ACCELERATE meeting progress

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Introduction and Motivation

- **Research Question:** How does the inclusion of stochastic effects influence the economic evaluation in the context of epidemics?

- **How do we perform these economic evaluations?** Using **epidemiological-economic (epi-econ) models**, which:
  1. Incorporate individual **behavioral responses** to infection risk.
  2. Capture the **trade-off** between health outcomes and economic variables.

Stochasticity in Epi-Econ Models

- Most epidemiological-economic models are developed by economists and include **deterministic** transmission rates.
- A small number of papers use **stochastic transmission rates** in epi-econ models, but few compare them directly to deterministic models.
- **Hong et al. (2021):** Focuses on how stochasticity affects *asset pricing*, not welfare analysis.
- **Our Project:** How do economic evaluations differ between **deterministic and stochastic** transmission models?

  $\Rightarrow$ We introduce stochasticity into an epi-econ model to explore this gap.

Why Do We Expect a Difference Between Deterministic and Stochastic Models

- Infection dynamics are **non-linear**; **stochastic effects** can lead to different epidemic paths (e.g., **early fade-out**, **secondary waves**).
- **Stochastic models** capture **worst-case** scenarios — relevant for welfare under **risk aversion**.
- **Behavioral responses** (e.g., reducing activity) depend on observed infections, which **fluctuate more** under stochasticity.
- **Economic cost distributions** (health vs. activity) are **wider** under stochastic models.

Optimal Policy under stochastic dynamics

- In stochastic models, optimal policy interventions may only need to reduce infections to a **small positive level**, rather than zero, to allow fade-out of the epidemic.
- Deterministic models require driving infections **all the way to zero** to eliminate the epidemic.
- This can introduce a **bias in economic evaluation**:
  - Stochastic outcomes can **reduce expected long-term costs**,
- **The same intervention may look more cost-effective in a stochastic model**

Model Overview

We introduce **stochastic transitions** into an existing, deterministic epi-econ model framework. Our starting point is the model proposed by **Farboodi et al. (2021)**.

- Individuals choose their level of **social activity** to reduce infection risk.
- Disease dynamics follow a standard **SIRD model**.
- Laissez-faire vs optimal policy
- This is a very **simple** framework, making it suitable for comparing **deterministic vs stochastic** economic evaluations.

Setup and Notation

We consider a population of homogeneous individuals who are unaware of their current health state, specifically whether they are susceptible or infected. Each individual's utility $u(t)$, depending on social activity $a(t)$, is described by:

$$u(a(t)) = \log(a(t)) - a(t) + 1$$

This specification ensures that the optimal activity is $a^*(t) = 1$, with a utility level of zero, so it can be interpreted as a **cost**.

Initial Welfare Function (Farboodi et al., 2021)

The individual maximizes the discounted difference between social activity costs and infection costs:

$$\max_{a(t)} \int_0^\infty e^{-(\rho+\delta)t} \left[\text{-social activity cost} - \text{infection cost}\right] dt$$

- $e^{-(\rho+\delta)t}$: discount factor capturing impatience and cure arrival
- Social activity cost: Utility lost by being less socially active than preferred
- Infection cost: Cost * probability dying

Implementation Challenges

- Attempted to implement this model several times in R.
- Model turned out te be very unstable- Only gets worse when adding stochasticity
- The original model operates in **continuous time**, which makes it badly suited for incorporating **stochastic dynamics**.
- **Our solution:** Simplify the welfare function to make it suitable for implementing stochasticity.

Welfare Function

We consider a myopic decision-maker maximizing instantaneous welfare:

$$W(a) = \log(a) - a + 1 - \beta a^2 N_s N_i \kappa$$

- First term: Social activity cost
- Second term: Expected infection cost
- No intertemporal maximization – suitable for stochastic modeling

SIRD Model and Force of Infection

The disease transmission splits the population into:

- Susceptible $N_s(t)$
- Infected $N_i(t)$
- Recovered $N_r(t)$
- Deceased $N_d(t)$

The force of infection is:

$$\text{Force of infection} = \beta\, a(t)^2\, N_s(t)\, N_i(t)$$

Differential Equations

$$\frac{dN_s(t)}{dt} = -\beta\, a(t)^2\, N_s(t)\, N_i(t)$$
$$\frac{dN_i(t)}{dt} = \beta\, a(t)^2\, N_s(t)\, N_i(t) - \gamma\, N_i(t)$$
$$\frac{dN_r(t)}{dt} = (1 - \pi)\,\gamma\, N_i(t)$$
$$\frac{dN_d(t)}{dt} = \pi\,\gamma\, N_i(t)$$

Optimal Activity Level

Take the derivative of $W(a)$:

$$\frac{1}{a} - 1 = 2\beta a N_s N_i \kappa$$

Define $M := \beta N_s N_i \kappa$. Solving this yields:

$$a^* = \frac{-1 + \sqrt{1 + 8M}}{4M} = \frac{-1 + \sqrt{1 + 8\beta N_s N_i \kappa}}{4\beta N_s N_i \kappa}$$

Motivation for Stochasticity

To better capture randomness in disease spread, we use binomial processes following Abrams et al. (2021) rather than stochastic β-shock only models.

Infection Transition Probability

- Rate of infection $= \beta a(t)^2 N_s(t) N_i(t)$
- $p_i = 1 - \exp(-\beta a(t)^2 N_i(t))$
- $I_{\text{new},t+1} \sim \text{Binomial}(N_s(t), p_i)$

Recovery and Death Transitions

Recovery:

- Rate: $(1-\pi)\gamma N_i(t)$
- Probability: $p_r = 1 - \exp(-(1-\pi)\gamma)$
- $R_{\text{new},t+1} \sim \text{Binomial}(N_i(t), p_r)$

Death:

- Rate: $\pi\gamma N_i(t)$
- Probability: $p_d = 1 - \exp(-\pi\gamma)$
- $D_{\text{new},t+1} \sim \text{Binomial}(N_i(t), p_d)$

Discrete-Time Population Dynamics

$$
\begin{aligned}
N_s(t+1) &= N_s(t) - I_{\text{new},t+1} \\
N_i(t+1) &= N_i(t) + I_{\text{new},t+1} - R_{\text{new},t+1} - D_{\text{new},t+1} \\
N_r(t+1) &= N_r(t) + R_{\text{new},t+1} \\
N_d(t+1) &= N_d(t) + D_{\text{new},t+1}
\end{aligned}
$$

Updated Simulation Results

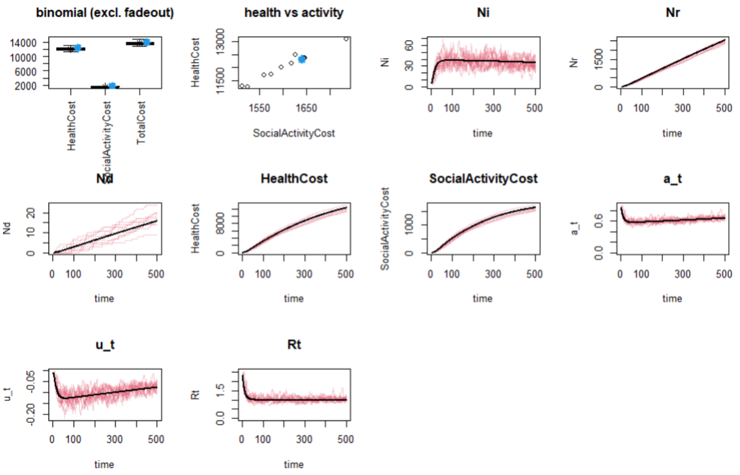

Figure: Simulation results using the revised welfare specification.

Discussion

- Variation in social and health costs is limited.
- Average almost equal to median... Implying that we see no real fade-out effects.
- Optimal policy implementation doesn't work so far...
- Tried playing around with R0 and initial Ns or Ni, but no big differences so far...

Conclusion

- How does **stochasticity** affect **economic evaluation** in epidemic models?
- To do so, we simplify the welfare function used in **Farboodi et al. (2021)** to make it tractable in a stochastic, discrete-time setting.
- Results show a **divergence** in economic evaluation outcomes under stochastic dynamics.
- Pity that optimal policy isn't working out for stronger conclusions.

Original Simulation Results (Farboodi et al. 2021)

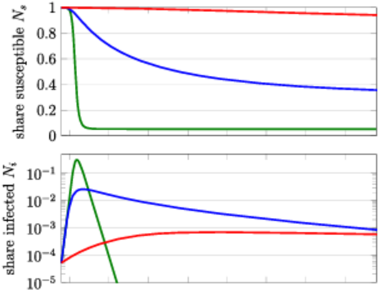

Figure: *

Susceptibles and infected shares

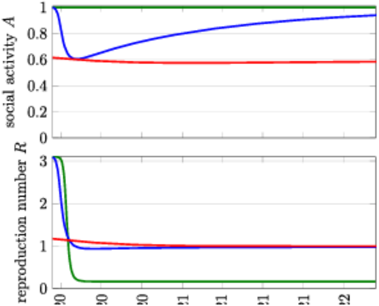

Figure: *

Social activity and reproduction number

Figure: Results from Farboodi et al. (2021).