Effectiveness of social distance strategies for protecting a community from a pandemic with a data-driven contact network based on census and real-world mobility data

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Key findings

1. School closures do not have a major impact on controlling the epidemic, despite closing them infections keep occurring within the households and the community layers.
2. Passive social distance strategies are not enough to contain the epidemic, active strategies need to be established. For instance, large scale testing, remote symptoms monitoring, isolation and contact tracing.
3. School closures and Self distancing at 90% of adoption is a feasible strategy for minimizing the effects of the epidemic, but only if they are applied for a large period of time.
4. If high resolution mobility data is available, our data-driven approach with real world data can ingest new cities or countries quite easily to measure the impact of social distance strategies and the epidemic.

Background

Current situation of emergency is global. In less than three months of social distance strategies that they started to be in place, there are more than 23 countries with more than 1.000 infected cases by COVID-19. Each of them with different mitigation and suppression strategies that use social distance tactics. The result of this variance in strategies is that the balance of infected cases and deaths by country are different, putting millions of people at risk of death or saving millions of lives. Our report has preliminary results that try to respond to the following answers to the COVID-19 epidemic and the mitigation strategies based on social distance. What is the impact of current social distance strategies over the epidemic? For how long do they need to be in place? How many people will be infected? Who has been infected? How do R(t) and the epidemic dynamic change based on adding strategies? What is the probability of having a second outbreak? If so, How much time do we have to get ready? Which is the best strategy to minimize the current epidemic and get ready for a second outbreak? In this report you will find data, methods, social distance strategies defined and what if cases. We use real world mobility and census data to build a colocation network at three different layers (community, households and schools) a data-driven SEIR model where we test six different social distance strategies (i) school closures, (ii) self-distancing and teleworking, (iii) self-distancing and teleworking plus School closure (iv) Restaurants, nightlife and cultural closures, (v) non-essential workplace closures and (vi) total confinement. We test the impact of establishing these strategies at different stages of the epidemic curve and for different periods of time.

Data & Methods

Mobility and synthetic data for building the contact network

We used detailed mobility data and sociodemographic data from the Boston area, from CubeIQ and US Census respectively. We use it to generate one network describing the contact patterns of about 85.000 agents in the Boston area during a period of four months and three layers (Community, Households and Schools). The community layer is based on mobility data, the households are built using census data and, lastly, children belonging to the same geographical location are linked together to create the school layer. In the community layer, links are built using co-location data, with weights proportional to the time two individuals have been in the same place. Note that the data does not allow to disentangle if the contacts take place in the context of the workplace or in the general community.

Adults population   **Children population**
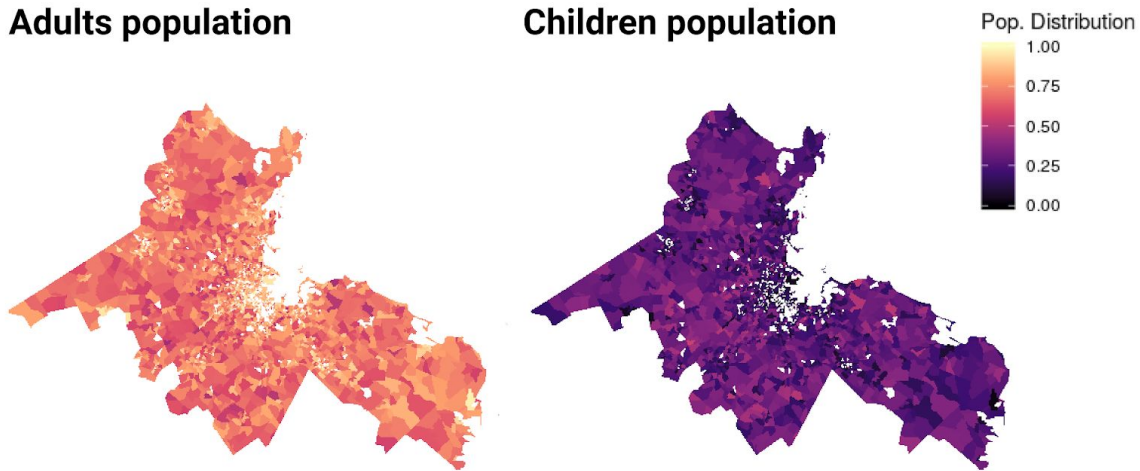
In the previous chart we can see the distribution of adults and children in the population by US Census block groups in the Boston area. The Adult population comes from real world mobility data and children are synthetically generated with the help of the US Census data about Household type by size and Family type by presence of children under 18 years.

Calibrating layer weights using historical ILI data and a SIR model

Initially, the weight of each link measures a different quantity. Links in households and schools have a weight equal to 1. Conversely, links in the community layer are a measure of time, since it is the product of the fraction of time that individuals i and j have been in the same place.

To obtain the relative weights of these layers, we implement a SIR model to simulate the propagation of a typical ILI [1]. In particular:

-    An infected individual i can transmit the disease to j with probability
$$rho \cdot w\_ij \cdot w\_layer$$
-    An infected individual recovers with probability 1/3

Then, we have four free parameters (rho, w_school, w_households, w_community). We fit the model to a typical ILI scenario, namely, R0=1.3 and the fraction of infections that should take place in each setting is 0.18, 0.30 and 0.52 for schools, households and the community+workplaces respectively.

SEIR model for modelling the COVID-19 epidemic

With the values obtained in the previous model, we can weight each link by their relative importance in the propagation of a disease that is transmitted by droplets, such as influenza or covid-19. The next step is to modify the previous model to include the special characteristics of this new disease.

- A susceptible individual *j* can be infected by an infected individual *i* if there is a link between them. This will happen with probability

$$rho \cdot w\_ij \cdot w\_layer$$

  Note that in this case w_layer is no longer a free parameter.
- If an individual is infected, it will move to the exposed compartment. Following [citeFerguson] we consider that individuals in this state cannot infect, nor be infected again, up to 12h before their symptom onset, since several studies have shown that the serial interval is slightly smaller than the incubation period. The individual will leave the compartment after a certain number of days, sampled from a log-normal distribution with mean 5.2 [2].
- The probability of moving to the recovered compartment is set so that the generation time is 7.5 [3,4].
- After recovery individuals are assumed to be immune to becoming reinfected by the virus.

Once the model is set, we fit the only free parameter, rho. We choose its value such that R0=2.6 [3,4].

Social distance strategies tested

We explore against the baseline six different strategies for protecting the population from a pandemic:

I. **School closures** are simulated by removing all the schools from the system simultaneously;

II. **Self-distancing and teleworking** are simulated by taking a random fraction of the population and removing all their interactions in the community+workplace layer;

III. **Self-distancing and teleworking plus School closure.**

IV. **Restaurants, nightlife and cultural closures** are simulated by removing the interactions that take place in any place that falls into that category according to Foursquare's taxonomy of places;

V. **Non-essential workplace closures**, leaving open Hospitals, Salons, Barbershops, Grocery Stores, Dispensaries, Supermarkets, Pet Stores, Pharmacies, Urgent Care Centers, Dry Cleaners, Drugstores, Maternity Clinics, Medical Supplies and Gas Stations;

VI. **Total confinement** with school and non-essential workplace closures within the metropolitan area.

In all cases we test the impact of establishing these strategies at different stages of the epidemic curve and for different periods of time.

What if cases of social distance strategies

We have tested what would happen if the restrictions are applied after 100 cases have been detected and then removed after 15, 30, 60 and 90 days. The time when the restrictions are

implemented will be denoted by a gray vertical line, while the time when they are lifted will be represented by a line matching the color of the legend. Besides, all simulations are aligned to the time when there are 50 cases in the population, this is denoted by an asterisk next to 0 in the plots.

In all cases we compute: the evolution of the number of infected individuals in the population; the evolution of the number of the total number of cases; the effective reproduction number; how new infections are distributed across the different settings as a function of time and in total.

To obtain the effective reproduction number we keep track of how many individuals each person infects. Then, we associate this R_i to the time where the individual showed symptoms for the first time. That is, if someone shows symptoms at t=1 and infects someone at t=2 and t=3, we would have R(t=1) = 2, R(t=2) = 0, R(t=3) = 0.

1. School closures

We observe that the overall effect of the closure is not too high, especially if it is imposed for only a month or less. The spreading is characterized by one large peak, after which the epidemic is not able to sustain itself in the population. The effective reproduction number clearly increases once the restrictions are lifted, but there are not enough susceptible individuals in the population to go above 1 and cause a new outbreak.
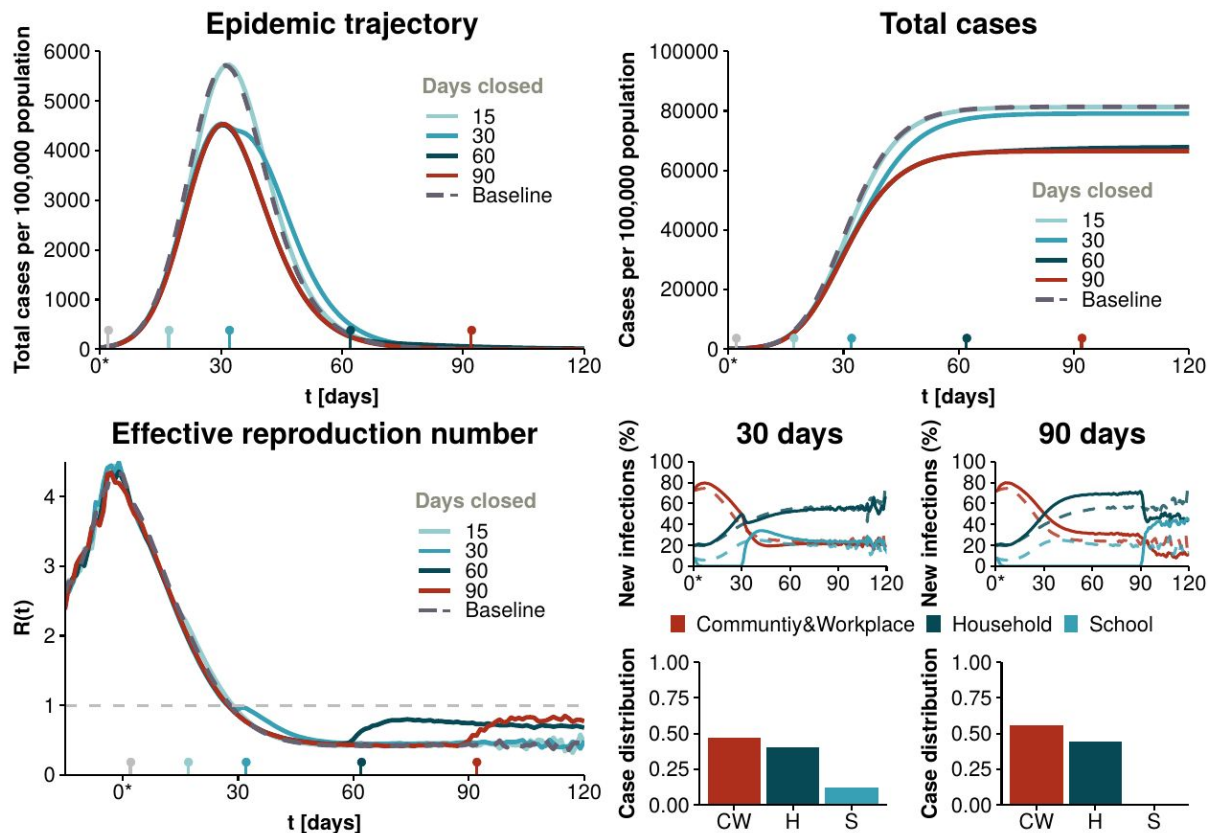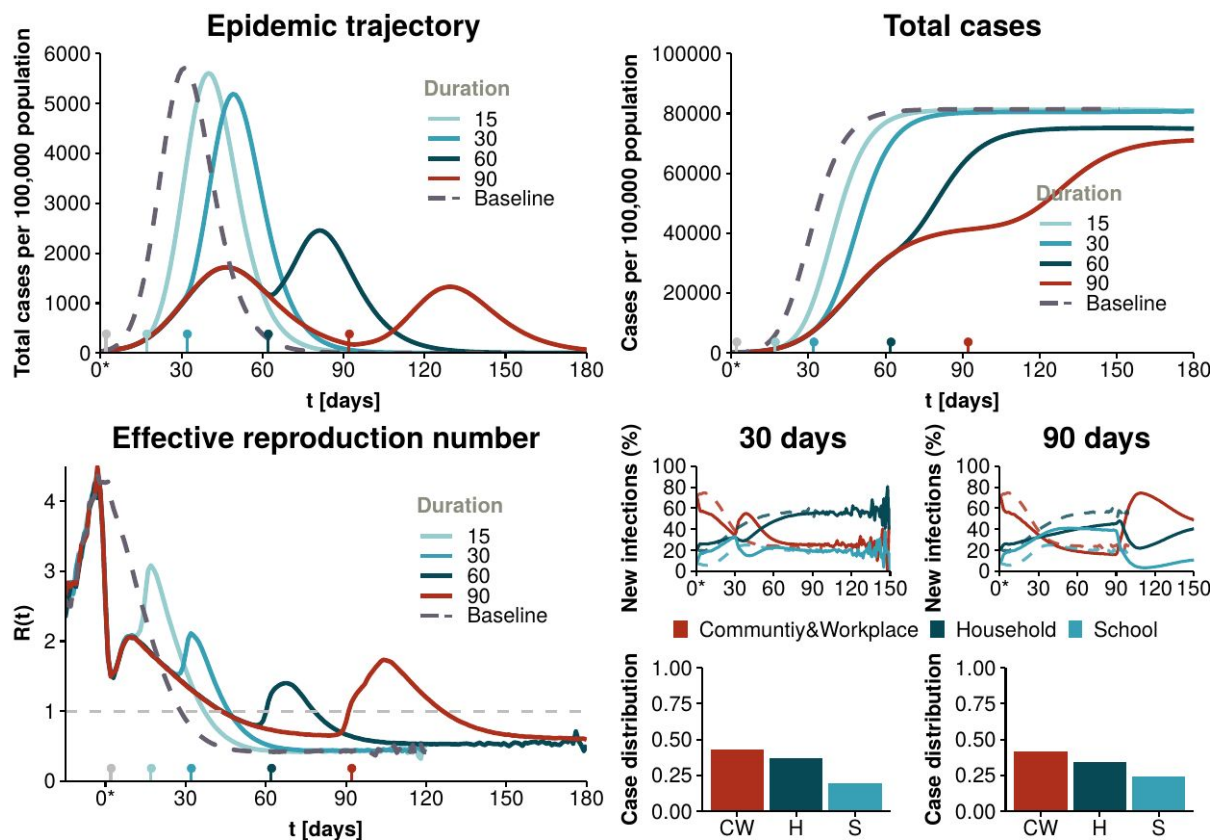
S1. School closure after 100 cases

2. Telework and social distancing

In this strategy, we flag all individuals that have at least one interaction in the community + workplace (CW) layer. Then, in each run, we select a random fraction (adopters) of this subset of individuals and remove their connections from the cw layer (for as long as the strategy is imposed). After that, they recover their connections.

When the number of adopters is relatively low (50% of the population with connections in the community layer), if the restrictions are lifted within a month there is a small delay but the total number of cases is the same. On the other hand, if the restrictions are applied for 2 months or more, there is a first medium-size peak, followed by a slow decay. Once the restrictions are lifted, the epidemic is able to spread again and produce a second peak of noticeable size, so that the total number of cases is quite close to the baseline scenario. The effective reproduction number clearly shows that even if it is below 1, if the restrictions are removed too early it can go again beyond that threshold and produce the second peak.

Conversely, when the fraction of adopters is very high (90%), we observe that the first peak is really small. Then, the disease might be able to spread for long periods of time with an effective reproduction number close to 1 through the school layer. Once the restrictions are

lifted, since almost the whole population is susceptible, we recover a behavior equivalent to the baseline scenario.
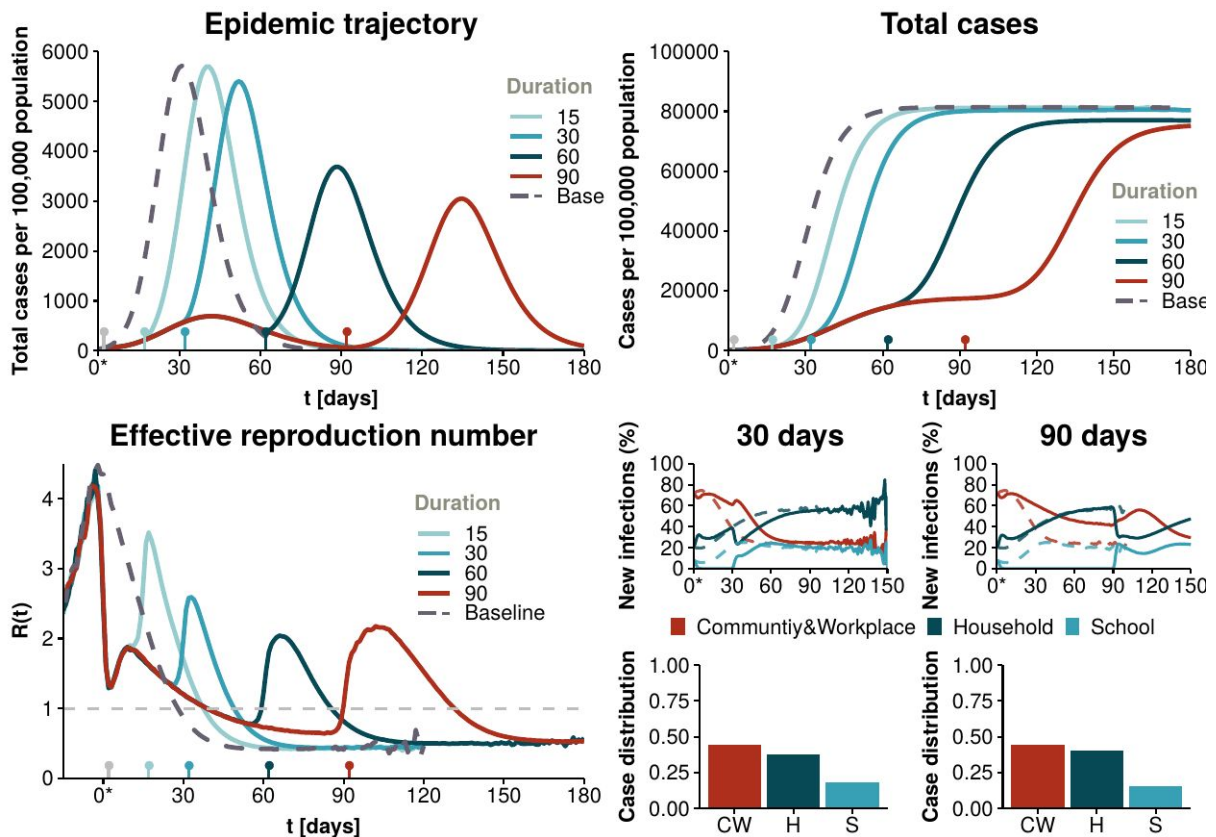

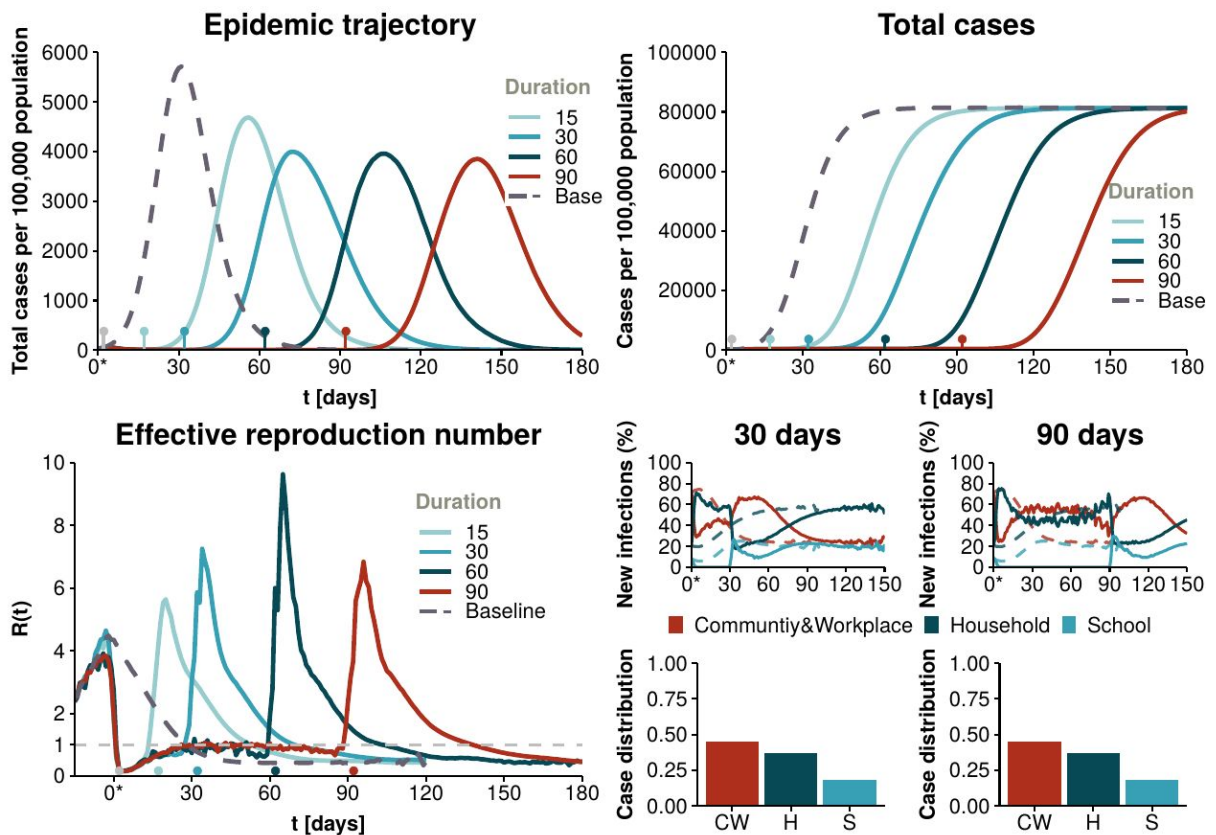**S2. Social distancing (50%) after 100 cases**
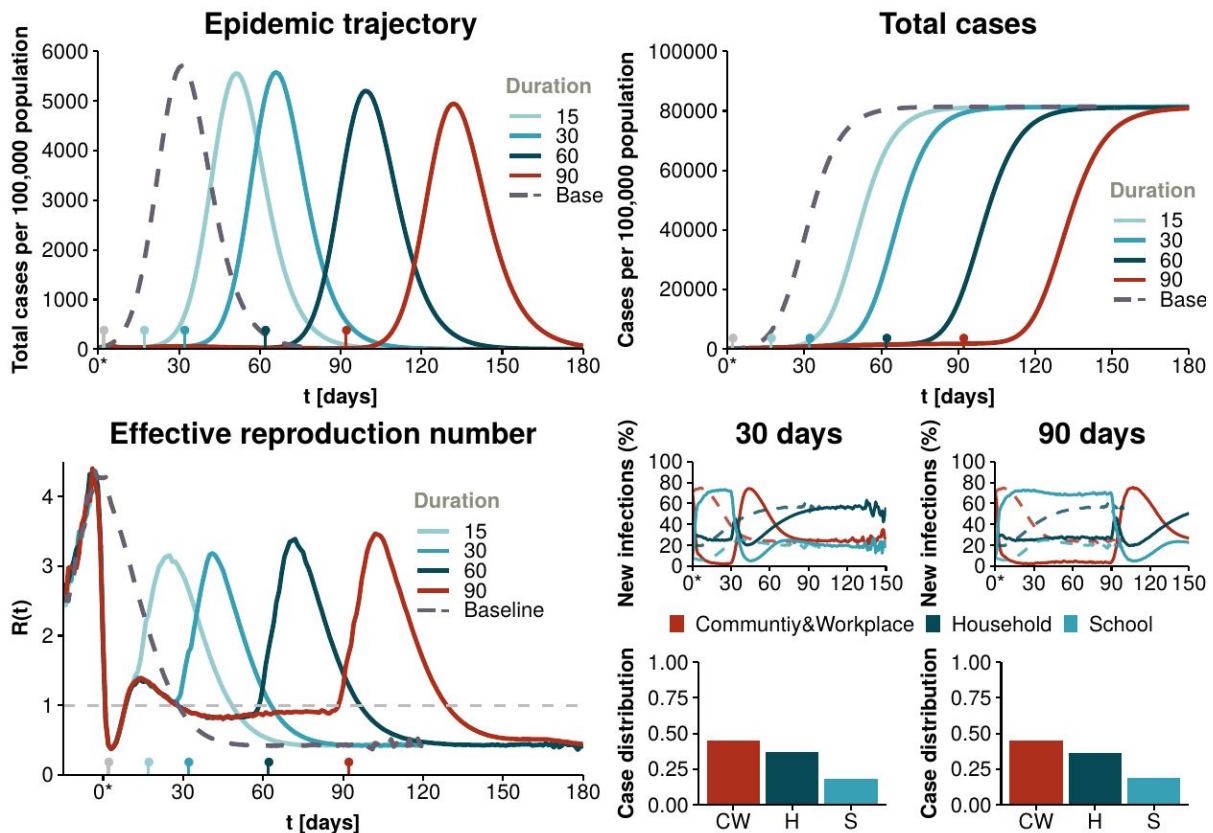
S2. Social distancing (90%) after 100 cases

3. Self-distancing plus School closure

Since we have observed that the epidemic is able to spread through schools even if the social distancing is very high, our next strategy is to also close schools. In this case, if the fraction of adopters is low the first peak is much lower, but then the second peak is much higher than in the previous case, resulting in an epidemic of roughly the same size. If the number of adopters is high, we note that in this case, even for restrictions of 3 months, the disease is able to spread through the few links that are present in the household and community layers.

S3. Social distancing (50%) + School closure after 100 cases

S3. Social distancing (90%) + School closure after 100 cases

## 4. Restaurants, nightlife and cultural closures

If restrictions are focused on a small set of public places such as restaurants, nightlife and cultural places, we obtain results compatible with strategy 2 with 50% adopters. The difference is that in this case the first peak is slightly larger, resulting in a small second peak.
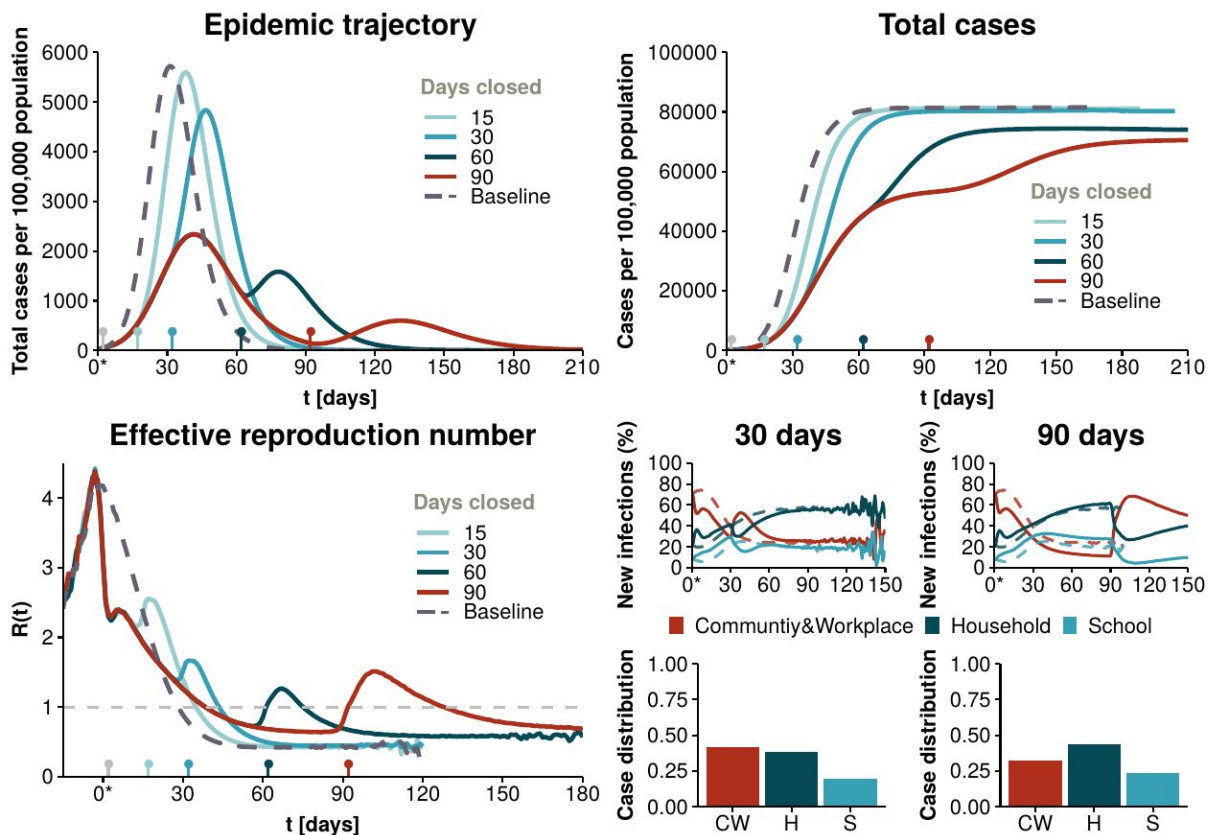
S4. Restaurants and cultural closure after 100 cases

5. All non-essential places closed

If the previous policy is extended to all non-essential places, we obtain results compatible with strategy 3 with a small fraction of adopters.
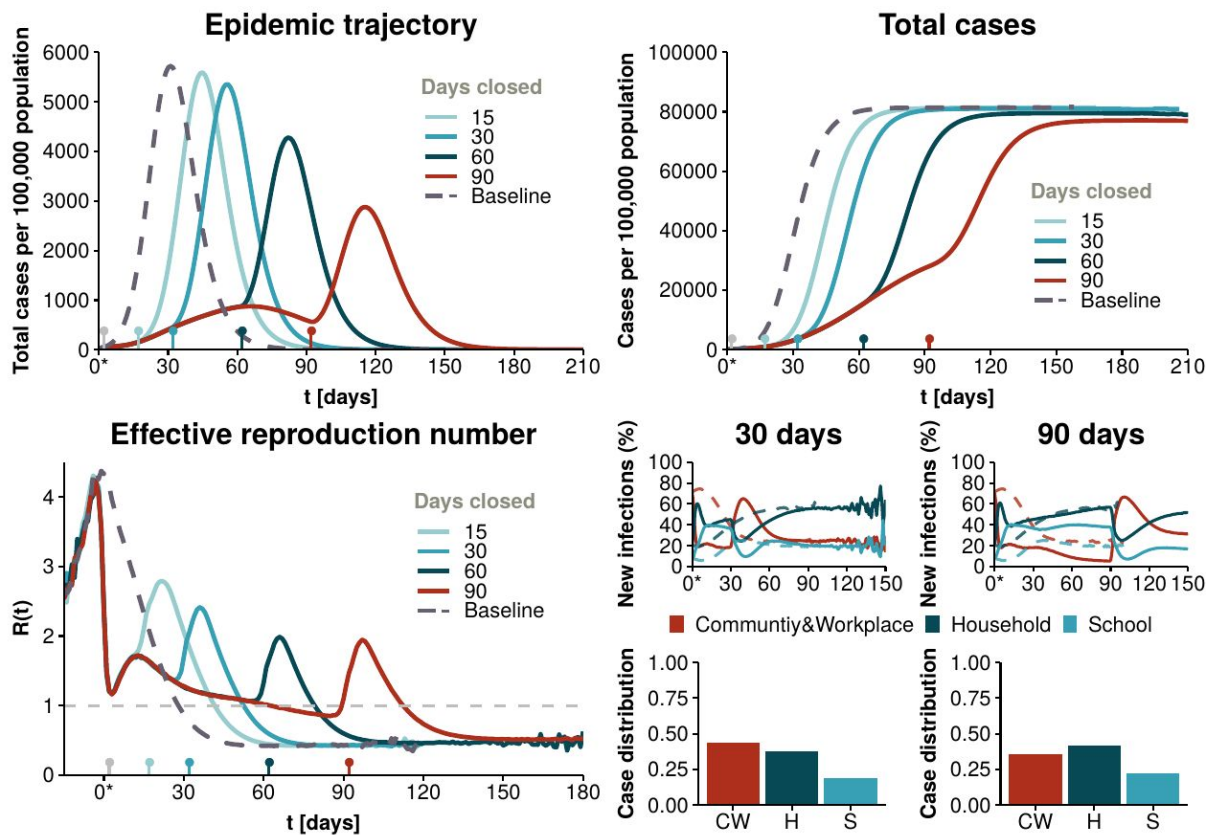
**S5. Non−essential closure after 100 cases**

6. Total confinement

Lastly, we analyze the situation in which all non-essential places and schools are closed. As expected, the results are similar to strategy 3 with a large fraction of adopters.
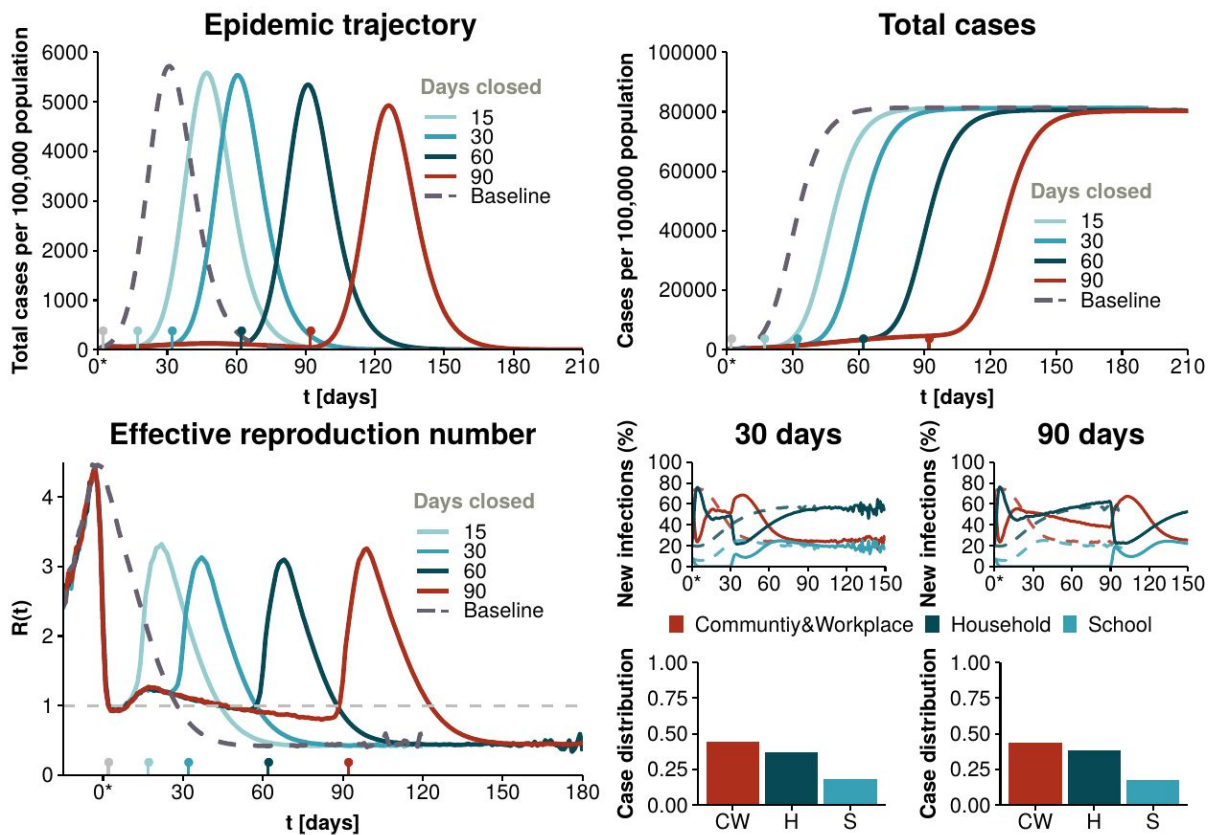
S6. Total closure after 100 cases

Second peak

In many cases we have seen that there is a second peak after the containment measures are lifted. In this plot we show the probability of having that peak. The best strategy will be the one that has a second peak, but with low probability so that with effective contact tracing and similar measures there is a low probability of having a second peak.

60 days

90 days
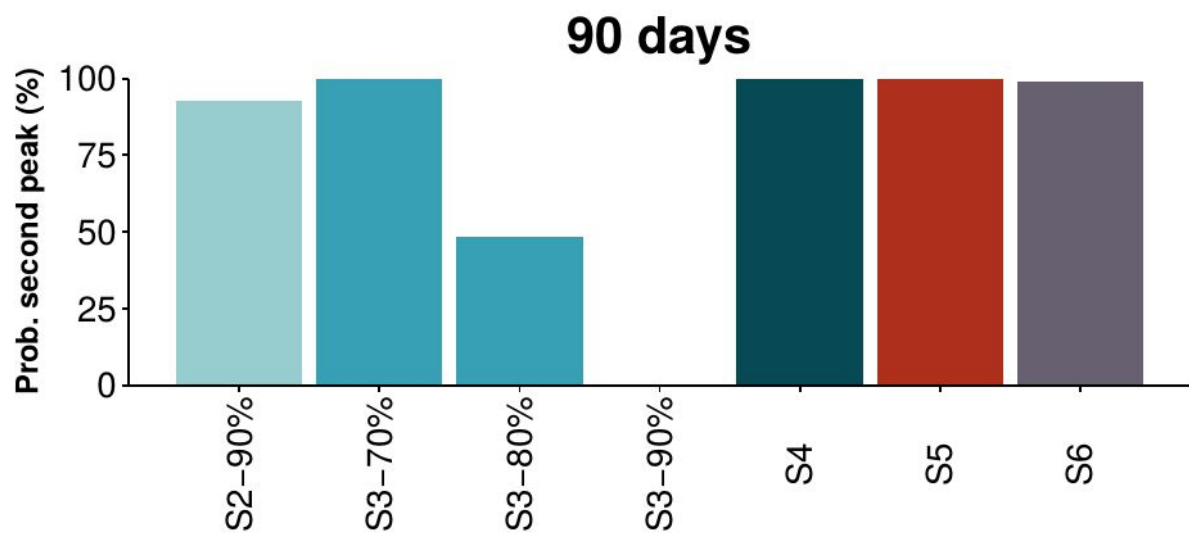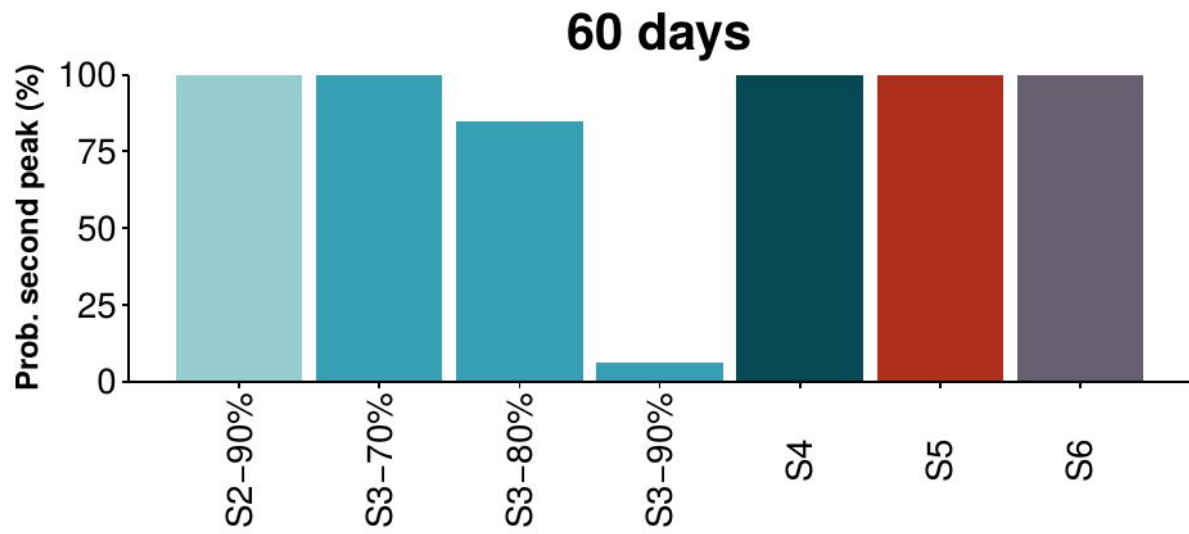
Caveats

-We do not consider age.

-Children are not present in the community layer.

-The mobility data is based towards neighborhoods with a larger amount of family households than the average.

-Currently we do not distinguish between mild and critical cases.

-There is a lot of uncertainty on the epidemic parameters, so the arrival of the peak or the duration of the restrictions cannot be taken as an exact quantity but an indication of the overall behavior.

-The population is closed.

- Co-location data does not imply concurrence

- We build schools by mixing children from the same US Census tract.

- When we implement restrictions over some places, we consider that the relationships in the others are not affected. Similarly, once restrictions are removed, we consider that the population goes back to normal, but if people are more aware, weark masks, reduce some contacts, etc… Although we can consider all these as examples of active measures rather than passive.