Online Appendix for "The Effects of Hosting the Olympic and Paralympic Games on COVID-19 in Tokyo: Real-time Analyses and Ex-post Evaluation"

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A Estimating the Number of Potential Spectators

In Fujii et al. (2021a), we estimated the expected number of spectators during the Olympics period based on the maximum capacity of each venue as well as the number of tickets sold. On April 11, the TOCOG revealed that 42 percent of the tickets for all the competition venues had already been sold. Therefore, we estimated the number of spectators per day by adding up 42 percent of the capacity of the venue for each match played in a day. The estimated number of spectators was 2,866,290 for 19 days from July 23 to August 8 or 150,857 per day. The average number of spectators per day, 150,857, is slightly more than 1 percent of the population in Tokyo (13.8 million).

We also estimated the number of volunteers per day during the Olympic Games. All volunteers are divided into two categories: Field Casts and City Casts. Field Casts are required to work at least 10 days to support the operation of the Games. There were 80,000 Field Casts in total, of which about 10,000 had withdrawn (according to the Bureau of Olympic and Paralympic Games Tokyo 2020 Preparation), so the remaining 70,000 would be mobilized.[1] City Casts are required to work at least 5 days to provide sightseeing and transportation information to tourists. There were 30,000 City Casts in total and about 4,000 had withdrawn, so the remaining 26,000 would be mobilized.

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[1]Correctly, Field Casts were divided into Olympic and Paralympic personnel, and considering the overlap, about 54,000 people should have been considered as the Olympic-Games volunteers.

We assumed that these 70,000 Field Casts and 26,000 City Casts work only 10 days and 5 days out of the 17 days, respectively.[2] Also, assuming that there would be an additional 10 percent cancellation of volunteers and that they would be assigned according to the number of spectators ratio of the venue, we estimate the number of volunteers per day in Tokyo was estimated as follows:

$$\begin{aligned}
&\text{The number of volunteers per day} \\
&= (26,000 \times \frac{10 \text{ days}}{17 \text{ days}} + 70,000 \times \frac{5 \text{ days}}{17 \text{ days}}) \times 0.9 \times \frac{\text{the average number of spectators in Tokyo}}{\text{the average number of spectators in all venues}} \\
&\fallingdotseq 43,941 \times \frac{150,857}{253,499} \fallingdotseq 26,000
\end{aligned}$$

According to this calculation, the number of volunteers for the Tokyo Olympic Games was estimated to be 26,000 per day. The average number of spectators and volunteers per day was 176,857 (=150,857+26,000).

This number is substantially higher than the average number of participants in other large-scale events (including music concerts and cultural events) in Tokyo from January 1, 2021 to June 6, 2021. Figure 1 shows the distribution of the total number of participants in large-scale events per day. We will shortly describe how we estimated the number of participants in selected large-scale events from January 1 to June 6 in 2021 in Appendix A.1. The estimated number of participants per day is less than 10,000 for slightly below 50 percent of the total day counts, possibly reflecting weekdays and a strict upper limit imposed during the initial period of the third state of emergency. We estimated that 15,341 people per day joined the selected large-scale events during the period on average. If we look at the average number of large-scale event participants in Tokyo after May 12, the most recent period after the prohibition period of spectators in place since April 25, the average number is 20,375 per day.[3]

A.1 Large-scale events in Tokyo

We define "large-scale events" as sports games, music concerts, or cultural events which are expected to attract more than 1,000 people per day.

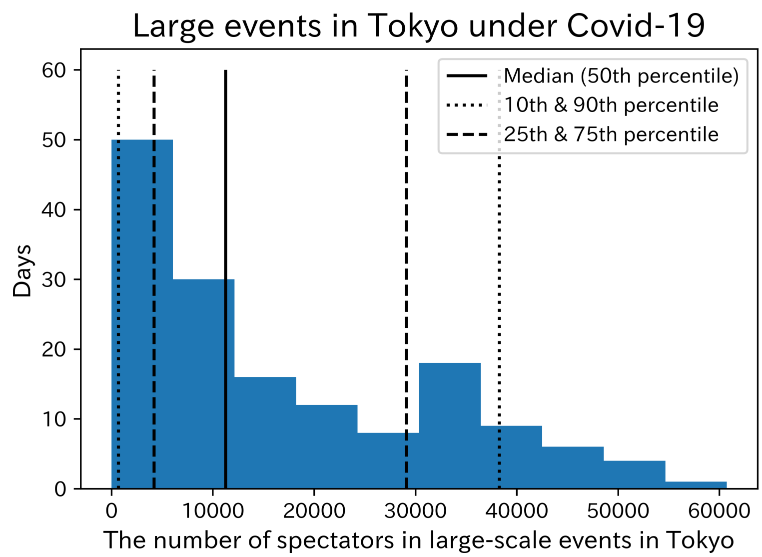
First, we considered the major sports leagues held in Tokyo: J-League (soccer), NPB (baseball), B-League (basketball), Japan Rugby League ONE (rugby), JRA G1 Race (horse racing), NJPW (professional wrestling), Tokyo BIG6 Baseball League (baseball), V-League (volleyball), and GST (sumo). We obtained information on the schedule of games and the number of spectators in these leagues by web scraping.

Next, we made a list of 40 large event venues in Tokyo with a capacity of 2,000 people or more, because at the time, all event venues could only hold 50 percent or less of their capacity due to an administrative order by the Tokyo Metropolitan Government. We manually looked

[2]It would have been more appropriate to assume that the volunteers operated for 19 days, including the two days before the opening ceremony.

[3]We need to keep in mind that the estimated numbers of event participants are underestimated; we selected only significant events held in Tokyo and estimated the number conservatively by multiplying 0.5 to the number of tickets sold.

Figure 1: Large-scale events in Tokyo from January 2021 to June 2021



Source: Authors' calculations. See Appendix A for details. See Fujii et al. (2021b).

up event information from the websites of each of the listed venues and counted the number of people mobilized. For events where the number of attendees was unknown, it was assumed that 25 percent of the venue's capacity would be mobilized.

Finally, we summed up the number of visitors for all the sports games, music events, and cultural events that we had calculated earlier, and estimated the average number of participants and spectators per day for large-scale events in Tokyo.

B Multi-group macro-SIR model

The model is formulated in discrete time with a model period being weekly. We separated the population in Tokyo into four groups: three spectator groups for each week during the Olympic Period (from July 23rd to August 8th) and a non-spectator group. Spectator groups possibly increase the risk of infection depending on their activities during and after the Games. As in Fujii and Nakata (2021a), the model comprises two parts: the epidemiological part and the economic part. The main differences from Fujii and Nakata (2021a) are the epidemiological part: we introduced the spectator groups that behave differently for the three weeks of the Olympic Period. A group is indexed as $j \in J = \{1, 2, 3, 4\}$ where $j = 1,\ 2,\ 3$ denote the spectator groups for the first, second, third week of the Olympic Period and $j = 1$ indicates the non-spectator group, respectively.

The dynamics of the spread of COVID-19 from time t to $t+1$ are described as follows:

$$
\begin{aligned}
S_{j,t+1} &= S_{j,t} - N_{j,t} - V_{j,t} && (1)\\
I_{j,t+1} &= I_{j,t} + N_{j,t} - N^{IR}_{j,t} - N^{ID}_{j,t} && (2)\\
H_{t+1} &= H_t + N^{IH}_t - \gamma^H_t H_t - N^{ID}_t && (3)\\
R_{t+1} &= R_t + N^{IR}_t + V_t && (4)\\
D_{t+1} &= D_t + N^{ID}_t && (5)
\end{aligned}
$$

where $S_{j,t}$ and $I_{j,t}$ denote the number of susceptible and infected individuals in group j at the beginning of time t. Variables without subscript j denote the aggregate number over J: $S_t = \sum_{j\in J} S_{j,t}$ and $I_t = \sum_{j\in J} I_{j,t}$ denote the total number of susceptible and infected residents in Tokyo at the beginning of time t. H_t denotes the number of patients in a state of severe disease at the beginning of time t. R_t and D_t denote the cumulative number of recovered patients and deaths by time t. For each group $j \in J$, the total population is denoted by $POP_{j,t}$ and defined as follows: for any t,

$$POP_{j,t} = S_{j,t} + I_{j,t} + R_{j,t} + D_{j,t}. \tag{6}$$

Since the definition of the populations includes the deceased patients because of Covid-19 and since we do not consider the births and deaths from other sources, the population of each group is time-invariant: for any t,

$$POP_{j,t} = POP_{j,0}. \tag{7}$$

The total population in Tokyo is denoted as POP_0, which is a sum of $POP_{j,0}$ over J.

The flow variables $N_{j,t}$, $N^{IR}_{j,t}$, and $N^{ID}_{j,t}$ represent the number of newly infected, recovered, and deceased individuals from time t to time $t+1$. They are specified as follows:

$$
\begin{aligned}
N^{IR}_{j,t} &= \gamma_t I_{j,t} && (8)\\
N^{ID}_{j,t} &= \delta_t I_{j,t}. && (9)
\end{aligned}
$$

N_t, N^{IR}_t, and N^{ID}_t denote the aggregate number of each flow in Tokyo. For the inflow to the state of recovery, γ_t potion of the infectious population will recover from the disease from time t to time $t+1$. We call this value the recovery rate. For the inflow to the cumulative stock of deaths, δ_t denote the portion of the infected at time t who passed away by the beginning of time $t+1$. We refer to this ratio as a fatality rate hereafter. The inflow into the state of severe disease is denoted as

$$N^{IH}_t = \delta^{ICU}_t N_t. \tag{10}$$

Here, δ^{ICU}_t portion of newly infected individuals is diagnosed as a severe symptomatic case at each period. We assume that the severity rate δ^{ICU}_t is proportional to δ_t:

$$\delta^{ICU}_t = \theta_t \delta_t. \tag{11}$$

In addition, $V_{j,t}$ denotes the number of people who effectively get immunity by vaccination from time t to $t+1$. For each group j, $V_{j,t}$ is the sum of individuals who successfully obtain immunity after each vaccination dose, which is specified as follows:

$$V_{j,t} = E_1 V_{j,t-2}^1 + (E_2 - E_1) V_{j,t-2}^2. \tag{12}$$

By the law of large number, we assume that the portion of vaccinated persons who obtain the immunity after each dose is equal to the probability of obtaining the immunity after each time of vaccination. We denote the probabilities of obtaining immunity for the first and second dose by E_1 and E_2, respectively. We also assume that vaccination becomes effective two weeks after the shots.

The matching function for newly infected individuals, specified as follows:

$$N_{j,t} = \tilde{\beta}_t \frac{S_{j,t} \sum_{k \in J} \rho_{j,k} I_{k,t}}{POP_0} \tag{13}$$

where $\tilde{\beta}_t = \beta_t (1 - h\alpha_t)^2$. Here, $\tilde{\beta}_t$ denotes the transmission rate of the disease at time t, and β_t denotes the "raw" transmission rate that actualizes if no one reduces the economic activity. We measure the impact of the reduction of economic activity on the size of the newly infected by mobility, $m_t = 1 - h\alpha_t$ where α_t is the decline in economic activity. The coefficient h captures the effectiveness of the economic restrictions on mobility, and the exponent k is the mobility elasticity of the transmission rate. The contact rate $\rho_{j,k}$ represents how frequently an individual of Group j interacts with Group k. See Fujii and Nakata (2021a) for a detailed explanation of the specifications.

B.1 Calibration

As in Fujii and Nakata (2021a), we collected data on N_t, N_t^{ID}, V_t^1, V_t^2 and Y_t to construct the paths of the variables and time-varying parameters based on the dynamics specified above. The number of newly infected individuals, N_t, and the number of new deaths due to Covid-19 in Tokyo, N_t^{ID}, are retrieved from Nippon Hoso Kyokai (NHK). The numbers of new vaccinations for first and second doses are collected from the two sources. First, the vaccinations from February 17th, 2021, to April 9th, 2021, are reported in the Ministry of Health, Labour and Welfare. Since only the national level number of vaccinations in this period is available, we distributed the number according to the population share of each prefecture. Second, the number of cumulative vaccine shots for each prefecture is updated on the Prime Minister's Office of Japan website. We compute the difference of the two sequential updates every week as the number of new vaccinations for a particular week. In addition, the Prime Minister's Office of Japan also reported the number of elderly people (aged 65 or older) who receive vaccinations at the national level. We use this elderly share at the national level to impute the number of vaccinated elderly people in Tokyo. Economic output, Y_t, is computed based on monthly estimates of real GDP reported by the Japan Center for Economic Research.

To retrieve the dynamics of the model variables, we impose the following initial conditions: $S_0 = 13,820,00$, $I_0 = 0$, $R_0 = 0$, and $D_0 = 0$. S_0 is based on the population of Tokyo

Table 1: Parameter Values

Variable	Symbol	Values	Target
Recovery rate	γ	7/12	12 days
Recovery rate from severe case	γ^H	7/28	28 days
Effectiveness of first vaccination (risk of infection)	E_1	0.625	SPI-M-O Summary (March 31st, 2021)
Effectiveness of second vaccination (risk of infection)	E_2	0.895	SPI-M-O Summary (March 31st, 2021)
Effectiveness of first vaccination (risk of death and severe case)	D_1	0.8	SPI-M-O Summary (March 31st, 2021)
Effectiveness of second vaccination (risk of death and severe case)	D_2	0.94	SPI-M-O Summary (March 31st, 2021)
Size of first-week visitor	n_1	$\{542860, 336430\}$	
Size of second-week visitor	n_2	$\{1608824, 895412\}$	
Size of third-week visitor	n_3	$\{1208606, 695303\}$	
Probability of going straight home	p	$\{0.2, 0.5, 0.8\}$	
Probability of high-risk restaurants	q	0.4	

in 2019. The recovery rate from the infectious population group to the recovered group, γ, is set to 7/12, targeted to the average duration of staying the infectious population as 12 days. Similarly, the recovery rate from severe case, γ^H, is set to 7/28, targeted to the average duration of 28 days. The effectiveness of first and second vaccinations in reducing infection risk, E_1 and E_2, are set to 0.625 and 0.895, respectively. These values are obtained from the SPI-M-O's Summary report (March 31st, 2021) on the website of the Government of the UK. In addition, we set the mobility elasticity of the transmission rate to 2.0 based on the quadratic matching assumption. These predetermined parameters are reported in Table 1.

Based on the initial conditions, the predetermined parameters, and the dynamics specified in eq.(1) – eq.(13), the time-varying parameters δ_t, θ_t, β_t, α_t, and h_t are retrieved as discussed in Fujii and Nakata (2021a). As mentioned above, there is no difference among the four groups until the Olympic Games starts. Hence, we set $\rho_{j,k} = 1$ when we recover the paths of model variables and time-varying parameters from January 2020 to the time of analysis (second week of June 2021).

We use our model to projects the spread of Covid-19 and economic activities during the Olympic period. The initial period of the simulation is the third week of June, denoted as T. The initial values of S_T, I_T, R_T, and D_T are obtained as the last period values from the previous section. The projected path of fatality rates δ_t, the severity rate θ_t, and the raw transmission rate β_t are determined in a way that is similar to how those projections are set in Fujii and Nakata (2021a). The details are discussed in Appendix B.2.

When the Olympics start, our model is no longer equivalent to a single-group model, as spectator groups visit the competition venues and spread the disease relative to the rest of the population. Let T_1, T_2, and T_3 denote a particular week when group j ($j = 1, 2, 3$) visits the venues, respectively. We model this relative difference in risk of infection and transmission by $\rho_{i,j}$, a contact rate from group i to group j. The contract rates are separated into two types: diagonal elements $\rho_{i,i}$ and off-diagonal elements $\rho_{i,j}$ ($i \neq j$). Diagonal elements represent the risk of transmission and infection increase by interaction within a spectator group on a particular week. Off-diagonal elements represent the effects of the increased risk of infection that the non-spectator groups $j \neq i$ face by the increased mobility of the spectator group i at time T_i. These off-diagonal elements should be non-symmetric: the risk exposure should increase by the behavior of a spectator group but not by the rest of the population. Hence, we assume that $\rho_{i,j} > 1$ and $\rho_{j,i} = 1$ at time T_i. Note that $\rho_{i,j} = 1$ if $t \neq T_i$ as there is no heterogeneity except at the time of visiting the venues.

We compute the difference of the two sequential updates every week as the number of new vaccinations for a particular week. In addition, the Prime Minister's Office of Japan also reported the number of elderly people (aged 65 or older) who receive vaccinations at the national level. We use this elderly share at the national level to impute the number of vaccinated elderly people in Tokyo.

B.2 Details on projected paths of infection rates and fatality rates

This section explains how we obtain the paths of the fatality rate δ_t and the raw transmission rate β_t used in a simulation.

As in Fujii and Nakata (2021a), we retrieved the average values over the most recent four months as the baseline, but using the simple average for a simulation might suffer from bias if some trends exist over time. For instance, if infectivity become weaker as time passes, using the simple average of the past raw transmission rates is likely to overestimate the infection in a simulated path. This overestimation can be decomposed into the two channels: the lack of adjustment in the past values and in the simulated paths. Hence, to correct this type of bias, we first need to eliminate these trends when we obtain the past four-month average of parameters of interest. Then, we need to apply these trends in the simulated paths based on the simulated paths of the trends. In this paper, we assume that the existence of variants and vaccination affect β_t and δ_t.

The simulated values of β_t and δ_t at time t can be expressed as

$$\beta_t = \sum_{\tau=1}^{17} \frac{\beta_{T+1-\tau}}{\text{Variant Effects}_{T+1-\tau} * \text{Vaccine Effects}_{T+1-\tau}} * \text{Variant Effects}_t * \text{Vaccine Effects}_t$$

and

$$\delta_t = \sum_{\tau=1}^{17} \frac{\delta_{T+1-\tau}}{\text{Variant Effects}_{T+1-\tau} * \text{Vaccine Effects}_{T+1-\tau}} * \text{Variant Effects}_t * \text{Vaccine Effects}_t$$

where T denotes the last period before the simulation starts. In addition, we modify the above equations in three ways. First, we have already considered the vaccine effects for β_t by subtracting the effectively vaccinated individuals from the susceptible population. Therefore, we did not include the vaccine effects for β_t. Second, the treatment of the vaccine effects at each period is difficult because of data availability. Hence, we assume the linear trend of vaccine effects.

Third, we use the average fatality rate weighted by the infectious population. One potential problem of using the sample average for δ_t lies in a lag between new deaths and the size of the infectious population. Because of the lag, the fatality rate δ_t tends to be high when I_t starts decreasing after a peak, and δ_t is low when I_t increases. To adjust this potential bias, we compute the average fatality rate weighted by the proportion of I_t in the sampling period. Note that without the adjustment of variant effects, this weighted average is equivalent to the share of all deaths among the sum of infectious population in the sampling period:

$$\begin{aligned}\bar{\delta} &= \sum_{\tau=1}^{17} \frac{I_{T+1-\tau}}{\sum_{\tau'=1}^{17} I_{T+1-\tau'}} \delta_{T+1-\tau} \\ &= \sum_{\tau=1}^{17} \frac{I_{T+1-\tau}}{\sum_{\tau'=1}^{17} I_{T+1-\tau'}} \frac{D_{T+1-\tau} - D_{T-\tau}}{I_{T+1-\tau}} \\ &= \frac{D_T - D_{T-17}}{\sum_{\tau'=1}^{17} I_{T+1-\tau'}}\end{aligned}$$

where $\bar{\delta}$ represents the weighted average of the fatality rates.

Below, we first discuss how to eliminate the variant effects from the past values of β_t and δ_t. Next, we explain the vaccine effects in detail. Lastly, we show the resulting simulated paths for β_t and δ_t.

To adjust the effects of Alpha and Delta variants, two things are noted. First, Delta variant had not yet spread in Japan at the time of analysis, so we did not adjust Delta-variant effect in the past values. Based on the screening test for the L452R variant in Tokyo, the share of positive cases are 3.2% between June 7th and June 13th (Tokyo Metropolitan Government, 2021). Second, we assume that Alpha variant is dominant by the the first incidence of Delta variant. By assuming so, we abstract from modeling the original strain of virus when we introduce the effects of Delta variant. Based on the assumption, we eliminate the effects of Alpha variant from β_t and δ_t in the sampling period using the following equations:

$$\beta_t^0 = \beta_t/(1 + p_t^\alpha r^\alpha) \tag{14}$$

$$\delta_t^0 = \delta_t/(1 + p_t^\alpha r_d^\alpha) \tag{15}$$

where p_t^α is the share of Alpha variant, r^α is the relative infectivity of Alpha variant to the original strain of virus, and r_d^α is the relative fatality of Alpha variant. We set $r^\alpha = 0.3$ and $r_d^\alpha = 0.4$.

For the effects of vaccination, we assume that vaccination reduces the spread and deaths associated with COVID-19 through three channels:

a). Infection prevention effects: vaccination reduces the number of newly infectious people at each period by reducing the risk of infection and transmission,

b). Death prevention effects: a vaccinated individual faces a lower fatality rate conditional on infection, and

c). Composition effects: the targeted vaccination for a high-mortality group such as the elderly would reduce the fatality rate on average by reducing the ratio of the high-mortality group in the infectious population.

We model the infection prevention effects by the reduction of the susceptible population as described in the dynamics of S_t. Hence, no adjustment to β_t is needed as discussed above. To adjust the fatality rate conditional on infection, we need to adjust the second and third channels. However, we abstract from the second effect: to compute the death prevention effect, we need to know the number of infected individuals for each vaccination dose, which is not available. Considering that not many vaccine receivers would be infected, the abstraction would not have large quantitative impacts.

For the composition effects, we did not adjust the past values of the fatality rate but rather adjusted the weighted average of the past values assuming a linear trend. To be precise, we need to adjust each value of δ_t before taking the average and obtain the average of these adjusted values. Without the adjustment, the past averages did not take the reduction of the fatality rates in the past weeks into account and, thereby, are overestimated. However, it is difficult to make such an adjustment because of the existence of a lag between the infection and death and a lack of data regarding the number of deaths by age and by the number of vaccination. In addition, the effects of vaccination at the time of analysis would not be large considering that only less than 20% of population receives vaccination and the lag of effectiveness. Therefore, we believe that abstraction from the adjustment to each of the past values has quantitatively small effects.

To determine the path of the composition effect for δ_t, we made the following two assumptions. First, the declines of the fatality rates are faster initially until individuals aged 65 or older finish receiving the vaccination. Second, the fatality rate approaches to zero as the number of people receiving the vaccination increases.[4] Based on these assumptions, we model the decline of the fatality rate due to the vaccination as the sum of two linear functions. In the first stage, the prioritized vaccination to the elderly reduces the fatality rate by reducing the share of the elderly among the infectious population. In the second stage, the vaccination to the young population reduces the fatality rate to zero if everyone receives the vaccination and if the vaccines are fully effective.

Hence, the path of the vaccine-adjusted fatality rate is expressed as the following:

$$\delta_t = (1 - v_t^e)(\delta_0 - \delta_{ss}) + (1 - v_t^y)\delta_{ss} \tag{16}$$

where

$$v_t^e = \frac{\sum_{\tau=1}^{t-2} D_1 V_{1,\tau}^e + (D_2 - D_1) V_{2,tau}^e}{Pop_0^e}$$

denotes the number of the elderly who are effectively prevented from deaths because of the

[4]In reality, after the prioritized vaccination to the elderly ends, the fatality and severity rates are likely to increase. This is because as more and more young individuals receive the vaccination, the share of young individuals among the infectious population would increase. Therefore, the share of old individuals among the infectious population rises, which increase the fatality and severity rates. The assumptions made here are valid if all the population receive the vaccination.

vaccination,

$$v_t^y = \frac{\sum_{\tau=1}^{t-2} D_1 V_{1,tau}^y + (D_2 - D_1) V_{2,tau}^y}{Pop_0^y}$$

is the number of young individuals who are effectively prevented from deaths because of the vaccination, D_i denotes the effectiveness of ith vaccination in the reduction of death and severe conditions, $V_{i,t}^j$ is the number of individuals who receive ith dose of vaccinations in age group $j \in \{y, e\}$, Pop_0^j represents the population size in each age group j, δ_0 is the initial fatality rate that prevails in an economy if no one receives a vaccination, and δ_{ss} indicates the fatality rate after all individuals aged 65 or older are effectively prevented from death due to vaccination, which is computed as

$$\begin{aligned}\delta_{ss} &= \delta_0 \times \frac{\text{Fatality rate of youth}}{\text{Fatality rate of total population}} \\ &\equiv \lambda\delta_0,\end{aligned}$$

We set λ to 0.1063/1.53 for the fatality rate and to 0.3692/1.62 for the severity rate based on Ministry of Health, Labour and Welfare (2021) and Nishiura (2021a).

In this specification, we observe that if all the elderly are effectively prevented from death by Covid-19 and if no individuals in the non-elderly group receive a vaccination, the fatality rate is equal to the fatality rate among the non-elderly group as discussed above: i.e.,

$$\delta_t \to \delta_{ss} \quad \text{as} \quad \sum_{\tau=1}^{t-2} V_\tau^e \to Pop_0^e \quad \text{and} \quad \sum_{\tau=1}^{t-2} V_\tau^y = 0.$$

Similarly, if every individual is effectively prevented from deaths due to Covid-19, no one will die of Covid-19: i.e,

$$\delta_t \to 0 \quad \text{as} \quad \sum_{\tau=1}^{t-2} V_\tau^y \to Pop_0^y \quad \text{and} \quad \sum_{\tau=1}^{t-2} V_\tau^e = Pop_0^e.$$

Based on the specification in eq. (16), we have enough information to determine δ_t except for δ_0. However, we have the information regarding the past fatality rates. Hence, we can retrieve δ_0 from the weighted average of variant-adjusted fatality rates $\bar{\delta}$ and eq. (16) by assuming that $\bar{\delta}$ represents the fatality rate at the end of the data period T:

$$\begin{aligned}\delta_0 &= \bar{\delta} + v_T^e(\delta_0 - \delta_s s) + v_T^y \delta_s s \\ &= \bar{\delta} + v_T^e(\delta_0 - \lambda\delta_0) + v_T^y \lambda\delta_0 \\ &= \bar{\delta} + \delta_0\{v_T^e(1-\lambda) + v_T^y\lambda\}\end{aligned}$$

and, thereby,

$$\delta_0 = \frac{\bar{\delta}}{1 - v_T^e(1-\lambda) + v_T^y\lambda}. \tag{17}$$

From eq. (16) and eq. (17), we can retrieve the path of fatality rates adjusted by the composition effect of vaccination.

Based on the past average, the composition effect of vaccination, and the effect of Alpha and Delta variant, our simulated path of β_t and δ_t are computed as follows:

$$\beta_t = \bar{\beta}(1 + p_t^{\alpha} r^{\alpha})(1 + p_t^{\delta} r^{\delta})$$
$$\delta_t = \{(1 - v_t^e)(\delta_0 - \delta_{ss}) + (1 - v_t^y)\delta_{ss}\}(1 + p_t^{\alpha} r_d^{\alpha})(1 + p_t^{\delta} r_d^{\delta})$$

where $\bar{\beta}$ is given by the four-month average of β_t^0 in eq. (15), δ_0 is given by eq. (17) based on the weighted average of variant-adjusted fatality rate, p_t^{δ} is the share of Delta variant, r^{δ} is the relative infectivity of Delta variant to Alpha variant, and r_d^{δ} is the relative fatality of Delta variant. We set $r^{\alpha} = 0.2$ and $r_d^{\alpha} = 0$.

B.3 Elements of Contact Matrix

In this appendix, we discuss the calibration methods of contact matrix P_t. Briefly speaking, we compute how the infection risks will be increased if spectators visit restaurants after watching the Olympic Games based on Chiba's method. We impose several assumptions for simplicity. First, we assume that the spectators increase the infection risk among the rest of population only through the interaction at restaurants and bars. Hence, if spectators go straight home after the Games on a particular day, the infection risk will not be increased. Second, we assume that there exist two types of restaurants and bars: low-risk and high-risk. Let p denote the ratio of spectators in group i who go straight home and $1 - p$ denote the ratio of spectators in group i who dine at restaurants. Also let q be the ratio of high-risk restaurants in Tokyo. Therefore, the increase in infection risks owing to the spectators depends on the number of spectators visiting either type of restaurant, determined by the number of spectators n_j $(j \in \{1, 2, 3\})$, the probability of dine at restaurants p, and the ratio of high-risk restaurants q.

We first discuss how these parameters determine the off-diagonal elements $\rho_{ij,t}$ $(i \neq j)$ at time T_j and then move to the explanation of the determination of the diagonal elements $\rho_{ii,t}$ at time T_i.

The off-diagonal element ρ_{ij,T_j} $(i \neq j)$ reflects the relative increase of infection risks for susceptible population among non-spectator group i owing to the increased mobility of spectator group j at jth week of the Olympics. In particular, we assume that $(1-p)$ portion of spectators visit restaurants after watching the games. Among them, q potion of them dine at high-risk restaurants, whereas $(1-q)$ of them visit low-risk restaurants. These increase of the people at the restaurants increase the infection risks for non-spectators who happened to visit these places.

Chiba (2021) quantifies the infection risk considering the number of interactions at these locations. In particular, she quantifies the infection risk of a representative agent by summing up the risk factors in six types of locations: home, workplace, school, high-risk restaurants, low-risk restaurants, and other miscellaneous places. The risk factor at each location is calculated as the product of relative infection risk per interaction and the expected number of interactions at the location. Specifically, the quantified risk is computed as

$$\text{Infection Risk}_t = \sum_{\ell \in L} \text{Infection Risk per Interaction}_{\ell,t} * E[\text{Number of Interaction}_{\ell,t}] \quad (18)$$

where $L = \{\text{home, workplace, school, high-risk restaurants, low-risk restaurants, others}\}$. Based on Chiba's estimate, we set the relative infection risks per interaction at home, workplace, school, high-risk restaurants, low-risk restaurants, and others to 0.8, 0.04, 0.075, 25, 2, 0.3, respectively. We assume that these relative infection risks per interaction at these locations are fixed regardless of whether the Olympic Games are held.

The expected number of interactions at each location is calculated as the product of the number of average people to interact per visit at the location and probability of visiting the location:

$$E[\text{Number of Interaction}_{t,\ell}] = \text{Average Interactions per Visit}_{t,\ell} * P(\text{Visiting Location}_{t,\ell}). \quad (19)$$

We assume that the expected number of interactions at location ℓ do not change over time except for high- or low-risk restaurants; we fix the expected number of interactions at home, workplace, school, and other miscellaneous places at 2.25, 10, 0, 4.5, respectively. The expected number of interaction at high- or low-risk restaurants before and after the Olympics are set to 0.065 and 0.0585, respectively. Based on these numbers, the quantified infection risk of a representative agent during the normal time is equal to 4.668 from eq. (18) and eq. (19)

During the Olympics, the expected number of interaction at high- and low-risk restaurants will increase as we assume that some fractions of spectators will visit these restaurants after watching the games. The increase in infection risks for the non-spectator group, the off-diagonal element, is solely from the increase in the number of average people to interact per visit at high- and low-risk restaurants. We assume that the the number of average people to interact per visit during the Olympics will be increased by $(\overline{n}/POP_0)(1-p)q$ for high-risk restaurants and by $(\overline{n}/POP_0)(1-p)(1-q)$ for low-risk restaurants, where $\overline{n} = (n_1 + n_2 + n_3)/19$ is the average number of spectators per day. Hence, the number of average people to interact per visit at high-risk restaurants during the Olympics is given by

$$\begin{aligned} &\text{Average Interactions per Visit}_{\text{Olympics Period,High}} \\ &= (\overline{n}/POP_0)(1-p)q + \text{Average Interactions per Visit}_{\text{Normal Time,High}}. \end{aligned} \quad (20)$$

Similarly, the number of average people to interact per visit at low-risk restaurants during the Olympics is given by

$$\begin{aligned} &\text{Average Interactions per Visit}_{\text{Olympics Period, Low}} \\ &= (\overline{n}/POP_0)(1-p)(1-q) + \text{Average Interactions per Visit}_{\text{Normal Time,Low}}. \end{aligned} \quad (21)$$

The average number of interactions in high- and low-risk restaurants during the normal time is set to 4.

Based on eq. (18), eq. (19), eq. (20), and eq. (21), we can calculate the increases in infection risks for the non-spectator groups, or the off-diagonal elements, by assuming that

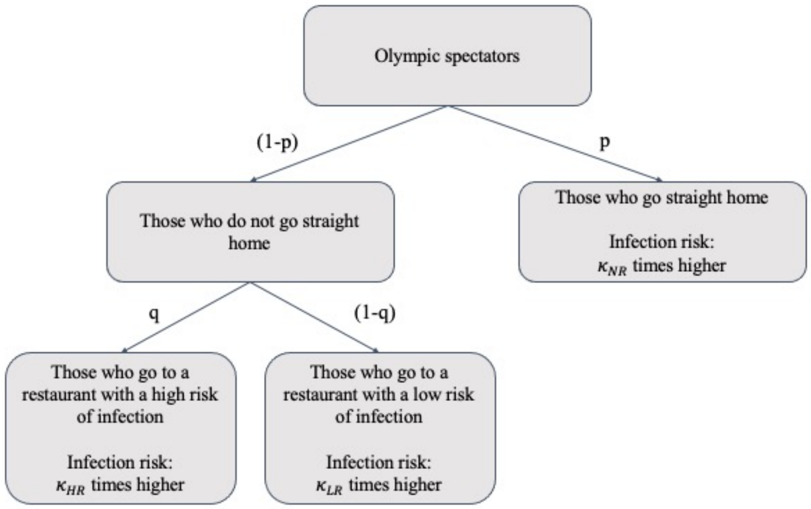


Figure 2: The Composition of Diagonal Elements

the non-spectator groups do not alter the probability of visiting high- or low-risk restaurants between the normal time and the Olympic Periods. By assuming the same probability of eating out at a particular type of restaurants, we can compute the relative increase of infection risks solely from the increase of customers at these places due to a spectator group.

Next, we discuss how the diagonal elements ρ_{ii,T_i} are determined. This diagonal element implies the relative increase of infection risks among spectator group i at the ith week of the Olympics. We further decompose the spectators into three groups. The first group is the people who go straight home after watching the games. They face higher infection risks than non-spectators through the interaction at the venues. The relative strength of infection risk at the venue is denoted by κ_{NR}. The second group is the spectators who visit high-risk restaurants after watching the games. They face the risks of κ_{HR}, which represents the infection risk conditional on that the visit of high-risk restaurants. Hence, this value is computed based on Chiba's model described above by assuming that the probability of going to high-risk restaurants is unity. Similarly, the third group is composed of the spectators who visit low-risk restaurants after watching game, facing the risk of κ_{LR}. The conditional increase in infection risk of the third group, κ_{LR}, is calculated by assuming that they visit low-risk restaurants for sure. The decomposition of the diagonal elements of the contract matrix is shown in Figure 2.

Based on κ_{NR},κ_{HR}, and κ_{LR}, we can compute the diagonal elements as the mean of these values based on the probability of going straight home, p, and the probability of eating at high-risk restaurants conditional on eating out, q. The expected increase of the infection risk among spectator group i compared to the rest of the population at the ith week of the Olympics, which is the diagonal element ρ_{ii,T_i}, can be written as

$$\rho_{ii,T_i} = \frac{1}{7}\left(p\kappa_{NR} + (1-p)\left(q\kappa_{HR} + (1-q)\,\kappa_{LR}\right)\right) + \frac{6}{7} \tag{22}$$

Here, we assume that, on average, 1/7 portion of group i visit the venues on a particular day of their tickets.

C Background

Some inquisitive readers must have already wondered why a team of economists ended up analyzing the effects of the Olympic and Paralympic Games on COVID-19 to begin with. Before explaining the context of our analyses of the Games, we first explain why.

As the third wave of infection started to gain momentum in Tokyo in December 2021, the government started to discuss the possibility of issuing the state of emergency (SOE), which would become the second SOE issued in Tokyo during the COVID-19 crisis with the first one being the one in April and May 2020. However, there was no quantitative analysis available to the public of how the second SOE would mitigate the rise of infection or affect economic activity. To be able to investigate such a question, two of the authors of this present paper—Daisuke Fujii and Taisuke Nakata—developed a model that combines a standard SIR model and a simple production function and estimated key parameters of the model using data in Tokyo. In early January 2021 after the government issued the SOE and infection started to come down, we used the model to analyze how the timing of departure from the SOE would affect the course of infection and economy (Fujii and Nakata (2021a)). Our analysis found that the presence of a short-run trade-off between infection control and economy did not necessarily imply the existence of trade-off in the medium- and long-term and that it would be possible for the government to achieve lower cumulative COVID-19 deaths and smaller economic loss by maintaining the current SOE until infection declines to a very low level—perhaps around 100 or 200 new cases per day.

Our analysis resonated well with the public and policymakers in Japan who wanted a framework to think about how to balance infection control and economic activity. Many perceived the aforementioned implications of our analysis as sensible. Furthermore, our approach of weekly updating the outlook on COVID-19 and economy reflecting incoming data—as well as our communication style in which reports were written in plain languages so that non-experts can easily understand—was novel in the context of experts' analyses during the COVID-19 crisis in Japan.[5] In February, media started to frequently report our analysis and we started to receive inquiries from the government and public-health experts.

While we initially expected that our main contribution was to develope a framework to think about how to balance infection control and economic activity, we soon realized that our outlook on COVID-19 itself was a contribution. In March, we started to receive requests for analyses from the government as well as public-health experts, and many of the requests were purely about projecting infection under various scenarios. The public also started to focus on our COVID-19 outlook, instead of our analysis of how to balance infection control and economic activities.

Behind this increased demand for our analysis was the absence of medium-term COVID-19 outlook provided by the government and public-health experts in Japan. As discussed in Fujii and Nakata (2021b) and Nakata (2021), throughout 2021, weekly reports provided to

[5] A regular update of an outlook is common in central banking community in which one of the authors had spent most of his career.

the Advisory Board on COVID-19 for the Ministry of Health, Labor, and Welfare featured short-term, mechanical outlook that abstracted from vaccination, mobility measures, and variants of concern, except for a brief period of time.[6] Our weekly reports as well as other COVID-19 reports filled in the gap in the analytical system for Japan's COVID-19 policy.

D Related Analyses

D.1 Before the Games

Several studies came out in mid-June that investigated the effects of allowing spectators as well as the aforementioned indirect effects of hosting the Games on infection.

On June 16, Furuse et al. (2021a) presented scenario analyses showing various possibilities about how the Games would affect infection in Tokyo. Their main focus was quantifying the indirect effects, but they also analyzed spectator effects by assuming that spectators would increase mobility in Tokyo one percentage point.

On June 17, Kurahashi (2021) released a report that used an estimated SEIR model to examine the effects of out-of-state Olympics-spectators on Tokyo's infection. He concluded that allowing spectators at full capacity can increase the number of daily new cases by about 20 percent. His results are quantitatively similar to our finding in June-17 report.

On June 18, the Cabinet Office released a report summarizing the findings of several simulations studies on spectator and indirect effects, including our May-21 simulation, Furuse et al. (2021a) and Kurahashi (2021) (Office (2021)). Most studies concluded that, if the Games were to contribute nontrivially to an increase in the mobility of people in Tokyo areas, that could nontrivially contribute to the spread of COVID-19.

On June 18, a group of public-health experts—A Voluntary Independent Group of Experts for COVID-19 Response in Japan—released a report called "Recommendations about COVID-19 risks related to holding the 2020 Tokyo Olympic and Paralympic Games" and handed the report to relevant parties including the Tokyo Organizing Committee of the Olympic and Paralympic Games and the Prime Minister.[7] The report emphasized indirect effects of the Games, echoing key takeaways from our May-21 and June-17 and using our simulation results in the May-21 report as well as Furuse et al. (2021a) to support their key messages.[8]

[6]See, for example, Nishiura (2021b), Nishiura (2021c), Furuse (2021b), Furuse et al. (2021a), Furuse et al. (2021b), and Furuse (2021a) for those exceptions. It is useful to note that the team of simulation experts under the AI & Simulation Project of the Cabinet Office—which provided weekly outlook in the second half of 2021—provided outlook much less frequently during the first half of 2021. Thus, often time, the outlook our team provided was the only outlook the public can count on. Behind the absence of COVID-19 outlook was the lack of proper investment in research on mathematical epidemiology prior to the COVID-19 crisis. According to Inaba (2021), a mathematician specialized in population dynamics and epidemiology at the University of Tokyo, "research on mathematical epidemiology is very outdated in Japan. There are no proper textbooks nor university courses on this topic. The COVID-19 crisis exposed this weakness."

[7]`https://corona.go.jp/minister/pdf/kishakaiken_shiryo_20210618.pdf`

[8]They used the term "contradictory messages" to refer to what we call "indirect effects."

D.2 After the Games

After the closing ceremony of the Paralympic Games, four research papers came out that estimated the effects of the Games on infection in Tokyo.

Linton et al. (2021) present a simulation study—which they suggest that they conducted a week before the Tokyo Olympics began—demonstrating that the effect of allowing spectators on infection would have been limited, a finding that confirms various analyses before the Games, including our analyses and those of Furuse et al. (2021a) and Kurahashi (2021).

The other three papers are those that aimed to causallly estimate the effect of hosting the Gmaes on infection using synthetic control methods discussed in the main body of the paper. See Esaka and Fujii (2021), Yamamoto et al. (2022), and Yoneoka et al. (2022).

E Identification Challenges of the Indirect Effect

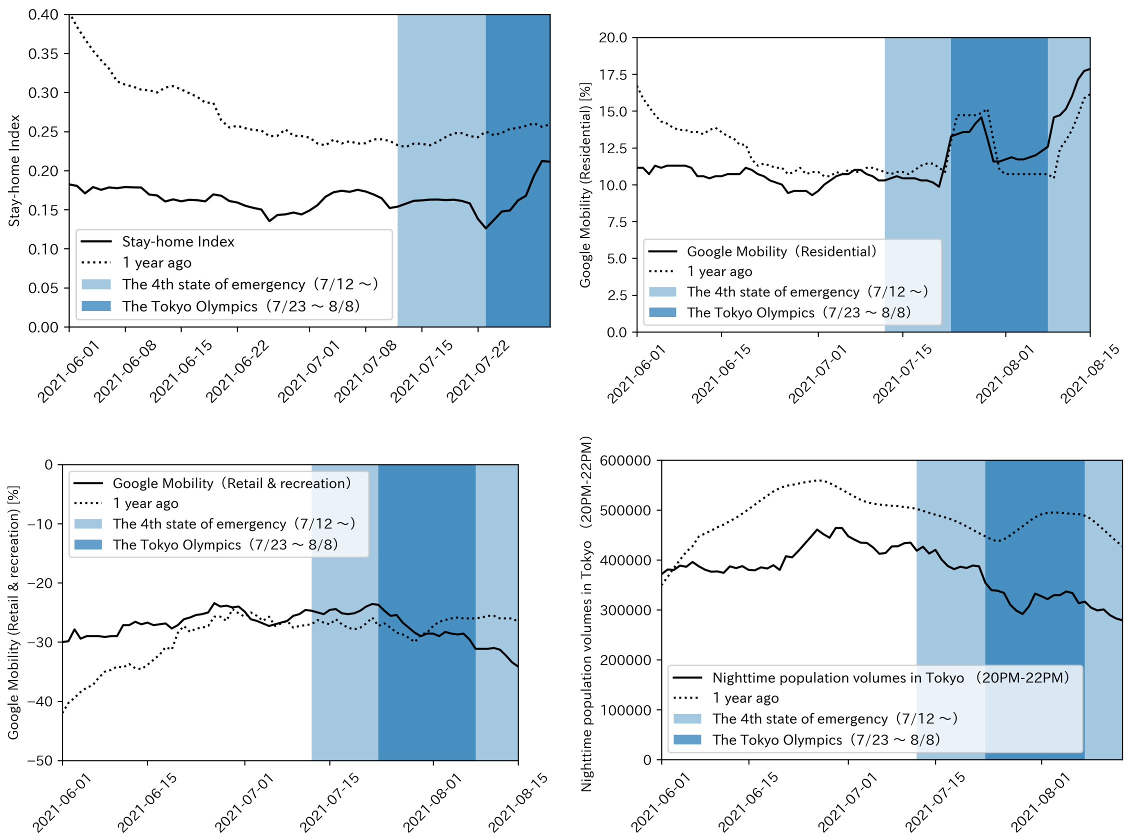
Quantifying the indirect effect of the Games on COVID-19 is challenging because it is difficult, if not impossible, to credibly estimate the causal effects of hosting the Games on people's behaviors. With this caveat noted, we will discuss some anecdotes and facts.

On the one hand, there exists anecdotal evidence that people might have become less cautious with infection during the Games. According to social media and television media coverage, some bars and restaurants were crowded with few people wearing masks. People gathered on streets to watch some Olympic events that took place on public roads (for example, marathons and road bikes). These stories suggest that the Games indeed might have promoted festive moods among Tokyo residents and contributed to the spread of COVID-19.

On the other hand, some have argued that the Games induced people to stay home to watch the Games on television. Some measures of mobility before and during the Olympic Games—shown in Figure 3—are qualitatively in line with such an argument. The "Stay-home" index rose after the Olympic Games started. Google Mobility (retail and recreation) and night-time population in central Tokyo declined more than they did in the previous year after the Games started. Google Mobility (residential) rose more on average than in the previous year. However, it is difficult to draw a firm conclusion as different mobility data suggest different quantitative relevance. The difficulty of drawing a firm conclusion is exacerbated by the fact that, during the Olympic Games, the number of new cases rose rapidly in Tokyo and ICU beds became scarce, which likely caused people to stay home regardless of whether the Olympic Games took place.

Another factor that makes it challenging to quantify the indirect effect of the Game on infection is that Japanese people seemed to have mixed and complex feelings about the Games. According to the poll conducted by Asahi newspaper a few days before the Olympic Games started, 55 percent were against hosting the event while 33 percent were in favor (Asahi Simbun, 2021). Yet, a study shows 56 percent of households with TV watched the opening ceremony (Video Research Ltd., 2021). After the Olympic Games, polls show that 60 percent of people thought that the Olympic Games contributed to the spread of COVID. Yet 64 percent felt positive about having hosted the Games and only 25 percent felt the Games should have been canceled (Yomiuri Shimbun, 2021). Given these mixed feelings among Tokyo residents, any calculation regarding how people would have behaved under the

Figure 3: Mobility Measures in Tokyo around the Olympics



Source: Google Community Mobility Reports, Mizuno et al. (2020), Nakanishi et al. (2021), and authors' calculations.

counterfactual of no Games is likely to be highly speculative.

F Ex-post assessments by public-health experts

In this subsection, we discuss ex-post assessments by public health experts of the effects of the Olympic Games on infection.

At the Fifth Round-table Meeting with Experts that took place on August 20, 2021 in which we presented our August-20 report, the TOCOG presented a detailed report on COVID-19 infection during the Olympic Games.[9] The TOCOG report pointed out that the actual number of infections was below that was predicted by ex-ante simulation studies—one of which was our May-21st report—and emphasized the success of various infection control measures taken in the Olympic Village and at competition venues. In a press conference after the Meeting, Nobuhiko Okabe, Chair of the Round-Table, assessed that there was no

[9] See `https://www.2020games.metro.tokyo.lg.jp/docs/%E7%AC%AC2%E5%9B%9E%E6%9D%B1%E4%BA%AC2020%E5%A4%A7%E4%BC%9A%E9%96%8B%E5%82%AC%E9%83%BD%E5%B8%82%E6%9C%AC%E9%83%A8%E4%BC%9A%E8%AD%B0.pdf`

major spillover of infection from the Games-related staff and foreign visitors, yet cautioned that, given that the number of daily new infection was much higher than the level before the Olympic Games started, the same infection control measures might not lead to as much success during the Paralympic Games (M3.com (2021)).

On August 12, a day before the Closing Ceremony of the Olympic Games, Shigeru Omi—Chair of the Advisory Committee on the Basic Action Policy—stated that it was "absolutely clear" that several infections at the competition venues did not play an important role in the rapid rise in infection since late July (Omi (2021)). He also pointed out various factors that had been present even before the Olympic Games began—including the emergence of the Delta variant—which contributed to the rise of infection . However, he also emphasized that, even though he had not seen any formal analyses, he believed that the Olympic Games had an effect on people's "awareness" (Chuo-Koron (2021)).

In early September, Hiroshi Nishiura—an epidemiologist who provided various simulation analyses to the Advisory Board on COVID-19 of the Ministry of Health, Labour, and Welfare throughout the COVID-19 crisis and who called for cancellation of the Games in media on numerous occasions—stated that he knew that there would be not much risk at competition venues and that it was clear that mobility and contact among people did not materially increase during the Olympic Games (Ronza (2021) and BuzzFeed (2021)). For the indirect effect, he stated that there was no doubt that the main effect of the Olympic Games was psychological, while acknowledging the difficulty of quantifying such psychological effects.

All in all, consensus among public-health experts seems to be in line with our assessment that the direct effect of welcoming foreign visitors was limited and that it is difficult to evaluate the indirect effects, though public-health experts tend to emphasize the possibility that the indirect effects might have been large, instead of the possibility that the indirect effects might have been small, in their communication with the public.

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