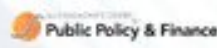


Webinar: The benefits of targeted COVID-19 policies

WITH DARON ACEMOGLU
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

Friday, May 8, 12:30 PM ET
Pre-Registration Required



PRINCETON ECONOMICS



Intro: MARKUS BRUNNERMEIER

Twitter: @MarkusEconomist

Markus' intro

- Previous/future webinars
 - Ramanan Laxminarayan:
 - Daron Acemoglu:
 - Jeremy Stein

Epidemiology models

On the benefits of targeted policies

Fed-Treasury credit programs

- Speakers



Ramanan Laxminarayan

- <https://www.youtube.com/watch?v=z1yHjM7szBk>

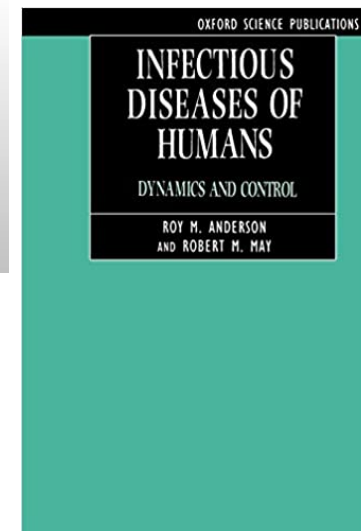
IndiaSIM: Agent-based model?

- Multiple sites of introduction through incoming passengers
- Population structure
 - District Level Household Survey (updated with latest NFHS data and census)
 - 67 regions representing 34 states rural and urban regions
 - Heterogeneity by region, household (e.g., wealth) and individual characteristics
- Heterogeneous mixing
 - Understand effect across demography and geography



cddep.org

Leading textbook



- Agent based models to capture behavioral response
- Expectations play limited role

Anderson
& May

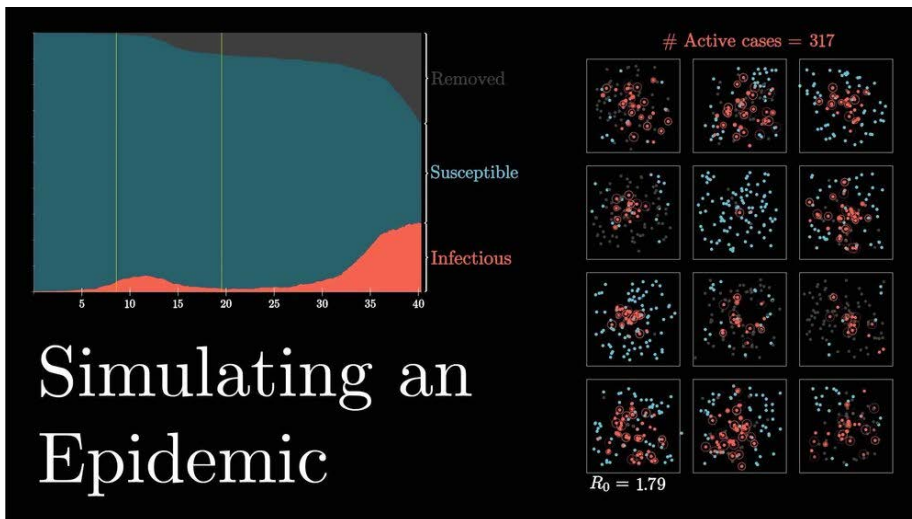
Nice simulations

- 3blue1brown:
Grant Sanderson

<https://www.youtube.com/watch?v=gxAaO2rsdls>

- Random Corporation

<https://www.rand.org/pubs/tools/TLA173-1/tool.html>



Location: New York

Choose a location.

New York

Current intervention level: 5

New York currently has policies in place that most closely match a level 5 intervention.

New intervention level: 5

Choose an intervention strength.



New intervention start date: May 8

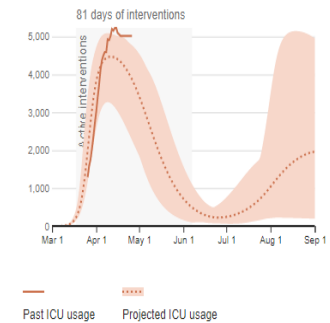
Choose the date when New York will move to intervention level 5. Assumes an end date of June 6 for all interventions.



New York currently has policies in place that most closely match a level 5 intervention. Select another intervention level to see projected outcomes.

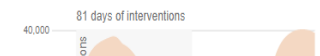
September 1.

Demand for ICU beds with current intervention



2,000 projected demand for ICU beds on September 1.

Demand for hospital beds with current intervention



Ex-ante vs. ex-post targeting

- Trade-off: Ex-ante vs. ex-post targeting (flexibility)

- German “emergency break”

- “Regional targeting” in Germany
- Lockdown region if
 - More than 50 out of 100,000 inhabitants
 - Infected within a week



- Enforceability? Incentive to monitor your neighbor?

Ethics: Statistical Value of Life

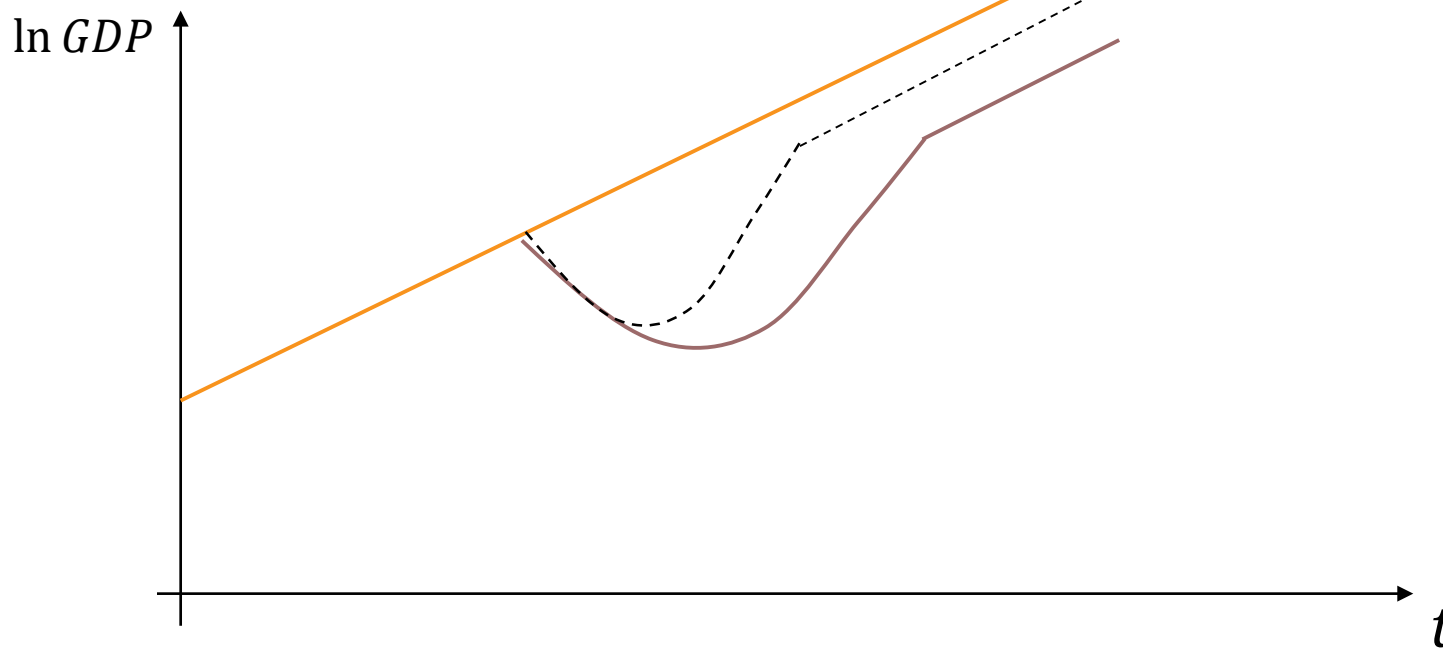
- Infer from wage difference between hazardous and non hazardous occupations
 - Impacted by risk aversion

- Should targeted policy includes
 - statistical value of life
 - Angus Deaton is critical of this concept (see earlier webinar)
 - Expected life expectancy

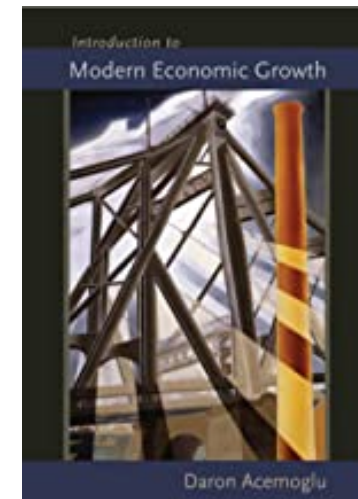
- Q: Doesn't matter since only externality (spreading virus) should be taken into account.

Epidemics & Growth

- Interact epidemic model with (endogenous) growth model
 - Across different **exit strategies**/testing
 - Paul Romer's webinar



New chapter for



End of MARKUS' INTRODUCTORY REMARKS

Now

Please ask questions in Q&A box

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A Multi-Risk SIR Model with Optimally Targeted Lockdown

Daron Acemoglu

Victor Chernozhukov

Iván Werning

Michael D. Whinston

April 2020.

Introduction

- ▶ SIR models are playing an increasingly central role in understanding and policy-making in the context of the COVID-19 pandemic.
- ▶ One of the key trade-offs is between economic and public health outcomes.
- ▶ But “optimal policy” coming from baseline models assuming homogeneous vulnerability and economic participation may be misleading.

Varieties of Heterogeneity

- ▶ Many dimensions of heterogeneity—occupation, productivity, issues related to joint labor supply.
- ▶ Risk factors are particularly important (COVID-19 characterized as two separate diseases by some medical professionals, a deadly one for older populations or those with comorbidities, and similar to seasonal flu for younger, healthier groups).

Age Group	Mortality rate
20-49	0.001
50-64	0.01
65+	0.06

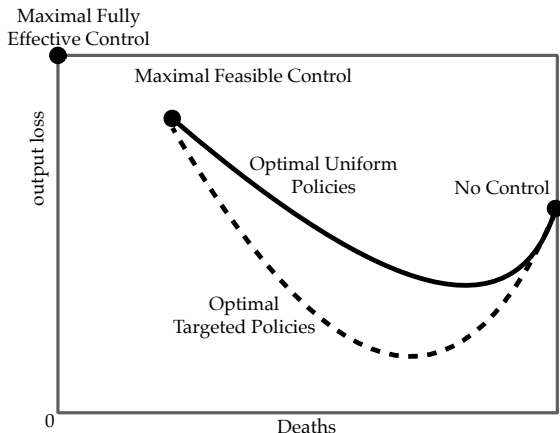
Table: Mortality rates (conditional on infection) from COVID-19.

What We Do

- ▶ Develop a multi-risk SIR model and characterize dynamics of infection in this context.
 - ▶ In practice, apply this to a setting with three groups, young, middle-aged and old (65+).
- ▶ Set up an optimal control problem for this environment—allowing targeting by group.
- ▶ Characterize and contrast optimal uniform and optimal targeted policies using parameter values from the literature for COVID-19.
- ▶ Clarify how the trade-offs change with targeted policies.

Summary of Main Findings

- ▶ Big gains and significantly improved trade-offs from targeted policy.
- ▶ Most of the gains can be realized by very simple semi-targeted policies that just treat the 65+ group differentially.



Important Caveats

- ▶ We are not epidemiologists.
- ▶ These are really sensitive topics . . .
- ▶ There is huge amount of uncertainty about both the disease parameters and the relevant economic parameters.
- ▶ We welcome comments, suggestions and criticisms.

Outline

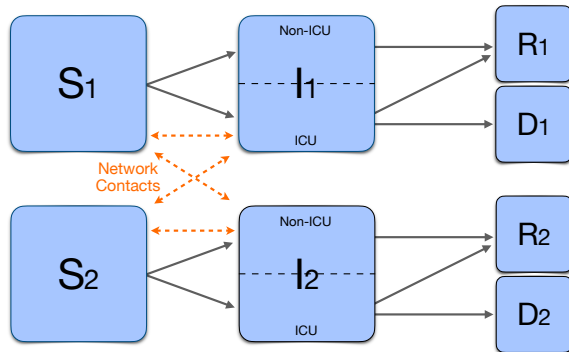


Figure: MR-SIR: Multiple-Risk Susceptible Infected Recovered Model. Solid lines show the flows from one state to another. Dashed lines emphasize interactions that take place across risk groups.

Key Equations

- ▶ In classic SIR:

$$\text{new infections} = \beta SI.$$

- ▶ In our model, absent lockdowns and isolations:

$$\text{new infections in group } j = \beta S_j \frac{\sum_k \rho_{jk} I_k}{(\sum_k \rho_{jk} (S_k + I_k + R_k))^{2-\alpha}}$$

where $\{\rho_{jk}\}$ are social contact rates between group j and k .

- ▶ Here $\alpha \in [1, 2]$ is the returns to scale in matching.
- ▶ We normalize: $\sum_j N_j = 1$.
- ▶ As usual:

$$S_j(t) + I_j(t) + R_j(t) + D_j(t) = N_j.$$

Infection Dynamics

- ▶ Before the vaccine, $t \in [0, T)$, for group j :

$$\dot{I}_j = \beta M_j (1 - \theta_j L_j) S_j \sum_k \rho_{jk} (1 - \theta_k L_k) I_k - \gamma_j I_j,$$

$$M_j = \left(\sum_k \rho_{jk} [(S_k + I_k + R_k)(1 - \theta_j L_k)] \right)^{\alpha-2},$$

where $\rho_{jk} \geq 0$ are contact coefficients and I have assumed no testing/tracing/isolation for the slides (these are allowed in the paper and quantitative analysis below).

- ▶ Employment is then given by

$$E_j(t) = (1 - L_j(t))(S_j(t) + I_j(t) + R_j(t)).$$

Parameters

- ▶ $\gamma_j = \delta_j^d(t) + \delta_j^r(t)$: exit rate from infection due to recovery or death.
- ▶ $\delta_j^d(t) = \psi_j(\text{total infections})$: probability of death for individual of type j depending on overcapacity in the hospital system.
- ▶ ρ_{ij} : social contact rate between individuals of group i and j .
- ▶ β : infection rate.
- ▶ $L_j(t)$: time-varying lockdown.
 - ▶ $L_j(t) \leq \bar{L}_j \leq 1$, where $\bar{L}_j < 1$ allows for “essential” workers.
- ▶ θ_j : effectiveness of lockdown.
- ▶ w_j : economic contribution of an individual from group j .
- ▶ χ_j : additional non-pecuniary cost of death.

An Aggregation Result

- ▶ Our MR-SIR model generalizes the standard SIR model.
- ▶ Suppose $\beta_{jk} = \beta$ and $\gamma_j = \gamma$.
- ▶ Consider uniform lockdowns $L_j(t) = L(t)$ for all j .
- ▶ Suppose further that infection rates are initially identical across groups, so that $S_j(0)/N_j$, $I_j(0)/N_j$ and $R_j(0)/N_j$ are independent of j .
- ▶ Then the model behaves identically to a homogeneous SIR model.
 - ▶ except deaths that naturally vary by group.

Optimal Control

- ▶ Social objective:

$$\min \int_0^{\infty} e^{-rt} \sum_j (w_j(N_j - E_j(t)) + \chi_j \delta_j^d(t) l_j(t)) dt$$

- ▶ $\chi_j \delta_j^d(t) l_j(t)$: non-pecuniary costs of deaths
- ▶ With vaccine (and cure) arriving at T , integration-by-parts yields

$$\int_0^T e^{-rt} \sum_j \Psi_j(t) dt, \tag{1}$$

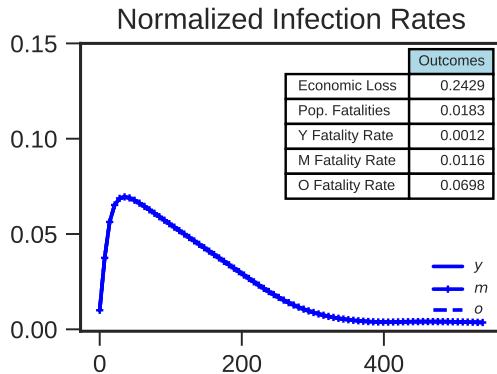
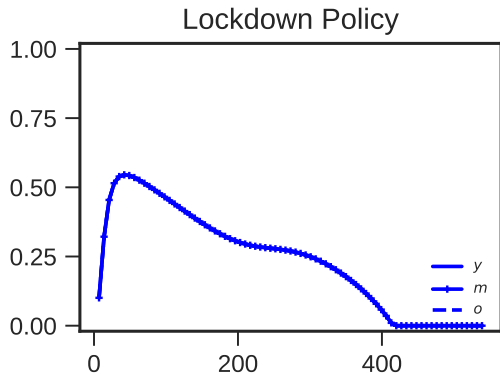
where, allowing for partial isolation of the infected and identification of the recovered, the flow cost for group j is given by

$$\begin{aligned} \Psi_j(t) = & w_j S_j(t) L_j(t) + w_j l_j(t) (1 - \eta_k (1 - L_j(t))) \\ & + w_j (1 - \kappa_j) R_j(t) L_j(t) + \left[\frac{(1 - e^{-r\Delta_j}) w_j}{r} + \chi_j \right] \delta_j^d(t) l_j(t). \end{aligned}$$

Parameter Choices

- ▶ Fatality rates (conditional on infection) from the table above.
- ▶ $N_y = 0.53$, $N_m = 0.26$, and $N_o = 0.21$.
- ▶ $w_o = 0$ and $w_y = w_m = 1$.
- ▶ $\bar{L}_o = 1$ and $\bar{L}_j = 0.7$.
- ▶ $\theta_j = 0.75$
- ▶ probabilities of detection and isolation in the baseline: $\phi_j = \tau_j = 0$
- ▶ probability of identifying recovered individuals: $\kappa_j = 1$
- ▶ $\gamma_j = 1/18$.
- ▶ $\beta\rho_{ij} = \bar{\beta} = 0.2$ (later allow $\rho_{ij} = \rho$ for $i \neq j$ where $\rho = 0.5$).
- ▶ $\delta_j^d(t) = \underline{\delta}_j^d \cdot [1 + \hat{\lambda} \cdot \text{total infections}]$. We set $\hat{\lambda}$ such that if there is a 30% infection rate in the overall population, then mortality rates are 5 times the base mortality rates.

Optimal Uniform Policy

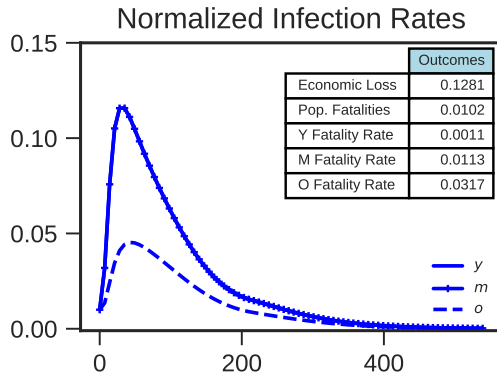
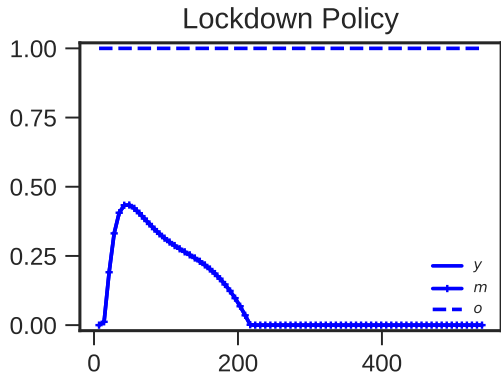


Base: Uniform Policy for $\theta = 0.75$ $\alpha = 2.0$ $\rho = 1.0$ $\chi = 20$

- ▶ Both high numbers of lives lost (1.8% of adult population) and big economic damage (24.3% of one year's GDP).

Optimal Semi-Targeted Policy

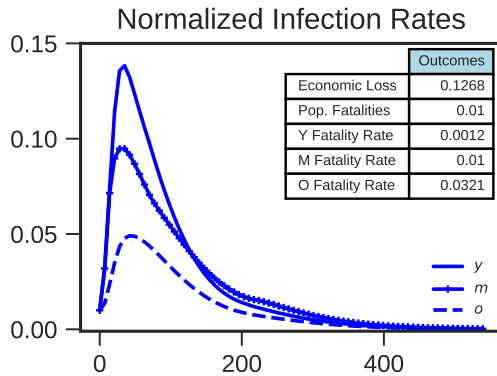
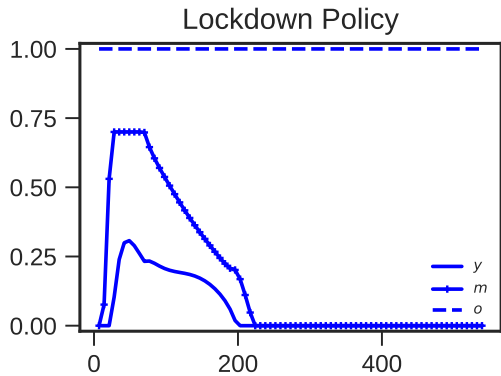
- ▶ Just applying a more strict lockdown on the oldest age group improves things significantly.
- ▶ Overall mortality rate declines from 1.8% to 1%, and economic losses decline from 24% of one year's GDP to under 13%.



Base: Semi-Targeted Policy for $\theta = 0.75$ $\alpha = 2.0$ $\rho = 1.0$ $\chi = 20$

Optimal Fully-Targeted Policy

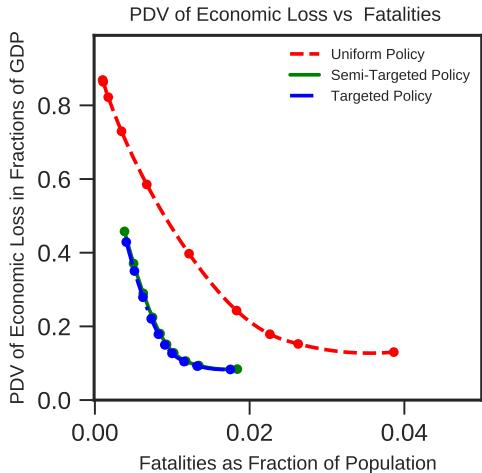
- ▶ The young and the middle-age treated differently, but small gains relative to optimal semi-targeted policy.



Base: Targeted Policy for $\theta = 0.75$ $\alpha = 2.0$ $\rho = 1.0$ $\chi = 20$

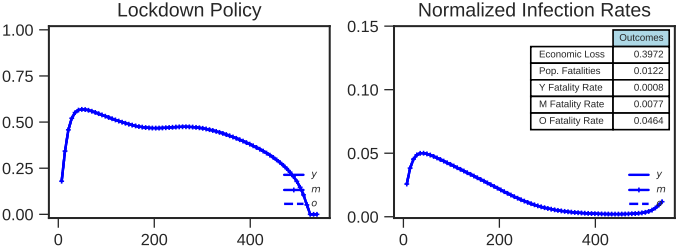
The “Pareto” Frontier

- ▶ The advantage of semi-targeted policies true for different values of χ .

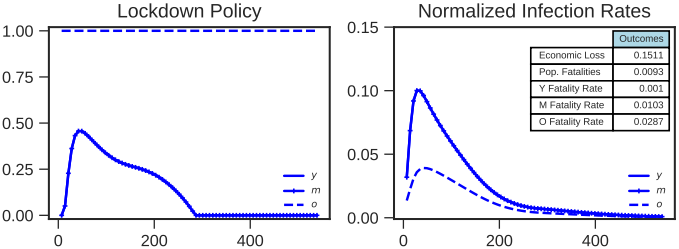


Base: Outcomes for $\theta = 1$, $\alpha = 2$, $\rho = 1$, $T = 546$; $\chi \in \{0, 5, 10, 20, \dots, 80\}$

With Greater Value of Life, Another Interesting Contrast

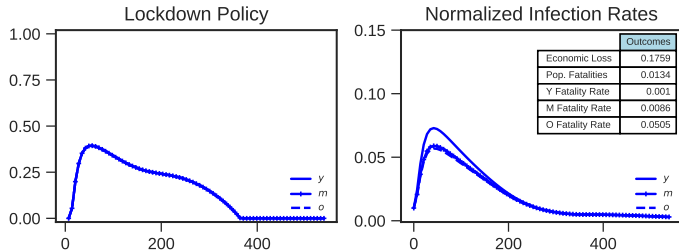


Base: Uniform Policy for $\theta = 0.75$ $\alpha = 2.0$ $\eta = 1$ $\rho = 1.0$ $\chi = 30$

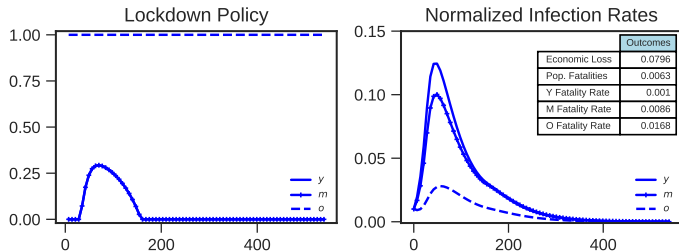


Base: Semi-Targeted Policy for $\theta = 0.75$ $\alpha = 2.0$ $\eta = 1$ $\rho = 1.0$ $\chi = 30$

Bigger Gains with Between-Group Distancing

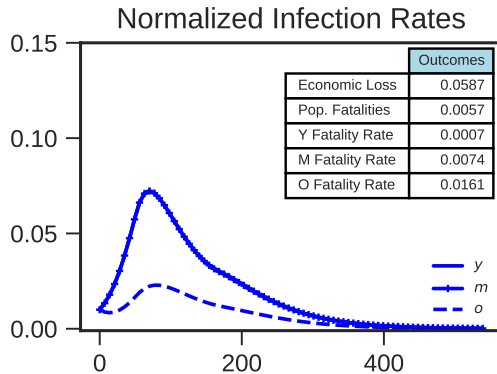
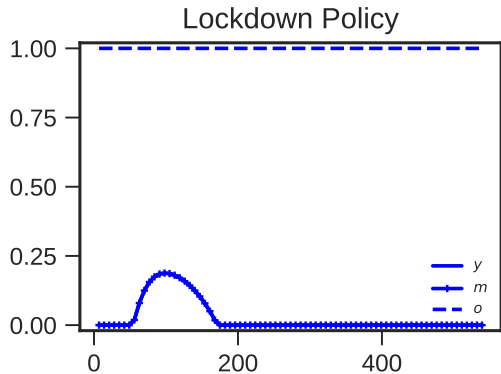


CS1: Uniform Policy for $\theta = 0.75$ $\alpha = 2.0$ $\rho = 0.5$ $\chi = 20$



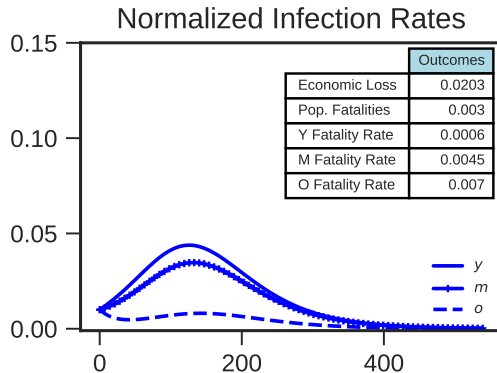
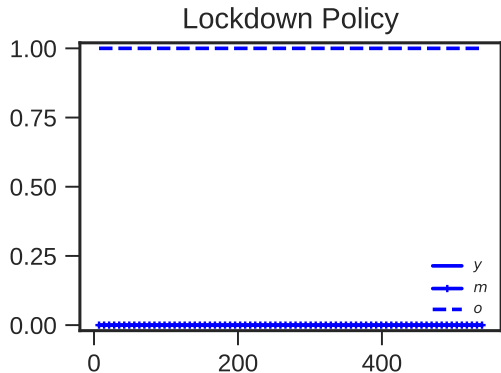
CS1: Semi-Targeted Policy for $\theta = 0.75$ $\alpha = 2.0$ $\rho = 0.5$ $\chi = 20$

Even Bigger Gains with Testing-Tracing



Base with Testing: Semi-Targeted Policy for $\theta = 0.75$ $\alpha = 2.0$ $\rho = 1.0$ $\chi = 20$

Combining Between-Group Distancing and Testing-Tracing



Group Dist and Testing: Semi-Targeted Policy for $\theta = 0.75$ $\alpha = 2.0$ $\rho = 0.5$ $\chi = 20$

Conclusion

- ▶ Still much to be done. But our research suggests targeted (semi-targeted) policies can do much better, especially with some between-group social distancing and testing-tracing:

