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A Behavioural SIR Model and its Implications for Physical Distancing[*]

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Abstract

The paper proposes a behavioural-compartmental-epidemiological model with heterogenous agents who choose whether to enact physical distancing practices. Motivated by the evidence on individual physical distancing behaviour during the COVID-19 outbreak, our model extends the standard compartmental-epidemiological models by including endogenous physical distancing behaviour, drawing on discrete choice theory. This approach can account for two important factors: (i) the limited information about the contagion dynamics available for individuals and (ii) the heterogeneity in the individual ability and preferences concerning physical distancing. Despite its simplicity, the model provides policy indications about the timing and size of mitigating policies and the level and quality of information available for the public.

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1 Introduction

The COVID-19 pandemic has led to a widespread implementation of Non Pharmaceutical Interventions (NPIs) and in particular physical distancing measures. However, the timing of implementation has greatly varied across countries, with some (most notably UK and USA) lagging behind. Interestingly, figure 1 shows that the response of citizens was somehow independent from the government's prescription: people started avoiding public places and going to work, and begun wearing protective gear even before measures were imposed[1].

[Figure 1 here]

Figure 1 highlights the importance of explicitly taking into account the individuals' behaviour when modelling the contagion dynamics of COVID-19 in order to estimate the effects of imposing or lifting NPIs. This paper introduces the simplest possible framework to take the informational limitations regarding the exact number of infections into account. Our starting point is the baseline epidemiological model (known as SIR model) which describes the evolution of an epidemic by modelling the transition rates of individuals between three compartments: susceptible (S), infected (I) and recovered (R)[2].

We extend this class of models by allowing the daily transmission rate to endogenously change due to both policies in place and agents' choices. More specifically, heterogeneous agents face a binary choice regarding physical distancing or not. This choice is based on two pieces of information: the number of *confirmed* infected cases and the government's NPIs related to physical distancing. In order to emphasise both the behavioural and the epidemiological components of our model, we refer to our model as Behavioural

[1] In the UK measures were imposed on 23/3/2020 while in the USA in most cases after 20/3/2020. Survey data are publicly available at https://yougov.co.uk/topics/international/articles-reports/2020/03/17/personal-measures-taken-avoid-covid-19.

[2] For a recent discussion of this approach and its relevance to economics issues see Atkeson (2020b).

SIR (BeSIR) model.

Although the main motivation for this work is theoretical and methodological, our model provides some preliminary but relevant insights about the timing of applying and lifting the measures. In particular: (i) harsher late measures are in general less efficient than early mild ones, even when individual actions are partially independent from NPIs, and (ii) an early lifting of measures might not lead to a complete restart of social and economic activities due to individuals' autonomous assessments and choices.

2 Methods

2.1 Relevant Literature

Along the lines of the rapidly expanding literature in economics and epidemiology, our model extends the popular SIR model (Kermack and McKendrick, 1927) by explicitly modelling individual behaviour, endogenising physical distancing choices. Limiting our survey to the papers that are more closely related to ours, within the epidemiology literature Eksin et al. (2019) endogenise the reaction of susceptible individuals with an ad-hoc physical distancing rule based on the number of infected individuals. Works like Goenka et al. (2014) or the more recent Eichenbaum et al. (2020) provide a microfoundation for individual behaviour, under the assumption of perfect information about the actual number of infections. Our BeSIR model differs from Eksin et al. (2019) as agents behaviour is microfounded, while contrary to Goenka et al. (2014) and Eichenbaum et al. (2020), we introduce cognitive and informational limitation in the public by assuming that the only available piece of information is the daily *confirmed* cases, which might differ from the actual number of infected individuals.

We model the decision about physical distancing as a binary choice drawing on the discrete choice literature (McFadden, 2001; Train, 2009) and its applications to dynamic models (Brock and Hommes, 1997; Lux, 1995, among others). This approach has two important advantages: (i) it allows for heterogeneity of agents on a micro level and (ii) it can be easily applied to the data.

2.2 Model

Consider a large population of agents N, who face a choice between physical distancing (D) or not (C). At each point in time N is split between three compartments: susceptible (S_t), infected (I_t) and removed (R_t) individuals, such that for all t

$$N = S_t + I_t + R_t.$$

The change between different compartments is given by the following difference equations

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

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

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

where β_t is the average number of contacts per individual per day and γ is the daily probability that an infected individual becomes recovered. Physical distancing is assumed to decrease the average number of daily contacts per individual such that

$$\beta_t = \beta_0(1 - P_t^D). \tag{4}$$

where $\beta_0 P_0^D$ is the rate of infection in the absence of mitigating behaviours, defining P_0^D as the normal level of physical distancing in the absence of an epidemic, and P_t^D is the average level of physical distancing at time t or, equivalently, the average probability of an individual choosing D at time t. Along the lines of discrete choice models (McFadden, 2001; Train, 2009), we assume that individual choice (and hence P_t^D) depends on a vector of observable factors x_t and *unobservable* individual characteristics ϵ_i, with $i = \{1, \ldots, N\}$ and ϵ_i assumed to follow a logistic distribution (Train, 2009). The utility of individual i of choosing D is

$$U_t^i = \alpha x_t + \epsilon_i, \tag{5}$$

where α is a row vector of the intensity of choice, which quantifies the relative weight of the observable components with respect to the unobservable factors. Since any individual i chooses to physically distance themselves if $U_t^i > 0$, the probability P_t^D of choosing D at t is[3]

$$P_t^D = \frac{1}{1 + e^{-\alpha x_t}}. \tag{6}$$

We consider two observable factors: the variation in daily confirmed cases and the costs c_n of choosing D. Considering that the public focus on a single number as a proxy of the infection dynamics, we assume that the relative variation in the gross total number of confirmed cases during the outbreak includes also those that in the meantime have recovered. The parameter c_n quantifies the social and economic costs of social distancing, and are reduced when NPIs are in place (due to the absence of social activities and potential loss of income). Hence we define

$$x_t = \begin{bmatrix} \Delta(I_t + R_t)/N \\ -c_n \end{bmatrix} \tag{7}$$

Without loss of generality, we assume that

$$\alpha = \begin{bmatrix} \alpha_x & 1 \end{bmatrix} \tag{8}$$

with α_x depending (exogenously) on the level of information about the actual new cases.

Hence from (6), (7) and (8) we can express (4) as

$$\beta_t = \frac{\beta_0 e^{-\alpha_x \Delta(I_t+R_t)/N + c_n}}{1 + e^{-\alpha_x \Delta(I_t+R_t)/N + c_n}}. \tag{9}$$

Equations (1), (2), (3) and (9) constitute our BeSIR model. The model includes two policy parameters: c_n, which is related to NPIs, and the switching intensity α_x, which depends the level of information about infections. The cost c_n is reduced by the imposition of fines for non compliance with NPIs

[3]For details see Train (2009).

and the diminished opportunities of socialising. The switching intensity can be affected by policy makers by providing clearer and more accurate data (for example by increasing the number of tests) or by further disseminating information about the evolution of the outbreak.

3 Simulations

We set $\gamma = 1/7$ and $R_0 = 2.7$ (Atkeson, 2020a). The data used to calibrate the level of physical distancing start in early March (the 1^{st} for the UK and the 2^{nd} for the US). The share of total people enacting physical distance is proxied by the average of those who have declared of avoiding going to work and avoiding public places. Setting $P_0^D = 0.1$, we calibrate $\beta_0 = 0.43$ and $c_0 = 0.954$ as shown in the appendix.

In order to assign a reasonable value to α_x, we assume that an increase in the contagion rate of 5% will lead all those who can to physically distance, and therefore calculate $\alpha_x = 88$, such that for $\Delta(I_t + R_t)/N = 0.05$ we have $P_t^D = 0.9$ for $N = 10^7$, as detailed in the appendix, considering that frontline workers and other categories of people cannot choose to stay home. Initial conditions are $I_0 = 400, R_0 = 50$. Finally, we define t_i, c_i as the time of the implementation of NPIs and their size, respectively.

The simulations show the effects of different timing, duration, and strength of NPIs.

[Figure 2 here]

Figure 2 shows the baseline simulation with $t_i = 40, c_i = 0.25$. The different compartments seem to follow the general pattern observed in the data. Interestingly, the probability of physical distancing initially spikes after the intervention and then falls in a non-monotonic fashion, which resembles to what we observe in figure 1.

[Figure 3 here]

Figure 3 compares the effectiveness of timing vis-a-vis size of NPIs. Earlier, although less strict, measures are more effective in limiting the spread, compared stricter measures but later interventions.

[Figure 4 here]

Figure 4 shows the behaviour of the model's variables when physical distancing measures are lifted (early) before the infection peak (black line) and (late) after the peak (red line). An early lifting, and the consequent contraction in physical distancing behaviour, can possibly lead to a second wave of infection (as seen in the dynamics of I), which is curbed only when individuals spontaneously enact distancing measures. The resurgence in new infection in case of later lifting is substantially more contained.

[Figure 5 here]

As displayed in figure 5, better information can significantly improve the effectiveness of measures. However, the effect of the size of intervention is still larger than the one on the level of information.

4 Discussion

This paper introduces a baseline BeSIR model in which individuals' physical distancing behaviours are modelled along the lines of discrete choice theory. This approach can provide useful insights on the effectiveness of NPIs and on the timing of lifting compulsory physical distancing measures. The evidence shows that people act to some extent independently from government's measures, and therefore behavioural factors must be taking into consideration in assessing the potential effects of timing and size of policies on infection, society, and economy.

This paper aims to introduce a modelling framework that takes into account how the autonomous reaction of the public the pandemic, which is partially independent from NPIs, and considers and informational and cognitive limitations about the outbreak and the consequence of collective and individual actions. At the present stage, our contribution is mainly methodological and theoretical. However, this approach can be easily extended to larger models to include (a) more compartments, such as ‘exposed’ and ‘deceased’, whose consideration can change the aggregate physical distancing behaviour, and (b) different social groups with different abilities and attitudes towards physical distancing. The framework is flexible enough to include a stochastic element in the dynamics of infection, due for example to the opening of national and regional borders. Finally, given the suitability of the discrete choice microfoundations for empirical testing, the present framework can be extended through a more refined estimations of a more comprehensive model, in particular when more empirical and survey data will be available.

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Appendix

In order to determine β_0, we consider that $\frac{\beta_0(1-P_0^D)}{\gamma} = R_0$, such that$\beta_0 = \frac{2.7}{6.3} \approx 0.43$. In order to quantify the values of c_0, α_x, we first assume that $P_0^D = 0.1$ at $t = 0$ when $\Delta(I_t + R_t)/N \approx 0$. Accordingly, without NPIs,

$$\frac{1}{1 + e^{c_0}} = 0.1,$$

such that $c_0 = log(9) \approx 0.954$. With this result, we can estimate α_x. Given that $\frac{1}{1+e^{-\alpha_x + log9}} = 0.9$,, it follows that $\alpha_x \approx 88$.

Figures

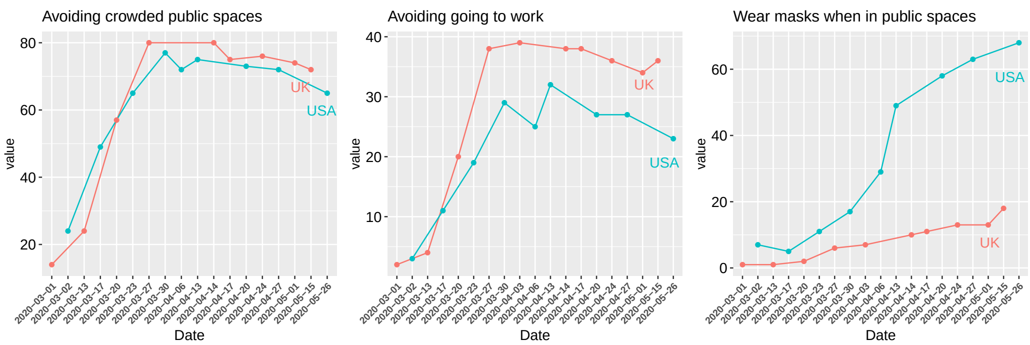

Figure 1: Physical distancing measures in the UK and USA.

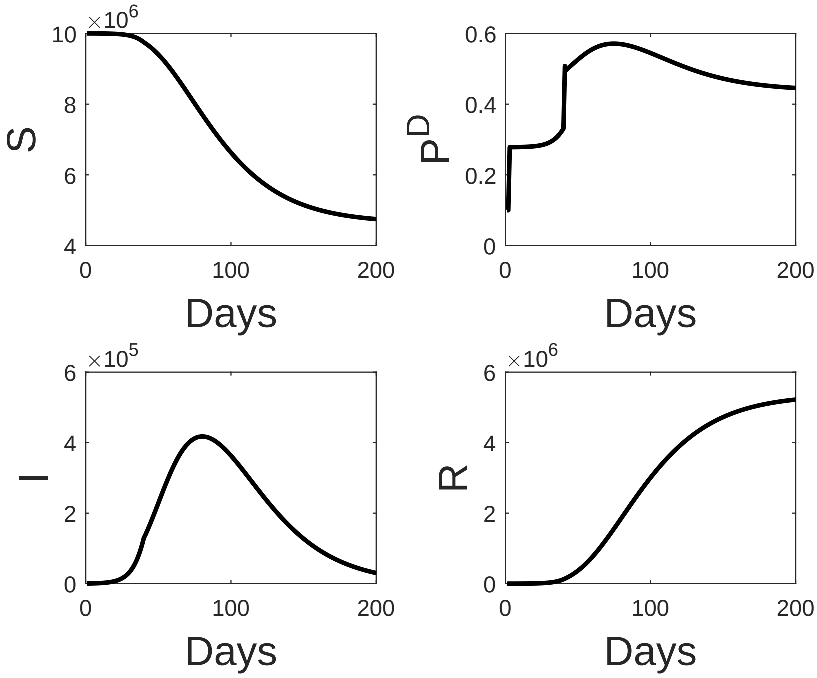

Figure 2: Baseline simulation.

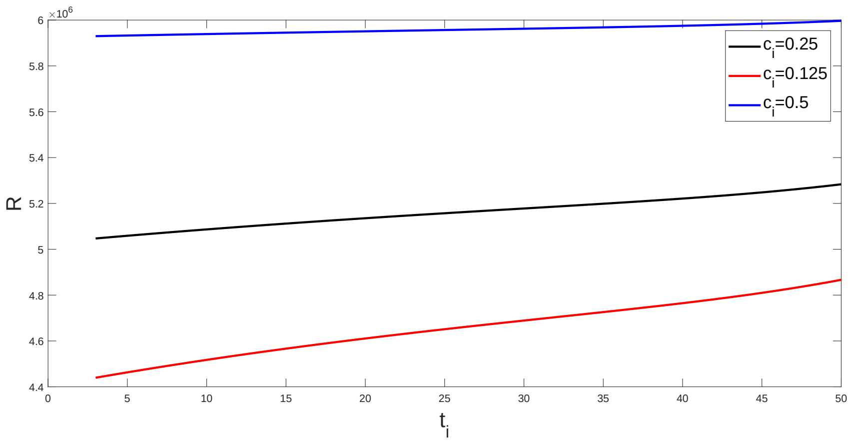

Figure 3: Steady state of R as a function of t_i for different values of c_i.

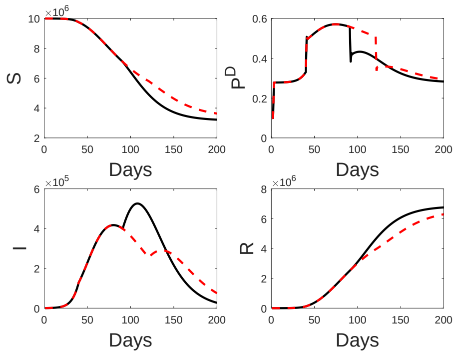

Figure 4: Simulation with lifting of measures at time 90 (black continuous line) and 120 (red dashed line).

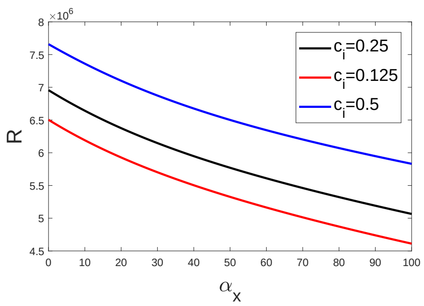

Figure 5: Steady state of R as a function of α_x for different values of c_i.