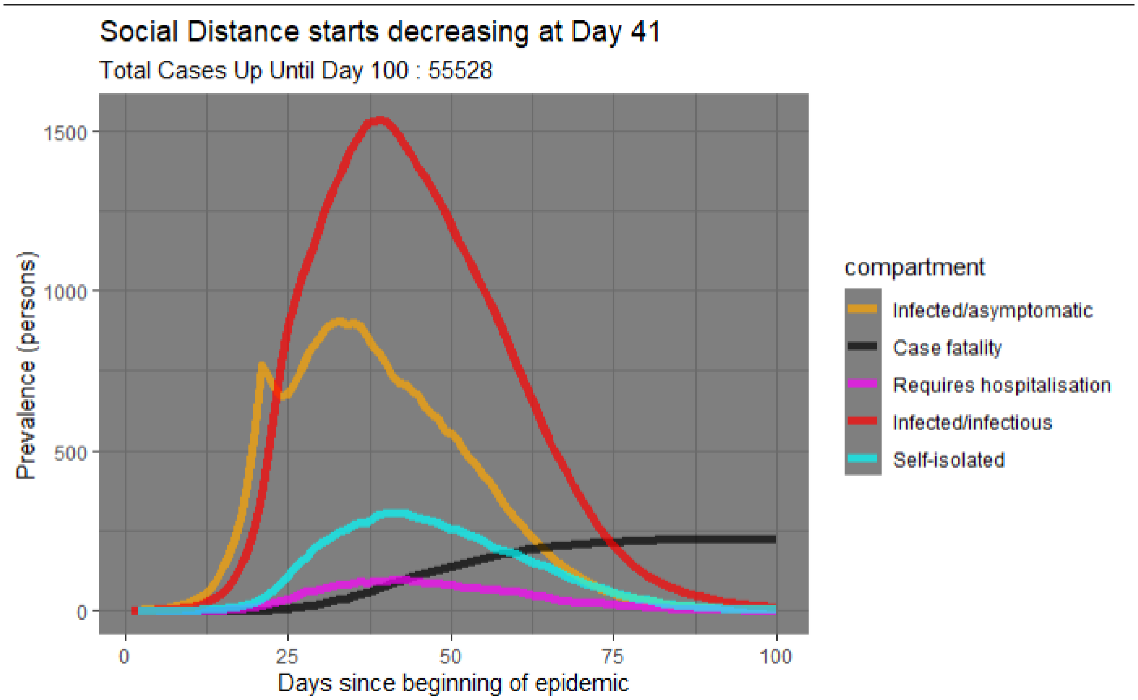
Experiment 2a: Relaxing Social Distancing After a Period of Social Distancing

```
decreasing_social_distance <- function(t){
         ifelse(t <= 20,13,#Day 0 to day 20
         ifelse(t > 20 & t <= 40,5,  #Day 20 to 40
         ifelse(round(5+(0.3*(t-40)),0) <= 13,round(5+(0.3*(t-40)),0),
                13)))#All others
}

dec_day20<- simulate(ncores = 4,
                   act.rate.i = decreasing_social_distance(1:366),
                   act.rate.e = decreasing_social_distance(1:366))

plot_sims(dec_day20,100,
          sim_title ="Social Distance starts decreasing at Day 41",
          day_stats = 100)
```

There are many reasons why social distancing might decrease after 26 days of social distancing (from March 13th to April 14th). For instance, President Trump has been announcing that he would like to have the US open again by around May. Another reason might be that when the peak is reached people might start feeling optimistic that the pandemic is over, therefore, they might not be a compelled to follow stay at home orders as much. Another reason might be that people get tired of the order and start becoming non-compliant.

In this experiment I want to see what would happen if the stay at home order would occur at day 20, remained constant for 20 days after that and then continue to increase in the following fashion until it reaches the baseline of 13.

$$exposures = 5 + 0.3 * (t - 25)$$



Results As we can see, the severity of the pandemic is still better off than if nothing were done, but it still not as good as if the order was followed for the remainder of the disease.

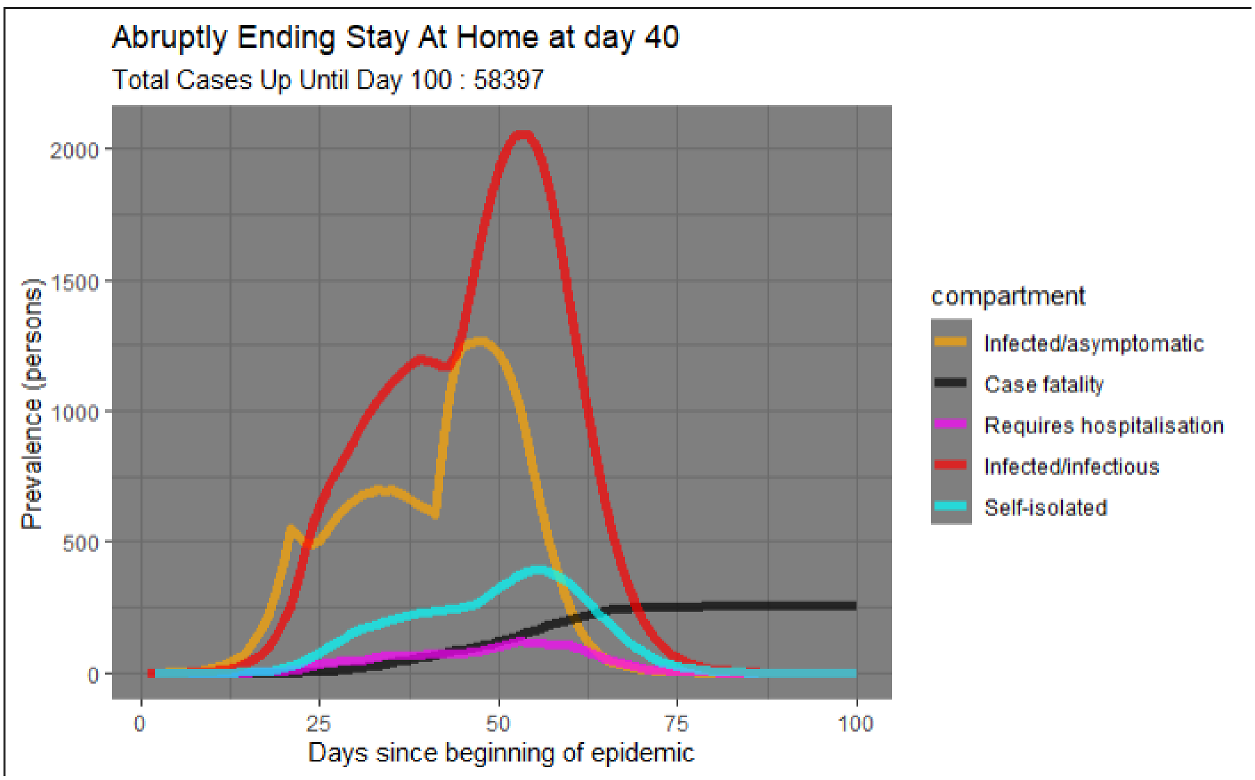
Interestingly, the increase in act rates right at the peak of the pandemic, elongates the peak and though the path seems largely unaltered, there is still a significant increase in overall cases. Thus, this situation needs to be explored further.

In the next study I want to compare a slowly decreasing social distancing to an abrupt stop to stay at home orders.

Experiment 2b: Abruptly ending social distancing after 40 days

In this condition, social distancing is enacted starting on day 20, and it continues as a constant of 5 for 20 more days, starting on day 41, all social distancing is lifted and act rates go back to 13.

```
decreasing_social_abruptend <- function(t)ifelse(t <= 20, 13,
                                    ifelse(t > 20 & t <= 40, 5,13))

sd_abrupt_end <- simulate(ncores = 4,
                   act.rate.i = decreasing_social_abruptend(1:366),
                   act.rate.e = decreasing_social_abruptend(1:366))

plot_sims(sd_abrupt_end,100,
          sim_title ="Abruptly Ending Stay At Home at day 40",
          day_stats = 100)
```



As we can see these results are dramatic. Comparing this simulation with the original simulation where there were no interventions, the overall number of cases is smaller and the peaks are lower when social distancing is practiced for a period of time than if it was not enacted at all, but they are much worse than when the decrease in social distancing is gradual (Experiment 2a), even though they both happen at day 20 which is closely after the peak.

Experiment 3 : Ending Social Distancing After the Peaks

I would like to replicate Experiment 2a and 2b, but on day 40 rather than 20 in the pandemic. This will allow us to see what the best course of action might be going forward in real life.

<u>This is important because there are two competing forces:</u>

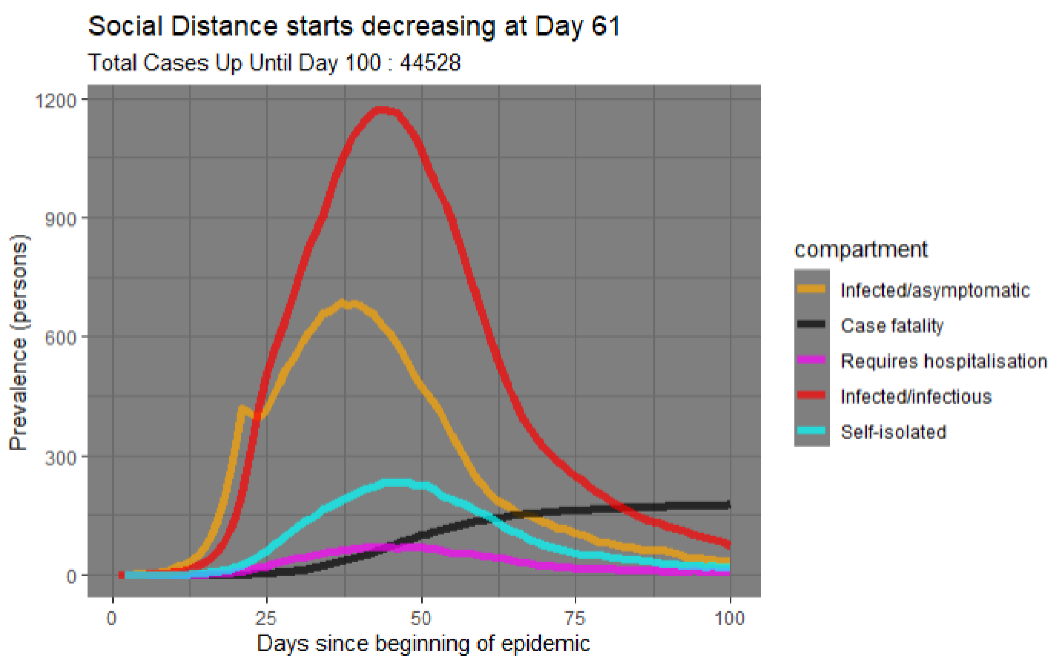
On one hand, the government wants to keep everyone safe and not overwhelm the health care system. We have shown in the previous experiments that social distancing works, works best when it is enacted earlier but it is still effective even if the order is enacted a little later. But we have also seen that decreasing social distancing right after the peak of the pandemic can have catastrophic results, depending on the amount of decreasing that happens over time. Therefore, we can see that the safest course of action is, of course, to continue social distancing as long as possible.

However, economic factors might not make it feasible for social distancing to be in place for a full year, or even 6 months. For instance, unemployment claims continue to rise as workers continue to be laid off and businesses are unable to operate. Thus, government officials are hard pressed to find the earliest point at which it is safe to lift orders.

This next study will compare three conditions: Decreasing social distancing at the same rate as 2a, but after the peak is over (starting at 60), decreasing social distancing at a higher rate, and abruptly ending social distancing at day 60

Experiment 3a: Decreasing social distancing starting at day 40

```
decreasing_social_distance_day60 <- function(t){
         ifelse(t <= 20,13,#Day 0 to day 20
         ifelse(t > 20 & t <= 60,5,  #Day 20 to 40
         ifelse(round(5+(0.3*(t-60)) <= 13,0),round(5+(0.3*(t-60)),0),
                13)))#All others
}

dec_day60<- simulate(ncores = 4,
                     act.rate.i = decreasing_social_distance_day60(1:366),
                     act.rate.e = decreasing_social_distance_day60(1:366))

plot_sims(dec_day60,100,
          sim_title ="Social Distance starts decreasing at Day 61",
          day_stats = 100)
```

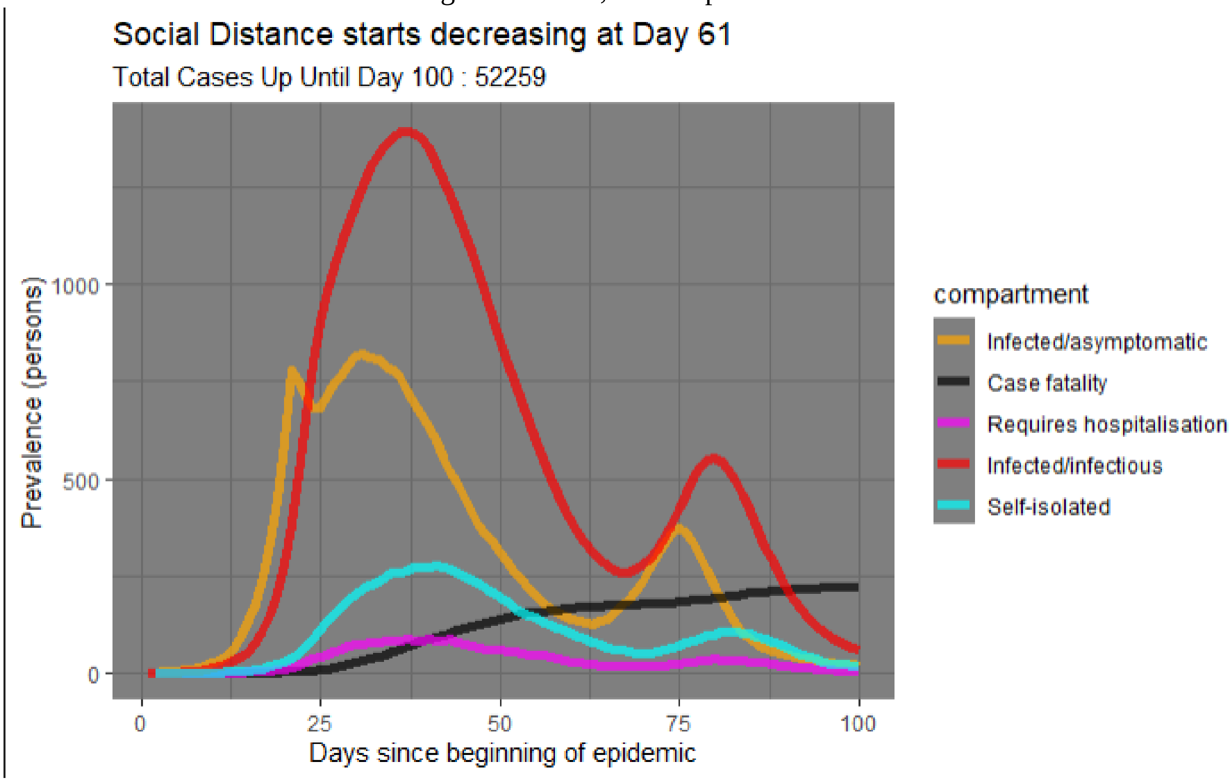


As expected, decreasing social distancing gradually after day 60, is better than after 40, but there is no dramatic advantage here, for instance the peak of infected/infectious individuals only differs by roughly 250 cases. Maybe full social distancing needs to last longer than 60 days.

Experiment 3b: Decreasing social distancing starting at day 60, but at a faster rate

```
decreasing_sd_faster_day60 <- function(t){
        ifelse(t <= 20,13,#Day 0 to day 20
        ifelse(t > 20 & t <= 60,5,   #Day 20 to 40
        ifelse(round(5+(0.6*(t-60)) <= 13,0),round(5+(0.6*(t-60)),0),
               13)))#All others
}

fastdec_day60<- simulate(ncores = 4,
                  act.rate.i = decreasing_sd_faster_day60(1:366),
                  act.rate.e = decreasing_sd_faster_day60(1:366))

plot_sims(fastdec_day40,100,
          sim_title ="Faster Social Distance starts decreasing at Day 61",
          day_stats = 100)
```

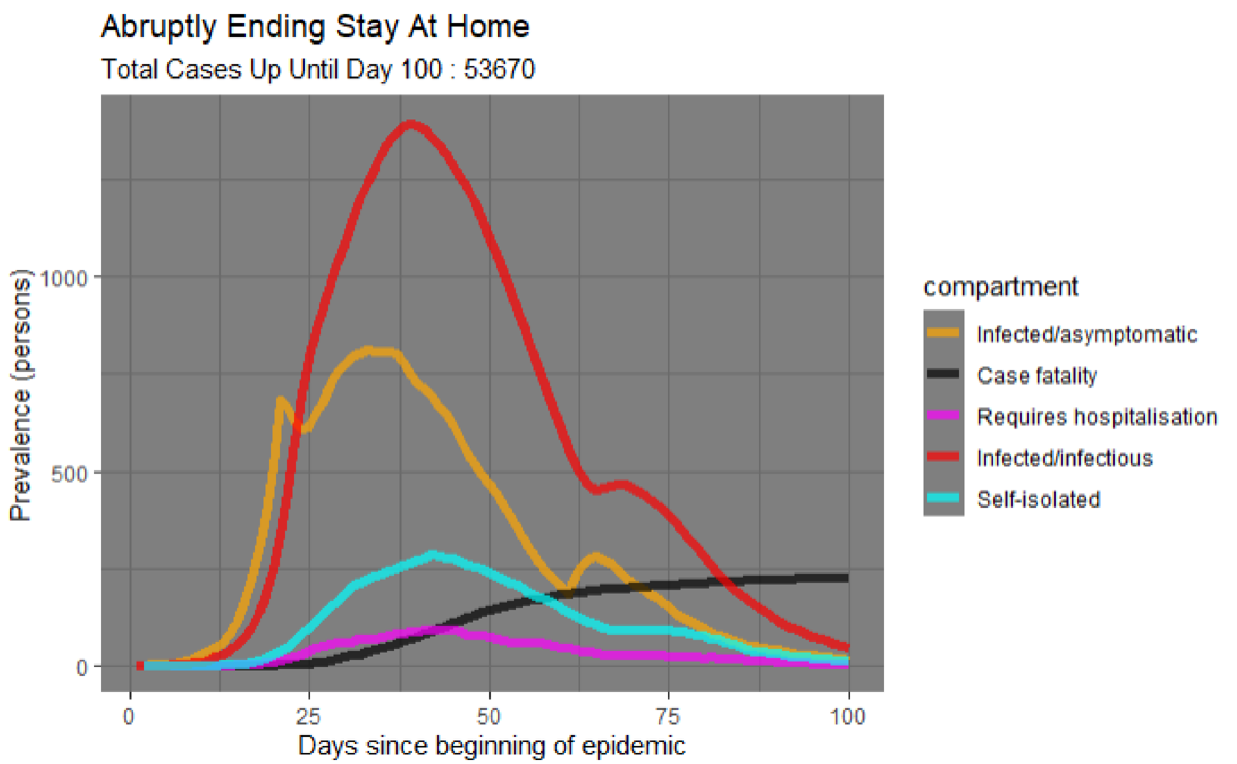
This is a reduction in social distancing much faster, than Exp. 3a.



Perhaps not so interesting is the fact that a faster decrease in social distance leads to an reuptake of the pandemic, but it is surprising the extent to which the distributions become bimodal.

Exp 3c: Ending social distancing abruptly at day 60

```
decreasing_social_abruptend60 <- function(t)ifelse(t <= 20, 13,
                                    ifelse(t > 20 & t <= 60, 5,13))

abrupt_end_day60 <- simulate(ncores = 4,
                    act.rate.i = decreasing_social_abruptend60(1:366),
                    act.rate.e = decreasing_social_abruptend60(1:366))

plot_sims(abrupt_end_day60,100,
          sim_title ="Abruptly Ending Stay At Home",
          day_stats = 100)
```



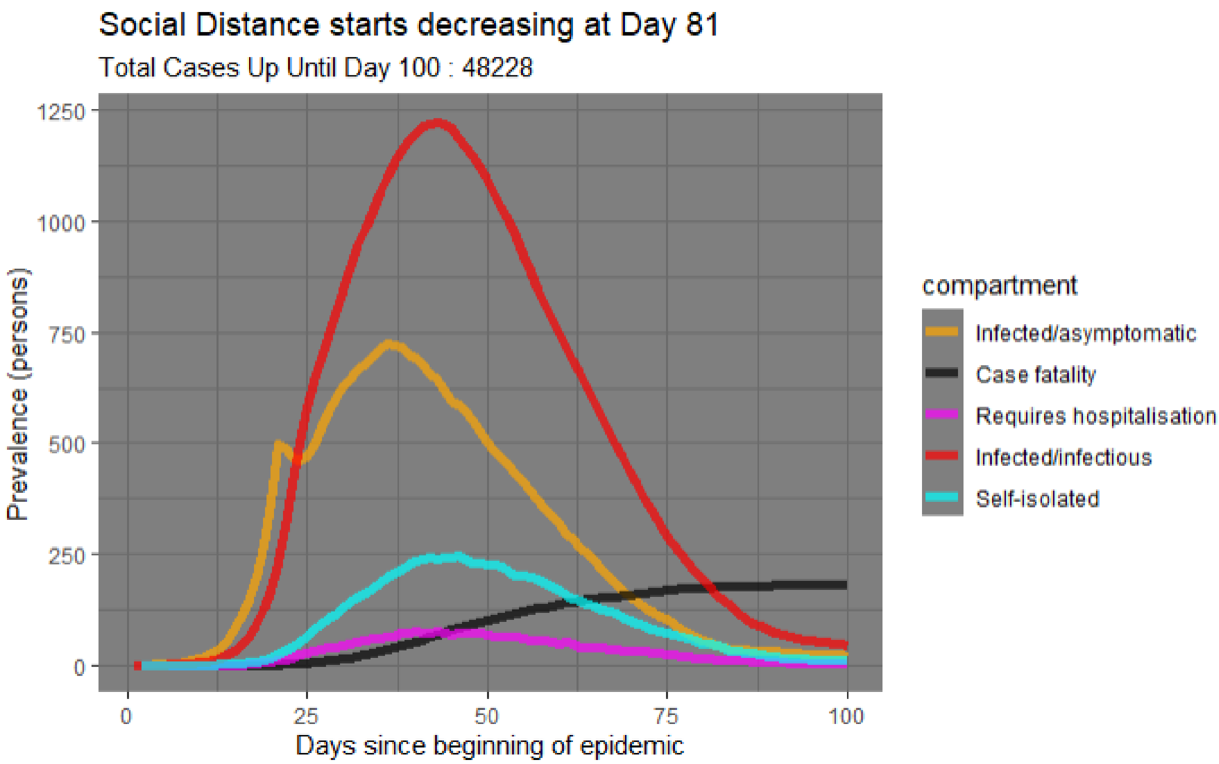
Looking at the differences between Exp 3b and Exp 3c, we can see that there are differences, but they are not nearly as dramatic as those happening in the pandemic.

Experiment 4

Finally, I will compare the slower decrease in social distancing starting at day 80, with the abrupt end in day 80. As we have seen in the previous experiment, the effect of the intervention is smaller as time goes on, therefore, maybe day 80, once the peak is well in the past, lifting social distancing gradually, might be equal to abruptly lifting social distancing.

Experiment 4: Ending Social Distancing on Day 80

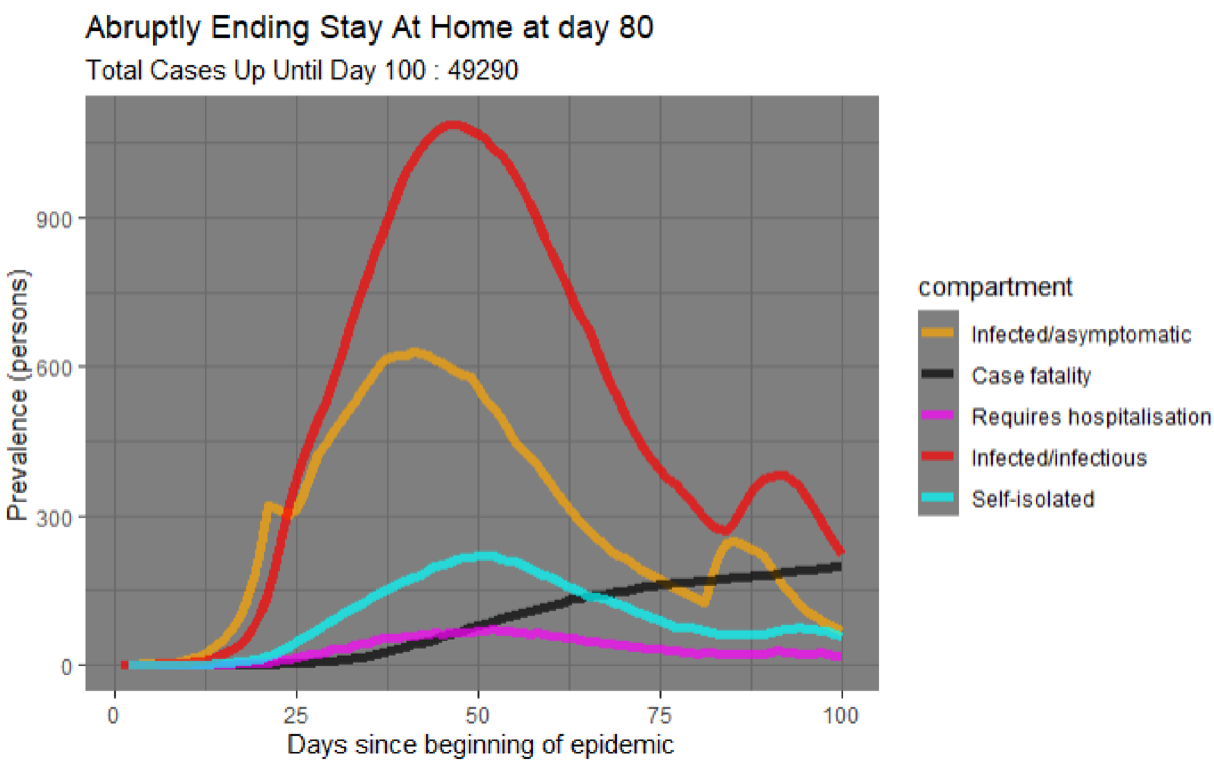
```
decreasing_social_distance_day80 <- function(t){
         ifelse(t <= 20,13,#Day 0 to day 20
         ifelse(t > 20 & t <= 80,5,  #Day 20 to 40
         ifelse(round(5+(0.3*(t-80)) <= 13,0),round(5+(0.3*(t-80)),0),
                13)))#All others
}

dec_day80<- simulate(ncores = 4,
                     act.rate.i = decreasing_social_distance_day80(1:366),
                     act.rate.e = decreasing_social_distance_day80(1:366))

plot_sims(dec_day80,100,
          sim_title ="Social Distance starts decreasing at Day 81",
          day_stats = 100)
```



This is consistent with the patterns we have seen in the past. However, day 80 is well after the peaks, one would expect that decreasing social distancing at this point would have less consequences than shown here.

Exp 4b: Ending social distancing abruptly at day 80

```
decreasing_social_abruptend80 <- function(t)ifelse(t <= 20, 13,
                                        ifelse(t > 20 & t <= 80, 5,13))

abrupt_end_day80 <- simulate(ncores = 4,
                     act.rate.i = decreasing_social_abruptend80(1:366),
                     act.rate.e = decreasing_social_abruptend80(1:366))

plot_sims(abrupt_end_day80,100,
          sim_title ="Abruptly Ending Stay At Home at day 80",
          day_stats = 100)
```



Surprising that even at day 80 consequences of ending social distancing abruptly are much larger than ending it gradually.

Conclusions

Based on this in depth study on the lifting of social distancing, we can conclude that any form of lift in social distancing orders results in larger amount of cases and higher peaks in prevalence. However, the extent to which the pandemic worsens depends on the time in which social distancing is lifted and whether it is lifted gradually or abruptly such that lifting social distancing rules at a later time has lesser consequences. However, ending social distancing gradually is always preferable to ending it abruptly. Thus, government officials have the difficult task of finding the safest but earliest time to lift social distancing orders, but no matter than they do it, they should do it gradually rather than abruptly.

Set up code used to perform simulations above

```
simulate <- function(

  # control.icm params
  type = "SEIQHRF",
  nsteps = 366,
  nsims = 8,
  ncores = 1,
  prog.rand = FALSE,
  rec.rand = FALSE,
  fat.rand = TRUE,
  quar.rand = FALSE,
  hosp.rand = FALSE,
  disch.rand = TRUE,
  infection.FUN = infection.seiqhrf.icm,
  recovery.FUN = progress.seiqhrf.icm,
  departures.FUN = departures.seiqhrf.icm,
  arrivals.FUN = arrivals.icm,
  get_prev.FUN = get_prev.seiqhrf.icm,

  # init.icm params
  s.num = 9997,
  e.num=0,
  i.num = 1,#jan. 26th
  q.num=0,
  h.num=0,
  r.num = 0,
  f.num = 0,
```

```
# param.icm params
inf.prob.e = 0.02,
act.rate.e = 13, #Based on population density
inf.prob.i = 0.05,
act.rate.i = 13, #Based on LA figures
inf.prob.q = 0.02,
act.rate.q = 2.5,
quar.rate = 1/30,
hosp.rate = 1.5/100, #Based on LA figures.
disch.rate = 1/15,
prog.rate = 1/10,
prog.dist.scale = 5,
prog.dist.shape = 1.5,
rec.rate = 1/20,
rec.dist.scale = 35,
rec.dist.shape = 1.5,
fat.rate.base = 1/50,
hosp.cap = 40,
fat.rate.overcap = 1/25,
fat.tcoeff = 0.5,
vital = TRUE,
a.rate = (10.5/365)/1000,
a.prop.e = 0.01,
a.prop.i = 0.001,
a.prop.q = 0.01,
ds.rate = (7/365)/1000,
de.rate = (7/365)/1000,
di.rate = (7/365)/1000,
dq.rate = (7/365)/1000,
dh.rate = (20/365)/1000,
dr.rate = (7/365)/1000,
out="mean"
{
```

```r
control <- control.icm(type = type,
                       nsteps = nsteps,
                       nsims = nsims,
                       # ncores = ncores,
                       prog.rand = prog.rand,
                       rec.rand = rec.rand,
                       infection.FUN = infection.FUN,
                       recovery.FUN = recovery.FUN,
                       arrivals.FUN = arrivals.FUN,
                       departures.FUN = departures.FUN,
                       get_prev.FUN = get_prev.FUN)

init <- init.icm(s.num = s.num,
                 e.num = e.num,
                 i.num = i.num,
                 q.num = q.num,
                 h.num = h.num,
                 r.num = r.num,
                 f.num = f.num)
```

```r
  param <-  param.icm(inf.prob.e = inf.prob.e,
                      act.rate.e = act.rate.e,
                      inf.prob.i = inf.prob.i,
                      act.rate.i = act.rate.i,
                      inf.prob.q = inf.prob.q,
                      act.rate.q = act.rate.q,
                      quar.rate = quar.rate,
                      hosp.rate = hosp.rate,
                      disch.rate = disch.rate,
                      prog.rate = prog.rate,
                      prog.dist.scale = prog.dist.scale,
                      prog.dist.shape = prog.dist.shape,
                      rec.rate = rec.rate,
                      rec.dist.scale = rec.dist.scale,
                      rec.dist.shape = rec.dist.shape,
                      fat.rate.base = fat.rate.base,
                      hosp.cap = hosp.cap,
                      fat.rate.overcap = fat.rate.overcap,
                      fat.tcoeff = fat.tcoeff,
                      vital = vital,
                      a.rate = a.rate,
                      a.prop.e = a.prop.e,
                      a.prop.i = a.prop.i,
                      a.prop.q = a.prop.q,
                      ds.rate = ds.rate,
                      de.rate = de.rate,
                      di.rate = di.rate,
                      dq.rate = dq.rate,
                      dh.rate = dh.rate,
                      dr.rate = dr.rate)

  sim <- icm.seiqhrf(param, init, control)
  sim_df <- as.data.frame(sim, out=out)

  return(list(sim=sim, df=sim_df))
}
```

PLOT FUNCTION: Created to make later code looks flow better

```r
plot_sims <- function(sim_results,days_in_plot,sim_title,day_stats){

  # define a standard set of colours to represent compartments
  compcols <- c(s.num = "yellow", e.num = "orange", i.num = "red",
                q.num = "cyan", h.num = "magenta", r.num = "lightgreen",
                f.num = "black")
  complabels <- c(s.num = "Susceptible", e.num = "Infected/asymptomatic",
                  i.num = "Infected/infectious", q.num = "Self-isolated", h.num =
"Requires hospitalisation",
                  r.num = "Recovered", f.num = "Case fatality")

  #Data for graph:::
  results <- sim_results$df %>%
    # use only the prevalence columns
    select(time, s.num, e.num, i.num, q.num, h.num, r.num, f.num) %>%
    # examine n number of days
    filter(time <= days_in_plot) %>%
    pivot_longer(-c(time),
                 names_to = "compartment",
                 values_to = "count")%>%

      filter(compartment %in% c("e.num", "i.num",
                                "q.num", "h.num", "f.num"))


  #Total I cases until day_stats
  cases_at_day <- results %>%
                  filter(compartment == "i.num") %>%
                  filter(time <= day_stats)

  cases_at_day <- sum(cases_at_day$count,nan.rm = T)

        results %>%
        ggplot(aes(x = time, y = count,colour = compartment)) +
        geom_line(size = 2, alpha = 0.7) +
        scale_colour_manual(values = compcols, labels = complabels) +
        theme_dark() + labs(title = sim_title,
                            subtitle = paste0("Total Cases Up Until Day ",
                              day_stats,
                              " : ",
                              as.character(round(cases_at_day,0))),
                            x = "Days since beginning of epidemic",
```