Decision support model for epidemic-related public transportation restrictions

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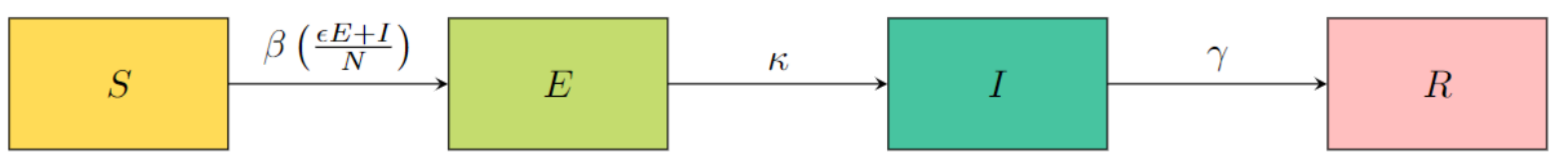
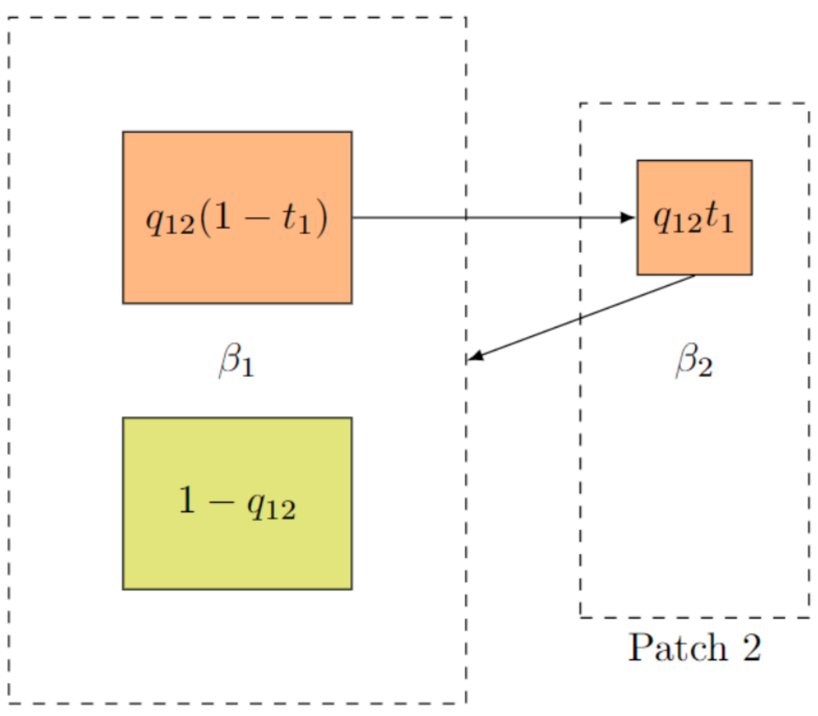
Background

- The COVID-19 pandemic caused extreme drops in public transportation ridership for long periods of time, and many transportation agencies faced unprecedented revenue losses resulting in employee lay-offs and reduced services [1][2].
- Public transportation service reductions disproportionately affected already vulnerable populations [3].
- This model is a flexible tool for designing public transportation restriction policies for future viral epidemics, and it is applicable for a wide range of policy prioritization strategies.

Methods

Two-patch ODE model with Lagrangian mobility





Two patches with different infection risks:

- Patch 1 is the home environment (home, work, school)
- Patch 2 is the transportation environment (bus, subway car)

- q_{12} = proportion of population which uses public transportation
- t_1 = proportion of time each rider spends on public transportation

$$\dot{S} = (1-q_{12})\left(-\beta_1 S\left(\frac{\epsilon E+I}{N}\right)\right) + q_{12}\left(-(1-t_1)\beta_1 S\left(\frac{\epsilon E+I}{N}\right) - t_1\beta_2 S\left(\frac{\epsilon E+I}{N}\right)\right),$$

$$\dot{E} = (1-q_{12})\left(\beta_1 S\left(\frac{\epsilon E+I}{N}\right)\right) + q_{12}\left((1-t_1)\beta_1 S\left(\frac{\epsilon E+I}{N}\right) + t_1\beta_2 S\left(\frac{\epsilon E+I}{N}\right)\right) - \kappa E,$$

$$\dot{I} = \kappa E - \gamma I,$$

$$\dot{R} = \gamma I.$$

Modeling transportation restrictions

Three variables of interest describe the restriction:

- day the restriction is implemented
- length of the restriction (l)
- strength of the restriction (ρ)

We explore the impact of varying the proportion of the population using public transportation (q_{12}).

Cost framework

Cost is calculated for the total amount of lost potential revenue for the duration of the restriction(s):

$$C = \phi\rho q_{12} N l$$

$$C_{total} = \phi q_{12} N(\rho_1 l_1 + \rho_2(1-\rho_1) l_2)$$

Social vulnerability framework

We use a modified version of the CDC Social Vulnerability Index to calculate traits (S) in the population caused by restrictions:

- a is the prop. of the population that will lose their only vehicle
- b is the prop. of the a population that will face unemployment
- c is the prop. of the ab population that will face housing cost burden

$$S = q_{12}N(a+ab+abc)(\rho_1 + \rho_2(1-\rho_1))$$

Results

Case study: COVID-19-like outbreak in Ithaca, NY

Effects of restriction parameters on final epidemic size

Fig. 1

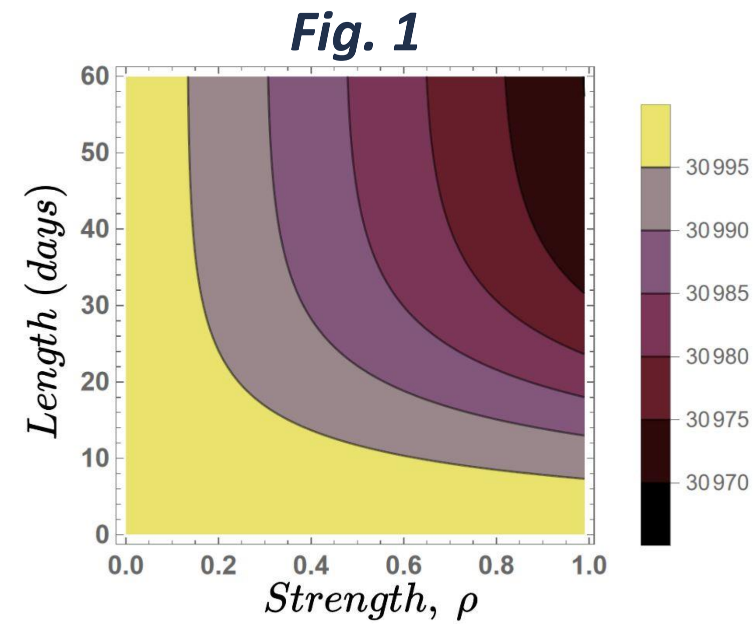
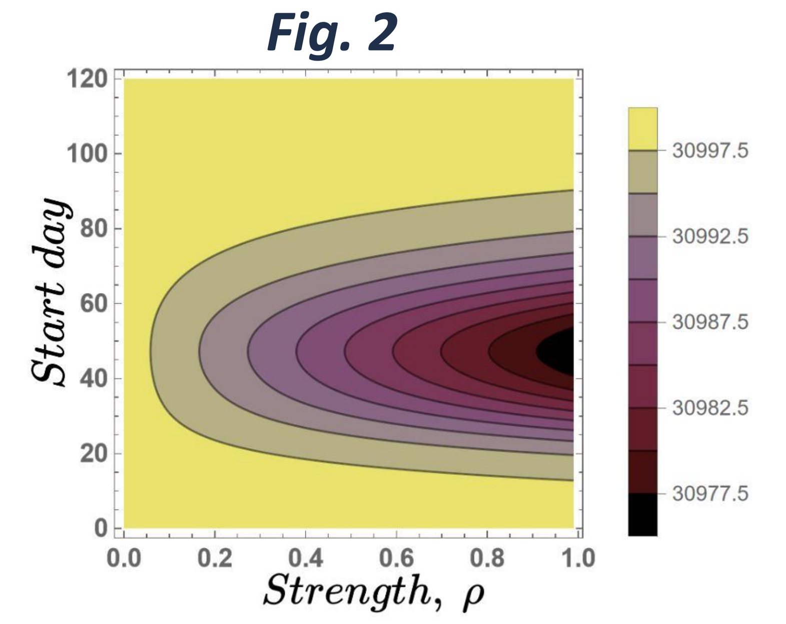


Fig. 2



Figs. 1-3 show the effects of the restriction strength, length, and start date on the final epidemic size.

Fig. 3

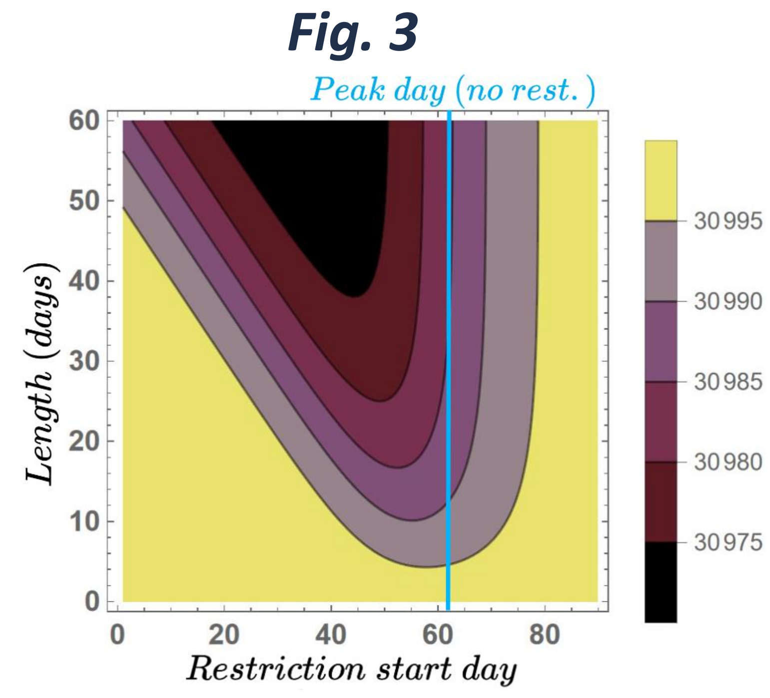


Fig. 4

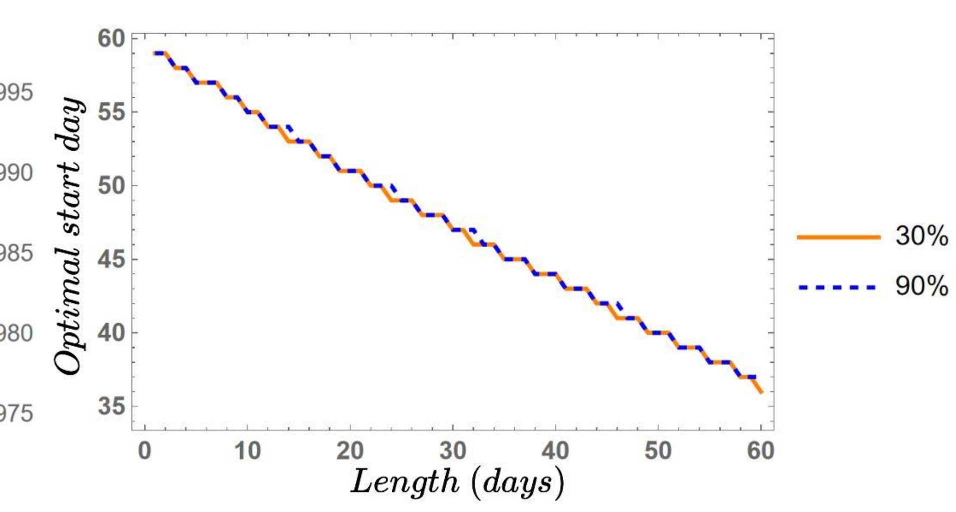
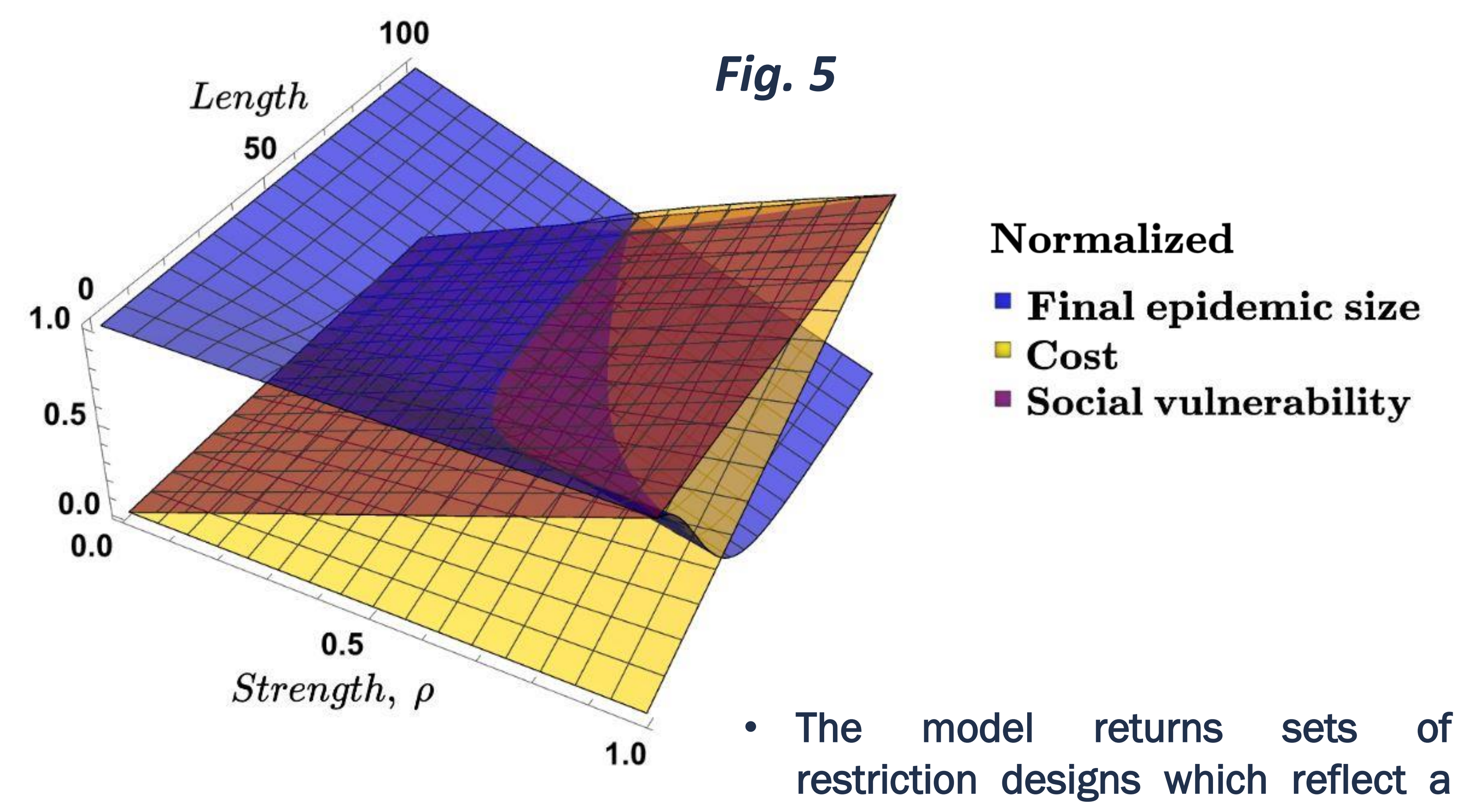


Fig. 4 shows that the most effective start date is almost entirely a function of the length of the restriction, not of the strength.

Combining the analysis metrics

Fig. 5



- The model returns sets of restriction designs which reflect a wide range of priorities (such as minimizing cost, minimizing length, etc).
- Fig. 5 shows the full range of restriction design possibilities and their associated relative final sizes, costs, and SV traits. The model assumes that the most effective start date is used.
- Fig. 6 shows a few restriction designs for Ithaca if the policymakers' goal is to minimize final size and cost.

Length in days (l)	Strength (ρ)
25	1.0
32	0.68
62	0.61
100	0.50

Fig. 6

Future work

- Adding behavioral complexity and increased population heterogeneity to the model
- Making Patch 2 infection risk vary to represent changes in rider density, cleaning frequency, etc.
- Adding a spatial network component or more patches to represent specific public transportation routes and Patch 1 environments
- Calibrating the SEIR parameters with a historical outbreak in a city and using the model to compare actual and ideal public transportation responses

References

[1] S. Subbarao and R. Kadali, "Impact of COVID-19 pandemic lockdown on the public transportation system and strategic plans to improve PT ridership: A review," *Innovative Infrastructure Solutions*, vol. 7, p. 97, 2022. doi: 10.1007/s41062-021-00693-9.

[2] C. Goldbaum, "M.T.A. warns of doomsday subway cuts without 12 billion in federal aid," *The New York Times*, Aug. 2020. [Online]. Available: https://www.nytimes.com/2020/08/26/nyregion/nyc-subway-bus-service-cuts.html

[3] A. Kar, A. L. Carrel, H. J. Miller, and H. T. K. Le, "Public transit cuts during COVID-19 compound social vulnerability in 22 us cities," *Transportation Research Part D: Transport and Environment*, vol. 110, p. 103 435, 2022. doi: 10.1016/j.trd.2022.103435.

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