Dynamic Network Analysis of COVID-19 with a Latent Pandemic Space Model

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Abstract: In this paper, we propose a latent pandemic space modeling approach for analyzing coronavirus disease 2019 (COVID-19) pandemic data. We developed a pandemic space concept that locates different regions so that their connections can be quantified according to the distances between them. A main feature of the pandemic space is to allow visualization of the pandemic status over time through the connectedness between regions. We applied the latent pandemic space model to dynamic pandemic networks constructed using data of confirmed cases of COVID-19 in 164 countries. We observed the ways in which pandemic risk evolves by tracing changes in the locations of countries within the pandemic space. Empirical results gained through this pandemic space analysis can be used to quantify the effectiveness of lockdowns, travel restrictions, and other measures in regard to reducing transmission risk across countries.

Keywords: coronavirus; network modeling; pandemic nowcasting; pandemic risk visualization; pandemic network analysis; pandemic space

1. Introduction

Since early 2020, many countries have been affected by the novel coronavirus disease 2019 (COVID-19) pandemic. Large numbers of confirmed cases of COVID-19 have been reported in the time since the World Health Organization’s (WHO) declaration of COVID-19 as a global pandemic on 11 March 2020 [1]. By 22 July 2020, there had been 14,780,939 confirmed cases and 608,839 deaths [2]. There is no doubt that the outbreak of COVID-19 has resulted in a serious threat to public health. To stop the spread of the disease and to reduce the risk from the pandemic, different countries have adopted various levels of control measures, including, but not limited to, quarantining, social distancing regulations, travel restrictions, and the locking down of entire cities.

There has been growing interest in research into various aspects of the COVID-19 pandemic, including the ways in which the disease is spreading [3–5]. There is also a lot of ongoing research into the various psychological [6,7], environmental [8,9], economic [10,11], and financial [12,13] impacts of COVID-19 and the policies that have been adopted in response to these. There have been several studies carried out to evaluate the effectiveness and impacts of social distancing measures [14]. The findings of these studies have shown that lockdown measures, in particular, appear to be one of the most effective approaches to limiting the spread of infections [15]. Studies have also shown that the imposition of travel restrictions has been effective in reducing correlations in the numbers of infected people across different countries [16,17]. In this paper, we develop a dynamic pandemic network...
model to evaluate the performances of several major policies in terms of controlling the spread of COVID-19. The policies include travel restrictions, lockdowns, and reopenings, and the adoption of these policies in different countries is investigated using a pandemic space concept. The pandemic space considered here is not an absolute space, which defines a coordinate system with objects inside the space linked under the governance of Euclidean geometry [18]. Rather, the pandemic space refers to the relationship between objects under the context of interest [19]. In our case, to have a numerical representation of similarities in the prevalence of the pandemic between countries, we insert a coordinate system and project our pandemic space onto the Euclidean space. By defining the pandemic space, any similarity in the level of prevalence can be quantified by the distance between countries within the space. In fact, the concept behind pandemic space is similar to the idea of social space that is used in social network analysis, and has various applications in different fields [20–22]. In social network analysis, the tightness of the social relationship between two individuals is assessed by measuring the distance between them in a social space. Typically, the locations of the individuals in a social space are latent variables and have to be estimated using data. Similarly, in our pandemic network analysis, we study the effect of COVID-19 related policies by tracking the distance between countries in a pandemic space.

With reference to the classical SIR model [23], we may describe the manner in which a pandemic evolves as moving through four stages. In stage zero, there are no confirmed cases, or occasionally there might be a few cases in a country. At this stage, the contribution to the pandemic risk is low. Then, during the first stage, the daily number of new confirmed cases increases and accelerates, indicating the beginning of rapid transmission and an increase in the pandemic risk. The second stage begins some time after the initial outbreak, and is characterized by the imposition of control measures against the outbreak and a deceleration in the daily number of new confirmed cases, which peaks during this stage. It is at this stage that the contribution to the pandemic risk is at its highest. Finally, in the third stage, the daily number of new confirmed cases drops. During this stage, the contribution to the pandemic risk is decreasing. As shown in Appendix E, one characteristic between stages is that the correlation of the daily number of new confirmed cases between countries is low when their contributions to the pandemic risk are in different stages. Therefore, when a country has adopted a better policy to control the spread of the disease, that country will enter the next stage faster than other countries. Even if a country has reached a later stage, a loophole in the preventive measure can lead to another wave of rapid transmission.

To express stochastically the effect on the pandemic risk of the stage at which a country finds itself within the pandemic space, we constructed dynamic pandemic networks that link pairs of countries based on whether those two countries are highly correlated. We did this because we knew that those countries that are in the same stage, except when both are in stage zero, are highly correlated. Given a snapshot of the dynamic network at any particular time point, a situation of high connectedness implies that there is similar prevalence, either an upward, a flattened, or a downward trend in the pandemic risk, in most countries. We expect that in a situation like this, there may occur major events related to COVID-19 and that these events may happen either across a group of several countries or right across the whole world. These major events might include, but are not limited to, rapid transmission of the disease across countries at a time when people remain unaware of its infectiousness and severity, simultaneous lockdown restrictions and border closures across a group of countries, and large-scale vaccination. Otherwise, we should see multiple clusters or groups, which would be indicative of a situation in which there are different levels of prevalence or different stages of pandemic evolution in different countries.

By taking this pandemic space perspective, it is possible to detect similarities in the prevalence of each country in contributing to the pandemic risk by measuring the distance between two countries in the pandemic space. When two countries get closer in the pandemic space, we expect that they will exhibit similar patterns of infections (or a higher probability of being linked together in the pandemic network) and that there will be a similar level of prevalence between these two countries. While by using dynamic pandemic
networks, it is possible to detect occasional fluctuations in the linkages between two countries at consecutive time points, we can use the pandemic space to detect fluctuations more accurately and robustly based on the distance between two countries over time. Our model can also estimate similar cases where they may not be linked through the pandemic networks.

There are several ways to measure the distances between countries in the pandemic space. One possible approach is to use the network statistics in pandemic network data [24]. There have been recent research papers published that propose the use of COVID-19 pandemic network data to predict and estimate the pandemic risk across countries [25–28]. The authors of those papers based their conclusions on the study of pandemic risk scores and network connectedness, using network density, the clustering coefficient, and the assortativity coefficient. These statistics are useful for tracking pandemic risk and can also offer an early indication of an acceleration in the number of confirmed cases. Our main contribution in this paper is to construct the pandemic space using a latent pandemic space modeling approach, which provides a view of the pandemic network data that is different from that provided by an analysis that relies on using network statistics.

We first performed latent pandemic space modeling [29] using the pandemic network data to determine a time-dependent location for each country, and then measured the distance between every pair of countries via their coordinates in the pandemic space. This practice of applying latent space modeling to analyze network data can be dated back to the use of multidimensional scaling on sociometric data [30]. Since then, there have been further advancements in the analysis of social network data of both static [31] and dynamic [21] networks. Our proposed pandemic space concept, together with the latent space modeling, enables us to visualize clusters of countries representing different levels or stages of pandemic risk contribution at any time point and keep tracking the risk over time. Furthermore, this latent pandemic space model can estimate the size of an effect on the risk of pandemic based on distance in the pandemic space, and the country-specific effect of the distance on the probability of being linked.

The remainder of the paper proceeds as follows. Section 2 describes the statistical methods that we have used to construct the pandemic space. Section 3 gives the results of our analysis, while Section 4 provides a discussion of results. Finally, Section 5 offers some conclusions.

2. Materials and Methods

2.1. Construction of Pandemic Network

As mentioned in the introduction, we built the pandemic space from dynamic pandemic networks using latent pandemic space modeling. The dynamic pandemic networks consisted of 164 countries, visualized as nodes in the networks. We list the details of the 164 countries, including the total infected numbers in those countries as of 22 July 2020, in Appendix D. The edges among the countries in the pandemic networks change every day in our study period. With reference to the number of confirmed cases in the WHO’s situation reports [32], we linked a pair of countries by an edge in day \( t \) if, for the last 14 days (i.e., from day \( t - 13 \) to day \( t \)), the correlation between the daily change in square root of the cumulative number of cases was larger than 0.5 [25–27]. The study period was from 21 January 2020 to 22 July 2020. Following this [16,25], we made use of a moving-window scheme to calculate the 14-day historical correlation. We constructed the network starting from the fourteenth day onward. In the statistical estimation, we regarded the fourteenth day in the data (i.e., 4 February 2020) as day 1 in our network. The data were sufficient for us to create time-varying pandemic networks of \( T = 170 \) days.

Denote \( C_{it} \) as the number of confirmed cases of COVID-19 in country \( i \) on day \( t \), where \( i = 1, \ldots, n \), and \( t = -12, \ldots, T \). We performed square root transformation to the number of cases in country \( i \) from day \( t - 1 \) to day \( t \) before calculating the daily increment of cases, i.e.,

\[
D_{it} = \sqrt{C_{it}} - \sqrt{C_{i(t-1)}}.
\]
to make the counts more stable statistically [26,27,33]. Then, to determine the growth pattern between country \( i \) and \( j \), we computed the 14-day historical correlation between \( D_{it} \) and \( D_{jt} \) for \( i \neq j, i, j = 1, \ldots, n, \) and \( t = 1, \ldots, T \), i.e.,

\[
\rho_{ijt} = \frac{\sum_{k=1}^{14} (D_{it(t-k+1)} - \overline{D}_{it})(D_{jt(t-k+1)} - \overline{D}_{jt})}{\sqrt{\sum_{k=1}^{14} (D_{it(t-k+1)} - \overline{D}_{it})^2} \sqrt{\sum_{k=1}^{14} (D_{jt(t-k+1)} - \overline{D}_{jt})^2}}
\]

(2)

where \( \overline{D}_{it} = \sum_{k=1}^{14} D_{it(t-k+1)} \) is the 14-day moving average. Finally, for the pandemic network at day \( t \), we assigned the \((i, j)\) entry of the adjacency matrix \( Y_t \) to be 1 if the historical correlation \( \rho_{ijt} \) was greater than 0.5 [27], and 0 otherwise. The collection of all adjacency matrices formed the dynamic network of pandemic \( Y \). In case when the correlation was undefined, we followed the approach in Appendix A to determine the corresponding value in \( Y_t \).

### 2.2. Pandemic Space via Latent Space Modeling

A novelty of the latent space modeling approach is its ability to construct a pandemic space from which we can study the tightness between the pandemic situations in different countries over time graphically. Assume that each country has a latent position on the \( s \)-dimensional pandemic space, where \( s = 2 \) in our case for the sake of visualization. Each country moves in the pandemic space every day to reflect the change in pandemic risk. If two countries are close to each other, the probability that they will have co-movement in country moves in the pandemic space every day to reflect the change in pandemic risk. If

\[
p(\pi|\tau^2) := \prod_{i=1}^{n} N(Z_{it}|0, \tau^2 I_s).
\]

Furthermore, we assume that the transition of a latent position in the pandemic space from \( t-1 \) to \( t \) is also normally distributed, with the joint density

\[
p(Z_t|Z_{t-1}, \sigma^2) := \prod_{i=1}^{n} N(Z_{it}|Z_{it(t-1)}, \sigma^2 I_s),
\]

for \( t = 2, 3, \ldots, T \), where \( I_s \) is the \( s \times s \) identity matrix and \( N(z|\mu, \Sigma) \) is the (multivariate) normal density evaluated at \( z \) with mean \( \mu \) and covariance matrix \( \Sigma \). The parameter \( \tau^2 \) is involved in the calculation of the average initial distance, \( E[|Z_{i1} - Z_{j1}|] \), in the pandemic space between countries on day 1. Since the distance \( |Z_{i1} - Z_{j1}| \) is involved in specifying the distribution of the daily transition in the latent position, \( |Z_{it} - Z_{jt(t-1)}| \). It can be shown that \( |Z_{it} - Z_{jt(t-1)}| \) is distributed as \( \sigma \sqrt{\chi^2_2} \) and has a mean of \( \sigma \sqrt{nT/2} \). This mean helps us to understand how fast a country contribution of pandemic risk can build up or fall off due to the changes in latent positions. If this mean is large, we expect that two countries separated by long distance on the pandemic space might get closer over a short period of time.
To connect the latent position to the pandemic network, we first re-write the joint density of the adjacency matrix $Y_t$ at day $t$ to be

$$P(Y_t | Z_t) = \prod_{i<j} P(y_{ijt} = 1 | Z_t)^{y_{ijt}} P(y_{ijt} = 0 | Z_t)^{1-y_{ijt}}$$

$$= \prod_{i<j} p(y_{ij}),$$

where

$$p(y_{ij}) = \frac{\exp(y_{ij}\eta_{ij})}{1 + \exp(y_{ij})}$$

also depends on $\eta_{ij} = \log P(y_{ij} = 1 | Z_t) - \log P(y_{ij} = 0 | Z_t)$. Then, we model $\eta_{ij}$, the logit of the conditional probability, with

$$\eta_{ij} = \beta \left( 2 - d_{ij} \left( \frac{1}{r_i} + \frac{1}{r_j} \right) \right), \quad (3)$$

where the parameters carry the following meaning:

- $d_{ij} = ||Z_{it} - Z_{jt}||$, the distance between two countries in the pandemic space;
- $\beta > 0$, the overall effect of distance on the link probability $P(y_{ij})$ and the associated pandemic risk;
- $r_i > 0$ (with constraint $\sum r_i = 1$), can be interpreted as the country-specific effect of the distance on the link probability.

The parameters $r_i$ and $r_j$ are two factors based on country $i$ and $j$ respectively to adjust the effect of the distance $d_{ij}$ on the logit of the link probability $\eta_{ij}$. Comparing two pairs of countries, $i$ and $j$, and $i'$ and $j'$, if the ratio of the country-specific risk factors of country $i$ to country $i'$ is the same as the ratio between country $j$ to country $j'$, i.e., $r_i/r_{i'} = r_j/r_{j'} = k$ for some $k > 1$, these two pairs have the same probability of being linked when $d_{ij} = kd_{ij'}$. In other words, even though the distance between country $i$ and $j$ is $k$ times of the distance between country $i'$ and $j'$, their high country-specific risk factors counterbalance the distancing effect, leading to the same link probability, which implies a similar level of prevalence risk between country $i$ and $j$ and between country $i'$ and $j'$. An application of the country-specific risk is that when the distance between country $i$ and $j$ is equal to the harmonic mean of their corresponding country-specific risk, i.e., $d_{ij} = 2/(r_i^{-1} + r_j^{-1})$, these two countries have a probability 0.5 of being linked together. Based on $r_i$ and $r_j$, it is useful to determine a cut-off distance to classify countries $i$ and $j$ into a cluster, or a group, based on the possibility of their being in the same stage in contributing to the pandemic risk. With the latent space location of country $i$ as the center and $r_i$ as the radius, we can draw a circle around country $i$. Graphically, we can determine whether a pair of countries, say country $i$ and $j$, have a probability of being linked together exceeding 0.5 by considering whether their pandemic space locations lie inside the circles for country $i$ and $j$ simultaneously.

Parameter $\beta$ works like a regression coefficient to measure the effect of the distance $d_{ij}$ on the logit link $\eta_{ij}$. It also determines the maximum probability for two countries being linked together. The maximum is attained when two countries coincide in the pandemic space, that is, when $d_{ij} = 0$. In this case, the conditional probability is $\exp(2\beta)/(1 + \exp(2\beta))$, which is strictly increasing and reaches 1 when $\beta \to \infty$. Therefore, in the pandemic space, even if two countries are separated by a distance of zero, this does not imply that there must be a link between them, as $\beta$ is finite.

One remark on the position of countries on the pandemic space is that any distance-preserving transformation in the pandemic space gives an identical value of $\eta_{ij}$. We followed the approach in Appendix B to handle the identifiability issue.
2.3. Estimation of Parameters

We adopted Bayesian methods for estimating the unknown parameters $\tau^2$, $\sigma^2$, $r_i$, and $\beta$ in the latent space model. First of all, we assigned a normal prior for $\beta$, an inverse gamma prior for $\tau^2$ and $\sigma^2$, and a Dirichlet prior for $r$. All the priors were set to be uninformative to allow variability. However, the full posterior is highly complex and intractable. Therefore, we performed Markov chain Monte Carlo (MCMC) sampling with a total of 200,000 iterates to obtain the posterior estimate. This approach has been widely adopted in many previous Bayesian analyses [29,34–40]. All full conditional densities required for MCMC are listed in Appendix C.

Denote $\zeta^{(l)}$ as the parameter $\zeta$, which is one of the parameters to be estimated in the $l$-th iteration, and $\hat{\zeta}^{(l)}$ as the proposed value in the $l$-th iteration, which was randomly drawn from the proposal distribution with density $f_\zeta(\cdot; \theta_\zeta)$, where $\theta_\zeta$ governs the step size of the proposal. At the beginning of Markov chain Monte Carlo (MCMC), we set an initial value $\hat{\zeta}^{(0)}$ for each parameter. We also set this value to be the prior mean. In each iteration, we sequentially sampled all unknown parameters from proposal distribution. In particular, during the $l+1$-th iteration, we

1. Draw $\beta$ from $N(\beta^{(l)}, \theta_\beta)$ with truncation on the non-positive values.
2. Draw $\log \tau^2$ from $N(\log \tau^{(l)}, \theta_{\log \tau^2})$.
3. Draw $\log \sigma^2$ from $N(\log \sigma^{(l)}, \theta_{\log \sigma^2})$.
4. Draw $r$ from Dirichlet distribution with concentration parameter $\theta_r r^{(l)}$.
5. Draw $Z_{it}$ from $N(Z_{it}^{(l)}, \theta_{Z_{it}} I_s)$, for $i = 1, \ldots, n$, and $t = 1, \ldots, T$.

In each of the above steps, we calculate the acceptance probability

$$a(\zeta^{(l+1)}, \zeta^{(l)}) = \min \left\{ 1, \frac{\pi(\zeta^{(l+1)})f_\zeta(\zeta^{(l+1)})}{\pi(\zeta^{(l)})f_\zeta(\zeta^{(l)})} \right\},$$

where $\pi(\zeta)$ is the posterior density of $\zeta$, to decide whether to accept the proposed value $\hat{\zeta}^{(l+1)}$ as the next current value, i.e., setting $\zeta^{(l+1)} = \hat{\zeta}^{(l+1)}$. If not, we reject the proposed value and keep the current value, i.e., setting $\zeta^{(l+1)} = \zeta^{(l)}$.

We also implemented the following MCMC adaptations to improve the convergence of results [41,42]. In the first stage, which consists of the first 5% of iterates, we allowed the Markov chain to move in order to find the best initial position. In the second stage, we controlled the acceptance rate by adjusting the step size (i.e. $\theta_\zeta$) until we completed the first 30% of iterates. After the MCMC adaptations, we let the chain burn-in by neither changing the step size nor including them into our sample for the next 20% of iterates. Finally, after the burn-in period, we took the last 50% of iterates to estimate the posterior. In order to reduce the autocorrelation and speed up the convergence, we recorded one observation for every 100 iterations. Moreover, starting from the 10% of total iterates, every time after we recorded an observation, we calculated the effective sample size, which was measured by the reciprocal of autocorrelation in the latest 100 iterates, and used it to determine the probability for each parameter to be sampled in the next iteration. This probability was fixed after we completed 30% of total iterates. In Figure 1, we provide a plot of the posterior to show the convergence. The plot on the left-hand side shows the posterior in each MCMC iteration. The plot on the right-hand side focuses on the post-burn-in period, with which our posterior estimates and standard deviation were calculated.
3. Results

In this section, we present the statistical results from the latent pandemic space model. As mentioned in previous sections, we linked two countries together and believed that they had a similar level of prevalence if the growth pattern of their confirmed COVID-19 cases showed a certain extent of similarity. Using a 14-day moving-window scheme allowed us to gather enough observations to calculate moving correlations, and also reduce fluctuation due to a single-day spike in the data. The WHO’s situation report records the daily number of confirmed cases since 21 January 2020. As we needed 14 days data to calculate the correlation, the study period of our pandemic network was from 4 February 2020 to 22 July 2020.

Before analyzing the modeling results, we followed [25] to present Figure 2, which shows the pandemic network on the eighteenth day of each month. We can see that in February, there are only a few edges. One month later, we see that there are many more edges in the pandemic network, indicating that more countries are experiencing similar levels of prevalence. If we also take into account the daily number of confirmed cases at that time, it begins to appear that there were major events that accelerated the pandemic risk during that period. After that, although the number of edges in April to June was fewer than in March, indicating a diverging scenario in the daily number of confirmed cases, most countries had at least one link to another country, showing that the pandemic risk (between countries, or community transmission) may be lower but had not disappeared. For July, we again found an increment in the number of edges. We believe that this should be interpreted as signaling an upcoming change in the pandemic risk. This signal can also be detected in the preparedness risk score [25].

In our estimated pandemic space, we can visualize the above changes in network connectedness in terms of the distances between countries. A shorter distance implies a higher probability of connection and thus a synchronized change in the prevalence of cross-border or community transmission in two countries. Figure 3 shows the pandemic space on the eighteenth day in each month with the top five countries having the highest number of confirmed cases of COVID-19. As of 22 July 2020, the five countries which contributed around 60% of the total number of infections were the United States of America, Brazil, India, the Russian Federation, and South Africa [2]. In Figure 3, the radii of those circles surrounding the country names represent the country-specific effects. Depending on whether the distance between two countries is smaller than or larger than both radii of their corresponding circles, we can determine whether the probability of a link between them is more than or less than 50%. In particular, if two countries have the same country-specific effect, and if the center of one circle lies on the boundary of the second circle, and vise
versa, the probability of the two countries being linked is exactly 50%. Since all circles have similar radii in our case, we can simply consider whether their centers are included in both circles in order to classify whether or not there is a similar level of prevalence between two countries. Therefore, excluding those marginal cases, among the top five countries in the figure, USA–India, USA–South Africa, USA–Russia, Brazil–Russia, Brazil–South Africa, and Russia–South Africa had potentially similar levels of prevalence on 18 March 2020; and USA–India, India–South Africa, and Brazil–South Africa had potentially similar levels of prevalence on 18 July 2020.

Figure 2. Snapshots of the pandemic network on the eighteenth day of each month from February to July 2020.
Figure 3. Snapshots of the latent positions of those countries that were in the top 5 list in terms of the cumulative number of confirmed COVID-19 cases on the eighteenth day of each month from February to July 2020. Inclusion of centers in two circles implies that the corresponding pair of countries had a similar level of prevalence, either because of possible transmission between the countries or because there was a common trend in the severity of community transmission. The line segment between two countries refers to a link between them on that day in the pandemic network. To view an animation of the changes in the latent positions in the pandemic space, please go to “Top 5 list” (https://drive.google.com/file/d/18ENvRXQIvaWJFSyBregzB_sLQ3Ewm7P7/view?usp=sharing), or “All countries” (https://drive.google.com/file/d/1a0oWJJm47N9cQExg02_RhpEWIcQu56n/view?usp=sharing).
Figure 4 studies the pandemic risk between countries. We again selected those countries which were in the top five list in terms of the cumulative number of confirmed COVID-19 cases and produced boxplots of the distance between each pair of countries over time. To construct the boxplots, we calculated the distance according to the latent coordinates in the pandemic space, a total of 10 distances from the top five countries in each day. In Figure 4, we categorize the countries by continent according to the WHO’s classification, which has also been implemented in the literature on pandemic network research [25]. We created daily boxplots for the five regions—Africa, the Americas, Asia, the Eastern Mediterranean, and Europe—and we aggregated the top five countries in each of the five regions and labeled them as “Top 5”. In general, it is unlikely that all countries would be separated by small distances, as this would imply a high degree of similarity in prevalence between all countries. However, if this is the case, we will see that the boxplots are short and located at a low position. Based on the variability and maximum distances, we have a conservative measure of classifying the periods of high pandemic risk based on the network connectedness. From the “Top 5” graph for the whole world, the pandemic emerges in February 2020, when the median distances are large. The situation seems to get worse in late February 2020, when the median distance drops more than 50% in a week. In fact, the highest levels of connectedness are mid-March and late June to mid-July 2020, at the times of the two main waves of the pandemic. In addition to the two periods previously identified, there are also two other periods of high connectedness or potentially high pandemic risk in the five regions: one in Europe during mid-May 2020, and the other in the Americas during mid-June 2020.

Besides intra-continental pandemic risk, we also studied inter-continental risk. In Figure 5, we calculated for each day the median distances between clusters of the top five countries from each continent. For example, if country A belongs to Africa, and country B belongs to the Americas, we include the distance between A and B when we calculate the median for the Africa-Americas distance (i.e., the second plot in the first row of the matrix plot in Figure 5). We observe that the distances in all plots decrease from around 0.125 in late February to 0.025 in mid-March, showing that the “inter-continental risk” builds up quickly in this period. The distances stay in the range of 0.025 to 0.05 for most of the time after March. For the plots among Africa, the Americas, and Asia, the minimum distance over the whole period of study is attained in mid-March. The distance between Europe and the Americas is relatively small in early June and early July. From Figure 5, we cannot observe any sign that the pandemic is coming to an end as the distances are mostly below 0.05 till mid-July 2020.

Table 1 summarizes the results with the estimate (posterior mean) and the standard deviation (SD) of each parameter in our pandemic space model. The parameter \( \beta \) determines the highest probability of linking two countries when they have the same location, or \( d_{ijt} = 0 \). Based on the estimate of \( \beta \), the highest probability was 72.40%. The parameter \( \tau \) and \( \sigma \) are the standard deviations of latent coordinates on the first day, and of the daily transition in coordinates, respectively. Therefore, in this pandemic space, we can estimate the mean distance between countries on the first day by \( \tau \sqrt{\pi} = 0.1504 \), and the average distance each country travels in one day by \( \sigma \sqrt{\pi}/2 = 0.0100 \). Consistent with the results shown in Figure 4, the initial pandemic risk between countries is small. Potentially high pandemic risk (i.e., small distance) can be seen in two weeks from mid-February, with reference to Figure 5, such that the median of distances is not greater than 0.05 for most of the time. From the latent space modeling, we can deduce that the COVID-19 pandemic evolves quickly and that the outbreak situation can become worse within a matter of just two weeks.

The variable \( \text{invr} \) is the mean of the inverse of country-specific risk factor, \( r_i^{-1} \). Based on our model assumptions, the sum of all country-specific risk factors is fixed to be 1 for the sake of identifiability. If \( \text{invr} \) attains its minimum value, which is the number of countries, every country has the same probability of linking to another country provided that their distances are the same. On the other hand, countries having larger \( r_i \) will have a relatively
higher probability of linking to another country. In this study, the estimate of $invr$ is close to the minimum, implying that there is no country dominating the contribution to the pandemic risk. From another perspective, if we compare the country-specific risk factor $r_i$, Serbia and New Zealand have the minimum and maximum country-specific risk at 0.0057 and 0.0066, respectively. The minimum and maximum are not far from the mean value of country-specific risk of 0.0061. We list the country-specific risk factor for each of the 164 countries in Appendix D.

**Figure 4.** Time series of the boxplots of the distance among countries, which are in the top 5 in terms of the cumulative number of confirmed COVID-19 cases in the whole world or in each of the five continents.
4. Discussion

Although the exact date depends on each country, most countries set up their travel restriction policies by 31 March 2020 [43]. Therefore, we set 31 March 2020 as a cutoff date for further discussion. Prior to travel restrictions coming into effect, a traveler who was an asymptomatic COVID-19 carrier could transmit the disease to other people in different countries. After the cutoff date, most incoming air traffic was prohibited and many lockdown policies were put in place. The main focus switched to the question of when a suitable time to reopen would be, and another focus was which countries had relatively smaller contributions to the pandemic risk.
In Figure 3, we notice that for 18 March 2020, the first period of increasing pandemic risk observed in Figure 4, there were six pairs of countries out of a total of 10 that had similar levels of prevalence. This result coheres with the rapid increase in the number of edges in the pandemic network. In fact, referring to the literature [27,44], the number of confirmed cases and the network connectedness accelerated during this period. We believe that the importation and exportation risk of COVID-19 cases via air travel poses a risk in the transmission of COVID-19 [45]. Within one month after the declaration of the COVID-19 pandemic, by which time most countries had imposed travel restriction, we see from Figures 3–5 the effectiveness of such measures in increasing the distance between countries in the pandemic space compared to the situation in March 2020.

Although none of the 10 country pairs had similar levels of prevalence until mid-July 2020, the distances in the 10 country pairs were not as large as they appear to have been in February 2020. The pandemic risk still existed and had the potential to lead to another wave of rapid transmission if travel restrictions were lifted [46]. We also see that on 18 July 2020, there was one edge between USA and India, and one edge between India and South Africa. The close distances between them put those countries into the cluster of similar prevalence, together with the Brazil–South Africa pair, which had no link on that day. Instead of importation and exportation, we believe that the reason behind this closing distance was the partial re-opening of the two countries’ economies [47] and the permitting of inter-state air travel [48]. In fact, these measures may also be considered the reason behind the period of increased risk in Europe during mid-May 2020 and in the Americas during mid-June 2020. Figure 5 provides another view from the inter-continental perspective, showing that while most of the restrictions on international air travel remained valid, the inter-continental distances in July 2020 stayed in the low-value range (below 0.05), implying that the similarity in the levels of prevalence across continents was still quite high in mid-July 2020.

To investigate the effectiveness of lockdown policy, we refer to the “Top 5 in Europe” plot in Figure 4, as most of the European countries experienced a lockdown in late March to late April 2020. Between mid-March and late March 2020, the median distance stayed small and the boxplots are short, indicating that the impact from the first wave of transmission lasted for at least half a month before the lockdown. After two weeks of lockdown (i.e., by around mid-April 2020) the median distance increased to a relatively high level, and for the same time period in the graph, the boxplots become taller. Similarity in the levels of prevalence between countries is weakened as the implementation of social distancing measures restricts opportunities for transmission of the disease, though it should be noted that the effectiveness of measures against the transmission of COVID-19 varies across countries. We also discovered that the median distances of the boxplot dropped again after early May 2020. However, we found that the daily number of new cases was decreasing at that time, indicating that they had a decreasing contribution to pandemic risk. Around that period of time, most European countries began to re-open in a stepwise manner [49,50]. We believe that the imposition of a lockdown is effective in reducing the pandemic risk, as the distances among countries during periods of lockdown were larger than those before the lockdown in the pandemic space. However, by beginning the process of reopening at a time when the daily number of new cases has not yet reached a stable low value, the distances among countries may decrease again, together with further waves of mass transmission.

5. Conclusions

In this paper, we developed the pandemic space approach, which was built upon the concept of dynamic latent space modeling, to explore the pandemic risk across countries around the world. Using the pandemic space, we investigated and provided hints on whether the various control measures adopted in different countries, including travel restrictions and lockdowns, were effective at reducing the pandemic risk or not. We first constructed the pandemic network using 14-day data in a moving window scheme. We linked two countries together if their correlation in terms of numbers of infections was
high. We followed this rule to build a daily network from 4 February 2020 to 22 July 2020. Then, based on the pandemic network, we performed latent space modeling to produce our pandemic space.

The pandemic space allowed us to identify country pairs that had potentially high transmission risks in some periods, or a synchronized increase in the severity of community transmission. We also explained the different pandemic periods using the maximum distances and the height from time series boxplots of distances. We also investigated the inter-continental risk with the time series of the median distance between each pair of continents. Moreover, using the parameters obtained from our estimation, we examined the highest probability of two countries being linked, the country-specific effect, the initial average distance, and the speed to build up the pandemic risk. As in other papers [28,51–53], using this pandemic space analysis, we concluded that both lockdown and travel restrictions are effective at reducing the pandemic risk across countries. Nevertheless, these two measures, and probably also other control measures, are not sufficient to wipe out the risk of pandemic across countries.

Future works might include considerations of exogenous variables, such as statistics related to travel between countries, the number of people who have received at least one vaccine dose, and lockdown activities, so as to make it possible to conduct Bayesian predictions about similarities in levels of prevalence between countries and the pandemic risk. It would also be interesting to consider pandemic spaces with higher dimensions and interpretations of the latent dimensions in the pandemic space in future research.

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Abbreviations
The following abbreviations are used in this paper:

Eastern Med. Eastern Mediterranean

Appendix A. Handling Missing Values
To allow every country to have a location in the pandemic space on each day, we impute those missing links between countries as empty; i.e., \( y_{ijt} = 0 \). In the pandemic network, a pair of countries has a missing link when the correlation at time \( t \) is undefined—i.e., there have been no confirmed COVID-19 cases in the previous 14 days for at least one country in that pair. It is reasonable to claim that the pandemic risk between these countries is negligible when a country has had no new cases in 14 consecutive days.

Appendix B. Identifiability of Latent Position
Since the \( \eta_{ijt} \) in Equation (3) depends on the distance between countries in the pandemic space instead of their coordinates, if we hold other variables unchanged, any distance preserving transformation in the pandemic space, like translation, reflection and rotation, gives an identical value of \( \eta_{ijt} \). To handle the identifiability issue on latent positions, we use the Procrustes transformation [54] to translate and rotate the whole space at time \( t \) such...
that the sum of squared distance traveled by all countries from $t - 1$ to $t$, and from $t$ to $t + 1$ is minimized; i.e.,

$$\min_{Z_i} \sum_{i=1}^{n} \|Z_{it} - Z_{i(t-1)}\|^2 + \|Z_{it} - Z_{it+1}\|^2.$$

(A1)

**Appendix C. Posterior Distribution**

We denote $\phi$ as all parameters, including $\beta$, $\tau^2$, $\sigma^2$, $r_i$, and $Z_{it}$, which are not specified as arguments but appearing in the following posterior density function. We first write the likelihood of $Y$, as a product of conditional distribution:

$$P(Y|\phi) = \prod_{t=1}^{T} \prod_{i \neq j} p(y_{ijt}) = \prod_{t=1}^{T} \prod_{i} \sum_{i=1}^{n} \|Z_{it} - Z_{i(t-1)}\|^2$$

Then, we derive the following posterior densities:

- The joint posterior density of $Z_{it}$ is

$$\pi(Z_{it}|Y, \phi) \propto \prod_{j \neq i} p(y_{ijt}) \cdot N(Z_{it}|Z_{i(t-1)}, \sigma^2 I_s),$$

for $t = 1, \ldots, T$, where $Z_{0i}$ is a zero vector of length $s$, $Z_{i(T+1)} = Z_{iT}$, and

$$\sigma^2_{(t)} = \begin{cases} 
\sigma^2 & \text{if } t = 2, \ldots, T, \\
\tau^2 & \text{if } t = 1, \\
0 & \text{otherwise}.
\end{cases}$$

- The posterior densities of $\tau^2$ and $\sigma^2$ are

$$\pi(\tau^2|Y, \phi) = IG \left( \nu_{\tau^2} + \frac{1}{2} s n, \xi_{\tau^2} + \frac{1}{2} \sum_{i=1}^{n} \|Z_{it}\|^2 \right)$$

(A2)

and

$$\pi(\sigma^2|Y, \phi) = IG \left( \nu_{\sigma^2} + \frac{1}{2} s n (T - 1), \xi_{\sigma^2} + \frac{1}{2} \sum_{i=1}^{n} \sum_{t=2}^{T} \|Z_{it} - Z_{i(t-1)}\|^2 \right)$$

(A3)

respectively, where $\nu_{\tau^2}$ and $\nu_{\sigma^2}$ are the shape parameters in the inverse gamma prior, and $\xi_{\tau^2}$ and $\xi_{\sigma^2}$ are the scale parameters of the inverse gamma prior.

- The posterior density of $\beta$ is

$$\pi(\beta|Y, \phi) \propto \prod_{t=1}^{T} \prod_{i \neq j} p(y_{ijt}) \cdot N(\beta|\nu_{\beta}, \xi_{\beta}),$$

(A4)

where $\nu_{\beta}$ and $\xi_{\beta}$ are the mean and variance respectively of the normal prior.

- The joint posterior density of $r = (r_1, \ldots, r_n)$ is

$$\pi(r|Y, \phi) \propto \prod_{t=1}^{T} \prod_{i \neq j} p(y_{ijt}) \cdot \prod_{i=1}^{n} a_i^{r_i - 1},$$

(A5)

where $a_i$, for $i = 1, \ldots, n$, are the concentration parameters of the Dirichlet prior.

**Appendix D. Table of Countries**
Table A1. A list of the 164 countries considered in this study, their total number of cases as of 22 July 2020, their corresponding continents, their ranks in their continents, and their estimated country-specific risks. Countries are listed in descending order of the total number of cases.

| Country Name                  | Total Number of Cases | Continent       | Rank in Continent | Country-Specific Risk Factor |
|-------------------------------|-----------------------|-----------------|-------------------|------------------------------|
| United States of America      | 3,805,524             | Americas        | 1                 | 0.0059                       |
| Brazil                        | 2,118,646             | Americas        | 2                 | 0.0062                       |
| India                         | 1,192,915             | Asia            | 1                 | 0.0064                       |
| Russian Federation            | 789,190               | Europe          | 1                 | 0.0060                       |
| South Africa                  | 381,798               | Africa          | 1                 | 0.0061                       |
| Peru                          | 357,681               | Americas        | 3                 | 0.0060                       |
| Mexico                        | 349,396               | Americas        | 4                 | 0.0061                       |
| Chile                         | 334,683               | Americas        | 5                 | 0.0060                       |
| The United Kingdom            | 296,912               | Europe          | 2                 | 0.0062                       |
| Iran                          | 278,827               | Eastern Med.    | 1                 | 0.0060                       |
| Spain                         | 278,528               | Europe          | 3                 | 0.0059                       |
| Pakistan                      | 267,428               | Eastern Med.    | 2                 | 0.0063                       |
| Saudi Arabia                  | 255,825               | Eastern Med.    | 3                 | 0.0058                       |
| Italy                         | 244,752               | Europe          | 4                 | 0.0060                       |
| Turkey                        | 221,500               | Europe          | 5                 | 0.0061                       |
| Bangladesh                    | 210,510               | Asia            | 2                 | 0.0060                       |
| Colombia                      | 202,005               | Americas        | 6                 | 0.0061                       |
| Germany                       | 166,511               | Europe          | 6                 | 0.0059                       |
| Argentina                     | 130,774               | Americas        | 7                 | 0.0059                       |
| Canada                        | 111,124               | Americas        | 8                 | 0.0062                       |
| Qatar                         | 107,430               | Eastern Med.    | 4                 | 0.0063                       |
| Iraq                          | 97,159                | Eastern Med.    | 5                 | 0.0061                       |
| Indonesia                     | 89,869                | Asia            | 3                 | 0.0060                       |
| Egypt                         | 89,078                | Eastern Med.    | 6                 | 0.0061                       |
| Kazakhstan                    | 76,799                | Europe          | 8                 | 0.0063                       |
| Ecuador                       | 76,217                | Americas        | 9                 | 0.0063                       |
| Sweden                        | 74,766                | Europe          | 9                 | 0.0061                       |
| Philippines                   | 70,764                | Asia            | 4                 | 0.0064                       |
| Oman                          | 69,887                | Eastern Med.    | 7                 | 0.0059                       |
| Belarus                       | 66,348                | Europe          | 10                | 0.0065                       |
| Belgium                       | 65,093                | Europe          | 11                | 0.0062                       |
| Ukraine                       | 60,995                | Europe          | 12                | 0.0060                       |
| Bolivia                       | 60,991                | Americas        | 10                | 0.0061                       |
| Kuwait                        | 60,434                | Eastern Med.    | 8                 | 0.0063                       |
| United Arab Emirates          | 57,498                | Eastern Med.    | 9                 | 0.0057                       |
| Dominican Republic            | 54,797                | Americas        | 11                | 0.0060                       |
| Panama                        | 54,426                | Americas        | 12                | 0.0062                       |
| Israel                        | 52,431                | Europe          | 13                | 0.0061                       |
| Netherlands                   | 52,073                | Europe          | 14                | 0.0059                       |
| Portugal                      | 48,898                | Europe          | 15                | 0.0061                       |
| Singapore                     | 48,434                | Asia            | 5                 | 0.0061                       |
| Poland                        | 40,782                | Europe          | 16                | 0.0060                       |
| Guatemala                     | 40,229                | Americas        | 13                | 0.0061                       |
| Romania                       | 39,133                | Europe          | 17                | 0.0062                       |
| Nigeria                       | 37,801                | Africa          | 2                  | 0.0061                       |
| Bahrain                       | 37,316                | Eastern Med.    | 10                | 0.0061                       |
| Afghanistan                   | 35,813                | Eastern Med.    | 11                | 0.0061                       |
| Armenia                       | 35,693                | Europe          | 18                | 0.0062                       |
| Country Name                  | Total Number of Cases | Continent | Rank in Continent | Country-Specific Risk Factor |
|-------------------------------|-----------------------|-----------|-------------------|------------------------------|
| Honduras                     | 34,611                | Americas  | 14                | 0.0061                       |
| Switzerland                  | 33,655                | Europe    | 19                | 0.0060                       |
| Kyrgyzstan                   | 29,359                | Europe    | 20                | 0.0059                       |
| Ghana                        | 28,989                | Africa    | 3                 | 0.0062                       |
| Azerbaijan                   | 28,242                | Europe    | 21                | 0.0060                       |
| Japan                        | 26,303                | Asia      | 6                 | 0.0057                       |
| Ireland                      | 25,802                | Europe    | 22                | 0.0060                       |
| Algeria                      | 24,278                | Africa    | 4                 | 0.0064                       |
| Serbia                       | 21,605                | Europe    | 23                | 0.0061                       |
| Republic of Moldova          | 21,442                | Europe    | 24                | 0.0059                       |
| Austria                      | 19,818                | Europe    | 25                | 0.0058                       |
| Uzbekistan                   | 18,171                | Europe    | 26                | 0.0061                       |
| Nepal                        | 17,994                | Asia      | 7                 | 0.0061                       |
| Morocco                      | 17,742                | Eastern Med. | 12           | 0.0061                       |
| Cameroon                     | 16,522                | Africa    | 5                 | 0.0060                       |
| Cote d Ivoire                | 14,531                | Africa    | 6                 | 0.0063                       |
| Czechia                      | 14,324                | Europe    | 27                | 0.0062                       |
| Kenya                        | 14,168                | Africa    | 7                 | 0.0061                       |
| Republic of Korea            | 13,879                | Asia      | 8                 | 0.0058                       |
| Denmark                      | 13,302                | Europe    | 28                | 0.0057                       |
| Puerto Rico                  | 12,940                | Americas  | 15                | 0.0062                       |
| El Salvador                  | 12,582                | Americas  | 16                | 0.0065                       |
| Australia                    | 12,428                | Asia      | 9                 | 0.0062                       |
| Venezuela                    | 12,334                | Americas  | 17                | 0.0057                       |
| Costa Rica                   | 11,534                | Americas  | 18                | 0.0064                       |
| Sudan                        | 11,127                | Eastern Med. | 13           | 0.0061                       |
| Ethiopia                     | 11,072                | Africa    | 8                 | 0.0062                       |
| North Macedonia              | 9412                  | Europe    | 29                | 0.0061                       |
| Bulgaria                     | 9254                  | Europe    | 30                | 0.0059                       |
| Norway                       | 9038                  | Europe    | 31                | 0.0065                       |
| Senegal                      | 8985                  | Africa    | 9                 | 0.0060                       |
| Malaysia                     | 8815                  | Asia      | 10                | 0.0064                       |
| Bosnia and Herzegovina       | 8786                  | Europe    | 32                | 0.0062                       |
| Democratic Republic of the Congo | 8533              | Africa    | 10                | 0.0063                       |
| Finland                      | 7351                  | Europe    | 33                | 0.0063                       |
| Guinea                       | 6625                  | Africa    | 11                | 0.0062                       |
| Gabon                        | 6433                  | Africa    | 12                | 0.0064                       |
| Mauritania                   | 5985                  | Africa    | 13                | 0.0064                       |
| Luxembourg                   | 5725                  | Europe    | 34                | 0.0062                       |
| Djibouti                     | 5027                  | Eastern Med. | 14           | 0.0062                       |
| Central African Republic     | 4561                  | Africa    | 14                | 0.0062                       |
| Croatia                      | 4422                  | Europe    | 35                | 0.0062                       |
| Hungary                      | 4366                  | Europe    | 36                | 0.0060                       |
| Albania                      | 4290                  | Europe    | 37                | 0.0060                       |
| Greece                       | 4048                  | Europe    | 38                | 0.0062                       |
| Paraguay                     | 3748                  | Americas  | 19                | 0.0060                       |
| Zambia                       | 3326                  | Africa    | 15                | 0.0060                       |
| Thailand                     | 3261                  | Asia      | 11                | 0.0063                       |
| Somalia                      | 3135                  | Eastern Med. | 15           | 0.0062                       |
| Maldives                      | 3044                  | Asia      | 12                | 0.0060                       |
| Nicaragua                    | 3004                  | Americas  | 20                | 0.0058                       |
| Country Name          | Total Number of Cases | Continent   | Rank in Continent | Country-Specific Risk Factor |
|----------------------|-----------------------|-------------|-------------------|-----------------------------|
| Lebanon              | 2980                  | Eastern Med. | 16                | 0.0061                      |
| Congo                | 2851                  | Africa      | 16                | 0.0061                      |
| Sri Lanka            | 2730                  | Asia        | 13                | 0.0058                      |
| Montenegro           | 2567                  | Europe      | 39                | 0.0061                      |
| Cuba                 | 2449                  | Americas    | 21                | 0.0059                      |
| Equatorial Guinea    | 2350                  | Africa      | 17                | 0.0063                      |
| Estonia              | 2022                  | Europe      | 40                | 0.0060                      |
| Slovakia             | 2021                  | Europe      | 41                | 0.0060                      |
| Slovenia             | 1977                  | Europe      | 42                | 0.0059                      |
| Lithuania            | 1949                  | Europe      | 43                | 0.0060                      |
| Eswatini             | 1894                  | Africa      | 18                | 0.0064                      |
| Iceland              | 1839                  | Europe      | 44                | 0.0058                      |
| Benin                | 1690                  | Africa      | 19                | 0.0061                      |
| Rwanda               | 1655                  | Africa      | 20                | 0.0061                      |
| Tunisia              | 1394                  | Eastern Med. | 17              | 0.0061                      |
| Namibia              | 1366                  | Africa      | 21                | 0.0065                      |
| New Zealand          | 1205                  | Asia        | 14                | 0.0066                      |
| Latvia               | 1193                  | Europe      | 45                | 0.0062                      |
| Jordan               | 1181                  | Eastern Med. | 18              | 0.0063                      |
| Liberia              | 1108                  | Africa      | 22                | 0.0062                      |
| Niger                | 1108                  | Africa      | 23                | 0.0061                      |
| Suriname             | 1079                  | Americas    | 22                | 0.0065                      |
| Georgia              | 1073                  | Europe      | 46                | 0.0060                      |
| Burkina Faso         | 1065                  | Africa      | 24                | 0.0062                      |
| Uruguay              | 1064                  | Americas    | 23                | 0.0059                      |
| Cyprus               | 1040                  | Europe      | 47                | 0.0061                      |
| Chad                 | 889                   | Africa      | 25                | 0.0060                      |
| Andorra              | 884                   | Europe      | 48                | 0.0063                      |
| Jamaica              | 809                   | Americas    | 24                | 0.0059                      |
| Togo                 | 790                   | Africa      | 26                | 0.0066                      |
| San Marino           | 716                   | Europe      | 49                | 0.0060                      |
| Malta                | 675                   | Europe      | 50                | 0.0060                      |
| United Republic of Tanzania | 509 | Africa | 27 | 0.0059 |
| Viet Nam             | 401                   | Asia        | 15                | 0.0059                      |
| Mauritius            | 343                   | Africa      | 28                | 0.0061                      |
| Guyana               | 337                   | Americas    | 25                | 0.0059                      |
| Guam                 | 319                   | Asia        | 16                | 0.0060                      |
| United States Virgin Islands | 308 | Americas | 26 | 0.0063 |
| Mongolia             | 287                   | Asia        | 17                | 0.0058                      |
| Cayman Islands       | 203                   | Americas    | 27                | 0.0063                      |
| Cambodia             | 197                   | Asia        | 18                | 0.0061                      |
| Faroe Islands        | 191                   | Europe      | 51                | 0.0060                      |
| Gibraltar            | 180                   | Europe      | 52                | 0.0061                      |
| Bahamas              | 174                   | Americas    | 28                | 0.0061                      |
| Bermuda              | 153                   | Americas    | 29                | 0.0062                      |
| Brunei Darussalam    | 141                   | Asia        | 19                | 0.0062                      |
| Trinidad and Tobago  | 137                   | Americas    | 30                | 0.0062                      |
| Gambia               | 132                   | Africa      | 29                | 0.0060                      |
| Aruba                | 115                   | Americas    | 31                | 0.0061                      |
| Seychelles           | 108                   | Africa      | 30                | 0.0060                      |
| Barbados             | 106                   | Americas    | 32                | 0.0059                      |
| Bhutan               | 92                    | Asia        | 20                | 0.0064                      |
| Liechtenstein        | 87                    | Europe      | 53                | 0.0061                      |
Table A1. Cont.

| Country Name                  | Total Number of Cases | Continent  | Rank in Continent | Country-Specific Risk Factor |
|-------------------------------|-----------------------|------------|-------------------|-----------------------------|
| Monaco                        | 81                    | Europe     | 54                | 0.0060                      |
| Sint Maarten                  | 79                    | Americas   | 33                | 0.0058                      |
| Antigua and Barbuda           | 76                    | Americas   | 34                | 0.0061                      |
| French Polynesia              | 62                    | Asia       | 21                | 0.0062                      |
| Saint Vincent and the Grenadines | 50                 | Americas   | 35                | 0.0060                      |
| Saint Martin                  | 46                    | Americas   | 36                | 0.0062                      |
| Curacao                       | 28                    | Americas   | 37                | 0.0061                      |
| Fiji                          | 27                    | Asia       | 22                | 0.0060                      |
| Saint Lucia                   | 23                    | Americas   | 38                | 0.0059                      |
| New Caledonia                 | 22                    | Asia       | 23                | 0.0059                      |
| Greenland                     | 13                    | Europe     | 55                | 0.0058                      |

Appendix E. Effects of Infection Parameters and Recovery Parameters in the SIR Model on Correlations

In this appendix, we demonstrate with heatmaps the 14-day historical correlations of the daily number of new confirmed cases between pairs of countries under the susceptible-infected-recovered (SIR) model. The SIR model assumes that among the population $N$ who get infected with a certain kind of disease, people can be divided into three classes. The first class “susceptible”, $S(t)$, contains individuals who are at risk at time $t$. The second class “infected”, $I(t)$, contains those individuals who have been infected and are able to spread the diseases. The third class “recovered”, $R(t)$, contains those who have recovered from the infection and have become immune to the disease. We can use the following mathematical equations to formulate the relationship among these three classes:

$$\frac{dS(t)}{dt} = -\frac{\beta S(t)I(t)}{N},$$
$$\frac{dI(t)}{dt} = \frac{\beta S(t)I(t)}{N} - \gamma I(t),$$
$$\frac{dR(t)}{dt} = \gamma I(t),$$

where $\beta$ is the infection parameter and $\gamma$ is the recovery parameter. In our demonstration, we assume that the recovery parameter is equal to one-tenth of the infection parameter for simplicity. Moreover, we allow countries 1 and 2 to have infection parameters $\beta_1$ and $\beta_2$, respectively. We repeat the calculation after changing these two parameters to be combinations of 0.14, 0.17, 0.2, 0.25, 0.33, 0.5, and 1. Following Equation (1), we first calculate the square root transformed daily number of new cases, $D_t = \sqrt{S(t-1)} - \sqrt{S(t)}$. Then, we calculate the correlation by Equation (2) from $t = 1$ to $t = 170$. Notice that in the first 13 days, there are insufficient data to calculate the correlation. Therefore, the corresponding entries are colored in grey. In Figure A1, the x-axis and y-axis in each plot refer to the number of days since the first confirmed case in the two countries. The region in green represents the scenarios when the correlation between the two countries is greater than 0.5. We can roughly see three stages: one at the bottom left, a bridge in the middle, and one at the top right.
Figure A1. The $x$-axis and $y$-axis in each plot refer to the number of days since the first confirmed case in each of the two countries, respectively. The region in green represents the scenarios when the correlation between the two countries is greater than 0.5.

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