Social distancing and contagion in a discrete choice model of COVID-19

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Abstract

We present an epidemic model in which heterogenous agents choose whether to enact social distancing practices. The policy maker decides on the timing and the extent of policies that incentivise social distancing. We evaluate the consequences of interventions and find that: (i) the timing of intervention is paramount in slowing the contagion, and (ii) a delay cannot be compensated by stronger measures.

Keywords

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We present an epidemic model in which heterogenous agents choose whether to enact social distancing practices. The policy maker decides on the timing and the extent of policies that incentivise social distancing. We evaluate the consequences of interventions and find that: (i) the timing of intervention is paramount in slowing the contagion, and (ii) a delay cannot be compensated by stronger measures.

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1   Introduction

The social and economic effects of COVID-19 has led to the integration of epidemic models, like the popular SIR (Kermack and McKendrick, 1927), into economics (Atkeson, 2020; Eichenbaum et al., 2020). The vast impact of COVID-19 is due to the fact that the entire population is susceptible to contagion and no pharmaceutical treatment or vaccine is currently available. Consequently, national authorities are resorting to non-pharmaceutical treatments to slow down the spread of the infection. In discussing these measures, Anderson et al. (2020) stress two crucial points. First, given the very large reproduction number (estimated to be higher than 2) mitigation strategies are paramount and social distancing appears as the most effective and feasible. Second, in enacting social-distancing policies, individual behaviour is crucial: "*Personal, rather than government action, in western democracies might be the most important issue.*"

   We present an epidemic model in which the spread of an outbreak can be mitigated by social-distancing practices, which depend on individual choices as in Eichenbaum et al. (2020). However, in consideration of the high level of uncertainty generated by the pandemic and its rapid evolution, our contribution differs by assuming that individual decisions are based on a imperfect information set, which is limited to the data about confirmed cases. We model the decision about social 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). The model can provide a qualitative preliminary analysis of (i) the consequences of late intervention and (ii) the effectiveness of increasing the severity of measures to compensate for the delay.

2   Model

Consider a large population of agents N, in a closed space, who face a choice between social distancing (D) or not (C). For all t, let s_t be the share of individuals who choose D at time t and $1 - s_t$ the share of people who choose

C.

2.1 Contagion

Let h_t be the share of confirmed infected cases over total population in period t and assume that it evolves according to

$$h_{t+1} = h_t(1 + \alpha - d_{t+1}), \tag{1}$$

where α is the rate of growth of confirmed cases without mitigating measures and $d_{t+1} \leq \alpha \ \forall t$ captures the reduction of α due to social distancing. In order to model the evolution of d_t, we postulate that:

A1: $d_t \leq a$ since we are interested in the total number of cases, abstracting from recoveries and deaths (identified as *removed* in SIR terminology). Accordingly, h_t cannot decrease;

A2: $d_{t+1} > d_t$ for $s_t > 0$, which means that, as long as the share of socially distancing agents is positive, the rate of increase of h_t will be decreasing over time.

A3: $d_{t+1} = d_t$ for $s_t = 0$, which means that the spread can slow down only with social distancing[1].

Accordingly, we define

$$d_{t+1} = d_t + \beta s_t(\alpha - d_t), \tag{2}$$

where $\beta \in (0,1)$ quantifies the impact of social distancing on α. The dynamics implied by equations (1-2) provide a good fit on the Chinese data, as shown by Figure 1.[2] For the fit, we set $\alpha = 0.404$, $\beta s_t = 0$ until period $t = 14$, and $\beta s_t = 0.095$ from $t \geq 14$ with s_t constant, considering that

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[1]However, if $h_t > 0$, we also have $s_t > 0$, since infected individuals enact social distancing, as discussed below.

[2]Data source: `https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data/csse_covid_19_time_series?fbclid=IwAR20302irrZwTKNf8-3k01OXRp8jSIrSZXpS-RcOv2nuLcVIDKEyKQXJ9Go`

measures were imposed on day 14 after the first recorded cases.

[Figure 1 here]

2.2 Social Distancing

All individuals with confirmed infection choose D, while the rest of the population choose between D and C with a probability P_t^D such that the share of individuals who are socially distancing at $t+1$ is

$$s_{t+1} = h_t + (1 - h_t)P_t^D. \tag{3}$$

Along the lines of discrete choice models (McFadden, 2001; Train, 2009), individual choice (and hence P_t^D) depends on a vector of observable factors x_t and *unobservable* individual characteristics ϵ_i with $i = \{1, \ldots, N\}$. Since information is limited, the two factors influencing individual decisions are assumed to be the expected number of confirmed cases of the next day $\mathbb{E}(h_{t+1} - h_t)$ and the costs c of choosing D, which can be affected by government policies. Hence

$$x_t = \begin{bmatrix} \mathbb{E}(h_{t+1} - h_t) \\ -c \end{bmatrix} \tag{4}$$

Individual utilities are

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

where ϵ follows a logistic distribution and γ is a row vector which captures the intensity of choice. Assuming that agent i chooses D if $U_t^i > 0$, the probability P_t^D of any individual choosing D at t is[3]

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

We model the expectations $\mathbb{E}(h_{t+1} - h_t)$ as dependent on d_t, since from (1) it follows that $h_{t+1} - h_t = h_t(\alpha - d_t)$. Considering that the exact value of d_t cannot be computed because ϵ_i is not observable and information about

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[3]For details, see Train (2009).

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individual choices are imperfect, agents use the approximation $\tilde{d}_t$, calculated as

$$\tilde{d}_t = \delta d_{t-1} + (1 - \delta)\tilde{d}_{t-1}, \tag{7}$$

where $\delta \in (0, 1]$ is the relative importance of the actual value in the previous period.

3   Simulations

We estimate $\alpha = 0.35$ using the average growth of h in Italy and UK and $\beta = 0.10$ on Chinese data, assuming a high compliance with social distancing measures ($s = 0.9$). The other parameters are calibrated as $\gamma = [4\ 4]$, $\delta = 0.5$.[4] The initial value of h is $h_1 = 4 \times 10^{-6}$, corresponding the proportion of cases over population of the first data record in Wuhan, while $d_1 = \tilde{d}_1 = s_1 = 0$. We define t_i and c_i as the time of policy intervention and the social-distancing costs after intervention, respectively.

[Figure 2 here]

Figure 2 shows the cumulative cases (top panel) and the daily variation (bottom panel) for three different values of c which correspond to no intervention ($c = c_i = 0.5$), mild measures ($c_i = 0.45$ from period $t_i = 7$), and strict measures ($c_i = 0.35$ from period $t_i = 7$). The different policies have effects not only on the new daily cases, dramatically flattening the curve as in the standard SIR models, but also on the cumulative number. The higher incentives to social distancing are successful in substantially reducing the time for the extinction of the contagion (the point where $\Delta h = 0$). In terms of social costs, the reduction in the contagion and in the cumulative number of cases reduces the probability for the outbreak to overwhelm the health system capacity.

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[4] The values of γ are chosen to ensure reasonable values for P^D: for $c = 0.5$ and $h_t = 0.5$, we have $P_t^D = 0.5$ and for $h_t = 0$, we have $P_t^D = \frac{1}{1+e^2} \approx 0.12$.

[Figure 3 here]

Figure 3 shows the relevance of the timing of intervention for on the (long-run) steady state value of the cumulative confirmed cases h, for different values of c. The steady state value of h is increasing in t_i and decreasing in the strength of the intervention. Particularly in the initial stages of the outbreak, an early intervention has a strong impact. For example, for the same level of intervention, an implementation at day 10 rather than at day 5 more than doubles the final total number of confirmed cases.

[Figure 4 here]

Figure 4 provides further insights on the joint effect of timing and size of policies on the long run level of h. The plot demonstrates that, although the extent of the measures matters, the effect of timing dominates: for any possible level of $c \in [0, 0.45]$, an early intervention always delivers a lower total number of cases.

[Figure 5 here]

Finally, Figure 5 compares the results for an early and mild intervention ($t_i = 7, c_i = 0.45$) with a later and stronger one ($t_i = 21, c_i = 0.25$). Besides reducing the total number of cases, the early measure anticipates and lowers the peak in their growth, considerably easing the pressure on the health system.

4   Discussion and conclusions

Both the COVID-19 pandemic and the policies enacted to tackle it are having vast social and economic consequences. Our model provides a basic framework for analysing the effectiveness of mitigating policies. A more precise assessment will be possible only with more available data. Nonetheless, our analysis can provide some basic policy indications and contributes in defining

a path for future research on the topic by identifying the role of three main factors.

4.1   Individual choices

In applying SIR models, one should consider that individuals make choices in matter of social distancing, and these decisions play a decisive role in the evolution of total number of people infected and the shape of the curve of daily confirmed cases. Consequently, individual decision mechanisms should be taken into account in formulating and evaluating policies. In particular, the delay in the effects of individual decisions should be considered when imposing or lifting restrictions.

4.2   Time of intervention

The timing of policy interventions significantly impacts on the cumulative number of cases, its evolution over time, and the total time required for the contagion to die out. In particular, the analysis reveals that early mild measures seem to be in general more effective than late harsher policies. Given the vast impact of the restrictions on businesses, an untimely policy intervention requiring stricter limitations may not only have a large costs in terms of human lives but also huge economic implications.

4.3   Uncertainty

Given the importance of individual decisions, the provision of reliable information deserves careful consideration. For example, mass-testing can provide a more accurate estimation of the actual extent of the pandemic and exert effects in two ways: (i) directly, by leading confirmed cases to self-isolate, and (ii) indirectly, by affecting the public perception of the probability of getting infected and therefore the attitude towards social distancing.

Acknowledgments

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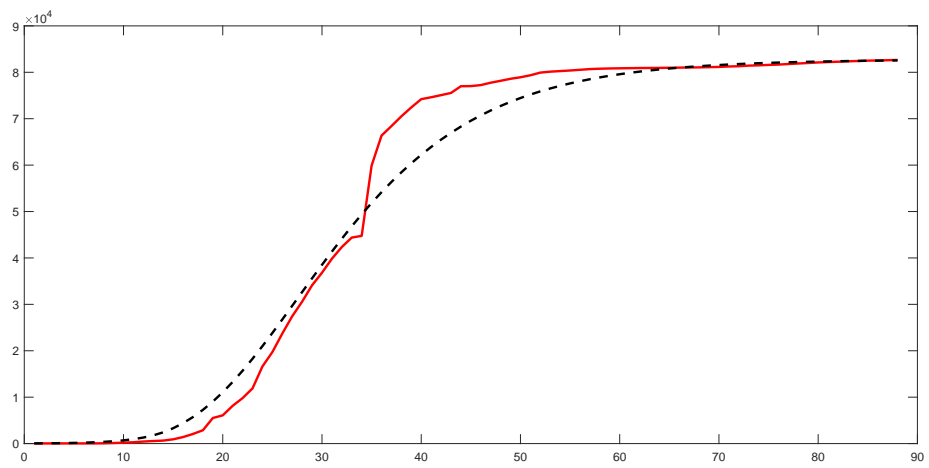
Figures

Figure 1: Number of confirmed cases, China (continuous red line) and simulations (dashed black line).
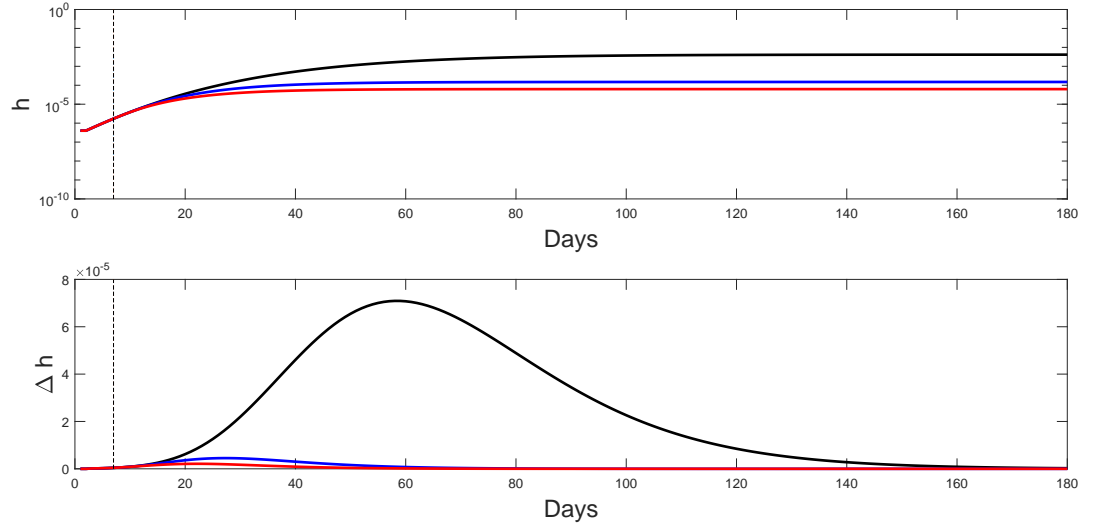
Figure 2: Simulations results with no intervention (black line), $c_i = 0.45$ (blue line), and $c_i 0.35$ (red line). The dashed line marks the intervention.
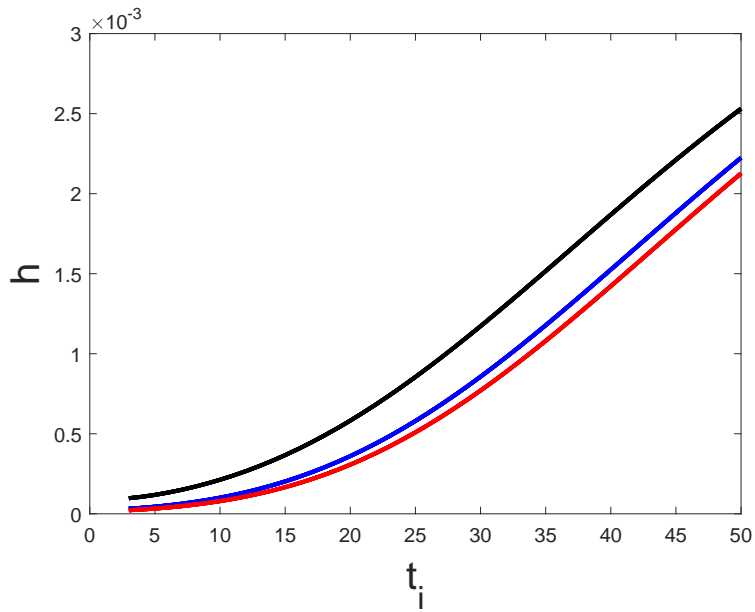

Figure 3: Steady state of h_t as a function of t_i for $c_i = 0.45$ (black line), $c_i = 0.35$ (blue line) and $c_i = 0.25$ (red line).
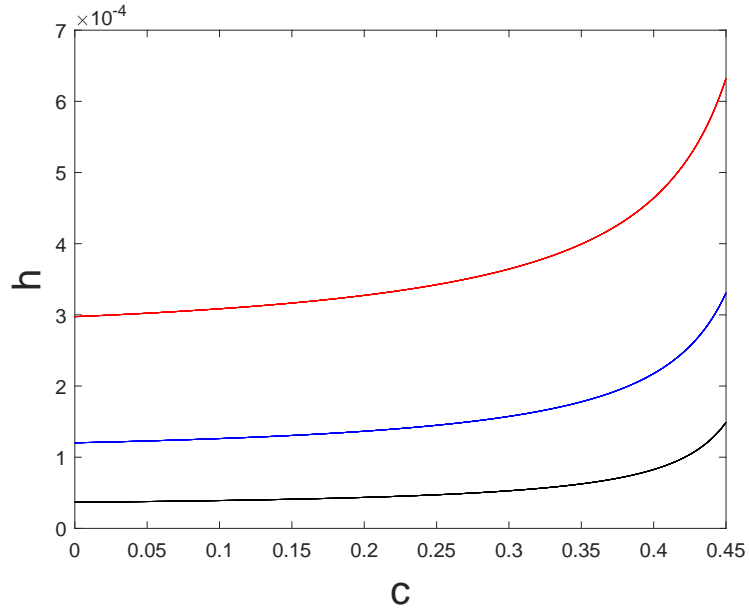
Figure 4: Steady state of h_t as a function of c_i for $t_i = 7$ (black line), $t_i = 14$ (blue line) and $t_i = 21$ (red line).
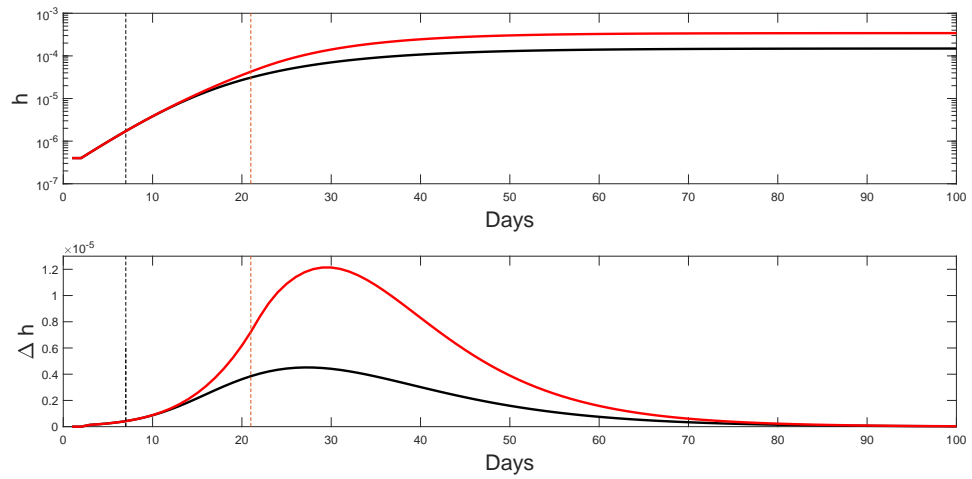

Figure 5: Simulations results for $c_i = 0.45, t_i = 7$ (black line) and $c_i = 0.25, t_i = 21$ (red line). The dashed lines mark the interventions.

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