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Impact of the COVID-19 pandemic on travel behavior: A case study of domestic inbound travelers in Jeju, Korea

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Abstract

This study analyzes a large-scale navigation dataset that captures travel activities of domestic inbound visitors in Jeju, Korea in the first nine months of 2020. A collection of regression models are introduced to quantify the dynamic effects of local and national COVID-19 indicators on their travel behavior. Results suggest that behavior of inbound travelers was jointly affected by pandemic severity locally and remotely. The daily number of new cases in Jeju has a greater impact on reducing travel activities than the national-level daily new cases of COVID-19. The impacts of the pandemic did not diminish over time but produced heterogeneous effects on travels with different trip purposes. Our findings reveal the persistence of COVID-19's effects on travel behavior and the variability in travelers' responses across tourism activities with different levels of perceived health risks. The implications for crisis management and recovery strategies are also discussed.

Keywords: COVID-19, Pandemic, Travel behavior, Tourism activity, Tourist behavior, Risk perception, Behavior change, Google Trends

1 Introduction

In the 21st century, we have witnessed several pandemics, such as SARS, MERS, Ebola, etc., threating the global economy and human lives. By the end of 2021, the pandemic had caused approximately 290 million infections and over 5 million deaths (WHO, 2022). The COVID-19 pandemic has had an enormous influence on many different sectors of tourism, ultimately reshaping the entire tourism industry (Gössling et al., 2021; Hall et al., 2020). The World Tourism Organization stated that tourism is one of the industries that were hit the hardest by the pandemic (Dolnicar & Zare, 2020; UNWTO, 2021).

As such, significant efforts have been devoted to investigate the impact of COVID-19 pandemic on tourist arrivals or changes in travel behavior (González-Torres et al., 2021; Sigala, 2020; Yang et al., 2020; Zheng et al., 2021). Given that many national or city governments have implemented travel restrictions in the early stage of the pandemic to contain the spread of the virus, most of the current studies investigate the tourist behavior in such contexts. The statistical estimation of tourist arrivals or changes in travel behavior usually encompass the effects of both the travel restrictions and the pandemic itself. However, as travel restrictions are gradually lifted in many countries, we are entering an era of coexistence with the virus. It is urgent to understand the independent impact of the pandemic itself on tourist behavior in a context without policy intervention.

Besides, as travel decisions are multifaceted, trips involve a multiplicity of partial decisions (e.g., destinations, accommodation, attractions, restaurants, and shopping) that are largely made following a dynamic, successive, and multistage contingent process (Dellaert et al., 1998; Jeng & Fesenmaier, 2002; Park & Fesenmaier, 2014). Different tourism activities encompass different levels of perceived importance and flexibility for travelers to adjust their plans in response to environmental changes (Park & Fesenmaier, 2014). This implies that the impacts of the pandemic would be heterogenous across different tourism activities. Thus, another critical question going forward is which of those behavioral changes will persist for a long time even after the pandemic. Answering this question could inform tourism recovery and produce real changes in tourism landscapes in the future (Bae & Chang, 2021; Khan et al., 2021; Salon et al., 2021). This implies the importance of investigating travel behavior over a longer time span (e.g., multiple waves) to capture the potential sticky effects of COVID-19 on behavior changes.

In view of the above research gaps, the first objective of this study is to assess the direct impact of the COVID-19 pandemic on travel changes of domestic visitors at the destination. It is achieved through a case study of Jeju, the Republic of Korea (hereafter Korea), where the government has never implemented a lockdown strategy. People can visit any place at any time in Korea without restrictions. It provides an experimental context that is (almost) free from the potential effect of an extraneous variable in estimating the relationships between the COVID-19 and travel behavior of domestic visitors in Jeju. Domestic visitor and domestic inbound traveler here denote the same meaning, both referring to a visitor who is a Korean domestic resident but not a resident of Jeju.

The second purpose of this study is to assess the dynamic impacts of the pandemic on travel behavior regarding the time-lag effects of the disease spread, and their potential variations at different stages of the pandemic (i.e., first wave outbreak, stable period, and second wave outbreak). In general, national and local pandemic status may influence visitors' risk perception and then have an impact on their travel decisions. However, given that visitors typically plan their trips and book services in advance, there may be a corresponding time-lag effects of the pandemic on their travel changes (Huang et al., 2020). And time-lag effects could also vary across different stages of the pandemic when variations in the severity of the pandemic provoke changes in visitors' risk perceptions. Therefore, this study analyzes the time-lag effects of multiple COVID-19 indicators on the changes in the number of trips during the first wave outbreak, the stable period, and the second wave outbreak.

The third purpose of this study is to assess the heterogeneous effects of the pandemic on multifaceted tourism activities in destination. Using tourism mobility big data (i.e., navigation data), we extract time series data on overall travel changes and travel changes of ten different activity types in Jeju. Multivariate linear regression models are constructed for different activity types in each pandemic period to quantify the heterogeneous effects of COVID-19 on travel changes of domestic visitors in Jeju.

This research provides important contributions to tourism literature and industry. As opposed to the previous studies that focused mainly on changes in visitor arrivals to a city or country, this study, considering the notion of multifaceted travel decisions, reveal the heterogeneous effects of COVID-19 pandemic on ten different travel activities at the destination. The findings of this study contribute to tourism literature on crisis management, particularly for the pandemic crisis. Besides, the results of this research suggest important implications for Destination Marketing Organizations (DMOs) to design destination management to respond to the COVID-19 pandemic. It is expected to facilitate DMOs in developing systematic and valid strategies for stakeholders associated with multiple travel services.

2 Literature Review

2.1 Impact of pandemic on tourists' travel behavior

Studies assessing the impact of COVID-19 pandemic on tourism have considered the aspect of macroeconomics focusing on the changes of national visitor arrivals. Specifically, Yang et al. (2020) applied a dynamic stochastic general equilibrium (DSGE) model to estimate the effect of the pandemic on the tourism industry and suggested that an increase in the health disaster risk results in a decline in tourism demand. Karabulut et al. (2020) assessed the percentage of the words relevant to pandemic episodes in the Economist Intelligence Unit (EIU) country reports by adopting the "Discussion about Pandemics Index" proposed by Ahir et al. (2018). They suggested that in countries with low-income economies, the pandemic has a negative effect on tourism demand. Indeed, a 10% increase in the pandemic index generates a 2.1% decrease in visitor arrivals. A set of studies have utilized machine learning methods (e.g., long short-term memory approach) to anticipate the future effect of the pandemic on visitor arrivals (Fotiadis et al., 2021; Polyzos et al., 2021).

While extant studies have adopted advanced statistical methods to estimate the effects of the pandemic or forecast future tourism demand at destinations, few efforts have been made to remove confounding errors from travel restrictions by local or national governments. As Park and Fesenmaier (2014) argued, travelers display a great deal of flexibility in their travel decision-making process for different travel activities. Once changing the environment (or context) in planning their trips (e.g., health crisis), travelers are likely to use different heuristics in deciding diverse travel activities that contain different perceived importance and complexity (Hwang & Fesenmaier, 2011). This suggests the importance of estimating the impact of the pandemic on multifaceted travel activities as opposed to assessing a single measurement of visitor arrivals.

Furthermore, unlike consumers who purchase general goods, travelers generally need to plan their trips and book services or products ahead (Park et al., 2011). Based on different natures of travel products, the impacts of COVID-19 pandemic on a multiplicity of travel activities could vary in terms of different time-lag effects (McKercher, 2016). Findings in some recent tourism studies also suggest that changes in traveler perceptions during the pandemic may affect their travel behaviors in the post-pandemic era (Hang et al., 2020; Li et al., 2020). Cashdan and Steele (2013) indicate that travelers are more likely to be collectivistic when they perceive health risks, which makes them choose domestic rather than international destinations. This behavior supports their country's economy, demonstrating the presence of tourist ethnocentrism (Kock et al., 2019). Zenker and Kock (2020) argued in their study that travelers would tend to evade crowdedness and require less human touch with self-service or technological support such as service robots. This suggests the importance of investigating the dynamic impact of COVID-19 on travel behavior over a longer time span (e.g., multiple waves) to capture stickiness changes. It will be important to governments and stakeholders in developing strategies to respond to public health crises.

However, these current studies have primarily focused on capturing changes in overall visitor arrivals, providing limited insights into pandemic impacts on distinct tourism activities. While some studies have gained a better understanding of changes in travel decision-making by utilizing surveys, they suffer from common issues such as lack of timeliness and representativeness. Tourism mobility big data (e.g., mobile phone data, navigation data) could provide a real-time view of travel behavioral change by capturing multifaced activities at a high spatial-temporal resolution.

2.2 Governmental and industrial response strategies

Some scholars have discussed national or industrial recovery strategies to respond to health crises (Sharma & Nicolau, 2020). Using the UNWTO's strategies and tactics in respect to 23 criteria for managing the pandemic crisis, Collins-Kreiner and Ram (2021) presented the current status of adopting the UNWTO's recovery strategies in seven countries, i.e., Australia, Austria, Brazil, China, Israel, Italy, and Japan. They identified that the tourism sectors have not fully formalized the comprehensive responsive strategies and rehabilitation plans to the pandemic crisis while variations do exist across different countries.

Considering the nature and massive effects of the COVID-19 pandemic, the development of a collaborative integration approach between industry and government is much needed (Assaf & Scuderi, 2020). In this vein, other scholars have investigated tourism and hospitality firms' strategies to protect themselves against and survive a global pandemic. They have identified that: (1) firm characteristics such as low enterprise valuation ratio, limited debt, and intensive investment policies, as well as larger size, better cash flows, and internationalization; (2) operating in collectivist countries; (3) strong and quick government policies (e.g., working from home) would likely help tourism firms manage potential epidemic crises (Kaczmarek et al., 2021; Song et al., 2021).

Besides, rebuilding the emotional connection with tourists is also considered to be an indispensable action to promote tourism recovery and increase tourism resilience. Qiu et al. (2020) discussed resident perceptions of the health risks generated by tourism activity and examined their willingness to pay the social costs to diminish public health risks. Other studies (Hang et al., 2020; Zhang et al., 2020) focused on the emotional changes of employees in the hospitality industry during the pandemic. Chen (2020) identified key determinants (e.g., unemployment, pandemic-induced panic, and lack of social support) that cause staff's stress during the COVID-19 pandemic.

It is crucial to address the balance between economic recovery and public health crisis management in tourism from the perspective of cultural, social and lifestyle integration. However, formulating effective recovery strategies is based on a comprehensive understanding of long-term changes in tourism demand and travel decision-making. This suggests the importance of estimating the impact of the pandemic on multifaceted tourism activities to better understand the response of travelers when they have health concerns, which will provide important implications in developing recovery strategies for different tourism sectors.

3 Study Area and Datasets

3.1 Study area

Jeju Special Self-Governing Province (hereafter Jeju) is an administrative region in the southwestern part of Korea, consisting of Jeju island and its subsidiary islands (Figure 1B), with a total area of 1,847.2 km^2 and a population of over 600,000 (Statistics Korea, 2021). The administrative area of Jeju Province is divided into two municipalities, with Jeju City as the capital. As one of the most popular tourism destinations in Korea, Jeju receives over 15 million visitors annually, with 86% and 14% of domestic and international visitors, respectively (Jeju Tourism Organization, 2019).

In 2020, the number of international visitors to Jeju decreased by more than 90% due to lockdowns or border shutdowns implemented by many countries to prevent and control the epidemic (Jeju Special Self-Governing Tourism Association, 2020). However, domestic visitors were still free to visit Jeju as the Korean government had never imposed strict travel restrictions on inter-city travel. It provides an ideal case to understand changes in travel behavior of domestic visitors during the pandemic, which are independent of the potential influence of travel bans.

3.2 COVID-19 timeline of Korea

Figure 1A demonstrates the timeline of the COVID-19 pandemic in Korea and Jeju from January to September in 2020 and the policy responses of Korean central government and Jeju government during this period. The first confirmed case of COVID-19 in Korea was reported on January 20, 2020. In the following month, the number of confirmed cases ranged from zero to two per day. The situation deteriorated rapidly until February 19, when a cluster of infections associated with a religious group was identified in Daegu, Korea's third-largest city. The daily number of confirmed cases nationwide rose sharply over the next few weeks, peaking at 909 on February 29. In response, the Korean government implemented a package of containment measures, including international travel restrictions, school closures, bar and club closures, and gathering restrictions targeting religions. The situation was quickly brought under control. From mid-April to mid-August, the number of daily confirmed cases nationwide was under 50. During this stable period, the government gradually relaxed the social distance restrictions.

In mid-August, the second wave of the nationwide outbreak was triggered by a Seoul cluster. Like the Daegu outbreak, this outbreak was linked to a religious group. In response, the government traced and tested most of the close contacts and reinstated the social distancing restrictions on August 23. By September 20, daily cases had fallen below 100. However, throughout this entire period from January to September, the Korean government has never imposed any strict lockdown measures and inter-city/inter-province travel bans.

The first confirmed case in Jeju was reported on February 22, 2020, almost a month after the first case in Korea. Until mid-August, the number of confirmed cases on Jeju were between 0 and 3 per day. From mid-August to mid-September, the number of confirmed cases reported on Jeju continued to increase, reaching a peak on August 31, 2020, when six confirmed cases were reported on one day. By the end of September, a total of 59 confirmed cases had been reported in Jeju. Compared to other areas in Korea, Jeju has not experienced a large-scale local outbreak where most of these cases were imported cases, those who have visited the epicenter of the COVID-19 outbreak (e.g., Daegu or Seoul) or related oversea travelers (Figure 1B).

The policy response of the local government has largely followed the lead of the central government. From February 23, Jeju followed the policy of the central government to impose the package of containment measures and announced relaxation on May 19, which was two weeks after the national announcement of ending the social distancing campaign on May 6. At the beginning of the second wave of the nationwide outbreak, Jeju enhanced the level of social distancing on August 22, 2020, one day earlier than that announced by central government. However, Jeju had never taken any extra measures to restrict domestic visitors.

Based on the COVID-19 timeline of Korea, four periods of the pandemic in 2020 are identified for the following analysis: the pre-outbreak period (January 20-February 18), the first wave outbreak (February 19-April 12), the stable period (April 13-August 11), and the second wave outbreak (August 12-September 30).

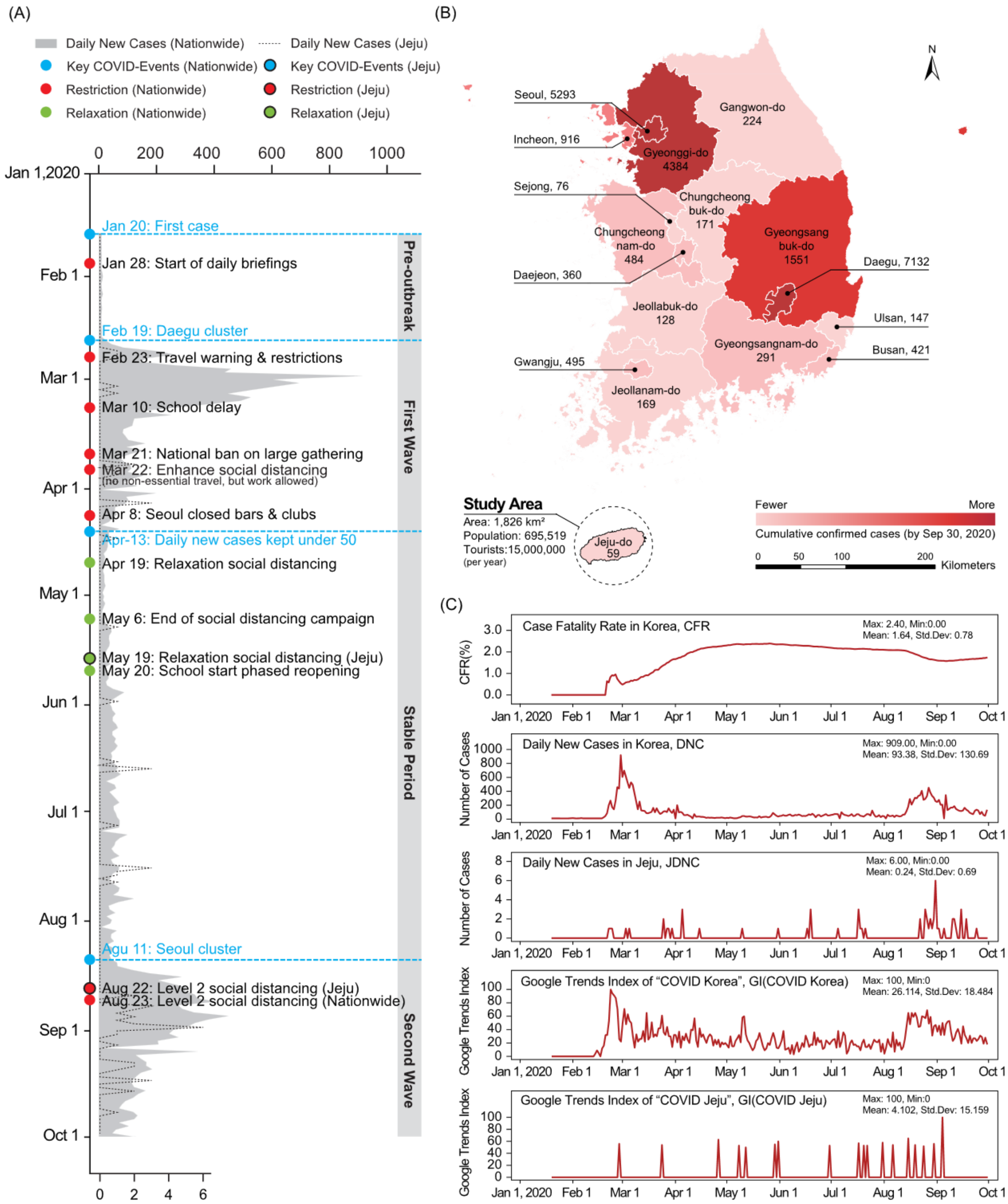

Figure 1. The COVID-19 pandemic in Korea by the end of September 2020: (A) Timeline of the COVID-19 pandemic in Korea and Jeju from January 1, 2020 to September 30, 2020[1]; (B) Province-level distribution of cumulative COVID-19 confirmed cases in Korea by September 30, 2020 [2]; (C) COVID-19 indicators and Google Trends Index from January 1, 2020 to September 30, 2020, including case fatality rate in Korea (the percentage of people who die from COVID-19 among all individuals confirmed with the disease in Korea), daily new cases in Korea, daily new cases in Jeju, Google Trends Index of search term "COVID Korea", and Google Trends Index of search term "COVID Jeju".

3.3 COVID-19 indicators

COVID-19 data is obtained from the census data released by the Ministry of health and welfare, Republic of Korea. In the pandemic context, both national and destination pandemic status may influence travelers' decision-making (He et al., 2020; Xiong et al., 2020; Zhou, 2020). This study introduces two national-level indicators (*case fatality rate* and *daily new cases*) and one local indicator (*Jeju daily new cases*).

Case fatality rate in Korea (*CFR*): the percentage of people who die from COVID-19 (*D*) among all individuals confirmed with the disease (*C*) in Korea, calculated as $CFR = D/C \times 100$. *CFR* is an epidemiology measure that assesses disease severity and predicts disease course or outcome, with comparatively high rates indicating relatively poor outcomes (Nishiura, 2010; Read et al., 2020).

Daily new cases in Korea (*DNC*): the absolute number of new cases confirmed with COVID-19 per day in Korea. It is a direct indicator to assess the extent of disease transmission and reflect the control programs. More new confirmed cases per day indicate a faster transmission and, therefore, a higher risk of infection for each individual at the national level.

Daily new cases in Jeju (*JDNC*): the absolute number of new cases confirmed with COVID-19 per day in Jeju. Similar to *DNC*, *JDNC* reveal the extent of disease prevalence in Jeju, where a higher value indicates a poor condition.

3.4 Google Trends Index

Internet search data has been widely used for public sentiment monitoring and behavior prediction (Choi & Varian, 2012; Sun et al., 2019; Effenberger et al., 2020; Gligorić et al., 2022). During the pandemic, variations in the volume of the search queries for COVID-19 could help researchers capture changes in public sentiment and risk perceptions of the COVID-19 pandemic. In this study, we collect time series internet search data for COVID-19 in Korea using the Google Trends tool, which enables users to retrieve time series data on search queries for a specific keyword made to Google in a given geographic area and a defined timeframe. The resulting Google Trends Index ranges from 0 to 100, where 100 represents the highest share of that search term in a time series (https://support.google.com/trends/).

To capture variations in search volume for COVID-19 at the national and local levels, two keywords "COVID Korea" and "COVID Jeju" were used to retrieve Google Trends Index (GI)

[1] The timeline is organized by authors based on https://ourworldindata.org/covid-exemplar-south-korea#licence.
[2] Data Sources: http://ncov.mohw.go.kr/en.

from January 1, 2020 to September 30, 2020. The search area was limited to the Republic of Korea. As shown in Figure 1C, the trends of *GI(COVID Korea)* and *GI(COVID Jeju)* were synchronized with the trends of the number of national and Jeju daily new cases, respectively.

3.5 Navigation dataset

This study uses a navigation dataset to capture changes in travel behavior of domestic visitors for multifaceted activities in Jeju. The dataset is obtained from one of the largest telecommunication companies in Korea that provide navigation services to travelers. This dataset tracks the travel history of domestic inbound travelers who used the company's navigation service (through mobile app) and conducted travel movements in Jeju from January 1, 2020 to September 30, 2020. As shown in Table 1, each record in this dataset documents the travel date, origin and destination locations (at 100m*100m grid cell level), the destination type, as well as the number of trips occurred with the identical OD flow in terms of corresponding destination type. The destination type here is generated based on a specific point of interest (POI) (e.g., restaurant or attraction), which people usually use as a navigation destination. Although the destination type does not fully represent the purpose of the trip, it can indicate the type of actual activity performed to a large extent. To distinguish Jeju as a general tourism destination, this study refers to the type of trip destination here as *activity type*. From January 1, 2020 to September 30, 2020, this dataset documents 5,849,031 trips generated by domestic inbound travelers in Jeju.

Table 1 Example of travel records in the navigation dataset

Date	Origin (Longitude)	Origin (Latitude)	Destination (Longitude)	Destination (Latitude)	Activity (POI Type)	Numbers of Trips Occurred
2020-01-01	126.***	33.***	126.***	33.***	Restaurant	5
2020-01-02	127.***	33.***	126.***	34.***	Cafe	4
……	……	……	……	……	……	……
2020-09-30	125.***	32.***	126.***	32.***	Market	3
2020-09-30	127.***	33.***	127.***	34.***	Attraction	2

To better understand the representativeness of the navigation dataset, we calculate the total number of trips per month and compare it with the official statistics on the monthly number of inbound travelers (Figure 2). The official number of inbound travelers here mainly represent the number of domestic visitors, as international travelers were restricted by travel bans in 2020. The Pearson correlation coefficient between them is 0.894, significant at 0.01 level. This demonstrates the consistency between the number of trips in this navigation dataset and the number of domestic inbound travelers who visited Jeju. Given the nature of navigation data, records in this dataset reveals the number of trips occurred instead of the number of travelers. Therefore, the change in the number of trips reflected in this dataset consists of two parts: 1) the overall change in the number of inbound travelers, and 2) the change in the frequency of domestic visitors traveling around the island during the pandemic.

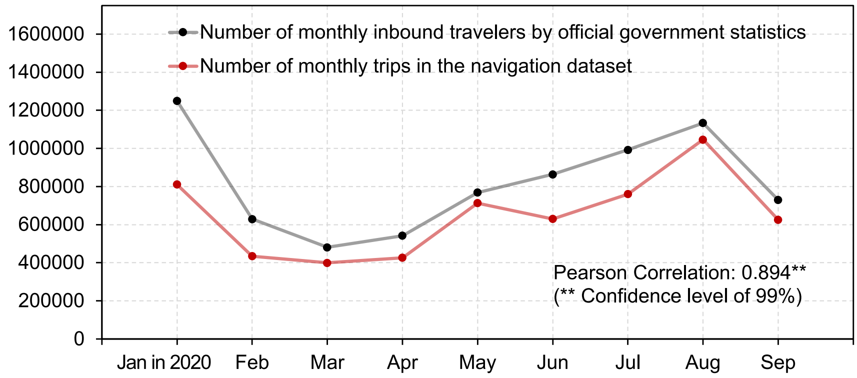

Figure 2. Correlation between the number of monthly inbound travelers by official government statistics and the number of monthly trips in the navigation dataset.

As shown in Figure 3, eleven time series data on daily trips of domestic visitors from January 1, 2020 to September 30, 2020 are extracted from the navigation dataset. The first is the overall daily trips of domestic visitors in Jeju (Figure 3A), calculated as the total number of trips per day in this dataset. Figure 3B demonstrates the time series of daily trips of ten different activity types, generated based on activity (POI type) of each record (Table 1). The ten activity types include restaurant, attraction, lodging, car facility, café, transportation facility, leisure sport, large distribution store, cultural life facility, and market. Trips for these ten types of activities together account for 90% of the total. Table A.1 in Appendix lists more details of the ten activity types (i.e., the specific activity venues included in each activity type). Data on March 16 (data missing) and data from April 30 to May 3 (golden holiday) have been excluded to avoid the impact of extreme values.

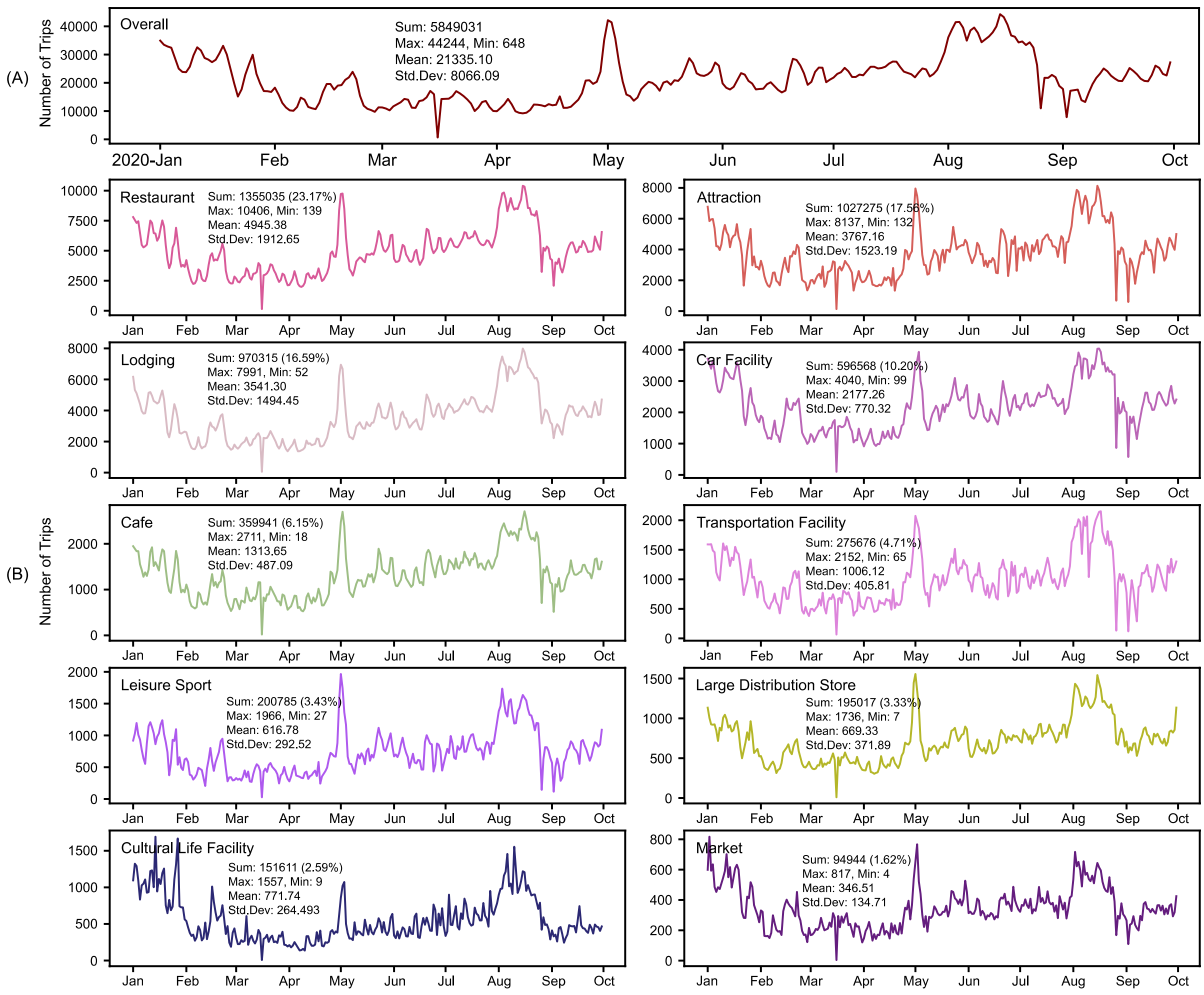

Figure 3. Time series of daily trips extracted from the navigation dataset: (A) Overall daily trips of domestic visitors; (B) Daily trips of domestic visitors for the ten activity types.

4 Methods

4.1 Estimating daily travel change

Methodologically, it is challenging to draw meaningful conclusions from daily trips time series data due to the presence of trends and seasonalities. To overcome these hurdles, we calculate the difference in the number of daily trips relative to centered moving average of the number of trips over 30 days for each time series of domestic visitors' daily trips (Zhou et al., 2017). The formula is as follow:

$$\Delta t_i^m = t_i^m - T_i^m \tag{1}$$

where t_i^m refers to the number of trips for activity type m on day i. T_i^m donates the average number of daily trips over 30 days centered on day i for activity type m (i.e., 30-days moving average centered on day i). Thus, Δt_i^m is the difference number of trips for activity type m on day i relative to the average daily trips for activity type m within 30 days.

4.2 Identify optimal time lag of dependent variables through cross-correlation analysis

Time-lag effects of physical and social factors on human behavior have been observed in numerous domains, such as transportation, tourism management, and public policy (Bian, 2021; Karl, 2016; Effenberger, 2020). Travelers usually plan their trips and book services a few weeks (2-4 weeks for Korean travelers in general) before their departure date (KTDB, 2019). This implies that diverse external or internal factors may trigger visitors to use different heuristics in deciding diverse tourism activities that contain different perceived importance and complexity (Park & Fesenmaier, 2014). During the COVID-19 pandemic, the disease spread and their potential variations at different stages of the pandemic may influence visitors' risk perception and then have an impact on their travel decisions. And there may be a delay between the time they perceive the health risk and the time they respond behaviorally, which then manifests as time-lag effects of COVID-19 on their travel behavior. Given the coronavirus incubation period is 5 to 6 days on average and generally less than 14 days, visitor behavior may be largely influenced by potential changes in pandemic severity over the past 14 days. Thus, the time-lag effect within 0 to 14 days is analyzed in this study.

Cross-correlation analysis is employed in this study to identify optimal time lag between dependent variables (i.e., overall daily travel changes) and independent variables (i.e., COVID-19 indicators and Google Trends Index about COVID-19) in three different periods of the pandemic (i.e., the first wave outbreak, stable period, and the second wave outbreak). Cross-correlation analysis is a widely used statistical tool for evaluating the strength and direction of time-lag relationships between time series variables (Akal, 2004; Shi et al., 2018; Höpken et al., 2019). It is achieved by calculating the correlation coefficient of two time series at a given set of time lags. And the optimal time lag of two time series is identified when the maximum correlation appears.

In this study, we assume that travel changes of domestic visitor were negatively affected by the COVID-19. Thus, by performing cross-correlation analysis for two variables for a given time lag ranging from 0 to 14 days, a series of correlation coefficients and corresponding time lags can be obtained, from which the optimal time lag is identified as the lag days with the peak negative correlation coefficient. All independent variables here have been performed natural logarithmic transformation to be consistent with the subsequent regression analysis. Figure C.1. in appendices shows the results of cross-correlation analysis.

Table 2 Optimal time lag of overall daily travel change to independent variables

Independent Variables	First Wave		Stable Period		Second Wave	
	Optimal Time Lag	Correlation Coefficient	Optimal Time Lag	Correlation Coefficient	Optimal Time Lag	Correlation Coefficient
CFR	4 days	-0.509***	1 day	-0.008	14 days	0.079
DNC	4 days	-0.628***	5 days	-0.241***	7 days	-0.570***
JDNC	4 days	-0.295***	5 days	-0.224***	4 days	-0.468***
GI(COVID Korea)	5 days	-0.723***	0 day	-0.172***	9 days	-0.600***
GI(COVID Jeju)	2 days	-0.204***	6 days	-0.212***	3 days	-0.251***

* Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

Table 2 exhibits the optimal time lag of each pair of dependent variable and independent variable in three periods. In general, the optimal time lags of national-level indicators, i.e., *CFR*, *DNC*, and *GI(COVID Korea)*, were shorter at the first wave outbreak than that at the stable period and the second wave outbreak. On the contrary, the optimal time lags of Jeju local indicators, i.e., *JDNC* and *GI(COVID Jeju*), were almost the same in the first and second waves. This suggests that during the first wave outbreak, both local and national level pandemic had short-term time-lag effects on travel behaviors of domestic visitors. However, in the second wave, national pandemic had a longer time-lag effect, while local pandemic still produced a shorter time-lag effect.

4.3 Multivariate linear regression models

Considering that the impact of COVID-19 on visitors' travel behavior could vary at different stages of the pandemic, we formulate three sets of multilinear regression models based on the three following periods identified in this study, namely, the first wave outbreak, stable period, and the second wave outbreak. For each period, there are an overall model and ten models regarding different activity types. In total, 33 regression models (11*3) are developed to estimate the dynamic effects of COVID-19 on travel changes of domestic visitors regarding different activity types and periods. The model of a given type of activity in a given period is given by the following form:

$$\Delta t_i = \beta_0 + \beta_1 * \ln CFR_i + \beta_2 * \ln DNC_i + \beta_3 * \ln JDNC_i$$
$$+ \beta_4 * \ln GI(COVID\ Korea)_i + \beta_5 * \ln GI(COVID\ Jeju)_i + \varepsilon_i \qquad (2)$$

Where Δt_i refers to the changes in the number of trips for a given type of activity on day *i*. Independent variables, i.e., *CFR*, *DNC*, *JDNC*, *GI*(*COVID Korea*), and *GI*(*COVID Jeju*), indicate the corresponding variables with optimal time lags based on cross-correlation analysis (Table 2). β_1 to β_5 are the coefficients of the corresponding time-lag independent variables. β_0 is the intercept and ε_i is the random error. All independent variables are performed a natural log transformation to make the variables more normally distributed and the interpretation more straightforward. Descriptive statistics of all variables are shown in Table B.1 in appendix. Table B.2 and Figure B.1. in the appendix shows the results of normality test of dependent variables.

5 Results

5.1 Changes in travel behavior during different pandemic periods

Figure 4 illustrates the travel changes of domestic visitors in Jeju during the COVID-19 pandemic. Using the average daily trips before COVID-19 in 2020 (January 1 to January 19) as baseline, we calculate overall average daily trip change (Figure 4A), and average daily trip change of ten activity types at four periods of the pandemic (Figure 4B).

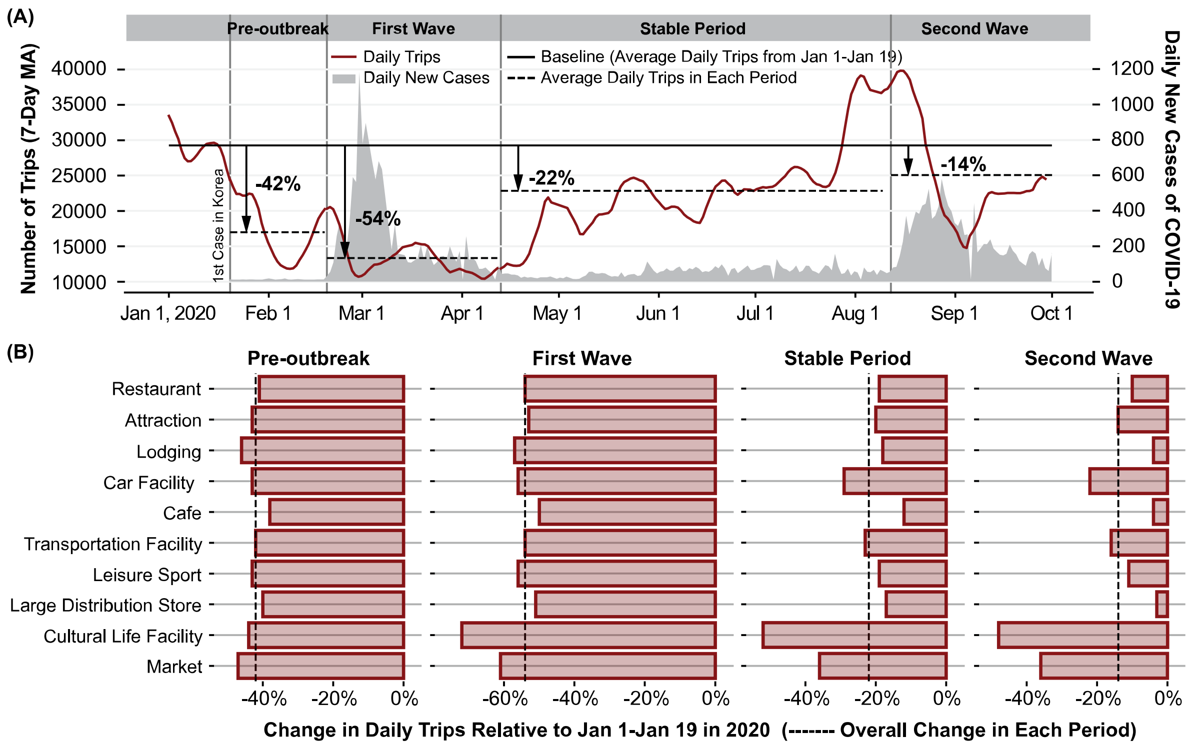

Figure 4. Travel changes in Jeju by periods and activity types: (A) Overall daily trips from January to September in 2020, and changes in overall average daily trips in four periods; (B) Changes in average daily trips for the ten activity types in four periods.

As shown in Figure 4A, the overall average daily trips of domestic visitors in Jeju dropped by 42% from the baseline (overall average daily trips during January 1 to January 19 in 2020). After the first wave outbroke in Daegu, it dropped further to 54% below the baseline. Although there were only a few cases in Jeju during these periods, there was a sharp travel reduction of domestic visitors in Jeju. In the stable period, the average daily trips gradually recovered and peaked in mid-August (peak tourism season of Jeju). However, on average, the number of daily trips by domestic visitors on the island was still 22% lower than the baseline. After the second wave of nationwide outbreak, the domestic visitor trips sharply dropped again but rebounded rapidly within one month. The average daily trips were still 14% lower than the baseline. This suggests that: 1) changes in travel behavior of domestic visitors depend largely on the severity of the nationwide pandemic, especially when there are no large-scale local outbreaks in tourist destination; 2) fluctuations in daily trips of domestic visitors were weaker in the second wave of the outbreak than that in the first wave outbreak.

In Figure 4B, the travel reduction for different activity types displays a high degree of consistency in the pre-outbreak period. However, the recovery in the number of trips across different types was more heterogeneous. For instance, the trips to places associated with large gatherings of people, such as cultural life facilities (e.g., theater) and markets (e.g., traditional market), was persistently 40% less than the corresponding baseline levels. Trips tied to essential tourism activities, such as lodging, cafe, and restaurant, dropped less and recovered more quickly. The average daily trips to lodging and café almost returned to the corresponding baseline levels in the second wave of the pandemic. The heterogeneity in travel changes across activities was probably because the travel reduction at the early stage of the pandemic was essentially contributed by the reduction in domestic visitor arrivals, while the activity preferences of domestic visitors might have changed in the following periods. These changes in behavioral preferences may be related to the importance of the activity itself and the level of exposure, or to social distancing measures targeting particular activity places.

5.2 Overall impact of COVID-19 on travel behavior

Regression analyses are performed for overall travel changes and travel changes for the ten activity types for three periods of the pandemic, i.e., the first wave outbreak, the stable period, and the second wave outbreak (details in Methods, Equation 2). Table 3, Table 4, and Table 5 demonstrate the regression results for each period, respectively. The first model in each table, i.e., Model 1-1, Model 2-1, and Model 3-1, refers to the overall model for the corresponding period, then models for the ten activity types. We did not perform regression analysis for the pre-outbreak period due to missing and invalid data of multiple independent variables in this period.

According to the results of Model 1-1 in Table 3, Model 2-1 in Table 4, and Model 3-1 in Table 5, overall travel changes of domestic visitors during the first and second waves were strongly affected by the COVID-19 situation at national and local levels (Model 1-1: $R^2 = 0.607$, $p = 0.000$. Model 3-1: $R^2 = 0.491$, $p = 0.000$), but were only slightly affected during the stable period (Model 2-1: $R^2 = 0.136$, $p = 0.001$). During the first wave outbreak, national-level indicators (i.e., *CFR*, *DNC*, and *GI(COVID Korea)*) and local-evel indicator (i.e., *JDNC*) had negative impacts on overall daily travel changes. During the stable period and the second wave outbreak, overall daily travel changes were negatively affected by national-level indicators (i.e., *DNC*, and *GI(COVID Korea)*) and local-level indicators (i.e., *JDNC*, and *GI(COVID Jeju)*).

By comparing the coefficients of independent indicators in Model 1-1, Model 2-1, and Model 3-1, we find that *CFR* had a strong effect (coefficient = -2358.672, $p < 0.05$) during the first wave but had no effect in the other two periods. This is probably because *CFR* changed drastically during the first wave outbreak, which may strongly influence the risk perception of visitors. Then, it was roughly constant at 2% during the stable period and the second wave outbreak and the importance of *CFR* in influencing visitors' risk perceptions decreased accordingly.

In all the three periods, *JDNC* had a greater impact than *DNC*. The coefficients of *JDNC* in Model 1-1, Model 2-1, and Model 3-1 are about 2 to 3 times higher than the coefficients of *DNC*. For instance, in Model 1-1, the coefficient of *DNC* is -532.810 ($p < 0.05$), the coefficient of *JDNC* is -1495.895 ($p < 0.1$). This indicates that each 1% increase in *DNC* during the first wave outbreak would result in the number of trips in Jeju dropping by 5 (-532.810/100). For each 1% increase in *JDNC*, that number drop by 15 (-1495.895/100). This suggests that increases in the number of new cases locally and nationally would jointly lead to decreases in trips of domestic visitors at the destination, but local indicators would have a greater impact.

For the search interest in COVID-19, *GI(COVID Korea)* had a greater impact than *GI(COVID Jeju)* in the three periods. For example, in Model 3-1, the coefficient of *GI(COVID Korea)* is -3640.479 ($p < 0.05$), the coefficient of *GI(COVID Jeju)* is -1181.134 ($p < 0.1$). *GIs* reflect trends in public sentiment and subjective risk perceptions. Considering that there were only a few local cases in Jeju, the local pandemic received less online attention than the national pandemic. As a result, the importance of *GI(COVID Jeju)* in influencing visitors' risk perceptions was secondary to that of *GI(COVID Korea)*.

Table 3 Regression results: First wave

Model No.	Dependent Variable	Adj. R^2	*F* stats	*P* value	Obs.	Intercept	*CFR*	*DNC*	*JDNC*	*GI (COVID Korea)*	*GI (COVID Jeju)*
1-1	Overall	0.607	17.053	0.000	53	9687.163***	-2358.672**	-532.81**	-1495.895*	-1598.145***	-544.091
1-2	Restaurant	0.532	12.817	0.000	53	2108.028***	-520.628**	-113.399*	-372.073*	-351.882***	-91.638
1-3	Attraction	0.563	14.408	0.000	53	2028.496***	-514.601**	-87.582	-342.839*	-355.133***	-160.77*
1-4	Lodging	0.597	16.409	0.000	53	1577.982***	-346.105**	-71.711*	-260.614*	-288.278***	-83.696
1-5	Café	0.403	8.028	0.000	53	484.175***	-115.977	-27.139	-103.689	-80.551**	-6.478
1-6	Car Facility	0.553	13.861	0.000	53	962.127***	-298.383**	-70.668**	-154.86	-124.125**	-49.032
1-7	Transportation Facility	0.503	11.521	0.000	53	485.174***	-150.824**	-42.397***	-44.784	-52.425	-39.938*
1-8	Leisure Sport	0.612	17.404	0.000	53	465.691***	-75.307	-21.846**	-44.004	-88.957***	-26.447
1-9	Large Distribution Store	0.277	4.978	0.001	53	237.283***	-46.898	-21.508*	-22.424	-33.519	6.353
1-10	Cultural Life Facility	0.454	9.648	0.000	53	241.528***	-64.905*	-13.595*	-30.741	-39.587**	-1.188
1-11	Market	0.475	10.403	0.000	53	163.456***	-11.798	-4.18	-34.025*	-38.497***	-13.939*

* Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

Table 4 Regression results: Stable period

Model No.	Dependent Variable	Adj. R^2	*F* stats	*P* value	Obs.	Intercept	*CFR*	*DNC*	*JDNC*	*GI (COVID Korea)*	*GI (COVID Jeju)*
2-1	Overall	0.136	4.651	0.001	117	17629.84	-8076.467	-941.144**	-2944.223**	-1550.46**	-569.243*
2-2	Restaurant	0.109	3.848	0.003	117	4137.861	-2029.279	-187.891**	-664.294**	-348.455**	-129.561*
2-3	Attraction	0.130	4.468	0.001	117	3945.405	-1910.893	-216.894***	-742.133***	-299.368**	-91.438
2-4	Lodging	0.133	4.558	0.001	117	2825.72	-1322.866	-145.749**	-440.31**	-242.681**	-121.029**
2-5	Café	0.052	2.274	0.052	117	781.269	-364.194	-42.247*	-117.854	-65.734	-28.608
2-6	Car Facility	0.124	4.283	0.001	117	1423.551	-498.53	-99.744**	-237.631*	-157.457**	-69.923**
2-7	Transportation Facility	0.155	5.241	0.000	117	1021.228	-351.798	-67.449***	-198.499**	-121.558***	-32.727*
2-8	Leisure Sport	0.002	1.041	0.397	117	658.551	-405.334	-32.802	-77.687	-19.672	-12.154
2-9	Large Distribution Store	0.078	2.975	0.015	117	825.052	-423.155	-26.532	-124.766**	-76.921***	-7.099
2-10	Cultural Life Facility	0.083	3.109	0.012	117	457.234	-227.043	-23.612*	-77.74*	-33.546	-19.47**
2-11	Market	0.123	4.246	0.001	117	324.412	-140.426	-16.897**	-32.533	-32.133**	-14.116**

* Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

Table 5 Regression results: Second wave

Model No.	Dependent Variable	Adj. R^2	*F* stats	*P* value	Obs.	Intercept	*CFR*	*DNC*	*JDNC*	*GI* *(COVID Korea)*	*GI* *(COVID Jeju)*
3-1	Overall	0.491	10.450	0.000	50	15763.963*	4206.562	-1149.663*	-2684.224**	-3640.479**	-1181.134*
3-2	Restaurant	0.497	10.667	0.000	50	3447.131*	1029.211	-224.289	-647.661**	-858.3***	-268.07***
3-3	Attraction	0.355	6.404	0.000	50	3355.87	509.885	-228.921	-413.269	-704.516**	-234.612**
3-4	Lodging	0.550	12.983	0.000	50	2379.563	1104.818	-192.561**	-510.688***	-645.157***	-189.156***
3-5	Café	0.458	9.265	0.000	50	859.987	292.19	-73.478*	-175.813**	-198.891**	-60.025**
3-6	Car Facility	0.408	7.760	0.000	50	1269.49	520.187	-112.162	-301.518**	-304.52*	-128.261**
3-7	Transportation Facility	0.415	7.949	0.000	50	912.65	282.173	-56.142	-141.7*	-233.805**	-86.358***
3-8	Leisure Sport	0.346	6.182	0.000	50	434.02*	-26.107	-22.951	-80.73**	-77.364*	-5.458
3-9	Large Distribution Store	0.463	9.453	0.000	50	804.624*	141.557	-56.248*	-92.532*	-172.597**	-58.204***
3-10	Cultural Life Facility	0.459	9.304	0.000	50	306.256	224.291	-33.433*	-80.387**	-91.972**	-35.966***
3-11	Market	0.334	5.908	0.000	50	255.396*	1.209	-22.088**	-25.238	-38.339*	-12.113

* Significant at 0.1 level. ** Significant at 0.05 level. *** Significant at 0.01 level.

5.3 Impact of COVID-19 on travel behavior across different activity types

By comparing the regression results of models for the ten activity types in Table 3, Table 4, and Table 5, we find that travel behavior of domestic visitors in terms of Lodging (Model 1-4, Model 2-4, and Model 3-4), Restaurant (Model 1-2, Model 2-2, and Model 3-2), and Attraction (Model 1-3, Model 2-3, and Model 3-3) were strongly affected by COVID-19 during the pandemic. In each period, R^2 of Lodging, Restaurant, and Attraction models were generally higher than that of other models. The coefficients of independent variables were generally larger than those in other models, implying that the changes in independent variables would result in more decreases in the number of trips for these activity types than for other types.

Regarding Car Facility (Model 1-6, Model 2-6, and Model 3-6) and Transportation Facility (Model 1-7, Model 2-7, and Model 3-7), the fits of these models were close to that of Lodging, Restaurant, and Attraction models, but the coefficients of the independent variables were smaller. Besides, the coefficients in Car Facility models are generally larger than that in Transportation Facility models. Car Facility here refers to car service facilities, such as parking lot, rental car, and patrol station (Table A.1 in appendix). Transportation Facility indicates public transport facilities, like airport, bus stop (Table A.1 in appendix). As we mentioned before, self-driving is the most popular way to travel in Jeju. The regression results suggests that the changes in independent variables would result in more decreases in the number of trips for car services than for public transports in Jeju.

According to Model 1-8, Model 2-8, and Model 3-8, travel behavior for Leisure Sport (e.g., golf clubs) was only affected by COVID-19 during outbreak periods, i.e., the first and second waves (Model 1-8, $R^2 = 0.612$, $p = 0.000$. Model 3-8, $R^2 = 0.\ 346$, $p = 0.000$). But it was not influenced by COVID-19 during the stable period (Model 2-8, $R^2 = 0.002$, $p = 0.397$). For the other activity types, including Large Distribution Store (e.g., supermarkets and discount stores), Market, Café, and Cultural Life Facility (e.g., museums & memorials), changes in the number of trips were mainly influenced by national-level indicators during the first wave outbreak. During the second wave outbreak, travel changes were influenced by both the national and local pandemic, but the increase in local-level indicator would result in more decreases in the number of trips.

6 Discussion and Conclusion

In this study, we assess the dynamic effects of COVID-19 pandemic on domestic visitors' travel behavior regarding multi-travel activities and different stages of the pandemic under a soft social distancing context. The results of this research provide important contributions to tourism literature on crisis management, particularly for the pandemic crisis. Previous studies have focused mainly on changes in tourist arrivals to a city or country. This study, considering the notion of multifaceted travel decisions, suggested the heterogeneous effects of COVID-19 pandemic on ten different travel activities at the destination. In a similar vein, taking advantage of different nature and categories of travel products, this study demonstrated distinctive time-lag effects of the pandemic on diverse travel activities and the differences in impacts at different stages of the pandemic. Furthermore, as opposed to extant studies that dismissed to manage potential effects of the government policy (e.g., travel restrictions) on their statistical modeling, this study explored travel mobility at the destination setting free from travel restrictions. This can help understand the active behavioral responses and travel decision-making of domestic visitors during a pandemic.

The results suggest that even there were no strict travel restriction measures, domestic visitors in Jeju did actively adjust their travel behavior according to the national and local COVID-19 status. Unlike behavioral responses in other crises (e.g., terrorism), during the COVID-19 pandemic, travelers were not only affected by the outbreak at the destination but also remotely affected by the national outbreak. Although the epicenters of the outbreak (e.g., Daegu for the first wave and Seoul for the second wave) were far from Jeju, the travel behavior of domestic visitors in Jeju was notably affected. The possibility of close contact with other domestic travelers, on transport facilities (e.g., planes, trains) or at public activity places (e.g., restaurant, lodging, attraction), may arise the risk perception of visitors. However, increases in local-level indicators would result in more decreases in the number of trips compared to the national-level indicators. Therefore, in the long term, the control of the epidemic in the destination plays an important role in the recovery of local tourism.

Our findings also reveal the persistence of COVID-19's effects on travel behavior and the variability in travelers' responses across various tourism activities with different levels of perceived health risks. Generally, the explanatory degree of models for the first and second waves are very close, suggesting that there was no significant decrease in the explanation degree of COVID-19 indicators for travel changes in Jeju. Increases in COVID-19 indicators would result in more decreases in the number of trips in the second wave outbreak than that in the first wave outbreak. This suggests that the impacts of COVID-19 on tourism activities did not decrease over time. The heterogeneity effects of COVID-19 on travel behavior across different activity types suggests that visitors were selectively dropping or picking parts of activities rather than cutting off all activities or stopping travel. Visitors were learning to live with the coronavirus in a more resilient way and to find a balance between travel and prevention.

The findings of this research provide important implications for Destination Marketing Organizations (DMOs) designing destination management in response to the COVID-19 pandemic. Travels tied to the essential tourism activities (e.g., Lodging), face-to-face services (e.g., Restaurant, Café), and transportation (e.g., Car Facility) were strongly influenced by COVID-19. The indoor activities or places gathering populations, such as museums, concert halls, and traditional markets, suffered more long-term effects. These are expected to facilitate DMOs in developing systematic and valid strategies for stakeholders associated with multiple travel services.

We want to point out a limitation of this research. Given that our dataset only documents the origin and destination of each trip, and stops added during a trip are not recorded, it may lead to an underestimation of such visits. Considering over 85% of domestic visitors use rental cars to travel around the island and navigation is often used on car trips, our dataset can still capture a partial view of changes in domestic visitors' travel behavior (Jeju Tourism Organization, 2020). Nevertheless, this study contributes to the tourism literature on crisis management by revealing the dynamic effects of COVID-19 pandemic on multifaced tourism activities over different pandemic stages. The findings in this study can provide implications for destination management and policymaking in other tourism destinations.

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Appendices

A Details about the ten activity types

Table A.1 Details about the ten activity types

Activity types	Example of specific activity venues
Restaurant	Chicken, snack bar, bakery, fast food, etc.
Attraction	Beach, famous mountain, park, waterfalls/valleys, etc.
Lodging	Hotel, condo/resort, pension, motel, etc.
Car Facility	Parking lot, rental car, patrol station, gas station, etc.
Café	Café, theme café, novelty café, traditional tea house, etc.
Transportation Facility	Airport, harbor, bus stop, public/national rest areas, etc.
Leisure Sport	golf course, amusement facilities, horse riding, water sports, etc.
Large Distribution Store	Supermarket, discount store, duty free shop, etc.
Cultural Life Facility	Museums, memorials, gallery, concert hall, theater, etc.
Market	Traditional market, agricultural/livestock products market, etc.

B Descriptive statistics of dependent and independent variables

Table B.1 Descriptive statistics of dependent and independent variables

	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
First wave					
Dependent variables					
Overall	53	-5169.516	9264.032	-33.762	3166.412
Restaurant	53	-1141.839	2222.387	-17.499	731.354
Attraction	53	-1285.903	1787.677	7.276	689.035
Lodging	53	-795.645	1534.968	-10.219	513.676
Café	53	-351.806	543.323	-6.336	189.689
Car Facility	53	-611.065	855.258	-6.523	340.988
Transportation Facility	53	-302.710	476.129	3.275	180.962
Leisure Sport	53	-185.839	474.194	2.341	144.402
Large Distribution Store	53	-237.871	318.548	-8.020	108.596
Cultural Life Facility	53	-121.967	259.000	-2.371	87.445
Market	53	-133.968	199.774	-2.449	59.280
Independent variables (with optimal time lag)					
CFR (4 days)	53	0.000	1.074	0.636	0.302
DNC (4 days)	53	0.000	6.813	4.559	1.588
JDNC (4 days)	53	0.000	1.386	0.152	0.333
GI(COVID Korea) (5 days)	53	0.000	4.615	3.431	0.791
GI(COVID Jeju) (2 days)	53	0.000	4.043	0.152	0.774
Stable period					
Dependent variables					
Overall	117	-7463.387	9254.704	19.181	3581.096
Restaurant	117	-1846.581	2035.806	6.794	845.426
Attraction	117	-2197.161	1951.387	8.398	787.315
Lodging	117	-1377.484	1657.452	-2.867	603.845
Café	117	-387.194	591.710	0.351	216.768

Car Facility	117	-870.677	1096.444	-0.570	381.302
Transportation Facility	117	-611.065	682.926	-1.978	236.517
Leisure Sport	117	-335.000	586.355	5.523	189.069
Large Distribution Store	117	-378.355	536.419	0.350	154.256
Cultural Life Facility	117	-245.290	385.704	0.753	114.519
Market	117	-178.129	230.710	1.097	69.520
Independent variables (with optimal time lag)					
CFR (1 day)	117	1.110	1.223	1.174	0.032
DNC (5 days)	117	0.000	4.736	3.339	0.875
JDNC (5 days)	117	0.000	1.386	0.071	0.247
GI(COVID Korea) (0 day)	117	1.386	4.111	2.968	0.477
GI(COVID Jeju) (6 days)	117	0.000	4.111	0.309	1.075
Second wave					
Dependent variables					
Overall	50	-15697.484	10113.226	150.289	5226.947
Restaurant	50	-3310.065	2368.000	30.633	1177.306
Attraction	50	-3966.194	2045.935	21.259	1105.223
Lodging	50	-1936.419	1840.000	36.302	882.022
Café	50	-958.613	657.935	11.874	318.342
Car Facility	50	-1734.710	832.000	21.934	549.140
Transportation Facility	50	-1105.161	591.806	14.306	332.049
Leisure Sport	50	-281.516	315.931	-10.593	130.888
Large Distribution Store	50	-778.419	390.484	6.880	241.360
Cultural Life Facility	50	-266.387	384.903	6.237	152.018
Market	50	-222.452	140.323	-0.974	75.426
Independent variables (with optimal time lag)					
CFR (14 days)	50	0.947	1.133	1.039	0.076
DNC (7 days)	50	0.000	6.091	4.845	1.048
JDNC (4 days)	50	0.000	1.946	0.345	0.525
GI(COVID Korea) (9 days)	50	2.079	4.248	3.569	0.500
GI(COVID Jeju) (3 days)	50	0.000	4.615	0.417	1.264

Table B.2 Normality Test of Dependent Variables (Shapiro-Wilk)

	First Wave			**Stable Period**			**Second Wave**		
	Statistic	N	Sig.	Statistic	N	Sig.	Statistic	N	Sig.
Overall	0.940	53	0.010	0.978	117	0.046	0.946	50	0.023
Restaurant	0.937	53	0.008	0.977	117	0.046	0.964	50	0.133
Attraction	0.965	53	0.120	0.993	117	0.791	0.905	50	0.001
Lodging	0.929	53	0.004	0.988	117	0.406	0.980	50	0.543
Cafe	0.968	53	0.171	0.967	117	0.005	0.948	50	0.029
Car Facility	0.958	53	0.060	0.983	117	0.152	0.904	50	0.001
Transportation Facility	0.943	53	0.013	0.989	117	0.504	0.925	50	0.004
Leisure Sport	0.906	53	0.001	0.956	117	0.001	0.972	50	0.283
Large Distribution Store	0.972	53	0.251	0.990	117	0.543	0.938	50	0.011
Cultural Life Facility	0.933	53	0.005	0.969	117	0.009	0.976	50	0.401

Market	0.974	53	0.312	0.968	117	0.007	0.953	50	0.047

Note: the test rejects the hypothesis of normality when the sig. is less than or equal to 0.05.

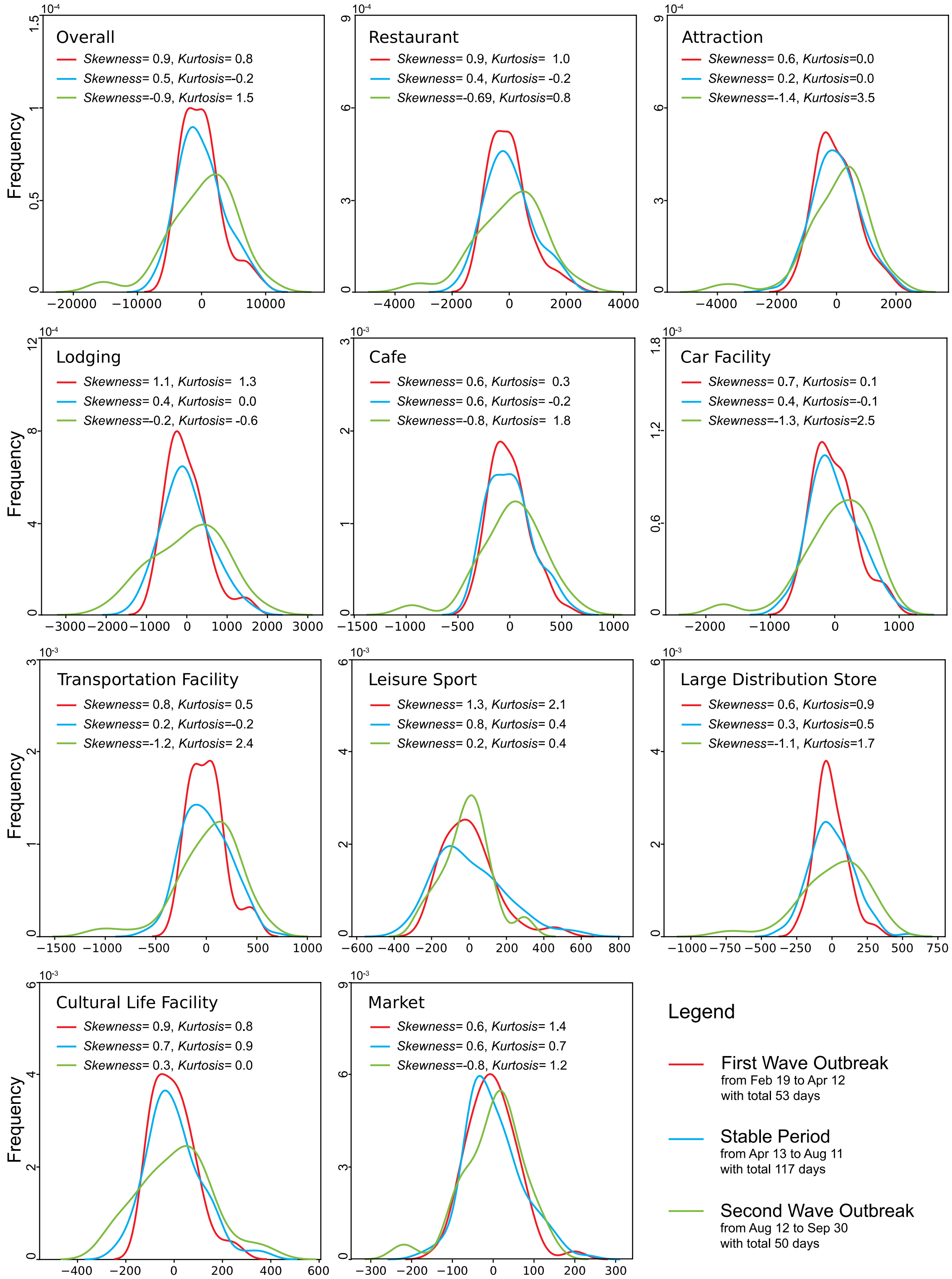

Figure B.1. Frequency distribution of dependent variables.

C Identify optimal time lag of dependent variables through cross-correlation analysis

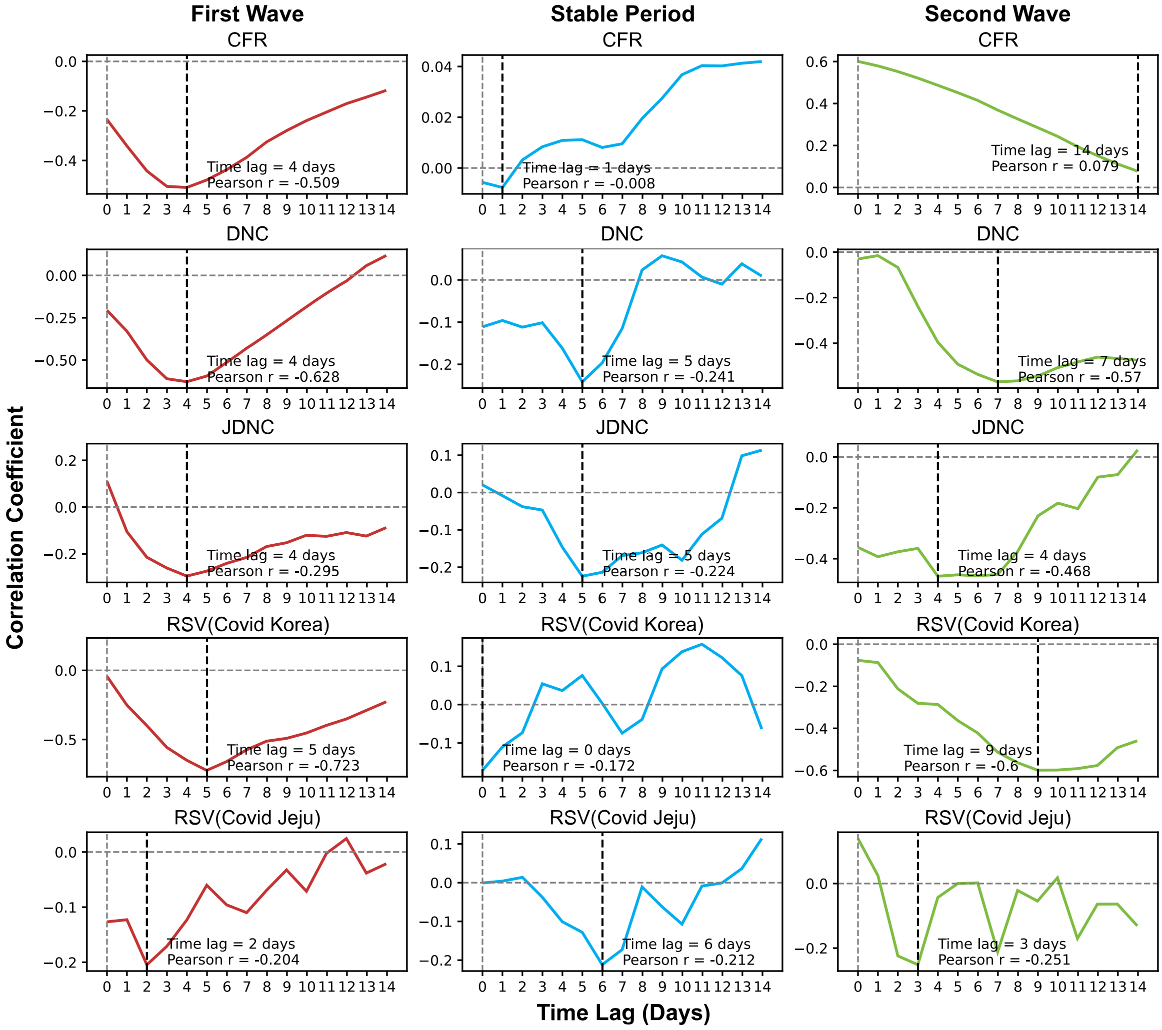

Figure C.1. Identify optimal time lag of dependent variables through cross-correlation analysis.