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Abstract

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18 Introduction

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38 Models and Methods

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. ¹
Wuhan, China	10 Jan	8 Feb	Pei & Shaman ⁵

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_t or $\mu\beta_t$. 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.⁴ and Pei & Shaman⁵, 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

$$70 \quad Y_t = \int_0^t \alpha_s \frac{E(s)}{Z} ds, \quad Y_0 = 0. \quad (3)$$

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

$$72 \quad (X_t \mid \tilde{X}_{t-1}) \sim \text{Poi}((Y_t - \tilde{X}_{t-1}) \cdot p_t), \quad X_1 \sim \text{Poi}(Y_1 \cdot p_1). \quad (4)$$

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.⁴, 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 **Model fitting.** To fit our model (Eq. (1)) to the data \mathbf{X} and estimate the model parameters θ , we apply
 86 a Bayesian inference approach. We define the following flat priors on the model parameters $P(\theta)$:

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

88 where T is the number of days in the data \mathbf{X} . Most priors follow Li et al.⁴, except λ , which is used to
 89 enforce that the transmission rates are lower after the start of the NPIs ($\lambda < 1$). The likelihood function
 90 is defined in Eq. (5). The posterior distribution on the model parameters $P(\theta | \mathbf{X})$ is then estimated
 91 using an affine-invariant ensemble sampler for Markov chain Monte Carlo (MCMC) implemented in
 92 the `emcee` Python package².

93 Results

94 Several studies have described the effects of non-pharmaceutical interventions in several countries^{1,3}.
 95 These studies have assumed that the epidemiological dynamics change at a specific date, as in
 96 Eq. (6), set the change date τ to the official NPI date τ^* , and fit the model once for $t < \tau^*$ and once
 97 for $t \geq \tau^*$ (see [TABLE2](#) for a summary of official NPI dates.) For example, Li et al.⁴ estimate the
 98 dynamics in China before and after τ^* at Jan 23. Thereby, they effectively estimate (β, α_1) and (λ, α_2)
 99 separately.

100 Here we estimate the posterior distribution of *effective* start date of the NPI, $P(\tau | \mathbf{X})$, as well as
 101 maximum a priori (MAP) estimates, $\hat{\tau}$, by jointly estimating $\tau, \beta, \lambda, \alpha_1, \alpha_2$ on the entire time series
 102 per region (e.g. Italy, Austria), rather than splitting the region time series at τ^* . [FIGURE](#) shows a
 103 comparison the official dates τ^* and our MAP estimates $\hat{\tau}$, with confidence intervals. In most cases
 104 analyses, we find that $\hat{\tau}$ and τ^* differ significantly: that is, the effective start of NPI was either advanced
 105 or delayed compared to the official date. In the following, we describe our findings on delayed and
 106 advanced start of NPI.

107 **Delayed effective start of NPI.** We find that our MAP estimates $\hat{\tau}$ often differ significantly from the
 108 official dates τ^* . For example, in Italy, the first case officially confirmed on Feb 21, a lockdown was
 109 delayed in Northern Italy on Mar 8, with social distancing implemented in the rest of the country, and
 110 the lockdown was extended to the entire nation on Mar 11³. That is, the official date τ^* is either Mar
 111 8 or 11. However, we estimate the effective date $\hat{\tau}$ at Mar 16 (the posterior probability that τ is later
 112 than Mar 11 is $(P(\tau > \tau^*) = ???)$). Similarly, in Wuhan, China, lockdown was declared on Jan 23⁴, but
 113 we estimate that the effective start of NPIs to be 3-4 days later $(P(\tau > \tau^*) = ???)$.

114 **Advanced effective start of NPIs.** In contrast, in some regions we estimate an effective start of
 115 NPIs $\hat{\tau}$ that is *earlier* than the official date τ^* . For example, social distancing was encouraged starting
 116 on Mar 8¹, but mass gatherings still occurred on Mar 8, including a march of 120,000 people for the
 117 [International Women's Day](#), and a football match between [Real Betis and Real Madrid](#) (2-1) with a
 118 crowd of 50,965 in Seville. A national lockdown was only announced on Mar 14 (τ^*)¹. Nevertheless,
 119 we estimate the effective start of NPI $\hat{\tau}$ at Mar 8 or 9, rather than Mar 14 $(P(\tau < \tau^*) = ???)$.

120 **Match between effective and official start of NPI.** We have also found a single case in which the
121 official and effective dates match: Switzerland ordered a national lockdown on Mar 20 (τ^*), after
122 banning public evens and closing schools on Mar 13 and 14¹. Indeed, our MAP estimate $\hat{\tau}$ is Mar 20,
123 and the posterior distribution shows two density peaks: a smaller one between Mar 10 and Mar 14,
124 and a taller one between Mar 17 and Mar 22. It's also worth mentioning that Switzerland was the first
125 to mandate self isolation of confirmed cases¹.

126 Discussion

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

150 **Acknowledgements**

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