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Inferring the effective start dates of non-pharmaceutical interventions during COVID-19 outbreaks

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ARTICLE INFO

Article history:
Received 14 July 2021
Revised 19 September 2021
Accepted 26 December 2021

Keywords:
SEIR
COVID-19
public health epidemic
infectious disease
NPI

Word count
3,494

ABSTRACT

Background: During Feb-Apr. 2020, many countries implemented non-pharmaceutical interventions (NPIs), such as school closures and lockdowns, to control the COVID-19 pandemic caused by the SARS-CoV-2 virus. Overall, these interventions seem to have reduced the spread of the pandemic. We hypothesized that the official and effective start dates of NPIs can be noticeably different, for example, due to slow adoption by the population, and that these differences can lead to errors in the estimation of the impact of NPIs.

Methods: SEIR models were fitted to case data from 12 regions to infer the effective start dates of interventions and compare these with the official dates. The impact of NPIs was estimated from the inferred model parameters.

Results: We infer mostly late effective start dates of interventions. For example, Italy implemented a lockdown on Mar 11, but we infer the effective start date on Mar 17 (±3.45 days 95% CI). Moreover, we find that the impact of NPIs can be underestimated if it is assumed they start on their official date.

Conclusions: Differences between the official and effective start of NPIs are likely. Neglecting such differences can lead to underestimation of the impact of NPIs, which could cause decision-makers to escalate interventions and guidelines.

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Background

The COVID-19 pandemic has resulted in the implementation of extreme non-pharmaceutical interventions (NPIs) in many affected countries. These interventions, from social distancing to lockdowns, have been applied in a rapid and widespread fashion. NPIs are designed and assessed using epidemiological models, which follow the dynamics of infection to forecast the effect of different mitigation and suppression strategies on the levels of infection, hospitalization, and fatality. These epidemiological models usually assume that the effect of NPIs on infection dynamics begins at the officially declared date (Flaxman et al., 2020; Gatto et al., 2020; Li et al., 2020).

Adoption of public-health recommendations is often critical for effective response to infectious diseases, and has been studied in the context of HIV (Kaufman et al., 2014) and vaccination (Dunn et al., 2015; Wiyeh et al., 2018), for example. However, behavioural and social change does not occur immediately, but rather requires time to diffuse in the population through media, social networks, and social interactions. Moreover, compliance to NPIs may differ between different interventions and between people with different backgrounds. For example, in a survey of 2,108 adults in the UK during Mar 2020, Atchinson et al. (2021) found that those over 70 years old were more likely to adopt social distancing than young adults (18-34 years old), and that those with lower income were less likely to be able to work from home and to self-isolate. Similarly, compliance to NPIs may be impacted by personal experiences. Smith et al. (2020) have surveyed 6,149 UK adults in late Apr 2020 and found that people who believe they have already had COVID-19 are more likely to think they are immune, and less likely to comply with social distancing guidelines. Compliance may also depend on risk perception as perceived by the the number of domestic cases or even by reported cases in other regions and countries. Interestingly, the perceived risk of COVID-19 infection has likely caused a reduction in the number of influenza-like illness cases in the USA starting from mid-Feb 2020 (Zipfle and Bansal, 2020).
Table 1

| 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 13 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 |

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 (\( \tau^* \)) 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. (2020), date for Wuhan, China from Pei and Shaman (2020). See Figure for a visual presentation.

Here, we hypothesize that there is a significant difference between the official start of NPIs and their effective adoption by the public and therefore their effect on infection dynamics. We use a Susceptible-Exposed-Infected-Recovered (SEIR) model and a Markov Chain Monte Carlo (MCMC) parameter estimation framework to infer the effective start date of NPIs from publicly available COVID-19 case data in 12 geographical regions. We compare these estimates to the official dates, and find that they include mostly late effects of NPIs on infection dynamics. We conclude by demonstrating how differences between the official and effective start of NPIs can confound assessments of their impacts.

Methods

Data. We use daily confirmed case data \( X = (X_1, \ldots, X_T) \) from 12 regions during Jan–Apr 2020. These incidence data summarising the number of individuals \( X_t \) tested positive for SARS-CoV-2 (using RT-qPCR tests) on each day \( t \). Data for Wuhan, China, from Jan 10 to Feb 8, 2020 were retrieved from Pei and Shaman (2020). Data for 11 European countries, from Feb 20 to Apr 24, 2020, were retrieved from Flaxman et al. (2020). Where there were multiple sequences of days with zero confirmed cases (e.g., France), we cropped the data to begin with the last sequence so that our analysis focused on the first sustained outbreak rather than isolated imported cases. For official NPI dates see Table 1.

SEIR model. We modelled SARS-CoV-2 infection dynamics by following the number of susceptible \( S \), exposed \( E \), reported infected \( I_r \), unreported infected \( I_u \), and recovered \( R \) individuals in a population of size \( N \). This model distinguishes between reported and unreported infected individuals: the reported infected are those that have enough symptoms to eventually be tested and thus appear in daily case reports, to which we fitted the model. This model is inspired by Li et al. (2020) and Pei and Shaman (2020), who used a similar model with multiple regions and constant transmission and reporting rates to study COVID-19 dynamics in China and in the continental USA.

Susceptible (\( S \)) individuals become exposed due to contact with reported or unreported infected individuals \( (I_r \) or \( I_u \)) at a rate \( \beta_1 \) or \( \mu \beta_1 \), respectively. The parameter \( 0 < \mu < 1 \) represents the decreased transmission rate from unreported infected individuals, who are often subclinical or even asymptomatic (Ferretti et al., 2020; Thompson et al., 2020). The transmission rate \( \beta_1 \geq 0 \) may change over time \( t \) due to behavioural changes of both suscepti-

ble and infected individuals. Exposed individuals, after an average latent period of \( Z \) days, become reported infected with probability \( \alpha_1 \) or unreported infected with probability \( 1 – \alpha_1 \). The reporting rate \( 0 < \alpha_1 < 1 \) may also change over time due to changes in human behaviour. Infected individuals remain infectious for an average period of \( D \) days, after which they either recover, or become ill enough to be quarantined. In either case, they no longer infect other individuals, and therefore effectively become recovered (\( R \)).

The model is described by the following set of equations,

\[
\begin{align*}
\frac{dS}{dt} & = -\beta_1 S \left( \frac{I_r}{N} + \mu \frac{I_u}{N} \right) \\
\frac{dE}{dt} & = \beta_1 S \left( \frac{I_r}{N} + \mu \frac{I_u}{N} \right) - \frac{E}{Z} \\
\frac{dI}{dt} & = \alpha_1 \frac{E}{Z} - \frac{I}{Z} \\
\frac{dR}{dt} & = (1 - \alpha_1) \frac{E}{Z} - \frac{R}{Z} \\
\frac{dU}{dt} & = \frac{U}{Z} - \frac{U}{Z}
\end{align*}
\]

where \( N \) is the population size. The initial numbers of exposed \( E(0) \) and unreported infected \( I_u(0) \) are free model parameters (i.e., inferred from the data), whereas the initial number of reported infected and recovered is assumed to be zero, \( I_r(0) = R(0) = 0 \), and the number of susceptible is \( S(0) = N - E(0) - I_r(0) \).

Likelihood function. For a given vector \( \theta \) of model parameters the expected cumulative number of reported infected individuals \( (L_i) \) until day \( t \), following Eq. 1, is

\[
Y_i(\theta) = \int_0^t \alpha_1 \frac{E(s)}{Z} \, ds. \quad Y_0 = 0.
\]

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). We denote by \( X_t \) the observed number of confirmed cases in day \( t \), and by \( \tilde{X}_t \) the cumulative number of confirmed cases until end of day \( t \),

\[
\tilde{X}_t = \sum_{i=1}^t X_i.
\]

Therefore, at day \( t \) the number of reported infected yet-to-be confirmed individuals is \( (Y_i(\theta) - \tilde{X}_{t-1}) \). We assume that \( X_i \) conditioned on \( \tilde{X}_{t-1} \) is Poisson distributed, such that

\[
\begin{align*}
(X_i \mid \theta) & \sim \text{Pois}(p_t Y_i(\theta) \cdot p_t). \\
(X_t \mid \tilde{X}_{t-1}, \theta) & \sim \text{Pois} \left( \left( Y_i(\theta) - \tilde{X}_{t-1} \right) \cdot p_t \right), \quad t = 2, \ldots, T.
\end{align*}
\]

Hence, the likelihood function \( L(\theta \mid X) \) for a parameter vector \( \theta \) given the confirmed case data \( X = (X_1, \ldots, X_T) \) is defined by the probability to observe \( X \) given \( \theta \),

\[
L(\theta \mid X) = P(X \mid \theta) = P(X_1 \mid \theta) \cdot P(X_2 \mid X_1, \tilde{X}_1, \theta) \cdot \ldots \cdot P(X_T \mid \tilde{X}_{T-1}, \theta).
\]

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

\[
\beta_t = \begin{cases} 
\beta_1, & t < \tau, \\
\beta \lambda, & t \geq \tau, 
\end{cases} \quad \alpha_t = \begin{cases} 
\alpha_1, & t < \tau, \\
\alpha_2, & t \geq \tau
\end{cases} \quad \text{for } p_t = \begin{cases} 
1/9, & t < \tau, \\
1/6, & t \geq \tau
\end{cases}
\]

where \( 0 < \lambda < 1 \). That is, we assume that the transmission rate, \( \beta \), the reporting rate, \( \alpha \), and the confirmation rate, \( p_t \), change after the implementation of NPIs, for example due to increased awareness and reduced contact rate in the population, and implementation of measures such as testing by the authorities. The values for \( p_t \) follow Li et al. (2020), who estimated the average time between...
infection and reporting in Wuhan, China, at 9 days before the start of NPIs and 6 days after start of NPIs.

Following Li et al. (2020), the effective reproduction numbers before and after the start of NPIs were
\[
R_1 = \alpha_1 \beta D + (1 - \alpha_1) \mu D, \\
R_2 = \alpha_2 \lambda D + (1 - \alpha_2) \mu \lambda D.
\]
(7)

The relative reduction in the effective reproduction number due to NPIs is \(R_1 - R_2\).

Parameter estimation. To estimate the model parameters from the daily case data \(X\), we applied a Bayesian inference approach. Model fitting was calibrated for case data up to Mar 28, 2020, and then applied to data up to Apr 11, 2020 (for Wuhan, China, model fitting was applied for data up to Feb 8, 2020.) We start our model \(\Delta t\) days (Gatto et al., 2020) before the outbreak (defined as consecutive days with increasing confirmed cases) in each country. The model in Eqs. 1 and 6 is parameterised by the vector \(\theta\), where
\[
\theta = \left( Z, D, \mu, \beta, \lambda, \alpha_1, \alpha_2, E(0), I_q(0), \Delta t, \tau \right).
\]
(8)

The likelihood function is defined in Eq. 5. We defined the following prior distributions on the model parameters \(P(\theta)\):
- \(Z \sim \text{Uniform}(2, 5)\)
- \(D \sim \text{Uniform}(2, 5)\)
- \(\mu \sim \text{Uniform}(0.2, 1)\)
- \(\beta \sim \text{Uniform}(0.8, 1.5)\)
- \(\lambda \sim \text{Uniform}(0, 1)\)
- \(\alpha_1, \alpha_2 \sim \text{Uniform}(0.02, 1)\)
- \(E(0) \sim \text{Uniform}(0, 3000)\)
- \(I_q(0) \sim \text{Uniform}(0, 3000)\)
- \(\Delta t \sim \text{Uniform}(1, 5)\)
- \(\tau \sim \text{TruncatedNormal}\left( \frac{t_5 - t^*}{t_5 - t^*}, \frac{t^* - t_1}{t_5 - t^*}, 5, T - 2 \right)\)

where the prior for \(\tau\) is a truncated normal distribution shaped so that the date of the first and last NPI, \(\tau^0\) and \(\tau^*\) (Table 1), are at minus and plus one standard deviation, and taking values only between 5 and \(T - 2\), where \(T\) is the number of days in the data \(X\). We also tested an uninformative uniform prior, \(\text{Uniform}(1, T - 2)\). WAIC (Eq. 10) of a model with this uniform prior was either higher, or lower by less than 2, Kass and Raftery (1995) compared to WAIC of a model with the truncated normal prior. The uninformative prior resulted in non-negligible posterior probability for unreasonable \(\tau\) values, such as Mar 1 in the United Kingdom. We therefore decided to use the more informative truncated normal prior for \(\tau\). Other priors follow Li et al. (2020), with the following exceptions. \(\lambda\) is used to ensure transmission rates are lower after the start of the NPIs (\(\lambda < 1\)). We checked values of \(\Delta t\) larger than 5 days and found they generally produce lower likelihood and unreasonable parameter estimates, and therefore chose \(\text{Uniform}(1, 5)\) as the prior for \(\Delta t\). We also tried to estimate the value of \(p_i\) before and after \(\tau\), instead of keeping it fixed at 1/9 and 1/6. The model with fixed values was supported by the evidence (lower WAIC, see Eq. 10) in 9 of 12 countries. Moreover, the estimates for Wuhan, China were 1/9 and 1/6, as in Li et al. (2020). Hence, we fixed the values of \(p_i\) to those used in Li et al. (2020) (see Eq. 6) in the analysis reported below.

The posterior distribution of the model parameters \(P(\theta | X)\) is estimated using the affine-invariant ensemble sampler for Markov chain Monte Carlo (MCMC) (Goodman and Weare, 2010), implemented in the emcee Python package (Foreman-Mackey et al., 2013). We use the default configuration with the stretch move and stretch scale parameter \(a = 2\). For the main analysis we use 50 chains (or walkers) per region, with 7M samples per chain (no thinning was applied; 68M for Wuhan). The integrated autocorrelation time (IAT) (Foreman-Mackey et al., 2013; Goodman and Weare, 2010) was averaged across parameters and chains for each region. The average IAT was between 31.9K for Wuhan and 187K for Germany (Fig. S2). We examined the trace plots for \(\tau\) in all regions (Fig. S3). All chains seem to converge to the stationary distribution, in most cases before 2M samples. Thus, we discarded the first 2M samples as burn-in samples. The only exception is Spain, in which a single chain converged at around 6M samples. We considered this chain as part of the burn-in and removed it from the analysis. Therefore, 50 chains with 5M samples and IAT between 32K and 187K give an effective sample size between 1,336 and 7,523. We ran additional chains with 2M samples and a different initialization (i.e. seed). The estimated posterior distributions of \(\tau\) were very similar to our main analysis, further increasing our confidence in the convergence of our inference. For the models with fixed \(\tau\) and without \(\tau\), in some countries, we use less than 7M samples per chain because the IAT converged sooner. In these cases the effective sample size was between 1,451 (Germany) and 7,443 (Wuhan) in the fixed \(\tau\) model and between 6,230 (Norway) and 94,339 (Italy) in the model without \(\tau\).

Model comparison. We perform model selection using two methods. First, we compute WAIC (widely applicable information criterion) (Gelman et al., 2013),

\[
\text{WAIC}(\theta, \hat{X}) = -2 \log \mathbb{E}[\mathcal{L}(\theta | \hat{X})] + 2\mathbb{V}[\log \mathcal{L}(\theta | \hat{X})]
\]
(10)

where \(\mathbb{E}[-]\) and \(\mathbb{V}[-]\) are the expectation and variance operators taken over the posterior distribution \(P(\theta | \hat{X})\). We compare models by reporting their relative WAIC; lower is better (Table S2).

We also plot posterior predictions: we sample 1,000 parameter vectors from the posterior distribution \(P(\theta | \hat{X})\) fitted to data up to Apr 11, 2020, use these parameter vectors to simulate the SEIR model (Eq. 1) up to Apr 24, and plot the predicted dynamics (Figure S4).

Both the accuracy (i.e. overlap of data and prediction) and the precision (i.e. the tightness of the predictions) are good ways to visually compare models. We also compute the expected posterior RMSE (root mean squared error) of these predictions (Table S1).

Results

Several studies have described the effects of non-pharmaceutical interventions in different geographical regions (Flaxman et al., 2020; Gatto et al., 2020; Li et al., 2020). Some of these studies have assumed that the parameters of the epidemiological model change at a specific date (Eq. 6), and set the change date \(\tau\) to the official NPI date \(\tau^*\), usually the lockdown start date (Table 1). They then fit the model once for time \(t < \tau^*\) and once for time \(t \geq \tau^*\). For example, Li et al. (2020) estimate the infection dynamics in China before and after \(\tau^*\), which is set at Jan 23, 2020. Thereby, they effectively estimate the transmission and reporting rates before and after \(\tau^*\) separately.

Here, we estimate the joint posterior distribution of the effective start date of NPIs, \(\tau\), and the transmission and reporting rates before and after \(\tau\) from the entire data, rather than splitting the data at \(\tau\). This is done under the simplifying assumption that all interventions start at a specific date, despite the reality that the durations between the first and last NPIs were between 4 and 12 days (Table 1, Figure S1). We then estimate \(\bar{\tau}\) as the median of the marginal posterior distribution of \(\tau\). Credible intervals (CI) are calculated as the highest density intervals (Kruschke, 2014), and their upper and lower boundaries are reported as \(\bar{\tau} \pm \text{lower} \) in days relative to \(\bar{\tau}\).

We compare the posterior predictive plots of a model with free \(\tau\) with those of a model with \(\tau\) fixed at \(\tau^*\) and a model without \(\tau\) (i.e. transmission and reporting rates are constant). All three models were fitted to case data up to Apr 11, 2020, used to predict out-of-sample case data up to Apr 24, 2020, and these predictions were then compared to the real case data. The model with free \(\tau\)
clearly produces better and less variable predictions (Figure S4): In 7 of 11 European countries, the expected posterior RMSE (root mean squared error) of the out-of-sample predictions is lowest for the model with a free τ (Table S1). The RMSE is lower for the fixed τ model in Denmark, Norway, and Sweden, where the difference is small (<9%) and Switzerland, where the estimated and official dates match (Figure 1). A similar trend appears when we compare the models using WAIC (Eq. 10); the model with free τ is strongly preferred in 9 out of 12 regions, the exceptions being Denmark, Norway, and Switzerland (Table S2). Indeed, we estimate low effect of NPIs on transmission in Denmark and Sweden (i.e. λ = 0.7 and 0.74, respectively; see Table 2). This may interfere with the inference of τ due to unidentifiability. Notably, the data for Sweden and Denmark do not have a single “peak” during the evaluated dates, possibly leading to wide credible intervals on τ (Figure 1) and poor WAIC in the model with free τ, whereas the duration between the first and last interventions was especially long in Norway (Table 1).

We compare the official (τ*) and effective (τ) start of NPIs and find that in most regions the effective start date differs from the official date: in 10 of 12 countries the 75% credible interval on τ does not include τ* (7 of 12 countries when considering a 95% credible interval; Figure 1). The exceptions are Norway and Switzerland (see below). The former also has a wide credible interval, perhaps because it has the longest duration between the first and last NPIs (Table 1).

Late effective start of NPIs. In half of the examined regions, we estimate that the effective start of NPIs τ is later than the official date τ*.

In Italy, the first case was officially confirmed on Feb 21, 2020. School closures were implemented on Mar 5 (Flaxman et al., 2020), 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 (Gatto et al., 2020). That is, the first and last official NPI dates are Mar 5 and Mar 11. However, we estimate the effective date (τ) 6 days after the lockdown, at Mar 17 (±3.0 days 95% CI; Figure 2).

In Wuhan, China, a lockdown was ordered on Jan 23, 2020 (Li et al., 2020), but we estimate the effective start of NPIs to be 10 days later, at Feb 2 (±2.9 days 95% CI). Yet, there is low but noticeable posterior probability for Jan 25 (Figure 2), for which the effect of NPIs on transmission is considerably lower (Figure S6).

In Spain, social distancing was encouraged starting on Mar 8, 2020 (Flaxman et al., 2020), but mass gatherings still occurred on Mar 8, including a march of 120,000 people for the International Women’s Day (Minder and New York Times, 2020), and a football match between Real Betis and Real Madrid (final score 2–1) with a crowd of 50,965 in Seville (ESPN, 2020). A national lockdown was only announced on Mar 14 (Flaxman et al., 2020). Nevertheless, we estimate the effective start of NPIs 11 days later, at Mar 25 (±1.7 days 95% CI; Figure 2).

Similarly, in France we estimate the effective start of NPIs at Mar 24, 2020 (±1.6 days 95% CI; Figure 2). This is a week later than the official lockdown, which started at Mar 17, and more than 10 days after the earliest NPI, banning of public events, which started on Mar 13 (Flaxman et al., 2020).

Early effective start of NPIs. In some regions we estimate an effective start of NPIs that is earlier than the official date (Figure 1). The only conclusive early case is Germany, in which we estimate the effective start of NPIs at Mar 19, 2020 (±0.9 days 95% CI; Figure 3). This estimate falls between the first and last official NPI dates, Mar 12 and Mar 22 (Table 1). Therefore, when we refer to this case as “early”, we mean that the effective date (Mar 19) occurs before the official lockdown date (Mar 22), not that it occurs before all NPIs. Interestingly, Germany had the second longest du-

### Table 2 Parameter estimates for different regions.

| Region        | τ*      | f       | τΔHDI   | τΔHDIos | Z   | D | μ | β | α1 | λ | α2 | E(0) | l0(0) | Δτ |
|---------------|---------|---------|---------|---------|-----|---|---|---|----|---|----|------|------|----|
| Austria       | Mar 16  | -2.8240 | 2.5130  | -4.2967 | 3.5110 | 3.9362 | 3.6066 | 0.6385 | 1.1468 | 0.1592 | 0.1370 | 0.2667 | 128.634 | 111.2741 | 2.2407 |
| Belgium       | Mar 18  | -1.5528 | 2.3908  | -3.4283 | 2.2380 | 4.0266 | 3.6358 | 0.5031 | 1.0780 | 0.2536 | 0.4572 | 0.1927 | 327.7634 | 417.8771 | 2.1455 |
| Denmark       | Mar 18  | -5.3104 | 2.0589  | -7.4123 | 15.7701 | 4.0140 | 3.4301 | 0.4149 | 1.0594 | 0.5146 | 0.6977 | 0.2041 | 268.2553 | 370.4863 | 2.2678 |
| France        | Mar 17  | -0.4310 | 0.5557  | -1.4388 | 2.6488 | 4.2107 | 3.0919 | 0.4713 | 1.0555 | 0.3823 | 0.3789 | 0.4142 | 412.7334 | 1324.2711 | 1.6487 |
| Germany       | Mar 22  | -0.5544 | 0.9207  | -0.9874 | 0.2905 | 3.3686 | 3.6944 | 0.6963 | 1.1670 | 0.1464 | 0.2735 | 0.3464 | 555.4142 | 5126100 | 2.1134 |
| Italy         | Mar 11  | -0.9537 | 2.4978  | -2.0064 | 0.3043 | 4.1810 | 2.6012 | 0.5307 | 0.9845 | 0.5554 | 0.3819 | 0.4918 | 1046.1239 | 934.9495 | 1.6776 |
| Norway        | Mar 24  | -3.9815 | 4.5891  | -12.0256 | 5.5891 | 4.0587 | 3.1077 | 0.3949 | 1.0343 | 0.1564 | 0.3105 | 0.2447 | 471.9163 | 828.4834 | 2.0465 |
| Spain         | Mar 14  | -0.7436 | 0.6951  | -1.4311 | 1.6951 | 4.0898 | 3.2785 | 0.5791 | 1.1420 | 0.3861 | 0.2521 | 0.3091 | 263.3634 | 866.9249 | 1.6239 |
| Sweden        | Mar 18  | -4.9651 | 4.0108  | -6.9652 | 11.2502 | 4.0167 | 3.3536 | 0.3691 | 1.0414 | 0.1304 | 0.7359 | 0.3024 | 398.0938 | 541.5147 | 2.4724 |
| Switzerland   | Mar 20  | -1.5556 | 1.2313  | -1.7802 | 3.1982 | 3.9322 | 3.5641 | 0.6174 | 1.1477 | 0.1671 | 0.2452 | 0.2787 | 277.1029 | 3129.5496 | 2.0510 |
| United Kingdom| Mar 24  | -1.4515 | 1.2782  | -2.1466 | 2.2780 | 3.9944 | 3.4811 | 0.6180 | 1.1208 | 0.1939 | 0.4468 | 0.2597 | 288.9485 | 3503028 | 2.0867 |

See Eq. 1 for model parameters. All estimates are posterior medians. 75% and 95% credible intervals (HDI) are given for τ in days relative to f. τ* is the official last NPI date (Table 1).

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**Fig. 1. Official vs. effective start of non-pharmaceutical interventions.** The difference between τ and τ* the official start of NPIs is shown for different regions. The effective date is delayed in UK, Austria, Italy, France, Belgium, Spain, and Wuhan, China, compared to the official date (red markers). In contrast, the estimated effective dates in Sweden, Denmark, and Germany are earlier than the official dates (blue markers), although uncertainty is low only for Germany (i.e., zero is not in 95% CI). The credible intervals for Sweden, Denmark, and Norway are especially wide, see text and Figure 3 for possible explanation. Here, the markers show τ, the marginal posterior median (Table 2). τ* is the last NPI date (a lockdown, except in Sweden; Table 1). Thin and bold lines show 95% and 75% credible intervals, respectively. Figure S5 shows a similar summary when estimating τ using case data up to Mar 28, 2020, rather than Apr 11, 2020.
Fig. 2. Late effect of non-pharmaceutical interventions. Posterior distribution of \( \tau \), the effective start date of NPI, is shown as a histogram of MCMC samples. The red line shows the official last NPI date \( \tau^* \). The black line shows the estimated effective start date \( \hat{\tau} \). Shaded area shows a 95% credible interval.

Fig. 3. Early and exact effect of non-pharmaceutical interventions. Posterior distribution of \( \tau \), the effective start date of NPI, is shown as a histogram of MCMC samples. Red line shows the official last NPI date \( \tau^* \). The black line shows the estimated effective start date \( \hat{\tau} \). The shaded area shows a 95% credible interval.

ration between first and last NPIs after Norway (10 and 12 days respectively; Table 1). However, the credible interval for the effective start date in Germany is narrow (1.91 days), whereas it is very wide in Norway (17.61 days). The significantly earlier estimate of \( \hat{\tau} \) relative to \( \tau^* \) can suggest that early NPIs in Germany more effectively reduced transmission rates compared to other countries. Another possible interpretation is that the German population anticipated the lockdown and reacted before it started.

We also estimate an early effective start of NPIs in Denmark, Norway, and Sweden. However, the credible intervals are quite wide (Figure 1), and the evidence did not support the model with free \( \tau \) over the model with \( \tau \) fixed at the official date (Tables S1 and S2). Indeed, Denmark and Sweden had the smallest estimated effect of NPIs on transmission rates, which probably hinders our ability to estimate \( \tau \) in these countries (Table 2). Moreover, in Sweden the number of daily cases continued to grow through Apr 11, rather than “peak” (Figure S4). In Denmark, the opposite occurred:
there were seemingly two "peaks", on Mar 11 and on Apr 8 (Figure S4); the first "peak" may be a result of stochastic events, for example due to a large cluster of cases or an accumulation of tests. We suspect that these missing and additional "peaks" increase the uncertainty in our inference.

The estimated effective start date in Norway is Mar 22, 2020, 2 days earlier than the official date of Mar 24. However, the posterior distribution is very wide (\(\pm 15.2\) days 95% CI); it covers the range between Mar 10, two days before the first NPI, and Mar 27, three days after the last NPI (Table 1, Figure S1). The high uncertainty might be due to the long duration between the first and last NPIs; however, Germany had the second longest duration between first and last NPIs, and the corresponding posterior distribution is very narrow (Figure 3). There may also be an unidentifiability issue between \(\tau\) and the effect of NPIs on transmission (Figure S6).

**Exact effective start of NPIs.** We find one case in which the official and effective dates match and the credible interval is narrow. Switzerland ordered a national lockdown on Mar 20, 2020, after banning public events and closing schools on Mar 13 and 14 (Flaxman et al., 2020). Indeed, the posterior median \(\hat{\tau}\) is Mar 19 (\(\pm 13.2\) days 95% CI, see Figure 3). Notably, Switzerland was the first to mandate self-isolation of confirmed cases (Flaxman et al., 2020).

**Assessment of impact of NPIs.** The effective reproduction number \(R\) is the average number of secondary cases caused by an infected individual after an epidemic is already underway (Bar-On et al., 2020). We infer model-based effective reproduction numbers before and after the implementation of NPIs from model parameters (Eq. 7). We then estimate the impact of NPIs as the relative reduction in the reproduction number (Flaxman et al., 2020), \(\Delta R = (R_1 - R_2)/R_1\), where \(R_1\) and \(R_2\) are the reproduction numbers before and after the start of NPIs. We compare the impacts estimated using the fixed \(\tau\) model and the free \(\tau\) model. That is, we compare the impact estimate \(\Delta R\) assuming that NPIs started at the official date \(\tau^*\), versus the estimate when inferring the effective start of NPIs from the data.

**Discussion and Conclusions.**

We have inferred the effective start date of NPIs in 12 regions using SEIR models under an MCMC parameter estimation framework. We find examples of mostly late but also early effective start of NPIs relative to the official date (Figure 1).

In most investigated regions we find late effective start of NPIs. For example, in Italy and in Wuhan, China, the effective start of the lockdowns seems to have occurred 5 or more days after the official date (Figure 2). These differences might be explained, in some cases, by low compliance or non-adherence to guidelines. In Italy, for example, the government plan to implement a lockdown in the northern provinces leaked to the public, which led to people leaving these provinces before the lockdown started (Gatto et al., 2020). Late effect of NPIs may also be due to the time required by both the government and the citizens to prepare for a lockdown, and for new guidelines to be adopted by the population.

By contrast, in some regions we inferred reduced transmission rates even before official lockdowns were implemented, although this is only conclusive in Germany (Figure 3). An early effective date might be due to early adoption of social distancing and similar behavioural adaptations in parts of the population, possibly due to earlier NPIs or NPIs being applied in other regions. Adoption of these behaviours may occur via media and social net-
works, rather than official guidelines, and may be influenced by increased risk perception due to domestic or international COVID-19 reports (Arthur et al., 2021). Indeed, the evidence supports a change in infection dynamics (i.e. a model with fixed or free τ) even for Sweden (Table S1, Table S2, Figure S4), where a lockdown was not implemented within the investigated time.

Interestingly, the effective start of NPIs in France and Spain is estimated to have started on Mar 24 and 25, 2020, respectively, although the official NPI dates differ significantly: the first NPI in France is only one day before the last NPI in Spain. The number of daily cases was similar in both countries until Mar 8, but diverged by Mar 13, reaching much higher numbers in Spain (Figure S8). This may suggest correlations between effective starts of NPIs in different countries due to international or global events.

As expected, we have found that the evidence supports a model in which the transmission rate changes at a specific time point over a model with a constant transmission rate (Tables S1 and S2). It may be interesting to check if the evidence supports a model with two or more change-points, rather than one, or even a continuous change. Multiple change-points could reflect escalating NPIs (e.g. school closures followed by lockdowns), or an intervention followed by a relaxation. However, both inference and interpretation of such models will be harder, as multiple change-points or continuous change are also likely to result in parameter unidentifiability, for example due to simultaneous implementation of NPIs (Flaxman et al., 2020).

As different countries experiment with various intervention strategies, we expect similar shifts to continue to occur: in some cases the population will be late to comply with new guidelines, whereas in other cases the population will adopt restrictions, and possibly relaxations, even before they are formally announced. Attempts to assess the impact of NPIs (Banholzer et al., 2020; Flaxman et al., 2020) generally assume they start at their official date. However, late effective start of NPIs, such as we have inferred, can lead to underestimation of the impact of NPIs (Figures 4 and S7). Such underestimation may lead decision-makers to enforce stricter guidelines, rather than enforce earlier implementation of the guidelines (Pei et al., 2020).

Our results highlight the complex interaction between personal, regional, and global determinants of behavioural response to an epidemic. Therefore, we emphasize the need to further study heterogeneity in compliance and behaviour over both time and space. This can be accomplished both by surveying differences in compliance within and between populations (Atchison et al., 2021), and by incorporating specific behavioural models into epidemiological models (Arthur et al., 2021; Fenichel et al., 2011; Walters and Kendall, 2013).

Abbreviations

NPI, non-pharmaceutical interventions; CI, credible interval; MCMC, Markov chain Monte Carlo; SEIR, susceptible-exposed-infected-recovered; WAIC, widely applicable information criterion; RMSE, root mean squared error; IAT, integrated autocorrelation time; COVID-19, coronavirus disease 2019; SARS-CoV-2, severe acute respiratory syndrome coronavirus 2.

Declarations

Ethics approval and consent to participate. Not applicable. Consent for publication. Not applicable.

Availability of data and materials. We use Python 3 with NumPy, Matplotlib, SciPy, Pandas, Seaborn, and emcee. Source code is publicly available under a permissive open-source licence at github.com/yoavram-lab/EffectiveNPI, Data for Wuhan, China, retrieved from Pei and Shaman (2020). Data for 11 European countries retrieved from Flaxman et al. (2020).

Competing interests. The authors declare that they have no competing interests.

Funding. This work was supported in part by the Israel Science Foundation (3811/19 and 552/19, YR). The funding body had no role in designing, performing, or analysing the study.

Authors contributions. YO and YR designed the research. IK and YR performed the research and wrote the manuscript. All authors read and approved the final manuscript.

Acknowledgements

We thank Yinon M. Bar-On, Lilach Hadady, Oren Kolodny, Zohar Yakhini, Tim CD Lucas, and two anonymous reviewers.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1086/j.ijidd.2012.364

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