Computers, Environment and Urban Systems 114 (2024) 102181

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

Unraveling changes of spending behavior in pandemic cities: A nationwide study of South Korea

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ARTICLE INFO

Keywords:
Cities
Consumer spending
Geolocated transactions
Behavior change
COVID-19
Spatial big data

ABSTRACT

The COVID-19 pandemic, unprecedented in scale and impact, has significantly influenced consumer spending. This study leverages a longitudinal transaction dataset from South Korea to analyze how the pandemic, social distancing policies, and pandemic-related search interest have shaped spending within and across cities. We examine transaction volume and expenditure amount as city-level indicators of activity intensity and consumption demand across four stages of the early pandemic. The study finds that: (1) Social distancing caused reductions in both residents' and travelers' spending. The increase in search interest coincided with a rise in residents' spending but a decline in travelers' spending; (2) Resident transactions experienced a moderate and persistent decline across all stages, while expenditure rebounded after the 1st national outbreak. Traveler transactions and expenditure showed similar trends, with declines during outbreaks and recoveries during stable periods; (3) Disparities across cities were associated with proximity to outbreak centers and socioeconomic attributes. Cities with larger populations or those closer to epicenters experienced greater reductions in spending, while less densely populated cities saw increased traveler spending during the 2nd stable period; (4) Travelers' spending from distant cities significantly decreased during the 1st outbreak but gradually recovered as the pandemic continued, indicating evolving behavior and adaptation; (5) Changes across spending categories exhibited significant heterogeneity. Residents showed increased demand for essential goods and online shopping, while recreation-related industries struggled throughout. These findings highlight the characteristics and disparities among consumers, cities, and industries, providing information for policymakers to formulate tailored support programs for industries experiencing increased demand or significant impacts. This study emphasizes the need to develop robust strategies for crisis management and economic resilience to mitigate the impacts of future health crises.

1. Introduction

Throughout the course of history, several significant pandemics, such as SARS, MERS, and Ebola, have exerted a profound and lasting influence on societies and economies worldwide. These outbreaks have resulted in widespread disruptions, loss of life, and substantial social upheaval. Fortunately, each major pandemic has imparted invaluable lessons that have deepened our understanding of infectious diseases and shaped our preparedness and response strategies. However, since early 2020, the global economy and the daily lives of individuals worldwide have been profoundly affected once again by an unprecedented public health crisis – a pandemic of coronavirus disease 2019 (COVID-19). Compared to previous pandemics, the virus displayed a significantly higher level of infectiousness, leading to its rapid global spread and impact. To control the spread of the virus, many countries implemented strict containment measures such as lockdown strategies and stay-at-home orders during the initial stages of the pandemic, resulting in significant impacts on human mobility, economic activity and global financial markets (Coibion et al., 2020; Ge et al., 2022; Guerrieri et al., 2022; Zhong et al., 2022). These measures not only restricted mobility but also served as a means of communicating the severity of the local pandemic (Yang et al., 2021).

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https://doi.org/10.1016/j.compenvurbsys.2024.102181
Received 27 March 2024; Received in revised form 5 July 2024; Accepted 22 August 2024
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The severity and consequences of the pandemic have shown differences across regions, as stated in existing research (Baum-Snow et al., 2022; Fraiberger et al., 2020; Keil et al., 2022; Lee et al., 2021; Zhai et al., 2021). Factors such as the local outbreak severity, socioeconomic attributes, and healthcare facilities' availability contribute to the divergent outcomes observed among regions (Baum-Snow et al., 2022; Fraiberger et al., 2020; Hou et al., 2021; Keil et al., 2022; Poole et al., 2020; Wei et al., 2023). While many studies have investigated disparities among income groups and communities within individual cities, there is a lack of nationwide research focusing on disparities among different cities. Specifically, few studies analyze how and why cities differ in their response and outcomes during the pandemic on a national scale. Understanding these inter-city disparities is crucial for developing effective strategies tailored to the unique challenges faced by various cities and for enhancing preparedness for potential future crises.

Previous studies have suggested that COVID-19-related shocks have significantly influenced consumer demand and spending behavior (Baker et al., 2020). Psychological factors such as COVID-19-related fear, perceived economic instability, and anxiety can also lead to changes in spending behavior (Di Crosta et al., 2021). Notably, behaviors like irrational stockpiling and panic buying due to fear of supply shortage and mobility restrictions were widely reported during the initial stages of the pandemic (Hall et al., 2021; Khayru, 2021; O'Connell et al., 2021; Watanabe, 2020). Additionally, the pandemic has led to an increased reliance on online shopping (Kim, 2020). According to a survey conducted by McKinsey, online customers in most spending categories experienced a growth of more than 10 % during the pandemic, and most respondents expressed that they will continue shopping online even though physical stores reopen (Arora et al., 2020). Furthermore, the impact of the pandemic varied across different spending categories. Studies indicated that social distancing measures and lockdowns in the US boosted spending on groceries by 29 % compared to the month in the prior year while spending in restaurants, fast food, and coffee shops decreased by 27 % (Felix et al., 2020).

Despite numerous studies have documented the pandemic-induced change in consumer spending, most have focused on countries and regions that implemented strict interventions like lockdowns, including the United Kindom (Chronopoulos et al., 2020; O'Connell et al., 2021), the United States (Alexander and Karger, 2021; Cox et al., 2020; Dong et al., 2021; Dunn et al., 2020; Dunphy et al., 2022a; Dunphy et al., 2022b; Li et al., 2021; Wheat and Duguid, 2022; Yang et al., 2021; Zhao et al., 2022), Denmark and Sweden (Sheridan et al., 2020), Spain (Carvalho et al., 2021; Montalvo et al., 2020), and China (Chen et al., 2021). These studies mostly examined spending changes before and after the implementation of lockdown measures. Few studies have investigated the spontaneous changes in spending behavior in countries that did not enforce strict containment measures, although evidence suggesting that the impact of COVID-19 on consumer spending is not only related to national lockdowns but also related to individuals' perceptions of risk (Dunphy et al., 2022a). Moreover, some studies indicate that the economic contraction is primarily due to the pandemic itself, irrespective of whether governments implemented strict measures (Sheridan et al., 2020).

Another gap in existing studies is that most research focused on specific consumer groups within cities (Baker et al., 2020; Chetty et al., 2020; Cox et al., 2020; Dong et al., 2021; Li et al., 2021; Montalvo et al., 2020; O'Connell et al., 2021; Yang et al., 2021), mainly residents and their corresponding local consumption patterns. However, travelers constitute a significant source of spending in business and tourism cities, and their spending behavior can have a significant impact on the economy. The differences in spending between residents and travelers may be overlooked in existing studies. Additionally, existing research tends to consider expenditure amount alone, neglecting the fact that the transaction volume and expenditure amount can reflect activity intensity and consumption demand, respectively (Chen et al., 2021; Dong et al., 2021; Yang et al., 2021).

To address the aforementioned research gaps, we conduct a regression analysis using a card transaction dataset collected in South Korea. South Korea serves as a pertinent case study due to its early exposure to the COVID-19 outbreak and its distinctive approach of not implementing strict lockdown measures. The longitudinal dataset spans 22 months, from January 2019 to October 2020. We utilize two city-level indicators: transaction volume, representing mobility, and expenditure amount, reflecting economic activity. Additionally, we integrate a policy factor to represent consumer response to the implementation of social distancing measures. Search interest in "Coronavirus" collected from Google Trends is used to monitor consumers' perception of the severity of the pandemic. Our model is designed to provide quantitative insights into several research questions: 1) How did social distancing policies and search interest affect spending behavior? 2) How did consumer spending change during different stages of the pandemic compared to the corresponding period in 2019? 3) What differences existed in spending behavior changes between residents and travelers across cities? 4) How did the spending behavior changes differ depending on the distance traveled by travelers? 5) What were the differences in spending behavior changes across various spending categories? Through this analysis, our study aims to reveal the heterogeneous effects of the pandemic on cities, consumer groups, and spending categories by examining the changes in spending behavior during a pandemic. The changes in transaction volume can serve as an indicator of the impact on activity intensity, while changes in expenditure can provide insights into the economic effects across different groups and categories.

We hope that this research will offer valuable insights into the spontaneous behavioral changes in consumer spending during the pandemic and their corresponding economic impacts. These insights can be particularly useful as more countries adopt strategies to coexist with the virus. Additionally, our study aims to inform governments and policymakers in formulating policies towards different cities, consumer groups, and spending categories to effectively respond to potential future pandemics.

2. Literature review

An increasing number of studies have examined consumer spending responses to COVID-19 in general or to specific policies, including the effect of strict interventions and recovery after relaxing restrictions and introducing stimulus payments. Large increases in demand for storable goods before lockdown and following the announcement of the World Health Organization (WHO) describing COVID-19 as a pandemic were documented in the UK (Chronopoulos et al., 2020; O'Connell et al., 2021). Similar stockpiling behavior was also found in New Zealand (Hall et al., 2021). The state-closure strategies implemented by the US government significantly caused a decrease in consumer spending but only accounted for a small portion of the observed decreases, which highlighted the need to analyze the spontaneous actions of consumers (Dunphy et al., 2022a). Similarly, a comparison between Denmark and Sweden revealed that social distancing laws were responsible for only a small portion of the decrease in consumer spending (Sheridan et al., 2020). Another research found that the stay-at-home orders in the US led to large reductions in spending in mobility-related sectors (Alexander and Karger, 2021). China, as the first outbreak country, experienced a 32 % decline in daily offline consumption, and the decrease was more pronounced in the dining-and-entertainment and travel categories (Chen et al., 2021). Many countries implemented economic stimulus measures to boost consumption since 2020 and relaxed their interventions after gaining some control over the pandemic. Yang et al. (2021) used card spending amount and mobile device-based location tracking data from SafeGraph to find the stimulus payment in the US had a significant immediate and short-term effect of boosting spending and gradually increased foot traffic. Some other studies also found that the economic stimulus policies implemented by the Japanese government resulted in a sustained one-month increase in consumption (Kubota

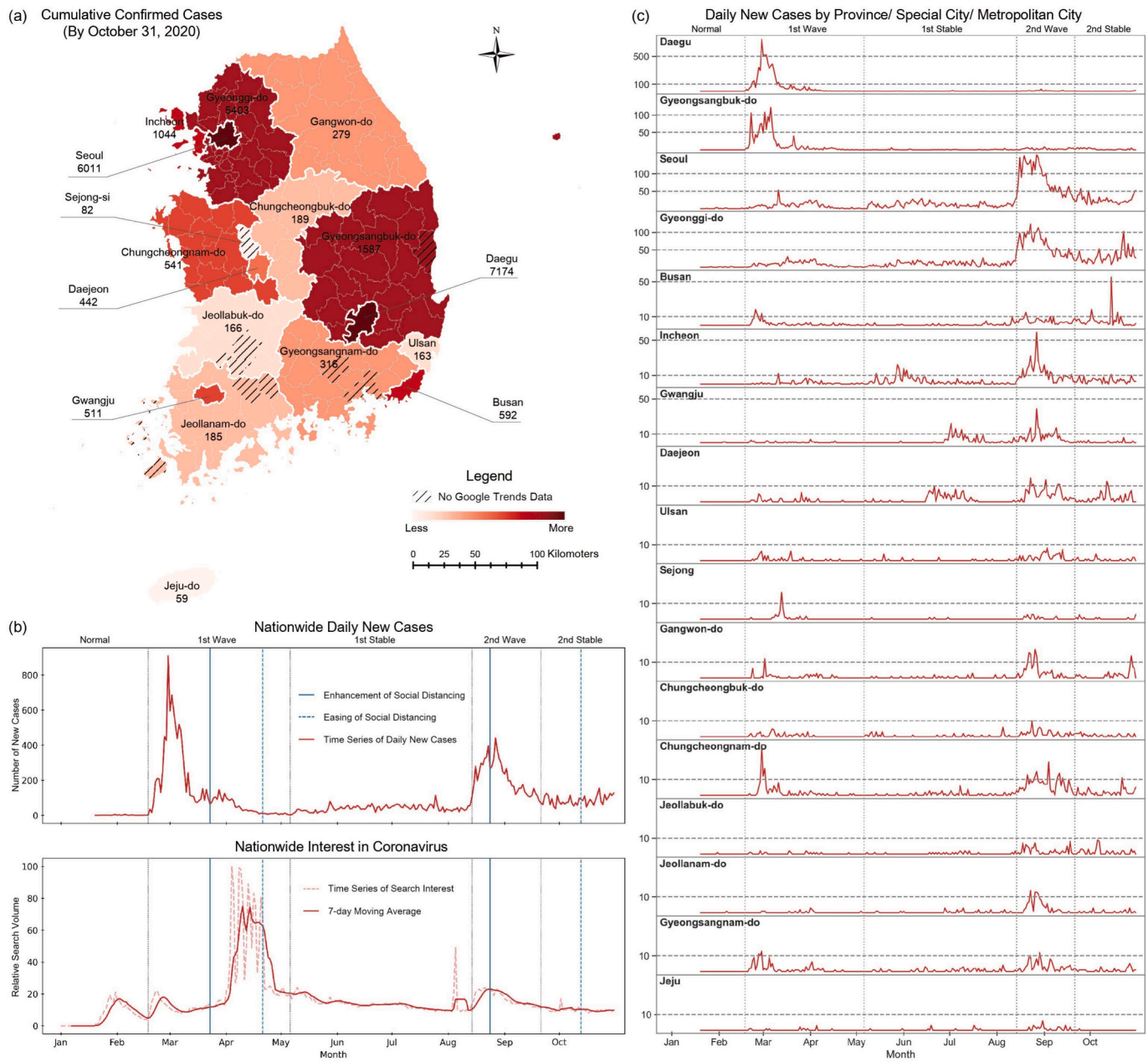

Fig. 1. Research area and time series of daily new cases and search interest. (a) Cumulative confirmed cases in first-level administrative divisions (by October 31, 2020); (b) Nationwide daily new cases and nationwide search interest; (c) Daily new cases by first-level administrative divisions (i.e., provinces, special city, and metropolitan cities).

et al., 2021), while those implemented by the US government led to a two-week increase in consumption (Karger and Rajan, 2020), with growth observed in specific categories such as categories enhanced public health and reduced food insecurity and even non-essential and undesirable goods including liquor and cigar among low-income population (Li et al., 2021). Besides, the face mask mandate also played an important role in assisting the economy in countries with high levels of social distancing and even after state reopening in the US (Dunphy et al., 2022b; Zhao et al., 2022).

Several studies have focused on the heterogeneous changes in spending behavior among different social groups during the pandemic. One study found that the reduction in spending among high-income individuals, particularly in categories requiring personal interaction, led to widespread and persistent job losses, especially among low-income workers (Chetty et al., 2020). Another study reported that while all households increased their demand for storable goods before lockdown, the increase was greater among wealthier households (O'Connell et al., 2021). Similar findings were observed in Spain (Carvalho et al., 2021), the US (Cox et al., 2020), and the UK (Hacioglu Hoke et al., 2020), where pandemic-induced declines in spending were steeper in affluent neighborhoods. The study conducted in the US also suggested a rapid rebound in spending among low-income households since mid-April 2020 (Cox et al., 2020). However, another study in Spain found that the recovery of spending in low-income families was not more intense than in high-income families (Montalvo et al., 2020). As for other social characteristics, a study in the US reported few differences in spending across individuals with different political beliefs, but significant heterogeneity was observed among demographic groups (Baker et al., 2020). For example, people with children stockpiled more, whereas men stockpiled less in the early stages of the pandemic.

Furthermore, there are also studies that revealed changes in spending behavior for certain consumption categories during the COVID-19 pandemic. Firstly, categories related to travel and recreation were found to be most affected, such as airlines and entertainment (Brinke et al., 2022), music (Denk et al., 2022), and hotels (Mendez-Carbajo, 2021; Sucheran, 2021). However, there was a widespread increase in spending on durable goods (Tauber and Van Zandweghe, 2021) and groceries (Dunn et al., 2020; Mendez-Carbajo, 2021), as people preferred cooking at home instead of dining out (Mendez-Carbajo, 2021). Some studies also found that the large impacts on the accommodation and restaurant could be partially offset by the sales of food and beverages (Dunn et al., 2020). Another widely reported change in spending behavior was that consumers were more willing to shop online during the pandemic (Ali, 2020; Brinke et al., 2022; Khayru, 2021; Sayyida et al., 2021; Wheat and Duguid, 2022), and some consumers tended to continue shopping online even after the reopening of the physical stores (Arora et al., 2020). In addition, a related study in Latvia found that businesses with higher shares of online transactions before the outbreak performed better than others during the pandemic (Brinke et al., 2022).

To summarize, although there has been increasing investigation of pandemic-induced spending changes, several research gaps that deserve further investigation remain. Firstly, there is a need to better understand spontaneous behavioral changes compared to those under strict interventions, as highlighted in some studies (Dunphy et al., 2022a; Sheridan et al., 2020). Secondly, there is a lack of research on the differences in spending changes between travelers and residents. Thirdly, further analysis is needed to examine the difference in changes between the frequency of spending activity and the amount of expenditure and the relationship between these two attributes. To address these gaps, this study develops a multiple regression model to quantitatively analyze spontaneous spending changes across different consumer groups and spending categories, considering both transactions and expenditure, as detailed in the following sections.

3. Study area and dataset

3.1. Study area

South Korea, located in East Asia, is a sovereign nation occupying the southern part of the Korean Peninsula. The country covers an area of approximately 100,363 km^2 and has a population of about 51.8 million people. The country is divided into 17 first-level administrative divisions, including six metropolitan cities, one special city, one special self-governing city, and nine provinces (do) with one of these being one special self-governing province. These administrative divisions are further subdivided into municipal-level divisions such as cities (si), counties (gun), and districts (gu). Our study concentrates on a comprehensive analysis of nationwide cities, including six metropolitan cities, one special city, and 145 municipal-level divisions (collectively referred to as "cities" hereafter), as illustrated in Fig. 1(a). Certain cities, such as Sejong, are excluded from this analysis due to insufficient Google Trends search volume, as illustrated in Fig. 1(a).

3.2. COVID-19 and policy responses in South Korea

Our research period spans from January 1, 2019, to October 31, 2020. During this time, South Korea experienced two waves of the COVID-19 outbreak, as illustrated in Fig. 1(b) and (c). The first confirmed case was reported on January 20, 2020. In the initial stage of the pandemic (January 20 to February 17), confirmed cases were primarily limited to travelers from overseas or their close contacts. The first wave (February 18 to May 5) witnessed a significant increase in community transmission, especially in Daegu and Gyeongsangbuk-do, mainly related to a specific religious group. South Korea's proactive strategy, known as the 3Ts-Testing, Tracing, and Treating-was effective in preventing further spread.

The effectiveness of the 3Ts measures relied heavily on public cooperation, a sufficient supply of protective equipment, and controlled close contact among individuals. The government promoted social distancing and public awareness, limiting or prohibiting high-risk activities and ensuring a stable supply of protective equipment such as face masks. The Korean Society for Preventive Medicine supported a campaign for social distancing, a non-pharmaceutical intervention to prevent community spread by minimizing contact and separating low-risk from high-risk groups (Government of the Republic of Korea, 2020).

Unlike many countries that enforced lockdowns, South Korea implemented social distancing while keeping society open and maintaining daily routines. This approach included refraining from social gather-rings, delaying school openings, encouraging remote work, and implementing differentiated levels of social distancing based on the outbreak's trajectory. The levels first included "Distancing in Daily Life", "Eased Social Distancing", "Social Distancing", and "Enhanced Social Distancing". During the initial social distancing period (February 29 to March 21), the government recommended avoiding group activities and maintaining safe distancing. During the enhanced social distancing period (March 22 to April 19), staying at home and closing high-risk facilities for religion, indoor sports, and entertainment were advised. As the spread declined, "Eased Social Distancing" was announced on April 20, later changing to "Distancing in Daily Life" on May 6. During this period, the focus was on keeping physical distance from others and following hygiene practices, such as wearing face masks and disinfecting surroundings.

From May 6 to August 13, the situation was relatively stable, characterized by small-scale community infections originating from multiple epicenters in the Seoul metropolitan area (Seoul, Gyeonggi Province, and Incheon) and spreading to other regions, with an average of 41 new cases per day. A new three-level social distancing scheme was announced on June 28, systematized based on previous experience and triggered by the severity of the outbreak. The second wave began on August 14, triggered by community infections from various hotspots in the Seoul metropolitan area, leading to a nationwide spread. The government responded swiftly by introducing social distancing measure level 2 on August 23, which helped to reduce new cases to two-digit figures as of September 20. High-risk facilities were advised to shut down, and gatherings of more than 50 people indoors or 100 people outdoors would be banned when level 2 measures were introduced. This level 2 social distancing measure was announced to be relaxed on October 11.

Based on the country-level and province-level daily new cases obtained from the Ministry of Health and Welfare of South Korea and the document released by the government, five stages in 2020 are defined for the following analysis, as marked in Fig. 1(b) and (c): the normal period (Stage 0, January 1 to February 17), the first outbreak wave (Stage 1, February 18 to May 5), the first stable period (Stage 2, May 6 to August 13), the second outbreak wave (Stage 3, August 14 to September 20), and the second stable period (Stage 4, September 21 to October 31). To monitor policy responses, we focus on the "Enhanced Social Distancing" period from March 22 to April 19 and the nationwide level 2 social distancing measures from August 23 to October 11 (collectively referred to as enhanced social distancing hereafter).

3.3. Search interest time series

Due to the lack of city-level daily new cases in South Korea, we rely on search interest time series collected from Google Trends to measure the severity of the pandemic. Google Trends provides aggregated statistics on the popularity of search queries within the Google search engine. As one of the most widely used tools for analyzing relative internet search volumes, Google Trends plays a crucial role in public health research (Arora et al., 2019). It may capture the progression of an epidemic more broadly and promptly since individuals often search

Table 1
Example of transaction records.

Date	City of Consumption	City of Registration	Category	Consumer Group	Transactions	Expenditure
2019-01-01	Yongsan-gu	Yongsan-gu	First-class hotel	Resident	22	1,369,500.0
2019-01-01	Yongsan-gu	Guro-gu	Other leisure	Traveler	8	76,000.0
2019-01-01	Yongsan-gu	Jongno-gu	General Korean food	Traveler	97	3,090,700.0
...	...	...	...	...	...	...

Table 2
Reclassified spending categories.

Category	Share of Resident Transactions (%)	Share of Resident Expenditure (%)	Share of Traveler Transactions (%)	Share of Traveler Expenditure (%)	Note
Transportation	4.62	10.25	12.25	9.64	Airline, tourism, express bus, railroad, ferry, taxi, car rental, fuels, and car services.
Recreation	4.04	3.93	2.41	2.56	Indoor and outdoor recreation, sports area, culture, and entertainment places.
Restaurant and Bar	24.97	23.68	21.24	16.27	Restaurants, bars, and pubs.
Store and Supermarket	48.26	29.94	26.40	15.03	Store, supermarket, food and beverage, and health food.
Interpersonal Services	2.01	3.23	0.64	1.16	Barbershop, beauty salon, cosmetics, sauna, etc.
General Merchandise	2.31	3.01	1.39	2.57	Optical products, clothing, fabrics, shoes, accessories, books, toys, cars, stationery, etc.
Home and Internet Shopping	0.28	0.60	17.83	27.94	Home shopping, Internet PG, Internet Mall, etc.
Total	86.48	74.64	82.16	75.17	/

online for information when symptoms appear, even before visiting medical institutions (Milinovich et al., 2014). These online search data potentially reflect public concern, awareness, reactions, or anxiety about an event through information-seeking behaviors (Ayyoubzadeh et al., 2020; Gligoric et al., 2022; Husnayain et al., 2020). During the COVID-19 pandemic, numerous studies have shown that relative search volume can be used to monitor and predict the outbreak's progression, with public search interest often peaking before the number of new cases (Effenberger et al., 2020; Husnayain et al., 2020; Husnayain et al., 2021; Strzelecki, 2020).

Google Trends provides time series data of search interest for specified queries, which can be input as plain text or entity identifiers from the Freebase knowledge base (Bollacker et al., 2008; Gligoric et al., 2022). It returns the relative search volume for the specified period, normalized on a scale from 0 to 100, with 100 being the highest search interest (Google trends, n.d.). In this study, we used the entity identifier "/m/01cpyy" to obtain the search interest in "Coronavirus" across languages. Time series were retrieved across 152 cities in our study area from January 1 to October 31, 2020. Since Google Trends only allows downloading daily data for a maximum of eight months, we retrieved daily and weekly data and adjusted the daily data with weekly data to obtain continuous daily data for the entire research period. This resulted in 152 time series at daily granularity. Each time series was normalized to a range between 0 and 1 to reflect the changes in search interest for "Coronavirus" across each city during our research period. Time lags between −14 and +14 days were considered in the analysis. After comparing the proportion of cities with statistically significant coefficients at different time lags, we determined that a time lag of −7 days was most appropriate for residents and −4 days for travelers.

3.4. Credit card transaction data

Credit card transaction data consists of financial information obtained through the transfer of funds between a cardholder's account and a business's account. This aggregated and anonymized dataset provides valuable insights into consumer spending patterns and trends, which have been extensively studied to measure consumer spending (Carvalho et al., 2021; Chen et al., 2021; Chronopoulos et al., 2020; Dunn et al., 2020; Dunn et al., 2021; Wheat and Duguid, 2022). In South Korea, credit cards are the most popular payment method, with credit card expenditure surpassing 800 trillion South Korean won in 2019 and continuing to grow annually (Statistics Korea, 2023).

In this study, we utilize a credit card dataset collected by BC Card, one of the largest credit card companies in South Korea. The original dataset comprises over 7 billion transactions, with a cumulative expenditure exceeding 200 trillion KRW, recorded across 250 municipal-level divisions (si, gun, and gu) in Korea. To align the regions with the search interest data collected from Google Trends, we further aggregate these divisions into the 152 cities specified in Section 3.1. The dataset covers transactions from January 1, 2019, to October 31, 2020, and is anonymized and aggregated by transaction date, city of consumption, city of registration, transaction category, and consumer group, resulting in a total of 130,128,622 records (see Table 1).

3.4.1. Consumer groups

Consumers are categorized into two groups based on the relationship between their city of consumption and city of credit card registration: residents and travelers, as recorded in the dataset. Residents are defined as consumers whose city of credit card registration matches their city of consumption, indicating local spending behavior. Travelers, on the other hand, are those whose city of consumption differs from their city of registration, encompassing individuals engaging in out-of-town expenditures for purposes such as tourism, business, or other activities. This reflects a city's ability to attract economic activity from outside its area.

3.4.2. Spending indicators

The dataset captures two spending indicators: transaction volume and expenditure amount. Transaction volume refers to the aggregated number of consumption actions performed by a consumer group within a specific day, city, and spending category. This indicator provides insight into the frequency and intensity of consumer spending across different locations and time periods. The expenditure amount represents the total monetary value of these consumption actions, offering a measure of the economic demand for specific categories of goods and services in a particular city at a given time. These indicators together provide a comprehensive view of consumer behavior and economic activity.

3.4.3. Distance groups of travelers

Travelers are classified into four groups based on the Euclidean distance between their origin and destination cities, calculated using the geometric center coordinates of the cities. The first group includes travelers from cities within 20 km, representing short-distance intra-provincial travel. The second group encompasses travelers from cities located between 20 and 50 km away. The third group includes travelers from cities within a range of 50 to 100 km. The final group consists of travelers originating from cities more than 100 km away. We interpret the spending of travelers from different distances as a city's economic catchment area, reflecting its ability to attract spending from varying distances.

3.4.4. Reclassification of spending categories

The dataset includes detailed records of consumer spending across more than 200 categories, initially organized into 34 major categories based on the BC card company's coding system. These categories include accommodations, transportation, leisure, cultural entertainment, shopping, education, and food and beverages. For the purpose of this study, these categories have been reclassified into seven broader groups: transportation, recreation, restaurant and bar, store and supermarket, interpersonal services, general merchandise, and home and internet shopping. For residents, the analysis examines spending patterns across all seven reclassified categories. For travelers, the analysis focuses on four key categories—transportation, recreation, restaurant and bar, and store and supermarket—considering their relevance to non-local consumer behavior and share in total consumption. Home and internet shopping is attributed exclusively to residents, as we find the city of consumption for these transactions corresponds to the location of online trading companies rather than the actual consumer's location. Besides, the overall spending, encompassing all categories recorded in the dataset, is analyzed for each consumer group. For further details on the reclassified categories, please refer to Table 2.

4. Methodology

4.1. Quantify spending changes during four pandemic stages

To quantify changes in spending behavior, we conduct a regression analysis aimed at measuring spending changes during each stage of the pandemic compared to the corresponding period in 2019, when COVID-19 had not yet occurred, while controlling for various effects, including seasonal variations, social distancing policies, and pandemic severity. The regression models are established at the city level, focusing on specific consumer groups, spending categories, and spending indicators within each city. For each city, we develop 16 models for residents (covering overall spending and 7 categories, with 2 spending indicators, resulting in 8 × 2) and 18 models for travelers (covering 4 distance groups, overall spending and 4 categories, with 2 spending indicators, resulting in (4 + 5) × 2). The number of models differs due to the varying number of spending categories considered and dimensions analyzed for the two consumer groups as outlined in Section 3.4.

The general form of the model is as follows:

$$\begin{aligned} lny_t &= \alpha + \beta_s Stage_{t,s} + \gamma Year_t \\ &+ \delta_s \left(Stage_{t,s} \times Year_t \right) \\ &+ \lambda SD_t + \mu RSV_t \\ &+ \eta_d DoW_{t,d} + \theta_m Month_{t,m} + \varepsilon_t \end{aligned} \tag{1}$$

In this equation, the dependent variable lny_t represents the log-transformed total consumer spending for a specific spending indicator on day t. The total number of days analyzed in this research is 609, where $t \in \{t | 1 \le t \le 609, t \in N^*\}$ refers to the sequential numbering of days starting from January 1, 2019. $Stage_{t,s}$ is a set of dummy variables indicating the stage of the pandemic as defined in Section 3.2, with the corresponding dates in 2019 serving as the control group. $Stage_{t,s} = 1\{Stage_t = s\}$ is 1 if day t falls within stage $s (s = 1, 2, 3, 4)$, and 0 otherwise. Stage 0 (normal period) is the reference stage. The year effect is controlled for using the dummy variable $Year_t = 1\{t \in [305, 609]\}$, which is 1 if day t is in 2020, and 0 if it is in 2019. This variable controls for overall differences between the two years. The interaction term captures the changes in spending for each pandemic stage in 2020 compared to the corresponding periods in 2019. The coefficients $\delta_s (s = 1, 2, 3, 4)$ are of primary interest as they measure the impact of the pandemic stages on spending behavior.

The variable SD_t is a dummy variable representing the implementation of enhanced social distancing policies, with SD_t equal to 1 if day t is during a period of enhanced social distancing and 0 if social distancing measures were either not in place or were relaxed. This controls for the impact of social distancing policies on spending. The variable RSV_t represents the relative search volume (RSV) collected from Google Trends, serving as an indicator of the pandemic's severity in each city. Each city has its own time series for RSV, providing a measure of public concern and attention related to the pandemic. A time lag of −7 days for residents and − 4 days for travelers is applied to RSV_t.

The model also accounts for seasonal effects, including the day-of-the-week effect controlled by the dummy variable $DoW_{t,d} = 1\{DoW_t = d\}$, and the month-of-the-year effect controlled by the dummy variable $Month_{t,m} = 1\{Month_t = m\}$. $DoW_{t,d}$ is 1 if day t is weekday d, where d takes values from 1 to 7 representing Monday to Sunday. $Month_{t,m}$ is 1 if day t is in month m, where m takes values from 1 to 10 representing January to October. Besides, ε_t is the error term capturing unobserved factors affecting spending on day t.

The coefficients are estimated using the ordinary least squares (OLS) method. For each model, a set of coefficients of interest $[\delta_1, \delta_2, \delta_3, \delta_4, \lambda, \mu]$ is obtained. Specifically, δ_1, δ_2, δ_3 and δ_4 represent the spending changes during stages 1 through 4 of the pandemic, after controlling for the influence of social distancing policies and the RSV related to "Coronavirus", as well as seasonal effects. The coefficient λ captures the impact of enhanced social distancing policies, indicating how these measures influence spending behavior. The coefficient μ reflects the impact of public concern and attention related to the pandemic's severity, as measured by RSV from Google Trends. For further analysis, the coefficients of interest are converted to percentages using the formula $100*(e^x - 1)$ for each coefficient x, providing a more accurate interpretation of the magnitude of the effects.

4.2. Analyze disparities in overall spending changes across cities

Hierarchical agglomerative clustering is employed to analyze the disparities in overall spending changes across 152 cities. The method is a bottom-up approach where each data point starts in its own cluster and clusters are iteratively merged based on their similarity until only one cluster remains. This results in a hierarchical tree structure called a dendrogram (Hong et al., 2021; Lukasova, 1979; Murtagh and Legendre, 2014).

The input data comprises the overall spending changes during four stages across two consumer groups and two spending indicators, resulting in a 152*16 matrix where each row is the spending changes during four pandemic stages of resident transactions, resident expenditure, traveler transactions, and traveler expenditure in a city. Ward's linkage method is used as the criterion to decide which clusters to merge at each step of the hierarchical clustering process. It minimizes the increase in total within-cluster variance when two clusters are merged:

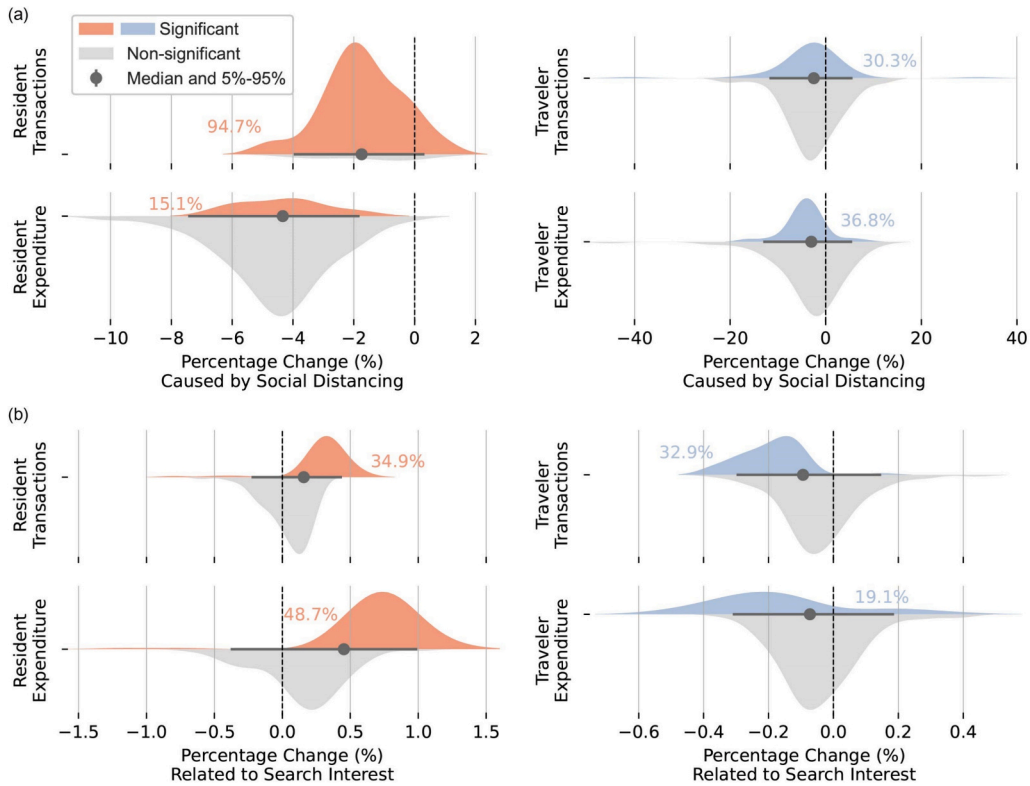

Fig. 2. Impacts of social distancing and search interest. (a) Percentage changes caused by social distancing. (b) Percentage changes related to search interest. The numbers in orange or blue are the percentage of cities with significant coefficients within 95 % confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$\Delta(C_i, C_j) = \sum_{k \in C_i \cup C_j} \left\| \overrightarrow{x_k} - \overrightarrow{m_{C_i \cup C_j}} \right\|^2 - \sum_{k \in C_i} \left\| \overrightarrow{x_k} - \overrightarrow{m_{C_i}} \right\|^2 - \sum_{k \in C_j} \left\| \overrightarrow{x_k} - \overrightarrow{m_{C_j}} \right\|^2 = \frac{|C_i||C_j|}{|C_i| + |C_j|} \left\| \overrightarrow{m_{C_i}} - \overrightarrow{m_{C_j}} \right\|^2 \tag{2}$$

where $\overrightarrow{m_{C_i}}$ is the center of cluster i and $|C_i|$ is the number of data points in it. $\overrightarrow{x_k}$ is an element within a cluster. Δ is called the merging cost of combining the cluster C_i and C_j. The number of clusters is selected as five based on the dendrogram and considering balanced cluster size. To provide a more comprehensive depiction of the characteristics within each city group, we collect and analyze socioeconomic attributes for 152 cities from the Korean Statistical Information Service (KOSIS), including population and population density, Regional Gross Domestic Product, population proportion in prime working age (25–54), and elderly population proportion (over 65).

Statistical analysis is applied to assess the significance of differences in input variables and socioeconomic attributes among the clustered groups. A one-way Welch's ANOVA test determines whether differences across clusters are statistically significant. Subsequent post-hoc testing using the Games-Howell method analyzes specific pairwise differences where significant disparities exist.

5. Analysis results

5.1. Factors influencing spending behavior: social distancing and search interest

The results of the estimated coefficients for the social distancing policy and relative search volume on overall transactions and expenditure for residents and travelers are shown in Fig. 2. As illustrated in Fig. 2(a), the implementation of the enhanced social distancing policy generally caused a suppressive effect on both residents and travelers. For resident transactions, the coefficients were significant across nearly all cities, indicating that the social distancing policy had a statistically significant impact on most study areas. The median effect on resident transactions is −1.72 %, signifying that throughout the research period, the implementation of the enhanced social distancing policy by the Korean government led to a median reduction of 1.72 % in the transaction frequency of residents. For travelers, this figure stands at −2.49 %, indicating a more pronounced impact on the transaction frequency of travelers due to the enhanced social distancing policy. Regarding expenditure, the median impact on the resident group is −4.34 %, while for the traveler group, it is −3.02 %. This suggests that resident expenditure was more substantially affected by social distancing measures compared to traveler expenditure.

In terms of search interest, the relationship between consumer spending and the search interest in "Coronavirus" varied significantly between the two consumer groups. Search interest had a stimulative effect on both transactions and expenditure for residents. With a 7-day time lag applied to the residents' relative search volume, the median increases of 0.16 % in transactions and 0.45 % in expenditure indicate that an increase in search interest by one unit results in a 0.16 % and 0.45 % increase in transaction frequency and expenditure, respectively, after seven days. In contrast, for travelers, an increase in search interest led to a reduction in spending, with the median effects on transactions and expenditure being −0.09 % and − 0.07 %, respectively. Considering the 4-day time lag for travelers, these results imply that an increase in search interest by one unit results in a 0.09 % and 0.07 % decrease in transaction frequency and expenditure, respectively, four days later.

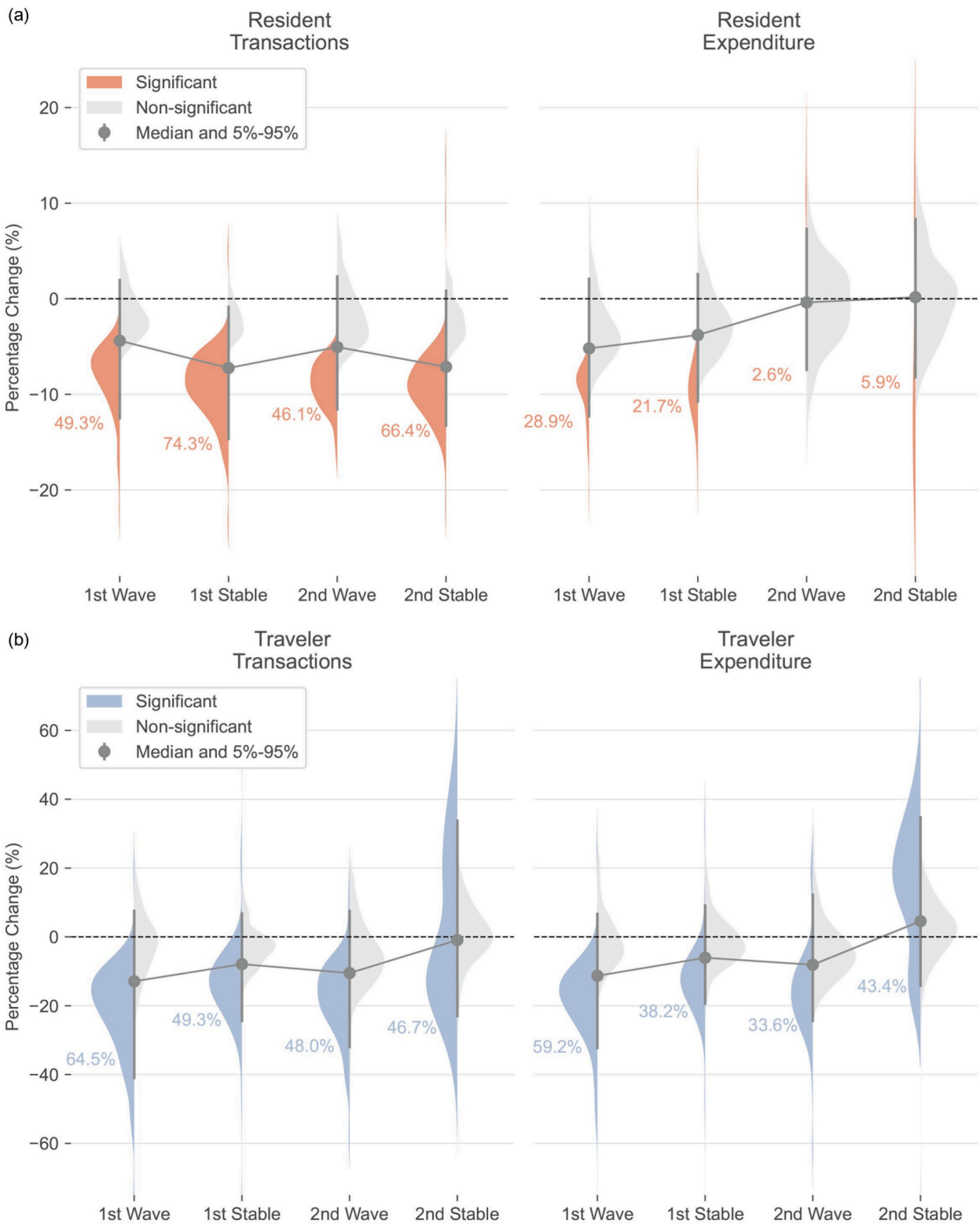

Fig. 3. Changes of overall spending. (a) Resident transactions and expenditure; (b) Traveler transactions and expenditure. The numbers in orange (a) or blue (b) are the percentage of cities with significant coefficients within 95 % confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.2. Changes of overall spending during pandemic stages: Residents and travelers

The percentage changes of overall transactions and expenditure of residents (Fig. 3(a)) and travelers (Fig. 3(b)) show that the pandemic had varying impacts on the spending of both groups. During the initial stages of the outbreak, there was a noticeable difference in the magnitude of spending changes between travelers and residents, with travelers experiencing a significantly greater decline in spending. Specifically, in the first outbreak wave, resident transactions decreased by a mean of

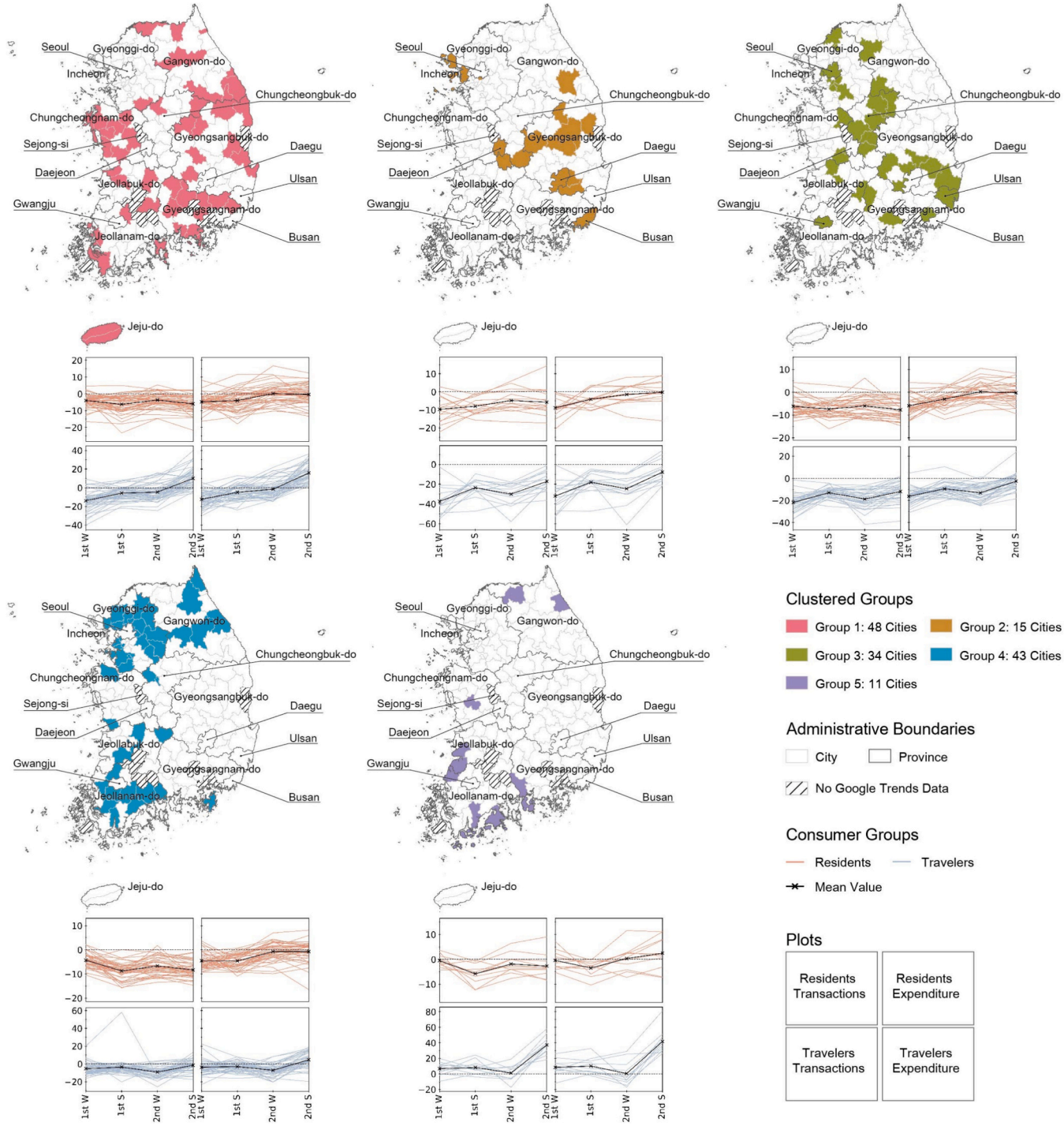

Fig. 4. Clustering results and corresponding spending changes across four pandemic stages.

4.89 %, while traveler transactions faced an average decline of 14.16 %. In general, the impact of the pandemic on travelers' spending was approximately three times compared to its impact on residents' spending.

The percentage changes across four stages show that the pandemic had a more significant impact on travelers' spending, while a moderate but persistent effect on residents' spending. During the two outbreak waves of the pandemic, travelers experienced more substantial decreases in their spending. In contrast, during both stable periods, travelers' spending had a relatively smaller decline. Notably, in the second stable period, travelers' expenditure in over half of the cities recovered to and even exceeded the pre-pandemic level. Conversely, residents' transactions experienced a smaller decline during the two outbreak waves compared to the two stable periods. These findings imply that high uncertainty and risk faced by travelers during the outbreak waves may significantly influence the decision-making process regarding travel plans.

Furthermore, the changes in travelers' transactions and expenditure show a similar trend. In contrast, the impact on residents' transactions was more pronounced compared to that on expenditure. As shown in

Table 3
Descriptive statistics of city clusters.

		Group 1	Group 2	Group 3	Group 4	Group 5	National Average
Number of Cities		48	15	34	43	11	
Mean of Input Variables, %							
Resident Transactions	1st Wave	−4.00	−9.71	−6.18	−4.28	−0.54	−4.89
	1st Stable	−6.31	−8.01	−7.44	−8.78	−5.82	−7.40
	2nd Wave	−3.74	−4.82	−6.00	−6.71	−1.89	−5.07
	2nd Stable	−6.01	−5.75	−7.77	−8.32	−2.72	−6.80
Resident Expenditure	1st Wave	−4.84	−8.88	−5.96	−4.55	−0.43	−5.09
	1st Stable	−4.03	−4.11	−3.03	−4.65	−3.50	−3.95
	2nd Wave	0.08	−1.49	0.19	−0.75	0.33	−0.27
	2nd Stable	−0.48	0.24	−0.25	−0.74	2.46	−0.26
Traveler Transactions	1st Wave	−13.99	−37.53	−21.85	−5.45	6.65	−14.16
	1st Stable	−5.91	−23.67	−13.01	−3.66	8.18	−7.61
	2nd Wave	−4.74	−30.11	−18.75	−9.27	1.13	−11.28
	2nd Stable	9.97	−17.33	−11.99	−1.62	37.11	0.99
Traveler Expenditure	1st Wave	−12.43	−32.12	−16.31	−3.87	8.36	−11.31
	1st Stable	−5.03	−18.13	−9.47	−3.10	9.95	−5.69
	2nd Wave	−1.63	−24.68	−13.09	−7.28	0.44	−7.96
	2nd Stable	15.78	−7.94	−2.64	4.62	41.71	7.99
Mean of Socioeconomic Variables							
Population		121,761	748,121	663,124	234,948	44,670	332,495
Population Density		305.07	1040.94	2294.13	1388.03	83.11	1118.26
Area, km^2		680.82	832.55	581.73	535.95	585.12	625.36
Age Group 25–54, %		36.63 (5.32)	37.03 (7.11)	40.91 (6.52)	41.28 (6.71)	31.53 (3.44)	38.58 (6.69)
Age Group over 65, %		24.41 (6.93)	24.51 (9.10)	19.44 (8.09)	19.27 (8.19)	31.85 (4.76)	22.38 (8.40)
GDP, million		5,362,858	21,075,870	26,115,650	9,104,533	1,418,238	12,374,720

Note: Mean values are shown with the standard deviation in parentheses. Statistically significant differences between groups are based on Welch's ANOVA and Games-Howell post-hoc test (results are shown in Tables A.1 and A.2).

Fig. 3(a), residents' transactions showed a decline of around 5 % across four stages, while the percentage change in residents' expenditure experienced an average decline of 5 % during the first wave, then gradually increased in the next three stages to a pre-pandemic level. This finding suggests that residents tended to maintain their daily demands during the pandemic.

5.3. Geographical disparities: cities with distinctive patterns

Based on the overall spending changes during the four stages of the pandemic, the cities are classified into five groups using a hierarchical agglomerative clustering method, as detailed in Section 4.2. Fig. 4 illustrates the clustering results and the corresponding spending changes across the four stages. Table 3 presents the descriptive statistics of the input variables for the hierarchical agglomerative clustering method and the socioeconomic variables for each group, revealing distinct characteristics based on spending dynamics across the pandemic stages. Statistically significant differences among groups are identified based on Welch's ANOVA and Games-Howell post-hoc test, and the results are shown in Tables A.1 and A.2.

We classify the 152 cities into five groups. Group 1 includes 48 cities spread across all provinces of South Korea, excluding the six metropolitan cities, Seoul and Gyeonggi Province. Residents in this group exhibited consumer spending trends similar to those depicted in Fig. 3 (a), with changes aligning closely with the national average. Despite significant initial impacts on travelers' spending during the first wave of the pandemic, this group experienced sustained recovery across all four stages, unaffected by the second wave. Moreover, their travelers' spending surpassed pre-pandemic levels during the second stable period. This group has a relatively low population density (305 people/km^2). These findings suggest that this group became increasingly attractive to travelers compared to pre-pandemic levels, possibly due to lower population density.

Even though Group 2 only includes 15 cities, it covers most metropolitan cities in South Korea, such as Daegu, Incheon, Busan, Daejeon, and some cities in Gyeongsangbuk-do. This group experienced the largest decline in spending during the first wave, which is due to Daegu and part of Gyeongsangbuk-do being the epicenter of South Korea's first wave of the pandemic. For instance, transactions by residents in this group decreased by 9.71 %, while travelers' spending declined by 37.53 % during the first wave. Despite gradual recovery across the four stages, travelers' spending remained below pre-pandemic levels during the second stable period. The significant impact can be attributed to a significant economic impact and reduced activity intensity during the early stages of the COVID-19 outbreak in the epicenter.

Group 3 includes Seoul, Ulsan, and cities along the connecting line between them. Similar to Group 2, travelers' spending in this group was severely affected and failed to recover to pre-pandemic levels during the second stable period. Additionally, residents in this group experienced greater impacts than the national average on consumer spending, likely due to Seoul being the epicenter of South Korea's second wave of the pandemic. Seoul, as the political and economic center of South Korea, has high population mobility, which is leading to pronounced economic impacts during outbreaks. This dynamic made the city more susceptible to pronounced economic impacts during the outbreak. Furthermore, cities along the Seoul-Ulsan corridor also coincide with South Korea's Gyeongbu High-Speed Railway line, where reduced travel numbers during the pandemic likely contributed to decreased travelers' spending. The highest population density (2294.13 people/km^2) and high percentage of working-age populations (40.91 %) in these areas may have heightened awareness of infection risks, further deterring consumer spending.

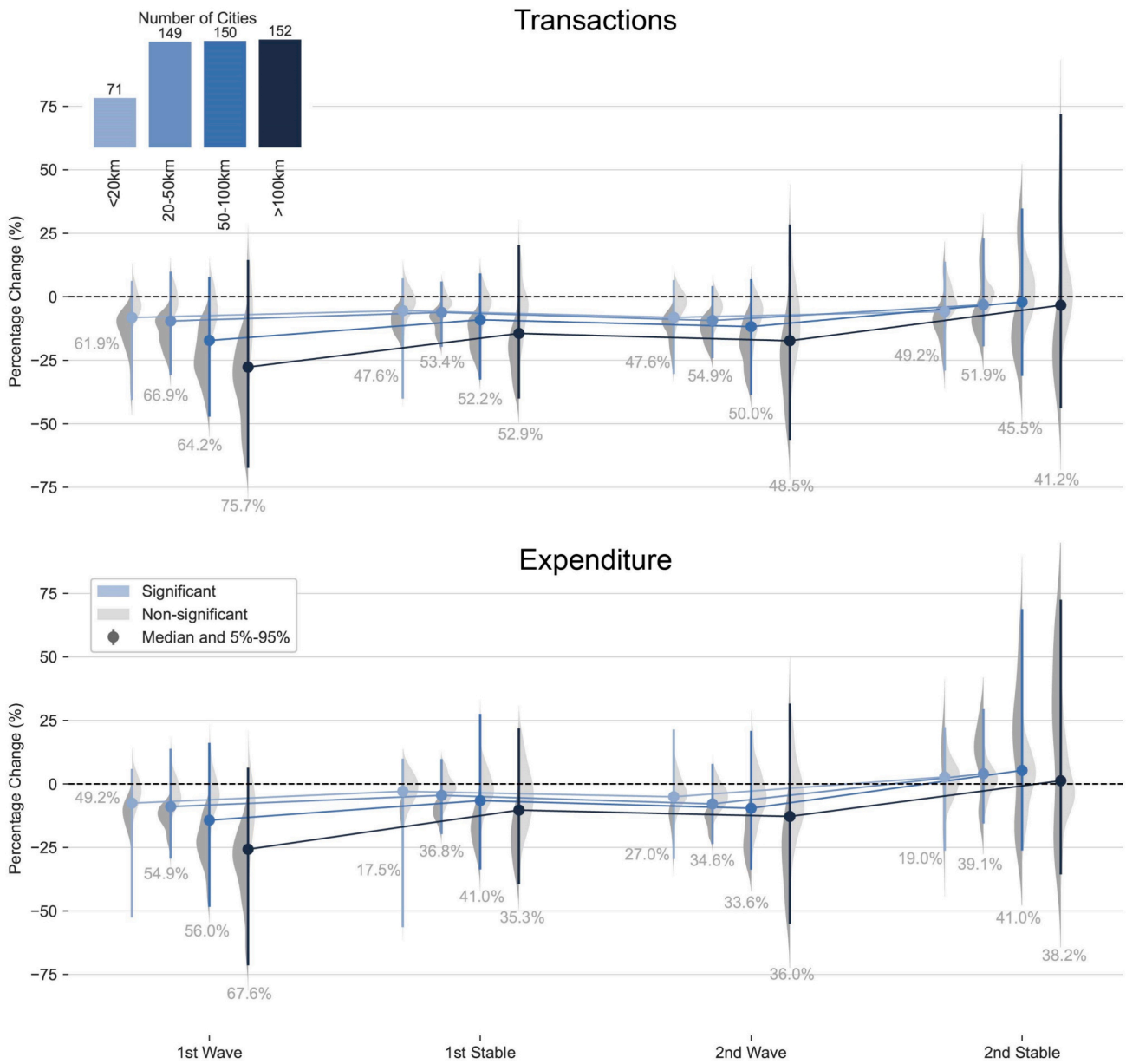

Fig. 5. Changes of travelers' spending by distance groups. The numbers in gray indicate the percentage of cities with statistically significant coefficients within 95 % confidence intervals. Outliers, representing the top and bottom 5 % of cities, have been excluded from this figure. The bar chart displays the number of cities within each distance interval after removing the outliers.

Group 4 includes most cities in Gyeonggi Province, southwestern South Korea, and some cities in the northeastern region. Residents in this group experienced consumer spending changes similar to those in Group 3, with impacts greater than the national average. However, travelers' spending of this group was minimally affected. This resilience could be attributed to the highest percentage of working-age populations, particularly in cities surrounding Seoul in Gyeonggi Province. These areas typically serve as regions that supply travelers to Seoul rather than receive them. Therefore, travelers' spending in these areas remained relatively stable during the pandemic.

Group 5 comprises a few cities scattered across the southwestern and northeastern regions of South Korea. Cities in this group experienced the smallest declines in consumer spending, with traveler transactions and expenditure showing minimal impacts or even significant growth during the second stable period. This outcome may be attributed to extremely low population densities, the smallest proportion of working-age populations, and the highest proportion of elderly populations. These factors likely contributed to stable consumer demand and restricted mobility during the pandemic. The low population density and high proportion of elderly residents may have resulted in less frequent travel and reduced economic disruption, allowing these areas to maintain their economic activity during the pandemic.

5.4. Distance effect of travelers' spending behavior

As shown in Fig. 5, the percentage changes in transactions and expenditure of travelers from four different distance groups are compared. By using Welch's ANOVA and Games-Howell post-hoc test, statistically significant differences between distance groups are identified and the results are shown in Tables A.3, A.4, A.5, and A.6.

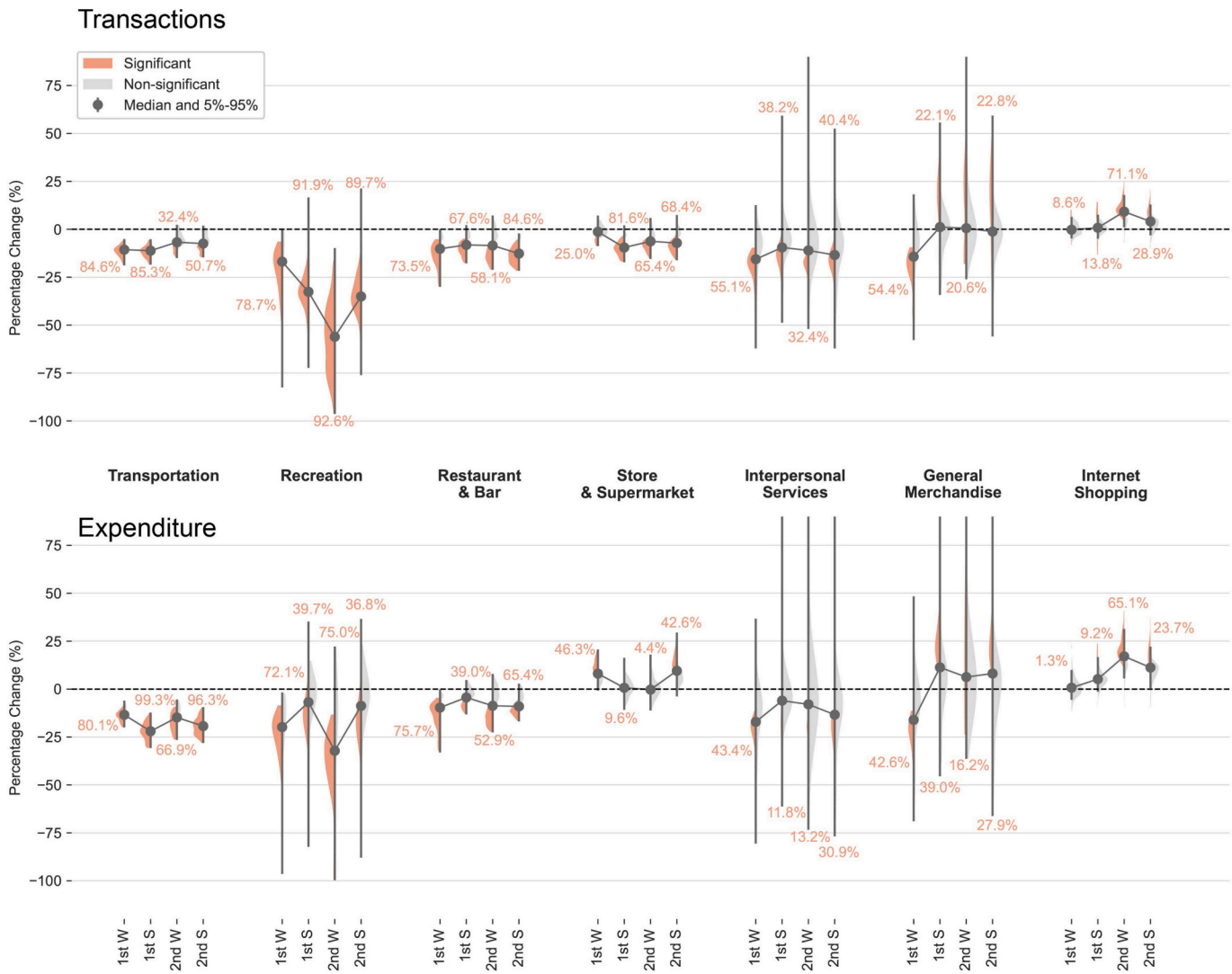

Fig. 6. Changes of residents' spending across spending categories. The numbers in orange indicate the percentage of cities with statistically significant coefficients within 95 % confidence intervals. Outliers, representing the top and bottom 5 % of cities, have been excluded from this figure.

During the first wave of the pandemic, the changes in spending were more pronounced for spending of travelers from farther areas compared to those from closer regions, indicating a more severe impact on long-distance consumer activity. Spending originating from travelers over 100 km away experienced the most significant impact, with the median changes exceeding −25 % in both transactions and expenditure. Similarly, travelers' spending from the 50–100 km range also faced substantial declines, with the median changes around −15 % in transactions and expenditure. In contrast, travelers' spending within 20 km and from the 20–50 km range experienced relatively milder effects, with median reductions not exceeding 10 % in both transactions and expenditure. These findings suggest that during the outbreak of the pandemic, there was a preference for shorter-distance travel, with spending from farther areas being significantly reduced.

However, this pattern was primarily evident during the initial three stages of the pandemic. As the pandemic evolved, the disparities in spending changes from different distance ranges gradually diminished. By the end of the second stable period, the percentage changes in spending from different distances became relatively similar. This finding highlights the significant recovery ability of travelers' spending from farther areas.

Furthermore, the trends exhibited by travelers' spending changes from different distance ranges across the four stages are consistent with the trend of travelers' overall spending changes (as shown in Fig. 3(b)). During the second stable period, the median percentage changes in transactions and expenditure for all distances were near or exceeded zero, indicating that spending in nearly half of the cities had already recovered compared to pre-pandemic levels in 2019.

5.5. *Heterogeneous effects of the pandemic on different spending categories*

By comparing the percentage changes in transactions and expenditure across spending categories mentioned in Section 3.4, we find that the impact of the COVID-19 pandemic across categories shows significant heterogeneity for both residents and travelers.

For residents, as shown in Fig. 6, expenditure on essential and storable goods (e.g., stores and supermarkets) increased, despite a decline in transactions observed throughout the research period. Meanwhile, both transactions and expenditure on essential but non-storable goods experienced a slight decrease and remained relatively stable across the four stages, including categories such as transportation and restaurant and

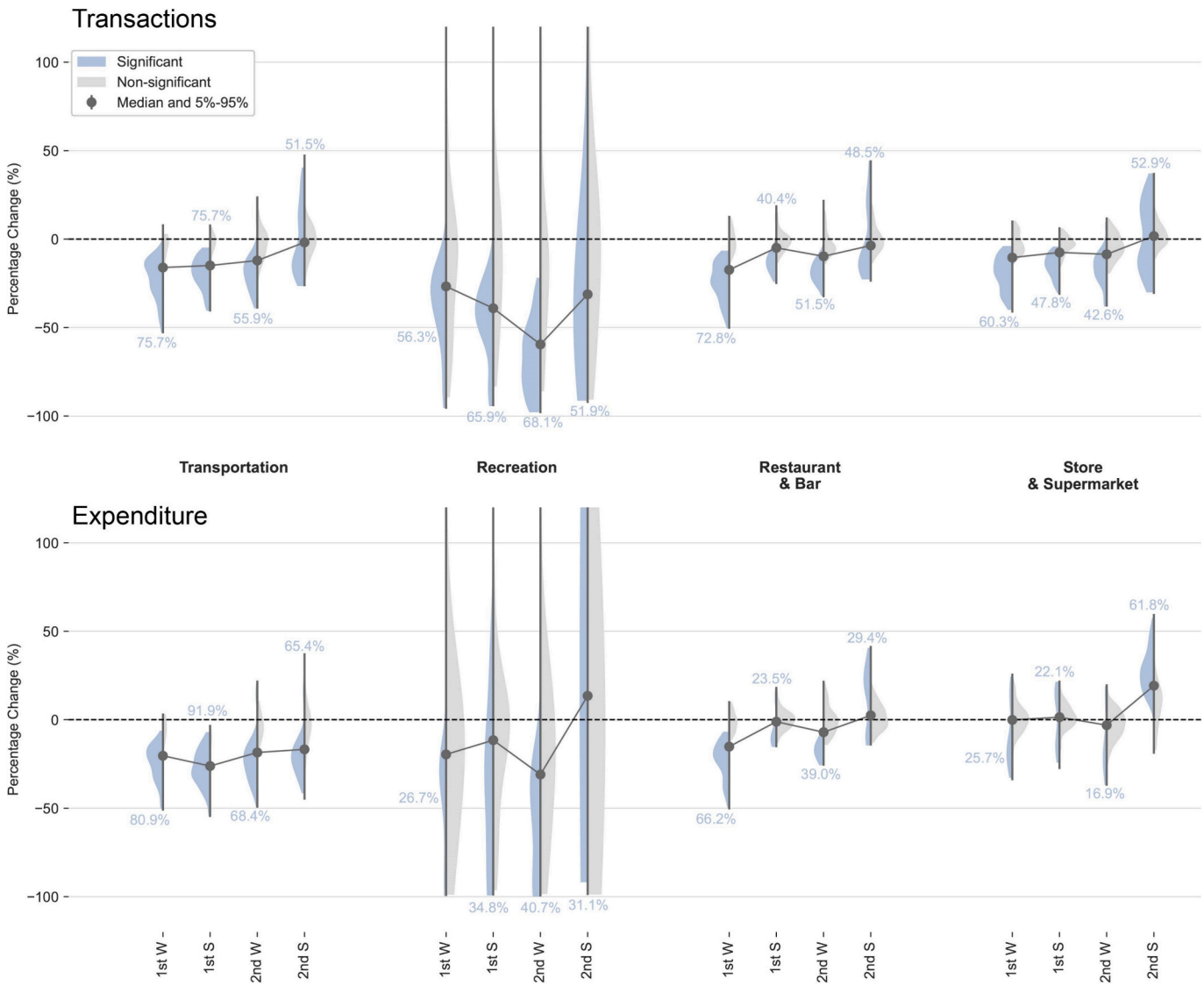

Fig. 7. Changes of travelers' spending across spending categories. The numbers in blue indicate the percentage of cities with statistically significant coefficients within 95 % confidence intervals. Outliers, representing the top and bottom 5 % of cities, have been excluded from this figure. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

bar. In contrast, spending on non-essential goods, particularly in the recreation category, was most severely affected during the pandemic, especially during the second wave when the outbreak spread more widely across the whole country, with the median change in transactions below −50 %.

Interpersonal services also faced significant effects during the pandemic, especially during the first wave of the outbreak. The impact on this category highlighted the challenges faced by service-based businesses that heavily rely on interpersonal interactions. Besides, although the coefficients for general merchandise are non-significant in most cities, there was a notable increase during the first stable period, suggesting a certain impact during the first wave of the pandemic.

Moreover, the pandemic accelerated the trend towards online shopping. The percentage changes in both transactions and expenditure, compared to the corresponding period in 2019, exhibited a significant growth trend, particularly during the second wave of the pandemic. Notably, all cities across the entire country showed significant increases during this period, which was contrasted with the trends observed in all other categories. This trend may indicate that consumers showed a greater inclination to avoid shopping in physical stores and minimize their exposure to the virus by embracing online shopping.

From a nationwide perspective, there was little difference among cities in the impact of COVID-19 on four categories, i.e., transportation, restaurant and bar, store and supermarket, and internet shopping. This finding implies that these categories experienced a relatively uniform effect across cities, regardless of the outbreak center or the extent of the pandemic. However, there were significant differences among cities in the impact on three other categories, i.e., recreation, interpersonal services, and general merchandise. For instance, during the first wave of the pandemic, the percentage change in transactions for recreation exhibited a median value of approximately −20 %, with a minimum value approaching −75 % and a maximum value around 0 %.

For travelers, as shown in Fig. 7, the trends showed across the analyzed categories were similar to dynamics of overall spending (as shown in Fig. 3(b)) except for recreation, which experienced a more significant decline during the second wave of the pandemic. Similar to residents, the difference in percentage changes among cities in recreation was much more significant compared to the other three categories. This difference among cities may be related to the functional characteristics of cities, such as tourism cities being more severely impacted.

Moreover, similar to residents, the travelers' expenditure on essential and storable goods, namely, stores and supermarkets, did not experience as significant a decline as transactions, indicating a reduction in the frequency of consumption rather than in demand. However, unlike residents, the trends in transactions and expenditure for stores and supermarkets were similar among travelers, suggesting that travelers did not show the same stockpiling behavior observed in residents' spending changes. In addition, spending on essential but non-storable goods, namely, transportation and restaurants and bars, was less affected by the pandemic compared to the non-essential category, i.e., recreation.

6. Discussion and conclusion

This study analyzes the impact of the COVID-19 pandemic on spending activity and the economy across all cities in a country that did not implement lockdown strategies. The pandemic-related impacts at different stages were efficiently estimated by controlling the implementation of social distancing policy, search interest in "Coronavirus", and seasonal effects. The research is conducted from multiple perspectives, comparing the differences among residents and travelers, the geographical disparities among cities, the differences among travelers' spending across distances, and the differences across spending categories.

6.1. Consumer reactions

Our results show that the enhanced social distancing policy significantly impacted both residents and travelers, with travelers experiencing a larger reduction in transactions, while residents saw a more pronounced decrease in expenditure. This reflects the different ways in which each group responded to government-imposed measures. For residents, the reduction in transactions likely resulted from government recommendations to avoid group activities, close religious institutions, indoor sports, and entertainment facilities, and encourage staying at home. These measures disrupted regular spending activities such as dining out, shopping and attending entertainment venues. However, residents' overall expenditure was more significantly affected, possibly due to a substantial decrease in non-essential spending. Residents might still engage in essential spending (e.g., groceries, healthcare) but reduce non-essential spending due to limited access to non-essential services and heightened safety concerns under social distancing implementation.

Travelers, on the other hand, experienced a larger reduction in transactions. This could be attributed to the general hesitancy to travel during the pandemic. Enhanced social distancing policies likely led to a decline in traveler arrivals and discouraged those already traveling from frequenting public spaces and businesses. Since travelers' transactions are often related to dining out, tourism, leisure, and experiences, which were heavily restricted by social distancing policies, their overall transaction frequency dropped more significantly. However, travelers' expenditure was less affected compared to residents, potentially because those who did travel continued to spend on necessary services (e.g., restaurants, accommodations, transport) even less frequently.

The search interest in "Coronavirus" reflects proactive information-seeking behavior indicative of public concern and attention, serving as a measure of the severity of the pandemic. The findings suggest that the increase in search interest coincided with a rise in residents' spending but a decline in travelers' spending. The positive relationship between search interest in "Coronavirus" and resident transactions and expenditures suggests that increased awareness and information-seeking behavior may prompt residents to engage in preventive spending. This could include stockpiling essential goods, purchasing health-related products, or adapting to new consumption patterns such as online shopping. For travelers, the negative relationship between search interest and consumption patterns may reflect a heightened sense of risk and uncertainty associated with travel during the pandemic. Increased search interest in "Coronavirus" could correlate with rising concerns about health and safety, leading to reduce their spending, cancel travel plans, and avoid crowded places. The uncertainty and potential health risks discourage spending more severely for travelers than for residents who are adapting to a prolonged stay in a relatively familiar environment.

Furthermore, different optimal time lags are found for the two groups. The 7-day time lag in the effect of search interest on residents' transactions and expenditures suggests a more gradual adjustment period where residents respond to evolving information over time. The shorter time lag for travelers indicates a quicker response to changes in perceived risk levels, aligning with their temporary stay in cities and their need to make prompt decisions about travel and spending.

6.2. Pandemic-induced spending shifts

After we control the effects of seasons, policies, and people's interest in "Coronavirus", the changes in spending reveal the fundamental impacts of the pandemic on consumer behavior and economic structures. These changes represent long-term intrinsic shifts in spending patterns that are not directly influenced by short-term external factors. They signify adjustments in consumer priorities and habits brought about by the pandemic itself, independent of government interventions or heightened awareness.

The overall spending changes show that both residents and travelers changed their behavior according to the outbreak. Notably, our findings show that both consumer groups experienced significant reductions in spending during the early stages of the pandemic, with an average reduction of around 5 % for residents and 14 % for travelers during the first wave. Compared to travelers, the impact of the pandemic on residents was more moderate and stable in the long term. The difference in trends exhibited between resident transactions and expenditure across four stages suggests the tendency of residents to maintain their daily demand and the presence of stockpiling behavior under the context of the pandemic. Irrational stockpiling behavior could have immediate and long-term impacts on the economy, society, and local communities (Chen et al., 2020). Residents' more stable spending patterns indicate their ability to adapt and respond to changing circumstances with relatively less disruption to their daily lives. They benefit from timely information and are able to adjust their behavior quickly. In contrast, travelers face higher uncertainty and risk, including the possibility of sudden travel restrictions, unpredictable developments of the pandemic, and the risk of infection. This heightened uncertainty leads to more severe spending reductions among travelers, particularly during the initial stages of the pandemic. Such impacts are particularly significant for cities that rely heavily on tourism, as reduced travelers' spending can hinder economic recovery. The differences in the impact on spending between travelers and residents underscore the unique challenges faced by these two consumer groups during a pandemic. These findings emphasize the need for targeted interventions to support both groups

effectively.

The disparities in overall spending changes across cities suggest that policymakers and businesses should tailor their interventions and strategies based on the specific characteristics and consumption demands of different cities. Our analysis reveals that the impact on spending was closely related to the proximity of cities to the epicenter of the outbreak. Cities that were close to the epicenter of the outbreak, such as Group 2 and Group 3, experienced a greater impact on their spending. This can be attributed to the heightened infection risks impacting spending habits. Socioeconomic characteristics also play a significant role in shaping spending patterns across cities. Cities with lower population densities, such as Group 1 and Group 5, demonstrated less impact and greater resilience. Residents and attracted travelers in these cities likely perceived lower infection risks and were better adapted to social distancing measures, leading to relatively smaller declines in spending compared to higher-density cities. The larger decline observed in cities with higher population densities (Group 2 and Group 3) can also be attributed to their greater exposure to the virus and higher infection risks. Our finding suggests that the cities with lower population density, such as Group 1 and Group 5, became preferred destinations for travelers seeking safer environments during the pandemic. This highlights the potential for tourism and related industries in less densely populated cities in the post-pandemic era. These cities can seize the opportunity to attract travelers by implementing targeted measures aimed at enhancing their tourism offerings.

Our findings also reveal that spending by travelers from distant cities experienced more pronounced reductions early in the pandemic but exhibited recovery towards the latter stages of our research periods. This finding underscores travelers' tendency to limit their spending to certain distances when they were concerned about health risks during the pandemic. Moreover, it highlights the evolving pattern of how the pandemic influenced travelers' spending behaviors, reflecting their adaptation to the presence of the new virus and the ability to adjust travel behaviors in response to the pandemic. This indicates travelers' ability to navigate the challenges posed by the pandemic, despite the initial severity of its impact.

The heterogeneity observed in the impact of the pandemic on spending categories for both residents and travelers suggests the necessity for targeted interventions tailored to specific categories, considering their unique characteristics. For example, residents exhibited increased demand for essential and storable goods, suggesting preventive shopping driven by heightened pandemic awareness. Recreation-related industries faced substantial declines due to restrictions on social gatherings and leisure activities. These findings emphasize the importance of implementing differentiated support programs during and post-pandemic to sustain essential goods supply chains and revive the hardest-hit sectors. Furthermore, the trend towards online shopping highlighted in our study challenges traditional brick-and-mortar stores, prompting structural changes in the industrial structure. Businesses must adapt swiftly to these changes by enhancing their digitization and logistics capabilities to meet evolving consumer preferences and mitigate disruptions in supply chains. Additionally, spending changes can also influence workforce management and pricing strategies. For instance, reduced spending on recreation and interpersonal services may lead to decreased employment rates and prices within these industries, which requires managers to make proactive adjustments to operational strategies (Felix et al., 2020; Mendez-Carbajo, 2021).

6.3. Policy implications

This study offers insights into the differential impacts of the pandemic across various perspectives. The findings provide essential policy guidance for policymakers and governments to develop targeted support measures that address specific challenges and promote economic recovery. By leveraging these insights, policymakers can effectively handle the post-pandemic era and prepare for future potential health risks.

Interventions should be tailored to the specific needs of residents and travelers, taking into account the different challenges they face during and after the pandemic. For residents, governments can raise public awareness through social media, ensuring clear communication on health protocols to help control the pandemic and economic support measures to stimulate spending. Governments can support economic activities and small businesses by stimulating spending through offering subsidies and tax breaks for essential goods and services. Besides, encouraging online shopping and facilitating digital infrastructure upgrades can also help residents adapt to new spending patterns.

For travelers, it is important to restore confidence in the safety of travel. Governments should reassure travelers by enforcing strict health and safety standards in areas and transport hubs that attract tourists. Providing financial incentives, such as travel subsidies and discounts on accommodation, can encourage travel. Flexible cancellation policies are another important way to reduce the financial risks associated with travel interruptions due to possible health risks posed by pandemics.

To support economic recovery across different spending categories, targeted interventions should prioritize industries that were most affected by the pandemic. Industries related to essential goods should be supported to meet increased demand, including by encouraging production and distribution. For the most affected recreation-related industries, targeted financial aid and support programs can help them survive. Besides, it is important to build long-term economic resilience strategies for cities, which should focus on developing diverse local economies beyond tourism. In addition, cities relying heavily on recreation-related industries should enhance destination attractiveness and economic sustainability and reduce dependency on traditional industries.

6.4. Limitations and future work

This study provides a significant contribution to understanding the impact of social distancing policies and search interest, as well as the changes in consumer spending across different population groups and spending categories during the pandemic. These findings have practical implications for future policymaking by governments and relevant decision-making institutions as we discussed above.

However, the study has several limitations. First, due to the lack of city-level COVID-19 daily new cases data, we use search interest as a proxy for the severity of the pandemic. While search interest has been found in some studies to be highly correlated with new cases and useful for predicting outbreak peaks, most of these studies were conducted within the first four months of the pandemic (Effenberger et al., 2020; Husnayain et al., 2020; Husnayain et al., 2021; Strzelecki, 2020). As a subjective information-seeking behavior, it tends to peak when a new virus emerges, as seen in Fig. 1(b), where Korea's search volume for "Coronavirus" peaked during the first wave. Over time, as public awareness of COVID-19 increased, the ability of search interest to represent the severity of the pandemic and public concern likely diminished. Thus, using search interest to measure the severity of the pandemic has limitations. We use limited daily new cases from six metropolitan cities and one special city in place of search interest in our models and find differences in the results, as shown in Appendices Section B. The results indicate that search interest cannot fully substitute for daily new cases to represent the severity of the pandemic. However,

incorporating search interest into the model allows us to control the severity of the pandemic to a certain extent, thereby reducing the confounding effects during the estimation process.

Additionally, we use national-level implementation dates for enhanced social distancing policies. In practice, different cities may have variations in policy implementation. For example, Seoul, as the epicenter of the second wave, implemented an enhanced Level 2 social distancing policy from August 30 to September 13, within the national Level 2 period from August 23 to October 11. These variations could impact our results. However, due to the large scale of our study involving 152 cities, collecting detailed policy implementation specifics for each city was not feasible. These city-specific policy factors, therefore, are not considered in our current models.

Except for social distancing measures, South Korea implemented a stimulus payment scheme during the pandemic to restore the economy. In future research, it would be valuable to evaluate the outcomes and impact of these stimulus policies, which would provide insights into their effectiveness in mitigating the economic impact of the pandemic. Future work may also focus on investigating the post-pandemic consumer spending behavior, specifically whether consumers will revert to pre-pandemic consumption patterns and levels or maintain their current behavior. Some studies suggest that consumers may have adapted to new spending behaviors, forming a specific "COVID-19 generation" (Roggeveen and Sethuraman, 2020; Zwanka and Buff, 2021). Further research is needed to provide empirical evidence to support these claims. Subsequent research in this area could help governments better support businesses and consumers in the post-pandemic economy.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT3.5 in order to check the grammar and improve its clarity and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Mengqi Sun: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Yang Xu:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Data curation, Conceptualization. **Chen Zhong:** Writing – review & editing. **Mengyao Ren:** Writing – review & editing. **Sangwon Park:** Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgements

The authors would like to thank the editor and anonymous reviewers for their valuable comments that improved this article. This research was partly supported by the National Natural Science Foundation of China (Grant No. 42171454) and Hong Kong Polytechnic University Research Grant (Grant No. 4-ZZNC).

Appendix A. Results of Welch's ANOVA and Games-Howell post-hoc tes

Table A.1
Welch's ANOVA for city groups.

		F-statistics	*p*-value
Input Variables			
Resident Transactions	1st Wave	11.45	0.000***
	1st Stable	3.65	0.012*
	2nd Wave	6.11	0.001**
	2nd Stable	5.63	0.001**
Resident Expenditure	1st Wave	5.90	0.001**
	1st Stable	3.03	0.028*
	2nd Wave	0.23	0.918
	2nd Stable	0.61	0.659
Traveler Transactions	1st Wave	67.06	0.000***
	1st Stable	45.31	0.000***
	2nd Wave	28.72	0.000***
	2nd Stable	66.17	0.000***
Traveler Expenditure	1st Wave	45.38	0.000***
	1st Stable	22.30	0.000***
	2nd Wave	16.86	0.000***
	2nd Stable	70.25	0.000***
Socioeconomic Variables			
Population		16.02	0.000***
Population Density		9.76	0.000***
Area, km^2		3.39	0.016*
Age Group 25–54, %		21.87	0.000***
Age Group over 65, %		25.12	0.000***
GDP, million		16.15	0.000***

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A.2
Games-Howell post-hoc test for city groups.

Pair of Groups		1–2	1–3	1–4	1–5	2–3	2–4	2–5	3–4	3–5	4–5
Input Variables											
Resident Transactions	1st Wave	0.034*	0.002**	0.725	0.021*	0.487	0.073	0.002**	0.043*	0.000***	0.004**
	1st Stable	0.596	0.249	0.006**	1.000	1.000	0.944	0.723	0.443	0.623	0.187
	2nd Wave	0.885	0.041*	0.000***	0.988	0.962	0.796	0.794	0.945	0.104	0.023*
	2nd Stable	0.852	0.163	0.009**	0.543	0.995	0.935	0.322	0.967	0.030*	0.009**
Resident Expenditure	1st Wave	0.217	0.456	1.000	0.024*	0.758	0.184	0.002**	0.349	0.003**	0.028*
	1st Stable	0.488	0.730	0.969	0.993	0.025*	0.633	0.315	0.088	0.961	0.808
	2nd Wave	0.936	1.000	0.999	0.995	0.898	0.966	0.995	0.988	0.985	1.000
	2nd Stable	0.889	1.000	0.997	0.654	0.933	0.936	0.962	1.000	0.707	0.710
Traveler Transactions	1st Wave	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.004**
	1st Stable	0.000***	0.000***	0.839	0.124	0.002**	0.001**	0.000***	0.000***	0.000***	0.004**
	2nd Wave	0.000***	0.000***	0.199	0.281	0.008**	0.000***	0.000***	0.000***	0.000***	0.049*
	2nd Stable	0.000***	0.000***	0.000***	0.000***	0.226	0.000***	0.000***	0.000***	0.000***	0.000***
Traveler Expenditure	1st Wave	0.001**	0.045*	0.000***	0.000***	0.007**	0.000***	0.000***	0.000***	0.000***	0.001**
	1st Stable	0.000***	0.006**	0.479	0.005**	0.062	0.000***	0.000***	0.000***	0.001**	0.016*
	2nd Wave	0.000***	0.000***	0.020*	0.983	0.037*	0.000***	0.005**	0.006**	0.101	0.523
	2nd Stable	0.000***	0.000***	0.000***	0.000***	0.583	0.003**	0.000***	0.000***	0.000***	0.000***
Socioeconomic Variables											
Population		0.815	0.001**	0.001**	0.002**	0.657	1.000	0.679	0.082	0.000***	0.000***
Population Density		0.193	0.035*	0.111	0.014*	0.916	0.537	0.131	0.677	0.010*	0.013*
Area, km^2		0.475	0.832	0.047*	0.805	0.212	0.031*	0.201	0.705	1.000	0.605
Age Group 25–54, %		1.000	0.020*	0.004**	0.000***	0.392	0.287	0.039*	0.999	0.000***	0.000***
Age Group over 65, %		1.000	0.039*	0.016*	0.000***	0.365	0.312	0.049*	1.000	0.000***	0.000***
GDP, million		0.552	0.003**	0.001**	0.001**	1.000	0.946	0.450	0.344	0.001**	0.000***

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$
a. The pair of groups: e.g., '1–2' means the comparison between Group 1 and Group 2
b. Numbers indicate *p*-values.

Table A.3
Welch's ANOVA for travelers' transactions from different distance groups.

Stages	F-Statistics	*p*-value
1st Wave	41.705	0.000***
1st Stable	13.825	0.000***
2nd Wave	11.234	0.000***
2nd Stable	1.330	0.265

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A.4
Games-Howell post-hoc test for travelers' transactions from different distance groups.

Pair of Groups / Stages	1–2	1–3	1–4	2–3	2–4	3–4
1st Wave	1.17	8.33	19.81	7.16	18.64	11.48
	(0.817)	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)
1st Stable	0.68	4.43	7.96	3.75	7.29	3.54
	(0.906)	(0.003**)	(0.000***)	(0.002**)	(0.000***)	(0.103)
2nd Wave	2.56	5.92	9.35	3.36	6.79	3.42
	(0.113)	(0.000***)	(0.000***)	(0.019*)	(0.002**)	(0.305)
2nd Stable	−1.51	−3.27	0.54	−1.75	2.05	3.80
	(0.707)	(0.305)	(0.995)	(0.739)	(0.755)	(0.393)

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.
a. The pair of groups: e.g., '1–2' means the comparison between Group 1 and Group 2.
b. Numbers outside parentheses indicate differences between the two groups, and numbers inside parentheses indicate *p*-values.

Table A.5
Welch's ANOVA for travelers' expenditure from different distance groups.

Stages	F-Statistics	*p*-value
1st Wave	46.217	0.000***
1st Stable	8.893	0.000***
2nd Wave	3.992	0.008**
2nd Stable	1.248	0.293

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A.6
Games-Howell post-hoc test for travelers' expenditure from different distance groups.

Pair of Groups	1–2	1–3	1–4	2–3	2–4	3–4
Stages						
1st Wave	2.04	7.57	19.33	5.53	17.30	11.77
	(0.283)	(0.000***)	(0.000***)	(0.001**)	(0.000***)	(0.000***)
1st Stable	1.99	5.35	6.97	3.37	4.98	1.61
	(0.243)	(0.001**)	(0.000***)	(0.046*)	(0.006**)	(0.796)
2nd Wave	2.20	3.81	6.69	1.61	4.49	2.88
	(0.292)	(0.096)	(0.009**)	(0.678)	(0.104)	(0.569)
2nd Stable	−1.27	−1.11	−5.00	0.17	−3.73	−3.89
	(0.834)	(0.946)	(0.219)	(1.000)	(0.453)	(0.523)

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.
a. The pair of groups: e.g., '1–2' means the comparison between Group 1 and Group 2.
b. Numbers outside parentheses indicate differences between the two groups, and numbers inside parentheses indicate *p*-values.

Appendix B. Comparison of results of using daily new cases and Google Trends

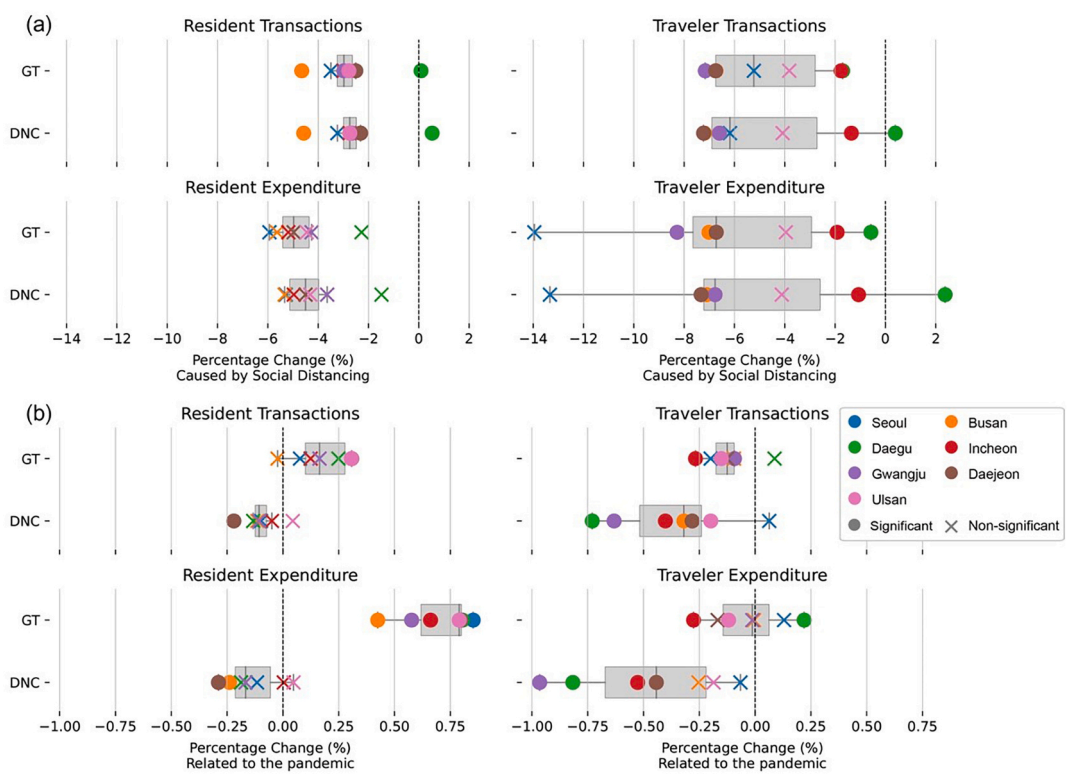

Fig. B.1. Percentage changes caused by social distancing and pandemic-related variables (Search interest (GT) vs. Daily new cases (DNC)) in major Korean cities.

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