Pandemics, Incentives, and Economic Policy

Discussion of Chang, Martinez, Velasco

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Introduction

> Second generation SIR model

* SIR models have a long tradition
* Why do we need economists?
  * some say, economists good at model incentives
  * more than that: comparative advantage modeling expectations
    * takes a while to "Bellmanized"
  * point of paper is to argue expectations matter
* CMV: one of a second generation of SIR models
  * incorporating incentives: Atkeson, Lebeau, CMV

> mmatching

- We assume a physical matching

$$m = \Delta \frac{(2 \cdot S \cdot I)}{N}.$$

- Laws of motion:

$$S_{t+1} = S_t - \underbrace{m\,(S, I, R)}_{\text{matches}}$$

$$I_{t+1} = I_t + \underbrace{m\,(S, I, R)}_{\text{infection flow}} - \delta I_t$$

$$R_{t+1} = R_t + \delta I_t.$$

- SIR Model from 1920's
  - hard to believe epidemologists did not update since
  - Alexis Toda (UCSD) provides an analytic solution
  - I criticize: what is m?

> SIRi model...

* Add incentives:

$$j \in \mathbb{J} = \{activities, location, \ actions\}$$

* Enriched model:

$$\underbrace{\{S^j\}_{j\in\mathbb{J}}}_{\text{succeptible}}, \ \underbrace{I}_{\text{infected}}, \ \underbrace{R}_{\text{recovered}}$$

* Fraction:

$$S^j_{t+1} = S^j_t - \underbrace{m^j\left(S^j, I, R\right)}_{\text{iinfection rate}} + \sum_{z\in\mathbb{I}} \phi^{jz} S^z_{t+1} - \sum_{z\in\mathbb{I}} \phi^{zj} S^j_{t+1} \ \forall j \in \mathbb{J}$$

$$I_{t+1} = I_t + \sum_{z\in\mathbb{J}} \underbrace{m^j\left(S^j, I, R\right)}_{\text{infection flow}} - \delta I_t$$

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> Modified CMV model

* Comment #1: CMV may be hard to take to data
  * measure: preferences
* In CMV, marginal utility
  * concavity: important for interior solutions
* I will borrow from discrete choice literature (McFadden-Heckman)
  * assume choice are not bang-bang as in paper
  * rather, use extreme value noise:

$$j \to k$$

if

$$V^k + \varepsilon^k = \max_{j \in \mathbb{J}} \left\{ V^j + \varepsilon^j \right\}$$

where ε extreme value I

* We need V^j
  * forward looking and endogenous as in paper
* Virtue:

$$\phi^{jk} \text{ closed form}$$

> Key: Transition rates ϕ^{iz} and m^{i}

- There's a value to each activity.
- Value of recovered:

$$V^{R} = \text{no health hazard}$$

- Value of infected is:

$$V^{I} = u^{I} + \beta\left[\gamma\left((1-\delta)\, V^{R} + \delta \underbrace{V^{D}}_{\text{death}}\right) + (1-\gamma)\, V^{I}\right]$$

- Value of susceptible j:

$$V^{j}_{t} = u^{j} + \beta\left(\left(1 - p^{j}_{t}\right)\mathbb{E}\left[\max_{k\in\mathbb{J}}\left\{V^{k}_{t+1} + \varepsilon^{jk}\right\}\right] + p^{j}_{t}\cdot V^{I}\right)$$

- The infection probability is:

$$p^{j}_{t} = \frac{m^{j}\left(S^{j}_{t}, I_{t}, R_{t}\right)}{S^{j}_{t}}.$$

> "Analytic" Version

* Extreme value distribution:

$$\phi_t^{jk} = \frac{\exp\left(V_t^{km} + c_t^{jk}\right)}{\sum_{m \in \mathbb{J}} \exp\left(V_t^{km} + c_t^{jm}\right)}.$$

where c^{jk} can be thought of as a travel/activity/switching costs

* Value of susceptible j:

$$V_t^j = u^j + \beta \left(\left(1 - p_t^j\right) \sum_{k \in \mathbb{J}} \phi^{jk} V_t^k + p_t^j \cdot V^I \right)$$

> 2 case example

* Two states:

$$j \in \{e, h\}, c_t^{jj'} = 0$$

* In this case:

$$\phi_t^{jj} = \frac{1}{+\exp\left(V_t^{jj'} - V_t^{jj}\right)}.$$

* Value of susceptible j:

$$V_t^e = u^e + \beta \left((1 - p_t^e) \sum_{k \in \{e,h\}} \phi^{ek} V_t^k + p_t^e \cdot V^I \right)$$

$$V_t^h = u^h + \beta \left(\left(1 - p_t^h\right) \sum_{k \in \{e,h\}} \phi^{hk} V_t^k + p_t^h \cdot V^I \right)$$

> Applications

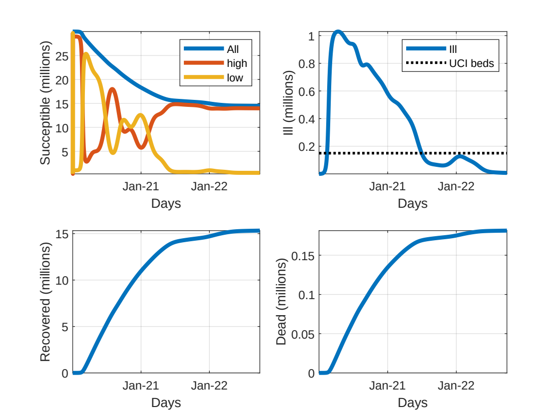
- Paper:
  - evaluates: CARES act, optimal lockdowns
  - animal spirits: hard time, need complementarity
- Here: three comparisons
  - super strict, strict, no lockdowns
  - timing: before or after
  - add UCI units

> Peru Application

* Add a seasonal
* Force overreaction of policy

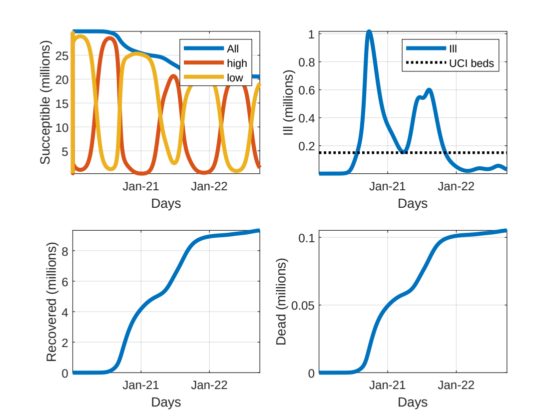
> Laissez Faire

Outcome: one long wave, 200k deaths



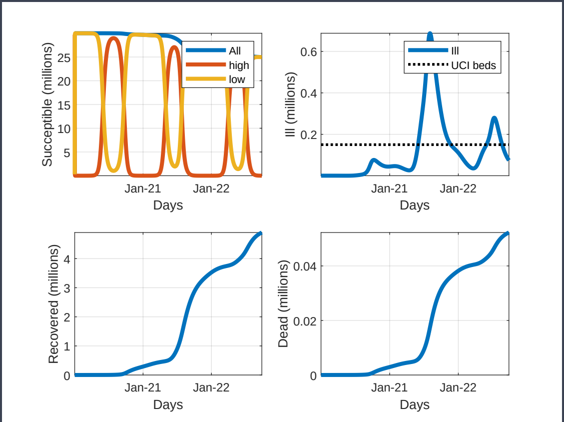
> Regular lockdown

Outcome: two waves, 105k deaths



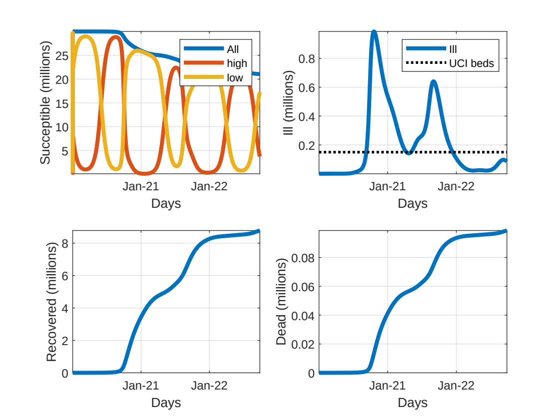
> Strict lockdown

Outcome: two waves much later, 50k deaths



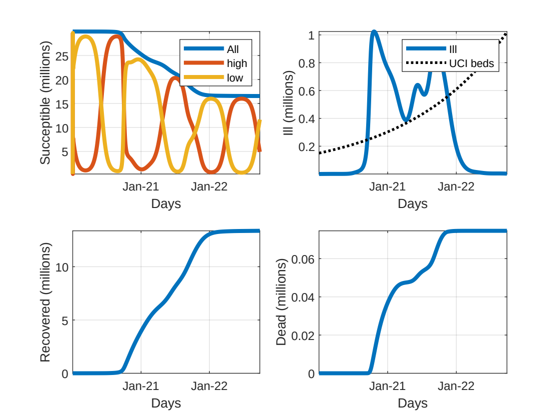
> Strict lockdown + 1 month later

Outcome: saves 7k



> Mild lockdown + 1 month later + UCI Doubling

Outcome: saves 20k lives



Conclusion

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* Nice to see SIRi models
    * not clear how different predictions are

* More effort to fit numbers
    * discrete choice literature can be useful
    * Covid is not over yet