How COVID-19 affects people's mobility in tourism cities

Abstract

This study uses statistical change-point analysis to investigate the impact of the COVID-19 pandemic on people's mobility in tourism cities. Based on the collected data sample containing mobility time series of nine tourism cities on three categories of places - Retail and Recreation, Parks and Transit Stations, we find apart from the mobility reduction observed on all place categories, most cities experienced a three-phase pattern. Moreover, a time lag between the mobility decrease and introduction of lockdown measures is detected, suggesting that the latter is not the reason for people to reduce movement. Further, the mobility reduction is found less significant on Parks and appeared earlier on Transit Stations. The findings provide useful insights on how tourism, hospitality and travel sectors are affected by crisis events.

Keywords: mobility, tourism cities, COVID-19, change-point detection

1 Introduction

The COVID-19 pandemic is believed to have a lasting impact on communities and the world's economy. Tourism, hospitality and travel are the first sectors of the economy to bear the brunt of this impact, and the world's key tourism cities are hardest hit (Fernandes, 2020). Understanding how global tourism cities are affected by the outbreak of COVID-19 will facilitate the development of government policy and cooperation strategy in order to respond to the COVID-19 pandemic for both local and world hospitality business and economies. Since the impact of COVID-19 on tourism, hospitality and travel sectors is caused by its restriction on people's mobility, the first step to investigate such impact should focus on understanding how people's mobility changed in key tourism cities around the world. Moreover, due to limited medical capacity and no vaccine situation, nonpharmaceutical interventions such as travel restriction, social distancing and lockdown have become the main strategy adopted by many countries to contain the outbreak (Gössling et al., 2020). Although it is widely believed that these interventions further affect tourism, hospitality and travel sectors as they restrict people's mobility by rigid enforcement, it is still unclear how people's mobility respond to these interventions specifically in tourism cities. This research aims to fill the knowledge gap of the impact of COVID-19 on people's mobility in tourism cities by analysing people's mobility changes with the consideration of enforced restrictive measures in the world's most visited cities during the COVID-19 outbreak.

2 Data and method

We select the world's most visited cities by looking at the number of international visitors published by MasterCard (Hamel, 2019). The top twenty cities which have the largest number of visitors are selected, including Bangkok, Paris, London, Dubai, etc. Next, we search the mobility data of these selected twenty cities from Google mobility project (Google, 2020), and find data are available on nine of them: Bali, Dubai, Hong Kong, London, Makkah, New York, Osaka, Tokyo and Singapore. The mobility data on these nines cities are recorded on a daily basis and are across three different categories of places, which are *Retail and Recreation*, *Parks* and *Transit Stations*. The category of Retail and Recreation refers to the places such as restaurants, cafes, shopping centres, and museums, the Parks category represents places like national parks, public beaches and gardens, etc., and the Transit Stations category stands for public transport hubs such as train, bus and underground stations. These three categories are commonly accepted as important aspects when investigating issues in tourism related research (Gunn et al., 2004). We collect the daily mobility data for the period between 15 February and 17 April 2020.

To analyse the temporal pattern and the variability of the mobility in response to the COVID-19 pandemic and restrictive measures, this study uses statistical change-point analysis (Eckley et al., 2011) on the collected mobility time series. Change-point analysis has been widely applied to research which focuses on the detection of significant changes in time series. More specifically, it can identify a point (called *change-point*) in time where the statistical properties of prior data are different from the statistical properties of subsequent data (Eckley et al., 2011), making this method suitable for this research. We use the *EnvCpt* package (Beaulieu & Killick, 2018) in *R* to automate the process and the package has the advantage of identifying multiple change-points and can return the slope of the regression lines between changes. More specifically, the package relies on the pruned exact linear time (PELT) algorithm (Killick et al., 2012) to determine the optimal number of change-points. The algorithm balances between fit and complexity by minimising

$$\sum_{i=1}^{m+1} [\, C(y_{(\tau_{i-1}+1):\tau_i})] + \beta f(m)$$

over the number of change-points m, the change-point locations $\tau_{i=1:m}$ and the parameters within the cost function C for the segments divided by the change-points, where $y_1 \cdots y_n$ are the given time series data and $\beta f(m)$ is a penalty to guard against over fitting. The cost function used in the study is negative log-likelihood and is then optimised using maximum likelihood estimates of the parameters of those models which are applied to capture the statistical properties of given data.

To capture all possibilities for both short term and long term variability presented in our time series sample, a total of twelve models (Beaulieu & Killick, 2018) are fitted to our data. The models are described as follows:

(1) 'Mean', a constant mean with a white-noise background. More specifically, we have

$$y_t = \mu + e_t \, ,$$

where y_t is the time series, t is the time, μ is the mean and e_t represents the normal-distributed white noise errors.

(2) 'Mean+AR(1)', a constant mean with first-order autoregression. The model can be formalised as follows:

$$y_t = \mu + \varphi y_{t-1} + e_t \, ,$$

where φ is the first-order autocorrelation coefficient.

(3) 'Mean+AR(2)', a constant mean with second-order autoregression, we have

$$y_t = \mu + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + e_t \, ,$$

where both φ_1 and φ_2 are the autocorrelation coefficients.

(4) 'Trend', a linear trend. It can be formalised as follows.

$$y_t = \lambda + \beta t + e_t \, ,$$

where λ represents the intercept parameter and β represents the trend parameter.

(5) 'Trend+AR(1)', a linear trend with first-order autoregression. Similar to Model (2), we have

$$y_t = \lambda + \beta t + \varphi y_{t-1} + e_t \, .$$

(6) 'Trend+AR(2)', a linear trend with second-order autoregression with model

$$y_t = \lambda + \beta t + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + e_t \, .$$

(7) 'Mean+CP', multiple change-points in the mean with a background of white-noise. More formally, we have

$$y_t = \begin{cases} \mu_1 + e_t, & t \leqslant c_1 \\ \mu_2 + e_t, & c_1 < t \leqslant c_2 \\ \vdots, & \vdots \\ \mu_m + e_t, & c_{m-1} < t \leqslant n \end{cases}$$

where $\mu_1, \cdots, \mu_m$ are the mean of the m segments and $c_1, \cdots, c_{m-1}$ represent the change-points between the segments with the length of the time series n.

(8) 'Mean+AR(1)+CP', multiple change-points in the mean with first-order autoregression,

$$y_t = \begin{cases} \mu_1 + \varphi_1 y_{t-1} + e_t, & t \leqslant c_1 \\ \mu_2 + \varphi_2 y_{t-1} + e_t, & c_1 < t \leqslant c_2 \\ \vdots, & \vdots \\ \mu_m + \varphi_m y_{t-1} + e_t, & c_{m-1} < t \leqslant n \end{cases}$$

where $\varphi_1, \cdots, \varphi_m$ are the coefficients of the first-order autocorrelation in each segment.

(9) 'Mean+AR(2)+CP', multiple change-points in the mean with second-order autoregression,

$$y_t = \begin{cases} \mu_1 + \varphi_1 y_{t-1} + \varphi_1' y_{t-2} + e_t, & t \leqslant c_1 \\ \mu_2 + \varphi_2 y_{t-1} + \varphi_2' y_{t-2} + e_t, & c_1 < t \leqslant c_2 \\ \vdots, & \vdots \\ \mu_m + \varphi_m y_{t-1} + \varphi_m' y_{t-2} + e_t, & c_{m-1} < t \leqslant n \end{cases}$$

where $\varphi_1, \cdots, \varphi_m$ and $\varphi_1', \cdots, \varphi_m'$ are the coefficients of the first-order and second-order autocorrelation in each segment respectively.

(10) 'Trend+CP', multiple change-points in the trend with white-noise. More for-

mally, we have

$$y_t = \begin{cases} \lambda_1 + \beta_1 t + e_t, & t \leqslant c_1 \\ \lambda_2 + \beta_2 t + e_t, & c_1 < t \leqslant c_2 \\ \vdots, & \vdots \\ \lambda_m + \beta_m t + e_t, & c_{m-1} < t \leqslant n \end{cases}$$

where $\lambda_1, \cdots, \lambda_m$ and $\beta_1, \cdots, \beta_m$ are the intercept and trend parameters in each segment.

(11) 'Trend+AR(1)+CP', multiple change-points in the trend with first order autoregression,

$$y_t = \begin{cases} \lambda_1 + \beta_1 t + \varphi_1 y_{t-1} + e_t, & t \leqslant c_1 \\ \lambda_2 + \beta_2 t + \varphi_2 y_{t-1} + e_t, & c_1 < t \leqslant c_2 \\ \vdots, & \vdots \\ \lambda_m + \beta_m t + \varphi_m y_{t-1} + e_t & c_{m-1} < t \leqslant n \end{cases}$$

(12) 'Trend+AR(2)+CP', multiple change-points in the trend with second-order autoregression. The model can be formalised as follows.

$$y_t = \begin{cases} \lambda_1 + \beta_1 t + \varphi_1 y_{t-1} + \varphi_1' y_{t-2} + e_t, & t \leqslant c_1 \\ \lambda_2 + \beta_2 t + \varphi_2 y_{t-1} + \varphi_2' y_{t-2} + e_t, & c_1 < t \leqslant c_2 \\ \vdots, & \vdots \\ \lambda_m + \beta_m t + \varphi_m y_{t-1} + \varphi_m' y_{t-2} + e_t & c_{m-1} < t \leqslant n \end{cases}$$

Based on the Akaike information criterion (AIC), which is twice the model likelihood penalised by the number of parameters fitted (Akaike, 1974), the best model with the smallest AIC is selected and the change-points are returned. This approach has been widely used in change-points analysis (Beaulieu & Killick, 2018). In this way, our analysis determines whether, and when, the mobility on a place category change significantly, and then compares the detected change-points on the three place categories across the countries in our data sample.

3 Results and Discussion

Figure 1-3 show the mobility changes of the nine cities over time as well as the change-points identified with respect to different place categories. The x-axis is the time stamp with the range of $[0, 63]$ to represent the test period from 15th February to 17th April. The y-axis is the percentage change in the mobility with zero corresponds to the baseline which is the normal mobility level of the city before the outbreak of COVID-19. The solid vertical lines depict the change-point locations (i.e., time stamps) on the x-axis obtained from our change-point detection analysis, and the dash vertical line marks the lockdown date enforced by the corresponding country government (Wikipedia, 2020). It is worth noting that Osaka and Tokyo did not have lockdown but school closure, thus the dash vertical line show the dates for school closure. The slope of the regression lines between changes is presented in individual figures. The effect of the certain type of days (e.g., weekend and public holiday) on the mobility patterns is considered in the analysis of this research. We check manually whether the detected change points happen in ordinary days or weekends/public holidays. However, no such effect is identified to contribute on the shift of mobility change.

As shown in the figures, all cities in our sample had experienced a reduction in the mobility on the three place categories. In particular, New York, Makkah and Dubai exhibited the biggest decline (i.e., dropped over 80%) in the categories of Retail and Recreation, Parks and Transit Stations respectively. However, cities did not experience the same process on the reduction of mobility. The detected change-points divide the mobility changing process into phases. From the results we can see that most of the cities in our data sample have two change-points and exhibit three phases. The exceptions are Tokyo and Osaka owning fewer phases and Makkah experiencing more than three phases except for the Park category. Moreover, Tokyo and Osaka did not experience the sharp decrease. Their mobilities present a continuous and fluctuated decline during the test period. In general, these two Japanese cities showed a smaller mobility decrease and different mobility pattern from other cities in our sample. This supports the observations by other studies which find larger mobility reductions were observed in places more severely hit by the epidemic (Pullano et al., 2020).

Further to the cities that exhibit three phases in their mobility changing process, their first phase is normally a gentle decline (the average reduction is 9.2%) followed by a sharp decrease in phase two (the average reduction is 48.6%). The change of the mobility turns to be gentle again in phase three as the mobility had already reached to a quite low level at the beginning of phase three. Focusing on the sharp decrease and the introduction date of lockdown measures, a number of interesting findings are identified. The sharp decrease for Dubai, London and New York happened at the beginning of phase two, while their lockdown dates are close to the end of phase two. This finding suggests that these cities had their sharp mobility decrease before the enforcement of their lockdown policy; that is, the lockdown policy is not the reason for the sharp mobility decrease. Interestingly, a short-term mobility increase was detected on Retail and Recreation in London just before the lockdown was enforced, while it was not detected in Dubai and New York, and other place categories. This finding may suggest that retail and recreation industry in London needs to prepare for the short-term boost in future similar situations.

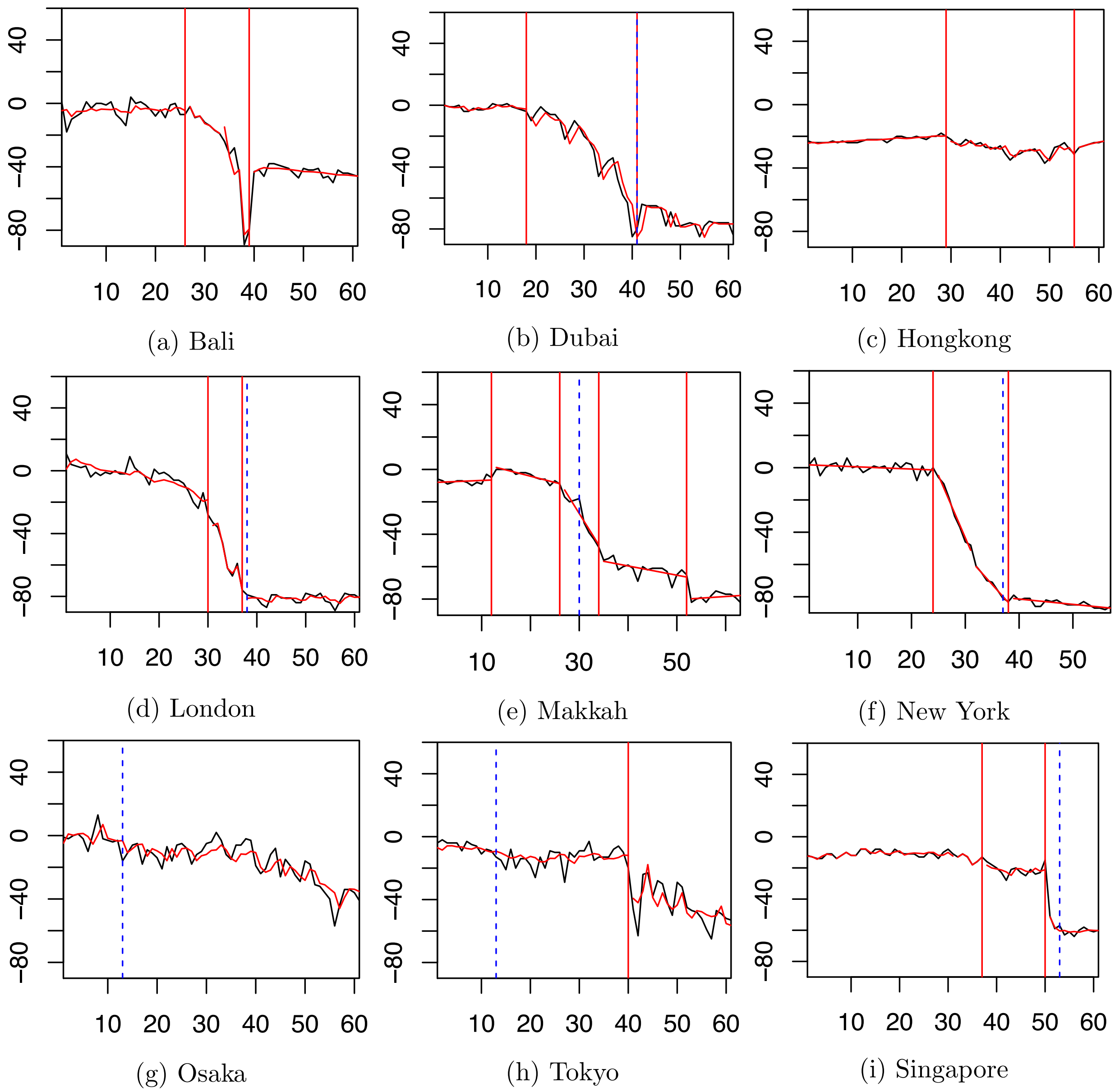
Unlike Dubai, London and New York, Makkah and Singapore performed differently. They showed a trend of mobility decrease in phase three after the lockdown policy was introduced. This is in line with the results in the study (Pullano et al., 2020) which found that the mobility reduction in France happened when strict lockdown measures were enforced. These findings suggest that the tourism and hospitality practitioners in different countries may need to bring in solutions to respond to crisis at different times.

Further investigating the cities Dubai, London and New York, which had the sharp mobility reduction in phase two, we look at the different place categories. The mobility change showed the same pattern on Retail & Recreation and Transit Stations in all three cities, however the mobility reduction on Parks in London is much smaller. This finding might suggest that the mobility changes in London are strongly associated with local citizens and workers who stopped going to shops, restaurants and work places both before and after the lockdown. As the parks in London were open for exercise purposes, the mobility on Parks only reduced a little from the beginning of the second phase and stayed at the same level even after lockdown policy was enforced.

Another interesting finding is that the mobility change in the Parks category for the cities which do not have the 3-phase pattern is also not as significant as other two categories, such as Osaka and Tokyo, suggesting Parks might be less affected by the pandemic. Further to the mobility on the Transit Stations category, New York, London, Tokyo and Makkah are the first in the sample to have change-points during the test period. Moreover, their first change-points on Transit Stations appeared earlier than their first change-points on Retail and Recreation and Parks. This finding might indicate that mobilities on Transit Stations have a quicker response to the COVID-19 crisis compared with Retail & Recreation and Parks. People stopped travel and commuting first during the pandemic in our data sample. This finding contradicts the observation of anomalous mobility increase in China (out of Wuhan) and Italy (from north to south) before the enforcement of lockdown (Bonaccorsi et al., 2020).

4 Conclusion

This study uses statistical change-point analysis to investigate the mobility change in tourism cities during the COVID-19 pandemic. Our results suggest that most cities in our data sample experienced mobility reduction in three phases on Retail and Recreation, Parks and Transit Stations. The sharp reduction for Dubai, London and New York happened in the second phase before the introduction of lockdown measures, suggesting lockdown was not the reason for the sharp reduction. In contrast, the reduction in Makkah and Singapore happened after the lockdown. Moreover, the reduction is found to be less significant in Parks for most cities and appears first within the Transit Stations category, which contradicts the findings of other research on China and Italy. Exceptional patterns are detected in some cities and are discussed. The findings of the research could help both academics and practitioners in tourism, hospitality and travel sectors predict mobility changes at the investigated places for future similar crisis. Despite the valuable insights obtained by the study, there are several limitations which can be addressed in future research. As only Google data are applied in this research, future research could find and employ other data sources. It will help us develop a more comprehensive understanding on the effect of COVID-19. Moreover, this research uses the three place categories - Retail and Recreation, Parks and Transit Stations following the structure of the data source. Future research could adopt a different approach of categorising places, which might provide fresh angles to study the change of mobility in tourism cities during the pandemic period.

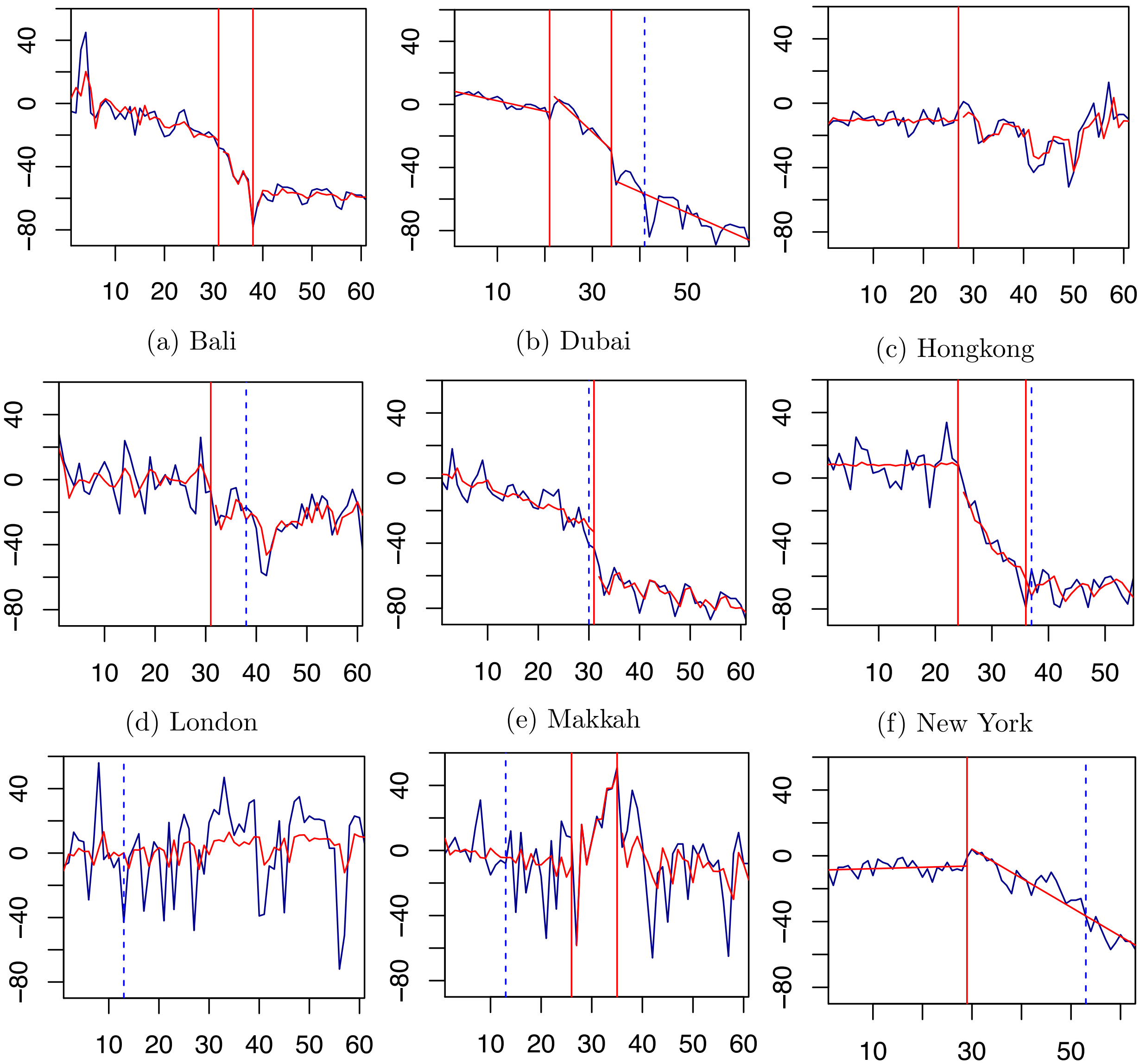


(a) Bali (b) Dubai (c) Hongkong

(d) London (e) Makkah (f) New York

(g) Osaka (h) Tokyo (i) Singapore

Figure 1: Change-points (solid lines) detected on mobility in Retail and Recreation category, compared with the date when lockdown policy was introduced (dotted lines), where y-axis represents the percentage change in mobility and x-axis has a date range of $[0, 63]$ matching the period between 15th Feb and 17th April.

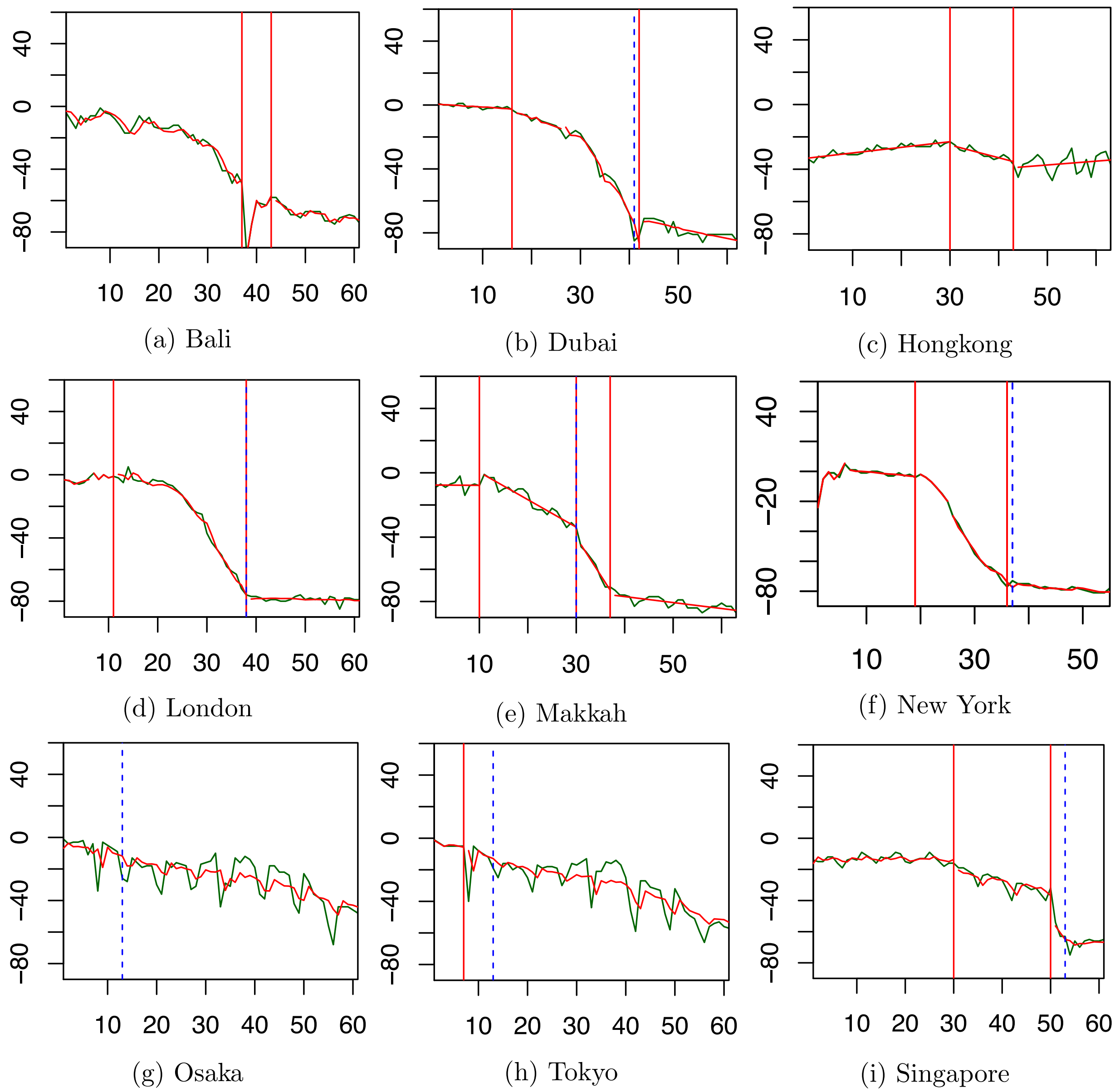


(a) Bali (b) Dubai (c) Hongkong

(d) London (e) Makkah (f) New York

(g) Osaka (h) Tokyo (i) Singapore

Figure 2: Change-points (solid lines) detected on mobility in Parks category, compared with the date when lockdown policy was introduced (dotted lines), where y-axis represents the percentage change in mobility and x-axis has a date range of $[0, 63]$ matching the period between 15th Feb and 17th April.



(a) Bali (b) Dubai (c) Hongkong

(d) London (e) Makkah (f) New York

(g) Osaka (h) Tokyo (i) Singapore

Figure 3: Change-points (solid lines) detected on mobility in Transit Stations category, compared with the date when lockdown policy was introduced (dotted lines), where y-axis represents the percentage change in mobility and x-axis has a date range of $[0, 63]$ matching the period between 15th Feb and 17th April.

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