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ABSTRACT

Background The Tokyo 2020 Summer Olympic Games (23 July–8 August 2021) were held in the middle of Japan's fifth wave of COVID-19, when the number of cases was on the rise, and coincided with the fourth state of emergency implemented by the host city, Tokyo.

Aim This study aimed to assess whether the hosting of the Games was associated with a change in the number of COVID-19 cases in Japan using a synthetic control method.

Methods A weighted average of control countries with a variety of predictors was used to estimate the counterfactual trajectory of daily COVID-19 cases per 1 000 000 population in the absence of the Games in Japan. Outcome and predictor data were extracted using official and open sources spanning several countries. The predictors comprise the most recent country-level annual or daily data accessible during the Games, including the stringency of the government's COVID-19 response, testing capacity and vaccination capacity; human mobility index; electoral democracy index and demographic, socioeconomic, health and weather information. After excluding countries with missing data, 42 countries were ultimately used as control countries.

Results The number of observed cases per 1 000 000 population on the last day of the Games was 109.2 (7-day average), which was 115.7% higher than the counterfactual trajectory comprising 51.0 confirmed cases per 1 000 000 population. During the Olympic period (since 23 July), the observed cumulative number of cases was 61.0% higher than the counterfactual trajectory, comprising 143 072 and 89 210 confirmed cases (p=0.023), respectively. The counterfactual trajectory lagged 10 days behind the observed trends.

Conclusions Given the increasing likelihood that new emerging infectious diseases will be reported in the future, we believe that the results of this study should serve as a sentinel warning for upcoming mega-events during COVID-19 and future pandemics.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ We revealed the association between the hosting of the Tokyo 2020 Summer Olympic Games and the daily number of COVID-19 cases in Japan by using a synthetic control method to approximate the counterfactual trend in the daily number of COVID-19 cases.
⇒ We estimated the weights such that the weighted averages of the preintervention infection rates and predictors of control units (countries except Japan) were close to those of Japan.
⇒ It was challenging to rule out the possible confounding impact of an event that may have occurred almost simultaneously with the Games.
⇒ The study was unable to make definitive assessments of individual-level mechanisms regarding the relationship between the Games and COVID-19 cases.

INTRODUCTION

The COVID-19 pandemic poses major political, socioeconomic, scientific and public health challenges to countries across the globe. Large-scale mass gathering events, such as sporting, musical and religious functions, have historically been a major source of infectious disease transmission and represent a major public health challenge.[1]

The Tokyo 2020 Summer Olympic Games (23 July 23–8 August 2021) were held in the middle of Japan's fifth wave of COVID-19, when case numbers were on the rise, and coincided with the fourth state of emergency implemented by the host city, Tokyo. The Japanese public, government and scientific community were split in terms of whether or not they believe the Olympics should be hosted because of COVID-19 infection concerns.[2] The government went to great lengths to minimise risk during the event: active vaccination was recommended to all those affiliated with the Games, including the athletes, and all possible countermeasures against infection were taken,[3] including the banning of spectators. The evidence base concerning risk assessment and decision-making to minimise the transmission of infectious diseases during mega-events is still evolving and needs to be expanded.[1 4]

For example, a series of studies concerning COVID-19 infection risk in upcoming sporting mega-events such as FIFA World Cup Qatar 2022 conducted by Dergaa and colleagues concluded that stringent public health policies such as a tight ‘bubble system’ for players were key components to ensuring the successful containment of COVID-19.[5–8] With the ongoing pandemic and the inevitable future spread of emerging infections around the world, it is important to evaluate the impact of the Tokyo Games on the spread of COVID-19.

We examined the association between the hosting of the Tokyo Games and the daily number of COVID-19 cases in Japan by using a synthetic control method (SCM) to approximate the counterfactual trend in the daily number of COVID-19 cases, assuming the absence of the Games. The SCM has been widely used in the social sciences[9] and is increasingly used in epidemiology to assess the impact of public health interventions such as tobacco control policies, soft drink taxation, social welfare reform and COVID-19 interventions.[10–13]

According to the Japanese Olympic Committee, the total number of infected people involved in the Olympics was 547.[14] However, rather than transmission from infected Olympic affiliates to Japanese locals, we hypothesise that the hosting of the Tokyo Games may have influenced the behavioural psychology of the public, which had previously been practising self-restraint under the state of emergency. If the Games indirectly encouraged lower compliance with public health guidance, there may have been a tangible impact on Japan’s infection landscape.

METHODS

Approach

In this study, we employed the SCM, which is particularly suitable for population-level studies and allows for appropriate comparisons when random assignment of an intervention is not possible.[15] While other modelling methods such as the difference-in-differences approach are available, the SCM can be easily applied to specific cases where there are multiple control units and it is difficult to select the optimal group of controls for comparison with only one treated unit.

We evaluated the impact of the Tokyo Games on daily confirmed cases of COVID-19 (per 1 000 000) by estimating the counterfactual trajectory of cases assuming the Olympics were not held in Japan and comparing it with the observed trajectory. Daily confirmed cases of COVID-19 were smoothed by using the 7-day moving average in order to adjust for day-of-the-week effects. The counterfactual (or synthetic control) consists of a weighted combination of the COVID-19 incidence in countries in which the Games were not held (hereafter, ‘donor pool’). If the synthetic control closely reproduces the observed trajectory during the period before the start of the Olympics (preintervention period) in Japan, we can have confidence in the validity of the estimated counterfactual trajectory after the start of the Tokyo Games. An important advantage of this approach is that it does not require the identification of an individual comparison country that is sufficiently similar to the Olympics host (ie, Japan).[16]

After removing countries that had ≥10% missing values in the number of COVID-19 tests, vaccination rate and stringency index or countries that have any completely-missing outcomes, the following 42 countries were included in the donor pool: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Czech Republic, Dominican Republic, Ecuador, Estonia, France, Germany, Greece, Guatemala, Hong Kong, Indonesia, Ireland, Israel, Italy, Latvia, Lithuania, Malaysia, Malta, Mexico, New Zealand, Norway, Paraguay, Peru, Russia, Slovakia, Slovenia, South Korea, Switzerland, Thailand, Trinidad and Tobago, Turkey, Ukraine, United Kingdom, United States, Uruguay and Vietnam. The candidate predictor set and further details can be found in the online supplemental appendix.

We constructed the counterfactual as follows[17 18]: first, we used the donor pool and the candidate predictor set to estimate the weights that are optimised to attain the smallest mean squared prediction error (MSPE) during the preintervention period. More precisely, the SCM completes the following two-step minimisation task iteratively to find optimal values of the predictor weight vector $V \in R^M$ and the country weight vector $W \in R^J$:

$$W^* \left(V\right) = \min_W \sum_{m=1}^{M} v_m \left(X_{1m} - \sum_{j=2}^{J+1} w_j X_{jm}\right)^2, \quad \text{s.t. } \sum_{j=2}^{J+1} w_j = 1 \text{ and } w_j \geq 0$$

where $W^* \left(V\right) = \left(w_2^*, \ldots, w_{J+1}^*\right)^T$, $V = \left(v_1, \ldots, v_M\right)^T$, M is the number of predictors, J is the number of control countries and X_1 and X_j are the predictor vectors for the treated country (ie, Japan) and the other J countries, respectively. Then, the weight vector V is optimised via the following:

$$\min_V \sum_{t=1}^{T_0} \left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* \left(V\right) Y_{jt}\right)^2, \quad \text{s.t. } \sum_{m=1}^{M} v_m = 1 \text{ and } v_m \geq 0$$

where $t \in \left\{1, \ldots, T_0\right\}$ is the preintervention period and Y_{1t} and Y_{jt} are the number of COVID-19 cases in Japan and the other countries at time of t. The conjugate gradient method was used for the optimisation. Kinn[19] proved that the SCM proposed by Abadie *et al*[18] is equivalent with the (restricted version of the) L1 penalty. This implies that the method tends to assign positive weights to only a subset of the donor pool and predictors; thus, it works similarly to Lasso-based (Lasso: least absolute shrinkage and selection operator) variable selection. Second, by using the country weights (online supplemental figure 1 and online supplemental table 2), we estimate the path of the counterfactual in the period after the start of the Games (postintervention period). To check whether there is a meaningful effect due to the intervention, as shown by Abadie *et al*,[18] Fisher’s exact p values were calculated by dividing the postintervention MSPE by the preintervention MSPE. For inference, the SCM was repeated by regarding one country in the donor pool as a treated country and the remaining countries and Japan as an alternative donor pool generating placebo synthetic controls: online supplemental figure. *R* V.4.0.5 and the *tidysynth* package were used for the analysis.

If the effect of the Games on daily confirmed cases is mediated by behavioural factors, these changes may not necessarily manifest on the opening day of the Tokyo Games; for example, behaviours could change after the announcement that it would be held without spectators (8 July). Furthermore, there is a time lag—between infection, onset of disease and testing—before the effects of the Games manifest in the number of daily confirmed cases. Therefore, we performed a sensitivity analysis in which we also constructed counterfactuals in the same manner for the 7 days before and after the opening ceremonies as the intervention timing.

Data

In this study, outcome and predictor data were extracted using official and open sources spanning dozens of countries. Data on the daily confirmed cases of COVID-19, the stringency of the government's COVID-19 response, testing capacity and vaccination capacity were obtained from Our World in Data[20]; data on human mobility was obtained from Google's COVID-19 Community Mobility Reports[21]; other demographic, socioeconomic, health and weather data were obtained from Our World in Data, the World Bank[22] and the United Nations.[23] The electoral democracy index, a measure of political freedom, was downloaded from the Varieties of Democracy (V-Dem) project.[24] The online supplemental appendix presents summary statistics for all predictors.

Patient and public involvement

No patients or members of the public were involved in the design, analysis or dissemination plan of our study. Our study relies on population-level data from a large number of countries, and all data used were obtained from existing public sources.

RESULTS

Figure 1A shows the observed and counterfactual (ie, the weighted average of 42 countries) trajectories of daily cases per 1 000 000 on the vertical axis, where the days relative to Olympic beginning ceremony are shown on the horizontal axis and a vertical line is drawn on day 0. The counterfactual trajectory tracks along the observed trajectory well prior to the Games (left side of the vertical line). Figure 1B displays the differential between the observed and counterfactual trajectories over the same period. The difference between the observed and counterfactual values became positive after the start of the Olympics (right side of the vertical line). The SCM revealed that as of the closing day of the Olympics (day 16), the number of daily observed cases per 1 000 000 population was 109.2, which was 115.7% higher than the counterfactual trajectory comprising 51.0 confirmed cases per 1 000 000

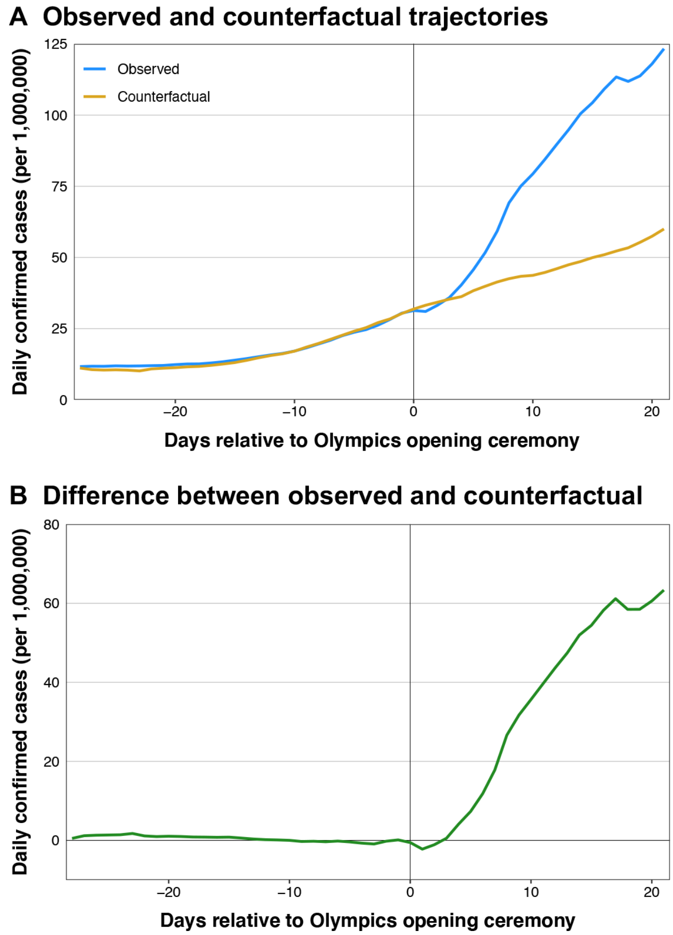

Figure 1 Observed and counterfactual daily confirmed COVID-19 cases per million people: (A) shows the observed and counterfactual trajectories of daily cases per 1 000 000. (B) shows the differential between the observed and counterfactual trajectories.

population. During the Olympic period, the observed cumulative number was 60.4% higher than the counterfactual scenario, with 143 072 and 89 210 confirmed cases (p=0.023), respectively. There was a lag of approximately 10 days between the observed and counterfactual confirmed cases: the counterfactual daily total would have been approximately 6400 on the day of the closing ceremonies, but in reality, it was reached 10 days earlier (29 July 2021).

The results of the sensitivity analyses (online supplemental appendix), in which counterfactuals were constructed by shifting the timing of the intervention (ie, the opening ceremonies) by ±7 days, were consistent with our main findings.

DISCUSSION

Our intention was to add to the evidence base concerning risk assessment and decision-making to minimise the transmission of infectious diseases during mega-events. Using the SCM, we assessed whether the hosting of the Tokyo 2020 Olympic Games was associated with an increase in the number of COVID-19 cases in Japan. Based on the difference between the observed and counterfactual trajectories, we found that approximately 53 900 excess infections were reported over the course of the Olympic period. This estimate was consistent with prior results reported by Yamamoto *et al*.[25] which compared Tokyo with other prefectures in Japan and found that the number of observed cases per 1 000 000 population in Tokyo was approximately 100, while the number of counterfactual cases per 1 000 000 population was approximately 50, as of the closing day of the Olympics.

Though previous research has found that the Olympics and major sporting events do not substantially increase the risk of infectious disease outbreaks,[26] never before have the Games been hosted during a pandemic of this scale. In Japan, the Olympic 'bubble' was partitioned from society and was largely successful in insulating new cases of imported COVID-19 from the general public; however, we found that the hosting of the Games led to a non-trivial increase in the reporting of new infections. Though international-to-local transmission was minimised, we believe that this apparent paradox could be explained by the fact that local-to-local transmission increased for a variety of reasons. First, the Olympics inherently brought about a festive atmosphere to Japan, which had previously been strictly adhering to COVID-19 countermeasures.[27] For example, many restaurants began ignoring operation hour curfews, likely due to the perceived double standard of hosting the Olympics during a state of emergency.[28] Furthermore, as the Olympics neared and after they began, the initial wave of public resistance to hosting began to ease,[29] suggesting that Japanese locals may have been swayed by the 'Olympic spirit,' which may have also bled into their behaviour. Prior research on sporting events in the wake of terrorism incidents has found that attendees were largely dismissive or even defiant of the risk of attending, which has been attributed to the enticing and exciting nature of the Games.[30 31] In the context of the Tokyo Games, this may have manifested as decreased adherence to social distancing protocols or, in some cases, the intentional flaunting of infection control measures. Second, even during non-Olympic times, athletes may serve as role models for the general public with respect to infection prevention measures[32]; these effects were likely amplified during the Games. The exceptions made for athletes to enter Japan when most non-Japanese persons were barred entry, in conjunction with high-profile reporting of Olympians violating infection control rules,[33] may have had an impact on adherence in the general public. Finally, despite the lack of spectators and tourists in Tokyo during the Games, the human mobility during the Olympics was greater than during the previous, third state of emergency.[34] In the midst of the rise of the more infectious Delta variant, insufficiently reduced levels of domestic mixing would directly increase the risk of exposure to COVID-19 among locals.

A previous modelling study of the Games has found that infection prevention measures were ostensibly responsible for controlling transmission at the national level, but the surge in Tokyo case numbers was likely related to local transmission, which may have been attributable to mobility and spread of the Delta variant.[35] Notably, as of July 2021, Japan's vaccine rollout was relatively slow, and major efforts were made to get as many locals vaccinated as possible before the start of the Games. At the time of the opening ceremony, the government achieved a two-dose immunisation rate of only approximately 30% among those living in Japan. In order to minimise the spread and burden of infectious diseases during mega-events, efforts should be made prior to the events to improve vaccination coverage in the host areas and the broader population, beyond the recommendation of the vaccination of athletes and other relevant persons including staff. In addition, we encourage consideration of additional health needs of not only those participating in the events but also those who work and reside around the event locations as well as the communities where most human traffic occurs as a result of the events. Preparations should be made at the clinic and hospital levels to accommodate an influx of patients who may be affected by changes in social behaviour that can precipitate or further propagate disease outbreaks.

Limitation

We note that it was challenging for the SCM to rule out the impact of an event that may have occurred almost simultaneously with the Games. For instance, several other events such as consecutive holidays occurring between 22 and 25 July 2021 and the beginning of summer vacation may have confounded our findings. To address such a concern, we implemented two more SCM analyses where we shifted the timing of the intervention from 23 July to 16 and 30, respectively. The results did not change our interpretation of the results (online supplemental figures 3 and 4). Second, we were unable to make definitive assessments of individual-level mechanisms regarding the relationship between the Games and COVID-19 cases. Our analyses did not include data regarding behavioural changes or routes of transmission during the Olympics. Further research to address these questions is merited. Finally, 42 countries were included in the donor pool in this study, of which five countries (Germany, Hong Kong, Italy, Thailand and South Korea) received non-negligible weights. In each of these countries, the daily infection cases were on a slight upward trend during the Olympics, with the exception of Thailand, which was experiencing a sharp increase in caseload. Hong Kong had a small number of daily cases (less than 10). The weights were determined by the list of predictors, including the lagged infection status, to attain the optimal MSPE during the pre-Olympic period. Note that the SCM estimates weights such that the weighted averages of the preintervention infection rates and predictors of the donor pool were close to those of Japan. The weights are estimated using covariates included in the predictor set, but the number of covariates we included in the estimation process is limited, and we cannot account for unobserved covariates that may have played a role in the transmission of COVID-19. However, based on the predictors we considered, the current result was optimal in the sense that the SCM estimated country-specific weights that minimised the prethreshold MSPE.

Conclusion

Using a synthetic control design, we assessed whether the hosting of the Games was associated with a change in the number of COVID-19 cases in Japan. Based on the difference between the observed and counterfactual trajectories, we found that approximately 60 excess daily cases per 1 000 000 population and 53 900 excess total infections were reported as of the closing day of the Olympic and over the course of the Olympic period, respectively. The counterfactual trajectory lagged 10 days behind the observed trends. Given the ubiquity of infectious disease and the increasing frequency with which new epidemics have been reported since the turn of the millennium, we believe that our findings should serve as a sentinel warning for upcoming mega-events during COVID-19 and future pandemics. In particular, we urge further research with respect to the Beijing 2022 Winter Olympic Games in order to ensure a safe and healthy event for all participants, spectators and the Chinese populace.

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Contributors DY, AE, KF, TK, YT, TT, HM, KS and SN conceived and designed the study and take responsibility for the accuracy of the data analysis. DY, AE, KF, TK, YT, CG and SN analysed and interpreted the data. DY and AE conducted statistical analysis and drafted the article. DY, AE, KF, TK, YT, TT, HM, CG, KS and SN made critical revision of the manuscript for important intellectual content and gave final approval for the manuscript. SN is responsible for the overall content as guarantor.

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1. Data

1.1 Predictor descriptions and sources

Predictor	Description	Source
New COVID-19 cases (outcome variable)	New confirmed cases of COVID-19 (7-day average) per 1,000,000 people.	Our World in Data [1]
0-week lagged cases	New confirmed cases of COVID-19 (7-day average) per 1,000,000 people at the intervention date	Our World in Data [1]
1-week lagged cases	New confirmed cases of COVID-19 (7-day average) per 1,000,000 people one week before the intervention date	Our World in Data [1]
2-week lagged cases	New confirmed cases of COVID-19 (7-day average) per 1,000,000 people two weeks before the intervention date	Our World in Data [1]
3-week lagged cases	New confirmed cases of COVID-19 (7-day average) per 1,000,000 people three weeks before the intervention date	Our World in Data [1]
4-week lagged cases	New confirmed cases of COVID-19 (7-day average) per 1,000,000 people four weeks before the intervention date	Our World in Data [1]
Stringency index	The Government Response Stringency Index, which is a composite COVID-19 measure as of a given date based on 9 response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest response).	Our World in Data [1]
Number of tests for COVID-19	The daily number of new tests for COVID-19 per 1,000 people (7-day average).	Our World in Data [1]
COVID-19 vaccination	The total number of people who received two doses at a given date prescribed by the vaccination protocol per 100 people in the total population.	Our World in Data [1]
Gross domestic product (GDP)	GDP per capita at purchasing power parity (constant 2011 international dollars) for the most recent year available.	Our World in Data [1]
Age	The median age of the population for 2020 (UN's population projection).	Our World in Data [1]
Human Development Index	A composite index for 2019 measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge, and a decent standard of living.	Our World in Data [1]
Life expectancy	Life expectancy at birth in 2019.	Our World in Data [1]

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Number of hospital beds	The number of hospital beds per 1,000 people for the most recent year available.	Our World in Data [1], Government of the Hong Kong Special Administrative Region [2]
Diabetes prevalence	The prevalence of diabetes (% of population aged 20 to 79) in 2017.	Our World in Data [1]
Temperature	The average daily temperature.	ClimatView [3]
Precipitation	The amount of daily precipitation.	ClimatView [3]
Human mobility (retail and recreation)	These are human mobility data estimated from Google users' location history data, and refer to the percentage change in mobility compared to baseline (median value from January 3 to February 6, 2020, set for each day of the week). The data is categorized into six locations, defined by Google: retail and entertainment (cafes, museums, etc.), groceries and pharmacies, parks (including public and national parks), transit stations, workplaces, and residences.	Google COVID-19 Community Mobility Reports [4]
Human mobility (groceries and pharmacies)		Google COVID-19 Community Mobility Reports [4]
Human mobility (transit stations)		Google COVID-19 Community Mobility Reports [4]
Human mobility (workplaces)		Google COVID-19 Community Mobility Reports [4]
Human mobility (parks)		Google COVID-19 Community Mobility Reports [4]
Human mobility (residential)		Google COVID-19 Community Mobility Reports [4]
Surface area	The country's surface area (sq. km).	World Bank [5]
Population (0–14)	The population aged 0–14 for 2020 (% of total population).	World Bank [6]
Population (65–)	The population aged 65 and above for 2020 (% of total population).	World Bank [7]
Population density	The number of people per sq. km of land area for 2020.	World Bank [8]
PM2.5	The mean annual exposure to PM2.5 air pollution for 2017 (micrograms per cubic meter).	World Bank [9], and The Hong Kong University of Science and Technology [10]
Infant mortality rate	The infant mortality rate for 2019 (per 1,000 live births).	World Bank [11], and Macrotrends LLC [12]
Health expenditure	The health expenditure for 2018 (% of GDP).	World Bank [13], and Macrotrends LLC [14]

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Unemployment rate	The unemployment rate for 2020 (% of total labor force) (ILO estimate).	World Bank [15]
International migrant stock	The international migrant stock for 2015 (% of population), which represents the total number of international migrants present in a given country at a particular point in time (% of population).	World Bank [16]
Household size	The average household size for 2019 (number of members).	United Nations [17]
Electoral democracy index	The aggregated index (scaled between 0 and 1) of five democratic traits: freedom of association, free and fair elections, freedom of expression, elected officials, and suffrage.	Varieties of Democracy (V-Dem) data set, version 10 [18]
Asia flag	Whether the country belongs to the Asian region defined in Our World in Data: Hong Kong, Indonesia, Israel, Malaysia, South Korea, Thailand, Turkey, Vietnam	Our World in Data [1]

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1.2 Summary statistics of predictors during the study period (June 25 – August 13, 2021) in Japan and the countries in the donor pool

	Japan		Control countries	
Predictor	Mean (Standard deviation)	Median [Min, Max]	Mean (Standard deviation)	Median [Min, Max]
New COVID-19 cases	43.62 (37.51)	25.42 [11.66, 123.32]	107.74 (118.61)	61.93 [0.11, 699.68]
Stringency index	51.18 (1.23)	50.46 [50.46, 53.24]	53.77 (15.68)	50.93 [22.22, 92.59]
Number of tests for COVID-19	0.52 (0.11)	0.47 [0.39, 0.73]	3.94 (6.48)	2.47 [0.11, 49.17]
COVID-19 vaccination	23.17 (7.18)	23.06 [11.46, 36.83]	30.79 (19.60)	32.80 [0.15, 78.32]
Gross domestic product (GDP)	39002.22	39002.22	30338.88 (15640.25)	29502.76 [6171.88, 67335.29]
Age	48.20	48.20	37.78 (6.34)	39.65 [22.90, 47.90]
Human Development Index	0.92	0.92	0.86 (0.08)	0.88 [0.66, 0.96]
Life expectancy	84.63	84.63	78.80 (3.70)	78.80 [71.72, 84.86]
Number of hospital beds	13.05	13.05	4.03 (2.44)	3.09 [0.60, 12.27]
Diabetes prevalence	5.72	5.72	7.15 (2.66)	6.81 [3.28, 16.74]
Temperature	25.62 (1.79)	25.49 [22.61, 28.60]	20.82 (6.15)	20.80 [4.56, 33.40]
Precipitation	10.99 (8.63)	8.71 [1.24, 41.53]	2.95 (4.96)	1.35 [0.00, 68.00]
Human mobility (retail and recreation)	-6.42 (6.50)	-8.12 [-13.85, 18.33]	1.63 (19.98)	1.55 [-60.94, 93.88]
Human mobility (groceries and pharmacies)	7.18 (3.51)	7.23 [1.06, 16.60]	21.92 (21.01)	19.44 [-87.09, 188.38]

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Human mobility (transit stations)	-19.37 (4.88)	-18.66 [-31.08, -9.38]	-7.09 (32.80)	-6.97 [-74.88, 215.88]
Human mobility (workplaces)	-12.90 (13.83)	-8.12 [-58.35, -4.62]	-16.99 (16.43)	-17.27 [-78.80, 24.90]
Human mobility (parks)	0.24 (13.03)	-0.65 [-19.04, 48.52]	51.36 (79.82)	45.40 [-67.10, 437.75]
Human mobility (residential)	5.78 (3.89)	4.62 [1.67, 19.77]	3.14 (6.61)	3.20 [-14.32, 33.82]
Surface area	377974.00	377974.00	1630627.43 (3545524.20)	262040.00 [320.00, 17098250.00]
Population (0-14)	12.45	12.45	19.41 (5.06)	18.02 [12.54, 33.34]
Population (65-)	28.40	28.40	14.99 (5.27)	16.29 [5.04, 23.30]
Population density	345.23	345.23	328.08 (1093.46)	101.40 [3.34, 7125.52]
PM2.5	11.70	11.70	16.09 (7.55)	14.40 [5.96, 44.31]
Infant mortality rate	1.80	1.80	6.97 (5.68)	4.45 [1.26, 23.50]
Health expenditure	10.95	10.95	7.91 (2.63)	7.68 [2.87, 16.89]
Unemployment rate	2.97	2.97	6.95 (3.30)	6.12 [1.02, 16.85]
International migrant stock	1.61	1.61	10.17 (9.02)	8.99 [0.08, 38.95]
Household size	2.33	2.33	2.98 (0.73)	2.71 [2.10, 4.81]
Electoral democracy index	0.73	0.73	0.61 (0.23)	0.72 [0.10, 0.86]

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1.3 Balance table of Japan and the countries in the donor pool

Predictor	Japan	Counterfactual values in Japan	Control countries*
4-week lagged cases	11.7	11.1	80.7
3-week lagged cases	12.1	11.1	77.9
2-week lagged cases	14.5	13.9	83.1
1-week lagged cases	20.9	21.2	103.3
0-week lagged cases	31.3	31.9	116.4
Stringency index	51.7	65.5	54.0
Number of tests for COVID-19	0.5	3.1	3.8
COVID-19 vaccination	18.7	35.0	27.6
Gross domestic product (GDP) per capita	39002.2	44083.9	30338.9
Age	48.2	46.1	37.8
Human Development Index	0.9	0.9	0.9
Life expectancy	84.6	82.3	78.8
Number of hospital beds	13.1	6.4	4.0
Diabetes prevalence	5.7	7.6	7.1
Temperature	24.8	22.0	20.8
Precipitation	10.3	4.4	3.0
Human mobility (retail and recreation)	-6.9	-0.2	0.0
Human mobility (groceries and pharmacies)	6.1	24.4	21.0
Human mobility (transit stations)	-19.6	-5.3	-8.6
Human mobility (workplaces)	-10.3	-10.2	-16.9
Human mobility (parks)	-1.3	98.2	47.7
Human mobility (residential)	4.9	2.8	3.0
Surface area	377974.0	276711.9	1630627.4
Population (0-14)	12.4	13.6	19.4
Population (65-)	28.4	20.8	15.0

Population density	345.2	1628.5	328.1
PM2.5	11.7	16.8	16.1
Infant mortality rate	1.8	2.9	7.0
Health expenditure	11.0	9.5	7.9
Unemployment rate	3.0	5.4	6.9
International migrant stock	1.6	18.2	10.2
Household size	2.3	2.4	3.0
Electoral democracy index	0.7	0.7	0.6
Asia	1.0	0.3	0.2

* the weighted average of each country with the estimated country-specific weights

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2 Detailed values of the estimated weights in Supplementary figure 1

Unit	Weight	Type
Argentina	0.000000	Control Unit Weights (W)
Australia	0.000000	Control Unit Weights (W)
Austria	0.000000	Control Unit Weights (W)
Belgium	0.000000	Control Unit Weights (W)
Brazil	0.000000	Control Unit Weights (W)
Canada	0.000000	Control Unit Weights (W)
Chile	0.000000	Control Unit Weights (W)
Czechia	0.000000	Control Unit Weights (W)
Dominican Republic	0.000000	Control Unit Weights (W)
Ecuador	0.000000	Control Unit Weights (W)
Estonia	0.000000	Control Unit Weights (W)
France	0.000000	Control Unit Weights (W)
Germany	0.546934	Control Unit Weights (W)
Greece	0.000000	Control Unit Weights (W)
Guatemala	0.000000	Control Unit Weights (W)
Hong Kong	0.202785	Control Unit Weights (W)
Indonesia	0.000000	Control Unit Weights (W)
Ireland	0.000000	Control Unit Weights (W)
Israel	0.000000	Control Unit Weights (W)
Italy	0.182394	Control Unit Weights (W)
Latvia	0.000000	Control Unit Weights (W)
Lithuania	0.000000	Control Unit Weights (W)
Malaysia	0.000000	Control Unit Weights (W)
Malta	0.000000	Control Unit Weights (W)
Mexico	0.000000	Control Unit Weights (W)
New Zealand	0.000000	Control Unit Weights (W)
Norway	0.000000	Control Unit Weights (W)
Paraguay	0.000000	Control Unit Weights (W)
Peru	0.000000	Control Unit Weights (W)
Russia	0.000000	Control Unit Weights (W)
Slovakia	0.000000	Control Unit Weights (W)
Slovenia	0.000000	Control Unit Weights (W)
South Korea	0.018249	Control Unit Weights (W)
Switzerland	0.000000	Control Unit Weights (W)
Thailand	0.044508	Control Unit Weights (W)
Trinidad and Tobago	0.000000	Control Unit Weights (W)
Turkey	0.000000	Control Unit Weights (W)
Ukraine	0.000000	Control Unit Weights (W)
United Kingdom	0.003632	Control Unit Weights (W)
United States	0.000000	Control Unit Weights (W)

Uruguay	0.001498	Control Unit Weights (W)
Vietnam	0.000000	Control Unit Weights (W)
Human mobility (groceries and pharmacies)	0.000258	Variable Weights (V)
Number of tests for COVID-19	0.000020	Variable Weights (V)
Human mobility (parks)	0.001486	Variable Weights (V)
COVID-19 vaccination	0.000426	Variable Weights (V)
Precipitation	0.000244	Variable Weights (V)
Human mobility (residential)	0.000899	Variable Weights (V)
Human mobility (retail and recreation)	0.000564	Variable Weights (V)
Stringency index	0.000080	Variable Weights (V)
Temparature	0.000062	Variable Weights (V)
Human mobility (transit stations)	0.001947	Variable Weights (V)
Human mobility (workplaces)	0.000716	Variable Weights (V)
Asia dummy	0.000612	Variable Weights (V)
0-week lagged cases	0.114212	Variable Weights (V)
Health expenditure	0.001406	Variable Weights (V)
Electoral democracy index	0.000915	Variable Weights (V)
Diabetes prevalence	0.000094	Variable Weights (V)
Gross domestic product (GDP) per capita	0.001646	Variable Weights (V)
Number of hospital beds	0.000115	Variable Weights (V)
Houseshold size	0.006016	Variable Weights (V)
Human development index	0.014728	Variable Weights (V)
Life expectancy	0.000825	Variable Weights (V)
Median age	0.016651	Variable Weights (V)
International migrant stock	0.000065	Variable Weights (V)
Infant mortality rate	0.000539	Variable Weights (V)
PM2.5	0.001206	Variable Weights (V)
Population (0-14)	0.006568	Variable Weights (V)
Population (65-)	0.003053	Variable Weights (V)
Population density	0.000025	Variable Weights (V)
Surface area	0.000144	Variable Weights (V)
Unemployment rate	0.001469	Variable Weights (V)
3-week lagged cases	0.200372	Variable Weights (V)
2-week lagged cases	0.185709	Variable Weights (V)
1-week lagged cases	0.311175	Variable Weights (V)
4-week lagged cases	0.125753	Variable Weights (V)

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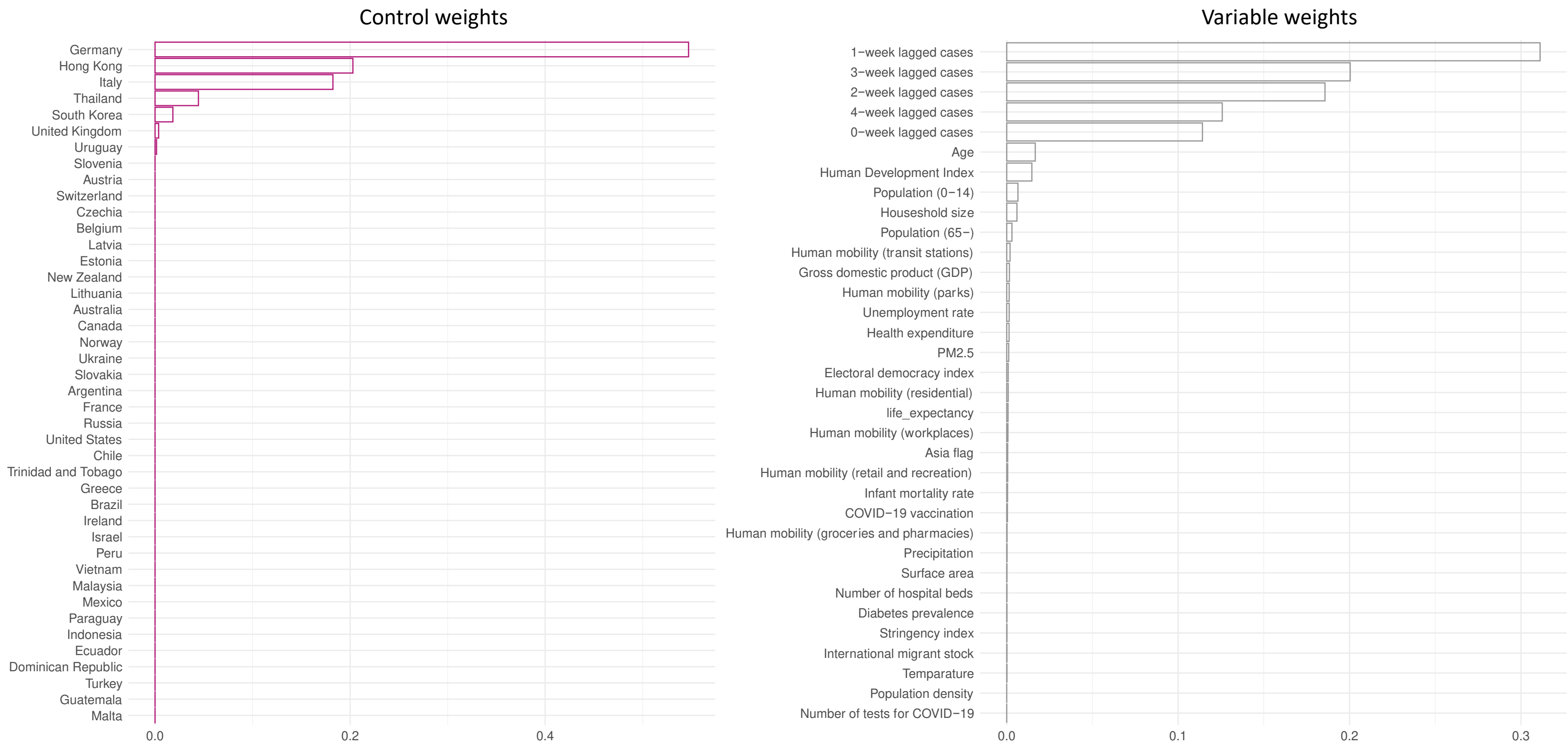
Supplementary figure 1: Estimated weights by (Left) countries in the donor pool and (Right) predictors.

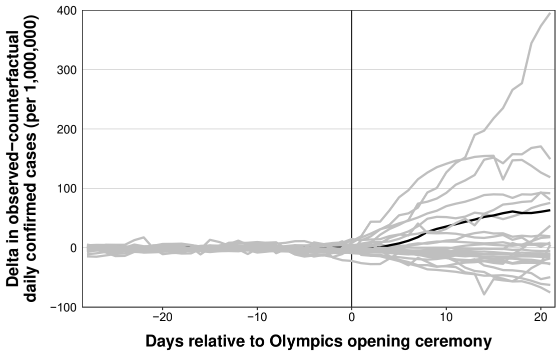
The weights were estimated using the conjugate gradient optimization method to attain the smallest mean squared prediction error (MSPE) during the pre-intervention period.



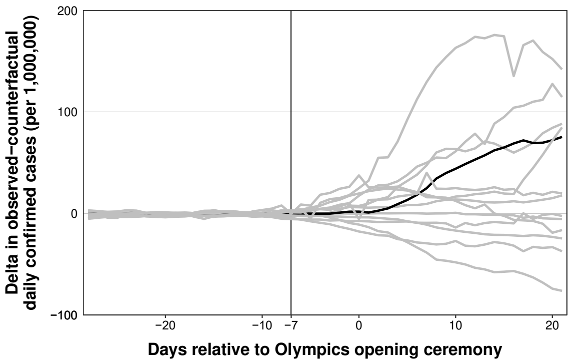
Supplementary figure 2: Placebo synthetic controls by permutating Japan and other countries in the donor pool.

We pruned any placebos that poorly fit the data in the pre-intervention period. If a placebo control has a mean squared prediction error that is 10 times greater than that of Japan, it has been removed from the corresponding figure.

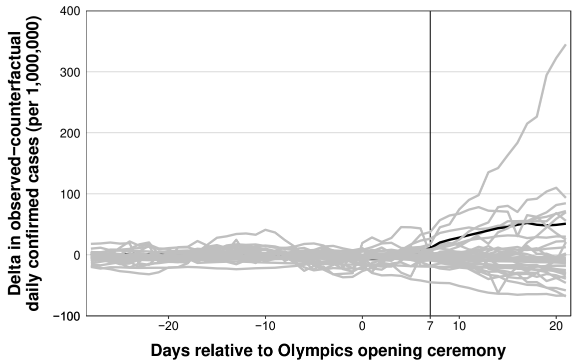
(A): The intervention timing: day of the opening ceremonies



(B): The intervention timing: -7 days before the opening ceremonies



(C): The intervention timing: +7 days after the opening ceremonies



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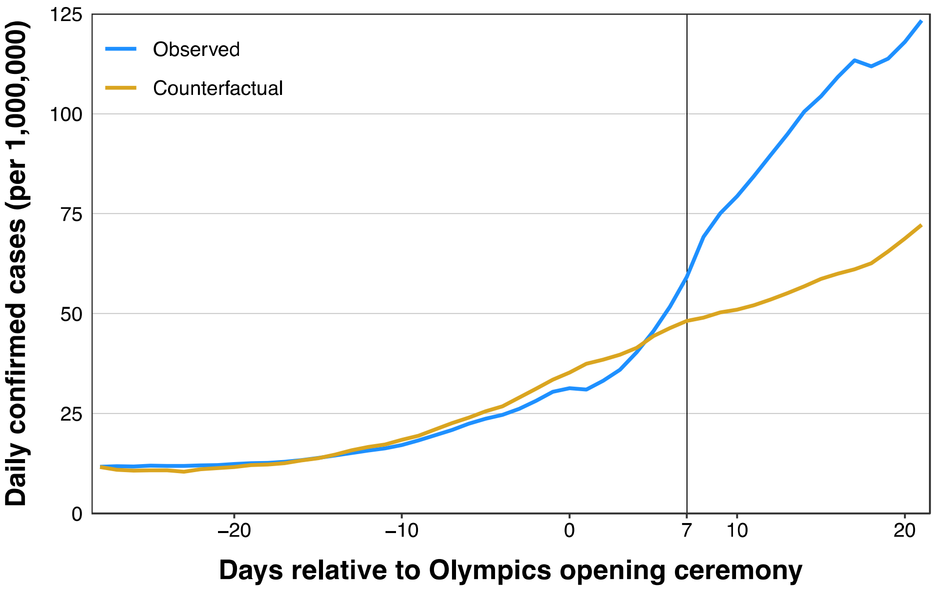
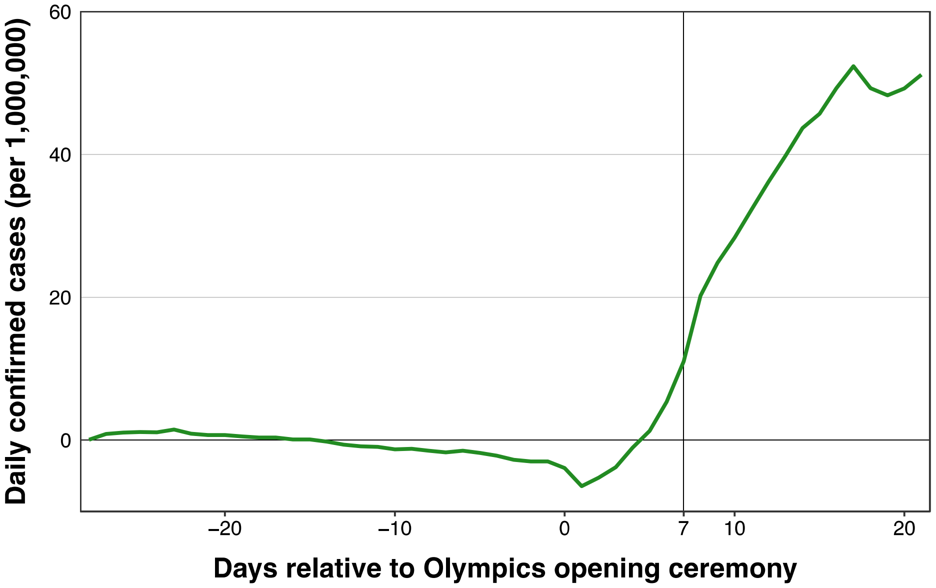
Supplementary figure 3: Observed and counterfactual daily confirmed COVID-19 cases per million people in which counterfactuals were constructed using +7 days after the opening ceremonies as the intervention timing.

Supplementary figure 3A shows the observed and counterfactual trajectories of daily cases per 1,000,000. Supplementary figure 3B shows the differential between the observed and counterfactual trajectories.

A. Observed and counterfactual trajectories

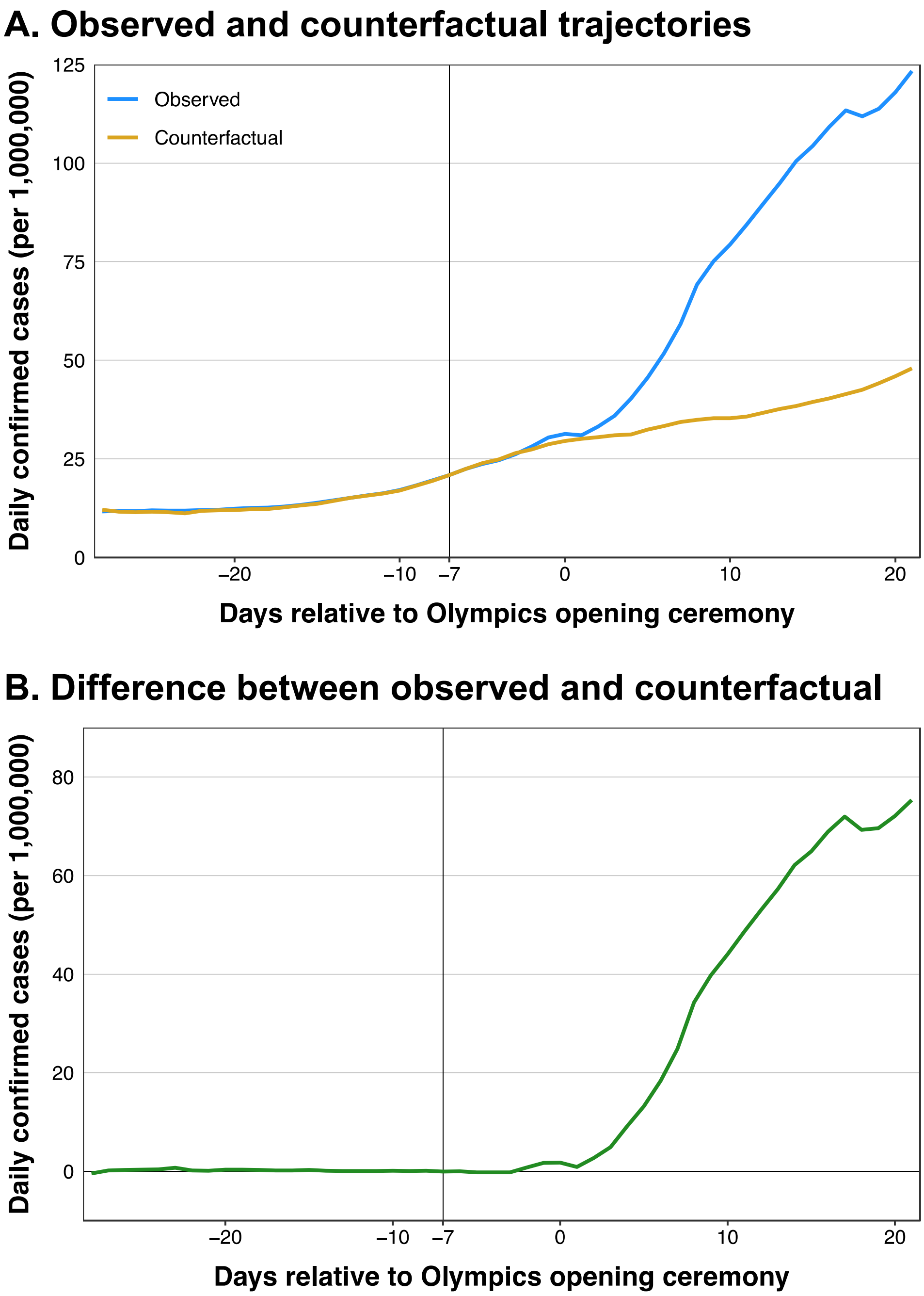


B. Difference between observed and counterfactual



Supplementary figure 4: Observed and counterfactual daily confirmed COVID-19 cases per million people in which counterfactuals were constructed using -7 days before the opening ceremonies as the intervention timing.

Supplementary figure 4A shows the observed and counterfactual trajectories of daily cases per 1,000,000. Supplementary figure 4B shows the differential between the observed and counterfactual trajectories.



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