Effects of worldwide interventions and vaccination on COVID-19 between waves and countries

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Abstract

Worldwide governments have rapidly deployed non-pharmaceutical interventions (NPIs) to mitigate the COVID-19 pandemic, together with the large-scale rollout of vaccines since late 2020. However, the effect of these individual NPI and vaccination measures across space and time has not been sufficiently explored. By the decay ratio in the suppression of COVID-19 infections, we investigated the performance of different NPIs across waves in 133 countries, and their integration with vaccine rollouts in 63 countries as of 25 March 2021. The most effective NPIs were gathering restrictions (contributing 27.83% in the infection rate reductions), facial coverings (16.79%) and school closures (10.08%) in the first wave, and changed to facial coverings (30.04%), gathering restrictions (17.51%) and international travel restrictions (9.22%) in the second wave. The impact of NPIs had obvious spatiotemporal variations across countries by waves before vaccine rollouts, with facial coverings being one of the most effective measures consistently. Vaccinations had gradually contributed to the suppression of COVID-19 transmission, from 0.71% and 0.86% within 15 days and 30 days since Day 12 after vaccination, to 1.23% as of 25 March 2021, while NPIs still dominated the pandemic mitigation. Our findings have important implications for continued tailoring of integrated NPI or NPI-vaccination strategies against future COVID-19 waves or similar infectious diseases.

Key words: COVID-19, SARS-CoV-2, Non-pharmaceutical interventions, Vaccination, Effectiveness

Main

As of 30 March 2021, the COVID-19 pandemic has spread worldwide, causing over 127 million confirmed cases and 2.8 million deaths[1]. Non-pharmaceutical interventions (NPIs) have been deployed across the world to curb the pandemic[2]. With the rollout of COVID-19 vaccine using different dosing and population targeting strategies[3], robust vaccination programs will enable the relaxation of NPIs[4,5]. However, given the delays in vaccine production and the inequality of vaccine allocations as well as the emergence of novel variants[6,7], NPIs should be maintained to avoid further resurgences before herd immunity can be achieved[4]. It is critical to understand the role of different NPIs and initial vaccination efforts to reduce COVID-19 transmission, before and after vaccine rollouts, thereby tailoring effective and integrated NPI-vaccination strategies for future COVID-19 waves.

The effectiveness of NPIs on pandemic mitigation had been shown by previous studies that mostly focused on the first wave of the pandemic before July 2020[5,8-12], with limited analysis of subsequent waves, regional diversity and integrated NPI-vaccination efforts. The implementation of NPIs in the first wave had, to some degree, changed human knowledge and perceptions, behaviours and responses to mitigate the outbreaks[13-17]. Whether NPI effectiveness increases with adherence or decreases with fatigue in the subsequent waves remains unclear. Additionally, the effects of NPIs may vary across countries with different country characteristics, such as health capacity, residential population density, aging ratio, humidity and air temperature[18,19]. The potential differences in NPI effectiveness across continents are rarely discussed in existing global analyses[12]. Moreover, vaccination is the most promising approach to lead the way out from this pandemic. However, the uneven distribution and allocation of vaccine rollout among countries and population groups might hinder the way to herd immunity[20]. Modelling studies have been conducted to simulate the combining effects of vaccination and NPIs for COVID-19 under various scenarios[5,21,22]. However, it is critically needed to understand how vaccination integrated with NPIs reduces COVID-19 transmission in the real world since the rollout of vaccines across multiple nations.

In this study we estimated the effects of individual NPIs and vaccination by identifying their contributions to the decay ratio of COVID-19 infections across waves and countries after the implementation of these measures. We used databases of global comparable outcomes, covering epidemiological[23], intervention policy[24], environmental and demographic data in 133 countries, territories and areas, from the earliest available dates to 25 March 2021. The deployment time and intensity of seven NPIs, including school closures, workplace closures, gathering restrictions, movement restrictions, public transport closures, international travel restrictions, and facial coverings, were considered in the data processing. We defined epidemic waves, mainly focusing on the first and second waves, according to the daily number of new confirmed cases reported and the changing pandemic situations in corresponding countries (see Methods and supplementary information [SI]). We also divided the 133 territories into four country groups, according to their geographical proximity, morbidity and mortality, implicitly related testing rate, to compare the regional variations in NPI efficacy. Data on vaccine rollouts[25] in 63 countries from 8 December 2020 to 25 March 2021 were also collated to assess the integrated impact of vaccination and non-pharmaceutical policy on COVID-19. More details can be found in Methods and SI.

Spatiotemporal Bayesian inference model to assess effects of NPIs and vaccination

A Bayesian inference model[10,15] was built to disentangle the individual effects of NPIs and vaccination by measuring their relative contributions on the decay ratio of COVID-19 infections (denoted as $\%\Delta\omega_t$), in the presence, absence and intensity change of these interventions. The decay ratio was defined as a percentage of reduction in the baseline growth rate by the instantaneous growth rate. In addition to interventions, there were many other factors (e.g., the transmissibility of new variants and the variation of case diagnosis and reporting) that might affect the transmission of COVID-19 over time. Therefore, the baseline growth rates in different waves and countries were assumed as the mean of the top three highest instantaneous, weekly growth rates in the corresponding wave and country. The instantaneous growth rate of transmission at each point of time was calculated as the current weekly number of new infections over the infections in the previous week. We used the decay ratio directly derived from the reported case data, rather than the reproduction number (Rt)[10,12], to avoid introducing the uncertainty of estimating Rt over time[26]. It should be noted that we estimated the relative effects of individual measures, while their combined effectiveness should be higher than individual effects, but not linearly accumulated (see Method).

We modelled NPI effects over time without assuming a functional relationship between effectiveness over time, which allows for variable community responses to the variation of each intervention. The effects of each NPI and vaccination with same intensity were assumed to be constant across countries in our model for each single estimation, and then decomposed for each country and week according to the corresponding decay ratio, intervention timing and intensity. The NPI with different intensities was modelled by the same effect parameter. The spatial variations in NPI and vaccination effectiveness across countries were controlled by employing the country-specific characteristics, including health capacity, residential population density, aging ratio, humidity and air temperature. All the estimations were performed by Markov chain Monte Carlo (MCMC). The reliability of our model was assessed by the cross-validation for overall intervention effects. Sensitivity analyses were also performed to assess model robustness in terms of our assumptions. More details on models and covariates can be found in Methods and SI.

Global impact of individual NPIs across waves

We estimated that three NPIs had substantial effects (>10%) on mitigating COVID-19 transmission in general (Fig. 1), including facial coverings (median 24.93%, interquartile range [IQR] 24.10 - 25.75%), gathering restrictions (24.01%, 22.38 - 25.65%) and international travel restrictions (11.23%, 9.93 - 12.56%). The effect of school closures (5.53%, 3.60 - 7.23%) performed moderately (1 - 10%) among all the seven NPIs, whereas workplace closures, public transport closures and movement restrictions had limited efficacy (<1%).

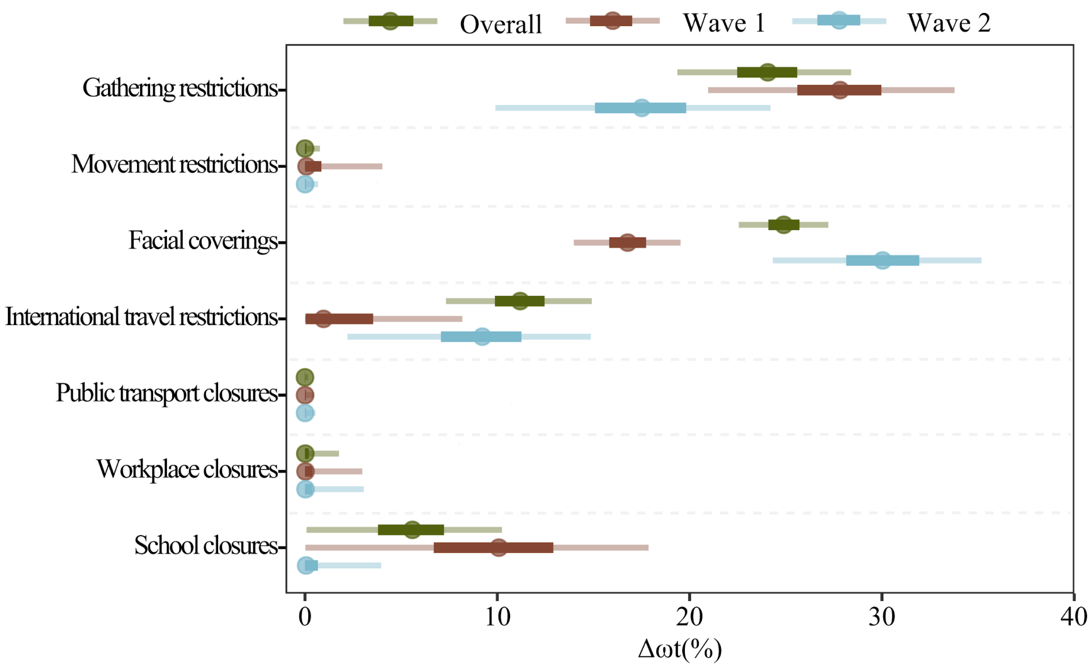

Fig. 1. Effects of individual NPIs on reducing the transmission of COVID-19 across waves within our data context. The overall effect represents the average performance of NPIs against COVID-19 in 133 countries (Fig. 2) by 25 March 2021 or the last dates before vaccination. Wave 1 refers to the average performance of NPIs against COVID-19 in the first wave of the 133 countries. The specific period of the first wave in each of 133 countries is not the same, indicating Wave 1 does not refer to a

particular time but the general period of the first outbreak. Wave 2 refers to the effects in the second wave. $\%\Delta\omega_t$ represents the decay ratio in the COVID-19 infection rate in 133 studied countries, territories and areas. The 5th, 25th (Q1), 50th (median), 75th (Q3), and 95th percentiles of estimates are presented, respectively. The uncertainty intervals of NPI effectiveness refer to the variance over the corresponding data context.

The efficacy of NPIs varied across waves. In the first wave, the most effective NPIs were gathering restrictions (median 27.83%, IQR 25.60 - 29.97%), facial coverings (16.78%, 15.82 - 17.74%), and school closures (10.08%, 6.70 - 12.91%). In the second wave, the efficacy of facial coverings surged to be the top-ranked one (30.04%, 28.14 - 31.94%). Another significant rise was the effect of international travel restrictions, from limited in Wave 1 (0.96%, 0.03 - 3.55%) to moderate in Wave 2 (9.22%, 7.07 - 11.25%). Meanwhile, the effects of gathering restrictions and school closures declined to 17.51% (IQR 15.08 - 19.82%) and 0.06% (0.00 - 0.67%) in the second wave, respectively. In both waves, workplace closures, public transport restrictions and movement restrictions presented limited effects (< 1%) in reducing the transmission.

Effectiveness of NPIs across countries by wave

Our analyses also revealed that the impact of individual non-pharmaceutical measures had obvious spatiotemporal variations across countries by waves before vaccine rollouts (Fig. 2).

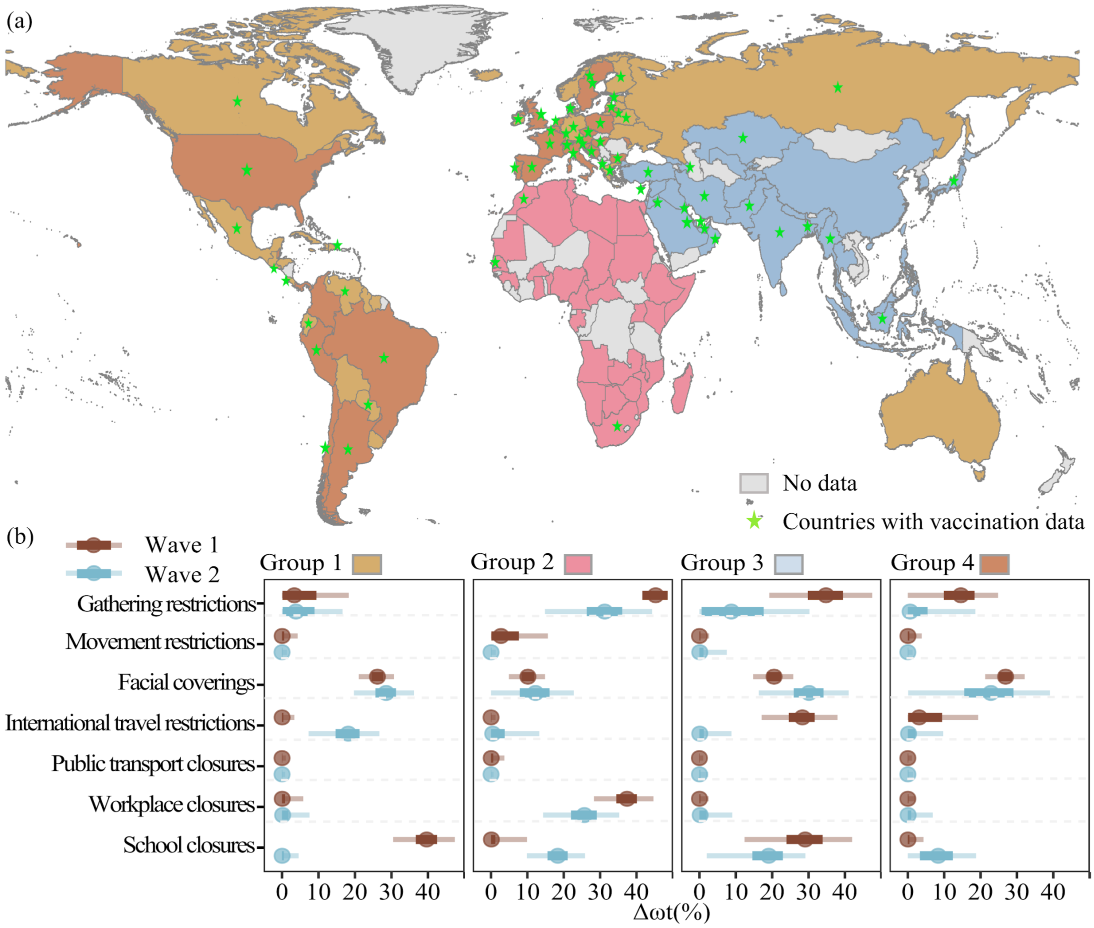

Fig. 2. The detailed cross-wave and -group effects of individual NPIs. (a) Country groupings, as determined by pandemic parameters and geographic proximity (see SI for more information). Countries with vaccination data in this study are marked by the green stars. (b) Effects of individual NPIs on reducing the transmission of COVID-19 across waves and groups. $\%\Delta\omega_t$ represents the decay ratio in COVID-19 infection rate. The 5th, 25th (Q1), 50th (median), 75th (Q3), and 95th percentiles of estimates are presented, respectively. The uncertainty intervals of NPI effectiveness refer to the variance over the corresponding spatiotemporal extent. A full list of countries and the corresponding time frames of different waves for each group can be found in SI Table C2 – C5.

The countries in Group 1 and Group 2 were predominantly comprised of European, American, and Oceanian countries with relatively low and high morbidity and mortality, respectively. Facial coverings had an important role in reducing transmission in both groups and waves ($\%\Delta\omega_t$ >10%). Gathering restrictions and workplace closures had substantial effects in both waves in Group 2, but only played moderate and limited roles, respectively, in Group 1 for both waves. School closures were the most effective NPI in the first wave in Group 1 (39.65%, 36.67 - 42.50%) but had limited effects in the second wave (0.03%, 0.00 - 0.50%). The opposite happened in Group 2, from 0.10% (0.00 - 1.19%) in Wave 1 to 18.36% (15.54 - 21.09%) in Wave 2. International travel restrictions and movement restrictions solely affected the pandemic transmission of Group 1 in the second wave (18.15%, 14.68 - 21.25%) and Group 2 in the first wave (2.74%, 0.10 - 7.67%), respectively. In other cases, their influences were limited. The effectiveness of public transport closures was below 1% in both groups among both waves.

Asian countries formed Group 3. Facial coverings and school closes had substantial impacts in both waves. The former's effect increased from 20.53% (IQR 18.58 - 22.40%) to 30.13% (25.94 - 34.13%), while the latter declined from 29.08% (23.94 - 33.88%) to 19.06% (14.55 - 22.95%). The other two effective, with declined effectiveness, NPIs were gathering restrictions (from 34.80% to 8.78%) and international travel controls (from 28.13% to 0.10%). Workplace closures, public transport closures and movement restrictions were limited effective in both waves.

Group 4 countries included mostly African countries, whose effective NPIs were similar to Group 1 and Group 3. Facial coverings were the only NPIs that had substantial effectiveness among both waves ((26.86%, 24.98 - 31.79) and (22.84%, 15.51 - 29.06%)). Gathering restrictions (15.58%, 9.91 - 18.35%) and international travel restrictions (3.11%, 0.08 - 9.42%) prevented the COVID-19 transmission in the first wave, while school closures (8.35%, 3.32 - 12.39%) showed moderate effects in Wave 2. The remaining three NPIs, including workplace closures, public transport closures, and movement restrictions had limited effects (< 1%) in both waves.

Effect of integrated COVID-19 vaccination and NPIs

We compared the effects of NPIs and the first-dose COVID-19 vaccination in 63 countries (Fig. 2a; listed in SI Table A2), from 8 December 2020 to 25 March 2021. Our results showed, the overall short-term effect of vaccination has been cumulatively rising with the increasing total vaccinated populations over time (averagely 5.1% population vaccinated by 25 March 2021 in the 63 study countries). The early impact of vaccination on reducing infections was only 0.71% (IQR 0.02 - 2.84%) within 27 days after vaccination (i.e. half a month since Day 12 after vaccination), given the induced antibody response and immunity might sufficiently prevent COVID-19 infections since the 12th day after receiving the first-dose vaccine[27]. However, the accumulative effectiveness slightly rose to 0.86% (0.57 - 3.26%) within 42 days after vaccination (i.e., a month since Day 12 after vaccination), and 1.23% (0.09 - 2.8%) by 25 March 2021. In the country - Israel - with the highest vaccinated population ratio (53.14%), the short-term effectiveness of vaccination had contributed to 8.62% (7.06 - 13.8%) in reducing COVID-19 transmission, as of 25 March 2021.

Nevertheless, at the early stage of the vaccination era, NPIs remained important and predominant for mitigating COVID-19 pandemic before most populations were infected or effectively vaccinated. In these countries with vaccine rollouts, gathering restrictions contributed to 39.62% (IQR 25.73 - 46.70%) of the suppression in infections, followed by international travel restrictions 15.38% (0.59 - 26.81%) and workplace closure 6.78% (0.58 – 22.79%) by 25 March 2021 (Fig. 3).

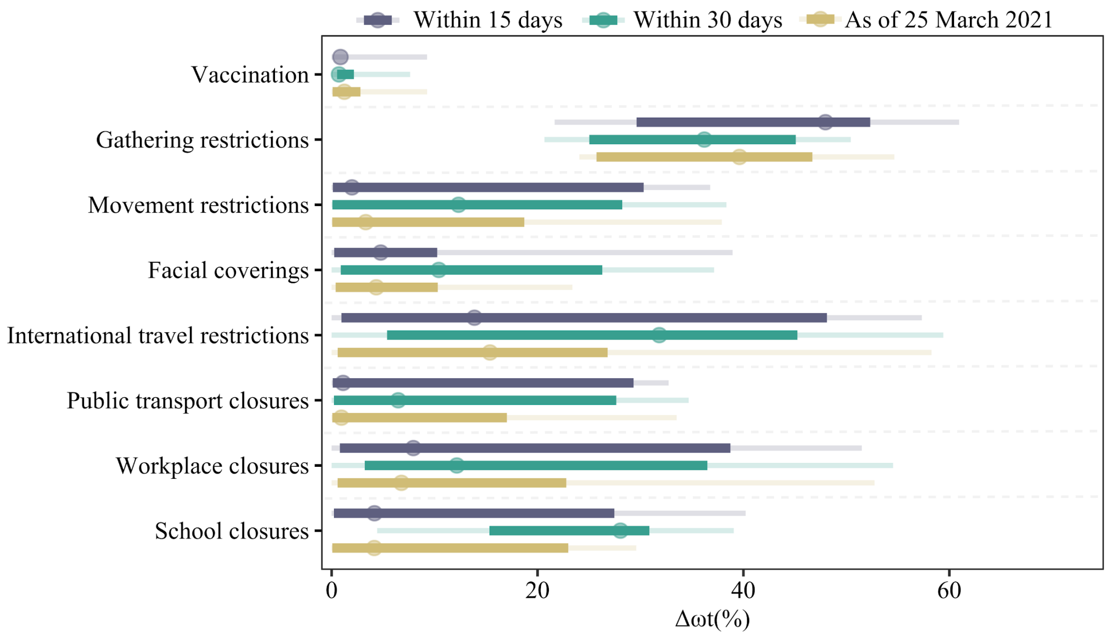

Fig. 3. Impact of integrated NPIs and the vaccination on COVID-19 transmission. $\%\Delta\omega_t$ represents the decay ratio in the suppression of COVID-19 infection rate. For 63 countries with vaccination data, effects of NPIs and the vaccination were evaluated for three periods, within 15 days and 30 days since the 12th day after vaccination and by 25 March 2021, as the induced antibody response and immunity may sufficiently prevent COVID-19 infections since Day 12 after receiving the first-dose vaccine[27]. The uncertainty intervals of NPIs and vaccination effectiveness refer to the variance over the corresponding period in the 63 countries.

Discussion

Based on longitudinal public health interventions and socio-demographic datasets across COVID-19 waves, our study revealed that NPI measures played important roles in mitigating the pandemic, with varied effects across waves and regions. The most effective NPIs were gathering restrictions, facial coverings and school closures in the first wave, which switched to facial coverings, gathering restrictions and international travel restrictions in the second wave. The effectiveness of facial coverings was statistically significant in both waves of four groups. Since the vaccine rollout, vaccinations have gradually contributed to the suppression of COVID-19 transmission, but NPIs still dominated the pandemic mitigation as of 25 March 2021. Our results presented NPI effectiveness along both spatial and temporal scales, and this study was the first impact assessment of integrating worldwide COVID-19 interventions and the vaccination in the real world, to our knowledge. These findings are crucial for continued tailoring and implementation of NPI strategies to mitigate COVID-19 transmission among future waves (e.g., as a result of new variants) or similar emerging infectious diseases, such as pandemic influenza.

Preliminary data showed vaccines could significantly reduce the severity of infections in older people[28], and our results also showed that vaccines have an increasing effect to reduce SARS-CoV-2 transmission in the whole population, while vaccination alone was still insufficient to fully contain the coronavirus spread, for the time being, considering the vaccinated population ratio in most countries below 10% by 25 March 2021. Mass vaccination is needed to confer broad protection to the coronavirus, through reducing the unevenness of vaccine distribution among regions and groups[20]. However, the efficacy of vaccines and herd immunity might be undermined due to the emergence of new variants of SARS-CoV-2, the wane of infection-associated immunity over time, and the changing attitudes and behaviours on vaccination, even with vaccine roll-out in full force[20]. Therefore, it is necessary to maintain the implementation of target and effective NPIs and closely monitor the changing efficacy of NPIs and vaccines across waves and countries for local intervention design.

We found that gathering restrictions and facial coverings significantly changed the pandemic trajectory in both waves, and gathering restrictions include both gathering cancellation[29] and closure of non-essential businesses[30-32]. The significant effects of these measures might be due to the virus most commonly spread through droplets or aerosols among people who were in close contact[33]. In contrast, public transport closures, movement restrictions, and workplace closures presented limited or moderate effects in both waves. Travel patterns have been significantly affected by the pandemic, causing a reduction in public transport usage[34]. Besides, facial coverings on public transport were required by numerous governments, which might reduce the risks of infection[35]. The decreasing usage of public transit and increasing personal protection measures might jointly explain the minor impact of public transport closures in both waves. The effect of movement restrictions contributed by both stay-at-home orders and internal movement restrictions in our study. The impact of movement restrictions, especially lockdowns, varied across previous studies, ranging from little effect[36] to as much as an 80% reduction in Rt[10]. Because lockdowns inherently encompass all other NPIs by definition, this might pose a problem for determining efficacy among NPI strategies alone[33]. Our study might underestimate the impact of movement restrictions and workplace closures due to differences in the timing, intensity, and combination of interventions (SI Fig. A3).

The effectiveness of school closures and international travel restrictions fluctuated in the two waves. School closures played an important role in the first wave epidemic mitigation, but not in the second one. School holidays were identified and corresponded to the highest intensity of school closures in both waves. In the second wave, education was primarily guaranteed in many countries like the United Kingdom and other European countries. Besides, health safety measures, including facial coverings and social distancing, were introduced by schools to adhere to. Due to the protection of other intervention measures, school closures might be avoided in the following waves of the pandemic. Contrary to the school closures, international travel restrictions had a relatively minor effect in the first wave but seemed important in the second wave (Fig. 1). Countries that quickly placed border controls might have reduced the seeding of the coronavirus between countries, but international travel restrictions cannot prevent local transmission at the community level in countries where the virus had already been introduced[37,38]. Previous models suggest that unless community-level transmission is reduced by no less than 50%, a reduction in 90% of international travel to and from epidemic centres might only modestly affect the epidemic trajectory[39]. The small effect of international travel restrictions in the first wave might be explained by the late implementation of this measure across countries. The increasing role of international travel restrictions observed in this study might be also due to increasing control efforts at community level which occurred during the second wave.

After controlling for local contextual confounders in our models, we observed variations in the efficacy of interventions across regions. In this study, we divided 133 countries into four groups based on mortality and morbidity, which were implicitly related to testing rate due to the highly correlation (see SI Table C1). Regardless, socio-economic, cultural and political characteristics could also affect the implementation and effectiveness of NPIs locally[33]. For example, workplace closures and gathering restrictions might have been implemented more thoroughly in countries with high morbidity and mortality such as Group 2, thereby increasing their efficacy as compared to countries in Group 1. Here we presented the overall trend of the group, not excluding individual countries such as the United States that had fragmented approaches and no NPIs were implemented very effectively (at least from the policy level).

We acknowledge that there are limitations in our analysis. First, we mainly focused on the comparison of NPIs for the first and second waves, as only a small number of countries had experienced the third wave by 25 March 2021 and the most recent wave might involve NPIs together with vaccination. To evaluate the pure effects of NPIs independent of vaccination, we excluded the dates with vaccination in the first and second waves. Meanwhile, the preliminary results of NPI effects in the third wave for a small group of countries are also provided in SI. Second, it should be noted that our study might have underestimated the effectiveness of the vaccination, as we only examined the initial, short-term effect of the first-dose vaccines as of 25 March, but vaccine and infection-induced immunity among populations could last longer, with accumulated long-term effects for reducing transmission. Additionally, some countries/populations have had the second-dose vaccine rollout, which was not estimated in our study, though the proportion of people vaccinated with two doses might be still low.

Overall, the disclosure of epidemic, publicized responses and the COVID-19 vaccination data allows us to estimate and compare the cross-wave effects of public health measures at both global and regional scales. Our work provides a quantitative basis and approach to explore historic spatial-temporal variation in the effectiveness of individual NPIs, integrating vaccinations. The continued pandemic burden across the globe and the non-decisive efficacy of the vaccination suggests the NPI implementation continues to be a priority for many countries, even with a full force vaccine rollout in the early stage of the vaccination era[5,20,40].

Methods

Data sources and processing

Epidemiological data. The daily number of confirmed cases reported by country were obtained from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU)[23]. To remove the influence of outliers and the fluctuation caused by the day-of-week effect, we smoothed daily case counts with the Gaussian kernel and adjusted them for the infection-to-confirmation reporting delay then. First, we set all negative case numbers to zero, as negative values in cases could sometimes appear when a country corrected historical data, because it had previously overestimated the number of cases[41]. Second, we smoothed case data by calculating the rolling average using a Gaussian window with a standard deviation of 2 days, truncated at a maximum window of 15 days[29]. Third, we adjusted the data by subtracting 12 days[15] from the reporting date in the first wave, accounting for the delay from infection to reporting. With respect to the second, even the third, wave, we slightly reduced the reporting delay to 10 days because of the potential increasing testing and diagnosis capacity. Sensitivity analyses were also conducted to assess the impact of different reporting delays on our estimates (see sensitivity analysis section in Methods).

Intervention policy data. We generated seven non-pharmaceutical measures from the nine NPIs (i.e. school closures, workplace closures, public events cancellations, gathering restrictions, public transport closures, stay-at-home orders, internal movement restrictions, international travel restrictions, and facial coverings), collated by the Oxford COVID-19 Government Response Tracker (OxCGRT)[24]. The intensity of the nine considered NPIs policies is scaled into discrete values between 0 to 1, where 0 represents an absence of the NPI and 1 represents the corresponding maximum intensity. The intensity of school closures is corrected as 1 during public and school holidays[42]. We processed public events cancellations and gathering restrictions into a single NPI (i.e., gathering restrictions) for each country in each day by their mean intensity, as the two NPIs documented in OxCGRT were highly collinear in terms of their timing and intensity of implementation across the 133 study countries. We also integrated stay-at-home orders and internal movement restrictions into movement restrictions for the same reason in the same way for each country.

Vaccination data. The COVID-19 vaccination data used in this study was obtained from the *Our World in Data*[25]. They regularly updated the first and second doses administered and daily vaccination rates at national scale from official sources in 93 countries as of 25 March 2021. We analysed the vaccination effect in 63 countries whose highest daily confirmed cases exceeded 100. The induced antibody response and immunity might sufficiently prevent SARS-CoV-2 infections since Day 12 after receiving the first dose[27]. Therefore, we adjusted the vaccination rates for the first dose administered to be rolled forward for 12 days, to account for the delay from vaccination to the generation of sufficient protective immunity.

Environmental and demographic covariates. To control for country-specific confounders in the estimates of intervention effectiveness varied across countries, we also assembled population density, aging ratio, health capacity index, air temperature, and humidity for all these 133 study countries. Within each country, population density (per square kilometre) was the ratio of the total population over the corresponding built-up area in 2014[43]. The total and age-grouping population data in 2019 were obtained from the United Nations to calculate the aging ratio (> 65 year old) among populations

[44]. Health capacity index was the arithmetic average of the five indices, including i) prevent, ii) detect, iii) respond, iv) enabling function, and v) operational readiness, developed to characterize the health security capacities in the context of the COVID-19 outbreak[45]. Air temperature and humidity were derived from the Global Land Data Assimilation System [46].

To further remove the day-of-week effect among case testing, diagnosis, and data reporting, all data used in this study were assembled and aggregated into a weekly dataset. The correlations between each two covariates were given to show their collinearity. The studied countries were selected by being documented in every dataset of epidemiological data, intervention policy data and environmental and demographic covariates. The details of data collection and processing are further provided in the Supplementary Information.

Defining waves and country groups

Waves. The inequality in pandemic development across worldwide countries has led some countries to confront more than one COVID-19 wave[47,48]. Based on the smoothed daily case data, we defined an epidemic wave in each country as below. In a period of three or more consecutive weeks for a country, if the daily numbers of cases in this period all exceeded 5% of the maximum daily number of cases in 2020 in this country, these weeks were considered to constitute an epidemic wave. The first and last days of the period were the start and end of the corresponding wave, respectively. However, considering that the first wave of this pandemic in most countries started from low-level community transmission caused by imported cases, we adjusted the start date of the first wave to the first date: i) when the number of daily cases exceeded 10 cases, for countries where the maximum number of daily new cases in the first wave were less than or equal to 300 cases; or ii) when the number of daily cases exceeded 20 cases, for other countries where their maximum daily cases in the first wave were greater than 300 cases. The details and full lists of waves by country can be found in SI. We focused on the first and second waves in the main text, and the results of the third waves that were only identified in a few countries are provided in SI.

Regional stratification. The reported COVID-19 morbidity and mortality could vary substantially in the study countries, based on the released epidemiological data. We investigated the spatial variation in NPIs effectiveness by dividing 133 countries into four country groups based on their COVID-19 morbidity and mortality together with geographical proximity (SI Fig. C2). Among the four groups, the grading thresholds for high morbidity and mortality were determined according to the principle of "small variance within groups and large variance between groups"[49,50]. Thresholds of 1800 per 100,000 persons for morbidity and 40 per 100,000 persons for mortality were chosen to select countries with both high morbidity and high mortality. Considering the geographical proximity between countries, Asian countries and African countries were assigned into two separate groups. A full list of countries in each group and the corresponding time frame of different waves of COVID-19 can be found in SI Table C2 – C5.

Model description

Transmission dynamics. The evolution of the COVID-19 in a society can be characterized by $\frac{dI}{dt} = \omega_t I_t$, where I represents the new cases, and ω_t is the instantaneous growth rate. We adopted a general linear formula[9,10,37] linking NPIs to the pandemic evolution. That is,

$$\omega_t = \omega_0 \exp(-\tau_t v_t) \prod_{i=1}^{n} \exp(-\alpha_{i,t} x_{i,t}) \prod_{j=1}^{m} \exp(-\beta_{j,t} y_{j,t}) + \varepsilon_t, \tag{1}$$

where ω_0 represents the baseline growth rate without interventions. $\alpha_{i,t}$ is the correlation between ω_0 and ω_t in terms of NPIs policy $x_{i,t}$ (visualized in SI Fig A3) on day t, and n is the number of NPIs. $\beta_{j,t}$ is the correlation between ω_0 and ω_t in terms of sociodemographic factors $y_{j,t}$, and m is the number of control variables. τ_t is the correlation between ω_0 and ω_t in terms of vaccination v_t, and ε_t is the error term representing the uncertainty of decay ratio at day t. The effect of NPI x_i in a period, such as the first wave of the pandemic, can be interpreted as a decay ratio in ω_0 by computing $e_i = 1 - \exp(-\alpha_i \overline{x_i})$, where α_i is the effect parameter and $\overline{x_i}$ is the average intensity of the NPI during that period. The highest effect of NPIs is 1, representing that the transmission is fully contained or interrupted. In contrast, the effect of vaccination is calculated by $1 - \exp(-\tau \max(v_t))$, ranged from 0 to 1 also with 1 representing that the transmission is fully contained or interrupted by vaccination. It should be noted that the combined NPIs effectiveness on day t should be calculated as $1 - \exp(-\sum_i \alpha_i x_{i,t}) = 1 - \prod_i (1 - e_i)$, instead of the sum of individual NPI effects.

Assessing the effects of interventions. We used the spatiotemporal Bayesian inference model to evaluate the effect parameters in Eq. (1) based on the observed real-time COVID-19 growth, identifying the relative NPIs and vaccination effectiveness. We assumed that the effects of NPIs on ω_t change across waves and country groups, but relatively stable for countries within the same group. The differences in NPIs effectiveness across country groups were assumed to be too large to be controlled by sociodemographic factors. We first evaluated the overall effectiveness of NPIs before the vaccination era. In addition to the overall NPIs effectiveness, we also evaluated respective NPIs effects in the first and second waves for each country group separately to show the potential large spatiotemporal diversity. For vaccination, we evaluated NPIs and vaccination effects for 63 countries regardless of their country groups. We also evaluated vaccination effects within different time periods after vaccinations as of 25 March 2021 to show cumulative effects of vaccine rollouts over time.

We aimed to compare relative effectiveness of COVID-19 interventions across countries and across waves. Specifically, the effect parameters were all pre-defined to have a gamma distribution[9] in spite of NPIs, sociodemographic factors and vaccination. Then, we placed 80% of their probability mass on positive effects for both NPIs and vaccination by left shifting their probability distributions with certain values[10]. While we put no information on effectiveness of sociodemographic factors, i.e., placing 50% of their probability mass on positive effects. Under the circumstance, NPIs and vaccination were more likely to contain the pandemic, while the state-variable effects were unknown. The baseline growth rate (ω_0) was defined as the mean of the top three highest growth rates of the confirmed COVID-19 new cases in the corresponding wave. The instantaneous transmission interval ($1/\omega_t$) in the following weeks was assumed to have a gamma distribution also.

Model validation. The reliability of our models and corresponding results were evaluated by the leave-forty-countries-out cross validation. We first calibrated our model using 70% countries (93), randomly selected from 133 countries, to estimate the overall NPIs effects in both the first and second waves. Then, we derived the instantaneous growth rates through the estimated NPIs overall effects for the remaining 30% countries (40) in terms of their implemented NPIs. We used mean square error, ranging from 0 to infinite with 0 represents the perfect prediction ability, to assess the difference between the predicted instantaneous growth rates and the corresponding empirical instantaneous growth rates. We repeated this procedure 50 times, where the average mean square error was (median 1.002, interquartile range [IQR] 0.519 – 1.209). Further, we standardised the predicted and empirical instantaneous growth rates, respectively, within each country and then analysed all the data with one-way ANOVA.

Sensitivity analysis. The robustness of models and parameters used in the study was also assessed by a series of sensitivity analyses. The parameters to be assessed included: i) the probability mass of NPIs and vaccination on negative effectiveness; ii) the probability mass of sociodemographic factors on negative effectiveness; and iii) the infection-to-report delay in the first wave (t_1) and the second wave (t_2). In this study, the default values for these parameters were 20%, 50% and t_1=12 and t_2=10, respectively. The comparison of parameter impacts on estimates were listed in SI Table B1, representing three scenarios with smaller and larger default parameter settings. The differences of NPI effects among three waves were tested using a Wilcoxon signed-rank test, a non-parametric statistical hypothesis test for comparing NPIs effects between pairs of the three waves. Moreover, we repeated the estimations twice for NPIs effectiveness with default setting, except for the initial full infection rate, as the highest growth rate and the mean of the top five highest growth rates, respectively, of the confirmed COVID-19 new cases in the corresponding wave.

Using an R package, rstan[51], this model infers posterior distributions of each NPI effectiveness with the Markov chain Monte Carlo (MCMC) sampling algorithm. To analyse the extent to which modelling assumptions affect the results, our sensitivity analyses included epidemiological parameters, prior distributions, and the structural assumptions introduced above. MCMC convergence statistics are shown in SI Fig. B6 - B7.

Data and code availability

All source code and data necessary for the replication of our results and figures are available at: https://github.com/wxl1379457192/NPIs_code

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Author contributions

YG, WBZ, HYL, WY, CWR and SJL conceived and designed the study, built the model, collected data, finalised the analysis, interpreted the findings, and wrote the manuscript. MGH, XLW, YZS and MXL collected data, interpreted the findings, and revised drafts of the manuscript. NWR, LF, ZJL, WZY and AJT interpreted the findings, and commented on and revised drafts of the manuscript. All authors read and approved the final manuscript.

Ethical approval

Ethical clearance for collecting and using secondary data in this study was granted by the institutional review board of the University of Southampton (No. 61865). All data were supplied and analysed in an anonymous format, without access to personal identifying information.

Role of the funding source

The funder of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report. The corresponding authors had full access to all the data in the study and had final responsibility for the decision to submit for publication. The views expressed in this article are those of the authors and do not represent any official policy.

Competing interests

The authors declare no competing interests.

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Supplementary Information

Contents

A Supplementary method

A.1 Detailed model description

In the pre-vaccination era

We employed a Susceptible-Infected-Removed (SIR) model[1] to describe the evolution of COVID-19 for each country. The infected populations at country c on time t were attributed to the number of COVID-19 cases on time $t-1$ by the following equation

$$I_{c,t} = I_{c,t-1},$$

where $\omega_{c,t-1}$ was the instantaneous growth rate[2] of COVID-19, affected by the basic transmission rate (i.e. basic reproduction number), interventions, and the susceptible population ratio, while I was the number of infections. The instantaneous growth rate was the inverse of the serial interval (the time between successive cases in a chain of transmission), which was commonly characterized by a gamma distribution[3]. Considering the huge susceptible populations at the early stage of the pandemic and vaccine rollouts, and no country has reached herd immunity[4], for the time being, we assumed that the basic growth rate in the pre-vaccination era with no interventions was approximately constant. However, the observed instantaneous growth rate ($I_{c,t}/I_{c,t-1}$), derived from the empirical daily confirmed cases, usually possessed a decreasing trend within each wave. For example, the first COVID-19 outbreak in China had a basic reproduction number of 3.54[5], but following the multipronged interventions, the reproduction number were reduced to 0.28 as of 8 March 2020. Nevertheless, most of the population in China are still susceptible to coronavirus by 31 March 2021, due to the sustained containment of the disease and the small proportion of Chinese vaccinated.

As previous works[2,6,7], we assumed that the decreasing transmission rate in each wave was contributed by interventions, especially NPIs in the pre-vaccination era. Then, we decomposed the variation in the empirical instantaneous growth rate in country c

into the variation in the timing and intensity of NPIs implemented during the corresponding period in country c. To this end, we modelled the efficacy of seven NPIs in country c using the following formula,

$$\omega_{c,t-1} = \frac{I_{c,t}}{I_{c,t-1}} = \prod_{i=1}^{7} \exp\left(-\alpha_{c,i,t-1} x_{c,i,t-1}\right), \tag{1}$$

where $x_{c,i,t-1}$ is the state of NPI i in country c on time $t-1$ (see Fig. A3), and $\alpha_{c,i,t-1}$, the corresponding coefficient of NPI i, was used to measure the effect of each intervention. We assumed that $\alpha_{c,i,t-1}$ has a gamma distribution over time,

$$\alpha_{c,i,t-1} \sim \text{Gamma}(1/7, 1) - \log(1.000382)/7.$$

We put this prior on $\alpha_{c,i,t-1}$ such that about 80% probability mass of NPI effectiveness on positive effect (see Fig. A2).

However, if there was rare variation in the timing and intensity of each NPI implementation, we cannot derive a reliable result from Eq. (1). We, thus, jointly estimated NPI effects through numerous countries by assuming $\alpha_{c,i,t-1}$ being constant across countries. The variation of NPI effects across countries was controlled by socio-demographic factors with the following equation,

$$\omega_{c,t} = \omega_{c,0} \prod_{i=1}^{7} \exp\left(-\alpha_{i,t} x_{c,i,t}\right) \prod_{j=1}^{5} \exp\left(-\beta_{j,t} y_{c,j,t}\right), c \in \{1, \dots, C\} \tag{2}$$

where $\omega_{c,0}$ was the baseline growth rate in country c, and $\beta_{j,t}$, the coefficient of the socio-demographic factor $y_{c,j,t}$, was used as a proxy of the impact of this factor on the decay of the baseline growth rate. The correlation coefficients for the socio-demographic factors were also assumed to have a gamma distribution, but with 50% probability mass on their positive effects (see Fig. A2),

$$\beta_{c,j,t} \sim \text{Gamma}(1/5, 1) - \log(1.09)/5.$$

However, the absolute values of instantaneous growth rate might vary heterogeneously across countries[8]. We added the baseline growth rate in Eq. (2) for country c to make the NPI effects being comparable across countries, by defining the NPI efficacy as a proportion of reduction from the baseline growth rate.

In the pre-vaccination era, to differentiate the performance of NPIs across waves and country groups, we first estimated the overall effect of NPIs covering the whole 133 countries as of 25 March 2021. Then, the relative NPI effects were evaluated in each country group and wave, respectively. To make Eq. (2) solvable, $\alpha_{i,t}$ were set to be constant for the practical estimation, where the variation in the NPI efficacy was captured by setting different data contexts in terms of space and time. The effect of NPIs on ω_t might change across waves and country groups, but somewhat being stable for countries within the same country group and wave.

We estimated coefficients in Eq. (2) jointly for all countries within any particular above data context by an individual hierarchical model,

$$\frac{1}{\omega_{c,t-1}} \sim \mathrm{Gamma}(\mu, \sigma),$$

$$\mu = \frac{1}{\omega_{c,0} \prod_{i=1}^{7} \exp\left(-\alpha_i x_{c,i,t-1}\right) \prod_{j=1}^{5} \exp\left(-\beta_j y_{c,j,t-1}\right)}.$$

The above model was fitted using an adaptive Hamiltonian Monte Carlo (HMC) sampler in Stan, a probabilistic programming language. We ran 5 chains for 2000 iterations with 200 iterations of warmup and a thinning factor 1 to obtain 9000 posterior samples. Posterior convergence was assessed using the Rhat statistic and by diagnosing divergent transitions of the HMC sampler.

In the vaccination era

A safe and effective vaccine could help to protect the susceptible in two distinct ways[9]: direct protection, where high-risk populations are vaccinated to prevent infections or severe diseases, and indirect protection, where those in contact with high-risk individuals are vaccinated to reduce transmission. Vaccination curbs the pandemic by reducing the susceptible ratio among the whole population. In contrast, NPIs are designed and implemented to reduce contacts between susceptible and infectious populations, and interrupt the virus spread, thereby reducing transmission rate consequently. To understand the short-term effect of vaccination on containing COVID-19 transmission in the whole population in each country, as of 25 March 2021, we linked vaccination to the instantaneous transmission rate with a similar form to that for NPIs, so that the impact of vaccination was comparable to NPIs. Finally, our spatiotemporal Bayesian inference model for differentiating the performance of NPIs and vaccination was,

$$\omega_t = \omega_0 \exp(-\tau_t v_t) \prod_{i=1}^{7} \exp(-\alpha_{i,t} x_{i,t}) \prod_{j=1}^{5} \exp(-\beta_{j,t} y_{j,t}) + \varepsilon_t \qquad (3)$$

where v_t was the vaccination parameter (i.e., the accumulated proportion of population vaccinated) on time t and τ_t was the corresponding coefficient to measure the effect of vaccination. We assumed that τ_t had a same gamma distribution as the coefficients of NPIs,

$$\tau_t \sim \mathrm{Gamma}(1/7, 1) - \log(1.000382)/7.$$

We also put this prior on τ_t such that about 80% probability mass of vaccination effectiveness on positive effect (see Fig. A2).

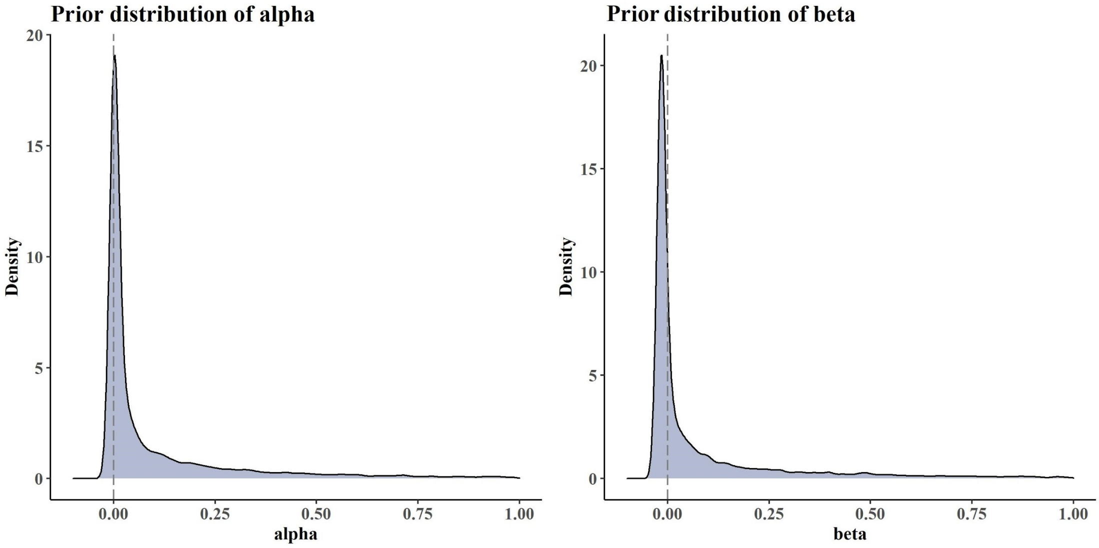

Fig. A1. The prior distribution of effect parameters of NPIs and vaccination (left) and the correlation parameter of the socio-demographic factors (right).

A.2 Details in data processing

The datasets used in this study were all publicly available and detailed below. Countries documented in all these datasets were studied, including a total of 133 countries, territories and areas. Here, we detail how we assembled and processed each dataset into final integrated, experimental datasets for this study.

Epidemiological data

We collected daily confirmed COVID-19 case data for countries $c \in \{1, \dots, 133\}$ from the earliest available dates to 25 March 2021. The daily confirmed cases used in our study were originally collected by the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU)[10], which can be obtained from the GitHub (https://raw.githubusercontent.com/owid/covid-19-data/master/public/data/owid-covid-data.csv). We processed epidemiological data country by country with the following steps: i) All negative numbers of reported cases were set to zero; ii) The daily numbers of cases were smoothed by calculating the rolling average using a Gaussian window with a standard deviation of 2 days, truncated at a maximum window size of 15 days[11]; iii) We defined periods of the first wave and the second wave (see Methods in main text); iv) To account for the delay from infection to reporting, we replaced the reporting dates of daily cases by subtracting 12 days in the first wave[7]. With respect to the second, even the third, wave, we subtracted the reporting dates by 10 days. A few country samples are illustrated in Fig. A2 to show the smooth procedure and waves.

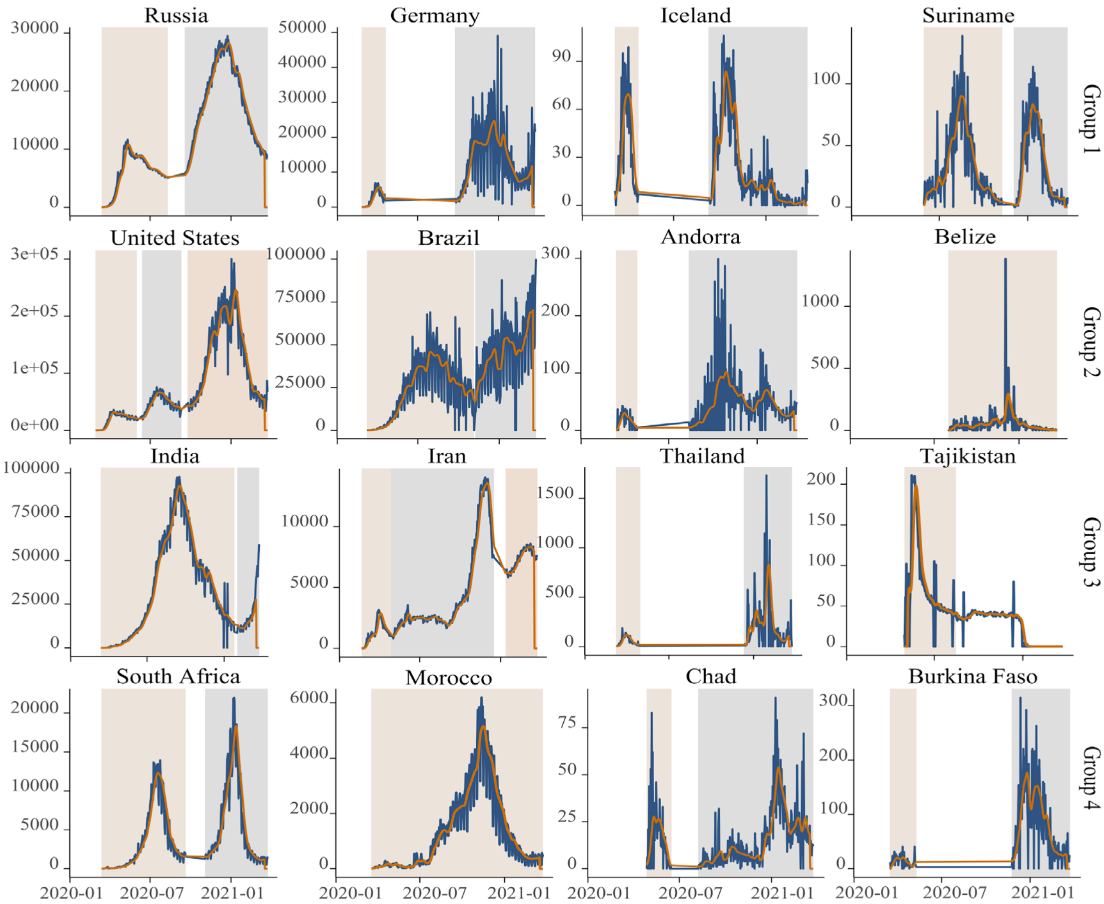

Fig. A2. Illustrations of raw data (in blue) and corresponding smoothed data (in orange) of daily confirmed active cases. Here we only show the top two countries and the last two countries in each country group vis-a-vis cumulative cases. The waves are depicted by the shadows with different colours.

The dataset used in the estimation of the overall efficacy of NPIs was generated by pooling up the start date of the first wave, instead of aggregating all the countries in terms of dates. Similarly, the dataset used for the second wave was generated by pooling up the start date of the second wave for all countries. Then, we aggregated the daily time series of confirmed cases into weekly dataset by summing all new cases in the corresponding week. To define the effect of NPIs before vaccine rollouts in our NPI effectiveness estimation, we only used case data before the date when country *c* started COVID-19 vaccination programme among populations. Sensitivity analyses were also conducted to evaluate the impact of different infection-to-report delays in our estimates.

Policy data

We employed nine NPIs (the definitions were given in Table A1) collated by the Oxford COVID-19 Government Response Tracker (OxCGRT)[12]. For each record of policy data, intensity of the nine considered NPI policies was scaled into discrete values between 0 to 1 by dividing the corresponding highest intensity value listed in Table A1, where 0 represented an absence of the NPI and 1 represented the corresponding maximum intensity. We used the timing of public and school holidays[13] to adjust the intensity of school closures to 1 at that days. Then, we integrated the NPIs policy data into the prepared datasets of weekly confirmed cases, and the weekly intensity of each NPI was the mean of corresponding daily intensity values in each week. Finally, public events cancellations and gathering restrictions were further aggregated into a single parameter (gathering restrictions) with their average intensity for each record, and stay-at-home orders and internal movement restrictions were also aggregated into movement restrictions in the same way (for example see Fig. A3).

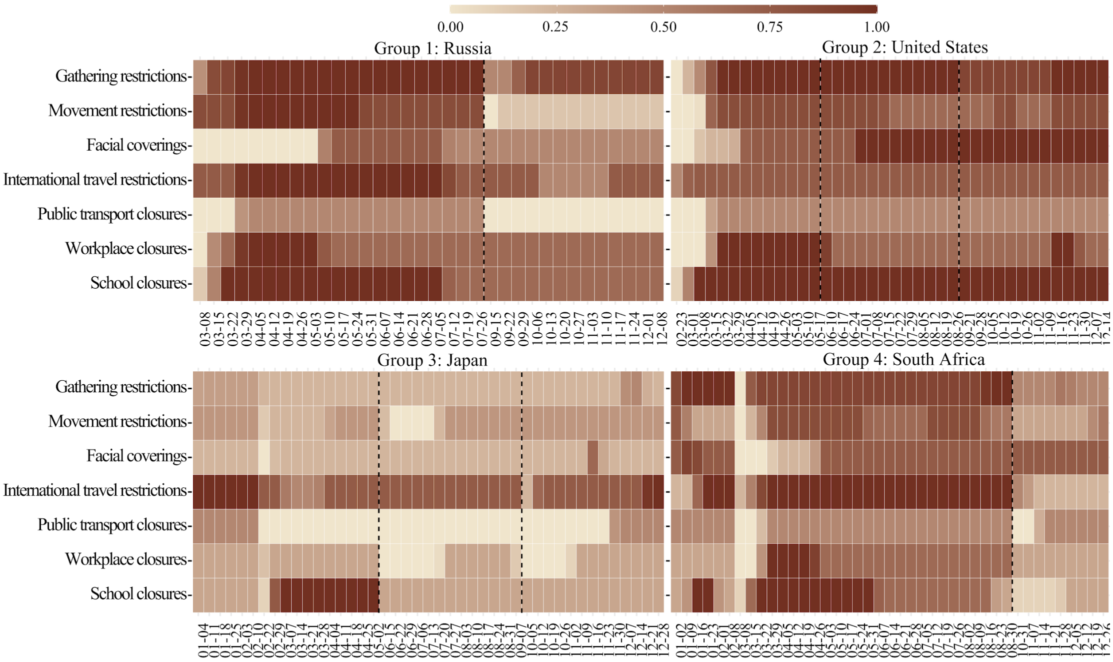

Fig. A3. Illustrations of timing and intensity of NPIs implementation for Russia, United States, Japan and South Africa.

Table A1. Definition of the employed nine NPIs from the Oxford COVID-19 Government Response Tracker (OXCGRT) in terms of their intensity.

NPIs	Intensity	Description
School closures	1	Closing or all schools open with alterations is recommended
	2	Closing some levels or categories is required
	3	Closing all levels is required
Workplace closures	1	Closing workplace is required
	2	Closing some sectors or categories of workers is required
	3	Closing non-essential workplaces is required
Public events cancellations	1	Cancelling public events is recommended
	2	Cancelling public events is required
Gathering restrictions	1	Above 1000 people
	2	Between 101-1000 people
	3	Between 11-100 people
	4	10 people or less
Public transport closures	1	Closing is recommended
	2	Closing is required
Stay-at-home orders	1	Stay at home is recommended
	2	Stay at home with exceptions for daily exercise, grocery shopping, and 'essential' trips is required
	3	Stay at home with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc) is required

NPIs	Intensity	Description
Internal movement restrictions	1	Travel between regions/cities is not recommended
	2	Internal movement is restricted in place
International travel restrictions	1	Screening arrivals
	2	Quarantine arrivals from some or all regions
	3	Ban arrivals from some regions
	4	Ban on all regions or total border closure
Facial coverings	1	Recommended
	2	Required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible
	3	Required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible
	4	Required outside the home at all times regardless of location or presence of other people

Note: International travel controls were deployed for foreign travellers only, not citizens.

Vaccination data

We obtained the data of COVID-19 vaccination from *Our World in Data*[14]. The total number of people who received at least one vaccine dose was considered as the vaccination proxy. Since the vaccinated population might have the sufficient vaccine-induced antibody response and immunity to prevent SARS-CoV-2 infections at Day 12 after receiving the first dose[15], we adjusted the dates of vaccination data by adding 12 days for further integrating with case data and being comparable with the effect of NPIs. The vaccination intensity by day was the cumulative injection rate among the total population of each country. A full list of countries and their cumulative injection rates until 25 March 2021 is shown in Table A2. As we explored the short-term effects of vaccinations and NPIs in the early stage of vaccine rollouts, we assembled and analysed daily datasets. For each date in the vaccination, we used the smoothed data of daily confirmed cases adjusted for the infection-to-report delay by 12 (or 10) days, corresponding to the date in the first (second or third) wave. We analysed the vaccination effect in 63 countries whose highest daily confirmed cases exceeded 100.

Environmental and demographic covariates

Population density is intrinsically a very factor influencing infection rate, especially for megacities[16,17], and the elderly are more vulnerable to the pandemic due to the severe infections[18]. Different aging ratios across countries might also affect the mobility and mortality[19]. The different growth rates of COVID-19 infections would also fluctuate due to disparate testing and case detection capacities[20]. The per capita health capacity may help us control this kind of variation. In addition, COVID-19 seems to possess higher transmission rates in wintertime[21].

To control for country-specific confounders in the estimates of intervention effectiveness across countries, we assembled population density, aging ratio, health capacity index, air temperature, and humidity for all these 133 study countries. We integrated these data into the datasets of confirmed cases and vaccination, respectively, in terms of corresponding documented dates. With respect to the weekly datasets, environmental conditions were aggregated into weekly with the mean value. Moreover, each environmental and demographic covariate was normalized in each dataset by dividing the corresponding maximum value independently to eliminate dimensional effects.

Table A2. The list of studied 63 countries in the analysis of vaccination effects.

Group	Country	Vaccination (%)	Country	Vaccination (%)
Group 1	Denmark	6.2386	Mexico	1.0648
	Norway	5.7779	Dominican Republic	0.2359
	Finland	5.4182	Belarus	0.2224
	Estonia	5.2514	Albania	0.2064
	Greece	4.7062	El Salvador	0.0926
	Cyprus	3.6641	Ecuador	0.0359
	Canada	3.1128	Paraguay	0.0142
	Russia	1.6338	Venezuela	0.0005
	Costa Rica	1.1332		
Group 2	United Kingdom	27.7743	Sweden	4.4561
	Chile	15.6673	Germany	4.4527
	United States	13.6490	Austria	4.2055
	Switzerland	6.0876	Luxembourg	4.1866
	Hungary	5.2804	France	4.1277
	Ireland	5.2158	Belgium	4.0455
	Poland	5.1635	Czech Republic	3.5826
	Italy	5.1058	Croatia	3.0557
	Lithuania	5.0742	Brazil	2.8598
	Slovenia	5.0449	Latvia	1.9936
	Spain	4.7448	Bulgaria	1.9660
	Portugal	4.7021	Argentina	1.0082
	Netherlands	4.6290	Peru	0.8217
Group 3	Israel	53.1398	Myanmar	0.6933
	United Arab Emirates	35.4668	Azerbaijan	0.6436
	Bahrain	16.7837	Jordan	0.4898
	Turkey	7.5772	Indonesia	0.4497
	Qatar	3.5819	Kazakhstan	0.0746
	Kuwait	3.1839	Pakistan	0.0350
	Bangladesh	1.5745	Japan	0.0141
	India	1.5739	Iran	0.0120
	Oman	0.9445		
Group 4	Morocco	6.8842	Senegal	0.0238
	South Africa	0.2136		

B Validation and sensitivity analysis

B.1 Cross validation

We used Cross-Validation (CV) to validate our model. We used the data of 70% countries (93), randomly sampled from 133 study countries, to build the model and estimate the overall NPI effects. To examine the performance of models, the instantaneous growth rates derived from the data of remaining 30% countries (40) were compared with the growth rates predicted by models using the corresponding implemented NPIs and country-specific characteristics in these countries. The difference between the predicted and empirically calculated instantaneous growth rates was evaluated by the mean square error (MSE). In general, MSE ranged from 0 to infinite with 0 representing the perfect prediction ability. For each of 40 countries in the validation dataset, MSE was the mean of the squared error of the instantaneous growth rates at each point of time. We used the average MSE of these 40 countries to represent the reliability of our model. This process has been repeated 50 times independently, generating 76,862 pairs of predicted and empirical instantaneous growth rates, and the average MSE was (median 1.002, interquartile range [IQR] 0.519 – 1.209). Moreover, the predicted and empirical instantaneous growth rates were standardised within each country independently and respectively, by subtracting the mean and then dividing the standard error, for comparing instantaneous growth rates across countries. All the independently standardised values were shown in Fig. B1 and analysed by one-way ANOVA. The results showed that our model explained 43% variance ($var(predictions)/(var(predictions) + var(residuals))$) in the empirical instantaneous growth rates, with P value < 0.001. Fig. B2 illustrated four countries that were confronting different numbers of waves.

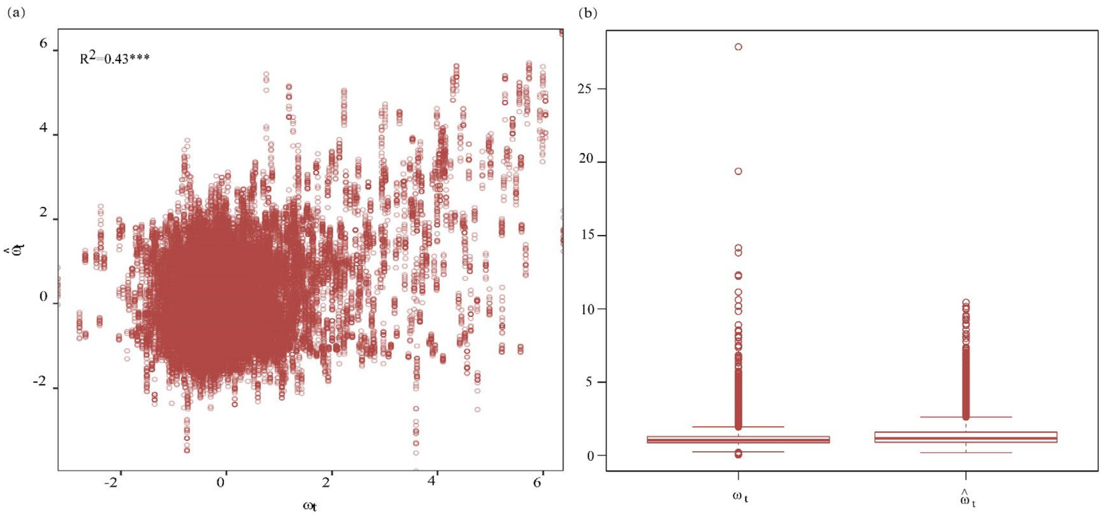

Fig. B1. The results of 50 times cross-validation. (a) The scatter plot of the standardised 76862 pairs instantaneous growth rates. (b) The box plots of the predicted ($\widehat{\omega}_t$) and empirical (ω_t) instantaneous growth rates, respectively. (***: p < 0.001)

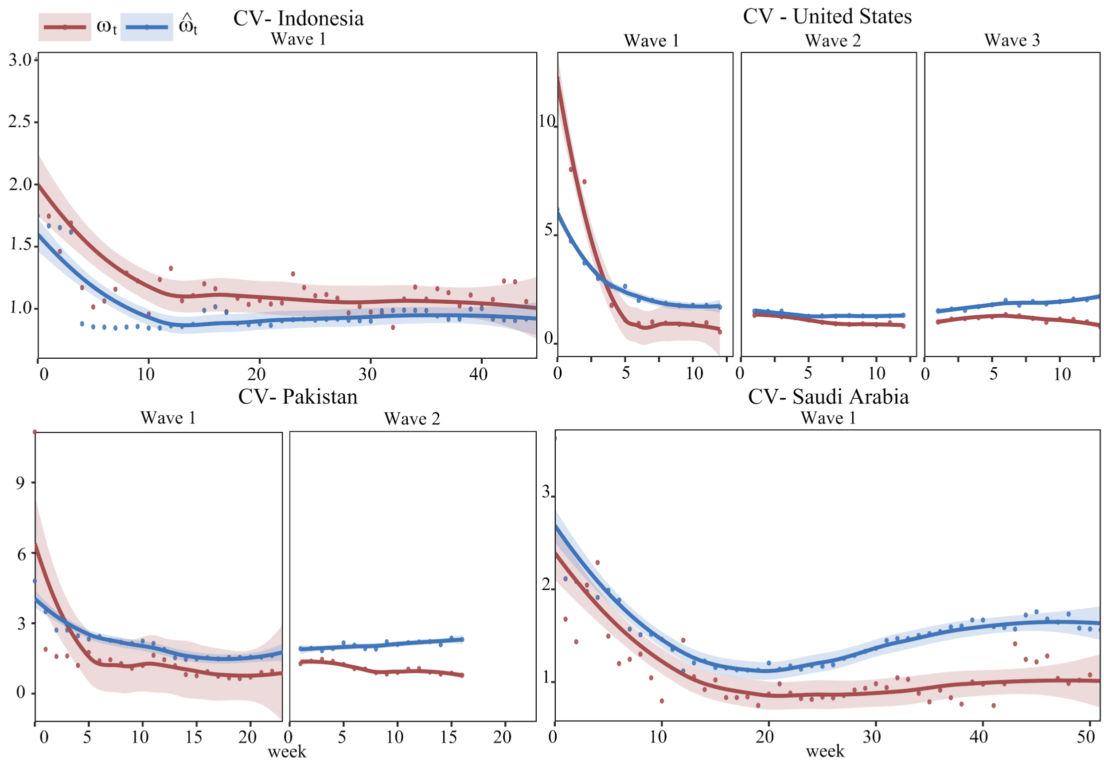

Fig. B2. Comparison between the predicted instantaneous growth rates on each point of time and the empirical instantaneous growth rate. The predicted instantaneous growth rates ($\widehat{\omega}_t$) were represented by blue dots, where the empirical instantaneous growth rates (ω_t) were represented by red dots. The corresponding lines were fitted by locally weighted scatterplot smoothing, where the shadowed area representing 95% confidence interval.

B.2 Sensitivity analysis

We designed three scenarios (Table B1) to perform sensitivity analyses based on our model assumptions, including 1) the probability that NPIs or vaccination performed negatively in reducing COVID-19 transmission; 2) the probability that country-specific characteristics had negative impacts on reducing COVID-19 transmission; 3) the infection-to-confirmation delay in the first wave and 4) the infection-to-confirmation delay in the second wave. Then, we calibrated our model with different scenarios. Results showed that the relative importance and ranks of NPIs for the reduction in ω_0 were not significantly changed under the three scenarios (Fig. B3). For a specific policy, the decay ratio in the COVID-19 infection rate was slightly varied among three scenarios.

Table B1. Three scenarios in the sensitivity analysis of the model

	Probability in NPI or vaccination negative effect	Probability in country-specific characteristics negative effect	Infection to confirmation delay (days)	
	α	β	t_1	t_2
Scenario 1 (Lower bound)	10%	40%	10	8
Scenario 2 (Default setting)	20%	50%	12	10
Scenario 2 (Upper bound)	30%	60%	14	12

Moreover, we repeated the estimation twice for NPI effectiveness under the default setting (scenario 2), to test the impact of the baseline growth rate derived by other approaches: 1) the highest weekly growth rate of the confirmed COVID-19 new cases in the corresponding wave; or 2) the mean of the top five weekly highest growth rates in the corresponding wave. The results showed that the relative effects of NPIs varied slightly between different baseline growth rates, whereas the ranks of NPIs in terms of their efficacy were stable between them (Figs. B4 and B5).

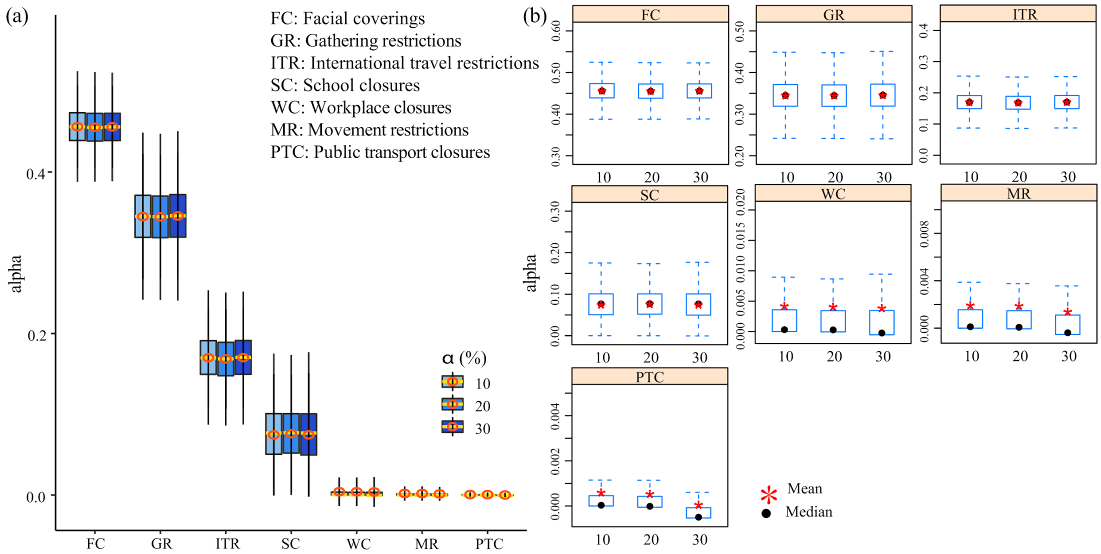

Fig. B3. Sensitivity analysis of the model assumption. (a) Comparison of the decay ratio in the COVID-19 infection rate for seven NPIs under three scenarios listed in Table B1. NPIs are ranked by the decay ratio ($\%\Delta\omega_t$). (b) Comparison of the three scenarios for the efficacy of individual NPIs.

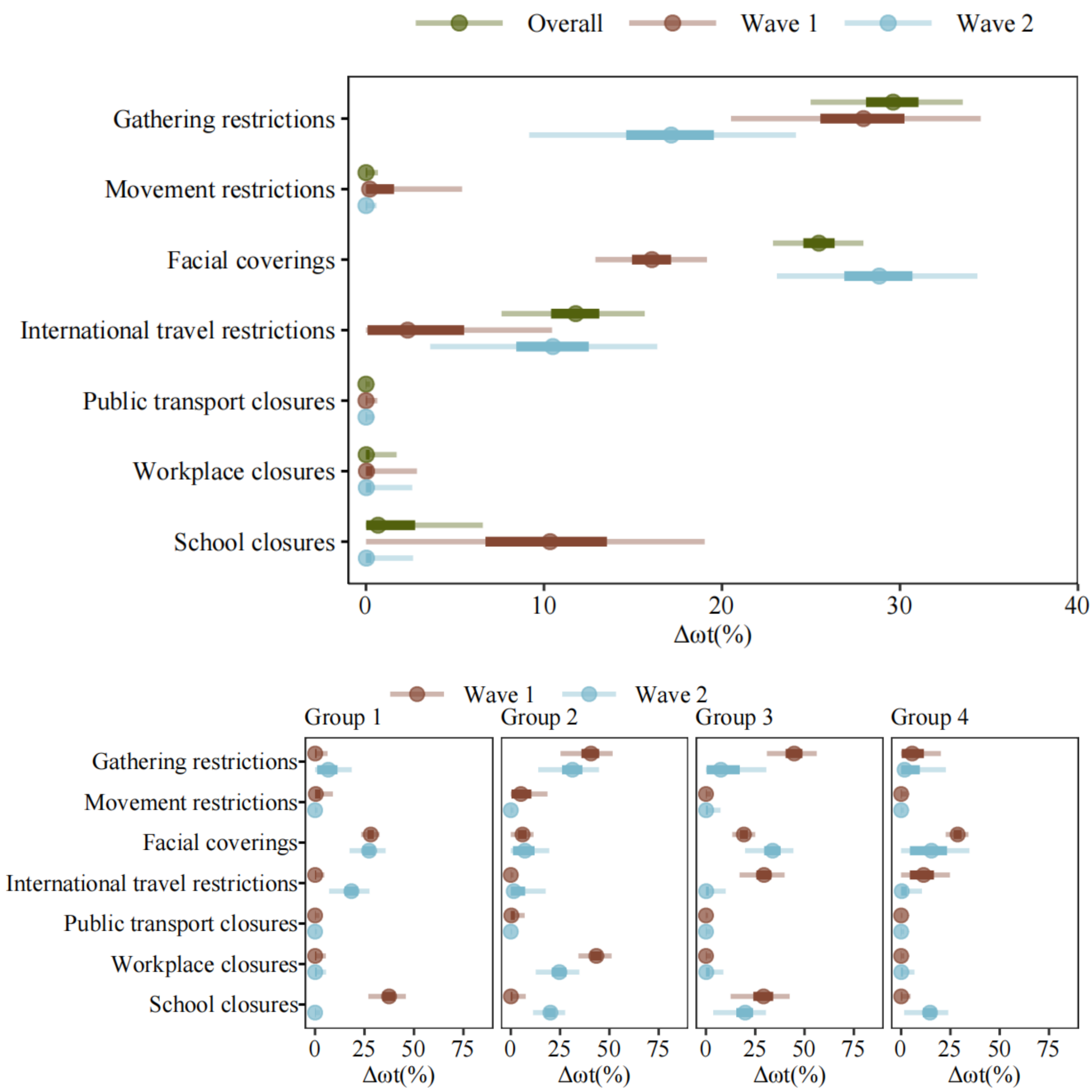

Fig. B4. The spatiotemporal effects of NPIs between country groups and waves, using the highest weekly growth rate as the baseline growth rate in the corresponding wave.

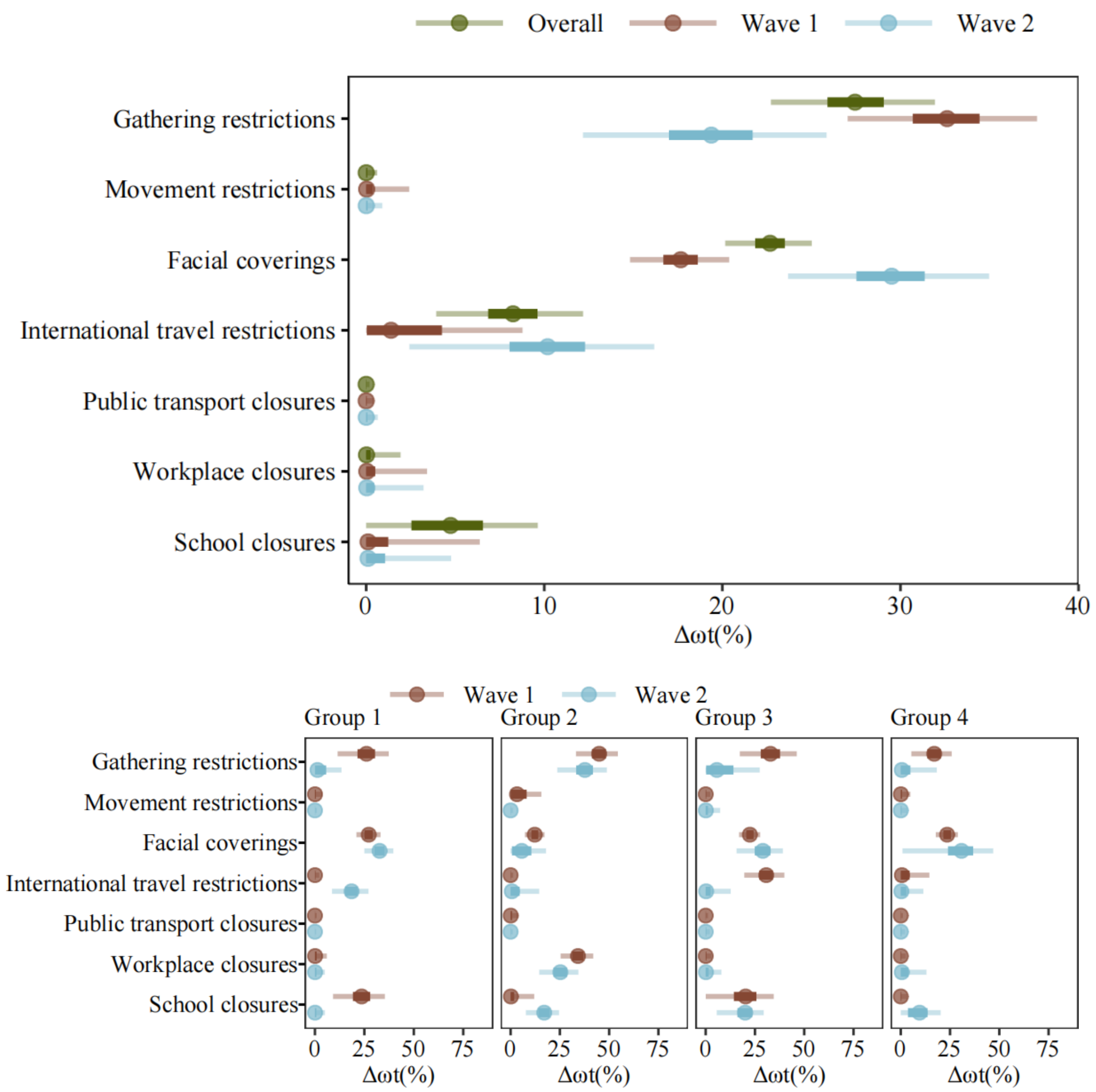

Fig. B5. The spatiotemporal effects of NPIs between country groups and waves, using the mean of the top five highest weekly growth rate as the baseline growth rate in the corresponding wave.

B.3 MCMC convergence

We calibrated our model with Markov chain Monte Carlo (MCMC) sampling algorithm. We used R-hat statistic and relative effective sample size to present MCMC performance during our model calibration. The results showed that our model calibrations with MCMC had a good convergence (see Fig. B6) and the sample size was effective in decomposing the variation in decay ratios into NPI effectiveness (see Fig. B7).

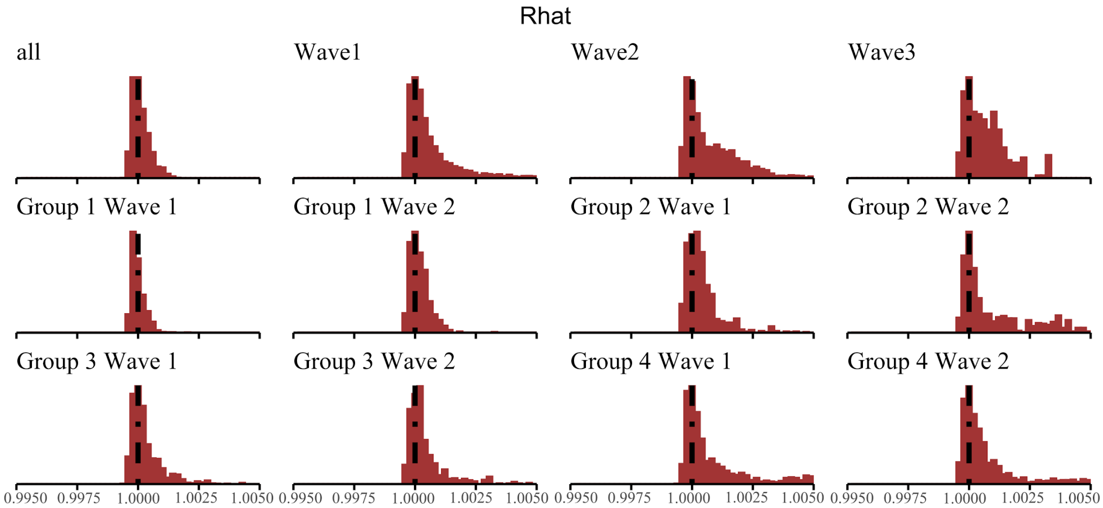

Fig. B6. R-hat statistic taken from a run using the default model with default settings and values for all parameters. Values are close to 1, indicating convergence.

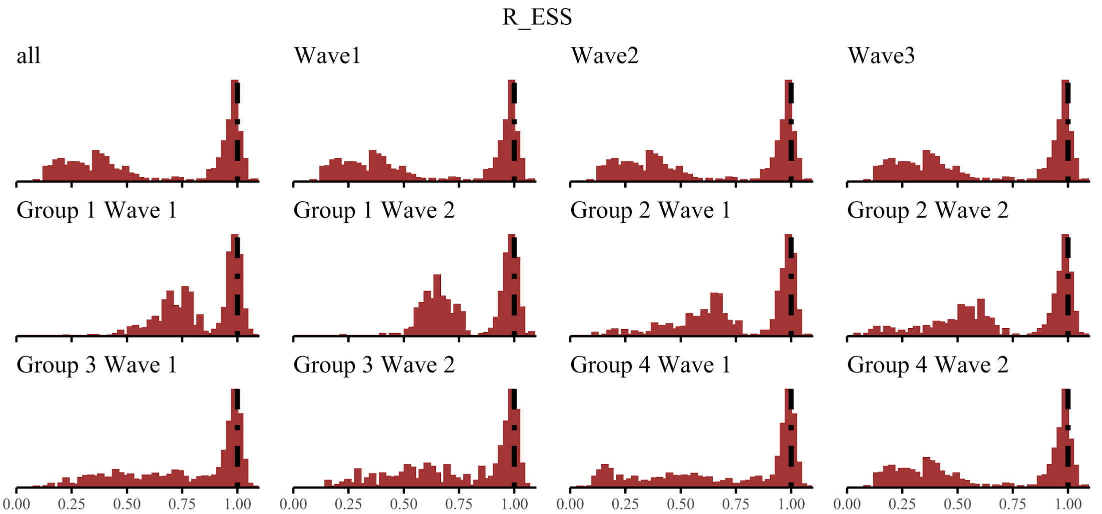

Fig. B7. Relative effective sample size taken from a run using the default model with default settings and values for all parameters. Value 1 indicates perfect decorrelation between samples. Values above (below) 1 indicate that the effective number of samples is higher (lower) than the actual number of samples due to negative (positive) correlation, respectively.

C Additional results

C.1 Collinearity

Nine common NPIs were analysed in this study, including school closures, workplace closures, public events cancellations, gathering restrictions, public transport closures, stay-at-home orders, internal movement restrictions, international travel restrictions, and facial coverings. To avoid the multicollinearity caused by high correlations and constraints in models to separately identify the NPI effect, we conducted a correlation analysis of NPI variables above. As shown in Fig. C1, NPIs having some causal meanings did have higher correlation coefficients (about 0.5). For this reason, we defined a "movement restrictions" variable using the average of intensities of stay-at-home orders and internal movement restrictions, and generated a new "gathering restrictions" variable from the average of intensities of public events cancellations and gathering restrictions.

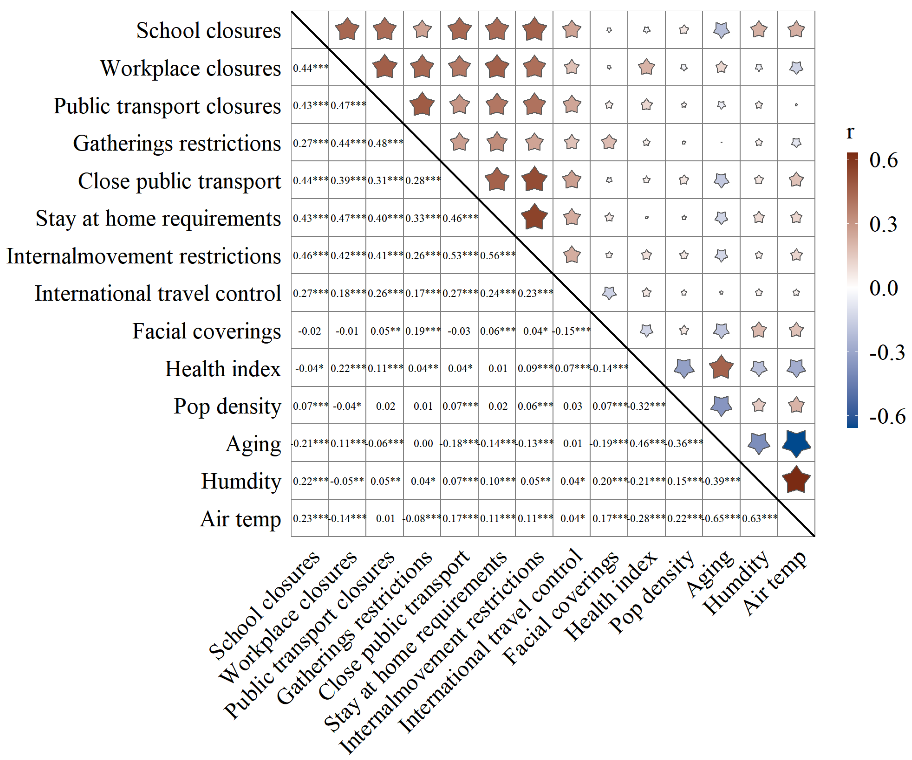

Fig. C1. Correlations between all collected explanatory variables in initial. (*: p < 0.05; **: p < 0.01; ***: p < 0.001).

C.2 Country groups and waves

To differentiate the performance of NPIs against COVID-19 across countries and waves, we divided the 133 study countries into four country groups based on their morbidity and mortality of COVID-19 together with geographical proximity (see Fig. C2) and then defined waves for each country (Table C1 – C4). In fact, the capacity of testing and diagnosis was a major confounder in different NPI effects across countries. However, the testing rate was not generally available for all the 133 countries. We used the number of testing per thousand people on 25 March 2021 to represent the testing rate in each country having testing data, where the morbidity and mortality of this country were represented by the total cases/deaths per million people at that day, respectively. Then, we tested the Pearson's product-moment correlation between the total tests per thousand people and the total cases/deaths per million people, respectively (see Table C1). The results showed that the testing rate was correlated to the morbidity and mortality indicating we divided 133 countries into four country groups implicitly by the testing rate.

Table C1. Pearson's product-moment correlation between the total tests per thousand people and the total cases/deaths per million people, respectively.

	Correlation	**P value**
The total cases per million people	0.5307 (95% CI, 0.3821, 0.6525)	2.089e-09
The total deaths per million people	0.2527 (95%CI, 0.0696,0.4193)	0.007457

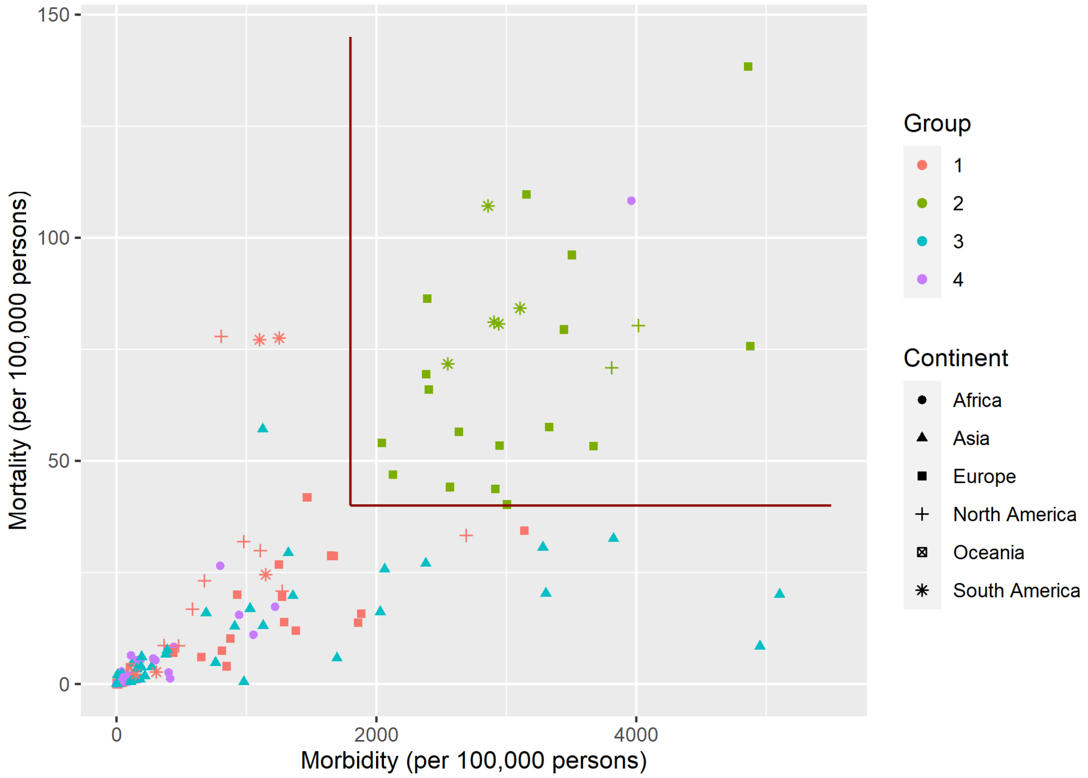

Fig. C2. Distribution of the 133 study countries in terms of morbidity and mortality. The red lines represent the grading thresholds for high morbidity and mortality.

Table C2. The start date and end date of each wave in each country of Group 1.

Country	Start Date (dd/mm/yy)			End Date (dd/mm/yy)		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Albania	04/24/20	01/09/21		01/04/21	03/25/21	
Australia	03/14/20	06/20/20		04/19/20	09/18/20	
Austria	03/10/20	09/01/20		05/01/20	03/25/21	
Bahamas	07/22/20			02/01/21		
Belarus	04/02/20	08/16/20		08/11/20	03/25/21	
Belize	08/08/20			03/25/21		
Bolivia	04/13/20	11/30/20		11/01/20	03/25/21	
Canada	03/14/20	09/20/20		06/20/20	03/25/21	
Costa Rica	03/26/20			03/25/21		
Croatia	03/19/20	10/10/20		04/24/20	03/25/21	
Cuba	03/28/20	07/31/20		05/20/20	03/25/21	
Cyprus	03/24/20	10/13/20	02/13/21	04/25/20	02/04/21	03/25/21
Denmark	03/10/20	07/27/20		05/10/20	03/25/21	
Dominican Republic	03/23/20	11/01/20		09/05/20	03/25/21	
Ecuador	03/19/20			03/25/21		
El Salvador	05/01/20	09/20/20		09/15/20	03/25/21	
Estonia	03/14/20	10/13/20		04/30/20	03/25/21	
Finland	03/13/20	08/05/20		06/07/20	03/25/21	
Germany	03/03/20	10/01/20		04/20/20	03/25/21	
Greece	03/11/20	08/10/20	01/22/21	04/10/20	01/11/21	03/25/21
Guatemala	04/22/20			03/25/21		
Guyana	08/02/20			03/25/21		
Haiti	05/12/20	12/03/20		10/05/20	03/25/21	
Honduras	04/03/20	02/04/21		01/12/21	03/25/21	
Iceland	03/13/20	09/16/20		04/22/20	12/23/20	
Ireland	03/17/20	09/01/20	12/10/20	05/23/20	11/10/20	03/25/21
Jamaica	04/18/20	08/15/20	12/28/20	05/10/20	10/30/20	03/25/21
Latvia	03/20/20	09/25/20		04/15/20	03/25/21	
Lithuania	03/22/20	10/01/20		05/01/20	03/25/21	
Mexico	03/20/20	11/15/20		11/01/20	03/25/21	
Norway	03/06/20	09/01/20	02/15/21	05/10/20	01/18/21	03/25/21
Paraguay	05/04/20	11/07/20		10/20/20	03/25/21	
Poland	03/17/20	02/03/21		01/12/21	03/25/21	
Portugal	03/15/20	09/20/20	12/23/20	05/10/20	12/13/21	03/25/21
Russia	03/20/20	09/25/20		08/10/20	03/25/21	
Suriname	06/06/20	12/10/20		11/09/20	03/25/21	
Trinidad and Tobago	08/09/20			03/25/21		
Ukraine	03/26/20	02/13/21		02/05/21	03/25/21	
Uruguay	03/23/20			03/25/21		
Venezuela	05/18/20	01/02/21		12/20/20	03/25/21	

Table C3. The start date and end date of each wave in each country of Group 2.

Country	Start Date (dd/mm/yy)			End Date (dd/mm/yy)		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Andorra	03/21/20	08/19/20		04/27/20	03/25/21	
Argentina	03/22/20			03/25/21		
Belgium	03/08/20	08/10/20		05/10/20	01/03/21	
Bosnia and Herzegovina	03/27/20	10/10/20		10/01/20	03/25/21	
Brazil	03/15/20	11/15/20		11/05/20	03/25/21	
Bulgaria	03/18/20	10/10/20	02/01/21	08/25/20	01/15/21	03/25/21
Chile	03/17/20			03/25/21		
Colombia	03/21/20	10/01/20		10/01/20	03/25/21	
Czechia	03/12/20	09/20/20	12/04/20	04/20/20	11/23/20	03/25/21
France	03/03/20	08/10/20		04/25/20	03/25/21	
Hungary	03/21/20	09/06/20		05/15/20	03/25/21	
Italy	02/24/20	10/01/20	02/10/21	06/10/20	01/25/21	03/25/21
Luxembourg	03/16/20	10/05/20		04/21/20	03/25/21	
Moldova	03/28/20	01/17/21		12/28/20	03/25/21	
Netherlands	03/07/20	07/30/20	11/29/20	05/20/20	11/03/20	03/25/21
Panama	03/21/20	11/15/20		11/01/20	03/25/21	
Peru	03/19/20	07/15/20	01/02/21	07/01/20	12/04/20	03/25/21
Slovenia	03/12/20	09/25/20		04/15/20	03/25/21	
Spain	03/04/20	07/13/20		04/30/20	03/25/21	
Sweden	03/07/20	09/25/20		07/05/20	03/25/21	
Switzerland	03/06/20	10/05/20		04/23/20	03/25/21	
United Kingdom	03/04/20	09/10/20	12/01/20	06/10/20	11/22/20	03/25/21
United States	03/06/20	06/20/20	10/01/20	06/01/20	09/10/20	03/25/21

Table C4. The start date and end date of each wave in each country of Group 3.

Country	Start Date (dd/mm/yy)			End Date (dd/mm/yy)		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Afghanistan	04/03/20	11/20/20		08/15/20	03/25/21	
Azerbaijan	03/30/20	10/10/20		08/05/20	03/25/21	
Bahrain	03/24/20	08/31/20	11/27/20	08/10/20	11/10/20	03/25/21
Bangladesh	04/08/20	11/15/20		10/01/20	03/25/21	
China	01/29/20	11/13/20		03/10/20	02/01/21	
Georgia	09/05/20			03/25/21		
India	03/20/20	02/08/21		01/25/21	03/25/21	
Indonesia	03/18/20			03/25/21		
Iran	02/27/20	05/05/20	01/19/21	04/30/20	12/17/20	03/25/21
Iraq	03/24/20	01/15/21		12/26/20	03/25/21	
Israel	03/16/20	06/01/20	11/27/20	05/08/20	11/01/20	03/25/21
Japan	03/05/20	06/25/20	10/15/20	05/17/20	09/25/20	03/25/21
Jordan	03/28/20	01/22/21		01/09/21	03/25/21	
Kazakhstan	03/29/20			09/10/20		
Kuwait	04/03/20	12/26/20		11/22/20	03/25/21	
Kyrgyzstan	04/09/20	10/01/20		08/26/20	03/25/21	
Lebanon	03/24/20			03/25/21		
Malaysia	03/09/20	10/01/20		06/13/20	03/25/21	
Myanmar	08/26/20			01/29/21		
Nepal	05/15/20	07/30/20		07/10/20	03/25/21	
Oman	04/06/20	08/27/20		08/09/20	03/25/21	
Pakistan	03/16/20	10/26/20		09/01/20	03/25/21	
Philippines	03/18/20	01/01/21		11/14/20	03/25/21	
Qatar	03/12/20	01/10/21		08/10/20	03/25/21	
Saudi Arabia	03/18/20			03/25/21		
Singapore	03/20/20	07/13/20		06/28/20	09/15/20	
South Korea	02/21/20	08/10/20	11/10/20	04/20/20	09/30/20	03/25/21
Sri Lanka	04/21/20	10/03/20		07/21/20	03/25/21	
Syria	07/04/20	10/01/20		09/20/20	03/25/21	
Tajikistan	05/07/20			08/15/20		
Thailand	03/16/20	12/18/20		04/30/20	03/25/21	
Turkey	03/20/20	11/21/20	01/23/21	05/25/20	01/12/21	03/25/21
United Arab Emirates	03/25/20	08/15/20		08/08/20	03/25/21	
Uzbekistan	04/03/20			12/01/20		

Table C5. The start date and end date of each wave in each country of Group 4.

Country	Start Date (dd/mm/yy)			End Date (dd/mm/yy)		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Algeria	03/23/20	10/14/20		10/13/20	03/25/21	
Angola	06/29/20			03/25/21		
Benin	05/07/20	06/08/20		05/21/20	03/25/21	
Botswana	06/30/20	10/20/20		10/05/20	03/25/21	
Burkina Faso	03/23/20	12/01/20		05/10/20	03/25/21	
Cameroon	04/01/20			03/05/21		
Cape Verde	05/06/20	12/28/20		12/01/20	03/25/21	
Central African Republic	05/14/20			08/05/20		
Chad	05/04/20	08/15/20		06/15/20	03/25/21	
Congo	04/18/20	12/01/20		09/20/20	03/25/21	
Cote d'Ivoire	04/07/20	12/19/20		09/05/20	03/25/21	
Djibouti	04/08/20	05/09/20		05/06/20	07/01/20	
Egypt	03/19/20	10/20/20		08/20/20	03/25/21	
Eswatini	06/10/20	12/01/20		10/30/20	03/25/21	
Ethiopia	05/22/20	01/15/21		12/29/20	03/25/21	
Gabon	04/21/20	01/01/21		08/15/20	03/25/21	
Gambia	07/23/20	01/23/21		09/30/20	03/25/21	
Ghana	04/10/20	10/17/20		09/20/20	03/25/21	
Guinea	04/05/20			03/25/21		
Kenya	05/06/20	10/07/20	02/15/21	09/01/20	01/06/21	03/25/21
Libya	06/09/20			03/25/21		
Madagascar	05/20/20			10/18/20		
Malawi	05/28/20	12/15/20		09/05/20	03/25/21	
Mauritania	05/19/20	11/01/20		10/10/20	03/25/21	
Morocco	03/25/20			03/25/21		
Mozambique	06/01/20	12/20/20		11/04/20	03/25/21	
Namibia	06/27/20	11/13/20		10/20/20	03/25/21	
Nigeria	04/16/20	11/30/20		09/20/20	03/25/21	
Senegal	03/27/20	11/25/20		11/01/20	03/25/21	
Somalia	04/17/20	08/20/20	02/01/21	08/05/20	12/25/20	03/25/21
South Africa	03/20/20	11/10/20		09/20/20	03/25/21	
Sudan	04/21/20	11/05/20		09/15/20	03/25/21	
Tunisia	03/27/20			03/25/21		
Uganda	05/30/20			03/25/21		
Zambia	05/08/20	12/01/20		11/02/20	03/25/21	
Zimbabwe	05/29/20	11/10/20		09/20/20	03/25/21	

C.3 The highest efficacy in theory

To understand the uncertainty of estimates of NPI effectiveness, here, we also demonstrate the potential impact of NPIs on reducing COVID-19 transmission with their highest intensity, where the results in the main text were associated with the empirical average intensity in the real world. NPIs effects with the empirical average intensity demonstrated that gathering restrictions (contributing 27.83% in the infection rate reductions), facial coverings (16.79%) and school closures (10.08%) were the most effective NPIs in the first wave, and changed to facial coverings (30.04%), gathering restrictions (17.51%) and international travel restrictions (9.22%) in the second wave. Fig. C3 – C4 showed that NPIs effects with the highest intensity only increased the decay ratio contributed by each NPIs without changing their relative efficacy ranks.

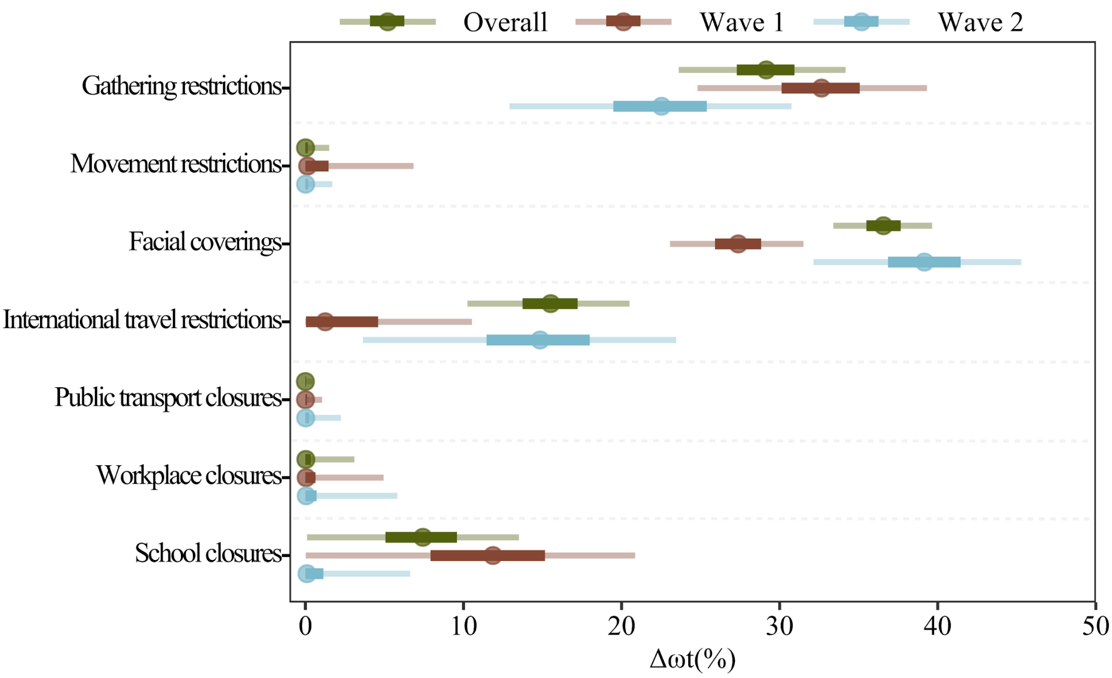

Fig. C3. The theoretically highest efficacy of NPIs in contrast to Fig. 1. The coefficients (α_i) of NPIs parameters in different time were calibrated by the default model setting with corresponding data contexts. The effectiveness of NPI i was calculated by $1 - \exp(-\alpha_i)$.

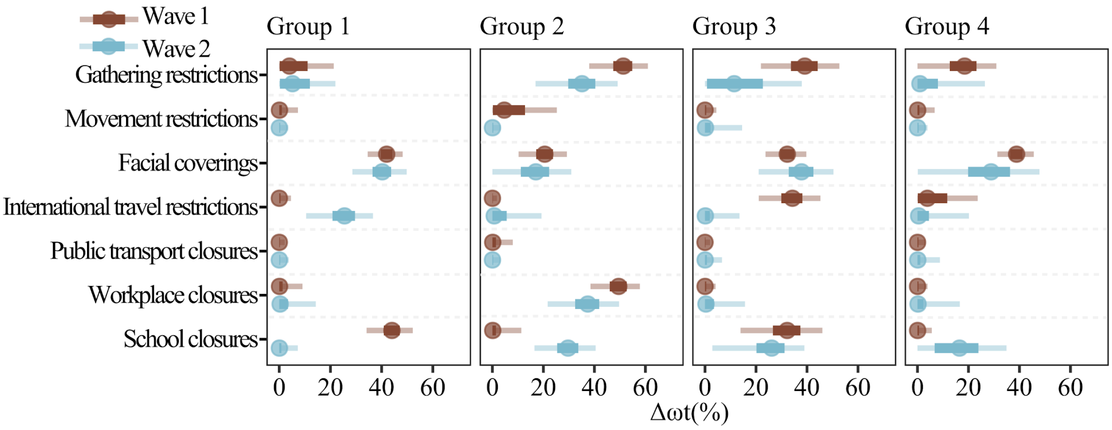

Fig. C4. The theoretically highest efficacy of NPIs in contrast to Fig. 2. The coefficients (α_i) of NPIs parameters in different space and time were calibrated by the default model setting with corresponding data contexts. The effectiveness of NPI i was calculated by $1 - \exp{(-\alpha_i)}$.

C.4 Efficacy of COVID-19 interventions in the third wave

Only 22 countries, including Cyprus, Greece, Ireland, Jamaica, Norway, Portugal, Bulgaria, Czechia, Italy, Netherlands, Peru, United Kingdom, United States, Bahrain, Iran, Israel, Japan, South Korea, Turkey, Kenya, Somalia, presented a third wave. Therefore, we estimated the effects of COVID-19 interventions for the 22 countries jointly regardless of their country groups. However, the results were less robust than those in the first and second waves because of the limited data. The most effective NPI in the third wave of COVID-19 worldwide was school closures (median 36.46%, interquartile range [IQR] 29.93 - 41.78%), followed by international travel control (6.72%, 0.15 - 26.84%) played a moderate role in reducing, whereas other NPIs had limited efficacy (< 1%) (see Fig. C5). The differences of NPI effects among three waves were tested using a Wilcoxon signed-rank test, a non-parametric statistical hypothesis test for comparing NPIs effects between pairs of the three waves (see Fig. C6). The results showed that the relative effects of NPIs were significantly changed between waves.

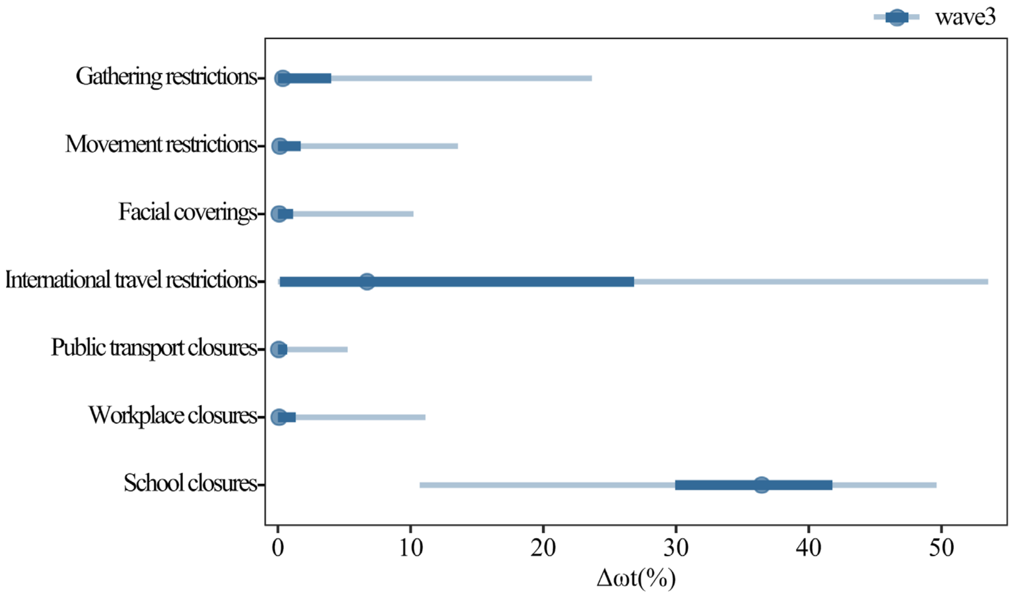

Fig. C5. Effectiveness of COVID-19 interventions in the third wave.

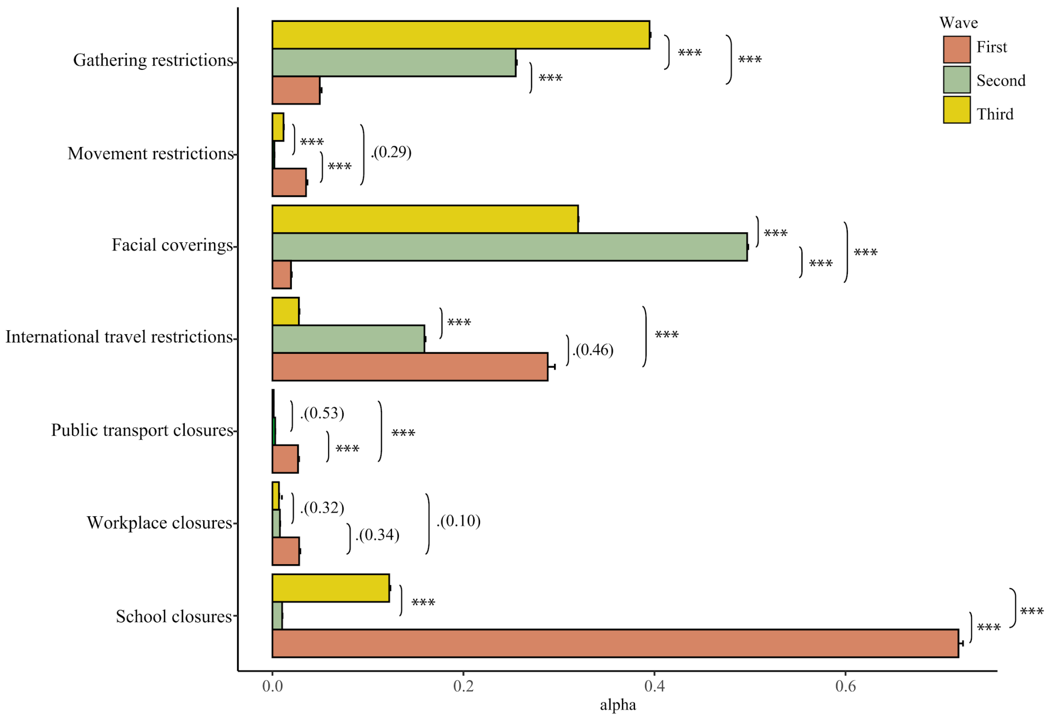

Fig. C6. Difference of NPI effects among the three COVID-19 waves. The comparison indicates that effects of policies were significantly changed between waves. In general, effects of policies in the second wave were higher than those in the first wave, and effects in the third wave were higher than those in the second wave. In the first wave, COVID-19 interventions with relatively high effects included gathering restrictions, facial coverings, and school closures. In the second wave, the primary effective interventions were workplace closures, facial coverings, and international travel restrictions. In the third wave, the major NPIs with effectiveness were gathering restrictions, international travel restrictions, and school closures. NPIs were ranked by the decay ratio in the COVID-19 infection rate estimated in the first wave. (*: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$).

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