behavioral epidemiology: an economic model to evaluate optimal policy in the midst of a pandemic

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motivation

- covid-19: the world perhaps faces its biggest challenge since world war II (angela merkel, march 2020).
- in formulating social and economic policy responses:
  - a set of SIR-models have been salient,
  - epidemiologists/scientists are leading the way on a war footing,
  - 'flatten the curve' & 'peak infections' are colloquial parlance.
- economists have been trying to help in:
  - understanding and explaining tradeoffs confronting policy,
  - making sense of data emerging from testing and rate of deaths,
  - helping refine the models used by epidemiologists.
- goal of this paper: combine the three said objectives.

- policy:
  - instruments– lockdown and testing;
  - tradeoffs– total output versus fatalities.
- data:
  - on # of tests, hospitalized, recovered, dead;
  - use it to calibrate key parameters.
- modeling:
  - introduce behavioral response in disease dynamics;
  - let that interact with optimal policy.
- novelty of the paper:
  - combine lockdown, testing and behavioral response;
  - use data to discipline seed and behavioral parameters.

why behavioral response?

- standard SIR-models are mechanical, there is no agency.
- think of forecasts for weather versus disease spread:
  - it does not matter whether you take an umbrella;
  - but it matters if you social distance.
  - prophet's dilemma!
- also, it is our comparative advantage as economists
  - to think about behavior;
  - and more so when "equilibrium" considerations are important.

why behavioral response?

"results indicate that including adaptive human behavior significantly changes the predicted course of epidemics and that this inclusion has implications for parameter estimation and interpretation and for the development of social distancing policies. acknowledging adaptive behavior requires a shift in thinking about epidemiological processes and parameters."

fenichel et all [2011], proceedings of the national academy of sciences.

roadmap

- model:
  - two worlds– social and economic;
  - incorporate policy– lockdown and testing;
  - mechanical part– disease dynamics;
  - introduce behavioral response for social distancing.
- government's problem:
  - optimality conditions;
  - numerical algorithm to find the optimum.
- calibrate parameters:
  - discuss the data;
  - estimation.
- results and future work.

- objective data on the epidemic (for the US as a whole):
  - ideal– confirmed cases, tests, hospitalized, recovered, dead;
  - godly– add actual infected cases to ideal;
  - reliable– confirmed/tests, dead;
  - noisy– hospitalized;
  - not usable– recovered.
- other empirical observations:
  - likelihood of meeting infected people socially or at work;
  - tradeoffs from social distancing through revealed preference;
  - extent of economic lockdown;
  - probability of arrival of vaccine.
- attempt to write down a model that takes objec data as input.

model: states

- there is a mass $N = 1$ of agents.
- at any given point in time an agent can be in one of 5 states:
  - susceptible (S)– not infected yet;
  - infected (I)– contracted the virus;
  - hospitalized (H)– requiring hospital care/bed;
  - recovered (R)– recovered from the virus and immune;
  - dead (D).
- importantly for covid-19:
  - I can be symptomatic or asymptomatic;
  - R can be known or unknown;
  - the question of immunity is still open: we will assume it.

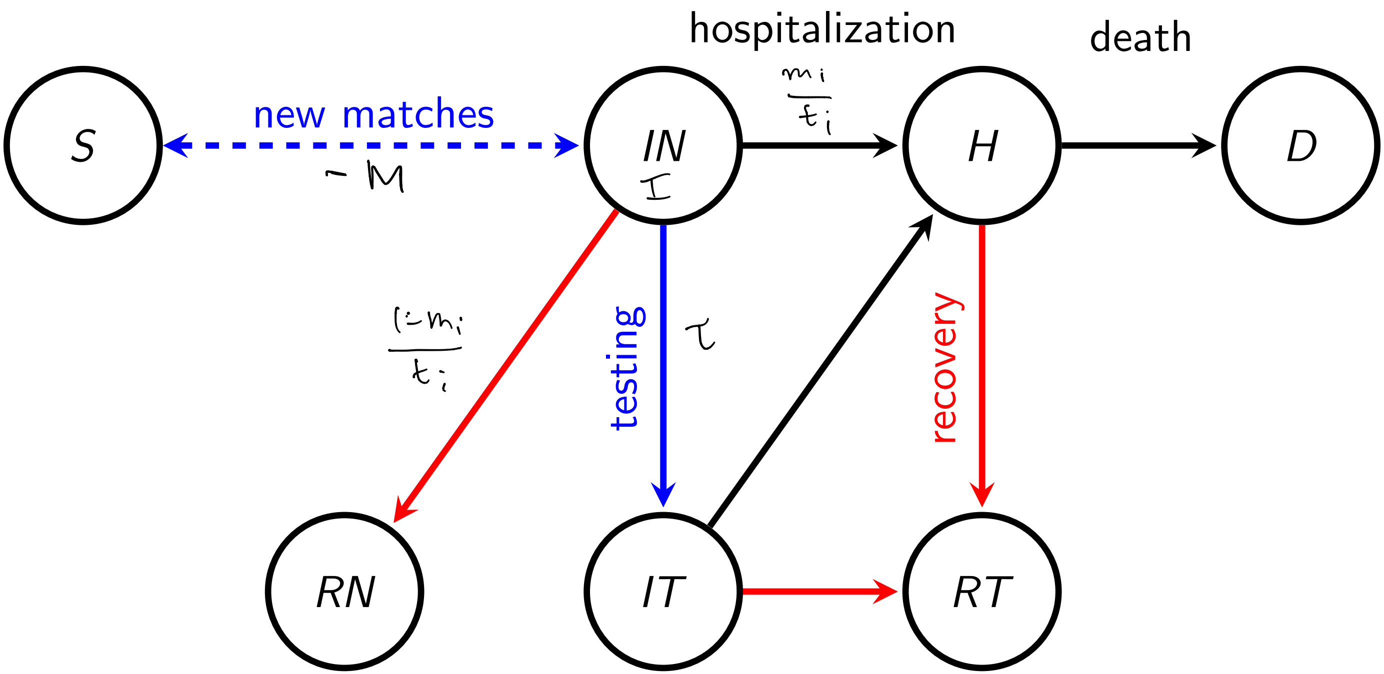
model: key features

- two words in which agents meet:
  - economic– produce output;
  - social– hang out which gives utility;
  - in each world, agents randomly matched.
- tracing and testing:
  - separates I into IN (not-tested) and IT (tested & quarantined);
  - separates R into RN (not-tested nor H) and RT (tested or H);
  - fraction $\tau(1-\gamma)$ of {S,IN} and τ of {RN} are tested;
  - exogenously specified efficacy of tracing, γ.

model: key features

- economic output and lockdown:
  - those in states in {IT, H, D} cannot contribute to output;
  - total (flow) output is given by $Y = \lambda(S + IN + R)$;
  - $1 - \lambda \equiv$ extent of lockdown.
- vaccine:
  - arrives according to a negative binomial distribution;
  - allows us to control the first possible date of arrival, and
  - chooses mean & variance separately (unlike geometric distrib);
  - output after vaccine arrival: $Y = 1 - D$.
- social distancing
  - to sd or not to sd, {S,IN,RN} decide, with probability α;
  - α is determined in equilibrium.

model: transitions



model: mechanical disease dynamics

$$S_{t+1} = S_t - \underbrace{\beta_w(\lambda_t)^2 S_t IN_t - \beta_s S_t IN_t}_{\text{FM}}$$

$$IN_{t+1} = (1-\tau_t)\left[IN_t(1-1/t_i) + \beta_w(\lambda_t)^2 S_t IN_t + \beta_s S_t IN_t\right]$$

$$IT_{t+1} = IT_{t+1}(1-1/t_i) + \tau_t\left[IN_t(1-1/t_h) + \beta_w(\lambda_t)^2 S_t IN_t + \beta_s S_t IN_t\right]$$

$$H_{t+1} = H_t(1-1/t_h) + (IN_t + IT_t)m_i/t_i$$

$$RN_{t+1} = RN_t + IN_t(1-m_i)/t_i$$

$$RT_{t+1} = RT_t + IT_t(1-m_i)/t_i + H_t(1-m_h)/t_h$$

$$D_{t+t} = D_t + H_t m_h/t_h$$

model: regarding seed parameters

- in newspaper articles you may have seen R_0, what's that?
- total prevalence in our model is given by

$$\beta = \eta\beta_s + (1-\eta)\beta_w$$

where η is the fraction of matches/prevalence at work.

- moreover, $\beta = R_0/t_i$ or $R_0 = \beta \cdot t_i$.

model: testing

- every period X_t tests are made available.
- effective tests:
  - $\hat{X}_t = X_t - H_t^{\text{new}} = X_t - IN_t m_i / t_i$;
  - CDC prioritizes testing of all hospitalized.
- accuracy of tracing is given by γ:
  - prob of being traced and tested before H,

$$\tau_t = \frac{\hat{X}_t}{(1-\gamma)(S_t + RN_t) + I\tilde{N}_t}$$

.

  - so, $\tau_t I\tilde{N}_t$ infected are tested in period t;
  - prior: for low $\hat{X}$, you should expect $\gamma \in [0.85, 1)$.
- for simplicity testing is history indepen & no anti-body tests.

model: behavioral response

- in their social realms, agents make distancing decisions.
- captured by three parameters:
  - cost of social distancing, $c \in \mathit{unif}[0, \bar{c}]$;
  - disutility from getting infected, ϕ_+;
  - disutility from infecting others, ϕ_-.
- behavioral response:
  - matters for those in states $\{$S,IN,RN$\}$;
  - is based on the agent's belief about being infected.

model: behavioral response

- testing & behavioral response produce rich heterogeneity.
- to keep things tractable, assume agents respond myopically.
- the mechanical model had 7 states $\{$S,IN,IT,H,RN,RT,D$\}$.
- to incorporate behavioral response, in addition
  - introduce $k-$ time since the last trace/test;
  - a sufficient statistic to keep track of all relevant beliefs.
- let S_t^k, IN_t^k, RN_t^k be
  - fractions who participate on social activities at time t;
  - and were last tested at time k.

$\vdots$

behavioral equilibrium

- let α_t^k be probability/fraction agent who received the last test at k participates in social activities at time t.
- total number of {S,IN,RN} who participate in social activities

$$\hat{S}_t = \sum_{k=1}^{t} \alpha_t^k S_t^k, \quad \hat{IN}_t = \sum_{k=1}^{t} \alpha_t^k IN_t^k, \quad \hat{RN}_t = \sum_{k=1}^{t} \alpha_t^k RN_t^k$$

- agent's belief of being susceptible and infected:

$$x_t^k = \frac{S_t^k}{S_t^k + IN_t^k + RN_t^k} \quad \text{and} \quad y_t^k = \frac{IN_t^k}{S_t^k + IN_t^k + RN_t^k}$$

- equations from the mechanical system have to be updated:

$$S_{t+1} = S_t - \beta_w(\lambda_t)^2 S_t IN_t - \beta_s \hat{S}_t \hat{IN}_t, \text{ etc.}$$

behavioral equilibrium

- cost-benefit of social distancing pins down:

$$\boxed{\underbrace{1-\alpha_t^k}_{\text{fraction of social distancers}} = \underbrace{x_t^k \hat{IN}_t \cdot \beta_s \frac{\phi_+}{\bar{c}}}_{\text{cost from getting infected}} + \underbrace{y_t^k \hat{S}_t \cdot \beta_s \frac{\phi_-}{\bar{c}}}_{\text{cost from infecting others}}}$$

Theorem

fix the lockdown and testing λ and τ. $\exists$ unique social distancing equilibrium where at time t fraction α_t^k of agents who got tested at time k participate in social activities. moreover, until the discovery of vaccine, the economy evolves according to a well-defined system of equations for $\{S, \hat{S}, IN, \hat{IN}, IT, RN, \hat{RN}, RT, H, D\}$.

optimal policy

- p_t is the probability of vaccine arrival at time t.
- expected number of survivals is given by:

$$\bar{N} = \sum_{t=1}^{\infty} (1 - D_{t+1}) p_t$$

- total expected output is given by:

$$\bar{Y} = \sum_{t=1}^{\infty} \left\{ \sum_{k=1}^{t} \delta^{k-1} (1 - \delta) \lambda_k (S_k + IN_k + R_k) + \delta^t (1 - D_{t+1}) \right\} p_t$$

- objective function of the government is given by:

$$\Pi = \bar{Y} + \xi \bar{N}$$

where $\xi \geqslant 0$ is the "pareto weight" on survivals.

optimal policy

- govt decides policy, taking as given:
  - disease dynamics and behavioral response.
- specifically, it chooses lockdown (λ_t) to max Π, subject to
  - state constraints:

$$S^k_{t+1} =, IN^k_{t+!} =, IT_{t+1} =, RN^k_{t+1} =, RT_{t+1} =, H_{t+1} =, D_{t+1} =;$$

  - resource and feasibility constraints:

$$\lambda_t \in [\bar{\lambda}, 1] \quad \text{and} \quad \tau_t = \frac{\hat{X}_t}{(1-\gamma)(S_t + RN_t) + \tilde{IN}_t}$$

- this is a "large" problem!

calibrating parameters: method

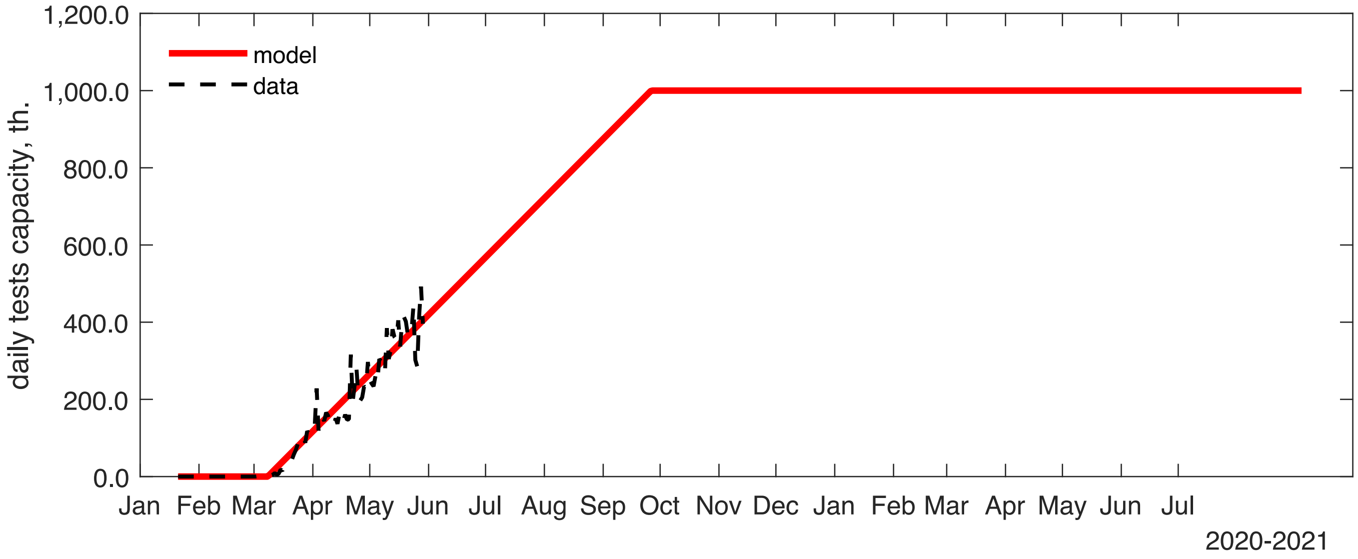
- we calibrate parameters by fitting model to data in 2 stages.
- in stage 1, use data from arizona to pin down medical param:
  - we see $\{$H,RT,D$\}$;
  - $D_{t+t} = D_t + H_t m_h/t_h \mapsto m_h/t_h$;
  - $RT_{t+1} = RT_t + IT_t(1 - m_i)/t_i + H_t(1 - m_h)/t_h \mapsto (1 - m_i)/t_i$;
  - $H_{t+1} = H_t(1 - 1/t_h) + (IN_t + IT_t)m_i/t_i \mapsto m_H$ & t_H.
- infection-fatality rate (IFR) from latest medical studies:
  - equal 0.35% (conservative estimate), could be as low as 0.2%;
  - we use 0.35%.
- in our model, $IFR = m_i \times m_h$, which delivers m_i & t_i.

calibrating parameters: method

- in stage 2, we fit the model to the data on:
  - deaths and positive/negative tests.
- identification is weak, we fix $\eta = 0.5$, $I_0 = 100$, $\phi_- = 0.1\phi_+$.
  - calibration then estimates: $\{\beta, \gamma, \phi_+, \lambda\}$.
  - for simplicity we break λ into three parts for march, april, may.
- dates for the pandemic:
  - start, $t = 1$, is set at jan 22, 2020.
  - we use data till may 31, 2020, so till $t = 131$.
- minimize the following:

$$\sum_{t=1}^{131}(D_t - \tilde{D}_t)^2/(max_t \tilde{D}_t)^2 + \sum_{t=1}^{131}(X_t^+ - \tilde{X}_t^+)^2/(max_t \tilde{X}_t^+)^2$$

calibrated parameters: testing



calibrated parameters

parameter	**value**	**definition**
seed		
β_w	0.1495	matching prob in eco act
β_s	0.1495	matching prob in social act
t_i	10.4072	initial infection period

- this implies $R_0 = \beta \cdot t_i = 2.938$.

calibrated parameters

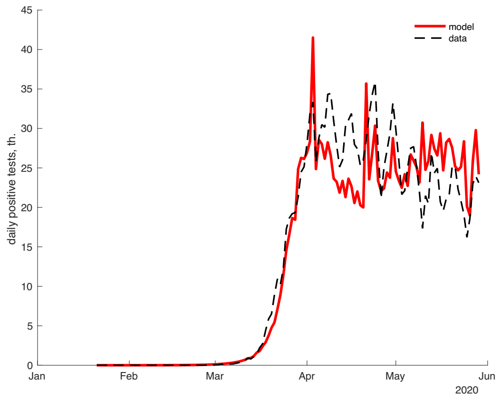
parameter	**value**	**definition**
structural		
t_h	9.2312	average hospital stay
m_i	0.00134	hospitalization % of infected
m_h	0.2618	death as % of hospitalization
γ	0.8632	efficacy of tracing
M	540	expected day of vaccine arrival
V	180	variance of vaccine arrival
ξ	10	pareto weight on survivals
$(\lambda_i)_{i=1}^{3}$	(1,0.3,0.3)	lockdown in march, april, may
$\bar{\lambda}$	0.3	share of essential services
$\delta = \frac{1}{1+r}$	r= 5%	discounting

calibrated parameters

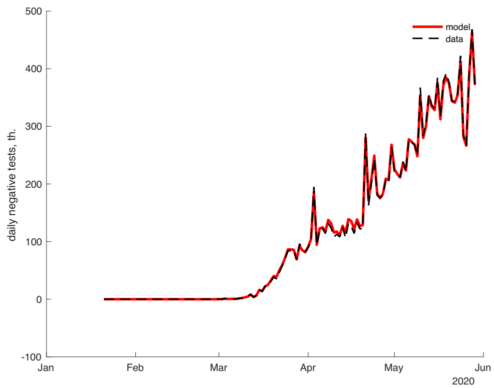
parameter	value	definition
behavioral		
$\phi_+/\bar{c}$	27.5008	disutility from getting infected
$\phi_-/\bar{c}$	2.75008	disutility of infecting others

- this implies on average you are willing to social distance
  - for approximately one year to avoid getting infected;
  - and a little over a month to avoid infecting others.

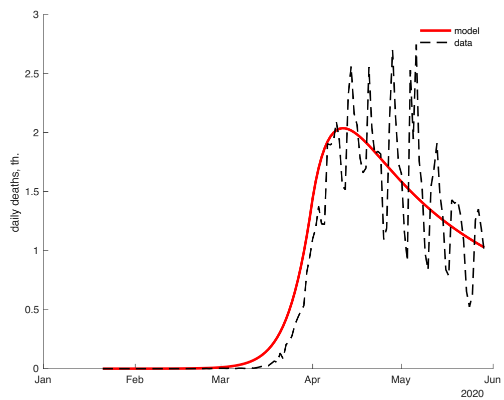
model fit to the matched



(a) positive tests

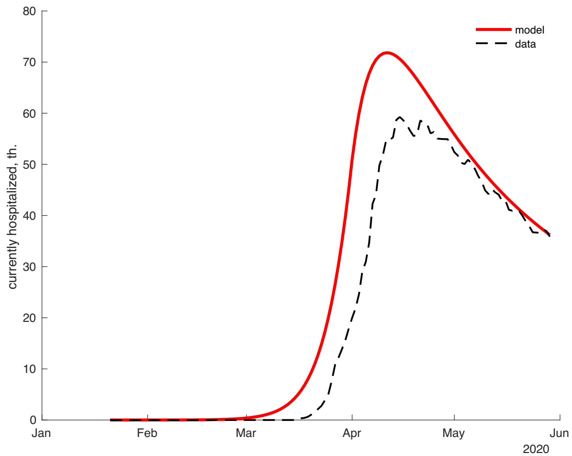


(b) negative tests

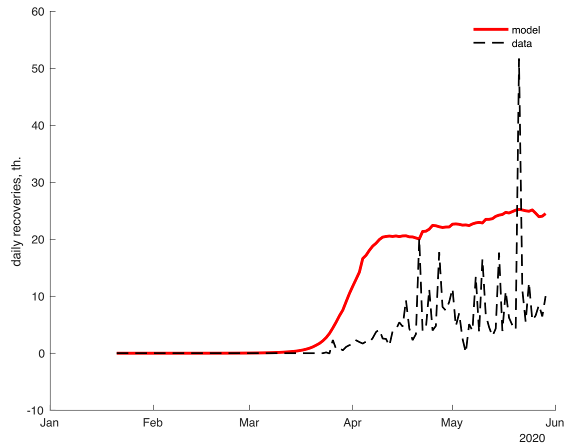


(c) deaths

model fit to the unmatched



(a) hospitalized

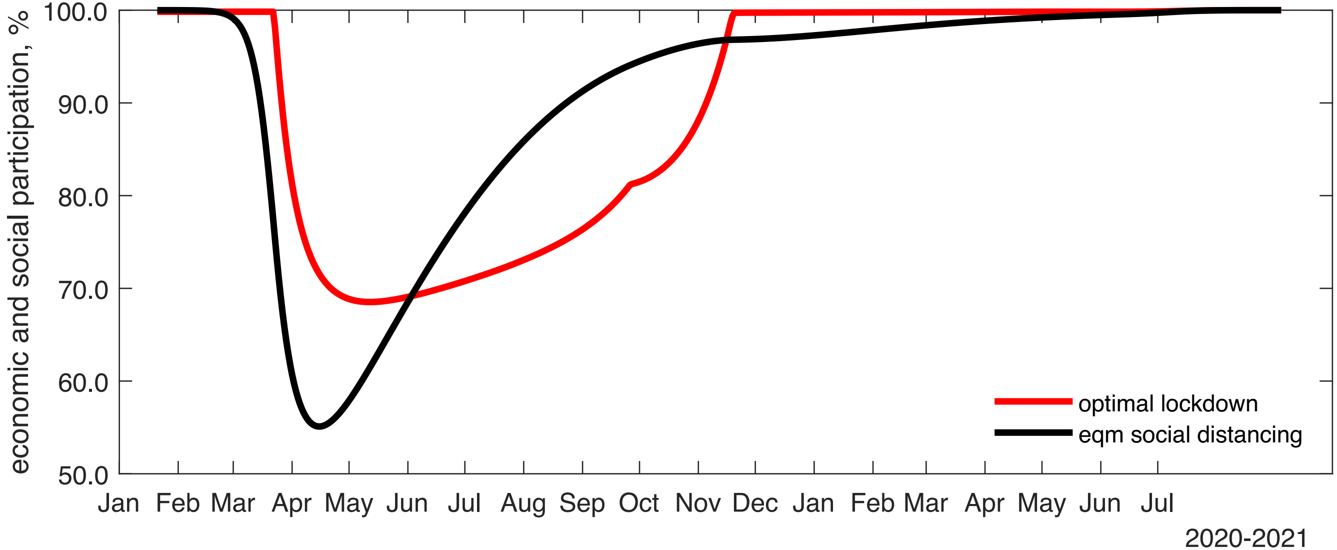


(b) recovered

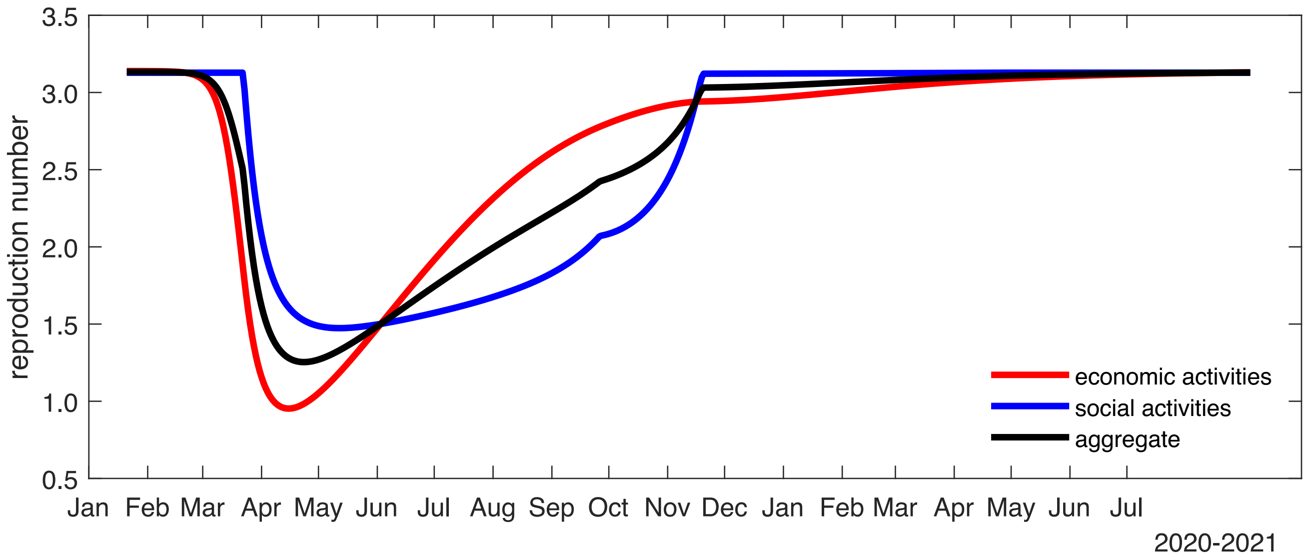
numerical algorithm

- a variation of so called forward-backward sweep algorithm.
- truncate the problem for some sufficiently large terminal time.
- pick λ and solve the state equations forwards.
- solve the adjoint equations (FOCs w.r.t. state variables) backwards for dual variables.
- update λ to λ' by pointwise optimizing the Lagrangian.
- repeat until convergence.

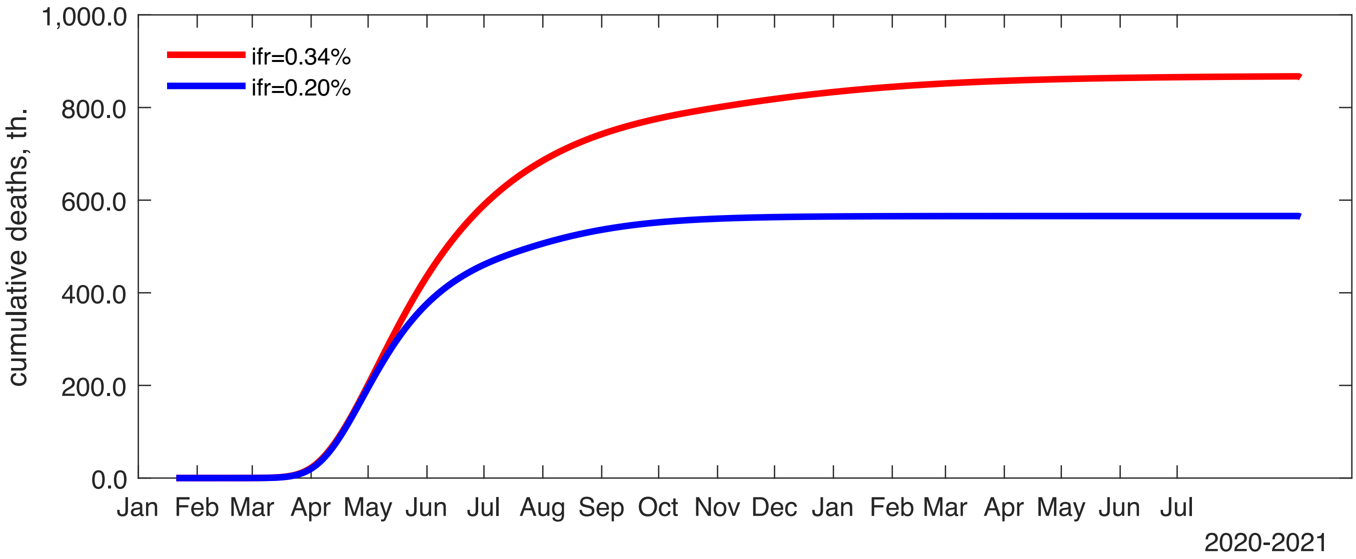
predictions under optimal policy: deaths



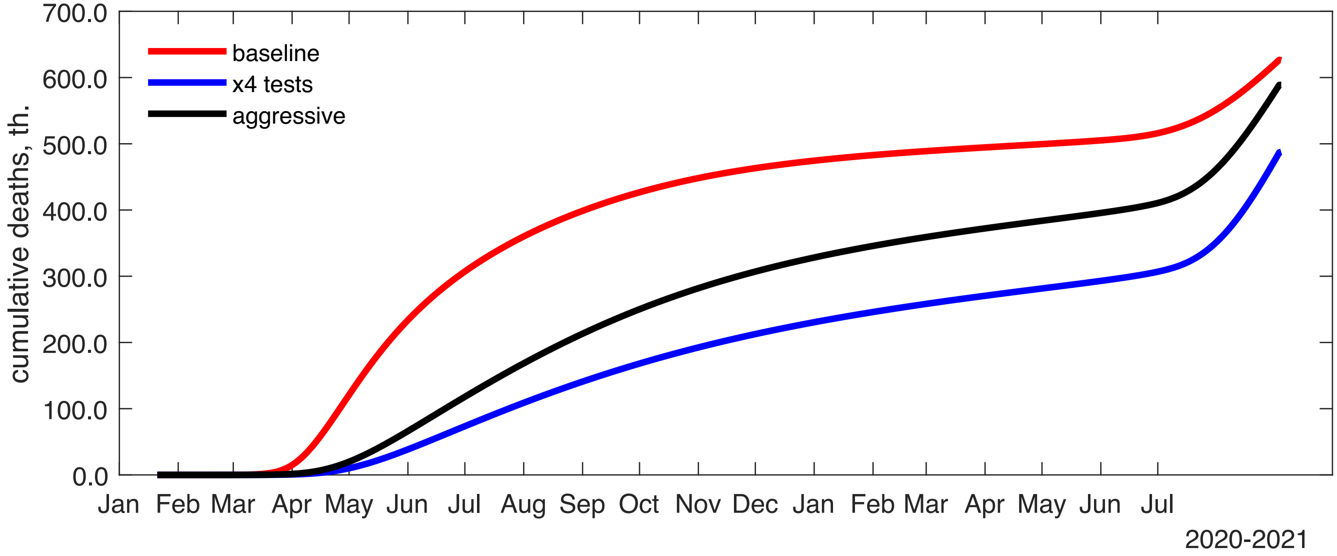
predictions under optimal policy: deaths



predictions under optimal policy: deaths



predictions under aggressive testing



what's next?

- in this paper:
  - wait/pray for better data for the us;
  - use data from south korea, germnay, and italy;
  - understand how our model performs under different scenarios;
  - better way to get η and ϕ_-.
  - impossibility result on "identifying" the model, viz. IN.
- beyond: this is realistically a "developed country" paper, why?
  - india cannot afford such a long lockdown.
  - how to decide optimal policy in the absence of social security.
- spatial considerations absent here, seems first-order relevant.
- shouldn't lockdown be an instrument of learning?
  - in many countries lockdown informed behavioral parameters.