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Despite vaccination, China needs non-pharmaceutical interventions to prevent widespread outbreaks of COVID-19 in 2021

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COVID-19 vaccination is being conducted in over 200 countries and regions to control SARS-CoV-2 transmission and return to a pre-pandemic lifestyle. However, understanding when non-pharmaceutical interventions (NPIs) can be lifted as immunity builds up remains a key question for policy makers. To address this, we built a data-driven model of SARS-CoV-2 transmission for China. We estimated that, to prevent the escalation of local outbreaks to widespread epidemics, stringent NPIs need to remain in place at least one year after the start of vaccination. Should NPIs alone be capable of keeping the reproduction number (R_t) around 1.3, the synergetic effect of NPIs and vaccination could reduce the COVID-19 burden by up to 99% and bring R_t below the epidemic threshold in about 9 months. Maintaining strict NPIs throughout 2021 is of paramount importance to reduce COVID-19 burden while vaccines are distributed to the population, especially in large populations with little natural immunity.

The novel coronavirus disease 2019 (COVID-19) pandemic is far from over, with cases still surging in many countries across the globe, particularly with India suffering from a catastrophic second wave¹. In 2020, epidemic suppression and/or mitigation have relied on non-pharmaceutical interventions (NPIs), including social distancing, school closure, mask use and case isolation. Although effective and widely adopted to limit severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) transmission and reduce COVID-19 burden, these interventions entail enormous economic costs and negatively affect quality of life². Additionally, in many countries, relaxation of NPIs has led to a resurgence of the epidemic as herd immunity has not been reached thus far³.

Effective vaccines against COVID-19 remain the only foreseeable means of both suppressing the infection and returning to pre-pandemic social and economic activity patterns. Globally, several vaccines have been licensed, and vaccination programmes have been initiated in more than 200 countries/regions, including China⁴. However, the projected global production and delivery capacities are likely to be inadequate to provide COVID-19 vaccines to all individuals who are still susceptible to SARS-CoV-2 infection⁵. The effectiveness of COVID-19 vaccination campaigns will depend on several factors, including pre-existing immunity, vaccine supply, willingness to receive the vaccine and strategies for vaccine allocation and deployment⁵.

To avoid widespread transmission of SARS-CoV-2, since the end of the first COVID-19 wave in the spring of 2020, China has implemented strict NPIs and has successfully controlled local outbreaks, preventing a second widespread wave of COVID-19. Since December 2020, China has given conditional approval or emergency use approval for seven COVID-19 vaccines. As of 1 June 2021, 681.9 million doses (roughly corresponding to 24.3% of the population) have been administered⁶. However, such a coverage is still extremely low, and thus China remains highly vulnerable to importations of SARS-CoV-2 and onward transmission, as proved by several local outbreaks that occurred in the first four months of 2021, the largest of which occurring in Heilongjiang Province led to 636 reported cases and spilled over to a neighbouring province (over 300 cases were reported in Jilin)⁷. At present, estimating whether and when NPIs can be lifted, and the extent to which we need to rely on NPIs while vaccines roll out, represents a top priority for policy making.

This question has not been well addressed in China, one of the few countries in the world where nearly the entire population is still susceptible to SARS-CoV-2 infection and home to almost 1.4 billion individuals (roughly 18% of the world population). To fill this gap, we built on top of the wide body of work adopting mathematical models of the infection transmission process to evaluate vaccination programmes^{8–12}. In particular, we developed an age-structured stochastic model to simulate SARS-CoV-2 transmission triggered by cases imported in Mainland China, based on a susceptible–infectious–

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removed (SIR) scheme (Supplementary Fig. 1). We consider a situation with (i) no ongoing widespread SARS-CoV-2 transmission, (ii) nearly no immunity in the population and (iii) high risk of importing SARS-CoV-2-infected individuals, possibly leading to an upsurge of COVID-19 cases. Since COVID-19 vaccines are expected to continue rolling out throughout 2021–2022, we consider also alternative scenarios where SARS-CoV-2 infections leading to an outbreak are imported when 10%, 20% (close to the coverage as of the end of May 2021) and 30% of the Chinese population has already been vaccinated (according to the simulated vaccination programme).

In the model, we account for heterogeneous mixing patterns by age¹³ and progressive vaccine deployment among different population segments based on a priority scheme (essential workers, older adults, individuals with underlying conditions, etc.)¹⁴. Further, we overlay a disease burden model on the transmission model to estimate the number of symptomatic cases, hospitalizations, intensive care unit (ICU) admissions and deaths under different vaccination scenarios and based on empirical data^{15–20}. The resulting integrated model is informed by data on COVID-19 natural history, age-mixing patterns specific to China quantified during the pre-pandemic period and the size of the different vaccination targets in the Chinese population (for example, individuals with pre-existing conditions). A qualitative model description is reported in Methods section, a summary of model parameters and data sources is reported in Supplementary Table 1 and all other details are reported in Supplementary Files 1–5.

The combined effects of NPIs and vaccination programmes are evaluated in terms of their ability to reduce the disease burden caused by outbreaks arising from possible importation of cases.

We considered a baseline vaccination scenario where: (1) vaccination starts 15 days after an outbreak triggered by 40 breakthrough imported SARS-CoV-2 infections; (2) vaccine efficacy (VE) against SARS-CoV-2 infections for a two-dose schedule (with a 21-day interval) is set at 80%²¹; (3) vaccination coverage is capped at 70% across all ages¹⁴; (4) 6 million doses are administered daily (4 per 1,000 individuals, informed by the ongoing COVID-19 vaccination programme⁶, and estimates of vaccine supply till 2021 in China^{22–26}); (5) the first priority target consists of older adults and individuals with underlying conditions (descriptions in detail shown in Supplementary Table 2); (6) there is no prior population immunity from natural infection, which aligns with the situation in most of China, where there has been little circulation of SARS-CoV-2 as of May 2021 (ref. ³); (7) we assume an initial reproductive number $R_t = 2.5$ at the start of the outbreak^{27–32}, in the absence of NPIs and vaccination; (8) children under 15 years of age were considered to have a lower susceptibility to SARS-CoV-2 infection as compared with adults (that is, individuals aged 15–64 years), while individuals aged 65+ years had the highest susceptibility to infection (Supplementary Table 1)^{33,34}; (9) we let the model run for 2 years. To evaluate the impact of the baseline assumptions on our results, we conduct comprehensive sensitivity analyses.

Results

Main analysis. In the absence of NPIs, the vaccination programme is too slow to lower and delay the epidemic (Fig. 1a) and does not effectively reduce COVID-19 burden. R_t falls below the epidemic threshold (<1) 69 days after the epidemic start (Fig. 1b), but this is primarily attributable to immunity gained through natural infection rather than vaccination. Indeed, in this time frame, 52.2% of population gets infected, while only 6.7% of population has been vaccinated (Fig. 1c). The cumulative number of symptomatic cases and deaths over a 2-year period only decrease by 3.3% (95% CI 3.1–4.7%) and 6.7% (95% CI 4.5–8.9%), respectively, as compared with a reference scenario where there is no vaccination and no NPIs, which would lead to 306.7 million (95% CI 282.7–320.6 million) symptomatic cases, 99.3 million (95% CI 92.6–104.5 million)

hospitalizations, 7.2 million (95% CI 6.0–7.8 million) ICU admissions and 9.4 million (95% CI 7.7–10.3 million) deaths (Fig. 2).

Provided that NPIs are in place and can keep R_t at 1.3 in the absence of vaccination (‘moderate NPIs scenario’), the vaccination programme could reduce COVID-19 burden by about 99% compared with the ‘reference scenario’, with 5.5 million (95% CI 2.5–13.4 million) symptomatic cases, 1.8 million (95% CI 0.8–4.4 million) hospitalizations, 73,500 (95% CI 7,300–152,100) ICU admissions and 76,700 (95% CI 8,200–165,700) deaths (Fig. 2). In this context, vaccination decreases COVID-19 burden by about 40% (Fig. 2) compared with a situation with moderate NPI alone, and R_t falls below the epidemic threshold about 9 months after the epidemic start (Fig. 1h). At the time that R_t falls below 1, we estimate that 50.8% of the total population would have been vaccinated, while 0.8% would have been naturally infected (Fig. 1i). This highlights that a relevant proportion of the population would still be susceptible to SARS-CoV-2 at that time. Although in the long term vaccination can ultimately lead to the suppression of transmission, it is necessary to maintain NPIs for one year after the onset of vaccination. Indeed, if NPIs are relaxed from moderate ($R_t = 1.3$) to mild ($R_t = 1.5$) 9 months after vaccination start, the cumulative number of symptomatic cases could double (Extended Data Figs. 1 and 2), and the cumulative death toll could increase from 76,700 to 173,000 (Extended Data Fig. 3). In contrast, a small increase in cumulative deaths from 76,700 to 81,700 is expected if this relaxation occurs one year after vaccination start (Extended Data Fig. 3), while earlier or more drastic relaxations of NPIs lead to substantial increases in deaths (Extended Data Fig. 3).

A combination of more stringent NPIs (that is, capable of keeping $R_t = 1.1$) and vaccination (‘vax + strong NPIs’ scenario) could suppress the epidemic, with $<2,300$ symptomatic cases, and <50 deaths on average. Although the majority of the reduction of COVID-19 burden is ascribable to NPIs in this case (over 85%), the deaths averted due to vaccination are about 1.2 million (Figs. 1j–l and 2).

If we consider a set of mild NPIs (‘vax + mild NPIs’ scenario), even a relatively low initial reproduction number under NPIs of $R_t = 1.5$ could still lead to a disastrous epidemic, with nearly 2 million deaths. Despite the high death toll of the resulting epidemic, NPIs and vaccination would jointly reduce around 80% of the disease burden compared with a scenario with no NPIs and no vaccination (namely, 239 million symptomatic cases and 8.2 million deaths averted) (Figs. 1d–f and 2).

Vaccine distribution capacity. Should the daily vaccination rollout be limited to 1.3 million doses (1 per 1,000 individuals, a slower rate than during the 2009 H1N1 pandemic), vaccination would not effectively reduce COVID-19-related deaths unless there was adoption of stringent NPIs. In a scenario where vaccination capacity reaches 10 million doses administered per day (7 per 1,000 individuals), vaccination would reduce COVID-19-related deaths to $<5,000$ for moderate NPIs and <30 for strong NPIs. Should the daily vaccination capacity be increased to 15 million doses (10 per 1,000 individuals), vaccination could effectively reduce deaths to $<100,000$ (similar to the annual influenza-related death toll in China³⁵) even in the presence of mild NPIs. However, even if the daily vaccination capacity could be increased to 30 million doses (20 per 1,000 individuals), in the absence of NPIs, we estimate that over 7.7 million deaths would still occur (Fig. 3). Similar patterns are estimated for the number of symptomatic cases, hospitalizations and ICU admissions (Extended Data Fig. 4 and Supplementary Figs. 2 and 3).

Increasing daily vaccination capacity could largely shorten the time needed to control SARS-CoV-2 transmission. For instance, when considering a daily capacity of 10 million and 15 million doses and moderate NPIs, R_t would drop below 1 about 8 and 6 months, respectively, after epidemic onset (compared with the 9.3 months

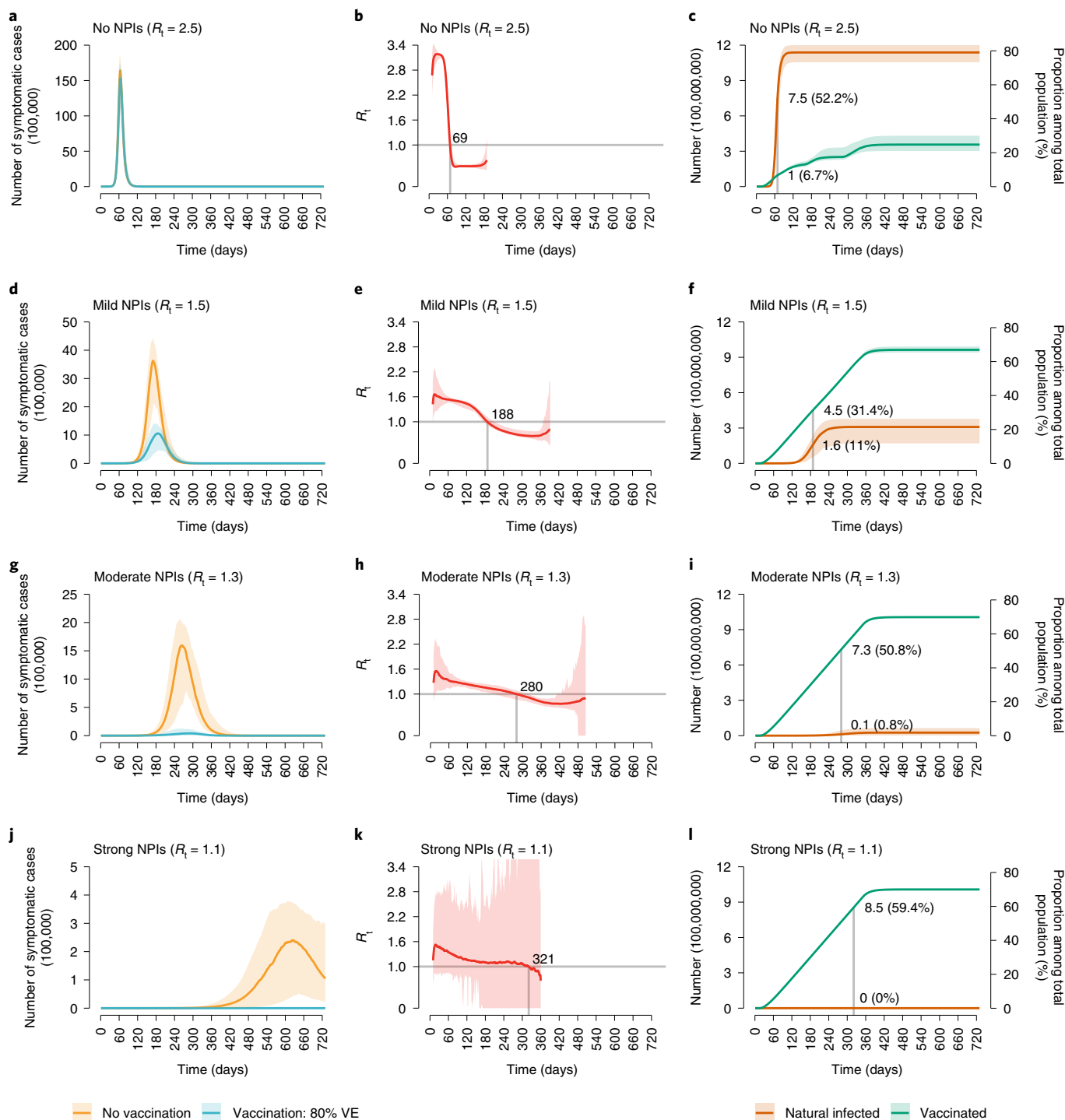


Fig. 1 | Time series of symptomatic cases, effective reproductive number, R_t , and population infected and vaccinated. **a**, Number of symptomatic cases over time as estimated in the no-NPIs scenario (initial $R_t = 2.5$) in the absence or presence of vaccination. **b**, Net reproduction number R_t over time, as estimated using a Bayesian framework (Supplementary File 5) from the time series of symptomatic cases in the no-NPIs scenario in the presence of vaccination. The horizontal line indicates the epidemic threshold $R_t = 1$, and the vertical line indicates where R_t crosses this threshold. Note that, for the first few generations of cases, R_t shows an increasing pattern linked to the highly stochastic nature of epidemics in their initial phase when epidemics with initially larger R_t are more likely to survive⁶⁹. For the same reason, the adopted methodology tends to overestimate R_t in the epidemic tail⁶⁹; as such, R_t is shown in the core part of the epidemic only. **c**, Absolute numbers and proportion of the Chinese population infected and vaccinated over time in the no-NPIs scenario in the presence of vaccination. The population of China in 2020 is 1,439,324,000 (ref. ⁵⁷). **d-f**, As in **a-c** but for the mild NPIs scenario (initial $R_t = 1.5$). **g-i**, As in **a-c** but for the moderate NPIs scenario (initial $R_t = 1.3$). **j-l**, As in **a-c** but for the strong NPIs scenario (initial $R_t = 1.1$). Line denotes median, and shadow denotes quantiles 0.025 and 0.975.

estimated with the baseline capacity of 6 million doses). At that time, over 60% of the population would be vaccinated and $\leq 0.1\%$ would be naturally infected. An upscale in the daily capacity to 10

(Extended Data Figs. 5 and 6) or 15 million doses (Extended Data Figs. 7 and 8) would allow a relaxation of NPIs from moderate to mild already 6–9 months after vaccination start, that is, 3–6 months

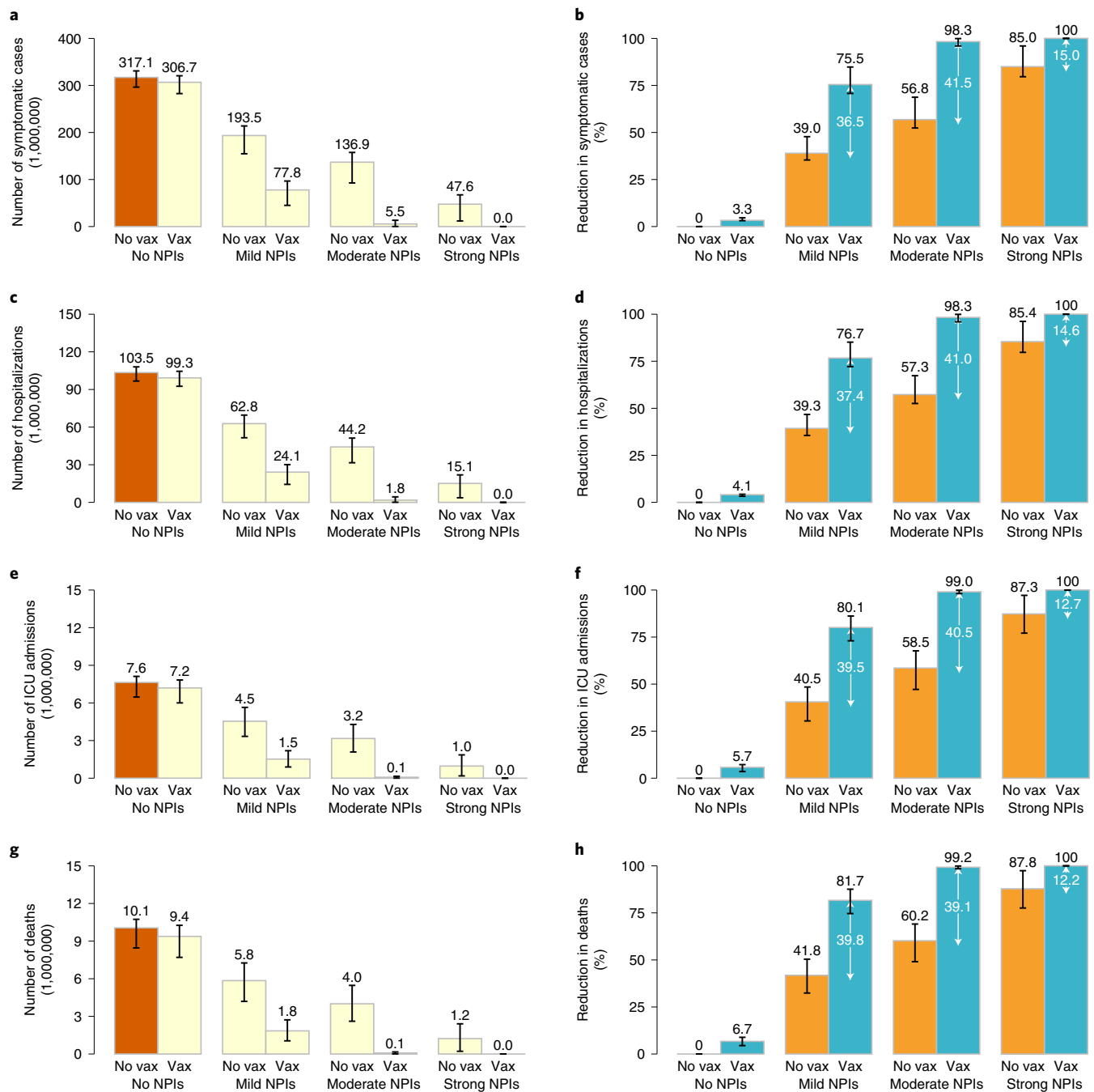


Fig. 2 | Burden of COVID-19 in the main analysis. **a**, Cumulative number of symptomatic cases as estimated under the different scenarios in the absence or presence of vaccination over the simulated 2-year period. No vaccination + no NPIs with $R_t = 2.5$ at the beginning of the outbreak is called the 'reference scenario', described using dark orange bars. Light-yellow bars indicate scenarios including vaccination and/or different levels of NPIs. **b**, Reduction in the cumulative number of symptomatic cases with respect to the reference scenario. Orange bars and values written in black indicate the contribution of NPIs; blue bars and values written in black indicate the overall contribution of vaccination and NPIs, while the values written in white indicate net contribution of vaccination. **c,d**, As in **a,b** but for hospitalized cases. **e,f**, As in **a,b** but for cases admitted to ICU. **g,h**, As in **a,b** but for deaths. Number denotes median, and error bars denote quantiles 0.025 and 0.975.

earlier with respect to the baseline. On the other hand, more drastic relaxations of NPIs (for example, from moderate to no NPIs) would still lead to substantial increases in symptomatic cases and deaths (Extended Data Figs. 5–8).

Vaccination prioritization. We consider alternative vaccination scenarios that prioritize essential workers (staff working in health-care, law enforcement, security and community services, individuals

employed in cold chain, etc.) to maintain essential services and then explore different prioritization strategies for the rest of the population. Our results suggest that the relative timing of the epidemic and of the vaccination rollout play a key role in determining the most effective strategy. In particular, if we consider vaccination to start two weeks after 40 cases are detected, there is no clear prioritization strategy that minimizes deaths, as the outcome of the vaccination campaign depends heavily on the timing at which the epidemic

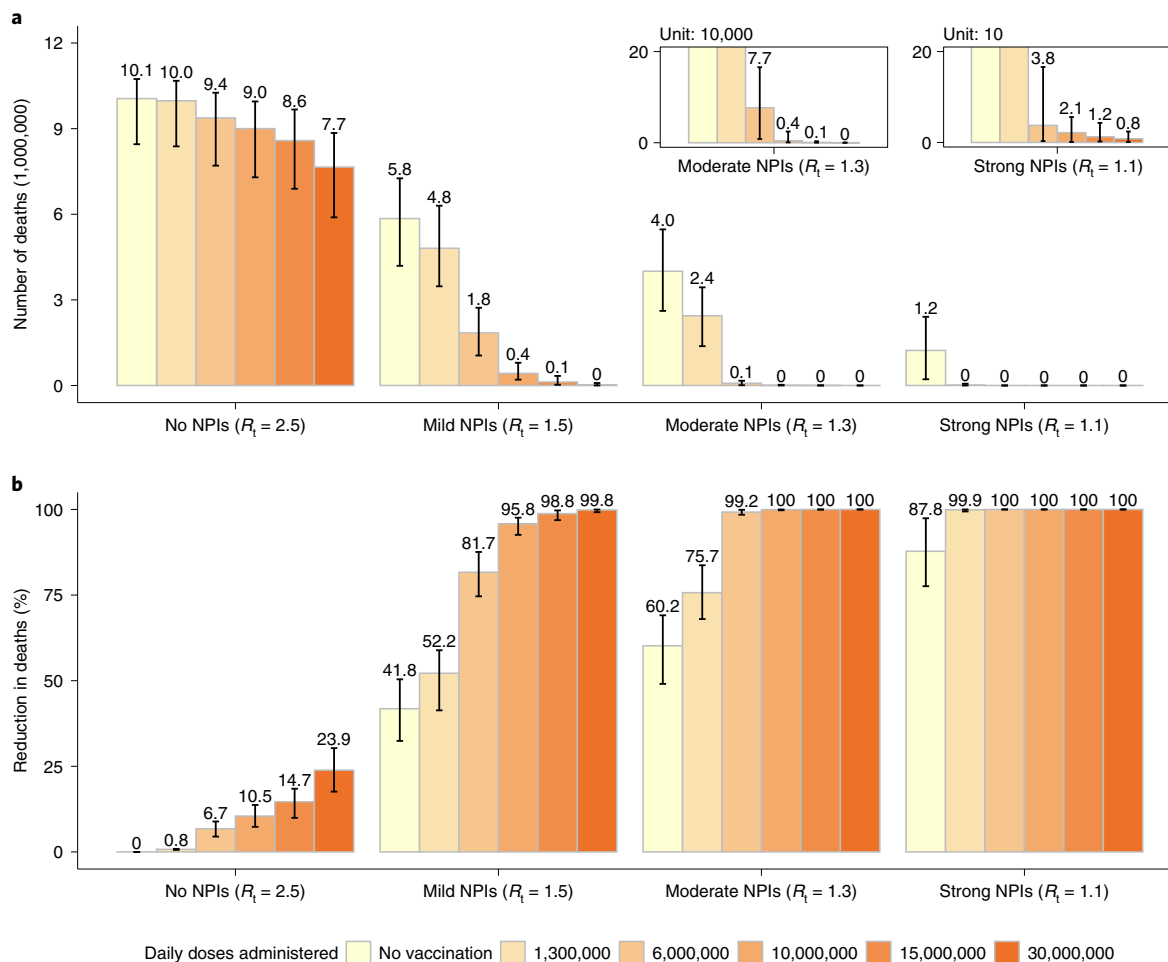


Fig. 3 | Impact of daily vaccine administration capacity on COVID-19 deaths. **a**, Cumulative number of COVID-19 deaths (millions) as estimated in the different scenarios under progressively increasing values of the daily vaccination capacity. **b**, Proportion of deaths averted compared with the reference scenario, that is, no vaccination + no NPIs with $R_t = 2.5$ at the beginning of the outbreak. Number denotes median, and error bars denote quantiles 0.025 and 0.975.

unfolds (Fig. 4 and Supplementary Figs. 4 and 5). Instead, if the epidemic is already underway when the vaccination campaign starts (>5,000 cases), prioritizing working-age groups minimizes the number of deaths when $R_t \leq 1.3$. In contrast, prioritizing older adults and individuals with underlying conditions is more effective when $R_t \geq 1.5$ (direct benefits are higher; Fig. 4 and Supplementary Figs. 4 and 5). Two results are independent of the adopted prioritization strategy: (i) if $R_t \geq 1.5$, then an epidemic cannot be avoided, and (ii) when $R_t = 1.1$, over 99% of deaths can be averted (Supplementary Figs. 4 and 5).

Population immunity at the onset of an outbreak. In December 2020, vaccination started in China, while measures to detect imported cases and case surveillance are in place. The number of doses distributed per day has changed over time, following an increasing trend and with a daily average of about 6 million doses over the period between late March and mid May 2021 (Supplementary File 7). As of 1 June 2021, the vaccination coverage is about 24.3%⁶. The effectiveness of the vaccination programme and NPIs in preventing new COVID-19 outbreaks and limiting COVID-19 burden will thus depend on the level of vaccine-induced immunity in the population should an outbreak of locally transmitted cases start to unfold.

To simulate this situation, we initialize the model by considering different fractions of vaccinated population (SA1: 10%; SA2: 20%; SA3: 30%) at the time the infection is seeded. Given a certain level

of NPIs in the absence of immunity, increasing proportions of vaccinated individuals will decrease the effective reproduction number (for example, $R_t = 1.1$ in the absence of immunity corresponds to R_t below the epidemic threshold if 10% or more of the population has been vaccinated).

Should 30% of the population already have been vaccinated before the start of a new wave, continuing the vaccination programme while adopting mild NPIs would reduce the death toll by 98% (42,400 deaths as compared with 1.8 million if no one was vaccinated). However, in the absence of NPIs, even if 30% of population were already vaccinated before the start of a new wave, carrying on with the vaccination programme alone would not be enough to prevent a widespread epidemic leading to 6 (95% CI 4–7) million deaths (Fig. 5).

Vaccination coverage. No significant difference in willingness to vaccinate between age groups has been reported in China^{36–38}. Accordingly, we use a homogeneous vaccine coverage of 70% among all age groups in the main analysis. Here, we present the results of a set of sensitivity analyses assuming vaccination coverage of 50% (SA4) and 90% (SA5) among all age groups, and considering heterogeneous coverage by age: (1) 70% for adults ≥ 20 years and 50% for younger individuals (SA6), (2) 90% for adults ≥ 20 years and 70% for younger individuals (SA7) and (3) 70% for adults ≥ 20 years and no vaccination for younger individuals (SA8).

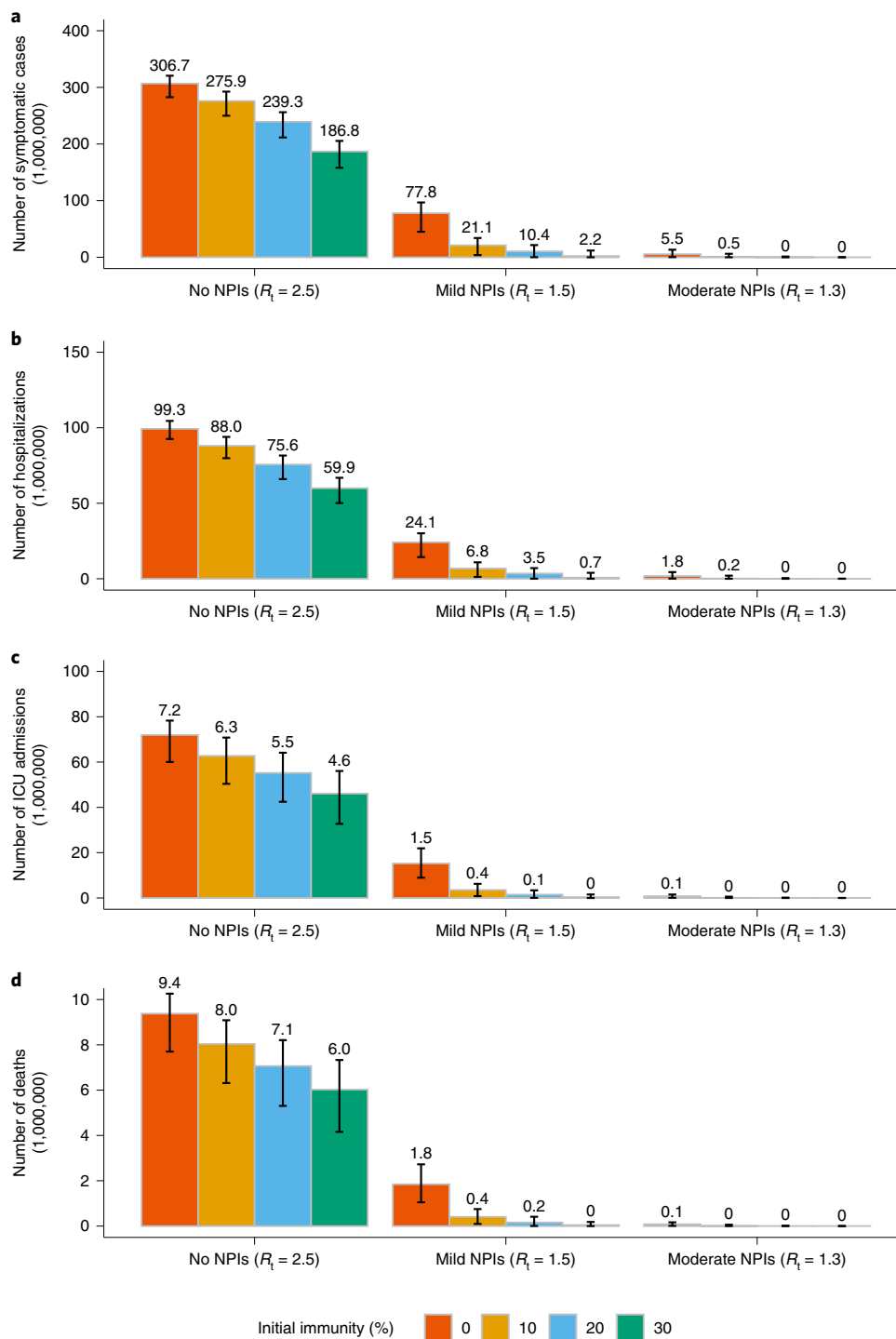


Fig. 5 | Cumulative burden of COVID-19, provided a percentage of population is immune before epidemic starts. In this additional analysis, the epidemic starts when 10%, 20% or 30% of population has been vaccinated. **a–d**, Cumulative number of symptomatic cases (**a**), hospitalizations (**b**), cases admitted to ICU (**c**) and deaths (**d**) as estimated over the simulated 2-year period. Number denotes median, and error bars denote quantiles 0.025 and 0.975.

R_t (that is, 1.7, 1.9 and 2.1, about 30–60% increased transmissibility with respect to the main analysis⁴⁵) to account for enhanced transmissibility, and use a mean death hazard ratio of 1.64 to account for higher mortality⁴⁷. With the assumption of VE of 80% against the new variant, COVID-19 burden substantially increases compared with the scenario based on the historical lineage. The number of symptomatic cases increases from 2,000 to 173 million, and deaths

increase from <50 to 7 million even when strict NPIs are implemented (Extended Data Fig. 9).

Alternative vaccination parameters and scenarios. A further set of sensitivity analyses are conducted to evaluate the impact of baseline assumptions on our results for $R_t = 1.3$ (moderate NPIs). Provided that vaccination can only protect against illness (SA11)

but not SARS-CoV-2 infections, COVID-19-related deaths increase by 33-fold with respect to the baseline: from 76,700 to 2.66 million (Supplementary Fig. 6). In this case, maintaining stringent NPIs measures in place for a prolonged time horizon would be necessary as such vaccine would not be effective to suppress transmission (as reported previously⁴⁹). Assuming a shorter duration of vaccine-induced protection of 6 months (SA12) instead of lifelong protection (that is, longer than the 2-year time horizon considered; Supplementary Fig. 6) has a similarly large effect on projections.

In our main analysis, we use the contact matrix estimated from a contact survey conducted in Shanghai before the COVID-19 pandemic¹³. Should a new COVID-19 wave start to unfold in China, it is unclear to what extent pre-pandemic contact patterns could be representative of such a situation. Therefore, we add a sensitivity analysis in which we assume the mixing patterns estimated in Shanghai in March 2020⁵⁰, when schools were still closed as a response to the COVID-19 pandemic (SA13). For $R_t = 1.3$ and the baseline parameters for the vaccination, the estimated number of deaths would be 16,000 as compared with 76,700 estimated using the pre-pandemic mixing patterns (79% decrease; Supplementary Fig. 6). In fact, the relative contribution of the adult population (which is the main target of the vaccination campaign) to the overall transmission as compared with children is higher than when considering pre-pandemic mixing patterns (when schools were open and school-age individuals had the highest number of contacts).

Other factors such as excluding detected symptomatic cases from vaccination (SA14 and SA15), the time interval between two doses (SA16 and SA17) and assuming an all-or-nothing vaccine (SA18) do not substantially affect estimates of deaths and symptomatic infections (Supplementary Figs. 6 and 7). A similar trend is observed for hospitalized cases and ICU admissions.

Discussion

Using a stochastic dynamic model of SARS-CoV-2 transmission and COVID-19 burden tailored to the epidemiological situation in China, we find that, in the absence of NPIs and independently of the vaccine prioritization strategy and capacity of the vaccination campaign, timely rollout of an effective vaccine (VE 80%) would not be enough to prevent a local outbreak from escalating to a major widespread epidemic. Provided that NPIs are in place and capable of bringing R_t to 1.3, a daily vaccine rollout of 4 doses per 1,000 individuals could reduce COVID-19 burden by around 99%, and bring R_t below the epidemic threshold about 9 months after the start of the vaccination campaign. A relaxation of NPIs that brings the value of R_t to 1.5 could not prevent sustained epidemic growth, which would cause 1.8 million deaths. A net reproduction number of 1.5 could only be sustained when accompanied by an improvement of the vaccine administration capacity up to 10 doses per 1,000 individuals per day. Relaxation of NPIs in the first 6–9 months of vaccine rollout could lead to substantial increases of COVID-19 burden if daily vaccination capacity could not be enhanced to 10–15 million doses.

Bubar et al. evaluated COVID-19 vaccine prioritization strategies and found that prioritizing older adults is a robust strategy to minimize deaths across countries when $R_t = 1.5$, while prioritization shifted to the 20–49-year-old group when $R_t = 1.15$ (ref. ⁵¹). The broad scope of that multi-country analysis does not account for features of COVID-19 epidemiology and vaccination programme that are unique to China. In particular, differently from most countries where natural immunity is building up after widespread epidemics, China has been able to suppress SARS-CoV-2 transmission for most of 2020. As a result, prior immunity is very low, thus calling for specifically tailored analysis. Nonetheless, our findings confirm that, if NPIs can maintain transmission rates at low levels during the vaccination campaign, strategies that target indirect benefits perform better, while if transmission rates remain high, strategies maximizing direct benefits may save more lives⁵¹.

As highlighted in vaccination studies in Italy⁵², in the race between the vaccination campaign to build population herd immunity and the progress of the epidemic, the speed of vaccine deployment is critical. Considering the average vaccine distribution capacity of the current COVID-19 vaccination campaign in China⁶, we use 6 million doses administered per day in the baseline analysis. Several manufacturers state that a total of 3.9 billion doses of COVID-19 vaccine could be produced in 2021, equivalent to about 10 million doses per day^{22–26}. China committed to provide COVID-19 vaccines to >100 countries, which could reduce the number of doses to be distributed locally. Even if these candidate vaccines could be licensed and manufactured smoothly, it would take about one year to vaccinate 70% of the population.

Six months after initiating vaccination programme, roughly 24.3% of Chinese population has been vaccinated⁶. Limited vaccine production capacity, particularly at the initial stage, could slow the speed of vaccine rollout. Slower rates of vaccine production and administration may result in a longer period of SARS-CoV-2 transmission. It is thus crucial to keep monitoring local outbreaks and invest resources in outbreak management (as currently done in China) to keep R_t close to the epidemic threshold at least for the next 1–2 years. In the very unique context of China, a value of R_t of 1.3 would result in about 76,700 cumulative deaths, comparable to the annual influenza-related death toll in China³⁵. The development of detailed logistical plans and tools to support an increased vaccination capacity as well as effective logistic (vaccine transport, storage and continuous cold-chain monitoring) are key factors for a successful mass vaccination campaign.

In the early phase of COVID-19 spread in Wuhan in 2019, before interventions were put in place, R_0 was estimated to be in the range 2.0–3.5 (refs. ^{27–32}). Given the knowledge of mechanisms of SARS-CoV-2 transmission, and the devastating consequences of an uncontrolled COVID-19 epidemic, the Chinese population would maintain cautious behaviour (such as cleaning hands often, coughing or sneezing in bent elbow, avoiding close contact with someone who is sick, etc.) even without the need to impose NPIs. As such, in our analysis simulating an epidemic triggered by imported cases, we decided to consider an initial reproduction number of 2.5, which is at the lower end of the estimated spectrum.

SARS-CoV-2 variants are circulating globally and quickly became dominant in countries such as the United Kingdom and Italy (lineage B.1.1.7) and South Africa (lineage B.1.351). Recently, variant B.1.617 identified in India has raised global concern. Mainland China border control screenings have already identified imported cases with SARS-CoV-2 lineage B.1.1.7 and B.1.617. Our study shows that the spread of new more transmissible and/or more lethal variants could substantially decrease the net benefit of vaccination. Strict border quarantine and isolation as well as genomic surveillance will be key while vaccines roll out in China.

Our analysis on the VE shows that, if we consider VE of 60%, both the number of symptomatic cases and deaths are estimated to double as compared with the baseline vaccination coverage of 80%. Given that the final composition of a nationwide rollout will likely include a combination of vaccines with varying efficacy, monitoring VE on the ground will remain a priority.

Here, we propose a general framework to evaluate the impact of COVID-19 vaccination programmes in the absence/presence of NPIs and to explore priority target populations to minimize multiple disease outcomes. The proposed modelling framework is adaptable to other country-specific contexts. However, this requires the collection of country-specific data about the epidemiological situation (for example, landscape immunity of the local population, prevalence of infections), vaccination parameters (for example, vaccine supply and capacity of immunization services, efficacy of different vaccines, target age groups), socio-demographic characteristics of the population (for example, size of the priority

population by age group, age-mixing patterns) and the priorities of the pandemic responses (for example, limiting the death toll or preventing infections).

Our study has a number of limitations. First, we integrate the impact of NPIs through a simple reduction in the value of R_t at the beginning of the outbreak, homogeneously across age groups. However, our analysis does not suggest which combination of NPIs should be adopted to lower R_t to a certain level or how this would affect transmission rates in different age groups. Li et al. estimated that individual NPIs, including school closure, workplace closure and public events bans, were associated with reductions in R_t of 13–24% on day 28 after their introduction⁵³. Further studies are needed to pinpoint the specific NPIs to be adopted in parallel with the vaccination campaign and their impact on the quality of life of the population.

Second, in China, vaccines have not been licensed for children, so we assume a 50% lower or equivalent VE for them compared with other adults. Although we show that variations in these rates do not substantially affect the overall effect of the vaccination campaign, further data on age-specific VE could help refine priority groups. Our sensitivity analyses on vaccine coverage reveal the importance of extending the vaccination to the young population once the use of vaccines is authorized for that age segment of the population.

Third, we assumed that immunity after natural infections lasts longer than the time horizon considered (2 years). If this is not the case, waning of immunity would inflate the rate of susceptible individuals and thus require booster vaccinations. This could become an issue with the emergence of immune-escape variants, as reported in South Africa⁵⁴. Given limited information at this stage, we did not consider this scenario in our analyses, but this is an important area of future research.

Fourth, age-mixing patterns are key to assess the impact of vaccination as individuals of different ages are exposed to different transmission risks. In the main analysis, we assumed the mixing patterns to correspond to those estimated before the COVID-19 pandemic, indicating the goal of a return to pre-pandemic interactions. We have also performed a sensitivity analysis based on the mixing patterns estimated in China in March 2020⁵⁰, after the lockdown was lifted but schools were still closed. How the population would mix in case of a new wave of COVID-19 starts to unfold in China remains to be seen.

Moreover, our study is performed at a national scale and thus our estimates of the impact of vaccination should be interpreted cautiously at the local scale. In fact, spatial heterogeneities within China in terms of risk of case importation, socio-demographic characteristics of the population, mixing and mobility patterns, vaccination coverage and capacity may affect our results⁵⁵.

Enhanced vaccination efforts in conjunction with NPIs have been successfully used during the COVID-19 outbreak in Ruili City (Yunnan Province, China) in March–April 2021. Our analysis, however, focuses on the assessment of whether and to what extent we need to rely on NPIs to prevent a COVID-19 epidemic while vaccines are rolled out. As such, our results cannot be used to guide a reactive spatially targeted strategy. To properly capture the peculiarity of that context, specific modelling tools mirroring the interventions adopted in China as a response to emerging outbreaks are needed.

Finally, it would be interesting to analyse adaptive vaccination prioritizations that change as the epidemiological situation evolves over time, but that would require the development of dynamic optimization algorithms that lie beyond the scope of this work⁵⁶. Nonetheless, our study provides estimates of the effect of relaxing NPIs over the course of the epidemic.

In conclusion, vaccination alone could substantially reduce COVID-19 burden, but in the foreseeable future may not be enough to prevent local outbreaks from escalating to major widespread epidemics due to limitation in the vaccine production and supply

(particularly at the initial stage of the vaccination), as well as the capacity of vaccination system. This is especially relevant in contexts where most of the population is still susceptible to SARS-CoV-2 infection, as is the case in most of China. Maintaining NPIs (such as social distancing, testing, case isolation and contact tracing, wearing masks and limitation on large gatherings) throughout 2021 is necessary to prevent resurgence of COVID-19 epidemics until a sufficiently high level of immunity is reached, which depends on the transmissibility of the variants circulating at that time.

Methods

SARS-CoV-2 transmission and vaccination models. We developed a model of SARS-CoV-2 transmission and vaccination, based on an age-structured stochastic SIR scheme, accounting for heterogeneous mixing patterns by age as estimated in Shanghai¹³. The Chinese population was distributed into 18 age groups (17 age groups of 5 years from 0 to 84 years and one age group for individuals aged 85 years or older)⁵⁷. Each age group was further split into two subgroups: individuals with or without underlying conditions, where the former was considered to be associated with an increased risk of severe outcome of COVID-19 (ref. ¹⁴).

In the main analysis, susceptibility to SARS-CoV-2 infection was assumed to be heterogeneous across ages. Children under 15 years of age were considered less susceptible to infection compared with adults aged 15–64 years, while the older adults more susceptible^{33,34}. Homogeneous susceptibility across age groups was explored in sensitivity analysis SA19. Asymptomatic and symptomatic individuals were assumed to be equally infectious^{33,34}, and infectiousness was also assumed to be the same across age groups^{33,34}.

Vaccine is administered with a two-dose schedule. In the baseline model, we assumed that: (i) vaccination reduces susceptibility to SARS-CoV-2 infection; (ii) only susceptible individuals are eligible for vaccination, that is, we excluded all individuals that have experienced SARS-CoV-2 infection; (iii) duration of vaccine-induced protection lasts longer than the time horizon considered (2 years).

The baseline model is shown schematically in Supplementary Fig. 1 and is described by differential systems presented in Supplementary Files 1 and 2.

Model initialization. In China, the first pandemic wave of COVID-19 was controlled by intense NPIs^{58,59}. Almost the entire population of Mainland China is still susceptible to COVID-19 (ref. ³). As such, the model is initialized with a fully susceptible population.

China has been facing mounting pressure from imported COVID-19 cases. Containment of COVID-19 has been possible only through a combination of measures such as complete or partial lockdown, citywide mass screening using reverse-transcriptase polymerase chain reaction (RT-PCR) testing, tracing of contacts and contacts of contacts of COVID-19 cases, which were promptly applied wherever COVID-19 transmission emerged in Mainland China⁶⁰. Despite all the efforts, containment of COVID-19 appears to be hit and miss, and sporadic outbreaks inevitably occur. Simulations are thus initialized with 40 cases, roughly corresponding to the number of cases with symptoms onset in Beijing before the detection of a local outbreak on 11 June 2020 (ref. ⁶¹).

Vaccination scenarios. To explore the impact of vaccination, we ran a set of simulations in which neither NPIs nor vaccination are implemented as a reference scenario (no vax + no NPIs, that is, effective reproductive number $R_t = 2.5$ at the beginning of simulations^{17,28,58}), and compared it with a scenario in which vaccination only is implemented (vax + no NPIs). Further, we considered different sets of simulations in which NPIs are used to bring R_t respectively down to 1.5 (mild NPIs), 1.3 (moderate NPIs) and 1.1 (strong NPIs), with (vax + mild/moderate/strong NPIs) or without vaccination programme (no vax + mild/moderate/strong NPIs). In the main analysis, vaccination is assumed to begin 15 days after the epidemic start. Alternative scenarios about the seeding of the epidemic were explored as sensitivity analyses. In particular, we considered the epidemic to start when 10% (SA1), 20% (SA2) and 30% (SA3) of the Chinese population has already been vaccinated.

The model is run considering daily time steps. Gradual delivery of vaccine doses is implemented by vaccinating a fixed number of individuals each day. Although manufacturers state that a total of 3.9 billion doses of vaccines could be available by the end of 2021 (refs. ^{22–26}), scale-up and delivery will take months. On the basis of the 2009 H1N1 influenza pandemic vaccination programme implemented in Mainland China⁶², in the main analysis we assumed that 6 million doses of COVID-19 vaccines could be administered each day (4 doses per 1,000 individuals) until uptake reaches 70% for all groups¹⁴. Different values of the daily vaccine administration capacity, that is, 1.3 (SA20), 10 (SA21), 15 (SA22) and 30 (SA23) million doses per day, are explored in separate sensitivity analyses. Sensitivity analyses were also performed on the vaccination coverage, which is assumed to be either homogeneous (SA4 and SA5)¹⁴ or heterogeneous by age (SA6, SA7 and SA8).

In the main analysis, vaccination is administered to susceptible individuals only. This represents an ideal scenario where we assume that all infected individuals can be identified (for example, either via RT-PCR while infected or via

serological assays later on) and that SARS-CoV-2 infection confers long-lasting immunity. Since infection ascertainment could be challenging and pose additional strain on the health system, we also consider two sensitivity analyses in which only detected symptomatic cases are excluded from vaccination (SA14 and SA15).

In the context of fast RT-PCR-based mass screening if there is an outbreak, under-ascertainment of symptomatic cases could be only related with the sensitivity of RT-PCR tests. The sensitivity is quite high (98%) if the interval between symptom onset and RT-PCR test is within 7 days, but decreases to 68% if the time interval is 8–14 days (ref. ⁶³). The mean time interval from symptom onset to the date of collection of the sample for PCR testing was estimated to be 4.7 days in Hunan³³. Accordingly, we considered as ascertainment probabilities of symptomatic cases 70% (SA14) and 90% (SA15).

Vaccination schedule and efficacy. Since December 2020, China has given conditional approval or emergency use approval for seven COVID-19 vaccines. The National Health Commission recommends that inactivated vaccines are administered on a two-dose schedule with an interval of ≥ 21 days, recombinant subunit vaccines administered on a three-dose schedule with an interval of ≥ 28 days, and recombinant adenovirus type-5-vectored vaccines administered one dose. For simplicity, in the main analysis, we modelled the administration of an inactivated vaccine developed by the Beijing Institute of Biological Products⁶⁴, which entails a two-dose schedule across all age groups with an interval of 21 days. In separate sensitivity analyses, we explored an interval of 14 and 28 days (SA16 and SA17).

China approved its first local COVID-19 vaccine (developed by Sinopharm) for general public use on 31 December 2020, with an estimated VE of 79.3%²¹. In the main analysis, we used a VE of 80% against infection in individuals aged 20–59 years. In the developed model, vaccination confers partial protection, that is, vaccinated individuals are 80% less likely to develop infection upon an infectious contact. Sensitivity analyses using a VE of 60% (SA9) and 90% (SA10) were performed separately. The alternative values of VE were selected on the basis of published upper efficacy of vaccines of 94–95% and in such a way to cover a plausible efficacy range of forthcoming vaccines^{65–67}.

Phase 2 clinical trials demonstrated that vaccine immunogenicity was lower among older individuals than in younger adults⁶⁴. And for other inactivated vaccines such as influenza vaccine, a lower VE is observed in children compared with young adults⁶⁸. Accordingly, we assumed an age-dependent VE. In particular, given a baseline efficacy VE among individuals aged 20–59 years (80% in the main analysis), we assumed a 50% lower VE in individuals < 20 and ≥ 60 years of age (namely 40%). A scenario without age-specific variations in VE was explored as sensitivity analysis SA24.

Individuals vaccinated with the first dose could still develop infections without any immune protection, while the second dose vaccination could produce the expected VE after an average of 14 days. In the main analysis we assume both natural infection-induced and vaccine-induced immunity to SARS-CoV-2 infection does not wane within the considered time horizon (2 years). In additional sensitivity analyses, we considered an average duration of vaccine-induced protection of 6 months (SA12) and 1 year (SA25). We also consider a sensitivity analysis assuming that vaccination is effective in preventing symptomatic illness but not infection (SA11), and another one assuming an all-or-nothing vaccine, that is, the vaccine confers full protection to VE percent of vaccinated individuals (SA18).

Priority order of vaccination. The doses available to be distributed daily (6 million in the main analysis) are assigned by considering the following order of priority¹⁴: In the main analysis, healthcare workers are considered as the top priority (tier 1 of the vaccination strategy); law enforcement and security workers, personnel in nursing home and social welfare institutes, community workers and workers in energy, food and transportation sectors are included in tier 2; adults ≥ 60 years of age with underlying conditions, and adults ≥ 80 years of age without underlying conditions, who are at the highest risk of severe/fatal COVID-19, are considered in tier 3; individuals aged < 60 years with pre-existing medical conditions and pregnant women are included in tier 4; individuals aged 20–59 years without underlying conditions are included in tier 5; school-age children and younger children aged ≤ 5 years without underlying conditions are recommended for vaccination in tier 6 (Supplementary File 3).

Different priority orders are explored as sensitivity analyses. Healthcare workers and the other essential workers listed above are fixed in tier 1 and 2 of vaccination, while the remaining population is vaccinated as described in Supplementary Table 2 by considering different orders of prioritization only based on age and disregarding the presence of underlying conditions (SA26: first prioritization to old adults; SA27: first prioritization to working-age groups; SA28: first prioritization to school-age groups). We explore the impact of 5,000 initial cases on the prioritization strategy (SA29). To understand the impact in terms of number of infections by age, we compare the prioritization strategy when we account for the uncertainty in the contact matrix and in the susceptibility to infection by age, or not (in this context, median values of contact numbers and relative susceptibility are used).

COVID-19 burden model. The main output of above transmission model is the age-specific number of new infections per day in the subpopulation with or

without underlying conditions. On top of that, we developed a model of COVID-19 disease burden to estimate the number of symptomatic cases, hospitalization, ICU admissions and deaths in different scenarios in the presence/absence of vaccination.

We computed the age-specific number of symptomatic infections in individuals with and without underlying conditions on a daily basis by applying an age-specific probability of respiratory symptoms of 18.1%, 22.4%, 30.5%, 35.5% and 64.6% respectively for 0–19, 20–39, 40–59, 60–79 and 80+ years of age, as estimated from contact tracing data in Lombardy²⁰. We assume that individuals with and without underlying conditions have the same age-specific probability of developing symptoms.

The daily age-specific number of hospital admissions in the two subpopulations was computed by applying the age-specific proportion of laboratory-confirmed symptomatic cases requiring hospitalization (Supplementary File 4), delayed by an average time of 3.8 days between symptom onset and hospitalization¹⁷.

The daily age-specific number of patients admitted to ICU in the two subpopulations was computed by applying to hospitalized cases an age-specific probability of being admitted to ICU¹⁵, and distinguishing patients requiring intensive care in survivors and non-survivors. Survivors are admitted to ICU after an average time of 7 days from hospitalization. Non-survivors are admitted to ICU after an average time of 8 days after hospitalization¹⁶.

The daily age-specific number of deaths in the two subpopulations was computed by applying the age-specific fatality ratio among symptomatic cases (Supplementary File 4), delayed by an average time of 13.9 days between symptom onset and death¹⁸.

Data analysis. For each scenario, 200 stochastic model realizations were performed. The outcome of these simulations determined the distributions of the number of symptomatic infections, hospitalizations, ICU admissions and deaths. We defined 95% credible intervals as quantiles 0.025 and 0.975 of the estimated distributions. We used a Bayesian approach to estimate R_t from the time series of symptomatic cases by date of symptom onset and the distribution of the serial interval¹⁷. The methods are described in detail in Supplementary File 5.

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this paper.

Data availability

Data used in this study can be downloaded from GitHub at https://github.com/DXW-sola1015/2021_Yang_COVID-19-Vax_China_Code.

Code availability

The code used to generate these analyses is available on GitHub at https://github.com/DXW-sola1015/2021_Yang_COVID-19-Vax_China_Code.

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References

1. New cases of COVID-19 in world. *Johns Hopkins University Coronavirus Research Center* <https://coronavirus.jhu.edu/data/new-cases> (2021).
2. Zhao, J. et al. Disease burden attributable to the first wave of COVID-19 in china and the effect of timing on the cost-effectiveness of movement restriction policies. *Value Health* **24**, 615–624 (2021).
3. Chen, X. et al. Serological evidence of human infection with SARS-CoV-2: a systematic review and meta-analysis. *Lancet Glob. Health* **9**, e598–e609 (2021).
4. Coronavirus (COVID-19) vaccinations. *Our World in Data* <https://ourworldindata.org/covid-vaccinations> (2021).
5. Wang, W. et al. Global, regional, and national estimates of target population sizes for covid-19 vaccination: descriptive study. *Br. Med. J.* **371**, m4704 (2020).
6. Introduction to the promotion of COVID-19 vaccination (as of June 1, 2021). *Press Conference of the Joint Prevention and Control Mechanism of the State Council* <http://www.nhc.gov.cn/xcs/yqjzqk/202106/9db49006ea4d4ab78e5a59a318cfea4f.shtml> (2021).
7. Outbreak report. *National Health Commission of the People's Republic of China* http://www.nhc.gov.cn/xcs/yqtb/list_gzbd.shtml (2021).
8. Anderson, R. M. & May, R. M. Vaccination and herd immunity to infectious diseases. *Nature* **318**, 323–329 (1985).
9. Agur, Z., Cojocaru, L., Mazor, G., Anderson, R. M. & Danon, Y. L. Pulse mass measles vaccination across age cohorts. *Proc. Natl Acad. Sci. U. S. A.* **90**, 11698–11702 (1993).
10. Chao, D. L., Halloran, M. E. & Longini, I. M. Jr. Vaccination strategies for epidemic cholera in Haiti with implications for the developing world. *Proc. Natl Acad. Sci. U. S. A.* **108**, 7081–7085 (2011).
11. Ferguson, N. M., Donnelly, C. A. & Anderson, R. M. The foot-and-mouth epidemic in Great Britain: pattern of spread and impact of interventions. *Science* **292**, 1155–1160 (2001).

12. Wu, J. T., Peak, C. M., Leung, G. M. & Lipsitch, M. Fractional dosing of yellow fever vaccine to extend supply: a modelling study. *Lancet* **388**, 2904–2911 (2016).
13. Zhang, J. et al. Patterns of human social contact and contact with animals in Shanghai, China. *Sci. Rep.* **9**, 15141 (2019).
14. Yang, J. et al. Who should be prioritized for COVID-19 vaccination in China? A descriptive study. *BMC Med.* **19**, 45 (2021).
15. Yang, J. et al. Disease burden and clinical severity of the first pandemic wave of COVID-19 in Wuhan, China. *Nat. Commun.* **11**, 5411 (2020).
16. Xie, J. et al. Clinical characteristics and outcomes of critically ill patients with novel coronavirus infectious disease (COVID-19) in China: a retrospective multicenter study. *Intensive Care Med.* **46**, 1863–1872 (2020).
17. Zhang, J. et al. Evolving epidemiology and transmission dynamics of coronavirus disease 2019 outside Hubei Province, China: a descriptive and modelling study. *Lancet Infect. Dis.* **20**, 793–802 (2020).
18. Deng, X. et al. Case fatality risk of the first pandemic wave of novel coronavirus disease 2019 (COVID-19) in China. *Clin. Infect. Dis. ciaa578* (2020).
19. Guan, W. et al. Clinical characteristics of coronavirus disease 2019 in China. *N. Engl. J. Med.* **382**, 1708–1720 (2020).
20. Poletti, P. et al. Association of age with likelihood of developing symptoms and critical disease among close contacts exposed to patients with confirmed SARS-CoV-2 infection in Italy. *JAMA Netw. Open* **4**, e211085 (2021).
21. Sinopharm COVID-19 vaccine licensed in China. *Sinopharm* <http://www.sinopharm.com/s/1223-3763-38840.html> (2021).
22. Current development and production capacity of domestic COVID-19 vaccine. *CNWest* <http://news.cnwest.com/szyw/a/2020/12/04/19343015.html> (2021).
23. Chairman of Cansino Bio. After the increase in production capacity, the company's COVID-19 vaccine will be released in large quantities. *Huanqiu Net* <https://baijiahao.baidu.com/s?id=1692936657439211781&wfr=spider&for=pc> (2021).
24. The first batch of BBIBP-CorV (Sinopharm) has shipped. *Sinopharm* <http://www.sinopharm.com/s/1223-3769-39020.html> (2021).
25. Sinovac claims that the annual production capacity of COVID-19 vaccine will reach 2 billion doses by June. *Reuters* <https://cn.reuters.com/article/sinovac-biotech-covid-vaccine-0303-idCNKCS2AV0DL> (2021).
26. Chinese and foreign media enter the 1 billion-level COVID-19 vaccine production base. *Sinopharm* <http://www.sinopharm.com/s/1223-4126-39018.html> (2021).
27. Wu, J. T., Leung, K. & Leung, G. M. Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study. *Lancet* **395**, 689–697 (2020).
28. Li, Q. et al. Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. *N. Engl. J. Med.* **382**, 1199–1207 (2020).
29. Abbott, S., Hellewell, J., Munday, J., group, C.n.w. & Funk, S. The transmissibility of novel coronavirus in the early stages of the 2019-20 outbreak in Wuhan: exploring initial point-source exposure sizes and durations using scenario analysis. *Wellcome Open Res.* **5**, 17 (2020).
30. Chinazzi, M. et al. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science* **368**, 395–400 (2020).
31. Natsuko, I. et al. Report 3: transmissibility of 2019-nCoV. *Imperial College London* <https://doi.org/10.25561/77148> (2020).
32. Report of the WHO–China joint mission on coronavirus disease 2019 (COVID-19). *World Health Organization* [https://www.who.int/publications/i/item/report-of-the-who-china-joint-mission-on-coronavirus-disease-2019-\(covid-19\)](https://www.who.int/publications/i/item/report-of-the-who-china-joint-mission-on-coronavirus-disease-2019-(covid-19)) (2021).
33. Hu, S. et al. Infectivity, susceptibility, and risk factors associated with SARS-CoV-2 transmission under intensive contact tracing in Hunan, China. *Nat. Commun.* **12**, 1533 (2021).
34. Sun, K. et al. Transmission heterogeneities, kinetics, and controllability of SARS-CoV-2. *Science* **371**, eabe2424 (2021).
35. Li, L. et al. Influenza-associated excess respiratory mortality in China, 2010–15: a population-based study. *Lancet Public Health* **4**, e473–e481 (2019).
36. Wang, J. et al. Acceptance of COVID-19 vaccination during the COVID-19 pandemic in China. *Vaccines* **8**, 482 (2020).
37. Wang, J. et al. The changing acceptance of COVID-19 vaccination in different epidemic phases in China: a longitudinal study. *Vaccines (Basel)* **9**, 191 (2021).
38. Shao, G., Ding, W., Yu, Y., Ma, H. & Zhijie, A. Willingness of parents to vaccinate family members with coronavirus disease 2019, influenza, and pneumococcal vaccines, Anyang City, May to June 2020. *Chinese J. Vaccine Immun.* **26**, 629–633 (2020).
39. Supply vaccines to eliminate human diseases. *Sinovac* http://www.sinovac.com.cn/?optionid=468&auto_id=1877 (2021).
40. The application for conditional marketing of CansinoBio Coronavirus Vaccine Convidecia™ was accepted by the National Medical Products Administration. *CanSinoBio* <http://www.cansinotech.com.cn/html/1/1/179/180/806.html> (2021).
41. Products instruction. *Beijing Institute of Biological Products* <https://www.bjbp.com/?p=75> (2021).
42. Palacios, R. et al. Double-blind, randomized, placebo-controlled phase III clinical trial to evaluate the efficacy and safety of treating healthcare professionals with the adsorbed COVID-19 (inactivated) vaccine manufactured by Sinovac - PROFISCOV: a structured summary of a study protocol for a randomised controlled trial. *Trials* **21**, 853 (2020).
43. The interim analysis data of the COVID-19 inactivated vaccine phase III clinical trial of Sinopharm Wuhan Institute of Biological Products released. *Wuhan Institute of Biological Products* <http://www.wibp.com.cn/Chs/Detail.aspx?id=14669> (2021).
44. About variants of the virus that causes COVID-19. *Centers for Disease Control and Prevention* <https://www.cdc.gov/coronavirus/2019-ncov/transmission/variant.html> (2021).
45. Davies, N. G. et al. Estimated transmissibility and impact of SARS-CoV-2 lineage B.1.1.7 in England. *Science*, eabg3055 (2021).
46. Stefanelli, P. et al. Co-circulation of SARS-CoV-2 variants B.1.1.7 and P.1. Preprint at *medRxiv* <https://doi.org/10.1101/2021.04.06.21254923> (2021).
47. Challen, R. et al. Risk of mortality in patients infected with SARS-CoV-2 variant of concern 202012/1: matched cohort study. *Br. Med. J.* **372**, n579 (2021).
48. Davies, N. G. et al. Increased mortality in community-tested cases of SARS-CoV-2 lineage B.1.1.7. *Nature* **593**, 270–274 (2021).
49. Meehan, M. T. et al. Age-targeted dose allocation can halve COVID-19 vaccine requirements. Preprint at *medRxiv* <https://doi.org/10.1101/2020.10.08.20208108> (2020).
50. Zhang, J. et al. The impact of relaxing interventions on human contact patterns and SARS-CoV-2 transmission in China. *Sci. Adv.* **7**, eabe2584 (2020).
51. Bubar, K. M. et al. Model-informed COVID-19 vaccine prioritization strategies by age and serostatus. *Science* **371**, 916–921 (2021).
52. Giordano, G. et al. Modeling vaccination rollouts, SARS-CoV-2 variants and the requirement for non-pharmaceutical interventions in Italy. *Nat. Med.* **27**, 993–998 (2021).
53. Li, Y. et al. The temporal association of introducing and lifting non-pharmaceutical interventions with the time-varying reproduction number (R) of SARS-CoV-2: a modelling study across 131 countries. *Lancet Infect. Dis.* **21**, 193–202 (2021).
54. Wibmer, C. K. et al. SARS-CoV-2 501Y.V2 escapes neutralization by South African COVID-19 donor plasma. *Nat. Med.* **27**, 622–625 (2021).
55. Huang, B. et al. Integrated vaccination and physical distancing interventions to prevent future COVID-19 waves in Chinese cities. *Nat. Hum. Behav.* **5**, 695–705 (2021).
56. Han, S. et al. Dynamic optimization of COVID-19 vaccine prioritization in the context of limited supply. Preprint at *In Review* <https://doi.org/10.21203/rs.3.rs-257573/v1> (2021).
57. World population prospects 2019. *Population Division, Department of Economic and Social Affairs, United Nations* <https://population.un.org/wpp/> (2019).
58. Pan, A. et al. Association of public health interventions with the epidemiology of the COVID-19 outbreak in Wuhan, China. *JAMA* **323**, 1915–1923 (2020).
59. Li, Z. et al. Active case finding with case management: the key to tackling the COVID-19 pandemic. *Lancet* **396**, 63–70 (2020).
60. Xing, Y., Wong, G. W. K., Ni, W., Hu, X. & Xing, Q. Rapid response to an outbreak in Qingdao, China. *N. Engl. J. Med.* **383**, e129 (2020).
61. The COVID-19 outbreak in Beijing. *Xinhua net* http://www.xinhuanet.com/politics/2020-06/19/c_1126135352.htm (2020).
62. Report of H1N1 pandemic influenza vaccination from Ministry of Health. *The Central People's Government of the People's Republic of China* <http://www.gov.cn/gzdt> (2020).
63. Xiao, A. et al. Dynamic profile of RT-PCR findings from 301 COVID-19 patients in Wuhan, China: a descriptive study. *J. Clin. Virol.* **127**, 104346 (2020).
64. Xia, S. et al. Safety and immunogenicity of an inactivated SARS-CoV-2 vaccine, BBIBP-CorV: a randomised, double-blind, placebo-controlled, phase 1/2 trial. *Lancet Infect. Dis.* **21**, 39–51 (2021).
65. Callaway, E. COVID vaccine excitement builds as Moderna reports third positive result. *Nature* **587**, 337–338 (2020).
66. Voysey, M. et al. Safety and efficacy of the ChAdOx1 nCoV-19 vaccine (AZD1222) against SARS-CoV-2: an interim analysis of four randomised controlled trials in Brazil, South Africa, and the UK. *Lancet* **397**, 99–111 (2021).
67. Polack, F. P. et al. Safety and efficacy of the BNT162b2 mRNA Covid-19 vaccine. *N. Engl. J. Med.* **383**, 2603–2615 (2020).
68. Yang, P. et al. Influenza vaccine effectiveness against medically-attended influenza illness during the 2012–2013 season in Beijing, China. *Vaccine* **32**, 5285–5289 (2014).
69. Liu, Q. H. et al. Measurability of the epidemic reproduction number in data-driven contact networks. *Proc. Natl Acad. Sci. USA* **115**, 12680–12685 (2018).

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Author contributions

H.Y. conceived the study. H.Y., S.M. and M.A. designed and supervised the study. J.Y., J.Z., J.C., W.W., Q.W., W.Z., Z.Z., K.D. and G.Z. participated in data collection. V.M., G.G., P.P. and F.T. developed the model. J.Y., V.M. and X.D. analysed the model outputs and prepared the tables and figures. J.Y. prepared the first draft of the manuscript. H.Y., V.M., C.V. and M.A. commented on the data and its interpretation, and revised the content critically. All authors contributed to review and revision and approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

Competing interests

H.Y. has received research funding from Sanofi Pasteur, GlaxoSmithKline, Yichang HEC Changjiang Pharmaceutical Company and Shanghai Roche Pharmaceutical Company. M.A. has received research funding from Seqirus. None of this research funding is related to COVID-19. All other authors report no competing interests.

Ethics approval

All these data were in the public domain. Ethical review for the re-use of these secondary data is not required.

Additional information

Extended data is available for this paper at <https://doi.org/10.1038/s41562-021-01155-z>.

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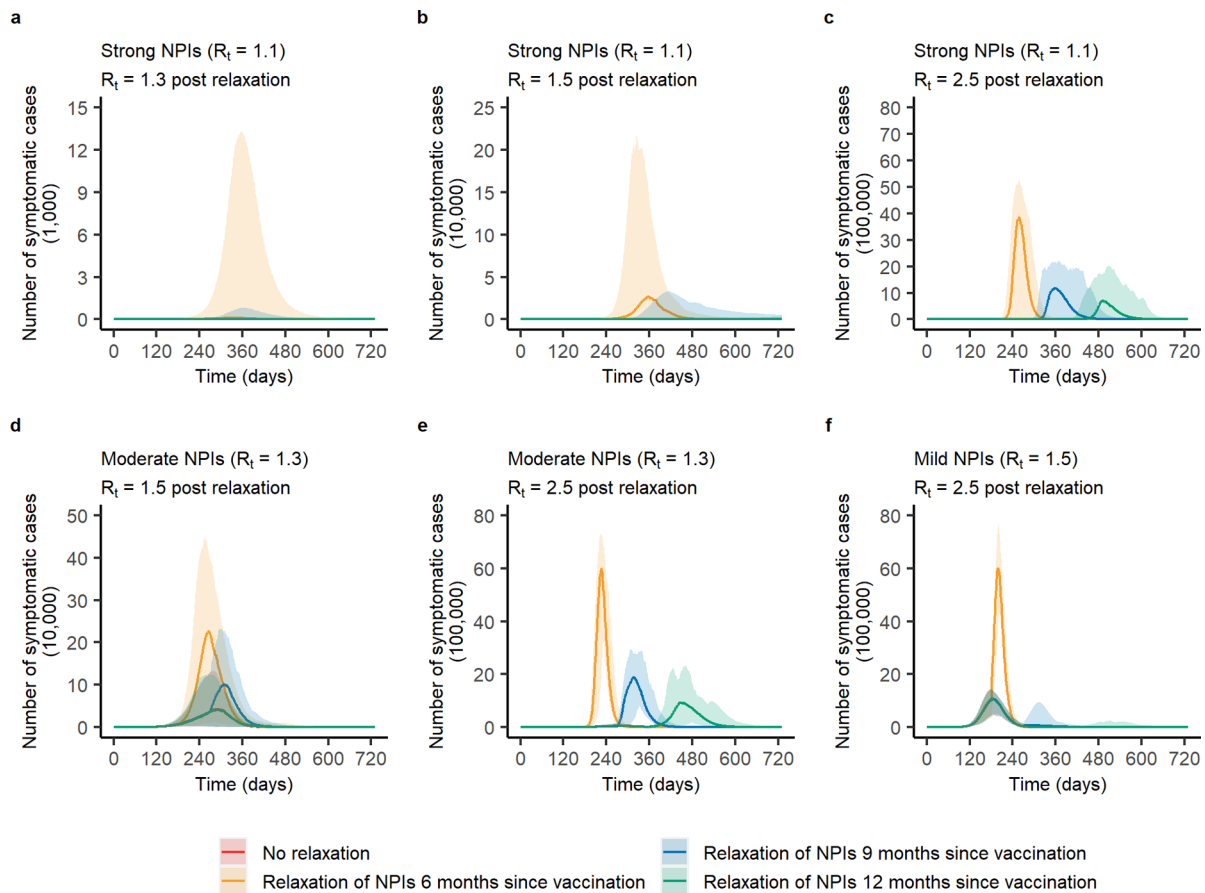
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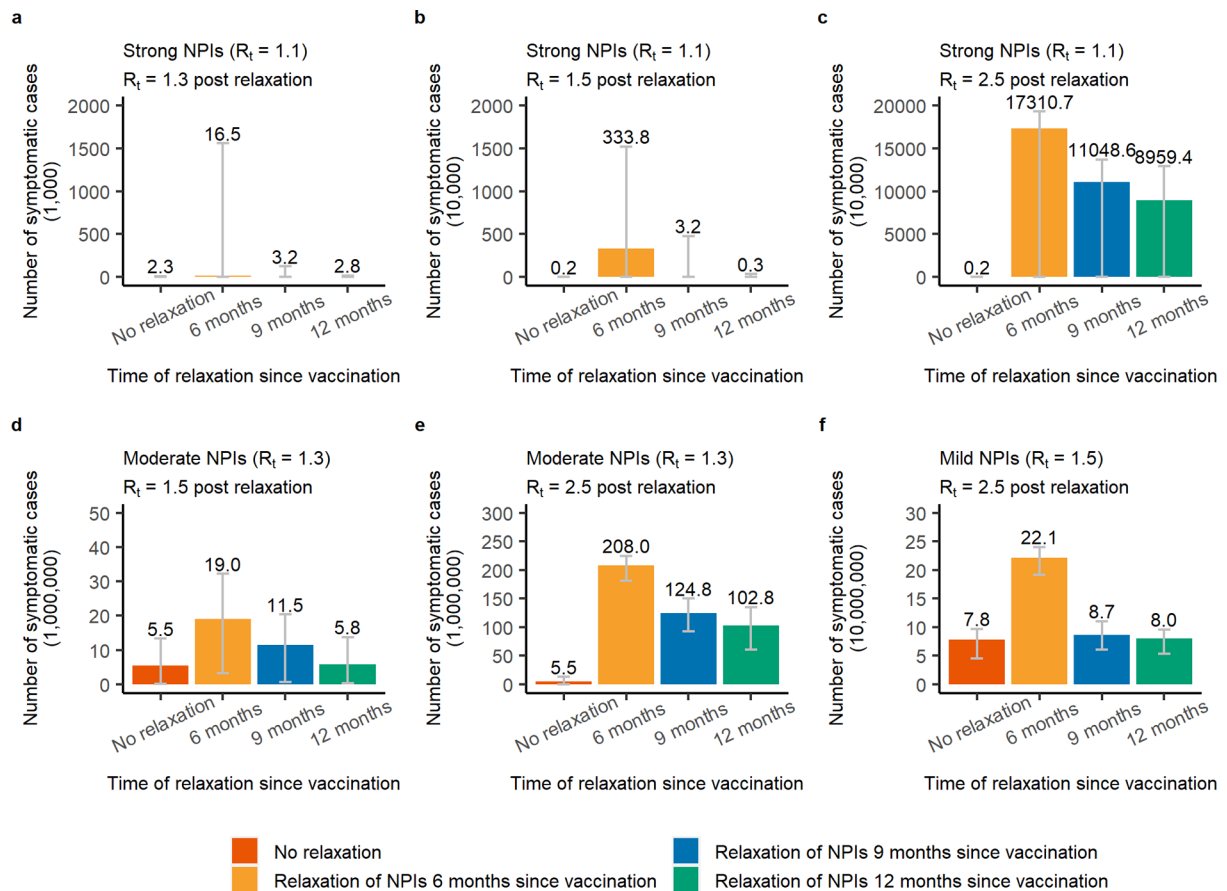


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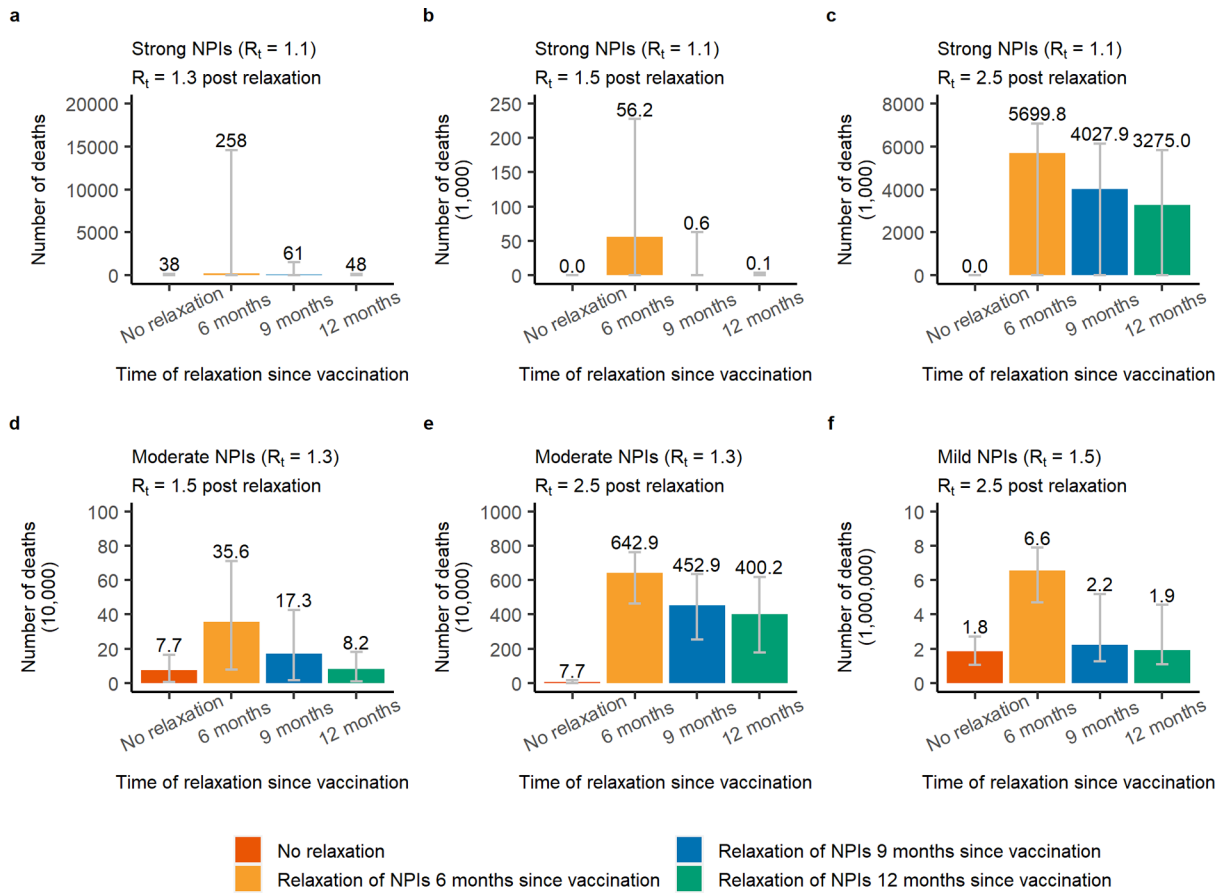
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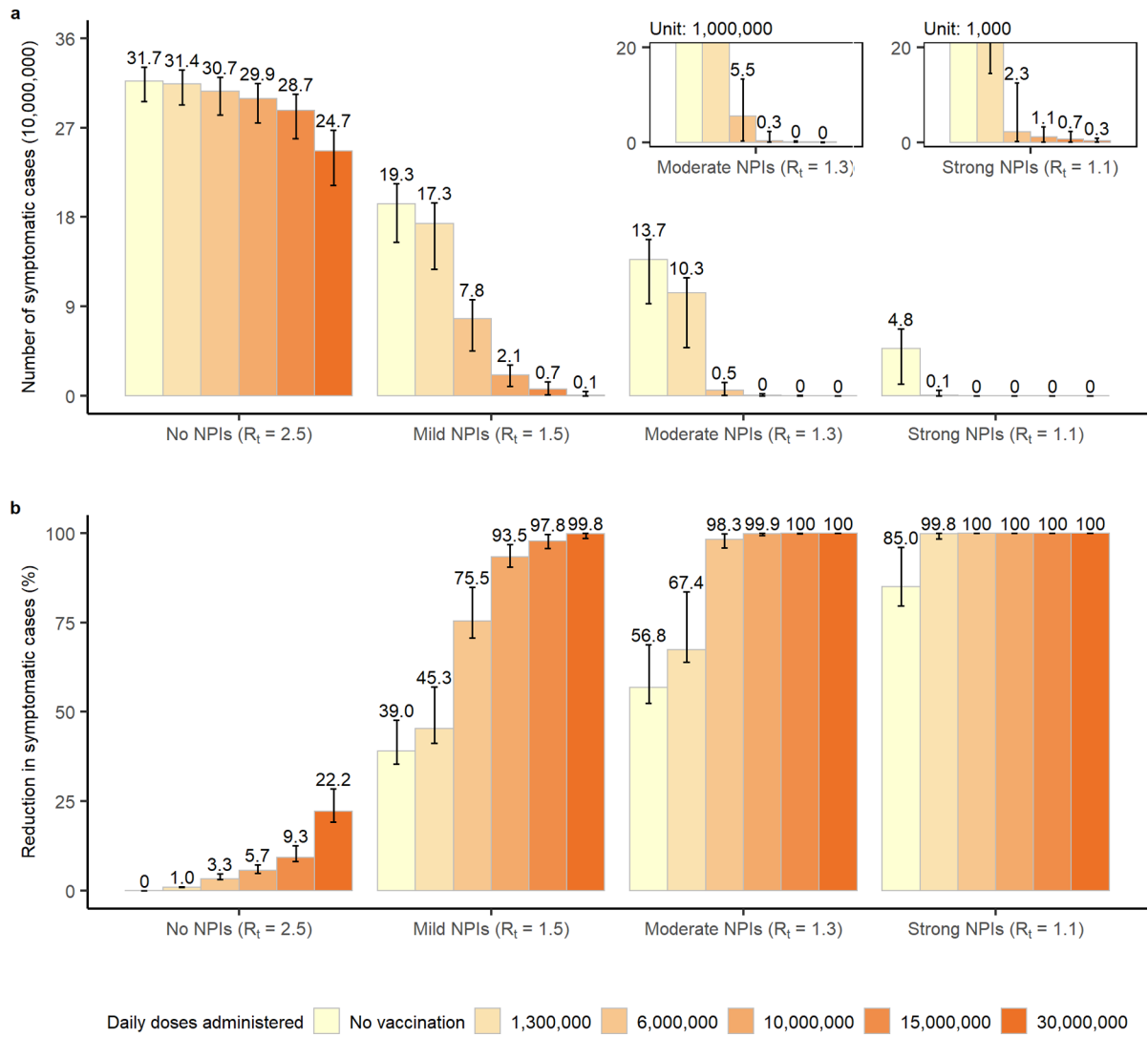
Extended Data Fig. 1 | Time series of symptomatic cases given relaxation of NPIs 6, 9 and 12 months since vaccination, provided a vaccination capacity of 6 million doses per day. a-c, For scenario with strong NPIs ($R_t = 1.1$), we increment the value of R_t to 1.3, 1.5, 2.5 after 6, 9, and 12 months since vaccination, respectively; **d-e,** for $R_t = 1.3$, we increment the value of R_t to 1.5 and 2.5 after 6, 9, 12 months, respectively; **f,** for $R_t = 1.5$, we increment the value of R_t to 2.5 after 6, 9, 12 months, respectively. Line denotes median, and shadow denotes quantiles 0.025 and 0.975. Note that the red line is barely visible as it is almost entirely overlapping with the green one.



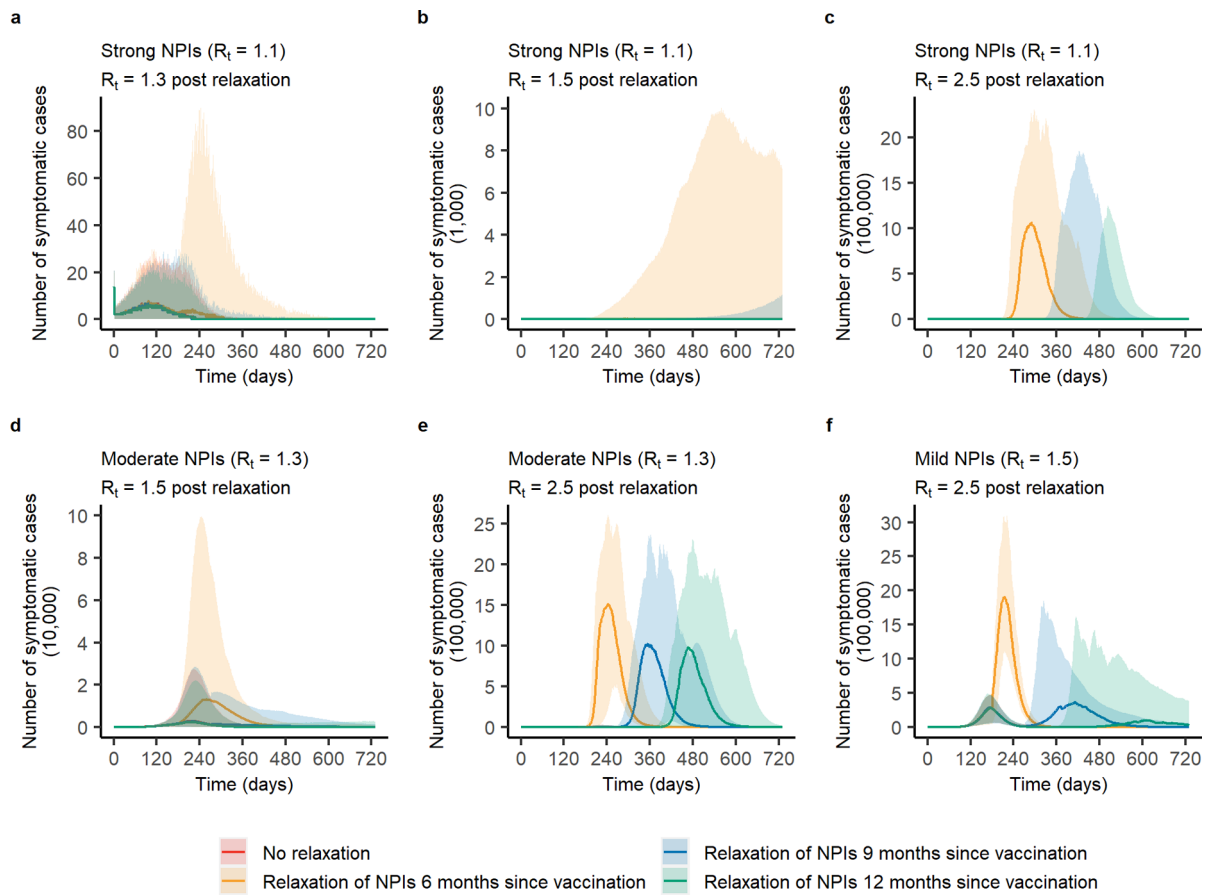
Extended Data Fig. 2 | Cumulative number of COVID-19 symptomatic cases given relaxation of NPIs 6, 9 and 12 months since vaccination, provided a vaccination capacity of 6 million doses per day. a-c, For scenario with strong NPIs ($R_t = 1.1$), we increment the value of R_t to 1.3, 1.5, 2.5 after 6, 9, and 12 months since vaccination, respectively; **d-e,** for $R_t = 1.3$, we increment the value of R_t to 1.5 and 2.5 after 6, 9, 12 months, respectively; **f,** for $R_t = 1.5$, we increment the value of R_t to 2.5 after 6, 9, 12 months, respectively. Number denotes median, and error bars denote quantiles 0.025 and 0.975.



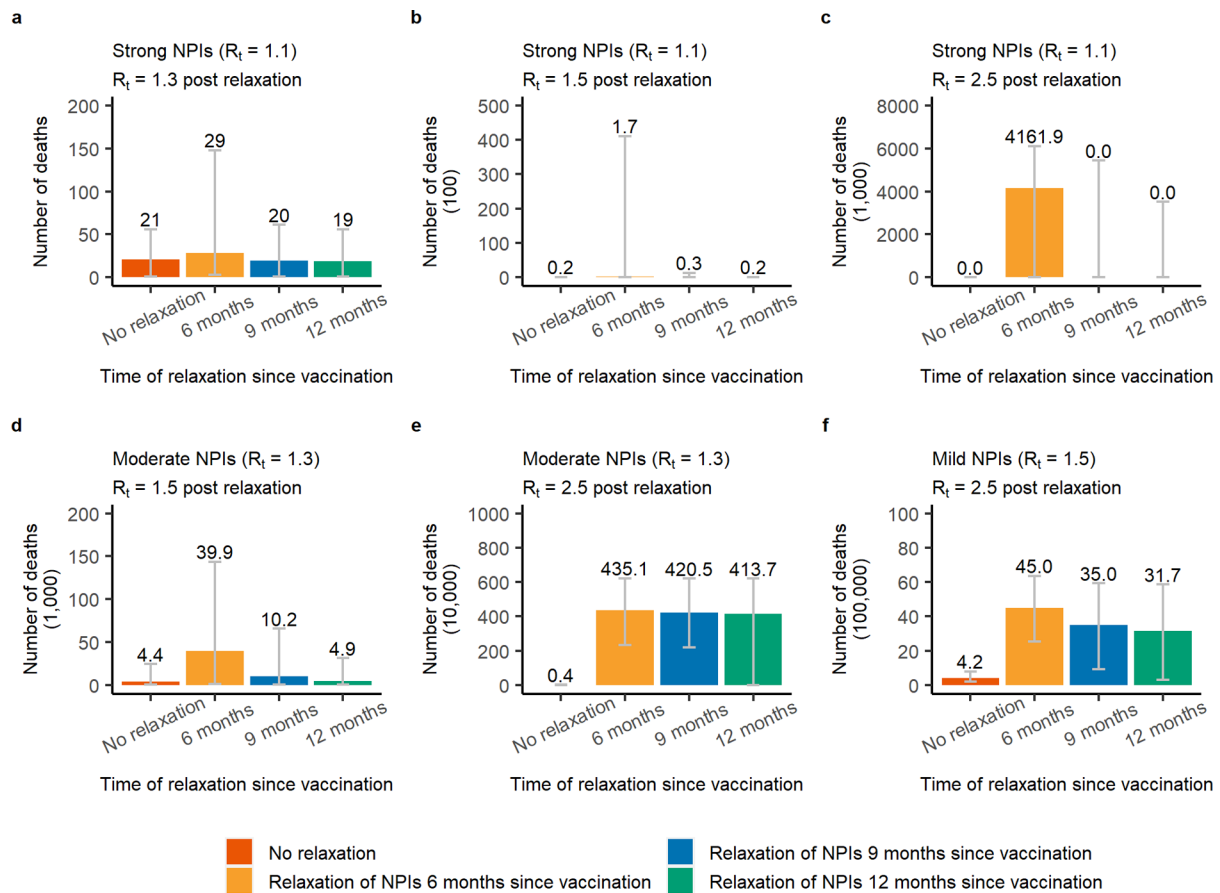
Extended Data Fig. 3 | Cumulative number of COVID-19 deaths given relaxation of NPIs 6, 9 and 12 months since vaccination, provided a vaccination capacity of 6 million doses per day. a-c, For scenario with strong NPIs ($R_t = 1.1$), we increment the value of R_t to 1.3, 1.5, 2.5 after 6, 9, and 12 months since vaccination, respectively; **d-e**, for $R_t = 1.3$, we increment the value of R_t to 1.5 and 2.5 after 6, 9, 12 months, respectively; **f**, for $R_t = 1.5$, we increment the value of R_t to 2.5 after 6, 9, 12 months, respectively. Number denotes median, and error bars denote quantiles 0.025 and 0.975.



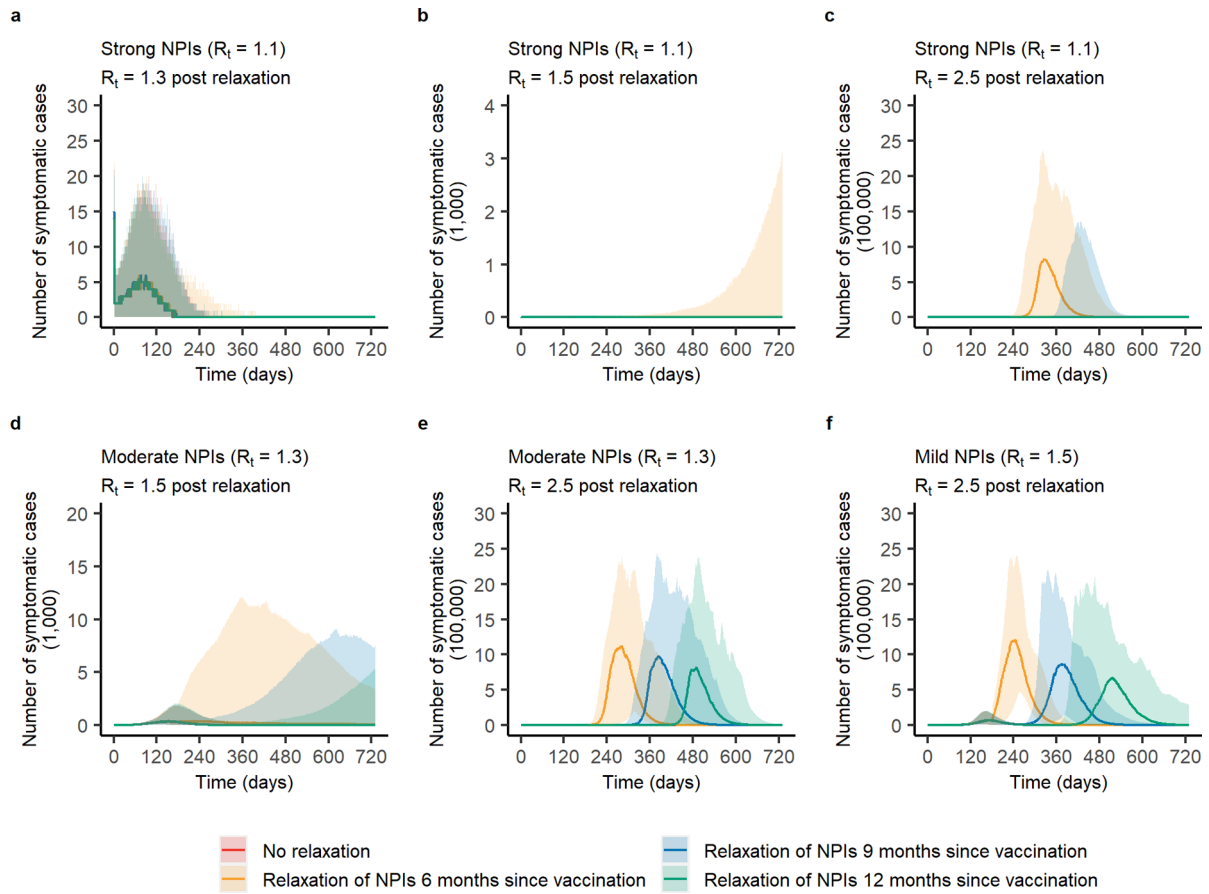
Extended Data Fig. 4 | Impact of daily doses administered on COVID-19 symptomatic cases. **a**, Cumulative number of COVID-19 symptomatic cases as estimated in the different scenarios under progressively increasing values of the daily vaccination capacity; **b**, Proportion of symptomatic cases averted compared to the *reference scenario*, that is, no vaccination + no NPIs with $R_t = 2.5$ at the beginning of the outbreak. Number denotes median, and error bars denote quantiles 0.025 and 0.975.



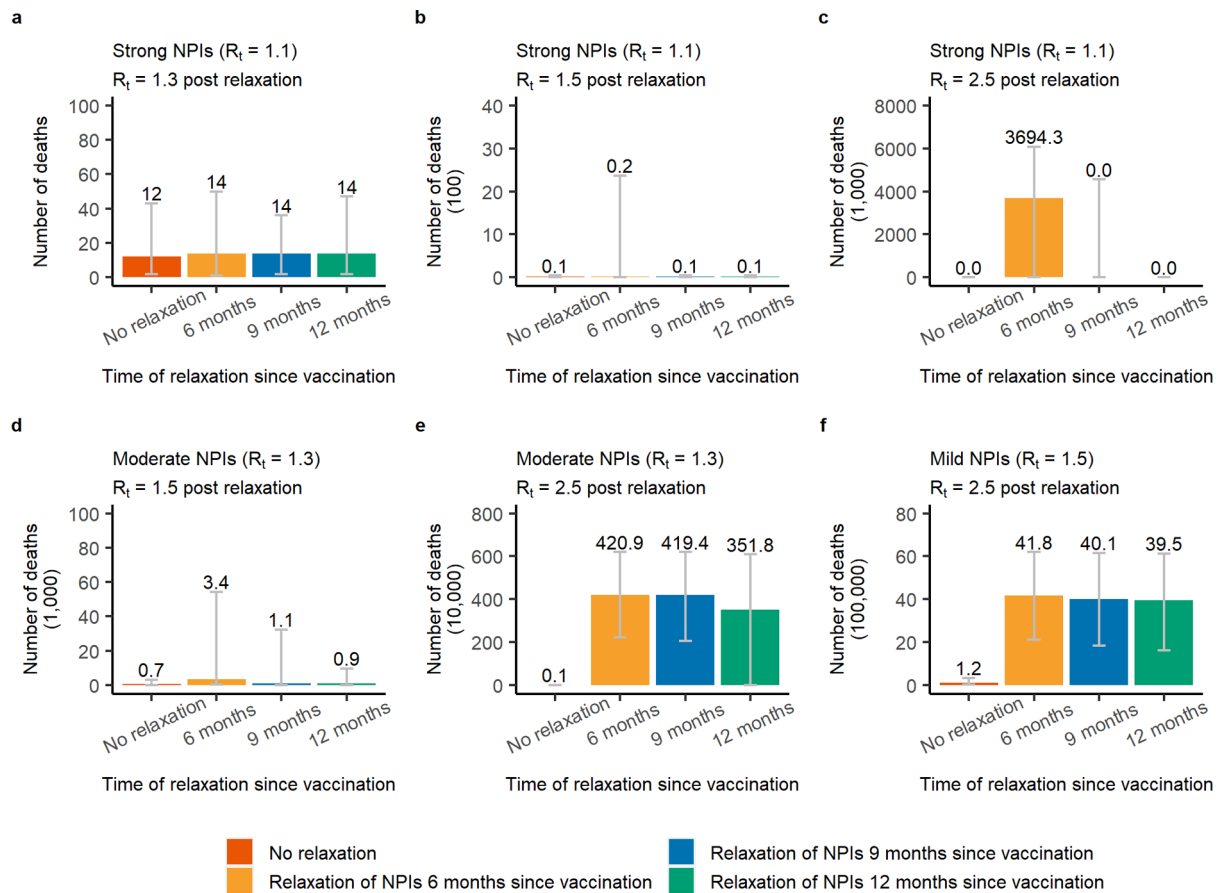
Extended Data Fig. 5 | Time series of symptomatic cases given relaxation of NPIs 6, 9 and 12 months since vaccination, provided a vaccination capacity of 10 million doses per day. **a-c**, For scenario with strong NPIs ($R_t = 1.1$), we increment the value of R_t to 1.3, 1.5, 2.5 after 6, 9, and 12 months since vaccination, respectively; **d-e**, for $R_t = 1.3$, we increment the value of R_t to 1.5 and 2.5 after 6, 9, 12 months, respectively; **f**, for $R_t = 1.5$, we increment the value of R_t to 2.5 after 6, 9, 12 months, respectively. Line denotes median, and shadow denotes quantiles 0.025 and 0.975. Note that the red line is barely visible as it is almost entirely overlapping with the green one.



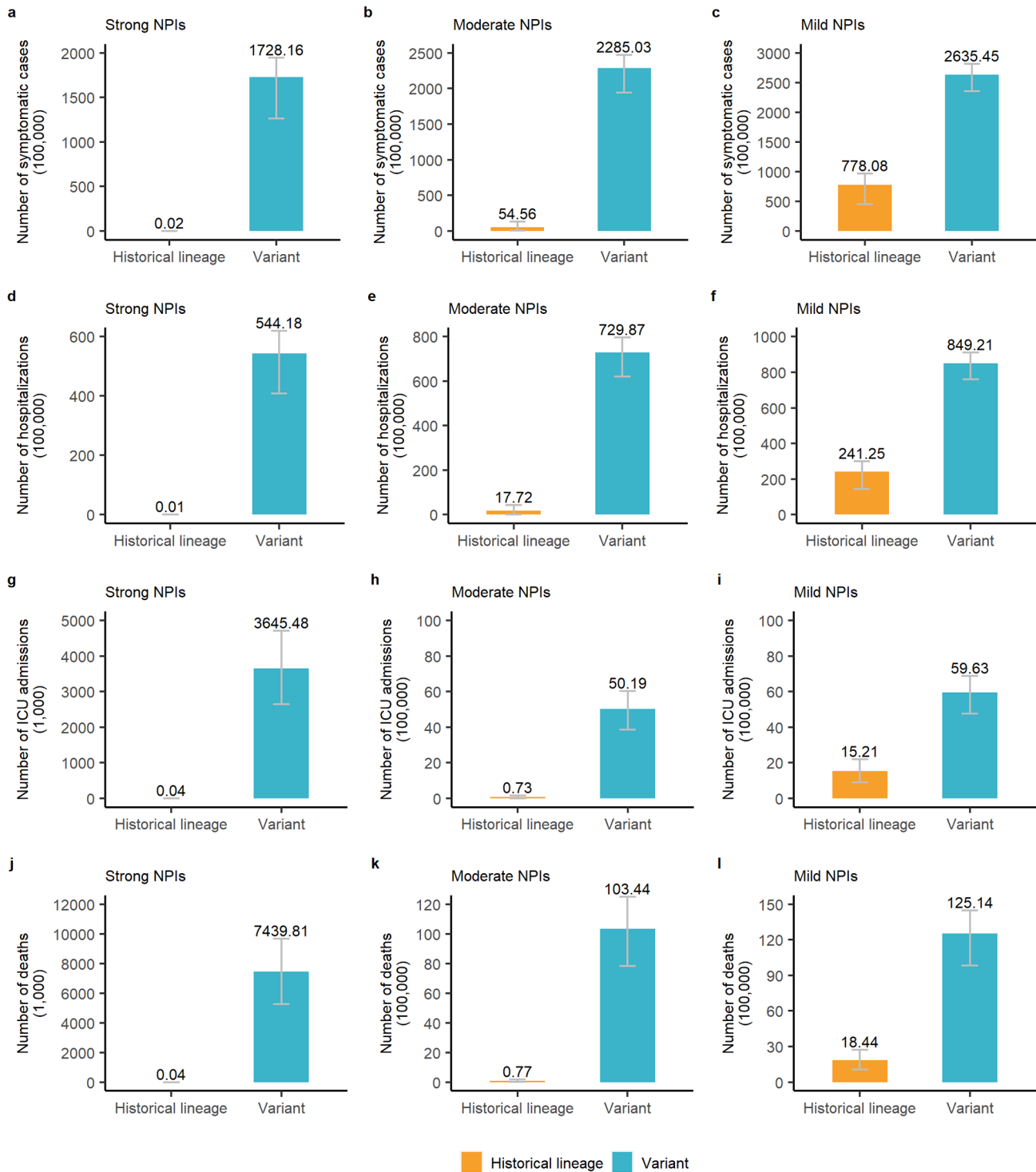
Extended Data Fig. 6 | Cumulative number of COVID-19 deaths given relaxation of NPIs 6, 9 and 12 months since vaccination, provided a vaccination capacity of 10 million doses per day. a-c, For scenario with strong NPIs ($R_t = 1.1$), we increment the value of R_t to 1.3, 1.5, 2.5 after 6, 9, and 12 months since vaccination, respectively; **d-e,** for $R_t = 1.3$, we increment the value of R_t to 1.5 and 2.5 after 6, 9, 12 months, respectively; **f,** for $R_t = 1.5$, we increment the value of R_t to 2.5 after 6, 9, 12 months, respectively. Number denotes median, and error bars denote quantiles 0.025 and 0.975.



Extended Data Fig. 7 | Time series of symptomatic cases given relaxation of NPIs 6, 9 and 12 months since vaccination, provided a vaccination capacity of 15 million doses per day. **a-c**, For scenario with strong NPIs ($R_t = 1.1$), we increment the value of R_t to 1.3, 1.5, 2.5 after 6, 9, and 12 months since vaccination, respectively; **d-e**, for $R_t = 1.3$, we increment the value of R_t to 1.5 and 2.5 after 6, 9, 12 months, respectively; **f**, for $R_t = 1.5$, we increment the value of R_t to 2.5 after 6, 9, 12 months, respectively. Line denotes median, and shadow denotes quantiles 0.025 and 0.975. Note that the red line is barely visible as it is almost entirely overlapping with the green one.



Extended Data Fig. 8 | Cumulative number of COVID-19 deaths given relaxation of NPIs 6, 9 and 12 months since vaccination, provided a vaccination capacity of 15 million doses per day. a-c, For scenario with strong NPIs ($R_t = 1.1$), we increment the value of R_t to 1.3, 1.5, 2.5 after 6, 9, and 12 months since vaccination, respectively; **d-e,** for $R_t = 1.3$, we increment the value of R_t to 1.5 and 2.5 after 6, 9, 12 months, respectively; **f,** for $R_t = 1.5$, we increment the value of R_t to 2.5 after 6, 9, 12 months, respectively. Number denotes median, and error bars denote quantiles 0.025 and 0.975.



Extended Data Fig. 9 | Cumulative burden of COVID-19, SARS-CoV-2 variants compared to non-variants. We consider higher values of R_t to account for enhanced transmissibility of SARS-CoV-2 variants. **a**, The number of symptomatic cases in the context of strong NPIs, $R_t = 1.1$ for historical lineage, while $R_t = 1.7$ for variants; **b**, the number of symptomatic cases in the context of moderate NPIs, $R_t = 1.3$ for historical lineage, while $R_t = 1.9$ for variants; **c**, the number of symptomatic cases in the context of mild NPIs, $R_t = 1.5$ for historical lineage, while $R_t = 2.1$ for variants. **d-f**, as **a-c** but for the number of hospitalizations. **g-i**, as **a-c** but for the number of ICU admissions. **j-l** as **a-c** but for the number of deaths. Number denotes median, and error bars denote quantiles 0.025 and 0.975.

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Data and code used in this study can be downloaded from GitHub at https://github.com/DXW-sola1015/2021_Yang_COVID-19-Vax_China_Code.

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