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Abstract

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18 Introduction

19 The COVID-19 pandemic has resulted in extreme non-pharmaceutical interventions (NPIs) in many
20 affected countries. These interventions, from social distancing to lockdowns, are applied in a rapid
21 and widespread fashion. The NPIs are designed and assessed using epidemiological models, which
22 follow the dynamics of the viral infection to forecast the effect of different mitigation and suppression
23 strategies on the levels of infection, hospitalization, and fatality. However, compliance to NPIs differ
24 between interventions and people and may be impacted both by the number of domestic cases as well
25 as by the number of cases in other regions and countries. For example, using a survey of 2,108 adults
26 in the UK during Mar 2020, Atchison et al.² report that those over 70 years old were more likely to
27 adopt social distancing than young adults (18-34 years), and that those with lower income were less
28 likely to be able work from home and to self-isolate.

29 However, most epidemiological models assume the effect of NPIs on the epidemiological dynamics
30 to begin at their officially declared date (e.g. Gatto et al.⁶, Li et al.⁷). Even models that allow the
31 effect of NPIs to by more dynamics usually assume that it increases or decreases as a function of time
32 (e.g. Banholzer et al.³). Here we apply a *Susceptible-Exposed-Infected-Recovered* (SEIR) disease
33 transmission model and *Markov Chain Monte Carlo* (MCMC) parameter estimation framework to
34 estimate the effective start date of NPIs in several geographical regions using publicly available
35 confirmed COVID-19 case data.

36 Models and Methods

37 All source code will be publicly available under a permissive open-source license at [github.com/yoavram-](https://github.com/yoavramlab/EffectiveNPI)
38 [lab/EffectiveNPI](https://github.com/yoavramlab/EffectiveNPI).

39 **Data.** We use daily confirmed case data $\mathbf{X} = (X_1, \dots, X_T)$ from several different countries. These
40 incidence data summarize the number of individuals X_t tested positive for SARS-CoV-2 RNA (using
41 RT-qPCR) at each day t . Data was retrieved for X regions, see Table 1 for details and references. In
42 regions in which there were multiple sequences of days with zero confirmed cases (e.g. France), we
43 cropped the data to begin with the last sequence so that our analysis focuses on the first community-
44 transmitted outbreak rather than isolated imported cases.

Region	Start date	End date	Reference
Austria	X Feb		Flaxman et al. ⁴
Wuhan, China	10 Jan	8 Feb	Pei and Shaman ⁸

Table 1: Reference for confirmed cases incidence data. All dates in 2020.

45 **SEIR model.** We model SARS-CoV-2 infection dynamics by following the number of susceptible
46 S , exposed E , reported infected I_r , and unreported infected I_u individuals in a population of size N .
47 This model distinguishes between reported and unreported infected individuals: the reported infected
48 are those that have enough symptoms to eventually be tested and thus appear in daily case reports, to
49 which we fit the model.

50 Susceptible (S) individuals become exposed due to contact with reported or unreported infected
51 individuals (I_r or I_u) at a rate β_r or $\mu\beta_r$. The parameter $0 < \mu < 1$ represents the decreased transmission
52 rate from unreported infected individuals, who are often subclinical or even asymptomatic. The

53 transmission rate $\beta_t \geq 0$ may change over time t due to behavioral changes of both susceptible and
 54 infected individuals. Exposed individuals, after an average incubation period of Z days, become
 55 reported infected with probability α_t or unreported infected with probability $(1 - \alpha_t)$. The reporting
 56 rate $0 < \alpha_t < 1$ may also change over time due to changes in human behavior. Infected individuals
 57 remain infectious for an average period of D days, after which they either recover, or becomes ill
 58 enough to be quarantined. They therefore no longer infect other individuals, and the model does not
 59 track their frequency. The model is described by the following equations:

$$\begin{aligned}
 \frac{dS}{dt} &= -\beta_t S \frac{I_p}{N} - \mu \beta_t S \frac{I_s}{N} \\
 \frac{dE}{dt} &= \beta_t S \frac{I_p}{N} + \mu \beta_t S \frac{I_s}{N} - \frac{E}{Z} \\
 \frac{dI_r}{dt} &= \alpha_t \frac{E}{Z} - \frac{I_r}{D} \\
 \frac{dI_u}{dt} &= (1 - \alpha_t) \frac{E}{Z} - \frac{I_r}{D}.
 \end{aligned} \tag{1}$$

61 The initial numbers of exposed $E(0)$ and unreported infected $I_u(0)$ are considered model parameters,
 62 whereas the initial number of reported infected is assumed to be zero $I_r(0) = 0$, and the number of
 63 susceptible is $S(0) = N - E(0) - I_u(0)$. The vector θ of model parameters is

$$\theta = \left(Z, D, \mu, \{\beta_t\}, \{\alpha_t\}, \{p_t\}, E(0), I_u(0) \right). \tag{2}$$

65 This model is inspired by Li et al.⁷ and Pei and Shaman⁸, who used a similar model with multiple
 66 regions and constant transmission β and reporting rate α to infer COVID-19 dynamics in China and
 67 the continental US, respectively.

68 **Likelihood function.** The *expected* cumulative number of reported infected individuals until day t
 69 is

$$Y_t = \int_0^t \alpha_s \frac{E(s)}{Z} ds, \quad Y_0 = 0. \tag{3}$$

We assume that reported infected individuals are confirmed and therefore observed in the daily case
 report of day t with probability p_t (note that an individual can only be observed once, and that p_t may
 change over time, but t is a specific date rather than the time elapsed since the individual was infected).
 Hence, we assume that the number of confirmed cases in day t is binomially distributed,

$$X_t \sim \text{Bin}(n_t, p_t),$$

where n_t is the *realized* (rather than expected) number of reported infected individuals yet to appear
 in daily reports by day t . The cumulative number of confirmed cases until day t is

$$\tilde{X}_t = \sum_{i=1}^t X_i, \quad X_0 = 0.$$

Given \tilde{X}_{t-1} , we assume n_t is Poisson distributed,

$$(n_t \mid \tilde{X}_{t-1}) \sim \text{Poi}(Y_t - \tilde{X}_{t-1}), \quad n_1 \sim \text{Poi}(Y_1).$$

71 Therefore, $(X_t \mid \tilde{X}_{t-1})$ is a binomial conditioned on a Poisson, which reduces to a Poisson with

$$(X_t \mid \tilde{X}_{t-1}) \sim \text{Poi}\left((Y_t - \tilde{X}_{t-1}) \cdot p_t\right), \quad X_1 \sim \text{Poi}(Y_1 \cdot p_1). \tag{4}$$

73 For given vector θ of model parameters (Eq. (2)), we compute the expected cumulative number
 74 of reported infected individuals $\{Y_t\}_{t=1}^T$ for each day (Eq. (3)). Then, since \tilde{X}_{t-1} is a function of
 75 X_1, \dots, X_{t-1} , we can use Eq. (4) to write the probability to observe the confirmed case data $\mathbf{X} =$
 76 (X_1, \dots, X_T) as

$$77 \quad \mathbb{L}(\theta \mid \mathbf{X}) = P(\mathbf{X} \mid \theta) = P(X_1 \mid \theta)P(X_2 \mid \tilde{X}_1, \theta) \cdots P(X_T \mid \tilde{X}_{T-1}, \theta). \quad (5)$$

78 This defines a *likelihood function* $\mathbb{L}(\theta \mid \mathbf{X})$ for the parameter vector θ given the data \mathbf{X} .

79 **NPI model.** To model non-pharmaceutical interventions (NPIs), we set the beginning of the NPIs
 80 to day τ and define

$$81 \quad \beta_t = \begin{cases} \beta, & t < \tau \\ \beta\lambda, & t \geq \tau \end{cases}, \quad \alpha_t = \begin{cases} \alpha_1, & t < \tau \\ \alpha_2, & t \geq \tau \end{cases}, \quad p_t = \begin{cases} 1/9, & t < \tau \\ 1/6, & t \geq \tau \end{cases}, \quad (6)$$

82 where $0 < \lambda < 1$. The values for p_t follow Li et al.⁷, who estimated the average time between infection
 83 and reporting in Wuhan, China, at 9 days before the start of NPIs (Jan 23, 2020) and 6 days after start
 84 of NPIs. The parameter τ is then added to the parameter vector θ (Eq. (2)).

85 **Parameter estimation.** To estimate the parameters θ of our model (Eq. (1)) from the data \mathbf{X} , we
 86 apply a Bayesian inference approach. We define the following flat priors on the model parameters
 87 $P(\theta)$:

$$\begin{aligned} & Z \sim \text{Uniform}(2, 5) \\ & D \sim \text{Uniform}(2, 5) \\ & \mu \sim \text{Uniform}(0.2, 1) \\ & \beta \sim \text{Uniform}(0.8, 1.5) \\ 88 \quad & \lambda \sim \text{Uniform}(0, 1) \\ & \alpha_1, \alpha_2 \sim \text{Uniform}(0.02, 1) \\ & E(0) \sim \text{Uniform}(0, 3000) \\ & I_u(0) \sim \text{Uniform}(0, 3000) \\ & \tau \sim \text{Uniform}(1, T - 1), \end{aligned} \quad (7)$$

89 where T is the number of days in the data \mathbf{X} . Most priors follow Li et al.⁷, except λ , which is used to
 90 enforce that the transmission rates are lower after the start of the NPIs ($\lambda < 1$). The likelihood function
 91 is defined in Eq. (5). The posterior distribution on the model parameters $P(\theta \mid \mathbf{X})$ is then estimated
 92 using an *affine-invariant ensemble sampler for Markov chain Monte Carlo* (MCMC) implemented in
 93 the emcee Python package⁵.

94 **Model selection.** We perform model selection using DIC (deviance information criterion)⁹,

$$\begin{aligned} 95 \quad & DIC(\theta, \mathbf{X}) = 2\mathbb{E}[D(\theta)] - D(\mathbb{E}[\theta]) \\ & = 2 \log \mathcal{L}(\mathbb{E}[\theta] \mid \mathbf{X}) - 4\mathbb{E}[\log \mathcal{L}(\theta \mid \mathbf{X})], \end{aligned} \quad (8)$$

96 where $D(\theta)$ is the Bayesian deviance, and expectations $\mathbb{E}[\cdot]$ are taken over the posterior distribution
 97 $P(\theta \mid \mathbf{X})$. We compare models by reporting their relative DIC; lower is better.

98 Results

99 Several studies have described the effects of non-pharmaceutical interventions in different regions^{4,6,7}.
100 These studies have assumed that the parameters of the epidemiological model change at a specific
101 date, as in Eq. (6), and set the change date τ to the official NPI date τ^* . They then fit the model once
102 for $t < \tau^*$ and once for $t \geq \tau^*$ (see TABLE2 for a summary of official NPI dates.) For example, Li
103 et al.⁷ estimate the dynamics in China before and after τ^* at Jan 23. Thereby, they effectively estimate
104 (β, α_1) and (λ, α_2) separately.

105 Here we estimate the posterior distribution of *effective* start date of the NPI, $P(\tau | \mathbf{X})$, as well as
106 maximum a priori (MAP) estimates, $\hat{\tau}$, by jointly estimating $\tau, \beta, \lambda, \alpha_1, \alpha_2$ on the entire time series
107 per region (e.g. Italy, Austria), rather than splitting the region time series at τ^* . In all examined cases
108 the effect of an NPI is significant: the DIC of a model without NPI ($\beta_t \equiv \beta, \alpha_t \equiv \alpha, p_t \equiv p$ for all t)
109 was higher than the DIC of a model with NPI (Eq. (6)) by at least Z. Therefore, FIGURE compares
110 the official dates τ^* and our MAP estimates $\hat{\tau}$, with confidence intervals. It can be seen that in most
111 regions $\hat{\tau}$ and τ^* differ significantly: that is, the effective start of NPI was either advanced or delayed
112 compared to the official date. Do we want to report DIC of model with τ compared to model with
113 fixed $\tau = \tau^*$? Or just that $(P(\tau \neq \tau^*) > zzz)$? Or confidence intervals?

114 In the following, we describe our findings on delayed and advanced start of NPI.

115 **Delayed effective start of NPI.** We find that our MAP estimates $\hat{\tau}$ often differ significantly from the
116 official dates τ^* . For example, in Italy, the first case officially confirmed on Feb 21, a lockdown was
117 delayed in Northern Italy on Mar 8, with social distancing implemented in the rest of the country, and
118 the lockdown was extended to the entire nation on Mar 11⁶. That is, the official date τ^* is either Mar
119 8 or 11. However, we estimate the effective date $\hat{\tau}$ at Mar 16 (the posterior probability that τ is later
120 than Mar 11 is $(P(\tau > \tau^*) = ???)$). Similarly, in Wuhan, China, lockdown was declared on Jan 23⁷, but
121 we estimate that the effective start of NPIs to be 3-4 days later $(P(\tau > \tau^*) = ???)$.

122 **Advanced effective start of NPIs.** In contrast, in some regions we estimate an effective start of
123 NPIs $\hat{\tau}$ that is *earlier* than the official date τ^* . For example, social distancing was encouraged starting
124 on Mar 8⁴, but mass gatherings still occurred on Mar 8, including a march of 120,000 people for the
125 International Women's Day, and a football match between Real Betis and Real Madrid (2-1) with a
126 crowd of 50,965 in Seville. A national lockdown was only announced on Mar 14 (τ^*)⁴. Nevertheless,
127 we estimate the effective start of NPI $\hat{\tau}$ at Mar 8 or 9, rather than Mar 14 $(P(\tau < \tau^*) = ???)$.

128 **The exception that proves the rule.** We have also found a single case in which the official and
129 effective dates match: Switzerland ordered a national lockdown on Mar 20 (τ^*), after banning public
130 events and closing schools on Mar 13 and 14⁴. Indeed, our MAP estimate $\hat{\tau}$ is Mar 20, and the posterior
131 distribution shows two density peaks: a smaller one between Mar 10 and Mar 14, and a taller one
132 between Mar 17 and Mar 22. It's also worth mentioning that Switzerland was the first to mandate self
133 isolation of confirmed cases⁴. This seems to be

134 Discussion

135 We have estimated the effective start date of NPIs in several geographical regions using an SEIR
136 epidemiological model and an MCMC parameter estimation framework. We find that in most of
137 the examined regions the effective and official NPI start dates differ significantly **FIGURE**. We find
138 examples of both advanced and delayed response to NPIs: for example, in Italy and Wuhan, China,
139 the effective start of the lockdowns seems to have occurred 3-5 after the official date. This could be
140 explained by low compliance: in Italy, it seems that a leak about the intent to lockdown Northern
141 provinces results in people leaving those provinces⁶. However, delayed effect of NPIs could also be
142 due to the time required by both the government and the citizens to organize for a lockdown. In contrast,
143 in Spain and France transmission rates seem to have been reduced even before official lockdowns were
144 imposed, possibly due to adoption of social distancing and similar behavioral adaptations in part of
145 the population, maybe in response to domestic or international COVID-19-related reports.

146 As several countries (e.g. Austria, Israel) have begun to relieve lockdowns and ease restrictions, we
147 expect similar delays and advances to occur: in some countries people will begin to behave as if
148 restrictions were eased before the official date, and in some countries people will continue to self-
149 restrict even after restrictions are officially removed. Such delays and advances could confuse analyses
150 and lead to wrong conclusions about the effects of NPI removals.

151 **Conclusions.** We have estimated the effective start date of NPIs and found that they often differ
152 from the official dates. Our results emphasize the complex interaction between personal, regional, and
153 global determinants of behavioral. Thus, our results highlight the need to further study variability in
154 compliance and behavior over both time and space. This should be accomplished both by surveying
155 differences in compliance within and between populations², and by incorporating specific behavioral
156 models into epidemiological models¹.

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159

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