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# 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

23 business and economies. Since the impact of COVID-19 on tourism, hospitality and  
24 travel sectors is caused by its restriction on people’s mobility, the first step to inves-  
25 tigate such impact should focus on understanding how people’s mobility changed in  
26 key tourism cities around the world. Moreover, due to limited medical capacity and  
27 no vaccine situation, nonpharmaceutical interventions such as travel restriction, social  
28 distancing and lockdown have become the main strategy adopted by many countries  
29 to contain the outbreak (Gössling et al., 2020). Although it is widely believed that  
30 these interventions further affect tourism, hospitality and travel sectors as they re-  
31 strict people’s mobility by rigid enforcement, it is still unclear how people’s mobility  
32 respond to these interventions specifically in tourism cities. This research aims to fill  
33 the knowledge gap of the impact of COVID-19 on people’s mobility in tourism cities  
34 by analysing people’s mobility changes with the consideration of enforced restrictive  
35 measures in the world’s most visited cities during the COVID-19 outbreak.

## 36 2 Data and method

37 We select the world’s most visited cities by looking at the number of international  
38 visitors published by MasterCard (Hamel, 2019). The top twenty cities which have the  
39 largest number of visitors are selected, including Bangkok, Paris, London, Dubai, etc.  
40 Next, we search the mobility data of these selected twenty cities from Google mobil-  
41 ity project (Google, 2020), and find data are available on nine of them: Bali, Dubai,  
42 Hong Kong, London, Makkah, New York, Osaka, Tokyo and Singapore. The mobility  
43 data on these nine cities are recorded on a daily basis and are across three different  
44 categories of places, which are *Retail and Recreation*, *Parks* and *Transit Stations*. The  
45 category of Retail and Recreation refers to the places such as restaurants, cafes, shop-  
46 ping centres, and museums, the Parks category represents places like national parks,  
47 public beaches and gardens, etc., and the Transit Stations category stands for public  
48 transport hubs such as train, bus and underground stations. These three categories are

49 commonly accepted as important aspects when investigating issues in tourism related  
50 research (Gunn et al., 2004). We collect the daily mobility data for the period between  
51 15 February and 17 April 2020.

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

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

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

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

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

$$y_t = \mu + e_t,$$

74 where  $y_t$  is the time series,  $t$  is the time,  $\mu$  is the mean and  $e_t$  represents the normal-  
75 distributed white noise errors.

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

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

76 where  $\varphi$  is the first-order autocorrelation coefficient.

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

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

77 where both  $\varphi_1$  and  $\varphi_2$  are the autocorrelation coefficients.

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

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

78 where  $\lambda$  represents the intercept parameter and  $\beta$  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

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

79

(7) ‘Mean+CP’, multiple change-points in the mean with a background of white-

80

noise. More formally, we have

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

81

where  $\mu_1, \dots, \mu_m$  are the mean of the  $m$  segments and  $c_1, \dots, c_{m-1}$  represent the

82

change-points between the segments with the length of the time series  $n$ .

83

(8) ‘Mean+AR(1)+CP’, multiple change-points in the mean with first-order au-

84

toregression,

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

85

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

86

(9) ‘Mean+AR(2)+CP’, multiple change-points in the mean with second-order au-

87

toregression,

$$y_t = \begin{cases} \mu_1 + \varphi_1 y_{t-1} + \varphi'_1 y_{t-2} + e_t, & t \leq c_1 \\ \mu_2 + \varphi_2 y_{t-1} + \varphi'_2 y_{t-2} + e_t, & c_1 < t \leq c_2 \\ \vdots, & \vdots \\ \mu_m + \varphi_m y_{t-1} + \varphi'_m y_{t-2} + e_t, & c_{m-1} < t \leq n \end{cases}$$

88

where  $\varphi_1, \dots, \varphi_m$  and  $\varphi'_1, \dots, \varphi'_m$  are the coefficients of the first-order and second-order

89

autocorrelation in each segment respectively.

90

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

91 mally, we have

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

92 where  $\lambda_1, \dots, \lambda_m$  and  $\beta_1, \dots, \beta_m$  are the intercept and trend parameters in each seg-  
93 ment.

94 (11) ‘Trend+AR(1)+CP’, multiple change-points in the trend with first order au-  
95 toregression,

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

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

$$y_t = \begin{cases} \lambda_1 + \beta_1 t + \varphi_1 y_{t-1} + \varphi'_1 y_{t-2} + e_t, & t \leq c_1 \\ \lambda_2 + \beta_2 t + \varphi_2 y_{t-1} + \varphi'_2 y_{t-2} + e_t, & c_1 < t \leq c_2 \\ \vdots, & \vdots \\ \lambda_m + \beta_m t + \varphi_m y_{t-1} + \varphi'_m y_{t-2} + e_t & c_{m-1} < t \leq n \end{cases}$$

98 Based on the Akaike information criterion (AIC), which is twice the model likeli-  
99 hood penalised by the number of parameters fitted (Akaike, 1974), the best model with  
100 the smallest AIC is selected and the change-points are returned. This approach has  
101 been widely used in change-points analysis (Beaulieu & Killick, 2018). In this way, our  
102 analysis determines whether, and when, the mobility on a place category change sig-  
103 nificantly, and then compares the detected change-points on the three place categories  
104 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



132 mobility decrease and different mobility pattern from other cities in our sample. This  
133 supports the observations by other studies which find larger mobility reductions were  
134 observed in places more severely hit by the epidemic (Pullano et al., 2020).

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

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

157 Further investigating the cities Dubai, London and New York, which had the sharp  
158 mobility reduction in phase two, we look at the different place categories. The mobility  
159 change showed the same pattern on Retail & Recreation and Transit Stations in all

160 three cities, however the mobility reduction on Parks in London is much smaller. This  
161 finding might suggest that the mobility changes in London are strongly associated with  
162 local citizens and workers who stopped going to shops, restaurants and work places both  
163 before and after the lockdown. As the parks in London were open for exercise purposes,  
164 the mobility on Parks only reduced a little from the beginning of the second phase and  
165 stayed at the same level even after lockdown policy was enforced.

166 Another interesting finding is that the mobility change in the Parks category for  
167 the cities which do not have the 3-phase pattern is also not as significant as other  
168 two categories, such as Osaka and Tokyo, suggesting Parks might be less affected by  
169 the pandemic. Further to the mobility on the Transit Stations category, New York,  
170 London, Tokyo and Makkah are the first in the sample to have change-points during  
171 the test period. Moreover, their first change-points on Transit Stations appeared earlier  
172 than their first change-points on Retail and Recreation and Parks. This finding might  
173 indicate that mobilities on Transit Stations have a quicker response to the COVID-  
174 19 crisis compared with Retail & Recreation and Parks. People stopped travel and  
175 commuting first during the pandemic in our data sample. This finding contradicts the  
176 observation of anomalous mobility increase in China (out of Wuhan) and Italy (from  
177 north to south) before the enforcement of lockdown (Bonaccorsi et al., 2020).

## 178 4 Conclusion

179 This study uses statistical change-point analysis to investigate the mobility change in  
180 tourism cities during the COVID-19 pandemic. Our results suggest that most cities in  
181 our data sample experienced mobility reduction in three phases on Retail and Recre-  
182 ation, Parks and Transit Stations. The sharp reduction for Dubai, London and New  
183 York happened in the second phase before the introduction of lockdown measures, sug-  
184 gesting lockdown was not the reason for the sharp reduction. In contrast, the reduction  
185 in Makkah and Singapore happened after the lockdown. Moreover, the reduction is

186 found to be less significant in Parks for most cities and appears first within the Transit  
187 Stations category, which contradicts the findings of other research on China and Italy.  
188 Exceptional patterns are detected in some cities and are discussed. The findings of the  
189 research could help both academics and practitioners in tourism, hospitality and travel  
190 sectors predict mobility changes at the investigated places for future similar crisis. De-  
191 spite the valuable insights obtained by the study, there are several limitations which  
192 can be addressed in future research. As only Google data are applied in this research,  
193 future research could find and employ other data sources. It will help us develop a more  
194 comprehensive understanding on the effect of COVID-19. Moreover, this research uses  
195 the three place categories - Retail and Recreation, Parks and Transit Stations following  
196 the structure of the data source. Future research could adopt a different approach of  
197 categorising places, which might provide fresh angles to study the change of mobility  
198 in tourism cities during the pandemic period.

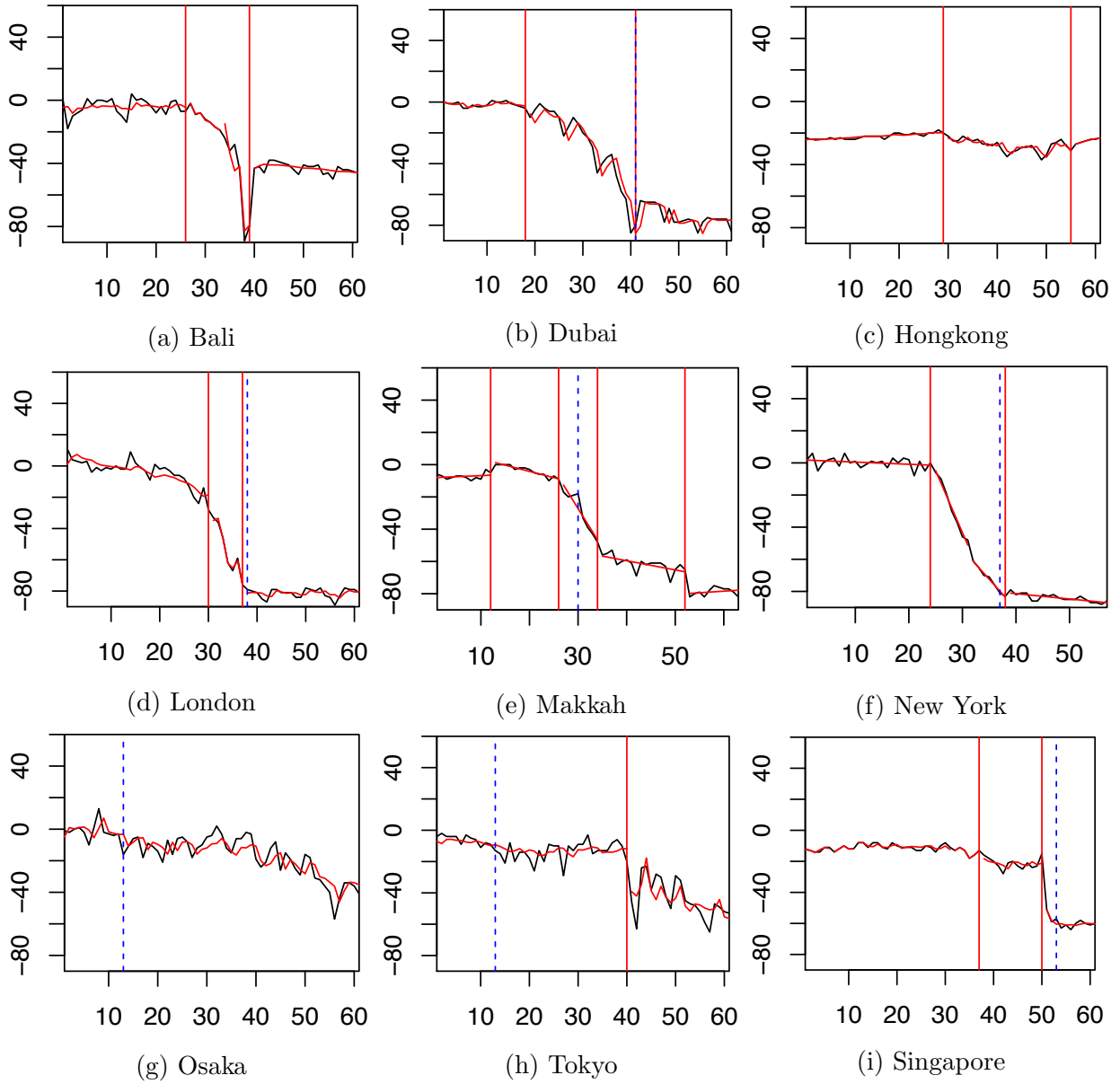


Figure 1: Change-points (solid lines) detected on mobility in Retail and Recreation category, compared with the date when lockdown policy was introduced (dotted lines), where  $y$ -axis represents the percentage change in mobility and  $x$ -axis has a date range of  $[0, 63]$  matching the period between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

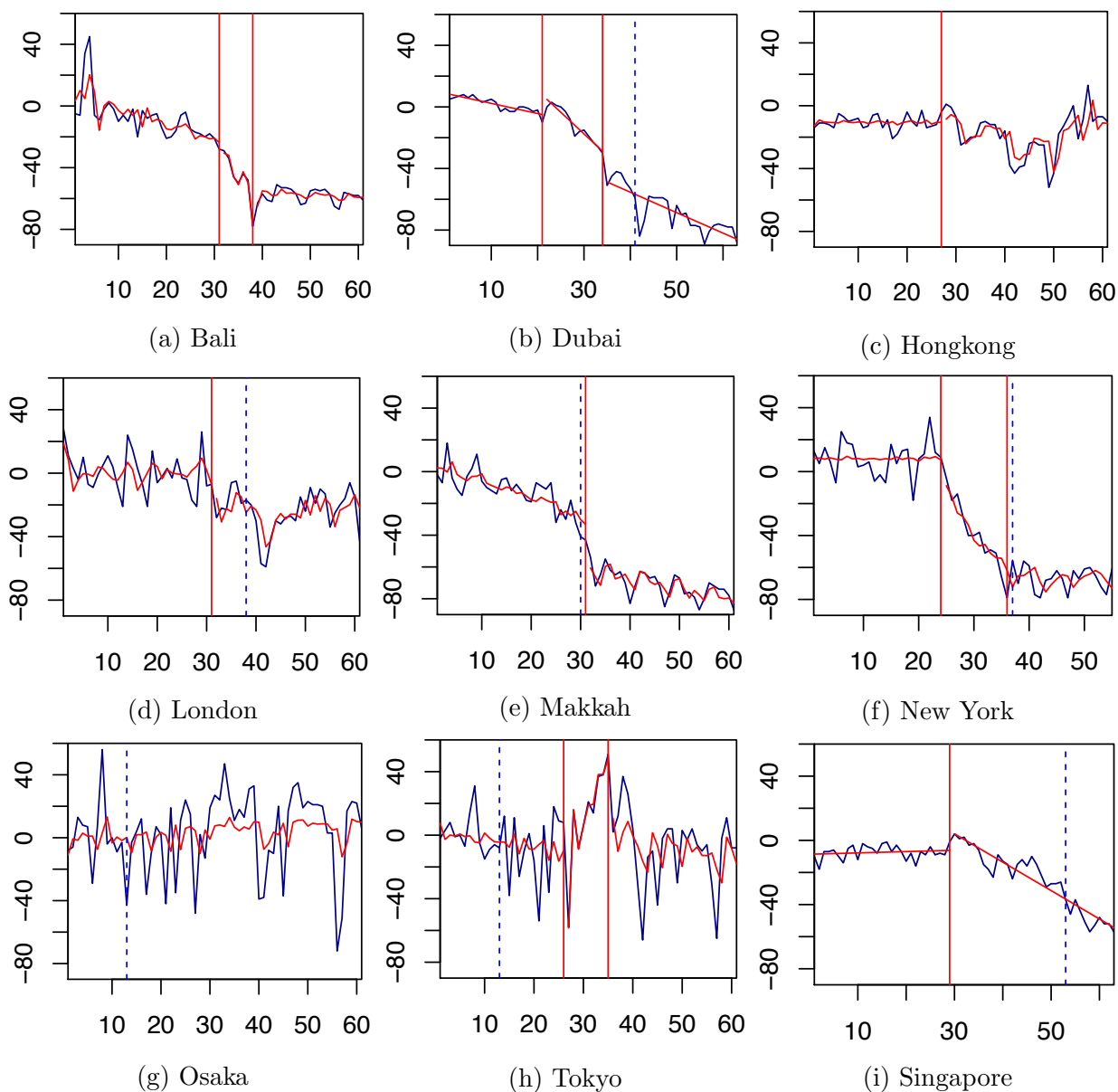


Figure 2: Change-points (solid lines) detected on mobility in Parks category, compared with the date when lockdown policy was introduced (dotted lines), where  $y$ -axis represents the percentage change in mobility and  $x$ -axis has a date range of  $[0, 63]$  matching the period between 15th Feb and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

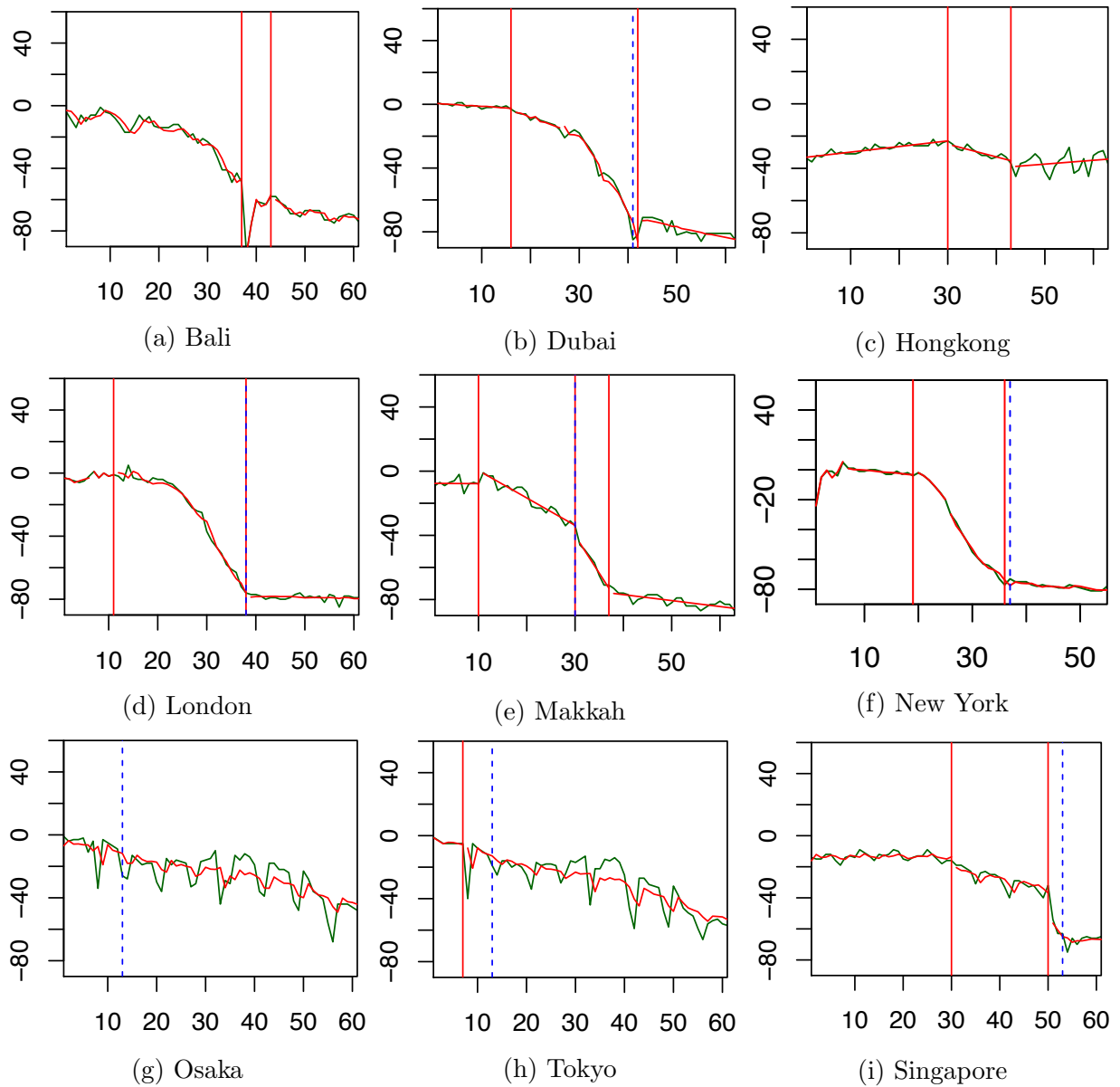


Figure 3: Change-points (solid lines) detected on mobility in Transit Stations category, compared with the date when lockdown policy was introduced (dotted lines), where  $y$ -axis represents the percentage change in mobility and  $x$ -axis has a date range of  $[0, 63]$  matching the period between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

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