The Macroeconomics of Epidemics

Discussion by Andy Atkeson
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Interaction of Macroeconomics and Epidemics

SIRD Model

Disease State S,I,R,D + **Transmission Rate** → **Updated Disease State**

Transmission Rate Model

Natural Forces, Human Activity, Prophylactic Use → **Transmission Rate**

Economic Model

Information and Personal Risk/Reward, Policies → **Human Activity, Prophylactic Use**

This paper: Equilibrium and Optimal Policy

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My discussion

- Can we measure what is happening with transmission?
  - Atkeson, Kopecky, Zha, with thanks to Jim Stock
  - Future research should compare predicted vs. actual transmission
- Policy Counterfactuals
  - Would a one-week delay in mitigation have raised or lowered long-run cumulative deaths?
  - Answer depends on the state or country you look at

Measuring Transmission

- Panel data on deaths by state, Census region, and country
  - Invert the SIRD model to recover panel data on
    - disease state $S(t), I(t), R(t), D(t)$,
    - effective reproduction number $\mathscr{R}(t)$,
    - and transmission rates $\beta(t)$
- Empirical Implementation
  - Bayesian estimation from noisy reported deaths data

SIRD Model

$$1 = S(t) + I(t) + R(t) + D(t)$$

$$\frac{dS(t)}{dt} = -\mathscr{R}(t)\gamma I(t)$$

$$\frac{dI(t)}{dt} = \left(\mathscr{R}(t) - 1\right)\gamma I(t)$$

$$\frac{dR(t)}{dt} = (1 - \nu)\gamma I(t)$$

$$\frac{dD(t)}{dt} = \nu\gamma I(t)$$

$$\mathscr{R}(t) \equiv \frac{\beta(t)}{\gamma}S(t)$$

Effective Reproduction Number $\mathscr{R}(t)$

Recovery Rate γ

Infection Fatality Rate ν

Transmission Rate $\beta(t)$

Normalized Transmission Rate $\frac{\beta(t)}{\gamma}$

Basic Reproduction Number $\mathscr{R}(0) = \frac{\beta(0)}{\gamma}$

Transmission in the ERT model

Equation 1 from the paper

$$\beta(t) = \underline{\pi_1} C^S(t) C^I(t) + \underline{\pi_2} N^S(t) N^I(t) + \underline{\pi_3(t)}$$

Consumption Expenditures	$C^S(t), C^I(t)$
Labor Hours	$N^S(t), N^I(t)$
Residual Transmission	$\pi_3(t)$

Can we compare this model to data on $\beta(t)$ to date?

Measuring $\beta(t)$
Inputs: Deaths Data and Fatality and Recovery Rates

$D(t)$ **Cumulative Deaths**

$\frac{dD(t)}{dt}$ **Daily Deaths**

$\frac{d^2D(t)}{dt^2}$ **Change in Daily Deaths**

Have to be estimated from noisy reported numbers

Pick parameters for fatality and recovery rates $\nu, \ \gamma$

Invert SIRD model

$$R(t) = \frac{1-\nu}{\nu} D(t)$$

$$I(t) = \frac{1}{\gamma\nu} \frac{dD(t)}{dt}$$

Recover Distribution of Population across States

$$S(t) = 1 - I(t) - R(t) - D(t)$$

$$\mathscr{R}(t) = 1 + \frac{1}{\gamma} \frac{\frac{d^2 D(t)}{dt}}{\frac{dD(t)}{dt}}$$

Estimate Effective Reproduction Number

$$\frac{\beta(t)}{\gamma} = \mathscr{R}(t) \frac{1}{S(t)}$$

Estimate Normalized Transmission Rate

Empirical Implementation

- Reported Deaths are Noisy
- AKZ empirical approach
    - Use mixture of Weibull distributions to model scaled daily deaths
    - Bayesian estimation
    - 10 large US states, 9 Census Regions, 16 countries

Results for New York through 6/25

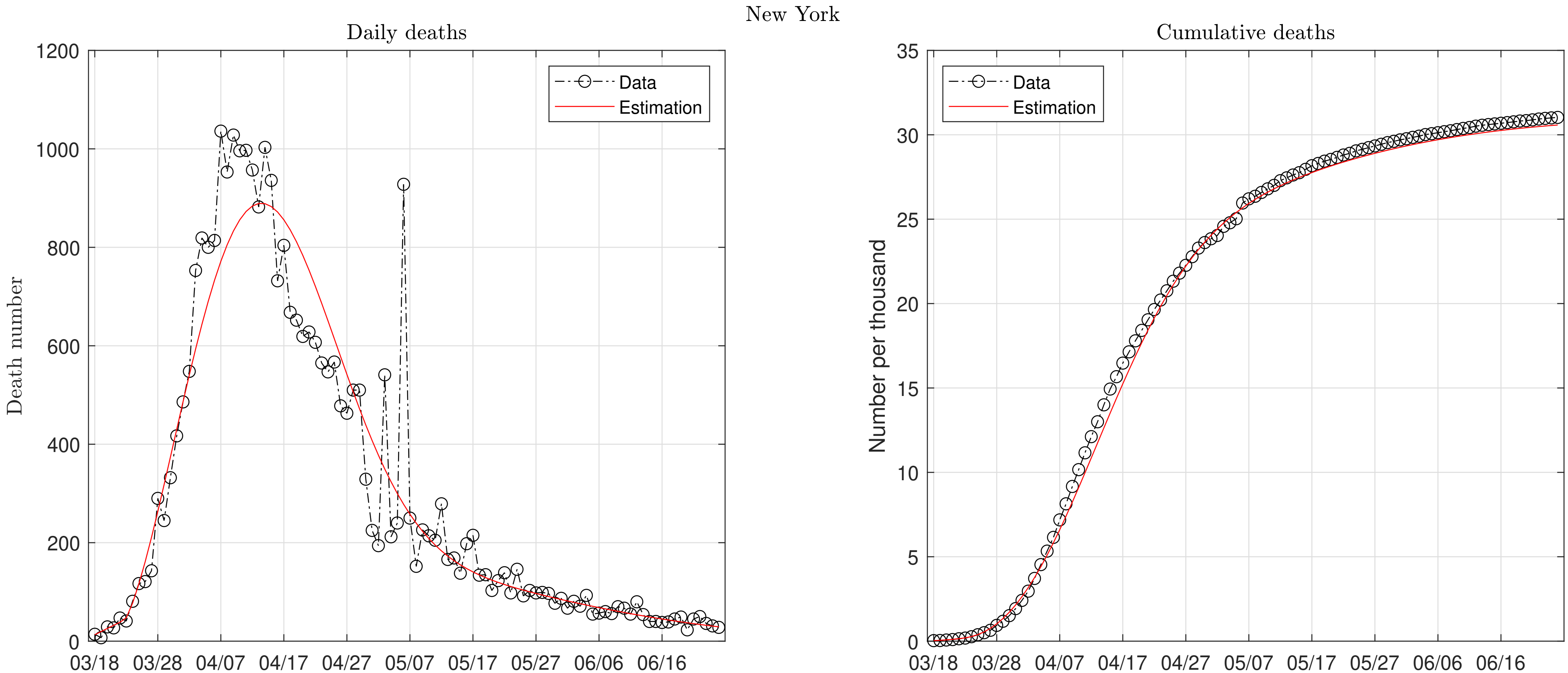


Figure 1: Data and fitted paths of deaths in New York. The death pattern is fitted with two Weibull functions.

Results for California through 6/25

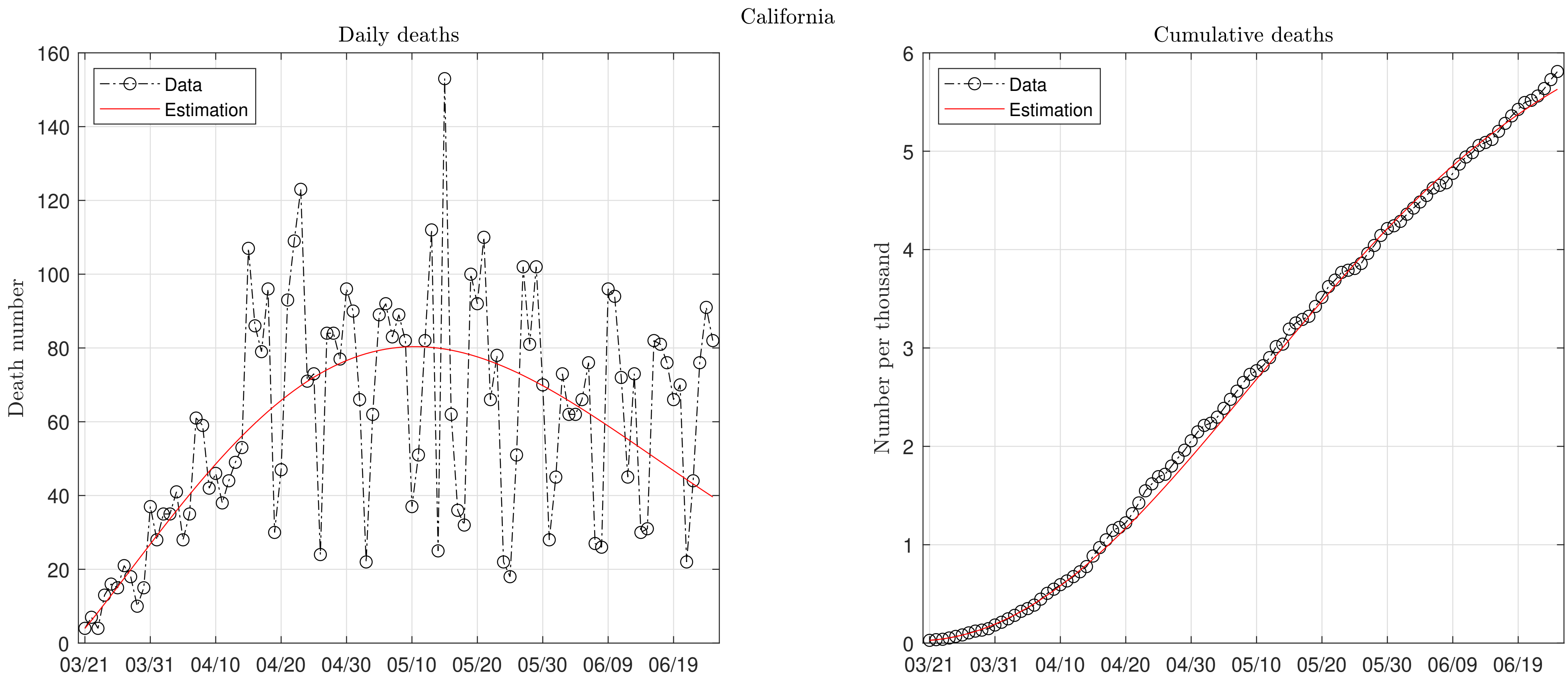
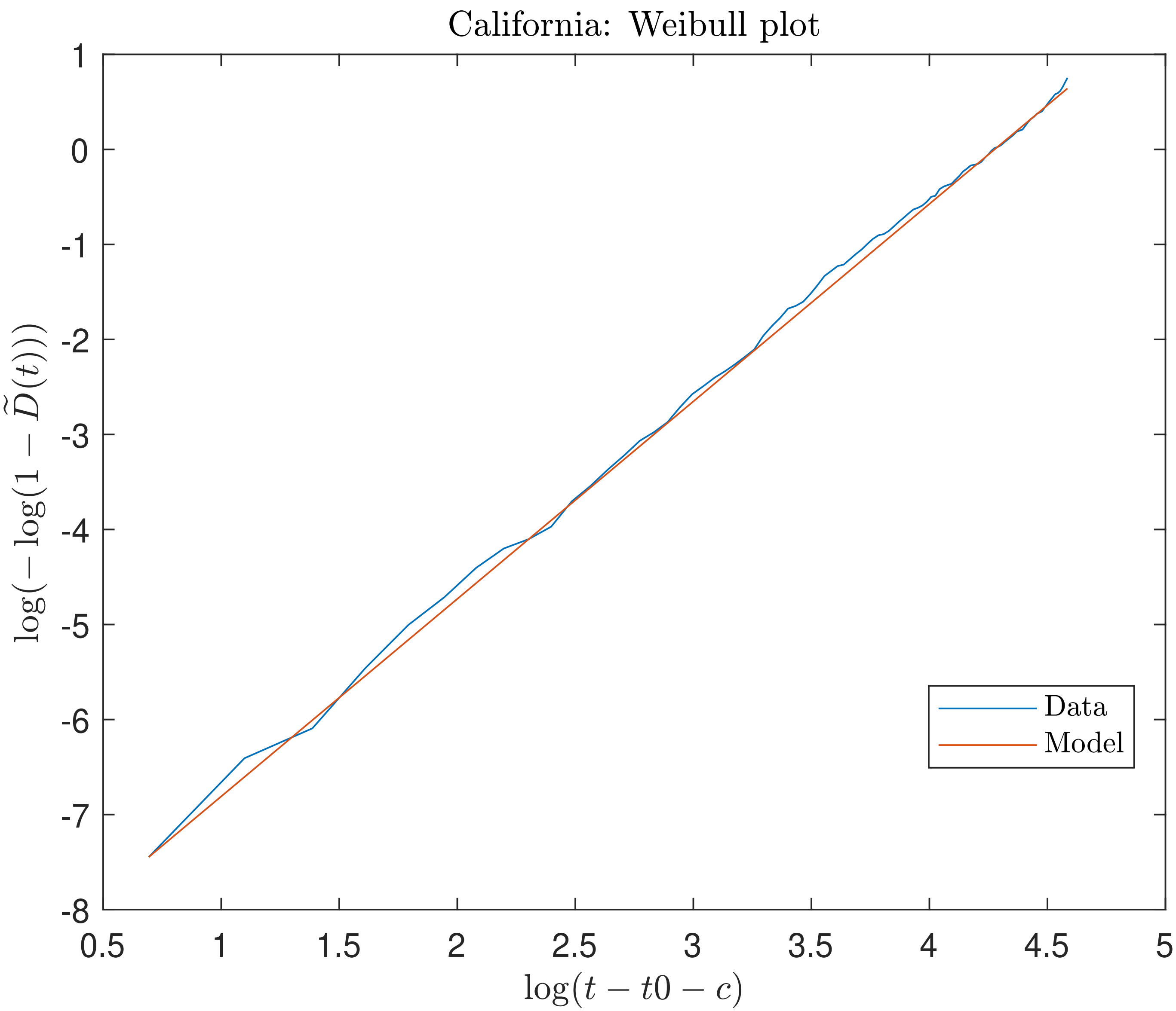
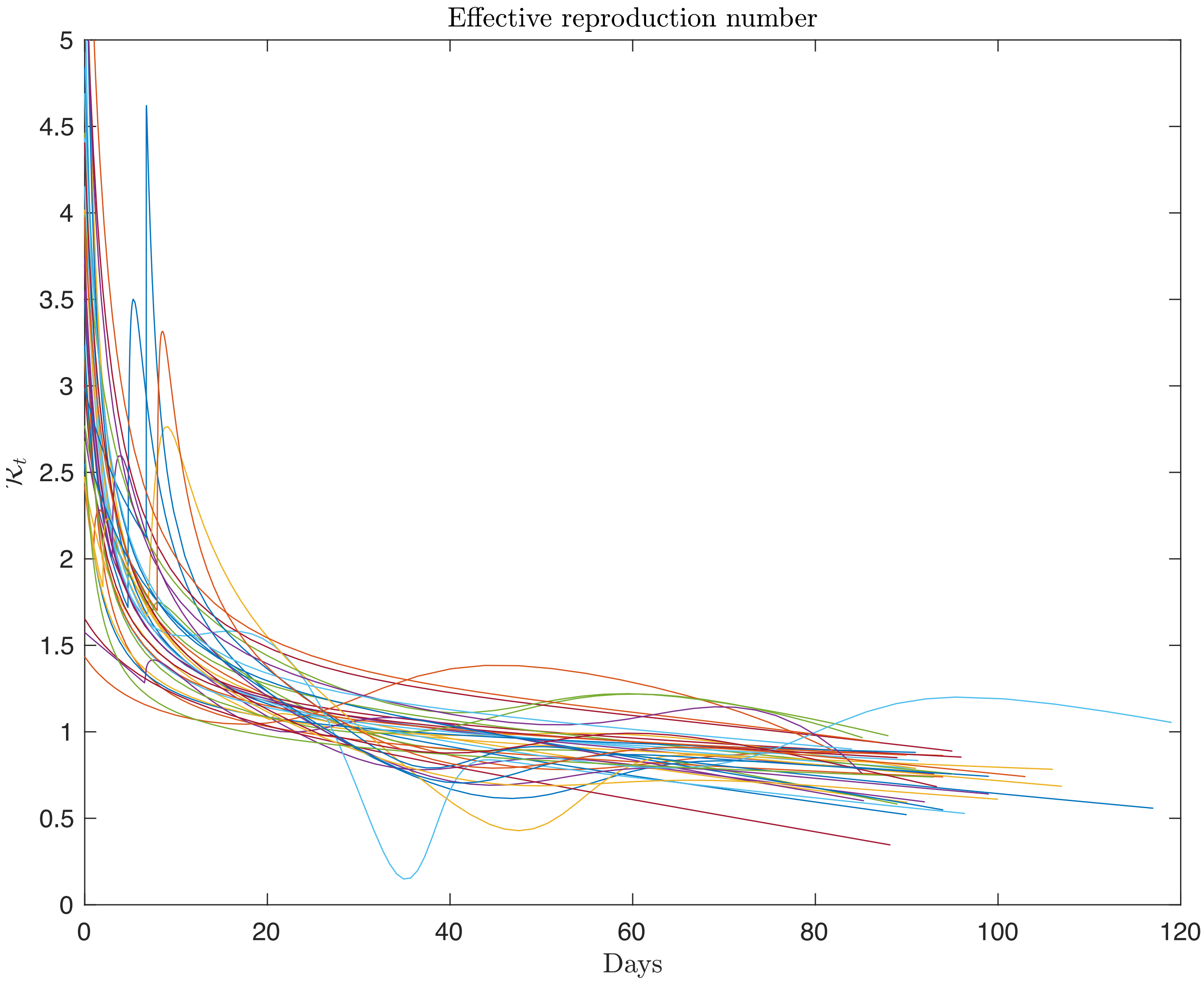


Figure 55: Data and fitted paths of deaths in California. The death pattern is fitted with one Weibull function.

Specification Check: Weibull Plot for California Model and Data are straight lines



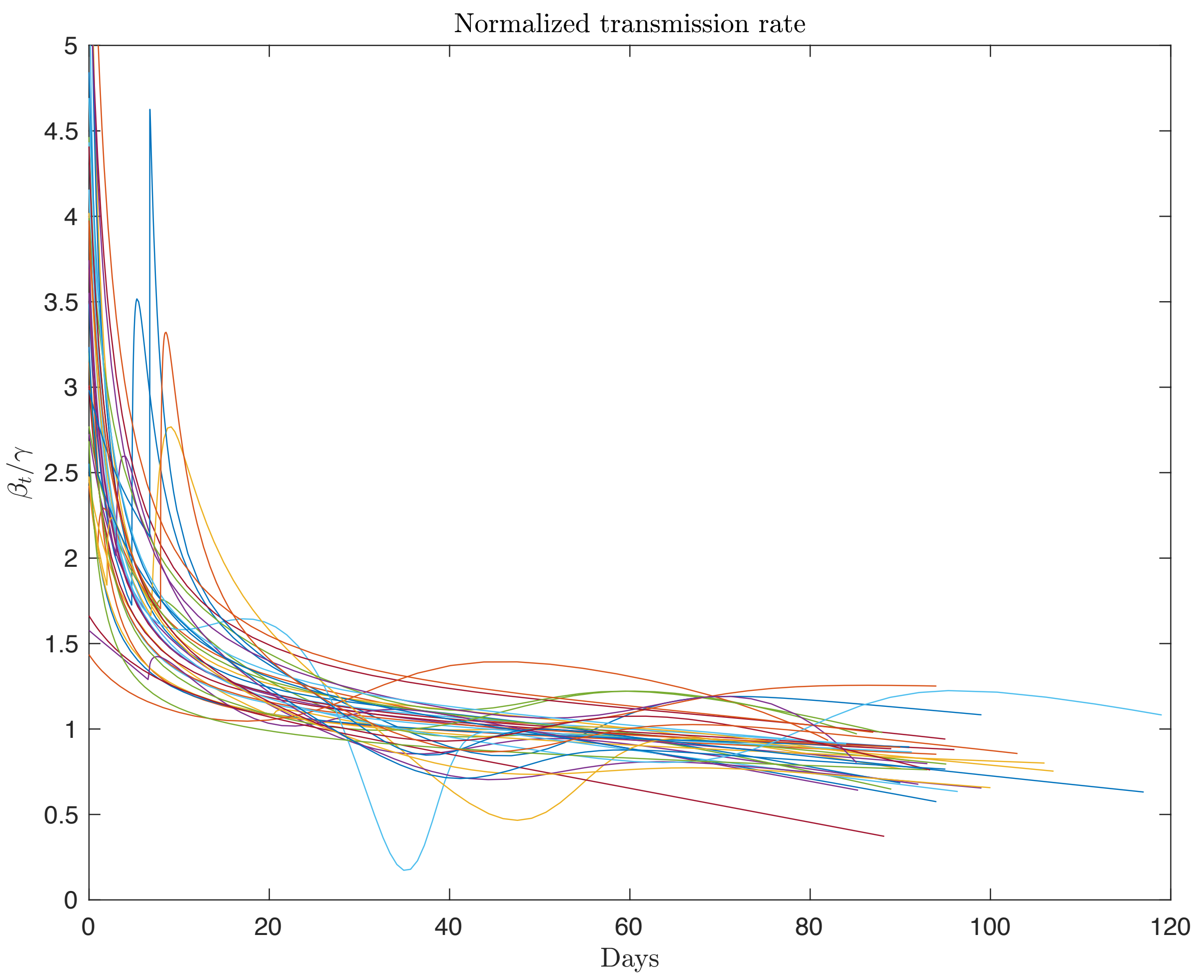
Estimated Effective Reproduction Numbers for 10 big states, 9 Census regions, 22 countries



A big drop in $\mathscr{R}(t)$ everywhere

Why? Herd Immunity?

Estimated Normalized Transmission Rates for 10 big states, 9 Census regions, 22 countries



Transmission rates fell everywhere

Are the declines in economic and human activity so tightly correlated everywhere?

Do we really understand the link between economic activity and disease transmission?

Policy Experiments in ERT

- ERT: We conclude that it is important for policymakers to resist the temptation to delay optimal containment measures for the sake of initially higher short-run levels of economic activity.

- But…

- ERT: As a practical matter, policymakers could face intense pressure to prematurely end containment measures because of their impact on economic activity.

- Does this political pressure change constrained optimal policy?

Counterfactual Experiments in AKZ

- Baseline Scenarios:
  - Estimate the path of $\beta(t)/\gamma$ from start of the epidemic until present
  - Two scenarios for transmission going forward 200 days
    - Optimistic (A): $\beta(t)/\gamma = 0.8$
    - Pessimistic (B): $\beta(t)/\gamma = 1.6$ (premature opening up)
- Counterfactual: delay path of transmission rate by one-week, with high initial transmission for first seven days
  - $\tilde{\beta}(t) = \beta(0)$ for $t < 7$
  - $\tilde{\beta}(t) = \beta(t - 7)$ otherwise

Baseline and Counterfactual Long Run Deaths

Table 2: Cumulative deaths at the end of the sample and at the end of the forecast period in the U.S.

	Forecast scenario A				Forecast scenario B			
	Baseline		Counterfactual		Baseline		Counterfactual	
	Death	S/N	Death	S/N	Death	S/N	Death	S/N
New York	30931	0.68	70595	0.28	40810	0.58	70595	0.28
New Jersey	14271	0.68	22486	0.49	20385	0.54	22506	0.49
Massachusetts	8007	0.77	33025	0.04	17226	0.50	33025	0.04
Illinois	7843	0.88	37805	0.40	36863	0.42	37806	0.40
Pennsylvania	6710	0.90	24160	0.62	37631	0.41	24395	0.62
Michigan	6127	0.88	20920	0.58	28750	0.43	20937	0.58
California	6550	0.97	63286	0.68	124236	0.37	73862	0.62
Connecticut	4310	0.76	16960	0.05	8589	0.52	16960	0.05
Florida	3852	0.96	16760	0.84	67362	0.37	59898	0.44
Louisiana	3166	0.86	15239	0.35	13238	0.43	15239	0.35
Total	129326	0.89	602514	0.57	983579	0.42	847764	0.43

Scenario A: future $\beta(t)/\gamma = 0.8$.

One-week delay in mitigation would lead to many more deaths in the long run

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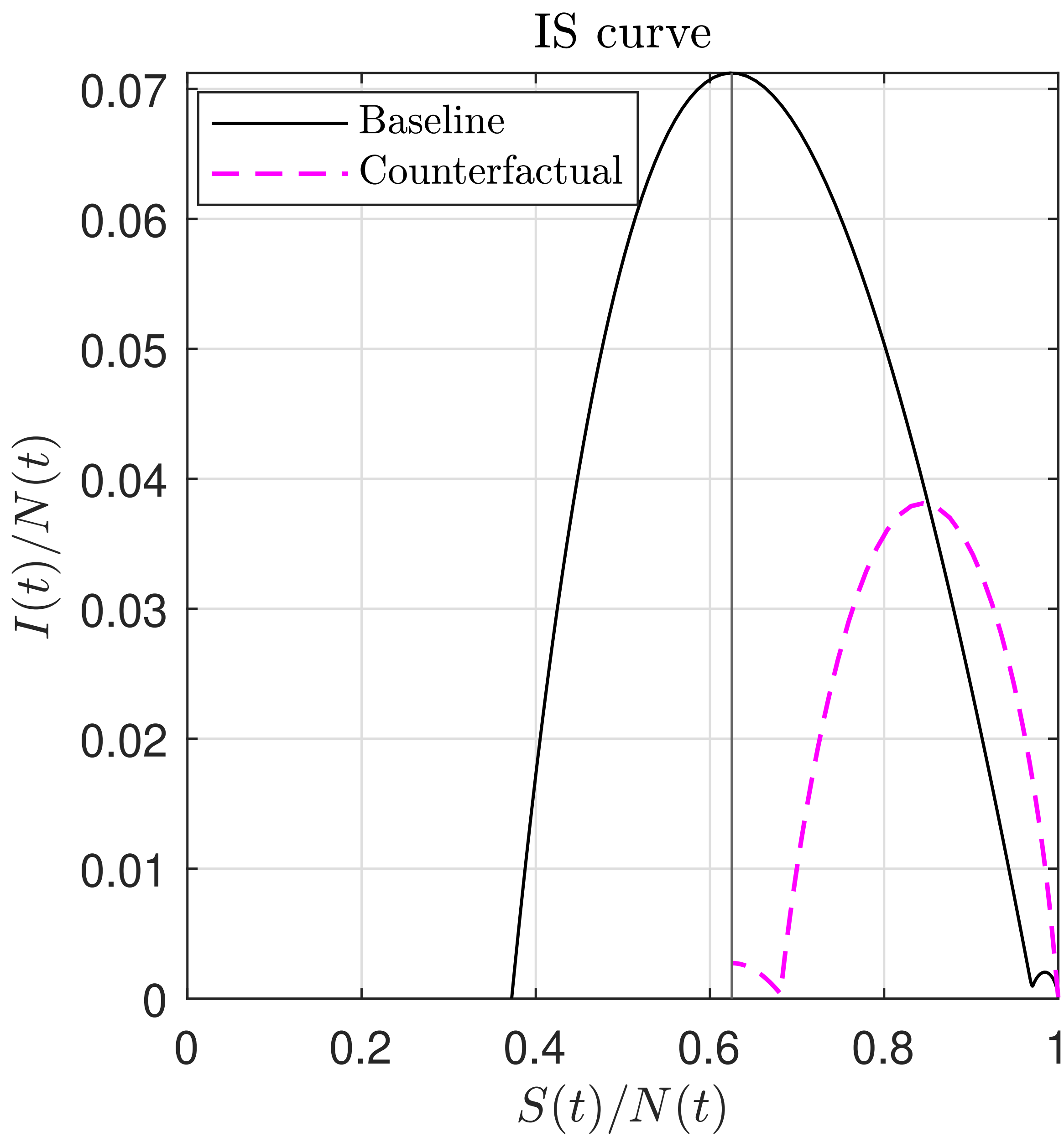
Scenario B: future $\beta(t)/\gamma = 1.6.$

One-week delay in mitigation would lead to fewer deaths in the long run!

IS - Curve for California



Phase diagram
Lucasz Rachel

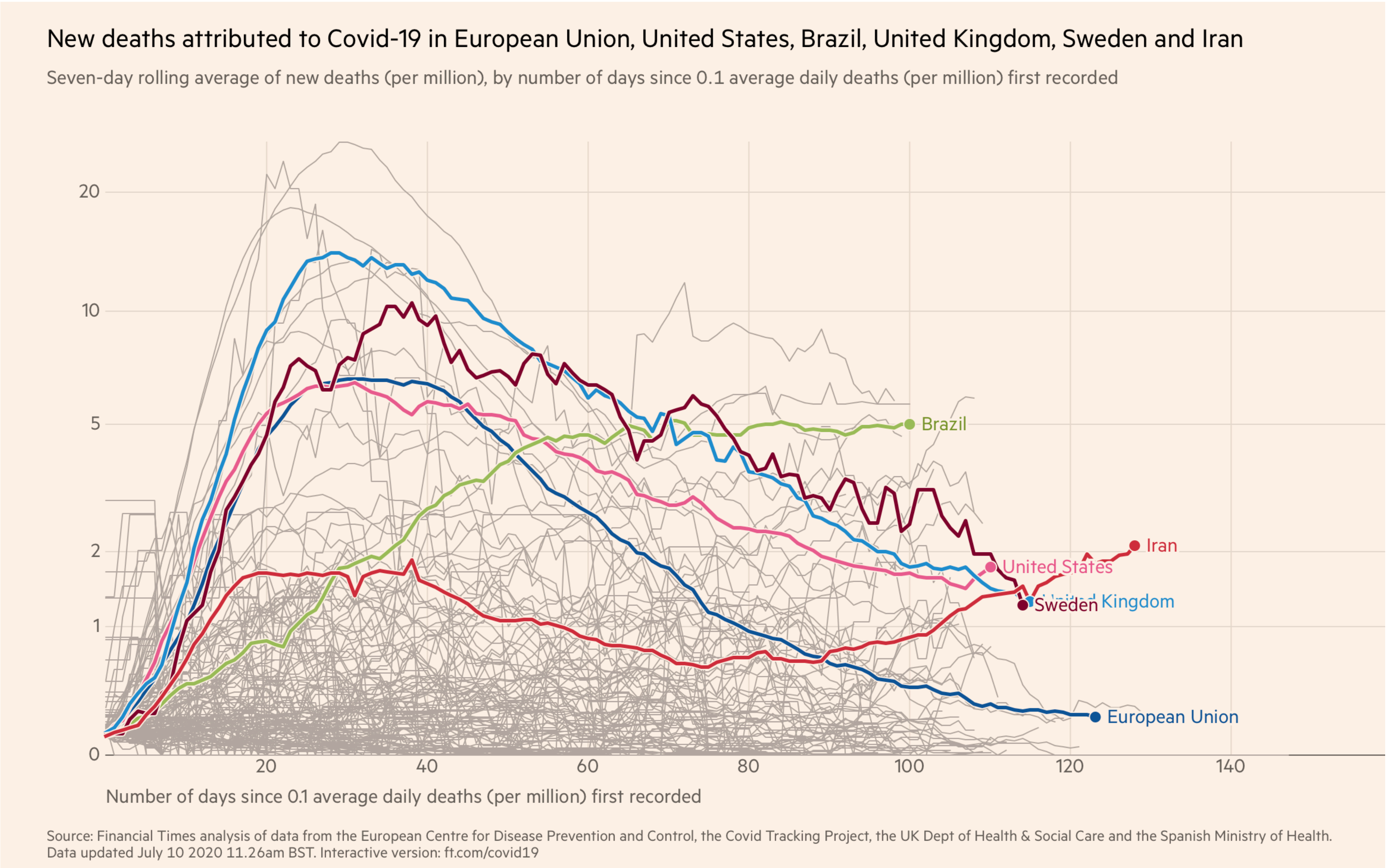
Baseline:
tiny first wave
big second wave

Counterfactual
bigger first wave
makes second
wave smaller

Wrapping Up

- Going forward, macro research on pandemics should compare model transmission to data transmission
  - This is true for all macro papers on this topic
- There has been a big drop in transmission everywhere
  - Why?
  - How does it relate to changes in human activity in different locations?
- Evaluating policy to date is very complicated if we don't know what transmission rates are possible going forward

The effective reproduction number $\mathscr{R}(t)$ is the slope of log daily deaths



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