Delhi School of Economics Winter School

Epidemics, growth and economic behavior:
Traditional approaches and new covid-driven research

3. Epi-econ modelling: Extensions

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Macro problems

- Unprecedented pb: **economic assessment of (global) NPIs under health system capacity constraints and radical uncertainty (asymptomatic, a.o).** However, the vast majority of epi-econ models consider frictionless central planner problems with continuous time and continuous lockdown intensity!!!
- Other novelty **for the overwheling majority of economists**: modeling of epidemic diffusion through the incorporation of compartmental epidemiological sub-models. Epi-econ modelling. However, most the compartmental models are simplistic, and can hardly serve for the design of policy.
- Major complication 1: strong heterogeneity across economic sectors (demand vs supply-constrained sectors). Close look at the supply chain needed.
- Major complication 2: Heterogeneity of social contacts across socioeconomic classes.
- Major complication 3: Under radical uncertainty, public authorities can hardly their decisions maximizing expected social welfare onver an infinite horizon: rather sequential decisions along with learning.

Micro problems

- No way to understand epidemic diffusion if the incentives for individuals to comply with NPIs are not understood! Need to understand the determinants of this compliance and to identify it through adequate micro data.
- Huge complications: heterogenous incentives (eg. age) and decisions under radical uncertainty (no science and governments' lack of credibility, already before Covid- rise of populism, also invidivuals learning). Role of social communities and networks in epidemic dynamics.
- **Mental health** should be thoroughly included in epi-econ models for realism. How to incorporate mental health in epi-econ settings? And how to identify it empirically?

Outlines of this lecture

1. Introduction: Introduction: new Covid-induced research
2. Balancing economic and epidemiological interventions in the early stages of pathogen emergence
3. Economic behavior in the face of epidemics, mental health and control policies
4. Concluding: open problems

Policy frictions and learning of the "global player"

- The optimal health policy problem typically adressed in the recent Covid literature considers infinite horizons, and especially, continuous time control variables. This is far unrealistic: governments face short time horizons under emergency and have to deal with a number of heavy **frictions**.
- Optimal policies are rather piecewise constant and should be searched in this functional set with finite number of phases to reflect frictions.
- Other frictions: capacity constraints (notably on testing) , implementation delays....
- Moreover, governments also "learn" just like individuals under radical uncertainty but do "global players" learn in the same way?

Dobson, Ricci, Boucekkine et al, 2022

BALANCING ECONOMIC AND EPIDEMIOLOGICAL INTERVENTIONS IN THE EARLY STAGES OF PATHOGEN EMERGENCE

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ABSTRACT. The global pandemic of Covid-19 has underlined the need for more coordinated responses to emergent pathogens. These responses need to balance epidemic control in ways that concomitantly minimize hospitalizations and economic damages. We develop a hybrid economic-epidemiological modelling framework that allows us to examine the interaction between economic and health impacts over the first period of pathogen emergence when lockdown, testing, and isolation are the only means of containing the epidemic. This operational mathematical setting allows us to determine the optimal policy interventions under a variety of scenarios that might prevail in the first period of a large scale epidemic outbreak. Combining testing with isolation emerges as a more effective policy than lockdowns, significantly reducing deaths and the number of infected hosts, at lower economic cost. If a lockdown is put in place early in the course of the epidemic, it always dominates the "laissez faire" policy of doing nothing.

Major contributions 1

- First of all, the development of an expanded SEIR model accounting for a larger set of possible states for the hosts in an attempt to consider the dynamics of isolating and testing contacts of infected hosts, that may themselves develop infections. This is made possible by the interdisciplinary nature of this research.
- Second, the conceptual design of realistic epidemic control policies subject to inefficiencies resulting from "economic frictions" inherent in the implementation of such policies.
- A partial list of these frictions includes incomplete information, transactions costs associated with initiating multiple rounds of lockdowns in rapid succession, incomplete enforcement, and costs associated with transitions in and out of lockdown.
- By improving the realism of both epidemic dynamics and policy modelling we can better understand the structure of the mechanisms through which public health and economic factors interact.

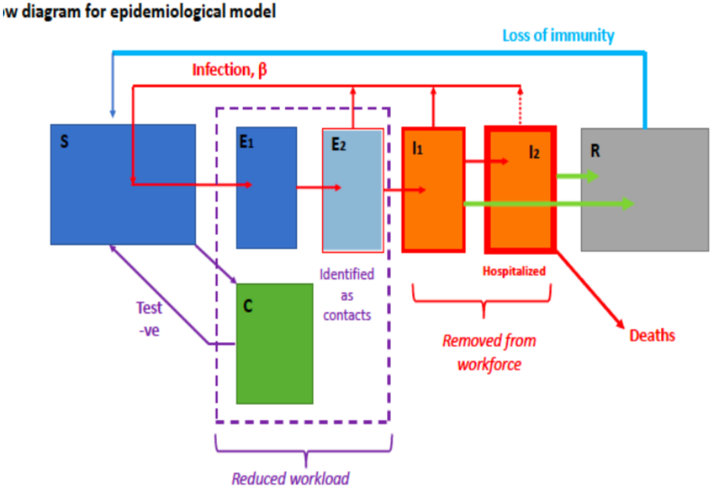
Major contributions 2

- Unlike the majority of epi-econ models, we use a finite-horizon model in order to concentrate on short-term outcomes.
- More precisely, we build a framework that provides insights on how policy makers should respond in the first two years of a novel emergent pathogen for which:
  1. there is very limited epidemiological information,
  2. there are no available specific drugs or vaccines,
  3. tests for infectivity are in the early stages of development, and
  4. tracing may not be efficient

Major contributions 3

- Given these constraints, a lockdown is one of the main tools available to policy-makers. We specifically depart here from the common assumption that lockdown policies can be adjusted in continuous time and consider that they take place in a finite number of phases, the lockdown parameters (intensity of the lockdown and duration) being optimally chosen at each phase. **This requires a novel numerical optimization approach**.
- In addition, we incorporate technological implementation delays (e.g. in efficient testing) and capacity constraints (e.g. in test/mask production). This in turn allows to compare optimal control policies for countries at different levels of development, or governments with different levels of concern for the welfare of their citizens/workforce.
- Last but not least, we reltivdetermine the optimal menu (lockdown phases, testing phases), with or without implementation delays.

Epi model, Dobson et al., 2022



The compartmental epidemic model 1

- We have modified the basic SEIR formulation by dividing the exposed (E) and infectious (I) classes into two sequential classes, E_1 and E_2 and I_1 and I_2.
- Exposed hosts, who are not yet infectious are classified as E_1, while asymptomatic, contagious hosts are classified as E_2. We assume that E_1 individuals transform to E_2 at an exponential rate determined by φ_1. The pre-symptomatic hosts, E_2, transform to symptomatic infected hosts, I_1, at a rate φ_2. Both E_2 and I_1 are infectious.
- This rate largely determines the duration of time during which exposed hosts are able to transmit infection before they show symptoms of infection. If φ_2 is large (~ 365) (around one day), then exposed hosts quickly exhibit signs of symptoms and can be identified as infectious (as occurred with SARS).
- In contrast, if φ_2 is slower ($\sim$365/7) (a week), then asymptomatic hosts may transmit the disease for up to a week before showing symptoms, as in the case of Covid-19 (or many years in the case of HIV or TB, when φ_2 may range from 0.1 to 0.5).

The compartmental epidemic model 2

- In a similar way, infected hosts, I_1, may become sick and get hospitalized, I_2. These hosts have a higher mortality rate, but are assumed to be in relative isolation and are thus unable to transmit the pathogen, except to unprotected health care workers.
- The majority of the pathogen-induced mortality occurs in the I_2 class.
- We also include an additional class, C, into our model structure, these are contacts of infectious hosts who do not develop infection. Contact tracing identifies $C + E_1 + E_2$ as contacts of infected hosts, testing is used to differentiate uninfected contacts, C, from exposed hosts (E_1 and E_2); the former can return to work, the latter remain in isolation and go on to develop infection.

Main equations of the epi model

$$
\begin{aligned}
\dot{S} &= \mu N - \mu S - (1-p)^2 \beta \frac{S\left(E_2(1-\gamma) + \gamma I_1\right)(1+c)}{N} \\
&\quad + \phi R + \tau \left(r + \frac{1-r}{1+c} \right) C s_p + \delta C - \tau r S (1 - s_p) \\
\dot{C} &= (1-p)^2 \beta (cS - (1-\epsilon_C)C) \frac{E_2(1-\gamma) + \gamma I_1}{N} \\
&\quad + \tau r S(1-s_p) - \mu C - \tau \left(r + \frac{1-r}{1+c} \right) C s_p - \delta C \\
\dot{E}_1 &= (1-p)^2 \beta (S + (1-\epsilon_C)C) \frac{E_2(1-\gamma) + \gamma I_1}{N} \\
&\quad - (\mu + \varphi_1) E_1 - \tau \left(r + \frac{1-r}{1+c} \right) s_e E_1 \\
\dot{E}_2 &= \varphi_1 E_1 - (\mu + \varphi_2) E_2 - \tau \left(r + \frac{1-r}{1+c} \right) s_e E_2 \\
\dot{I}_1 &= \varphi_2 E_2 + \tau s_e \left(r + \frac{1-r}{1+c} \right) (E_1 + E_2) - (\mu + \mu_{I_1} + (1-\eta)\delta_1 + \eta \delta_1) I_1 \\
\dot{I}_2 &= \eta \delta_1 I_1 - (\mu + p_M \delta_2 + (1-p_M)\delta_2) I_2 \quad (\text{where} \quad \mu_{I_2} = p_M \delta_2) \\
\dot{R} &= (1-\eta)\delta_1 I_1 + (1-p_M)\delta_2 I_2 - (\mu + \mu_R + \phi) R + \nu V_w
\end{aligned}
$$

The economic structure

$$Y(t) = \underbrace{A(t)\left[(1-p(t))L(t)\right]^{\alpha}}_{\text{production function}} - \underbrace{\Phi(x(t))}_{\text{testing cost}}$$

where

$$\begin{aligned}
A(t) &= A_0(1-p(t))^{\Delta} \\
L(t) &= S(t) + \epsilon_C\left[C(t) + E_1(t) + E_2(t)\right] + R(t) \\
\Phi(x) &= \rho_0 x + \exp\left(\frac{\rho_1}{N-x}\right) - \exp\left(\frac{\rho_1}{N}\right) \\
x(t) &= \tau\left[C(t) + E_1(t) + E_2(t) + rS(t)\right],
\end{aligned}$$

Optimal interventions

The objective of the policy-maker is to maximize the Total Social Welfare (TSW) function, this is given by:

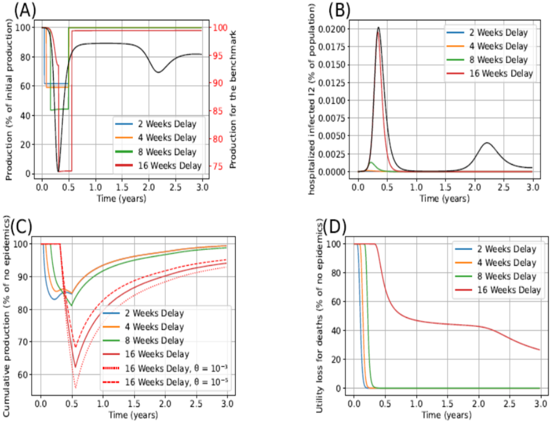
$$TSW(T) = \int_0^T U(Y(t)) - \theta V(D_c(t))\,\mathrm{d}t \qquad (1)$$

with:

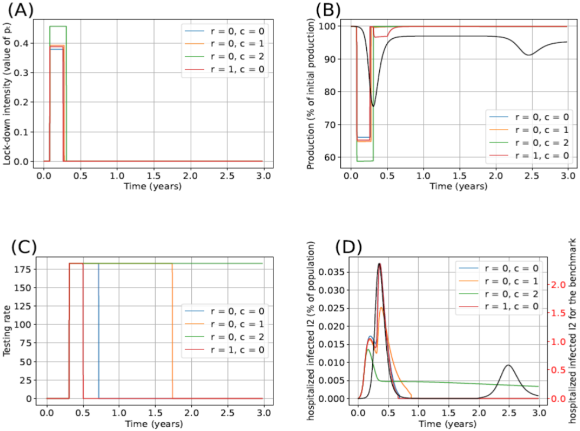
$$U(Y) = \frac{Y^{1-\sigma}}{1-\sigma}$$
$$V(D_c) = \frac{D_c^{\omega}}{\omega}$$

In the above expressions, $U(Y)$ stand for the satisfaction (utility) from consuming goods and services, while $V(D_c)$ stands for the direct utility loss of lives lost.

Some results 1: lockdown (alone) vs *laissez-faire*



Some results 2: optimal combination lockdown with testing



Adda, Boucekkine and Thuilliez, 2022

An economic-epidemiological model with endogenous behavior and learning: theory and tests.*

Very preliminary - Do not cite or circulate

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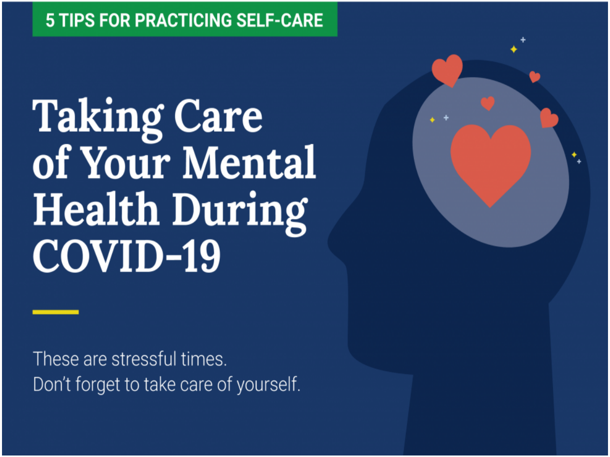
Homo economicus in the face of epidemic control

- The standard epidemic diffusion equation builds on a crucial parameter, usually denoted β, the so-called **transmission rate**, which measures the intensity of contagion of susceptible individuals iby infected individuals at any time.
- Generally speaking, the transmission rates, β, are the product of the contact rates times the transmission probability upon contact. However, while the latter are intrinsic transmission probabilities, and as such, will be taken as biological parameters in calibrations, the contact rates depend on individuals' mobility, and as such, they are endogenous.
- While the β have been largely endogenized at the macro level in the recent epi-econ burst via epidemic control policies (like lockdown), individual mobility decisions in response to this control are seldom taken into account. And are even more rarely taken to data.

We summarize here in a few slides this behavioral part of the theory devoloped by Adda, Boucekkine et Thuilliez (2022).

Key point: Mental health



Heterogenous multiclass populations: the epidemic model with all susceptibles asymptomatic

$$S_{i,t+1} - S_{i,t} = -\left(\sum_{i'=1}^{n} \beta_{ii't} \frac{I_{i',t}}{N_{i't}}\right) S_{i,t}, \tag{2}$$

$$I_{i,t+1} - I_{i,t} = \left(\sum_{i'=1}^{n} \beta_{ii't} \frac{I_{i',t}}{N_{i't}}\right) S_{i,t} - \gamma_{it} I_{i,t}, \tag{3}$$

$$R_{i,t+1} - R_{i,t} = \gamma_{it} I_{i,t}, \tag{4}$$

$$N_{i,t+1} = N_{i,t} - \gamma_{it} I_{i,t}. \tag{5}$$

Individual mobility: spatial setting

- Let $\bar{d}$ measures the stringence of the lockdown: in the French context, it used to correspond to the 1 km distance the individuals who decide to leave home should not exceed. The associated reference spatial set is therefore a circle of radius $\bar{d}$: if an individual decides to go beyond this circle, she has to pay a penalty if caught.
- Modelling epidemic diffusion settings is a an old topic in epidemiology ranging from the directed spatial diffusion model of Milner (2008) to the discrete space version of Sattenspiel et al (1995). We borrow a simpler model of individual mobility using a spatial kernel with constant population density, f, over space (Hu, 2013).
- Easy to extend to space partitioned in a finite number of regions with different densities.

Individual mobility: social contacts

- Differently from Hu (2013), our population is heterogenous with $n \geq 2$ classes. Therefore, we cannot work with the benchmark assumption that individuals have the same (constant) fraction k $(0 < k < 1)$ of contacts among the calculated effective population. The old may have more contacts than the young or vice versa.
- In line with the sociological literature, we assume that the inter and intra-class counterparts of the constant number k is a square matrix $K\left(k_{ij}\right)$, where $i, j = 1, 2, ..., n$. Any element k_{ij} of this matrix gives the (average) fraction of contacts an individual in class i may have among the calculated effective population in class j.
- Remaining hot question: how to compute the number of contacts an individual of class i might have when moving within or outside the circle?

Computing contacts for homogenous populations

- We build on the nonlinear spatial kernel proposed by Hu (2013). For an homogenous population (density f) and individuals confined within a circle of radius, r_{max}, with a constant fraction of contact k among effective population, the contact rate, $c(f)$ of a given individual is given by:

$$c(f,k) = \int \phi_{f,k}(r)\, d\theta dr = 2\pi \int_0^{r_{max}} \phi_{f,k}(r)\, rdr$$

- $\phi_{f,k}(r)$ is the spatial kernel, which is parameterized by the density f and the contact fraction k. We choose:

$$\phi_{f,k}(r) = k\ f\ e^{-(\frac{f}{f_0})^{\alpha}\ r^{\beta}},$$

where f_0, α and β are parameters to be calibrated. Functions $\phi_{f,k}(r)$ are generalized exponentials. The case $\alpha = 1$ and $\beta = 2\alpha$ yields the well-known Gaussian density:

$$\phi_{f,k}(r) = k\ f\ e^{-\frac{f}{f_0}\ r^2}.$$

Computing contacts: generalization

- We first set $r_{max} = d_{i,j}$ in the contact rates formulas above, resulting in endogenous contact rates.
- We can easily compute the contact rate of an individual j in class i with individuals in class i' adapting the formula above and using the social contact matrix K:

$$c^j_{i,i'}(f, K) = k_{i,i'} \; f \int_0^{d_{ij}} \; e^{-\frac{f}{f_0} \; r^2} \; 2\pi r dr$$

- Because the integral on the right hand side can be computed explicitly, one gets a nice closed-form expression for the contact rate $c^j_{i,i'}(f, K)$. Indeed, we can readily show that:

$$c^j_{i,i'}(f, K) = \pi k_{i,i'} \; f_0 \; \left(1 - e^{-\frac{f}{f_0} \; d^2_{i,j}}\right).$$

Learning in a world of uncertainty

- We consider a world in a state θ which can take two values: 1 if confinement is needed and 0 else. At time t=0, an individual j of class i has a prior belief $q_{ij}(0)$ that the world is in state 1. Similar to Adhvaryu (2014).
- Then at each time $t \geqslant 1$, agents receive a public signal between two different possible signals R_{t0} and R_{t1} depending on the number of hospitalizations at time $t-1$: If this number is below a certain threshold the signal is R_{t0}, else it is R_{t1}.
- Indeed, we assume people know the distribution of signals conditionally to the state of the world: $P(R_{ti}|\theta), i = 0, 1$. Therefore, people infer the new belief using the following Bayesian formula:

$$
\begin{aligned}
q_{ij}(t) &= P(\theta = 1 | q_{ij}(t-1); R_{t-1i}) \\
&= \frac{P(R_{ti}|\theta = 1) P_{t-1}(\theta = 1)}{P(R_{ti}|\theta = 1) P_{t-1}(\theta = 1) + P(R_{ti}|\theta = 0) P_{t-1}(\theta = 0)} \\
&= \frac{q_{ij}(t-1) P(R_{ti}|\theta = 1)}{q_{ij}(t-1) P(R_{ti}|\theta = 1) + (1 - q_{ij}(t-1)) P(R_{ti}|\theta = 0)}
\end{aligned}
$$

Individual decisions timing

We shall consider the following timing at each decision period $t \geq 1$ for any individual j of class i.

1. For given prior belief $q_{ij}(t-1)$ at the beginning of period t, the individual solves her optimization problem for period t , takes and exercizes her consumption and mobility decisions for the period.

2. At the end of period t, after receing the public information and collecting own private information, the individual updates her belief and forms $q_{ij}(t)$

Individual decisions: mental health

- Define d_{ij}^* the desired travel distance in the absence of the epidemic that is individual specific. Prior to the Covid crisis, each individual chooses a travel distance $d_{ij}(t) = d_{ij}^*(t)$ for any prior date t.
- During the epidemic, individuals have their travel curtailed either for fear of being fined or for fear of contamination. Denote by the $m_{ij}(t)$ the cumulative missed distance since the start of the epidemic to time t. This stock evolves as:

$$m_{ij}(t) = (1-\delta)m_{ij}(t-1) + \frac{d_{ij}^*(t) - d_{ij}(t)}{d_{ij}^*(t)} \quad (6)$$

  where δ is the depreciation rate of this stock.
- We model mental health as:

$$h_{ij}(t) = 1 + \frac{\alpha_m(i,j)}{2}\, m_{ij}(t)\ \left(1 + \left(d_{ij}^*(t) - d_{ij}(t)\right)^{\alpha_d}\right) \quad (7)$$

  with $\alpha_d \geq 0$. The term $\left(d_{ij}^*(t) - d_{ij}(t)\right)^{\alpha_d}$ captures the short-run impact of mobility restrictions on mental health while the stock variable $m_{ij}(t)$ represents the long-run effect of these mobility restrictions.

Individual program

The agent solves the following program by choosing the optimal distance travelled in each period, t, taking into account the presence of a lockdown and the prevalence of the disease:

$$\max_{d_{ij}} \; V(C_{ij}, d_{ij}) = C_{ij}(d_{ij}) - \gamma_d(h_{ij}, \bar{D}, t)(d^*_{ij} - d_{ij})^2 - \aleph(d_{ij}, I_{t-1})$$

with

$$C_{ij}(d_{ij}) = rW_{ij} - I_L(t)q_{ij}(t-1)\,Tax\; max(0; d_{ij} - \bar{d}),$$

$$\gamma_d(h_{ij}, \bar{D}, t) = \gamma_0 + \gamma_1 I_L(t)(\bar{D} + t_L - t) + \gamma_3 h_{ij}$$

$$\aleph(d_{ij}, I(t-1)) = \aleph_j \left(\sum_{i'=1}^{n} k_{i,i'} I_{i'}(t-1) \right) f_0 \left(1 - e^{-\frac{f}{f_0}\,(d_{i,j})^2} \right).$$

Tradeoffs involved by mobility

- We can decompose the marginal benefit of mobility, MBM_{ij}, as:

$$2\gamma_d(h_{ij}, \bar{D}, t)\,(d^*-d)+\gamma_3\frac{\partial\gamma_d}{\partial h_{ij}}\;\frac{\partial h_{ij}}{\partial m_{ij}}\frac{\partial m_{ij}}{\partial d}(d^*-d)^2+\gamma_3\frac{\partial\gamma_d}{\partial h_{ij}}\;\frac{\partial h_{ij}}{\partial d}\;(d^*-d)^2.$$

  The first term of the marginal benefit measures the welfare benefit from closing the gap with the desirable distance d^*, while the two last terms measure respectively the long and short-run effect of mobility on mental health.

- The marginal cost of mobility, MCM_{ij} is given by:

$$MCM_{ij} = q_{ij}\,Tax\;I_d + \frac{\partial\aleph(d, I(t-1))}{\partial d},$$

  where I_d is an indicator lockdown violation by the individual.

The particular case, $\alpha_d = 0$ (matched by our data)

- $\alpha_d = 0$ covers the case where the short-term impact of mobility restrictions on mental health is found negligible.
- Subsequently, the first-order optimality condition can be developed as:

$$2\gamma_d(h_{ij}, \bar{D}, t)\,(d^* - d) + \gamma_3 \frac{\alpha_m(i,j)}{d^*}\,(d^* - d)^2 = q_{ij}\, Tax\ I_d + 2\Theta_{ij} \frac{f}{f_0}\ d\ e^{-\frac{f}{f_0} d^2},$$

with

$$\Theta_{ij} = \aleph_j \left(\sum_{i'=1}^{n} k_{i,i'} I_{i'}(t-1) \right) f_0.$$

One optimality property (among many)

Let's focus at the minute on the interplay between the density parameter f, the policy variable, $\bar{d}$, and the state variables, $I_i(t-1)$.

Proposition

Denote by $d^f = \sqrt{\frac{f_0}{2f}}$, and suppose $\bar{d} < d^f < d^*$. Then if $F(\bar{d}) < G(\bar{d})$, there exist a unique solution, d^o, to the FOC, such that $d^o < \bar{d}$. d^o is optimal.

Proposition 1 can be therefore rephrased as follows: If the population density is intermediate (or not too small) such that the threshold $\bar{d}$ is smaller than d^f, and provided the infection rates are large enough, the individual will comply strictly with the lockdown.

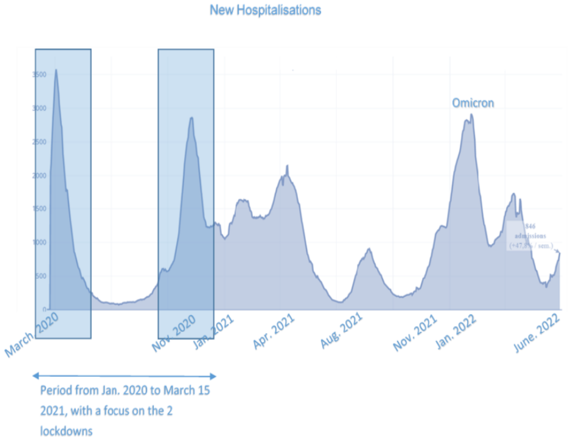
Paris

- Individuals in Paris have potentially a choice to leave the capital and its cramped living spaces to settle elsewhere in France, where we assume they have family.
- Hence their choice is binary, stay in Paris or move out to a pre-specified place. We assume that they are unable to forecast the epidemic and their precise mobility decisions in the future.
- They base their judgement on their desired mobility in Paris (d^*_{ij}) and on the announced length of the lockdown.

$$Prob(Leaving_{ij}) = \Phi(\bar{D}d^*_{ij} - cst_i) \tag{8}$$

where cst_i is a fixed cost of leaving that can vary by class. Hence, the longer the lockdown the more individuals are prone to leave.

Application: France during the two first lockdowns



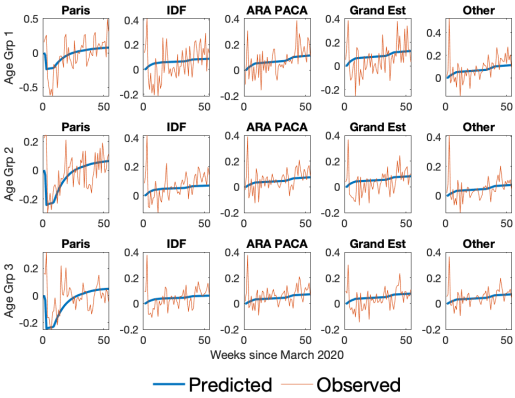
Five datasets

1. For the pandemic, **daily cases and hospitalizations** by age and region are available from **Santé Publique France**. These data will be compared to the predictions of the SIR model.
2. For **mobility**, we use mobile phones data (**Orange, SFR**) to calculate weekly variations of mobility by age.
3. For **mental health**, we use data from from **Open Health Company**
   - We could use different sources (SNDN, Surveys), our data fits with different sources.
   - We use weekly sales of psychotropic drugs (Antipsychotics, Anxiolytics, Opioids, Antidepressants) by age group and pharmacy (geolocalised).
   - Weekly changes in volume sold or quantity of substance are used to estimate the mental health portion of the model.

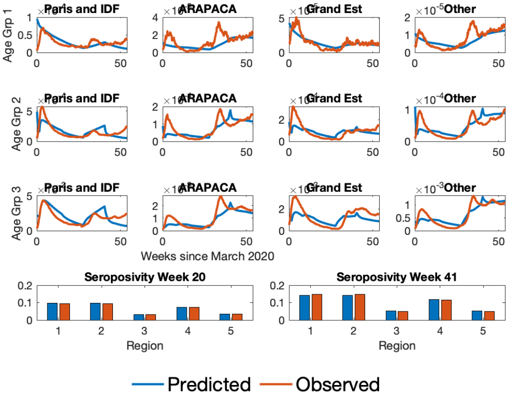
Drugs Consumption

- We use data on **weekly** sales of psychotropic drugs in France (aggregated data from individual sales receipts from a representative sample of French pharmacies).
- 4D Dataset: Time (week) x Place (Pharmacy) x Drugs class x Age group
- Antipsychotics (ATC code N05A), anxiolytics (N05B), hypnotics and sedatives (N05C) and antidepressants (N06A)
- Drug Usage= Packs sold x Pills in pack x mg/Pills

Mental health fit



Hospitalisations fit



Open problems 1: Two-sided learning and belief manipulation

- In the previous optimal mobility problem, individuals learn along the way about the opportunity of holding a lockdown and complying with it.
- Under radical uncertainty, not only the individuals learn, the scientists and...the public authorities also do.
- So, an ideal setting should include a **two-sided learning scheme**.
- However, this learning scheme cannot be symmetric, and strategic aspects can hardly be omitted. Normally the public authorities have a better information. **There exist an incentive for these authorities to use their superior information to manipulate beliefs in order to reach their objectives in terms of epidemic control.**
- Analogous case in the literature: Cisternas (2018) on inflation control.

Open problems 2: biodiversity dynamics and zoonotic diseases

- Much has been said about the connection of zoonotic diseases with biodiversity depletion. Preservation policies discussed. A nice analysis can be found in Augeraud et al. (2021).
- However, almost systematically authors reduce the analysis of biodiversity dynamics to deforestation, that's to land use (habitat destruction). Clearly there is much more in biodiversity dynamics than deforestation.
- Moreover, the literature omits the key (real) zoonotic disease transmission mechanism: consumption of bush meat.
- A much better combination of multispecies math ecological models with two-sector agricultural modeling is needed. Ongoing work on this (data on bush meat consumption in a sample of African villages).