Social determinants of health and infection rates

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Introduction

- Epidemiological models are used to understand infection dynamics
- The recent pandemic highlighted the importance of such models
  - Policy design regarding measures
  - Timing of measures
- As measures are costly it is important to take into account how people react to measures and in absence of these measures
- Decisions are influenced by socioeconomic factors influencing decisions
- Incorporate insights from the Social Determinants of Health (SDH) literature on epidemiological models

Lecture overview

- Introduce most used epidemiological models
  - SIR
  - Extensions: SIRD; SEIR; SEIRD
  - Other types
- Extend these to incorporate insights from relevant SDH
  - Socioeconomic compartmental model
- Applications related to COVID-19
- Political Economy of Health

Compartmental Models

- Based on seminal work of Kermack and McKendrick (1927)
- Split the population in health compartments
- Analyse the dynamics of people moving from one compartment to the next
- The most standard compartments are
  - **Susceptible** (S): can get infected
  - **Infected** (I) and also infectious
  - **Removed** (R): after infection not susceptible
- Model: $S \to I \to R$

SIR model setup

- Population of N individuals
- Study the evolution across compartments over time t
- At each point in time a person can be S, I or R
    - S_t: susceptible at t
    - I_t: infected at t
    - R_t: removed at t
    - $S_t + I_t + R_t = N$
- We are interested in the evolution of each of the states (S_t, I_t, R_t) from one period to the next
    - ie. from t to $t+1$
    - for example what is S_{t+1} depending on S_t, I_t, R_t

Infection Dynamics 1

- Susceptible individuals get infected if they meet an infected person with some probability
- The number of susceptible at $t+1$ is

$$S_{t+1} = S_t - \frac{\beta S_t I_t}{N}, \tag{1}$$

- This captures two things regarding the evolution of susceptible
- Depends positively
    - How many people are susceptible
    - How many people are infected
- β captures the probability of a person in S getting infected for a given I_t
- Note that β is fixed- more on this later

Infection Dynamics 2

- Infected individuals stay infected for some time before becoming removed
- The number of infected at $t+1$, I_{t+1} is

$$I_{t+1} = I_t + \frac{\beta S_t I_t}{N} - \gamma I_t, \tag{2}$$

- This captures
  - inflow from S
  - outflow to R: γ is the average daily probability that an infected individual becomes removed.
- Based on the previous, the evolution of R_t is

$$R_{t+1} = R_t + \gamma I_t, \tag{3}$$

Infection growth rate

- A key way to summarise the evolution of an epidemic is by looking how quickly I_t grows
- Compare the outflow rate with the inflow rate
- From equation (2), we get the growth rate of infections $\frac{I_{t+1}-I_t}{I_t}$:

$$\frac{I_{t+1} - I_t}{I_t} = \frac{\beta S_t}{N} - \gamma \tag{4}$$

- The growth rate of infections is positive if

$$\frac{\beta S_t}{N} - \gamma > 0 \tag{5}$$

- Note that this depends on S_t

Basic reproduction number

- At the beginning of the epidemic where everyone is assumed to be S
- $S_t \equiv N$, then (5) is equivalent to

$$\beta - \gamma > 0, \ \ or,$$

$$\frac{\beta}{\gamma} > 1 \tag{6}$$

- $\frac{\beta}{\gamma}$ is known as the *basic reproduction number* and expressed as R_0
- If $R_0 > 1$ infections grow
- If $R_0 < 1$ infections die out
- $R_0 = 1$ captures an *endemic equilibrium*

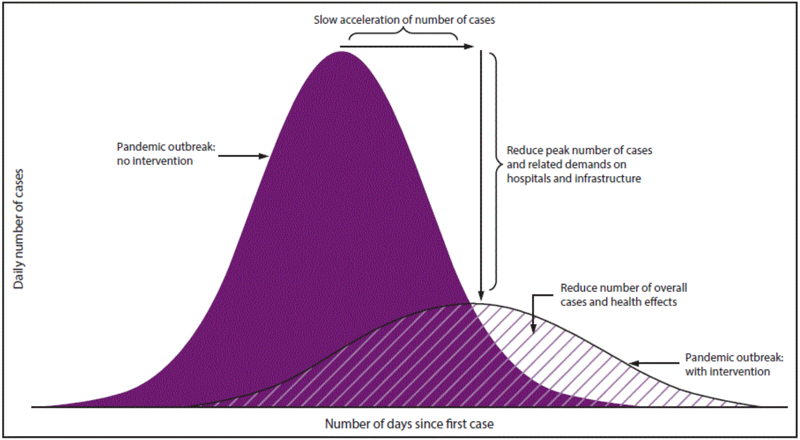
Non Pharmaceutical Interventions

- The possibility of getting infected (β) is presented as a constant
- However it is not a constant as it is possible for people to reduce contacts
- Non Pharmaceutical Interventions (NPIs) aim to increase physical distancing
    - Reduce β
    - Reduce the (basic) reproduction number to values less than 1
    - Slow down infection dynamics
- This highlights that β is a variable which can be influenced by policies

Infection dynamics

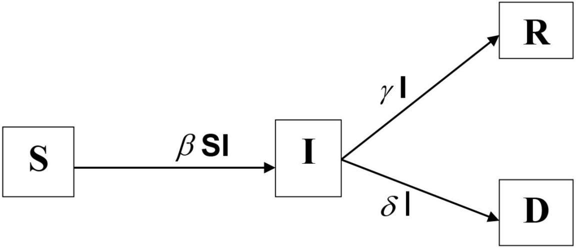
Graph from US CDC

Infection dynamics for different values of β



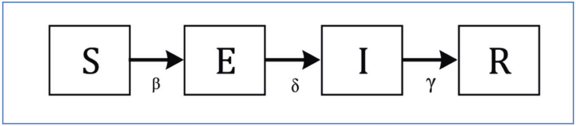
Other compartmental models: SIRD

Similar as the SIR model but R stands for recovered and D for deceased



Other compartmental models: SEIR

Similar as the SIR model but susceptible first become Exposed before being Infectious



The E compartment captures the state of infected individuals during the virus' incubation period

More compartmental models

Depending on the period and characteristics it may be important to:

- Include other compartments
  - SEIRD: takes into account both deaths and incubation period
  - SIRS: allows for removed to become again susceptible
- Split existing compartments into smaller ones
  - influences of factors leading to differential infection rates
  - influences of factors leading to differential mortality rates

Going back to β

- The probability of getting infected (β) is not constant but is a variable
- Is it an exogenous or endogenous variable?
  - exogenous: the policy maker can control this (to some extent)
  - endogenous: it is influenced by other variables in the model

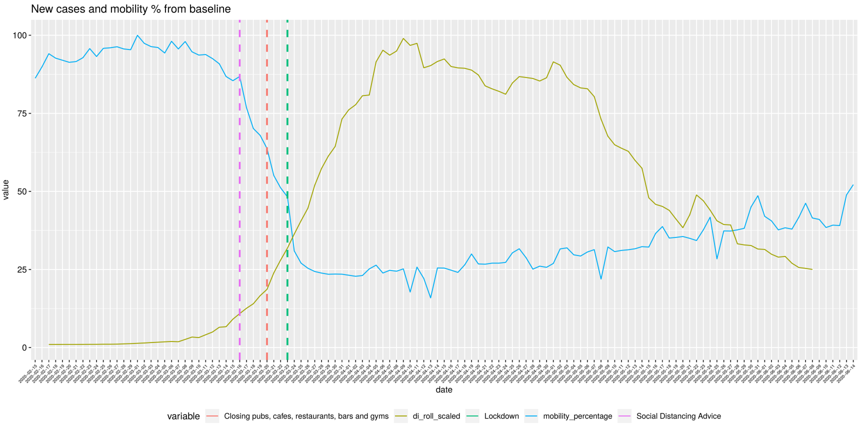
Going back to β

- The probability of getting infected (β) is not constant but is a variable
- Is it an exogenous or endogenous variable?
    - exogenous: the policy maker can control this (to some extent)
    - endogenous: it is influenced by other variables in the model
- What do you think?

People react

Graph: Galanis et al. (2021, PLoS One)

COVID-19 has shown that people react themselves



Physical Distancing is endogenous

- We see that β is a decreasing function of I_t
- Hence as long as I_t is changing, so is $\beta(I_t)$

This implies two important things for policies

1. In absence of measures the increase of infections may not be as rapid as expected
    - Still a high rate of infections but may take some days longer to reach the peak
2. NPIs may not be as efficient
    - Especially when infections fall $\rightarrow$ increase in $\beta(I_t)$

A Behavioural SEIR model

- Use Machine Learning methods to approximate $\beta(E_t)$

  Note that in a SEIR model the 'new cases' are Exposed

  $$\beta(E_t) = aE_{t-2} + b$$

- It takes two periods to influence decisions
  - get infected (exposed) at t
  - the results of the test are out at $t + 1$
  - this has an impact on physical distancing decision at t

BeSEIR insights

- Even if β is endogenous, timing of NPIs matters
- Lower intensity NPIs earlier on are more effective than the opposite
- Lifting measures early (when cases/deaths fall) may not be desirable
- While people act over and above NPIs they do not all act uniformly
- Decisions are constrained
    - Economically
    - Socially

Socioeconomic conditions are key

- Socioeconomic conditions matter for decisions
- Not everyone can take the same measures
- UK example
  - University lecturers
  - Bus drivers, doctors, nurses . . .
- Worse socioeconomic conditions imply higher β
- Also imply higher death rates

Social Determinants of Health

- The fact that socioeconomic conditions have direct and indirect effects on health is well known
- This is the basis of a growing literature on Social Determinants of Health (SDH)
- With respect to compartmental models, SDH influence
  - contagion dynamics
  - mortality
- For example
  - poverty $\rightarrow$ more difficult to take measures
  - housing conditions, sanitation etc. have similar effects
  - worse infrastructures
    - contagion
    - mortality

A Socioeconomic Compartmental model

Standard $SIRDS$ model where parameters are socioeconomically determined

$$S_{t+1} = S_t + \epsilon R_t - \beta(S_t + \epsilon R_t) I_t / N, \tag{7}$$

where $0 \leq \epsilon \leq 1$ capturing immunity

$$I_{t+1} = I_t + \beta(S_t + \epsilon R_t) I_t / N - \gamma I_t, \tag{8}$$

$$R_{t+1} = (1 - \epsilon) R_t + \gamma(1 - \delta) I_t, \tag{9}$$

$$D_{t+1} = D_t + \gamma \delta I_t \tag{10}$$

where δ is the case fatality ratio (CFR)

Social Determinants' impacts on β and δ

SD1: Conditions of employment (c_1)

- physical distancing and isolation, informal work, possibility to work from home etc.

SD2: Conditions of housing (c_2)

- obstacles for physical distancing and isolation, substandard infrastructures including water, sewage and sanitation

SD3: Access to and quality of health infrastructure (c_3)

- both between and within inequalities matter

We can write β and δ as

$$\beta = \beta_0 + a_1 c_1 + a_2 c_2 - a_3 c_3 \tag{11}$$

$$\delta = \delta_0 + b_1 c_1 + b_2 c_2 - b_3 c_3 \tag{12}$$

Long run effects on socioeconomic conditions

- What are the factors which impact socioeconomic conditions
- This is a long list of variables which to some extent differ across countries
- However there are some key global trends identified in political economy literatures
- Globalisation: opening of boarders for move of capital across countries
  - Captured by trade openness
  - Influence on variables related to SDH
- Financiallisatfion: growth of financial sector and operations
  - Captured by different measures of debt
  - Influence on key SDH related to housing, work and others