

# Inference of delayed and advanced effect of non-pharmaceutical interventions during COVID-19 outbreaks

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## Abstract

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## 20 Introduction

21 The COVID-19 pandemic has resulted in implementation of extreme non-pharmaceutical interventions  
22 (NPIs) in many affected countries. These interventions, from social distancing to lockdowns, are  
23 applied in a rapid and widespread fashion. The NPIs are designed and assessed using epidemiological  
24 models, which follow the dynamics of the viral infection to forecast the effect of different mitigation and  
25 suppression strategies on the levels of infection, hospitalization, and fatality. These epidemiological  
26 models usually assume that the effect of NPIs on disease transmission begins at the officially declared  
27 date (e.g. Flaxman et al.<sup>6</sup>, Gatto et al.<sup>8</sup>, Li et al.<sup>10</sup>).

28 Adoption of public health recommendations is often critical for effective response to infectious dis-  
29 eases, and has been studied in the context of HIV<sup>9</sup> and vaccination<sup>4,14</sup>, for example. However,  
30 behavioral and social change does not occur immediately, but rather requires time to diffuse in the  
31 population through media, social networks, and social interactions. Moreover, compliance to NPIs  
32 may differ between different interventions and between people. For example, in a survey of 2,108  
33 adults in the UK during Mar 2020, Atchison et al.<sup>2</sup> found that those over 70 years old were more  
34 likely to adopt social distancing than young adults (18-34 years old), and that those with lower income  
35 were less likely to be able to work from home and to self-isolate. Similarly, compliance to NPIs may  
36 be impacted by personal experiences. Smith et al.<sup>12</sup> have surveyed 6,149 UK adults in late April  
37 and found that people who believe they have already had COVID-19 are more likely to think they are  
38 immune, and less likely to comply with social distancing measures. Compliance may also depend on  
39 risk perception as perceived by the the number of domestic cases or even by reported cases in other  
40 regions and countries. Interestingly, the perceived risk of COVID-19 infection has likely caused a  
41 reduction in the number of influenza-like illness cases in the US starting from mid-February<sup>15</sup>.

42 Here, we hypothesize that there is a significant difference between the official start of NPIs and their  
43 adoption by the public and therefore their effect on transmission dynamics. We use a *Susceptible-*  
44 *Exposed-Infected-Recovered* (SEIR) epidemiological model and *Markov Chain Monte Carlo* (MCMC)  
45 parameter estimation framework to estimate the effective start date of NPIs from publicly available  
46 COVID-19 case data in several geographical regions. We compare these estimates to the official  
47 dates and find both delayed and advanced effect of NPIs on COVID-19 transmission dynamics. We  
48 conclude by demonstrating how differences between the official and effective start of NPIs can confuse  
49 assessments of the effectiveness of the NPIs in a simple epidemic control framework.

## 50 Models and Methods

51 **Data.** We use daily confirmed case data  $\mathbf{X} = (X_1, \dots, X_T)$  from several different countries. These  
52 incidence data summarize the number of individuals  $X_t$  tested positive for SARS-CoV-2 RNA (using  
53 RT-qPCR) at each day  $t$ . Data for Wuhan, China retrieved from Pei and Shaman<sup>11</sup>, data for 11  
54 European countries retrieved from Flaxman et al.<sup>6</sup>. Regions in which there were multiple sequences  
55 of days with zero confirmed cases (e.g. France), we cropped the data to begin with the last sequence  
56 so that our analysis focuses on the first sustained outbreak rather than isolated imported cases. For  
57 dates of official NPI dates see Table 1.

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

Country	First	Last
Austria	Mar 10 2020	Mar 16 2020
Belgium	Mar 12 2020	Mar 18 2020
Denmark	Mar 12 2020	Mar 18 2020
France	Mar 13 2020	Mar 17 2020
Germany	Mar 12 2020	Mar 22 2020
Italy	Mar 5 2020	Mar 11 2020
Norway	Mar 12 2020	Mar 24 2020
Spain	Mar 9 2020	Mar 14 2020
Sweden	Mar 12 2020	Mar 18 2020
Switzerland	Mar 13 2020	Mar 20 2020
United Kingdom	Mar 16 2020	Mar 24 2020
Wuhan	Jan 23 2020	Jan 23 2020

**Table 1: Official start of non-pharmaceutical interventions.** The date of the first intervention is for a ban of public events, or encouragement of social distancing, or for school closures. In all countries except Sweden, the date of the last intervention is for a lockdown. In Sweden, where a lockdown was not ordered during the studied dates, the last date is for school closures. Dates for European countries from Flaxman et al.<sup>6</sup>, date for Wuhan, China from Pei and Shaman<sup>11</sup>.

Susceptible ( $S$ ) individuals become exposed due to contact with reported or unreported infected individuals ( $I_r$  or  $I_u$ ) at a rate  $\beta_t$  or  $\mu\beta_t$ . The parameter  $0 < \mu < 1$  represents the decreased transmission rate from unreported infected individuals, who are often subclinical or even asymptomatic. The transmission rate  $\beta_t \geq 0$  may change over time  $t$  due to behavioural changes of both susceptible and infected individuals. Exposed individuals, after an average incubation period of  $Z$  days, become reported infected with probability  $\alpha_t$  or unreported infected with probability  $(1 - \alpha_t)$ . The reporting rate  $0 < \alpha_t < 1$  may also change over time due to changes in human behavior. Infected individuals remain infectious for an average period of  $D$  days, after which they either recover, or becomes ill enough to be quarantined. They therefore no longer infect other individuals, and the model does not track their frequency. The model is described by the following equations:

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

The initial numbers of exposed  $E(0)$  and unreported infected  $I_u(0)$  are considered model parameters, whereas the initial number of reported infected is assumed to be zero  $I_r(0) = 0$ , and the number of susceptible is  $S(0) = N - E(0) - I_u(0)$ . This model is inspired by Li et al.<sup>10</sup> and Pei and Shaman<sup>11</sup>, who used a similar model with multiple regions and constant transmission  $\beta$  and reporting rate  $\alpha$  to infer COVID-19 dynamics in China and the continental US, respectively.

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

$$Y_t = \int_0^t \alpha_s \frac{E(s)}{Z} ds, \quad Y_0 = 0. \tag{2}$$

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,

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

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

$$(X_t \mid \tilde{X}_{t-1}) \sim \text{Poi}\left((Y_t - \tilde{X}_{t-1}) \cdot p_t\right), \quad X_1 \sim \text{Poi}(Y_1 \cdot p_1). \quad (3)$$

For given vector  $\theta$  of model parameters (Eq. (6)), we compute the expected cumulative number of reported infected individuals  $\{Y_t\}_{t=1}^T$  for each day (Eq. (2)). Then, since  $\tilde{X}_{t-1}$  is a function of  $X_1, \dots, X_{t-1}$ , we can use Eq. (3) to write the probability to observe the confirmed case data  $\mathbf{X} = (X_1, \dots, X_T)$  as

$$\mathbb{L}(\theta \mid \mathbf{X}) = P(\mathbf{X} \mid \theta) = P(X_1 \mid \theta)P(X_2 \mid \tilde{X}_1, \theta) \cdots P(X_T \mid \tilde{X}_{T-1}, \theta). \quad (4)$$

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

**NPI model.** To model non-pharmaceutical interventions (NPIs), we set the beginning of the NPIs to day  $\tau$  and define

$$\beta_t = \begin{cases} \beta, & t < \tau \\ \beta\lambda, & t \geq \tau \end{cases}, \quad \alpha_t = \begin{cases} \alpha_1, & t < \tau \\ \alpha_2, & t \geq \tau \end{cases}, \quad p_t = \begin{cases} 1/9, & t < \tau \\ 1/6, & t \geq \tau \end{cases}, \quad (5)$$

where  $0 < \lambda < 1$ . The values for  $p_t$  follow Li et al.<sup>10</sup>, who estimated the average time between infection and reporting in Wuhan, China, at 9 days before the start of NPIs (Jan 23, 2020) and 6 days after start of NPIs. The parameter  $\tau$  is then added to the parameter vector  $\theta$  (Eq. (6)).

**Parameter estimation.** To estimate the parameters of our model from the data  $\mathbf{X}$ , we apply a Bayesian inference approach. We start our model  $\Delta t$  days before the outbreak (defined as consecutive days with increasing confirmed cases) in each country<sup>8</sup>. The model in Eq. (1) is parameterized by the vector  $\theta$ , where

$$\theta = \left( Z, D, \mu, \{\beta_t\}, \{\alpha_t\}, \{p_t\}, E(0), I_u(0) \right), \tau, \Delta t. \quad (6)$$

101 The likelihood function is defined in Eq. (4). We define the following prior distributions on the model  
 102 parameters  $P(\theta)$ :

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

104 where  $\text{TruncatedNormal}(\mu, \sigma, a, b)$  is a truncated normal distribution with mean  $\mu$  and standard deviation  $\sigma$  taking values between  $a$  and  $b$ ;  $T$  is the number of days in the data  $\mathbf{X}$ ; and  $\tau^*$  is the official  
 105 start of the NPI. Most priors follow Li et al.<sup>10</sup>, with the following exceptions.  $\lambda$  is used to ensure  
 106 transmission rates are lower after the start of the NPIs ( $\lambda < 1$ ). We checked values of  $\Delta t$  larger than  
 107 five days and found they generally produce lower likelihood and unreasonable parameter estimates.  
 108 For the effective start of NPIs  $\tau$  we have also tested an uninformative uniform prior  $U(1, T - 1)$ . DIC  
 109 (see definition below) was lower for the truncated normal prior in most countries, except **Germany?**.  
 110 More importantly, the uninformative prior could result in non-negligible posterior probability for un-  
 111 reasonable  $\tau$  values, such as Mar 1 in the United Kingdom (this was due to MCMC chains being stuck  
 112 in low posterior regions of the parameter space). We therefore decided to use the more informative  
 113 truncated normal prior.

115 The posterior distribution of the model parameters  $P(\theta \mid \mathbf{X})$  is then estimated using an *affine-*  
 116 *invariant ensemble sampler for Markov chain Monte Carlo* (MCMC) implemented in the `emcee`  
 117 Python package<sup>7</sup>. The maximum a posteriori

118 **Model selection.** We perform model selection using DIC (deviance information criterion)<sup>13</sup>,

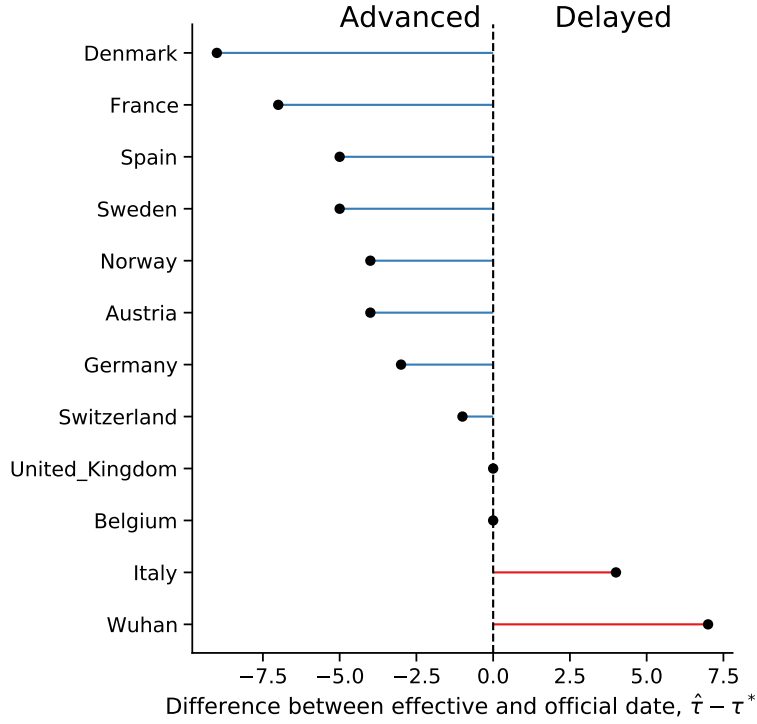
$$\begin{aligned}
 DIC(\theta, \mathbf{X}) &= 2\mathbb{E}[D(\theta)] - D(\mathbb{E}[\theta]) \\
 &= 2\log \mathcal{L}(\mathbb{E}[\theta] \mid \mathbf{X}) - 4\mathbb{E}[\log \mathcal{L}(\theta \mid \mathbf{X})],
 \end{aligned} \tag{8}$$

120 where  $D(\theta) = -2\log \mathcal{L}(\theta \mid \mathbf{X})$  is the Bayesian deviance, and expectations  $\mathbb{E}[\cdot]$  are taken over the pos-  
 121 terior distribution  $P(\theta \mid \mathbf{X})$ . We compare models by reporting their relative DIC; lower is better.

122 **Source code.** We use Python 3 (Anaconda) with the NumPy, Matplotlib, SciPy, Pandas, Seaborn,  
 123 and `emcee` packages. All source code will be publicly available under a permissive open-source  
 124 license at [github.com/yoavram-lab/EffectiveNPI](https://github.com/yoavram-lab/EffectiveNPI).

## 125 Results

126 Several studies have described the effects of non-pharmaceutical interventions in different geographical  
 127 regions<sup>6,8,10</sup>. These studies have assumed that the parameters of the epidemiological model change  
 128 at a specific date, as in Eq. (5), and set the change date  $\tau$  to the official NPI date  $\tau^*$  (Table 1). They  
 129 then fit the model once for time  $t < \tau^*$  and once for time  $t \geq \tau^*$ . For example, Li et al.<sup>10</sup> estimate the  
 130 dynamics in China before and after  $\tau^*$  at Jan 23. Thereby, they effectively estimate  $(\beta, \alpha_1)$  and  $(\lambda, \alpha_2)$   
 131 separately. Here we estimate the posterior distribution  $P(\tau \mid \mathbf{X})$  of the *effective* start date of the NPIs by



**Figure 1: Official and effective start of non-pharmaceutical interventions.** The difference between  $\hat{\tau}$  the effective and  $\tau^*$  the official start of NPI is shown for different regions. For values of  $\hat{\tau}$  the MAP estimate, see TABLE2. For  $\tau^*$  values, see Table 1.

jointly estimating  $\tau, \beta, \lambda, \alpha_1, \alpha_2$  on the entire data per region (e.g. Italy, Austria), rather than splitting the data at  $\tau^*$ . We then estimate the maximum a posteriori (MAP) estimate  $\hat{\tau} = \operatorname{argmax}_{\tau} P(\tau | \mathbf{X})$ . using median or argmax?

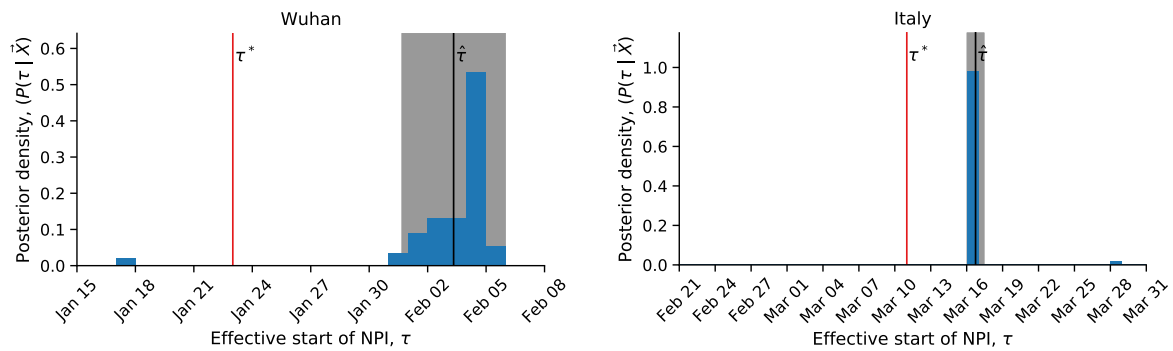
We find that a model that considers an NPI (Eq. (5)) is a better fit to the data than a model without an NPI, i.e. with constant  $\beta$  and  $\alpha$  ( $\Delta DIC > ?$  for all regions.) We compare the official  $\tau^*$  and effective  $\hat{\tau}$  start of NPIs and find that in most regions the effective start of NPI significantly differs from the official date (Figure 1): the 95% credible interval on  $\hat{\tau}$  does not include  $\tau^*$ , and the DIC of the model with free  $\tau$  parameter is lower than that of a model with a fixed  $\tau \equiv \tau^*$  ( $\Delta DIC > ?$ .) The exception that proves the rule is Switzerland, where the effective and official dates are the same. Another important exception is the United Kingdom?

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

**Delayed effective start of NPI.** In both Wuhan, China, and in Italy we find that our estimated effective start of NPI  $\hat{\tau}$  is significantly later than the official date  $\tau^*$  (Figure 1).

In Italy, the first case officially confirmed on Feb 21, a lockdown was declared in Northern Italy on Mar 8, with social distancing implemented in the rest of the country, and the lockdown was extended to the entire nation on Mar 11<sup>8</sup>. That is, the official date  $\tau^*$  is either Mar 8 or 11. However, we estimate the effective date  $\hat{\tau}$  at Mar 16 ( $\pm 0.7$  days 95% CI ; Figure 2). Similarly, in Wuhan, China, a lockdown was ordered on Jan 23<sup>10</sup>, but we estimate the effective start of NPIs to be several days later at around Mar 2 ( $\pm 2.65$  days 95% CI Figure 2).

**Advanced effective start of NPIs.** In contrast, in some regions we estimate an effective start of NPIs  $\hat{\tau}$  that is *earlier* than the official date  $\tau^*$  (Figure 1). In Spain, social distancing was encouraged starting

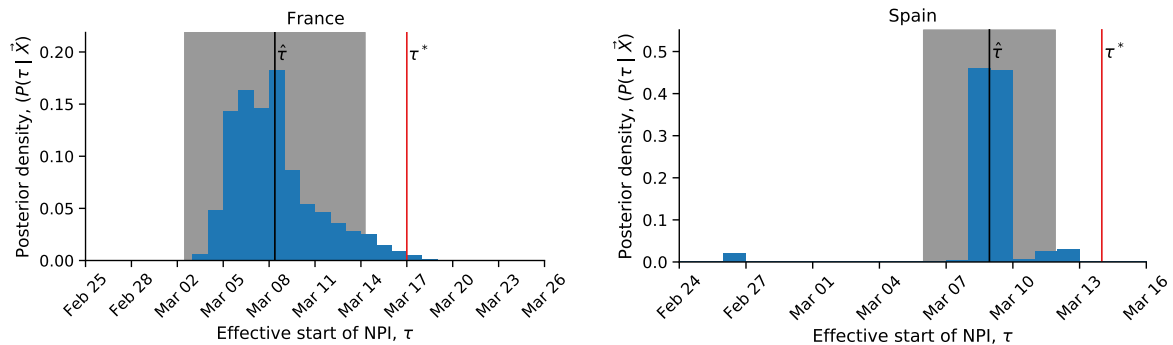


**Figure 2: Delayed effect of non-pharmaceutical interventions in Italy and Wuhan, China.**

on Mar 8<sup>6</sup>, but mass gatherings still occurred on Mar 8, including a march of 120,000 people for the [International Women's Day](#), and a football match between [Real Betis and Real Madrid](#) (2:1) with a crowd of 50,965 in Seville. A national lockdown was only announced on Mar 14<sup>6</sup>. Nevertheless, we estimate the effective start of NPI  $\hat{\tau}$  at Mar 8 or 9 ( $\pm 2.96$  95%CI), rather than Mar 14 (Figure 3).

Similarly, in France the official lockdown started at Mar 17 ( $\tau^*$ ), with initial NPIs at Mar 13<sup>6</sup>. However, we estimate the effective start of NPIs  $\hat{\tau}$  at Mar 8 ( $\pm 5.9$  days 95% CI). Although the credible interval is wide, spanning from Mar 2 to Mar 13, the official lockdown start at Mar 17 is later still (Figure 3).

Interestingly, the effective start of NPIs  $\hat{\tau}$  in both France and Spain is estimated at Mar 8, although the official dates are differ by three days. Moreover, the number of daily cases was similar until Mar 8 in both countries, but diverged by Mar 13, reaching significantly higher numbers in Spain (Figure S1).



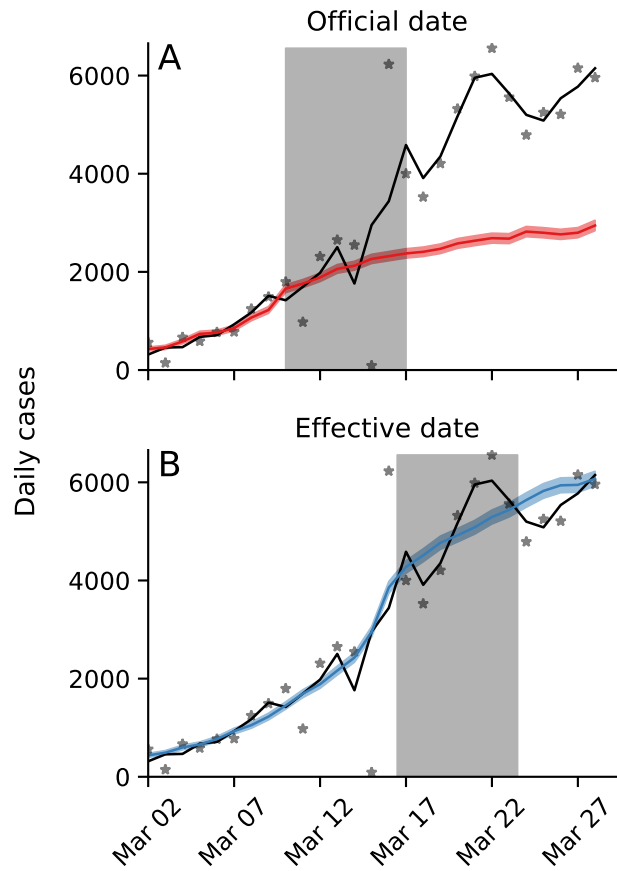
**Figure 3: Advanced effect of non-pharmaceutical interventions in France and Spain.** Posterior distribution of  $\tau$ , the effective start date of NPI, is shown as a histogram of MCMC samples. Red line shows the official NPI date  $\tau^*$ . Black line shows the MAP estimate  $\hat{\tau}$ . Shaded area shows a 95% credible interval (area in which  $P(|\tau - \hat{\tau}| | \mathbf{X}) = 0.95$ ).

**The exception that proves the rule.** We find one case in which the official and effective dates match: Switzerland ordered a national lockdown on Mar 20, after banning public events and closing schools on Mar 13 and 14<sup>6</sup>. Indeed, our MAP estimate  $\hat{\tau}$  is Mar 20, and the posterior distribution shows two density peaks: a smaller one between Mar 10 and Mar 14, and a taller one between Mar 17 and Mar 22. It's also worth mentioning that Switzerland was the first to mandate self isolation of confirmed cases<sup>6</sup>.

**Effect of delays and advances of real-time assessment.** The success of non-pharmaceutical interventions is assessed by health officials using various metrics, such as the decline in the growth rate

172 of daily cases. These assessments are made a specific number of days after the intervention began,  
 173 to accommodate for the expected serial interval<sup>3</sup> (i.e. time between successive cases in a chain of  
 174 transmission), which is estimated at about 4-7 days<sup>8</sup>.

175 However, a significant difference between the beginning of the intervention and the effective change  
 176 in transmission rates can invalidate assessments that assume a serial interval of 4-7 days and neglect  
 177 the delayed or advanced population response to the NPI. Such a case is illustrated in Figure 4 using  
 178 data and parameters from Italy. Here, a lockdown is officially ordered on Mar 10 ( $\tau^*$ , but its delayed  
 179 effect on the transmission dynamics starts on Mar 15 ( $\hat{\tau}$ ). If health officials assume the dynamics to  
 180 immediately change at  $\tau^*$ , they will expect the number of cases to follow the dashed red line. However,  
 181 the number of cases will actually follow the black line, leading to a significant different ( $\Delta$ ) between  
 182 the projections and the realization.



**Figure 4: Delayed effective start of NPI leads to under-estimation of daily confirmed cases.** Real number of daily cases in Italy in black (markers: data, line: time moving average). Model predictions, assuming a 50% decrease in transmission rate after the NPI starts, are shown as colored lines with 95% confidence intervals. Shaded box illustrates a serial interval of seven days. (A) Using the official date  $\tau^*$  for the start of the NPI, the model under-estimates the number of cases seven days after the start of the NPI. (B) Using the effective date  $\hat{\tau}$  for the start of the NPI, the model correctly estimates the number of cases seven days after the start of the NPI. Here, model parameters are MAP estimates for Italy (TABLE) but with  $\lambda = 0.5$  and  $\alpha_1 = \alpha_2$ .



## 183 Discussion

184 We have estimated the effective start date of NPIs in several geographical regions using an SEIR  
185 epidemiological model and an MCMC parameter estimation framework. We find examples of both  
186 advanced and delayed response to NPIs (Figure 1).

187 For example, in Italy and Wuhan, China, the effective start of the lockdowns seems to have occurred  
188 3-5 after the official date (Figure 2). This could be explained by low compliance. In Italy, for example,  
189 a leak about the intent to lockdown Northern provinces results in people leaving those provinces<sup>8</sup>.  
190 However, delayed effect of NPIs could also be due to the time required by both the government and  
191 the citizens to organize for a lockdown.

192 In contrast, in most investigated countries, such as Spain and France, transmission rates seem to  
193 have been reduced even before official lockdowns were implemented (Figure 3). This advanced  
194 response is possibly due to adoption of social distancing and similar behavioral adaptations in parts  
195 of the population, maybe in response increased risk perception due to domestic or international  
196 COVID-19-related reports. This finding may also suggest that severe NPIs, such as lockdowns,  
197 were unnecessary, and that milder measures that were adopted by the population, possibly due to  
198 government recommendations, media coverage, and social networks, could have been sufficient for  
199 epidemic control. **check if this is true** Indeed, the evidence supports a change in transmission dynamics  
200 (i.e. a model with  $\tau$ ) even for Sweden, in which a lockdown was not implemented, suggesting that  
201 lockdowns may not be necessary if other NPIs are adopted early enough during the outbreak<sup>3</sup> (Sweden  
202 banned public events on Mar 12, encouraged social distancing on Mar 16, and closed schools on  
203 Mar 18<sup>6</sup>.)

204 Attempts to assess the effect of NPIs<sup>3,6</sup> generally assume a 7 day delay between the implementation  
205 of the intervention and the observable change in dynamics, due to the characteristic serial interval of  
206 COVID-19<sup>8</sup>. However, the delays and advances we have estimated can confuse these assessments and  
207 lead to wrong conclusions about the effects of NPIs (Figure 4).

208 We have found that the evidence supports a model in which the parameters change at a specific  
209 time point  $\tau$  over a model without such a change-point. It may be interesting to investigate if the  
210 evidence favors a model with *two* change-points, rather than one. Two such change-points could reflect  
211 escalating NPIs (e.g. school closures followed by lockdowns), a mix of NPIs and changes in weather,  
212 a mix of domestic and international effects on risk perception, or other similar factors.

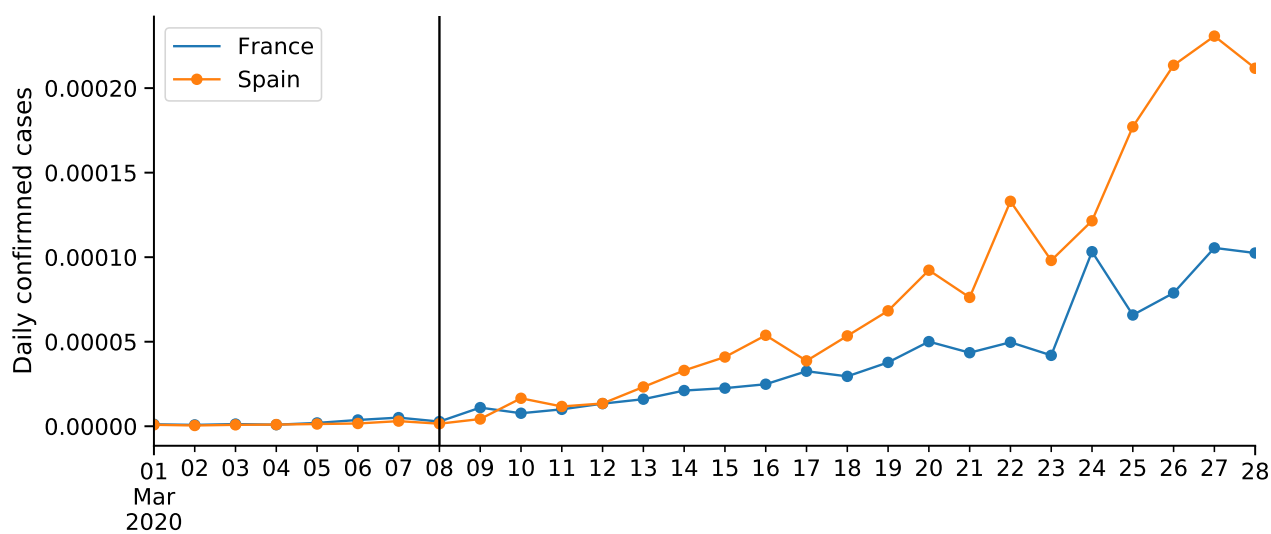
213 As several countries (e.g. Austria, Israel) begin to relieve lockdowns and ease restrictions, we expect  
214 similar delays and advances to occur: in some countries people will begin to behave as if restrictions  
215 were eased even before the official date, and in some countries people will continue to self-restrict  
216 even after restrictions are officially removed.

217 **Conclusions.** We have estimated the effective start date of NPIs and found that they often differ  
218 from the official dates. Our results emphasize the complex interaction between personal, regional,  
219 and global determinants of behavioral. Thus, our results highlight the need to further study variability  
220 in compliance and behavior over both time and space. This can be accomplished both by surveying  
221 differences in compliance within and between populations<sup>2</sup>, and by incorporating specific behavioral  
222 models into epidemiological models<sup>1,5</sup>.

## 223 Acknowledgements

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**Figure S1: COVID-19 confirmed cases in France and Spain.** Number of cases proportional to population size (as of 2018). Vertical line shows Mar 8, the effective start of NPIs  $\hat{t}$  in both countries.