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COVID-19 Epidemics Monitored Through the Logarithmic Growth Rate and SIR Model

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Abstract

The SIR model is often used to analyse and forecast an epidemic. In this model, the number of patients exponentially increases and decreases in the early and late phases; hence the logarithmic growth rate K is constant at the phases. However, in the case of COVID-19 epidemics, K never remains constant but increases and decreases linearly. Simulation showed that a situation in which smaller epidemics were repeated with short time intervals makes the changes in K ; it also showed relationship between K to the mean infectious time τ and the basic reproduction number R_0 . Using this relationship, we analysed epidemic data from 279 countries and regions. The changes in K represented the state of the epidemics and were several weeks to a month ahead of the changes in the number of confirmed cases. If the negative peaks of K could not be reduced to 0.1, the number of patients remained high. To control the epidemic, it was important to observe K daily, not to allow K to remain positive continuously and to terminate a peak with a series of K -negative days. To accomplish this, it was necessary to shorten τ by finding and isolating a patient earlier.

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Keywords

Compartmental Model; Exploratory Data Analysis; Principle of Parsimony; Parametric Analysis; Data Distribution

Introduction

An appropriate mathematical model is needed to analyse various data, such as those used in epidemiology. Without a model, we would be unable to understand the increase or decrease in numbers; a model allows us to process these numbers according to specific ways of thinking. Whether a model is appropriate and whether it is case-by-case, its appropriateness cannot be mathematically determined. However, it is at least fairly straightforward to distinguish whether it is scientific.

Models are always simpler than reality and this leads to a gap between the calculated or estimated results from the model and reality. This gap can be solved by increasing the number of parameters to be used; however, in most cases, such parameters are set under certain assumptions. Although these assumptions need to be verified, many of them are left unverified; hence this situation is not very scientific [1]. This option is avoided in science because the more such assumptions are made, the less objective the results become. This is where the so-called parsimony parametric attitude originates: the mathematical models that can be used in science are necessarily simple.

Data analyses for epidemics should be conducted scientifically. If unverified assumptions underlie the model, the results of the analysis will vary depending on these assumptions. It is difficult to debate between those who do and do not accept the assumptions and therefore, the information cannot be shared between them. Moreover, the results of the analysis of the epidemic data are related to political decisions on the response to the pandemic and hence they could worsen the damage. In such scenarios, the basic property of science that it can be disproved becomes significant.

Let us consider some of the models used to study the COVID-19 epidemics. A relatively early report used a model similar to the SEIR model which describes Susceptible (S), Exposed (E), Infectious (I) and Recovered (R) people. This was analysed by assuming a distribution of serial intervals that was simplified using Laplace transformation [2,3]. The correctness of these assumptions has not yet been verified. Furthermore, they used SARS and MERS data instead of coronavirus disease 2019 (COVID-19) data to adapt the method and then built various estimates [2]. Some used the simpler SIR model, where S was assumed to be the entire population, to estimate the mean infectious time τ and R_0 and concluded that R_0 was 1.23, a very low value [4]. Some have also used the SIRD model, which separates Dead (D) from recovered people [5,6]. Jacobian matrices representing this model were devised according to

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each idea and R_0 was estimated as the largest eigenvalue of the next generation matrix [7]. Both these models were based on various assumptions; however, the validity of these models was highly questionable because they reported that R_0 was almost 1.0 for India and Indonesia, both of which had severe epidemics. In a study using a more complex modified SIRD model, as many as 10 different parameters were set and R_0 was no longer used [8]. A study of infection in India compared parameters and predictions obtained from five models in parallel. Each model was able to make various predictions; however, they led to quite different conclusions [9].

It is well known that different models estimate R_0 differently [10,11]. Therefore, R_0 , which is expected to be an objective parameter by nature, is valid "only if the model and the assumptions underlying the model are valid". This is a problem caused by a non-parsimonious approach.

Among the compartmental models, SIR is the most basic mathematical model used in modern epidemiology and is the basis for a family of compartmental models [12,13]. The model has the advantage of being valid with only minimal assumptions, as provided in the Materials and Methods section. This model explains the kinetics by representing the speed of change in the number of corresponding individuals using simultaneous differential equations.

According to the SIR model, the number of infected people increases exponentially until the fraction of susceptible individuals diminishes and then decreases by half at each constant period. In each exponential increase or decrease phase, the logarithms of I change linearly over time. The logarithmic growth rate, K , indicates the slope of the linear change. Therefore, it should take a constant value in both the stable phases.

However, as far as COVID-19 cases are concerned, K increases and decreases in a linear fashion and never remains constant; therefore, the actual cases do not directly fit this model [14]. This conflict raises questions about the use of SIR and related models to understand and predict the status of the COVID-19 epidemics. This could be because variants of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) repeat in short intervals with small epidemics that target only a limited population; if the next peak arrives before the previous peak converges, then the early stages of exponential increase will be masked by the previous one. If so, the biphasic pattern is altered. To test this possibility, in this study, simulations were performed and compared with the actual data of the epidemics using exploratory data analysis [15].

Here, we used the SIR model exclusively because it is the simplest and most basic model. For example, the SIER model uses just one more parameter than SIR; the latency from the time of infection to the time of infecting others. The latency may differ among patients; however, it is rarely measured because it is difficult to identify the infectious time [16-18]. It is also difficult to estimate the number of infections from the data because the effect is indistinguishable from other parameters that affect the speed. By presuming a common half-life of exposed patients,

the SEIR model can also be applied; however, this approach increases assumptions that are difficult to prove. In addition, the latency period in COVID-19 is probably not long because the infectious phase starts before the appearance of symptoms [16-18].

In addition to the falsifiability of the model itself, the application of the model to the data and the calculation methods therein are also important. Unlike previous research, we do not use the total population of the entire country for the initial S, nor do we estimate R_0 based on the same [4]. This is simply because the number of susceptible persons is difficult to evaluate. Despite this epidemic, COVID-19 is still in the process of acclimatisation to humans and has limited infectivity; additionally, behavioural changes help many people to avoid infection [19]. Therefore, it is not practical to consider the whole population for S. Instead, we estimate the parameters more objectively from the logarithmic growth rate K, which can be evaluated without relying on a model. In addition, the parameters were estimated without making.

Materials and Methods

The Materials and Methods should be described with sufficient details to allow others to replicate and build on the published results. Please note that the publication of your manuscript implicates that you must make all materials, data, computer code and protocols associated with the publication available to readers. Please disclose at the submission stage any restrictions on the availability of materials or information. New methods and protocols should be described in detail while well-established methods can be briefly described and appropriately cited.

Simulating the SIR Model

Here, the model was modified slightly to correspond to the number of people, rather than the percentage [12]. Infection occurs when an infectious person contacts a susceptible person at a constant expectation of infection, β , per day. This reduces the number of S. Hence,

$$dS/dt = -\beta I \times S/P \quad (1)$$

Where, P denotes the total population. The expectation is $\beta = R_0/\tau$, where R_0 is the basic reproduction number, which shows the expected number of each infectious person infected in a suitable condition, $S/P \approx 1$. τ is the mean infectious time; the length was set to 5 days in the simulations [20]. The reduced number from S represents infectious patients, which will be reduced at a constant rate $1/\tau$,

$$dI/dt = \beta IS/P - I/\tau \quad (2)$$

The reduced number represents the recovered individuals as

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$$dR/dt = I/\tau \quad (3)$$

Equations 1-3 represent the model. According to equation 2, when $S/P \approx 1$ and $S/P \approx 0$, dI/dt becomes a first-order reaction of I ; hence, I increases and decreases exponentially, respectively [21]. Therefore, a peak was formed (Fig. 1). The R system was used to simulate the differential equations. The R code used is shown in Fig. 1 [22,23].

The logarithmic growth rate K is the slope of the logarithm of the exponential change I (Fig. 1). Because the slope is constant, K should also be the same (black) [14]. Here, it is defined as because 2 was used as the base of the logarithms instead of e , $1/|K|$ shows the doubling time ($K > 0$) or half-life ($K < 0$), directly. R_0 is a value that depends on the SIR model and is affected by τ , while K is a more physically determined parameter that is independent of the model and valid as long as the subject changes exponentially. When $S/P \approx 0$ ($K < 0$), the number of patients after t days will be $2^{-t/\tau} = 2^{Kt}$ times. This results in $\tau = 1/(-K)$. When $S/P \approx 1$ ($K > 0$), the number of patients after t days becomes $R_0 t/\tau = 2^{Kt}$ times. This results in $R_0 = 2K\tau$.

Note that when R_0 is low, the exponential infection stops, leaving some S_0 uninfected. From equation 2, we obtain

$$dI/dt = (\beta S/P - 1/\tau) I. \quad (2')$$

When $\beta S/P - 1/\tau > 0$, an exponential increase was observed. Because $\beta = R_0/\tau$, this can be transformed to $R_0 > P/S$. This results in $S > P/R_0$, which shows the limit of the exponential increase, but does not directly represent the number of people who can escape the infection, as the infection may continue after the exponential increase and vice versa. For example, the simulation showed that 70% and 20% of people may be left uninfected when R_0 is 2 and 3, respectively (Fig. S1).

The simulation was performed using the Euler method. For the simulation, S_0 was chosen because it corresponded to the general size of infections; however, this size did not affect the overall shape. The size of R_0 was chosen to avoid difficulties in the calculation, which will be discussed later and the size of τ was chosen as reported in some cases [20]. I was chosen as a small number to start from the beginning of the infection.

Because the simulation results in exponentially varying outcomes, the calculations were somewhat unstable, resulting in differences between the input and output parameters. Therefore, we used the calculation results (Fig. 1) to estimate the R_0 and τ values in the simulation instead of using the input values. For example, in the case of Fig. 1A, K took two constant phases at 0.4 and -0.2; hence, $\tau = 1/(-0.2) = 5$ and $R_0 = 20.4 \times 5 = 4$.

The closer the peaks are to each other or the wider they are, the higher the negative peak of K (Fig. 2). This effect was simulated as follows. For a given R_0 , we set various mean infection times and estimated a single peak of I using the SIR model. Bimodal peaks were artificially synthesised by superimposing the peaks at intervals of 40 d. As discussed later with real data,

this interval is longer than the ordinal condition but is a possible length. The negative peak sandwiched between two identical peaks was measured and τ was estimated as $1/(-K)$ and then compared to the original constant phase. It was confirmed that R_0 did not move significantly during the simulation to change τ . At each R_0 , simulations were performed until the peaks were too close together and the valleys were no longer observed.

We simulated the effect of τ on the estimation of R_0 from the peak of $K' \equiv dK/dt$. A series of R_0 values were set under a certain τ and the peak of I was estimated using the SIR model. These peaks were superimposed 20 days after the peak at $\tau = 5$ and $R_0 = 5$. The K and K' values were calculated from the synthesised bimodal peaks and the slope of the rising edge of the latter K peak was estimated from the peak of K' . This K' value was compared with the R_0 of the latter peak, estimated in the second constant phase.

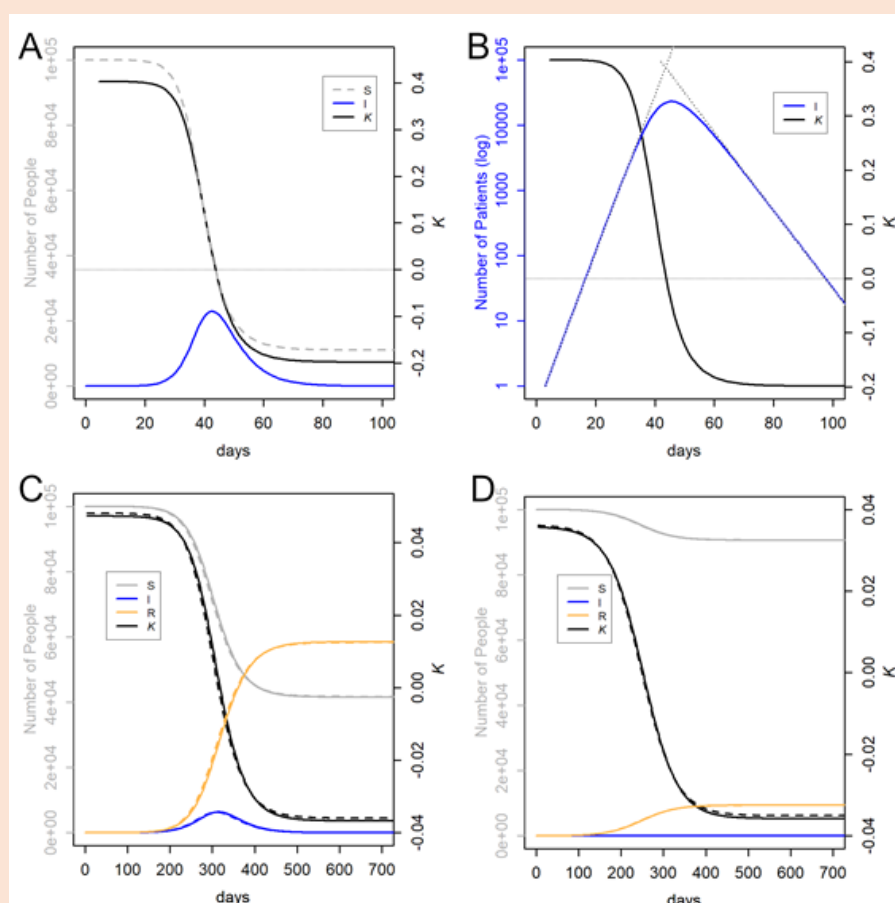


Figure 1: Data simulation using the SIR model. (A, B) When the initial parameters are $S_0 = 1E5$, $I_0 = 1$, $R_0 = 4$, and $\tau = 5$. (A) Changes in the number of people. (B) I in the logarithmic scale. The thin dotted lines are the exponential increase $y = R_0 t/\tau$ and decrease $y = S_0 \times 2^{-(t+41)/\tau}$ at t th day, respectively. The former means every τ day, the number will become R_0

times, and the latter means every τ day the number becomes half. (C) The inputs were 1.5 people for R_0 and 15 days for τ , while the values obtained from this are $R_0 = 2.4$ and $\tau = 27$.

Solid and dotted lines show the results by the Euler method and Runge-Kutta method, respectively [27]. (D) The input were $R_0 = 1.05$ and $\tau = 2$, while output were $R_0 = 2.0$, and $\tau = 28$. 90% of S were left uninfected. The peak of I was 120, and therefore hardly shows up in the graph (blue).

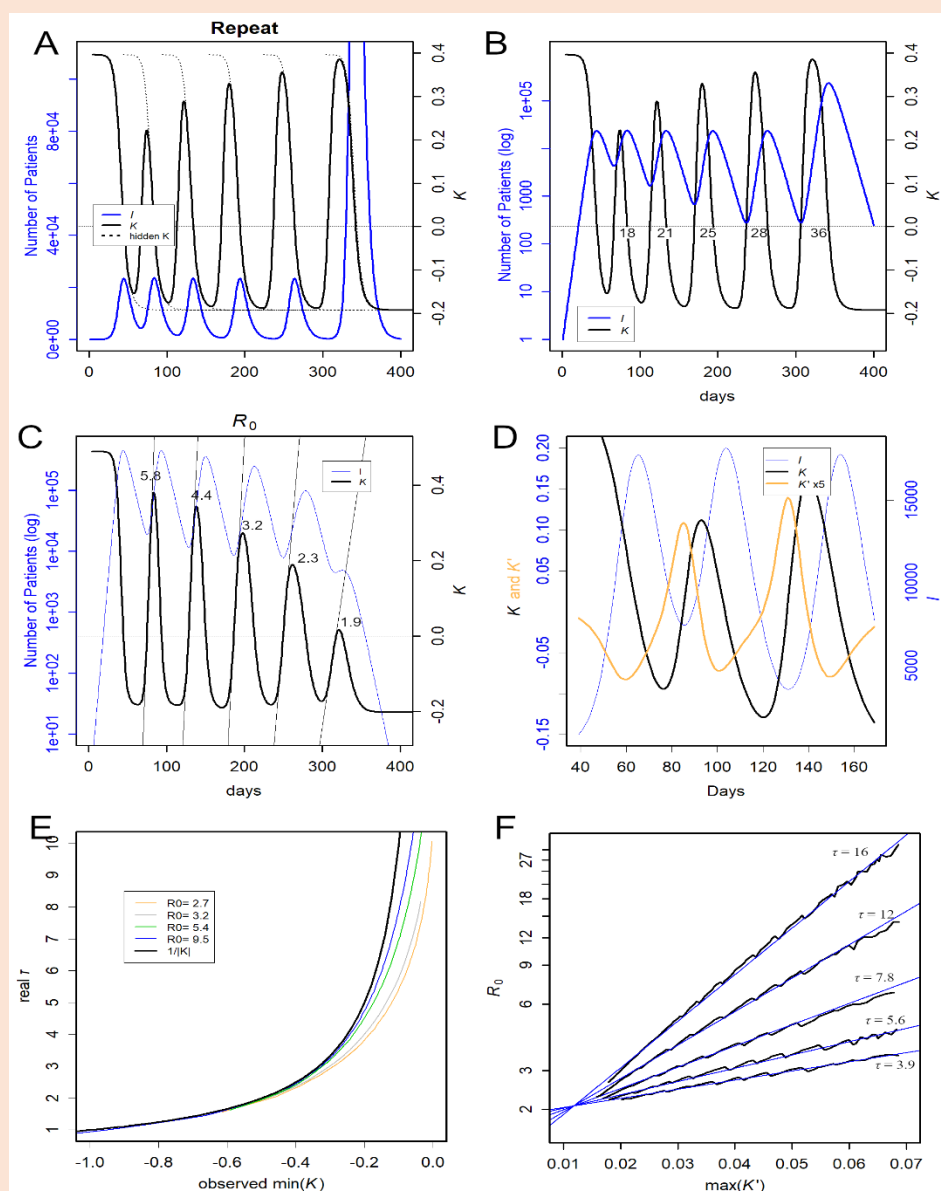


Figure 2: Simulation of repeated epidemics. (A) New epidemics started after 40, 90, 150, 220, and 290 days from the first one. Each epidemic started from $I_0 = 1$ and $S_0 = 1E5$, but $S_0 = 1E6$ was observed only for the last time. (B) Semi-log display of I . The numbers indicate

the days when K was positive. (C) Infection was initiated every 40 days at the indicated R_0 . The thin solid line indicates the slope of K . (D) Comparison of K and K' . The peak of K' is near the middle of the upward slope of K . (E) Relationship between the observed negative peak of K and the mean infectious time, τ , of the used data. $1/|K|$ (black), which is used for the estimation of τ , is always larger than that in reality (coloured). (F) Relationship between the peak of K' and R_0 estimated by simulations at the τ presented. A semi-log plot. Blue straight lines present the estimated relationship deduced from τ (Fig. 3); these are not the regression lines.

Epidemic Data

Data on the number of infected people and fatalities were obtained from the Johns Hopkins University repository [24] on 1 September 2021. These values for Japan were obtained from the government's website [25]. In the actual data, I represented the daily confirmed cases; as they fluctuated, a moving average of a 9-day interval was used. K was calculated from the difference in the moving average over a 7-day period to avoid the influence of the day of the week and represented the moving average of the 9-day interval. The mortality rate was calculated as the number of deaths after 7 days per number of patients on a particular day. The moving average of the 9-day interval was used in this case.

Finding Peaks and Estimation of R_0 and τ

The peak of K' was found in the following way: the peak of K' occurred when dK'/dt changed from positive to negative (Fig. S2). The maximum K' during the 4 days before and after this change was recorded as the peak day and peak height. In practice, dK'/dt fluctuates; therefore, we used a 9-day moving average to calculate the same. The intervals of the peaks were estimated using peak dates. The negative peak of K was also detected in the same way using K' and the peak heights were used to estimate τ . As shown in Fig. 4B, the regression was effective at -0.04 ; however, only values less than -0.08 were used to avoid the noise of interference for safety. By using the K' peaks and τ , a series of R_0 values in a country was also estimated using the equation presented in the legend of Fig. 3.

The changes in I of a country were approximated by the SIR model using the least number of peaks. The number of confirmed cases in South Africa had three obvious peaks; in addition to these three, two concealed peaks were temporarily placed in between. The S_0 of each peak was estimated from the fragments of data that were roughly dissected vertically. For the three obvious peaks, R_0 and τ were estimated from the peaks of K' and negative peaks of K (Fig. 4); for the two minor peaks, which were a combination of the smaller peaks, the average values were used. The increase and decrease in each of the peaks were estimated using the SIR model

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and summed. As I of the real data presents the number of confirmed cases in the day, the simulation data for I will become larger for τ as it corresponds to the total number of days for τ . Hence, the number dS/dt was used here instead.

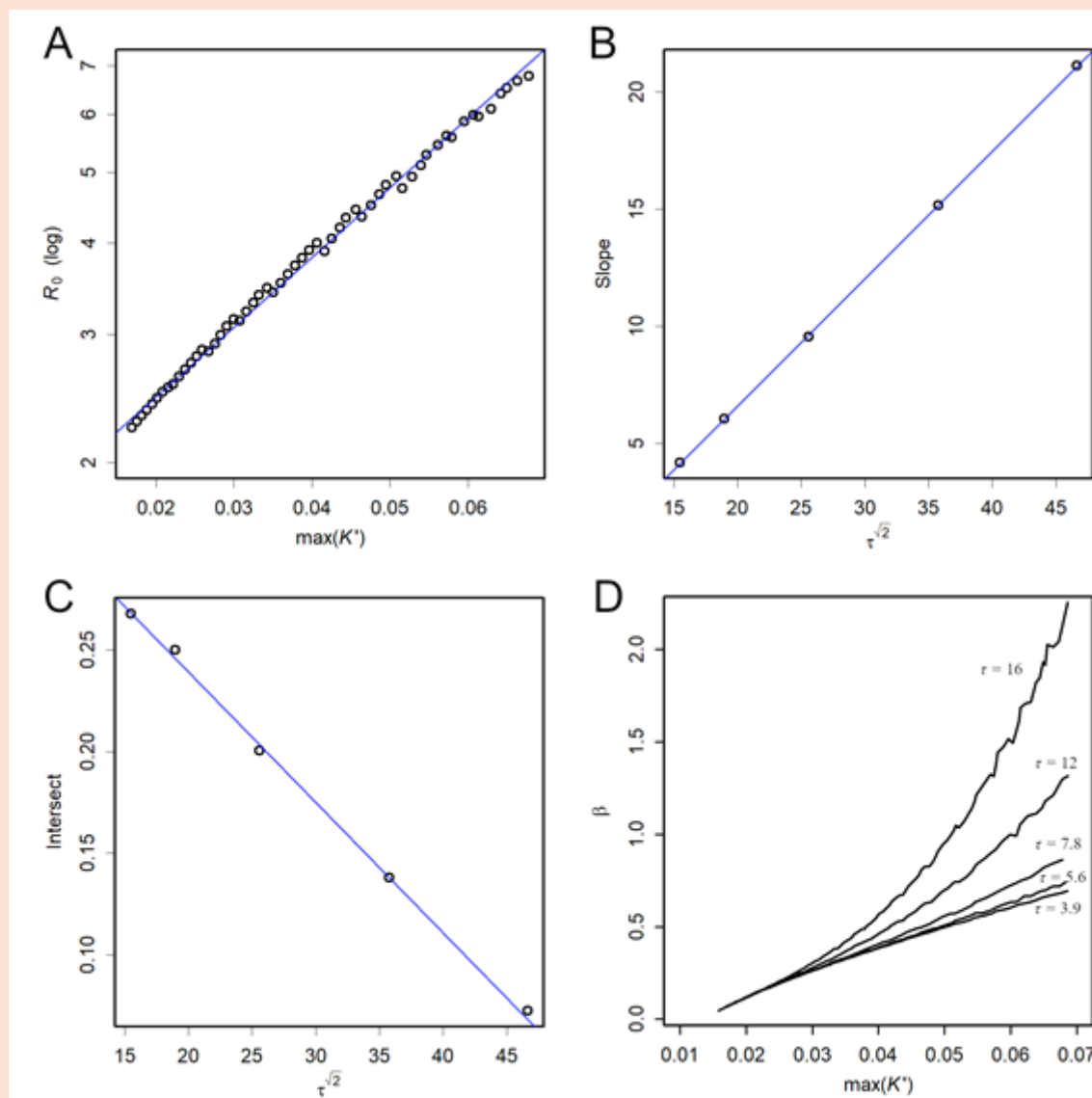


Figure 3: Relationships between the mean infectious time τ and other parameters. (A)

Simulated relationship between the peaks of K' and R_0 . Here, the regression line was robustly estimated by the line function of R [15]. (B) Relationship between τ and the slope of the regression line in (A). The slope is. (C) Relationship between τ and the intersect of the regression line in (A). The intersect is. These values were used in estimating the relationships in Fig. 2F. (D) Simulated relationship between K' peak and β . When τ is small the relationship is almost linear, while this would likely become exponential when τ is larger.

Quantile-Quantile (QQ) Plot

The Quantile-Quantile (QQ) plot compares the quantiles of data with those of a particular distribution. This was done to find a suitable model for the data [15]. The peak heights, peak intervals, R_0 and mortality rates were determined. For the theoretical values, the exponential distribution, which is frequently used to describe intervals of randomly occurring events and the normal distribution was tested. By comparing the quantiles of the real data and the theoretical value, a linear relationship was obtained if the data followed the distribution model [26]. It should be noted that because the mode of the exponential distribution is in the lowest class, the plot at the upper classes becomes thin (Fig. S3).

There is a limit to the resolution of the short intervals of peaks; two peaks that are too close are counted as one. Therefore, the short intervals were neglected in such cases. This is problematic because the mode of the exponential distribution has the smallest values; in fact, it is named because the probability density function decreases exponentially. When there are such missing intervals, the regression line of the QQ plot does not pass through the origin, although the smallest interval should be zero. The distribution of the data was evaluated by compensating for this missing data by adding a set of arbitrary negative values to the data so that the line passed through the origin. The added values do not appear in the plot; therefore, the missing data will create a space in the smallest area. As a property of exponential distribution, such compensation does not change the shape of the distribution on the QQ plot, but only shifts it horizontally in parallel. Therefore, the slope, which represents the mean, was maintained.

Research manuscripts reporting large datasets that are deposited in a publicly available database should specify where the data have been deposited and provide the relevant accession numbers. If the accession numbers have not yet been obtained at the time of submission, please state that they will be provided during review. They must be provided prior to publication.

Interventionary studies involving animals or humans and other studies that require ethical approval, must list the authority that provided approval and the corresponding ethical approval code.

Results

Data Simulation for a Single Epidemic

In a simulation of a single epidemic observed alone, K inherently showed biphasic constant values (Fig. 1). In panels A and B, K became constant at 0.4, when $S/P \approx 1$ and at -0.2, when $S/P \approx 0$, representing $R_0 = 4$ and $\tau = 5$. As a result, I increased and decreased exponentially; therefore, the changes became linear when considered in logarithmic form (Fig. 1). The dotted

lines in Panel B show an exponential increase and decrease with the estimated constant rates, respectively.

It should be noted that simulations using these exponentially divergent differential equations are sometimes unstable and the output often differs from the input parameters. Here, we used the relatively simple Euler method (Fig. 1) for the calculation; we also tried the more sophisticated Runge-Kutta method (dotted line); however, these made little substantive differences [27]. This dissociation between the input and output tends to be larger when R_0 is small. The instability was especially apparent in the condition of input $R_0 < 2$; the output of R_0 always showed a steady tendency to increase (Fig. 1). Under such conditions, the exponential increase was likely to stop, leaving many S uninfected (Fig. 1 and S1); the computational values of τ and R_0 tended to increase. This is a type of artificial error; unfortunately, it was unavoidable. Thus, $R_0 < 2$ was difficult to reproduce.

Data Simulation for Repeated Epidemics

In a real-world scenario, K increases and decreases linearly and never becomes constant [14]. In the simulation, such a linear upward and downward trend was observed when the peaks had overlapping tails. Fig. 2 shows the cases where the infection from a new strain started after 40, 90, 150, 220 and 290 days from the first one. Each S_0 was $1E5$, but only the last peak was given 10 times the number of people. The constant phase disappeared because the previous peaks masked the increase in the earlier days of I , when I was still small; the original K of the infections that started late are shown by the dotted lines (Fig. 2).

The movement of K precedes the movement of I by several weeks (Fig. 2). The exponential increase begins before K turns upward; however, this turning occurs several weeks before I begins to rise visibly. Similarly, it takes several weeks after K shows a downward trend for I to actually decrease; when K becomes positive, I is in the valley bottom between peaks; when K becomes negative, I is at the peak top.

The peak top of K decreased as the peak approached the previous peak. The period when K is positive (indicated by the numbers in Fig. 2) also changes; the closer it is to the previous peak, the shorter it becomes. It should be noted that the total number of I became ten times higher just by increasing this period from 28 to 36 days.

Relationships between the Parameters and K

K can be measured directly from the data, independent of the model, but it will not be constant under successive epidemic conditions. However, it is still possible to measure the increase or decrease of K as K' . Once the relationship between this and other parameters such as R_0 and τ

is known, it will be possible to estimate them parsimoniously. Here, this possibility was investigated accordingly.

Compared to the sensitive change in the peak tops because of the overlapping peaks, the negative peak did not change significantly (Fig. 2), which also appeared when the width of the peak was changed by altering R_0 (Fig. 2). This may allow the estimation of the mean infectious time from the negative peaks of K , as $1/(-K)$. If the peaks are close together (Fig. 2) or the widths of the peaks are wide (Fig. 2), interference will occur and a negative peak will be observed at a higher position than in the original biphasic state. However, if there is a period when the peak interval is sufficiently large to create a window of visibility, negative peaks of K can be observed. The effect of this interference between peaks was confirmed by simulations with various τ values over a set of twin peaks of the same size with a 40-day interval (Fig 2). As shown below in the real data, an interval of this magnitude can be expected in a few months (Fig. S3). Estimations using $\tau = 1/(-K)$ (Fig. 2) are always larger than the actual τ (coloured); thus, it is a safe method of estimation. Therefore, the K observed at a small level is appropriate for estimating the level of τ in the country. Additionally, a heavy interference is visibly apparent; hence, it can be simply eliminated, although the simulation was performed until just before the two peaks overlapped and merged into one.

The difference in R_0 appears in the slope of K . Fig. 2 is the result of simulating the epidemic at the presented R_0 , in which the epidemics started at 20-day intervals. The slopes may stably present R_0 compared to the peak tops (Fig. 2) and we can use the peak tops of K' to define the slope (Fig. 2). However, since $R_0 = \beta\tau$, the value of R_0 depends on τ at that time, even if the variants have similar infectivity. Because $R_0 = 2K\tau$, R_0 may intrinsically change its value exponentially. The simulation showed that the value of R_0 changed exponentially according to the slopes and that the difference in mean infectious time, τ , alters the estimation of R_0 (Fig. 2).

The relationship between K' , τ and R_0 is quantitatively estimated as mentioned here. Unfortunately, these relationships were not solved analytically but appeared empirically, as shown below. Fig. 3 shows the relationship between the K' peak and the logarithm of R_0 for $\tau = 9.9$, showing that they have a linear relationship over a wide range. Linearity was also observed for different values of τ (Fig. 2), but the slope and intercept varied with τ ; they showed a linear relationship defined as (Fig. 3). Therefore, when τ is available through the negative peak of K , we can translate the peak of K' to R_0 by using only τ (Fig. 3). We tried this in practice; the lines in Fig. 2F are not regression lines but relationships estimated from τ , showing agreement with the simulation. The length τ also affects the relationship between K' and β and the expectation of infections per day (Fig. 3).

In summary, τ can be estimated as $1/K$ when K is the lowest. The value of $\log(R_0)$ can be estimated using τ to obtain the two coefficients from Fig. 3 and by linearly transforming the maxima of K' (Fig. 3). The assumption used here is that the intervals between the epidemics

are sufficiently large to allow K to be sufficiently small. Otherwise, τ would be estimated to be larger than its true value. In this case, however, the epidemic would be in a severe state; in this sense, a larger estimate of τ is an error on the safer side.

Data Distributions Observed In Real Data

Here, we consider actual data by using the Johns Hopkins University repository which covers data from 279 countries and regions [24]. First, the intervals between peaks followed an exponential distribution (Fig. 4), which represented the intervals of randomly occurring events [26]. In the following method, the distribution of the data was confirmed by a QQ plot. This is a method of directly comparing the theoretical value of a distribution with the sorted data, which allows us to check the distribution style strictly down to the tail of the distribution compared to, for example, a histogram [15]. As the shorter intervals may have been missed, this distribution compensated for missing data (Materials and Methods). The data in the linear range of the QQ plot were probably generated by a common mechanism. Data outside this range are likely to be affected by some effects, including noise. The top 1% were above the regression line; these longer periods were reported in well-controlled countries, where peaks were rare. The slope of the regression line was 11.3 days; as a characteristic of the exponential distribution, this is the mean and standard deviation. According to this distribution, the 40-day interval corresponded to the 97th percentile (Fig. S3), with a frequency of approximately once every few months (Fig. S3).

When the peaks of K and K' were observed for all the countries, they were also distributed according to the exponential distribution (Fig. 4, S2). Although the peaks of K' and the negative peaks of K were detected from both sides of the negative and positive peak heights, all the data were used as is. Incidentally, the K and K' peaks appeared to be unrelated to the interval length (Fig. S4); hence, the distribution was not determined by the intervals. There were approximately 3600 peaks in K' and K between 2020-05-01 and 2021-07-01. Although many peaks may have been missed (Fig. 4), the distribution was clearly observed, suggesting that the missing peaks occurred randomly, possibly because of the short intervals and were not related to the peak height.

In the negative peaks of K , from which the mean infectious time could be estimated as $\tau = 1/(-K)$ (Fig 2), the slope was -0.082; hence, the mean of τ was 12 days (Fig. 4). The 10th percentile of the data was -0.2, representing five days, which was close to the value reported in the meta-analysis [20]. The grey horizontal line represents the upper limit of the linear relationship, which corresponds to $K = -0.04$. Data with larger values may be heavily affected by noise (Fig. 2).

The number of consecutive K-positive days was exponentially distributed (Fig. 4). It is possible that shorter intervals were missing; hence, this was compensated for. The average was 6 days, but the mode observed was 10 days.

A series of R_0 values in a country was estimated using the peaks of K' and estimated τ . Because R_0 is calculated as $R_0 = 2K\tau$, the logarithms of R_0 were compared with the theoretical value of the exponential distribution, although the relationship bent slightly downward (Fig. 4). The top 5% of the data had higher values than the regression line. The ratio was larger than the slope upward of K' (Fig. S2); therefore, this might have included the effect of the extension of τ in some countries, in addition to that of super-spreaders and the newest infectious variants. In fact, τ affects R_0 ; when τ is small, R_0 remains low and when R_0 is large, τ is always large (Fig. 4). The high values of τ more than $1/(-0.04) = 25$ may be affected by noise (Fig. 2,4); reduction of the noise by compressing Fig. 4E to the left would show a monotonic increase. When K could be reduced to -0.1 and, hence, τ was less than 10 days, R_0 could be maintained at a low level (Fig. 4), which might be less than the limit level of exponential increase (Fig. 4,S1).

Many of the smaller data in Fig. 4 may have been heavily affected by noise in measuring the slopes (Fig. 2); thus, the plot turned downward. The lower limit of the regression was approximately $R_0 = 2$ and measurements less than this level would be inaccurate because of noise. Since the missing data probably occurred independent of the magnitude of R_0 , they were not compensated for. Rather, this distribution should be considered to have a positive minimum value, the background; here, it was 1.7, that is, the intersection of the regression line. This extrapolated value could be the least value that could enable an exponential increase, which would result in detectable peaks of K . The slope was 0.1; hence, the mean of the basic reproduction number was $R_0 = 1.7 + 100.1 = 2.9$. Owing to the nature of the exponential distribution (Fig. S3), values smaller than 2 were frequently observed (Fig. 4). For safety, these values should be recognised as “less than 2 and larger than 1.7”.

The confirmed cases from South Africa were approximated by the SIR model using the estimated R_0 and τ and the least number of peaks estimated: three obvious peaks and two in between them (Fig. 4). The match was particularly close for the three obvious peaks, indicating that the estimates of R_0 and τ were reasonably accurate. Here, 21 peaks of K were identified; it would be possible to approximate the results with more accuracy by using all these peaks; however, estimations of the location of each peak and the assignment of S_0 would require fine tuning, such as an approach of repeating simulations to find the optimal solution.

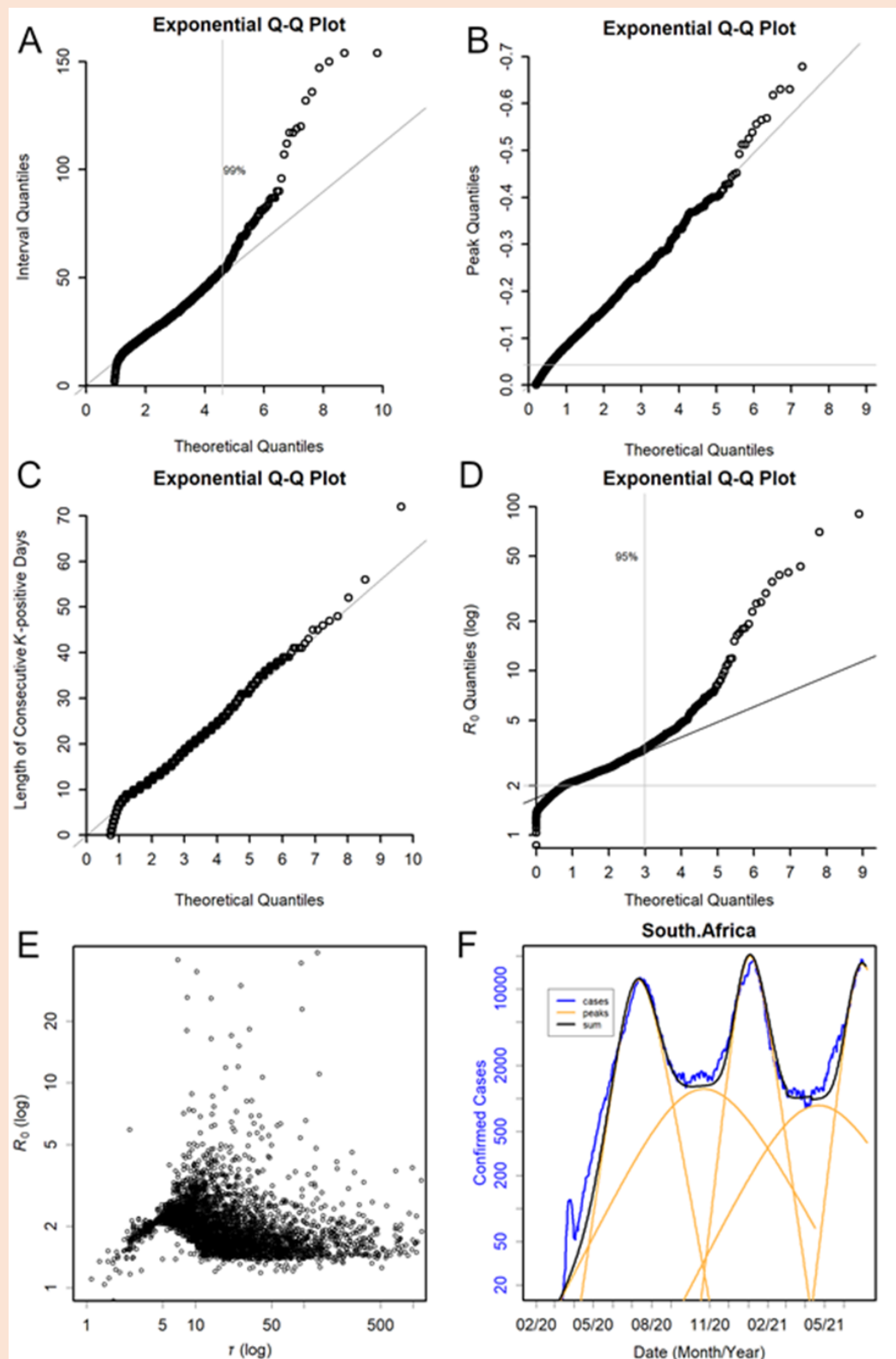


Figure 4: Distributions of peak-related values. (A) Correspondence of quantiles of the intervals between the peaks with that of the exponential distribution. If data obey this

distribution, a straight line is observed. The slope of the regression line was 11.3; this equals the mean and standard deviation of the distribution. The vertical grey line, which presents the upper limit of coincidence with the theoretical values, shows the percentile indicated. (B) Negative peaks of K. The horizontal grey line shows the upper limit of linear correlation; note that the y-axis is reversed. (C) Consecutive K-positive days. The slope was 6.2 days. (D) Estimated values of R_0 , semi-log plot. (E) Relationship between τ and R_0 . When τ were small, R_0 was always small, and when R_0 was large, τ was large. (F) Approximation of the confirmed cases by using estimated R_0 and τ . South Africa was chosen as an example because it is visually obvious the shape of the peaks.

Severe Epidemics Observed In Several Countries

A snapshot of the situation in a few countries is presented below (Fig. 5-7). The full set of results is shown in Figshare [23]. In almost all cases, K always increased or decreased linearly. Note that the scales of K and K', presented on the left-hand axis, are common among all the figures, but the number of confirmed cases on the right-hand axis varies significantly.

When the variant is replaced by a new one, the previous measures lose their effectiveness, people with certain lifestyles become the new targets as S_0 and a new epidemic begins. This phenomenon is evident in Fig. 5,6. The Philippines is an example that has two opposite aspects: success and failure of controlling epidemics (Fig. 5). Until April 2020, I remained low because there was no K-positive continuum. However, in May, when the variant changed, the K positives became consecutive and a large peak was reached. Thereafter, while the series of K-positives was halted, the negative days could not be controlled and I continued to remain high, creating a large peak associated with a new variant in January 2021. New variants produced peaks in South Africa and Tokyo (Fig. 5) [14,19]. As I did not drop completely, a few K-positive days in a row led to an explosion of the infection. Several countries showed this trend and Mexico is an extreme example (Fig. 5).

Although the Olympics were held in Tokyo, the mean infectious time in this city in June 2021 was 16 days. This shows that the measures were not working well and that the delta variant was spreading (Fig. 5) [28]. Since the opening of the Olympic Games (green vertical line), there has been an explosion of infection in this city, with an R_0 of 15. This is one of the worst data in the world to date (Fig. 4).

Similar examples of countries with poor control are shown in Fig. 6. The situation is particularly distressing in Panels A and B, with repetitive K-positives in the US and India. K increases not only when variants are new, but also when there is something new about the way people live. There were large elections in these countries. Politicians did not ask people to self-restrain; instead, they mobilised defenceless people for election rallies [29,30]. There was also a major religious event in India [31]. These countries allowed K-positive days to last for

unusually long periods, producing the world's first and second largest cumulative number of cases. It should also be noted that in both countries, all the series of R_0 detected were less than 2.

Another characteristic of these countries is that their mean infectious time was long. For example, in the US and India, the K negative peaks were greater than -0.05 (Fig. 6); therefore, the mean infectious times were probably longer than 3 weeks. Data for the other heavily infected countries seem to be the same (Fig. 5,6).

The effects of the vaccines are shown in Fig. 6. Vaccines have limited effectiveness in controlling epidemics, aside from reducing mortality. This is evident in the UK, Israel and the US, where vaccination is well underway. As K continues to rise, it is inevitable that new epidemics will appear in these countries. In fact, in all those countries, the number of confirmed cases decreased for a while but soon returned to the original level.

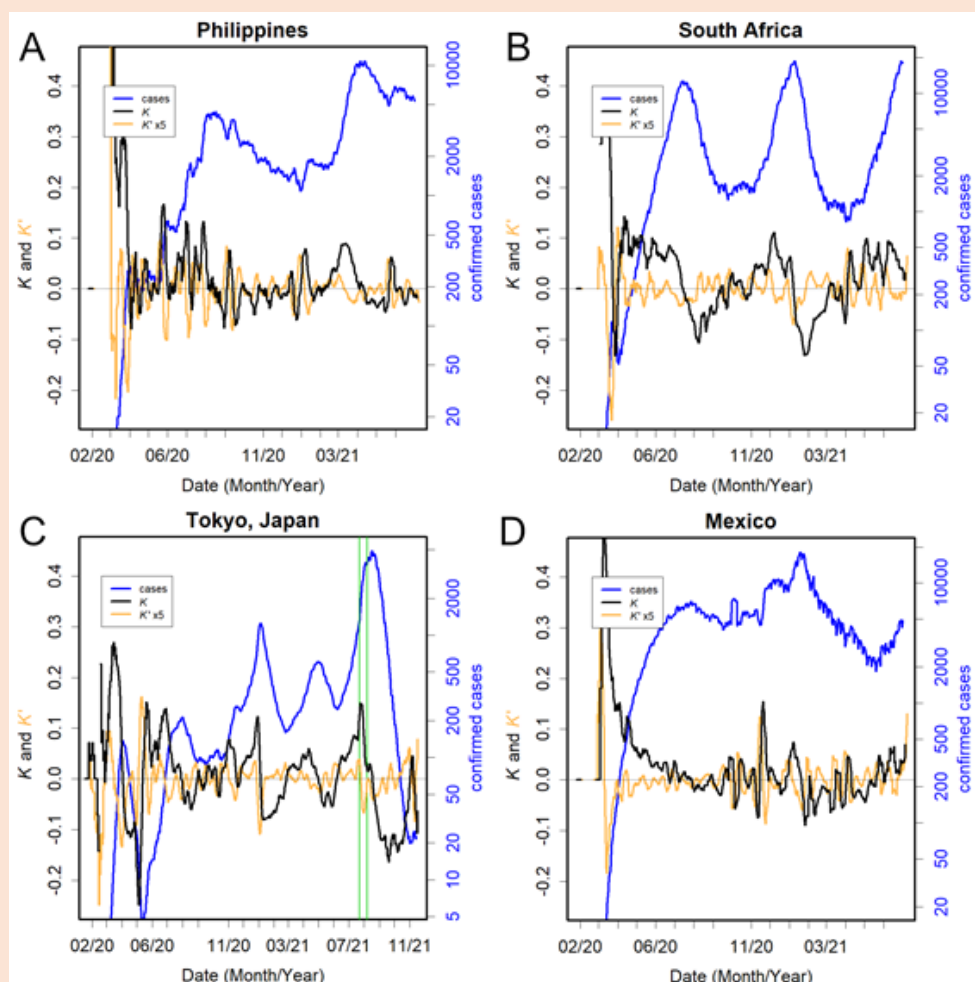


Figure 5: Actual data, a typical example of continuum of positive K . (A) The Philippines, (B) South Africa, (C) Tokyo (Japan), and (D) Mexico. Hereafter, each of these countries has

been selected as a typical example with the characteristics described in the Results section. The two green lines in Panel C indicate the duration of the Olympic Games held in this city.

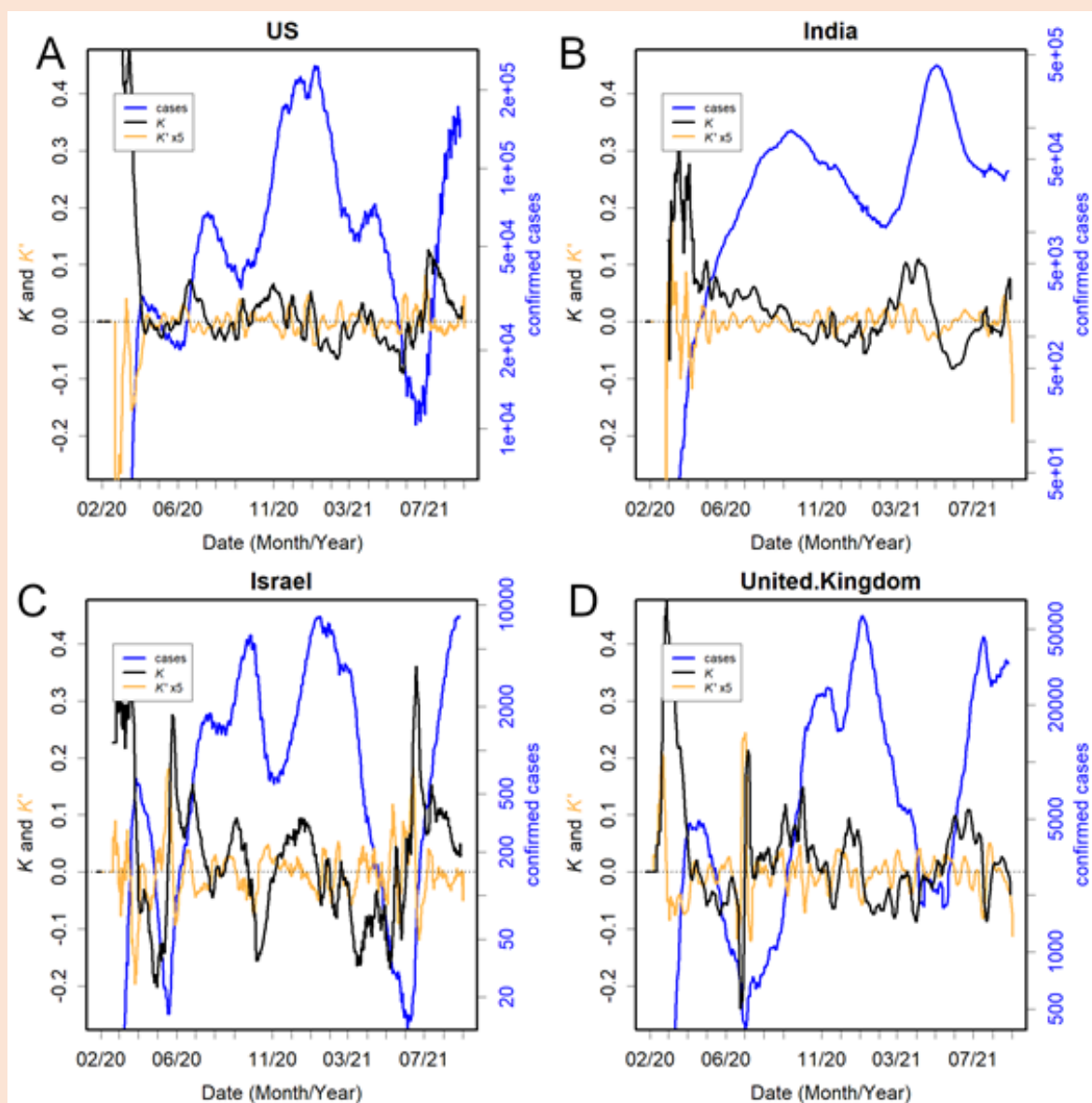


Figure 6: Countries with long-positive K . 2. (A) USA, (B) India, (C) Israel, and (D) UK. Vaccination coverage (2 doses) in these countries was 47%, 4%, 57%, and 49%, respectively (Our World in Data 2021, P 5 July).

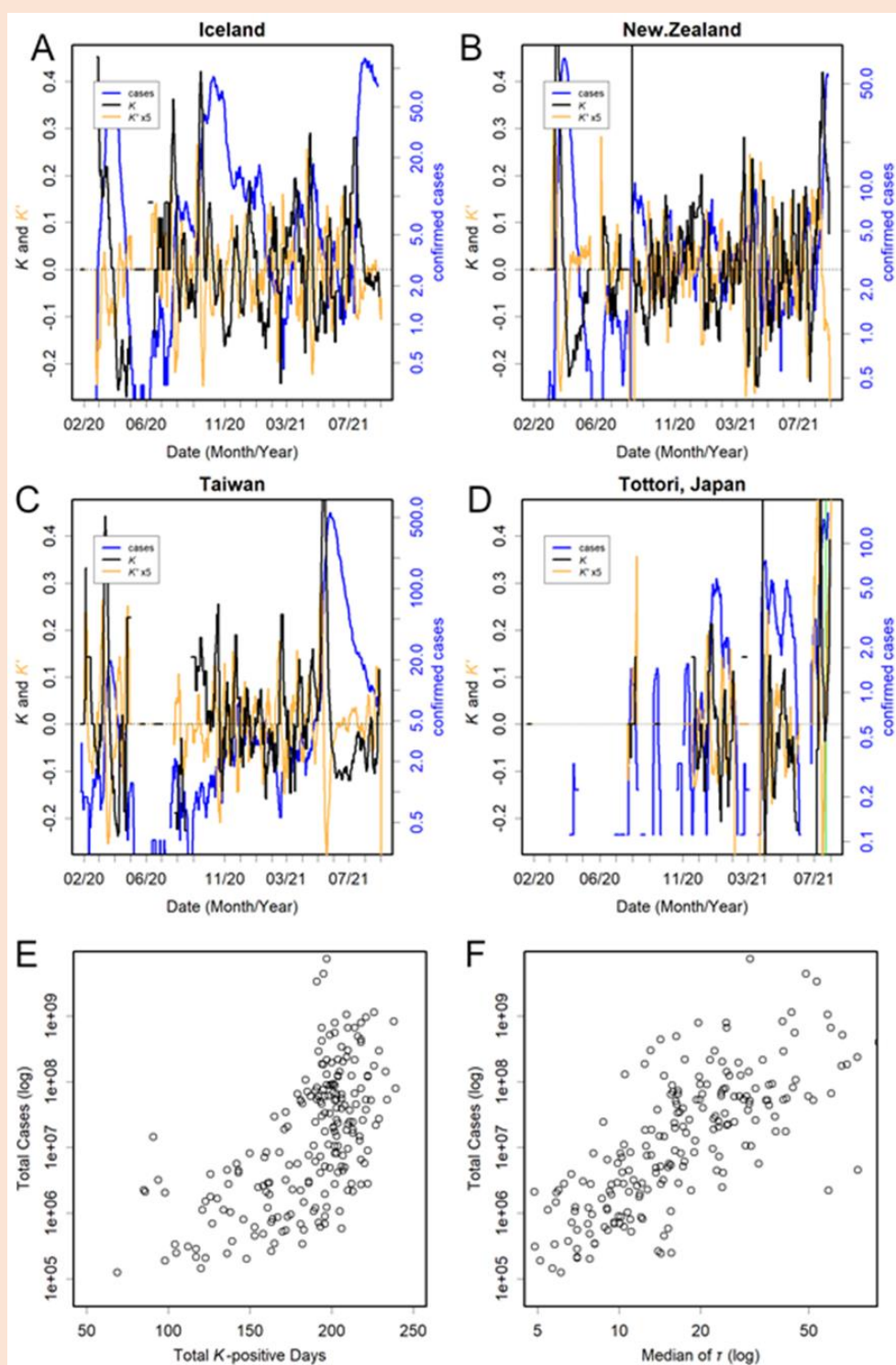


Figure 7: Regions with infections under control. (A) Iceland, (B), Taiwan, (C) New Zealand, and (D) Tottori, Japan. Relationships between the number of total confirmed cases and total

K-positive days (E), and median of τ (F). Pearson's correlation coefficient, $r = 0.80$ and 0.66 , respectively.

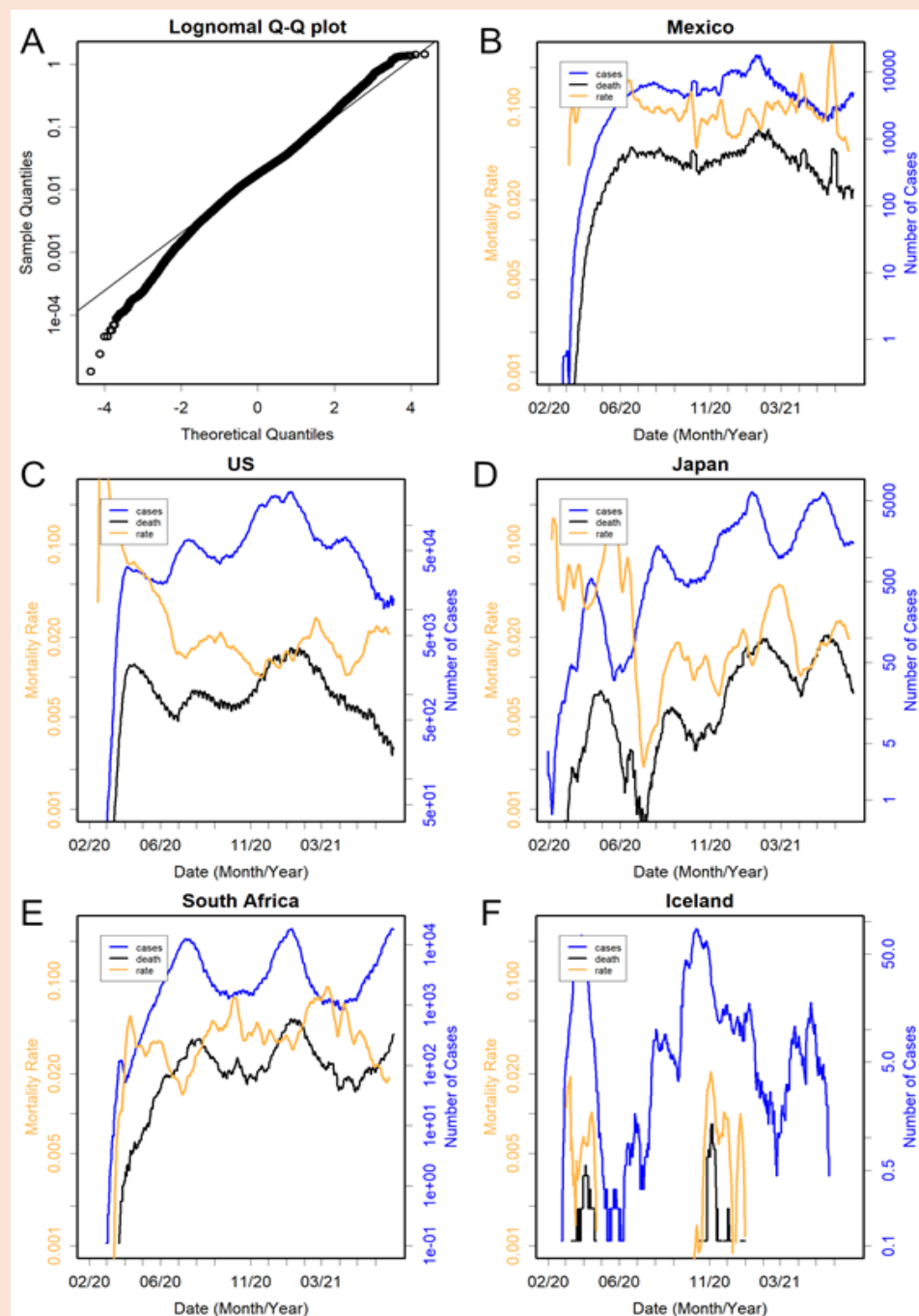


Figure 8: Number of deaths (black) and mortality rate. (A) Normal QQ plot of the logarithm of the mortality rate. (B-F) Situation in each country. Semi-log plot.

Common Characteristics of Well-Controlled Countries

One of the characteristics of a country that has controlled the epidemic well is that it is able to suppress the K positives immediately (Fig. 7). Hence, the values of K frequently increase and decrease. In these countries, I can even be zero, resulting in the interruption of the line because K cannot be calculated. Additionally, in these countries, the negative peaks of K are as low as -0.2 ; therefore, the mean infectious time would have been 5 days or even shorter, suggesting quick discovery and isolation of infected people. For example, in Iceland (Fig. 7), even if there were some K -positive days, they were quickly suppressed and did not cause epidemics. This trend has been observed in New Zealand (Fig. 7), Australia and China [23]. It takes constant effort to maintain this and these countries continue to do so. Taiwan (Fig. 7) experienced an outbreak of the highly contagious alpha variant in June 2021, with an R_0 of 4 [28]. However, a rapid response quickly reduced K and maintained the number of infected people under control. Tottori is a Japanese prefecture (Fig. 7) which had one outbreak of COVID-19 infection at the time of the Olympics, with $R_0 = 3.7$ at the peak; however, K converged within a few days. The mean infectious time was particularly short (2 days), which is one of the shortest in the world (Fig. 4). There seems to be a huge disparity between municipalities, even in the same country, as observed in Tokyo (Table S1). Naturally, there are fewer K -positive days in these countries and areas. A correlation was observed between the number of K -positive days and confirmed cases in the country (Fig. 7). This is probably because these countries are able to maintain a low τ . In fact, there was a positive correlation between τ and the number of confirmed cases (Fig. 7).

In addition to K , mortality rate was assessed. The rate was roughly log-normally distributed (Fig. 8A). The global average was 0.017, but it is worth noting that it had an exponential spread. This value varies considerably from country to country and mortality tends to be higher in countries where K does not decline (Fig. 8,5). This may be due to a lack of medical care. Even in countries where vaccines are widely available, the mortality rate does not necessarily decrease as much (Fig. 8). The rate increases or decreases with time, with the peak in mortality occurring a few months later than the peak in I (Fig. 8). The number of deaths and mortality rates were lower in countries where the epidemics were well controlled; this may be attributed to more affluent medical resources (Fig. 8F and Table S1).

Discussion

The results of the simulation, in which the infections were repeated at short intervals, showed a linear increase and decrease in K (Fig. 2), similar to the real data (Fig. 5-7). By observing changes in K , the important parameters R_0 and τ could be estimated (Fig. 3,4) and by using these parameters, the SIR model could approximate changes in the confirmed cases (Fig. 4). These results confirm the appropriateness of this well-established model for COVID-19

epidemics. The real data suggested that the epidemics with small S_0 started in a time-shifted manner with a mean interval of 11.3 days (Fig. S3). The S_0 of each epidemic might be determined by the infectivity of the variant, lifestyle and government measures.

By observing K , patterns of distributions of peak intervals, negative peaks of K , the slope of K and R_0 were revealed from the real data using the SIR model (Fig. 4). They were distributed according to the exponential distribution; this study was possible because K could be estimated simply and automatically (Table S2). Knowledge of the statistical distribution is advantageous not only for the accuracy of data analysis, but also because it provides information regarding the magnitude of the data as well as the hidden mechanism that causes the distribution [15]. In addition, the distribution was used to determine the confidence limits of the measurements (Fig. 4).

The simulation was surprisingly unstable, especially with $R_0 < 2$. Regardless of the size of the input R_0 or the iterative calculation methods used, R_0 became larger owing to a calculation artefact. It has been thought that if $R_0 > 1$, the infection will spread. In fact, this is the basis for the explanation that R_0 is the largest modulus of the eigenvalues in the next-generation matrix [7]. Originally, R_0 was a concept used in demography. However, when applied to infectious diseases, it is a competition with the rate at which patients heal and disappear from the field, reducing the effective reproduction number rapidly; the situation is quite different from that of a person raising children in a stable manner. Fig. 1C is an example of $R_0 = 2.5$, but even in this case, 42% of S were not infected and the epidemic was over. Fig. 1 shows the case of $R_0 = 2.0$, with fewer infections; the peak of I was too small to be regarded as an epidemic. Hence, $R_0 = 2$ would be the minimum value required to cause exponential growth.

The reason for the exponential distribution of the peak heights of K and K' (Fig. 4, S2) may be complicated. The distribution is often used to represent intervals of randomly occurring events; therefore, it appeared in the cases of the peak intervals and length of consecutive K -positive days (Fig. 4). However, this distribution may also occur if variable factors increase over time and the peak height is determined by the size of the factors when the peak occurs in a random manner (here, the timing of occurrence is unrelated to the size). A negative K peak was determined by how quickly a patient could be identified and isolated. Therefore, the accumulation of countermeasures may act as an increasing factor. Peaks of K' correlate with the infectivity of a virus. Infectivity is determined by sequence differences; therefore, accumulated mutations may act as an increasing factor. Additionally, as $R_0 = 2K\tau$, the logarithm of R_0 would have a pseudo-exponential character (Fig. 4). Much of the upwardly displaced data (Fig. 4) would have been affected by the extended τ (Fig. 4) rather than simply the increased infectivity (Fig. S2). Presumably, in cases where R_0 was large, medical care was more likely to be poor and patients could not be detected and isolated in time.

Here, we used the simplest SIR model and directly calculated the parameters without making assumptions [12]. The results of simulations using this model are consistent with reality (Fig.

4); therefore, there will be no major breakdowns. Since there are fewer assumptions, R_0 and other parameters have higher objectivity. This is easier than repeating simulations to find the optimal solution and more objective than calculating them using artificial intelligence [12]. These approaches would estimate the parameters with higher accuracy; however, this does not guarantee higher certainty. In addition, S is difficult to judge during an epidemic and the estimation from the eigenvalue of the next generation matrix is probably wrong on its basis [7]. In the past, models of infectious diseases have evolved to become more complex [12]. While this has been important for understanding how infectious diseases spread, it has been more of a hindrance to understanding the current state of infectious diseases with parameters that are too numerous, not directly measurable and not validated.

However, R_0 can only describe epidemic infections that have occurred in the past. K , which is model-independent and can be calculated simply (Table S1), is more suitable for determining the current situation and making short-term predictions. Therefore, it would be more beneficial for decision-making authorities.

Observing the daily changes in K is important for evaluating and forecasting the state of epidemics (Fig. 7). If R_0 is low, many susceptible individuals will escape the infection (Fig. S1); however, as the original S_0 is unknown, information on R_0 is not useful for predicting the scale of infection. If appropriate measures are taken, the epidemic converges to huge and vice versa, regardless of R_0 . Unfortunately, the magnitude of S_0 did not alter the slope of K (Fig. 2B). In fact, while K and K' were presented on the same scale among countries, the confirmed cases differed significantly (Fig. 5-7). Therefore, a single measurement of K was not useful for the evaluation. Rather, the scale of the epidemic can only be estimated from the continuous observation of the increase and decrease in K (Fig. 5-7).

The statistical distribution of τ necessitated revisions of both the isolation period and the decision to release a patient. In Japan, the isolation period is uniformly 10 days and no PCR test is performed when the isolation is lifted [32]. However, the mean infectious time in Tokyo was 16 days (Fig. 5). Furthermore, this estimated τ would have been shortened by the effort to find and isolate the patients; the period in which a patient excretes the virus must be longer than τ . Therefore, the isolation period must be longer. Furthermore, according to the SIR model, the average value represents half-life. This indicates that many patients may have been infectious upon release. Thus, the required period for isolation varies from person to person and this cannot be determined without testing.

The mean value of R_0 was 2.9, suggesting that in this situation, approximately 20% of the S_0 would be spared from infection and a lower R_0 should be more frequent (Fig. 4,S3), leaving more uninfected people (Fig. S1). However, ending the pandemic by herd immunity may not be achieved. If patients are left in a city, new variants that break the previous immunity start the next epidemic. Due to the large number of infected people, this virus is now mutating at a faster rate than the N1H1 influenza virus [19]. Termination of the pandemic is not expected,

given that the flu has not yet been terminated by herd immunity. Additionally, even small differences may result in a new set of S_0 values. In fact, approximately two-thirds of adults in India and Brazil are reported to have antibodies against coronavirus but the outbreak has not ended at all in these countries (Fig. 5) [19,33].

If K is consecutively positive for more than, for example, 10 days (Fig. 4), the number of patients will clearly increase; if the number of I is already high, it is almost inevitable that there will be a peak a few weeks to a month from that time. The longer K is positive, the more the number of I increases exponentially, resulting in more cases (Fig. 7). For example, in the case shown in Fig. 2, I increased tenfold after K remained positive for only eight more days. Therefore, it is important to not allow a series of K -positives to occur. Therefore, policy measures must be implemented to reduce K at an early stage. The large epidemics in the US and India were not caused by high R_0 ; they occurred because K was allowed to remain positive (Fig. 6). The large peaks were not caused by the speed of the infection, but because of the long period of lack of infection control. In Tokyo, this number reached 70 days before and after the Olympics (Fig. 5). This is one of the worst records in the world (Fig. 4). After the Olympics, τ in Tokyo was reduced to less than 6 days and the epidemic subsided rapidly (Fig. 5). This was simply because the burden that the event exerted on the city's healthcare system disappeared.

The more rapid the detection and isolation of a patient, the shorter the mean infectious time τ . This can be attributed to the negative K peak (Fig. 2). This value is probably 2 weeks or more if the patients are left untreated (Fig. 5,6). Fig. 4,7 show that τ should be maintained at a low value. The differences in τ depend on the measures taken by the government: more PCR testing, isolation of infected people and proper lockdown and testing of all people in the area when K is increased. Only regions that have been able to follow this protocol can successfully control epidemics and maintain their status (Fig. 7). Many other countries are unable to maintain a negative K value and thus the levels of I remain high (Fig. 5,6). This hides the initiation of new epidemics and provides a chance for new mutations to occur [14].

The benefits of reducing τ are also evident in the comparison between Tokyo (Fig. 5) and Tottori (Fig. 7). Here, although the cities are different in size, infections per population and death rate differed by an order of magnitude, with the rates in Tokyo being close to those in the US and UK and the rates in Tottori being close to those in countries with infections under control. In particular, there was a double-digit difference in deaths per population between the two cities (Table S1). In August 2021, the positivity rate of PCR tests in Tokyo remained above 20%. This is because the number of tests was too small; in contrast, individuals participating in the Olympics were taking the tests daily [34]. On 4 August 2021 the government asked medical institutions to keep all the patients who were not in critical condition at home and Tokyo decided to embrace this policy [35]. In fact, a bed could not be found for an emergency patient in 100 hospitals in Tokyo [36]. Of the positive patients who requested ambulance transport between 2 and 8 August, 2021, 57% were sent back home as there was no hospital

with the capacity to accept them. However, 7,000 medical personnel were mobilised for the Olympics [37]. Such an irresponsible policy meant the abandonment of disease control, including finding and isolating of patients; therefore, τ in this region would rise further, consequently expanding R_0 (Fig. 4) and the number of cases (Fig. 7). This huge difference is due to the policy of local governments on what to treat as important.

Unfortunately, vaccines seem to have limited effectiveness as a means of ending the epidemic (Fig. 5). This is probably related to the fact that they are not given to younger children and some people do not wish to be vaccinated. As of November 2021, 60% of the population of the USA and Brazil, nearly 70% of the population of the UK, Germany and France and nearly 80% of the population of Spain and Japan have been vaccinated [38]. However, the epidemic is not over in many of those countries; it seems to be under control for a while but increases again; several hundred thousand infections are reported every week in Germany and the UK these days [28]. This may indicate that the vaccine suppresses the infection to a large extent and that the strains that break through the required immunity do not appear easily, but will appear eventually. In addition, the effectiveness of the vaccine will have an expiration date. As with influenza, routine vaccination with newer strains is necessary. Furthermore, newer infective variants may break through acquired immunity. The simplest way to end the pandemic is to eliminate the virus, as in the cases of SARS and smallpox. Some of the countries with reduced τ have almost succeeded in doing this; however, the newer variant arising in the rest of the world is abolishing this attempt. COVID-19 elimination can only be accomplished through worldwide efforts. If the current situation cannot be improved, the epidemic will continue in countries where it is already prevalent.

The difference between countries where the infection was well controlled and those where it was not often observed was in whether the K was left positive or whether the K negative was sufficiently small, that is, whether τ was reduced or not. If these can be achieved, the epidemics can be controlled. These problems can only be solved by governments and not by individual efforts. The effectiveness of the measures can be determined by observing K over time.

While this issue was not evaluated in this study, PCR tests have not been carried out often enough in some countries, which signifies that the number of patients reported should be lower than the actual number. If medical resources for this are not available, a random sample test can be used to estimate the number of patients. In this case, we would need to sample a completely random selection of people, not just those with symptoms. The problem is that while we are relying on this, we will not be able to identify infected people, since there are many asymptomatic patients. As of November 2021, the number of cases in Japan has reduced considerably but has failed to reach zero and K is again on the rise in Tokyo (Fig. 5), because of insufficient PCR testing and isolation. It is the responsibility of the government to ensure sufficient opportunity for PCR testing at the earliest possible stage.

Conclusion

Simulations showed that the SIR model was effective for the COVID-19 epidemic. Accordingly, by continuously observing the logarithmic growth rate, K , we can predict the number of patients for the following few weeks up to a month. To control the epidemic, it is critically important to prevent K from remaining positive consecutively; rather, efforts must be undertaken to reduce K to end the peaks completely. It is essential to identify and isolate infected individuals to reduce the mean infectious time τ , which appears in the negative peaks of K . In order to control the spread of disease, reducing τ is not something that can be done individually but can be achieved with the responsibility of the government. The mean infectious time was 12 days on average, but it could become more than twice the value if the patients were left untreated. Since this represents the half-life, the criteria for isolation, such as those adopted in Japan, need to be more restrictive.

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Conflict of Interest

Author declare no conflict of interest.

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38. Our world in data. Coronavirus (COVID-19) Vaccinations 2021. [Last accessed on: October 18, 2022]
<https://ourworldindata.org/covid-vaccinations>

Supplementary Files

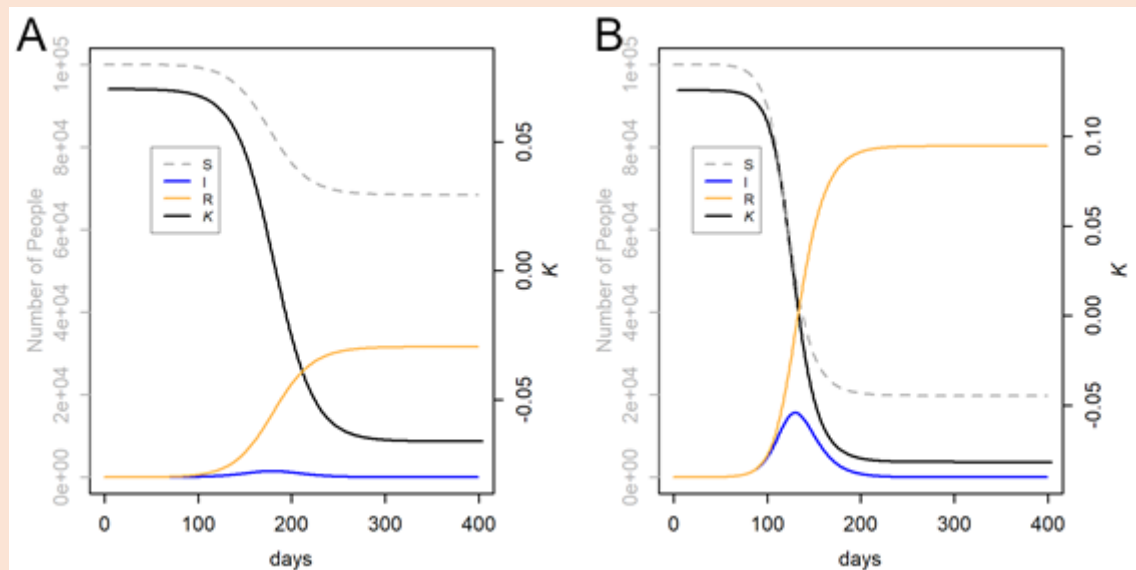


Figure S1: Simulation under different R_0 . (A) Close to the limit of exponential amplification: $R_0 = 2.1, \tau = 15$. Ca. 70% of S_0 remained uninfected, and the peak of I remained low. (B) Changes under average conditions: $R_0 = 2.9, \tau = 12$. Ca. 20% of S_0 remained uninfected.

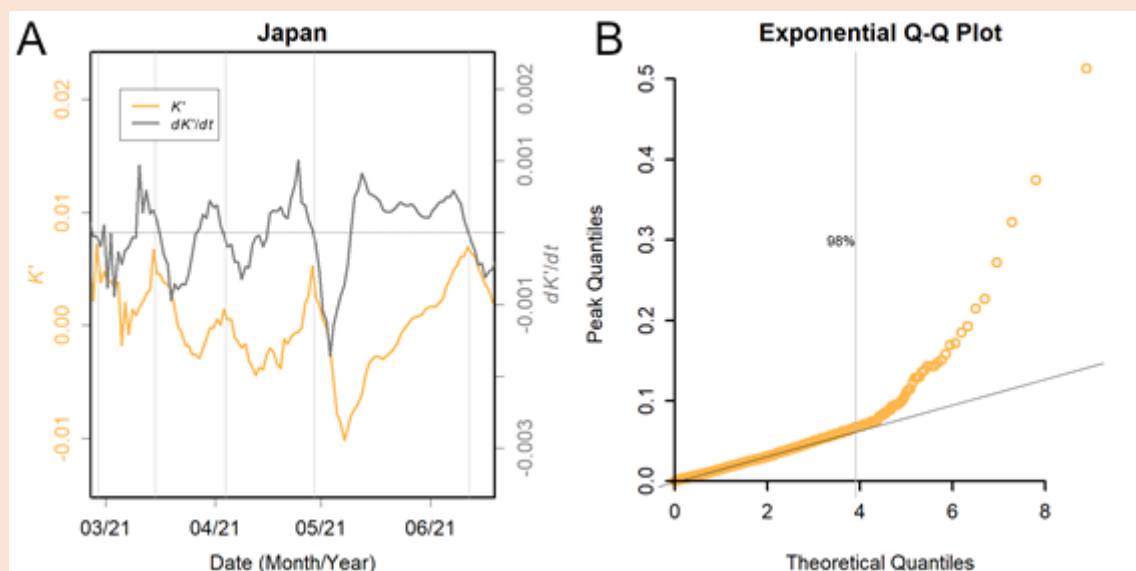


Figure S2: Examples of data. (A) Relationship between K' and dK'/dt . The peak of K' appears when dK'/dt becomes negative. Grey vertical lines show the positions of the found peaks. (B) Distribution of K' peaks. Correspondence of quantiles of the peaks with that of the

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theoretical values. The top 2% of data may represent the effects of the super spreaders and newest infectious variants.

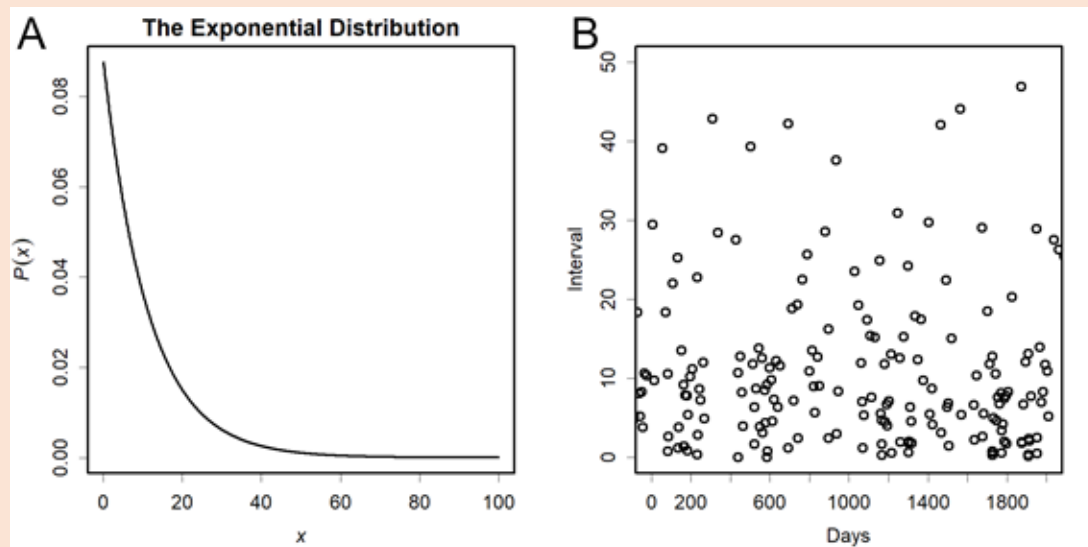


Figure S3: Exponential distribution. (A) Probability density function, rate = $1/11.3$. The density decreases exponentially. (B) Frequency of intervals. A random exponential distribution with ratio = $1/11.3$ was generated, where the vertical axis shows the respective value and the horizontal axis the total up to that value; higher values occur after such intervals of horizontal axis. Intervals of more than 40 days are observed several times over the course of 400 days.

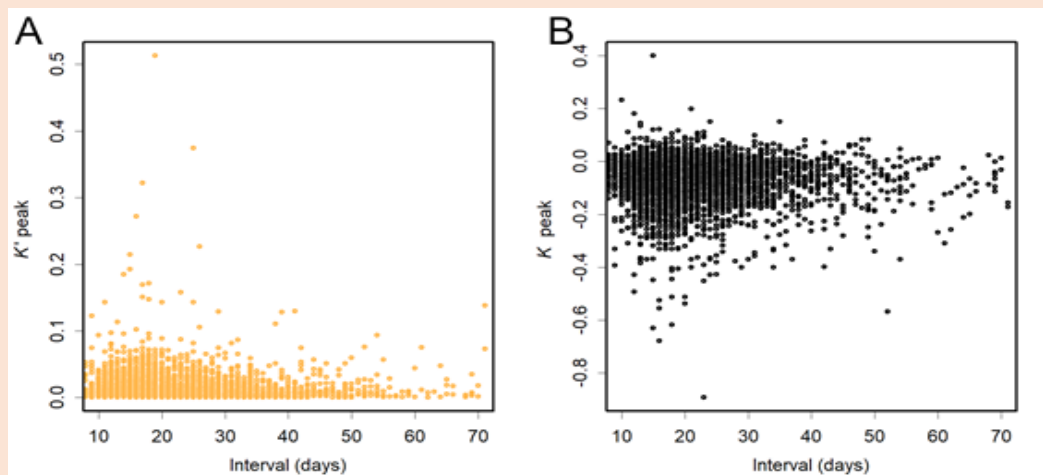


Figure S4: Relationship between the intervals of peaks and peak heights. (A) Peak of K' . Pearson's correlation coefficient, $r = -0.052$. (B) Negative peak of K . Pearson's correlation coefficient, $r = -0.022$.

Code	Area	Date	Positive	Cumulative	Ratio	Logratio	K	1/(-K)	
130001	Tokyo	1/14/2020	1	1					1
130001	Tokyo	1/15/2020	0	1					2
130001	Tokyo	1/16/2020	0	1					3
130001	Tokyo	1/17/2020	1	2					4
130001	Tokyo	1/18/2020	0	2					5
130001	Tokyo	1/19/2020	0	2					6
130001	Tokyo	1/20/2020	2	4					7
130001	Tokyo	1/21/2020	0	4	0	#NUM!			
130001	Tokyo	1/22/2020	1	5	#DIV/0!	#DIV/0!			
130001	Tokyo	1/23/2020	2	7	#DIV/0!	#DIV/0!			
130001	Tokyo	1/24/2020	1	8	1	0	#NUM!	#NUM!	
130001	Tokyo	1/25/2020	0	8	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	
130001	Tokyo	1/26/2020	1	9	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	
130001	Tokyo	1/27/2020	0	9	0	#NUM!	#DIV/0!	#DIV/0!	
130001	Tokyo	1/28/2020	1	10	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	
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130001	Tokyo	1/30/2020	0	11	0	#NUM!	#NUM!	#NUM!	
130001	Tokyo	1/31/2020	0	11	0	#NUM!	#DIV/0!	#DIV/0!	
130001	Tokyo	2/1/2020	1	12	#DIV/0!	#DIV/0!	#NUM!	#NUM!	
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130001	Tokyo	2/4/2020	1	17	1	0	#DIV/0!	#DIV/0!	
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130001	Tokyo	2/6/2020	1	19	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	
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130001	Tokyo	2/8/2020	0	21	0	#NUM!	#DIV/0!	#DIV/0!	
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130001	Tokyo	3/14/2020	6	103	3	0.226423	0.189533		
130001	Tokyo	3/15/2020	14	117	3.5	0.258194	0.249505		
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130001	Tokyo	4/3/2020	164	1518	1.802198	0.121394	0.099984		

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130001	Tokyo	4/4/2020	149	1667	1.568421	0.092759	0.080893		
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130001	Tokyo	5/1/2020	25	3319	0.892857	-0.02336	-0.07664	13.04794	
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130001	Tokyo	5/15/2020	6	3431	1.2	0.037576	-0.03635	27.50708	
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130001	Tokyo	6/24/2020	57	4237	1.965517	0.139273	0.109068		

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130001	Tokyo	6/25/2020	42	4279	1.75	0.115336	0.122008		
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130001	Tokyo	7/6/2020	169	5368	1.920455	0.134493	0.092778		
130001	Tokyo	7/7/2020	152	5520	1.321739	0.057491	0.079405		
130001	Tokyo	7/8/2020	133	5653	1.081301	0.01611	0.080529		
130001	Tokyo	7/9/2020	151	5804	1.466019	0.078843	0.08138		
130001	Tokyo	7/10/2020	161	5965	1.490741	0.08229	0.06467		
130001	Tokyo	7/11/2020	167	6132	1.621359	0.099601	0.058694		
130001	Tokyo	7/12/2020	168	6300	1.631068	0.100831	0.0609		
130001	Tokyo	7/13/2020	184	6484	1.088757	0.017526	0.052953		
130001	Tokyo	7/14/2020	164	6648	1.078947	0.015661	0.039309		
130001	Tokyo	7/15/2020	155	6803	1.165414	0.031549	0.024725		
130001	Tokyo	7/16/2020	169	6972	1.119205	0.023211	0.011184		
130001	Tokyo	7/17/2020	151	7123	0.937888	-0.01322	0.012712		
130001	Tokyo	7/18/2020	165	7288	0.988024	-0.00248	0.013863		
130001	Tokyo	7/19/2020	173	7461	1.029762	0.006044	0.015195		
130001	Tokyo	7/20/2020	211	7672	1.146739	0.02822	0.009898		
130001	Tokyo	7/21/2020	184	7856	1.121951	0.023716	0.016296		
130001	Tokyo	7/22/2020	189	8045	1.219355	0.040874	0.019213		
130001	Tokyo	7/23/2020	158	8203	0.934911	-0.01387	0.025956		
130001	Tokyo	7/24/2020	176	8379	1.165563	0.031575	0.02302		
130001	Tokyo	7/25/2020	180	8559	1.090909	0.017933	0.026202		
130001	Tokyo	7/26/2020	224	8783	1.294798	0.053247	0.022029		
130001	Tokyo	7/27/2020	219	9002	1.037915	0.00767	0.029902		
130001	Tokyo	7/28/2020	230	9232	1.25	0.04599	0.027018		
130001	Tokyo	7/29/2020	200	9432	1.058201	0.011659	0.031801		
130001	Tokyo	7/30/2020	193	9625	1.221519	0.041239	0.020858		
130001	Tokyo	7/31/2020	186	9811	1.056818	0.01139	0.021713		
130001	Tokyo	8/1/2020	231	10042	1.283333	0.051414	0.014233		
130001	Tokyo	8/2/2020	200	10242	0.892857	-0.02336	0.009952		
130001	Tokyo	8/3/2020	234	10476	1.068493	0.013654	-0.00757	132.0279	
130001	Tokyo	8/4/2020	223	10699	0.969565	-0.00637	-0.01309	76.40831	

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130001	Tokyo	8/5/2020	183	10882	0.915	-0.01831	-0.03518	28.42799	
130001	Tokyo	8/6/2020	130	11012	0.673575	-0.08144	-0.04213	23.73503	
130001	Tokyo	8/7/2020	163	11175	0.876344	-0.0272	-0.0523	19.11974	
130001	Tokyo	8/8/2020	140	11315	0.606061	-0.10321	-0.05786	17.28218	
130001	Tokyo	8/9/2020	141	11456	0.705	-0.07204	-0.05976	16.73375	
130001	Tokyo	8/10/2020	177	11633	0.75641	-0.05754	-0.04658	21.46807	
130001	Tokyo	8/11/2020	179	11812	0.802691	-0.0453	-0.04614	21.67328	
130001	Tokyo	8/12/2020	157	11969	0.857923	-0.03158	-0.02656	37.65341	
130001	Tokyo	8/13/2020	137	12106	1.053846	0.010809	-0.01755	56.99174	
130001	Tokyo	8/14/2020	145	12251	0.889571	-0.02412	-0.01248	80.09976	
130001	Tokyo	8/15/2020	165	12416	1.178571	0.033863	-0.01635	61.15911	
130001	Tokyo	8/16/2020	135	12551	0.957447	-0.00896	-0.02126	47.03215	
130001	Tokyo	8/17/2020	159	12710	0.898305	-0.0221	-0.03036	32.9386	
130001	Tokyo	8/18/2020	126	12836	0.703911	-0.07236	-0.04129	24.22178	
130001	Tokyo	8/19/2020	114	12950	0.726115	-0.06596	-0.05599	17.85915	
130001	Tokyo	8/20/2020	106	13056	0.773723	-0.05287	-0.06665	15.00344	
130001	Tokyo	8/21/2020	89	13145	0.613793	-0.1006	-0.07105	14.07413	
130001	Tokyo	8/22/2020	118	13263	0.715152	-0.0691	-0.06142	16.28019	
130001	Tokyo	8/23/2020	90	13353	0.666667	-0.08357	-0.058	17.24263	
130001	Tokyo	8/24/2020	123	13476	0.773585	-0.05291	-0.05592	17.88209	
130001	Tokyo	8/25/2020	123	13599	0.97619	-0.00497	-0.04256	23.49597	
130001	Tokyo	8/26/2020	93	13692	0.815789	-0.04196	-0.04034	24.78962	
130001	Tokyo	8/27/2020	88	13780	0.830189	-0.03836	-0.03665	27.28192	
130001	Tokyo	8/28/2020	86	13866	0.966292	-0.00707	-0.03639	27.478	
130001	Tokyo	8/29/2020	91	13957	0.771186	-0.05355	-0.03792	26.37097	
130001	Tokyo	8/30/2020	68	14025	0.755556	-0.05777	-0.03355	29.80354	
130001	Tokyo	8/31/2020	96	14121	0.780488	-0.05108	-0.02676	37.36235	
130001	Tokyo	9/1/2020	114	14235	0.926829	-0.01566	-0.01905	52.49685	
130001	Tokyo	9/2/2020	88	14323	0.946237	-0.01139	-0.00775	129.0034	
130001	Tokyo	9/3/2020	92	14415	1.045455	0.009161	0.008092		
130001	Tokyo	9/4/2020	108	14523	1.255814	0.046946	0.016591		
130001	Tokyo	9/5/2020	103	14626	1.131868	0.025529	0.016963		
130001	Tokyo	9/6/2020	88	14714	1.294118	0.053138	0.024069		
130001	Tokyo	9/7/2020	100	14814	1.041667	0.008413	0.022439		
130001	Tokyo	9/8/2020	107	14921	0.938596	-0.01306	0.001675		
130001	Tokyo	9/9/2020	106	15027	1.204545	0.038356	-0.00374	267.4307	
130001	Tokyo	9/10/2020	91	15118	0.98913	-0.00225	-0.01643	60.85656	
130001	Tokyo	9/11/2020	67	15185	0.62037	-0.0984	-0.00991	100.9156	
130001	Tokyo	9/12/2020	97	15282	0.941748	-0.01237	-0.01217	82.15421	
130001	Tokyo	9/13/2020	74	15356	0.840909	-0.03571	-0.0215	46.50325	
130001	Tokyo	9/14/2020	130	15486	1.3	0.054073	-0.02023	49.43861	

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130001	Tokyo	9/15/2020	93	15579	0.869159	-0.0289	-0.00246	406.6674	
130001	Tokyo	9/16/2020	93	15672	0.877358	-0.02697	-0.01248	80.13752	
130001	Tokyo	9/17/2020	94	15766	1.032967	0.006685	-0.00818	122.1948	
130001	Tokyo	9/18/2020	76	15842	1.134328	0.025977	-0.02453	40.76656	
130001	Tokyo	9/19/2020	65	15907	0.670103	-0.08251	-0.01467	68.1846	
130001	Tokyo	9/20/2020	72	15979	0.972973	-0.00565	-0.00641	155.9779	
130001	Tokyo	9/21/2020	97	16076	0.746154	-0.06035	-0.00439	227.8113	
130001	Tokyo	9/22/2020	113	16189	1.215054	0.040146	0.002246		
130001	Tokyo	9/23/2020	108	16297	1.16129	0.030818	0.025205		
130001	Tokyo	9/24/2020	104	16401	1.106383	0.020836	0.030198		
130001	Tokyo	9/25/2020	108	16509	1.421053	0.072423	0.043053		
130001	Tokyo	9/26/2020	95	16604	1.461538	0.078213	0.035435		
130001	Tokyo	9/27/2020	83	16687	1.152778	0.029302	0.023982		
130001	Tokyo	9/28/2020	112	16799	1.154639	0.029635	0.027119		
130001	Tokyo	9/29/2020	106	16905	0.938053	-0.01318	0.013912		
130001	Tokyo	9/30/2020	85	16990	0.787037	-0.04936	0.003953		
130001	Tokyo	10/1/2020	128	17118	1.230769	0.042794	0.002476		
130001	Tokyo	10/2/2020	98	17216	0.907407	-0.02003	-0.00283	353.5771	
130001	Tokyo	10/3/2020	99	17315	1.042105	0.0085	0.000676		
130001	Tokyo	10/4/2020	91	17406	1.096386	0.018965	0.01611		
130001	Tokyo	10/5/2020	108	17514	0.964286	-0.0075	0.012211		
130001	Tokyo	10/6/2020	112	17626	1.056604	0.011348	0.02054		
130001	Tokyo	10/7/2020	113	17739	1.329412	0.058684	0.023737		
130001	Tokyo	10/8/2020	138	17877	1.078125	0.015503	0.021668		
130001	Tokyo	10/9/2020	118	17995	1.204082	0.038276	0.029955		
130001	Tokyo	10/10/2020	115	18110	1.161616	0.030876	0.027264		
130001	Tokyo	10/11/2020	93	18203	1.021978	0.004481	0.014687		
130001	Tokyo	10/12/2020	138	18341	1.277778	0.05052	-0.00145	688.8943	
130001	Tokyo	10/13/2020	108	18449	0.964286	-0.0075	-0.01209	82.72163	
130001	Tokyo	10/14/2020	98	18547	0.867257	-0.02935	-0.02948	33.92134	
130001	Tokyo	10/15/2020	86	18633	0.623188	-0.09747	-0.03606	27.72883	
130001	Tokyo	10/16/2020	99	18732	0.838983	-0.03618	-0.05023	19.90987	
130001	Tokyo	10/17/2020	74	18806	0.643478	-0.09086	-0.04557	21.9458	
130001	Tokyo	10/18/2020	76	18882	0.817204	-0.0416	-0.0402	24.87829	
130001	Tokyo	10/19/2020	109	18991	0.789855	-0.04862	-0.02461	40.63694	
130001	Tokyo	10/20/2020	122	19113	1.12963	0.025121	-0.01427	70.07744	
130001	Tokyo	10/21/2020	102	19215	1.040816	0.008245	0.00728		
130001	Tokyo	10/22/2020	91	19306	1.05814	0.011647	0.020102		
130001	Tokyo	10/23/2020	118	19424	1.191919	0.036184	0.032007		
130001	Tokyo	10/24/2020	99	19523	1.337838	0.059986	0.021969		
130001	Tokyo	10/25/2020	96	19619	1.263158	0.048148	0.022745		

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130001	Tokyo	10/26/2020	129	19748	1.183486	0.03472	0.023562		
130001	Tokyo	10/27/2020	98	19846	0.803279	-0.04515	0.020325		
130001	Tokyo	10/28/2020	109	19955	1.068627	0.01368	0.01565		
130001	Tokyo	10/29/2020	99	20054	1.087912	0.017366	0.014596		
130001	Tokyo	10/30/2020	126	20180	1.067797	0.01352	0.018277		
130001	Tokyo	10/31/2020	113	20293	1.141414	0.02726	0.043434		
130001	Tokyo	11/1/2020	117	20410	1.21875	0.040772	0.052035		
130001	Tokyo	11/2/2020	173	20583	1.341085	0.060486	0.066661		
130001	Tokyo	11/3/2020	185	20768	1.887755	0.130953	0.075878		
130001	Tokyo	11/4/2020	156	20924	1.431193	0.073888	0.082039		
130001	Tokyo	11/5/2020	177	21101	1.787879	0.11975	0.086691		
130001	Tokyo	11/6/2020	184	21285	1.460317	0.07804	0.083475		
130001	Tokyo	11/7/2020	159	21444	1.40708	0.070386	0.070268		
130001	Tokyo	11/8/2020	167	21611	1.42735	0.073334	0.071014		
130001	Tokyo	11/9/2020	208	21819	1.202312	0.037973	0.060709		
130001	Tokyo	11/10/2020	223	22042	1.205405	0.038503	0.056258		
130001	Tokyo	11/11/2020	229	22271	1.467949	0.079115	0.0572		
130001	Tokyo	11/12/2020	223	22494	1.259887	0.047613	0.057767		
130001	Tokyo	11/13/2020	231	22725	1.255435	0.046884	0.062026		
130001	Tokyo	11/14/2020	231	22956	1.45283	0.076981	0.06725		
130001	Tokyo	11/15/2020	243	23199	1.45509	0.077301	0.062595		
130001	Tokyo	11/16/2020	289	23488	1.389423	0.067784	0.05951		
130001	Tokyo	11/17/2020	321	23809	1.439462	0.075076	0.056966		
130001	Tokyo	11/18/2020	287	24096	1.253275	0.046529	0.045712		
130001	Tokyo	11/19/2020	253	24349	1.134529	0.026013	0.02864		
130001	Tokyo	11/20/2020	266	24615	1.151515	0.029076	0.012361		
130001	Tokyo	11/21/2020	229	24844	0.991342	-0.00179	-0.0026	384.8087	
130001	Tokyo	11/22/2020	198	25042	0.814815	-0.04221	-0.01415	70.69345	
130001	Tokyo	11/23/2020	231	25273	0.799308	-0.04617	-0.01991	50.22665	
130001	Tokyo	11/24/2020	278	25551	0.866044	-0.02964	-0.02451	40.80033	
130001	Tokyo	11/25/2020	243	25794	0.84669	-0.0343	-0.0249	40.15491	
130001	Tokyo	11/26/2020	236	26030	0.932806	-0.01434	-0.01333	75.00289	
130001	Tokyo	11/27/2020	262	26292	0.984962	-0.00312	-0.00097	1032.575	
130001	Tokyo	11/28/2020	224	26516	0.978166	-0.00455	0.003582		
130001	Tokyo	11/29/2020	239	26755	1.207071	0.038787	0.014784		
130001	Tokyo	11/30/2020	281	27036	1.21645	0.040382	0.021971		
130001	Tokyo	12/1/2020	281	27317	1.010791	0.002212	0.025709		
130001	Tokyo	12/2/2020	301	27618	1.238683	0.044115	0.029474		
130001	Tokyo	12/3/2020	281	27899	1.190678	0.035969	0.026639		
130001	Tokyo	12/4/2020	293	28192	1.118321	0.023048	0.026133		
130001	Tokyo	12/5/2020	249	28441	1.111607	0.021807	0.033838		

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130001	Tokyo	12/6/2020	262	28703	1.096234	0.018937	0.030775		
130001	Tokyo	12/7/2020	336	29039	1.19573	0.036842	0.033175		
130001	Tokyo	12/8/2020	369	29408	1.313167	0.05615	0.032661		
130001	Tokyo	12/9/2020	336	29744	1.116279	0.022671	0.038105		
130001	Tokyo	12/10/2020	363	30107	1.291815	0.052771	0.042104		
130001	Tokyo	12/11/2020	322	30429	1.098976	0.019451	0.045897		
130001	Tokyo	12/12/2020	333	30762	1.337349	0.059911	0.042516		
130001	Tokyo	12/13/2020	329	31091	1.255725	0.046932	0.04859		
130001	Tokyo	12/14/2020	457	31548	1.360119	0.06339	0.043613		
130001	Tokyo	12/15/2020	432	31980	1.170732	0.032487	0.046248		
130001	Tokyo	12/16/2020	461	32441	1.372024	0.065187	0.041808		
130001	Tokyo	12/17/2020	396	32837	1.090909	0.017933	0.044128		
130001	Tokyo	12/18/2020	387	33224	1.201863	0.037896	0.040149		
130001	Tokyo	12/19/2020	383	33607	1.15015	0.028832	0.044933		
130001	Tokyo	12/20/2020	447	34054	1.358663	0.06317	0.041401		
130001	Tokyo	12/21/2020	543	34597	1.188184	0.035537	0.04686		
130001	Tokyo	12/22/2020	595	35192	1.377315	0.06598	0.052899		
130001	Tokyo	12/23/2020	561	35753	1.21692	0.040462	0.060947		
130001	Tokyo	12/24/2020	520	36273	1.313131	0.056144	0.06098		
130001	Tokyo	12/25/2020	571	36844	1.475452	0.080165	0.063716		
130001	Tokyo	12/26/2020	579	37423	1.511749	0.085174	0.061574		
130001	Tokyo	12/27/2020	608	38031	1.360179	0.063399	0.067889		
130001	Tokyo	12/28/2020	708	38739	1.303867	0.054685	0.076506		
130001	Tokyo	12/29/2020	762	39501	1.280672	0.050986	0.085948		
130001	Tokyo	12/30/2020	846	40347	1.508021	0.084665	0.097503		
130001	Tokyo	12/31/2020	915	41262	1.759615	0.116466	0.111448		
130001	Tokyo	1/1/2021	1161	42423	2.033275	0.146258	0.126228		
130001	Tokyo	1/2/2021	1296	43719	2.238342	0.166061	0.136769		
130001	Tokyo	1/3/2021	1328	45047	2.184211	0.161016	0.138759		
130001	Tokyo	1/4/2021	1525	46572	2.153955	0.158141	0.12956		
130001	Tokyo	1/5/2021	1396	47968	1.832021	0.124777	0.105425		
130001	Tokyo	1/6/2021	1365	49333	1.613475	0.098596	0.072958		
130001	Tokyo	1/7/2021	1178	50511	1.287432	0.052071	0.038502		
130001	Tokyo	1/8/2021	1040	51551	0.89578	-0.02268	0.000449		
130001	Tokyo	1/9/2021	963	52514	0.743056	-0.06121	-0.02627	38.06419	
130001	Tokyo	1/10/2021	900	53414	0.677711	-0.08018	-0.05262	19.00422	
130001	Tokyo	1/11/2021	902	54316	0.591475	-0.10823	-0.07391	13.53056	
130001	Tokyo	1/12/2021	1032	55348	0.739255	-0.06227	-0.08077	12.38143	
130001	Tokyo	1/13/2021	900	56248	0.659341	-0.08584	-0.08137	12.28932	
130001	Tokyo	1/14/2021	736	56984	0.624788	-0.09694	-0.08195	12.20204	
130001	Tokyo	1/15/2021	738	57722	0.709615	-0.0707	-0.07321	13.65946	

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130001	Tokyo	1/16/2021	701	58423	0.727934	-0.06545	-0.07975	12.53967	
130001	Tokyo	1/17/2021	598	59021	0.664444	-0.08425	-0.08193	12.20555	
130001	Tokyo	1/18/2021	718	59739	0.796009	-0.04702	-0.0772	12.95353	
130001	Tokyo	1/19/2021	611	60350	0.592054	-0.10803	-0.0763	13.10678	
130001	Tokyo	1/20/2021	551	60901	0.612222	-0.10112	-0.08046	12.42863	
130001	Tokyo	1/21/2021	540	61441	0.733696	-0.06382	-0.07834	12.76494	
130001	Tokyo	1/22/2021	540	61981	0.731707	-0.06438	-0.08164	12.24952	
130001	Tokyo	1/23/2021	443	62424	0.631954	-0.09459	-0.07696	12.99367	
130001	Tokyo	1/24/2021	427	62851	0.714047	-0.06942	-0.069	14.4919	
130001	Tokyo	1/25/2021	511	63362	0.711699	-0.07009	-0.0715	13.98612	
130001	Tokyo	1/26/2021	424	63786	0.693944	-0.0753	-0.07408	13.49943	
130001	Tokyo	1/27/2021	442	64228	0.802178	-0.04543	-0.07117	14.05068	
130001	Tokyo	1/28/2021	364	64592	0.674074	-0.08129	-0.07541	13.26058	
130001	Tokyo	1/29/2021	362	64954	0.67037	-0.08242	-0.07637	13.09372	
130001	Tokyo	1/30/2021	309	65263	0.697517	-0.07424	-0.06955	14.37883	
130001	Tokyo	1/31/2021	264	65527	0.618267	-0.0991	-0.07379	13.55242	
130001	Tokyo	2/1/2021	352	65879	0.688845	-0.07682	-0.07	14.28471	
130001	Tokyo	2/2/2021	371	66250	0.875	-0.02752	-0.06632	15.07771	
130001	Tokyo	2/3/2021	307	66557	0.69457	-0.07512	-0.06303	15.86426	
130001	Tokyo	2/4/2021	279	66836	0.766484	-0.05481	-0.05562	17.98063	
130001	Tokyo	2/5/2021	275	67111	0.759669	-0.05665	-0.05531	18.07985	
130001	Tokyo	2/6/2021	241	67352	0.779935	-0.05122	-0.06703	14.91789	
130001	Tokyo	2/7/2021	210	67562	0.795455	-0.04716	-0.06519	15.33942	
130001	Tokyo	2/8/2021	245	67807	0.696023	-0.07468	-0.06672	14.98702	
130001	Tokyo	2/9/2021	218	68025	0.587601	-0.10958	-0.06415	15.58853	
130001	Tokyo	2/10/2021	227	68252	0.739414	-0.06222	-0.06033	16.57542	
130001	Tokyo	2/11/2021	203	68455	0.727599	-0.06554	-0.05547	18.02643	
130001	Tokyo	2/12/2021	228	68683	0.829091	-0.03863	-0.04731	21.13624	
130001	Tokyo	2/13/2021	214	68897	0.887967	-0.02449	-0.03665	27.28551	
130001	Tokyo	2/14/2021	197	69094	0.938095	-0.01317	-0.033	30.30357	
130001	Tokyo	2/15/2021	225	69319	0.918367	-0.01755	-0.02621	38.15121	
130001	Tokyo	2/16/2021	184	69503	0.844037	-0.03495	-0.02916	34.28965	
130001	Tokyo	2/17/2021	190	69693	0.837004	-0.03667	-0.03176	31.4889	
130001	Tokyo	2/18/2021	186	69879	0.916256	-0.01803	-0.03931	25.44013	
130001	Tokyo	2/19/2021	171	70050	0.75	-0.05929	-0.04337	23.05707	
130001	Tokyo	2/20/2021	174	70224	0.813084	-0.04265	-0.03935	25.41009	
130001	Tokyo	2/21/2021	143	70367	0.725888	-0.06603	-0.03654	27.36941	
130001	Tokyo	2/22/2021	180	70547	0.8	-0.04599	-0.03971	25.18097	
130001	Tokyo	2/23/2021	178	70725	0.967391	-0.00683	-0.03413	29.29563	
130001	Tokyo	2/24/2021	175	70900	0.921053	-0.01695	-0.0364	27.47251	
130001	Tokyo	2/25/2021	153	71053	0.822581	-0.04025	-0.02385	41.93737	

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130001	Tokyo	2/26/2021	155	71208	0.906433	-0.02025	-0.01663	60.13952	
130001	Tokyo	2/27/2021	131	71339	0.752874	-0.0585	-0.01327	75.35911	
130001	Tokyo	2/28/2021	159	71498	1.111888	0.021859	-0.01294	77.27994	
130001	Tokyo	3/1/2021	184	71682	1.022222	0.00453	-0.00097	1033.038	
130001	Tokyo	3/2/2021	193	71875	1.08427	0.016675	0.003943		
130001	Tokyo	3/3/2021	163	72038	0.931429	-0.01464	0.020318		
130001	Tokyo	3/4/2021	189	72227	1.235294	0.043551	0.018464		
130001	Tokyo	3/5/2021	166	72393	1.070968	0.014131	0.019826		
130001	Tokyo	3/6/2021	172	72565	1.312977	0.05612	0.018786		
130001	Tokyo	3/7/2021	166	72731	1.044025	0.008879	0.023962		
130001	Tokyo	3/8/2021	197	72928	1.070652	0.01407	0.01866		
130001	Tokyo	3/9/2021	202	73130	1.046632	0.009393	0.022711		
130001	Tokyo	3/10/2021	181	73311	1.110429	0.021588	0.020147		
130001	Tokyo	3/11/2021	195	73506	1.031746	0.006441	0.019924		
130001	Tokyo	3/12/2021	204	73710	1.228916	0.042484	0.027195		
130001	Tokyo	3/13/2021	207	73917	1.203488	0.038175	0.029289		
130001	Tokyo	3/14/2021	172	74089	1.036145	0.007318	0.029436		
130001	Tokyo	3/15/2021	270	74359	1.370558	0.064966	0.030417		
130001	Tokyo	3/16/2021	227	74586	1.123762	0.024048	0.02974		
130001	Tokyo	3/17/2021	202	74788	1.116022	0.022624	0.027002		
130001	Tokyo	3/18/2021	208	74996	1.066667	0.013301	0.028731		
130001	Tokyo	3/19/2021	245	75241	1.20098	0.037745	0.019011		
130001	Tokyo	3/20/2021	227	75468	1.096618	0.019009	0.019344		
130001	Tokyo	3/21/2021	189	75657	1.098837	0.019425	0.023202		
130001	Tokyo	3/22/2021	266	75923	0.985185	-0.00308	0.026481		
130001	Tokyo	3/23/2021	258	76181	1.136564	0.026383	0.018053		
130001	Tokyo	3/24/2021	257	76438	1.272277	0.04963	0.014147		
130001	Tokyo	3/25/2021	248	76686	1.192308	0.036251	0.018528		
130001	Tokyo	3/26/2021	221	76907	0.902041	-0.02125	0.021511		
130001	Tokyo	3/27/2021	218	77125	0.960352	-0.00834	0.020361		
130001	Tokyo	3/28/2021	241	77366	1.275132	0.050092	0.013838		
130001	Tokyo	3/29/2021	290	77656	1.090226	0.017804	0.015324		
130001	Tokyo	3/30/2021	282	77938	1.093023	0.018332	0.028607		
130001	Tokyo	3/31/2021	262	78200	1.019455	0.003971	0.042359		
130001	Tokyo	4/1/2021	311	78511	1.254032	0.046653	0.039619		
130001	Tokyo	4/2/2021	313	78824	1.41629	0.071731	0.043687		
130001	Tokyo	4/3/2021	334	79158	1.53211	0.087931	0.050311		
130001	Tokyo	4/4/2021	280	79438	1.161826	0.030913	0.058853		
130001	Tokyo	4/5/2021	363	79801	1.251724	0.046274	0.052471		
130001	Tokyo	4/6/2021	386	80187	1.368794	0.064701	0.045429		
130001	Tokyo	4/7/2021	357	80544	1.362595	0.063765	0.032423		

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130001	Tokyo	4/8/2021	314	80858	1.009646	0.001979	0.03723		
130001	Tokyo	4/9/2021	349	81207	1.115016	0.022438	0.03915		
130001	Tokyo	4/10/2021	329	81536	0.98503	-0.00311	0.035453		
130001	Tokyo	4/11/2021	383	81919	1.367857	0.06456	0.037303		
130001	Tokyo	4/12/2021	485	82404	1.336088	0.059716	0.047615		
130001	Tokyo	4/13/2021	466	82870	1.207254	0.038818	0.05422		
130001	Tokyo	4/14/2021	518	83388	1.45098	0.076718	0.064851		
130001	Tokyo	4/15/2021	450	83838	1.433121	0.074166	0.061086		
130001	Tokyo	4/16/2021	487	84325	1.395415	0.068671	0.059209		
130001	Tokyo	4/17/2021	465	84790	1.413374	0.071306	0.059801		
130001	Tokyo	4/18/2021	461	85251	1.203655	0.038203	0.050499		
130001	Tokyo	4/19/2021	608	85859	1.253608	0.046584	0.045053		
130001	Tokyo	4/20/2021	574	86433	1.23176	0.04296	0.03706		
130001	Tokyo	4/21/2021	548	86981	1.057915	0.011603	0.029303		
130001	Tokyo	4/22/2021	536	87517	1.191111	0.036044	0.028173		
130001	Tokyo	4/23/2021	518	88035	1.063655	0.012719	0.024378		
130001	Tokyo	4/24/2021	505	88540	1.086022	0.017008	0.022351		
130001	Tokyo	4/25/2021	534	89074	1.158351	0.030296	0.025855		
130001	Tokyo	4/26/2021	670	89744	1.101974	0.020013	0.021837		
130001	Tokyo	4/27/2021	660	90404	1.149826	0.028774	0.023852		
130001	Tokyo	4/28/2021	653	91057	1.191606	0.03613	0.027224		
130001	Tokyo	4/29/2021	557	91614	1.039179	0.007921	0.023979		
130001	Tokyo	4/30/2021	590	92204	1.138996	0.026823	0.018502		
130001	Tokyo	5/1/2021	615	92819	1.217822	0.040615	0.009077		
130001	Tokyo	5/2/2021	554	93373	1.037453	0.007578	0.002484		
130001	Tokyo	5/3/2021	613	93986	0.914925	-0.01832	0.004412		
130001	Tokyo	5/4/2021	551	94537	0.834848	-0.0372	0.002975		
130001	Tokyo	5/5/2021	622	95159	0.952527	-0.01002	-0.00506	197.4629	
130001	Tokyo	5/6/2021	618	95777	1.109515	0.021419	-0.00952	105.022	
130001	Tokyo	5/7/2021	640	96417	1.084746	0.016765	-0.00983	101.7243	
130001	Tokyo	5/8/2021	570	96987	0.926829	-0.01566	-0.00478	209.0158	
130001	Tokyo	5/9/2021	494	97481	0.891697	-0.02362	-0.0102	98.08031	
130001	Tokyo	5/10/2021	555	98036	0.905383	-0.02049	-0.02614	38.25919	
130001	Tokyo	5/11/2021	546	98582	0.990926	-0.00188	-0.03731	26.80174	
130001	Tokyo	5/12/2021	493	99075	0.792605	-0.0479	-0.0467	21.41168	
130001	Tokyo	5/13/2021	399	99474	0.645631	-0.09017	-0.0509	19.64688	
130001	Tokyo	5/14/2021	475	99949	0.742188	-0.06145	-0.05249	19.05013	
130001	Tokyo	5/15/2021	384	100333	0.673684	-0.08141	-0.05892	16.97325	
130001	Tokyo	5/16/2021	382	100715	0.773279	-0.05299	-0.05801	17.2391	
130001	Tokyo	5/17/2021	476	101191	0.857658	-0.03165	-0.04865	20.55544	
130001	Tokyo	5/18/2021	435	101626	0.796703	-0.04684	-0.04844	20.64234	

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130001	Tokyo	5/19/2021	403	102029	0.817444	-0.04154	-0.03743	26.71349	
130001	Tokyo	5/20/2021	354	102383	0.887218	-0.02466	-0.03049	32.80059	
130001	Tokyo	5/21/2021	355	102738	0.747368	-0.06002	-0.03138	31.86349	
130001	Tokyo	5/22/2021	376	103114	0.979167	-0.00434	-0.02852	35.06593	
130001	Tokyo	5/23/2021	374	103488	0.979058	-0.00436	-0.02431	41.13015	
130001	Tokyo	5/24/2021	396	103884	0.831933	-0.03792	-0.02557	39.11593	
130001	Tokyo	5/25/2021	382	104266	0.878161	-0.02678	-0.02117	47.23042	
130001	Tokyo	5/26/2021	380	104646	0.942928	-0.01211	-0.0313	31.9473	
130001	Tokyo	5/27/2021	301	104947	0.850282	-0.03343	-0.04172	23.9666	
130001	Tokyo	5/28/2021	308	105255	0.867606	-0.02927	-0.04419	22.63036	
130001	Tokyo	5/29/2021	261	105516	0.694149	-0.07524	-0.04807	20.80196	
130001	Tokyo	5/30/2021	257	105773	0.687166	-0.07732	-0.0563	17.76345	
130001	Tokyo	5/31/2021	303	106076	0.765152	-0.05517	-0.0577	17.3306	
130001	Tokyo	6/1/2021	294	106370	0.769634	-0.05397	-0.06161	16.23106	
130001	Tokyo	6/2/2021	271	106641	0.713158	-0.06967	-0.05458	18.32025	
130001	Tokyo	6/3/2021	244	106885	0.810631	-0.04327	-0.04706	21.24799	
130001	Tokyo	6/4/2021	234	107119	0.75974	-0.05663	-0.04369	22.88945	
130001	Tokyo	6/5/2021	230	107349	0.881226	-0.02606	-0.03763	26.57701	
130001	Tokyo	6/6/2021	228	107577	0.88716	-0.02468	-0.02746	36.42083	
130001	Tokyo	6/7/2021	260	107837	0.858086	-0.03154	-0.01986	50.34735	
130001	Tokyo	6/8/2021	278	108115	0.945578	-0.01153	-0.01241	80.59501	
130001	Tokyo	6/9/2021	273	108388	1.00738	0.001515	-0.00353	283.2041	
130001	Tokyo	6/10/2021	256	108644	1.04918	0.009895	-0.00079	1264.199	
130001	Tokyo	6/11/2021	229	108873	0.978632	-0.00445	0.006829		1
130001	Tokyo	6/12/2021	274	109147	1.191304	0.036077	0.010124		2
130001	Tokyo	6/13/2021	222	109369	0.973684	-0.0055	0.010862		3
130001	Tokyo	6/14/2021	289	109658	1.111538	0.021794	0.013423		4
130001	Tokyo	6/15/2021	294	109952	1.057554	0.011533	0.022881		5
130001	Tokyo	6/16/2021	282	110234	1.032967	0.006685	0.02248		6
130001	Tokyo	6/17/2021	293	110527	1.144531	0.027822	0.033938		7
130001	Tokyo	6/18/2021	309	110836	1.349345	0.061751	0.035869		8
130001	Tokyo	6/19/2021	322	111158	1.175182	0.033269	0.043212		9
130001	Tokyo	6/20/2021	319	111477	1.436937	0.074714	0.051116		10
130001	Tokyo	6/21/2021	343	111820	1.186851	0.035306	0.049645		11
130001	Tokyo	6/22/2021	399	112219	1.357143	0.062939	0.046523		12
130001	Tokyo	6/23/2021	381	112600	1.351064	0.062014	0.043372		13
130001	Tokyo	6/24/2021	319	112919	1.088737	0.017522	0.035764		14
130001	Tokyo	6/25/2021	375	113294	1.213592	0.039898	0.038779		15
130001	Tokyo	6/26/2021	340	113634	1.055901	0.011211	0.03372		16
130001	Tokyo	6/27/2021	354	113988	1.109718	0.021456	0.0306		17
130001	Tokyo	6/28/2021	451	114439	1.314869	0.056417	0.035772		18

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130001	Tokyo	6/29/2021	456	114895	1.142857	0.027521	0.037094		19
130001	Tokyo	6/30/2021	463	115358	1.215223	0.040174	0.043811		20
130001	Tokyo	7/1/2021	414	115772	1.297806	0.053725	0.047415		21
130001	Tokyo	7/2/2021	476	116248	1.269333	0.049153	0.045305		22
130001	Tokyo	7/3/2021	451	116699	1.326471	0.058228	0.049503		23
130001	Tokyo	7/4/2021	444	117143	1.254237	0.046687	0.052361		24
130001	Tokyo	7/5/2021	552	117695	1.223947	0.041649	0.05278		25
130001	Tokyo	7/6/2021	601	118296	1.317982	0.056904	0.049033		26
130001	Tokyo	7/7/2021	620	118916	1.339093	0.060179	0.050038		27
130001	Tokyo	7/8/2021	545	119461	1.316425	0.056661	0.053856		28
130001	Tokyo	7/9/2021	532	119993	1.117647	0.022924	0.061604		29
130001	Tokyo	7/10/2021	619	120612	1.372506	0.065259	0.06708		30
130001	Tokyo	7/11/2021	634	121246	1.427928	0.073418	0.069813		31
130001	Tokyo	7/12/2021	879	122125	1.592391	0.095885	0.075557		32
130001	Tokyo	7/13/2021	954	123079	1.587354	0.095232	0.087333		33
130001	Tokyo	7/14/2021	911	123990	1.469355	0.079312	0.088402		34
130001	Tokyo	7/15/2021	872	124862	1.6	0.096867	0.091272		35
130001	Tokyo	7/16/2021	887	125749	1.667293	0.105358	0.089457		36
130001	Tokyo	7/17/2021	881	126630	1.423263	0.072743	0.087061		37
130001	Tokyo	7/18/2021	998	127628	1.574132	0.093508	0.088633		38
130001	Tokyo	7/19/2021	1316	128944	1.497156	0.083175	0.089048		39
130001	Tokyo	7/20/2021	1396	130340	1.463312	0.078463	0.091476		40
130001	Tokyo	7/21/2021	1412	131752	1.549945	0.090317	0.103353		41
130001	Tokyo	7/22/2021	1415	133167	1.622706	0.099772	0.112427		42
130001	Tokyo	7/23/2021	1606	134773	1.810598	0.122352	0.120525		43
130001	Tokyo	7/24/2021	1877	136650	2.130533	0.155888	0.12932		44
130001	Tokyo	7/25/2021	2138	138788	2.142285	0.157021	0.135959		45
130001	Tokyo	7/26/2021	2594	141382	1.971125	0.13986	0.139242		46
130001	Tokyo	7/27/2021	2754	144136	1.972779	0.140033	0.135594		47
130001	Tokyo	7/28/2021	2742	146878	1.941926	0.136784	0.121939		48
130001	Tokyo	7/29/2021	2567	149445	1.814134	0.122754	0.108996		49
130001	Tokyo	7/30/2021	2569	152014	1.599626	0.096819	0.095645		50
130001	Tokyo	7/31/2021	2515	154529	1.339904	0.060304	0.080225		51
130001	Tokyo	8/1/2021	2951	157480	1.380262	0.06642	0.064909		52
130001	Tokyo	8/2/2021	3249	160729	1.252506	0.046402	0.052727		53
130001	Tokyo	8/3/2021	3218	163947	1.168482	0.032091	0.044683		54
130001	Tokyo	8/4/2021	3165	167112	1.154267	0.029568	0.0419		55
130001	Tokyo	8/5/2021	3079	170191	1.199455	0.037483	0.032101		56
130001	Tokyo	8/6/2021	3127	173318	1.217205	0.04051	0.026259		57
130001	Tokyo	8/7/2021	3066	176384	1.219085	0.040828	0.026654		58
130001	Tokyo	8/8/2021	2920	179304	0.989495	-0.00218	0.03076		59

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130001	Tokyo	8/9/2021	3337	182641	1.027085	0.005508	0.039616		60
130001	Tokyo	8/10/2021	3811	186452	1.184276	0.034858	0.05188		61
130001	Tokyo	8/11/2021	4200	189992	1.327014	0.058312	0.060996		62
130001	Tokyo	8/12/2021	4989	193415	1.620331	0.09947	0.072667		63
130001	Tokyo	8/13/2021	5773	196761	1.846178	0.126363	0.068371		64
130001	Tokyo	8/14/2021	5094	199937	1.661448	0.104634	0.067468		65
130001	Tokyo	8/15/2021	4295	203084	1.47089	0.079527	0.066461		66
130001	Tokyo	8/16/2021	2962	206598	0.887624	-0.02457	0.055303		67
130001	Tokyo	8/17/2021	4377	210021	1.148517	0.028539	0.035312		68
130001	Tokyo	8/18/2021	5386	213139	1.282381	0.051261	0.020249		69
130001	Tokyo	8/19/2021	5534	215834	1.10924	0.021367	0.009545		70
130001	Tokyo	8/20/2021	5405	218229	0.936255	-0.01358	0.007431		71
130001	Tokyo	8/21/2021	5074	220377	0.996074	-0.00081	0.002279		72
130001	Tokyo	8/22/2021	4392	222111	1.022584	0.004603	-0.01217	82.15881	
130001	Tokyo	8/23/2021	2447	223634	0.826131	-0.03937	-0.02001	49.97896	
130001	Tokyo	8/24/2021	4220	224356	0.964131	-0.00753	-0.02108	47.43694	
130001	Tokyo	8/25/2021	4228	224494	0.784998	-0.04989	-0.02513	39.78582	
# it should be noted that 20-40% of PCR tests are positive in these days									

Table S1: Calculation of K in Tokyo. By using this table, K can be estimated easily.

	Tokyo	Tottori	Japan	England	US	Iceland	New Zealand
Mean Infectious Time	18	3	11	13	30	6	8
Population	1.4.E+07	5.7.E+05	1.3.E+08	6.7.E+07	3.3.E+08	3.6.E+05	4.9.E+06
Confirmed Cases	1.2.E+05	4.9.E+02	8.1.E+05	5.0.E+06	3.4.E+07	6.6.E+03	2.8.E+03
Death	2.2.E+03	2.0.E+00	1.5.E+04	1.3.E+05	6.1.E+05	2.9.E+01	2.6.E+01
Infection / Population	8.5.E-03	8.6.E-04	6.4.E-03	7.4.E-02	1.0.E-01	1.8.E-02	5.6.E-04
Death / Population	1.6.E-04	3.5.E-06	1.2.E-04	1.9.E-03	1.9.E-03	8.1.E-05	5.3.E-06
Death / Infection	1.9.E-02	4.1.E-03	1.9.E-02	2.6.E-02	1.8.E-02	4.4.E-03	9.4.E-03

Table S2: Numbers and rates of infections and deaths up to 6 July 2021. Exponential notation. The mean infectious time is the median of the series of estimated τ .