A Behavioural SIR Model: Implications for Physical Distancing Decisions

Corrado Di Guilmi[1,2,3], Giorgos Galanis[2,4,5], and Giorgos Baskozos[6]

[1]University of Technology Sydney - PO Box 123, Broadway, NSW 2007, Australia.; email: Corrado.DiGuilmi@uts.edu.au
[4]Goldsmiths, University of London, New Cross, London, SE14 6NW, London, UK; email: g.galanis@gold.ac.uk
[2]Centre for Applied Macroeconomic Analysis, Australian National University
[5]CRETA, University of Warwick, UK
[3]Center for Computational Social Science, Kobe University
[6]Nuffield Department of Clinical Neurosciences, University of Oxford, John Radcliffe Hospital, West Wing Level 6, OX3 9DU, UK; email: georgios.baskozos@ndcn.ox.ac.uk

Abstract

Early evidence during the first phase of the COVID-19 outbreak shows that individuals facing the risk of infection increased their levels of physical distancing even before relevant measures were imposed. Not taking individual behaviour into account can lead policy makers to overestimate the infection risks in absence of physical distancing measures and underestimate the effectiveness of measures. This paper proposes a behavioural-compartmental-epidemiological model with heterogenous agents who take physical distancing measures to reduce the risk of becoming infected. The level of these measures depends on the government's regulations and the daily new cases and is influenced by the individual perception of the infection risk. This approach can account for two important factors: (i) the limited information about the exact infection risks and (ii) the heterogeneity across individuals with regards to physical distancing decisions. We find that the intensity of measures required to reduce infections is directly related to the public perception of the risk of infection, and that harsher late measures are in general less effective than milder ones imposed earlier. The model demonstrates that the feedback effects between contagion dynamics and individual decisions make the extrapolation of out-of-sample forecasts from past data dangerous, in particular in a context with high uncertainty.

1 Introduction

The spread of the SARS-CoV-2 coronavirus has led almost all countries to implement Non Pharmaceutical Interventions (NPIs), and in particular physical distancing measures, in order to reduce infection risks. However, the timing of implementation has greatly varied across countries, with some (most notably UK and USA) lagging behind, especially during the first phase of the pandemic. This delay has led both individuals and firms to take physical distancing measures before governments' implementation of NPIs. Figure 1 shows that people in the UK started avoiding public places and going to work, and began wearing protective gear even before measures were imposed[1].

[Figure 1 here]

Figure 1 highlights the fact that individuals' behaviour changes when facing the risk of infection. Social foundations of illnesses and societal responses have been a key research topic in social epidemiology and social medicine (for example, see Marmot & Wilkinson, 2003; Manfredi & D'Onofrio, 2013; Verelst et al., 2016, and references therein). Given the autonomous response of individuals to the perceived risk of infection, incorporating social and behavioural perspectives in epidemiological models becomes paramount for estimating the effects of NPIs. Not taking into account the feedback effects between policy measures, rates of infection, and individual behaviour can lead to both overestimating the infection dynamics and underestimating the effectiveness of NPIs.

However, standard epidemiological models which build on the early works of Kermack & McKendrick (1927)[2], assume that the level of physical distancing depends exogenously on the level of measures imposed, hence not taking into account behaviour of individuals confronted with the risk of being infected and the heterogeneity of responses (Hong & Collins, 2006). Even though several models incorporating different factors affecting infection dynamics exist within this literature (for example, see Fenichel, 2013; Chen & Toxvaerd, 2014; Eksin et al., 2019; Galanis & Hanieh, 2021, and references therein), the consideration of physical distancing as an exogenous factor is prevalent within models that analyse the contagion dynamics of the current

[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 an overview of different types of mathematical epidemiological models see Hethcote (2000).

pandemic and aim to inform policy.[3]

The cross-fertilisation of epidemiology with economics has generated a fast growing stream of literature (for a discussion see Atkeson, 2020; Toxvaerd, 2020) that explicitly incorporates relevant individual decisions in epidemiological models (for example see Sethi, 1978; Chen, 2012; Toxvaerd, 2019; Eichenbaum et al., 2020; Toxvaerd, 2020, among others). The standard assumption is that agents possess full information on both the actual dynamics of the epidemics and the influence of their actions, and use this complete information set to decide about physical distancing.

We should note that a consistent inclusion of behavioural factors in epidemiological models should consider that not only full information about the evolution of contagion is usually not available to the agents, but also that the exact effect of individual decisions cannot be foreseen. Hence, in this context, it is more reasonable to assume that individuals use heuristics based on the available information and also that individual expectations, being based on subjective assessments, are heterogeneous. To the best of our knowledge, this paper presents the first attempt to propose a microfoundation of SIR models with boundedly rational agents.

Our starting point is the baseline epidemiological SIR model (Kermack & McKendrick, 1927) which describes the evolution of an epidemic by modelling the transition rates of individuals between three compartments: susceptible (S), infected (I) and recovered (R). We extend this model by allowing the daily transmission rate to endogenously change due to agents' choices, which can be affected by policy measures. Our behavioural component is modelled in the spirit to Simon's (1954) work on the use of heuristics due to individuals' informational and cognitive limitations, while the specific assumptions have similarities with the anchoring and adjustment heuristics (Tversky & Kahneman, 1974; Kahneman, 2003), which is widely applied in economic models (for example see Camerer et al., 2011; Hommes, 2013). More specifically, we assume heterogeneous agents who face a binary choice on whether to enact physical distancing or not. Their decision depends on the current NPIs imposed, the new confirmed cases, and is influenced by their risk perception.[4] The share of susceptible individuals who choose to physically distance affects the dynamics on the contagion, which in turn determines the individual perception about the risk of being infected, feeding back into the individual decisions.

From a methodological point of view, we model the physical distancing

[3]See the models by Prem et al. (2020); Kucharski et al. (2020); Flaxman et al. (2020) and the surveys by McBryde et al. (2020); Thomson (2020).

[4]For a discussion of the factors which influence individuals' risk perception see Sjöberg (2000).

choices drawing on the discrete choice theory (McFadden, 2001; Train, 2009) and its numerous applications in finance (for example see Lux, 1995; Brock & Hommes, 1997, 1998; Chiarella & He, 2001; Chiarella et al., 2006; Westerhoff & Dieci, 2006; Dieci & Westerhoff, 2016), macroeconomics (De Grauwe & Grimaldi, 2005; De Grauwe, 2012, 2011; Flaschel et al., 2018; Hommes et al., 2018, 2019; Hommes & Lustenhouwer, 2019; Assenza et al., 2021, among others), and politics (Di Guilmi & Galanis, 2021). This approach has two important advantages: (i) it allows for heterogeneity of agents' behaviours and (ii) it can be easily applied to the data. Our Behavioural SIR (BeSIR) model contributes to and connects the discrete choice and the epidemiological literature, and provides a policy-friendly framework.

We use the BeSIR model to study the effectiveness in reducing infection risk of measures that are different with respect to intensity and time of implementation. Although this work is mainly motivated by theoretical and methodological questions, we show that the BeSIR model can provide interesting indications about the effectiveness of policy measures of different intensities and implementation times. In particular we find that: (i) the intensity of measures required at any time to actually reduce the infection risk depends on both the infection level and the risk perception of the public; (ii) harsher late measures do not in general reduce the risk of infection compared to early mild ones, or, in other words, early interventions are substantially more effective of late measures of the same intensity; (iii) an early lifting of measures might not lead to a complete restart of social and economic activities due to individuals' autonomous assessments and choices.

The structure of the rest of the paper is as follows. Section 2 introduces our modelling framework; section 3 presents the results, first identifying short run equilibrium and analysing its implications, then numerically simulating the model to provide some policy indications; finally, the last section provides a concluding discussion.

2 Model

Consider a large population of agents N, each of whom makes a choice between physical distancing (D) or not (C) in the face of the risk of getting infected. Considering one day as the time unit, in each period the population is split between three compartments according to their condition with respect to the virus: susceptible (S_t), infected (I_t) and removed (R_t). Using a SIR model, we consider both recovered and deceased individuals as removed. The two categories are separated in SIRD (Susceptible-Exposed-Infectious-Recovered-Deceased) models. Given that the population size is fixed, the following identity holds for all t:

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

2.1 Infection dynamics

The dynamics between compartments are assumed to follow the standard SIR model. The evolution of susceptible individuals is given by

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

where β_t is the average number of contacts per individual per day. Equation (1) is the standard way to express the evolution of susceptible individuals in SIR models. Specifically, the dynamics of S is determined by the the probability of a susceptible individual contracting the virus when entering in contact with an infected person ($\frac{S_t I_t}{N}$) weighted by the average number of contacts per individual per day (β_t). Its rationale is in that the probability of becoming infected depends on both the number of infected individuals (I_t) and the share of susceptible ones over the total population (S_t/N). In the initial periods, S_t being relatively close to N, for any level of I_t a relatively large number of individuals are susceptible to infection, leading to a fast increase in the number of infected individuals as the virus spreads. However, as the infection progresses and S_t diminishes, less people are potentially at risk of infection and, hence, the growth rate of infections I_t declines.

The number of infected individuals evolves as follows:

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

where γ is the average daily probability that an infected individual becomes removed. Hence, $1/\gamma$ captures the average number of days that an individual remains infected. The quantity β/γ is known as the basic reproduction number, usually denoted by R_0, which is assumed to be higher than one[5], implying $\beta > \gamma$, otherwise the infection would die out quickly without any intervention, the reduction in S_t discussed above takes place.

Finally, the number of removed individuals is given by:

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

which ensures that $N = S_t + I_t + R_t$ for all t.

[5] Early estimates (Flaxman et al., 2020) find R_0 to be 3.8.

2.2 Individual behaviour

Our key addition to the standard SIR model is related to individual behaviour, which is at least partially independent of the measures taken by the government. More specifically, we take into account the fact that individuals recognise the risk of infection and autonomously enact physical distancing measures. The aggregate physical distancing level is given by the total number of people choosing D, while the share of D over the total population is quantified by the probability of an agent choosing D, which is identified by P_t^D. Hence, β_t, which quantifies the average number of daily contacts per individual in (1), can be expressed as a function of of P_t^D according to

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

where β is a positive constant measuring the sensitivity of the public to the possibility of being infected. Let P_0^D be the baseline level of physical distancing without measures (P_0^D can also be considered as the *normal* level of physical distancing in the absence of an epidemic). 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). More specifically individual i chooses D if the utility of choosing D, indicated by U_t^i, is positive. The utility U_t^i is given by

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

where α is a row vector which captures 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 if $U_t^i > 0$, the probability P_t^D of choosing D at t is

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

We consider two observable factors: daily confirmed cases per capita and the costs c_n of choosing D. We assume that the public focuses only the daily confirmed infections (which are equal to $S_t - S_{t-1}$) as an indicator of the infection dynamics for their heuristics. Thus, an increase in confirmed cases leads to an increase of physical distancing levels.[6]

[6] Early survey studies mostly focus on the relationship between cultural background and individual decisions about physical distancing (see for example Canning et al., 2020; Castle et al., 2021; Jefferson et al., 2020). However, there not seem to be an empirically grounded consensus about the drivers of individual decisions about physical distancing. Our choice of the daily number of infection finds support in the emphasis that daily media and official government communication have given to this measure.

Within the SIR framework, all infected individuals are also infectious since the incubation period, during which individuals are exposed but without symptoms, is not considered. In contrast, the SEIR (Susceptible-Exposed-Infectious-Removed) models explicitly include the incubation period. In this paper, we allow for a lag between contagion and recording of new cases in the extension of the present model that is numerically analysed in section 3.2.2.[7]

Figure 2 shows the confirmed cases in the UK and US in the first period before any NPIs were imposed.

[Figure 2 here]

The parameter c_n quantifies the social and economic costs of physical distancing in the absence of measures. We assume that these costs are reduced when NPIs are in place due to the absence of social activities and potential loss of income, such that a decrease in costs increases the physical distancing levels. Hence, we define

$$x_t = \begin{bmatrix} S_t - S_{t-1} \\ -c_n \end{bmatrix} \tag{7}$$

Without loss of generality, we assume that

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

with α_x capturing the relative importance of the first component. Intuitively α_x can be thought as a relative measure of the risk perception of individuals for a given number of new infection cases $(S_t - S_{t-1})$. Accordingly, from (6), (7) and (8), we can express (4) as

$$\beta_t = \frac{\beta e^{\alpha_x (S_t - S_{t-1}) + c_n}}{1 + e^{\alpha_x (S_t - S_{t-1}) + c_n}}. \tag{9}$$

Equations (1), (2), (3) and (9) constitute our BeSIR model. The model includes two policy parameters: c_n, which is directly related to NPIs, and the risk perception α_x, which can be impacted by the government, for example, by disseminating public information on the level of health risk and the transmissibility of the virus.

3 Results

This section provides an overview of the results. The model is first analytically solved to identify the critical threshold that the policy should target

[7] For a full treatment of a behavioural SEIR model, see Galanis et al. (2020).

in order to reduce the diffusion of the infection. The numerical simulations provide some indications about the impact of size and timing of containment measures.

3.1 Short run endemic equilibrium

The short run endemic equilibrium captures the situation where each infected individual infects exactly one susceptible person during the period in which they are infected. This situation corresponds to a reproduction number equal to 1, which is the critical threshold that a containment policy should achieve in order to avoid an exponential contagion. Following our discussion of equation (2), a unitary reproduction number implies that the following condition holds

$$\beta_t = \gamma \;\; \forall t. \tag{C1}$$

The equilibrium exists if and only if for a given level of I and S there exists a level of costs c_n such that C1 is satisfied. Note that this condition is equivalent to the condition of a stationary $I_t = I$ with $S_t \approx N$. This assumption allows us to simplify the short run endemic equilibrium condition C1 to

$$\frac{\beta e^{-\alpha_x \gamma I + c_n}}{1 + e^{-\alpha_x \gamma I + c_n}} = \gamma, \tag{10}$$

which gives the equilibrium value of c_n as a function of the level of risk perception α_x

$$c_n = ln(\gamma) - ln(\beta - \gamma) + \alpha_x \gamma I. \tag{11}$$

Equation (11) reveals that the cost level in the short-run endemic equilibrium depends positively both on the the infection level at the equilibrium and on the level of risk perception. More precisely, in order to achieve a unitary reproduction number, a more aggressive policy is required if the public is very sensitive to the probability of infection, quantified by β. The sensitivity to the daily number of infections, quantified by α_x, compounds the effect of the probability of removal, γ in raising c_n and therefore making physical distancing behaviour more likely.

The result in equation (11) highlights the complementarity of the two effects that influence individual decisions and provides an analytical representation of their interaction with the quantities of standard SIR models. However, (11) identifies a critical threshold rather than a desirable equilibrium, since a containment policy should aim to lower I to a level that makes the infection manageable for the health system. While the analytical solution provides insights about the required magnitude of measures, proxied by the level of c_n, numerical simulations are needed to quantify the effect of their timing.

It is worth noticing that we would achieve the same short-run endemic equilibrium by adopting a SEIR model, and imposing the unitary reproduction number condition as in C1. However, a difference would emerge in the adjustment phase, since the new actual cases would be not be equal to the confirmed cases due to the incubation period. Under the assumption of individuals reacting to new confirmed cases, the physical distancing practices would in general be less effective, especially during periods with high infection rates. We investigate through numerical simulations the consequences of introducing a lag between infection and new case recording in section 3.2.2.

3.2 Simulations

This subsection presents the result of numerical simulations of the model and the sensitivity analysis to the main parameters. We also propose some extensions to test the robustness of the results of the baseline version.

3.2.1 Baseline model

For the numerical simulations of the model, we set $\gamma = 1/5$ (Prem et al., 2020) and $R_0 = 3.8$ (Flaxman et al., 2020). 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 avoiding going to work and avoiding public places. Setting $P_0^D = 0.1$, we calibrate $\beta = 0.43$ 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 $P_t^D = 0.9$, as detailed in the appendix, which can be regarded as the maximum level for P^D considering that frontline workers and other categories of people cannot choose to stay home. 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 3 here]

Figure 3 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 4 here]

Figure 4 compares the effectiveness of timing *vis-a-vis* size of NPIs. The figures report the steady state of removed individuals (as a proxy of total infections) for three levels of c, corresponding to different intensities of interventions, and different times of implementation (expressed in days). It is evident that a stronger intensity of measures can never compensate for delay in implementation. The consideration of behavioural feedback shows that earlier, although less strict, measures are more effective in limiting the spread.

[Figure 5 here]

Despite we are now more than a year into the pandemic, the timing of the lifting on interventions is still subject to debate. Since lifting of measures in most cases has led to successive waves of contagion, it is crucial to achieve a more precise understanding of the resurgence of infection after restrictions are relaxed. Figure 5 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 infections in case of later lifting is substantially more contained.

Since the effects of measures seem to be compounded by the behavioural factors, extrapolating out-of-sample forecasts exclusively from previous trends can be dangerous. Indeed, in many instances, restrictions were eased as soon as the upward trend of infections showed signs of inversion, only to be followed by a new wave. However, the North-East panel of figure 5 shows that even a small rebound in the probability of infection can lead to the sizeable resurgence in cases (displayed in the South-West panel). This risk can be amplified by a lower level of compliance due to "tiredness" after long spells of lockdown and limitations.

Given the centrality of behavioural factors, we conclude the analysis with a sensitivity study on the level of risk perception, quantified by α_x.

[Figure 6 here]

Figure 6 plots the steady state levels of R as a function of α_x for different

levels of restrictions. Unsurprisingly, for the same intensity of behavioural factors, stricter measures are more effective. However, higher levels of risk perception α_x can significantly improve the effectiveness of measures. Furthermore, very high levels of α_x can compensate for lower levels of restrictions. This is visible from the fact that, in order to obtain the same level of R in the plot (say 6.5×10^6), in the absence of behavioural feedback ($\alpha_x = 0$), the measure must be relatively strict, while they can be relatively loose for very high levels of α_x.
In terms of policy, the results of the sensitivity analysis stress the need of a careful dissemination of information and of a strong contrast to misinformation, which can require stricter measures to compensate for a low perception of risk in the public.

3.2.2 Extensions

The behavioural component of our BeSIR framework implicitly assumes that individuals, in estimating the infection risk, factor in the imperfect monitoring of cases and are therefore aware that they observe only a (constant) fraction of the actual new cases. However, the low testing rates in the initial phase of the pandemic and the consequent higher uncertainty about the reliability of infection rates, might have possibly led to a lower level of risk perception for a given actual number of infections. In our model, this underestimation can be rendered by introducing a constant $0 < \varepsilon < 1$ in equation (9) such that it becomes:

$$\beta_t = \frac{\beta e^{\alpha_x \varepsilon (S_t - S_{t-1}) + c_n}}{1 + e^{\alpha_x (S_t - S_{t-1}) + c_n}} \quad \forall t < \tau. \tag{9-b}$$

assuming that the regime of low testing rates lasts up to period τ. Figure 7 presents the simulation of the model using (9-b) with $\varepsilon = 0.5$ and $\tau = 115$.

Comparing figures 3 and 7, we note that the infection rate peaks at a noticeably higher level in the latter while the probability of physical distancing rebounds and does not show the smooth decline visible in figure 3. However, in the long run, the number of recovered appears to be comparable in the two scenarios.

As mentioned above, a full consideration of possible delays between infection and recording due to the incubation period would require the adoption of a SEIR model. However, our BeSIR model is flexible enough to incorporate the case of lag in reporting. The probability (9) can be modified to include a variable lag L and be re-expressed as

$$\beta_t = \frac{\beta e^{\alpha_x (S_{t-L} - S_{t-L-1}) + c_n}}{1 + e^{\alpha_x (S_{t-L} - S_{t-L}) + c_n}}. \tag{9-c}$$

The results are shown in figure 8 for $L = 1$ and $L = 4$. In general, the effect is qualitatively similar to one displayed in figure 7 for initially lower α, with a higher share of infections at the peak and a rebound in the probability of physical distancing. It is possible to observe that, in this case, the percentage of infections is higher and that, comparing the two lines corresponding to the two different lags, the effect of increasing the lag in reporting seems to impact more the timing of the dynamics rather than the size of the outbreak. Overall, the baseline model appears to be robust to different specifications concerning the individual behaviour and reactions to the evolution of the contagion.

4 Concluding Remarks

Motivated by early data on individual behaviour facing the risk of infection from COVID-19, this paper aims to introduce a new modelling framework, the BeSIR model, which takes into account individual behaviour and use this novel approach for the assessment of policies aiming to reduce the risk of infection. The modelling strategy, consolidated by the extensive literature on discrete choices, is here applied to endogenise the physical distancing decisions, which are assumed to be dependent on the individual assessment of contagion risk and the cost of physical distancing, which is affected by policy measures. Consequently, the BeSIR model can be used for an analysis of the effectiveness of NPIs, which includes the possible reaction of the public to the evolution of the outbreak and the policy response.

The results show that the level of measures required to contain infections is directly related to the public perception of the infection risk and that harsher late measures are in general less effective than milder ones imposed earlier. Furthermore, the model demonstrates that the feedback effects between contagion dynamics and individual decisions make the extrapolation of out-of-sample forecasts from past data dangerous, in particular in a context with high uncertainty.

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, (b) different social groups with different abilities and attitudes towards physical distancing and (c) study in more detail the factors which influence the risk perceptions of individuals. 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 approach 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.

References

Assenza, T., Heemeijer, P., Hommes, C., & Massaro, D. (2021). Managing self-organization of expectations through monetary policy: A macro experiment. *Journal of Monetary Economics*, *117*, 170-186. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0304393219302181` doi: https://doi.org/10.1016/j.jmoneco.2019.12.005

Atkeson, A. (2020). *What will be the economic impact of covid-19 in the us? rough estimates of disease scenarios* (Working Paper No. 26867). National Bureau of Economic Research.

Brock, W., & Hommes, C. (1997). A rational route to randomness. *Econometrica*, *65*, 1059-1095.

Brock, W., & Hommes, C. (1998). Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic Dynamics and Control*, *22*, 1235-1274.

Camerer, C. F., Loewenstein, G., & Rabin, M. (2011). *Advances in behavioral economics.* Princeton University Press.

Canning, D., Karra, M., Dayalu, R., Guo, M., & Bloom, D. E. (2020). The association between age, COVID-19 symptoms, and social distancing behavior in the united states. *medRxiv*. Retrieved from `https://www.medrxiv.org/content/early/2020/04/23/2020.04.19.20065219` doi: 10.1101/2020.04.19.20065219

Castle, C., Di Guilmi, C., & Stavrunova, O. (2021). *Individualism and Collectivism as predictors of compliance with COVID-19 public health safety expectations* (Working Paper Series No. 2021/03). Economics Discipline Group, UTS Business School, University of Technology, Sydney. Retrieved from `https://ideas.repec.org/p/uts/ecowps/2021-03.html`

Chen, F. (2012). A mathematical analysis of public avoidance behavior during epidemics using game theory. *Journal of Theoretical Biology*, *302*, 18 - 28. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0022519312001191` doi: https://doi.org/10.1016/j.jtbi.2012.03.002

Chen, F., & Toxvaerd, F. (2014). The economics of vaccination. *Journal of Theoretical Biology*, *363*, 105 - 117. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0022519314004512` doi: https://doi.org/10.1016/j.jtbi.2014.08.003

Chiarella, C., Dieci, R., & Gardini, L. (2006). Asset price and wealth dynamics in a financial market with heterogeneous agents. *Journal of Economic Dynamics and Control*, *30*, 1755-1786.

Chiarella, C., & He, X. (2001). Asset price and wealth dynamics under heterogeneous expectations. *Quantitative Finance*, *1*, 509-526.

De Grauwe, P. (2011). Animal spirits and monetary policy. *Economic Theory*, *47*, 423-457.

De Grauwe, P. (2012). Booms and busts in economic activity: A behavioral explanation. *Journal of Economic Behavior & Organization*, *83*(3), 484-501.

De Grauwe, P., & Grimaldi, M. (2005). Heterogeneity of agents, transaction costs and the exchange rate. *Journal of Economic Dynamics and Control*, *29*, 691-719.

Di Guilmi, C., & Galanis, G. (2021). Convergence and divergence in dynamic voting with inequality. *Journal of Economic Behavior and Organization*, *187*, 137-158. doi: https://doi.org/10.1016/j.jebo.2021.04.013

Dieci, R., & Westerhoff, F. (2016). Heterogeneous expectations, boom-bust housing cycles, and supply conditions: A nonlinear economic dynamics approach. *Journal of Economic Dynamics and Control*, *71*, 21 - 44. Retrieved from http://www.sciencedirect.com/science/article/pii/S0165188915301184 doi: https://doi.org/10.1016/j.jedc.2016.07.011

Eichenbaum, M. S., Rebelo, S., & Trabandt, M. (2020). *The macroeconomics of epidemics* (Working Paper No. 26882). National Bureau of Economic Research.

Eksin, C., Paarporn, K., & Weitz, J. S. (2019). Systematic biases in disease forecasting - the role of behavior change. *Epidemics*, *27*, 96 - 105. Retrieved from http://www.sciencedirect.com/science/article/pii/S1755436518301063 doi: https://doi.org/10.1016/j.epidem.2019.02.004

Fenichel, E. P. (2013). Economic considerations for social distancing and behavioral based policies during an epidemic. *Journal of Health Economics*, *32*(2), 440 - 451. Retrieved from http://www.sciencedirect.com/science/article/pii/S0167629613000039 doi: https://doi.org/10.1016/j.jhealeco.2013.01.002

Flaschel, P., Charpe, M., Galanis, G., Proano, C. R., & Veneziani, R. (2018). Macroeconomic and stock market interactions with endogenous aggregate sentiment dynamics. *Journal of Economic Dynamics and Control*, *91*, 237 - 256.

Flaxman, S., Mishra, S., Gandy, A., et al. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in europe. *Nature*, *584*, 257 - 261.

Galanis, G., Di Guilmi, C., Bennett, D., & Baskozos, G. (2020). *The effectiveness of non pharmaceutical interventions in reducing the outcomes of the covid-19 epidemic in the uk, an observational and modelling study* (Tech. Rep.). Retrieved from `https://www.medrxiv.org/content/early/2020/12/16/2020.12.16.20248308` doi: 10.1101/2020.12.16.20248308

Galanis, G., & Hanieh, A. (2021). Incorporating social determinants of health into modelling of COVID-19 and other infectious diseases: A baseline socio-economic compartmental model. *Social Science & Medicine*, *274*, 113794. Retrieved from `https://www.sciencedirect.com/science/article/pii/S027795362100126X` doi: https://doi.org/10.1016/j.socscimed.2021.113794

Hethcote, H. W. (2000, December). The mathematics of infectious diseases. *SIAM Rev.*, *42*(4), 599-653. Retrieved from `https://doi.org/10.1137/S0036144500371907` doi: 10.1137/S0036144500371907

Hommes, C. (2013). *Behavioral rationality and heterogeneous expectations in complex economic systems*. Cambridge University Press.

Hommes, C., & Lustenhouwer, J. (2019). Inflation targeting and liquidity traps under endogenous credibility. *Journal of Monetary Economics*, *107*, 48–62.

Hommes, C., Lustenhouwer, J., & Mavromatis, K. (2018). Fiscal consolidations and heterogeneous expectations. *Journal of Economic Dynamics and Control*, *87*, 173–205.

Hommes, C., Massaro, D., & Weber, M. (2019). Monetary policy under behavioral expectations: Theory and experiment. *European Economic Review*, *118*, 193 - 212. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0014292119300960` doi: https://doi.org/10.1016/j.euroecorev.2019.05.009

Hong, S., & Collins, A. (2006). Societal responses to familiar versus unfamiliar risk: Comparisons of influenza and sars in korea. *Risk Analysis*, *26*(5), 1247-1257. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1539-6924.2006.00812.x doi: https://doi.org/10.1111/j.1539-6924.2006.00812.x

Jefferson, T., Spencer, E., Brassey, J., & Heneghan, C. (2020). Viral cultures for covid-19 infectivity assessment. systematic review. *medRxiv*. Retrieved from https://www.medrxiv.org/content/early/2020/09/29/2020.08.04.20167932 doi: 10.1101/2020.08.04.20167932

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review*, *93*, 1449-1475.

Kermack, W. O., & McKendrick, A. G. (1927). A contribution to the mathematical theory of epidemics. *Proceedings of the Royal Society of London, Series A 115*(772), 700-721.

Kucharski, A. J., Russell, T. W., Diamond, C., Liu, Y., Edmunds, J., & Funk, R. M., Sebastian Eggo. (2020). Early dynamics of transmission and control of COVID-19: a mathematical modelling study. *The Lancet Infectious Diseases*, *20*, 553 - 558.

Lux, T. (1995). Herd behaviour, bubbles and crashes. *Economic Journal*, *105*, 881-889.

Manfredi, P., & D'Onofrio, A. (2013). *Modelling the interplay between human behavior and the spread of infectious diseases.* Springer: New York.

Marmot, M., & Wilkinson, R. (2003). *Social determinants of health-second edition.* Oxford University Press.

McBryde, E. S., Meehan, M. T., Adegboye, O. A., Adekunle, A. I., Caldwell, J. M., Pak, A., ... Trauer, J. M. (2020). Role of modelling in covid-19 policy development. *Paediatric Respiratory Reviews*, *35*, 57 - 60. Retrieved from http://www.sciencedirect.com/science/article/pii/S1526054220300981 doi: https://doi.org/10.1016/j.prrv.2020.06.013

McFadden, D. (2001). Economic Choices. *American Economic Review*, *91*(3), 351-378.

Prem, K., Liu, Y., Russell, T. W., Kucharski, A. J., Eggo, R. M., & Davies, N. (2020). The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: a modelling study. *The Lancet Public Health*, *5*, 261 - 270.

Sethi, S. (1978). Optimal quarantine programmes for controlling an epidemic spread. *Journal of the Operational Research Society*, *29*, 265 - 268.

Simon, H. A. (1954). Bandwagon and underdog effects and the possibility of election predictions. *The Public Opinion Quarterly*, *18*(3), 245–253.

Sjöberg, L. (2000). Factors in risk perception. *Risk Analysis*, *20*(1), 1-12. Retrieved from `https://onlinelibrary.wiley.com/doi/abs/10.1111/0272-4332.00001` doi: https://doi.org/10.1111/0272-4332.00001

Thomson, R. N. (2020). Epidemiological models are important tools for guiding COVID-19 interventions. *The American Political Science Review*, *18*(152).

Toxvaerd, F. (2019). Rational disinhibition and externalities in prevention. *International Economic Review*, *60*(4), 1737-1755. Retrieved from `https://onlinelibrary.wiley.com/doi/abs/10.1111/iere.12402` doi: https://doi.org/10.1111/iere.12402

Toxvaerd, F. (2020). *Equilibrium social distancing* (Tech. Rep.). Cambridge Working Papers in Economics CWPE2021.

Train, K. (2009). *Discrete choice methods with simulation.* Princeton: Cambridge University Press.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131. Retrieved from `https://science.sciencemag.org/content/185/4157/1124` doi: 10.1126/science.185.4157.1124

Verelst, F., Willem, L., & Beutels, P. (2016). Behavioural change models for infectious disease transmission: a systematic review (2010-2015). *Journal of The Royal Society Interface*, *13*(124), 131-143.

Westerhoff, F. H., & Dieci, R. (2006). The effectiveness of Keynes-Tobin transaction taxes when heterogeneous agents can trade in different markets: A behavioral finance approach. *Journal of Economic Dynamics and Control*, *30*(2), 293 - 322. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0165188905000345` doi: https://doi.org/10.1016/j.jedc.2004.12.004

Appendix

In order to determine β, we consider that $\frac{\beta(1-P_0^D)}{\gamma} = R_0$, such that$\beta = \frac{2.7}{6.3} \approx 0.43$. 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

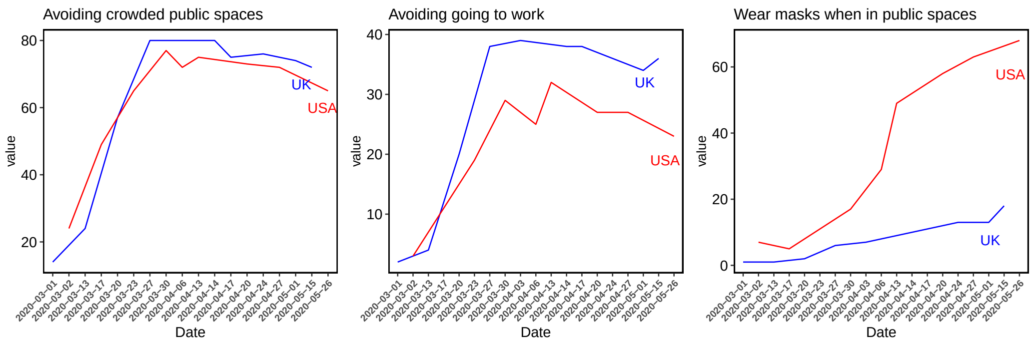

Figure 1: Physical distancing practices in the UK and USA. Survey data from COVID-19 Public Monitor created by YouGov and the Imperial College London, sourced at https://yougov.co.uk.

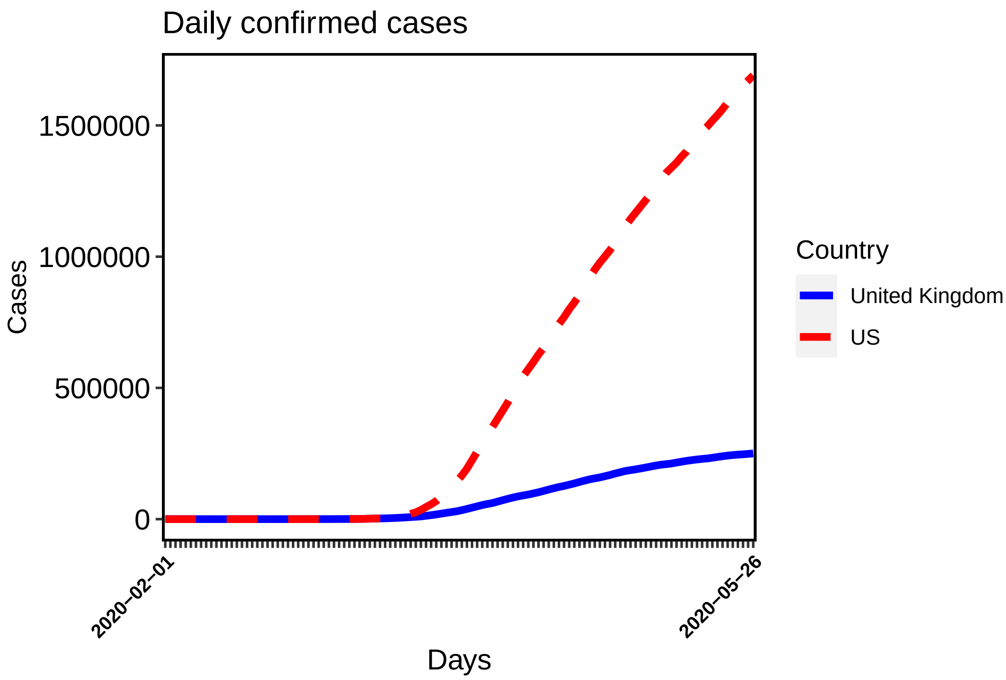

Figure 2: Daily confirmed cases in the UK and USA. Source: WHO Coronavirus Disease (COVID-19) Dashboard.

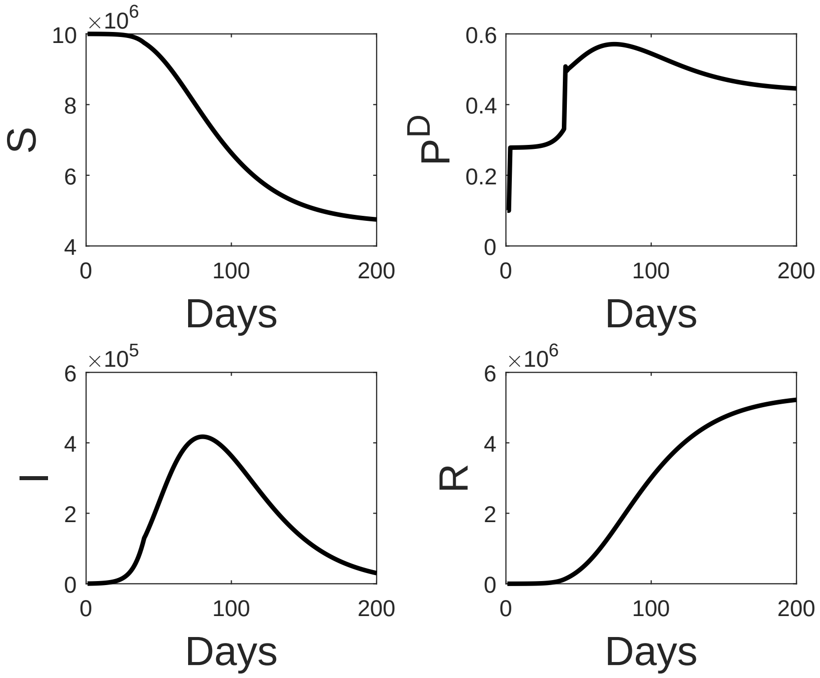

Figure 3: Baseline simulation: susceptible individuals (top-left), probability of physical distancing (top-right), infected individuals (bottom-left), removed individuals (bottom-right).

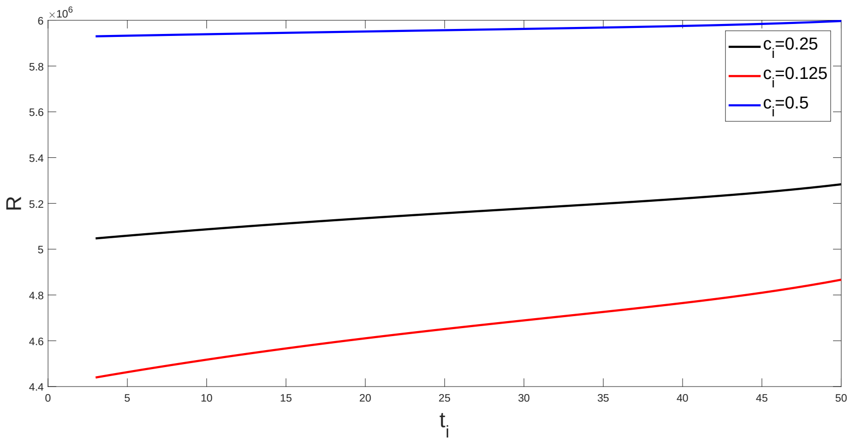

Figure 4: Steady state of R as a function of t_i for different values of c_i.

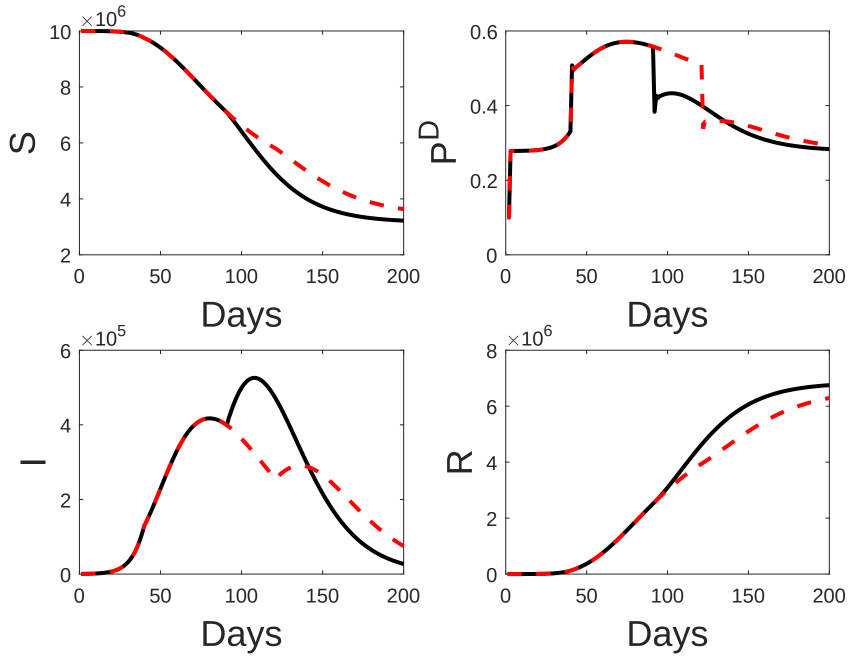

Figure 5: Simulation with lifting of measures at time 90 (black continuous line) and 120 (red dashed line): susceptible individuals (top-left), probability of physical distancing (top-right), infected individuals (bottom-left), removed individuals (bottom-right)

.

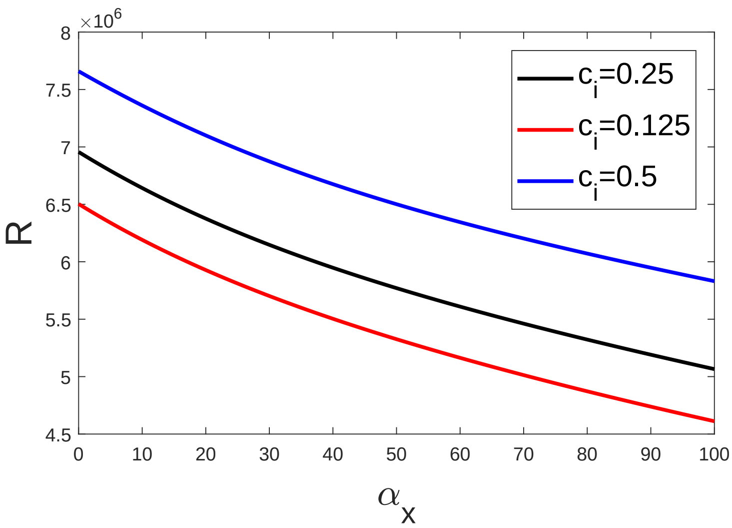

Figure 6: Steady state value of R_t as a function of α_x for different values of c_i.

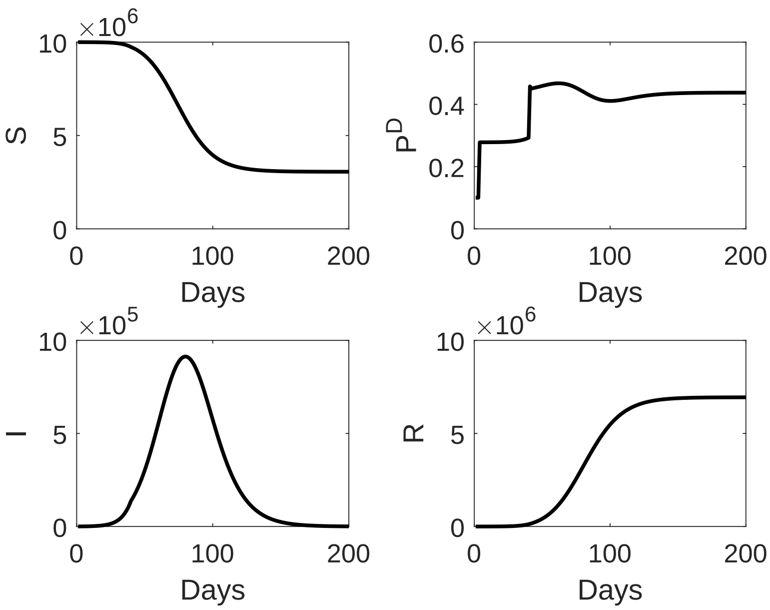

Figure 7: Simulation with probability defined as in 9-c, with $\varepsilon = 0.5$ and $\tau = 115$: susceptible individuals (top-left), probability of physical distancing (top-right), infected individuals (bottom-left), removed individuals (bottom-right)

.

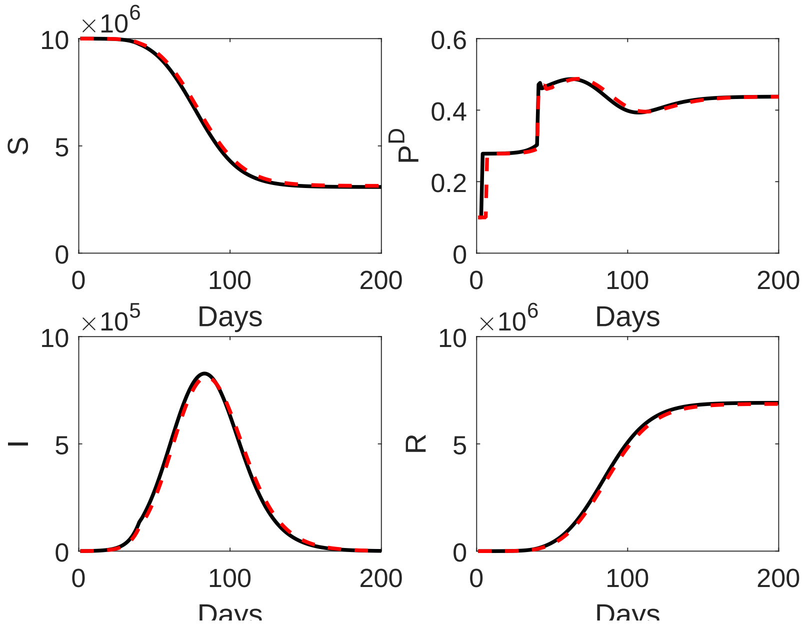

Figure 8: Simulation with probability defined as in (9-c) and lags equal to 1 day (black line) and 4 days (blue line): susceptible individuals (top-left), probability of physical distancing (top-right), infected individuals (bottom-left), removed individuals (bottom-right)

.

Declarations

Funding: this research did not receive any funding.
Conflicts of interest/Competing interests: none.
Availability of data and material: the data used are publicly available at https://yougov.co.uk.
Code availability: codes available upon request.