

Original Article



# Modeling Incorporating the Severity-Reducing Long-term Immunity: Higher Viral Transmission Paradoxically Reduces Severe COVID-19 During Endemic Transition

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## ABSTRACT

Natural infection with severe acute respiratory syndrome-coronavirus-2 or vaccination induces virus-specific immunity protecting hosts from infection and severe disease. While the infection-preventing immunity gradually declines, the severity-reducing immunity is relatively well preserved. Here, based on the different longevity of these distinct immunities, we develop a mathematical model to estimate courses of endemic transition of coronavirus disease 2019 (COVID-19). Our analysis demonstrates that high viral transmission unexpectedly reduces the rates of progression to severe COVID-19 during the course of endemic transition despite increased numbers of infection cases. Our study also shows that high viral transmission amongst populations with high vaccination coverages paradoxically accelerates the endemic transition of COVID-19 with reduced numbers of severe cases. These results provide critical insights for driving public health policies in the era of 'living with COVID-19.'

**Keywords:** COVID-19; SARS-CoV-2; Immunity; Severity; Endemic transition

## INTRODUCTION

The coronavirus disease 2019 (COVID-19) pandemic is ongoing, resulting in devastating impact on public health, economy, and society. To halt the current pandemic, COVID-19 vaccines have been rapidly developed at an unprecedented pace. These vaccines provide protective immunity against severe acute respiratory syndrome-coronavirus-2 (SARS-

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### Conflict of Interest

The authors declare no potential conflicts of interest.

### Abbreviations

COVID-19, coronavirus disease 2019; nAb, neutralizing Ab; NPIs, nonpharmaceutical interventions; SARS-CoV-2, severe acute respiratory syndrome-coronavirus-2.

### Author Contributions

Conceptualization: Shin EC, Hong H, Noh JY, Kim JK; Formal analysis: Hong H, Kim JK; Funding acquisition: Shin EC, Hong H, Noh JY, Choi S, Choi B, Kim JK; Investigation: Shin EC, Hong H, Noh JY, Lee H, Choi S, Choi B, Kim JK; Methodology: Hong H, Lee H, Choi S, Choi B, Kim JK; Software: Hong H; Supervision: Shin EC, Kim JK; Validation: Noh JY, Lee H, Choi S, Choi B; Visualization: Hong H, Kim JK; Writing - original draft: Shin EC, Hong H, Noh JY, Kim JK; Writing - review & editing: Shin EC, Hong H, Noh JY, Lee H, Choi S, Choi B, Kim JK.

### Data Availability Statement

Code and data used to perform the analysis and generate the figures in this paper are available on GitHub (<https://github.com/Mathbiomed/EndemicSIRS>).

CoV-2) to prevent infection and limit disease severity, which can also be achieved by natural infection. However, neutralizing Ab (nAb) titers decline after SARS-CoV-2 infection or vaccination in a pattern of initial rapid decay followed by a slower decrease (1,2), with the half-life of SARS-CoV-2-specific antibodies estimated to be 6–8 months (1,3). In addition, SARS-CoV-2 variants exhibit reduced the neutralizing activities of nAb. For example, sera from COVID-19 convalescent patients and vaccine recipients showed reduced neutralizing activities against the Delta (B.1.617.2) and the Omicron (B.1.1.529) variants (4,5), which became a predominant SARS-CoV-2 strains worldwide. Consequentially, waning humoral immunity to SARS-CoV-2 and the spread of nAb-escaping viral strains (e.g., the Omicron variant) reduce vaccine effectiveness against infection and pose an increasing risk of breakthrough infection over time (6,7). However, vaccine effectiveness against severe disease is relatively preserved, indicating that different immune components with different half-lives are responsible for preventing infection versus severe disease.

Natural infection or vaccination elicits not only nAbs but also virus-specific CD4<sup>+</sup> and CD8<sup>+</sup> memory T cells. nAbs can prevent infection and disease progression by interfering with viral entry to host cells. When hosts are infected, T cells produce effector cytokines and directly eliminate virus-infected cells, leading to rapid control of viral infection and reduction of disease severity. Compared with nAbs, SARS-CoV-2-specific memory T cells are maintained for a relatively long time (8). Intriguingly, the persistence of memory T-cell responses to SARS-CoV-1 for 17 years has been demonstrated (9). The long half-life of memory T cells explains the relatively preserved vaccine effectiveness against severe COVID-19 (10). SARS-CoV-2-specific T cells can reduce disease severity in patients and animals with SARS-CoV-2 infection. Mice immunized with vaccines expressing T-cell epitopes exhibited reduced lung pathology and better survival when challenged with SARS-CoV-2, even in the absence of nAbs (11,12). In addition, higher levels of CD8<sup>+</sup> T-cell immunity are associated with improved patient survival among patients with COVID-19 who have humoral immunodeficiency caused by anti-CD20 therapy (13). These data indicate that T cells contribute to severity-reducing immunity against SARS-CoV-2, particularly when nAb activity is suboptimal and insufficient.

SARS-CoV-2 is likely to ultimately become endemic and continue circulating among the human population as a common cold virus (14,15). Indeed, several countries are already considering implementing ‘living with COVID-19’ policies. However, the path to an endemic phase in terms of its duration and public health impact is likely to be highly variable, depending on multiple parameters such as vaccination rates, levels of immunity, transmission rates, and emergence of new variants. Most importantly, being able to control the burden of severe COVID-19 disease, which has the potential to overwhelm health care systems, will be crucial during this transition to an endemic phase.

To enable effective adaptation of public health policies to reduce the overall damage to the community, the future course of the pandemic has been simulated with mathematical models early after the emergence of COVID-19 (16–22). In addition, models incorporating immunity and vaccination were developed (19–21). In particular, a model demonstrated that infection-induced immunity in children may facilitate endemic transition of COVID-19 (22). However, previous studies did not incorporate the different kinetics of severity-reducing and infection-preventing immunities. Here, we estimate courses of endemic transition of COVID-19 and dynamical changes in progression rates for severe COVID-19 during the transition period, using a mathematical model based on the concept that severity-preventing immunity decay more slowly than infection-preventing immunity. Our results demonstrate that increasing

viral spread, for example by relaxing NPIs or emergence of new variants, paradoxically reduces progression rates to severe COVID-19 and stabilizes the development of severe cases during the endemic transition.

## MATERIALS AND METHODS

### Model parameters

We have used a plausible range for model parameters from the published literature (**Supplementary Table 1**) rather than a single parameter set to get robust model prediction against parameter perturbation.

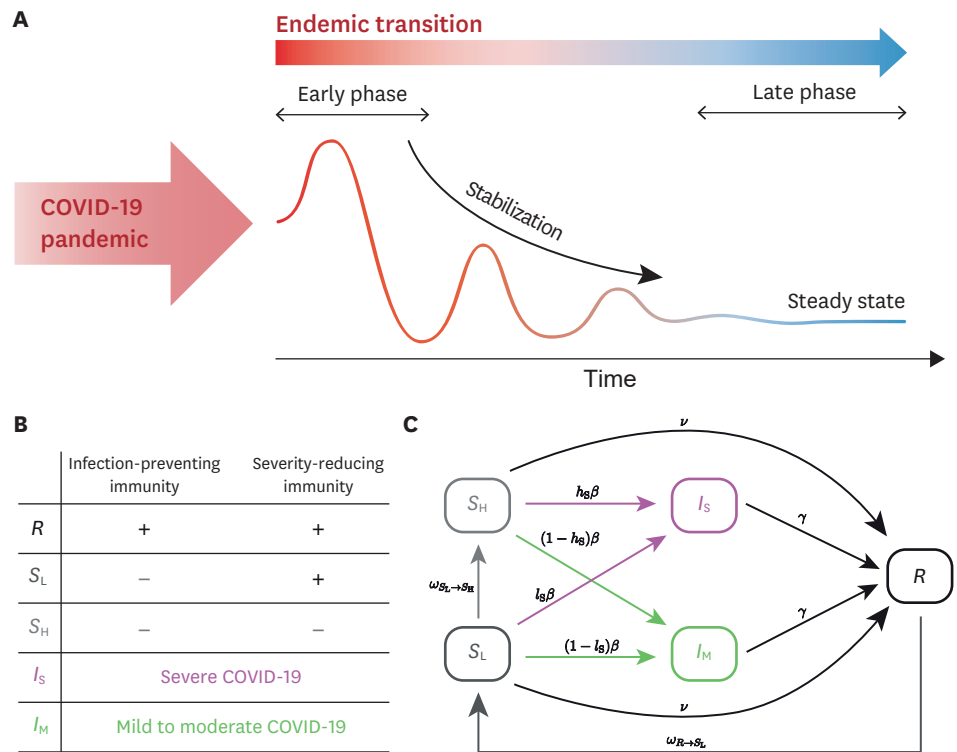
### Reproduction numbers and steady state formulae derivation

We derived formula for the basic reproduction number  $R_0$ , the average number of secondary infections by an infected individual when the whole populations are susceptible (see **Supplementary Data 1** for details). A reproduction number incorporating vaccination was also derived similarly. Furthermore, we derived the steady-state values of the variables in the model for a given set of parameters (see **Supplementary Data 1** for details). It allowed us to obtain the late-phase status without performing numerical simulation of the model.

## RESULTS

We developed a simple mathematical model based on the different kinetics of the two distinct immunities to predict the courses of endemic transition of COVID-19, from the early phase to the steady state (**Fig. 1A**), including dynamical changes in rates of progression to severe COVID-19 (**Fig. 1B and C**). Specifically, we extended the Susceptible-Infected-Recovered-Susceptible model, where individuals are separated into five populations: infected individuals with severe disease ( $I_S$ ); infected individuals with mild to moderate disease ( $I_M$ ); individuals susceptible to infection and without immunity ( $S_H$ ), thus a high probability of progression to severe COVID-19 ( $h_s$ ); susceptible individuals with only severity-reducing immunity ( $S_L$ ), thus a low probability of severe COVID-19 progression ( $l_s$ ); and recovered or vaccinated individuals ( $R$ ) with both infection-preventing and severity-reducing immunities (**Fig. 1B**; see **Supplementary Data 1** for details). Upon SARS-CoV-2 infection with a transmission rate  $\beta$ ,  $S_H$  and  $S_L$  can progress to severe ( $I_S$ ) or mild ( $I_M$ ) COVID-19. Because the probabilities of progression to severe disease are  $h_s$  and  $l_s$  for  $S_H$  and  $S_L$ , respectively (**Fig. 1C**), we refer to  $1 - \frac{l_s}{h_s}$  as the efficacy of severity-reducing immunity. A recovery rate is  $\gamma$ , and a vaccination rate per day is  $v$ . Infection-preventing and severity-reducing immunities wane from  $R$  to  $S_L$  and then to  $S_H$  at rates  $\omega_{R \rightarrow S_L}$  and  $\omega_{S_L \rightarrow S_H}$ , respectively, with  $\omega_{R \rightarrow S_L} > \omega_{S_L \rightarrow S_H}$  (15).

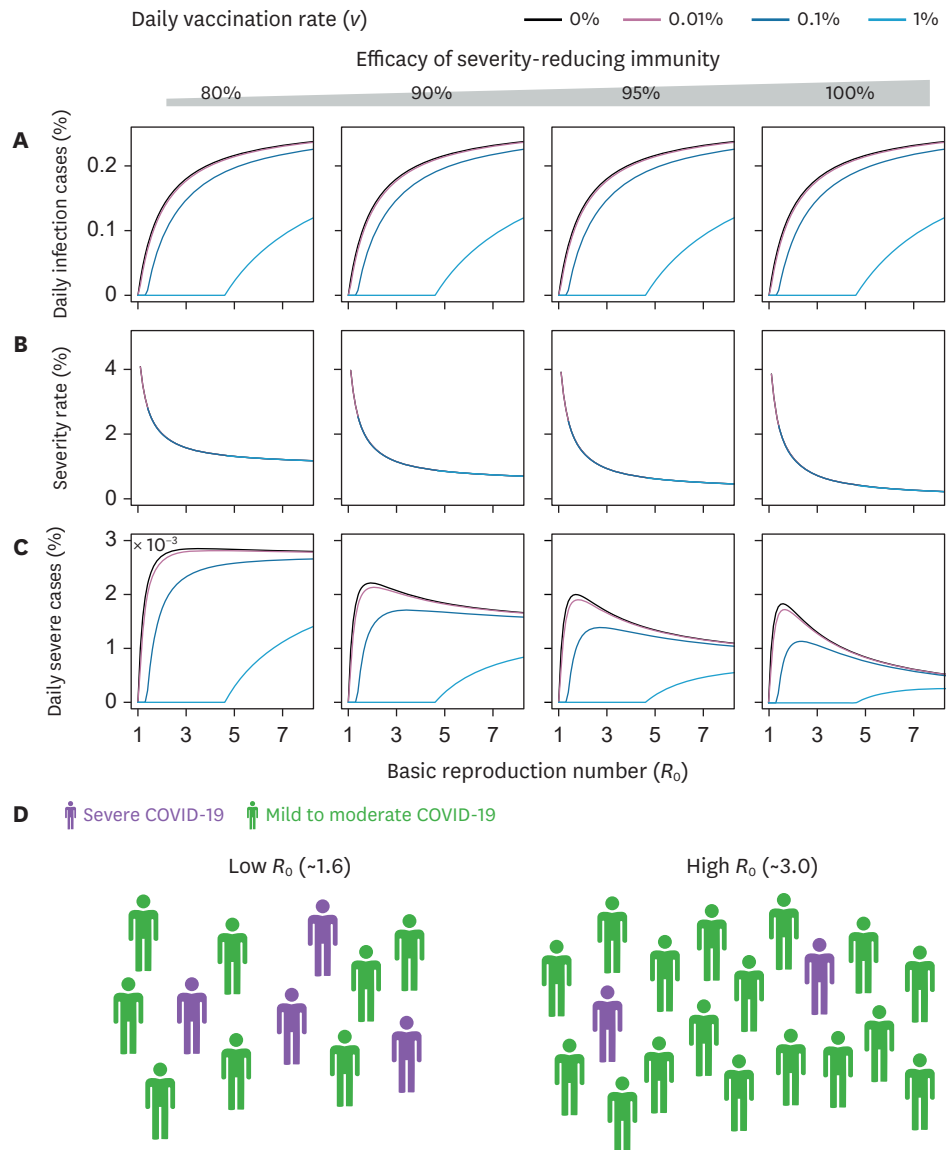
We first calculated the numbers of daily infections and severe disease at the steady state, i.e., the late phase during endemic transition, according to the level of transmissibility,  $R_0 = \frac{\beta}{\gamma}$  (see **Supplementary Data 1** for details). When the efficacy of severity-reducing immunity is 95% ( $l_s = 0.05h_s$ ), considering vaccine efficacy in preventing severe COVID-19 (23), higher  $R_0$  increases daily infection cases as expected (**Fig. 2A**, the third panel from the left). However, higher  $R_0$  decreases the rates of severe disease (i.e., proportion of severe cases among all cases) across a wide range of daily vaccination rates (**Fig. 2B**, the third panel from the left). Consequently, the relation between the number of daily severe cases and  $R_0$  is not monotonic (**Fig. 2C**, the third panel from the left). Specifically, when  $R_0$  is low ( $R_0 < 1.6$ ), caused for example by strict



**Figure 1.** A compartmental model for COVID-19 transmission dynamics incorporating different levels of immunity and disease severity. (A) Schematic illustration for the time-course of endemic transition of the COVID-19 pandemic. (B) The population is divided into five groups: recovered after being infected or vaccinated ( $R$ ); susceptible with a low probability ( $S_L$ ) or a high probability ( $S_H$ ) of experiencing severe disease when they are infected; infected with severe disease ( $I_S$ ), and infected with mild to moderate disease ( $I_M$ ).  $R$  carry both infection-preventing and severity-reducing immunities, and  $S_L$  possesses only severity-reducing immunity. (C) While  $S_H$  and  $S_L$  can be infected with the same rate  $\beta$ ,  $S_L$  has a lower rate ( $I_S$ ) of progressing to severe disease ( $I_S$ ) compared to  $S_H$  ( $I_S$ ) (i.e.,  $I_S > I_S$ ) due to the presence of severity-reducing immunity.  $I_M$  and  $I_S$  are converted to  $R$  at a rate  $\gamma$ . The infection-preventing and severity-reducing immunities wane at a rate of  $\omega_{R \rightarrow S_L}$  and  $\omega_{S_L \rightarrow S_H}$ , respectively.  $S_H$  and  $S_L$  can also obtain immunity by vaccination at a rate of  $\nu$ .

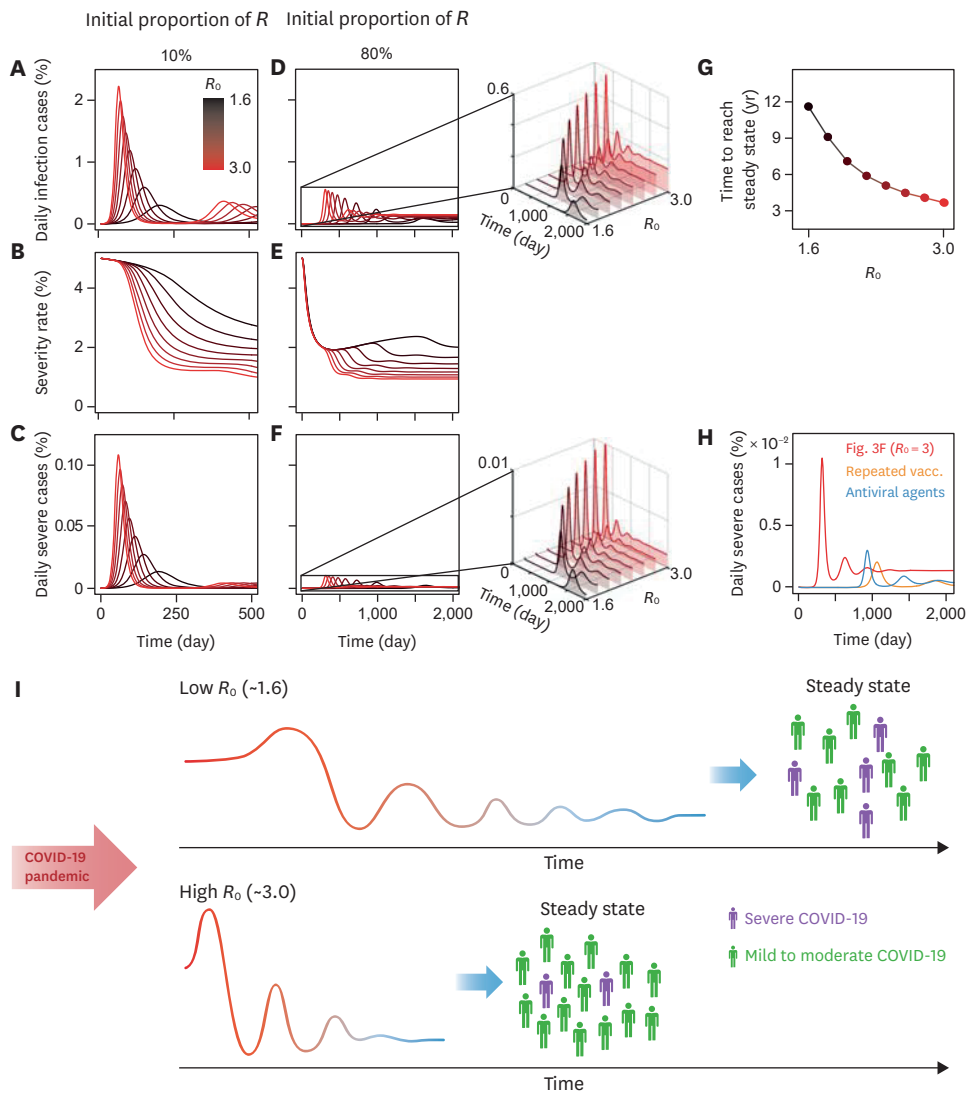
nonpharmaceutical interventions (NPIs) such as social distancing, the number of daily severe cases decreases with decreasing  $R_0$ . However, when  $R_0$  is greater than 1.6, we unexpectedly found that the number of daily severe cases decreases now with increasing  $R_0$ . This result is observed when the efficacy of severity-reducing immunity is  $\geq 90\%$ , but disappears when it is 80%.

When  $R_0$  is increased for example by relaxing NPIs or emergence of new variants, the  $S_L$  population (i.e., susceptible individuals with severity-reducing immunity) has a high chance of infection but is less likely to have severe disease due to their low rates ( $I_S$ ) for severe disease progression.  $S_L$  experiencing re-infection or breakthrough infection is converted to  $R$  by re-gaining infection-preventing immunity. In summary, high  $R_0$  reduces the proportion of  $S_H$  (non-immune population) and maintains individuals within a cycle of  $S_L \leftrightarrow R$ , leading to a paradoxical decrease in the number of severe cases ( $I_S$ ) at the late phase of endemic transition (Fig. 2D). However, this effect was not observed when a vaccination rate per day is extremely high (Fig. 2, sky blue lines). Similar patterns are demonstrated when we calculate the results in Fig. 2 based on the reproduction number incorporating vaccination ( $R_v$ ; Supplementary Fig. 1) and even when we change values for major parameters  $\gamma$ ,  $I_S$ ,  $I_S$ , and  $\omega_{S_L \rightarrow S_H}$  (Supplementary Figs. 2-5), which have not yet been exactly determined for COVID-19, within a reasonable range (Supplementary Tables 1 and 2).



**Figure 2.** A higher transmission rate can reduce cases of severe disease during the late phase of endemic transition. Steady-state values of the mathematical model over the basic reproduction number ( $R_0 = \frac{\beta}{\gamma}$ ), the average number of secondary infections by an infected individual when the whole populations are susceptible, with different daily vaccination rates ( $v$ ) and efficacy of the severity-reducing immunity ( $1 - \frac{\delta}{h_0}$ ). The daily vaccination rates were chosen based on the data of COVID-19 vaccination programs in each country (24). (A) As transmissibility ( $R_0$ ) increases, the percentage of daily infections ( $\gamma I_s + \gamma I_a$ ) in the whole populations increases. (B) The percentage of daily infections classified as severe decreases as  $R_0$  increases because infection prevents waning of severity-reducing immunity ( $S_i \rightarrow S_{i1}$ ). (C) Under strong NPIs ( $R_0 < 1.6$ ), the percentage of severe cases in the whole population increases as  $R_0$  increases. On the other hand, under weak NPIs ( $R_0 > 1.6$ ), the percentage of severe cases in the whole population decreases as  $R_0$  increases. (D) In summary, higher  $R_0$  increase the daily cases (green + purple) but decreases the severity rate and severe cases (purple). See **Supplementary Table 2** for the parameter values.

Although the daily severe cases at the late phase during endemic transition can be reduced by increasing  $R_0$ , the number of severe cases will transiently surge during the early phase of endemic transition, which may exceed critical care capacity. Therefore, we investigated transition dynamics during the time-course to an endemic phase under various conditions. When 10% of the population possess infection-preventing immunity, higher  $R_0$  robustly increases the number of daily infection cases during the time-course (**Fig. 3A**). Although



**Figure 3.** A higher transmission rate can accelerate the transition from the epidemic to the endemic phase without a substantial increase in severe cases. (A) The predicted dynamics of the proportion of daily infection cases in the whole population with varying  $R_0$  from 1.6 to 3.0 for initial infection-preventing immunity of 10% in the population (initial proportion of  $R$ ), acquired by natural infection or vaccination. During the early phase of the endemic transition, higher  $R_0$  increases the daily infection cases. (B, C) Although the percentage of severe cases among all infections becomes lower as  $R_0$  increases (B), the surge of percentage of severe cases across the whole population dramatically increases (C). (D-F) Predicted transition dynamics are shown for higher initial infection-preventing immunity of 80% (initial proportion of  $R$ ). The surge of severe cases is greatly reduced compared with when the initial immunity is 10% (F), because both infection cases (D) and rate of severe cases (E) decrease. Furthermore, higher  $R_0$  accelerates the stabilization of the number of daily cases (D) and severe cases (F). (G) Time to reach the stage when the number of severe cases fluctuates between 70% and 130% of the steady-state value. (H) The percentage of severe cases when two interventions are implemented. The red line is recalled from (F) when  $R_0=3.0$ , the orange line is dynamics from reduced waning rates ( $\omega_{R \rightarrow S}$  and  $\omega_{S \rightarrow S_i}$ ), and the blue line is dynamics from increased recovery rate ( $\gamma$ ) and decreased probability of experiencing severe disease ( $h_s$  and  $l_s$ ). See **Supplementary Table 2** for the parameter values. (I) A graphical summary of the results. Compared with the low  $R_0$ , the high  $R_0$  leads to an earlier endemic transition and a reduced severity rate and the number of severe cases.

higher  $R_0$  reduces rates for severe disease progression (**Fig. 3B**), the number of daily severe cases transiently, but sharply increases early during the time-course due to the robust increase in the number of infection cases (**Fig. 3C**).

The spike of severe cases is dramatically attenuated when a high proportion of the population (e.g., 80%) possess infection-preventing immunity, by natural infection or vaccination (**Fig. 3D-F**). Moreover, with higher  $R_0$ , the curves of severe cases are stabilized more quickly

to the steady state without fluctuation (**Fig. 3F**). Times to reach the steady state are estimated to be 12 and 4 years with  $R_0=1.6$  and 3.0, respectively (**Fig. 3G**). When the proportion of the population with infection-preventing immunity is 30% or 50%, similar patterns are observed while peaks of infection and severe cases occur earlier and are higher compared to 80% immunity (**Supplementary Fig. 6**). This demonstrates that permissive viral spread under high vaccination coverages accelerates the endemic transition with subsequent controllable COVID-19 disease burden. However, sharp peaks of severe cases in the early phase could still threaten overwhelming healthcare systems.

To circumvent this, we evaluated the effects of repeated vaccinations (i.e., boosters) and antiviral agents on the curves of severe cases. Repeated vaccinations, which increase the longevity of both infection-preventing and severity-reducing immunities (i.e., decrease in  $\omega_{R \rightarrow S_i}$  and  $\omega_{S_i \rightarrow S_{ii}}$ ) (25,26), reduced the peak of severe cases (**Fig. 3H**, orange line). Indeed, an additional third dose of the mRNA vaccine showed a 92% effectiveness in preventing severe COVID-19 disease compared with two-dose vaccination (27). Novel antiviral agents, which will increase the recovery rate  $\gamma$  and decrease progression to severe disease,  $h_s$  and  $l_s$ , also reduced the peak of severe cases (**Fig. 3H**, blue line). In fact, molnupiravir, a newly developed antiviral agent, has been shown to reduce the risk of hospitalization or death by 30% in patients with mild-to-moderate COVID-19 (28).

## DISCUSSION

As the COVID-19 pandemic is ongoing, predicting the future course of the pandemic is needed to enable effective adaptation of public health policies to reduce the overall damage to the community. The concept of an endemic transition of SARS-CoV-2 has been proposed (14,15,22), however the possible impact of severe COVID-19 cases during this transition has not been estimated. This is crucial for driving appropriate public health policies and ensuring that healthcare systems can subsequently withstand the disease burden.

For this, we developed a simple model focusing on two heterogeneous features: immunity and clinical severity. This allowed us to forecast courses of endemic transition of COVID-19 based on the concept that severity-preventing immunity decays more slowly than infection-preventing immunity. In particular, increasing viral spread, for example by relaxing NPIs, under high vaccination coverages paradoxically reduces progression rates to severe COVID-19 and stabilizes the development of severe cases during the transition to an endemic phase, with reduced numbers of severe cases.

Emergence of new SARS-CoV-2 variants can also change the course of the endemic transition and the number of severe cases. Natural selection of mutant viruses occurs under the pressure of increasing viral fitness or escaping from immunity. New variants with higher fitness that more efficiently enter host cells or replicate can change the course of endemic transition by increasing  $R_0$ . In the case of immune-evading variants, both  $\omega_{R \rightarrow S_i}$  and  $\omega_{S_i \rightarrow S_{ii}}$  can be increased in theory. Given that nAbs prevent infection by interfering with viral entry and are easily evaded by variants, the emergence of variants can reduce infection-preventing immunity and increase  $\omega_{R \rightarrow S_i}$ . However, variants rarely escape SARS-CoV-2-specific memory T cell responses that can prevent severe disease because T-cell epitopes are scattered across the viral proteome, suggesting that the emergence of variants minimally changes severity-reducing immunity or  $\omega_{S_i \rightarrow S_{ii}}$ .

Recently, the Omicron variant (B.1.1.529), a new variant of concern harbouring the high number of mutations in the spike protein, has emerged (29). The Omicron variant was estimated to have higher reproduction number than the Delta variant (30). It was also experimentally demonstrated that Omicron spike-pseudovirus exhibits greater efficiency of target cell entry than other SARS-CoV-2 pseudoviruses (31). Moreover, the Omicron variant has been shown to reduce the neutralizing activities of nAbs elicited by COVID-19 vaccination or infection with other SARS-CoV-2 strains (5,31). However, the Omicron variant is known to result in less severe infection than other SARS-CoV-2 strains. Low pathogenicity of the Omicron variant is explained by preferential infection of the upper airway rather than the lungs (32). Such distinct characteristics of the Omicron variant can be flexibly incorporated into our model. Importantly, spread of the Omicron variant with high transmissibility is likely to facilitate the endemic transition of COVID-19 according to our model prediction.

The limitation of our study is that some population heterogeneities such as age, underlying diseases, and cross-reactive immunity elicited by other coronaviruses were not incorporated in the model (20). Models containing population heterogeneities will allow more precise quantitative prediction. Although the present simple model does not explicitly describe the different characteristics of individuals, the model could implicitly describe them by changing the values of parameters, which represents the averaged effect of the heterogeneities. For instance, if a large portion of population has underlying disease or there are more elderly people in community, it can be incorporated to the model by increasing the rate of progression to severe disease (i.e.,  $h_s$  and  $l_s$ ).

In conclusion, we demonstrate that increasing viral spread, for example by relaxing NPIs or emergence of new variants, under high vaccination coverages paradoxically reduces progression rates to severe COVID-19 and stabilizes the development of severe cases during the endemic transition, with reduced numbers of severe cases (Fig. 3I). While our prediction needs to be interpreted appropriately depending on each country, it provides important insights for establishing or adjusting public health policies in the era of 'living with COVID-19'.

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## SUPPLEMENTARY MATERIALS

### Supplementary Data 1

Supplementary methods.

[Click here to view](#)



### Supplementary Table 1

Parameters of COVID-19 transmission model

[Click here to view](#)

### Supplementary Table 2

The parameter values and initial conditions used in Figures

[Click here to view](#)

### Supplementary Figure 1

Parallel figure of **Fig. 2** generated with varying the reproduction number incorporating vaccination ( $R_v$ ). (A) The percentage of daily infections, (B) severity rates, and (C) the percentage of daily severe cases at the steady state depending on the reproduction number incorporating vaccination,  $R_v = \frac{\omega_{R \rightarrow S_L}}{\omega_{R \rightarrow S_L} + v} R_0$ . Although  $R_v$  is used instead of  $R_0$ , the major patterns such as an initial increase followed by a decrease of daily severe cases are preserved compared with **Fig. 2**. See **Supplementary Table 2** for the parameter values.

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### Supplementary Figure 2

Parallel figure of **Fig. 2** generated by changing the recovery rate ( $\gamma$ ) and immunity waning rates ( $\omega_{R \rightarrow S_L}$  and  $\omega_{S_L \rightarrow S_{II}}$ ). (A) The percentage of daily infections, (B) severity rate, and (C) the percentage of daily severe cases at the steady state over the basic reproduction numbers ( $R_0$ ) with increased recovery rate ( $\gamma$ ) and reduced waning rates ( $\omega_{R \rightarrow S_L}$  and  $\omega_{S_L \rightarrow S_{II}}$ ). The major patterns, such as an initial increase followed by a decrease of the daily severe cases, are preserved compared with **Fig. 2**. See **Supplementary Table 2** for the parameter values.

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### Supplementary Figure 3

Parallel figure of **Fig. 2** generated by increasing the progression rates to severe cases,  $h_s$  and  $l_s$ , by five times. (A) The percentage of daily infections, (B) severity rate, and (C) the percentage of daily severe cases at the steady state over the basic reproduction numbers ( $R_0$ ). The major patterns, such as an initial increase followed by a decrease of the daily severe cases, are preserved compared with **Fig. 2**. See **Supplementary Table 2** for the parameter values.

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### Supplementary Figure 4

Parallel figure of **Fig. 2** generated by increasing the progression rates to severe cases,  $h_s$  and  $l_s$ , by 10 times. (A) The percentage of daily infections, (B) severity rate, and (C) the percentage of daily severe cases at the steady state over the basic reproduction numbers ( $R_0$ ). The major patterns, such as an initial increase followed by a decrease of the daily severe cases, are preserved compared with **Fig. 2**. See **Supplementary Table 2** for the parameter values.

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### Supplementary Figure 5

Parallel figure of **Fig. 2** generated by increasing the waning rate of severity-reducing immunity,  $\omega_{s_i \rightarrow s_{ii}}$ , by three times. (A) The percentage of daily infections, (B) severity rate, and (C) the percentage of daily severe cases at the steady state over the basic reproduction numbers ( $R_0$ ). The major patterns, such as an initial increase followed by a decrease of the daily severe cases, are preserved compared with **Fig. 2**. See **Supplementary Table 2** for the parameter values.

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### Supplementary Figure 6

The predicted dynamics of the proportion of daily cases among the whole population, the rate of severe disease among all infections, and the proportion of daily severe cases among the whole population, varying  $R_0$  from 1.6 to 3.0. See **Supplementary Table 2** for the parameter values.

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### Supplementary References

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