

# Modeling COVID-19 Prevalence in U.S. Prisons

Sam Briante<sup>a</sup>, Emma Broback<sup>a</sup>, Marcel Burgunder<sup>a</sup>, and Brandon Wolfson<sup>a</sup>

<sup>a</sup>University of California, Los Angeles

This manuscript was compiled on July 1, 2020

**This paper studies the spread of COVID-19 in a prison network created using a  $G(n, p)$  model with 3,000 nodes. Each node represents an incarcerated individual and each edge represents a point of direct contact. On this network, we simulate the spread of SARS-CoV-2 in the prison using an SIR model. In this model, we evaluate the impact of three public health intervention methods: halting new inmate intake, social distancing, and releasing individuals from the incarcerated population (1). We observe from the model that these intervention methods are effective in slowing the spread of SARS-CoV-2 by flattening the infection curve and decreasing the total number of inmates that eventually become infected.**

$G(n, p)$  model | SIR model | SARS-CoV-2 | Epidemiology | COVID-19

**D**uring the 2020 coronavirus pandemic, social distancing and stay-at-home orders have been implemented to reduce the virus' impact on various communities. However, the pandemic has exposed serious health inequities, revealing social determinants of who can stay home and reduce their risk of exposure to SARS-CoV-2, the virus that causes COVID-19. Due to overcrowding, a lack of ventilation, and unsanitary conditions, standard public health measures to mitigate the spread of SARS-CoV-2 in U.S. prisons are virtually impossible (3). Prison communities are vulnerable to sustained transmission of SARS-CoV-2 and the United States has the highest number of incarcerated individuals in the world (2). To reduce transmission rates in U.S. prisons, public health officials recommend halting new inmate intake and releasing incarcerated individuals from the prison population (4). This research paper creates a model of a standard U.S. prison as a theoretical  $G(n, p)$  network of individuals, where nodes represent incarcerated individuals and edges represent points of contact. By running a Susceptible-Infected-Recovered (SIR) model on this network, the edges become possible points of transmission of SARS-CoV-2. Hence, our model studies the spread of COVID-19 in a standard U.S. prison. We further integrate the aforementioned intervention methods in order to assess how effective they are in reducing COVID-19 prevalence.

## The Model

Using Python, we modeled the spread of SARS-CoV-2 by creating a compartment SIR model with the Epidemics on Networks (EoN) package (5), and simulated it on a  $G(n, p)$  network using the NetworkX package (6). The exact parameters used will be discussed later, and the source code for our model is attached to the end of this paper as an appendix.

Given a prison of 3,000 individuals, we modeled the population as a random network, where nodes represent incarcerated individuals and edges represent contacts where transmission of the virus is possible. Note: this model only considers the incarcerated individuals, and does not take into account those who work at the prison but are not incarcerated. We used a  $G(n, p)$  model of the network (this just fixes a number of nodes  $n$ , and determines the existence of any edge with a fixed probability  $p$ ). While a  $G(n, p)$  model significantly reduces modularity in a network, we assumed this would minimally affect the results, as chance of contact, and hence exposure to the virus, is very high in U.S. prison environments. To account for the modularity and the heterogeneity we considered modeling our network on a Stochastic Block Model. However, on a lower level, this would have made our project and its underlying code far more complex, tedious, and time consuming. Hence, for the purposes of this project we accepted the simplicity and assumptions of the  $G(n, p)$  model. Note that the generated  $G(n, p)$  graph was kept consistent for all experiments.

To model the infection spread in this network, we used the function "fast\_SIR" from the EoN package, which takes

### Significance Statement

As the novel coronavirus spreads throughout the world, it is crucial that institutions like U.S. prisons understand their potential for becoming epidemic hot spots and know measures that can be taken to mitigate the virus' spread. Our model displays how rapidly coronavirus can spread in a contained environment, and how critical interventions can be in minimizing its impact. The United States has the highest amount of incarcerated individuals in the world (2); hence, many are vulnerable to becoming infected with the virus. The model from this paper can be used to inform policymakers on the effectiveness of public health interventions in U.S. prisons, thus, decreasing the virus' toll on both the U.S. prison and general populations.

parameters such as recovery rate, transmission rate, and initial number infected. This function runs a stochastic simulation of an SIR model and records how many people are susceptible, infected, and recovered at each time. In short, the SIR model is a time-dependant epidemic infection spread model that partitions the population into either susceptible, infected (and contagious), or recovered (removed) groups. Notably, this model assumes that those who are infected and fall into the recovered class are never susceptible to the virus again. While there is little known about long-term immunity to SARS-CoV-2, there is evidence suggesting that short-term immunity exists, resulting in minimal impact on the model and its findings over a short period of time.

To make the model more realistic, we introduced a system by which individuals are added to and released from the prison population after each time step; we call this rate the background inmate turnover (see "Prison Data & Parameters" section). This is to account for regular discharges and intake of individuals into the incarcerated population. We assume that admitted and released inmates can be from any compartment (SIR). Admitted inmates have states that reflect the distribution of susceptible, infected, and recovered in the general U.S. population. Released inmates are selected randomly. The intake and release rate are the same, to keep the total population of the prison constant. Additionally, each added inmate is connected to each other inmate with probability  $p$ .

With coronavirus spreading rapidly through U.S. prisons, policymakers and public health officials are implementing various intervention methods. We modeled three main intervention methods: halting new inmate intake (stopped-intake intervention), social distancing (social distancing intervention), and a one-time release of incarcerated individuals from the network (one-time release intervention). We chose these intervention methods as they have been advocated for by many prison reform groups and implemented by governments California and other states (3). First, we ran a control simulation where no interventions occur. Then, we ran a set of simulations with the stopped-intake and social distancing interventions. Third, we ran a set of simulations with the stopped-intake, one-time release, and social distancing interventions. All intervention methods occur once 100 individuals in the network become infected (see "Results" section for more on this).

New inmates added to our prison are either susceptible, infected, or recovered in proportion to the general population, discussed further in the "Prison Data & Parameters" section. These proportions are kept constant. Thus, in the first set of simulations, with stopped-intake and social distancing interventions, infected individuals from outside the prison are prevented from entering. Also, this intervention prevents susceptible individuals from being introduced into the network, which would lead to higher transmission of the virus. In the second set of simulations, with the release and social distancing interventions, the population of the prison is reduced. During all simulations, we assume that  $p$  value of the network remains constant. A constant  $p$  value and decreasing population size imply that the average degree of nodes in the network will decrease, meaning fewer individuals in the population will be in contact with each other, reducing transmission.

Our model also measures the number of coronavirus-related deaths. To measure the number of deaths, we take a fraction of the recovered population and convert them to dead. However, we account for the inmate turnover to ensure that dead inmates are not added or released. Note, calculating deaths in this way assumes that the recovery rate and time-until-death rate (one over the average time from COVID-19 infection to death) are equivalent.

Many prisons have implemented the stopped-intake and one-time release interventions in order to make social distancing measures more feasible. We implement the social distancing intervention by reducing the disease's transmission rate, since social distancing reduces the likelihood of infection spread between two individuals. We examine a variety of different levels of social distancing in order to determine at which level is most effective.

An important thing to note is that the "fast\_SIR" algorithm produces data based on a single realization of the network spread (i.e. it is stochastic). This makes anomalies more common which is undesirable. Ideally, we could take the sample means of many different simulations of spread. However, this would have been a large undertaking, and for the simplicity of this project we'll accept our analysis of a single realization.

The general assumptions of our model are summarized below:

- The pandemic outside the prison doesn't change (i.e. distribution of susceptible, infected and recovered are constant)
  - This isn't realistic, however, this assumption will probably make little to no difference on the outcome of our model since since no new inmates are admitted after a certain threshold which is reached early on. The differences are probably barely measurable and don't change our analysis on what happens in the prison after the intervention.
- Numbers of inmates being added and released are constant and equal (except after stopped intake intervention).
  - While these numbers are fluctuating in reality, they are probably small, and wouldn't affect our model. Our results also indicate that the inmate turnover is so minimal that it has little effect.
- Inmates are isolated once they show symptoms.

- Our recovery rate represents the amount of time it takes for an infected individual to show symptoms. We assume that once an inmate shows symptoms they will be isolated and unable to infect other inmates. Thus, they are converted to the recovered state at this time.
- Recovery rate is the same as time-until-death rate.
  - Because we remove our dead inmates from the recovered compartment, once inmates show symptoms they are either converted to recovered or dead. In reality, inmates would be put in isolation after they show symptoms, and then die some time after that.
- Prison staff (i.e. people in prisons that aren't incarcerated) do not affect the system in any way.
  - This is definitely a simplification of the real world prison system, but accounting for it would be difficult and require a different network than our  $G(n, p)$ . For this project, we figured this assumption won't affect our results too much.
- Recovered individuals cannot become susceptible again.
  - Unfortunately, this may not be true, as the scientific community is still learning a lot about immunity to COVID-19. However, experts have estimated that immunity may last anywhere from three to six months (7). Given the time scales measured in our model, it is fair to assume no individual in the network will become susceptible again.
- Parameter assumptions; specifics on this are mentioned in the "Prison Data & Parameters" section below.

### Prison Data & Parameters

For our  $G(n, p)$  model we used a population size of  $N = 3000$  and an edge probability of  $p = 0.02$ , because, based on the likelihood of sharing bathrooms, dorm-style facilities, and the constant contact with others, an inmate can have, on average, 60 contacts per day (8). We assume that these parameters remain constant throughout our simulations.

We assume a background inmate turnover of 20 inmates. This means that, at each integer-valued time, 20 inmates are released from prison and 20 new inmates are admitted. The number 20 was chosen semi-arbitrarily, as 20 inmates being admitted and released each day from a prison of 3000 seems reasonable. More research is needed to pick a more accurate number. We release 500 inmates during the one-time release intervention; note, that this is a much greater release proportionally than we have observed prison administrators implement. We selected this number to examine the effects of a much larger release, but we also tested numbers much lower than 500, and close to actual inmate release numbers, but noticed that they made no significant difference.

From the UCLA Law COVID-19 Behind Bars Data Project, we estimate that the death rate of COVID-19 for individuals in prisons is 1.2% (9). Our transmission rate is set to 3% (denoted as  $\tau$ ) in the EoN package (10). In our model, we set the recovery rate ( $\gamma$ ), to 7%, assuming an infectious period of 14 days (11). We run our model for 60 time steps and the model begins with one infected node.

When we add new inmates from the general population we estimate that 0.35% of them will be infected (percent\_infected) and 0.15% of them will be recovered (percent\_recovered) based on the proportions of the general U.S. population that are infected and recovered (12).

The parameters discussed here, except those relating to the interventions, are held constant throughout all our experimental trials, see Table 1.

Parameter	Value
background_inmate_turnover	20
# of initial infected	1
death_rate	$1.2 \times 10^{-2}$
$\tau$	$3 \times 10^{-2}$
$\gamma$	$7 \times 10^{-2}$
max_time	60
$N$	3000
$p$	$\frac{1}{50}$
percent_infected	0.35%
percent_recovered	0.15%

**Table 1. Constant parameters. Note, when the interventions are enacted, they may affect the parameters listed. For example, the social distancing intervention updates  $\tau$  to reflect the lowered transmission rate.**

## Results

We explore the effects of three intervention methods on the spread of SARS-CoV-2 in a U.S. prison. The three methods we apply are: stopping the intake of any new inmates (stopped-intake intervention), implementing social distancing (social distancing intervention), and a one-time mass release of inmates (one-time release intervention). In our experiments, we explore 3 different cases:

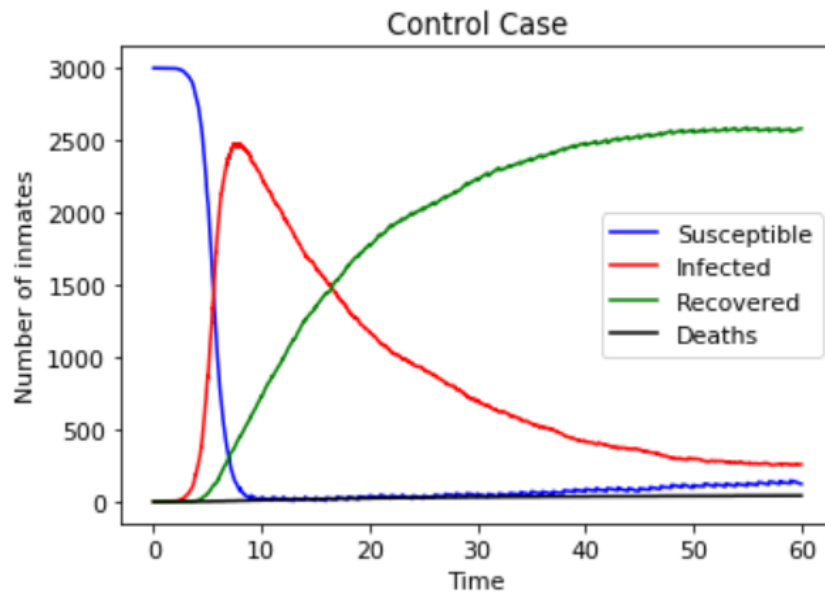
1. Control case: no interventions occur.
2. Intervention A: stopped-intake and social distancing interventions.
3. Intervention B: one-time release, stopped-intake, and social distancing interventions.

The parameters we vary in each case are summarized in [Table 2](#). Additionally, for the intervention cases, we introduce the interventions at the next integer-valued time after 100 infections have occurred.

Experiment	Release Number	Transmission rate after Intervention	Stop Intake
Control	0	unchanged	No
A1	0	$\tau/2$	Yes
A2	0	$\tau/4$	Yes
A3	0	$\tau/8$	Yes
B1	500	$\tau/2$	Yes
B2	500	$\tau/4$	Yes
B3	500	$\tau/8$	Yes

**Table 2. Experimental overview.** The "A" cases use the stopped-intake intervention and try three different levels of social distancing. The "B" cases release 500 inmates, in addition to doing the interventions of the "A" cases.

**Control Case.** In the control case, no interventions are employed. The resulting plot is shown in [Figure 1](#).



**Fig. 1.** Plot of control case. Plot shows number of susceptible, infected, recovered, and dead inmates as a function of time in days.

**Intervention A.** For intervention A, the stopped-intake and social distancing interventions are employed.

- Intervention A1: When the interventions are enacted, the transmission rate is halved, i.e.  $\tau/2$ . The resulting plot is shown in [Figure 2](#).

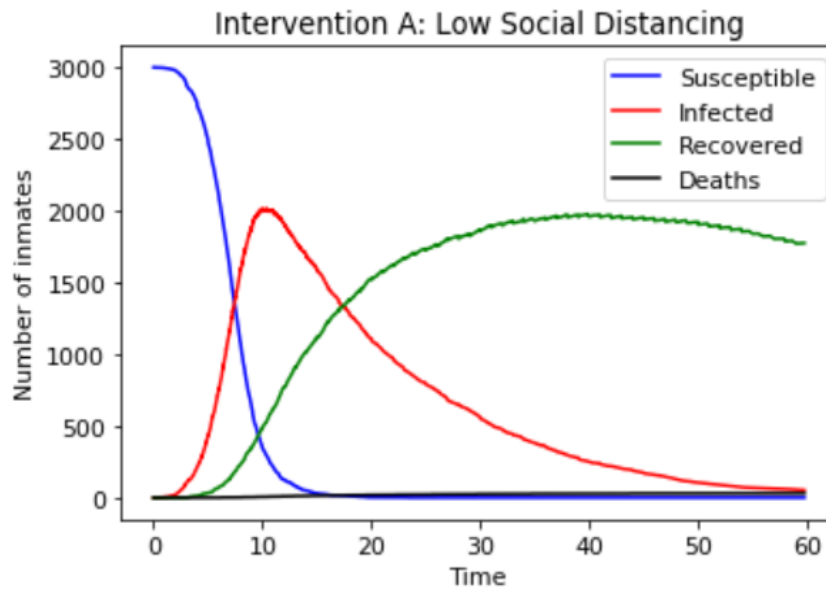


Fig. 2. Plot of Intervention A1. Plot shows number of susceptible, infected, recovered, and dead inmates as a function of time in days.

- Intervention A2: When the interventions are enacted, the transmission rate is quartered, i.e.  $\tau/4$ . The resulting is shown in Figure 3.

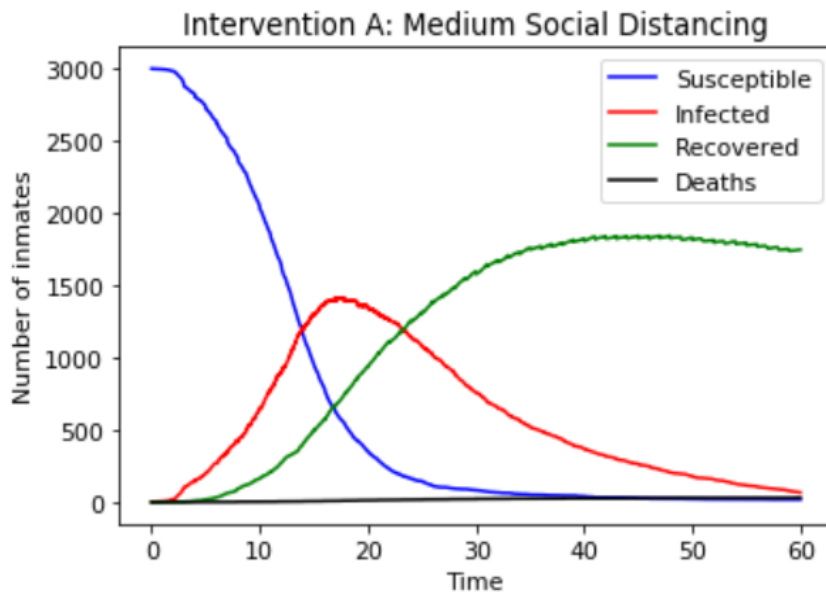


Fig. 3. Plot of Intervention A2. Plot shows number of susceptible, infected, recovered, and dead inmates as a function of time in days.

- Intervention A3: When the interventions are enacted, the transmission rate is divided by 8, i.e.  $\tau/8$ . The resulting plot is shown in Figure 4.

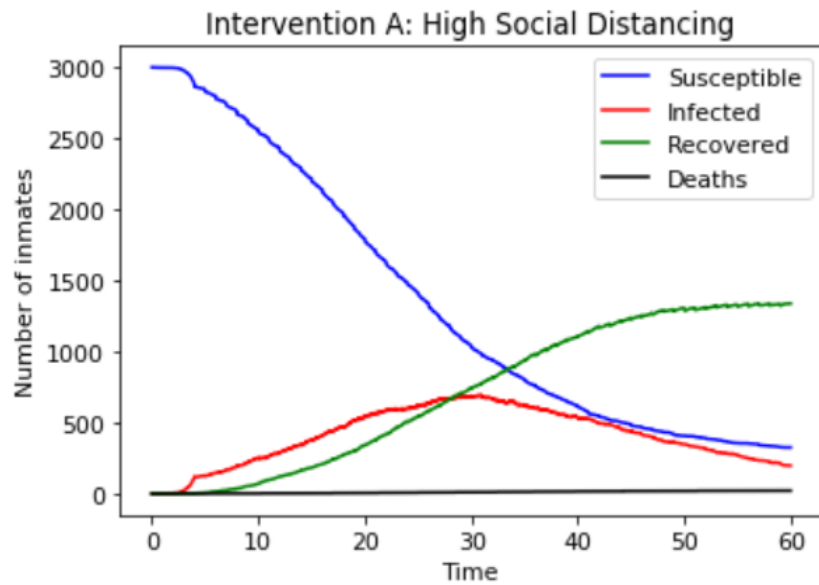


Fig. 4. Plot of Intervention A3. Plot shows number of susceptible, infected, recovered, and dead inmates as a function of time in days.

**Intervention B.** For intervention B cases, the one-time release, stopped-intake, and social distancing interventions are all employed.

- Intervention B1: When the interventions are enacted, the transmission rate is halved, i.e.  $\tau/2$ . The resulting plot is shown in Figure 5.

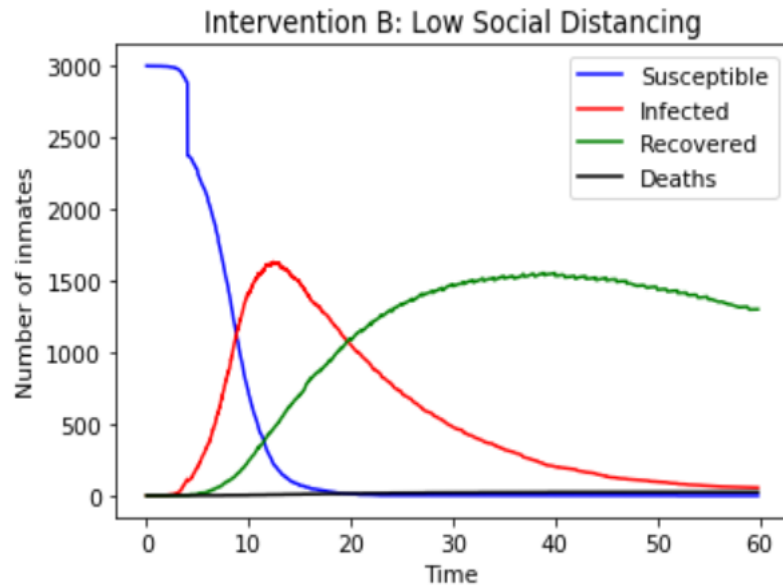


Fig. 5. Plot of Intervention B1. Plot shows number of susceptible, infected, recovered, and dead inmates as a function of time in days.

- Intervention B2: When the interventions are enacted, the transmission rate is quartered, i.e.  $\tau/4$ . The resulting plot is shown in Figure 6.

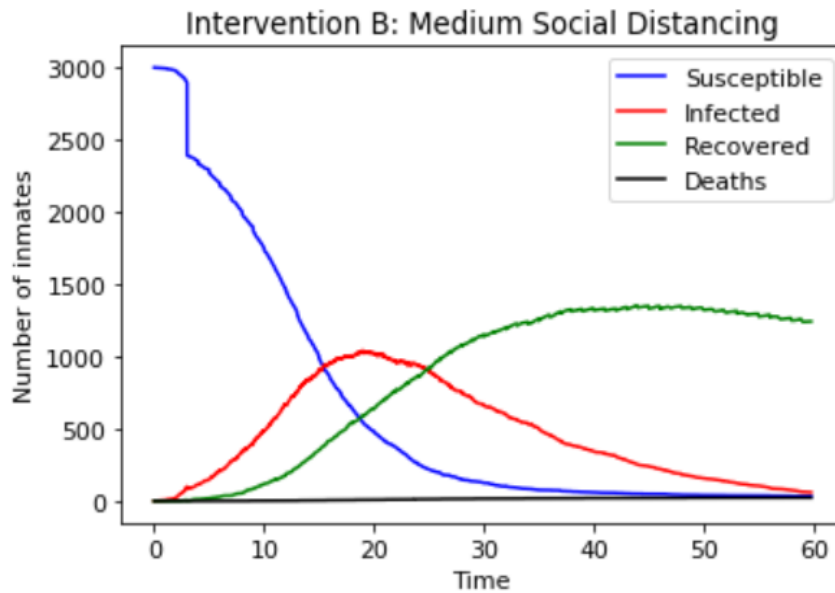


Fig. 6. Plot of Intervention B2. Plot shows number of susceptible, infected, recovered, and dead inmates as a function of time in days.

- Intervention B3: When the interventions are enacted, the transmission rate is divided by 8, i.e.  $\tau/8$ . The resulting plot is shown in [Figure 7](#).

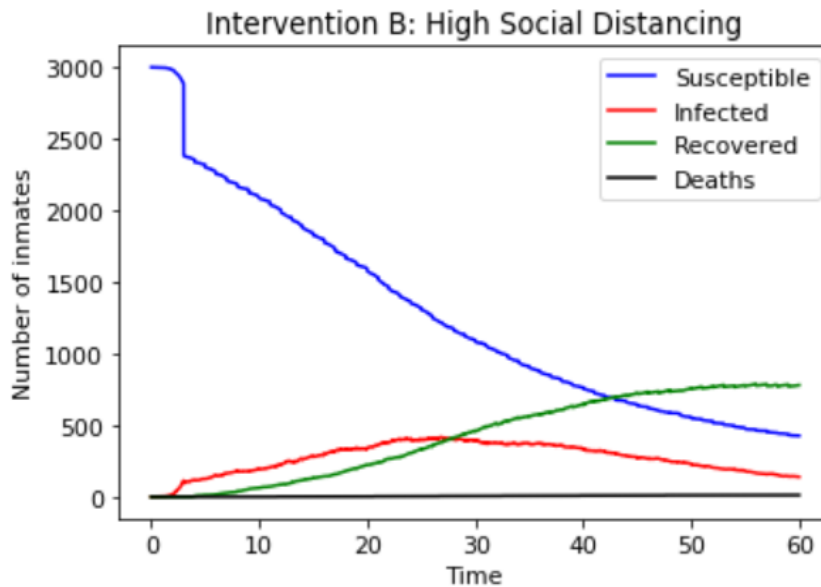


Fig. 7. Plot of Intervention B3. Plot shows number of susceptible, infected, recovered, and dead inmates as a function of time in days.

We summarize the results of the experiments, analyzing total infections, deaths, and time when the infection peaks, see [Table 3](#).

### Discussion

Our Control case gives us a baseline to compare the effects of the various intervention strategies. In the control case, infections peak at time 7.48, with a total of 3922 infected. From the plot, we can see that infections increase very quickly and then die out as people recover, see [Figure 1](#). Additionally, we can infer that all inmates eventually become infected.

Comparing the control case to our plots for intervention A, we can see that, by implementing greater social distancing measures, the peak of infections is delayed, see [Figure 1](#), [Figure 2](#), [Figure 3](#), and [Figure 4](#). This means that social distancing

Experiment	Number of Infected at Intervention	Total Infections	Death Toll	Time of Infection Peak
Control	N/A	3922	41	7.48
A1	102	2900	31	9.99
A2	102	2763	30	17.39
A3	116	2131	21	30.82
B1	115	2398	25	12.37
B2	100	2199	23	18.96
B3	114	1397	13	26.75

**Table 3. Summary of results.** "Number of Infected at Intervention" refers to the number of infected inmates at the time the interventions were enacted. "Total Infections" refers to the total number of inmates infected by the virus over the course of the simulation. "Death Toll" refers to the total number of inmates that die over the course of the simulation. "Time of Infection Peak" refers to the time of the simulation at which the number of current infections was at its maximum.

effectively flattens the curve. Halving the transmission rate delays the peak to time 9.99, and then halving it twice more delays the peak to times 17.39 and 30.82, respectively. This suggests that the relationship between the reduced transmission rates and the effective "flattening" is inversely proportional, with a complexity somewhere between linear and  $\log_2$ . We see this same pattern in our intervention B plots, see [Figure 5](#), [Figure 6](#), and [Figure 7](#).

It should be noted that, while social distancing effectively flattens the curve, even when the transmission rate is halved or quartered we can still expect all inmates to get infected. It's only after lowering the transmission rate to  $\frac{1}{8}$  of the original that we get some indication that the infection has been contained. In the experiments that we do this, while we cannot see the end of the pandemic on our graph, we can see that the slope at time 60 is more negative for the infected line than for the susceptible line, see [Figure 4](#) and [Figure 7](#). This suggests that, post-pandemic, we'd observe some individuals that never got infected. This indicates that reducing the virus' transmission rate to  $\frac{1}{8}$  of the original is a good lower bound for how effective our social distancing must be in order to eradicate the virus without yielding herd immunity.

Additionally, intervention B is far more effective than intervention A, given the additional release of 500 inmates. Since most inmates are susceptible at the time the interventions are enacted, most of the inmates released during the one-time release intervention are susceptible. This aligns with our empirical data, that between Intervention A1 and B1 we have a difference of  $2900 - 2398 = 502 \approx 500$  infected and between Intervention A2 and B2 we have a difference of  $2763 - 2199 = 564 \approx 500$ , see [Table 3](#). The only difference between these experimental cases is that 500 inmates are released at the intervention in Intervention B cases, see [Table 2](#). Notably, the times of infection peaks are practically the same (and in the case of A3 and B3, even sooner), with or without the one-time release intervention, for any particular level of social distancing, see [Table 3](#). This suggests that releasing inmates mainly just protects those inmates that are released, but does not help flatten the curve. However, we must also note that higher levels of social distancing are only possible when the prison population is reduced. At their normal occupancy, prisons are simply too crowded to allow high levels of social distancing. Hence, while the one-time release intervention may not directly flatten the curve, indirectly, it allows for greater levels of social distancing which do flatten the curve.

It should be noted that the relative background inmate turnover is so low that intake (or lack thereof) makes little impact on our conclusions. However, since everyone in the prison is likely to become infected (in most cases), stopping the inflow of inmates prevents new inmates from being introduced to a prison where the virus is rampantly found. This explains why the number of infected drops drastically from the control case to any intervention strategy, see [Table 3](#); in intervention A1, for example, the time of the peak is delayed by only 2.5 time steps but the number of infections drops from 3922 to 2900. This disparity comes mainly from the fact that no new inmates are being admitted to the prison. In the control case, observe that the prison only has 3000 inmates at any time, but there are 3922 total infections. This is because new inmates, who are most likely susceptible, are constantly being added to the prison and becoming infected. Hence, stopping inflow of inmates is an extremely effective measure in protecting many to-be-incarcerated individuals from getting the virus, but less effective in reducing the spread of the virus in the prison.

## Conclusion

Through our simulations, we learned about the mechanisms that make each of the interventions we tried effective. Stopping inmate intake works primarily by preventing new, susceptible would-be-inmates from being thrust into the virus-overrun environment of a prison and getting infected. Assuming they are safer outside the prison, major one-time releases of inmates can protect released inmates from the massive infections that will occur in the prison. Additionally, if enacted when the number of infections are low, one-time releases will release mostly susceptible inmates. However, our most significant discovery is that only social distancing will effectively flatten the curve. High levels of social distancing are only possible when prisons are less crowded. This means that interventions like stopping inmate inflow and major one-time inmate releases also have the indirect benefit of allowing greater social distancing.

In conclusion, stopping inmate inflow and major one-time inmate releases are useful in their own right, but their greatest



benefit comes from allowing high levels of social distancing to be enacted. This helps flatten the curve and can prevent SARS-CoV-2 from infecting everyone in a prison population. Hence, our experiments support the use of stopping inmate inflow, major one-time inmate releases, and high levels of social distancing in order to dramatically reduce the number of infections and deaths due to COVID-19 in U.S. prisons.

## References

1. PP Initiative, Criminal justice responses to the coronavirus pandemic. *Crim. justice responses to coronavirus pandemic | Prison. Policy Initiative* (year?).
2. What percent of the u.s. is incarcerated? (and other ways to measure mass incarceration) (Available at <https://www.prisonpolicy.org/blog/2020/01/16/percent-incarcerated/>) (2020).
3. ACLU, Flattening the curve: Why reducing jail populations is key to beating covid-19 (Available at <https://www.aclu.org/report/flattening-curve-why-reducing-jail-populations-key-beating-covid-19>) (2020).
4. D Morse, J Jouvenal, Inmates sharing showers and cells say social distancing isn't possible in maryland prisons. (2020).
5. J Miller, T Ting, Eon (epidemics on networks): a fast, flexible python package for simulation, analytic approximation, and analysis of epidemics on networks. *J. Open Source Softw.* 4, 1731 (2019).
6. AA Hagberg, DA Schult, PJ Swart, Exploring network structure, dynamics, and function using networkx in *Proceedings of the 7th Python in Science Conference*, eds. G Varoquaux, T Vaught, J Millman. (Pasadena, CA USA), pp. 11 – 15 (2008).
7. BL Jr., Dr. antony fauci says there's a chance coronavirus vaccine may not provide immunity for very long. (year?).
8. SA Josiah Rich, Opinion | we must release prisoners to lessen the spread of coronavirus. *The Wash. Post* (2020).
9. S Dolovich, Ucla law covid-19 behind bars data project (Available at [https://law.ucla.edu/centers/criminal-justice/criminal-justice-program/related-programs/covid-19-behind-bars-data-project/?fbclid=IwAR0rLWWud7ASR74j1mGLq-DoRWKkHBNTdcRqWPJFwrhfb9H\\_qpI1q6e-t0](https://law.ucla.edu/centers/criminal-justice/criminal-justice-program/related-programs/covid-19-behind-bars-data-project/?fbclid=IwAR0rLWWud7ASR74j1mGLq-DoRWKkHBNTdcRqWPJFwrhfb9H_qpI1q6e-t0)) (2020).
10. MA Otto, Covid-19 update: Transmission 5% or less among close contacts (2020).
11. CDC, Interim clinical guidance for management of patients with confirmed coronavirus disease (covid-19) (Available at <https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-guidance-management-patients.html>) (2020).
12. Worldometer, United states coronavirus (Available at <https://www.worldometers.info/coronavirus/country/us/>) (2020).

## Appendix

The source code for our project can be found [here](#). Exact link:

<https://github.com/bwolfson97/UCLA-Networks-Final-Project>