Estimating and Simulating a SIRD Model of COVID-19 for Many Countries, States, and Cities

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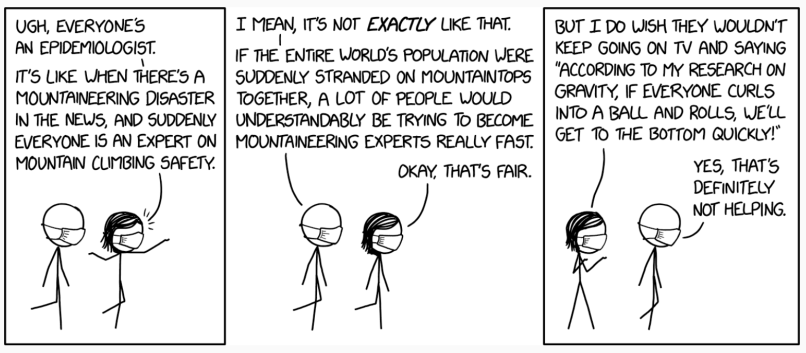
August 28, 2020

xkcd: Everyone's an Epidemiologist



Help macroeconomists with data and model

Outline

- Setup
  - SIR model with a time-varying $\mathcal{R}_{0t}$
  - Recover $\mathcal{R}_{0t}$ as the "Solow residual" of SIR to fit deaths
- Estimation and simulation
  - Different countries, U.S. states, and global cities
  - "Forecasts" from each of the last 7 days
- Re-opening and herd immunity
  - How much can we relax social distancing?

Our dashboard contains 30+ pages of results
for each of 100 cities, states, and countries

Basic Model

Notation

- Number of people who are (stocks):

$$
\begin{aligned}
S_t &= \text{Susceptible} \\
I_t &= \text{Infectious} \\
R_t &= \text{Resolving} \\
D_t &= \text{Dead} \\
C_t &= \text{ReCovered}
\end{aligned}
$$

- Constant population size is N

$$S_t + I_t + R_t + D_t + C_t = N$$

SIRD Model: Overview

- Susceptible get infected at rate $\beta_t I_t / N$

  New infections = $\beta_t I_t / N \cdot S_t$

- Fraction γ of Infectious resolve each day, so the average number of days that a person is infectious is $1/\gamma$ so $\gamma = .2 \;\Rightarrow 5$ days

- Fraction θ of Post-infectious cases resolve each day. E.g. $\theta = .1 \;\Rightarrow 10$ days

- Resolution happens in one of two ways:
  - Death: fraction δ
  - Recovery: fraction $1 - \delta$

SIRD Model: Laws of Motion

$$\Delta S_{t+1} = \underbrace{-\beta_t S_t I_t / N}_{\text{new infections}}$$

$$\Delta I_{t+1} = \underbrace{\beta_t S_t I_t / N}_{\text{new infections}} - \underbrace{\gamma I_t}_{\text{resolving infectious}}$$

$$\Delta R_{t+1} = \underbrace{\gamma I_t}_{\text{resolving infectious}} - \underbrace{\theta R_t}_{\text{cases that resolve}}$$

$$\Delta D_{t+1} = \underbrace{\delta \theta R_t}_{\text{die}}$$

$$\Delta C_{t+1} = \underbrace{(1-\delta)\theta R_t}_{\text{reCovered}}$$

Recyled notation $\mathcal{R}_0$: Initial infection rate

- Initial reproduction number $\mathcal{R}_0 \equiv \beta/\gamma$

$\mathcal{R}_0$	=	β	$\times$	$1/\gamma$
# of infections from one sick person		# of “adequate” contacts per day		# of days contacts are infectious

- $\mathcal{R}_0$ = expected number of infections via the first sick person
  - $\mathcal{R}_0 > 1 \Rightarrow$ disease initially grows
  - $\mathcal{R}_0 < 1 \Rightarrow$ disease dies out: infectious generate less than 1 new infection

- If $1/\gamma = 5$, then easy to have $\mathcal{R}_0 >> 1$

Basic Properties of Differential System (Hethcote 2000)

- Continuous time, constant β
  - Initial exponential growth rate of infections is $\beta - \gamma = \gamma\left(\mathcal{R}_0 - 1\right)$
- Let $s_t \equiv S_t/N$ = fraction susceptible
  - Infectious grow at $\beta - \gamma = \gamma\left(\mathcal{R}_0 s_t - 1\right)$
  - If $\mathcal{R}_0 s_t > 1$, the virus spreads, otherwise declines
- As $t \to \infty$, the total fraction of people ever infected, e^*, solves (assuming $s_0 \approx 1$)

$$e^* = -\frac{1}{\mathcal{R}_0}\log(1 - e^*)$$

Long run is pinned down by $\mathcal{R}_0$ (and death rate),

γ and θ affect timing

Social Distancing

- What about a time-varying infection rate β_t?
  - Disease characteristics – fixed, homogeneous
  - Regional factors (NYC vs Montana) – fixed, heterogeneous
  - Social distancing – varies over time and space
- Reasons why β_t may change over time
  - Policy changes on social distancing
  - Individuals voluntarily change behavior to protect themselves and others
  - Masks, superspreading events

Recovering β_t and $\mathcal{R}_{0t}$

- Recover β_t, a latent variable, from the data:
  - Like the Solow Residual of the SIRD model!

- Notation
  - D_{t+1}: stock of deaths as of the *end* of date $t+1$
  - $\Delta D_{t+1} \equiv d_{t+1}$: number of people who die on date $t+1$

- With algebra, "invert" the SIRD model to obtain:

$$\beta_t = \frac{N}{S_t}\left(\gamma + \frac{\frac{1}{\theta}\Delta\Delta d_{t+3} + \Delta d_{t+2}}{\frac{1}{\theta}\Delta d_{t+2} + d_{t+1}}\right)$$

$$S_{t+1} = S_t\left(1 - \beta_t \frac{1}{\delta\gamma N}\left(\frac{1}{\theta}\Delta d_{t+2} + d_{t+1}\right)\right)$$

Recovering β_t and $\mathcal{R}_{0t}$ (continued)

$$\beta_t = \frac{N}{S_t}\left(\gamma + \frac{\frac{1}{\theta}\Delta\Delta d_{t+3} + \Delta d_{t+2}}{\frac{1}{\theta}\Delta d_{t+2} + d_{t+1}}\right)$$

$$S_{t+1} = S_t\left(1 - \beta_t \frac{1}{\delta\gamma N}\left(\frac{1}{\theta}\Delta d_{t+2} + d_{t+1}\right)\right)$$

- Use data on d_t, and initial condition $S_0/N \approx 1$,
  - Iterate forward in time and recover β_t and S_{t+1}
- Uses *future* deaths over the next 3 days to tell us about β_t today
- More general point about SIRD models
  - State-space representation that we can exploit
  - Richer structure possible (heterogeneity, general functions)

An endogenous $\mathcal{R}_{0t}$ when simulating future outcomes

- Individuals react endogenously to risk
  - Much of the reaction is not even government-mandated
  - Could solve a complex dynamic programming problem

- Instead, Cochrane (2020) suggests:

$$\mathcal{R}_{0t} = \text{Constant} \cdot e^{-\alpha d_t}$$

  where d_t is daily deaths per million people.

- We estimate α from our data on $\mathcal{R}_{0t}$

Estimates and Simulations

Parameters assumed fixed and homogeneous

- $\gamma = 0.2$: average duration is 5 days (or $\gamma = 0.1$)
- $\theta = 0.1$: average duration post-infectious is 10 days.
  - average case takes 10+5 = 15 days to resolve.
  - Long tail for exponential distribution
- $\alpha = 0.05$: estimate α_i for each location i.
  - Tremendous heterogeneity across locations
  - $\mathcal{R}_{0t}$ falls by 5 percent with each daily death
  - We report results with $\alpha = 0$ and $\alpha = .05$.

Mortality rate (IFR): $\delta = 1.0\%$

- Evidence from seroepidemiological national survey in Spain:
  - Stratified random sample of 61,000 people
  - δ in Spain is between 1% and 1.1%.
- Correction by demographics to other countries
  - Most countries cluster around 1%.
  - U.S.: 0.76% without correcting for life expectancy and 1.05% correcting by it.

Heterogeneity in Mortality Rates by Age

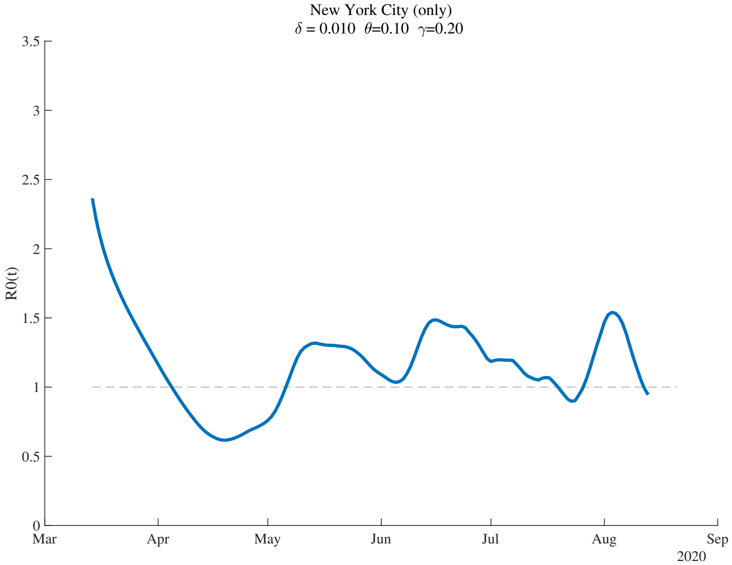
- Mortality rates vary substantially by age
  - IFR for ages 65-69 in Spain = 1%
- **Gompertz Law:** mortality rate grows exponentially with age
  - COVID-19: doubles for every 5-year age group (?)
  - 70 vs 20 year olds: 50 years = 10 doublings $\Rightarrow$ 1000-fold
  - 2 in 100 versus 2 in 100,000
- Our estimation does not feature this heterogeneity — lack of data

May underestimate herd immunity
if many young people are increasingly infected

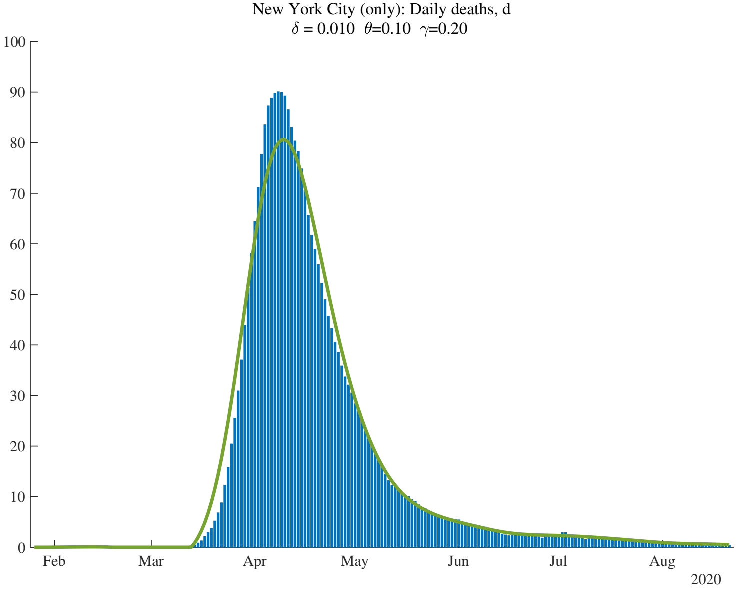
Estimation based entirely on death data

- Johns Hopkins University CSSE data
- Excess death issue
  - Currently no correction, just using the JHU/CSSE data
  - (previously adjusted upward by 33%)
- We use 7-day moving averages (centered)
  - Otherwise, very serious “weekend effects” in which deaths are underreported
  - Even zero sometimes, followed by a large spike
  - Further smoothing: HP-filter with smoothing parameter 800 after taking moving average

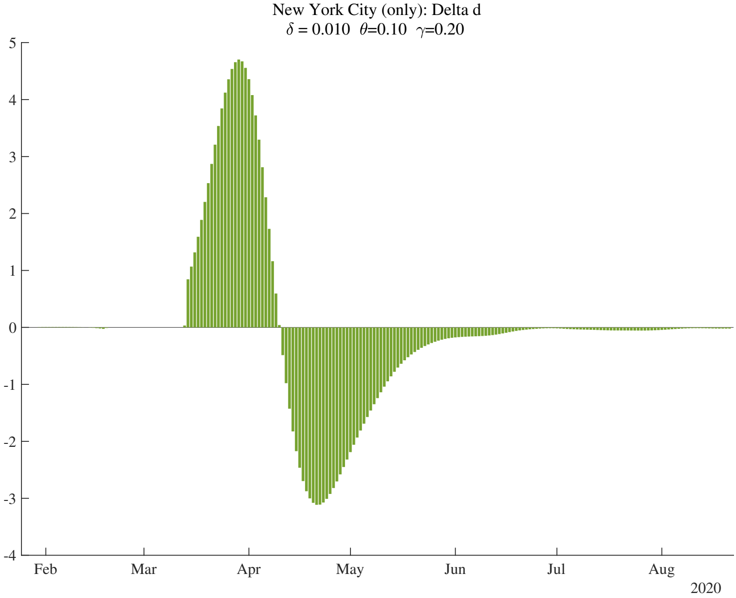
New York City: Estimates of $\mathcal{R}_{0t} = \beta_t/\gamma$



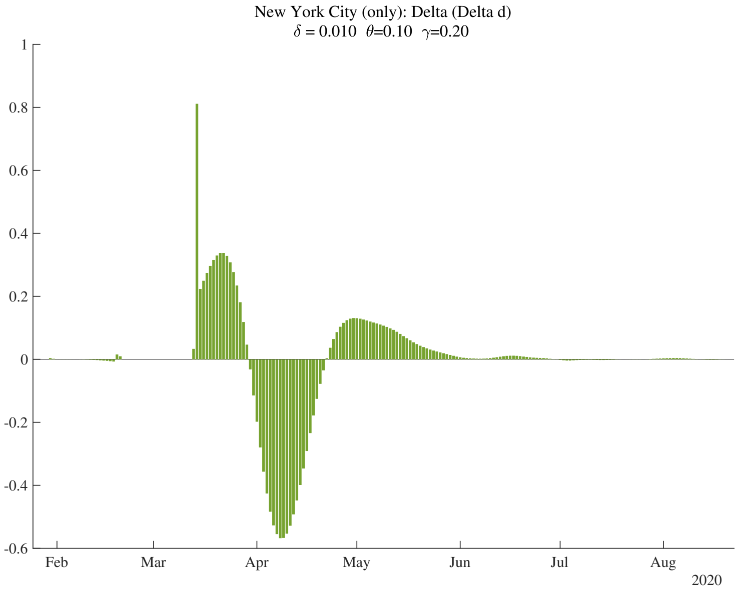
New York City: Daily Deaths and HP Filter



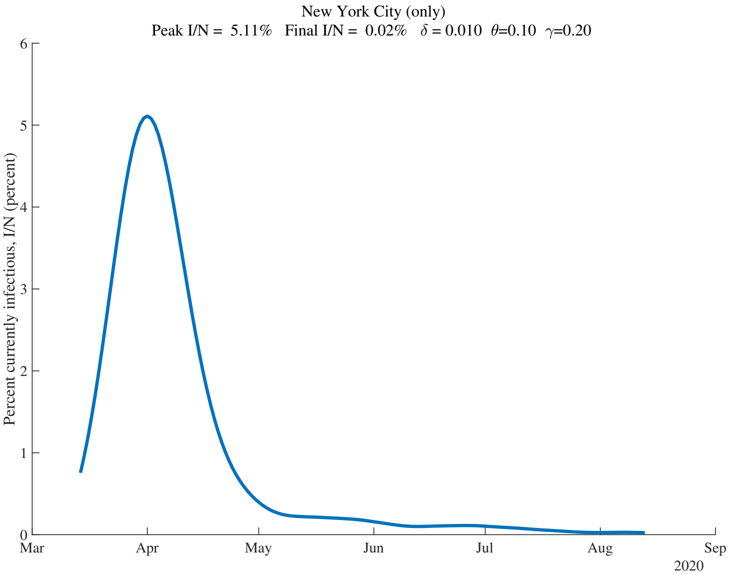
New York City: Change in Smoothed Daily Deaths



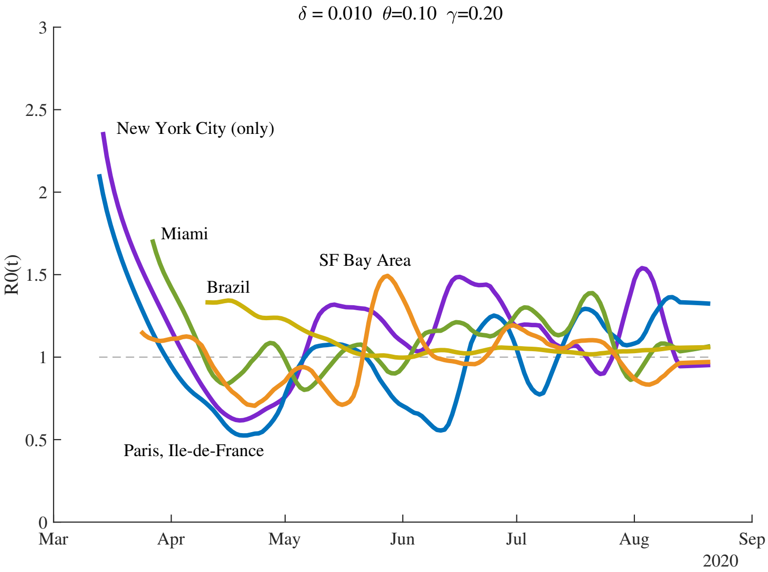
New York City: Change in (Change in Smoothed Daily Deaths)



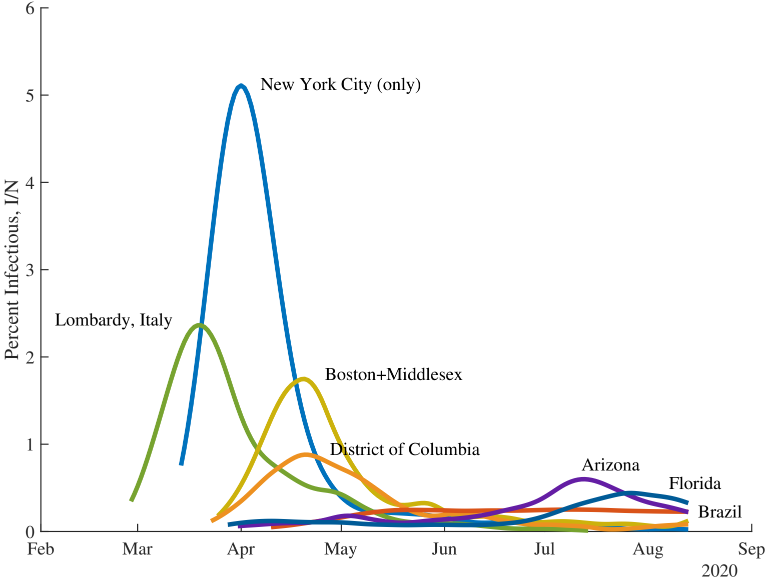
New York City: Percent of the Population Currently Infectious



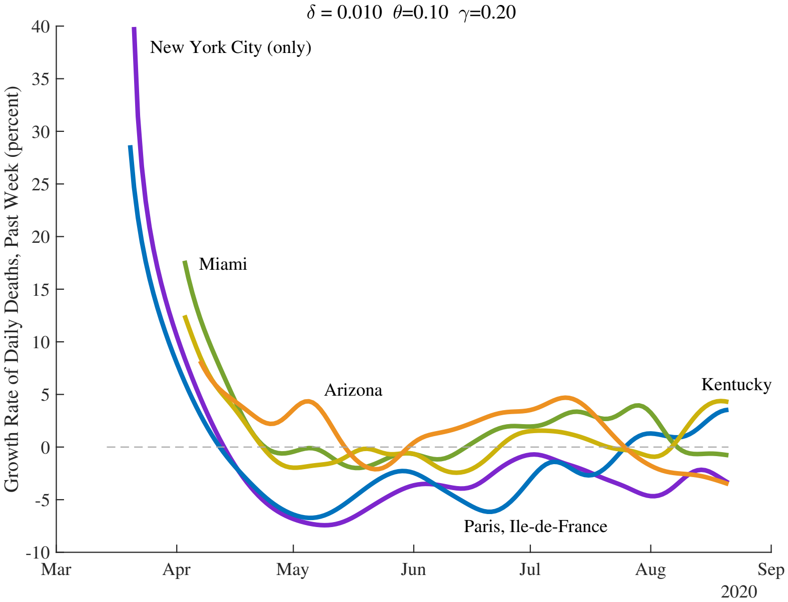
Estimates of $\mathcal{R}_{0t} = \beta_t/\gamma$



Percent of the Population Currently Infectious



Daily Growth Rate of Daily Deaths, Past Week



Dashboard Table (link)

	Total (pm) Deaths, t	Growth rate	— $\mathcal{R}_0$ — initial	today	% Ever infected	% Infectious peak	today
New York City (only)	2836	-	2.36	0.94	28.6%	5.11%	0.02%
Lombardy, Italy	1675	-	2.20	0.20	16.8%	2.36%	0.01%
Stockholm, Sweden	1465	-	2.20	0.20	14.7%	1.68%	0.03%
Madrid, Spain	1289	-	2.22	0.20	12.9%	2.37%	0.04%
Boston+Middlesex	1292	6.5%	2.08	1.90	13.1%	1.75%	0.12%
District of Columbia	853	2.7%	1.82	1.21	8.6%	0.88%	0.08%
Paris, France	837	-	2.13	0.72	8.4%	1.33%	0.02%
Miami	811	-	1.71	1.04	8.9%	0.69%	0.51%
London, U.K.	652	2.3%	2.11	1.10	6.6%	1.21%	0.00%
Arizona	644	-	1.24	0.82	6.8%	0.60%	0.22%
United States	532	-	1.80	1.02	5.5%	0.39%	0.15%
Brazil	532	-	1.33	1.06	5.6%	0.25%	0.23%
Texas	492	-	1.28	0.99	5.5%	0.52%	0.41%
Mexico	461	-	1.23	0.91	4.9%	0.28%	0.20%
California	304	-	1.35	1.01	3.2%	0.18%	0.16%
Kentucky	251	4.3%	1.51	1.27	2.6%	0.15%	0.14%
SF Bay Area	143	-	1.16	0.96	1.5%	0.08%	0.05%
Germany	111	-	1.50	1.04	1.1%	0.15%	0.00%
Israel	93	1.1%	1.17	1.06	1.0%	0.08%	0.08%
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Repeated "Forecasts" from the past 7 days of data

- After peak, forecasts settle down.
- Before that, very noisy!

Guide to Graphs

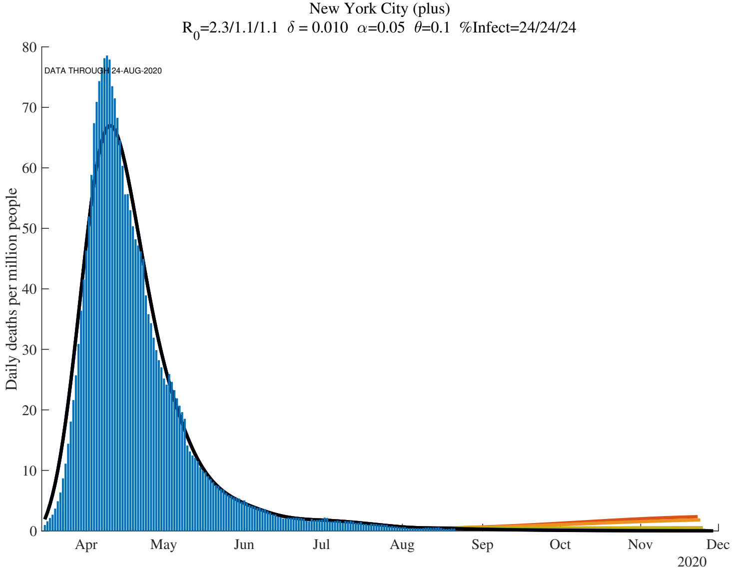
- 7 days of forecasts: Rainbow color order!
  ROY-G-BIV (old to new, low to high)
  - Black=current
  - Red = oldest, Orange = second oldest, Yellow =third oldest...
  - Violet (purple) = one day earlier
- For robustness graphs, same idea
  - Black = baseline (e.g. $\delta = 1.0\%$)
  - Red = lowest parameter value (e.g. $\delta = 0.8\%$)
  - Green = highest parameter value (e.g. $\delta = 1.2\%$)

Guide to Graphs (continued)

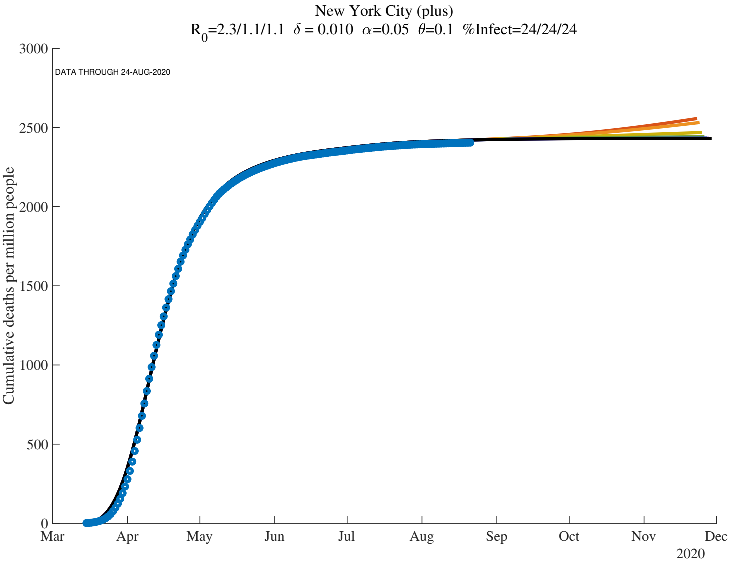
- $\mathcal{R}_0$ in subtitle:
  - Initial / Today / Final

- “%Infect”
  - Today / t+30 / Final
  - This is the percent ever infected
  - (so fraction δ will eventually be deaths)

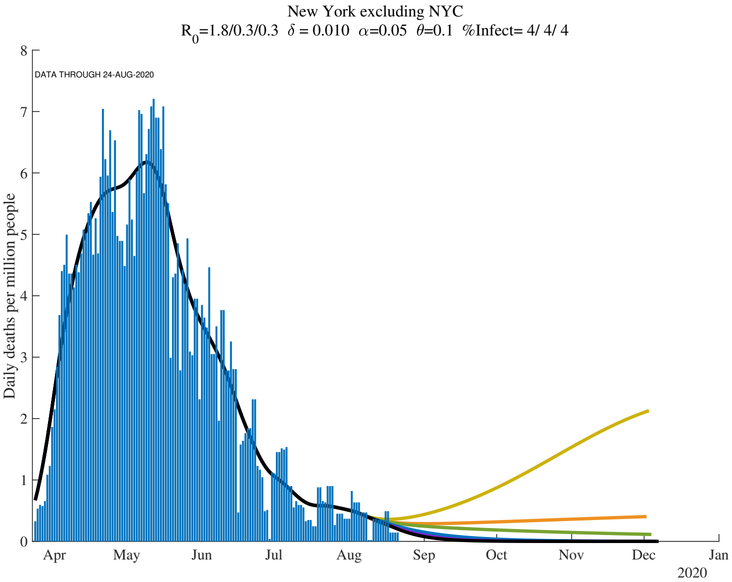
New York City (7 days): Daily Deaths per Million People



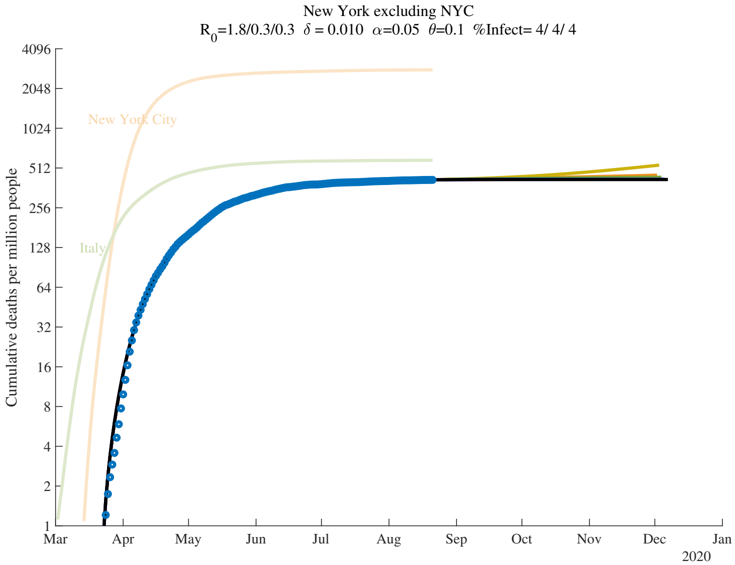
New York City (7 days): Cumulative Deaths per Million (Future)



New York excl NYC (7 days): Daily Deaths per Million People



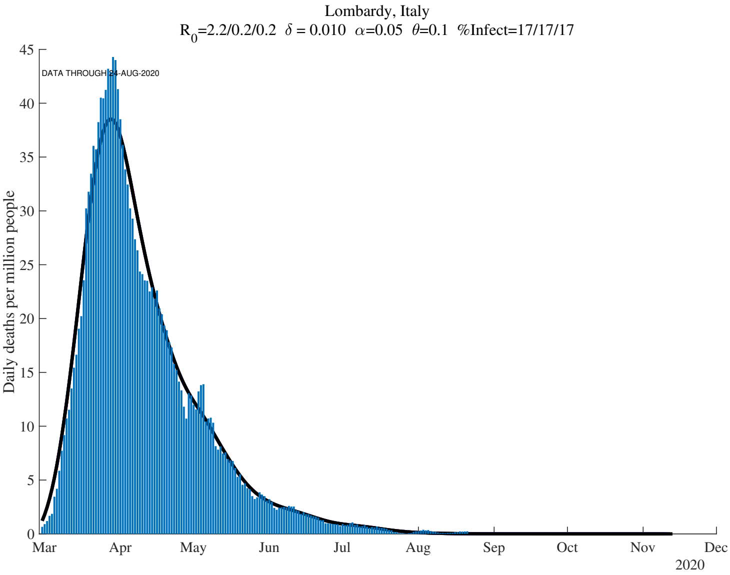
New York excl NYC (7 days): Cumulative Deaths per Million (Future)



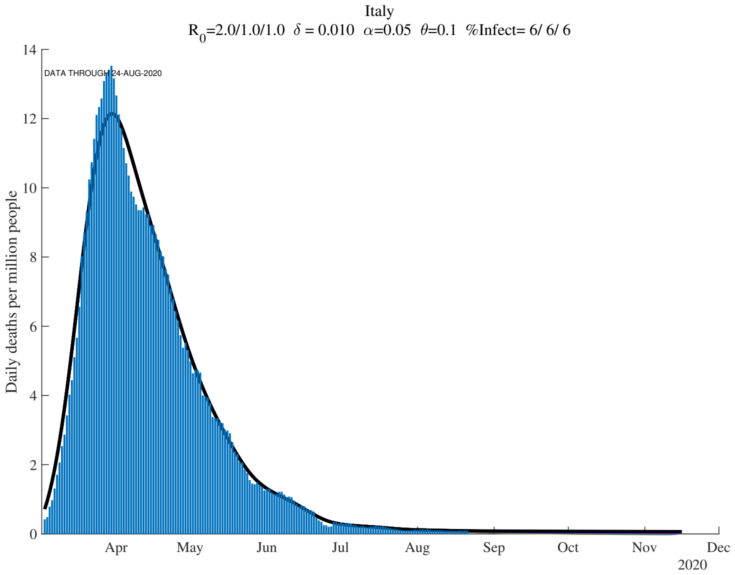
Stylized Experiences to Keep in Mind

	Total (pm) Deaths, t	Peak Daily Deaths (pm)
New York City (only)	2800	80
Paris = London = Washington DC	800	20
NY excl NYC = Atlanta	400	5

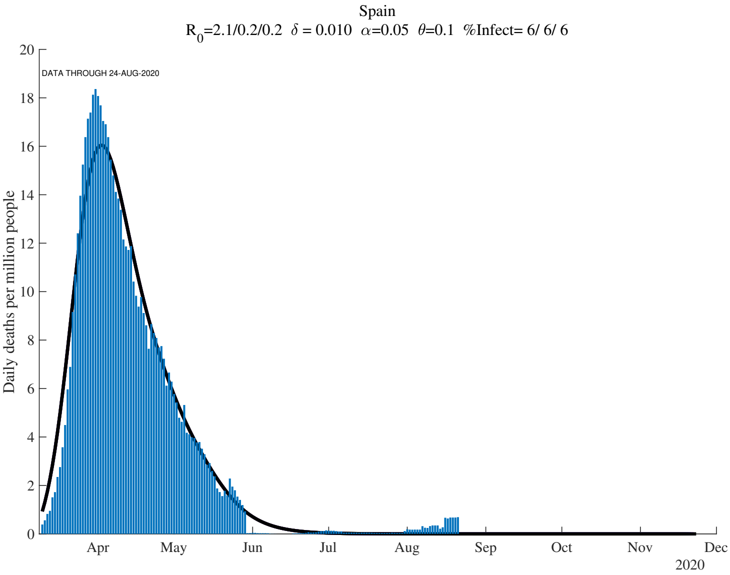
Lombardy (7 days): Daily Deaths per Million People



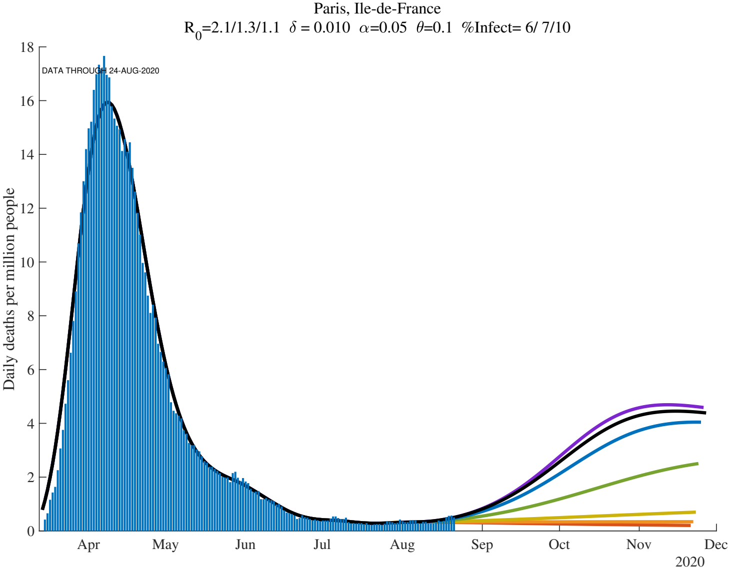
Italy (7 days): Daily Deaths per Million People



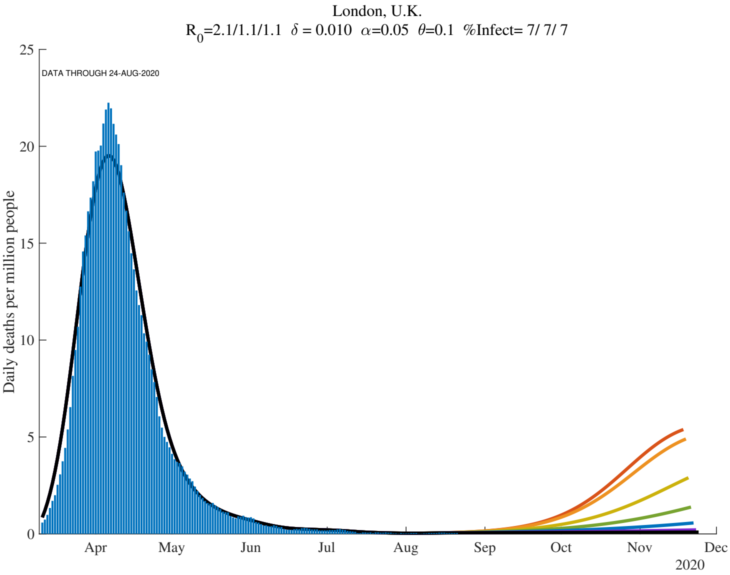
Spain (7 days): Daily Deaths per Million People



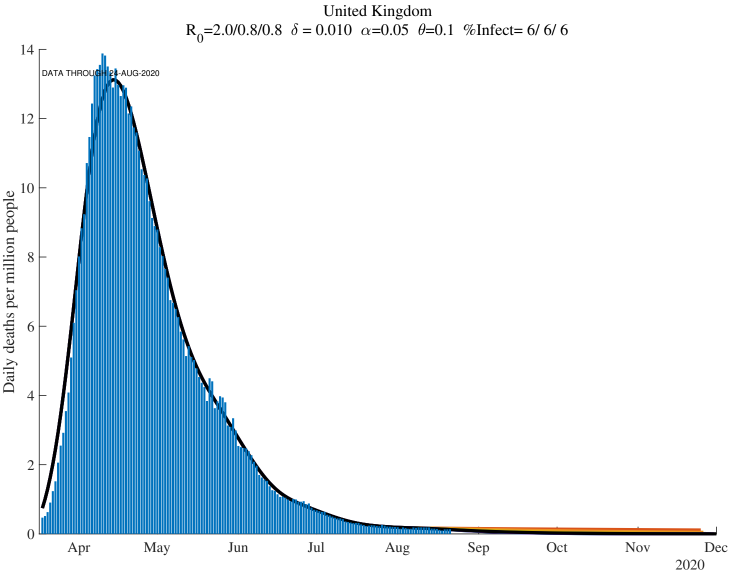
Paris (7 days): Daily Deaths per Million People



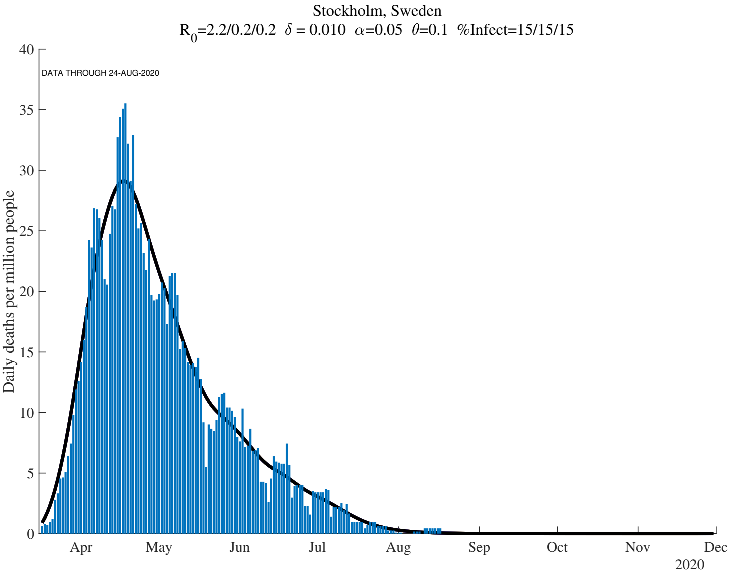
London (7 days): Daily Deaths per Million People



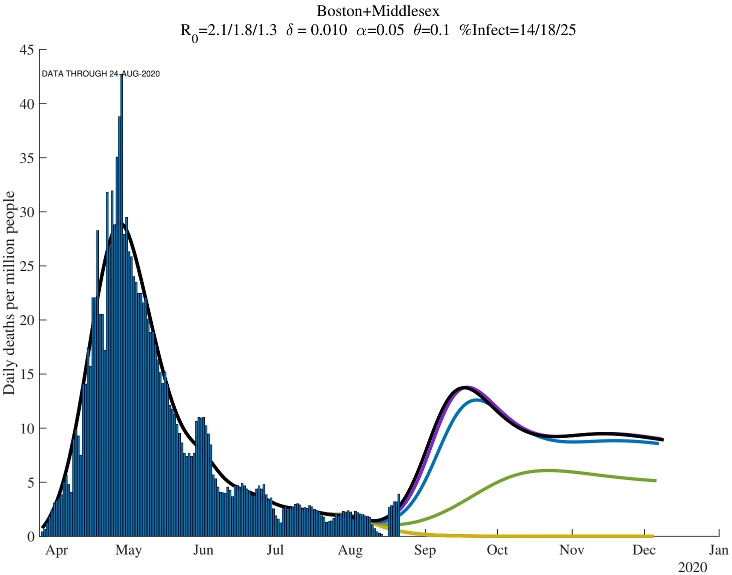
U.K. (7 days): Daily Deaths per Million



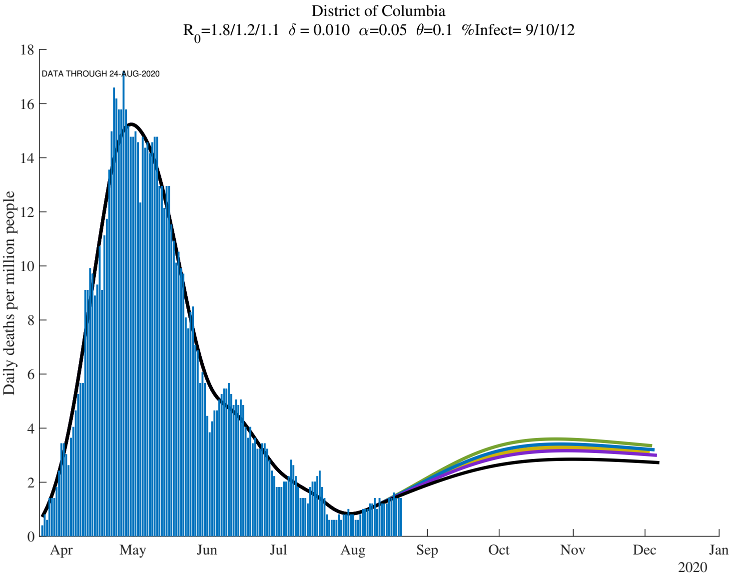
Stockholm (7 days): Daily Deaths per Million People



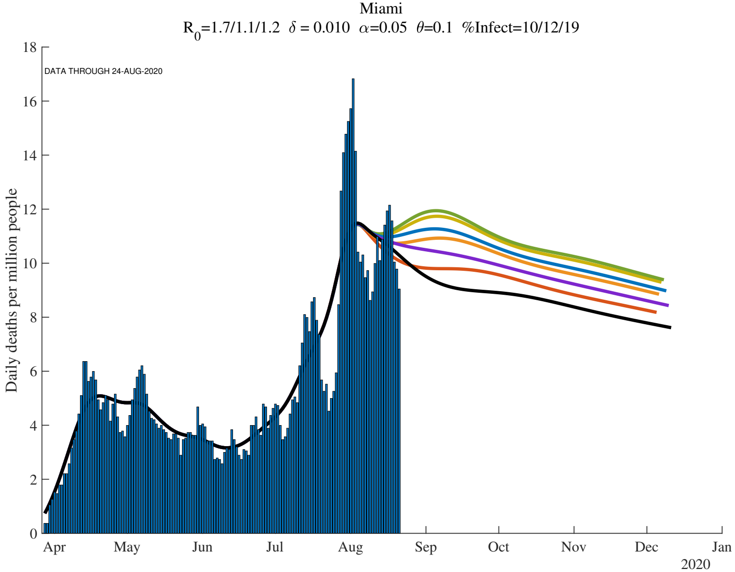
Boston (7 days): Daily Deaths per Million People



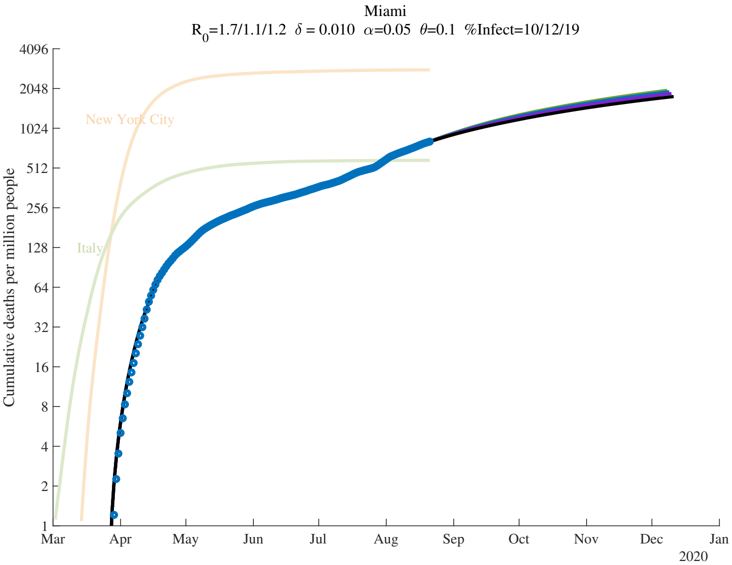
District of Columbia (7 days): Daily Deaths per Million People



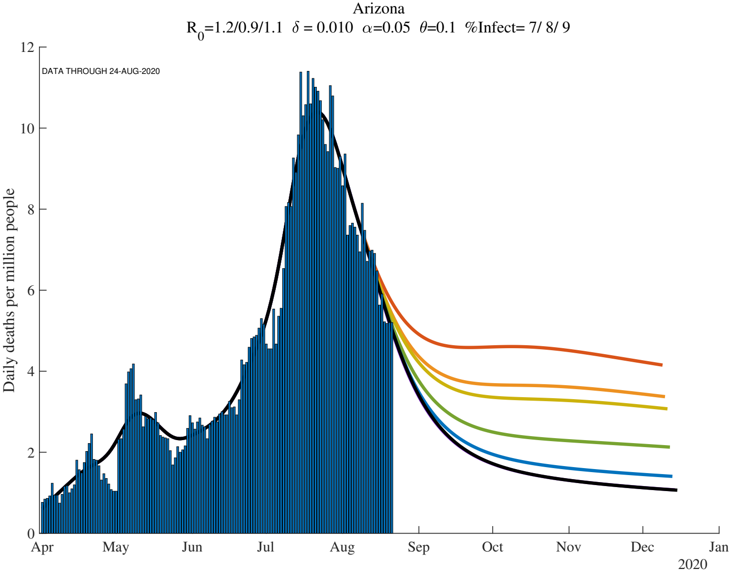
Miami (7 days): Daily Deaths per Million People



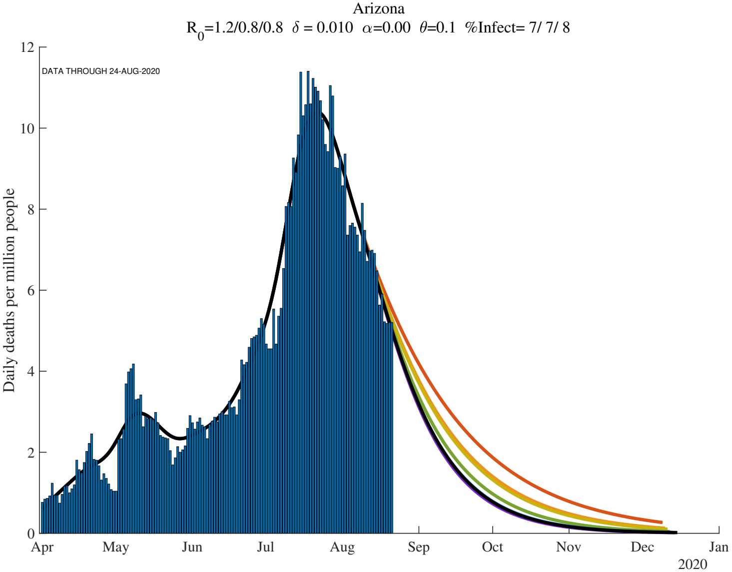
Miami (7 days): Cumulative Deaths per Million (Future)



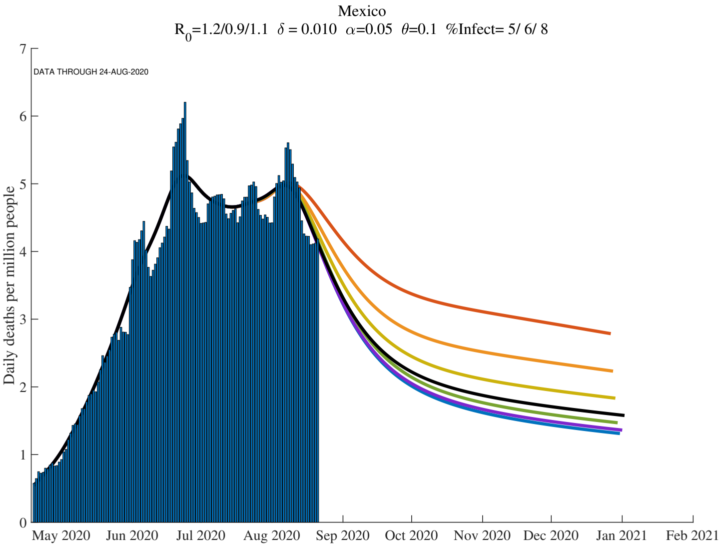
Arizona (7 days): Daily Deaths per Million People



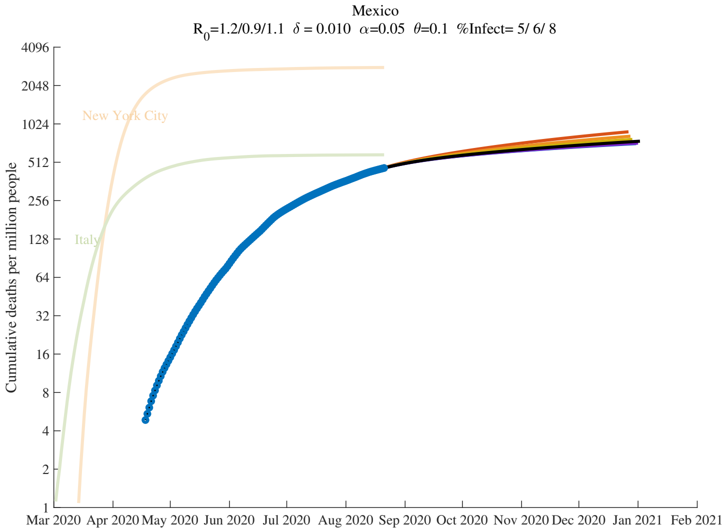
Arizona (7 days): Daily Deaths with $\alpha = 0$



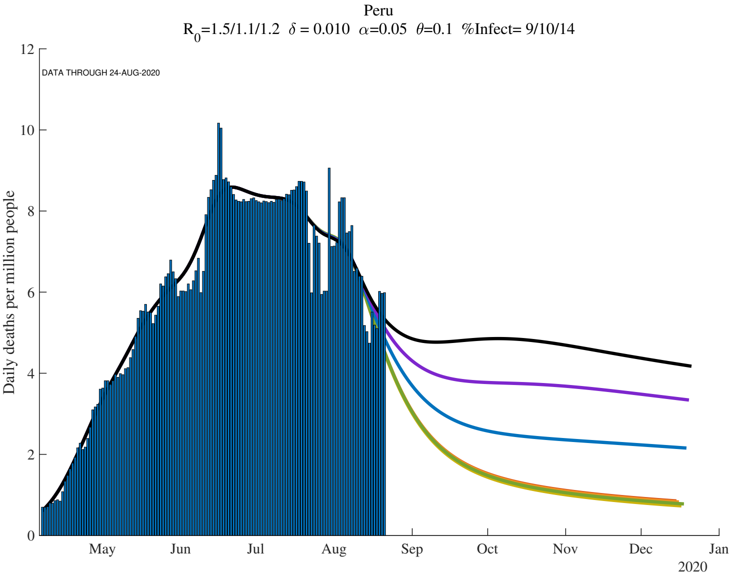
Mexico (7 days): Daily Deaths per Million People



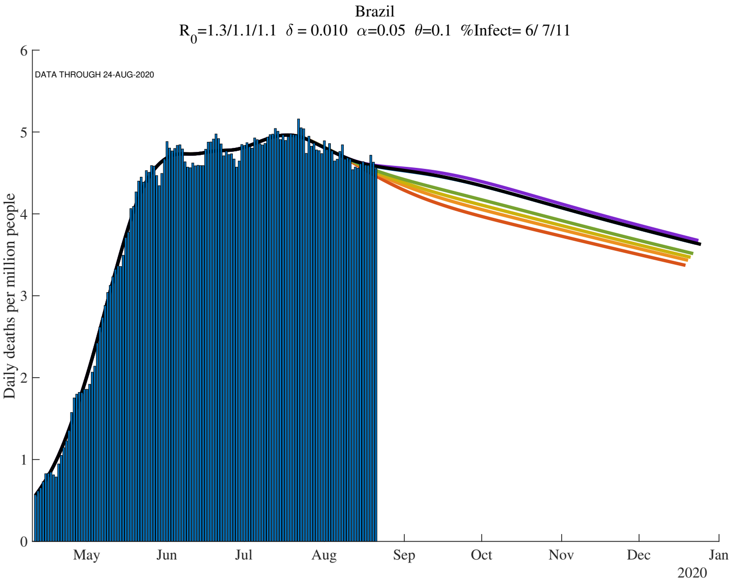
Mexico (7 days): Cumulative Deaths per Million (Future)



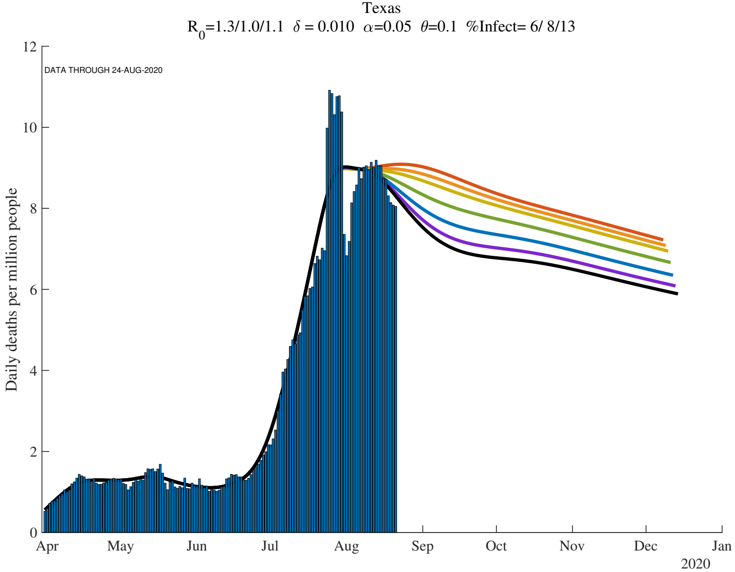
Peru (7 days): Daily Deaths per Million People



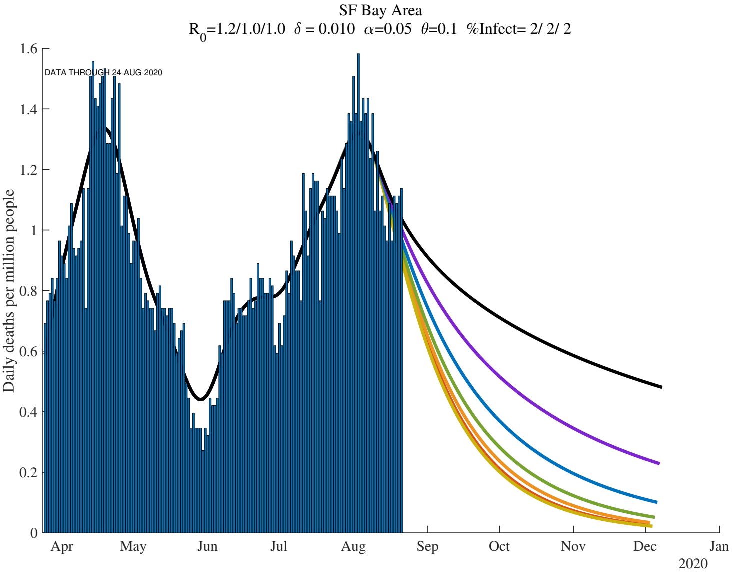
Brazil (7 days): Daily Deaths per Million People



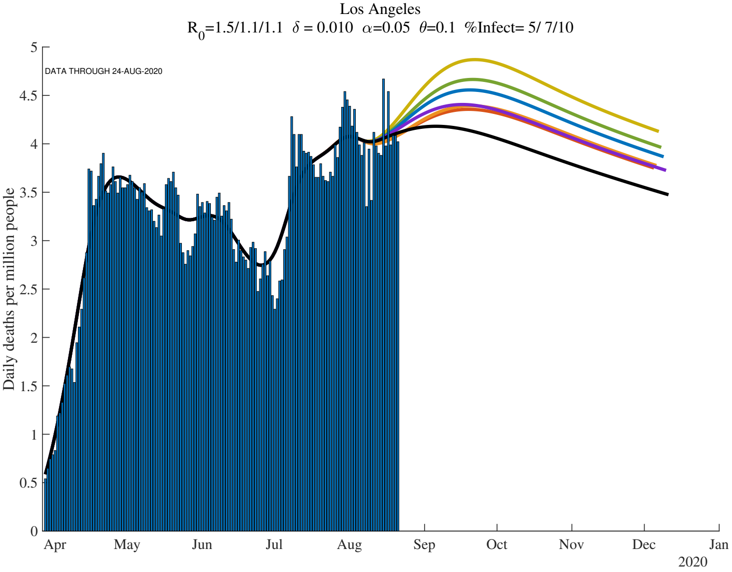
Texas (7 days): Daily Deaths per Million People



SF Bay Area (7 days): Daily Deaths per Million People



Los Angeles (7 days): Daily Deaths per Million People



Reopening and Herd Immunity

Percent Ever Infected would be very informative

	— Percent Ever Infected (today) —		
	$\delta = 0.5\%$	$\delta = 1.0\%$	$\delta = 1.2\%$
New York City (only)	57	29	24
Lombardy, Italy	34	17	14
Stockholm, Sweden	29	15	12
Madrid, Spain	26	13	11
Boston+Middlesex	27	14	11
Philadelphia	23	11	9
Belgium	18	9	7
District of Columbia	18	9	7
Paris, France	17	8	7
Miami	19	10	8
London, U.K.	13	7	5
Spain	12	6	5
Arizona	14	7	6
Italy	12	6	5
United States	11	6	5
Texas	12	6	5
Mexico	10	5	4
New York excluding NYC	8	4	3
Houston (Harris Co.)	10	5	4
Kentucky	6	3	2
SF Bay Area	3	2	1
Israel	2	1	1
Norway	1	0	0

Herd Immunity

- How far can we relax social distancing?
- Let $s(t) = S(t)/N$ = the fraction still susceptible
  - The disease will die out as long as

$$\mathcal{R}_0(t)s(t) < 1$$

  - That is, if the "new" $\mathcal{R}_0$ is smaller than $1/s(t)$
  - Today's infected people infect fewer than 1 person on average
- We can relax social distancing to raise $\mathcal{R}_0(t)$ to $1/s(t)$

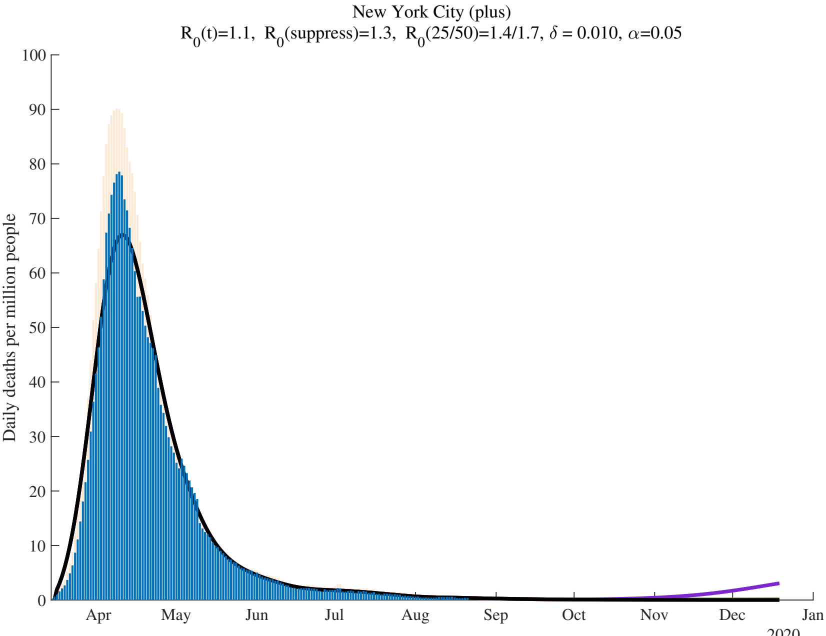
Herd Immunity and Opening the Economy? $\delta = 1.0\%$

	$\mathcal{R}_0$	$\mathcal{R}_0(t)$	Percent Susceptible t+30	$\mathcal{R}_0$(t+30) with no outbreak	Percent way back to normal
New York City (only)	2.4	1.0	71.4	1.4	31.8
Lombardy, Italy	2.2	0.2	83.2	1.2	49.9
Stockholm, Sweden	2.2	0.2	85.3	1.2	48.2
Madrid, Spain	2.2	0.2	87.1	1.1	46.0
Chicago	1.9	1.3	88.9	1.1	-40.0
Belgium	2.1	1.1	91.0	1.1	2.2
District of Columbia	1.8	1.2	90.5	1.1	-13.3
Paris, France	2.1	0.7	91.5	1.1	26.0
Miami	1.7	1.1	87.7	1.1	11.4
London, U.K.	2.1	1.1	93.4	1.1	-2.7
United Kingdom	2.0	0.8	93.9	1.1	19.2
Italy	2.0	1.0	94.1	1.1	1.8
Sweden	1.8	1.3	93.8	1.1	-61.5
United States	1.8	1.0	93.5	1.1	5.6
Brazil	1.3	1.1	92.7	1.1	6.8
France	2.0	1.2	95.2	1.1	-18.4
Mexico	1.2	0.9	94.1	1.1	42.2
California	1.4	1.0	95.6	1.0	8.0
Kentucky	1.5	1.2	95.3	1.0	-57.9
SF Bay Area	1.2	1.0	98.2	1.0	25.5
Germany	1.5	1.0	98.9	1.0	-5.8
Israel	1.2	1.0	98.3	1.0	-26.0
Norway	1.3	0.2	99.6	1.0	71.1

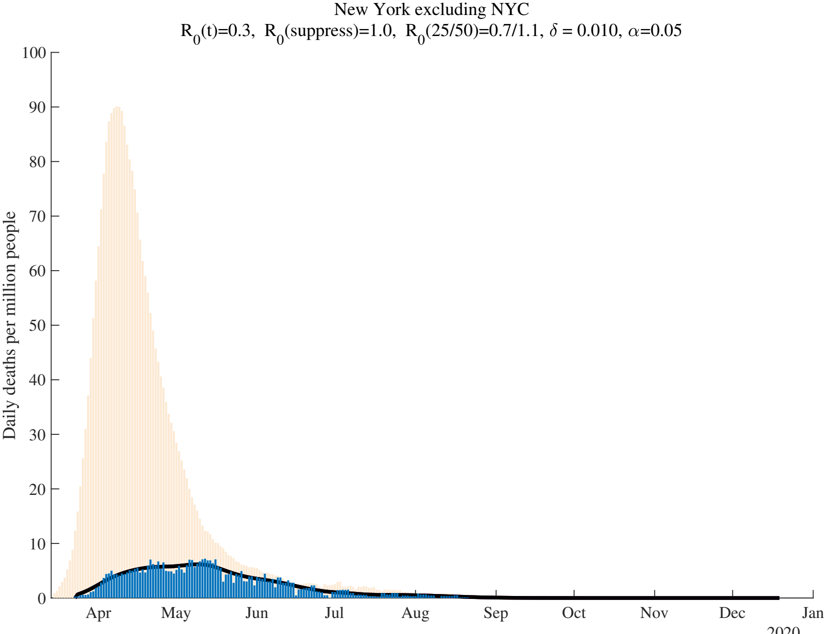
Simulations of Re-Opening

- Begin with the basic estimates shown already
- Different policies are then adopted starting around July 20
  - Black: assumes $\mathcal{R}_0$(today) remains in place forever
  - Red: assumes $\mathcal{R}_0$(suppress)$= 1/s(today)$
  - Green: we move 25% of the way from $\mathcal{R}_0$(today) back to initial $\mathcal{R}_0$ = "normal"
  - Purple: we move 50% of the way from $\mathcal{R}_0$(today) back to initial $\mathcal{R}_0$ = "normal"
- We assume these $\mathcal{R}_0$ values adjust to daily deaths via α
  - Each daily death reduces $\mathcal{R}_0$ by 5 percent

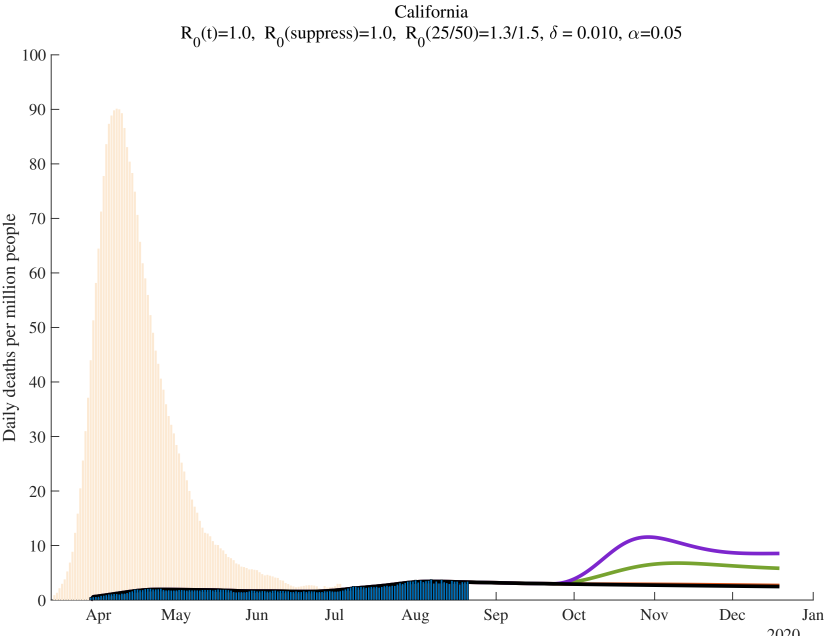
New York City: Re-Opening



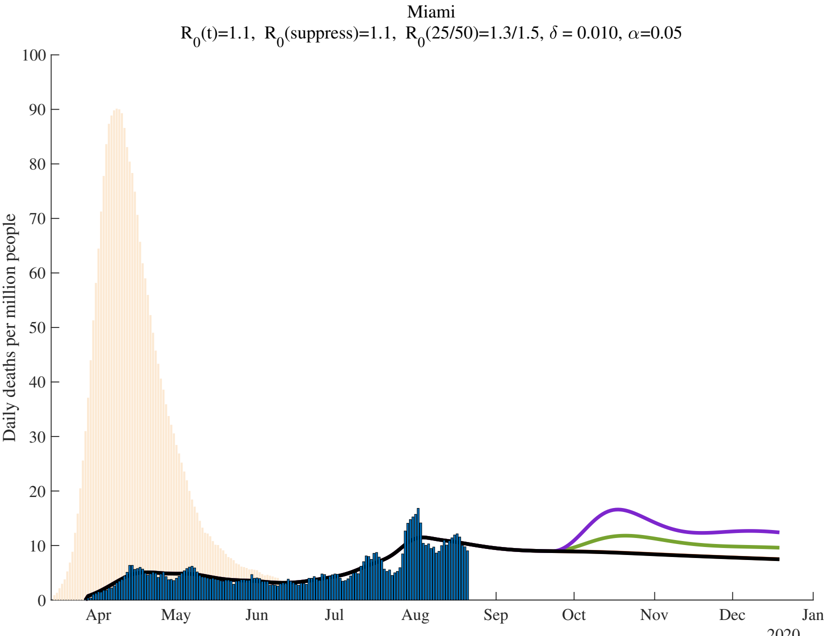
New York excluding NYC: Re-Opening



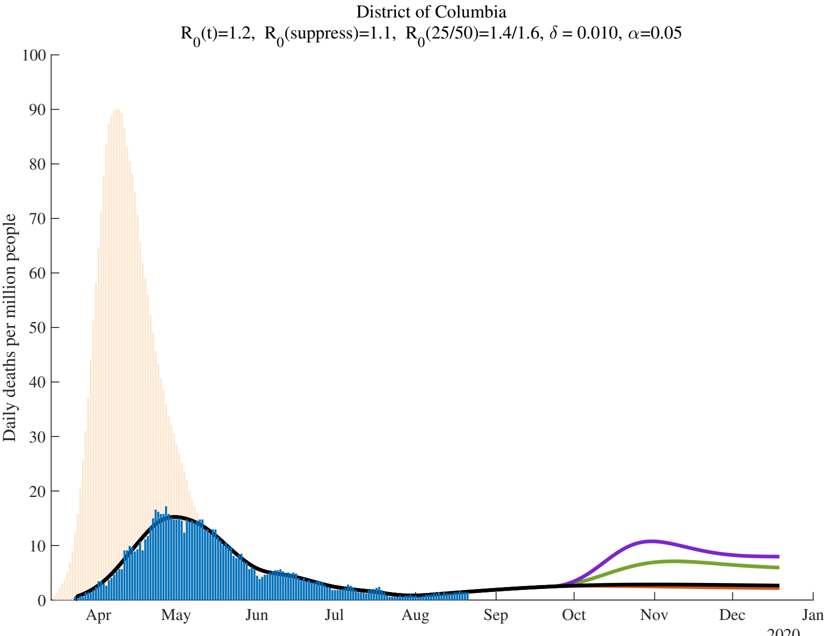
California: Re-Opening



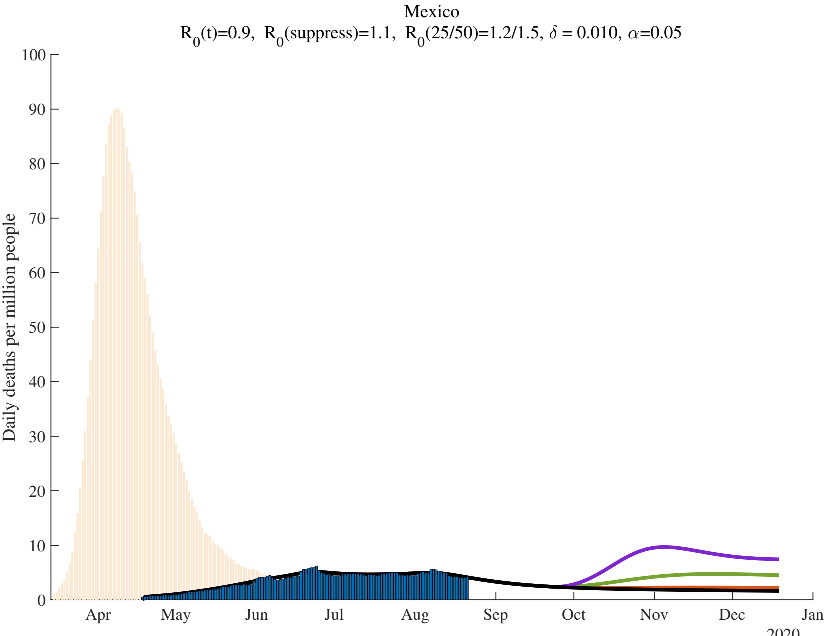
Miami: Re-Opening



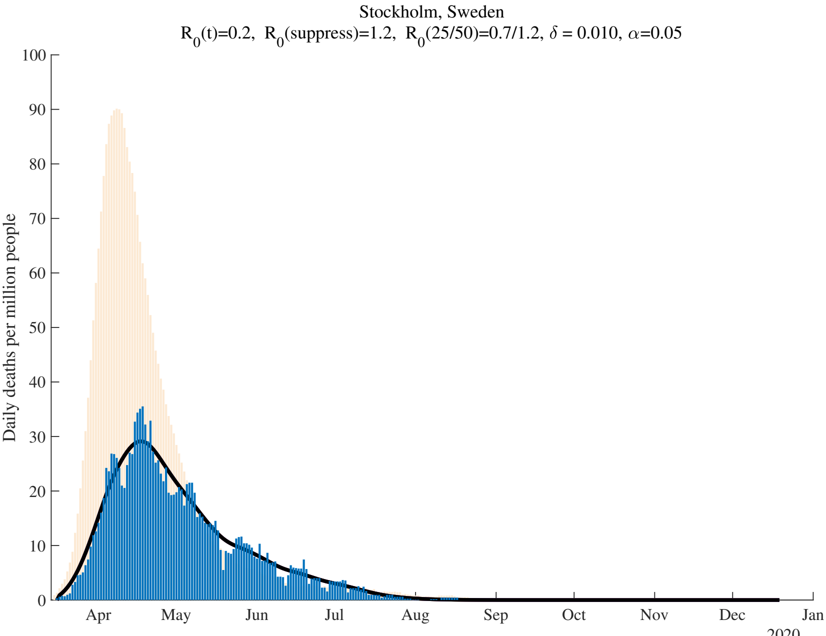
Washington, DC: Re-Opening



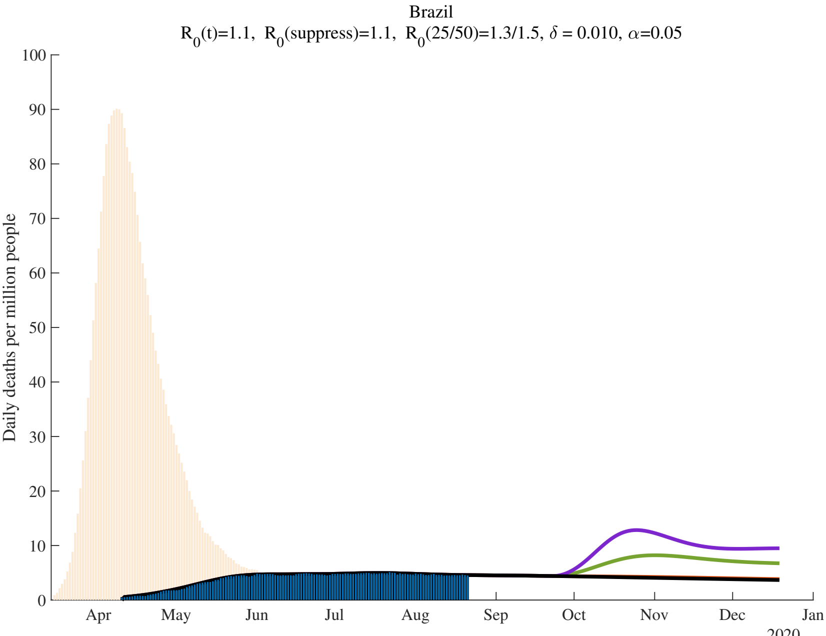
Mexico: Re-Opening



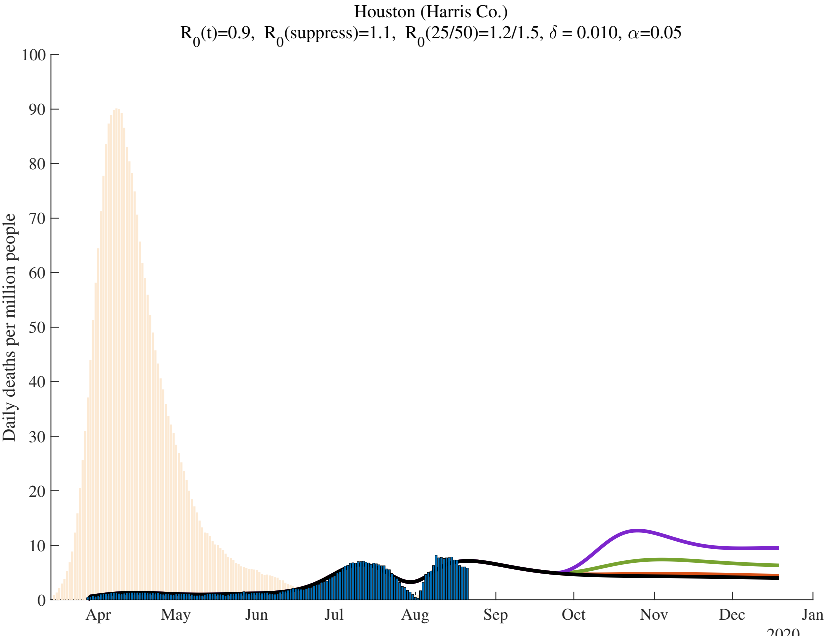
Stockholm: Re-Opening



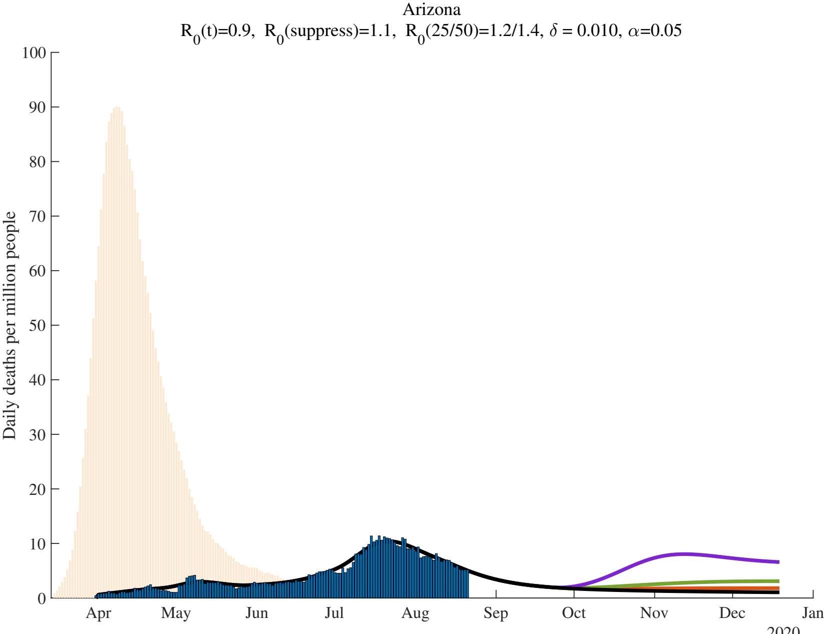
Brazil: Re-Opening



Houston: Re-Opening

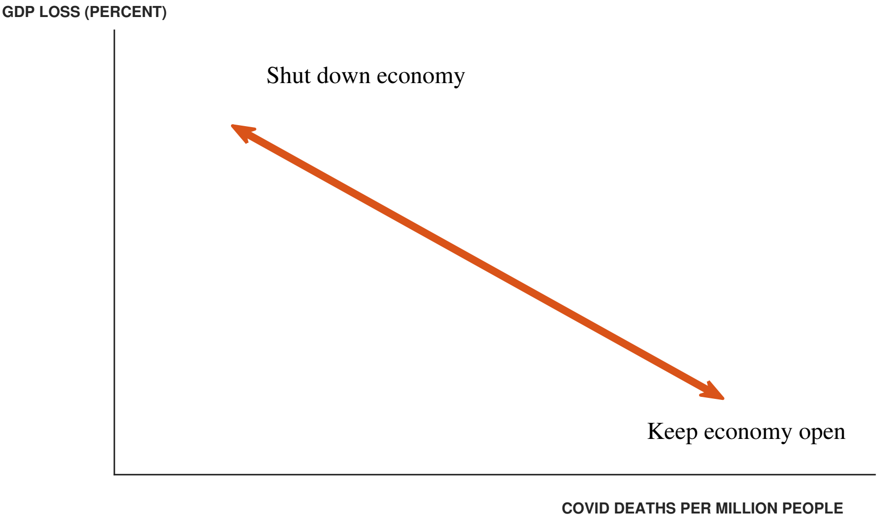


Arizona: Re-Opening

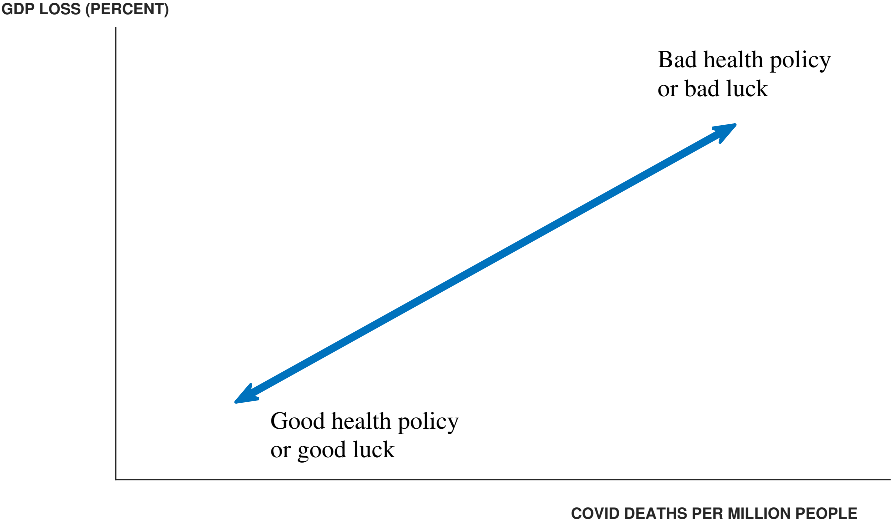


Macroeconomic Outcomes

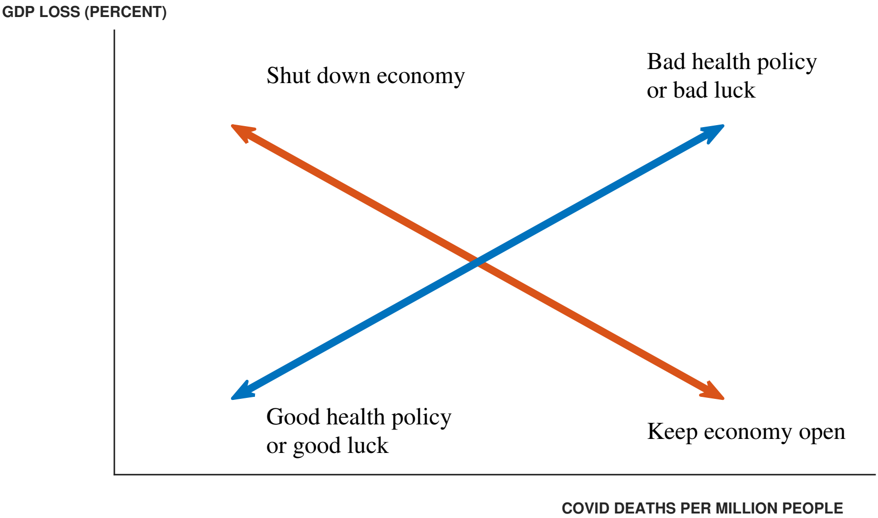
Economic Policy Trade Off, Holding Health Policy and Luck Constant



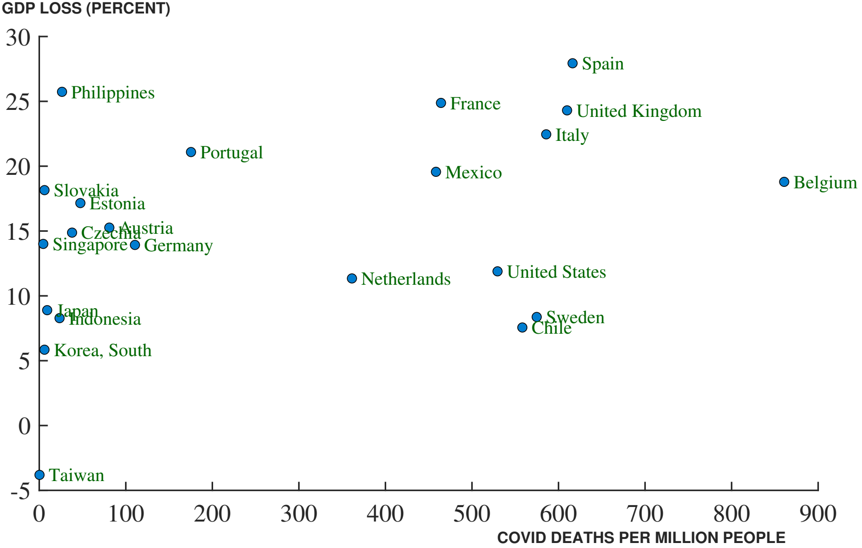
Health Policy Decisions and Luck Can Shift the Tradeoff



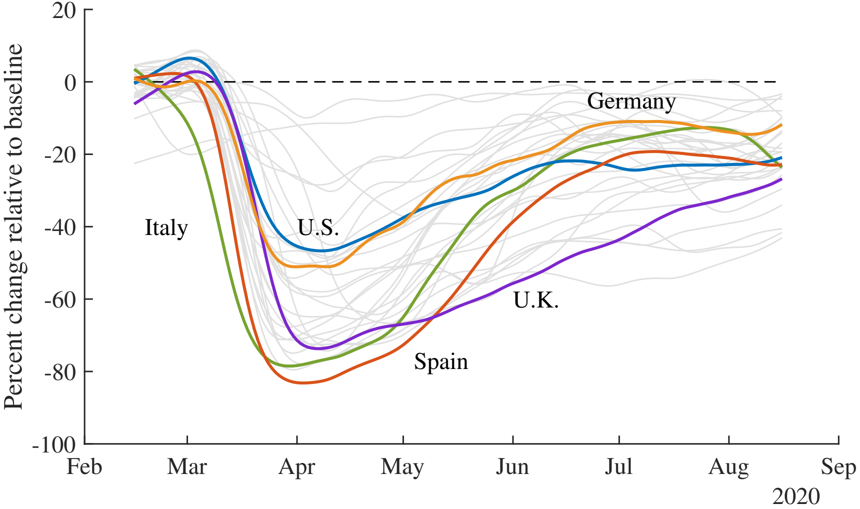
Putting together...



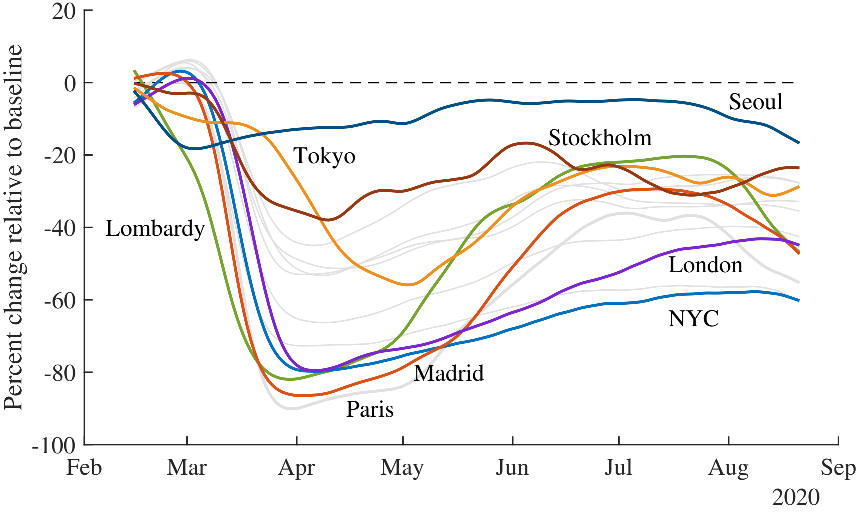
International Covid Deaths and Lost GDP, 2020



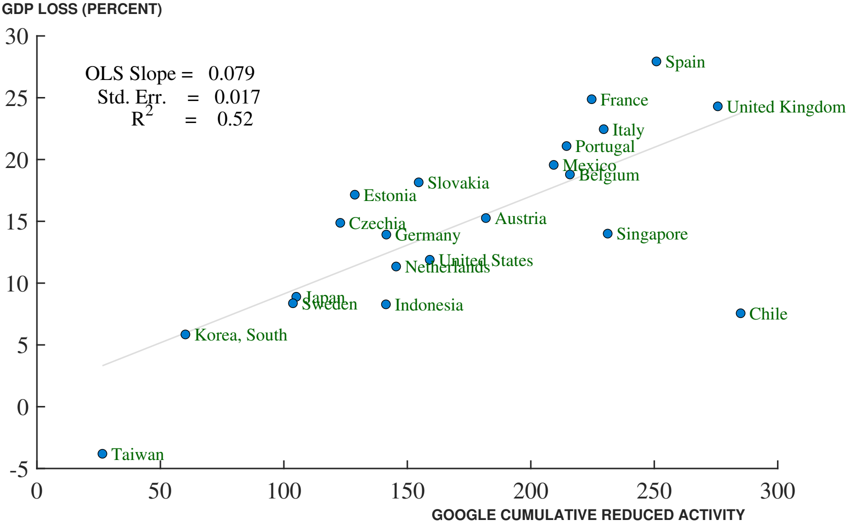
Google Activity Tracker: International Evidence



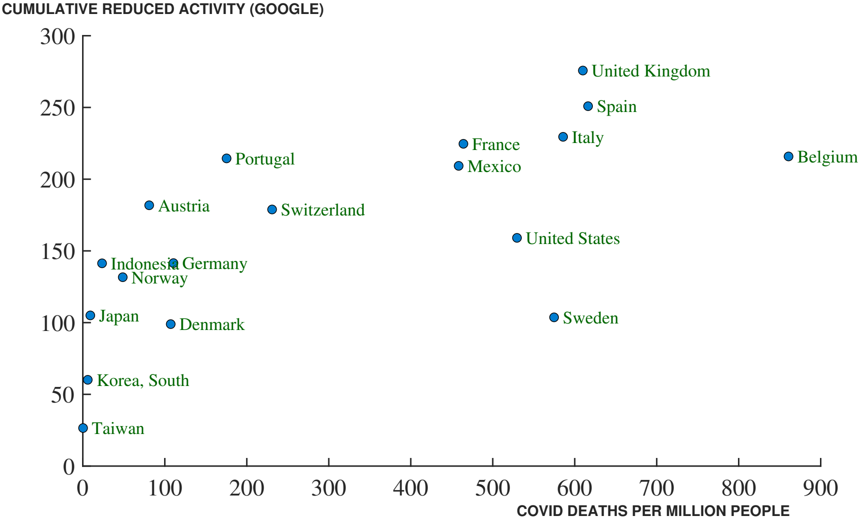
Google Activity Tracker for Key Global Cities



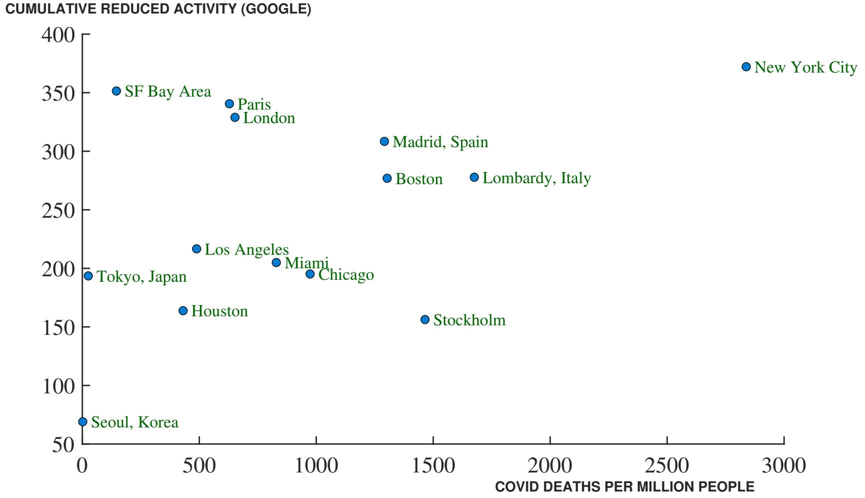
Cumulative Google Activity and Lost GDP



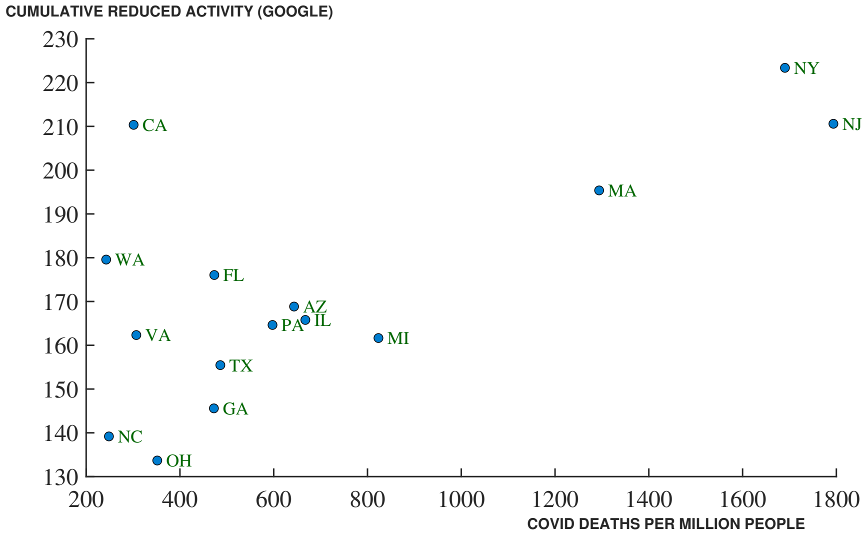
Covid Deaths and Cumulative Google Activity



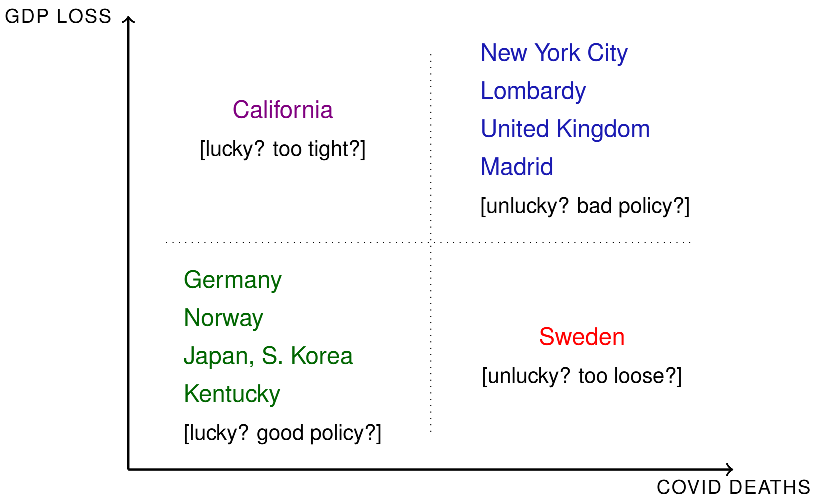
Global Cities: Covid Deaths and Cumulative Google Activity



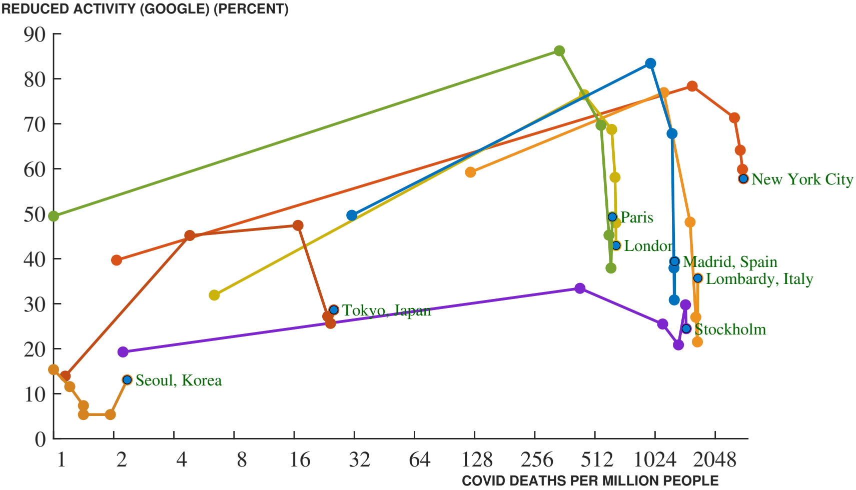
U.S. States: Covid Deaths and Cumulative Google Activity



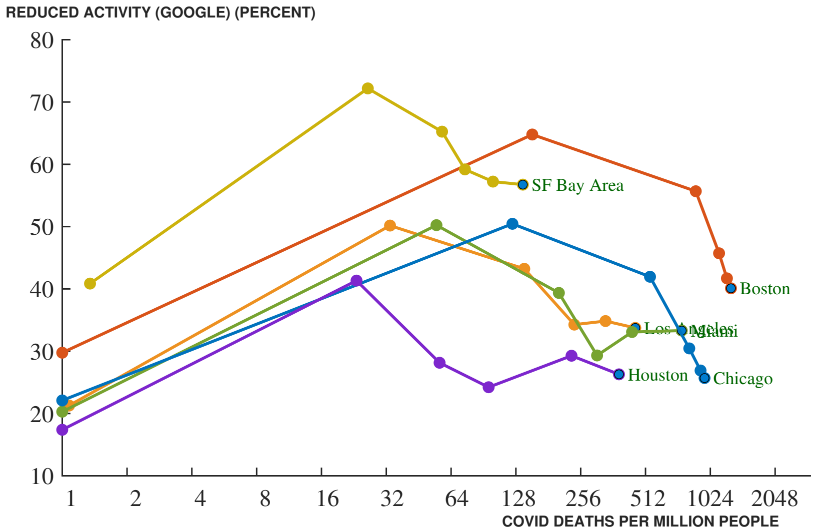
Summary


GDP LOSS
California
[lucky? too tight?]
New York City
Lombardy
United Kingdom
Madrid
[unlucky? bad policy?]
Germany
Norway
Japan, S. Korea
Kentucky
[lucky? good policy?]
Sweden
[unlucky? too loose?]
COVID DEATHS

Global Cities: Monthly Evolution from March to August



Global Cities: Monthly Evolution from March to August



Conclusions and Questions

Speculations based on model, we are not epidemiologists

- Things I wonder about
  - What is the distribution of outcomes for young people? (hospitalizations? long-term effects?)
  - What if every at risk person had an N95 mask?
  - What did Tokyo and Seoul do that we should learn from?
  - Next wave?
  - Paper/saliva tests

Our dashboard contains 30+ pages of results for each of 100 cities, states, and countries