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 $\rightarrow$ Updated Disease State

Transmission Rate Model

Natural Forces, Human Activity, Prophylactic Use $\rightarrow$ Transmission Rate

Economic Model

Information and Personal Risk/Reward, Policies $\rightarrow$ Human Activity, Prophylactic Use
This paper: Equilibrium and Optimal Policy

SIRD Model

Disease State
S,I,R,D

+ Transmission Rate

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Natural Forces,
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Economic Model

Information and
Personal Risk/Reward,
Policies

→ Human Activity,
Prophylactic Use
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 $\mathcal{R}(t)$,
    • and transmission rates $\beta(t)$

• Empirical Implementation

  • Bayesian estimation from noisy reported deaths data
SIRD Model

\[ 1 = S(t) + I(t) + R(t) + D(t) \]

\[ \frac{dS(t)}{dt} = - \mathcal{R}(t) \gamma I(t) \]

\[ \frac{dI(t)}{dt} = (\mathcal{R}(t) - 1) \gamma I(t) \]

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

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

\[ \mathcal{R}(t) \equiv \frac{\beta(t)}{\gamma} S(t) \]

Effective Reproduction Number \( \mathcal{R}(t) \)

Recovery Rate \( \gamma \)

Infection Fatality Rate \( \nu \)

Transmission Rate \( \beta(t) \)

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

Basic Reproduction Number \( \mathcal{R}(0) = \frac{\beta(0)}{\gamma} \)
Transmission in the ERT model

Equation 1 from the paper

\[ \beta(t) = \pi_1 C^S(t)C^I(t) + \pi_2 N^S(t)N^I(t) + \pi_3(t) \]

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

$D(t)$ \hspace{1cm} Cumulative Deaths

$\frac{dD(t)}{dt}$ \hspace{1cm} Daily Deaths

$\frac{d^2D(t)}{dt^2}$ \hspace{1cm} Change in Daily Deaths

Have to be estimated from noisy reported numbers

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

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

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

\[ S(t) = 1 - I(t) - R(t) - D(t) \]

\[ \mathcal{R}(t) = 1 + \frac{1}{\gamma} \frac{d^2D(t)}{dt} \frac{dD(t)}{dt} \]

\[ \frac{\beta(t)}{\gamma} = \mathcal{R}(t) \frac{1}{S(t)} \]

Recover Distribution of Population across States

Estimate Effective Reproduction Number

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

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

Figure 56: Weibull Plot of data and model for cumulative deaths in California. The death pattern is fitted with one Weibull function.
Estimated Effective Reproduction Numbers for 10 big states, 9 Census regions, 22 countries

A big drop in $\mathcal{R}(t)$ 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.

<table>
<thead>
<tr>
<th>State</th>
<th>Forecast scenario A</th>
<th>Forecast scenario B</th>
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<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Counterfactual</td>
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<tr>
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<td>Death</td>
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<td>New Jersey</td>
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<td>California</td>
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<td>Connecticut</td>
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<td>Florida</td>
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<td>Louisiana</td>
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<td>0.86</td>
</tr>
<tr>
<td>Total</td>
<td>129326</td>
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</table>

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

One-week delay in mitigation would lead to many more deaths in the long run.
Baseline and Counterfactual Long Run Deaths

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<th>State</th>
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<th>S/N</th>
<th>Forecast scenario B Baseline</th>
<th>Counterfactual</th>
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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!
Figure 63: IS phase diagram for California under pessimistic scenarios for disease transmission. The vertical line in each panel marks the value of $S$ corresponding to herd immunity. The solid black curve in each panel shows the path of outcomes under the baseline scenario. The dotted curve in each panel shows path of outcomes under the counterfactual scenario. The normalized transmission rates assumed in the forecast period are $(t) = 1.06$ (right panel) and $t = 1.33$ (left panel). Note that cumulative deaths can be computed using the fatality rate as $\frac{1 - \delta}{\delta} (1 - S(t)I(t))$. Thus, the model implications for long-run cumulative deaths can be computed from the value of $S$ at which the baseline and counterfactual curves hit the x-axes on the left-hand end of those curves.
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 $R(t)$ is the slope of log daily deaths.
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