CENTER FOR ADVANCED RESEARCH IN FINANCE

CARF Working Paper

CARF-F-539

The Effects of Hosting the Olympic and Paralympic Games on COVID-19 in Tokyo: Ex-Ante Analyses

Asako Chiba
Tokyo Foundation for Policy Research

Daisuke Fujii
University of Tokyo

Yuta Maeda
University of Tokyo

Masataka Mori
Middlebury College

Kenichi Nagasawa
University of Warwick

Taisuke Nakata
University of Tokyo

Wataru Okamoto
University of Tokyo

June 29, 2022

CARF is presently supported by Nomura Holdings, Inc., Sumitomo Mitsui Banking Corporation, The Dai-ichi Life Insurance Company, Limited, The Norinchukin Bank, MUFG Bank, Ltd. and Ernst & Young ShinNihon LLC. This financial support enables us to issue CARF Working Papers.

The Effects of Hosting the Olympic and Paralympic Games on COVID-19 in Tokyo: Ex-Ante Analyses*

Asako Chiba[†], Daisuke Fujii[‡], Yuta Maeda[§], Masataka Mori[¶],
Kenichi Nagasawa[‖], Taisuke Nakata[**], Wataru Okamoto[††]

June 29, 2022

Abstract

We present a series of quantitative analyses conducted from mid-May of 2021 to mid-June of 2021 that examined the effects of hosting the Tokyo 2020 Olympic and Paralympic Games on the spread of COVID-19 in Tokyo. Our ex-ante quantitative analyses pointed out that (i) the direct effects on the spread of COVID-19 of welcoming Games-related foreign visitors to Japan or allowing spectators in competition venues would be either limited or manageable, but (ii) a festive mood generated by the Games could greatly contribute to the spread of COVID-19 if it led to a decline in people's willingness to take preventive actions against infection. Ex-post, the key results of our ex-ante analyses are broadly in line with available circumstantial evidence as well as ex-post consensus by public-health experts on how the Games affected the spread of COVID-19 in Tokyo.

Keywords: Agent-Based Model, COVID-19, SIR Model, The Tokyo 2020 Olympic and Paralympic Games
JEL Codes: C53, E65, Z28

*Daisuke Fujii is supported by JSPS Grant-in-Aid for Scientific Research (KAKENHI), Project Number 17K13744. Taisuke Nakata is supported by JSPS Grant-in-Aid for Scientific Research (KAKENHI), Project Number 22H04927, the Research Institute of Science and Technology for Society at the Japan Science and Technology Agency, the Center for Advanced Research in Finance at the University of Tokyo, and the Tokyo Center for Economic Research. All errors are our own.

[†]Tokyo Foundation for Policy Research. Email: chiba@tkfd.or.jp
[‡]University of Tokyo. Email: dfujii@e.u-tokyo.ac.jp
[§]University of Tokyo. Email: ymaeda1010@gmail.com
[¶]Middlebury College. Email: mmori@middlebury.edu
[‖]University of Warwick. Email: Kenichi.Nagasawa@warwick.ac.uk
[**]University of Tokyo. Email: taisuke.nakata@e.u-tokyo.ac.jp (Corresponding Author)
[††]University of Tokyo. Email: watarokamoto@gmail.com

1 Introduction

The Olympic and Paralympic Games have a special place in the heart of athletes and sports fans around the world. For athletes, competing in the Games—or even winning a medal—is a lifetime achievement. Winning a medal in the Games can change the course of a sports history in the winner's country by inspiring a new generation of athletes. For sports fans, not only does the Games represent one of the best competitions in sports, it also represents a unique venue for appreciating diversity of the world in a way that is perhaps more memorable than in any other international sports events.

The Tokyo 2020 Olympic and Paralympic Games became one of the most unique—perhaps, controversial—Games the world has ever experienced. Though the event was originally scheduled to take place in the summer of 2020, the COVID-19 pandemic made it inevitable for the event to be postponed to the summer of 2021. However, with COVID-19 far from being under control in many parts of the world and with substantial uncertainty regarding the COVID-19 situation in Tokyo around the time of the event, many—both Japan and abroad—had expressed skepticism towards the feasibility of safely hosting the Games.

In this paper, we present a series of model-based quantitative analyses—conducted from mid-May to mid-June of 2021—that examined how the Olympic and Paralympic Games would affect the course of COVID-19 in Tokyo. The public debate on whether it would be safe to host the Games intensified circa April 2021. Commentators, policymakers, and public-health experts voiced their views in various venues. Yet, there had not been any quantitative evaluation of the effects of hosting the Olympic and and Paralympic Games on infection until our analysis in Section 2 was released to the public on May 21. Being the only quantitative analysis on this hotly debated issue, our analysis was widely read by policymakers and the public.[1] For almost a month, it was the only quantitative analysis on this issue until several other research groups released their analyses in mid-June. On June 17, we released a set of reports that investigated the questions that our May-21 report did not fully explore.

The purpose of collecting our original reports in a research paper is two-fold. The first purpose is to share our analyses with a wider audience of researchers and policymakers. Our reports were originally written in Japanese, and thus were not accessible to many non-Japanese researchers who might be interested in our analyses. Also, our report—intended to be accessible to many non-researchers—abstracted from many technical details, though we made replication codes available to the public at the time.[2] This paper fills in those gaps.

The second purpose is to describe in some details the context in which we conducted our analyses and how the public and policymakers perceived them in periods leading up to the Games. Throughout the COVID-19 crisis, model-based analyses—in particular, simulation-based scenario analyses on infection and hospitalization—played a key role in informing policy in many countries.

[1] See Appendix A for select media coverage of our analyses.

[2] Replication codes were provided to the public on May 21st. `https://covid19outputjapan.github.io/JP/files/Olympics_replication.zip`.

Proper investigations of model-based analyses during the COVID-19 crisis are likely to help future generations of researchers provide policymakers with better analyses and communicate better with the public. We believe that our unique experience of using model-based analyses to contribute to a heated national debate in real-time can provide researchers around the world with food for thought on the role of model-based analyses in informing public and policymakers.

Table 1: Reports

Date	Report Title	Authors
May 21, 2021	The Effects of Hosting the Olympic and Paralympic Games on COVID-19: A Quantitative Analysis	Fujii and Nakata [2021b]
June 17, 2021	The Effects of the Olympic and Paralympic Games on COVID-19: Summary	Fuji and Nakata [2021a]
June 17, 2021	The Effects of the Olympic Games on COVID-19: Direct Effects	Chiba et al. [2021]
June 17, 2021	The Effects of the Olympic and Paralympic Games on COVID-19: Indirect Effects	Fuji and Nakata [2021b]
	Supplementary Materials	
June 14, 2021	An Estimate of the Number of Spectators during the Olympic Games	Fuji et al. [2021b]
June 17, 2021	Large-scale Events under COVID-19 in Tokyo	Fuji et al. [2021c]
June 17, 2021	The Effects of the Increase in Human Mobility Associated with the Games on COVID-19	Chiba [2021a]
June 17, 2021	Details of the Analysis of Direct Effects	Fuji et al. [2021a]

Notes. These original reports—written in Japanese–are at `https://covid19outputjapan.github.io/JP/resources.html`.

Our May-21 analysis investigated how the arrival of the Games-related foreign visitors would affect infection in Tokyo.[3] We analyzed this issue by examining the effects of a temporary increase in susceptible and infectious populations in a single-group SIR model. An implicit assumption in the use of a single-group SIR model was that foreign visitors would behave and interact exactly as Tokyo residents would. In reality, Games-related visitors would be isolated and tested frequently. Thus, the effect of exogenous shocks to susceptible and infectious populations calculated in this model represented an upper bound of the effect of foreign visitors on infection in Tokyo. Under our baseline calibration, the upper bound was 15 new cases per day, a very small number in a city with about 14M population that generated a few thousand new cases per day when the Games began.

Our June-17 analysis investigated how allowing spectators at competition venues would affect infection in Tokyo.[4] Using an agent-based model as well as a multi-group SIR model, we found that the effect of allowing spectators at venues would depend importantly on the proportion of people who would stop by bars and restaurants before or after watching the Games. When that proportion is about 20 percent, the effects on infection one week after the close of the Olympic Games would be less than 50 new cases in both agent-based model and multi-group SIR models, very small in a city of about 14M population.

In both May-21 and June-17 reports, we investigated how the Games would influence the couse

[3]Fujii and Nakata [2021b].

[4]Fuji and Nakata [2021a], Chiba et al. [2021], and Fuji and Nakata [2021b].

of COVID-19 by affecting behaviors of Tokyo residents, for instance, by promoting festive moods and discouraging people and businesses from abiding by various requests by the government to control infection. We called this effect of the Games as the "indirect effect" because it was not directly related to foreign visitors and spectators that are more actively involved in the Games. We found that the indirect effect could become very large. One of the June-17 reports summarized key findings from our reports in Table 2.

Table 2: Effects of the Games on COVID-19 in Tokyo—Summary—

	Foreign Visitors	Tokyo Residents	
		Spectator Effects	Indirect Effects
Number of people	about 100 thousands	about 180,000 thousands	about 14M
New daily cases	below 15	10-80	can be very large
ICU beds	below 3	2-10	can be very large
Qualitative assessment	Limited	Manageable, but be careful with "announcement effects"	Need to be very careful

Notes. From Fuji and Nakata [2021a].

The paper is organized as follows. Section 2 provides readers with the context in which our analyses were conducted and discusses related work. Section 3 presents our analysis on the effect of the Games-related foreign visitors on COVID-19 in Tokyo. Section 4 presents our analysis on the effect of allowing spectators in competition venues. Section 5 presents our analyses on the indirect effects of hosting the Games. Section 6 discusses ex-post evaluation of how the Games might have influenced the infection in Tokyo. Section 7 concludes.

2 Context

2.1 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. We first explain why we got involved in COVID-19 analysis before discussing the context of our analyses of the Games.

As the third wave of infection started to gain momentum in Tokyo in December 2020, 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—constructed a model that combines a standard SIR model and a simple production function and estimated key parameters of the model using data in Tokyo. 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 Natata [2021]). 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—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 2021, Japanese 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 develop a framework to think about how to balance infection control and economic activity, we soon realized that our outlook on COVID-19 was a contribution. in itself. In March 2021, we started to receive requests for analyses from the government and public-health experts, many of which were purely about projecting infection under various scenarios. The public also paid more attention to our COVID-19 outlook, instead of our analysis of how to balance infection control and economic activity.

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 [2021a] and Nakata [2021], throughout 2021, weekly reports provided to 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] Even such a short-term, mechanical outlook was absent until February 2021 in the weekly meeting of the Advisory Board. Our weekly outlook as well as other COVID-19 analyses filled in the gap in the analytical system behind Japan's COVID-19 policy responses.

2.2 Context of our analyses of the Games

Around the time when the second SOE—which was issued in Tokyo on January 8, 2021—ended on March 22, 2021, infection remained relatively contained in many parts of Japan. However, the proportion of the Alpha variant started to increase rapidly in some regions. A few regions—Osaka,

[5] A regular update of an outlook is common in other fields, including central banking.

[6] See, for example, Nishiura [2021a], Nishiura [2021b], Furuse [2021a], Furuse et al. [2021a], Furuse et al. [2021b], and Furuse [2021b] 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."

in particular—saw a skyrocketing increase in new cases in late March and early April. In Tokyo, the proportion of the Alpha variant increased rapidly in April, from 20 percent at the beginning of the month to 80 percent at the end of the month. While the pace of the increase in the number of new cases was gradual throughout April, the government issued the third SOE in Tokyo on April 25 in the fear that a continued rise in new cases could soon pressure medical resources.

The public debate regarding the Olympic and Paralympic Games intensified circa April, with many expressing safety concerns. However, as the debate unfolded, there was no quantitative analysis examining the possible consequences of hosting the Games for infection.[7] Interestingly, there were only few medium-term and long-term projections of COVID-19 available in April and May that extended to late July and early September when the Games would take place. Thus, at least until our first report on May 21, Japanese policymakers and the public were not only un-informed about how the Games might affect the course of COVID-19, but also un-informed about the expected level of infection when the Games would take place.[8]

On May 12, we began our project examining the effect of the Games on the spread of COVID-19. We completed the analysis on May 18 and circulated the first draft of our report to members of the Office for COVID-19 and Other Emerging Infectious Disease Control (Cabinet Secretariat), the Subcommittee on Novel Coronavirus Disease Control, and the Advisory Committee on the Basic Action Policy, on May 19. After incorporating comments we received from them, we posted our report—which featured the analysis of how Games-related foreign visitors would affect infection in Tokyo—to our website on May 21. At 6pm on May 23, we held an online press conference to present our analysis to the public. About 60 people—mainly from media—attended the press conference. We also presented our report in an informal online study group of public health-experts that stated at around 9pm on the same day. Media reported our analysis on the following day.[9]

Upon observing initial responses from the public, we felt that the calibration of the risk scenario in the report could be modified to further emphasize what we refer to as "indirect effects" of the Games discussed in Section 5—the adverse effects of hosting the event on infection through promoting festive moods and discouraging people and businesses from abiding by various government's requests to contain the virus. The modified report was released to the public on May 24.[10] The May-24 report is identical to the May-21 report, except the calibration of the risk scenario in

[7] In a private conversation, one researcher who had conducted many simulation analyses on COVID-19 throughout the crisis told one of us that, given the intensity of the debate on the safety of hosting the Games, s/he was so afraid of potential public attention and anger that s/he decided not to conduct any related analysis.

[8] Research teams participating in the COVID-19 AI & Simulation Project, sponsored by the Cabinet Office, currently provides weekly updates to their model-based outlook. However, before the summer, their analyses were updated much less frequently. Overall, there were in total 4 projections in April and May from the Project that were publicly available: Kurahashi [2021a], Ohsawa [2021], Unemi [2021a], and Unemi [2021b]. The Advisory Board on COVID-19 for the Ministry of Health, Labor, and Welfare that met almost weekly in 2021 did not provide any medium-term projections until June 9, 2021. See Nishiura [2021b] and Furuse [2021a]. Thus, it is not suriprising that the public and policymakers valued our model-based medium-term outlook on COVID-19—which we provided the public with weekly from January 2021 to August 2021 and bi-weekly or monthly since September 2021. See `https://covid19outputjapan.github.io/JP/tokyo_latest.html`.

[9] See Appendix A for select media citations.

[10] `https://covid19outputjapan.github.io/JP/files/FujiiNakata_Olympics_Slides_20210524.pdf`

the main figure. Thus, in this paper, we refer to both May-21 and May-24 report as the May-21 report for the sake of brevity.

We presented our May-21 report to several members of the Tokyo Organising Committee of the Olympic and Paralympic Games (TOCOG) on May 25. We were invited to present our analysis at the Second Round-table Meeting with Experts by TOCOG on May 28.

The key result from the May-21 report—while the effect on the spread of infection associated with the Games-related foreign visitors would be limited, the Games could greatly increase infection if it led Tokyo residents to become more active and less willing to take cauitous behaviors in their every day lives—resonated well with the public and poilcymakers. Many involved in the preparation of the Games had sensed that the real danger would not be in infection control in the Olympic and Paralympic Village or comeptition venues but in how Tokyo residents would behave during the Games. Our report provided them with a quantitative analysis that was consistent with their prior belief. In media, commentators frequently emphasized the danger the Games-related visitors would bring in—sometimes using languages reminiscent of xenophobia—and our report played a role in directing people's attention from foreign visitors to Tokyo residents in thinking about how to host the Games in a safe way.

By early June 2021, the public debate shifted from whether it would be safe to host the Games to how to host the event in a safe way. In particular, the public debate began to focus on the question of whether it would be safe to allow spectators at competition venues. On June 2, we began our analysis on the effects of spectators on the spread of COVID-19. On June 16, we completed the analysis and circulated a set of reports to members of the aforementioned Office and Committees as well as the TOCOG. After reflecting comments we received, we released the reports to the public and held an online press conference on June 17, which were attended by about 50 people. We were invited to present our analyses at the Fourth Round-table Meeting with Experts by the TOCOG on June 18.

In our June-17 report, beyond our quantitative analysis, we emphasized the following two messages. First, the spectator effect and the indirect effect could not be completely separated. If the government allowed a large number of spectators in competition venues, some may perceive it as a signal that COVID-19 was under control and become less cautious. That is, allowing a large number of spectators in competition venues could amplify the indirect effect. We used the term the "announcement effect" to emphasize the inseparable nature of the spectator effect and the indirect effect associated with the Games.

Second, we emphasized uncertainty in the COVID-19 outlook through the Games and recommended the TOCOG and the government to be flexible in the number of spectators allowed. The TOCOG and the government were planning to make an announcement regarding the number of spectators in the second half of June, a month before the Games. In one month, the COVID-19 situation in Tokyo could change dramatically. Thus, there was a benefit in leaving flexibility, as opposed to making a firm non-state-contingent commitment regarding the number of spectators at this stage. In particular, we emphasized—regardless of the number of spectators they would announce in June—the need for them to clearly communicate to the public that, if infection rapidly would increase prior to, or during, the Games, they would be ready to ban all spectators in competition venues.

On August 20, we released a report—and presented it at the Fifth Round-table Meeting with Experts by the TOCOG—that provides an ex-post evaluation of our analysis drawing upon circumstantial evidence on how the Olympic Games influenced the course of COVID-19 in Tokyo.[11] Key takeaways from the report were that (i) our May-21 result seemed to be in line with the number of reported Games-related infection, (ii) our June-17 result on the effect of allowing spectators in venues could not be known because no spectators were allowed, and (iii) our warning in both reports regarding the indirect effects seemed to have been the right message at the time. In Section 5, we provide an update of our assessment.[12]

In conducting these quantitative analyses, we aimed to strike the right balance between timeliness and quality. Unlike a standard academic research, our goal was to contribute to the policy debate in real-time. In all reports, we could certainly have spent more time making the analysis more rigorous. However, to contribute to the policy debate in real-time, it was imperative that the analysis was delivered to the public and policymakers in a timely manner. Given the time constraint we faced, we aimed to maximize insights and policy implications subject to a certain quality standard. In particular, we took modelling approaches that were as simple as possible and thus as as error-free as possible, yet that were conducive to results that were as insightful and policy-relevant as possible.

2.3 Related Analyses

2.3.1 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.[13]

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 [2021b] 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 could increase the number of daily new cases by about 20 percent. His results were quantitatively similar to our finding in the June-17 report.

[11] See Fuji and Nakata [2021c].

[12] A report provided by the TOCOG at the same meeting contrasts the baseline results in our May-21 report with actual outcomes, showing that Olympics-related infection was more contained in reality than what our report suggested. `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`

[13] There were two micro-level simulation studies conducted before our May-21 report. Murakami et al. [2021] examine infection risks at the Opening Ceremony of the Olympic Games. Zhu et al. [2021] examine infection risks among athletes in the Olympics Village, assuming that they are fully isolated from the rest of Japan.

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 [2021b], among others (Cabinet 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 greatly 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.[14] 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.[15]

Our analysis on the indirect effect is similar to these analyses just described. Our analysis differs from them because we examine the effects of Games-related foreign visitors on infection in Tokyo.

2.3.2 After the Games

After the closing ceremony of the Paralympic Games, two 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 [2021b].

Esaka and Fujii [2021] conduct an empirical analysis applying synthetic control methods to cross-country data and argue that the Games significantly contributed the rise in infection in Tokyo. Yamamoto et al. [2022] apply synthetic control methods to regional data in Japan. They find that the Games greatly contributed to the increase in infection in Tokyo region, but note that the result is not robust and that the extent of the increase was difficult to estimate clearly due to an overlap with the fifth wave associated with the Delta variant.

3 Effects of foreign visitors

In this section, we present our analysis on how the increased inflow of foreign visitors associated with the Olympics and Paralympic Games would affect the spread of COVID-19 in Japan. As discussed in Section 1 and 2, we conducted this analysis in mid-May—roughly two months before the Games started.

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

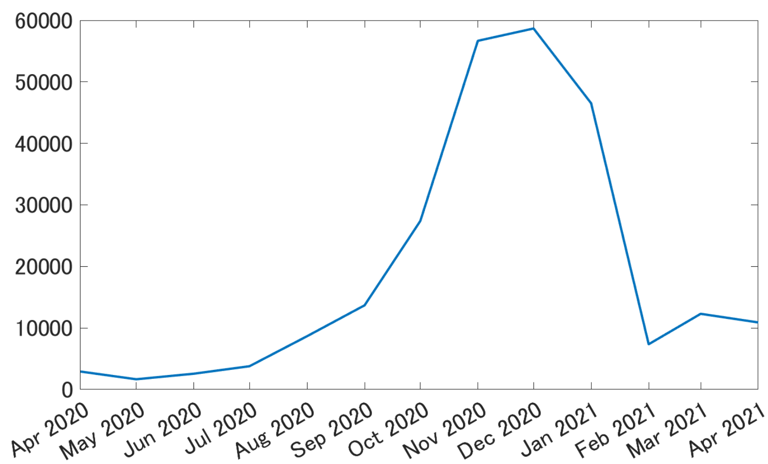
[15] They used the term "contradictory messages" to refer to what we call "indirect effects."

3.1 Background information

The Olympic Games took place between July 21 and August 8, and the Paralympic Games between August 24 and September 5. The majority of events were located in the metropolitan Tokyo area.

At the time of analysis, the estimated number of visitors was approximately 70,000 for the Olympic Games and 35,000 for the Paralympic Games. On the one hand, the size of this inflow was relatively large compared to the number of visitors from April 2020 to April 2021—shown in see Figure 1—when the average was approximately 20,000 people in a month. On the other hand, the size of this inflow represented only 0.75 percent of the population in Tokyo, which appeared too small to have large impacts on COVID-19 situations in a city of about 14M, especially given that all visitors were required to test for infection before and after arrival and that they were required to follow rules on where they could visit during their stay. Thus, the quantitative effects of welcoming foreign visitors on the spread of COVID-19 in Tokyo were a priori unclear and warranted an investigation.

Figure 1: Number of Foreign Visitors, Monthly



Source: Japan National Tourism Organization and authors' calculations. Data accessed at `https://www.jnto.go.jp/jpn/statistics/visitor_trends/index.html`. See Fujii and Nakata [2021b].

3.2 Model

To quantify the effects of increased inflows of foreign visitors on infection, we used a SIR model of Fujii and Natata [2021]. The model is formulated in discrete time with each period interpreted as one week. Let subscript t denote time period, S_t, I_t, R_t be the number of susceptible, infectious, and recovered individuals, respectively, D_t be the number of cumulative deaths, and H_t be the number of ICU patients. In addition, N_t is the number of newly infected individuals and V_t is the number of vaccine shots administered at period t. The path of vaccine shots V_t is given outside the model and all the other variables evolve according to the model

$$
\begin{aligned}
N_t &= \beta_t \frac{(1-h\alpha_t)^2}{POP_0} I_t S_t \qquad (1)\\
S_{t+1} &= S_t - N_t - V_t\\
I_{t+1} &= I_t + N_t - \gamma I_t - \delta_t I_t\\
R_{t+1} &= V_t + \gamma I_t\\
H_{t+1} &= H_t + \delta_t^{ICU} N_t - \gamma^{ICU} H_t - \delta_t I_t\\
D_{t+1} &= D_t + \delta_t I_t
\end{aligned}
$$

where POP_0 is the population at the initial period and $\{\beta_t, h, \alpha_t, \gamma, \gamma^{ICU}, \delta_t, \delta_t^{ICU}\}$ denotes the model parameters. Table 3 collects descriptions of these parameters and the values used in our analysis.

The equation (1) describes newly infected cases, and this part of the model is non-standard relative to the literature. Namely, the multiplicative factor $(1-h\alpha_t)^2$ is specific to our setting. This formulation follows the work of Fujii and Natata [2021] who used it to capture relationships between the spread of COVID-19 and economic activities. Here α_t represents the degree of reduction in economic activities, and a large α means that people slow down economic activities to reduce infections e.g., stay home to avoid social interactions. In terms of the model, when α is close to zero, reduction in economic activities is small and (1) indicates that there will be more newly infected cases. On the other hand, when α is larger (i.e., $1-h\alpha_t$ is closer to zero), there is more reduction in economic activities and infections tend to be lower. The parameter h represents the elasticity of economic loss on people's mobility, which plays a less prominent role in the current analysis and we refer interested readers to Fujii and Natata [2021] for details. The rest of the models is relatively standard, possibly with the exception of the ICU equation. Although standard approaches model the number of new ICU admitted patients to be a function of I_t, this feature does not seem to affect the results substantially.[16]

We chose Tokyo as the unit of analysis, and we applied the above SIR model using the infection data in Tokyo. As a consequence, we assumed all the visitors would stay in Tokyo, even though some events would take place in other regions of Japan. The main reason for this choice was that the majority of the venues were located in the Tokyo metropolitan area and we did not have accurate information on what fraction of visitors would move across different regions. Focusing on Tokyo would lead to an overestimate of effects because the size of visitors used in analysis would be larger than the actual one. Thus, our estimate should be be interpreted as an upper bound on the effects in Tokyo.

The most important modelling decision was that we used a single-group SIR model.[17]

[16] We modified this feature of our model for later analyses starting from the beginning of July 2021.

[17] Clearly, a more natural approach was to use a two-group SIR model, where Tokyo residents and foreign visitors were partitioned into their own groups. However, this approach would require specifying a contact rate matrix, which controls the frequency of interactions between Japanese residents and visitors in the model. We opted out of this

This modelling choice meant that visitors would interact with local residents at the same level as residents would do with other residents. This assumption was consistent with an overestimate of contact rates between Tokyo residents and foreign visitors because the majority of visitors stayed in designated facilities and the Japanese government required visitors to follow rules on where they could visit. Therefore, analogous to focusing on Tokyo as the unit of analysis, the use of a single-group model meant that our estimate would produce an upper bound on the effects of foreign visitors on infection.

3.3 Analysis

To study the effects of the inflow of the Games-related foreign visitors, we simulated the paths of new COVID cases and ICU using the above SIR model under two scenarios. The first scenario was "no Games" where the simulation was run in a normal way, and in the second scenario, the Olympic and Paralympic Games took place where (S_t, I_t) were increased at the start of the events and decreased at the end. We interpreted the differences in the new cases and ICU between these scenarios as the effects of increased inflows of visitors due to the Olympics and Paralympics. Economic activities were set at the same level in the two scenarios. In other words, Japanese residents were exercising the same degree of preventive measures with respect to infections. In this sense, we isolated the effects of inflows of the Games-related visitors from the effects of residents being less cautious due to the Games.

The first period of the simulations ($t = 1$) was the 2nd week of May, 2021 and the last period was the last week of December, 2021. For the scenario with the Games, (S_t, I_t) were increased at two periods: the first was the third week of July and the other was the third week of August. The first increase corresponded to the Olympic Games and the second to the Paralympic Games. As a baseline, 100 visitors were infected at arrival but screening did not detect them. According to the relative size, about 70 visitors for the Olympic Games were infected and about 30 for the Paralympic Games. The rest of 70,000/35,000 visitors were in S_t. Also, we assumed that these visitors departed at the end of the third week of August and the third week of September, respectively. In addition, we assumed that 50 percent of the visitors were fully vaccinated and the rest had no vaccination at baseline. The efficacy of vaccine, in terms of protection from infection, was assumed to be 76.75 percent, which was the average efficacy rates of AstraZeneca and Pfizer vaccines [Scientific Advisory Group for Emergencies, 2021]. To check robustness of our results, we also conducted sensitivity analysis by varying the number of infected visitors and the ratio of fully vaccinated visitors.

For model parameters, we either estimated them from data or calibrated them based on the information available at the time of analysis. The recovery rates γ, γ^{ICU} were chosen so that the means of recovery period were 12 days for "I to R" and and 28 days for "ICU to R." With γ and the data on newly infected cases, vaccine roll-outs, and deaths, we constructed the paths

scenario because it was challenging to specify the contact rate matrix with the available information at the time of analysis and also because we wanted to work with a framework that is a minimal departure from Fujii and Natata [2021] in order to minimize the possibility of mistakes.

(S_t, I_t, R_t, D_t) up to the initial time period. Then, we solved the equation for I_{t+1} to obtain δ_t. Also, given the past path of ICU patients, we backed out δ_t^{ICU}. For the transmission rate β_t, we estimated h and α_t using data on GDP and people's mobility, which in turn enabled us to estimate β_t using the equation (1). In this way, we obtained the past path of time-varying parameters.

Table 3: Model Parameters

Parameters	Description	Values used in analysis
β_t	the transmission rate	min: 0.98 max: 1.05
h	the elasticity of economic loss on mobility	2.22
α_t	the reduction in economic activities	min: 0.01 max: 0.13
γ	the recovery rate of infected individuals	7/12
γ^{ICU}	the recovery rate of ICU patients	7/28
δ_t	the death rate of infected individuals	min: 0.004 max: 0.015
δ_t^{ICU}	the transition rate from newly infected cases to ICU	min: 0.009 max: 0.033

Notes. The table collects descriptions of the model parameters and values used in the analysis. For time-varying parameters, we show the minimum and maximum values used. For further details, see Fujii and Natata [2021].

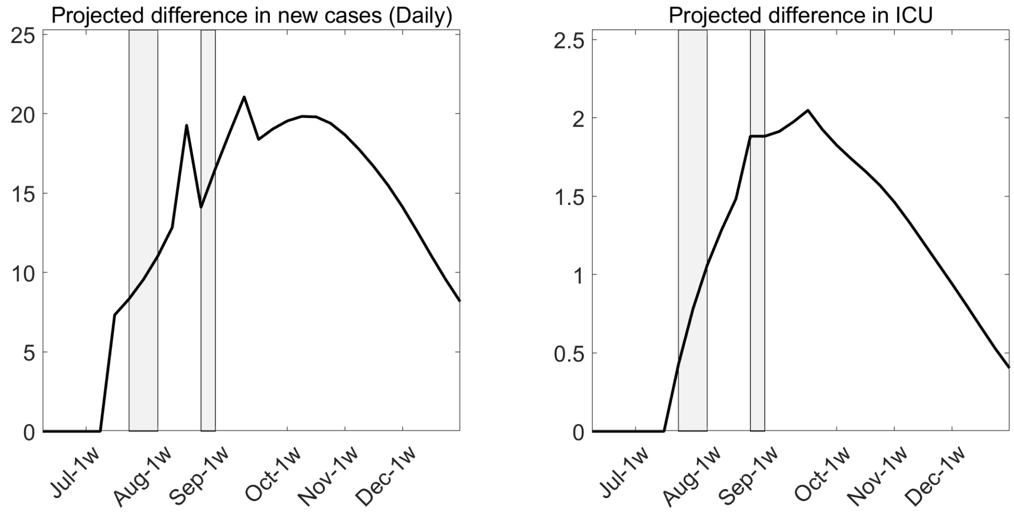
For the simulations, we needed to set the paths $\{V_t, \alpha_t, \beta_t, \delta_t, \delta_t^{ICU}\}_{t\geq 1}$. For the vaccine path, we assumed that 66,000 shots per day were administered in Tokyo, which would translate to 600,000 shots per day nationally. To construct V_t, we imposed that the efficacy of the first and the secnd shot was 62.5% and 89.5% [Scientific Advisory Group for Emergencies, 2021], respectively, for reducing infection and that there was a two-week lag between the time of vaccine administration and the development of immunity. The level of economic activities were set depending on whether the government issued the state of emergency (SOE). Since April 25, Tokyo was under the third SOE and various measures were taken to reduce people's mobility. In the model, α_t during the third SOE was set to the average of α_t in May 2020 and January 2021—these periods correspond to the first and second SOE. The third SOE would be lifted when the newly infected cases in one week fall below 450. In the simulations, the lifting of SOE occurred at the third week of June. After the third SOE was lifted, α_t would go back to the pre-pandemic level (February 2020) over the span of 10 weeks. For $\{\beta_t, \delta_t, \delta_t^{ICU}\}$, we used some weighted averages of their recent past values, and they were further adjusted for effects of COVID variants and vaccine rollout.

3.4 Results

Figure 2 displays the differences in new cases (daily) and ICU with the no-Games case as baseline. The number of daily new cases is about 15 people higher with the Games than without the Games on average throughout the simulation horizon. For ICU, the difference between the two scenarios were at most 2 people. In the second week of May, daily cases in Tokyo were around 800 and the number of ICU patients was around 70. We characterized these increases in new cases and ICU caused by the increased inflow of visitors as "limited."

As robustness checks of the main results, we conducted two sets of sensitivity analysis where we varied (i) the number of infected visitors and (ii) the ratio of fully vaccinated visitors. Figure 3

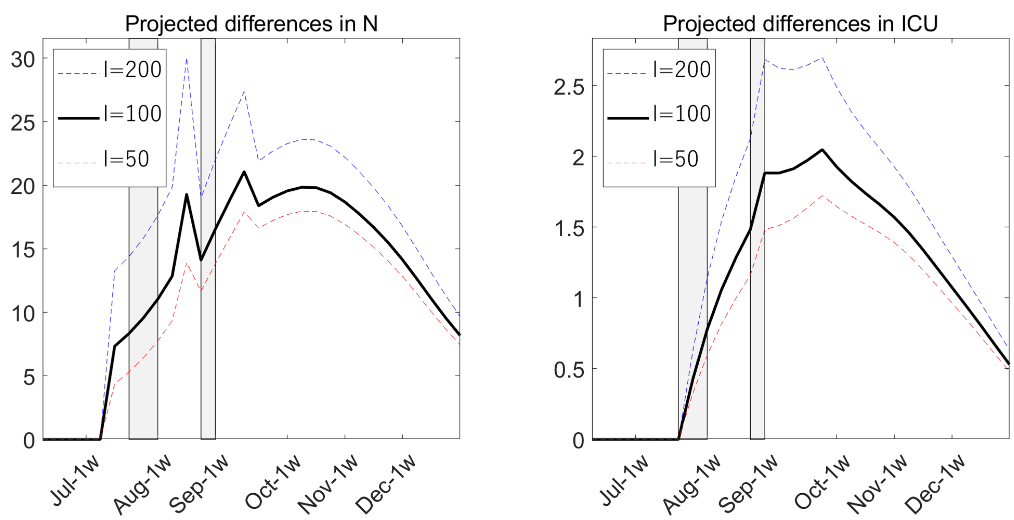
Figure 2: Effects of increased inflow of foreign visitors due to the Olympics and Paralympics



Source: Authors' calculations. See Fujii and Nakata [2021b].

shows the results of the first sensitivity analysis by changing the number of infected visitors over $\{50, 100, 200\}$. As seen from the figure, the results remained qualitatively unchanged when we changed the condition. Also, Figure 4 shows the results for the second sensitivity analysis where we changed the ratio of fully vaccinated visitors over {0%, 50%, 100%}. Analogous to the previous case, the results changed only moderately as the vaccination rate varied.

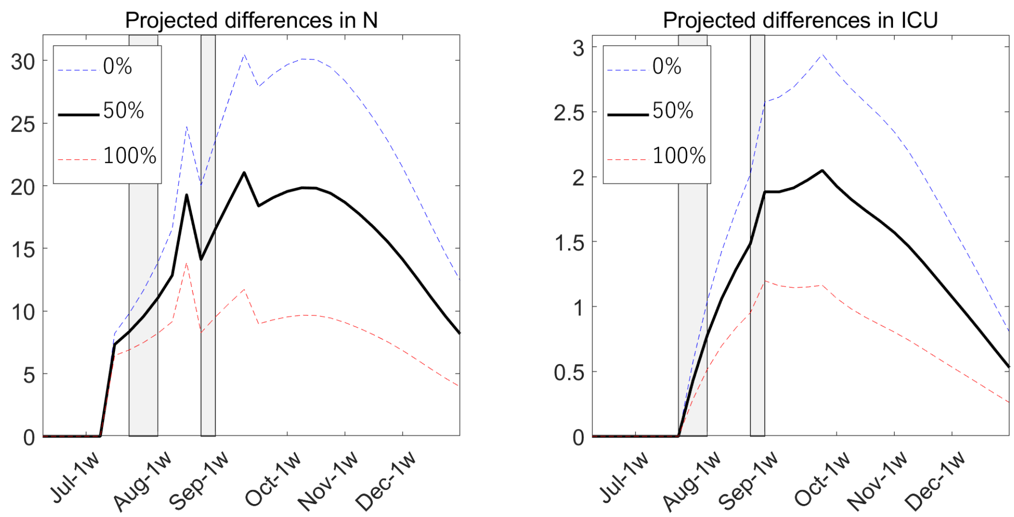
Figure 3: Sensitivity Analysis: Infected Visitors



Source: Authors' calculations. See Fujii and Nakata [2021b].

We reported two additional sets of analysis in our May-21 report—not shown here for the

Figure 4: Sensitivity Analysis: Vaccination Rate



Source: Authors' calculations. See Fujii and Nakata [2021b].

sake of brevity. For the first one, we looked at projections of new cases and ICU when SOE was lifted earlier and how the change affected the results of the above analyses. The second analysis considered a scenario where new variants with higher infection rates were brought into the country due to the increased inflows. For the latter analysis, there remained much uncertainty regarding newly emerging variants at the time of analysis, and our results were presented with this caveat. Yet, we highlighted the possibility that new variants could drastically change the projections due to their higher infection/mortality rates, and in hindsight, this point was qualitatively borne out by data.

4 Effects of spectators

The effects of the Games on infection would not be limited to those associated with the Games-related foreign visitors: Some Tokyo residents would go to watch the Games or volunteer at the competition venues. While infection risk at the competition venues was thought to be very small, spectators and volunteers might take high risk behaviours—such as going to restaurants and bars with friends—after watching the games or volunteering. If spectators and volunteers were more likely to be infected with COVID-19, so were their families and friends. We call these effects on infection associated with spectators and volunteers the "spectator effects."

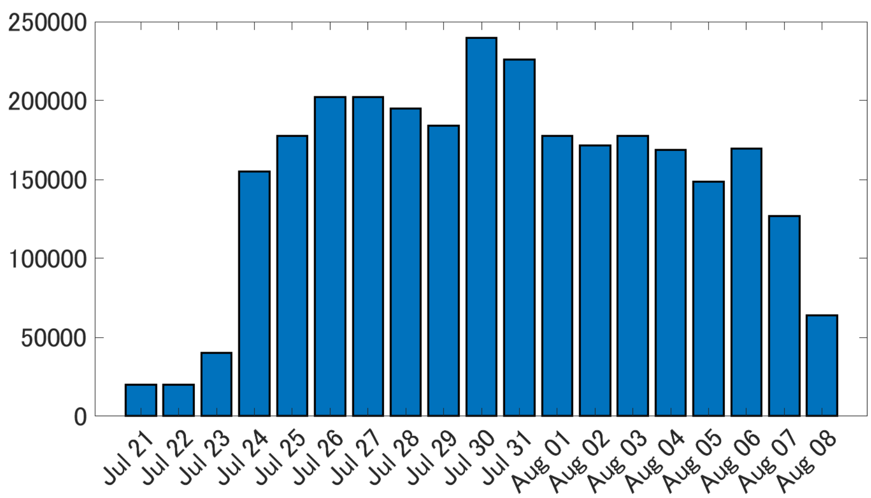
In this section, we present our analyses of the spectator effect from June-17 report. At the time of the analysis, we did not have enough time to collect information on the expected number of spectators for the Paralympic Games. Thus, our analysis focused on spectator effects for the Olympic Games only.

We used two distinct models to quantify the spectator effects. The first model was an agent-based model one of us, Asako Chiba, has used throughout the COVID-19 crisis to advise the Japanese government. Chiba's model is similar to that of Kerr et al. [2020]. The second model was a multi-group macro-SIR model that is a variant of Fujii and Natata [2021]. As a general principle, it is better to conduct the same issue using different models to see the robustness of key results from each model. For this report, Fujii-Nakata team collaborated with Asako Chiba in the hope that we could together provide the public with more robust analyses than each of us can individually could.

4.1 Background information

Before conducting model-based analyses, we first 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. Appendix B describes the details of the estimation method based on the available information at the time of analysis. 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).[18]

Figure 5: The expected number of spectators



Source: Authors' calculations. See Appendix B for details. See Fuji et al. [2021c].

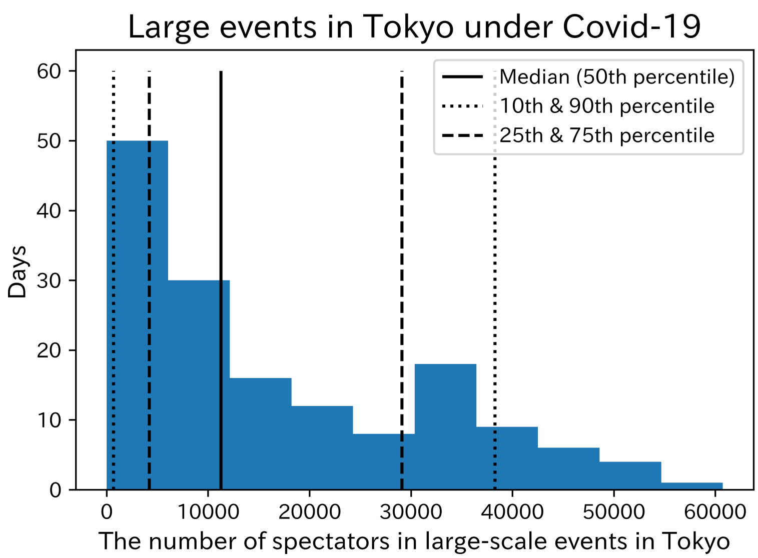
This number is substantially higher than the average number of participants and spectators in other large-scale events (including music concerts and cultural events) in Tokyo from January 1, 2021 to June 6, 2021. Figure 6 shows the distribution of the total number of participants in large-scale events per day.[19] The estimated number of participants per day is less than 10,000 for

[18]We also estimated the number of volunteers. The estimation method is described in Appendix B. The number of volunteers for the Tokyo Olympic Games was estimated to be 26,000 per day. The average number of spectators per day was estimated to be around 2 percent of the population in Tokyo.

[19]Appendix B describes how the number of participants in selected large-scale events is estimated from January

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.[20]

Figure 6: Large-scale events in Tokyo from January 2021 to June 2021



Source: Authors' calculations. See Appendix B for details. See Fuji et al. [2021c].

All in all, the expected number of spectators for the Olympic Games is higher than for other large-scale events in Tokyo in the first half of 2021, making it useful to conduct a quantitative analysis.

4.2 Analysis based on an agent-based model

The first model we used to investigate the spectator effects is an agent-based model. The structure of the model is basically the same as the one employed in Chiba [2021b] and Chiba [2021c], which are based on the work by Kerr et al. [2020].

Agent-based model describe the process where the virus spread through people's contacts in various places—layers—when people's detailed attributions are given. To analyze the direct impact of the spectators' mobility, we modify the model used in Chiba [2021b] and Chiba [2021c] in the

1 to June 6 in 2021.

[20]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.

following five ways.. First, the model introduced restaurants and bars—widely believed to be the riskiest places where the infections occur during the Olympic Games—as a layer. Second, in correspondence to the first modification, people's eating habits were added to their attributions. Third, the expected number of contacts in each place, which had been set to a fixed value in Chiba [2021b] and Chiba [2021c], was modified to be adjusted dynamically depending on the size of the population there. Fourth, as the analysis focuses on the short-run effects in Tokyo, we only use the census data of the residents in Tokyo obtain the joint probability distribution of attributions. Finally, we abstracted from people's flow betweenother prefectures and Tokyo.

To reproduce the population in Tokyo, agents were created using the joint probability distribution of age, sex, schooling/ working status, industry and family members obtained from the latest census data, as of 2015. The number of agents was 72,771, which means that the population is scaled down to 1/192. Using a survey conducted in March 2011 by Nomura Research Institute [2020], we set the frequency of eating out to three times per week for 25% of all residents in Tokyo, twice per month for 44%, and never for 33%. Agents interact with each other at six layers, namely: home, workplaces, nursing homes, high- and low-risk restaurants and bars, and other general activities.In each layer, each person contacts with a certain number of people (see Table 12 in Appendix C). These contact groups at home, workplace, and nursing home are determined at the beginning of the first period,[21] and kept fixed in the subsequent periods; Contacts in high- and low- risk restaurants and bars are updated every period depending on the number of spectators for the Games and their eating habits. At the beginning of every period, people are randomly selected with probabilities reflecting their frequencies of eating out. Of all visitors in bars and restaurants, 10% and 90% are assumed to be in high- and low-risk bars and restaurants, respectively (Foodist 2021). Similarly, contacts in the layer of the other general activities are shuffled every period.

Virus transmit from an infected person to a non-infected person with a certain probability when they contact in a layer. The probability depends on the relative risk of infection defined for each layer, the transmissiblity of the infected person determined by their viral loads, and the susceptibility of the non-infected person.

During the period of the Olympic Games, a certain number of residents in Tokyo were expected to watch games in competition venues and live broadcasting events.[22] The greatest concern was that a certain fraction of the spectators would stop by bars and restaurants before or after the games. People's gathering in stadiums and live broadcasting places itself was not regarded risky. In fact, the TOCOG had been planning to set strict rules on the spectators' behaviours in stadiums in the case they were allowed.[23] Therefore, our analysis focused on the increase in the number of contacts in high- and low-risk bars and restaurants, abstracting from the possibility of infection taking place in the stadiums and live broadcasting places, which was widely believed to be minor.

Table 4 illustrates scenarios tested in the simulations. Scenario 1 is the case without any

[21] One period in the simulations corresponds to one day.

[22] For simplicity, we assumed that all of the spectators were residents in Tokyo.

[23] The Tokyo Organising Committee of the Olympic and Paralympic Games [2021]

spectators, whereas Senarios 2, 3, and 4 are cases with spectators.[24] Scenario 2 is the baseline case when spectators are allowed. In this base case, the number of spectators is 243,000 per day[25]. 20% and 40% of them visit high- and low-risk bars and restaurants, respectively, whereas 40% go straight back home. In Scenario 3, the proportion of people who go straight back home is doubled to 80%. In Scenario 4, the number of spectators is doubled to 486,000, with the proportion of visiting bars and restaurants is the same as in Scenario 2.

Table 4: Key parameter values in the agent-based model

Scenario	Number of spectators	High-risk layer	Low-risk layer	No-risk layer
Scenario 1: w/o spectators	-	-	-	-
Scenario 2: with spectators (baseline)	423,000	20%	40%	40%
Scenario 3: with spectators (proportion of going straight home is doubled)	243,000	7%	13%	80%
Scenario 4: with spectators (total attendance is doubled)	486,000	20%	40%	40%

We also consider other interventions that had been taken in reality: PCR tests are conducted on 30% of the symptomatic cases every day andthose who turned out to be positive are quarantined. The test sensitivity was set to 70%. As for the vaccines, all of the health-care workers and 50% of the elderly who are aged over 65 were assumed to finish the second dose as of the opening ceremony. Their susceptibility is set to 5% of that before vaccination.[26] As working-from-home was still partly in place, workers who were in teleworkable jobs were assumed to work from home with probability 50% (Chiba 2021b for the definition of teleworkable jobs). As the mobility decreased due to the requirement that bars and restaurants should close at 20:00, the probability that people attend in the layer of high- and low-risk restaurants and the other general activities are assumed to decrease by 50% of the normal times. [27]

Once people in the model have caught the virus, they probablistically get worse or recover. As they develop symptoms, they become noninfectious, presymptomatic, moderate, severe, critical, and die in the worst case. The probabilities with which infected people get worse or recover depend on their age bucket. The duration of transition from one status to the next is assumed to follow a log-normal distribution with the moments defined for each status (see Table 11 in Appendix C).

[24]Figure 11 in Appendix outlines the proportion of infections taking place in each layer in Scenario 1.

[25]For simplicity, we call the sum of actual spectators and volunteer staffs as the number of spectators. 150,000 visit stadiums— which was estimated using the number of tickets sold and refunds—67,000 visit live broadcasting places, and 26,000 attend as volunteer staffs. See Appendix for the derivation of these figures.

[26]Polack et al. [2020], and US FDA [2020]

[27]Contacts among teachers and students at schools are ignored because they were closed for summer vacation during the period of the Olympic Games.

Figure 7 shows the projection of daily confirmed cases during the Olympic Games and its subsequent 10 days. The assumptions common to all scenarios are that the daily confirmed cases are 400 and that the number of recovered is 200,000 as of July 23rd, the opening day of the Games. Results shown are averaged over the values obtained in 1500 simulations.

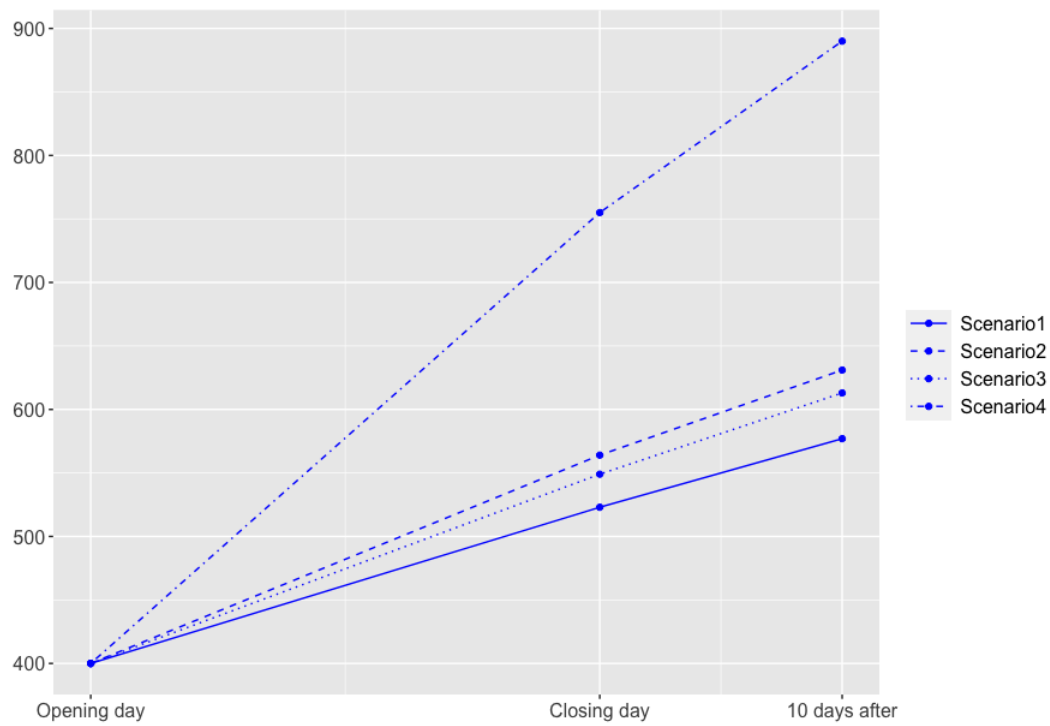


Figure 7: COVID-19 cases in Tokyo during the Olympic Games and its subsequent 10 days.

Scenario 2–the baseline case with spectators—adds 41 cases per day and 54 cases per day on the closing day and 10 days thereafter to those in Scenario 1–the case without any spectators. The additional cases are smaller when the proportion of going straight back home is doubled: the differences between Scenarios 1 and 3 are 26 on the closing day and 36 in 10 days. In scenario 4, where the total number of attendance is doubled, the additional cases are 232 on the closing day, which expand to 313 in 10 days.

To summarize, under the reasonable assumption regarding the total number of attendance and the rate of visiting bars and restaurants, the direct effect of allowing spectators on the cases are manageable. The reason is that the total number of attendance is relatively small compared to the size of the population in Tokyo: 243,000 of spectators in Scenario 2 accounts only for 1.7% of all population in Tokyo. Thus, even if 20% of those who come to stadiums and live-broadcasting places drop in at high-risk bars and restaurants, virus expansion is not markedly affected.

Nevertheless, it is worth noting that allowing spectators increases the risk of infection at the individual level. Table 5 demonstrates rough calculation of the amount of risk in each layer and in total.[28] As noted earlier in this section, people in the model are likely to get infected if they

[28] We abstracted from nursing homes . Only a small proportion of the total population in Tokyo live in the nursing

contact with many others at a place where the relative likelihood of transmission is high. Thus, one can roughly evaluate the risk at the individual-level in each layer by the multiplication of these two factors, and the total risk by summing up the risk in each layer. As shown in Table 5, total risk that a person is exposed amounts 129.0 if she visits high-risk bars and restaurants, which is much higher than 4.7, the amount of risk without any involvement in the high-risk activities. Such simple calculation shows that the total amount of risk that those who visit high-risk bars and restaurants face when spectators are allowed is substantially higher than that of average individuals when spectators are not allowed. However, such changes do not largely affect the situations at the macro-level, as those who visit high-risk bars and restaurants during the Olympic Games are limited in size.

Table 5: Risks in each layer and in total

	Home	Workplace	High-risk bars and restaurants	Low-risk bars and restaurants	Other general activities	**Total risk**
(a) Relative likelihood of transmission	.8	.04	25	2	.3	
(Representative person in Scenario 1)						
(b1) Expected number of contacts	2.25	10	.026	.234	4.5	
(c1) Relative risk (a) * (b1)	1.8	.4	.65	.468	1.35	**4.7**
(Visitor in high-risk bars and restaurants in Scenario 2)						
(b2) Expected number of contacts	2.25	10	5	.234	4.5	
(c2) Relative risk (a) * (b2)	1.8	.4	125	.468	1.35	**129.0**

4.3 Analysis based on a multi-group SIR model

Model: The second model used to investigate the spectator effects was a multi-group extension of Fujii and Natata [2021].

We allow for four groups indexed by $j \in J = \{1, 2, 3, 4\}$. $j = 1,\ 2,\ 3$ are for groups of people who go to a competition venue during the first, second, third week of the Olympic Games, respectively. $j = 4$ indicates a group of people who do not go to the competition venues.[29]

homes.

[29] We assume that the four groups are different from each other only concerning the decision and timing of being

One key difference between a single-group SIRD model and a multi-group SIRD model lies in the determination of the number of newly infected people. In a single-group SIRD model, the number of newly infected people is proportional to the matching between the susceptible and infectious population. In a multi-group SIRD model, the number of new cases for group i is determined by the matching between the susceptible population i and all the infectious population $j \in J$. The relative contribution of each matching is determined by contact rates $\rho_{ij,t}$ where $i, j \in J$. Here, ρ_{ij} denotes a contact rate between the infectious group i and the susceptible group j. See Appendix D for the detailed explanation of a multi-group SIRD model used in this paper.

In the space below, we discuss the details of the contact rates ρ_{ij}. Let P_t be a contact matrix whose elements are contact rates $\rho_{ij,t}$. Diagonal elements—$\rho_{ii,t}$—represent the relative risk of infection of a matching within one particular group $i \in J$ at time t. For instance, $\rho_{11,t}$ represents how likely the matching between the susceptible population among the first-week spectators and the infections population among the first-week spectators produces new cases within the first-week spectators at time t. As discussed above, agents in group $i \in \{1, 2, 3\}$ are different from the rest of the population only in the ith week of the Olympics. Therefore, $\rho_{ii,t} = 1$ when $t \neq T_i$ where T_i denotes the ith week of the Olympic Games. The contact rate ρ_{ii,T_i} captures the relative likelihood of infection resulted from the interaction among the spectators at ith week of the Olympic Games.

Off-diagonal elements—$\rho_{ij}(i \neq j)$—represent the relative strength of the matching between the susceptible population among group i and the infectious population among group j. For instance, ρ_{12,T_2} indicates how likely the matching between the susceptible population in the first-week spectators and the infectious population in the second-week spectators resulted in new cases among the first-week spectators at the second week of the Olympics. In other words, the effects of increased mobility of the second-week spectators on the new cases among the first-week spectators in the second week of the Olympics are captured by ρ_{12,T_2}. We assume that the interaction between the susceptible group i and the infectious group j resulted in greater number of new cases among group i only when the infectious group j is spectators at time t. Hence, we impose the following restriction: $\rho_{ij,t} = 1$ if $t \neq T_j$.

Next, we briefly discuss how the values of contact rates are determined. As discussed above, the contact rate $\rho_{ij,t}$ captures the relative increase of infection risks among group i caused by the interaction with group j at time t. In the context of this study, the increase of infection risks is due to the behavioral changes of spectators in the weeks of the Olympic Games. Hence, the values of contact rates ρ_{ij,T_j} can be calculated if we can quantify the relative increase of infection for group i caused by the spectators at jth week of the Olympics. To quantify this relative increase of infection

at the venues during the Olympic Periods either as spectators. In other words, we do not consider the different characteristics and behaviors among the four groups except whether they visit the competition venues at a specific date. In reality, a spectator who decided to watch the Olympic Games might be less concerned about the spread of disease than the rest of the population. In this case, representative spectators might have higher contact rates than non-spectators do, from which we abstract. In addition, agents in the model do not form an expectation of the future state of the spread of COVID-19 and economic activity. Hence, a representative individual in a spectator group acts exactly the same as a non-spectator group except when the spectator group is present at the competition venues. Therefore, the model can be reduced to a single-group SIRD model up to the first week of the Olympic Games.

risks, we follow the method used by Chiba (2021). In the model, the relative increase of infection is based on the parameters controlling the relative infections risks at several locations estimated by Chiba [2021b], the size of spectator groups, and their behaviors after watching the Olympic Games.

The behaviors of the spectators are measured by the likelihood of visiting restaurants after watching the games, denoted by $(1-p)$, and by the ratio of high-risk restaurants, denoted by q. For instance, if more spectators visit high-risk restaurants after watching the games, they are exposed to higher infection risks. In addition, non-spectators who are at the restaurants also face higher infection risks as the number of people at the restaurants is higher than usual as some of spectators are there additionally. The details are described in Appendix E.

For the share of visitors who go straight home, we choose the following three values: $p \in \{0.2, 0.5, 0.8\}$. The ratio of high-risk restaurants in Tokyo, q, is set to 0.4 in all simulation cases. The exact parameter values for each scenario are reported in Table 6. Based on the parameter values, we can calculate the relative infection κ and thereby the contact rates $\rho_{i,j}$. The resulting diagonal and off-diagonal elements of each scenario are presented in Table 7. As expected from the construction, the relative risk is higher if the number of spectators is larger and more people dine at restaurants after visiting the venues. We also observe that the decrease in the diagonal elements of a contact rate matrix is more significant if we reduce the probability of dining out at restaurants after the Games.

Table 6: Key Parameters

Variable	Symbol	Values
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

Table 7: Elements of the Contact-Rate Matrix

Diagonal Elements

	$p = 0.2$	$p = 0.5$	$p = 0.8$
100% Spectators	6.51	4.27	2.56
50% Spectators	5.70	3.95	2.51

Off-diagonal Elements

	$p = 0.2$	$p = 0.5$	$p = 0.8$
100% Spectators	1.10	1.06	1.02
50% Spectators	1.06	1.04	1.01

For the size of spectator groups, we consider two cases. In the first case, we assume that all individuals who purchase the tickets watch the Games at the competition venues. In the second case, we assume that 50 percent of individuals who have tickets watch the Games on site.[30] Based on these assumptions and the estimated number of spectators each day reported in Figure 5, we compute the size of each group $j \in \{1, 2, 3, 4\}$, denoted as n_j.

Analysis: The initial period of the simulation is the third week of June, denoted as T. The projected path of fatality rates, the severity rate, and the raw transmission rate in the baseline without spectators are determined in a way that is similar to how they are set in Fujii and Natata [2021] and is described in Appendix E.

As a baseline, we simulated the model assuming that no spectators were allowed. Then, we considered six scenarios in which spectators are allowed. The six scenarios are differentiated based on two dimensions; the size of spectator groups and the share of those who go straight home.

Results: Table 8 shows the spectator effects of the Games on the number of new cases per day. We report the largest deviation values from the baseline "no-Games" case. In all the scenarios we considered, the largest deviation occured in the first week of August, which is the last week of the Olympic Games.

Table 8: Direct Effects on Daily Number of Newly Infected (First Week of August)

	$p = 0.2$	$p = 0.5$	$p = 0.8$
100% Spectators	+ 81	+ 49	+ 22
50% Spectators	+ 24	+ 15	+ 7

As expected from the characteristics of the contact rate matrix, the number of newly infected people will be higher as the number of spectators and the probability of dining at restaurants increase. In the worst-case scenario in which 80 percent of total ticket holders do not go straight home after visiting the venues, the average number of newly infected individuals on a day would increase by 81. However, if we could restrict the number of spectators by half and successfully reduce dining-out rates, this incredase will be limited to 7 new cases per day.

In addition, the decrease in spectators by half would reduce the number of new cases by more than a factor of two. From eq.(14), the number of new cases for the spectator groups are determined by a quadratic matching of the susceptible and infected population. As we assume the constant fraction of each group j is distributed across susceptible and infected populations, doubling the number of spectators roughly doubles the number of susceptible and infected individuals in each group. Therefore, the newly infected cases will be roughly quadrupled through quadratic matching as both $I_{j,t}$ and $S_{j,t}$ are roughly doubled even if the reduction of contact rates is not as significant compared to a case of a low dining-out probability case. Still, encouraging the spectators to go straight home could mitigate the direct effects even if we allowed all tickets holders to watch the Games at the competition venues.

[30] We assumed that it was not possible to reduce the number of volunteers for managing the Olympic Games. Hence, the number of volunteers is 26,000 for each case.

5 Indirect Effects

In both May-21 and June-17 reports, we examined the possibility that the festive moods promoted by the Games would increase infection by increasing mobility among Tokyo residents or by discouraging people and businesses to abide by various requests by the government to control infection.

5.1 May-21 analysis

In the May-21 report, we conducted simulations where we increased the level of economic activities during the Games and interpreted the results of this exercise as indicating what would happen when the festive mood associated with hosting the Games caused people to become more active.

In terms of the simulation details, we lowered α_t—a variable capturing the decline in economic activity—by 1 or 3 percentage points when the Games would take place.[31] Admittedly, changing α_t in this way may not fully capture what would occur in reality, but this exercise provided a simple way to quantify the importance of the indirect effect.[32]

Figure 8 displays the effects of higher α (1 or 3 percentage points) on new cases and ICU relative to the no-Games case. The blue lines at the bottom are the same line as those in Figure 2. According to the figure, the effects of mobility change among residents would be much larger than those of increased inflows of visitors. Taking averages over the periods of July-September and October-December, the differences in new cases were about 130 and 160 for the 1 percentage point case and 450 and 570 for the 3 percentage points case. When there was no mobility change, the difference in new cases was about 15. For ICU, the average differences over the same periods were about 12 and 11 for the 1 percentage point case and 41 and 39 for the 3 percentage points case, whereas it was at most 2 in the case of no mobility change. Thus, our analysis suggested that changes in mobility would have greater impact on the spread of COVID-19 than the inflow of the Games-related foreign visitors.

The key reasons why the indirect effects are much larger that the effect of foreign visitors is the size of the population directyla affected. The indirect effects are about how the Games would affect the behaviors of the entire population in Tokyo—about 14M—which is much larger than the number of Games-related foreign visitors. Thus, even a small change in the behaviors of Tokyo residents could lead to a large increase in the number of new COVID-19 cases.

5.2 June-17 analysis

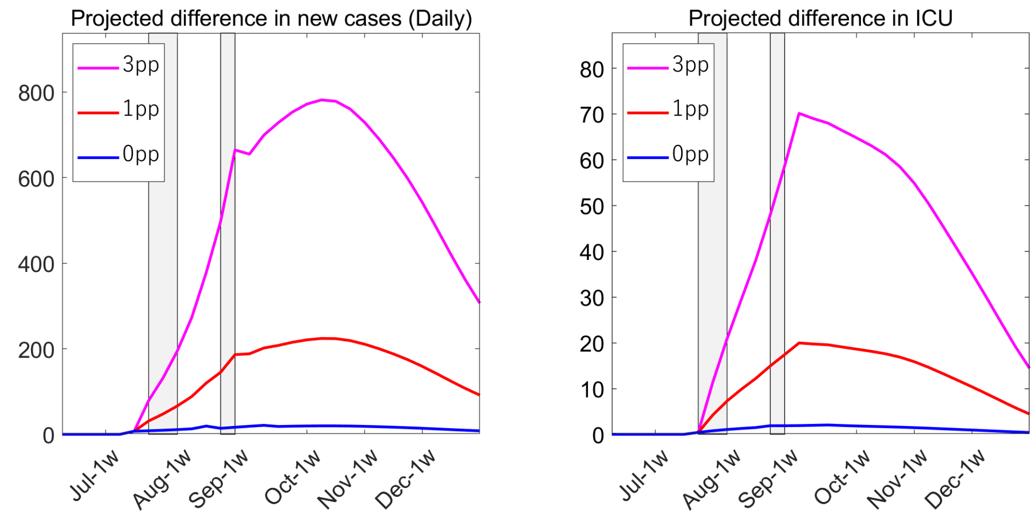
In the June-17 report, we conducted a similar exercise using updated data.

The baseline structure of the model was the same as that presented in Section 4. We modelled the indirect effects as the increase in the transmission rate $\tilde{\beta}_t$ from one week before the Olympics

[31] Note that the difference in α_t between November 2020 and January 2021 was about 3 percentage points: in November 2020, economic activities were at the highest level within the year since the pandemic started, and the economy slowed down in January 2021 due to the second SOE issued by the government.

[32] This approach of quantifying the indirect effect of the Games is consistent with that taken in Furuse et al. [2021a].

Figure 8: Indirect effects of the Games: May-21 Report



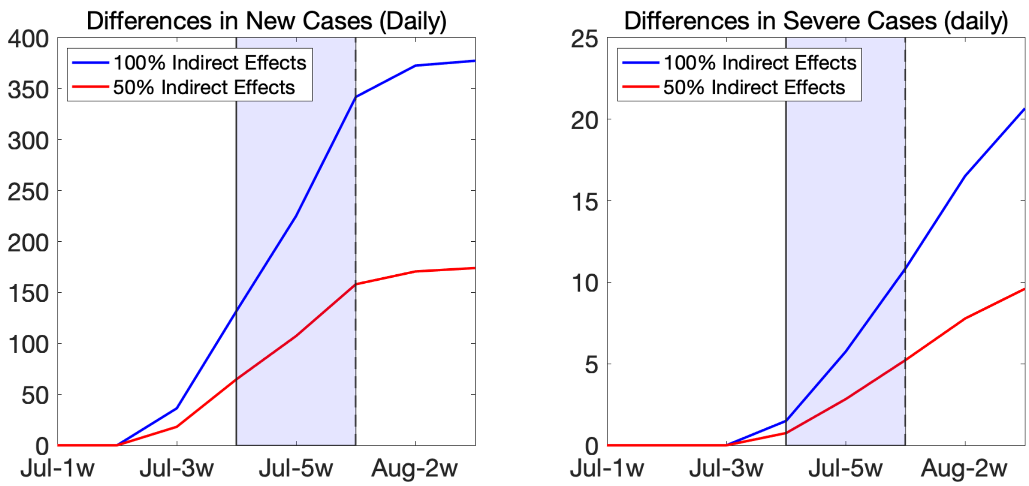
Source: Authors' calculations. See Section **??** for the data sources.

officially start to one week after its end. It has two interpretations. The first interpretation is the increase in the raw transmission rate β_t, as individuals reduce the degree of preventive measures at the individual level such as less usage of masks. The second interpretation is the increase in mobility. People might socialize with their friends more frequently under the festive atmosphere of the Games. The increase of $\tilde{\beta}_t$ was meant to capture both types of behavioral changes.

We specified the increase in the transmission rates in the following manner. First, we assumed that the transmission rate would increase to the level of a period between the end of March to the middle of April. The transmission rates were relatively high during this period, reflecting the end and beginning of Japan's academic and business year. According to our estimation, compared to the recent four months average, the average transmission rate from the end of March to the middle of April was 23 percent higher. Second, we allocated these increases to the five weeks, from the third week of July to the second week of August, in the following manner: 30 percent weight for the third week of July, 80 percent weights for the Olympic period, and 30 percent weight for the second week of August. Thus, the transmission rate would increase by 7 percent in one week before and after the Olympic period and by 19 percent during the Olympic period. These weights were equivalent to assign 100 percent weight for the Olympic period only. As a sensitivity analysis, we also considered the case in which the transmission rate would increase only by half of the baseline magnitude.

Figure 9 shows the differences in new cases and severe cases between the baseline scenario and each of the two scenarios with the indirect effects. According to the figure, the indirect effects would be much larger than the spectator effects. In the second week of August, new cases increase by almost 350 per day. This increase would be more than three times as many as the largest deviation in the direct effects. In addition, the increase of new cases and severe cases in the second week of

Figure 9: Indirect effects of the Games: June-17 Report



August in the full effect case would be slightly more than twice as much as the increase in the half effect case. This larger response reflected cumulative effects over time. If newly infected individuals increased, the size of the infected population would increase. This increase would further increase the number of newly infected people and server cases in the next week.

All in all, the key message from the analyses of the indirect effect in our May-21 and June-17 report was that the indirect effects of the Games could be much larger than the direct effects associated with foreign visitors or spectators.

6 Ex-post evaluation

The first three subsections are based on the report we released—and presented at the Fifth Roundtable Meeting with Experts—on August 20, 2021.

6.1 Effects of foreign visitors

We first highlight some of the differences between the assumptions used in our May-21 analysis and the actual outcomes.

First, we assumed that the number of the Games-related visitors was 105,000, but it was about 58,000 in reality [The Tokyo Organising Committee of the Olympic and Paralympic Games, 2021]. Second, the Delta variant was widespread in Tokyo when the Olympics started. At the time of analysis, there was no estimate of how quickly the Delta variant would become dominant and we abstracted from it.[33] Thus, our simulation featured a low value for the transmission rate. Partially due to this difference, the number of newly infected cases was about 1,500 per day in Tokyo in

[33] On June 9, Nishiura [2021b] and the National Institute of Infectious Diseases, independently, presented the first projections of the proportion of the Delta variant at the Advisory Board on COVID-19 (MHLW).

reality in late July when the Olympic Games started, whereas it was about 500 in our simulation. If we were to re-run our simulation taking these discrepancies into account, our estimate of the upper bound of the effect of the Games-related foreign visitors would be revised upward.

For ex-post evaluation, we turn to the data on the number of positive COVID-19 cases among Games-related visitors, staff, volunteers, and contractors, as published in the website of the TOCOG. According to this data, there were 863 positive cases between July 1 and September 8, making the average number of new cases was about 12 per day. For ICU cases, there is no reported incidence of severe cases related to the Games. These figures are close to our prediction of 15 new cases per day and at most 2 additional ICU patients.

It should be noted that direct comparison is not appropriate for two reasons. First, the observed number of positive cases does not include secondary (or higher-degree) transmissions, which would place downward bias on the observed number. Second, given the rapidly rising number of cases in Tokyo during the period, some of the identified cases are likely to have occurred outside the Olympics and Paralympics contexts. Among the 863 cases, 609 were residents of Japan, and most likely, not all the cases would trace back to infected visitors. This aspect leads to upward bias on the observed number. With these two types of biases working in the opposite directions, it is difficult to provide a definitive answer as to whether the correct effects of foreign visitors are large or smaller than the numbers mentioned in the previous paragraph. Our current conjecture is that those two biases are quantitatively small and that the realized numbers of cases and ICU patients that had origins in infected visitors was roughly in line with those in the previous paragraph.

6.2 Effects of spectators

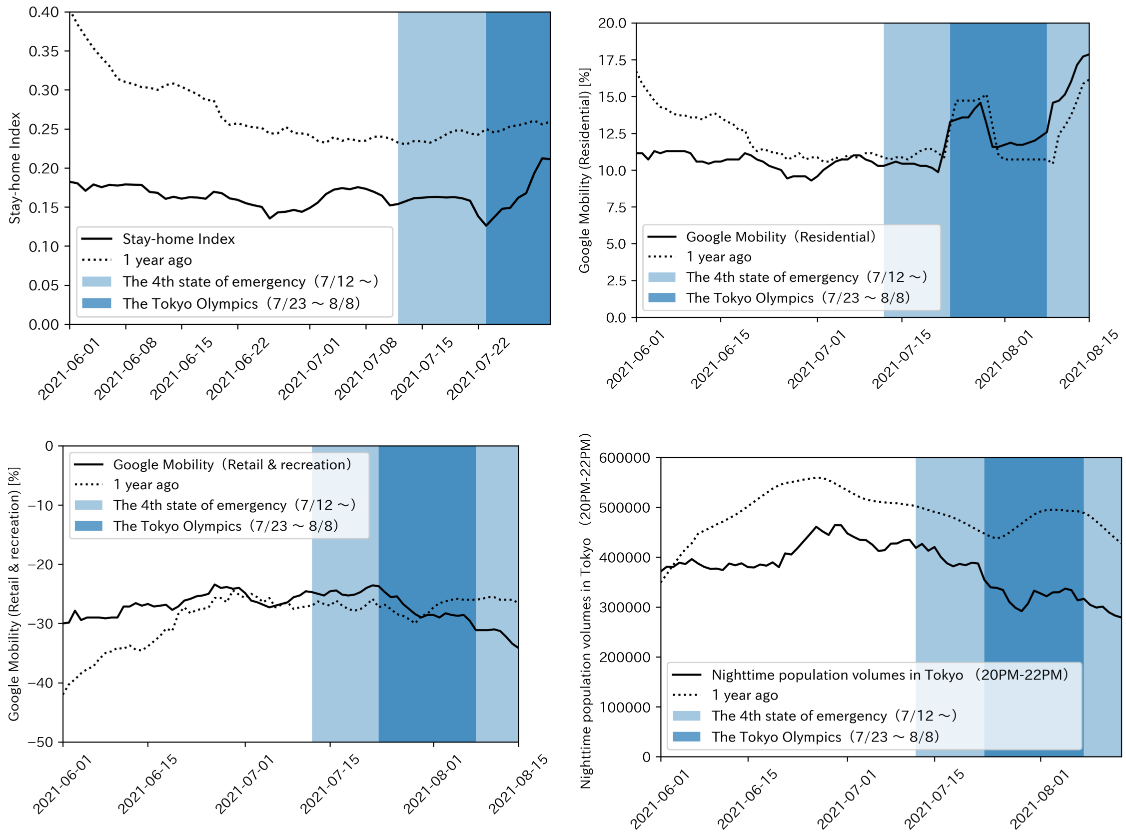
On July 8—about three weeks after our analysis and two weeks before the Games began—as the number of new cases started to increase rapidly, it was decided that all spectators in the Olympic Games would be banned in the competition venues in Tokyo. Thus, it is infeasible to compare our analysis against data. There were volunteers at the venues, who could have contributed to the spread of the virus. However, given their relatively small size, we conjecture that the effects of volunteers on COVID-19 in Tokyo were not minimal.

6.3 Indirect effects

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 exist anecdotal evidence that people might have become less cautious with infection during the Games. According to social media and TVs, some bars and restaurants were crowded with few people wearing masks. People gathered on streets to watch some Olympic events that took place on road (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.

Figure 10: Mobility Measures in Tokyo around the Time of the Olympic Games



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

On the other hand, some have argued that the Games induced people to stay home to watch the Games on TV. Some measures of mobility before and during the Olympic Games—shown in Figure 10—are qualitatively in line with such an argument. "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.[34]

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

[34]See Watanabe and Yabu [2021] and Inoue and Okimoto [2022] for empirical analyses of fear effects in Japan.

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 counterfactual of no Games is likely to be highly speculative.

6.4 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 (The Tokyo Organising Committee of the Olympic and Paralympic Games [2021]). 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 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.m [2021]).

On August 12, 2021, 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, pointing 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 (Omi [2021]). 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."[35]

In late August, 2021, Hiroshi Nishiura—a renowned 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[36]—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 (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

[35] In an interview on September 13, 2021 (Chuo-Koron [2021]), Shigeru Omi stated, "even though it is difficult to know whether the Games itself had influenced the spread of infection, I think the fact that the Games took place affected people's 'awareness' a little."

[36] See, for example, Bunshun [2021a], Ronza [2021], Bunshun [2021b], and Bunshun [2021c].

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.

7 Conclusion

In this paper, we presented a series of quantitative analyses conducted from mid-May of 2021 to mid-June of 2021 that examined the effects of hosting the Tokyo 2020 Olympic and Paralympic Games on the spread of COVID-19 in Japan.

Our ex-ante quantitative analyses pointed out that (i) the effects on the spread of the disease of welcoming additional foreign visitors to Japan or allowing spectators in competition venues would be either limited or manageable, (ii) while a festive mood generated by the event could greatly contribute to the spread of the disease if it led to a decline in people's willingness to take preventive actions. Ex-post, though it is likely infeasible to firmly establish the causal effects of the Games on the spread of COVID-19, the key results of our ex-ante analyses are broadly in line with available circumstantial evidence—as well as ex-post consensus among pubic-health experts in Japan—on how the event affected the spread of COVID-19 in Tokyo.

We also provided readers with the context in which we conducted our analyses and how the public and policymakers perceived them. We hope that our unique experience of using model-based analyses to contribute to a heated national debate in real-time can provide researchers around the world with food for thought on the role of model-based analyses in informing the public and policymakers.

References

The 11th meeting of the Covid-19 Advisory Board: Document 2-3 (in Japanese), author = Hiroshi Nishiura, year = 2021, url = https://www.mhlw.go.jp/content/10900000/000686295.pdf.

Asahi Shinbun. Limiting people's movement key to holding 'safe' Olympics: Study, 2021a. URL https://www.asahi.com/ajw/articles/14357743.

Asahi Shinbun. Olympics-related events could increase infection by hundreds (in Japanese), 2021b. URL https://www.asahi.com/articles/ASP6K72H4P6KULBJ010.html.

Asahi Simbun. Support for Suga administration is the lowest now: 31 percent (in Japanese), 2021. URL https://digital.asahi.com/articles/ASP7L756DP7HUZPS005.html.

BBC News. Tokyo Olympics: Why people are afraid to show support for the Games, 2021. URL https://www.bbc.com/news/world-asia-57395010.

Bunshun. The games should be postponed for one more year: An angry proposal by professor nishiura, April 2021a. URL https://bunshun.jp/denshiban/articles/b457.

Bunshun. An urgent proposal by Professor Nishiura: Cancel the Paralympic Games if infection does not come down, July 2021b. URL https://bunshun.jp/denshiban/articles/b1434.

Bunshun. Professor Nishiura's regret: I should have stopped the Olympic Games no matter how much criticism i would have received, July 2021c. URL https://bunshun.jp/denshiban/articles/b1434.

BuzzFeed. Despite delta variant, Olympic Games, and holidays, why infection declined? four hypotheses by Hiroshi Nishiura (in Japanese), 2021. URL https://www.buzzfeed.com/jp/naokoiwanaga/covid-19-nishiura-20210831-2.

Cabinet Office. COVID-19 simulations by experts, 2021. URL https://corona.go.jp/minister/pdf/kishakaiken_shiryo_20210618.pdf.

Asako Chiba. The effects of the increase in human mobility associated with the Games on COVID-19. *Mimeo*, 2021a. URL https://covid19outputjapan.github.io/JP/files/Olympics_Chiba.pdf.

Asako Chiba. The effectiveness of mobility control, shortening of restaurants' opening hours, and working from home on control of COVID-19 spread in Japan. *Health & Place*, 70:102622, 2021b.

Asako Chiba. Modeling the effects of contact-tracing apps on the spread of the coronavirus disease: Mechanisms, conditions, and efficiency. *PloS one*, 16(9):e0256151, 2021c.

Asako Chiba, Daisuke Fuji, and Taisuke Nakata. The effects of the Olympic and Paralympic Games on COVID-19: Summary. *Mimeo*, 2021. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_Olympics_Slides_20210616a_DirectEffects.pdf.

Chuo-Koron. Reasons why suga administration was defeated by covid-19: Interview with shigeru omi, November 2021. URL https://cir.nii.ac.jp/crid/1521136281233620096.

Taro Esaka and Takao Fujii. Quantifying the impact of the Tokyo Olympics on COVID-19 cases using synthetic control methods. 2021.

Financial Times. Tokyo warned locals pose greater Covid risk to olympics than visitors, 2021. URL https://www.ft.com/content/9efb00cc-1445-4e4b-8e35-2b342091800e.

Foodist. 95% of restaurants followed the anti-coronavirus guideline (in Japanese), Feb 2021. URL https://www.inshokuten.com/foodist/article/6024/.

Daisuke Fuji and Taisuke Nakata. The effects of the Olympic Games on COVID-19: Summary. *Mimeo*, 2021a. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_Olympics_Slides_20210616_Summary.pdf.

Daisuke Fuji and Taisuke Nakata. The effects of the Olympic and Paralympic Games on COVID-19: Indirect effects. *Mimeo*, 2021b. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_Olympics_Slides_20210616b_IndirectEffects.pdf.

Daisuke Fuji and Taisuke Nakata. The effects of the Olympic and Paralympic Games on COVID-19: Ex-post assessment. *Mimeo*, 2021c. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_OlympicsReview_Slides_20210820.pdf.

Daisuke Fuji, Yuta Maeda, Masataka Mori, Taisuke Nakata, and Wataru Okamoto. Details of the analysis of direct effects. *Mimeo*, 2021a. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_Olympics_Slides_20210616b_ModelDetails.pdf.

Daisuke Fuji, Taisuke Nakata, and Wataru Okamoto. An estimate of the number of spectators during the Olympic Games. *Mimeo*, 2021b. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_Olympics_Slides_20210614_Spreadsheet.pdf.

Daisuke Fuji, Taisuke Nakata, and Wataru Okamoto. Large-scale events under COVID-19 in Tokyo. *Mimeo*, 2021c. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_Olympics_Slides_20210616a_SportsMusic.pdf.

Daisuke Fujii and Taisuke Nakata. Medium-term outlook by the Advisory Board on COVID-19. *Mimeo*, July 2021a. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_Outlook_Slides_20210705.pdf.

Daisuke Fujii and Taisuke Nakata. The effects of hosting the Olympic and Paralympic Games on COVID-19: A quantitative analysis. *Mimeo*, 2021b. URL https://covid19outputjapan.github.io/JP/files/FujiiNakata_Olympics_Slides_20210521.pdf.

Daisuke Fujii and Taisuke Natata. Covid-19 and output in Japan. *Japanese Economic Review. Special Issue: SIR Model and Macroeconomics of COVID-19*, 72:609–650, 2021.

Yuki Furuse. COVID-19 projection with the SOE and vaccine rollout (in Japanese). *The Ministry of Health, Labor, and Welfare: Advisory Board on COVID-19*, Document 2, June 2021a. URL https://www.mhlw.go.jp/content/10900000/000790388.pdf.

Yuki Furuse. COVID-19 projection in Tokyo from July to September. *The Ministry of Health, Labor, and Welfare: Advisory Board on COVID-19*, Document 2, July 2021b. URL https://www.mhlw.go.jp/content/10900000/000803143.pdf.

Yuki Furuse, Yura Ko, Hitoshi Oshitani, and Motoi Suzuki. COVID-19 projections in Tokyo from June to September (in Japanese). *The Ministry of Health, Labor, and Welfare: Advisory Board on COVID-19*, Document 2, June 2021a. URL https://www.mhlw.go.jp/content/10900000/000793713.pdf.

Yuki Furuse, Yura Ko, Hitoshi Oshitani, and Motoi Suzuki. COVID-19 projections in Tokyo from June to September (in Japanese). *The Ministry of Health, Labor, and Welfare: Advisory Board on COVID-19*, Document 2, June 2021b. URL https://www.mhlw.go.jp/content/10900000/000790388.pdf.

Hisashi Inaba. Mathematical models for infection diseases: Introduction and an application to COVID-19, 2021. URL https://www.youtube.com/watch?v=eDSLDmaOH_8.

Tomoo Inoue and Tatsuyoshi Okimoto. Exploring the dynamic relationship between mobility and the spread of COVID-19, and the role of vaccines. *RIETI Discussion Paper Series, 22-E-011*, 2022.

Jiji Tsushin. The Olympic Games: Limiting people's movement key, effects of foreign visitors limited—an estimate from the University of Tokyo (in Japanese), 2021a. URL https://www.jiji.com/jc/article?k=2021053000182.

Jiji Tsushin. Olympics spectators: Going to restaurants and bars spread infection. going home straight key (in Japanese), 2021b. URL https://www.jiji.com/jc/article?k=2021061701225.

Cliff C Kerr, Robyn M Stuart, Dina Mistry, Romesh G Abeysuriya, Gregory Hart, Katherine Rosenfeld, Prashanth Selvaraj, Rafael C Nunez, Brittany Hagedorn, Lauren George, et al. Covasim: An agent-based model of COVID-19 dynamics and interventions. *medRxiv*, 2020.

Setsuya Kurahashi. Estimated effectiveness of priority vaccination by age group. *Cabinet Secretariat: Covid-19 AI and Simulation Project*, April 2021a. URL https://www.covid19-ai.jp/en-us/presentation/2021_rq3_countermeasures_simulation/articles/article037/.

Setusya Kurahashi. The effects of the Olympic Games and the delta variant on COVID-19. *Cabinet Secretariat: Covid-19 AI and Simulation Project*, June 2021b. URL https://www.covid19-ai.jp/en-us/presentation/2021_rq3_countermeasures_simulation/articles/article079/.

Kyodo Tsushin. More movement during Tokyo Games may increase infections: Expert, 2021. URL https://english.kyodonews.net/news/2021/05/c1e952dec5e0-more-movement-during-olympics-paralympics-may-increase-infections-panel.html.

Natalie M. Linton, Sung mok Jung, and Hiroshi Nishiura. Not all fun and games: Potential incidence of SARS-CoV-2 infections during the Tokyo 2020 Olympic Games. *Mathematical Biosciences and Engineering*, 18(6):9685–9696, 2021. URL https://www.aimspress.com/article/doi/10.3934/mbe.2021474.

m3.m. Mr. Okabe says, it is a half-time now after the Olympic Games. what we should do for the Paralympic Games.(in Japanese), 2021. URL https://www.m3.com/news/open/iryoishin/955009.

Mainichi Shinbun. Festive mood from the Olympics could increase infection by hundreds in Tokyo (in Japanese), 2021. URL https://mainichi.jp/articles/20210621/k00/00m/050/314000c.

Ministry of Health, Labour and Welfare. National surveillance for COVID-19 (preliminary), 2021. URL https://www.mhlw.go.jp/content/10906000/000782185.pdf.

Takayuki Mizuno, Takaaki Ohnishi, and Tsutomu Watanabe. Visualizing social and behavior change due to the outbreak of COVID-19 using mobile location big data. *Artificial Intelligence*, 35(5):667–672, 2020.

Michio Murakami, Fuminari Miura, Masaaki Kitajima, Kenkichi Fujii, Tetsuo Yasutaka, Yuichi Iwasaki, Kyoko Ono, Yuzo Shimazu, Sumire Sorano, Tomoaki Okuda, Akihiko Ozaki, Kotoe Katayama, Yoshitaka Nishikawa, Yurie Kobashi, Toyoaki Sawano, Toshiki Abe, Masaya M. Saito, Masaharu Tsubokura, Wataru Naito, and Seiya Imoto. COVID-19 risk assessment at the opening ceremony of the Tokyo 2020 Olympic Games. *Microbial Risk Analysis*, 19:100162, 2021. URL https://doi.org/10.1016/j.mran.2021.100162.

Miharu Nakanishi, Ryosuke Shibasaki, Syudo Yamasaki, Satoshi Miyazawa, Satoshi Usami, Hiroshi Nishiura, and Atsushi Nishida. On-site dining in Tokyo during the COVID-19 pandemic: Time series analysis using mobile phone location data. *JMIR mHealth and uHealth*, 9(5):e27342, 2021.

Taisuke Nakata. Outlook by the Advisory Board on COVID-19 in the second half of 2021. *Mimeo*, December 2021. URL https://covid19outputjapan.github.io/JP/files/Nakata_ABOutlook2021_20211223.pdf.

NHK. How would the Olympic Games affect infection? an estimate from the University of Tokyo (in Japanese), 2021. URL https://www.nhk.or.jp/politics/articles/lastweek/61196.html.

Nikkei. The effects of Olympics-related foreign visitors "limited": Limiting people's movement needed (in Japanese), 2021. URL https://www.nikkei.com/article/DGXZQOUA240FS0U1A520C2000000/.

Nikkei. Spectators could reach 200 thousands per day. going home straight key (in Japanese), 2021. URL https://www.nikkei.com/article/DGXZQOUE072400X00C21A6000000/.

Nikkei Shinbun. People's movement likely to increase after the soe: Possibility of another SOE during the Olympic Games (in Japanese), 2021. URL https://www.nikkei.com/article/DGXZQOUA185PD0Y1A610C2000000/.

Hiroshi Nishiura. A scenario analysis (in Japanese). *The Ministry of Health, Labor, and Welfare: Advisory Board on COVID-19*, Document 3, January 2021a. URL https://www.mhlw.go.jp/content/10900000/000718711.pdf.

Hiroshi Nishiura. A scenario analysis (in Japanese). *The Ministry of Health, Labor, and Welfare: Advisory Board on COVID-19*, Document 3, June 2021b. URL https://www.mhlw.go.jp/content/10900000/000790389.pdf.

Nomura Research Institute. The effects of Covid-19 on consumption in restaurants, leisure, and travel industries (in Japanese), Sep 2020. URL https://www.nri.com/jp/journal/2020/0923.

Yukio Ohsawa. Vaccination planning 2: Naturally and quickly. *Cabinet Secretariat: Covid-19 AI Simulation Project*, May 2021. URL https://www.covid19-ai.jp/en-us/presentation/2021_rq3_countermeasures_simulation/articles/article085/.

Shigeru Omi. Press conference transcript; August 12, 2021 (in Japanese), 2021. URL https://news.yahoo.co.jp/articles/8b7b459fc76e97f336ef2aa8c53b86c7163fc7cc?page=4.

Fernando P Polack, Stephen J Thomas, Nicholas Kitchin, Judith Absalon, Alejandra Gurtman, Stephen Lockhart, John L Perez, Gonzalo Pérez Marc, Edson D Moreira, Cristiano Zerbini, et al. Safety and efficacy of the BNT162b2 mRNA Covid-19 vaccine. *New England Journal of Medicine*, 383(27):2603–2615, 2020.

Ronza. Let's share the sense of urgency by Professor Nishiura who appeals the suspension of the Games, July 2021. URL https://webronza.asahi.com/business/articles/2021072600001.html.

Sankei Shinbun. The effects of Olympics-related foreign visitors 'limited': An estimate from the University of Tokyo (in Japanese), 2021. URL https://www.sankei.com/life/news/210523/lif2105230044-n1.html.

Scientific Advisory Group for Emergencies. SPI-M-O: Summary of further modelling of easing restrictions - roadmap step 2, 31 March 2021. Technical report, UK government, 2021. URL https://assets.publishing.service.gov.uk/government/uploads/system/

uploads/attachment_data/file/975909/S1182_SPI-M-O_Summary_of_modelling_of_easing_roadmap_step_2_restrictions.pdf.

The Tokyo Organising Committee of the Olympic and Paralympic Games. 47th executive board meeting minutes (in Japanese). September 2021. URL https://www.tokyo2020.jp/image/upload/production/47EBMeeting6.pdf.

The Tokyo Organising Committee of the Olympic and Paralympic Games. Fifth round-table meeting with experts. *Review of COVID-19 Management during the Olympic Games*, 2021. URL 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.

The Tokyo Organising Committee of the Olympic and Paralympic Games. 7th coordination meeting of anti-coronavirus for Tokyo Olympic and Paralympic Games (in Japanese), Jun 2021. URL https://www.2020games.metro.tokyo.lg.jp/9fa4faa595ab59d7c689363a04951123.pdf.

Tokyo Metropolitan Government. Screening for the L452R variant, 2021. URL https://stopcovid19.metro.tokyo.lg.jp/en/cards/variant/.

Tastuo Unemi. Simulation results on priority order of vaccination 5. *Cabinet Secretariat: Covid-19 AI and Simulation Project*, April 2021a. URL https://www.covid19-ai.jp/en-us/presentation/2021_rq3_countermeasures_simulation/articles/article039/.

Tastuo Unemi. Impact of non-vaccinated clusters 1. *Cabinet Secretariat: Covid-19 AI and Simulation Project*, May 2021b. URL https://www.covid19-ai.jp/ja-jp/presentation/2021_rq3_countermeasures_simulation/articles/article084/.

US FDA. Vaccines and related biological products advisory committee meeting., 2020. URL https://www.fda.gov/media/144434/download. Accessed on May 1, 2021.

Video Research Ltd. 73,268 thousands people watched the opening ceremony in Japan (in Japanese), 2021. URL https://www.videor.co.jp/press/images/press_20210726_02.pdf.

Wall Street Journal. Japan looks to extend COVID-19 state of emergency, 2021. URL https://www.wsj.com/articles/japan-looks-to-extend-covid-19-state-of-emergency-11622029625.

Tsutomu Watanabe and Tomoyoshi Yabu. Japan's voluntary lockdown. *PLos ONE*, 16(6):e0252468, 2021.

Norio Yamamoto, Toshiharu Mitsuhashi, Yuuki Tsuchihashi, and Takashi Yorifuji. Causal effect of the Tokyo 2020 Olympic and Paralympic Games on the number of COVID-19 cases under COVID-19 pandemic: An ecological study using the synthetic control method. *Journal of Personalized Medicine*, 12(2):209, 2022.

Yomiuri Shimbun. National telephone survey (august 2021) (in Japanese), 2021. https://www.yomiuri.co.jp/election/yoron-chosa/20210809-OYT1T50140/.

Wenhui Zhu, Jie Feng, Cheng Li, Huimin Wang, Yang Zhong, Lijun Zhou, Xingyu Zhang, and Tao Zhang. COVID-19 risk assessment at the opening ceremony of the Tokyo 2020 Olympic Games. *Frontiers in Public Health*, 9:730611, 2021. URL 10.3389/fpubh.2021.730611.

A Select media citation

Table 9: Select Media Citation of the May-21 Report

Date	News Outlet	Title
May 23	Sankei Shinbun [2021]	The Effects of Olympics-related Foreign Visitors "Limited": An Estimate from the University of Tokyo
May 24	NHK [2021]	How Would the Olympic Games Affect Infection? An Estimate from the University of Tokyo
May 24	Nikkei [2021]	The Effects of Olympics-related Foreign Visitors "Limited": Limiting People's Movement Needed
May 25	Asahi Shinbun [2021a]	Limiting People's Movement Key to Holding "Safe" Olympics: Study
May 26	Wall Street Journal [2021]	Japan Looks to Extend Covid-19 State of Emergency
May 28	Kyodo Tsushin [2021]	More Movement During Tokyo Games May Increase Infections: Expert
May 30	Jiji Tsushin [2021a]	The Olympic Games: Limiting People's Movement Key, Effects of Foreign Visitors Limited. An Estimate from the University of Tokyo
June 8	Financial Times [2021]	Tokyo warned locals pose greater Covid risk to Olympics than visitors
June 12	BBC News [2021]	Tokyo Olympics: Why people are afraid to show support for the Games

Table 10: Select Media Citation of the June-17 Reports

Date	News Outlet	Title
June 17	Jiji Tsushin [2021b]	Olympics spectators: Going to restaurants and bars spreads infection. Going home straight key.
June 18	Asahi Shinbun [2021b]	Olympics-related Events Could Increase Infection by Hundreds
June 18	Nikkei Shinbun [2021]	People's Movement Likely to Increase After the SOE: Possibility of another SOE during the Olympic Games
June 21	Mainichi Shinbun [2021]	Festive Mood from the Olympics Could Increase Infection by Hundreds in Tokyo
June 21	Nikkei [2021]	Spectators could reach 200 thousands per day. Going home straight key.

B Data used for the analysis of spectator effects

B.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 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.2 Number of spectators in the Olympic Games

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.

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.[37] 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.

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.[38] Also, assuming that there would be an additional 10 percent cancellation of volunteers, and they would be assigned according to the number of spectators ratio of the venue, the number of volunteers per day in Tokyo was estimated as follows:

$$
\begin{aligned}
&\text{The number of volunteers per day}\\
&= (26,000 \times \frac{10\text{ days}}{17\text{ days}} + 7,000 \times \frac{5\text{ days}}{17\text{ days}}) \times 0.9 \times \frac{\text{the average number of spectators in Tokyo}}{\text{the average number of spectators in all venues}}\\
&\fallingdotseq 43,941 \times \frac{150,857}{253,499} \fallingdotseq 26,000
\end{aligned}
$$

[37]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.

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

C Agent-based model

C.1 Parameters

Table 11: Probability and duration of developing symptoms depending on age.

	Duration of transition (days)	Probability of transition								
		∼9	10∼	20∼	30∼	40∼	50∼	60∼	70∼	80∼
(Worsen)										
Not infectious ⇒ Presymptomatic	∼ LN(4.6, 4.8)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Presymptomatic ⇒ Moderate	∼ LN(1.0, 0.9)	0.500	0.550	0.600	0.650	0.700	0.750	0.800	0.850	0.900
Moderate ⇒ Severe	∼ LN(6.6, 4.9)	0.000	0.000	0.000	0.155	0.151	0.198	0.365	0.360	0.408
Severe ⇒ Critical	∼ LN(3.0, 7.4)	0.000	0.000	0.000	0.029	0.029	0.147	0.368	0.491	0.490
Critical ⇒ Death	∼ LN(6.2, 1.7)	0.000	0.000	0.000	0.146	0.182	0.218	0.255	0.291	0.327
(Recover)										
Presymptomatic ⇒ Recovered	∼ LN(8.0, 2.0)	0.500	0.450	0.400	0.350	0.300	0.250	0.200	0.150	0.100
Moderate ⇒ Recovered	∼ LN(8.0, 2.0)	1.000	1.000	1.000	0.845	0.849	0.802	0.635	0.640	0.592
Severe ⇒ Recovered	∼ LN(14.0, 2.4)	1.000	1.000	1.000	0.971	0.971	0.853	0.632	0.509	0.510
Critical ⇒ Recovered	∼ LN(14.0, 2.4)	1.000	1.000	1.000	0.854	0.818	0.782	0.745	0.709	0.673

˜LN(a,b) depicts that the parameter following the Log-normal distribution with the expected value of a, and the standard deviation of b.

Table 12: Description of contacts in each layer.

Layer	Methods to construct networks	Average size of a group(number of people)	Relative likelihood of transmission
Home	Constructed based on the answers to the questions on family members.	3	.8
Workplace	Construct a group of individuals working for the same industry of a size that follows the firm-size distribution in the industry.	5	.04
Nursing home	A group of up to 20 adults over 60 years of age, adding up to 6 care workers for each group, is developed.	18	25
High-risk bars and restaurants	A group of a size of a Poisson random variable with parameter λ is developed. λ is set to 5 if no interventions are taken: the value changes proportionally to the whole number of people who exist in the layer. (i.e. If people are less likely to visit high-risk bars and restaurants due to a stringent intervention, λ decreases by the same proportion of that in the expected number of visitors.)	5	25
Low-risk bars and restaurants	(Same as above.)	5	2
Other general activities	(Same as above. λ is set to 10 if no interventions are taken.)	10	.3

C.2 Proportion of infections in each place

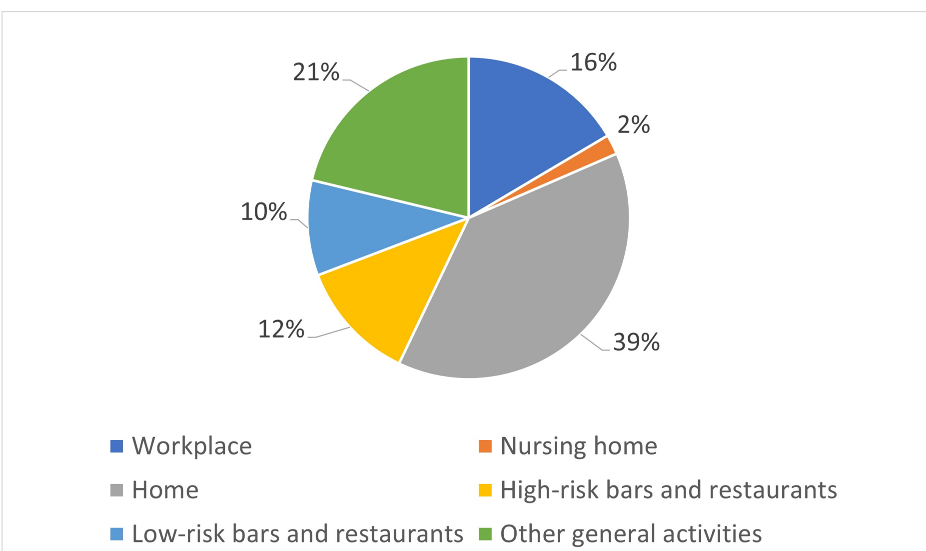


Figure 11: Proportion of infections in each place.

D 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 Natata [2021], the model comprises two parts: the epidemiological part and the economic part. The main differences from Fujii and Natata 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:

$$S_{j,t+1} = S_{j,t} - N_{j,t} - V_{j,t} \tag{2}$$
$$I_{j,t+1} = I_{j,t} + N_{j,t} - N^{IR}_{j,t} - N^{ID}_{j,t} \tag{3}$$
$$H_{t+1} = H_t + N^{IH}_t - \gamma^H_t H_t - N^{ID}_t \tag{4}$$
$$R_{t+1} = R_t + N^{IR}_t + V_t \tag{5}$$
$$D_{t+1} = D_t + N^{ID}_t \tag{6}$$

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,

$$POP_{j,t} = S_{j,t} + I_{j,t} + R_{j,t} + D_{j,t}. \tag{7}$$

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,

$$POP_{j,t} = POP_{j,0}. \tag{8}$$

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:

$$N^{IR}_{j,t} = \gamma_t I_{j,t} \tag{9}$$
$$N^{ID}_{j,t} = \delta_t I_{j,t}. \tag{10}$$

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

$$N^{IH}_t = \delta^{ICU}_t N_t. \tag{11}$$

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

$$\delta_t^{ICU} = \theta_t \delta_t. \tag{12}$$

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:

$$V_{j,t} = E_1 V_{j,t-2}^1 + (E_2 - E_1) V_{j,t-2}^2. \tag{13}$$

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:

$$N_{j,t} = \tilde{\beta}_t \frac{S_{j,t} \sum_{k \in J} \rho_{j,k} I_{k,t}}{POP_0} \tag{14}$$

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 Natata [2021] for a detailed explanation of the specifications.

D.1 Calibration

As in Fujii and Natata [2021], 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 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

Table 13: 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	

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 13.

Based on the initial conditions, the predetermined parameters, and the dynamics specified in eq.(2) – eq.(14), the time-varying parameters δ_t, θ_t, β_t, α_t, and h_t are retrieved as discussed in Fujii and Natata [2021]. 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 Natata [2021]. The details are discussed in Appendix D.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.

D.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 Natata [2021], 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:

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

$$\delta_t^0 = \delta_t / (1 + p_t^\alpha r_d^\alpha) \tag{16}$$

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.[39] 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:

$$\delta_t = (1 - v_t^e)(\delta_0 - \delta_{ss}) + (1 - v_t^y)\delta_{ss} \tag{17}$$

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 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

[39] 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.

Ministry of Health, Labour and Welfare [2021] and Nis.

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. (17), 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. (17) 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,

$$\delta_0 = \frac{\bar{\delta}}{1 - v_T^e(1-\lambda) + v_T^y\lambda}. \tag{18}$$

From eq. (17) and eq. (18), 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:

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

where $\bar{\beta}$ is given by the four-month average of β_t^0 in eq. (16), δ_0 is given by eq. (18) 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 $r_d^\alpha = 0$.

E 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

$$\text{Infection Risk}_t = \sum_{\ell \in L} \text{Infection Risk per Interaction}_{\ell,t} * E[\text{Number of Interaction}_{\ell,t}] \qquad (19)$$

where $L = \{\text{home}, \text{workplace}, \text{school}, \text{high-risk restaurants}, \text{low-risk restaurants}, \text{others}\}$. 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:

$$E[\text{Number of Interaction}_{t,\ell}] = \text{Average Interactions per Visit}_{t,\ell} * P(\text{Visiting Location}_{t,\ell}). \qquad (20)$$

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. (19) and eq. (20)

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

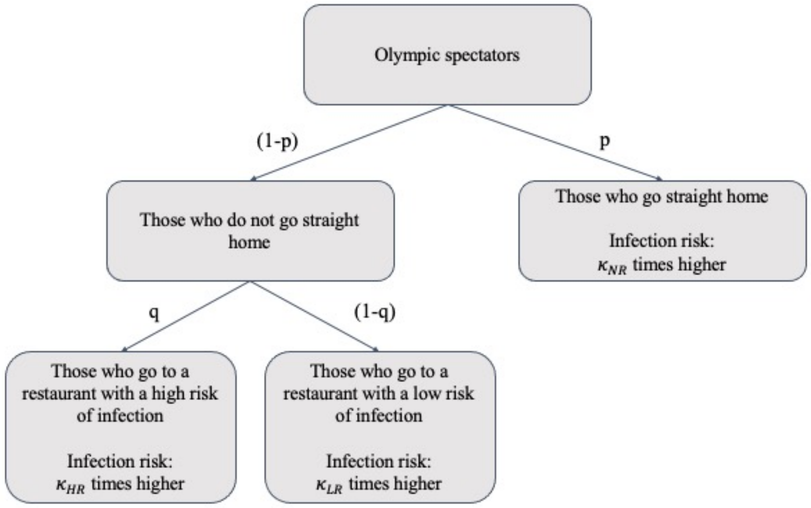


Figure 12: The Composition of Diagonal Elements

the Olympics is given by

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

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

$$\begin{aligned}&\text{Average Interactions per Visit}_{\text{Olympics Period, Low}}\\&= (\overline{n}/POP_0)(1-p)(1-q) + \text{Average Interactions per Visit}_{\text{Normal Time,Low}}.\end{aligned} \tag{22}$$

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

Based on eq. (19), eq. (20), eq. (21), and eq. (22), we can calculate the increases in infection risks for the non-spectator groups, or the off-diagonal elements, by assuming that 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 12.

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

$$\rho_{ii,T_i} = \frac{1}{7}\left(p\kappa_{NR} + (1-p)\left(q\kappa_{HR} + (1-q)\,\kappa_{LR}\right)\right) + \frac{6}{7} \tag{23}$$

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