

Late and early effective start of non-pharmaceutical interventions inferred during COVID-19 outbreaks

Ilia Kohanovski^a, Uri Obolski^{b,c}, and Yoav Ram^{a,*}

^aSchool of Computer Science, Interdisciplinary Center Herzliya, Herzliya 4610101, Israel

^bSchool of Public Health, Tel Aviv University, Tel Aviv 6997801, Israel

^cPorter School of the Environment and Earth Sciences, Tel Aviv University, Tel Aviv 6997801, Israel

*Corresponding author: yoav@yoavram.com

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Abstract

During February and March 2020, several countries implemented non-pharmaceutical interventions, such as school closures and lockdowns, with variable schedules to control the COVID-19 pandemic caused by the SARS-CoV-2 virus. Overall, these interventions seem to have successfully reduced the spread of the pandemic. We hypothesize that the official and effective start date of such interventions can significantly differ, for example due to slow diffusion of guidelines in the population, or due to unpreparedness of the authorities and the public. We use an SEIR epidemiological model and an MCMC inference framework to estimate the effective start of NPIs in several countries, and compare this effective dates to the official dates. We report our finding of both late and early effects of NPIs, and discuss potential causes and consequences of our results.

19 Introduction

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

27 Adoption of public health recommendations is often critical for effective response to infectious dis-
28 eases, and has been studied in the context of HIV⁹ and vaccination^{4,14}, for example. However,
29 behavioral and social change does not occur immediately, but rather requires time to diffuse in the
30 population through media, social networks, and social interactions. Moreover, compliance to NPIs
31 may differ between different interventions and between people. For example, in a survey of 2,108
32 adults in the UK during Mar 2020, Atchison et al.² found that those over 70 years old were more
33 likely to adopt social distancing than young adults (18-34 years old), and that those with lower income
34 were less likely to be able to work from home and to self-isolate. Similarly, compliance to NPIs may
35 be impacted by personal experiences. Smith et al.¹² have surveyed 6,149 UK adults in late April
36 and found that people who believe they have already had COVID-19 are more likely to think they are
37 immune, and less likely to comply with social distancing measures. Compliance may also depend on
38 risk perception as perceived by the the number of domestic cases or even by reported cases in other
39 regions and countries. Interestingly, the perceived risk of COVID-19 infection has likely caused a
40 reduction in the number of influenza-like illness cases in the US starting from mid-February¹⁵.

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

49 Models and Methods

50 **Data.** We use daily confirmed case data $\mathbf{X} = (X_1, \dots, X_T)$ from several different countries. These
51 incidence data summarize the number of individuals X_t tested positive for SARS-CoV-2 RNA (using
52 RT-qPCR) at each day t . Data for Wuhan, China retrieved from Pei and Shaman¹¹, data for 11
53 European countries retrieved from Flaxman et al.⁶. Regions in which there were multiple sequences
54 of days with zero confirmed cases (e.g. France), we cropped the data to begin with the last sequence
55 so that our analysis focuses on the first sustained outbreak rather than isolated imported cases. For
56 dates of official NPI dates see Table 1.

57 **SEIR model.** We model SARS-CoV-2 infection dynamics by following the number of susceptible
58 S , exposed E , reported infected I_r , and unreported infected I_u individuals in a population of size N .
59 This model distinguishes between reported and unreported infected individuals: the reported infected
60 are those that have enough symptoms to eventually be tested and thus appear in daily case reports, to
61 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.⁶, date for Wuhan, China from Pei and Shaman¹¹.

Susceptible (S) individuals become exposed due to contact with reported or unreported infected individuals (I_r or I_u) at a rate β_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 behavioral changes of both susceptible and infected individuals. Exposed individuals, after an average incubation period of Z days, become reported infected with probability α_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.¹⁰ and Pei and Shaman¹¹, who used a similar model with multiple regions and constant transmission β and reporting rate α 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,

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

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

$$82 \quad (X_t | \tilde{X}_{t-1}) \sim \text{Poi}\left((Y_t - \tilde{X}_{t-1}) \cdot p_t\right), \quad X_1 \sim \text{Poi}(Y_1 \cdot p_1). \quad (3)$$

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

$$87 \quad \mathbb{L}(\theta | \mathbf{X}) = P(\mathbf{X} | \theta) = P(X_1 | \theta)P(X_2 | \tilde{X}_1, \theta) \cdots P(X_T | \tilde{X}_{T-1}, \theta). \quad (4)$$

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

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

$$91 \quad \beta_t = \begin{cases} \beta, & t < \tau \\ \beta\lambda, & t \geq \tau \end{cases}, \quad \alpha_t = \begin{cases} \alpha_1, & t < \tau \\ \alpha_2, & t \geq \tau \end{cases}, \quad p_t = \begin{cases} 1/9, & t < \tau \\ 1/6, & t \geq \tau \end{cases}, \quad (5)$$

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

95 **Parameter estimation.** To estimate the parameters of our model from the data \mathbf{X} , we apply a
96 Bayesian inference approach. We start our model Δt days before the outbreak (defined as consecutive
97 days with increasing confirmed cases) in each country⁸. The model in Eq. (1) is parameterized by the
98 vector θ , where

$$99 \quad \theta = (Z, D, \mu, \{\beta_t\}, \{\alpha_t\}, \{p_t\}, E(0), I_u(0), \tau, \Delta t). \quad (6)$$

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

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

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

114 The posterior distribution of the model parameters $P(\theta \mid \mathbf{X})$ is then estimated using an *affine-*
 115 *invariant ensemble sampler for Markov chain Monte Carlo* (MCMC) implemented in the `emcee`
 116 Python package⁷. The maximum a posteriori

117 **Model selection.** We perform model selection using DIC (deviance information criterion)¹³,

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

119 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-
 120 terior distribution $P(\theta \mid \mathbf{X})$. We compare models by reporting their relative DIC; lower is better.

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

124 Results

125 Several studies have described the effects of non-pharmaceutical interventions in different geographical
 126 regions^{6,8,10}. These studies have assumed that the parameters of the epidemiological model change
 127 at a specific date, as in Eq. (5), and set the change date τ to the official NPI date τ^* (Table 1). They
 128 then fit the model once for time $t < \tau^*$ and once for time $t \geq \tau^*$. For example, Li et al.¹⁰ estimate the
 129 dynamics in China before and after τ^* at Jan 23. Thereby, they effectively estimate (β, α_1) and (λ, α_2)
 130 separately. Here we estimate the posterior distribution $P(\tau \mid \mathbf{X})$ of the *effective* start date of the NPIs by

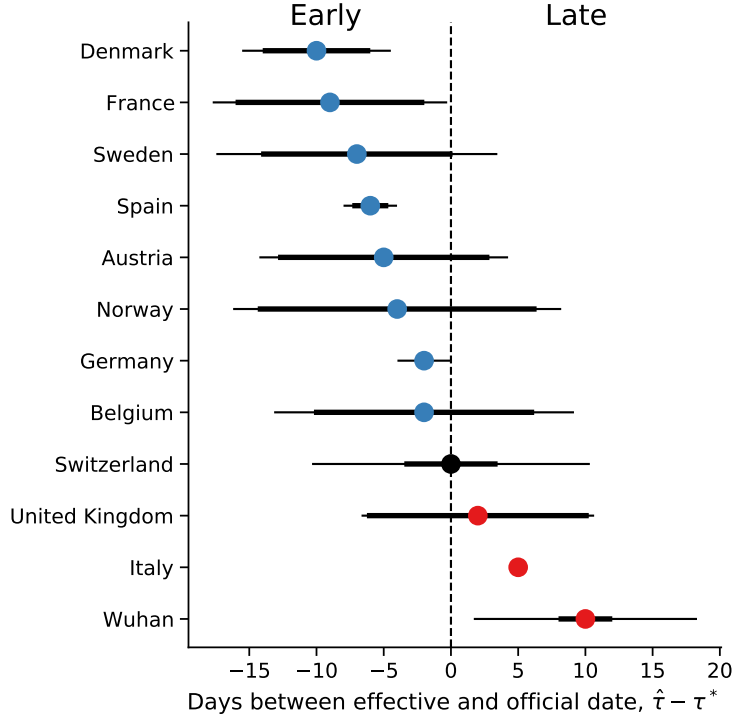


Figure 1: Official and effective start of non-pharmaceutical interventions. The difference between $\hat{\tau}$ the effective and τ^* the official start of NPI is shown for different regions. The effective NPI dates in Italy and Wuhan are significantly delayed compared to the official dates, whereas in Denmark, France, Spain, and Germany, the effective date is earlier than the official date. $\hat{\tau}$ is the posterior median, see Table 2. τ^* is the last NPI date, see Table 1. Thin and bold lines show 95% and 75% credible intervals (area in which $P(|\tau - \hat{\tau}| | \mathbf{X}) = 0.95$ and 0.75.)

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 τ^* . 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 β and α ($\Delta DIC > ?$ for all regions.) We compare the official τ^* 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 τ^* , and the DIC of the model with free τ 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 late and early effective start of NPI in detail.

Country	τ^*	τ	75% CI	95% CI	Z	D	μ	β	α_1	λ	α_2	$E(0)$	$I_u(0)$	Δt
Sweden	Mar 18	Mar 11	7.12	10.45	4.06	3.49	0.43	1.06	0.10	0.62	0.24	261.60	340.99	2.79
Belgium	Mar 18	Mar 16	8.19	11.15	3.96	3.61	0.47	1.10	0.18	0.80	0.36	236.36	307.03	2.66

Table 2: Parameter estimates for different regions. See Eq. (1) for model parameters. All estimates are posterior medians. 75% and 95% credible intervals given only for τ , in days. τ^* is the official last NPI date, see Table 1.

Late effective start of NPIs. 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 τ^* (Figure 1).

144 In Italy, the first case officially confirmed on Feb 21, a lockdown was declared in Northern Italy on
 145 Mar 8, with social distancing implemented in the rest of the country, and the lockdown was extended
 146 to the entire nation on Mar 11⁸. That is, the official date τ^* is either Mar 8 or 11. However, we
 147 estimate the effective date $\hat{\tau}$ at Mar 16 (± 0.7 days 95% CI ; Figure 2). Similarly, in Wuhan, China, a
 148 lockdown was ordered on Jan 23¹⁰, but we estimate the effective start of NPIs to be several days later
 149 at around Mar 2 (± 2.65 days 95% CI Figure 2).

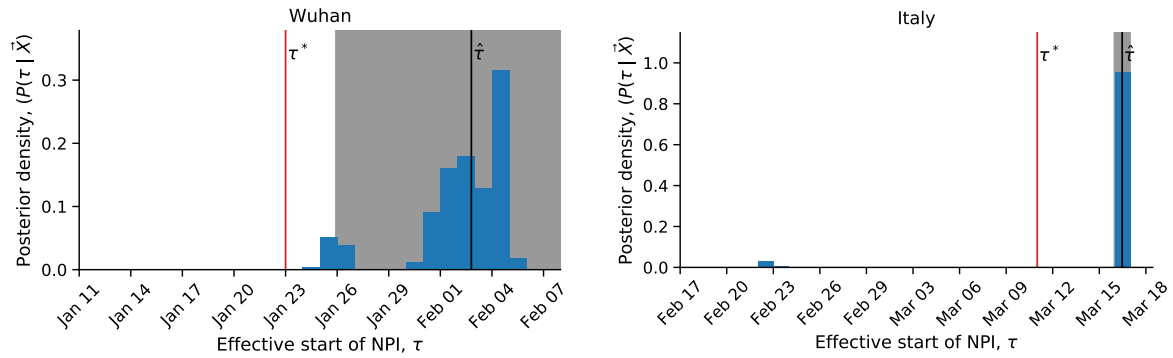


Figure 2: Late effect of non-pharmaceutical interventions in Italy and Wuhan, China. Posterior distribution of τ , the effective start date of NPI, is shown as a histogram of MCMC samples. Red line shows the official last NPI date τ^* . Black line shows the estimated $\hat{\tau}$. Shaded area shows a 95% credible interval (area in which $P(|\tau - \hat{\tau}| | \mathbf{X}) = 0.95$).

150 **Early effective start of NPIs.** In contrast, in some regions we estimate an effective start of NPIs $\hat{\tau}$
 151 that is *earlier* then the official date τ^* (Figure 1). In Spain, social distancing was encouraged starting
 152 on Mar 8⁶, but mass gatherings still occurred on Mar 8, including a march of 120,000 people for the
 153 [International Women's Day](#), and a football match between [Real Betis and Real Madrid](#) (2:1) with a
 154 crowd of 50,965 in Seville. A national lockdown was only announced on Mar 14⁶. Nevertheless, we
 155 estimate the effective start of NPI $\hat{\tau}$ at Mar 8 or 9 (± 2.96 95%CI), rather than Mar 14 (Figure 3).

156 Similarly, in France the official lockdown started at Mar 17 (τ^*), with initial NPIs at Mar 13⁶. However,
 157 we estimate the effective start of NPIs $\hat{\tau}$ at Mar 8 (± 5.9 days 95% CI). Although the credible interval is
 158 wide, spanning from Mar 2 to Mar 13, the official lockdown start at Mar 17 is later still (Figure 3).

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

163 **The exception that proves the rule.** We find one case in which the official and effective dates
 164 match: Switzerland ordered a national lockdown on Mar 20, after banning public evens and closing
 165 schools on Mar 13 and 14⁶. Indeed, our MAP estimate $\hat{\tau}$ is Mar 20, and the posterior distribution
 166 shows two density peaks: a smaller one between Mar 10 and Mar 14, and a taller one between Mar 17
 167 and Mar 22. It's also worth mentioning that Switzerland was the first to mandate self isolation of
 168 confirmed cases⁶.

169 **Effect of late and early effect of NPIs on real-time assessment.** The success of non-pharmaceutical
 170 interventions is assessed by health officials using various metrics, such as the decline in the growth
 171 rate of daily cases. These assessments are made a specific number of days after the intervention began,

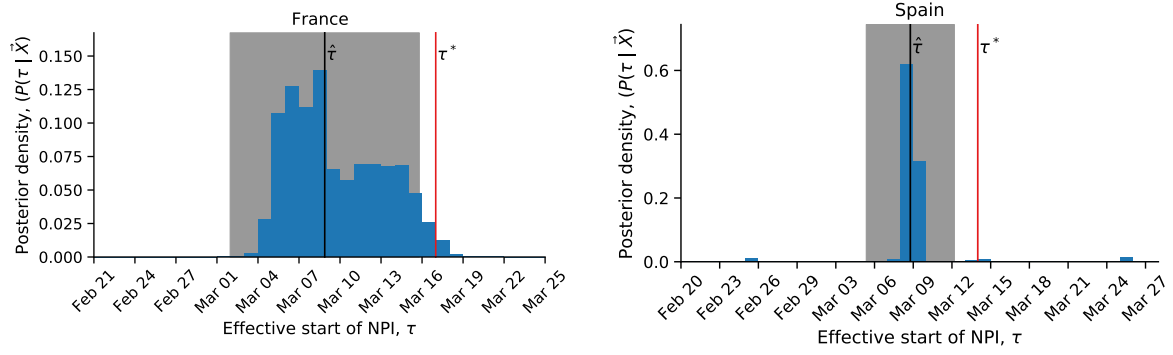


Figure 3: Early effect of non-pharmaceutical interventions in France and Spain. Posterior distribution of τ , the effective start date of NPI, is shown as a histogram of MCMC samples. Red line shows the official last NPI date τ^* . Black line shows the estimated $\hat{\tau}$. Shaded area shows a 95%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

172 to accommodate for the expected serial interval³ (i.e. time between successive cases in a chain of
 173 transmission), which is estimated at about 4-7 days⁸.

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

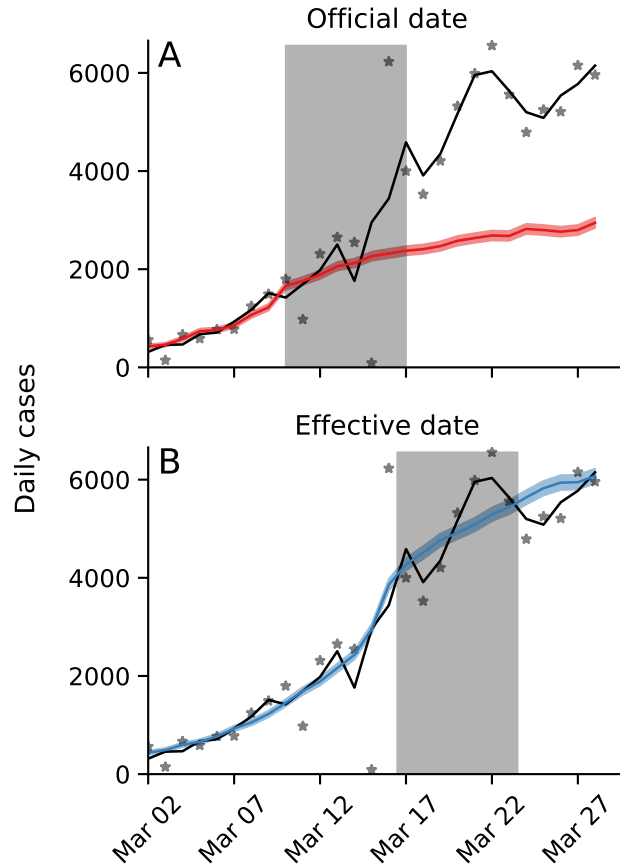


Figure 4: Late effective start of NPIs leads to under-estimation of daily confirmed cases. Real number of daily cases in Italy in black (markers: data, line: time moving average). Model predictions, assuming a 50% decrease in transmission rate after the NPI starts, are shown as colored lines with 95% confidence intervals. Shaded box illustrates a serial interval of seven days. **(A)** Using the official date τ^* 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 estimates for Italy (Table 2) but with $\lambda = 0.5$ and $\alpha_1 = \alpha_2$.

Discussion

We have estimated the effective start date of NPIs in several geographical regions using an SEIR epidemiological model and an MCMC parameter estimation framework. We find examples of both late and early effect of NPIs (Figure 1).

For example, in Italy and Wuhan, China, the effective start of the lockdowns seems to have occurred 3-5 after the official date (Figure 2). This could be explained by low compliance. In Italy, for example, a leak about the intent to lockdown Northern provinces results in people leaving those provinces⁸. However, late effect of NPIs could also be due to the time required by both the government and the citizens to organize for a lockdown.

In contrast, in most investigated countries, such as Spain and France, transmission rates seem to have been reduced even before official lockdowns were implemented (Figure 3). This early response is possibly due to adoption of social distancing and similar behavioral adaptations in parts of the population, maybe in response increased risk perception due to domestic or international COVID-19-related reports. This finding may also suggest that severe NPIs, such as lockdowns, were unnecessary, and that milder measures that were adopted by the population, possibly due to government recommendations, media coverage, and social networks, could have been sufficient for epidemic control. check if this is

198 **true** Indeed, the evidence supports a change in transmission dynamics (i.e. a model with τ) even for
199 Sweden, in which a lockdown was not implemented, suggesting that lockdowns may not be necessary
200 if other NPIs are adopted early enough during the outbreak³ (Sweden banned public events on Mar 12,
201 encouraged social distancing on Mar 16, and closed schools on Mar 18⁶.)

202 Attempts to assess the effect of NPIs^{3,6} generally assume a 7 day delay between the implementation
203 of the intervention and the observable change in dynamics, due to the characteristic serial interval of
204 COVID-19⁸. However, the late and early effects we have estimated can confuse these assessments and
205 lead to wrong conclusions about the effects of NPIs (Figure 4).

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

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

215 **Conclusions.** We have estimated the effective start date of NPIs and found that they often differ
216 from the official dates. Our results emphasize the complex interaction between personal, regional,
217 and global determinants of behavioral. Thus, our results highlight the need to further study variability
218 in compliance and behavior over both time and space. This can be accomplished both by surveying
219 differences in compliance within and between populations², and by incorporating specific behavioral
220 models into epidemiological models^{1,5}.

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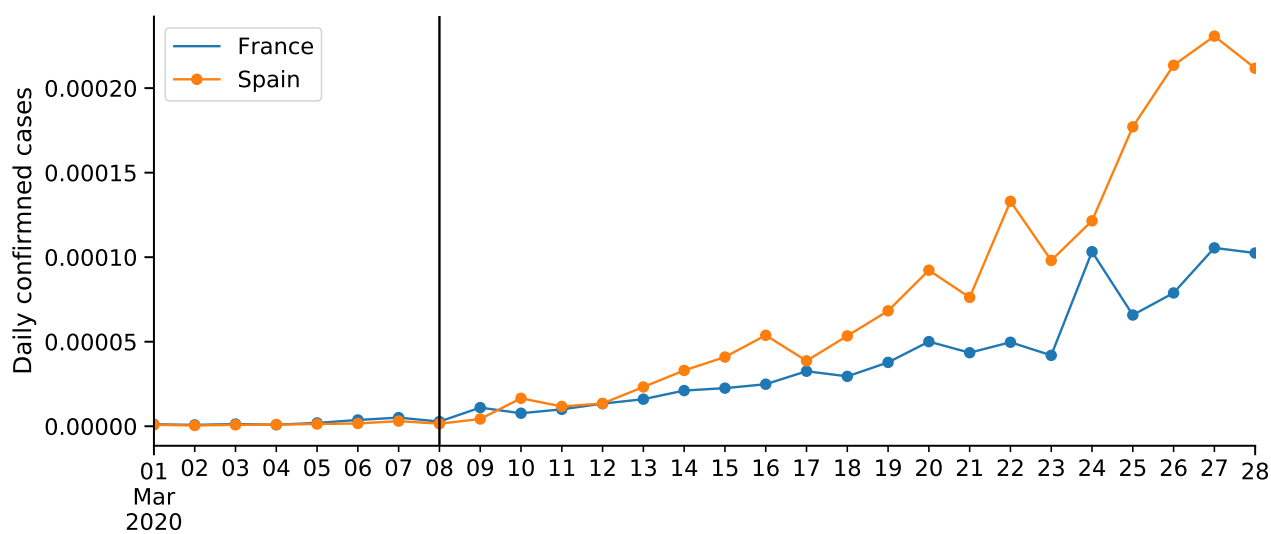


Figure S1: COVID-19 confirmed cases in France and Spain. Number of cases proportional to population size (as of 2018). Vertical line shows Mar 8, the effective start of NPIs \hat{t} in both countries.