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**UTILIZING CROWDSOURCED DATA TO CHARACTERIZE
PANDEMIC-INDUCED BEHAVIOR CHANGES AND TOURIST-
RESIDENT INTERACTIONS IN TOURISM CITIES**

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**Utilizing Crowdsourced Data to Characterize Pandemic-Induced
Behavior Changes and Tourist-Resident Interactions in Tourism
Cities**

MENGYAO REN

A Thesis Submitted in Partial Fulfilment of the Requirements for the
Degree of Doctor of Philosophy

December 2024

CERTIFICATE OF ORIGINALITY

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Abstract

Pandemics profoundly affect urban economies and daily life, with tourism-dependent cities experiencing heightened economic vulnerability and complex public health challenges. During the global COVID-19 pandemic, strict safety protocols and heightened health concerns led to significant behavioral shifts, including travel disruptions and reduced consumer spending. These changes caused unprecedented disruptions across sectors closely tied to tourism, such as hospitality, restaurants, and air transportation, resulting in declining incomes and rising unemployment in tourism-dependent cities. Moreover, these cities face a higher risk of disease transmission as travelers from diverse regions increase the risks of importing and spreading infectious diseases. Interactions between residents and inbound travelers at activity venues further amplify transmission risks, posing threats to both groups. Balancing disease control with economic stability presents a critical challenge for tourism-dependent cities. Minimizing travel restrictions to mitigate economic losses while effectively managing disease spread risks requires a nuanced approach. It is essential to understand how pandemics and policy responses influence the travel and spending behavior of the two stakeholders in tourism cities, i.e., tourists and residents, as well as their potential interactions in urban areas. These insights are crucial for designing resilient crisis response measures and long-term strategies for sustainable development.

This thesis comprehensively investigates pandemic-induced behavior changes and tourist-resident interactions in a tourism city, aiming to achieve the following objectives: (1) to assess the extent to which human behavior in tourism cities varies in response to the severity of the pandemic, both locally and remotely; (2) to assess the effects of policy responses, including social distancing and stimulus payments, on human behavior in tourism cities; (3) to assess the heterogeneous impacts of the pandemic and policy responses across various economic sectors; (4) to assess the extent to which the impacts of the pandemic and policy responses differ between residents and tourists; (5) to characterize the diverse interaction modes between tourists and residents across space, time, and activity venues, as well as variations in direct contact potential across different modes; (6) to construct indices to measure the potential for interactions between tourists and residents across various modes.

This thesis addresses six research objectives through three data-driven case studies conducted in a

tourism city. The first study utilizes car navigation data to model the dynamic effects of local and national COVID-19 conditions on the travel behavior of domestic inbound travelers in Jeju, Korea. The second study leverages a large-scale dataset of credit and debit card transactions to estimate the heterogeneous impacts of COVID-19 and policy responses on spending behavior of residents and domestic inbound travelers in Jeju. The third study presents an innovative analytical framework to uncover potential interactions between tourists and residents within a time-geographic lens. An empirical application of this framework in Jeju displays its effectiveness in revealing the complexity and dynamics of intergroup interactions across space, time, and activity venues.

This thesis provides essential empirical evidence, offering alternative viewpoints on the dynamics and complexity of risk perception and behavioral responses. It enriches the field of time geography by deepening the understanding of space-time path relationships among individuals and introducing a robust tool for analyzing intergroup interactions. Through multiple data-driven case studies, the research underscores the value of spatiotemporal big data in policy evaluation, crisis management, and other practical applications. The findings make significant contributions to the fields of crisis management, tourism geography, and urban studies, delivering valuable insights and addressing fundamental issues within these domains.

List of Publications

1. **Ren, M.**, Park, S., Xu, Y.*, Huang, X., Zou, L., Wong, M. S., & Koh, S. Y. (2022). Impact of the COVID-19 pandemic on travel behavior: A case study of domestic inbound travelers in Jeju, Korea. *Tourism Management*, 92, 104533. (ESI highly cited paper)
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3. Lin, Y., Xu, Y.*, Zhao, Z., Park, S., Su, S., & **Ren, M.** (2023). Understanding changing public transit travel patterns of urban visitors during COVID-19: A multi-stage study. *Travel Behaviour and Society*, 32, 100587.
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5. Cheng, J., Xu, Y.*, Jian, I. Y., **Ren, M.**, & Park, S. (2025). Spatial concentration of intra-urban tourist activities and inter-group differences between Asian, European and North American travelers in Korean cities. *Tourism Management*, 107, 105064.

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Chapter 1

Introduction

1.1 Background

In the 21st century, several major pandemics, including SARS, MERS, Ebola, and the recent global COVID-19 pandemic, have had profound effects on various aspects of society worldwide. Mobility and human contact are widely recognized as key drivers of infectious disease transmission (Baroyan & Rvachev, 1970; Herrera-Valdez, 2011). Human behavior in these two aspects underwent significant changes during pandemics, driven by both policy interventions and heightened health concerns. These changes include decreased intercity and intracity movement, reduced social gatherings, and altered spending patterns (Heroy et al., 2021; Weill et al., 2020; Gao et al., 2020a; Alexander and Karger, 2020). Industries closely tied to tourism, such as aviation, hotels, and restaurants, have experienced unprecedented disruptions (Fotiadis et al., 2021; Zheng et al., 2021; UNWTO, 2020b). Tourism-dependent cities have been particularly affected, facing declines in revenue and increased unemployment (Ntounis et al., 2022; OECD, 2020). Meanwhile, a travel destination serves as a place where residents and inbound travelers interact, which can facilitate disease transmission and increase health risks for both groups (Andersen et al., 2020; Xiong et al., 2020; Chang et al., 2021; Ren et al., 2022). These features present additional challenges for tourism-dependent cities, which must balance disease spread control with limiting restrictions on travel behaviors to mitigate economic losses during pandemics. Understanding how pandemics and associated policy responses influence the behavior of both residents and tourists, as well as the nature of their interactions within urban settings, is crucial for developing targeted strategies that protect public health while minimizing economic disruption.

Numerous studies have explored the impact of pandemics—COVID-19 in particular—on human mobility (Chang et al., 2019; Heroy et al., 2021; Santos et al., 2021), consumer spending (Wen et al., 2005; Alexander & Karger, 2020; Chetty et al., 2020), and tourism activity (Yang, et al., 2020;

Gössling et al., 2020; Sun et al., 2019). These relevant studies suggested that government policies play a critical role in driving behavioral changes. To control disease spread, many governments implemented social distancing measures, restricting activities in crowded environments such as restaurants and cinemas, as well as close-contact services like hairdressing and massage. Some governments also implemented economic stimulus measures to mitigate the economic downturn induced by the COVID-19 pandemic. These interventions often coincided with significant behavioral adaptations. However, most existing studies estimate the effects of these policies by modeling changes in behavior pre- and post-policy implementation. Since policy implementation usually aligns with shifts in the pandemic's state, it can be difficult to attribute observed behavioral changes solely to the policies themselves. Certain studies suggest that even in the absence of strict measures—or before they are enacted—individuals may alter their behavior in response to the severity of disease spread (Sheridan et al., 2020). These findings align with the Protection Motivation Theory, which suggests that when individuals perceive potential risks, they adopt coping strategies and behaviors to protect themselves from threats. It is necessary to distinguish the extent to which behavioral changes are driven by government policies versus the pandemic itself. This distinction can help tourism cities develop more resilient and minimally intrusive measures that complement individuals' proactive behavioral responses.

People's risk perceptions and coping behaviors may be influenced not only by the severity of the outbreak in their surrounding area (i.e., within their community or city associated with residents) but also by the severity of the outbreak in the external region (i.e., their country or internationally related to travelers) (Yang et al., 2023). People tend to show higher sensitivity and concern for risks occurring in their vicinity while perceiving risks in distant locations as less pressing. This conforms to the first law of geography, known as the distance decay effect (Tobler, 2004). However, health risks associated with pandemics can spread geospatially with population movements. Tourism cities are closely connected to other regions through tourist flows and can therefore expose people moving around the city, both residents and tourists, to a mixture of risks. Besides, travel decision-making is a dynamic, multi-stage process in which tourists face varying risks and policy restrictions at different stages, such as in their departure and destination cities. These combined factors influence tourists' travel intentions, destination choices, and activity preferences, ultimately contributing to the behavioral changes observed at the destination. Most existing studies primarily focus on local disease spread when examining behavioral changes (Lu & Wei, 2019; Wang et al., 2019; Weill et al., 2020; Carvalho et al., 2020; Coibion et al., 2020a). Neglecting behavioral changes induced by external outbreak situations

or policy factors is likely to result in tourism cities over- or under-estimating potential disease transmission and economic risks during public health crises.

Furthermore, residents and tourists, as the two key stakeholders in tourism cities, may exhibit different perceptions and coping behaviors in response to health threats. Residents generally have more information about their local environment and health-related services than tourists. According to the theory of information asymmetry (Bhargava & Chen, 2012), the party with less information is more likely to make decisions based on imperfect knowledge, lacking a full understanding of the true value of their choices. Considering the concept of product familiarity (Johnson & Russo, 1984), tourists are generally less familiar with a destination than residents. The low level of destination familiarity can induce a high-risk perception (i.e., physical risk as a type of vacation risk component), which affects information searching and decision-making behaviors (Horng et al., 2012; Roehl & Fesenmaier, 1992). As such, residents and tourists may exhibit distinct perceptions of local and external health risks due to disparities in the quantity and quality of information and differences in familiarity shaped by geographic and psychological distances. These variations result in diverse responses to outbreak-related factors originating locally or externally. Moreover, the importance and flexibility of various products and services differ between the two groups, prompting them to adopt distinct adaptive strategies in response to changing circumstances (Jeng & Fesenmaier, 2002; Payne et al., 1993). Understanding these differentiated behavioral changes driven by policies and pandemics is essential for designing target market strategies and pandemic control measures for each group.

Another issue closely related to disease transmission and to the risk perception of both groups is tourist-resident interactions in urban spaces. Tourists and residents share similar demands for various activities in cities, such as visiting stores and restaurants (Snepenger et al., 2003), utilizing natural resources (Sherlock, 2001), and participating in festivals (Derrett, 2003). Sharing these resources creates opportunities for residents and tourists to have encounters and interactions. During a pandemic, face-to-face contact, or even simply sharing the same facility without direct contact (i.e., dining at the same table at different times), can expose individuals to potential health risks posed by others. This can further influence their risk perception and shape their behavioral responses to various sources of health threats. However, the form and nature of relations between tourists and residents within cities can vary significantly, spanning co-location in space or activity venues simultaneously, to co-location in space or activity venues at different times, or even spatially separated. These diverse modes of interaction yield different levels of contact potential.

Although tourist-resident relations have long been a core issue in tourism literature, there is still a lack of theoretical and quantitative tools to effectively reveal when, where, and how potential

interactions between tourists and residents occur in cities. The concepts of “synchronous presence” and “asynchronous presence” in time geography can partially explain the different interaction modes between the two groups theoretically (Miller, 2005; Shaw & Yu, 2009). However, these concepts do not consider whether individuals engage in the same types of activities when they encounter in space and time, hindering the representation of the nature of potential interactions. From a quantitative perspective, several classic indicators have been widely used to quantify tourist-resident irritation or tourism impact on residents, such as Tourist Intensity and Tourist Intensity Rate (TIR) (Lundberg, 1974; McElroy, 2003; Dumbrovska & Fialova, 2014). These traditional measures are usually calculated from data at larger geographic scales (e.g., cities) and time scales (e.g., years). They are argued to be difficult in expressing spatial heterogeneity and temporal variation at a finer spatiotemporal scale (Mashkov & Shoval, 2023).

Therefore, it is urgent to develop a systematic analytical framework capable of theoretically and quantitatively revealing the potential interactions of tourists and residents. Addressing this issue will not only aid policymaking during pandemics but also contribute to more effective tourism management in a normal period. In recent years, problems such as over-tourism and overcrowding have become increasingly prevalent in tourism cities. These challenges are often linked to imbalanced tourist-resident interactions. Effective characterization of their potential interactions can empower tourism cities to cope with crises and contribute to the long-term sustainability of the tourism industry.

1.2 Literature Review

1.2.1 Pandemic-induced behavior changes

The societal devastation caused by infectious disease pandemics was profoundly demonstrated during the recent global COVID-19 pandemic. In response to the COVID-19 pandemic, countries worldwide have implemented interventions to restrict mobility and maintain social distance to slow the spread of the virus. These measures, along with the pandemic itself, have a significant impact on people’s physical and social activities (Heroy et al., 2021; Wang et al., 2022; Bennett et al., 2021). Economic sectors closely tied to travel and in-person services, such as tourism, hospitality, and restaurants, have been particularly hard hit, resulting in substantial job losses and reduced incomes for skilled and unskilled workers (UNCTAD, 2022; UNWTO, 2020a; Zheng et al., 2021; OECD, 2020; UNWTO, 2020b; Behsudi, 2020). As a response, economic stimulus measures like tax credits and stimulus

payments have been implemented to support the economy. However, it is important to note that these measures can also shape people's behavior and potentially accelerate the spread of the virus (Baker et al., 2020b; OECD, 2022; Kim and Lee, 2021; Li et al., 2020; Kim et al., 2020; Gourinchas, 2020). In this complex context, the interplay between disease spread and policy interventions could jointly reshape human behavior and pose significant challenges to different economic sectors. This subsection presents a systematic review of existing research on the effects of the pandemic and government policies on human mobility, tourism activities, and consumer spending, as well as the adaptive behavior of residents and tourists during crises.

1.2.1.1 Impact of the pandemic on mobility

Using large-scale mobility data collected from mobile devices (e.g., GPS, call detail records), some recent studies have captured a dramatic decrease in mobility during the COVID-19 pandemic (Gao et al., 2020; Pepe et al., 2020). Long-distance trips decreased more strongly than short-distance trips because of the containment measures targeting long-distance travel specifically, such as travel bans across country and state borders and cancellations of major events (Dueñas et al., 2021; Schlosser et al., 2020). Many individuals opted for domestic travel as an alternative to international trips (Donaire et al., 2021; Hall et al., 2020). Consequently, tourism destinations faced not only a decline in visitor arrivals but also a shift in the composition of their visitors. These findings underscore the critical importance of prioritizing the domestic tourism market during health crises.

Due to stay-at-home orders and bans on gatherings, people tended to visit public places less and spend more time at home to maintain social distancing (Weill et al., 2020; Xiong et al., 2020; Yabe et al., 2020). However, changes in mobility behaviors vary with socioeconomic and demographic characteristics. High-income people or well-educated people, who usually have a better home-office capacity, are more likely to reduce mobility and exhibit more social distancing (Hernando et al., 2020; Heroy et al., 2021; Hunter et al., 2021; Weill et al., 2020). Conversely, disadvantaged groups, such as those employed in face-to-face service industries, have to move for livelihoods and thus take higher health and economic risks (Molloy et al., 2021). Tourism-dependent cities were particularly vulnerable, as their economies typically rely heavily on service sector employment.

Beyond changes in travel intensity and distance, changes in travel behavior are also present in terms of travel purpose, travel time, and travel mode choice (Abdullah et al., 2020; Heiler et al., 2020; Persson et al., 2021). Using smartcard data obtained from the local subway operation system, Zhang et al. (2021) found that the daily commute flow decreased by 42% in Hong Kong, and trips to shopping areas and amusement areas dropped by 42% and 81%, respectively. However, the decline in different

types of travel flow combines two parts: 1) the decline of visiting different destinations and 2) the decline of subway usage. People's travel preferences and habits could change significantly when it comes to health issues. Some studies have shown that public transport use has declined more than private cars and slower modes of transport that do not require sharing space with others (Molloy et al., 2021; Persson et al., 2021; Salon et al., 2021).

1.2.1.2 Impact of the pandemic on tourism activities

Studies assessing the impact of the COVID-19 pandemic on tourism have considered the macroeconomic aspect, focusing on the changes in 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 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 great flexibility in their 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 on diverse travel activities that contain different perceived importance and complexity (Hwang & Fesenmaier, 2011). Some studies suggest that tourists increasingly gravitate towards outdoor and nature-based activities to seek destinations that facilitate social distancing and minimize the risk of virus transmission. This trend has led to an upswing in visitation to rural and natural areas, while urban and densely populated tourist hotspots have experienced a decline in demand. Consequently, alterations in tourism demand within cities during the pandemic may be attributed to a combination of changes in tourist arrivals and their activity preferences (Yang et al., 2020; Karabulut et al., 2020). This suggests the importance of estimating the impact of the pandemic on multifaceted travel activities instead of 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; Jun et al., 2007). Based on different natures of travel products, the impacts of the 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 for governments and stakeholders to develop strategies to respond to public health crises.

1.2.1.3 Impact of the pandemic on consumer spending

Consumer behaviors changed significantly during the pandemic for both health and economic reasons. Some recent studies have used survey data and near real-time spending data (e.g., bank account data, credit card transaction data, online payment platform spending records) to monitor responses of consumer spending to the pandemic and policy measures. Evidence suggests that consumer spending in the United States, Spain, Denmark, and Japan generally reduced at the early stage of the pandemic, coinciding with the shutdown of the economy and the strict confinement of the population (Carvalho et al., 2020; Chetty et al., 2020; García-Montalvo & Reynal-Querol, 2020; Li et al., 2020; Watanabe, 2020). Notably, spending reductions were concentrated on face-to-face contact services, such as restaurants and personal services (Alexander & Karger, 2020; Cox, 2020). Whereas people were embracing digital commerce, spending more on food delivery services and online shopping (Baker et al., 2020). However, people with different demographic characteristics responded in various ways and have differing attitudes, behaviors, and purchasing habits.

To mitigate the economic recession during the pandemic, countries worldwide have adopted economic stimulus packages, including wage subsidies, direct cash payments, and tax relief and loan repayment deferrals (Gourinchas, 2020). Some efforts have been devoted to assessing the effectiveness of these economic stimulus measures. Using population-scale debit card transaction data, Li et al. (2020) indicate that the stimulus payments issued in early April 2020 directly boosted daily spending

by about \$15.70 per card and \$3,307 per zip code in the United States. In South Korea, a consumption voucher program implemented by the central government led to increased food and overall household spending for 30% of households across all income groups (Kim & Lee, 2020).

Despite the temporary positive response shown by consumer spending, however, as Chetty et al. (2020) argued, the traditional macroeconomic tools have limited capacity to restore employment when health concerns constrain consumer spending. Different from previous recessions triggered by calamities like earthquakes or hurricanes, the economic decline arising from COVID-19 was driven primarily by adverse aggregate demand shocks in face-to-face service sectors (such as hospitality and leisure, transport and retail) rather than by aggregate supply shocks (Watanabe, 2020). Mulay et al. (2021b) used transaction data in the United States to examine the impact of stimulus payments, revealing time-varying consumer responses across sectors. After the first stimulus check, spending increased primarily on essential goods, while the third check drove higher spending on non-essential items, such as luxury and entertainment. This highlights the shifting effects of stimulus payments on consumer demand recovery. However, whether the impact of stimulus and social distancing on human behavior will conflict is still unclear. It is still a big challenge for policymakers to effectively respond to “flatten the recession curve” after flattening the infection curve.

Although existing research has utilized advanced statistical techniques to gauge the impact of the pandemic and the containment measures on spending behavior, few efforts have been made to explain behavioral responses in the context of soft social distancing measures, particularly the spending behavioral responses to COVID-19 itself without travel restrictions. Sheridan et al. (2020) conducted a study in Denmark and Sweden, utilizing a natural experiment, to analyze the impact of the virus and containment measures on consumer spending. They found that the pandemic itself was the primary reason for spending reductions, while the containment measures had a limited impact. These findings suggest that even in the absence of strict mobility restrictions, individuals may proactively adjust their behavior based on the severity of the pandemic, leading to spending reductions and changes in consumption patterns. It is critical to gain insights into the active spending responses to COVID-19 itself. Especially in the early stages of the pandemic, there was a lack of comprehensive knowledge and effective interventions for emerging infectious diseases. In such circumstances, individuals may exhibit tendencies towards overreacting or underreacting.

1.2.1.4 Adaptive behaviors during crises between residents and tourists

Protection Motivation Theory (PMT) explains how individuals perceive and evaluate specific threats and subsequently engage in protective behaviors (Rogers, 1975; Floyd et al., 2000). In tourism, the

application of protection motivation theory has focused on exploring tourists' perceptions and protective behaviors toward potentially risky destinations and activities (Wang et al., 2019; Slevitch & Sharma, 2008). However, while research has examined the protective behaviors of tourists, a significant research gap exists in understanding the differences between residents and tourists in their evaluations of and responses to health threats. At a destination, residents and tourists may have unequal access to information about the location and its healthcare services, leading to varying levels of trust in the local government. This idea is related to the theory of information asymmetry, which refers to the difference in the amount and quality of information that sellers and buyers have in consumer behavior (Mavlanova et al., 2012). Information asymmetry creates an imbalance of power. For instance, when a seller possesses more information than the buyer, the buyer is more likely to make a decision based on incomplete and/or misleading information (Park & Nicolau, 2015). This can result in a lack of trust and confidence in their decisions. Likewise, residents relatively have more information about healthcare issues/services in a particular place (i.e., where they live) than travelers, leading to an imbalance of power.

The different behaviors between residents and travelers at the same place can be attributed to destination familiarity. Perceived familiarity affects not only information-searching behaviors but also the decision-making process (Horng et al., 2012; Carneiro & Crompton, 2010; Roehl & Fesenmaier, 1992). Some studies suggest that individuals with low levels of familiarity with a product (or destination) are more likely to spend time and effort searching for information (Carneiro & Crompton, 2010). Based on the idea of utility maximization, people tend to keep gathering information until they can certify the acceptable values of their future decisions. Residents are relatively more familiar with a place as a residential area than travelers. This difference in perceived familiarity between residents and tourists can lead to varying costs and efforts in evaluating their abilities to cope with risks and uncertainties, ultimately resulting in distinct behavioral responses. A destination showed dynamic conditions of the pandemic denoting the first and second waves of COVID-19. To alleviate the outcomes of the pandemic, the government implemented several strategic policies such as social distancing and stimulus payments. Two stakeholder groups, residents and travelers, have different amounts and quality of information and levels of familiarity associated with geographical and psychological distances. The different characteristics lead to heterogeneous consumption behaviors in spending on travel products.

Furthermore, the multifaceted nature of travel products requires people to make multiple choices throughout their trips. Individuals have different levels of importance and risks to the diverse products/services, which leads to dynamic decision-making strategies (Jeng & Fesenmaier, 2002). The

concept of adaptive decision-maker suggests that individuals tend to use a variety of strategies to make judgments and choices in responding to changes in decision circumstances (Payne et al., 1993). This implies that people, including both residents and travelers, are likely to develop varying strategies across diverse travel products where individuals present different levels of decision flexibility and priority.

1.2.2 Tourist-resident interaction: significance, forms and measures

1.2.2.1 Tourist-resident interactions in the context of public health crises and overtourism

During the COVID-19 pandemic, interactions between tourists and residents increased the risk of disease transmission, posing health risks to both groups (Qiu et al., 2020; Fong et al., 2020). However, the nature of these interactions varies significantly across urban spaces, leading to differing levels of potential risk. For instance, casinos and resorts in urban destinations often primarily cater to tourists, with limited visits by residents, resulting in a lower risk of inter-group disease transmission. In contrast, shared spaces such as shopping districts and nightlife areas, frequented by both tourists and residents, carry a higher risk of inter-group transmission. Applying uniform intervention measures across different settings may cause unnecessary economic harm while failing to achieve effective disease control. Therefore, understanding the spatial and temporal patterns of tourist-resident interactions in urban environments is critical for designing resilient and targeted crisis response strategies.

Addressing this issue is essential not only for effective crisis management but also for promoting sustainable tourism development. Tourist-resident interaction, also known as tourist-host interaction or host-guest interaction, has long been a core topic in tourism literature. Positive interaction can contribute to the social and economic sustainability of tourism destinations by fostering cultural exchange and community integration, as well as enhancing the tourist experience while promoting local support for tourism development. However, excessive or low-quality interactions can lead to negative outcomes. In recent years, the rapid and unrestricted growth of tourism in some places has led to an increasing number of conflicts between tourists and residents. Many popular tourist destinations face an influx of tourists during peak seasons, which encroaches on residents' living spaces and resources, leading to heightened tensions and competition between the two groups. Such tension directly leads to problems such as congestion, overcrowding, and market price fluctuations. It can also lead to a perceived power imbalance for residents and contribute to anti-tourism sentiments, ultimately leading to overtourism and touristification (Woosnam et al., 2009; Mody et al., 2019; Jover

& Díaz-Parra, 2023). Understanding how tourists and residents coexist within urban spaces is therefore vital to balancing their interests, mitigating potential conflicts, and fostering resilient and sustainable tourism development.

1.2.2.2 Forms and outcomes of tourist-resident interaction

The form and nature of interaction between residents and tourists vary significantly, spanning intentional commercial or personal exchange-based encounters, to unintentional or spontaneous encounters, or relationships limited to sharing space without contact or communication (Krippendorf, 1987; Sharpley, 2014). These diverse forms of interactions yield different outcomes. Intentional encounters, such as interactions between tourism practitioners and tourists, directly influence the tourist experience and tourism development (UNESCO, 1976). This research area has gained significant attention due to its direct impact on tourism and the relative ease of data collection. The latter two types of interactions are more critical to residents' well-being and central to conflicts between tourists and residents. Unlike residents who are economically dependent on tourism, residents informally involved in tourism often hold more negative perceptions of tourists and tourism development (Gursoy, Chi, & Dyer, 2010; Escudero Gomez, 2019). This part of residents usually has similar demands for various activities with tourists, such as visiting stores and restaurants (Snepenger et al., 2003), utilizing natural resources (Sherlock, 2001), and participating in festivals (Derrett, 2003). This overlap creates opportunities for interaction between the two groups but also heightens competition for space and resources when local resources are strained (Namberger et al., 2019). However, research on unintentional interactions between tourists and residents is limited due to their spontaneous and unpredictable nature as well as the resulting challenges in data collection and measurement.

Such interactions and encounters between tourists and residents tend to be concentrated in specific locations rather than evenly distributed within cities (Belisle & Hoy, 1980; Sheldon & Var, 1984). Public resources in urban areas are often unevenly allocated, with tensions most pronounced in hotspots where residents and tourists converge. Residents living near or visiting these areas are more likely to experience crowding and develop negative attitudes toward tourism (Jurowski & Gursoy, 2004; Raymond & Brown, 2007; Sharma & Dyer, 2009). Temporal factors further exacerbate these dynamics. For example, city centers often serve as activity hotspots for both groups, where crowding intensifies during daily peak hours and peak tourist seasons (Jacobsen et al., 2019). The nature of interactions between residents and tourists also significantly affects outcomes (Teye et al., 2002). Positive intergroup connections, such as playing sports or attending events together, can foster

communication and knowledge exchange. However, disruptive behaviors like late-night noise in residential areas often create friction and resentment. Thus, understanding the specific context and nature of these interactions is critical, as different types of participation can lead to varying perceptions of tourism's impact on local communities.

1.2.2.3 Measurements for tourist-resident interaction in tourism study

In the tourism field, commonly used indicators for approximating the potential for tourist-resident interaction include *Tourist Intensity (TI)* and *Tourist Intensity Rate (TIR)*. *Tourist Intensity* is calculated as the ratio of tourists to the local population (Lundberg, 1974; McElroy, 2003), while *Tourist Intensity Rate* measures the number of tourists per 100 residents (Dumbrovska & Fialova, 2014). These indicators are rooted in Doxey's Irridex model (1975), which conceptualizes host community reactions to tourism as a four-stage process: Euphoria, Apathy, Annoyance, and Antagonism. The model posits that residents initially have a positive attitude toward tourism, but as tourism increases, its negative impacts generate irritation, eventually leading to hostility (Teye, Sonmez & Sirakaya, 2002). It asserts that irritation depends on the number of tourists and the degree of incompatibility between tourists and residents.

While these indicators have been widely used to explore tourism's effects on residents, they have faced criticism for their overly simplistic assumptions (Wall & Mathieson, 2006; Dyer et al., 2007; Mason & Cheyne, 2000; Tosun, 2002). A key limitation is the conceptualization of tourism's impact as a linear process driven solely by changes in tourist numbers. Additionally, these approaches assume that increases in tourist numbers have uniform effects on destination communities. Residents usually exhibit diverse perceptions and responses to tourism, influenced by individual attributes such as geographic location and involvement in tourism-related industries. The form, quality, and frequency of interactions between tourists and residents shape both groups' experiences and perceptions. Existing quantitative measures are inadequate for capturing the complex relationships of residents and tourists within cities.

Another limitation of traditional indicators is their reliance on data aggregated at broad geographic (e.g., city-wide) and temporal (e.g., annual) scales, limiting their ability to capture localized and time-sensitive dynamics (Mashkov & Shoval, 2023). Surveys commonly used in tourism research also fall short of revealing real-time interactions between tourists and residents, particularly concerning spatial distribution, timing, and activity venues. Recent advancements in big data analytics have allowed scholars to examine the spatiotemporal co-location patterns of residents and tourists in urban environments, shedding light on the dynamic interactions between these groups (Chen et al.,

2022). However, significant gaps remain in understanding the potential interactions between residents and tourists in urban contexts. Developing advanced theoretical frameworks and finer-grained quantitative methods is essential to address these limitations. Such innovations would enable more precise analyses of the multifaceted relationships between residents, tourists, and urban spaces, ultimately enhancing urban and tourism management practices.

1.2.3 Social interaction from a geographical perspective

1.2.3.1 Space-time path relationships and potential interaction modes in time geography

Time geography offers a perspective that helps us understand the complex and varied underlying interaction patterns between different population groups. In the field of time geography, space and time are connected through the concept of *space-time path*, as shown in Figure 1.1(A), which captures the sequence of activities an individual engages in at different locations throughout a time period (Hägerstrand, 1970). As shown in Figure 1.1(B), there are two basic types of space-time path relationships between different individuals that allow for potential interactions in physical space (Shaw & Yu, 2009; Miller, 2005; Parkes & Thrift, 1980; Golledge & Stimson, 1997; Janelle, 1995). Co-location in space but not in time describes the cases when activities in different space-time paths occupy the same location in different time windows. Individuals, in this case, can interact or communicate with each other through physical entities in the co-located place, such as leaving notes on a bulletin board. This mode of interaction, which Janelle (1995) termed *Asynchronous presence (AP)*, requires spatial coincidence but not temporal coincidence. Co-location in space and time describes the cases when activities occur at the same location and within a common time window. Individuals can meet and interact face-to-face with each other in this situation, a mode of interaction known as *Synchronous presence (SP)*.

Individuals in synchronous presence mode obviously have a higher potential for direct contact but are also more likely to generate competition due to the simultaneous need to use space. In asynchronous presence, individuals share space, but the possibility of conflict is lower due to differences in access time patterns. From this perspective, similarities and differences in the types of activities that individuals engage in are crucial to understanding the potential for interaction and competitive relationships. For example, residents and tourists may visit the city center at the same time, but tourists shopping in stores may not have a substantial impact on residents working in offices. On the contrary, residents and tourists who meet in restaurants for dining needs may increase each other's

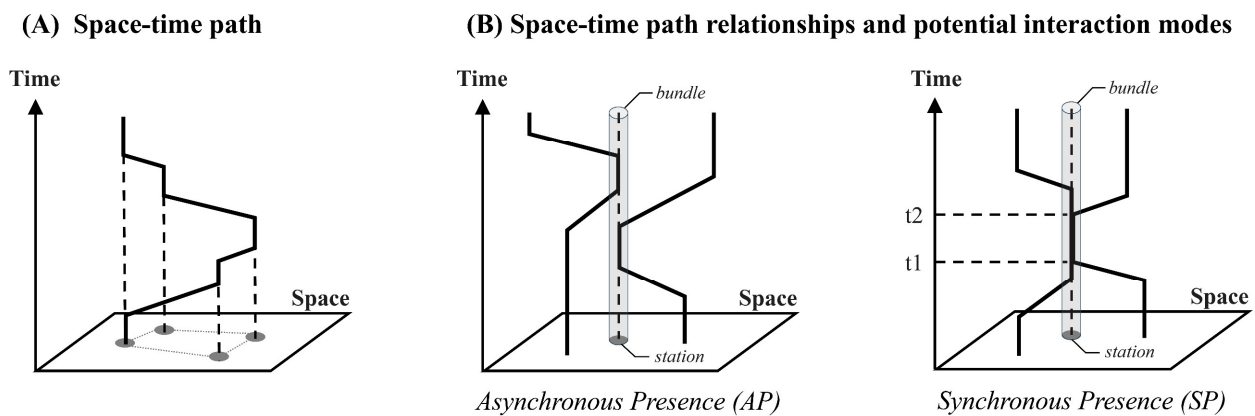


Figure 1.1 Examples of space-time path and space-time path relationships. (A) Space-time path; (B) Two types of space-time path relationships and the corresponding potential interaction modes (adapted from Shaw & Yu, 2009).

waiting time due to limited reception seats, resulting in a sense of crowding for both groups. However, although the activity sequence links the location and time in the space-time path, the activity dimension is not incorporated into analyzing the space-time relationship between individuals in the existing analytical framework. This study aims to extend an activity dimension to the existing framework to enrich our understanding of the relationships and interaction patterns between tourists and residents in different scenarios.

1.2.3.2 Measures of social interaction

Social segregation refers to the physical separation or uneven distribution of different population groups, restricting their interactions and social connections. Numerous techniques and indices have been formulated to measure spatial segregation from the five dimensions, i.e., *evenness*, *exposure*, *concentration*, *centralization*, and *clustering* (Duncan and Duncan, 1955; Theil and Finizza, 1971; Atkinson, 1970). Exposure measures segregation from the perspective of the possibility of interaction between different social groups (Bell, 1954; Lieberman, 1981; White, 1986; Farber et al., 2015). The most popular index of exposure is the Interaction index, also known as the Exposure index, which measures the probability that a member of one group will encounter another person of the other group within a given areal unit (Wong, 2002).

Relative to measures like tourism intensity, the advantage of segregation indices is their ability to capture spatial heterogeneity. Classical quantitative studies on social segregation primarily focus on measuring the degree of separation between different racial or socioeconomic groups in residential places, to inform the equitable allocation of public resources and promote social integration. These

measures are calculated from data at a finer spatial granularity, such as communities or neighborhoods. The interaction probability of different social groups is calculated at the local level and the probabilities for all spatial units are aggregated to obtain the overall probability. Therefore, these measures can reveal the spatial variation through the local level estimation and can also capture the weighted average interaction potential across the entire study area.

As human mobility increases, scholars have gradually recognized that people could experience segregation in various spaces in their daily lives, not just where they live (Wong and Shaw, 2011; Kwan, 2013). When people move out of their place of residence to engage in various activities, they redistribute in urban space and may encounter different others, which could reshape their experience of segregation/integration (Kwan and Schwanen, 2016; Park and Kwan, 2017). Some studies have reported that the extent of segregation in workplaces was considerably lower than that in residential areas (Ellis et al., 2004). The group composition of leisure-time activities, such as engaging in sports and attending events, was much more even, which may facilitate the formation of intergroup contacts (Kao and Joyner, 2004; Shinew et al., 2004). Temporally, the use of space in a city is determined by activities that are specific to certain times of day, days of the week, and seasons. Social segregation in urban space will also show temporal changes according to the clocks of these activities' occurrence (Silm and Ahas, 2014). Consequently, the research focus has shifted from static residential segregation measurement towards more dynamic, activity space segregation (Wong and Shaw, 2011; Åslund and Skans, 2010).

Some existing studies use traditional residential segregation indices to quantify segregation in activity places (workplaces and leisure activity places) (Ellis et al., 2004), or measure dynamic segregation in cities by calculating segregation indices in different time periods (Ellis et al., 2004; Palmer, 2013; Palmer et al., 2013; Farber et al., 2015; Järv et al., 2015; Silm and Ahas, 2014b; Le Roux et al., 2017). While this approach can effectively illustrate variations in interaction potential across time and activity, it fails to unveil the uneven distribution of different groups across different dimensions. For example, when two social groups access the same urban area at different times and engage in various activities, the measured potential for interaction may appear relatively low. However, when the constraints of time and activity are removed, merely observing the occupancy of space by different groups may lead to completely opposite conclusions. This does not mean that the latter measurement is meaningless; it at least reflects the fact that space is shared by the two groups, which is information that the former type of measurement cannot obtain. In traditional segregation measures, addressing uneven distribution along one dimension usually requires introducing an additional dimensional measure, such as the dissimilarity index. However, this study introduces a hierarchical

framework by progressively adding constraining dimensions to observe the diverse patterns of co-location that may occur among different groups in space, time, and activity. This approach aims to provide a new perspective on understanding how different groups co-use urban space in different ways.

1.3 Research Gaps and Objectives

1.3.1 Research gaps

While the existing literature provides valuable insights into the impacts of the COVID-19 pandemic on human behavior and tourist-resident interactions, several critical gaps remain unexplored. These gaps highlight the need for further research to address the following issues:

- (1) **Limited attention has been devoted to distinguishing the direct impacts of the pandemic itself on human behavior from those driven by policy responses.** Existing research has employed advanced statistical techniques to assess the impact of the COVID-19 pandemic on human behavior. Given that many national or city governments implemented strict travel restrictions during the early stages of the pandemic to curb the virus's spread, most studies investigate behavior changes in such contexts. Consequently, statistical estimates of behavior change typically include the effects of travel restrictions and those of the pandemic itself. Besides, most existing studies estimate the impacts of government policies by modeling changes in human behavior pre- and post-policy implementation. Considering that policy implementation frequently coincides with shifts in the pandemic's state, it becomes challenging to ascribe the observed behavioral changes solely to the enacted policies. Evidence suggests that even without strict mobility restrictions, individuals may adjust their behavior based on a pandemic's severity, resulting in changes in consumption patterns (Sheridan et al., 2020). This highlights the necessity of investigating spontaneous behavioral responses to variations in pandemic severity, independent of strict policy restrictions, to better understand risk perception and crisis response mechanisms. Furthermore, isolating the pandemic's direct effects when assessing policy impacts is essential for accurately determining policy effectiveness, thereby informing more resilient strategies for future crisis management.
- (2) **Existing studies primarily focus on the impact of local pandemic-related factors on human behavior, neglecting the influence of external factors.** Unlike localized crises such as earthquakes or hurricanes, the health risks associated with pandemics can spread across

geospatial terms. Tourism cities may expose both residents and tourists to multiple sources of risk due to being closely connected to other regions via travel flows. As such, individuals' risk perceptions and coping behaviors are influenced not only by the severity of the outbreak in their immediate area (e.g., local communities) but also by the severity of the outbreak in external regions (e.g., other countries or globally). Besides, travel decision-making is a dynamic, multi-stage process where tourists encounter different risks and policy restrictions at various stages. These combined factors shape tourists' travel intentions, destination choices, and activity preferences, contributing to behavioral changes at the destination. This suggests that behavioral responses to local and external pandemic conditions may vary in degree and exhibit time-lag effects.

- (3) **The heterogeneity of pandemic-induced behavioral changes across various activities remains underexplored.** Existing studies have predominantly focused on overall changes in tourist arrivals at destinations. However, travel decisions are multifaceted, involving multiple partial decisions—such as selecting destinations, accommodations, attractions, restaurants, and shopping—each made through a dynamic, successive, and multistage process (Dellaert et al., 1998; Jeng & Fesenmaier, 2002; Park & Fesenmaier, 2014). Different tourism activities vary in terms of perceived importance and flexibility in adjusting plans (Park & Fesenmaier, 2014; Jeng & Fesenmaier, 2002). Besides, the adaptive decision-making concept suggests that individuals tend to use various strategies to make judgments and choices in response to changing circumstances (Payne et al., 1993). Consequently, both residents and travelers are likely to develop distinct strategies for different activities, with each activity offering varying degrees of flexibility and priority in decision-making.
- (4) **A notable gap remains in understanding the differences in behavioral responses between tourists and residents in the presence of health threats.** Residents and tourists differ in their familiarity with the destination and access to information, which may influence their information-seeking and decision-making process. Additionally, residents and tourists may perceive local and external risks of disease spread differently due to differences in geographical and psychological distances, leading to distinct responses to pandemic-related factors. While many studies have independently examined behavioral changes in residents and tourists, few have explored these changes under comparable conditions, thereby minimizing the confounding effects of different environmental variables. Addressing this gap is essential for a deeper understanding of their respective response mechanisms and decision-making processes during health crises.

- (5) **It remains unclear how tourists and residents interact within cities regarding space, time, and activity venues.** This gap hinders our understanding of potential contact between the two groups, which is crucial for assessing disease transmission risks. Additionally, this issue is highly relevant for managing interactions and mitigating potential conflicts between tourists and residents during normal periods and tourism peaks. Existing research often examines how the overall demographic proportions of tourists and residents at a destination influence their attitudes and perceptions. However, it frequently overlooks the critical role of intergroup interactions and encounters in shaping their experiences and perceptions. Besides, residents and tourists may share urban spaces and facilities in diverse ways, with different spatiotemporal co-location patterns leading to varying modes of interactions and contact potentials. The concepts of “synchronous presence” and “asynchronous presence” from time geography partially explain these interaction patterns (Miller, 2005; Shaw & Yu, 2009). However, they fail to account for whether individuals engage in similar activities during spatial and temporal encounters, limiting their ability to fully characterize the nature of these interactions. A theoretical framework is required to effectively characterize the diverse interaction modes between tourists and residents across space, time, and activity venues, as well as the variations in contact potential associated with these modes.
- (6) **Existing tourism indicators are inadequate for capturing the interaction potential between tourists and residents across different interaction modes.** These traditional measures, such as tourist intensity or tourist intensity rate, typically rely on statistical or survey data to estimate tourist-resident ratios at large geographic (e.g., city-wide) and temporal (e.g., annual or monthly) scales. However, these measures fail to account for the spatial heterogeneity and temporal variability of interactions within urban settings. While recent advancements in big data offer valuable insights into the spatial and temporal distributions of tourists and residents, they often fall short in identifying activity-specific interactions, leaving critical questions unanswered—such as which type of activity venues most significantly contribute to intergroup interactions. This highlights the need for an innovative quantitative framework capable of systematically evaluating diverse interaction modes and capturing variations in interaction potential across space, time, and activity venues.

1.3.2 Research objectives

To address the above research gaps, this thesis aims to achieve the following six research objectives:

- (1) To assess the extent to which human behavior in tourism cities varies in response to the severity of the pandemic, both locally (within the tourism city) and remotely (in the origin regions of tourists).
- (2) To assess the effects of policy responses, including social distancing and stimulus payments, on human behavior in tourism cities.
- (3) To assess the heterogeneous impacts of the pandemic and policy responses across various economic sectors.
- (4) To assess the extent to which the impacts of the pandemic and policy responses differ between residents and tourists.
- (5) To characterize the diverse interaction modes between tourists and residents across space, time, and activity venues, as well as variations in direct contact potential across different modes.
- (6) To construct quantitative indices to measure the potential for interactions between tourists and residents across various modes.

Achieving these research objectives will provide a comprehensive understanding of how pandemics and related policy responses influence human behavior in tourism cities, with particular attention to the nuanced differences between residents and tourists. This research will contribute to the development of effective strategies for managing tourist-resident interactions, mitigating health risks, and fostering economic resilience. Moreover, it will enrich the theoretical framework of time geography and advance our understanding of intergroup interactions, offering valuable insights into the dynamics of tourist-resident engagements across space, time, and activity venues. The proposed quantitative framework and indices will offer practical tools for policymakers and urban planners to evaluate and enhance the sustainability and adaptability of tourism cities in the face of future global challenges.

1.4 Research Tasks and Research Outline

To achieve the research objectives, this thesis uses crowdsourced big data in Jeju, the Republic of Korea (hereafter Korea) to evaluate pandemic-induced behavioral changes and tourist-resident interactions. The research framework is illustrated in Figure 1.2. This thesis addresses six research objectives through three distinct studies.

Chapter 2 employs a large-scale navigation dataset to evaluate the behavior change of domestic inbound travelers in Jeju, Korea, during the COVID-19 pandemic. Since the Korean government did not impose restrictions on inter- or intra-urban mobility during the pandemic, this setting offers an experimental context to study travelers' dynamic behavioral responses without the confounding effects of mobility restrictions. To identify trends in travel behavior changes, the study first estimates the percentage change in travel frequency relative to the pre-pandemic period, analyzing data at both the daily level and across distinct pandemic stages, including the first-wave outbreak, the stable period, and the second-wave outbreak. Multivariate linear regression models are developed for the three pandemic stages to analyze behavior at both the overall level and across different activity types. These models incorporate multiple local and national COVID-19 indicators, such as daily new cases and cumulative fatality rates, alongside the Google search index for COVID-19 to account for subjective perceptions of health risks. Using cross-correlation analysis, the study highlights the varying time-lag effects of these factors on travel behavior at different pandemic stages.

Chapter 3 quantifies the impact of COVID-19 and policy responses on the spending behavior of both residents and domestic inbound travelers in Jeju, Korea, using a large-scale credit and debit card transaction dataset. Transaction data offers significant advantages in this context, as it captures human behavior dynamics from both activity participation (measured by the number of transactions) and economic perspectives (measured by expenditure). To better understand behavioral changes across consumer groups and activity venues, statistical analysis is employed to examine changes in activity participation and expenditures for the two groups at both an aggregate level and across nine distinct activity categories. Regression models are developed to quantify the impact of pandemic severity and policy responses on these changes, incorporating key indicators at both local and national levels, such as daily new confirmed cases in Jeju and Korea. Policy factors analyzed include the implementation of local and national social distancing measures during the first and second waves, as well as stimulus payments during the stable period of the pandemic. The analysis aims to disentangle the effects of the pandemic and policy measures on consumer behavior, highlighting the uneven distribution of these impacts across different economic sectors.

Chapter 4 introduces an innovative analytical framework to explore potential interactions between tourists and residents through a time-geographic lens. The framework extends the two types of space-time path relationships in time geography (i.e., *asynchronous presence* and *synchronous presence*) by incorporating the activity dimension, thereby expanding the potential interaction modes between individuals into four types (i.e., *asynchronous presence for the same type of activity*, *asynchronous presence for different types of activities*, *synchronous presence for the same type of*

activity, synchronous presence for different types of activities). This conceptualization clarifies the various modes of interaction between tourists and residents across space, time, and activity venues. A hierarchical framework consisting of three co-location scenarios (i.e., *co-location in space*, *co-location in space and time*, *co-location in space and time for the same type of activity*) is proposed to link theoretical concepts of interaction modes with measurable indices. Several quantitative indices are developed to assess the potential for tourist-resident interactions corresponding to the three co-location scenarios. Using a large-scale debit and credit card transaction dataset from Jeju, Korea, this study conducts an empirical analysis to demonstrate the effectiveness of the proposed framework in capturing the complexity and dynamics of tourist-resident interactions during normal periods, tourism peak season, and the COVID-19 pandemic.

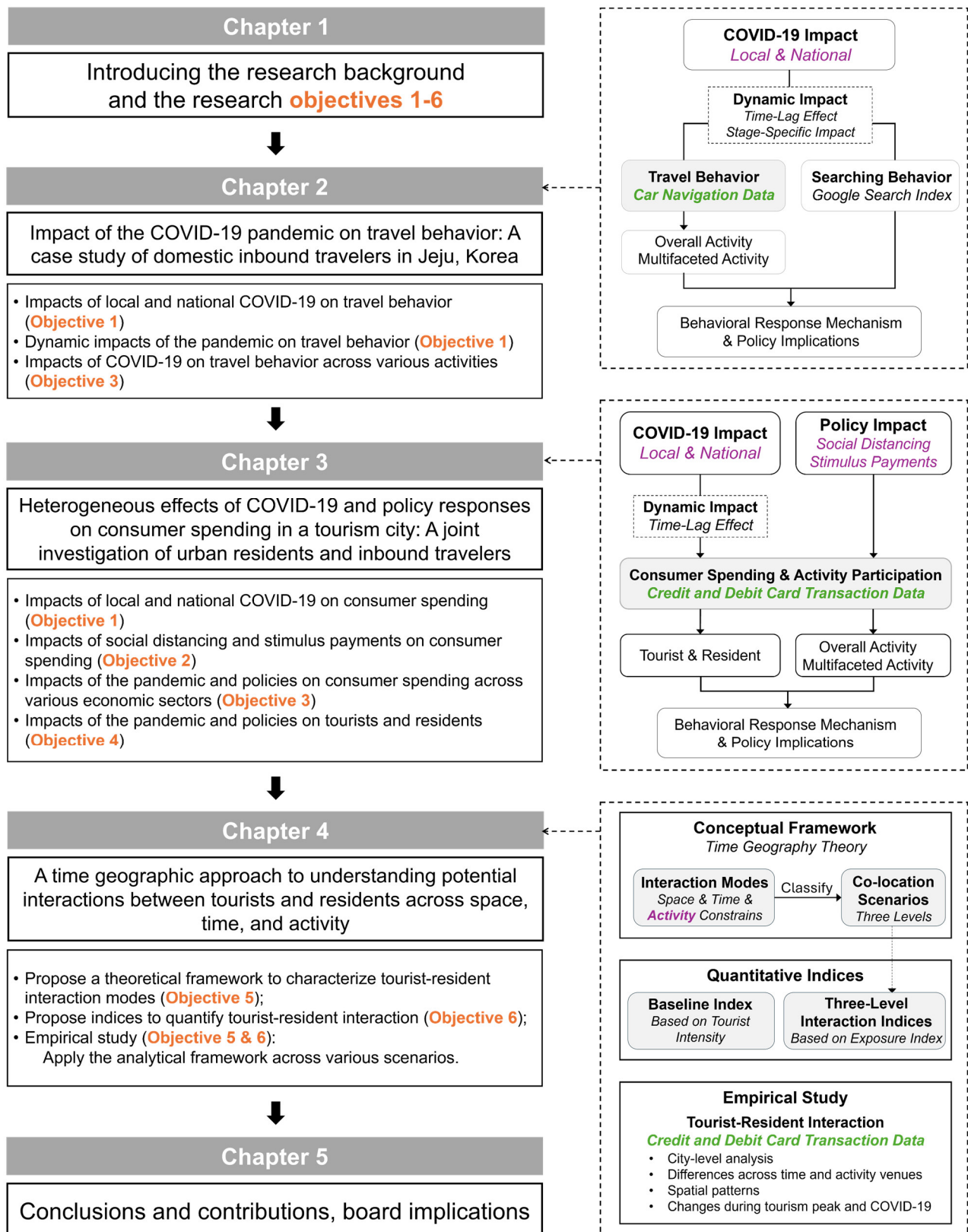


Figure 1.2 Research framework with detailed research objectives for each main chapter, as well as the data and methods used in each chapter.

Chapter 2

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

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2.1 Introduction

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 investigating the impact of the 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 estimations 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.

A critical challenge for tourism cities is the varying influences of local and external disease spread on risk perceptions and travel behavior. In general, people may show higher sensitivity and

concern for the corresponding risks occurring in their vicinity and may have lower perceptions of risks far from their geographic location. However, the nature of pandemic-related health risks, which can be geospatially spreadable, is likely to result in a more complex interplay between geographical proximity and perceived health risks. In this context, the concept of the distance decay effect, known as the first law of geography, becomes particularly relevant. Since different stages of a trip involve varying degrees of psychological and geographic distance to local and external risks, these differences can jointly shape tourists' travel intentions, destination choices, and activity preferences, contributing to behavioral changes at the destination.

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 heterogeneous 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 the 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, 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, the national and local pandemic status may influence visitors' risk perception and then impact their travel decisions. However, given that visitors typically plan their trips and book services in advance,

there may be a corresponding time-lag effect of the pandemic on their travel changes (Huang et al., 2020). And the time-lag effect 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 the destination. The adaptive decision-making concept suggests that people tend to use various strategies to make judgments and choices in response to changing environments (Payne et al., 1993). Given that different tourism activities vary in terms of perceived importance and flexibility, it is expected that the pandemic-induced behavior changes vary across activity types. 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, reveals the heterogeneous effects of the 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.

2.2 Study Area and Datasets

2.2.1 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 2.1B), with a total area of 1,847.2 km² and a population of over 670,000 (Statistics Korea, 2021). The administrative area of Jeju Province is divided into two municipalities, with Jeju City as the capital. Similar to many other

island destinations, Jeju is geographically isolated with limited land transport access and a high dependency on tourism. These features make such regions particularly vulnerable to economic and social disruptions during pandemics, given their reliance on tourist inflows (OECD, 2020). Thus, balancing public health control and economic recovery is even more important in such cities.

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 Tourism Association, 2020). However, Jeju remained a major domestic travel destination. According to Jeju Tourism Organization (2019), Jeju received over 15 million visitors annually before the pandemic, with 86% of domestic visitors. Since the Korean government did not impose strict inter-city travel restrictions during the pandemic, domestic tourism to Jeju remained largely uninterrupted. This context provides an ideal setting to examine spontaneous behavioral responses of domestic visitors, independent of the effects of travel bans.

2.2.2 COVID-19 timeline of Korea

Figure 2.1A demonstrates the timeline of the COVID-19 pandemic in Korea and Jeju from January to September in 2020 and the policy responses of the 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.

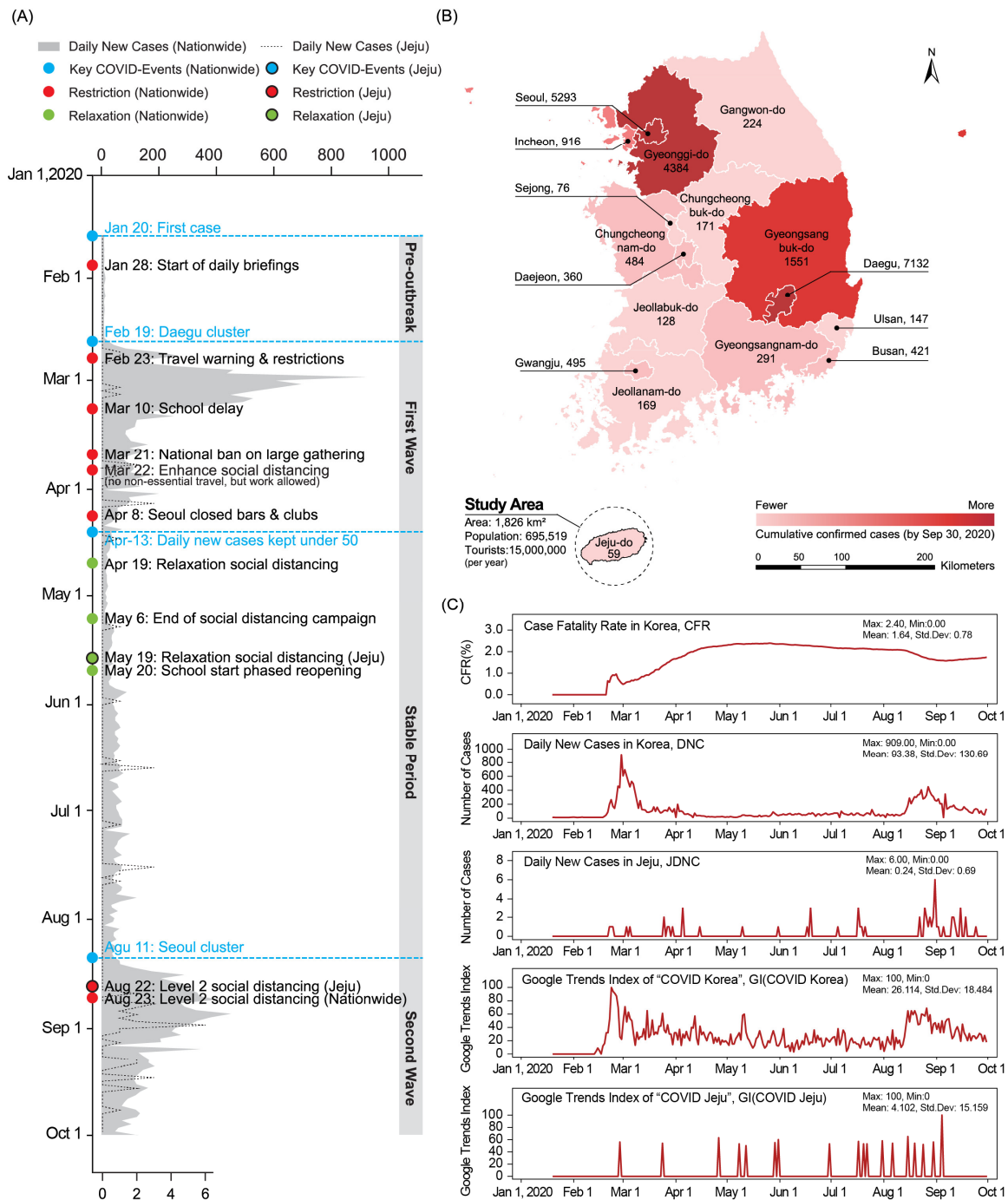


Figure 2.1 The COVID-19 pandemic in Korea by the end of September 2020: (A) Timeline of the COVID-19 pandemic in Korea and Jeju from January 1, 2020 to September 30, 2020; (B) Province-level distribution of cumulative COVID-19 confirmed cases in Korea by September 30, 2020; (C) COVID-19 indicators and 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 the search term “COVID Korea”, and Google Trends Index of the search term “COVID Jeju”.

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 in Jeju was 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 overseas travelers (Figure 2.1B).

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 a 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 the 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).

2.2.3 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*).

2.2.3.1 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).

2.2.3.2 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.

2.2.3.3 Daily new cases in Jeju (JDNC)

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

2.2.4 Google trends index

Internet search data has been widely used for public sentiment monitoring and behavior prediction (Choi & Varian, 2012; Effenberger et al., 2020; Gligorić et al., 2022; Sun et al., 2019; Zou et al., 2019). 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.

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) 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.

2.2.5 Navigation dataset

This study uses a navigation dataset to capture changes in travel behavior of domestic visitors for multifaceted activities in Jeju. The dataset was obtained from one of the largest telecommunications companies in Korea, which provides navigation services to travelers through its mobile application.

Table 2.1 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

This navigation app dominates the domestic market, with approximately 70% market share, around 20 million registered users, and 14 million monthly active users. Given that over 85% of domestic visitors use rental cars to travel around the island and that navigation apps are commonly used for car trips (Jeju Tourism Organization, 2020), this dataset offers a valuable lens through which to observe changes in domestic travel behavior.

This dataset tracks the travel history of domestic inbound travelers who used the company's navigation service and conducted travel movements in Jeju from January 1, 2020 to September 30, 2020. As shown in Table 2.1, 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 that occurred with the identical OD flow in terms of the 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.

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 2.2). The official number of inbound travelers here mainly represents 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 reveal 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

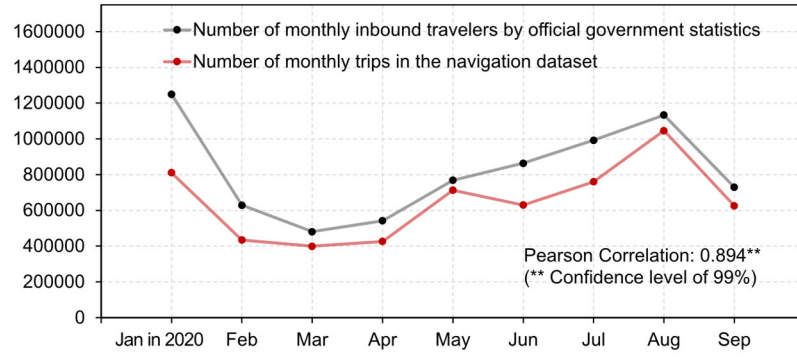


Figure 2.2 Correlation between the number of monthly inbound travelers by official government statistics and the number of monthly trips in the navigation dataset.

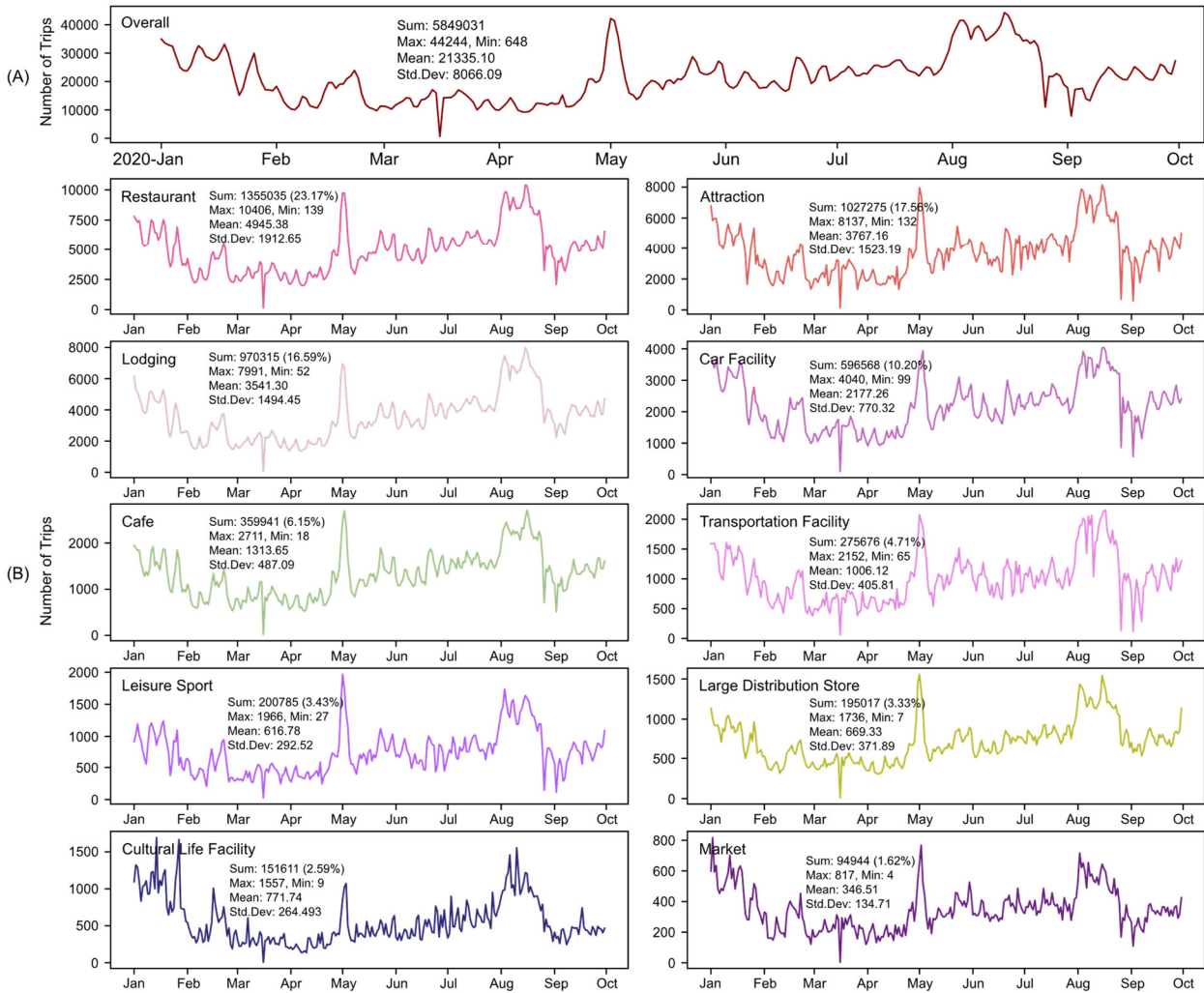


Figure 2.3 Time series of daily trips extracted from the navigation dataset: (A) Overall daily trips of domestic visitors; (B) Daily trips of domestic visitors for the ten activity types.

travelers, and 2) the change in the frequency of domestic visitors traveling around the island during the pandemic.

As shown in Figure 2.3, 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 2.3A), calculated as the total number of trips per day in this dataset. Figure 2.3B demonstrates the time series of daily trips of ten different activity types, generated based on the activity (POI type) of each record (Table 2.1). 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 2.6 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.

2.3 Methods

2.3.1 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 seasonality. To overcome these hurdles, we calculate the difference in the number of daily trips relative to the 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:

$$\Delta t_i^m = t_i^m - T_i^m \quad (\text{Equation 2.1})$$

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. This method also effectively controls differences in absolute travel volume across activity types, enabling meaningful estimates that are comparable across models.

2.3.2 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). While travelers typically plan and book their trips a few weeks in advance (generally 2-4 weeks for Korean travelers, according to KTDB, 2019), perceived risk can significantly shorten decision-making windows, leading to an increase in last-minute bookings (Roehl & Fesenmaier, 1992). 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 visitors 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 2.6 in appendices shows the results of cross-correlation analysis.

Table 2.2 Optimal time lag of overall daily travel changes to independent variables.

Independent Variables	First Wave		Stable Period		Second Wave	
	Optimal	Correlation	Optimal	Correlation	Optimal	Correlation
	Time Lag	Coefficient	Time Lag	Coefficient	Time Lag	Coefficient
<i>CFR</i>	4 days	-0.509***	1 day	-0.008	14 days	0.079
<i>DNC</i>	4 days	-0.628***	5 days	-0.241***	7 days	-0.570***
<i>JDNC</i>	4 days	-0.295***	5 days	-0.224***	4 days	-0.468***
<i>GI(COVID Korea)</i>	5 days	-0.723***	0 day	-0.172***	9 days	-0.600***
<i>GI(COVID Jeju)</i>	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 2.2 presents the optimal time lags between each pair of dependent and independent variables across three periods. Overall, national-level indicators, i.e., *CFR*, *DNC*, and *GI(COVID Korea)*, showed shorter optimal time lags during the first wave than during the stable period and second wave. In contrast, local-level indicators, i.e., *JDNC* and *GI(COVID Jeju)*, had similar time lags in both the first and second waves. This suggests that during the first wave, both national and local pandemic conditions had short-term effects on the travel behavior of domestic visitors. However, in the second wave, national-level factors exhibited longer time-lag effects, while local-level factors continued to influence travel behavior over shorter lags. This implies that visitors' risk sensitivity varies with their geographic and psychological distance from the threat. Furthermore, they appeared more responsive to risk during the early stages of the outbreak, reflecting a shorter decision-making window. This aligns with prior studies showing that perceived risk shortens planning horizons and prompts last-minute bookings.

2.3.3 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 in the following form:

$$\Delta t_i = \beta_0 + \beta_1 \ln CFR_i + \beta_2 \ln DNC_i + \beta_3 \ln JDNC_i + \beta_4 \ln GI(COVID\ Korea)_i + \beta_5 \ln GI(COVID\ Jeju)_i + \varepsilon_i \quad (\text{Equation 2.2})$$

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 2.2). 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, allowing the coefficients to be interpreted as elasticities. This transformation facilitates a more meaningful comparison of variable importance, as the coefficients reflect percentage changes rather than being influenced by the original measurement units. Descriptive statistics of all variables are shown in Table 2.7 in the Appendix. Table 2.8 and Figure 2.5 in the Appendix show the results of the normality test of dependent variables.

2.4 Results

2.4.1 Changes in travel behavior during different pandemic periods

Figure 2.4 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 the overall average daily trip change (Figure 2.4A), and the average daily trip change of ten activity types at four periods of the pandemic (Figure 2.4B).

As shown in Figure 2.4A, the overall average daily trips of domestic visitors in Jeju dropped by 42% from the baseline (overall average daily trips from January 1 to January 19 in 2020). After the first wave outbreak 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

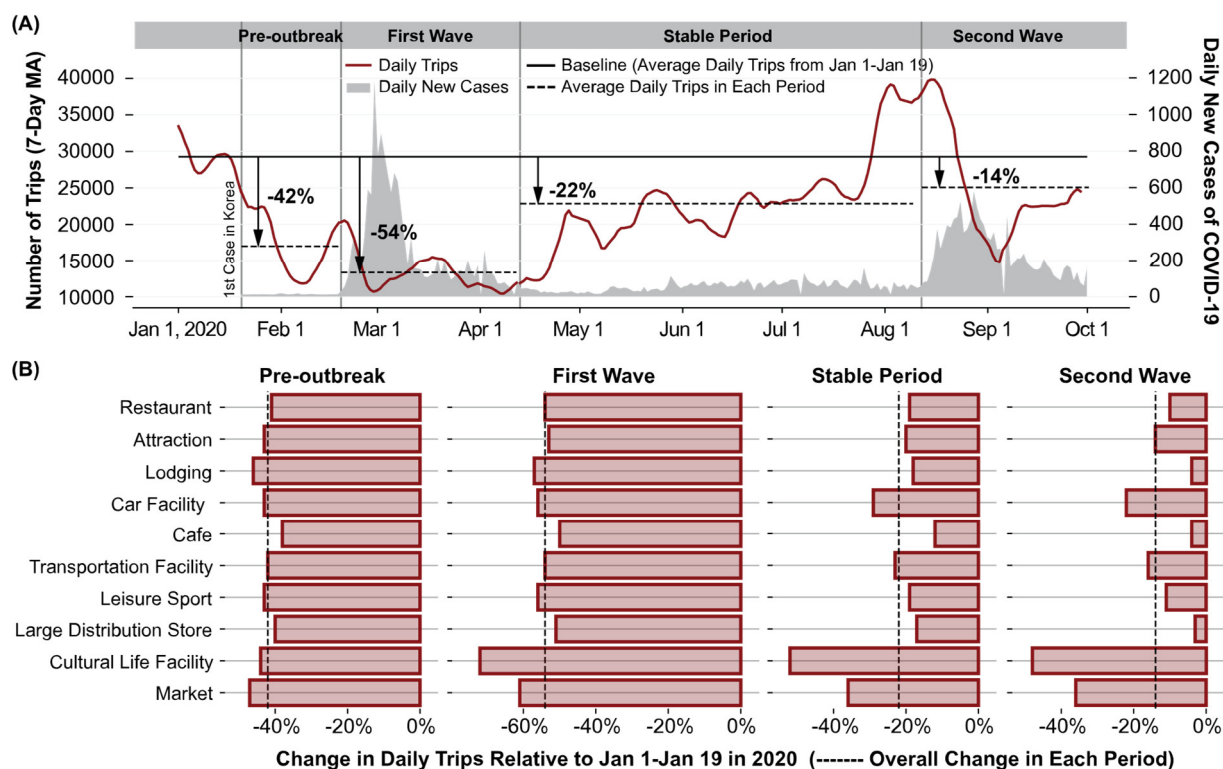


Figure 2.4 Travel changes in Jeju by periods and activity types: (A) Overall daily trips from January to September in 2020, and changes in overall average daily trips in four periods; (B) Changes in average daily trips for the ten activity types in four periods.

behavior of domestic visitors depends 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 2.4B, 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), were 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.

2.4.2 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 2.2). Table 2.3, Table 2.4, and Table 2.5 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 2.3, Model 2-1 in Table 2.4, and Model 3-1 in Table 2.5, 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, all national-level indicators (i.e., *CFR*, *DNC*, and *GI(COVID Korea)*) and a local-level 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 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 would drop by 15 (-1495.895/100). This suggests that increases in the number

Table 2.3 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 2.4 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 2.5 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.

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)*.

2.4.3 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 2.3, Table 2.4, and Table 2.5, 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 petrol station (Table 2.6 in Appendix). Transportation Facility indicates public transport facilities, like airport, bus stop (Table 2.6 in Appendix). As we mentioned before, self-driving is the most popular way to travel in Jeju. The regression results suggest that the changes in independent variables would result in more decreases in the number of trips for car services than for public transport 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.

2.5 Discussion and Conclusion

This study assesses the dynamic effects of the COVID-19 pandemic on travel behavior of domestic inbound travelers 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 the 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., earthquake or 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.

The 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. First, access to an island destination like Jeju relies heavily on air and sea transport, and the availability of these services can directly influence visitor numbers. This study primarily focused on local and external pandemic conditions as explanatory variables, and transport services were not modeled separately. However, fluctuations in service frequency and airfare during the pandemic may have influenced travel behavior. Future studies could incorporate transport service factors to better isolate potential confounding effects. Second, given that the 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. However, given the well-represented nature of the dataset, it is still considered valid in estimating changes in overall tourist travel as well as changes in different activity locations. Nevertheless, this study contributes to the tourism literature on crisis management by revealing the dynamic effects of the COVID-19 pandemic on multifaceted tourism activities over different pandemic stages. The findings in this study can provide implications for destination management and policymaking in other tourism destinations.

Appendices

2.A Details about the ten activity types

Table 2.6 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, petrol 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 facility, horse riding, water sports, etc.
Large Distribution Store	Supermarket, discount store, duty-free shop, etc.
Cultural Life Facility	Museum, memorial, gallery, concert hall, theater, etc.
Market	Traditional market, agricultural/livestock products market, etc.

2.B Descriptive statistics of dependent and independent variables

Table 2.7 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)					
<i>CFR</i> (4 days)	53	0.000	1.074	0.636	0.302
<i>DNC</i> (4 days)	53	0.000	6.813	4.559	1.588
<i>JDNC</i> (4 days)	53	0.000	1.386	0.152	0.333
<i>GI(COVID Korea)</i> (5 days)	53	0.000	4.615	3.431	0.791
<i>GI(COVID Jeju)</i> (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)

<i>CFR</i> (1 day)	117	1.110	1.223	1.174	0.032
<i>DNC</i> (5 days)	117	0.000	4.736	3.339	0.875
<i>JDNC</i> (5 days)	117	0.000	1.386	0.071	0.247
<i>GI(COVID Korea)</i> (0 day)	117	1.386	4.111	2.968	0.477
<i>GI(COVID Jeju)</i> (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)

<i>CFR</i> (14 days)	50	0.947	1.133	1.039	0.076
<i>DNC</i> (7 days)	50	0.000	6.091	4.845	1.048
<i>JDNC</i> (4 days)	50	0.000	1.946	0.345	0.525
<i>GI(COVID Korea)</i> (9 days)	50	2.079	4.248	3.569	0.500
<i>GI(COVID Jeju)</i> (3 days)	50	0.000	4.615	0.417	1.264

Table 2.8 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.

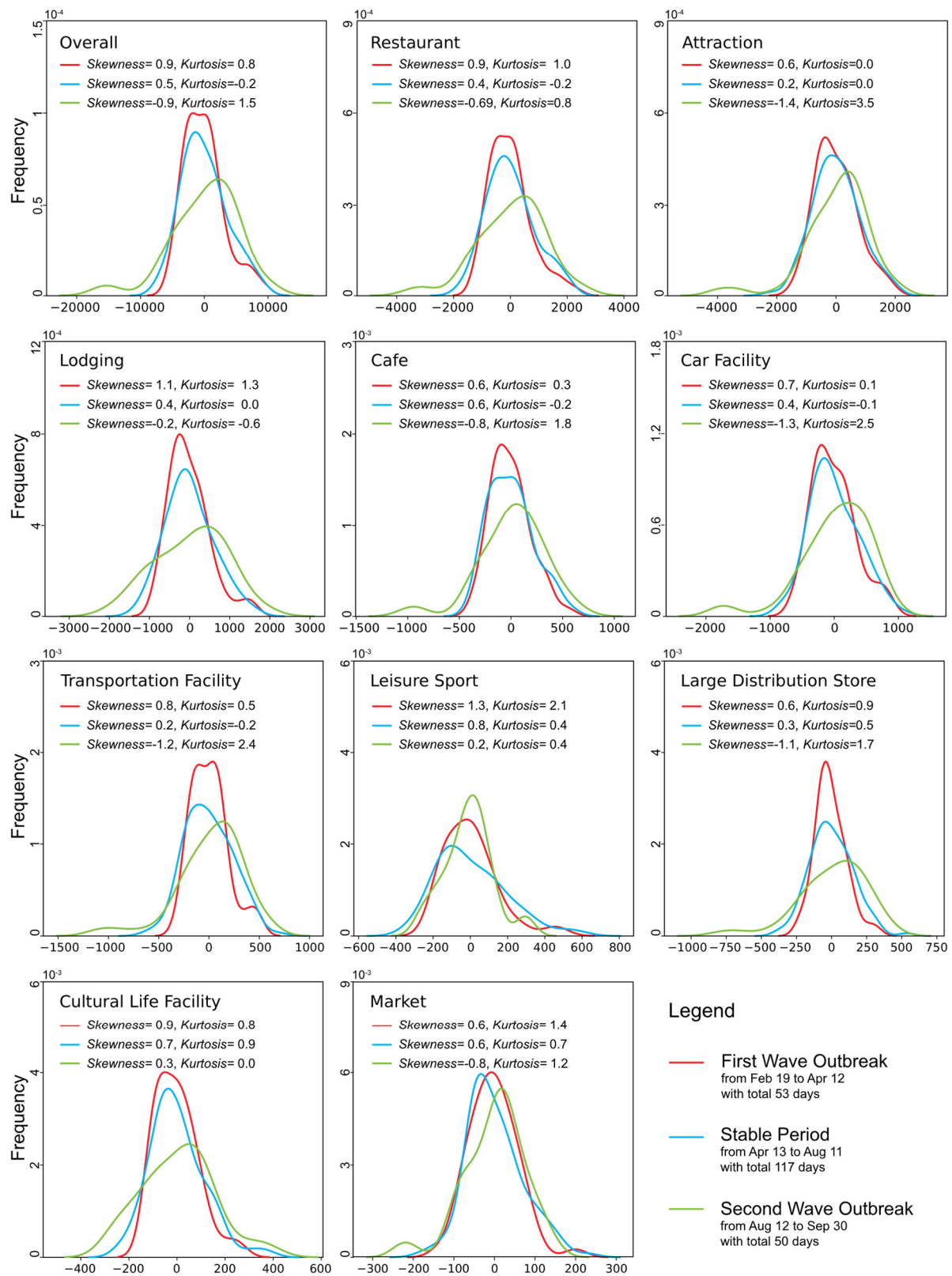


Figure 2.5 Frequency distribution of dependent variables.

2.C Identify optimal time lag of dependent variables relative to independent variables through cross-correlation analysis

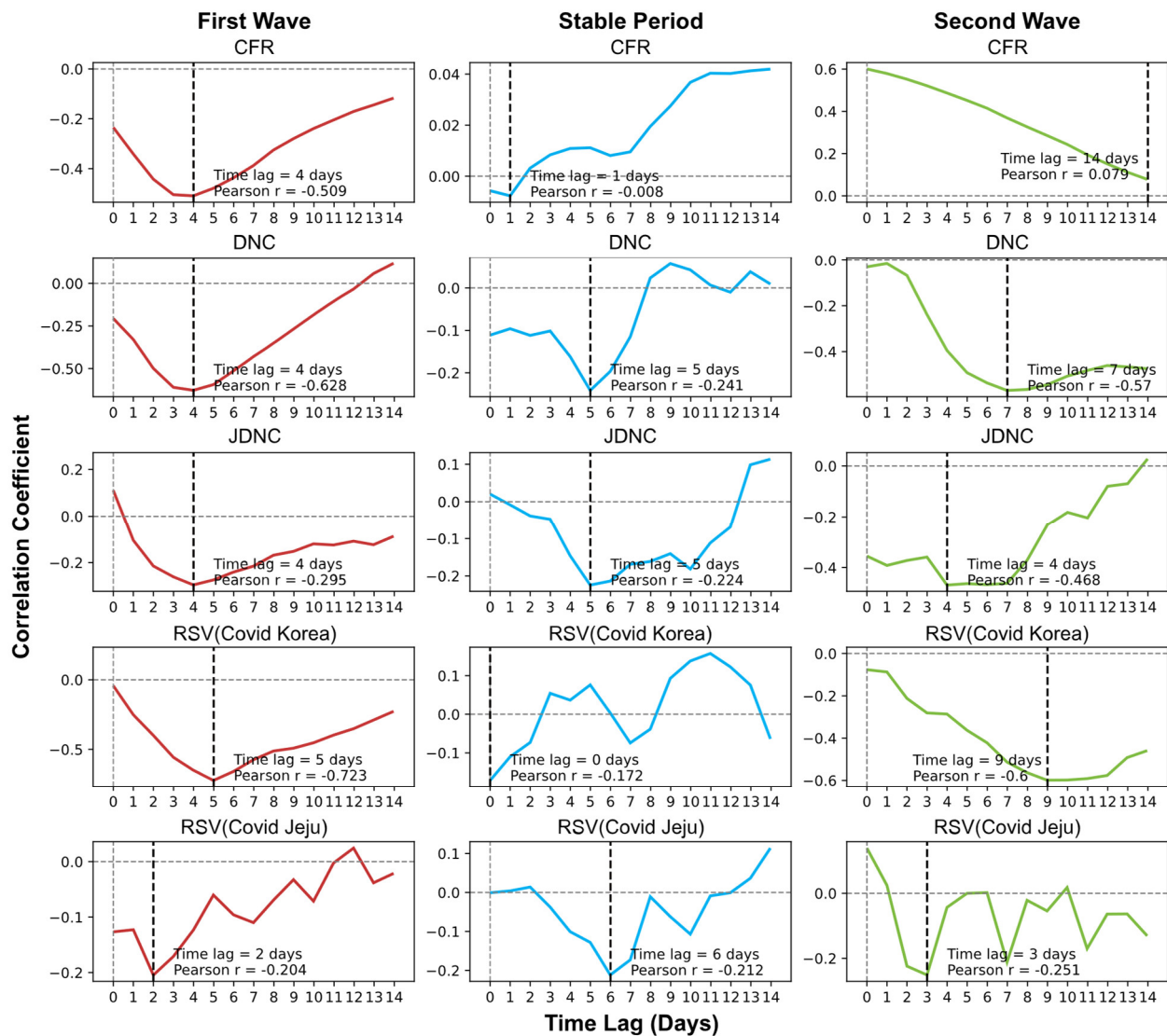


Figure 2.6 Identify optimal time lag of dependent variables through cross-correlation analysis.

Chapter 3

Heterogeneous effects of COVID-19 and policy responses on consumer spending in a tourism city: A joint investigation of urban residents and inbound travelers

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3.1 Introduction

During the global COVID-19 pandemic, industries closely associated with tourism, such as hotel, restaurant, and aviation industries, have all experienced unprecedented disruptions. Tourism-dependent cities have been particularly affected, facing declines in revenue and increased unemployment. Consequently, it is crucial for destination marketers to find ways to develop risk management strategies for mitigating economic losses while minimizing restrictions on tourist activity. A better understanding of the behavior patterns of both inbound travelers and local residents during a pandemic can provide valuable insights for enhancing the resilience of the tourism industry and effectively addressing similar potential threats in the future.

Numerous tourism studies have attempted to estimate the impact of COVID-19 on travel demand (Yang, et al., 2020; Santos et al., 2021), risk perceptions (Rahman et al., 2021), flow patterns (Park et al., 2022), and residents' attitudes toward tourism (Kamata, 2022). These relevant studies suggested the substantial effect of a pandemic as environment changes on travelers' planning and decision-making process. Most local and national governments executed a variety of policies in response to the COVID-19 pandemic to restrain travel behavior such as social distancing and lockdown or encourage

activities including stimulus payments (Li et al., 2021). Importantly, however, the research that explores the extent to which policy executions have influenced travel behaviors is largely limited. A travel destination is a place where residents and travelers interact, which potentially facilitates disease transmission, subsequently influencing the risk perceptions of both population groups (Ren et al., 2022). With a restriction on going on international trips, domestic travel used to gain more popularity (Donaire et al., 2021). This implies the importance of understanding different travel activities between two key stakeholders—residents and travelers—and their heterogeneous responses to local and national government policies.

Residents relatively have more information about the places in general and health-related services in particular than travelers. Based on the theory of information asymmetry (Bhargava & Chen, 2012), the party who has less information is likely to decide with imperfect information lack of understanding true values of their choices. Considering the concept of product familiarity (Johnson & Russo, 1984), travelers are relatively unfamiliar with the destination to visit compared to residents. The low level of destination familiarity can induce a high-risk perception (i.e., physical risk as a type of vacation risk component), which affects information searching and decision-making behaviors (Horng et al., 2012; Roehl & Fesenmaier, 1992). Furthermore, the protection motivation theory has primarily been employed to investigate tourists' perceptions and the adoption of protective behaviors concerning risky destinations and activities (Lu & Wei, 2019; Wang et al., 2019). People may show higher sensitivity and concern for the corresponding risks occurring in their vicinity and may have lower perceptions of risks far from their geographic location. This conforms to the first law of geography, known as the distance decay effect (Tobler, 2004). However, the health risks associated with pandemics can be spread in geospatial terms. This is likely to result in people's risk perception being influenced not only by the severity of the outbreak in their surrounding area (i.e., within their community or city associated with residents) but also by the severity of the outbreak in the external region (i.e., their country or internationally related to travelers) (Yang et al., 2023).

Besides, the extant tourism literature on COVID-19 failed to accommodate the multifaceted nature of tourism products. In other words, the previous research focused on the impact of COVID-19 on travel demand in a particular destination. Yet, travel products comprise an amalgamation of various products and/or services reflecting different levels of importance, involvement, and flexibility (Jeng & Fesenmaier, 2002; Park & Fesenmaier 2014). Based on adaptive decision makers (Payne et al., 1993), individuals are likely to show divergent strategies in making consumption decisions according to different travel products such as accommodation, transportation, restaurants, and indoor and outdoor

recreations. Thus, it is critical to investigate how individuals present dynamic decision-making processes for purchasing diverse products.

Therefore, based on the aforementioned research gaps, this study aims to address the following research questions: (1) To what extent does consumer spending in tourism cities vary in response to the severity of the pandemic, both locally (within the tourism city) and remotely (in the origin regions of travelers)? (2) How do policy responses, such as social distancing measures and economic stimulus, influence consumer spending in tourism cities? (3) To what extent do the impacts of the pandemic and policy responses differ between residents and inbound travelers? (4) To what extent do the impacts of the pandemic and policy responses vary across different economic sectors?

To address the research questions, this study analyzes the spending of residents and domestic inbound travelers in Jeju, Korea during the COVID-19 pandemic. The dataset covers a period from January 1, 2019, to September 30, 2020, encompassing over 300 million transactions and a total expenditure exceeding 11 billion won in Jeju. The study period spanned from January to September 2020, during which Korea experienced two waves of nationwide outbreaks and implemented a package of policy responses, including social distancing measures and stimulus payments at local and national levels. However, lockdown strategies were never implemented during this period. The soft social distancing measures in place did not impose inter- and intra-city travel restrictions, enabling residents and travelers to move freely across Korea. This unique context provides a natural experimental setting to observe the behavioral responses of residents and travelers under pandemic conditions. It also allows for a robust estimation of the effects of social distancing measures and stimulus payments on consumer behavior while appropriately accounting for the pandemic's overall influence. As such, a series of regression models were employed to examine the relationships between consumer behavior and various influencing factors, based on the following hypotheses: **H1** - Consumer spending in a tourism destination is jointly affected by pandemic conditions locally and remotely. **H2** - Social distancing measures suppress consumer spending. **H3** - Economic stimulus measures boost consumer spending. **H4** - The pandemic and policy responses produce heterogeneous effects on consumer spending between local residents and inbound travelers. **H5** - The pandemic and policy responses produce heterogeneous effects on consumer spending across different economic sectors.

By examining the above research hypotheses, this research aims to contribute to the existing body of tourism research by shedding light on the distinct behavioral responses of residents and travelers in various economic activities during health crises. This study seeks to theoretically enrich our understanding of the risk perceptions and coping strategies of two key stakeholders in travel destinations, residents and tourists, in the face of significant changes in environmental health risks.

Furthermore, our study intends to underscore the importance of jointly investigating local and external factors when analyzing the impacts of pandemics. This approach seeks to enable policymakers and stakeholders to better anticipate and prepare for forthcoming local and external risks, thereby enhancing the crisis management capacity and economic resilience of tourism cities.

3.2 Study Area and Data

3.2.1 Study area

This study analyzes the spending behavior of both residents and domestic inbound travelers during the pandemic in Jeju, Korea (Figure 3.1A). During the COVID-19 pandemic, the Korean government did not implement strict lockdown strategies. Instead, it adopted soft social distancing policies that allowed residents and travelers unrestricted access to any location in Korea. As a result, Jeju continued to receive a substantial number of tourists during the pandemic, averaging approximately 830,000 inbound visitors per month from January to September 2020, comparable to the island's resident population of 670,000. It provided experimental context to study the dynamic behavioral responses of residents and travelers to COVID-19 and government policies, largely free from the potential impact of mobility restrictions.

3.2.2 COVID-19 and policy responses in Korea

COVID-19 data for this study was sourced from the census data released by the Ministry of Health and Welfare, Republic of Korea. From January 20, 2020 (the date of the first reported COVID-19 case in Korea), until the end of September 2020, Korea experienced two waves of nationwide outbreaks. Figure 3.1B depicts the timeline of daily new COVID-19 cases and corresponding policy responses in Korea and Jeju. The first wave, spanning from February 19 to mid-April 2020, originated from a cluster in Daegu, while the second wave, occurring from mid-August to the end of September 2020, was centered in Seoul. Jeju recorded its first local case on February 22, 2020. During the first wave of the national outbreak, Jeju did not have a large-scale outbreak, with fewer than 10 confirmed cases per day. However, during the second wave, Jeju experienced a notable increase in daily new cases. In this context, both the national and local status of the outbreak may influence the behaviors of residents and travelers in Jeju.

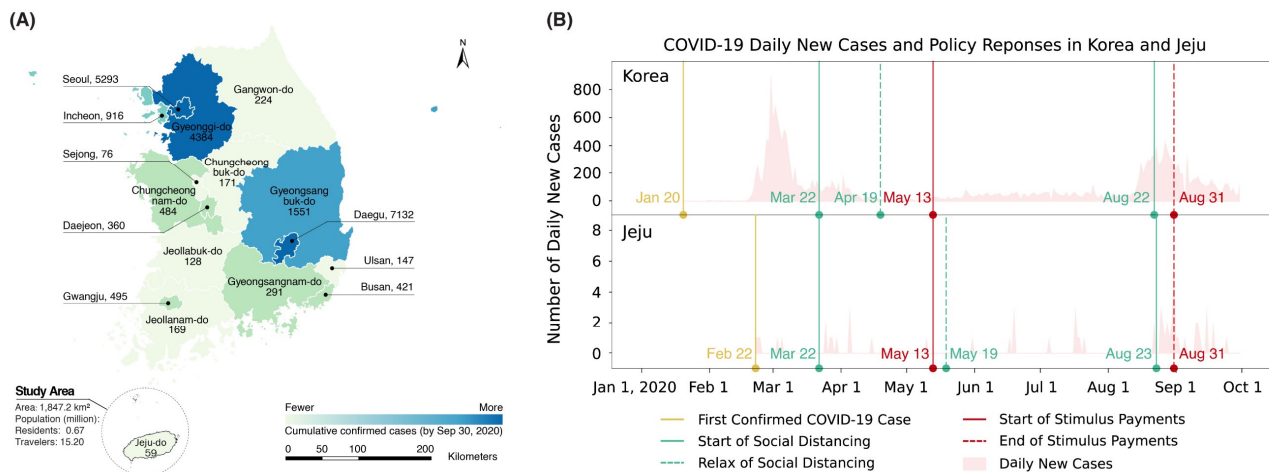


Figure 3.1 (A) Cumulative confirmed cases of COVID-19 in Korea by the end of September 2020, at the province level, and the location of Jeju Special Self-Governing Province in Korea. (B) Timeline of COVID-19 daily new cases and policy responses in Korea and Jeju, from the first confirmed case in Korea on January 20 to September 30, 2020.

Table 3.1 Description of COVID-19 and policy response variables.

Variables	Description
<i>DNC</i>	Number of daily new cases in Korea.
<i>JDNC</i>	Number of daily new cases in Jeju.
<i>KSD</i>	Dummy variables indicating the social distancing measures implemented by the national government of Korea from March 22, 2020, to April 19, 2020.
<i>JSD</i>	Dummy variables indicating the social distancing measures implemented by the local government of Jeju from March 22, 2020, to May 19, 2020.
<i>KJSD</i>	Dummy variables indicating the social distancing measures implemented by both the national and local governments from August 23, 2020, to September 30, 2020.
<i>Stimulus</i>	Dummy variables indicating the stimulus payments distributed from May 13, 2020, to August 31, 2020.

In terms of policy responses, both the national and local governments implemented social distancing measures in response to the 1st and 2nd waves of the national outbreak, respectively. During the 1st wave of the national outbreak, the national government implemented social distancing measures from March 22 to April 19. Meanwhile, the Jeju local government extended measures from March 22 to May 19, lasting a month longer than the national implementation period. In response to the 2nd wave outbreak, the national and local governments issued social distancing measures on August 22 and 23, respectively, which remained in place until the end of September. These measures were aimed at limiting the maximum number of people and hours of operation of various establishments (such as

restaurants, nightclubs, and indoor sports facilities). However, these measures did not impose strict travel restrictions, either within or between cities.

In terms of economic responses, a significant measure implemented in Korea is the emergency cash transfer payments in 2020. Under the stimulus payment scheme, every Korean citizen was entitled to receive consumption vouchers issued by the government. The scheme was initiated on May 1, 2020, allowing people to register for the vouchers, and the earliest transfers were issued on May 13, 2020. To ensure that the funds were used for purchases, the government provided citizens with pre-paid cards or credit card deposits and set a deadline of August 31, 2020, for spending the vouchers. Additionally, the payment could be utilized for small businesses and was not limited to the area of residence, allowing small businesses in the tourism industry to benefit.

Therefore, this study includes two COVID-19 continuous variables (i.e., the number of daily new cases in Korea and the number of daily new cases in Jeju) and four policy dummy variables as independent variables. The four dummy variables represent policy implementation, with a value of 1 assigned to the days when the respective measures were implemented, and 0 otherwise.

3.2.3 Credit and debit card transaction data

The credit and debit card data used in this study were obtained from one of the leading credit card companies in the country, with a market share of 21.8% and 20.9 million cardholders. Card payments are the predominant mode of consumer spending in South Korea, including Jeju. According to a Bank of Korea survey (BOK, 2023), credit and debit cards account for approximately 62% of all transactions. Card usage is particularly high in the retail, accommodation, and food service sectors. Additionally, many popular e-payment platforms (e.g., Samsung Pay, Kakao Pay, Naver Pay) are linked to users' bank-issued cards, meaning transactions made through these services are also recorded as card-based payments and included in this dataset. Given these factors, the dataset is considered broadly representative of consumer spending patterns in Jeju.

This dataset encompasses 39,772,559 aggregated transaction records from January 1, 2019, to September 30, 2020, capturing over 300 million transactions and a total expenditure of about 8 million USD in Jeju, Korea. The data analyzed in this study comprises aggregated expenditure amounts and the number of transactions. The aggregation was performed based on transaction date, consumption categories, and consumer groups (Table 3.2).

Table 3.2 Example of transaction records.

Date	Consumption category	Consumer type	Total Expenditure (USD)	Number of Transactions
2019-01-01	Korean Style Restaurants	resident	70.23	5
2019-01-01	Urban Transit Systems	traveler	282.34	3
.....			...	
2020-09-30	Convenience Store	traveler	564.67	8
2020-09-30	Hair Beauty	resident	1058.76	2

Table 3.3 Reclassified consumption categories and the percentage of each category in total expenditure and transactions.

Category	Example of Transaction Types	No. of subtypes	Share of Resident Expenditure	Share of Resident Transactions	Share of Traveler Expenditure	Share of Traveler Transactions
Transportation	Automotive Gas/Oil Stations, Renting of Motor Vehicles, Coastal Water Passenger Transport, Vehicle Parking Facilities, Urban Transit Systems, Charter Bus Transport, etc.	48	13.11%	8.06%	6.09%	5.41%
Accommodation	Hotels, Inns, Condominium, juvenile Camps, Renting of Non-Residential Buildings, etc.	23	1.42%	1.03%	8.58%	4.54%
Outdoor Recreation	Golf and Skiing Facilities, Amusement and Theme Park, Botanical and Zoological Gardens, Natural Parks, etc.	22	1.73%	1.05%	3.65%	2.71%
Indoor Recreation	Computer Game Room, Singing Room, Museum, Billiard Room, Bowling Alley, Swimming Pool, Library, Reading Room, Physical Fitness Facility, etc.	23	0.63%	1.13%	0.85%	1.36%
In-Person Service	Personal Care Services: Hair Beauty, Saunas, Skin Beauty, etc. Household Services: Household Laundry Services, Repair of Household Machinery, etc.	43	1.97%	1.49%	0.67%	0.64%
Restaurant	Korean Style Restaurants, Confectioners Shops, Pizza, Hamburger, Sandwich, Noodle Houses, Bars and Canteens, Chicken Shops, Lunch Counters, Western Style Restaurants, etc.	16	15.96%	21.48%	21.40%	23.93%
Food and Beverage Retail	Convenience Stores, Supermarkets, Retail & Wholesale of Food and Beverage, e.g., Fruit and Vegetables, Meat, Fish and Marine Products, Dairy Products, Rice Cakes, etc.	83	18.80%	35.35%	11.72%	27.28%
General Retail	Retail & Wholesale: Clothing, Cosmetics and Perfumery, Gifts, Novelties and Souvenirs, etc.	350	28.88%	16.43%	20.01%	16.00%
Total		608	82.49%	86.01%	72.97%	81.88%

This study examines consumer spending from three dimensions: consumer groups (residents and travelers), consumption categories (overall and eight specific categories), and consumption variables (expenditure and number of transactions).

- **Consumer groups:** The classification of consumer groups in this dataset, namely residents and travelers, is provided by the data provider based on the transaction records and registration information. For all transaction records in Jeju, users whose registration places are also in Jeju are classified as residents. Users registered in other Korean provinces or cities outside of Jeju Province are classified as travelers. As such, the traveler in this dataset specifically refers to domestic inbound travelers.
- **Reclassified consumption categories:** The dataset includes 22 broad consumption categories, each with five levels of sub-categories, resulting in over 1,500 specific consumption categories. To better capture changes in the consumption behavior of residents and travelers, with a focus on household and tourism-related spending, the authors manually reclassified the original categories into eight. They are transportation, accommodation, outdoor recreation, indoor recreation, in-person service, restaurants, food and beverage retail, and general retail. Together, these eight categories account for over 80% of the records in the dataset. Further details and examples of venues for each category can be found in Table 3.3. Ultimately, the study analyses consumer spending at the overall level and in eight reclassified categories.
- **Consumption variables:** Expenditure and the number of transactions is aggregated by date, consumer group, and consumption category. Both variables are analyzed in this study to provide insights into different aspects of consumer spending. Expenditure reflects the economic characteristics of consumption behavior, capturing variations in consumer demand across different sectors at an aggregate level. The number of transactions captures changes in consumption frequency and patterns, providing insight into activity-related characteristics.

Consequently, a total of 36 time series are derived from this dataset. This includes four overall consumption time series for resident expenditure, resident transactions, traveler expenditure, and traveler transactions, as well as 32 time series (four for each of the eight consumption categories). All time series were recorded at a daily granularity and span from January 1, 2019, to September 30, 2020. See Appendix Figure 3.7 for details. Descriptive statistics for all consumption variables are presented in Appendix Table 3.9.

3.3 Methods

This study aims to assess the impact of COVID-19 and government policies on daily expenditure and transactions of residents and travelers across various consumption categories, as well as at an overall level. A series of regression models were utilized to examine the relationship between consumer behavior and different factors. To ensure the robustness and validity of the models, several techniques were employed to control seasonal effects in the time series data and to identify the optimal time lags between the dependent and independent variables.

3.3.1 Seasonal adjustments of time series data

To mitigate the issue of spurious regressions arising from the autocorrelation of time series data, we first conducted an Augmented Dickey-Fuller (ADF) test. The results indicate that almost all the consumption time series reject the null hypothesis at the 5% significance level, providing evidence of non-stationarity and seasonal effects in the data (Appendix, Table 3.10). We next introduced control variables $Season_t$ and $SeasonPost_t$ to manage the seasonality, as shown in Equations (1)-(3):

$$\ln(y_t) = \beta_0 + Season_t + SeasonPost_t + \varepsilon_t \quad (\text{Equation 3.1})$$

Where:

$$Season_t = \sum_{m=Jan}^{Nov} \alpha_m * I(Month_t = m) + \sum_{w=Mon}^{Sat} \alpha_w * I(Weekday_t = w) + \alpha_h * Holiday_t \quad (\text{Equation 3.2})$$

$$SeasonPost_t = \left[\sum_{m=Jan}^{Aug} \alpha'_m * I(Month_t = m) + \sum_{w=Mon}^{Sat} \alpha'_w * I(Weekday_t = w) \right] * Post_t + \alpha'_h * Holiday_t \quad (\text{Equation 3.3})$$

Here y_t refers to the corresponding consumption indicator on day t , where $t = (1, \dots, 639)$ denotes the number of days starting from January 1, 2019.

Seasonal effects are accounted for by incorporating the variables $Season_t$ and $SeasonPost_t$. Both $Season_t$ and $SeasonPost_t$ consist of a set of dummy variables to capture the seasonal variations related to the month-of-year, day-of-week, and public holidays. Specifically, $Month_t$ indicates the month corresponding to day t . If $Month_t$ equals m , where m ranges from January to November, the dummy variable for month m is assigned a value of 1; otherwise, it is set to 0. Similarly, $Weekday_t$ indicates the day of the week corresponding to day t . If $Weekday_t$ matches w , where w represents Monday to Saturday, the dummy variable for the day of the week w is set to 1; otherwise, it is set to 0.

0. The variable $Holiday_t$ is a dummy variable that indicates whether day t falls on a public holiday. If day t is a public holiday, $Holiday_t$ is assigned a value of 1; otherwise, it is set to 0. $Season_t$ controls the seasonal effects throughout the entire period, while $SeasonPost_t$ captures the effects specifically after the outbreak by introducing the interaction term between the seasonal factors and the dummy $Post_t$. The variable $Post_t$ takes a value of 1 if day t is greater than or equal to 385, which corresponds to January 20, 2020, the day when the first cases of COVID-19 was reported in Korea. Otherwise, $Post_t$ is set to 0.

To validate the effectiveness of the seasonal adjustments, unit root tests were performed on the model residuals ε_t , which showed that all residuals are stationary (Appendix, Table 3.11). Besides, we performed Johansen cointegration tests for the de-seasonalized consumption time series and the independent time series variables. The results indicate the existence of statistically significant cointegration relationships among the time series (Appendix, Table 3.12).

3.3.2 Identify optimal time lags of COVID-19 variables through cross-correlation analysis

Determining the optimal time lag between time-series variables is critical for examining causal relationships between variables. Cross-correlation analysis is an extensively employed statistical methodology that quantifies the magnitude and direction of temporal relationships with time delays between variables within time series (Shi et al., 2018; Akal, 2004). This method involves computing the correlation coefficient between two time series at specific time lags, and the identification of the optimal time lag occurs when the maximum correlation is observed.

Based on concepts of risk perception and protective behavior, individuals often adjust their behavior based on recent changes in perceived or actual risk, which inherently introduces a time lag between risk factors and behavioral outcomes. The variations in information access and product familiarity between residents and travelers will further shape their risk perceptions and coping strategies, leading to potential differences in behavioral responses. This study assumes that local and national COVID-19 situations influenced the spending behavior of residents and travelers in the past two weeks. Thus, we perform cross-correlation analysis between a given seasonal adjusted consumption time series and a given COVID-19 variable, with a time lag range of 0-14 days, where the COVID-19 variable leads. Both the consumption variables and the COVID-19 variables have been logarithmically transformed to ensure consistency with subsequent regression analysis.

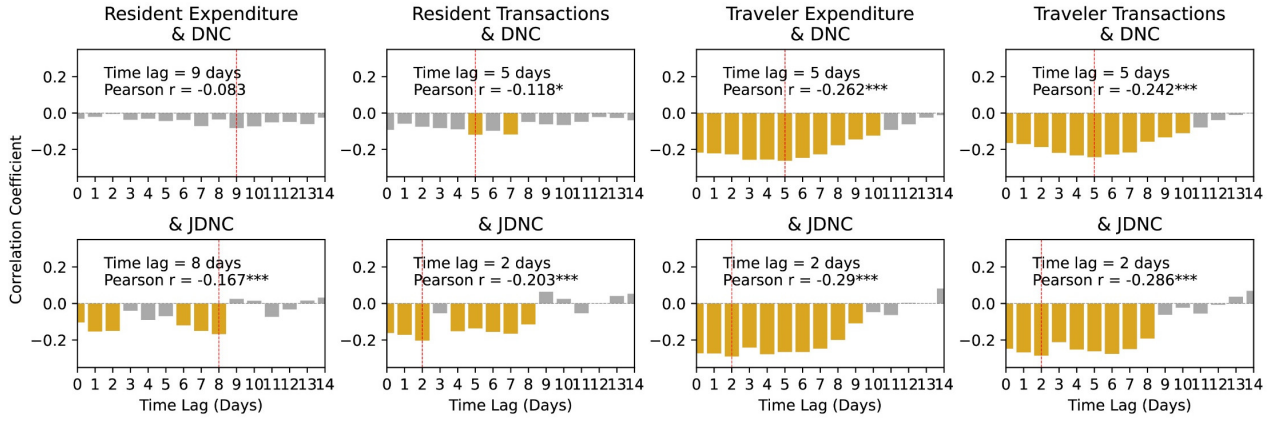


Figure 3.2 Cross-correlation analysis results for overall spending time series vs. national daily new cases (DNC), and overall spending time series vs. Jeju daily new cases (JDNC).

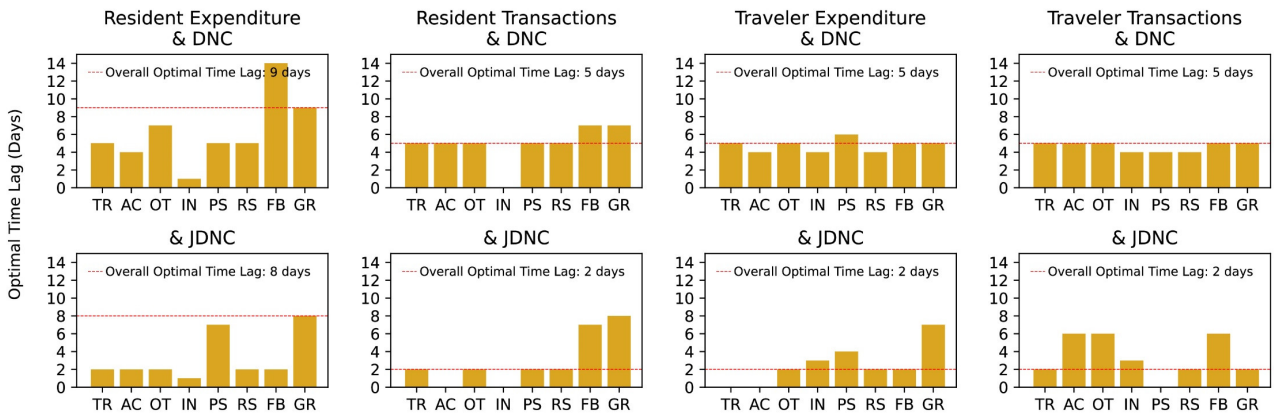


Figure 3.3 The optimal time lag of COVID-19 variables for different consumption categories' time series. The labels on the horizontal axis denote the abbreviations for the consumption categories, where: TR-Transportation, AC-Accommodation, OT-Outdoor Recreation, IN-Indoor Recreation, PS-In-Person Service, RS-Restaurant, FB-Food and Beverage Retail, GR-General Retail.

By conducting pairwise cross-correlation analysis on four overall consumption time series and two COVID-19 indicators, we have determined the optimal time lags that reflect the response of consumer behavior to COVID-19 at the overall level. The results of the time lag detection are illustrated in Figure 3.2. At the overall level, both residents and travelers exhibit longer optimal time lags in their response to national daily new cases compared to Jeju daily new cases, suggesting that nearby risks may induce higher risk perception and rapid response. For travelers, there is consistency in the time lags observed for both expenditure and transactions in response to the COVID-19 indicator. However, residents exhibit inconsistency, with expenditures showing a longer time lag compared to transactions.

Similarly, we assessed the optimal time lag between specific consumer groups and consumption variables with the COVID-19 indicators (Figure 3.3). Given that different groups may show varying perceived importance and flexibility of different activity types, it is reasonable to expect varying behavioral responses to pandemic-related risks. The results indicate that consumer spending exhibits distinct time lags in response to COVID-19 indicators across different categories. For travelers, there is a relatively consistent time lag observed for spending across all categories in response to national daily new cases, while there is greater heterogeneity in the response to Jeju daily new cases. In contrast, residents exhibit notable variations in their responses to both national and Jeju daily new cases across different categories, with the spending in retail displaying a longer time lag. The identified optimal time lags for each corresponding time series were incorporated into the respective regression models in the subsequent analyses.

3.3.3 Regression model

The final regression models incorporate two COVID-19 variables and four policy dummy variables, as well as control variables for the month-of-year, day-of-week, and public holidays both before and after the outbreak of COVID-19 in Korea. The model is formulated as follows:

$$\ln(y_t) = \beta_0 + \beta_1 * \ln(DNC_{t-lag1}) + \beta_2 * \ln(JDNC_{t-lag2}) + \beta_3 * KSD_t + \beta_4 * JSD_t + \beta_5 * KJSD_t + \beta_6 * Stimulus_t + Season_t + SeasonPost_t + \varepsilon_t \quad (\text{Equation 3.4})$$

Here y_t refers to the corresponding consumption indicator on day t , where $t = (1, \dots, 639)$ denotes the number of days starting from January 1, 2019. DNC_{t-lag1} indicates the number of national COVID-19 new cases on the day of $t - lag1$, where $lag1$ is the time lag determined through cross-correlation analysis. Similarly, $JDNC_{t-lag2}$ corresponds to the number of Jeju daily new cases on day $t - lag2$. To ensure meaningful and elastic estimations, log transformations are applied to the continuous variables, including the dependent variables and the national and Jeju daily new cases. Given the presence of zeros in the DNC and $JDNC$ observations, we applied an offset of 1 to all values before performing the logarithmic transformation to ensure that all observations are positive integers.

The policy dummy variables are denoted as KSD , JSD , $KJSD$, and $Stimulus$. KSD represents the first national social distancing measure. JSD indicates the first Jeju social distancing measures. $KJSD$ captures the combined effects of the second national and Jeju social distancing measures (as these were implemented almost simultaneously during the 2nd wave of the national outbreak). $Stimulus$ reflects

the stimulus payments. If day t falls within the implementation period of a particular policy, the corresponding dummy variable is set to 1; otherwise, it is set to 0. $Season_t$ and $SeasonPost_t$ refer to the control variables for seasonal adjustment, as detailed in Equations (3.2) - (3.3) in section 3.4.1.

As such, the regression models yield a set of coefficients $[\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6]$, capturing the effects of DNC , $JDNC$, KSD , JSD , $KJSD$, and $Stimulus$ on consumer spending, respectively. These coefficients are estimated for 4 overall consumption models (resident expenditure, resident transaction, traveler expenditure, and traveler transaction), and 4*8 category-specific models. The estimation results are summarized in Table 3.4 ~ Table 3.8 and the coefficients are visualized in Figure 3.5 and Figure 3.6. For the full regression results, please refer to Appendix Table 3.13 ~ Table 3.16.

3.4 Results

3.4.1 Year-over-year change in consumer spending during the pandemic

3.4.1.1 Overall resident spending was sensitive to the evolution of the pandemic but the degree of change was relatively stable over the entire study period

By comparing consumer spending by Jeju residents between 2020 and 2019 in Figure 3.4A, we obtained the year-over-year (YoY) difference - at the daily granularity - of the overall expenditure (purple line) and the total number of transactions (yellow line) to reveal changes occurred during the pandemic. The daily expenditure and transactions experienced a slight but discernible decline during the first national outbreak, followed by a notable recovery during the stable period and some fluctuations during the second national outbreak. The results show that the spending behavior of Jeju residents responded to the evolution of the pandemic. However, even when the pandemic situation was relatively severe (e.g., first and second national outbreaks), the daily reductions of expenditure and frequency of purchases were bounded, with the largest declines of 8.8% and 2.4%, respectively. We next obtain the YoY change over the entire study period – from January 20 to September 30, 2020 - of the overall expenditure (purple bar) and transactions (yellow bar in the bar graph in the lower left corner of Figure 3.4A). The results suggest that, although resident spending temporarily declined when the pandemic was severe, overall spending remained constant or even increased slightly over a relatively long period, with expenditure increasing by 0.06% and transactions increasing by 2.41%.

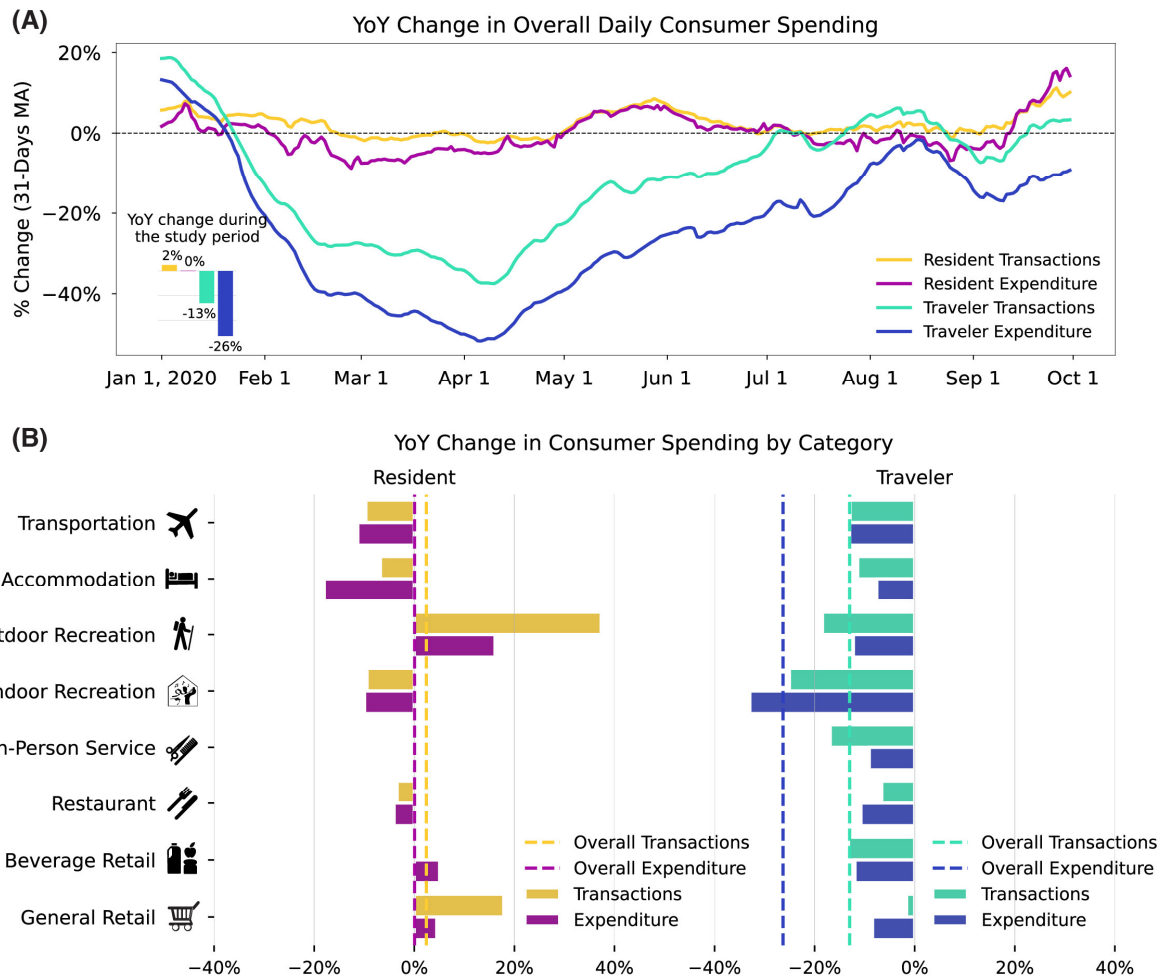


Figure 3.4 (A) The year-over-year (YoY) change in overall expenditure and transactions of residents and travelers at a daily granularity; the bar graph in the lower left corner shows the YoY change in overall expenditure and transactions of residents and travelers in the entire study period from January 20 to September 30, 2020. (B) The YoY change in expenditure and transactions of residents and travelers across different categories in the entire study period.

3.4.1.2 Overall traveler spending experienced a greater reduction and took longer to recover compared to resident spending

Compared to residents, traveler daily expenditure and number of transactions experienced greater declines since the first national outbreak, with the largest declines of 51.7% and 37.5%, respectively (Figure 3.4A). This downturn lasted for nearly six months and did not fully recover until August 2020. Then, another relatively slight and short-lived decline followed the second national outbreak. During the entire study period from January 20 to September 30, 2020, the reduction in traveler spending was

substantial, with expenditure decreasing by 26% and transactions decreasing by 13% (the bar graph in the lower left corner of Figure 3.4A). The results reveal strong responses of traveler spending to the evolution of the pandemic, even in the absence of strict travel restrictions.

3.4.1.3 Heterogeneity of year-over-year change across different consumption categories

We next compare the YoY change in consumer spending across different categories over the entire study period (Figure 3.4B and Appendix Fig.S2). For residents, we can observe considerable heterogeneity across spending categories, despite that the overall expenditure and purchase frequency changed slightly over the study period. Some categories exhibited notable increases, such as outdoor recreation, food and beverage retail, and general retail, while other categories presented notable decreases, such as transportation, accommodation, indoor recreation, and restaurants. Such a disparity highlights a great shift in the spending preferences of residents in certain aspects during the pandemic. For example, the number of transactions by residents decreased by about 10% for indoor recreation but increased by about 37% for outdoor recreation, indicating that residents did not reduce recreational activities in general but preferred outdoor rather than indoor recreation when they had health concerns or were restricted by policy. Similarly, residents spent about 4% less in restaurants but 5% more on food and beverage products during the pandemic, suggesting a shift in demand for food and beverage from out-of-home to in-home modes but generally unchanged or even slightly increased in terms of the amount.

Traveler spending declined in all categories, but the intensity of the decline varied significantly across categories (Figure 3.4B). It suggests that apart from the decrease in traveler arrivals and overall traveler spending, travelers also adjusted their preferences and priorities for different activities during the pandemic. Activities with flexible alternatives and a higher risk of disease spread (i.e., outdoor recreation, indoor recreation, and in-person service) experienced larger declines than other categories. However, activities that cannot be easily substituted, such as accommodation and restaurants, experienced a smaller decline.

3.4.2 Impacts of COVID-19 and policy responses on overall resident and traveler spending

This section presents the estimated coefficients of COVID-19 and policy variables in the overall expenditure and transactions models for residents and travelers (Figure 3.5 and Table 4).

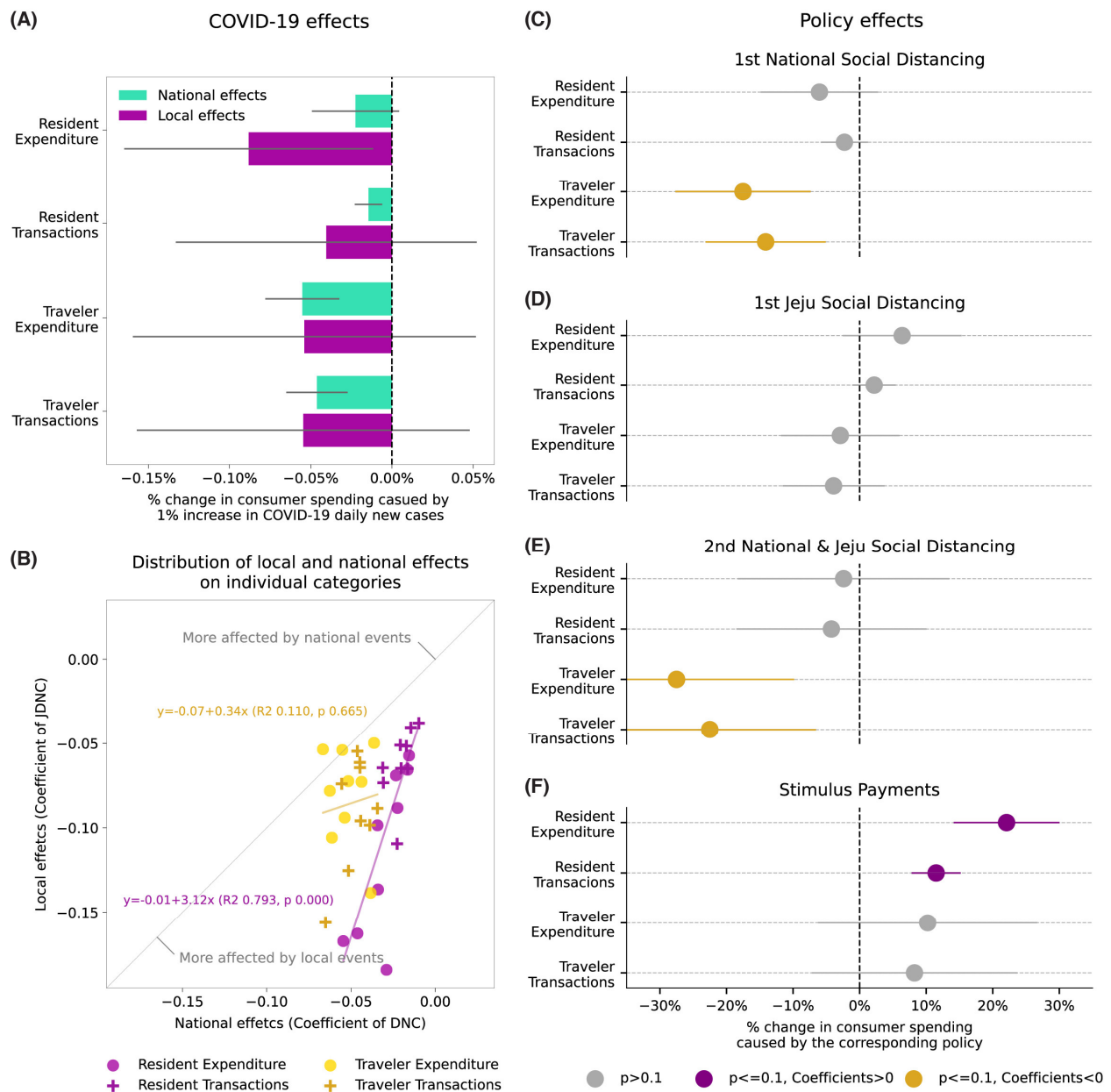


Figure 3.5 The effects of COVID-19 and policy responses on the overall expenditure and transactions of residents and travelers. (A) Local and national COVID-19 impacts on overall expenditure and transactions of residents and travelers. The purple and green bars demonstrate the coefficients of Jeju daily new cases and national daily new cases, respectively, and error bars mark 95% confidence intervals. (B) Distribution of local and national COVID-19 impacts on resident and traveler spending in different consumption categories. The yellow marks COVID-19 impact on traveler spending, and purple marks the impact on resident spending. (C)-(F) Policy effects on overall expenditure and transactions of residents and travelers. The yellow marks significant negative ($p < 0.1$), purple marks significant positive ($p < 0.1$), grey marks nonsignificant, and error bars mark 95% confidence intervals.

Table 3.4 Regression results of overall models.

	Model Resident Expenditure	Model Resident Transactions	Model Traveler Expenditure	Model Traveler Transactions
Constant, β_0	22.892***	12.445***	22.757***	12.190***
<i>DNC</i> , β_1	-0.022	-0.014***	-0.055***	-0.046***
<i>JDNC</i> , β_2	-0.088**	-0.04	-0.054	-0.055
<i>KSD</i> , β_3	-0.06	-0.023	-0.175***	-0.141***
<i>JSD</i> , β_4	0.064	0.022	-0.029	-0.039
<i>JSD</i> , β_5	-0.024	-0.042	-0.275***	-0.225***
<i>Stimulus</i> , β_6	0.221***	0.115***	0.102	0.082
R ²	0.427	0.481	0.873	0.815
Adj. R ²	0.388	0.446	0.865	0.803
N	639	639	639	639
F stat	21.565	27.442	159.785	122.251
P value	0.000	0.000	0.000	0.000
AIC	-574.886	-1428.96	-958.494	-1025.26
BIC	-392.03	-1246.1	-775.638	-842.407

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HCl).

3.4.2.1 Residents were affected more by local COVID-19 situations, while travelers were affected equally by local and national COVID-19 situations

As shown in Figure 3.5A, residents were sensitive to both local and national disease spread but were more concerned about the local situation. The estimated coefficients of Jeju daily new cases in the overall resident expenditure and transactions models are -0.088 and -0.04, respectively, indicating that a 1% increase in Jeju daily new cases led to 0.088% and 0.04% reductions in overall resident expenditure and transactions, respectively. The corresponding reductions caused by the national daily new cases were 0.022% and 0.014%, respectively, which were significantly smaller than the impact of the local situations. In addition, both COVID-19 variables had greater effects on expenditure than on transactions. It suggests that resident expenditure and activity participation decreased significantly when the spread of the disease was severe, but the decrease in expenditure was greater.

Travelers had the same level of sensitivity to local and national disease spread. Travelers' responses to the severity of disease spread were also consistent in terms of expenditure and activity participation. Each 1% increase in Jeju daily new cases resulted in 0.054% and 0.055% reductions in overall traveler expenditure and transactions. The corresponding reductions caused by national daily new cases were 0.055% and 0.046%, respectively. These findings are in line with our hypotheses **H1** & **H4** that consumer spending in Jeju was jointly affected by pandemic conditions locally and remotely, and the impacts were heterogeneous for residents and travelers.

The above finding is reaffirmed by the results of different categories of models (Figure 3.5B). By comparing the coefficients of Jeju and national daily new cases in different category models for residents and travelers, we find that the impact of local COVID-19 cases was about three times greater than the impact of national cases on resident spending in all categories. The purple fitted line in Fig.5B has a slope of 3.12, with an R^2 of 0.793 and a p -value of 0.0002 (Table 3.4). In comparison, local and national cases affected traveler spending to a comparable extent, given that most yellow points in the scatterplot are distributed around the $y=x$ reference line. The above observations reveal that residents and travelers have different perceptions of the health risks of national and local disease transmission.

3.4.2.2 Social distancing had a notable impact on travelers but a limited impact on residents

The effects of all social distancing measures on overall resident expenditure and transactions were insignificant (Figure 3.5C-E). It suggests that changes in resident spending during the pandemic were mainly the result of the active response to the spread of the disease, with limited impact from social distancing measures.

For travelers, social distancing measures implemented by local and national governments resulted in a substantial reduction in traveler spending. The first national social distancing led to a 17.5% and 14.1% reduction in overall traveler expenditure and activity participation, respectively. The corresponding reductions caused by the second national and Jeju social distancing were 27.5% and 22.5%. Conversely, the first social distancing measures issued by the local government only had a limited impact on both traveler expenditure and activity participation. It should be acknowledged that the notable decline is presumably due to two reasons. One is the decline in the number of tourist arrivals in Jeju. Another is that arrived travelers may reduce activity participation and overall expenditure when traveling around the island due to policy restrictions on certain activities.

The above findings partially support the hypothesis **H2** that social distancing measures would suppress consumer spending. However, such an effect was significant for travelers, while it had a limited impact on residents.

3.4.2.3 Stimulus payments boosted resident spending significantly but had a limited impact on travelers

As shown in Figure 3.5F, the stimulus payments positively affected resident spending, and the impact was more pronounced in expenditure (22.1%) than in transactions (11.5%). This suggests that the

policy had a greater impact on consumer spending in the economic aspect than on activity participation. During the period of the economic stimulus policy, consumers exhibited not only an increase in the frequency of their consumption but also a substantial increase in their expenditure per purchase.

However, the impact of stimulus payments on traveler spending in Jeju is found to be limited. Although these payments in Korea can be used for small businesses outside of their place of residence, specifically targeting the tourism industry, the results indicate a constrained effect. These findings align with the conclusions drawn from certain prior studies (Kim et al., 2020; Chetty et al., 2020; Watanabe, 2020). It has been observed that consumer vouchers and stimulus payments issued by governments during pandemics can effectively boost food and overall household spending. However, the impacts on the recovery of consumption in face-to-face service sectors such as hotels, leisure, transport, and retail are limited.

These findings offer partial support for our hypothesis **H3**, that stimulus payments effectively boosted consumer spending in Jeju, primarily among residents.

3.4.3 Heterogeneous effects of COVID-19 and policy responses on consumer spending across different consumption categories

This section presents the estimated coefficients of COVID-19 and policy variables in models of both groups' expenditure and transactions across different consumption categories. The summarized results have been shown in Figure 3.6 and Table 3.5 ~ Table 3.8.

3.4.3.1 Heterogeneous effects of local and national COVID-19 situations

For residents, as shown in Figure 3.6, the escalation of national COVID-19 cases resulted in declines in both expenditure and transactions across almost all categories. Similarly, an increase in local COVID-19 cases led to decreases in consumption, primarily in accommodation, outdoor and indoor recreation, and retail sectors. Specifically, a 1% increase in national COVID-19 cases was associated with a 0.02% decrease in both resident expenditure and transactions across nearly all categories. Furthermore, each 1% increase in Jeju COVID-19 cases caused approximately a 0.1% decrease in transactions, while expenditure on accommodation and general retail experienced a 0.2% decrease. These findings suggest that certain economic sectors suffer more than others when the disease spreads extensively. The decline in consumption frequency is considerably smaller compared to the decline in expenditure amount, indicating a significant reduction in the average amount spent per transaction. Consequently, these economic sectors are more likely to experience pronounced price fluctuations.

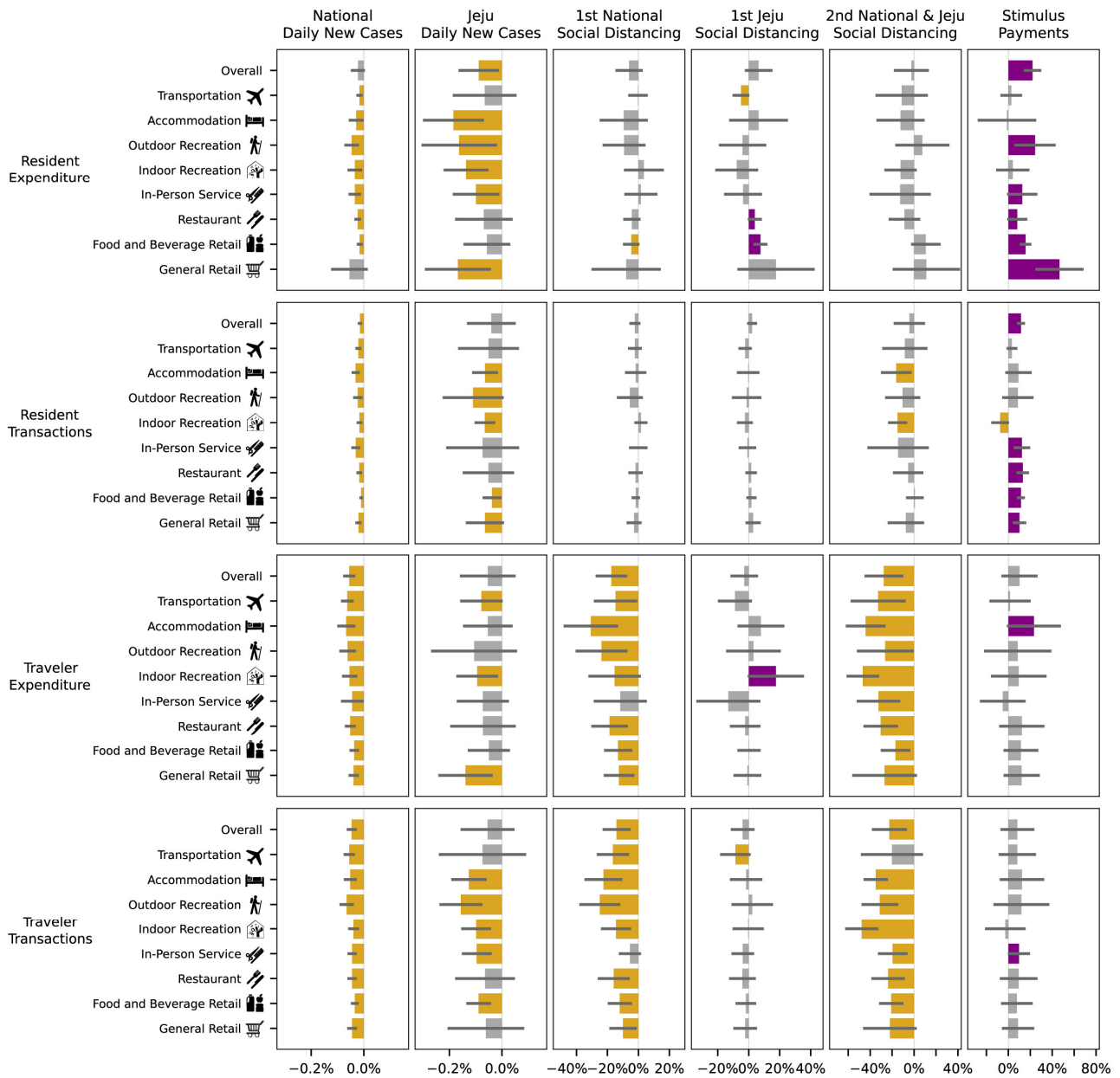


Figure 3.6 The effects of COVID-19 and policy responses on resident and traveler spending across different categories. The bars represent the estimated effects, where yellow marks significant negative ($p < 0.1$), purple marks significant positive ($p < 0.1$), grey marks nonsignificant, and error bars mark 95% confidence intervals. The estimated effect of national and Jeju daily new cases implies the % change in consumer spending caused by a 1% increase in the corresponding indicator. For other policy factors, the estimated effect implies the % change in consumer spending caused by the implementation of the corresponding policy.

For travelers, the increase in national COVID-19 cases triggered a relatively consistent expenditure and activity participation decline in almost all categories. Specifically, a 1% increase in the national COVID-19 cases reduced traveler expenditure and transactions by about 0.05% in most categories. The increase in local COVID-19 cases only caused declines in traveler spending in certain categories, such as transportation, indoor recreation, and general retail. A 1% increase in the Jeju COVID-19 cases reduced traveler expenditure and transactions by about 0.1% to 0.2%. This implies that as the national COVID-19 situation worsens, there is a high probability of experiencing a general reduction in tourist arrivals, resulting in a relatively consistent change in spending across all consumption categories. On the other hand, local COVID-19 conditions have an impact on tourists' activity choices and spending decisions at destinations, leading to significant variations in the effects across different categories.

The above findings confirmed the hypotheses **H1**, **H3**, and **H4** that consumer spending in Jeju was jointly affected by pandemic conditions locally and remotely and the impacts were heterogeneous across consumer groups and consumption categories.

3.4.3.2 The impact of social distancing was relatively consistent on expenditure and number of transactions but heterogeneous across categories

Although the impact of all social distancing measures on overall resident spending was insignificant, these measures had a negative impact on resident expenditure and transactions in certain categories, such as transportation, accommodation, and indoor recreation. The largest decreases occurred in accommodation and indoor recreation caused by the 2nd national and Jeju social distancing, where transactions fell by 16.3% and 15.0%.

For travelers, the first national social distancing and the second national and Jeju social distancing caused a substantial decline in traveler spending across all categories. However, the extent of the decline shows significant heterogeneity across categories. Traveler spending on accommodation, outdoor recreation, and indoor recreation experienced a greater decline than other categories. Conversely, traveler spending on food and beverage retail and general retail dropped less than others. The effect of the first Jeju social distancing on traveler spending was insignificant in most categories.

The impact of a given social distancing implementation on a given consumption category was relatively consistent in economic and behavioral aspects. It suggests that the decline in expenditure across sectors during the implementation of social distancing measures was a concomitant effect of reduced activity participation. Sectors, where social distancing measures imposed more strict activity

Table 3.5 Regression results of resident expenditure.

	Model - 0	Model - 1	Model - 2	Model - 3	Model - 4	Model - 5	Model - 6	Model - 7	Model - 8
	Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In-Person Service	Restaurant	Food and Beverage Retail	General Retail
<i>Constant</i> , β_0	22.892***	20.675***	19.337***	19.065***	18.171***	18.871***	21.406***	21.297***	21.551***
<i>DNC</i> , β_1	-0.022	-0.016***	-0.029**	-0.046***	-0.034**	-0.034***	-0.023***	-0.016***	-0.055
<i>JDNC</i> , β_2	-0.088**	-0.066	-0.184***	-0.163**	-0.136***	-0.098**	-0.069	-0.057	-0.167***
<i>KSD</i> , β_3	-0.060	-0.003	-0.095	-0.093	0.035	0.016	-0.042	-0.046*	-0.080
<i>JSD</i> , β_4	0.064	-0.050*	0.064	-0.040	-0.078	-0.037	0.039*	0.076***	0.176
<i>JSD</i> , β_5	-0.024	-0.113	-0.123	0.076	-0.123	-0.127	-0.087	0.107	0.112
<i>Stimulus</i> , β_6	0.221***	0.027	-0.013	0.243**	0.040	0.126*	0.081*	0.157***	0.466***
R2	0.427	0.792	0.623	0.365	0.347	0.431	0.587	0.315	0.206
Adj. R2	0.388	0.779	0.597	0.323	0.304	0.393	0.560	0.269	0.153
N	639.000	639.000	639.000	639.000	639.000	639.000	639.000	639.000	639.000
F stat	21.565	72.407	30.309	13.282	12.090	16.440	62.832	15.509	7.810
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-574.886	-742.100	3.344	116.747	-115.556	-47.632	-1017.185	-787.415	489.656
BIC	-392.030	-559.244	186.200	299.603	67.300	135.224	-834.329	-604.559	672.512

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HC1).

Table 3.6 Regression results of resident transactions.

	Model - 0	Model - 1	Model - 2	Model - 3	Model - 4	Model - 5	Model - 6	Model - 7	Model - 8
	Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In-Person Service	Restaurant	Food and Beverage Retail	General Retail
<i>Constant</i> , β_0	12.445***	9.847***	8.284***	8.310***	8.407***	8.295***	11.025***	11.414***	10.530***
<i>DNC</i> , β_1	-0.014***	-0.021***	-0.031***	-0.023**	-0.016***	-0.031***	-0.017***	-0.010***	-0.020***
<i>JDNC</i> , β_2	-0.040	-0.051	-0.064**	-0.109*	-0.065***	-0.073	-0.052	-0.038**	-0.065*
<i>KSD</i> , β_3	-0.023	-0.023	-0.018	-0.055	0.016	-0.001	-0.019	-0.017	-0.028
<i>JSD</i> , β_4	0.022	-0.023	-0.004	-0.013	-0.025	-0.009	0.016	0.018	0.028
<i>JSD</i> , β_5	-0.042	-0.084	-0.163**	-0.104	-0.150***	-0.145	-0.053	0.008	-0.075
<i>Stimulus</i> , β_6	0.115***	0.033	0.093	0.087	-0.075*	0.124***	0.132***	0.115***	0.101***
R2	0.481	0.611	0.794	0.789	0.847	0.450	0.441	0.554	0.519
Adj. R2	0.446	0.585	0.780	0.775	0.837	0.413	0.404	0.524	0.486
N	639.000	639.000	639.000	639.000	639.000	639.000	639.000	639.000	639.000
F stat	27.442	37.816	62.019	77.438	99.678	24.107	33.988	34.448	37.549
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-1428.957	-1094.459	-823.480	-260.679	-1127.388	-520.379	-1154.805	-1625.345	-678.036
BIC	-1246.101	-911.603	-640.624	-77.823	-944.532	-337.523	-971.949	-1442.489	-495.180

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HC1).

Table 3.7 Regression results of traveler expenditure.

	Model - 0	Model - 1	Model - 2	Model - 3	Model - 4	Model - 5	Model - 6	Model - 7	Model - 8
	Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In-Person Service	Restaurant	Food and Beverage Retail	General Retail
<i>Constant</i> , β_0	22.757***	19.912***	20.305***	19.540***	18.026***	17.625***	21.315***	20.660***	21.299***
<i>DNC</i> , β_1	-0.055***	-0.063***	-0.067***	-0.061***	-0.054***	-0.044**	-0.052***	-0.036***	-0.038***
<i>JDNC</i> , β_2	-0.054	-0.078*	-0.054	-0.106	-0.094**	-0.073	-0.072	-0.050	-0.138***
<i>KSD</i> , β_3	-0.175***	-0.147**	-0.307***	-0.239***	-0.154*	-0.117	-0.186***	-0.131***	-0.125**
<i>JSD</i> , β_4	-0.029	-0.089	0.079	0.031	0.175*	-0.132	-0.023	0.002	-0.009
<i>JSD</i> , β_5	-0.275***	-0.327**	-0.442***	-0.262**	-0.468***	-0.324***	-0.304***	-0.168**	-0.269*
<i>Stimulus</i> , β_6	0.102	0.016	0.233*	0.086	0.095	-0.051	0.123	0.115	0.122
R2	0.873	0.710	0.836	0.685	0.723	0.308	0.811	0.799	0.742
Adj. R2	0.865	0.691	0.825	0.664	0.704	0.262	0.798	0.786	0.725
N	639.000	639.000	639.000	639.000	639.000	639.000	639.000	639.000	639.000
F stat	159.785	64.233	97.871	38.675	53.151	12.843	105.592	99.606	70.635
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-958.494	-418.314	-275.262	65.001	71.963	143.607	-709.436	-947.553	-577.827
BIC	-775.638	-235.458	-92.406	247.857	254.819	326.463	-526.580	-764.697	-394.971

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HC1).

Table 3.8 Regression results of traveler transactions.

	Model - 0	Model - 1	Model - 2	Model - 3	Model - 4	Model - 5	Model - 6	Model - 7	Model - 8
	Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In-Person Service	Restaurant	Food and Beverage Retail	General Retail
<i>Constant</i> , β_0	12.190***	9.291***	9.159***	8.595***	8.105***	7.296***	10.822***	10.876***	10.421***
<i>DNC</i> , β_1	-0.046***	-0.055***	-0.051***	-0.065***	-0.039***	-0.044***	-0.045***	-0.034***	-0.045***
<i>JDNC</i> , β_2	-0.055	-0.074	-0.125***	-0.156***	-0.098***	-0.096***	-0.064	-0.088***	-0.061
<i>KSD</i> , β_3	-0.141***	-0.165***	-0.226***	-0.249***	-0.145***	-0.055	-0.159***	-0.120***	-0.100**
<i>JSD</i> , β_4	-0.039	-0.086*	-0.017	0.022	-0.004	-0.038	-0.041	-0.019	-0.023
<i>JSD</i> , β_5	-0.225***	-0.201	-0.349***	-0.312***	-0.477***	-0.195***	-0.237***	-0.208***	-0.220*
<i>Stimulus</i> , β_6	0.082	0.082	0.124	0.119	-0.028	0.097*	0.094	0.078	0.089
R2	0.815	0.686	0.866	0.742	0.764	0.697	0.772	0.830	0.767
Adj. R2	0.803	0.665	0.857	0.725	0.749	0.676	0.757	0.818	0.751
N	639.000	639.000	639.000	639.000	639.000	639.000	639.000	639.000	639.000
F stat	122.251	57.565	155.725	55.005	62.883	42.627	102.542	116.690	95.107
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-1025.263	-597.710	-693.163	-205.632	-318.965	-924.261	-892.039	-1127.822	-816.916
BIC	-842.407	-414.854	-510.307	-22.776	-136.109	-741.405	-709.183	-944.966	-634.060

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HC1).

restrictions, experienced correspondingly greater declines in expenditure, such as transportation, recreation (especially indoor facilities), hospitality, restaurants, and services that require in-person contact. In comparison, sectors associated with essential subsistence and lower health risks during the pandemic were less affected in both economic and behavioral aspects, such as retail and outdoor recreation.

3.4.3.3 Impact of stimulus payments on different economic sectors

For residents, the stimulus payments effectively increased their purchase frequency by approximately 10% in specific categories, such as in-person services, restaurants, food and beverage retail, and general retail (Figure 3.6). However, the impact of stimulus payments on expenditure varied significantly across sectors, with the largest increase observed in general retail at 46.6%. Notably, the rise in expenditure in general retail and food and beverage retail exceeded the increase in transaction frequency, indicating that residents spent more money per purchase in these retail sectors because of the policy. Besides, the stimulus payments boosted expenditure on outdoor recreation but led to a decrease in the frequency of consumption for indoor recreation, suggesting a shift in recreational activity preferences during the pandemic. Interestingly, in a seemingly vibrant consumer market, sectors like retail and recreation, with less risk of disease spread (i.e., outdoor recreation) benefited most from stimulus payments.

For travelers, the stimulus payments had a notable effect on increasing their purchase frequency by approximately 10% in in-person services, while also leading to a significant 23.3% increase in expenditure on accommodation. However, in comparison to residents, the impact of this policy on travelers' activity participation and expenditure was relatively limited. Nevertheless, the hospitality sector experienced substantial benefits from the stimulus payments.

3.4.3.4 Stimulus payments effectively boosted consumer spending in certain sectors without diminishing the effects of social distancing

Social distancing measures aim to mitigate the spread of the disease by reducing human mobility and interpersonal contact. Stimulus payments, on the other hand, are designed to encourage consumers to move out of their homes and engage in more activities to revitalize the economy and boost employment. Our results suggest that the stimulus payments did not diminish the effectiveness of social distancing at venues with high risks of disease spread, such as transportation, and indoor and outdoor recreation, while it effectively boosted consumer expenditure in other sectors that were less restricted by social distancing measures, such as retail. Indeed, our results demonstrate that social distancing policies and

stimulus payments can be jointly effective. We find that stimulus measures even reinforced the restrictive effect of social distancing in certain places (e.g., indoor recreation), as they directed consumers to spend their time and money elsewhere. The above findings are all in line with our hypotheses **H4** and **H5** that the policy responses produce heterogeneous effects on consumer spending across different economic sectors and consumer groups.

3.5 Discussion and Conclusion

The global pandemic instigated by COVID-19 presented urban economies with an unprecedented set of complex challenges. The pervasive spread of the virus and corresponding policy measures led to significant shifts in consumer spending within urban areas. Through an analysis of expansive credit and debit card transaction data, we have elucidated the varied impacts of disease transmission and policy responses at both local and national scales on the spending patterns of residents and domestic travelers.

3.5.1 Theoretical implications

Our findings underscore that both demographics exhibited sensitivity to local and national disease transmission severity. Specifically, residents showed heightened sensitivity to local disease spread, exhibiting strong reactions, particularly when engaging in activities necessitating physical contact, such as indoor and outdoor recreation. Conversely, travelers exhibited heightened concern regarding national-level disease spread when participating in activities such as public transportation and accommodation services, where they might interact more with other travelers. However, they were more sensitive to local disease spread while participating in activities that may involve increased interactions with residents, such as indoor and outdoor recreation and in-person services. This study carries significant implications for understanding the role of risk perception in shaping individual protective behaviors. Residents and travelers have access to different amounts and types of information and possess varying levels of familiarity associated with geographical and psychological distances. These differing characteristics lead to distinct risk perceptions and coping strategies.

This study highlights the heterogeneous impact of social distancing measures and stimulus payments on consumer behavior across multiple travel products (Wu & Carson, 2008). The research reveals that social distancing measures have minimal behavioral effects on residents but notably influence tourist behavior. Conversely, economic stimulus measures produce contrasting outcomes.

These distinct behavioral responses by residents and travelers to different policies demonstrate the existence of adaptive decision-making in response to changes in the decision environment (Payne et al., 1993). Furthermore, the influence of policies on consumer spending varies across economic sectors, with the retail, restaurant, accommodation, and outdoor recreation sectors benefiting more from stimulus payments, while indoor recreation sectors suffer more. These findings underscore the priority of physiological and safety needs in consumer decision-making, aligning with Maslow's hierarchy of needs theory (Maslow, 1943).

3.5.2 Policy implications

Our research findings underscore the joint impact of both local and national disease spread on local economies. This highlights the importance for island destinations similar to Jeju, such as Hong Kong, Singapore, and Hawaii, to consider the combined effects of local and external outbreaks during public health crises. Given the relative geographical independence of these destinations, disease transmission often occurs separately at the local and national levels. A tourism-oriented city geographically distant from the nationwide outbreak epicenter can still suffer substantial economic consequences as external risks infiltrate through inbound travelers. However, a surge in local COVID-19 cases often leads to larger declines in consumer spending across most sectors, emphasizing that controlling local disease spread is pivotal in mitigating economic losses over the long term.

Furthermore, the differential effects of policies on these two distinct groups emphasize the necessity of implementing tailored policies that account for the unique characteristics of each population. From a disease prevention standpoint, stricter measures may be required to regulate resident behavior in specific locales. From an economic recovery perspective, relying solely on general, nationwide economic tools may be insufficient in stimulating tourist expenditure in destination areas. Complementary economic instruments specifically targeted to travel destinations may be indispensable.

The heterogeneous impact of policies on consumer spending across different economic sectors highlights the importance of implementing a combination of economic stimulus and social distancing measures to achieve a balance between economic recovery and public safety (Hsiao et al., 2022; Gourinchas, 2020). A balanced policy approach can be accomplished through a nuanced design that distinguishes between venues eligible for consumption vouchers and those limited by social distancing norms (Kaplan et al., 2020; Dorn et al., 2022; Kim & Oh, 2021). Government interventions have

proven effective in directing spending towards industries that have been especially affected, thereby stimulating consumer spending and broader economic activity.

3.5.3 Limitations

We want to point out the limitations of this research. Firstly, while a single-destination analysis may have limitations in capturing the full diversity of tourist destinations, the general differences in behavioral responses between residents and travelers still provide insights that are broadly applicable to other tourism cities. Second, while the analysis for this study is based on a broadly representative dataset of debit and credit card transactions, it is acknowledged that a small proportion of transactions may be conducted in cash (22%) (BOK, 2023). However, given the high prevalence of card-based payments in the region and the widespread use of contactless payment (e.g., card-related e-money), particularly during the COVID-19 pandemic, the dataset remains highly representative of overall consumer behavior. Third, the classification of residents and travelers in this study is based on the categorization provided by credit card companies, which is determined by the user's registered location. The travelers in the dataset, apart from tourists, i.e., those visitors for leisure purposes, may also include a small percentage of other types of non-resident consumers, such as business or education-related visitors, or digital nomads who are temporary residents. Differences among various types of travelers were not adequately discussed in this study, which could be examined in future research. Fourth, this study employs multiple linear regression models rather than time series techniques, such as an error correction model, to estimate the effects of pandemic-related factors on consumer behavior. The latter may have the potential to be more effective in revealing both long-term and short-term relationships. However, to obtain more direct and interpretable results, the former is employed in this study to provide more practical insights for application and policy implications.

Appendices

3.A Descriptive statistics of consumption variables

Table 3.9 Descriptive statistics of consumption variables.

	Resident Expenditure					Resident Transactions				
	Obs.	Min	Max	Mean	SD	Obs.	Min	Max	Mean	SD
<i>Overall</i>	639	3.18E+09	1.90E+10	1.05E+10	1.95E+09	639	137101.00	355867.00	274294.59	25962.27
<i>Transportation</i>	639	3.81E+08	2.55E+09	1.37E+09	3.31E+08	639	8717.00	43688.00	22102.72	3140.82
<i>Accommodation</i>	639	3.86E+07	4.18E+08	1.49E+08	5.75E+07	639	1361.00	6215.00	2826.52	826.04
<i>Outdoor Recreation</i>	639	3.95E+07	3.21E+08	1.80E+08	5.18E+07	639	830.00	8111.00	2873.63	1167.82
<i>Indoor Recreation</i>	639	1.48E+07	1.58E+08	6.54E+07	1.67E+07	639	1142.00	5823.00	3102.70	772.62
<i>In-Person Service</i>	639	1.56E+07	3.77E+08	2.06E+08	4.87E+07	639	735.00	6995.00	4086.86	731.87
<i>Restaurant</i>	639	5.90E+08	2.54E+09	1.67E+09	2.52E+08	639	18907.00	76068.00	58912.95	6238.16
<i>Food and Beverage Retail</i>	639	1.09E+09	4.72E+09	1.97E+09	3.31E+08	639	60535.00	136052.00	96963.98	9130.90
<i>General Retail</i>	639	2.73E+08	9.42E+09	3.02E+09	1.36E+09	639	7880.00	73901.00	45062.68	7554.59

	Traveler Expenditure					Traveler Transactions				
	Obs.	Min	Max	Mean	SD	Obs.	Min	Max	Mean	SD
<i>Overall</i>	639	2.49E+09	1.35E+10	7.22E+09	1.85E+09	639	76042.00	310855.00	186556.56	40906.58
<i>Transportation</i>	639	1.35E+08	9.64E+08	4.40E+08	1.36E+08	639	2540.00	16136.00	10084.72	2333.26
<i>Accommodation</i>	639	1.30E+08	1.80E+09	6.19E+08	2.77E+08	639	2830.00	18844.00	8474.59	2932.29
<i>Outdoor Recreation</i>	639	4.30E+07	5.53E+08	2.64E+08	9.92E+07	639	1340.00	9772.00	5057.78	1694.10
<i>Indoor Recreation</i>	639	1.42E+07	1.63E+08	6.13E+07	2.68E+07	639	780.00	5811.00	2534.29	923.67
<i>In-Person Service</i>	639	2.09E+07	1.49E+08	4.83E+07	1.65E+07	639	450.00	1956.00	1201.81	228.43
<i>Restaurant</i>	639	4.61E+08	3.13E+09	1.54E+09	4.35E+08	639	16437.00	76552.00	44649.58	10112.69
<i>Food and Beverage Retail</i>	639	4.06E+08	1.39E+09	8.46E+08	1.88E+08	639	25527.00	83933.00	50889.18	11104.19
<i>General Retail</i>	639	3.65E+08	2.80E+09	1.44E+09	3.60E+08	639	9528.00	57100.00	29857.43	6953.62

3.B Time series of residents' and travelers' daily expenditures and transactions

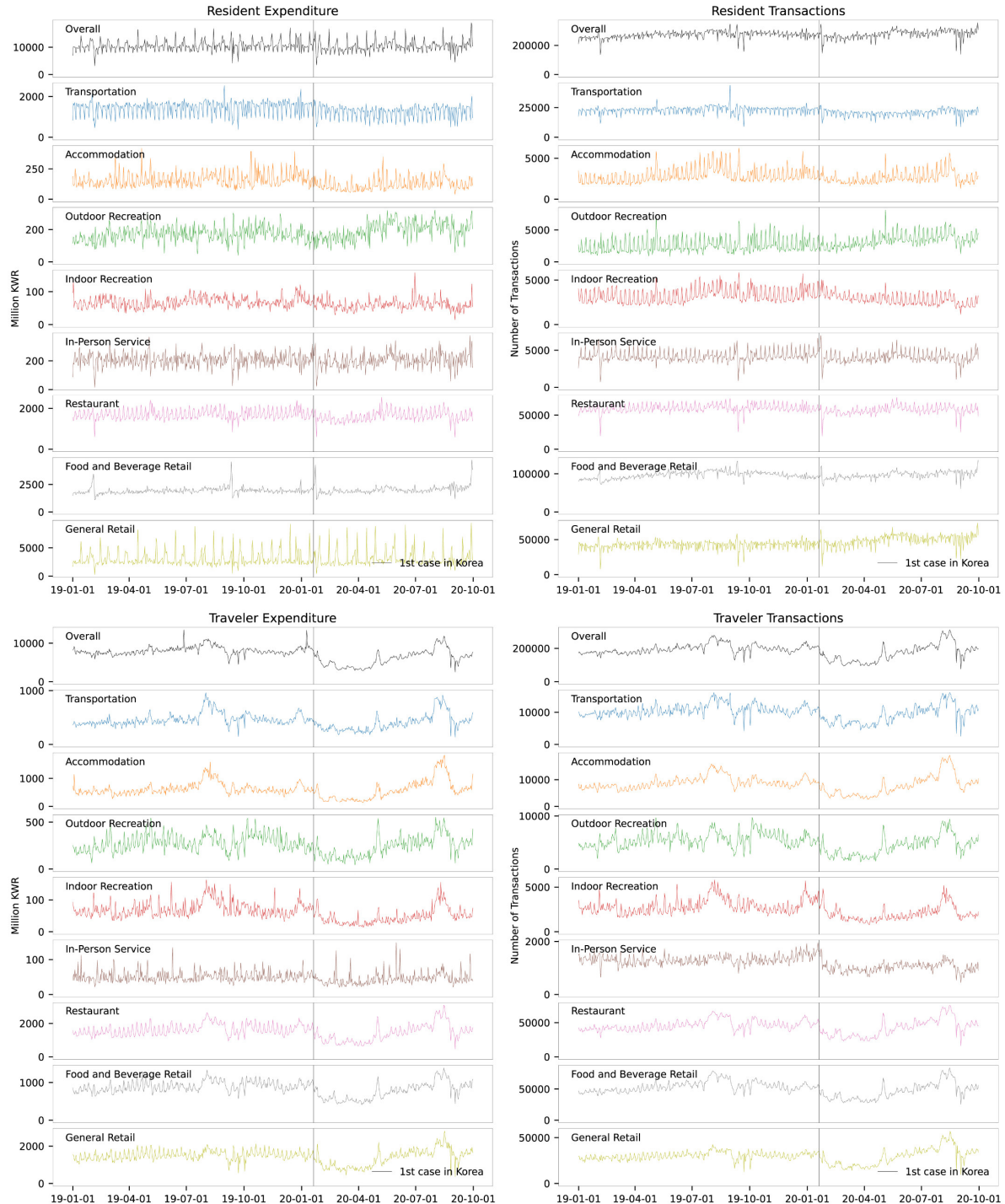


Figure 3.7 Time series data generated from transaction dataset across two consumer groups (i.e., resident and traveler), two consumption indicators (i.e., expenditure and transactions), and consumption categories (i.e., overall and eight categories).

3.C Time series of the year-over-year change in consumer spending by category at daily granularity

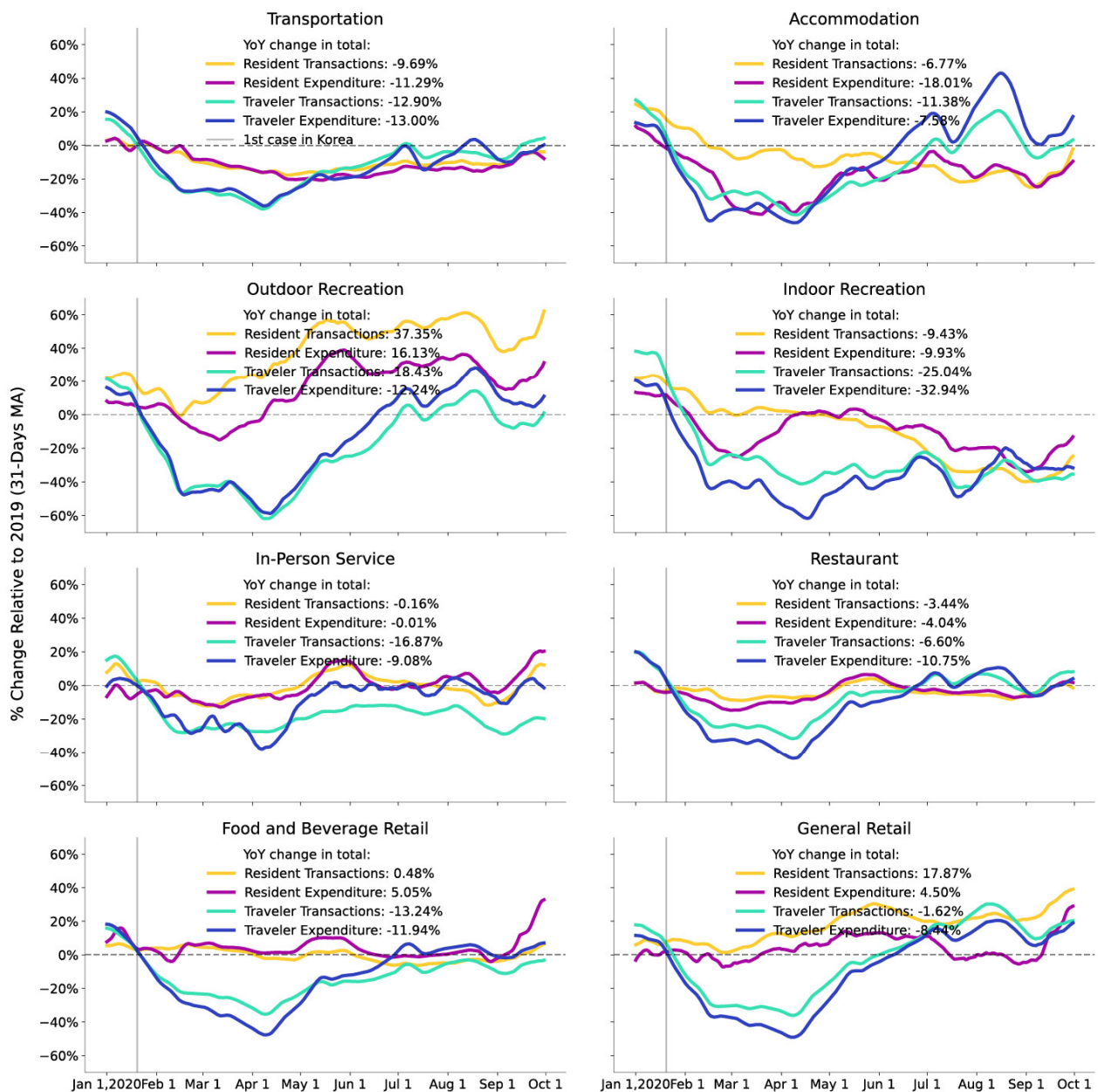


Figure 3.8 The year-over-year change in resident and traveler daily expenditure and transactions relative to 2019 across different categories.

3.D Unit root test results

Table 3.10 Unit root test results of original consumption time series data.

		Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In Person Service	Restaurant	Food and Beverage Retail	General Retail
Resident Expenditure	ADF test statistic	0.235	-0.362	-0.493	0.261	-0.401	-0.012	-0.211	0.638	-0.121
	p-value	0.757	0.552	0.499	0.764	0.536	0.680	0.610	0.855	0.643
	# lags used	16	20	20	20	20	20	20	16	16
	# observations	622	618	618	618	618	618	618	622	622
	critical value (1%)	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569
	critical value (5%)	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941
	critical value (10%)	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616
Resident Transactions	ADF test statistic	0.522	-0.169	-0.233	0.543	-0.455	-0.025	-0.137	0.717	1.218
	p-value	0.830	0.625	0.602	0.835	0.514	0.676	0.637	0.870	0.942
	# lags used	13	20	20	20	20	20	20	13	20
	# observations	625	618	618	618	618	618	618	625	618
	critical value (1%)	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569
	critical value (5%)	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941
	critical value (10%)	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616
Traveler Expenditure	ADF test statistic	-0.637	-0.675	-0.819	-0.329	-0.897	-0.655	-0.474	-0.218	-0.190
	p-value	0.439	0.423	0.363	0.565	0.330	0.432	0.507	0.607	0.618
	# lags used	14	16	14	20	13	15	20	19	20
	# observations	624	622	624	618	625	623	618	619	618
	critical value (1%)	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569
	critical value (5%)	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941
	critical value (10%)	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616
Traveler Transactions	ADF test statistic	-0.340	-0.337	-0.586	-0.507	-0.940	-0.726	-0.310	-0.212	-0.186
	p-value	0.561	0.562	0.461	0.493	0.312	0.402	0.572	0.609	0.619
	# lags used	18	18	20	19	14	20	19	19	19
	# observations	620	620	618	619	624	618	619	619	619
	critical value (1%)	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569
	critical value (5%)	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941
	critical value (10%)	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616

Table 3.11 Unit root test results of consumption time series data after seasonal adjustment.

		Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In Person Service	Restaurant	Food and Beverage Retail	General Retail
Resident Expenditure	ADF test statistic	-7.118	-20.699	-23.683	-7.031	-11.643	-23.159	-16.298	-10.842	-8.523
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	# lags used	20	0	0	19	2	0	1	3	20
	# observations	618	638	638	619	636	638	637	635	618
	critical value (1%)	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569
	critical value (5%)	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941
	critical value (10%)	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616
Resident Transactions	ADF test statistic	-7.837	-20.667	-8.768	-10.523	-7.301	-19.294	-20.147	-8.581	-15.689
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	# lags used	6	0	3	3	10	0	0	7	2
	# observations	632	638	635	635	628	638	638	631	636
	critical value (1%)	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569
	critical value (5%)	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941
	critical value (10%)	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616
Traveler Expenditure	ADF test statistic	-7.415	-7.074	-7.439	-11.959	-8.919	-7.789	-7.785	-7.729	-7.799
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	# lags used	16	7	14	1	3	18	8	7	16
	# observations	622	631	624	637	635	620	630	631	622
	critical value (1%)	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569
	critical value (5%)	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941
	critical value (10%)	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616
Traveler Transactions	ADF test statistic	-7.296	-7.300	-7.838	-10.356	-6.673	-6.929	-7.890	-7.422	-7.499
	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	# lags used	16	16	7	1	9	9	7	16	16
	# observations	622	622	631	637	629	629	631	622	622
	critical value (1%)	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569	-2.569
	critical value (5%)	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941	-1.941
	critical value (10%)	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616	-1.616

3.E Cointegration test results

Table 3.12 Cointegration tests for consumption time series with DNC & JDNC.

Consumption Time Series	Resident Expenditure				Resident Transactions				Traveler Expenditure				Traveler Transactions							
	Rank	r_0	r_1	test statistic	critical value	Rank	r_0	r_1	test statistic	critical value	Rank	r_0	r_1	test statistic	critical value	Rank	r_0	r_1	test statistic	critical value
Overall	3	0	3	370.2	29.8	3	0	3	405	29.8	3	0	3	245.3	29.8	3	0	3	243.8	29.8
		1	3	157.5	15.49		1	3	150.5	15.49		1	3	66.29	15.49		1	3	69.42	15.49
		2	3	4.793	3.841		2	3	4.668	3.841		2	3	4.701	3.841		2	3	4.665	3.841
Transportation	3	0	3	400.3	29.8	3	0	3	413	29.8	3	0	3	257.6	29.8	3	0	3	287	29.8
		1	3	152.1	15.49		1	3	149.9	15.49		1	3	91.68	15.49		1	3	108.8	15.49
		2	3	4.706	3.841		2	3	4.696	3.841		2	3	4.152	3.841		2	3	4.653	3.841
Accommodation	3	0	3	402.3	29.8	3	0	3	325.2	29.8	3	0	3	238.5	29.8	3	0	3	225.6	29.8
		1	3	156.4	15.49		1	3	136.9	15.49		1	3	69.43	15.49		1	3	64.87	15.49
		2	3	4.903	3.841		2	3	4.279	3.841		2	3	4.67	3.841		2	3	4.432	3.841
Outdoor Recreation	3	0	3	404.5	29.8	3	0	3	396.8	29.8	3	0	3	295.9	29.8	3	0	3	267.8	29.8
		1	3	157.5	15.49		1	3	158.5	15.49		1	3	124.9	15.49		1	3	103.4	15.49
		2	3	4.481	3.841		2	3	4.697	3.841		2	3	4.652	3.841		2	3	4.48	3.841
Indoor Recreation	3	0	3	361.8	29.8	3	0	3	328.2	29.8	3	0	3	334.4	29.8	3	0	3	285.6	29.8
		1	3	148.8	15.49		1	3	134.1	15.49		1	3	149.2	15.49		1	3	112.9	15.49
		2	3	5.242	3.841		2	3	4.927	3.841		2	3	4.728	3.841		2	3	4.759	3.841
In-Person Service	3	0	3	397.5	29.8	3	0	3	395.1	29.8	3	0	3	389.9	29.8	3	0	3	333.8	29.8
		1	3	154.3	15.49		1	3	143.2	15.49		1	3	155.6	15.49		1	3	127.3	15.49
		2	3	4.416	3.841		2	3	4.652	3.841		2	3	4.511	3.841		2	3	4.625	3.841
Restaurant	3	0	3	409.6	29.8	3	0	3	405.9	29.8	3	0	3	252.1	29.8	3	0	3	243.9	29.8
		1	3	148.3	15.49		1	3	153.3	15.49		1	3	77.01	15.49		1	3	74.12	15.49
		2	3	4.676	3.841		2	3	4.681	3.841		2	3	4.859	3.841		2	3	4.912	3.841
Food and Beverage Retail	3	0	3	305.6	29.8	3	0	3	371.3	29.8	3	0	3	259.9	29.8	3	0	3	251.9	29.8
		1	3	144.6	15.49		1	3	159.7	15.49		1	3	88.52	15.49		1	3	88.27	15.49
		2	3	4.436	3.841		2	3	4.6	3.841		2	3	4.659	3.841		2	3	4.471	3.841
General Retail	3	0	3	359	29.8	3	0	3	418	29.8	3	0	3	298.5	29.8	3	0	3	282	29.8
		1	3	157.1	15.49		1	3	158.2	15.49		1	3	131.5	15.49		1	3	99.98	15.49
		2	3	4.746	3.841		2	3	4.726	3.841		2	3	4.476	3.841		2	3	4.672	3.841

Johansen cointegration test using trace test statistic with 5% significance level.

3.F Regression results

Table 3.13 Regression results of all models about resident expenditure.

	Model - 0	Model - 1	Model - 2	Model - 3	Model - 4	Model - 5	Model - 6	Model - 7	Model - 8
	Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In-Person Service	Restaurant	Food and Beverage Retail	General Retail
<i>Constant, β_0</i>	22.892***	20.675***	19.337***	19.065***	18.171***	18.871***	21.406***	21.297***	21.551***
α_{Jan}	-0.073**	-0.056***	-0.255***	-0.158***	-0.079	-0.027	-0.081***	-0.049**	-0.093
α_{Feb}	-0.097**	-0.126***	-0.390***	-0.160**	-0.056	-0.135*	-0.120***	-0.086*	-0.100
α_{Mar}	-0.076**	-0.087***	-0.287***	0.034	-0.131**	-0.004	-0.100***	-0.090***	-0.035
α_{Apr}	-0.081**	-0.093***	-0.237***	0.069	-0.259***	-0.068*	-0.079***	-0.055**	-0.077
α_{May}	-0.019	-0.043	-0.215***	0.057	-0.164**	0.005	-0.037	-0.006	0.020
α_{Jun}	-0.058*	-0.053**	-0.216***	0.105**	-0.093	-0.045	-0.081***	-0.007	-0.072
α_{Jul}	-0.073*	-0.085***	-0.232***	0.024	0.099*	-0.068	-0.051**	0.004	-0.138
α_{Aug}	-0.024	-0.008	-0.052	0.041	0.072	-0.054	0.001	0.078***	-0.129
α_{Sep}	-0.062	-0.131***	-0.322***	-0.092	-0.052	-0.079	-0.137***	0.072	-0.098
α_{Oct}	-0.025	-0.039*	-0.132*	0.128**	-0.070	0.026	-0.036	0.021	-0.036
α_{Nov}	-0.028	-0.030	-0.189***	0.163***	-0.078	-0.069*	-0.054**	-0.023	0.001
α_{Mon}	0.290***	0.626***	-0.445***	-0.212***	-0.031	0.342***	-0.227***	0.107***	0.357***
α_{Tue}	0.273***	0.596***	-0.422***	-0.237***	-0.132***	0.248***	-0.182***	0.087***	0.327***
α_{Wed}	0.271***	0.540***	-0.416***	-0.209***	-0.150***	0.351***	-0.137***	0.084***	0.348***
α_{Thu}	0.273***	0.596***	-0.422***	-0.197***	-0.185***	0.360***	-0.144***	0.104***	0.355***
α_{Fri}	0.294***	0.590***	-0.358***	-0.276***	-0.191***	0.355***	-0.056***	0.126***	0.309***
α_{Sat}	0.218***	0.352***	0.094**	-0.066	0.062**	0.525***	0.094***	0.124***	0.218***
α_h	-0.267***	-0.441***	0.289***	0.173**	0.142**	-0.550***	-0.007	-0.095	-0.370**
α'_{Jan}	-0.007	-0.140	-0.060	-0.148	-0.167**	-0.184	-0.141*	0.068	0.112
α'_{Feb}	-0.041	-0.040	-0.097	0.015	-0.218***	0.038	-0.079**	0.019	-0.004
α'_{Mar}	0.042	-0.035	-0.280**	0.082	-0.164	0.033	-0.019	0.117***	0.199
α'_{Apr}	0.031	-0.081	-0.284**	0.285**	0.060	0.125	-0.030	0.032	0.129
α'_{May}	-0.105	-0.233***	-0.110	0.209	0.023	0.069	-0.001	-0.022	-0.176
α'_{Jun}	-0.142*	-0.193***	-0.033	0.041	-0.159	0.009	-0.028	-0.098**	-0.176
α'_{Jul}	-0.158*	-0.120*	0.082	0.150	-0.249**	0.002	-0.050	-0.107**	-0.228
α'_{Aug}	-0.146*	-0.094	0.116	0.158	-0.194*	0.108	-0.023	-0.102**	-0.244
α'_{Sep}	0.192*	0.118	0.167	0.342**	-0.121	0.385**	0.164*	0.087	0.341
α'_{Mon}	0.024	0.020	-0.001	0.075	0.177***	0.030	0.032	-0.017	0.039
α'_{Tue}	0.060	0.069*	0.020	0.212***	0.290***	0.093	0.069**	0.035	0.078
α'_{Wed}	-0.033	0.015	-0.121	0.060	0.103	-0.037	-0.004	-0.005	-0.105
α'_{Thu}	0.005	0.016	-0.049	0.070	0.217***	-0.036	0.052**	-0.011	-0.050
α'_{Fri}	0.056	0.044	0.024	0.133	0.199***	0.041	0.072**	0.045	0.083
α'_{Sat}	0.006	-0.005	-0.082	0.045	0.095*	-0.007	-0.005	0.002	-0.014
α'_h	0.084	0.159	-0.181**	-0.074	-0.081	0.177	-0.027	0.092	0.110
<i>DNC, β_1</i>	-0.022	-0.016***	-0.029**	-0.046***	-0.034**	-0.034***	-0.023***	-0.016***	-0.055
<i>JDNC, β_2</i>	-0.088**	-0.066	-0.184***	-0.163**	-0.136***	-0.098**	-0.069	-0.057	-0.167***
<i>KSD, β_3</i>	-0.060	-0.003	-0.095	-0.093	0.035	0.016	-0.042	-0.046*	-0.080
<i>JSD, β_4</i>	0.064	-0.050*	0.064	-0.040	-0.078	-0.037	0.039*	0.076***	0.176
<i>JSD, β_5</i>	-0.024	-0.113	-0.123	0.076	-0.123	-0.127	-0.087	0.107	0.112
<i>Stimulus, β_6</i>	0.221***	0.027	-0.013	0.243**	0.040	0.126*	0.081*	0.157***	0.466***
R2	0.427	0.792	0.623	0.365	0.347	0.431	0.587	0.315	0.206
Adj. R2	0.388	0.779	0.597	0.323	0.304	0.393	0.560	0.269	0.153
N	639	639	639	639	639	639	639	639	639
F stat	21.565	72.407	30.309	13.282	12.090	16.440	62.832	15.509	7.810
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-574.886	-742.100	3.344	116.747	-115.556	-47.632	-1017.185	-787.415	489.656
BIC	-392.030	-559.244	186.200	299.603	67.300	135.224	-834.329	-604.559	672.512

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HC1).

Table 3.14 Regression results of all models about resident transactions.

	Model - 0	Model - 1	Model - 2	Model - 3	Model - 4	Model - 5	Model - 6	Model - 7	Model - 8
	Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In-Person Service	Restaurant	Food and Beverage Retail	General Retail
<i>Constant, β_0</i>	12.445***	9.847***	8.284***	8.310***	8.407***	8.295***	11.025***	11.414***	10.530***
α_{Jan}	-0.067***	-0.032***	-0.180***	-0.146***	-0.061**	-0.016	-0.043***	-0.066***	-0.075***
α_{Feb}	-0.109***	-0.060***	-0.306***	-0.166***	-0.091***	-0.103**	-0.092**	-0.101***	-0.140***
α_{Mar}	-0.058***	-0.031**	-0.275***	-0.145***	-0.201***	-0.047**	-0.033*	-0.051***	-0.039
α_{Apr}	-0.029***	-0.015	-0.174***	-0.095**	-0.208***	-0.073***	-0.017	0.011	-0.058**
α_{May}	0.018	0.011	-0.077**	-0.078	-0.195***	-0.056**	0.014	0.059***	0.027
α_{Jun}	0.012	-0.003	-0.012	-0.016	-0.141***	-0.081***	0.001	0.087***	-0.047*
α_{Jul}	0.019	0.008	0.094**	0.024	0.067**	-0.089***	0.002	0.095***	-0.055**
α_{Aug}	0.059***	0.090***	0.236***	0.081*	0.102***	-0.066***	0.048**	0.136***	-0.061**
α_{Sep}	-0.015	-0.063*	-0.114***	-0.136**	-0.032	-0.122**	-0.055	0.082***	-0.092*
α_{Oct}	0.034***	0.008	-0.056*	0.073*	-0.001	-0.040	0.043**	0.092***	-0.029
α_{Nov}	0.011	0.000	-0.077***	0.140***	-0.079***	-0.019	0.014	0.048***	-0.038
α_{Mon}	0.100***	0.285***	-0.444***	-0.817***	-0.427***	0.034	-0.081***	0.036***	0.268***
α_{Tue}	0.075***	0.253***	-0.403***	-0.741***	-0.436***	-0.010	-0.062***	0.026**	0.173***
α_{Wed}	0.078***	0.227***	-0.394***	-0.688***	-0.430***	0.063**	-0.029**	0.024*	0.187***
α_{Thu}	0.088***	0.242***	-0.400***	-0.727***	-0.419***	0.070***	-0.024*	0.034***	0.208***
α_{Fri}	0.103***	0.247***	-0.321***	-0.727***	-0.316***	0.105***	0.012	0.047***	0.155***
α_{Sat}	0.133***	0.202***	0.017	-0.101**	0.006	0.345***	0.104***	0.069***	0.205***
α_h	-0.099**	-0.162***	0.446***	0.664***	0.385***	-0.305**	-0.119	-0.007	-0.260**
α'_{Jan}	-0.041	-0.048	-0.014	-0.174**	0.052	-0.122	-0.162**	-0.011	-0.024
α'_{Feb}	0.030	-0.029	0.047	-0.079	0.034	-0.040	-0.011	0.059**	0.063
α'_{Mar}	0.052*	-0.006	0.062	0.155*	0.077*	0.025	-0.005	0.081***	0.145***
α'_{Apr}	0.019	-0.043	-0.038	0.241***	0.011	0.047	-0.019	0.004	0.183***
α'_{May}	-0.022	-0.137***	-0.060	0.309***	0.036	0.020	-0.060	-0.051*	0.139***
α'_{Jun}	-0.055	-0.084*	-0.137*	0.168*	-0.050	-0.014	-0.120***	-0.120***	0.164***
α'_{Jul}	-0.068*	-0.056	-0.170**	0.219**	-0.266***	-0.037	-0.134***	-0.135***	0.136**
α'_{Aug}	-0.040	-0.022	-0.107	0.261***	-0.179***	-0.039	-0.126***	-0.114***	0.197***
α'_{Sep}	0.145*	0.144	0.131	0.498***	-0.200***	0.267	0.100	0.047	0.440***
α'_{Mon}	0.006	-0.022	0.094**	0.337***	0.105***	0.054	0.025	-0.012	-0.008
α'_{Tue}	0.054**	0.033	0.136***	0.388***	0.135***	0.120***	0.065**	0.022	0.072*
α'_{Wed}	0.002	-0.027	0.066	0.290***	0.114***	0.023	-0.002	-0.003	-0.006
α'_{Thu}	0.026	0.004	0.093**	0.329***	0.091***	0.050	0.036*	0.007	0.024
α'_{Fri}	0.048**	0.021	0.083**	0.363***	0.094***	0.093**	0.056**	0.039**	0.070*
α'_{Sat}	0.009	-0.028	-0.017	0.010	-0.005	0.009	-0.002	0.014	0.027
α'_h	0.049	0.046	-0.180*	-0.348***	-0.166**	0.098	0.024	0.053	0.133
<i>DNC, β_1</i>	-0.014***	-0.021***	-0.031***	-0.023**	-0.016***	-0.031***	-0.017***	-0.010***	-0.020***
<i>JDNC, β_2</i>	-0.040	-0.051	-0.064**	-0.109*	-0.065***	-0.073	-0.052	-0.038**	-0.065*
<i>KSD, β_3</i>	-0.023	-0.023	-0.018	-0.055	0.016	-0.001	-0.019	-0.017	-0.028
<i>JSD, β_4</i>	0.022	-0.023	-0.004	-0.013	-0.025	-0.009	0.016	0.018	0.028
<i>JSD, β_5</i>	-0.042	-0.084	-0.163**	-0.104	-0.150***	-0.145	-0.053	0.008	-0.075
<i>Stimulus, β_6</i>	0.115***	0.033	0.093	0.087	-0.075*	0.124***	0.132***	0.115***	0.101***
R2	0.481	0.611	0.794	0.789	0.847	0.450	0.441	0.554	0.519
Adj. R2	0.446	0.585	0.780	0.775	0.837	0.413	0.404	0.524	0.486
N	639	639	639	639	639	639	639	639	639
F stat	27.442	37.816	62.019	77.438	99.678	24.107	33.988	34.448	37.549
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-1428.957	-1094.459	-823.480	-260.679	-1127.388	-520.379	-1154.805	-1625.345	-678.036
BIC	-1246.101	-911.603	-640.624	-77.823	-944.532	-337.523	-971.949	-1442.489	-495.180

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HC1).

Table 3.15 Regression results of all models about traveler expenditure.

	Model - 0	Model - 1	Model - 2	Model - 3	Model - 4	Model - 5	Model - 6	Model - 7	Model - 8
	Overall	Transportation	Accommodation	Outdoor Recreation	Indoor Recreation	In-Person Service	Restaurant	Food and Beverage Retail	General Retail
<i>Constant, β_0</i>	22.757***	19.912***	20.305***	19.540***	18.026***	17.625***	21.315***	20.660***	21.299***
α_{Jan}	0.042*	-0.134***	-0.063	-0.220***	0.050	0.039	-0.073**	-0.021	-0.066***
α_{Feb}	-0.053**	-0.151***	-0.098*	-0.099*	0.033	-0.042	-0.127***	-0.128***	-0.080***
α_{Mar}	-0.081***	-0.204***	-0.273***	-0.113**	-0.169**	-0.044	-0.173***	-0.052**	-0.061***
α_{Apr}	-0.017	-0.114***	-0.100*	0.165***	0.087	0.067	-0.068**	0.063**	0.034
α_{May}	0.063***	-0.071*	-0.042	0.202***	-0.013	-0.032	-0.089***	-0.022	0.009
α_{Jun}	0.101***	0.001	0.042	0.131***	0.049	-0.028	0.003	0.033	0.043**
α_{Jul}	0.158***	0.103*	0.284***	0.044	0.196**	-0.022	0.067*	0.011	-0.009
α_{Aug}	0.214***	0.390***	0.523***	0.233***	0.534***	0.101**	0.268***	0.212***	0.142***
α_{Sep}	-0.083**	-0.116*	-0.087	-0.159*	0.102	-0.053	-0.140***	-0.045	-0.143***
α_{Oct}	0.019	0.052	0.018	0.317***	0.073	0.089	0.055	0.123***	0.038
α_{Nov}	-0.010	-0.058	-0.060	0.266***	-0.060	-0.001	-0.006	0.080***	0.057***
α_{Mon}	0.047***	0.072**	-0.094***	-0.268***	-0.103**	0.085	-0.165***	-0.107***	-0.132***
α_{Tue}	0.001	0.016	-0.184***	-0.337***	-0.140***	0.002	-0.204***	-0.136***	-0.238***
α_{Wed}	-0.017	-0.009	-0.192***	-0.361***	-0.156***	0.017	-0.212***	-0.144***	-0.254***
α_{Thu}	0.017	0.074**	-0.096***	-0.307***	-0.158***	0.046	-0.175***	-0.133***	-0.237***
α_{Fri}	0.041**	0.104***	-0.037	-0.151***	-0.076	0.174***	-0.052**	-0.050**	-0.245***
α_{Sat}	0.008	0.086**	-0.045	-0.003	0.073*	0.225***	0.090***	0.036*	-0.138***
α_h	0.010	0.120***	0.277***	0.369***	0.279***	-0.177**	0.186***	0.096***	0.108***
α'_{Jan}	-0.148***	-0.051	-0.080	-0.141	-0.088	-0.247***	-0.135***	-0.210***	-0.055
α'_{Feb}	-0.401***	-0.236***	-0.596***	-0.537***	-0.549***	-0.330***	-0.335***	-0.343***	-0.406***
α'_{Mar}	-0.293***	0.064	-0.199*	-0.312***	-0.494***	-0.169	-0.137**	-0.306***	-0.343***
α'_{Apr}	-0.320***	-0.012	-0.370***	-0.413***	-0.987***	-0.160	-0.226***	-0.402***	-0.349***
α'_{May}	-0.205**	0.013	-0.148	-0.148	-0.587***	0.065	-0.030	-0.177**	-0.071
α'_{Jun}	-0.092	0.088	0.074	0.090	-0.429***	0.048	0.004	-0.132	0.044
α'_{Jul}	-0.006	0.196*	0.137	0.225	-0.326*	0.076	0.104	0.004	0.141
α'_{Aug}	0.226**	0.362***	0.413***	0.400**	0.037	0.170	0.239**	0.067	0.239**
α'_{Sep}	0.449***	0.640***	0.889***	0.709***	0.420***	0.416***	0.556***	0.326***	0.625***
α'_{Mon}	-0.091**	-0.028	-0.070	0.052	0.087	0.141*	0.031	0.052	-0.014
α'_{Tue}	-0.049	0.012	0.040	0.122*	0.097	0.213**	0.055	0.114***	0.054
α'_{Wed}	-0.092**	-0.025	0.009	0.032	0.016	0.185**	-0.013	0.063	-0.024
α'_{Thu}	-0.088**	-0.042	-0.082	0.050	0.049	0.177*	0.032	0.093***	0.023
α'_{Fri}	-0.070**	-0.036	-0.048	0.030	0.027	0.091	-0.016	0.074**	0.071
α'_{Sat}	-0.022	-0.064	-0.045	-0.026	0.033	0.106	-0.031	0.033	-0.015
α'_h	0.074	-0.035	-0.055	-0.076	-0.164*	0.194	-0.079	0.006	0.001
<i>DNC, β_1</i>	-0.055***	-0.063***	-0.067***	-0.061***	-0.054***	-0.044**	-0.052***	-0.036***	-0.038***
<i>JDNC, β_2</i>	-0.054	-0.078**	-0.054	-0.106	-0.094**	-0.073	-0.072	-0.050	-0.138***
<i>KSD, β_3</i>	-0.175***	-0.147**	-0.307***	-0.239***	-0.154*	-0.117	-0.186***	-0.131***	-0.125**
<i>JSD, β_4</i>	-0.029	-0.089	0.079	0.031	0.175*	-0.132	-0.023	0.002	-0.009
<i>JSD, β_5</i>	-0.275***	-0.327**	-0.442***	-0.262**	-0.468***	-0.324***	-0.304***	-0.168**	-0.269*
<i>Stimulus, β_6</i>	0.102	0.016	0.233*	0.086	0.095	-0.051	0.123	0.115	0.122
R2	0.873	0.710	0.836	0.685	0.723	0.308	0.811	0.799	0.742
Adj. R2	0.865	0.691	0.825	0.664	0.704	0.262	0.798	0.786	0.725
N	639	639	639	639	639	639	639	639	639
F stat	159.785	64.233	97.871	38.675	53.151	12.843	105.592	99.606	70.635
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-958.494	-418.314	-275.262	65.001	71.963	143.607	-709.436	-947.553	-577.827
BIC	-775.638	-235.458	-92.406	247.857	254.819	326.463	-526.580	-764.697	-394.971

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HC1).

Table 3.16 Regression results of all models about traveler transactions.

	Model - 0	Model - 1	Model - 2	Model - 3	Model - 4	Model - 5	Model - 6	Model - 7	Model - 8
	Overall	Transpor- -tation	Accomm- -odation	Outdoor Recreation	Indoor Recreation	In-Person Service	Restau- -rant	Food and Beverage Retail	General Retail
<i>Constant, β_0</i>	12.190***	9.291***	9.159***	8.595***	8.105***	7.296***	10.822***	10.876***	10.421***
<i>α_{Jan}</i>	-0.059**	-0.076***	-0.124***	-0.099**	-0.001	-0.033	-0.096***	-0.067***	-0.040*
<i>α_{Feb}</i>	-0.108***	-0.105***	-0.171***	-0.034	-0.077	-0.094***	-0.149***	-0.104***	-0.095***
<i>α_{Mar}</i>	-0.137***	-0.103***	-0.305***	-0.135***	-0.341***	-0.198***	-0.175***	-0.102***	-0.102***
<i>α_{Apr}</i>	-0.075***	-0.062**	-0.157***	0.115***	-0.200***	-0.152***	-0.130***	-0.009	-0.050**
<i>α_{May}</i>	-0.022	-0.022	-0.034	0.146***	-0.173***	-0.140***	-0.088***	0.032	-0.031
<i>α_{Jun}</i>	0.047**	0.043	0.068*	0.143***	-0.070	-0.156***	-0.003	0.113***	0.037*
<i>α_{Jul}</i>	0.088***	0.069*	0.195***	0.062	0.100	-0.134***	0.059*	0.160***	0.038
<i>α_{Aug}</i>	0.240***	0.275***	0.400***	0.241***	0.353***	-0.054**	0.246***	0.321***	0.182***
<i>α_{Sep}</i>	-0.076**	-0.087*	-0.068	-0.104	-0.062	-0.178***	-0.118***	0.014	-0.117**
<i>α_{Oct}</i>	0.050*	0.064*	0.055	0.314***	-0.075	-0.126***	0.031	0.130***	0.006
<i>α_{Nov}</i>	-0.004	-0.005	-0.052	0.181***	-0.165***	-0.105***	-0.027	0.048**	0.000
<i>α_{Mon}</i>	0.018	0.006	-0.112***	-0.118***	-0.202***	-0.043**	-0.080***	-0.056***	-0.048**
<i>α_{Tue}</i>	-0.020	-0.054**	-0.135***	-0.140***	-0.197***	-0.088***	-0.095***	-0.065***	-0.141***
<i>α_{Wed}</i>	-0.031*	-0.083***	-0.124***	-0.165***	-0.227***	-0.009	-0.097***	-0.064***	-0.154***
<i>α_{Thu}</i>	-0.014	-0.045*	-0.098***	-0.139***	-0.207***	-0.046**	-0.083***	-0.053***	-0.127***
<i>α_{Fri}</i>	0.015	-0.037	-0.047**	-0.040	-0.133***	0.010	-0.045**	-0.017	-0.134***
<i>α_{Sat}</i>	0.022	0.037	0.015	0.061	0.036	0.123***	0.039**	0.033*	-0.076***
<i>α_h</i>	0.012	0.109***	0.161***	0.297***	0.264***	-0.089	0.046	0.061***	0.027
<i>α_{Jan}</i>	-0.097**	-0.130**	-0.166***	-0.147**	0.044	-0.137*	-0.144***	-0.151***	-0.068
<i>α_{Feb}</i>	-0.246***	-0.218***	-0.408***	-0.539***	-0.305***	-0.307***	-0.214***	-0.241***	-0.309***
<i>α_{Mar}</i>	-0.081	0.025	-0.127	-0.225**	-0.176**	-0.040	-0.021	-0.127***	-0.162**
<i>α_{Apr}</i>	-0.129**	-0.014	-0.276***	-0.450***	-0.452***	-0.127**	-0.060	-0.213***	-0.182***
<i>α_{May}</i>	-0.026	0.012	-0.186	-0.186	-0.273**	-0.133**	0.039	-0.135*	0.013
<i>α_{Jun}</i>	0.019	0.065	-0.080	-0.049	-0.235**	-0.098	0.039	-0.110	0.103
<i>α_{Jul}</i>	0.116	0.141	0.080	0.170	-0.179	-0.136*	0.116	-0.019	0.224**
<i>α_{Aug}</i>	0.230**	0.197*	0.288**	0.326**	0.065	-0.050	0.191*	0.077	0.343***
<i>α_{Sep}</i>	0.469***	0.524***	0.624***	0.694***	0.261***	0.081	0.492***	0.326***	0.574***
<i>α_{Mon}</i>	-0.048	-0.055	0.021	0.012	0.056	0.063*	0.016	0.006	0.006
<i>α_{Tue}</i>	-0.008	0.000	0.037	0.046	0.062	0.105***	0.032	0.029	0.078**
<i>α_{Wed}</i>	-0.051	-0.053	0.025	0.002	0.027	0.021	-0.033	-0.002	-0.003
<i>α_{Thu}</i>	-0.036	-0.051	-0.007	0.007	0.037	0.043	0.011	0.016	0.029
<i>α_{Fri}</i>	-0.033	-0.029	-0.008	-0.028	-0.006	0.036	-0.006	0.019	0.041
<i>α_{Sat}</i>	-0.009	-0.067	-0.003	-0.034	0.001	0.032	-0.010	0.018	0.014
<i>α_h</i>	0.028	-0.050	-0.025	-0.039	-0.188***	0.029	-0.024	0.037	0.005
<i>DNC, β_1</i>	-0.046***	-0.055***	-0.051***	-0.065***	-0.039***	-0.044***	-0.045***	-0.034***	-0.045***
<i>JDNC, β_2</i>	-0.055	-0.074	-0.125***	-0.156***	-0.098***	-0.096***	-0.064	-0.088***	-0.061
<i>KSD, β_3</i>	-0.141***	-0.165***	-0.226***	-0.249***	-0.145***	-0.055	-0.159***	-0.120***	-0.100**
<i>JSD, β_4</i>	-0.039	-0.086*	-0.017	0.022	-0.004	-0.038	-0.041	-0.019	-0.023
<i>JSD, β_5</i>	-0.225***	-0.201	-0.349***	-0.312***	-0.477***	-0.195***	-0.237***	-0.208***	-0.220*
<i>Stimulus, β_6</i>	0.082	0.082	0.124	0.119	-0.028	0.097*	0.094	0.078	0.089
R2	0.815	0.686	0.866	0.742	0.764	0.697	0.772	0.830	0.767
Adj. R2	0.803	0.665	0.857	0.725	0.749	0.676	0.757	0.818	0.751
N	639	639	639	639	639	639	639	639	639
F stat	122.251	57.565	155.725	55.005	62.883	42.627	102.542	116.690	95.107
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-1025.263	-597.710	-693.163	-205.632	-318.965	-924.261	-892.039	-1127.822	-816.916
BIC	-842.407	-414.854	-510.307	-22.776	-136.109	-741.405	-709.183	-944.966	-634.060

[1] *Statistically significant at 10% level. **Statistically significant at 5% level. ***Statistically significant at 1% level.

[2] Standard Errors are heteroscedasticity robust (HC1).

Chapter 4

A time geographic approach to understanding tourist-resident interaction across space, time, and activity

4.1 Introduction

Interactions between tourists and residents have long been a central concern in tourism research (Doxey, 1975; Krippendorf, 1987). These interactions influence residents' attitudes toward tourism, shape tourist experiences, and affect the social sustainability of destinations (Mody et al., 2019; Sharpley, 2014). In the era of mass tourism, the influx of tourists can disrupt local life, sometimes resulting in overcrowding and conflicts (Jurowski & Gursoy, 2004; Raymond & Brown, 2007; Sharma & Dyer, 2009). The COVID-19 pandemic further highlighted the urgency of understanding these dynamics, as physical proximity became a key factor in disease transmission. A nuanced understanding of where, when, and how these interactions occur is essential to address these challenges. However, existing approaches often fail to capture these details, limiting their utility in designing responsive and sustainable tourism strategies.

The most classic and widely used theory on tourist-resident interaction is Doxey's (1975) Irridex model, which conceptualized host community reactions to tourism as a four-stage process: Euphoria - Apathy - Annoyance - Antagonism. The model suggests that residents initially welcome tourism but may grow increasingly hostile as negative impacts accumulate (Teye, Sonmez & Sirakaya, 2002). This progression is driven by the volume of tourists and the degree of incompatibility between residents and tourists. Tourist intensity index (TI), based on this theory, measures the tourism pressure on the destination through the ratio of the total number of tourists and residents (Lundberg, 1974; McElroy, 2003). TI and other similar traditional indicators (i.e., tourist density rate, tourist penetration rate) reduce complex social dynamics to static population ratios, typically aggregated at broad spatial (e.g.,

city-wide) and temporal (e.g., annual) scales. While useful for identifying general trends, these approaches have been criticized for oversimplifying the impact of tourism on local communities by treating it as homogeneous (Wall & Mathieson, 2006; Dyer et al., 2007; Mason & Cheyne, 2000; Tosun, 2002), failing to capture the spatial concentration and temporal variability of interactions at finer resolutions (Mashkov & Shoval, 2023).

In addition, comparing tourist intensity across cities can be problematic. Two cities may exhibit similar tourist-resident ratios, yet the potential for interaction can vary significantly due to differences in the spatial and temporal behavior of the two groups. For instance, in cities like Las Vegas or Macau, tourists tend to concentrate in entertainment zones with minimal overlap with residential areas. In contrast, in cities such as New York or Hong Kong, tourists often seek authentic urban experiences in urban areas where locals live, work, and shop, resulting in a much higher potential for interaction. To address these limitations, it is important to develop more nuanced methods and theoretical frameworks for capturing and measuring interactions between tourists and residents.

Time geography, introduced by Hägerstrand (1970), provides an important framework for analyzing human activities across space and time. By conceptualizing individual movements as space-time paths constrained by physical, social, and institutional boundaries (e.g., capability, coupling, and authority constraints), this approach reveals the interplay between individuals and their environments in shaping behavior. This framework moves beyond static cartographic representations, emphasizing human activity as a dynamic process that evolves alongside environmental and social systems (Miller, 2005b; Neutens et al., 2011; Shaw, 2012; Sui, 2012).

A key concept in time geography is the space-time bundle, which describes the convergence of individuals' space-time paths in shared locales, creating opportunities for potential interaction (Parkes & Thrift, 1980; Golledge & Stimson, 1997; Miller, 2004). These bundles are categorized into two distinct modes: *Synchronous Presence (SP)* and *Asynchronous Presence (AP)* (Shaw & Yu, 2009; Miller, 2005; Janelle, 1995). SP refers to individuals co-located in both space and time, enabling a high potential for direct and immediate interaction (e.g., face-to-face conversations). AP refers to individuals co-located in space but not in time, engaging in interaction through delayed or indirect means (e.g., leaving messages on boards). These concepts reveal how spatial and temporal constraints jointly shape interactions, providing a deeper understanding of the diverse modes of social interaction and the varying potential for direct contact across those modes.

Although time geography provides a valuable framework for analyzing human activities and interactions across space and time, certain applications require more than understanding interaction

potential in these two dimensions; they also require precise identification of the activity venues where interactions occur. Activity is the underlying motivation for people to visit places. Activity venues not only influence the spatial and temporal dynamics of interactions but also shape the nature of their social interactions (Miller, 2004; Liu et al., 2024). For instance, people may gather in a commercial district during evening hours. While their co-location in space and time creates the potential for interaction, the specific activities they engage in determine whether they come into direct contact and whether they collaborate (e.g., participating in a festival) or compete (e.g., for limited restaurant seating). Such detail is essential for addressing challenges like assessing disease transmission risks associated with human contact, and mitigating competition and social tensions between user groups such as tourists and residents.

The growing availability of high-resolution spatiotemporal big data presents opportunities for analyzing human behavior more precisely. By enabling real-time tracking of movements and activities across various spatial and temporal scales, such big data can provide detailed insights into how people use space over time. Integrating semantically rich information such as activity tags (e.g., dining, shopping, entertainment) and venue categories (e.g., restaurants, parks, transit stops) can further enhance the analytical potential. By linking raw movement trajectories to specific behavioral patterns, researchers can better understand when and where interactions occur and what activity venues bring people together. This granularity supports a more nuanced analysis of the potential and dynamics of social interactions.

Grounded in time-geographic principles and leveraging the analytical power of high-resolution spatiotemporal data, this study aims to propose an analytical framework to quantify the potential for tourist-resident interactions in space, time, and activity. Specifically, this study expands the concept of space-time bundle by incorporating activity constraints, defining four modes of potential interaction: *Asynchronous Presence for Different Types of Activities (AP-DA)*, *Asynchronous Presence for the Same Type of Activity (AP-SA)*, *Synchronous Presence for Different Types of Activities (SP-DA)*, and *Synchronous Presence for the Same Type of Activity (SP-SA)*. To accommodate diverse application scenarios, a hierarchical framework is proposed that progressively adds constraints to space-time bundle, organizing the four interaction modes into three levels of co-location scenarios: *Co-location in Space*, *Co-location in Space and Time*, and *Co-location in Space and Time for the Same Type of Activity*. Building on this framework, global and local indices are developed to quantify interaction potential under each scenario.

This study applies the proposed framework to a geolocated credit and debit card transaction dataset from Jeju, Korea, to examine interactions between tourists and residents. The dataset spans

from January 1, 2019, to September 30, 2020, and contains aggregated transaction records within 600-meter grid cells at three-hour intervals, covering over 1,500 types of merchants. Compared to commonly used location-based service (LBS) data, such as mobile phone or GPS data, this dataset offers several distinct advantages for the current research context. First, it can distinguish between tourists and residents based on users' transaction locations and registered home addresses. Second, the dataset captures individuals' actual participation in specific activities, as reflected in transactions at commercial venues. These characteristics make the dataset particularly well-suited for this study, allowing for a detailed understanding of the spatial, temporal, and activity-based distribution of both groups, as well as their potential for interaction.

Using high-resolution spatiotemporal big data, the empirical analyses aim to 1) assess city-level interaction potential between tourists and residents across various co-location scenarios; 2) examine how interaction potential varies over time and across activity venues; 3) examine the spatial variation of the interaction patterns; and 4) explore changes in interaction potential and patterns across special periods (e.g., tourism peaks and COVID-19 outbreaks). These analyses contribute to a deeper understanding of the spatiotemporal dynamics that shape tourist-resident relationships in tourism cities. The findings offer valuable insights for managing overcrowding, optimizing resource allocation, and strengthening resilience to crises such as pandemics. This study advances time geography theory and provides a practical tool for analyzing the complex dynamics of human behavior in urban environments, with implications for crisis response, tourism management, and urban planning.

4.2 Methods

4.2.1 Theoretical framework

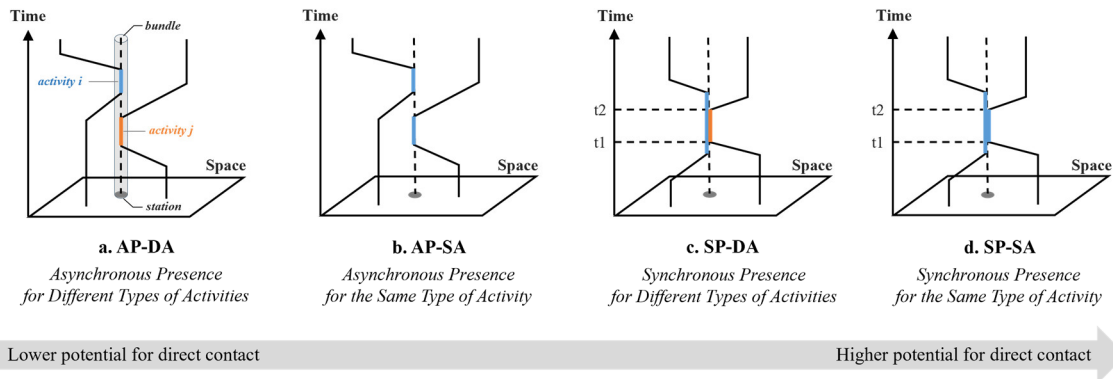
This subsection introduces a conceptual framework that defines four modes of interaction across space, time, and activities. By incorporating activity constraints into the existing concept of the space-time bundle (Figure 4.1A), it offers a more comprehensive understanding of these interactions.

- a. Asynchronous Presence for Different Types of Activities (AP-DA)* refers to situations in which individuals visit the same location at different times to engage in different activities. In this mode, interactions are limited to space sharing and have the lowest potential for direct contact. Instead, any sense of interactions is mediated by environmental or infrastructural elements—for example,

residents may perceive the presence of tourists through elements like souvenir shops or tourist centers.

- b. ***Asynchronous Presence for the Same Type of Activity (AP-SA)*** refers to situations in which individuals visit the same location at different times to engage in the same type of activity. In this mode, indirect contact may occur through shared facilities, such as using the same dining table or touching a door handle at different times. This mode of interactions can pose a risk of disease transmission during a pandemic.
- c. ***Synchronous Presence for Different Types of Activities (SP-DA)*** refers to individuals occupying the same location at the same time while engaging in different activities. This mode allows for a higher potential of direct contact. For example, a resident working in a business district may encounter a tourist on the street during lunch hour, creating opportunities for face-to-face interaction or conversation.
- d. ***Synchronous Presence for the Same Type of Activity (SP-SA)*** refers to individuals occupying the same location at the same time engaging in the same type of activity. This mode carries the highest potential for direct contact, such as dining at the same restaurant or attending the same movie screening. However, it may also increase the risk of competition or conflict between tourists and residents due to overlapping demands on shared spaces and services.

(A) Interaction Modes



(B) Co-location Scenarios

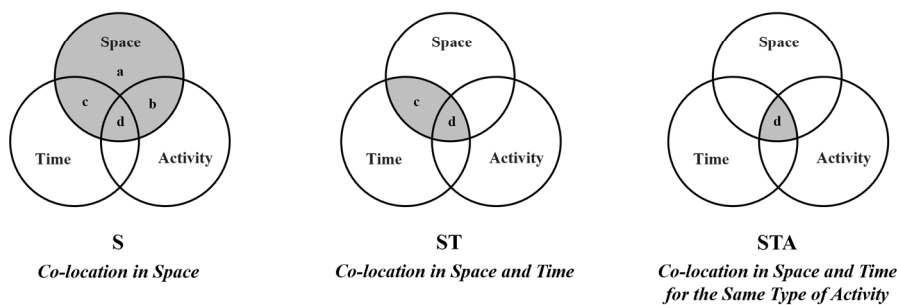


Figure 4.1 Conceptual framework of interaction modes and co-location scenarios.

These interaction modes represent a gradient of increasing potential for direct contact, beginning with spatial proximity as the foundational requirement, and progressing through temporal synchronization and activity alignment. To better understand how different population groups interact in urban environments, this study proposes a hierarchical framework that incrementally adds these constraints to co-location scenarios, organizing the four interaction modes into three distinct levels (Figure 4.1B):

- ***Co-location in Space (S)*** requires only spatial proximity, with no constraints on time or activity, encompassing all four modes, i.e., *AP-DA*, *AP-SA*, *SP-DA*, and *SP-SA*.
- ***Co-location in Space and Time (ST)*** adds temporal coincidence as a constraint, requires both spatial and temporal coincidence, narrowing the scope to *SP-SA* and *SP-DA*.
- ***Co-location in Space and Time for the Same Type of activity (STA)*** further requires activity alignment, limiting the scenario to *SP-SA* alone.

This framework generalizes the hierarchical relationships of interaction modes through progressively stricter constraints. It characterizes which interaction modes are represented by the observed co-location scenarios, thus effectively bridging the concepts of interaction modes to the quantitative measurements. Different scenarios can be analyzed in practical applications depending on the data source and specific requirements. For instance, analyzing co-location in space provides insights into the degree of spatial sharing among different groups. However, such observations often encompass multiple interaction patterns and may overestimate the actual potential for direct contact between groups. Observations of the latter two scenarios offer a more accurate depiction of actual contact potential. By comparing differences across scenarios, the framework also highlights the interaction potential of complementary modes not captured within a given scenario, thus enriching the understanding of intergroup interactions. The framework's flexibility ensures its applicability across datasets with varying information dimensions. It remains functional even when certain dimensions, such as activity types or time, are unavailable, making it a useful tool for diverse analytical contexts.

4.2.2 Global indices of tourist-resident interactions

Building on the theoretical framework, this study develops indices to quantify tourist-resident interaction potential across different co-location scenarios. These indices are adapted from the classic Exposure Index (E) used to measure social segregation (Lieberman, 1981; Wong, 2002). The Exposure Index is calculated as a weighted average of the proportion of group x in each spatial unit, with the

weighting term being the proportion of group y in each unit to the total population of group y . The theoretical maximum of this index equals the overall proportion of group x in the total population, which occurs only when both groups are evenly distributed across all units. This theoretical maximum value is introduced as a baseline index:

$$Baseline = X/(X + Y) \quad (\text{Equation 4.1})$$

Here, X and Y denote the total number of tourists and residents, respectively, within the study area. This index measures the potential for resident-tourist interaction under the assumption of an even distribution of both groups across urban space. It has a mathematical relationship with the classical Tourist Intensity (TI) index, defined as $TI = X/Y$, which can be expressed as $TI = Baseline/(1 - Baseline)$.

The interaction potential between the two groups in the scenario of *Co-location in Space* is quantified by the index S , defined as follows:

$$S = \sum_{i=1}^n \left[\left(\frac{x_i}{x_i + y_i} \right) \left(\frac{y_i}{Y} \right) \right] \quad (\text{Equation 4.2})$$

Here, x_i and y_i denote to the total number of tourists and residents in spatial unit i , respectively. n refers to the total number of spatial units in the whole study area. $X = \sum_{i=1}^n x_i$ and $Y = \sum_{i=1}^n y_i$. The index measures the overall probability that a resident shares a spatial unit with a tourist in the whole study area. Assuming that tourists and residents are evenly distributed across all spatial units, the ratio of tourists to residents in each unit i equals the overall ratio for the entire study area. Under this condition, the theoretical upper bound of S is equal to the *Baseline* (for a detailed mathematical derivation, see Appendix 4.A).

The interaction potential between the two groups in the scenario of *Co-location in Space and Time* is quantified by the index ST , defined as follows:

$$ST = \sum_{i=1}^n \sum_{t=1}^m \left[\left(\frac{x_{i,t}}{x_{i,t} + y_{i,t}} \right) \left(\frac{y_{i,t}}{Y} \right) \right] \quad (\text{Equation 4.3})$$

Here, $x_{i,t}$ and $y_{i,t}$ denote to the total number of tourists and residents in spatial unit i at time window t , respectively. m refers to the total number of time windows. This index measures the probability that a resident encounters a tourist in a spatial unit at the same time. Similarly, when the two populations are equally distributed over all time windows, the theoretical upper bound of ST is equal to the S (Appendix 4.A).

The interaction potential between the two groups in the scenario of *Co-location in Space and Time for the Same Type of Activity* is quantified by the index STA , defined as follows:

$$STA = \sum_{i=1}^n \sum_{t=1}^m \sum_{a=1}^w \left[\left(\frac{x_{i,t,a}}{x_{i,t,a} + y_{i,t,a}} \right) \left(\frac{y_{i,t,a}}{Y} \right) \right] \quad (\text{Equation 4.4})$$

Here, $x_{i,t,a}$ and $y_{i,t,a}$ refer to the total number of tourists and residents in spatial unit i at time window t engaging in activity a , respectively. w refers to the total number of activity types in spatial unit i in which residents and tourists engaged in. This index measures the probability that a resident encounters a tourist at a specific activity venue in a spatial unit at the same time. Similarly, when the two populations are equally distributed over all activity venues, the theoretical upper bound of STA is equal to the ST (Appendix 4.A).

Figure 4.2 illustrates the relationship among quantitative indices across different scenarios. The scale of each bar represents the probability of interaction between tourists and residents under a given scenario. In a limiting case where tourists and residents are evenly distributed across spatial units, time windows, and activity venues, all three indices reach their theoretical maximums, yielding: $Baseline = S = ST = STA$ (Appendix 4.A).

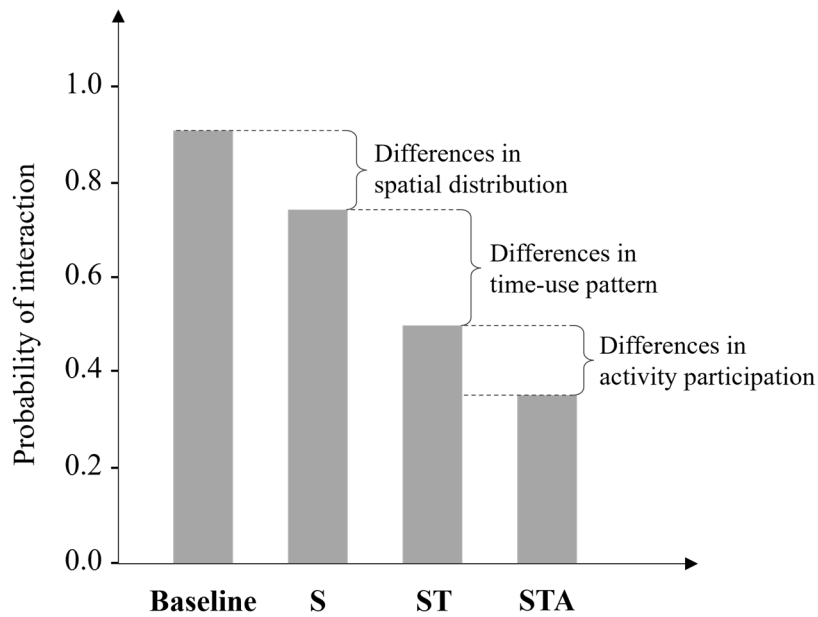


Figure 4.2 The relationship between interactions indices and interaction modes in different scenarios.

However, in real-world settings, the behavioral patterns of tourists and residents typically differ, leading to uneven distributions across spatial, temporal, and activity dimensions. Therefore, a reasonable hypothesis is: $Baseline > S > ST > STA$. As shown in Figure 4.2, the gap between

Baseline and *S* reflects differences in the spatial distribution of the two groups, highlighting the extent to which traditional tourism indicators may overestimate actual interaction potential. The difference between *S* and *ST* captures disparities in time-use patterns among individuals who are spatially co-located. Similarly, the gap between *ST* and *STA* reflects differences in activity participation when both groups are co-located in space and time. Collectively, these indices not only quantify the overall interaction potential between tourists and residents under varying co-location conditions but also reveals the heterogeneity of their distribution across space, time, and activity dimensions.

4.2.3 Decompose global indices by time and activity

In certain circumstances, comprehending the temporal variation of tourist-resident interactions and the differences in interaction potential across activity venues is crucial for visitor flow management and urban governance. For example, during the COVID-19 pandemic, differential implementation of social distancing measures across activity venues and time periods could strike a balance between outbreak control and reducing economic losses. Hence, we introduce time-based *ST* and *STA* indices by fixing a time window *t*:

$$ST_t = \sum_{i=1}^n \left[\left(\frac{x_{i,t}}{x_{i,t} + y_{i,t}} \right) \left(\frac{y_{i,t}}{Y} \right) \right] \quad (\text{Equation 4.5})$$

$$STA_t = \sum_{i=1}^n \sum_{a=1}^w \left[\left(\frac{x_{i,t,a}}{x_{i,t,a} + y_{i,t,a}} \right) \left(\frac{y_{i,t,a}}{Y} \right) \right] \quad (\text{Equation 4.6})$$

Where ST_t and STA_t denote *ST* and *STA* interaction potential of tourists and residents at time *t*, respectively. The time-fixed indices enable comparisons between different time periods, thus capturing the temporal trends of the corresponding scenario interaction potentials. The sum of the time-based interaction index for all time periods is equal to the overall interaction index, i.e., $ST = \sum_{t=1}^m ST_t$, and $STA = \sum_{t=1}^m STA_t$.

Similarly, to better understand the differences in interaction potential among activity venues, we introduced activity-based *STA* by fixing an activity type *a*. As shown in Equation 4.7, STA_a denotes *STA* interaction potential of tourists and residents at activity type *a*. The sum of the activity-based interaction index for all activity types is equal to the overall interaction index, i.e., $STA = \sum_{a=1}^w STA_a$.

$$STA_a = \sum_{i=1}^n \sum_{t=1}^m \left[\left(\frac{x_{i,t,a}}{x_{i,t,a} + y_{i,t,a}} \right) \left(\frac{y_{i,t,a}}{Y} \right) \right] \quad (\text{Equation 4.7})$$

We further decompose the STA index by fixing both time t and activity type a to obtain the time-activity-based STA , which could depict the temporal change in interaction potential at specific activity venue (Equation 4.8). The sum of $STA_{t,a}$ for all activity types and time periods is equal to the overall interaction index, i.e., $STA = \sum_{t=1}^m \sum_{a=1}^w STA_{t,a}$.

$$STA_{t,a} = \sum_{i=1}^n \left[\left(\frac{x_{i,t,a}}{x_{i,t,a} + y_{i,t,a}} \right) \left(\frac{y_{i,t,a}}{Y} \right) \right] \quad (\text{Equation 4.8})$$

By analyzing the interaction indices, we can gain deeper insights into how the interaction potential between different groups varies across time and activity venues. These findings can inform policymakers and stakeholders, supporting more effective and evidence-based decision-making.

4.2.4 Local indices of tourist-resident interactions

To identify varying co-location patterns between tourists and residents across different urban environments, we further introduce a set of local-level interaction indices. For each spatial unit i , we derive three indices S_i , ST_i , and STA_i , corresponding to the interaction potential in the three co-location scenarios:

$$S_i = \left(\frac{x_i}{x_i + y_i} \right) \left(\frac{y_i}{Y} \right) \quad (\text{Equation 4.9})$$

$$ST_i = \sum_{t=1}^m \left[\left(\frac{x_{i,t}}{x_{i,t} + y_{i,t}} \right) \left(\frac{y_{i,t}}{Y} \right) \right] \quad (\text{Equation 4.10})$$

$$STA_i = \sum_{t=1}^m \sum_{a=1}^w \left[\left(\frac{x_{i,t,a}}{x_{i,t,a} + y_{i,t,a}} \right) \left(\frac{y_{i,t,a}}{Y} \right) \right] \quad (\text{Equation 4.11})$$

By conducting local-level co-location analysis, we can compare inter-group co-location patterns across diverse urban environments. This analytical approach offers valuable insights into informing tourism management and urban governance strategies.

4.3 Study Area and Dataset

To demonstrate the effectiveness of the proposed framework, this study conducts an empirical analysis using a geolocated transaction dataset from Jeju, Korea. As illustrated in Figure 4.3A, Jeju Island comprises two major cities, Jeju City in the north and Seogwipo City in the south. The central urban areas of these two cities serve as the primary residential and commercial hubs. Additionally, the island

features small coastal villages, residential communities, tourist resorts, and a wide array of attractions. Before the COVID-19 pandemic, Jeju Island received approximately 250,000 tourist arrivals per week, alongside a local resident population of around 670,000. These characteristics make Jeju an ideal case study for examining tourist-resident interactions.

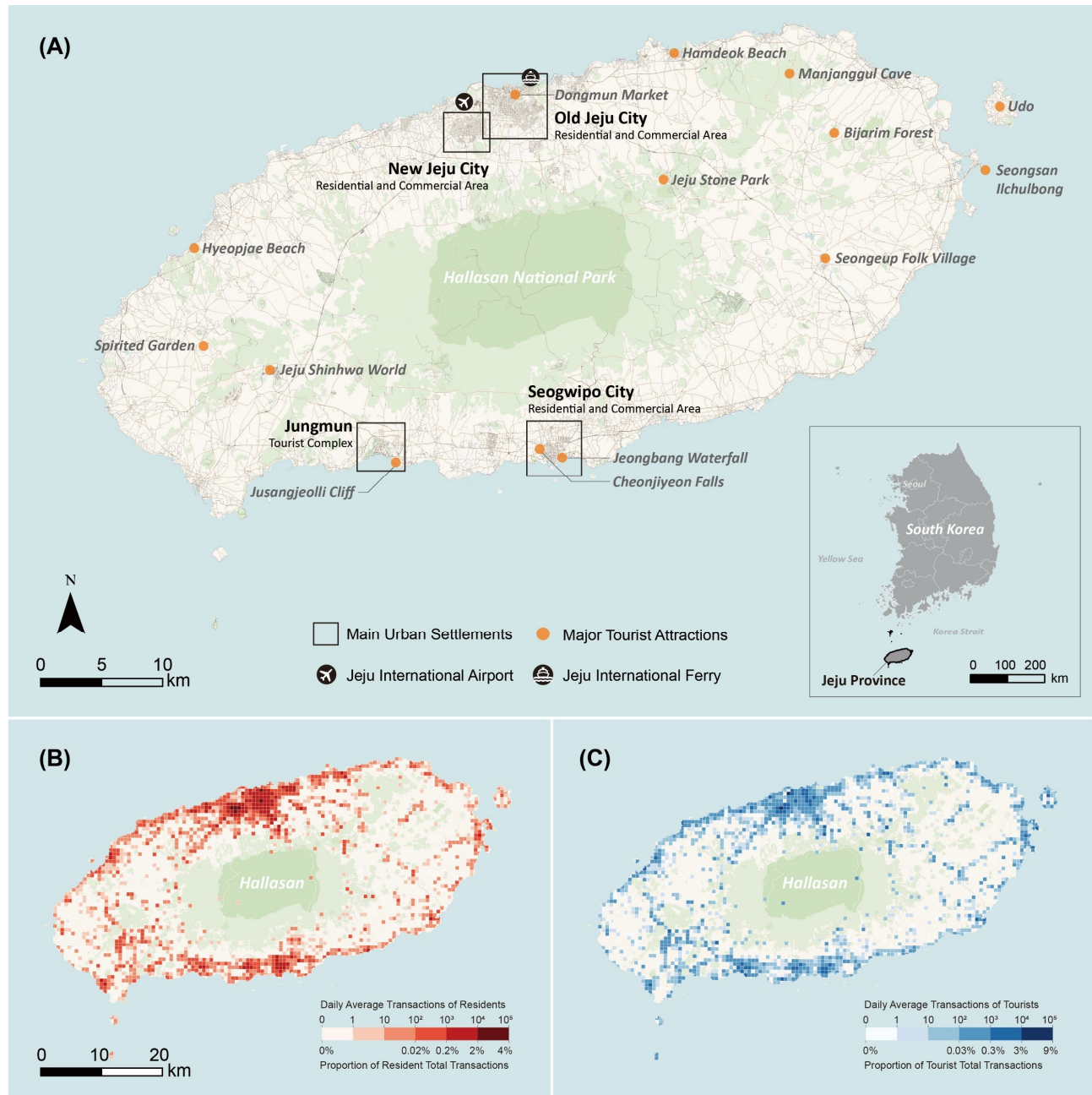


Figure 4.3 (A) The location of Jeju in Korea, and spatial distribution of tourist attractions, transport infrastructure and major urban areas in Jeju; (B) Average number of daily transactions by residents on 600m grid cells; (C) Average number of daily transactions by tourists on 600m grid cells.

Table 4.1 Example of transaction records in the dataset.

Date	Time	Grid ID	Spending venue	User type	Number of transactions	Total Expenditure (USD)
2019-01-11	6-9	***	convenience store	Resident	5	70.23
2019-01-23	21-0	***	Korean restaurant	Resident	10	282.34
...	...	...	...	...	...	...
2019-01-02	12-15	***	car rental	Tourist	5	564.67
2019-01-03	18-21	***	accommodation	Tourist	10	1058.76

The transaction dataset spans from January 1, 2019, to September 30, 2020, capturing over 300 million transactions with a total expenditure of approximately 8 million USD. As shown in Table 4.1, each record in the dataset is aggregated by date, time of day (in 3-hour intervals), location (600-meter grid cells), type of spending venue, and user type. The dataset provides information on the number of transactions and total expenditures for each group, offering a detailed overview of spatial and temporal consumption patterns. Figure 4.3B-C show the average number of daily transactions by residents and tourists on 600m grid cells.

The geolocated transaction data holds significant advantages in this research context, as it captures actual activity participation through recorded consumer behavior. Each transaction reflects a user's card usage at a commercial establishment, providing detailed information on the time of purchase and merchant attributes, including geographic location and business type. As a result, this dataset inherently incorporates the spatial, temporal, and activity dimensions of behavior, eliminating the need for supplementary data sources or indirect inference methods to reconstruct activity patterns. Moreover, transaction data enables the differentiation between residents and tourists by comparing the location of the transaction with the user's registered place of residence. These features significantly enhance the validity and reliability of analyzing potential interactions between population groups.

The category of spending venue serves as a proxy for activity type in this study. A total of 11 activity types are investigated in this study, which were derived from an initial set of 22 broad consumption categories and over 1,500 detailed subcategories. To better represent spending behaviors for both residents and tourists, household and tourism-related consumption categories were selected. The reclassified activity types include *food and beverage retail*, *general retail*, *restaurants*, *drinking places*, *transportation*, *accommodation*, *indoor recreation*, *outdoor recreation*, *health*, *in-person service*, and *education*. Overall, these categories account for over 90% of all transaction records. Further details and examples for each category are provided in Appendix 4.B Table 4.2.

In the empirical analysis, data were aggregated over selected periods to enhance reliability and address the issue of data sparsity. A normal period, from April 1 to May 31, 2019 (61 days), was first selected. During this period, consumption behavior of residents and tourists was relatively stable and did not coincide with the peak tourist season. The data were divided into eight 3-hour intervals across weekdays and weekends, yielding 16 distinct time windows. All records from this period were then aggregated by calculating the average values across 600-meter spatial units, 16 time windows, and 11 types of activity categories. Spatial units were excluded if the average value of any activity type in any time window was less than 1. After this filtering process, a total of 1,502 valid spatial units were retained for analysis. The normal period dataset is used in subsections 4.4.1, 4.4.2, and 4.4.3. In subsection 4.4.4, the same processing criteria was applied to four special periods for comparative analysis of changes in interaction: the 2019 tourism peak season (July 1-August 31), the first wave of COVID-19 (February 19-April 12, 2020), the stable period (April 12-August 10, 2020), and the second wave (August 11-September 30, 2020). For the three pandemic periods, the corresponding periods in 2019 (same calendar dates) are used as baselines to enable meaningful comparisons. For the tourism peak season, the normal period dataset serves as the comparative baseline.

4.4 Analysis Results

4.4.1 Overall characteristics of tourist-resident interaction potential

This study first calculated the overall potential for tourist-resident interaction at the city level during the normal period using the global indices defined in Equations 4.1-4.4. In Figure 4.4A, the *Baseline* index is 0.394, representing the probability of contact between tourists and residents under the assumption of an even distribution. When *Co-location in Space* is considered, the interaction potential decreases to 0.289 (*S*), indicating that spatial heterogeneity in the distributions of tourists and residents reduces their likelihood of co-presence. This suggests that traditional tourist intensity indices may overestimate actual interaction potential. Incorporating *Co-location in Space and Time* further reduces the value to 0.278 (*ST*), and when *Co-location in Space and Time for the Same Type of Activity* is considered, the index drops to 0.254 (*STA*). These results support the hypothesis that $Baseline > S > ST > STA$, demonstrating that spatial, temporal, and activity-based heterogeneity jointly shape the probability of contact between groups.

However, the relatively small changes in values from *S* to *ST* and *STA* suggest that when tourists

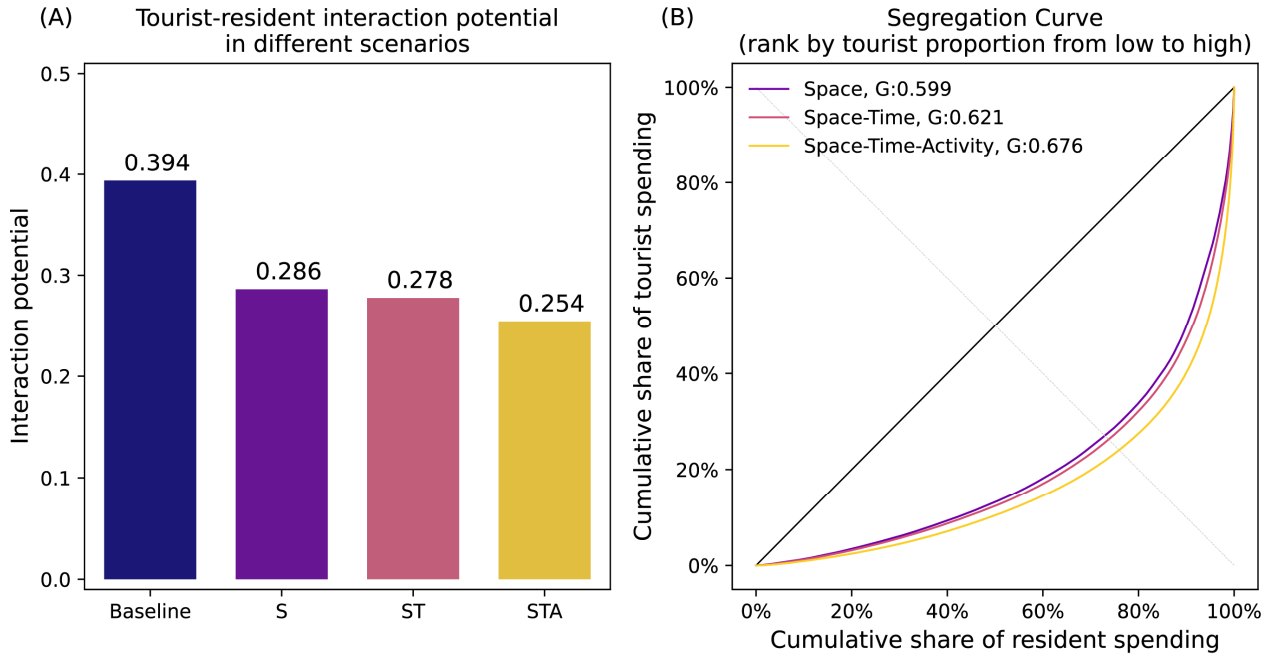


Figure 4.4 Tourist-resident interaction potential in different scenarios at the city level. (A) the estimates of the *Baseline* and interaction indices in different co-location scenarios; (B) segregation curves corresponding to the three co-location scenarios and the estimates of the Gini index.

and residents do share the same space, they are often also synchronized in time and engaged in similar activities. This pattern can be better understood in the context of Jeju Island's unique spatial and functional characteristics. As a nature-based destination, tourists in Jeju tend to spend the daytime visiting scattered natural attractions that are often located away from residential areas. Consequently, the spatial overlap between tourists and residents is relatively limited during these periods. However, when tourists return to urban centers for dining, shopping, or accommodation, typically in the evening or early night, their spatial and temporal presence begins to overlap with that of residents, who are also likely to be engaged in similar consumption-related activities during these times. Therefore, in those specific time windows and spaces where co-location does occur, it is highly likely to also involve synchronization in both time and activity. This finding reflects a destination-specific behavioral dynamic and may differ significantly in more densely populated urban tourism cities like New York or Hong Kong, where tourists and locals are more likely to co-occupy central urban areas throughout the day but engage in divergent activities. These contrasts highlight the crucial role of a city's spatial structure and environmental characteristics in shaping patterns of tourist-resident interaction.

To verify the effectiveness of the proposed indices in capturing behavioral heterogeneity among the two groups, we introduce the Lorenz curve and Gini coefficient for assessment (Figure 4.4B). The

Lorenz curve illustrates the degree of uneven distribution of tourists and residents across spatial, temporal, and activity dimensions, with curves closer to the diagonal indicating more even distributions (James & Taeuber, 1985). The Gini coefficient quantifies this inequality, calculated as the area between the diagonal and the Lorenz curve (see Appendix 4.C, Equation 4.20). The results align with the interaction indices: the spatial distribution (dark purple line) yields a Gini of 0.599; adding the temporal constraint (pink line) increases the Gini to 0.621; and incorporating the activity constraint (yellow line) raises it further to 0.676. These values indicate that spatial heterogeneity accounts for 89% of the total behavioral segregation ($0.599/0.676$), with 3% contributed by temporal differences and 8% by activity-related variations. This confirms that the indices not only measure interaction potential but also effectively reveal intergroup behavioral disparities across multiple dimensions.

4.4.2 Temporal and activity-based variations in overall interaction potential

This subsection demonstrates the effectiveness of the proposed framework in capturing temporal and activity-based variations in interaction potential. Figure 4.5A presents the time-based *ST* and *STA* index values across 16 time windows on weekdays and weekends. The results indicate that the interaction potential between tourists and residents is slightly higher on weekends than weekdays. Across different time periods, interaction potential is lowest during the nighttime hours (00:00-06:00), gradually increases from 06:00 onward, and peaks between 12:00 and 21:00, particularly during lunchtime (12:00-15:00) and dinnertime (18:00-21:00). These three periods collectively account for over 60% of the total daytime interaction potential. The difference between *ST* and *STA* values is smallest during the night and early morning, suggesting limited heterogeneity in tourist and resident activities during these times. In contrast, during peak daytime hours, *STA* values are significantly lower than *ST* values, indicating that while tourists and residents may be co-located in space and time, they might engage in different activities, thus reducing direct contact potential.

Figure 4.5B illustrates the distribution of *STA* interaction potential across various types of activity venues and how this distribution changes over time. Figure 4.5B (1) presents interaction potential by activity type, calculated using the activity-based *STA* index and expressed as a proportion of the total *STA*. The results indicate that *Food and Beverage Retail* (37%), *Restaurants* (27%), and *General Retail* (14%) contribute the highest overall interaction potential, while *Transportation* and *Drinking*

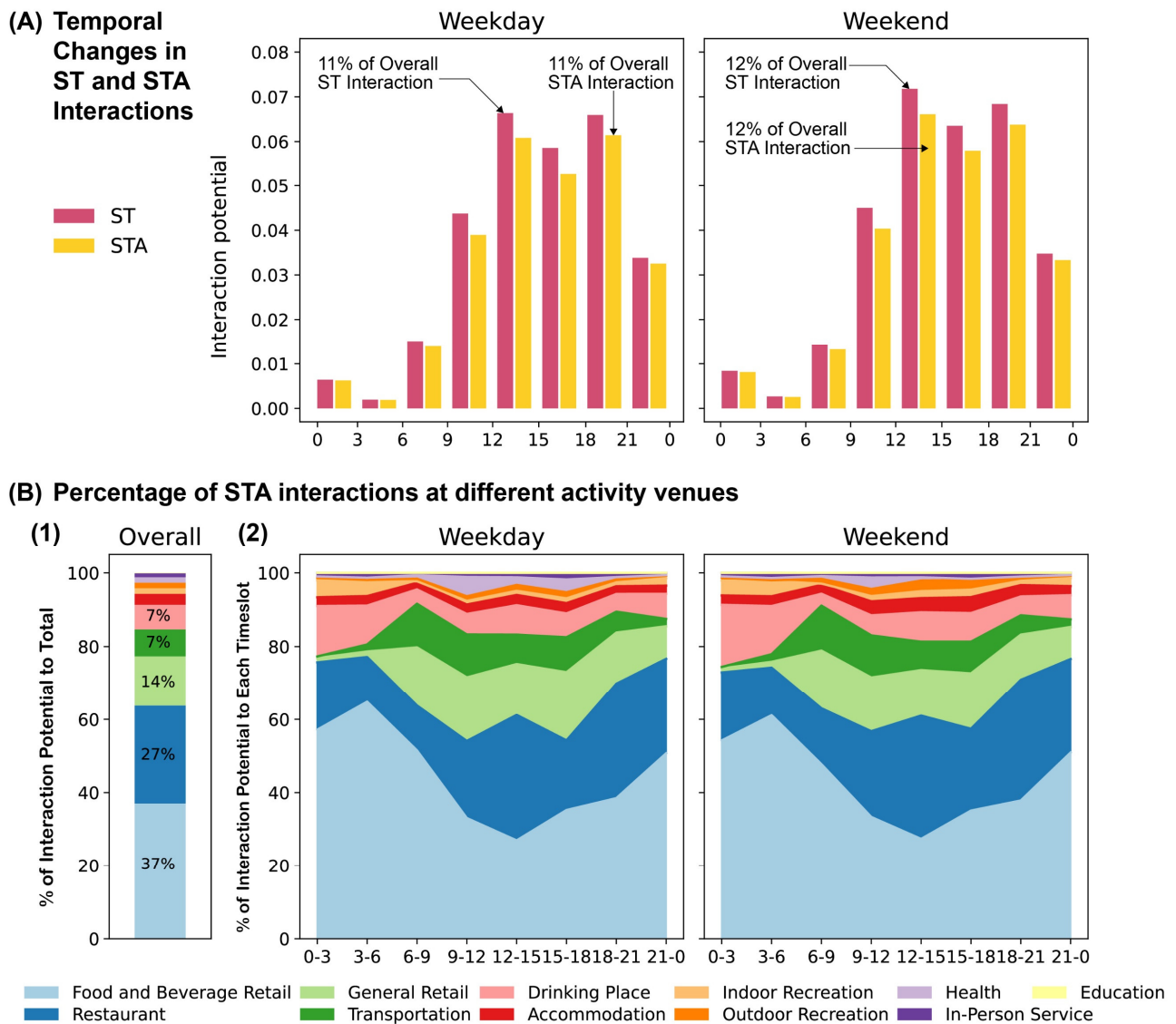


Figure 4.5 (A) Variations in tourist-resident interaction potential throughout the day on weekdays and weekends. (B) Distribution of *STA* interaction potential across activity venues: (1) Percentage of activity-based *STA* interaction potential relative to overall *STA*. (2) Percentage of activity-based *STA* interaction potential relative to *STA* interaction potential within each time window.

Place each account for approximately 7%. Other venues, such as *Accommodation* and *Indoor* and *Outdoor Recreation*, exhibit lower interaction potential.

Figure 4.5B (2) further explores temporal dynamics by calculating the interaction potential of each venue type within individual time windows, based on the time-activity-based *STA* index. The findings reveal temporal variations in activity-specific interaction potential. During daytime hours, *Restaurants*, *General Retail*, and *Transportation* venues show the highest levels of interaction potential, whereas *Drinking Places* and *Food and Beverage Retail* become more prominent during

nighttime hours. Notably, *Outdoor Recreation* venues exhibit higher interaction potential on weekends compared to weekdays. These patterns highlight that the direct contact potential between tourists and residents varied significantly across venues and over time, offering valuable insights for crowd management and the planning of public health interventions.

4.4.3 Spatial variations of tourist-resident interaction

Interaction patterns between tourists and residents may vary across urban spaces (Su et al., 2021; Su et al., 2022). To explore these patterns, this study applied hierarchical agglomerative clustering using local indices for the three co-location scenarios (S_i , ST_i , STA_i) across 1502 spatial units (Lukasova, 1979). Each row of the 1502×3 matrix was z-score normalized to enhance differentiation. Ward's linkage method guided the merging of clusters, and six clusters were selected based on the dendrogram and balanced cluster sizes. Figure 4.6A presents the interaction patterns of the six clusters, based on the mean standardized values of the three local indices for each cluster. From C1 to C6, the gap between S and ST increases, while the gap between ST and STA decreases. This pattern suggests a growing divergence in time-use patterns between tourists and residents, alongside a narrowing difference in their activity participation. For instance, in Cluster C1, tourists and residents appear to follow similar temporal routines but engage in different types of activities. In contrast, in Cluster C6, they participate in similar activities but follow different temporal routines. Figure 4.6B presents the

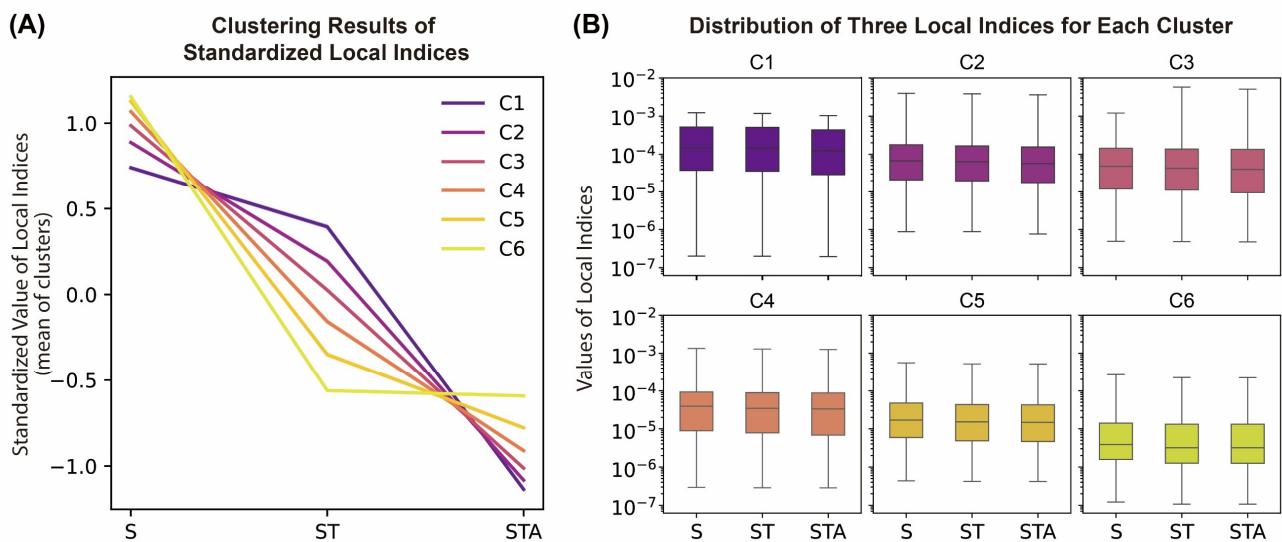


Figure 4.6 Results of hierarchical agglomerative clustering. (A) Mean standardized local indices for each cluster, y-axis show the z-score standardized value of local indices; (B) Distribution of local indices across clusters.

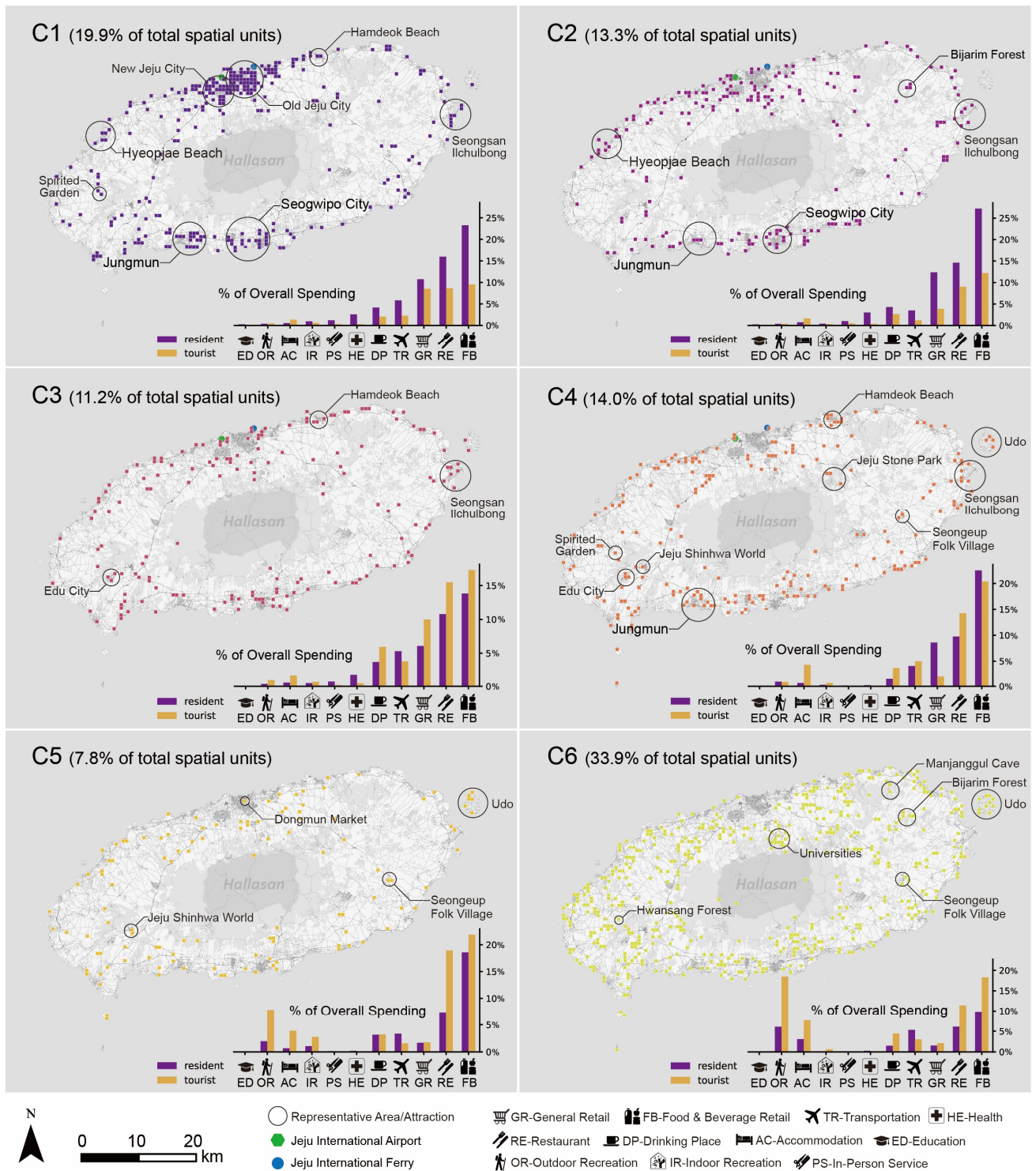


Figure 4.7 Spatial distribution of clusters and the proportion of consumer spending allocated to different activity venues within each cluster.

distribution of the absolute value of the three local indices for each cluster. The results show that interaction potential gradually decreases from C1 to C6. This suggests that areas with high interaction

potential may attract different groups at different times due to their high diversity of activities. However, the wide range of available options also leads to greater heterogeneity in activity venue usage between groups. In contrast, urban areas dominated by a single type of activity offer limited choices, which reduces their attractiveness to a broader range of users and results in lower overall interaction potential. Nevertheless, these areas tend to exhibit higher activity similarity between tourists and residents, as the limited activity options constrain behavioral divergence.

Figure 4.7 presents the distribution of spatial units across the six clusters, along with the spending proportion of residents and tourists at activity venues within each cluster. The proportions of spatial units in each cluster are C1 (19.9%), C2 (13.3%), C3 (11.2%), C4 (14.0%), C5 (7.8%), and C6 (33.9%). Spatial units in C1 and C2 are primarily located in central urban areas and smaller settlements, such as development zones and residential neighborhoods. In these areas, resident spending exceeds those of tourists, indicating a resident-dominated space where consumption is concentrated in restaurants, bars, and retail venues. Due to the high density and diversity of activity venues, these spaces exhibit high interaction potential, with tourists and residents demonstrating similar temporal patterns but differing in activity participation. Spatial units in C3 are near beaches, transportation hubs (e.g., airports), and tourist resorts. Here, tourist spending significantly surpasses those of residents, reflecting the dominance of tourism-oriented activities. Spatial units in C4 are located in small residential areas that also contain tourist hotspots, reflecting a mixed-use character. In these areas, the spending patterns of tourists and residents are relatively similar, indicating more balanced and integrated interaction patterns. C5 and C6 are characterized by single-function tourism areas, such as theme parks and remote islands. Tourist spending is predominant, particularly in indoor and outdoor recreational facilities. These spaces exhibit low overall interaction potential, with tourists and residents typically visiting at different times. These findings underscore the significant role that urban spatial characteristics and activity venue diversity play in shaping interaction patterns between tourists and residents.

4.4.4 Changes in tourist-resident interaction potential during special periods

This subsection presents the framework's ability to detect shifts in tourist-resident interaction potential during special periods. Four periods are analyzed: the tourism peak in 2019 (2019-07-01 to 2019-08-31), the first wave of the COVID-19 outbreak in 2020 (2020-02-19 to 2020-04-12), the stable period (2020-04-12 to 2020-08-10), and the 2nd wave (2020-08-11 to 2020-09-30). Each is compared against a corresponding base period: April-May 2019 for the tourism peak and the same timeframe in 2019

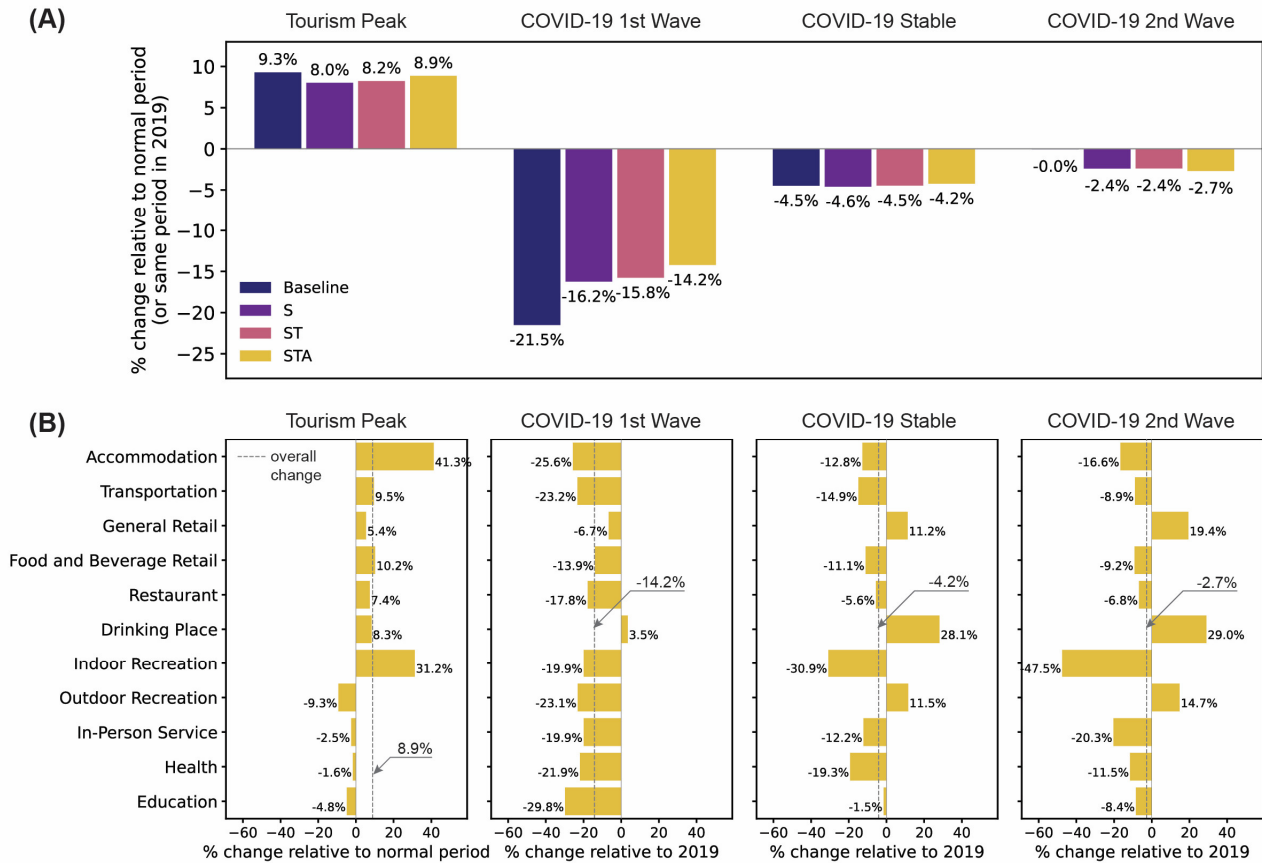


Figure 4.8 Changes in tourist-resident interaction potential during the four special periods relative to their corresponding base periods. (A) Changes in overall interaction potential for different co-location scenarios; (B) Changes in interaction potential in different activity venues.

for the other three. Overall interaction potential at the city level were calculated for each period and its base period, and percentage changes were then calculated to capture changes in interaction potential.

Figure 4.8A shows a clear rise in tourist-resident interaction potential during the peak tourism season and a sharp decline during the COVID-19 outbreak. While the *Baseline* index increased most during the peak, the smaller gains in interaction indices suggest tourists concentrated in specific areas, limiting actual contact with residents. Notably, the larger increases in *ST* and *STA* over *S* indicate reduced temporal and activity heterogeneity. During the pandemic, interaction potential dropped significantly, especially in the first wave. Although declines eased during the stable period and second wave, the interaction indices fell more than the *Baseline*, suggesting that beyond reduced tourist numbers, increased spatial, temporal, and activity separation further suppressed interaction potential.

As shown in Figure 4.8B, this study next examined changes in activity-based *STA* indices across the four special periods relative to their base periods. During the peak tourism season, interaction

potential rose sharply in accommodation and indoor recreation venues, suggesting increased tourist demand may have intensified competition with residents. In contrast, all venues saw significant declines during the first COVID-19 wave. The stable period and second wave revealed more varied trends: interaction potential for restaurants and food and beverage retail continued to decline, while general retail, drinking places, and outdoor recreation saw steady increases. Indoor recreation, however, continued to decline. These patterns align with studies showing a shift toward lower-risk, outdoor activities during the pandemic and reduced dine-in behaviors. Such changes likely reflect both individual risk preferences and government restrictions (e.g., capacity limits and reduced operating hours). These insights are valuable for evaluating and guiding policy responses during public health crises.

4.5 Discussion and Conclusion

This study advances the theoretical and practical understanding of social interactions by integrating activity constraints into the time-geographic framework. It introduces four interaction modes: *Asynchronous Presence for Different Types of Activities (AP-DA)*, *Asynchronous Presence for the Same Type of Activity (AP-SA)*, *Synchronous Presence for Different Types of Activities (SP-DA)*, and *Synchronous Presence for the Same Type of Activity (SP-SA)*. These modes are structured hierarchically into three co-location scenarios: *Co-location in Space*, *Co-location in Space and Time*, and *Co-location in Space and Time for the Same Type of Activity*. The framework provides a flexible and scalable lens for capturing the complex interplay of spatial proximity, temporal synchronization, and activity alignment in shaping intergroup contact. Its adaptability ensures broad applicability across diverse urban environments and research contexts. In addition, this study develops global and local indices that translate theoretical constructs into measurable indices. These indices not only quantify the interaction potential but also capture the heterogeneity of different groups in terms of space, time and activity, representing a methodological advancement over traditional static indicators such as Tourist Intensity. Grounded in the foundational principles of time geography, this framework enhances its relevance to contemporary urban challenges, including overcrowding and public health resilience in the context of pandemics.

The empirical analysis of geolocated transaction data from Jeju, Korea, reveals several key insights into intergroup interaction dynamics. First, notable differences in interaction potential emerge across the various co-location scenarios, underscoring the significance of spatial, temporal, and activity-based heterogeneity in shaping intergroup interaction potential. Among venue types,

restaurants, retail, and transportation hubs exhibit the highest potential for direct contact, emphasizing the need to consider activity dimensions alongside spatial and temporal factors when assessing interaction dynamics. Temporally, interaction potential tends to peak during midday and afternoon hours, particularly on weekends. Across different periods, it rises markedly during tourism peak seasons and declines sharply during the COVID-19 pandemic, demonstrating the context-sensitive and dynamic nature of social interactions. Spatial variation further reveals the critical role of urban spatial characteristics and land use in shaping where and how interactions occur.

These findings carry significant implications for sustainable tourism governance. By identifying venues and time periods with high contact potential, policymakers can develop targeted strategies to mitigate overtourism, allocate resources more effectively, and manage public health risks such as disease transmission. For example, implementing staggered schedules for popular activities or diversifying venue offerings in high-density areas could help alleviate crowding and reduce competition for space. The framework's demonstrated adaptability during the COVID-19 pandemic further underscores its value in promoting resilient and responsive urban systems.

This study has several limitations. As the data are aggregated, the spatial and temporal scales of aggregation can influence the measurement of interaction potential. This issue is well-known in geography as the Modifiable Areal Unit Problem (MAUP) (Kwan, 2012). Coarser spatial or temporal units may obscure underlying heterogeneity and result in overestimating co-location, while excessively fine units may lead to underestimation due to data sparsity. Limited by the data availability, this study employs the finest resolution available in the dataset (600 meters and 3-hour intervals). This level of accuracy captures only the potential exposure of individuals, rather than providing a direct measure of interaction. Nevertheless, by applying this dataset within the proposed analytical framework, the study captures the tourist-resident interaction potential by considering how the two groups co-locate in space, time, and activity contexts. Beyond the static, aggregate indicators focusing only on population ratios, this approach helps move the measurement closer to a more realistic depiction of interaction potential. Moreover, the proposed indices overcome the limitation of traditional measures in cross-city comparability by quantifying the cumulative weighted average probability of co-location between the two groups. More importantly, the proposed framework offers flexibility for future applications using more granular data sources (e.g., GPS or mobile phone data). In such applications, multi-scale comparisons can be conducted to detect the optimal resolution for measuring interaction potential, enhancing analytical robustness while preserving the framework's core advantage for capturing the multidimensional nature of inter-group interactions.

Appendices

4.A Theoretical maximum of the global indices

Assume that tourists and residents are evenly distributed across all spatial units. Then, for each spatial unit i , the ratio of tourists to residents is equal to the overall ratio in the study area, i.e.,

$$\frac{x_i}{y_i} = \frac{X}{Y} \quad \text{Equation 4.12}$$

where x_i and y_i denote the number of tourists and residents in unit i , and X and Y are the total numbers of tourists and residents in the entire study area. Let, $k = \frac{X}{Y}$, so that:

$$x_i = k \cdot y_i \quad \text{Equation 4.13}$$

Substituting into the expression for the interaction share in unit i :

$$\frac{x_i}{x_i + y_i} = \frac{k \cdot y_i}{k \cdot y_i + y_i} = \frac{k}{k + 1} = \frac{X}{X + Y} \quad \text{Equation 4.14}$$

Thus, the interaction index S becomes:

$$S = \sum_{i=1}^n \left[\left(\frac{X}{X+Y} \right) \left(\frac{y_i}{Y} \right) \right] = \frac{X}{X+Y} \cdot \frac{\sum_{i=1}^n y_i}{Y} = \frac{X}{X+Y} \quad \text{Equation 4.15}$$

Therefore, the theoretical upper bound of S is:

$$S = \frac{X}{X+Y} = \text{Baseline} \quad \text{Equation 4.16}$$

Similarly, when the two populations are equally distributed over all time windows, we have $\frac{x_{i,t}}{y_{i,t}} = \frac{x_i}{y_i}$ for

each time window t within spatial unit i . Therefore, similar to the equation 4.13 and 4.14, we have

$\frac{x_{i,t}}{x_{i,t} + y_{i,t}} = \frac{x_i}{x_i + y_i}$. Thus, the interaction index ST becomes:

$$ST = \sum_{i=1}^n \sum_{t=1}^m \left[\left(\frac{x_{i,t}}{x_{i,t} + y_{i,t}} \right) \left(\frac{y_{i,t}}{Y} \right) \right] = \sum_{i=1}^n \sum_{t=1}^m \left[\left(\frac{x_i}{x_i + y_i} \right) \left(\frac{y_i}{Y} \right) \right] = S \quad \text{Equation 4.17}$$

When the two populations are equally distributed over all activity venues, we have $\frac{x_{i,t,a}}{y_{i,t,a}} = \frac{x_{i,t}}{y_{i,t}}$ and

$\frac{x_{i,t,a}}{x_{i,t,a} + y_{i,t,a}} = \frac{x_{i,t}}{x_{i,t} + y_{i,t}}$. Thus, the interaction index STA becomes:

$$STA = \sum_{i=1}^n \sum_{t=1}^m \sum_{a=1}^w \left[\left(\frac{x_{i,t,a}}{x_{i,t,a} + y_{i,t,a}} \right) \left(\frac{y_{i,t,a}}{Y} \right) \right] = \sum_{i=1}^n \sum_{t=1}^m \left[\left(\frac{x_{i,t}}{x_{i,t} + y_{i,t}} \right) \left(\frac{y_{i,t}}{Y} \right) \right] = ST \quad \text{Equation 4.18}$$

Therefore, in a limiting case where tourists and residents are evenly distributed across spatial units, time windows, and activity venues, all three indices reach their theoretical maximums, yielding:

$$\text{Baseline} = S = ST = STA \quad \text{Equation 4.19}$$

4.B Reclassified consumption categories

Table 4.2 Reclassified consumption categories and the percentage of each category in total expenditure and transactions.

Category	Example of Transaction Types	No. of subtypes	Resident Transactions	Resident Expenditure	Tourist Transactions	Tourist Expenditure
Food and Beverage Retail	Convenience stores, supermarkets, retail & wholesale of food and beverage, e.g., fruit and vegetables, meat, fish and marine products, dairy products, rice cakes, etc.	83	35.35%	18.80%	27.28%	11.72%
Restaurant	Korean style restaurants, confectioner shops, pizza, hamburger, sandwich, noodle houses, bars and canteens, chicken shops, lunch counters, western style restaurants, etc.	16	21.48%	15.96%	23.93%	21.40%
General Retail	Retail & wholesale: clothing, cosmetics and perfumery, gifts, novelties and souvenirs, etc.	350	16.43%	28.88%	16.00%	20.01%
Transportation	Automotive gas/oil stations, renting of motor vehicles, coastal water passenger transport, vehicle parking facilities, urban transit systems, charter bus transport, etc.	49	8.06%	13.11%	5.41%	6.09%
Drinking Place	Non-alcoholic beverages places, other drinking places, general amusement drinking places	6	6.63%	5.05%	7.39%	3.69%
Health	General clinics, general hospitals, dental clinics, oriental medical clinics, child day care services, para-medical services, etc.	18	4.11%	6.85%	0.75%	0.97%
In-Person Service	Personal care services: hair beauty, saunas, skin beauty, etc. Household services: household laundry services, repair of household machinery, etc.	43	1.49%	1.97%	0.64%	0.67%
Indoor Recreation	Computer game room, singing room, museum, billiard room, bowling alley, swimming pool, library, reading room, physical fitness facility, etc.	23	1.13%	0.63%	1.36%	0.85%
Outdoor Recreation	Golf and skiing facilities, amusement and theme park, botanical and zoological gardens, natural parks, etc.	23	1.05%	1.73%	2.71%	3.65%
Accommodation	Hotels, inns, condominium, juvenile camps, renting of non-residential buildings, etc.	23	1.03%	1.42%	4.54%	8.58%
Education	General subject educational institute, private educational institute, fine arts schools, foreign language schools, sports education, universities, other technical and vocational secondary education, driving schools, etc.	25	0.36%	2.33%	0.08%	0.32%
Total			97.12%	96.73%	90.10%	77.96%

4.C Segregation curve and measures for evenness

To construct a segregation curve of tourists' and residents' spending, plot the cumulative proportion of tourist transactions as a function of the cumulative proportion of resident transactions after sorting observed units (i.e., spatial units, space-time units, or space-time-activity units) into descending order according to the percentage of resident transactions in the total transactions of the unit (Figure 4.9). The diagonal line indicates the condition of even distribution. The line for a completely segregated condition would lie along the x-axis from 0 to 1 and then rise along the y-axis. As such, the closer the curves are to the diagonal line, the more even the distribution of tourists and residents is across the observed units; conversely, the more separated they are.

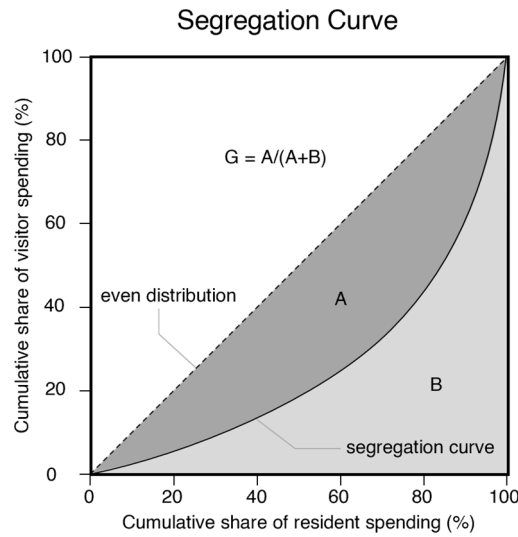


Figure 4.9 Segregation curve.

The Gini index is one of the most commonly used indicators of the evenness of social segregation, which has a determinate relationship to the segregation curve. It is always equal to the area between the diagonal and the segregation curve expressed as a fraction of the total area below the diagonal, i.e., $A/(A+B)$ in Figure 4.9. It is calculated as the mean absolute difference between minority proportions weighted across all pairs of areal units, expressed as a proportion of the maximum weighted mean difference (Massey and Denton, 1988). The formula is as follows:

$$G = \frac{\sum_i \sum_j t_i t_j |p_i - p_j|}{2T^2 P(1 - P)} \quad (\text{Equation 4.20})$$

Where t_i and t_j denote the total number of transactions in units i and j , respectively. p_i and p_j denote the proportion of resident transactions in units i and j , respectively. T denotes the total number of transactions for both tourists and residents across all units. P denotes the proportion of resident

transactions to the total transactions. G equals zero only if $p_i = P$ for all i , and equals 1 only if each cell contains a single type of population. Thus, G varies between 0 and 1 for the no-segregation and completely segregated conditions, respectively. This study uses the segregation curve and the Gini index to assess the uneven distribution of tourists' and residents' spending in the three scenarios.

Chapter 5

Conclusions

5.1 Conclusions and Contributions

This thesis systematically investigates human behavioral dynamics and interactions in a tourist city using crowdsourced data. Through the first and second case studies, it examines changes in human behavior in tourist cities during the COVID-19 pandemic, offering deeper insights into human crisis response mechanisms and decision-making processes. By carefully evaluating the impacts of policy responses on different groups, the study identifies the effectiveness and limitations of these policies, providing valuable guidance for managing similar events in the future. The third study introduces a time-geographic approach, uncovering diverse interaction patterns between residents and residents in urban spaces. This analytical framework theoretically enhances our understanding of the forms and nature of intergroup interactions while offering both conceptual and quantitative tools for addressing challenges such as overtourism and public health crises. The conclusions and contributions of this research are grounded in robust empirical analysis and provide significant implications for theory and practice in time geography, tourism geography, and crisis management.

(1) Local and remote pandemic risks have joint impacts on human activities in tourism cities.

The first and second case studies reveal that even in the absence of strict travel restrictions, individuals in tourism cities actively adjust their travel and consumption behaviors in response to both national and local COVID-19 conditions. This underscores the importance for island destinations, such as Jeju, Hong Kong, Singapore, and Hawaii, to account for the combined effects of local and external outbreaks during public health crises. These geographically independent destinations often experience disease transmission at distinct local and national or international levels. Tourism cities that are geographically distant from epidemic epicenters may still face significant economic consequences due

to the penetration of external risks through inbound tourists. This highlights the critical distinction between managing pandemic crises involving transmissible risks extending beyond local areas and other crises like earthquakes or terrorism, whose impacts are typically confined to specific regions. However, increases in local-level outbreak indicators tend to lead to greater declines in travel and consumption compared to national-level indicators. Thus, long-term epidemic control at the destination is essential for the recovery and resilience of the local tourism industry.

(2) Heterogeneous impacts of pandemic and policies on different economic sectors.

Empirical evidence in all three case studies reveal significant heterogeneous impacts of the pandemic and policy interventions across various sectors. Travel related to essential tourism activities (e.g., lodging), face-to-face services (e.g., restaurants, cafes), and transportation (e.g., car rental) were particularly affected by COVID-19. Indoor activities or venues where people gather, such as museums, concert halls, and traditional markets, experienced more lasting impacts. Similarly, the effects of policy interventions on consumer spending varied across sectors. The retail, restaurant, lodging, and outdoor recreation sectors benefited significantly from stimulus payments, while the indoor recreation sector faced greater constraints. These findings are consistent with Maslow's hierarchy of needs, which emphasizes prioritizing physiological and safety needs in consumer decision-making. A balanced policy approach can be achieved by tailoring interventions to align with public safety requirements. For example, distinguishing between venues eligible for consumer vouchers and those constrained by social distancing measures can help direct spending toward the most affected sectors, stimulating consumer demand and supporting broader economic recovery while maintaining public health priorities. These insights provide Destination Marketing Organizations (DMOs) and tourism stakeholders with a framework for developing systematic, targeted strategies to support diverse tourism services during and after public health crises.

(3) Different demographics exhibit distinct risk perceptions and adaptive coping strategies.

The second empirical study revealed distinct behavioral responses and adaptive decision-making patterns among tourists and residents. Residents demonstrated heightened sensitivity to local disease transmission, particularly when engaging in activities requiring physical contact, such as indoor and outdoor recreation. In contrast, tourists expressed greater concern about national disease transmission when participating in activities involving interaction with other travelers, such as public transportation and accommodation services. However, tourists were more sensitive to local disease transmission when engaging in activities involving interaction with residents, such as indoor and outdoor recreation and face-to-face services. These findings underscore the critical role of risk perception in shaping individual protective behaviors. Residents and tourists differ in their access to information, the types

of information they receive, and their levels of familiarity with destinations, which are influenced by geographic and psychological distance. These differences result in varying risk perceptions and coping strategies, which further shape distinct behavioral responses to policy interventions. For instance, social distancing measures had a limited impact on residents' behavior but significantly influenced tourists. Conversely, economic incentives yielded markedly different outcomes. These distinct responses highlight the adaptive decision-making processes that arise as individuals adjust to changes in their decision-making environments. Understanding these dynamics offers valuable insights for designing tailored policies to manage public health crises effectively.

(4) Various modes of interaction exist between tourists and residents in urban spaces. This study makes a significant contribution by introducing a time-geographic framework to analyze various interaction modes between tourists and residents in urban spaces. It characterizes four distinct interaction modes: *Asynchronous Presence for Different Types of Activities (AP-DA)*, *Asynchronous Presence for the Same Type of Activity (AP-SA)*, *Synchronous Presence for Different Types of Activities (SP-DA)*, and *Synchronous Presence for the Same Type of Activity (SP-SA)*. This framework enhances our understanding of how these groups interact across spatial, temporal, and activity dimensions, highlighting the differential potential for direct contact. By integrating activity constraints into the space-time bundle, the study addresses the limitations of traditional time-geographic concepts, providing a more nuanced analysis. Furthermore, the study organizes these interaction modes into a hierarchical framework, enabling more accurate estimates of interaction potential and informing resource management and conflict resolution, particularly in the contexts of overtourism and pandemics. Empirical findings underscore the heterogeneity of tourist-resident behavior in terms of space, time, and activity, and highlight the need to consider activity dimension constraints when assessing interaction potential. It addresses the limitations of traditional indicators regarding their inability to distinguish interaction modes and emphasizes the importance of context-specific approaches to estimating interaction potential.

(5) Significant heterogeneity exists in the interaction modes and potential between tourists and residents in terms of space, time, and activity venues. This study reveals significant variations in the interaction potential between tourists and residents across time and activity venues. Their interaction potential peaks during midday and afternoon, with weekends showing higher interaction potential than weekdays. Highly interactive venues, such as restaurants, retail spaces, and transportation hubs, accounted for 92% of overall interactions, highlighting key areas for targeted management. These findings inform policymaking and infrastructure planning, enabling tailored approaches to address dynamic urban demands and optimize resource allocation, particularly in high-

interaction spaces. Furthermore, the framework's adaptability to seasonal fluctuations and pandemic-related changes underscores its practical application in managing visitor flows, reducing congestion during peak periods, and supporting social distancing measures. Local-level analysis reveals the spatial heterogeneity of tourist-resident interaction patterns across urban spaces and their connection to environmental features. The study identifies six distinct spatial clusters, each representing varying degrees of temporal and activity-based heterogeneity. Areas near settlements typically exhibited more synchronous presence interactions, while more remote areas, such as theme parks, displayed asynchronous and homogeneous activity patterns. These findings provide essential guidance for optimizing resource allocation and public space design to balance the needs of residents and tourists.

5.2 Broad Implications

This thesis offers valuable insights into the role of risk perception in shaping individual protective behaviors. Variations in access to information and differences in familiarity with risk sources—driven by geographic and psychological distance—significantly influence coping strategies across diverse groups. These divergences underscore the need to tailor risk communication and policy interventions to address different populations' specific behaviors and needs. The observed differences in risk perceptions and adaptive responses highlight the complex interplay between individual experiences, informational contexts, and behavioral adjustments during crises. These insights contribute to the academic discourse on risk management and provide policymakers with practical guidance for enhancing community resilience and optimizing crisis response strategies.

This thesis presents several key implications for managing public health crises and their economic impacts. Tourism-dependent cities, even those geographically distant from national epidemic epicenters, remain vulnerable to risks introduced by incoming travelers. This underscores the importance of incorporating both local and external outbreak dynamics into crisis management strategies. Economic recovery policies must also address the specific vulnerabilities of tourism-dependent cities, as national-level measures alone may be insufficient to restore tourism spending. Tailored approaches, such as issuing consumer vouchers for targeted industries while implementing stricter social distancing measures in others, can help balance economic recovery with public health priorities. Additionally, managing the timing of public space and service facility usage by different demographic groups can reduce inter-group contact while ensuring orderly economic activity. Establishing specialized risk communication channels for diverse groups can further enhance consumer confidence and participation. By integrating these considerations, policymakers can develop

more effective strategies that balance public health with economic recovery, thereby strengthening resilience to future public health crises.

This thesis advances the understanding of spatiotemporal relationships and potential interaction patterns among individuals from a time-geographic perspective. Previous studies have predominantly examined the coincidence of space-time paths in spatial and temporal dimensions, often overlooking the role of activity dimensions. This oversight can lead to misinterpretations of potential interaction modes and overestimation of actual contact possibility between population groups. The proposed analytical framework effectively captures various modes of intergroup interaction across space, time, and activity dimensions. Additionally, the theoretical concepts introduced enhance understanding of the complexities underlying quantitative indices, providing valuable insights to support decision-making in areas such as marketing strategies and urban governance.

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