Evaluation of Effectiveness of Global COVID-19 Vaccination Campaign

Daihai He,[1] Sheikh Taslim Ali,[1] Guihong Fan, Daozhou Gao, Haitao Song, Yijun Lou, Shi Zhao, Benjamin J. Cowling, Lewi Stone

To model estimated deaths averted by COVID-19 vaccines, we used state-of-the-art mathematical modeling, likelihood-based inference, and reported COVID-19 death and vaccination data. We estimated that >1.5 million deaths were averted in 12 countries. Our model can help assess effectiveness of the vaccination program, which is crucial for curbing the COVID-19 pandemic.

The real-time evaluation of the effectiveness of vaccination campaigns at the population level is essential for public health policy makers and scientists working toward successful mitigation of the COVID-19 pandemic. Vaccination coverage against SARS-CoV-2 has increased globally and become even more crucial because of the emergence of variants of concern that have increased transmissibility and lethality (*1*). We assessed population-level effects of the COVID-19 vaccination campaign in 12 countries worldwide before November 14, 2021. Our modeling framework enabled us to disentangle the effects of vaccination and a time-varying transmission rate. We also fit the model to multiple waves of death in these countries before the Omicron variant was detected.

Author affiliations: The Hong Kong Polytechnic University, Hong Kong, China (D. He, Y. Lou); The University of Hong Kong, Hong Konga (S.T. Ali, B.J. Cowling); The Laboratory of Data Discovery for Health, Hong Kong Science and Technology Park, Hong Kong (S.T. Ali, B.J. Cowling); Columbus State University, Columbus, Georgia, USA (G. Fan); Shanghai Normal University, Shanghai, China (D. Gao); Shanxi University, Taiyuan, China (H. Song); Chinese University of Hong Kong, Hong Kong, China (S. Zhao); RMIT University, Melbourne, Victoria, Australia and Tel Aviv University, Tel Aviv, Israel (L. Stone)

DOI: https://doi.org/10.3201/eid2809.212226

The Study

We developed a transmission modeling approach to analyze diverse spatiotemporal datasets from different countries and attempted to evaluate the COVID-19 vaccination campaign in real time by adapting our related earlier work (*2*). The COVID-19 pandemic continues to be complex because of various short-term enforcements of public health and social measures (e.g., lockdowns), emergence of new virus variants, shifts in age profiles of infected persons, availability of multiple vaccines with different effectiveness, reinfection, and other factors. However, many of these factors are reflected in the key measure, the time-varying transmission rate, $\beta(t)$, which characterizes the changes in contact pattern in the population over time. Vaccination is intended to reduce the susceptibility of the population to the disease. Disentangling real-time variation in $\beta(t)$ and the effectiveness of vaccination is crucial for assessing the vaccination program and might only be achievable through mathematical modeling.

Country-specific mortality data generally provide a more reliable characterization of the key epidemic dynamics than data on reported confirmed COVID-19 cases, which rely on widely different testing and reporting systems that can vary temporally and spatially and be subject to various ascertainment rates. For our analysis, we obtained data from the World Health Organization, including daily confirmed COVID-19 death numbers (*3*,*4*) and the proportion of the population fully vaccinated (2 doses) for 12 countries: the United Kingdom, Italy, the United States, Spain, Russia, France, India, Brazil, Colombia, Mexico, Germany, and Canada (*5*). We used a partially observed Markov process (*6*) model and maximum-likelihood–based iterative filtering technique to fit and make predictions on the mortality

[1]These authors contributed equally to this work.

data by susceptible-exposed-infectious-recovered–type models (Appendix, https://wwwnc.cdc.gov/EID/article/28/9/21-2226-App1.pdf).

We estimated the transmission rate, $\beta(t)$, which reflects the simultaneous effect of all possible interventions, excluding vaccination, over the study period. The model assumed a 14-day delay between the 2 vaccine doses and the time for the vaccine to take effect. We set the unified vaccine efficacy (VE; represented by η) at 85% and examined vaccine effectiveness from 75% to 95% (Appendix). The COVID-19 surveillance data we used were originally collected from public domains; thus, neither ethical approval nor patient consent was applicable.

To evaluate effectiveness of vaccination and the lives saved, we compared the final model fit and simulations of the baseline scenario of vaccination to the counterfactual scenario of without vaccination by setting VE to $\eta = 0$. Vaccination coverage was defined as the proportion of the country's population that was fully vaccinated (i.e., either receiving 2 vaccine doses or receiving 1 vaccine dose after infection). We plotted vaccination coverage as a function of time for the 12 countries (Appendix Figure 1).

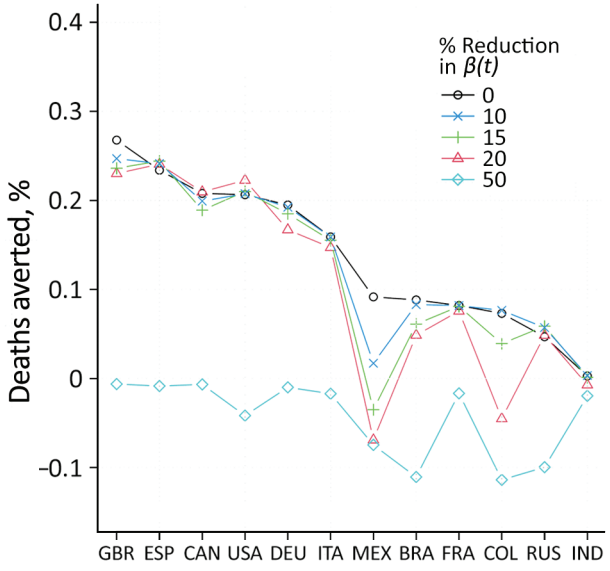

Figure. Deaths averted because of vaccination according to a model used to evaluate effectiveness of global COVID-19 vaccination campaign. The graph represents the difference in total deaths under the counterfactual scenario (without vaccination) and under the baseline scenario (with vaccination) as a percentage of the population. We compared 5 counterfactual scenarios under without-vaccination in which we set the transmission rates after April 16, 2021, to reduce by 0, 10%, 15%, 20%, and 50% compared with the baseline scenario. The y-axis 0.3% means 3 persons per 1,000 population were saved from COVID-19–related death because of vaccination. The absolute value of negative deaths averted results from substantial reduction in transmission rate, rather than vaccination. $\beta(t)$, time-varying transmission rate; BRA, Brazil; CAN, Canada; COL, Colombia; DEU, Germany; ESP, Spain; FRA, France; GBR, Great Britain (United Kingdom); IND, India; ITA, Italy; MEX, Mexico; RUS, Russia; USA, United States.

We compared and fitted the model to data on weekly confirmed waves of COVID-19 deaths in the 12 countries during 2020–2021 and reconstructed transmission rates (Appendix Figure 1, panels A–I). We then used the model to reconstruct COVID-19 deaths that would have occurred in these countries in the hypothetical without-vaccination counterfactual scenario (i.e., in complete absence of vaccination). Thus, we could compare the observed mortality rate against that of the model's without-vaccination scenario (Appendix Figure 1).

We found that vaccination campaigns saved the lives of up to 1,822,670 (0.069% of the total population) persons in these 12 countries (Appendix Table 2). For instance, the United States reported 416,842 confirmed deaths during January 1–November 14, 2021 (Appendix Figure 1, panel E). According to the model's without-vaccination predictions, had the United States not initiated a vaccination program, 1,102,958 deaths would have occurred there during the same time frame. Thus, vaccination saved 686,115 lives (0.2% of the population) in the United States during the study period. The model estimated that vaccination averted 182,464 (0.27% of the population) deaths in the United Kingdom; 109,367 (0.23% of the population) deaths in Spain; 78,969 (0.2% of the population) deaths in Canada; and 96,008 (0.16% of the population) deaths in Italy. Vaccination coverage in each of these countries was >60% (Appendix Table 2).

Vaccination seems to have prevented severe Delta waves in Italy, France, Germany, and Canada during the second half of 2021 (Appendix Figure 1). For Russia, India, Brazil, Colombia, and Mexico, where vaccine coverage was relatively low or delayed, vaccination had only a mild effect on the epidemic dynamics and mortality rates (Appendix Table 2).

Widely available vaccines might encourage risky behavioral practices among the population, which might be less prevalent in the absence of a countrywide vaccination campaign. Our idealized reconstruction method ignores this possibility and might have led to overestimation of both the transmission rate in the without-vaccination scenario and the number of deaths averted (*7*). To examine this possibility further, we plotted the changes in deaths averted by vaccination as a percentage of the population as calculated for 5 levels of transmission rate reduction (Figure). The reductions are intended to compensate for risky behaviors persons might engage in when vaccinated. We considered these as

5 counterfactual without-vaccination scenarios in which transmission rates after April 16, 2021, were reduced to 0 (scenario 1), 10% (scenario 2), 15% (scenario 3), 20% (scenario 4), and 50% (scenario 5) of the level of transmissibility in the baseline scenario. These counterfactual scenarios were intended to show that any overestimation of deaths averted based on the idealized counterfactual scenario 1 (0 reduction) was generally minimal unless the transmission rate was reduced by >25% (Appendix).

We conducted additional sensitivity analyses on the model performance and counterfactual scenarios to explore parameter ranges and several different model structures, constructing more complex models of imperfect vaccination (Appendix Tables 1–3, Figures 2, 3). Our estimates of deaths averted show reasonable robustness to changes in the model structure and parameters.

Conclusions

We used a disease transmission model and likelihood-based inference approach to evaluate effectiveness of COVID-19 vaccination in 12 countries. Our analysis indicated that vaccination averted >1.5 million deaths in the studied countries until November 14, 2021, or at least precluded the need to reintroduce more stringent public health and social measures to control transmission.

Of our several assumptions for this evaluation, we first assumed the infection fatality ratio was roughly constant over time (*1*,*8*,*9*). We evaluated a second model in which we allowed the infection fatality ratio to decrease because of vaccination (Appendix). In addition, we used a unified constant VE although VE differs across countries, demographic characteristics (*10*), and type of vaccine and its coverage (*11*). Nonetheless, our modeling framework enabled us to assess the effect of vaccination on a time-varying transmission rate. Our model can help assess effectiveness of the COVID-19 vaccination program, which is crucial for curbing the COVID-19 pandemic.

This study was supported by the Collaborative Research Fund (grant no. HKU C7123-20G) of the Research Grants Council of Hong Kong, China. D.G. was partially supported by the National Science Foundation of Shanghai (grant no. 20ZR1440600). H.S. was partially supported by the National Natural Science Foundation of China (grant no. 12171291), the Fund Program for the Scientific Activities of Selected Returned Overseas Professionals in Shanxi Province (grant no. 20200001), and the Fundamental Research Program of Shanxi Province (grant no. 20210302124018). B.J.C. is supported by the AIR@innoHK program of the Innovation and Technology Commission of the Hong Kong Special Administrative Region Government.

The funding agencies had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; or decision to submit the manuscript for publication.

D.H., S.T.A., and L.S. conceived the study and conducted the analysis. All authors discussed the results, drafted the manuscript, revised the manuscript, read the manuscript, and approved it for publishing.

B.J.C. has consulted for AstraZeneca, GlaxoSmithKline, Moderna, Pfizer, Roche, and Sanofi Pasteur.

About the Author

Dr. He is an associate professor in the Department of Mathematics, The Hong Kong Polytechnic University, Hong Kong Special Administrative Region, China. His primary areas of research are infectious disease modeling and mathematical epidemiology, with a focus on understanding mechanisms of virus transmission dynamic and control measures.

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Address for correspondence: Lewi Stone, RMIT University, 124 La Trobe St., Melbourne, Victoria 3000 Australia; email: lewistone100@gmail.com

Article DOI: https://doi.org/10.3201/eid2809.212226

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Appendix

Additional Methods

Transmission Models and Fitting

We make use of the classic susceptible-exposed-infectious-recovered (SEIR) model. The rate at which the susceptible population is vaccinated is denoted by $\tilde{v}(t)$. Studies note that vaccination induces different levels of protection, which are associated with different risks of breakthrough infection. For simplicity, we assume that vaccinated susceptible persons can be divided into 2 groups: a high protection group and a low protection group. The high protection group is assumed to enter the recovered class (R) and gain long-term full protection after vaccination. There are different approaches to deal with the low protection group. Thus, we analyzed 2 different models based on the 2 different ways to deal with the low protection group. In model 1, the low protection group comprises persons who remain in the Susceptible (*S*) class after vaccination and are available for infection and possibly revaccination; in model 2, the low protection group comprises persons who enter the V class after vaccination, where they become available for infection at reduced susceptibility.

Model 1

The equations of model 1 are derived from previous studies (*1*–*3*). Model 1 is:

$$\dot{S} = -\frac{\beta SI}{N} - \eta\tilde{v}S,$$
$$\dot{E} = \frac{\beta SI}{N} - \sigma\mathrm{E},$$
$$\dot{I} = \sigma E - \gamma\mathrm{I},$$
$$\dot{H} = \pi\gamma I - \kappa\mathrm{H},$$
$$\dot{D} = \theta\kappa\mathrm{H},$$
$$\dot{R} = \eta\tilde{v}\mathrm{S} + (1-\pi)\gamma\mathrm{I} + (1-\theta)\kappa\mathrm{H}.$$

where S, E, I, H, D, and R denote the mean number of the population that are susceptible (S), exposed (E), infectious (I), a delayed class of hospitalized (H) persons between infectious (I) and dead (D) and recovered (R), respectively. η is the proportion that become fully protected after vaccination (a proxy measure of vaccine efficacy). β is the transmission rate, σ is the rate at which exposed persons become infectious, γ is the recovery rate, π is the proportion of infectious persons that enter the delayed class H, κ the rate persons discharged from the delayed H class, and θ the proportion of deaths of the discharged persons. We suppose that reinfection and breakthrough infections are not significant in terms of contributing to deaths, which is a reasonable first approximation.

Following the literature, σ = 0.5 per day, γ = 0.33 per day and κ = 0.0833 per day, such that the mean generation time (sum of mean latent period and mean infectious period) is 5 days (*4*,*5*), and the mean duration from infection to death is 17 days, which are largely in line with observations (*6*). It is assumed that π = 0.15 for countries other than India where π = 0.03 (*7*,*8*), and β and θ are estimated through fitting. The choice of π is not our immediate interest because we do not fit data for H; hence it is not dealt with in our fitting exercise. The infection fatality rate (IFR) = $\theta\pi$. The choice of π = 0.03 in India was based on considerations of the infection to case ratio there (as high as 24:1), low reported deaths and high estimates of seroprevalence in India (*8*). Namely the reported deaths are relatively low per capita and all serologic studies in India suggest a large proportion of the population have been infected. We assume θ is in the range of 0.02–0.04, which means an IFR in the range of 0.3%–0.6% in the 11 countries except for India, which is reasonable (*7*). The IFR in India is 1/5 of that in the other 11 countries (*8*).

We allowed the time-dependent transmission rate, $\beta(t)$, to be estimated by an exponential cubic spline (*9*) with several nodes n_β = 10 and an upper limit of 608, such that the reproduction number (without vaccine) is in a reasonable range with an upper limit of 5. The choice of cubic

spline was the same as in our previous studies in modeling multiple waves of infections (*10–12*). Alternatively, one could use the mobility index data in the transmission instead of cubic spline. However, the mobility index data alone are insufficient (*7*,*13*,*14*). The emergence of new variants with increased transmissibility will increase the overall transmissibility in our 1-strain model.

Because the risk for infection is not uniform in the population and some persons might have strong protection compared with others, we assumed for initial conditions that 5% of the population were somehow protected or possibly had pre-existing cross-immunity from other coronaviruses (*15*). The initial *E* and *I* populations were equal and randomly chosen in the range of 0–10,000. The *H* class was given 1/10 the population of the *I* class, and the *D* class had 1/10 the population in the *H* class.

A partially observed Markov process (POMP) model with a maximum likelihood based iterated filtering technique was used to fit the mortality data (*11*). As mentioned, the transmission rate, $\beta(t)$, was taken as an exponential cubic spline (*9*) to account for the simultaneous impact of all possible interventions excluding vaccination. The fitting procedure can be found at https://kingaa.github.io/sbied. Appendix Figure 1 shows the fitting and simulation results of model 1 with vaccine efficacy (VE) set at 85%.

Model 2

In model 2, we extended model 1 by including an additional vaccinated compartment (*V*) for tracking the dynamics of vaccinated but only partially susceptible persons (*16*). Thus, we further consider reduced susceptibility, reduced fatality rate due to vaccination, or both. The equations for model 2 are:

$$\dot{S} = -\frac{\beta SI}{N} - \tilde{\nu}S,$$

$$\dot{V} = (1-\eta)\tilde{\nu}S - \frac{\psi\beta VI}{N},$$

$$\dot{E} = \frac{\beta SI}{N} + \frac{\psi\beta VI}{N} - \sigma E,$$

$$\dot{I} = \sigma E - \gamma I,$$

$$\dot{H} = \pi\gamma I - \kappa H,$$

$$\dot{D} = \theta\kappa H,$$

$$\dot{R} = \eta\tilde{v}S + (1-\pi)\gamma I + (1-\theta)\kappa H,$$

Here, ψ is the parameter that accounts for the reduced susceptibility of vaccinated persons, where $0<\psi\leq 1$. We show fitting results of model 2 with $\psi = 0.6$ (Appendix Figure 2).

Vaccination Rate

We downloaded data for the vaccination rate, $v(t)$, from the Our World in Data Web site (*17*,*18*), which is the proportion of the whole population vaccinated per unit of time. First, we calculated $\tilde{v}(t)$, the proportion of susceptible persons vaccinated per unit of time. The population is divided into 2 groups, vaccinated and unvaccinated; vaccination is only delivered to the unvaccinated group, which includes both susceptible and recovered persons. The rate at which susceptible persons are vaccinated is given as

$$\tilde{v}(t) = v(t)/(1 - \int_0^{t-1} v(s)\mathrm{ds})$$

where t is in units of days (*1–3*,*16*). We assume a delay of 14 days between the delivery of the second vaccine dose and the onset of protection, thus:

$$\tilde{v}(t+14) = v(t)/(1 - \int_0^{t-1} v(s)\mathrm{ds}).$$

Asymptomatic Cases

A large proportion of infections are asymptomatic and less infectious than symptomatic cases, as reported in our earlier works (*19*,*20*). However, we adopted a simple homogeneous model that aggregates both the symptomatic and asymptomatic cases following other previous studies, such as Yang and Shaman (*13*).

Discussion

It is possible that population behavioral patterns become more careless and unstable due the widespread availability of vaccines over time (*21*). This might modulate the transmissibility across the epidemic and consequently cause us to overestimate the total deaths averted because of a vaccination campaign. To assess the effects of the vaccination, we compared the scenarios of with-vaccination (baseline scenario) and without-vaccination (counterfactual scenario). To test the sensitivity of varied transmissibility, we considered 5 sets of simulations all without-

vaccination ($v(t) = 0$), but the transmission rate after April 16, 2021 was reduced by 0%, 10%, 15%, 20%, and 50% of the baseline scenario's level (reconstructed transmissibility from data with vaccination). We plotted the number of deaths that would have been averted as a percentage of the total population of each country with model 1 (VE = 85%) and these 5 counterfactual scenarios on transmissibility (Figure in main text).

Thus, if the reduction in model transmissibility is very large, say 50%, the disease will go extinct and few persons will die, which is not so different to the scenario under a successful vaccination policy. As such, we saw virtually no difference between the model simulations with 50% transmission reduction and what happened in all vaccinated countries (Figure in main text), because the vaccinations averted many of the possible deaths. Thus, the difference in deaths averted for the 2 scenarios appears as ≈0%.

If no reduction in transmission occurs (i.e., 0% reduction graph in Figure in main text) but vaccination is switched off, then most countries have major epidemics in this scenario and the differences in deaths averted is major compared to the vaccinated baseline. This is the scenario we discuss in the main text and which we are testing for possible overestimation.

We examined what happens in between those 2 extremes. Of note, according to Figure in main text, a 20% transmission reduction is not enough to bring about disease extinction and the *I* class is still able to grow exponentially in some phases for many countries. As such, we saw that for many countries, such as the United Kingdom, Spain, Germany, the United States, Italy, and France, this 20% reduction in transmission is not very different in terms of deaths averted than the 0% transmission reduction, and implies our overestimation not too large. We saw <15% difference in the deaths averted in 8 of the 12 countries, namely the United Kingdom, Italy, Russia, France, the United States, Spain, Germany, and Canada. On the other hand, with the 20% transmission reduction in 2 countries, Mexico and Columbia, the herd immunity threshold was crossed and the disease rapidly became extinct. This indicates that a 20% reduction in the transmission rate is probably too large to be reasonable, and that level of reckless behavior is unrealistic, which was confirmed by examining a scenario of 25% transmission reduction, which led to disease extinction in most countries.

Other than the above, we know of no other method to explore the effects of reckless behavior that might lead to overestimations but recognize this as a possible limitation of the method.

Sensitivity Analysis

In the above, we consider model 1 with VE = 85% and model 2 with susceptibility reduction $\psi = 0.6$. Here, we consider variations in the model. We consider model 1 with VE = 75% and VE = 95%. We consider model 2 with $\psi = 0.8$. In model 2, we further replace θ with the following equation:

$$\tilde{\theta} = \left(1 - \varepsilon \int_0^t v(s)\, ds\right) \theta$$

Namely, we assume that the death rate, $\tilde{\theta}$, drops while the proportion of vaccinated persons increases at a rate of the following:

$\int_0^t v(s)\, ds$, in which limit $\int_0^T v(s)\, ds = 1$

and the death rate, $\tilde{\theta}$, could drop by $\varepsilon = 25\%$. All together, we have 6 model variations (Appendix Table 1).

We fit these 6 model variations (including our baseline model, which is model 1 version 1 with VE = 85%) to the respective data to find the maximum-likelihood parameter estimates. All model variations fit the data reasonably well (Appendix Figure 2). We compared the model-estimated deaths in 2021 (up to November 14, 2021) in 12 countries under the 6 model variations (Appendix Tables 2, 3; Appendix Figure 3), together with the first counterfactual scenario of without-vaccination, $v(t) = 0$.

We found that the 12 countries fall in 2 groups, the first group of counties (including the United Kingdom, Spain, Canada, the United States, Germany, and Italy), had 0.1%–0.3% of their population saved from death while the second group of countries (including Mexico, Brazil, France, Colombia, Russia, and India) had <0.1% of their population saved. This pattern is insensitive to parameter values we considered, despite substantial changes across 6 model variations.

From this and a closer examination (Appendix Tables 2, 3), we concluded that our estimates of deaths averted show reasonable robustness to changes in the model structure and

parameters. We have further confirmed this with a study of much larger number of model variations than reported here.

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Appendix Table 1. Variations in parameter settings for models used to evaluate of effectiveness of global COVID-19 vaccination campaign*

Model	Variation	η	ψ	ε
Model 1	1	0.85	–	–
	2	0.75	–	–
	3	0.95	–	–
Model 2	1	0.85	0.6	0
	2	0.85	0.8	0
	3	0.85	0.8	0.25

*Model 1 is a Susceptible-Exposed-Infectious-Hospitalized-Died-Recovered (SEIHDR) model; model 2 is an extension of model 1 in which the vaccinated group (V) has reduced susceptibility (controlled by ψ) and reduced death rates (controlled by ε). η is the proportion of the population that becomes fully protected after vaccination, a proxy measure of vaccine efficacy.

Appendix Table 2. Estimated effects of vaccination on COVID-19 mortality in 12 countries during period January 1–November 14, 2021, according to model 1 used to evaluate of effectiveness of global COVID-19 vaccination campaign*

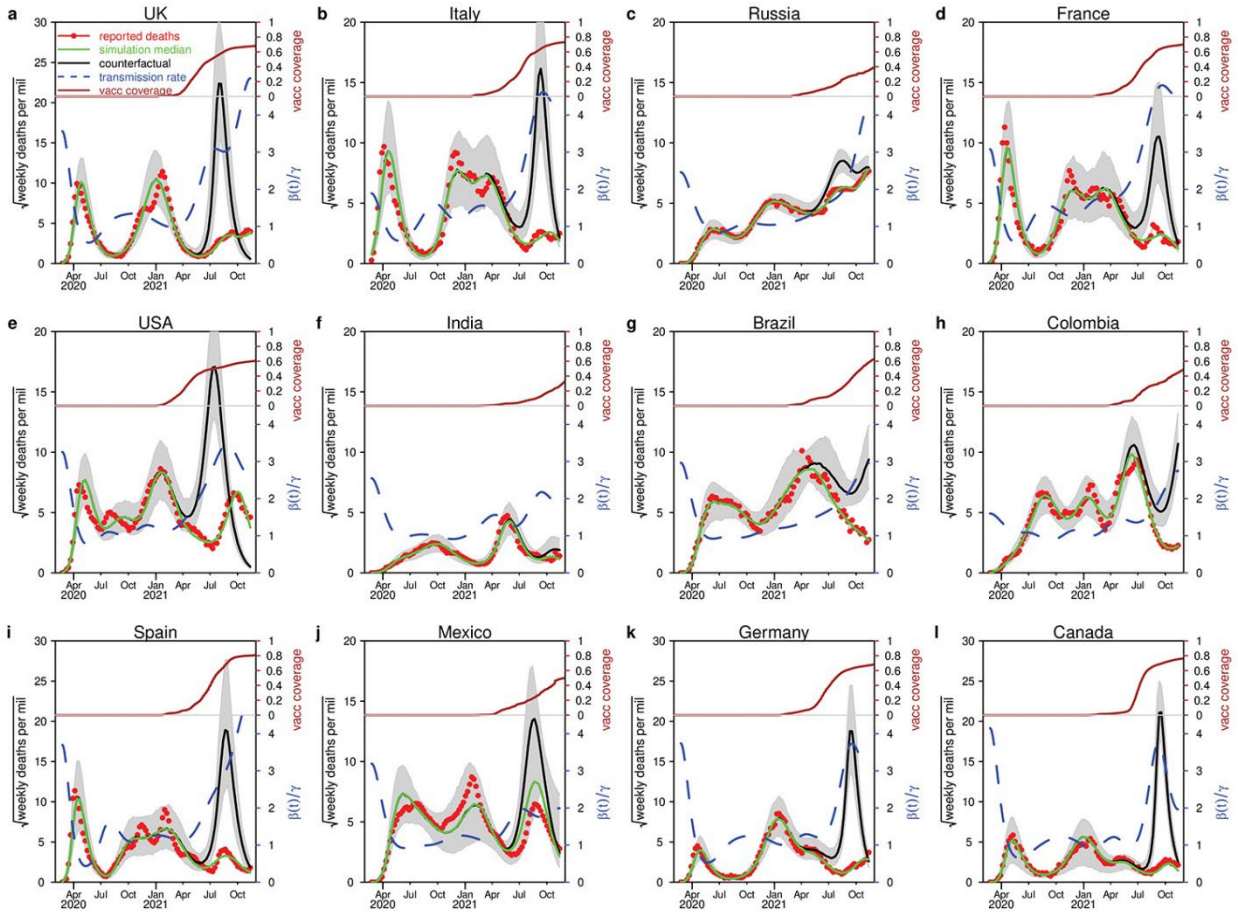
	Version 1			Version 2			Version 3		
	Estimated deaths		Lives	Estimated deaths		Lives	Estimated deaths		Lives
Countries	With vaccination	Without vaccination	saved, %†	With vaccination	Without vaccination	saved, %†	With vaccination	Without vaccination	saved, %†
United Kingdom	60,866	243,330	0.268	60,486	232,982	0.253	59,432	249,693	0.279
Spain	32,937	142,304	0.234	32,944	118,640	0.183	32,712	166,732	0.287
Canada	13,561	92,530	0.208	13,122	91,132	0.205	11,929	105,212	0.246
United States	416,842	1,102,958	0.206	415,762	902,871	0.147	418,884	828,990	0.123
Germany	65,806	229,486	0.195	65,742	241,046	0.209	65,176	198,762	0.159
Italy	59,262	155,270	0.159	59,400	136,902	0.128	58,641	162,886	0.173
Mexico	170,352	289,428	0.092	136,645	234,134	0.075	129,716	240,521	0.085
Brazil	404,648	593,256	0.088	408,048	552,938	0.068	407,292	582,875	0.082
France	46,446	100,016	0.082	46,829	93,682	0.072	46,746	104,241	0.088
Colombia	85,132	122,628	0.073	86,039	115,024	0.057	85,350	127,294	0.082
Russia	201,322	269,720	0.047	199,641	261,862	0.043	203,734	281,979	0.054
India	297,380	336,300	0.003	299,676	329,029	0.002	301,682	339,829	0.003

*Model-simulated COVID-19 deaths under the the actual, with vaccination, and the first counterfactual scenarios with different parameter choices. In version 1, η = 0.85; in version 2, η = 0.75; and in version 3, η = 0.95, in which η is the proportion of the population that becomes fully protected after vaccination, a proxy measure of vaccine efficacy.
†Deaths averted as a percentage of country's population.

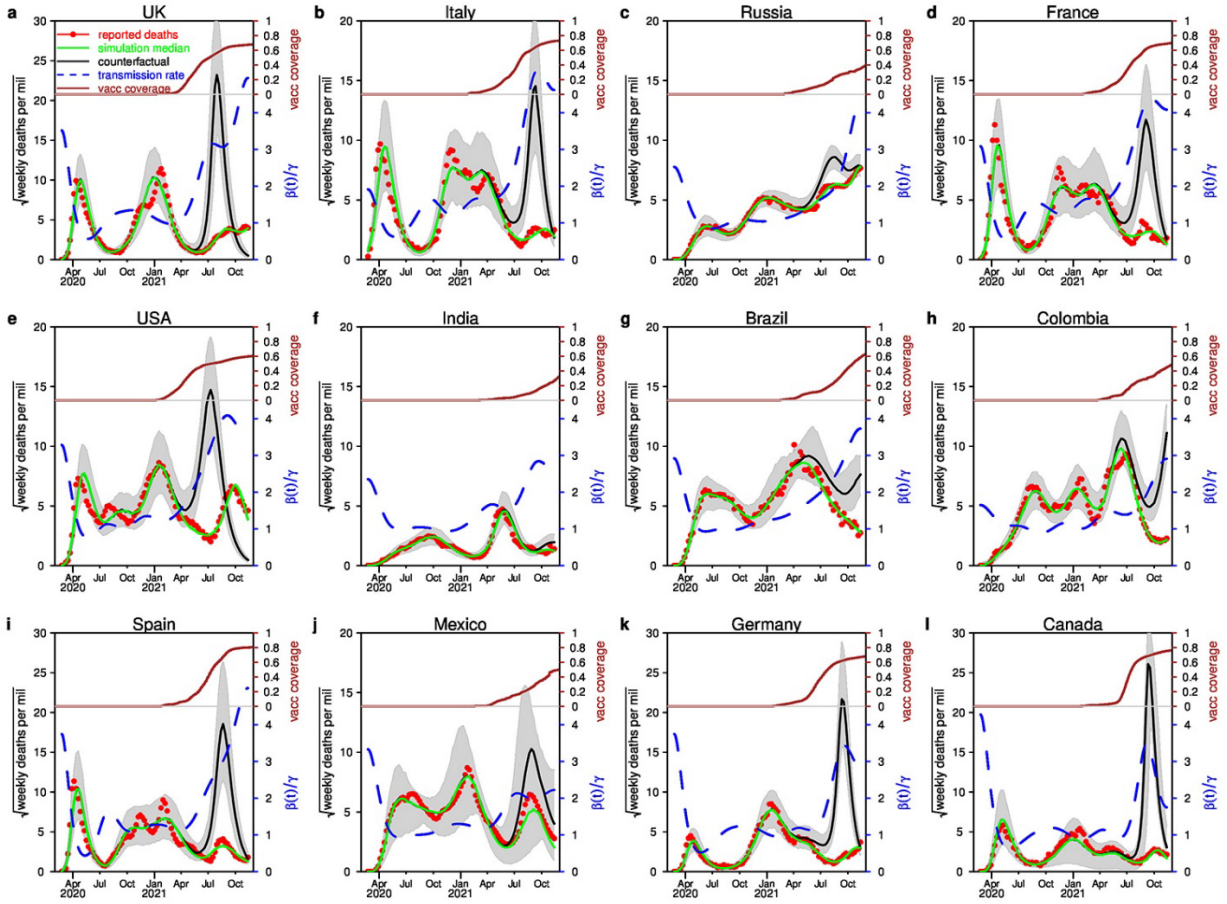
Appendix Table 3. Estimated effects of vaccination on COVID-19 mortality in 12 countries during period January 1–November 14, 2021, according to model 2 used to evaluate of effectiveness of global COVID-19 vaccination campaign*

	Version 1			Version 2			Version 3		
	Estimated deaths		Lives	Estimated deaths		Lives	Estimated deaths		Lives
Country	With vaccination	Without vaccination	saved, %†	With vaccination	Without vaccination	saved, %†	With vaccination	Without vaccination	saved, %†
United Kingdom	60,590	244,324	0.27	59,600	238,503	0.262	60,782	238,922	0.261
Spain	32,969	136,104	0.221	33,112	115,904	0.177	32,836	126,252	0.2
Canada	9,796	126,618	0.307	12,683	108,428	0.252	10,314	160,966	0.397
United States	421,184	784,416	0.109	418,939	982,228	0.169	411,548	1,177,809	0.23
Germany	67,052	282,824	0.257	65,364	238,346	0.206	66,072	291,765	0.269
Italy	59,604	139,901	0.133	59,532	177,586	0.195	59,624	151,994	0.153
Mexico	133,740	230,597	0.075	153,000	260,745	0.083	142,408	244,554	0.079
Brazil	408,042	522,342	0.053	407,606	583,784	0.082	407,471	573,858	0.078
France	47,396	111,377	0.098	46,915	102,264	0.085	47,588	96,064	0.074
Colombia	85,752	123,214	0.073	85,079	119,061	0.066	84,812	119,596	0.068
Russia	201,765	271,726	0.048	202,200	275,159	0.05	204,876	279,038	0.051
India	322,055	356,146	0.002	292,800	327,646	0.003	296,065	336,642	0.003

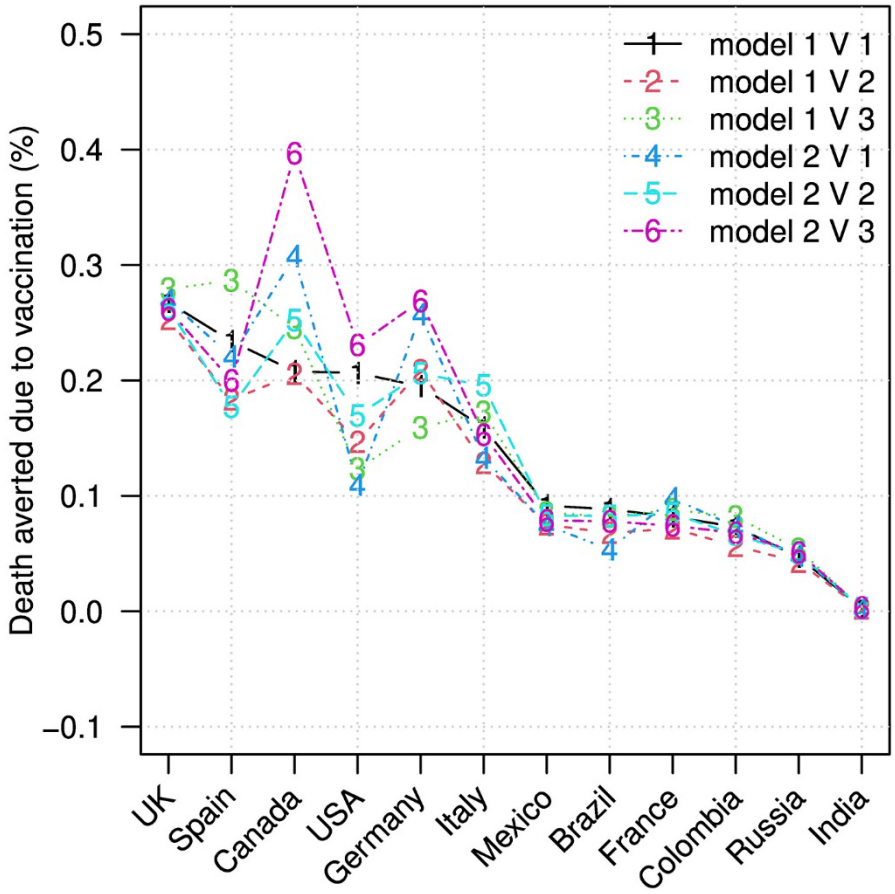
*Model-simulated COVID-19 deaths under the actual, with vaccination, and the first counterfactual scenarios with different parameter choices. In version 1, ψ = 0.6; in version 2, ψ = 0.8; in version 3, ψ = 0.8, and θ^{-} replaces θ. ψ, model parameter that accounts for the reduced susceptibility of vaccinated persons; θ, proportion of deaths of persons discharged from hospitals.
†Deaths averted as a percentage of country's population.



Appendix Figure 1. Modeled assessment of effectiveness of global COVID-19 vaccination campaign for 12 countries. We fit a state-space extended susceptible-exposed-infectious-recovered–type model (model 1) with a delayed class between infectious status to death and a death class in which $\eta = 0.85$, $n_\beta = 10$ to reported mortality data. Upper part of each panel shows the vaccination timing and real-time coverage (brown curve). Lower part of each panel shows reported COVID-19 deaths (red circles). Green curves indicated the median of 1,000 model simulations when vaccination was included in the model. Blue dashed curve shows the time varying transmission rate, $\beta(t)/\gamma$, as reconstructed by the model. Black curves show the counterfactual model simulations under the without-vaccination scenario when all other parameters are unchanged. Gray region indicates 95% CI of the simulations. The difference between green and black curves indicates the effects of vaccination in terms of saving lives (i.e., reduction in mortality) for these countries. Scales for the y-axes differ substantially to underscore patterns but do not permit direct comparisons. UK, United Kingdom; USA, United States.



Appendix Figure 2. Modeled assessment of effectiveness of global COVID-19 vaccination campaign for 12 countries. We fit a state-space model to weekly reported mortality data. Results represent model 2 version 1 in which η = 0.85, ψ =0.6, and n_β = 10. Red circles are reported COVID-19 deaths. Brown curve shows the vaccination timing and real-time coverage. Green curve shows the median of 1,000 model simulations when vaccination is included in the model. Black curve shows the outcome under the first counterfactual scenario (i.e., $v(t) = 0$); The gray region is the 95% confidence range of the simulations. The difference between green and black curves indicates the effects of vaccination in terms of deaths averted for these countries. Blue dashed curve shows the time varying transmission rate, $\beta(t)/\gamma$, as reconstructed by the model.



Appendix Figure 3. Death averted due to vaccination as a percentage of country's population as modeled assessment of effectiveness of global COVID-19 vaccination campaign for 12 countries. Against the first counterfactual scenario, we compare 6 model variations including the baseline model (model 1 version 1. UK, United Kingdom; USA, United States; V, version.