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Impact of Public Health Emergencies on General Recreational Behaviors of Urban Residents in Nanjing of China During the COVID-19 Outbreak in July 2021

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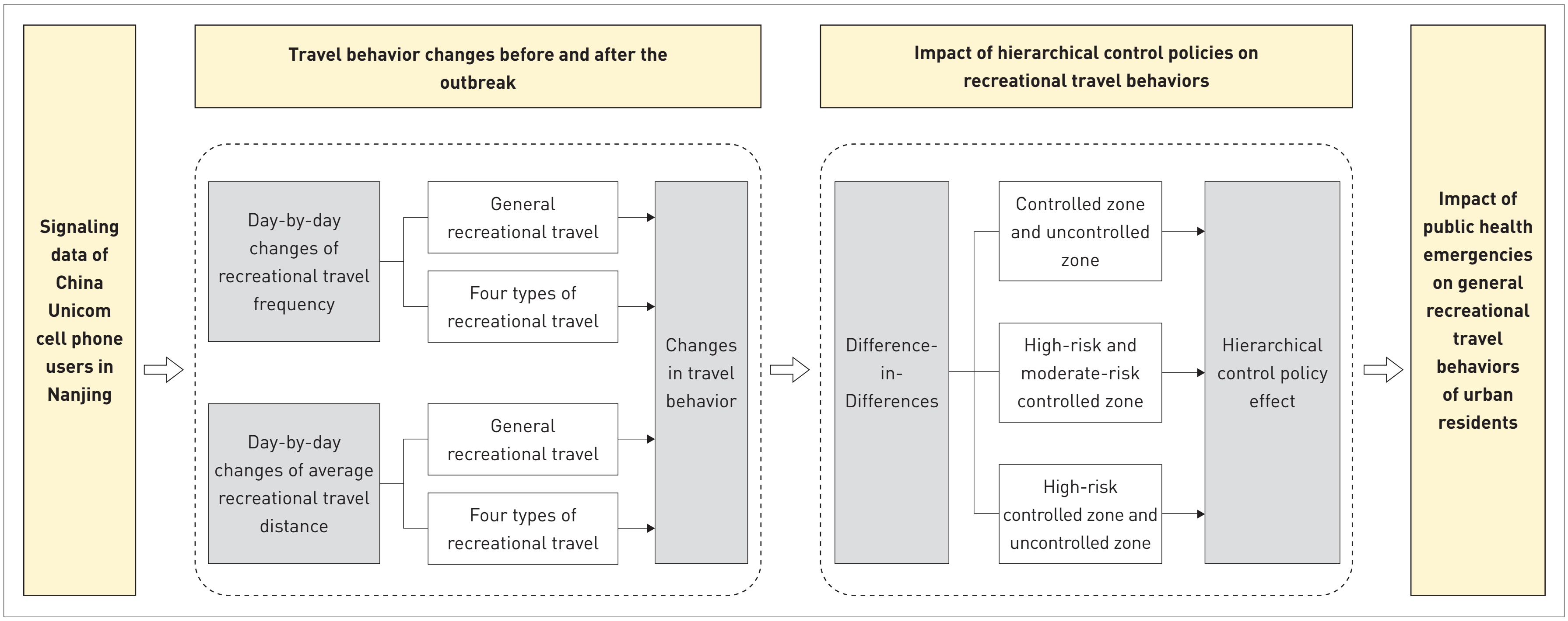
GRAPHICAL ABSTRACT



HIGHLIGHTS

- Public health emergencies may result in a decrease of residents' recreational travel frequency and an increase of travel distance
- Hierarchical control policies have varying degrees of impact on different types of recreational behaviors
- Recreational travels for natural attractions and commercial entertainment are significantly impacted by control policies
- This research provides a reference for reasonable layout of public recreational space in urban renewal and resilient city construction

KEYWORDS

Public Health Emergency;
General Recreational Behaviors;
Travel Frequency;
Travel Distance;
Hierarchical Control;
Planning of Urban Recreational Space

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ABSTRACT

In order to investigate the impact of public health emergencies on the “general recreational behaviors” of urban residents, this research takes the COVID-19 outbreak event in Nanjing of China in July 2021 as an example, based on cell phone signaling data, analyzes the spatial distribution and temporal changes of urban residents’ recreational travel behaviors before and after the outbreak, and then explores the impact of the hierarchical control policies on recreational travel behaviors via Difference-in-Differences (DID) method. It has found that after the outbreak, residents’ recreational travel frequency decreased significantly and their average travel distance increased; the frequencies of travel to all four types of recreational destinations decreased after the outbreak; in average travel distance, those to natural attractions and sports/fitness destinations tended to increase, while those to cultural leisure as well as commercial entertainment destinations tended to decrease after the outbreak. Further results indicate that the hierarchical control policies had varying degrees of impact on different types of recreational travel. This research provides an interpretation on the spatio-temporal pattern and mechanism of urban residents’ general recreational behaviors under public health emergencies, which can provide a reference for planning of urban recreational space.

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1 Introduction

The public health emergency means outbreak events that (may) cause serious injury to public health, such as critical infectious disease epidemics, mass unexplained diseases, major food poisoning and occupational poisoning, as well as other events that have a strong impact on public health[1]. As shown by historical records and relative model simulations—from the plague in the 14th and 15th centuries and the cholera in the 19th century to SARS and Influenza A H1N1 in the 21st century—people’s travel attitudes, willingness, and behaviors[2]~[4] would change during such public health emergencies.

“General recreational behaviors,” as an important type of travel covering rest, interaction, exercise, entertainment, shopping, sightseeing, and tour[5][6], are usually first impacted in public health emergencies as they are “unnecessary activities”[7][8]. However, given the significance of space for recreational behaviors in modern cities[9], public health emergencies have profound implications with urban planning as they would impact the general recreational spaces for natural/ecological conservation, sports and exercises, cultural and leisure events, and commercial and entertainment activities[10][11], etc. To clarify how general recreational behaviors are impacted by public health emergencies is important to improve urban resilience to crisis[12].

The COVID-19 pandemic had become one of the worldwide public health emergencies since December 2019. In areas with large-scale outbreaks, avoiding large-scale movement and gathering was recommended as an effective public health intervention[13][14]. Therefore, in addition to spontaneous travel reduction by residents[15]~[17], governments also would regulate population movement[18][19], which may impact residents’ routines and normal life styles[20]~[23], and negatively impact their recreational behaviors[24][25]. However, in face of public health emergencies, recreational activities can positively influence people’s physical and mental health[26][27], reducing mental stress, anxiety, and loneliness increased by quarantine[28][29]. It means that the negative impact of extensive travel regulation on residents’ recreational behaviors should be carefully considered, especially in the layout planning and management of urban recreational spaces. Research has found that the choice of recreational behaviors would be impacted by infection risk and health index① of different sorts of recreational places[30]~[32], as residents will make decisions considering factors of degree of risk, social norm, expertise, and mental and physical benefits[33]~[36]. So it is of great importance to clarify the spatial-temporal mechanism of such choices. However, current studies on the impact of public health emergencies on recreational travels by analyzing recreational behavior changes remain insufficient.

By studying the COVID-19 outbreak in Nanjing, Jiangsu Province, China in July 2021, this research probes into the temporal variation of citizens' recreational behaviors before and after the outbreak, as well as the related impact of hierarchical control policies by local government. During the about-one-month outbreak, a series of hierarchical control policies were applied in areas of different epidemic risk levels that have changed citizens' travel behaviors in varying degrees, offering a good case for studying the impact of public health emergencies on general recreational behaviors. Specifically, this paper aims to respond to the following questions. 1) How citizens' travel behaviors have been changed before and after a public health emergency? And 2) how would the hierarchical control policies impact people's recreational travel behaviors in a public health emergency? This paper can provide a reference for the layout planning of urban recreational places.

2 Data and Methods

2.1 Spatio-temporal Scope of Study Area

The study area covers 11 districts in Nanjing (Xuanwu, Qinhuai, Jianye, Gulou, Pukou, Qixia, Yuhuatai, Jiangning, Liuhe, Lishui, and Gaochun). The data used in this research was sourced from Unicom Smart Steps Data from July 1 to 31, 2021, covering the whole city; considering the occurrence time of the outbreak, the research examined 10 days before and after the day of outbreak (July 20) each, i.e., July 10 to 30, 2021, for a comparative analysis. Meanwhile, people of different age groups have varied recreational behavior patterns[37], while young people provide better data availability and representativeness of recreational behavior as the largest group of recreational place visits and cell phone usage. According to the age range by WHO in 2021, this research thus selected young people (18 ~ 45 years old)② of the permanent population in Nanjing as the object.

2.2 Research Framework

This research consists of three stages. 1) The first stage is data collection and processing. The data include the number of new infection cases per day, the total number of infection cases per day, and the changes of control areas in July, 2021 released by the government of Nanjing, as well as cell phone signaling data and Area of Interest (AOI) data. Through pre-processing, the location data were classified by control levels and recreational destination categories, and the recreational behaviors were represented by the frequency of recreational travels and the average travel distance with cell phone signaling data. 2) The second stage is analysis of the spatio-temporal behavior changes. Descriptive statistics were employed to portray the everyday temporal changes of recreational travel frequency and average travel distance. Finally, 3) the third stage is analysis of the impact of the hierarchical control policies on residents' recreational behaviors using the method of Difference-in-Differences.

2.3 Data Collection and Pre-processing

The data for this research include geographic data (i.e., the AOI data of recreational places in Nanjing obtained from Baidu Maps Open Platform), epidemic data (sourced from Nanjing Health Commission press conference release platform), and residents' travel data (i.e., the cell phone signaling data obtained from China Unicom Smartsteps Analysis Platform).

2.3.1 Geographic Data

As a kind of polygon data with units of geospatial entities, AOI data were used to identify locations related to recreation behaviors. The researchers downloaded the AOI data of Nanjing in 2021 from Baidu Maps Open Platform and selected the AOIs where recreational behaviors can be carried out, such as urban parks, green spaces, squares, and venues for science, education, culture, sports, shopping, business, and entertainment uses. At the same time, referring to relevant classification systems[5][6][11], the selected AOIs were categorized into four recreational destinations: natural attractions, commercial entertainment, cultural leisure, and sports/fitness (Table 1). The residential AOI data, covering residential area, apartment, community, were also selected.

① "Infection risk" here refers to the factors related to disease transmission, such as the impermeability of recreational places; "health index" refers to whether there have been infection cases in a given recreational place.

② This research regards that the changes of young people's recreational travel behaviors can properly represent that of general residents in the study area because: 1) preliminary analysis of the acquired data showed that young people (18 ~ 45 years old) accounted for more than 70% of all samples; 2) the young people's choices for recreational travels are less limited compared with juveniles, middle aged, and elderly people whose travel patterns are relatively fixed.

Table 1: Types of recreational AOIs in this study

Type	Quantity	Contents
Natural attractions	567	Urban parks, botanical gardens, zoos, natural scenic areas, etc.
Commercial entertainment	371	Emporiums, shopping malls, commercial streets, etc.
Cultural leisure	41	Cultural scenic areas, museums, libraries, exhibition halls, higher education institutions, cultural palaces, etc.
Sports/fitness	62	Urban squares, sports parks, fitness centers, stadiums, etc.

2.3.2 Epidemic Data

From July 10 to 19, 2021, Nanjing reported no new infection case; on July 20, 9 new cases were reported, and the number of new cases peaked a week later (on July 27), then declined till August 13 when no new case was reported in the city (Fig. 1).

In this health emergency, the disease prevention and control department of Nanjing Municipal formulated hierarchical control policies for the whole city based on the day-by-day epidemic trend and dynamic adjustment of control interventions was used for areas with varied risk levels. The researchers obtained and sorted out the epidemic data in Nanjing during the whole month of July, including the number of risk spots at each control level③ within each administrative area (mainly sub-districts, as well as townships, development zones, forest farms, etc. sub-districts hereafter), and then categorized the sub-districts into uncontrolled zone, moderate-risk zone, and high-risk zone (Table 2). During this emergency, a total of 20 sub-districts had been under control, accounting for 17.39% of all 115 sub-districts in Nanjing (Table 3).

2.3.3 Residents' Travel Data

Based on the total-volume signaling data of China Unicom cell phone users in Nanjing, the users' travel locations and stop information could be generated via DAAS (Data as a Service), an online data analysis platform. The research first filtered samples not residing in Nanjing within the time frame and not belonging to the required age group; then correlated the geographic data of starting points and residential AOIs, as well as those of the ending

③ If the riks spot is located in the moderate-risk (high-risk) controlled zone, it will be regarded as the "moderate-risk (high-risk) spot."

1. The number of infection cases of Nanjing in July and August day by day

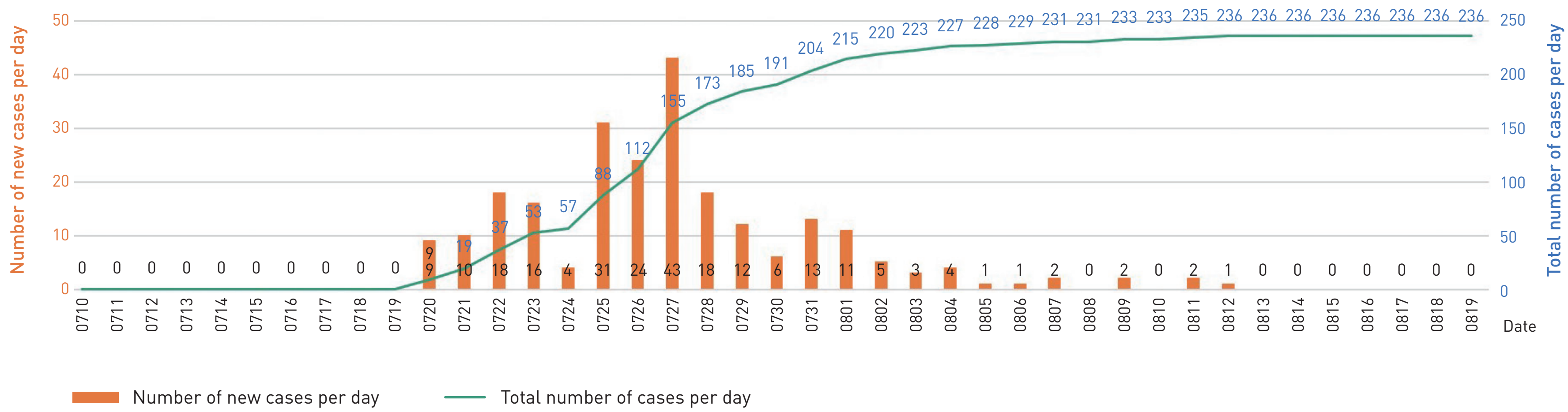

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Table 2: Zoning of pandemic risk levels

Pandemic risk level	Zone	Criteria
Risk0	Uncontrolled zone	With no risk spot
Risk1	Moderate-risk control zone	With one or several moderate-risk spot(s) and no high risk spot
Risk2	High-risk control zone	With one or several high-risk spot(s)

Table 3: Daily variation of numbers of sub-districts under different risk levels

Date	Number of Risk0 sub-districts	Number of Risk1 sub-districts	Number of Risk2 sub-districts	Percentage of sub-districts with risk
07-20	115	0	0	—
07-21	113	2	0	1.74%
07-22	113	2	0	1.74%
07-23	111	3	1	3.48%
07-24	111	3	1	3.48%
07-25	108	6	1	6.09%
07-26	104	10	1	9.57%
07-27	100	14	1	13.04%
07-28	97	17	1	15.65%
07-29	95	19	1	17.39%
07-30	95	19	1	17.39%

points and the recreational AOIs, and further screened out the travel data of users who stayed in the recreational AOIs (ending points) less than 10 minutes or longer than 16 hours. Finally, the above data were aggregated to obtain user recreation travel frequency and average travel distance.

2.4 Research Method: Difference-in-Differences

This research uses Difference-in-Differences (DID) to study the impact of the hierarchical control policies on recreational travels. In recent years, DID has been often used in evaluation on industrial, environmental, and economic policies[38]~[40], and its theoretical framework often builds on natural experiment[41], which evaluates changes of a variable under two situations—policy applied or not—under a counterfactual hypothesis, and usually involves four elements: the shock event, the treatment group, the control group, and the timeframe[42].

This research took July 20 when Nanjing government enacted the epidemic control policies as the time of shock event; July 10 to 30 as the timeframe; residents' recreational travel frequency and distance in risk sub-districts of different control levels as the described variables; and the resident population, the number of four types of recreational AOIs, and the average minimum distance of residential AOIs from the recreational AOIs as control variables[5] (Table 4). Then, according to control level, all the 115 sub-districts in Nanjing were divided into 3 pairs of treatment and control group: 1) controlled zones (Risk1 and Risk2) as the treatment group, and uncontrolled zones (Risk0) as the control group; 2) high-risk controlled zones (Risk2) as the treatment group, and moderate-risk controlled zones (Risk1) as the control group; and 3) high-risk controlled zones (Risk2) as the treatment group, and uncontrolled zones (Risk0) as the control group. Finally, the impact of the hierarchical control policies in residential areas on recreational travel behaviors would be derived through the following formula:

$$\gamma_{i,t} = \alpha + \mu_i + \lambda_t + \theta D_{i,t} + \beta X_{i,t} + \varepsilon_{i,t}\ , \qquad (1)$$

where $\gamma_{i,t}$ is the dependent variable, i.e., the response variable; i (i = 1, ..., N) represents individuals; t (t = 1, ..., T) is time; μ_i is fixed effect of sub-district; λ_t is fixed effect of time; θ is treatment effect; $D_{i,t}$ is a dummy variable in treatment period varying by individual, if the individual i is treated in period t, $D_{i,t}$ takes 1 in all subsequent periods, otherwise takes 0; β is the coefficient of control variable; $X_{i,t}$ is a control variable varying with time and individual; $\varepsilon_{i,t}$ is the error of model; and α is a constant.

This research conducted the DID experiment on STATA platform. DID effectiveness requires both random event and random division, but the samples of high-risk controlled zones were too few to meet such a precondition. In order to reduce experimental errors and avoid the endogenous interference as much as possible, Propensity Score Matching (PSM)-DID was used in analyses involving high-risk controlled zones. Based on the introduction of PSM[43] by Sascha O. Becker and Andrea Ichino, the researchers first expanded the sample size of high-risk controlled zones to the same size of moderate-risk controlled and uncontrolled zones, then conducted DID on a balanced basis to evaluate the exact policy effectiveness.

3 Research Results

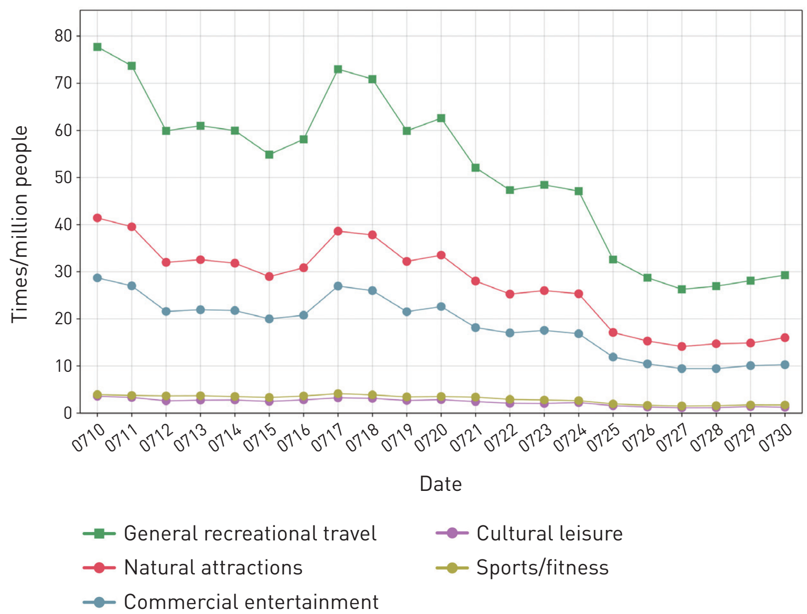
3.1 Changes of General Recreational Travel Before and After the Outbreak

3.1.1 Changes of Recreational Travel Frequency

Statistics show that since the outbreak on July 20, the travel frequencies for the four types of recreational AOIs all decreased

Table 4: Variables and data sources in the DID models

Variable type	Variable	Data source
Response variable	Travel frequency	China Unicom Smartsteps Analysis Platform
	Average travel distance	
Explanatory variable	Control policy	Nanjing Health Commission news release platform and other news channels
Control variable	Permanent resident population	WorldPop
	Number of the four types of recreational AOIs within a given sub-district	Baidu Maps Open Platform
	Average minimum distance (m) to the four types of recreational AOIs	



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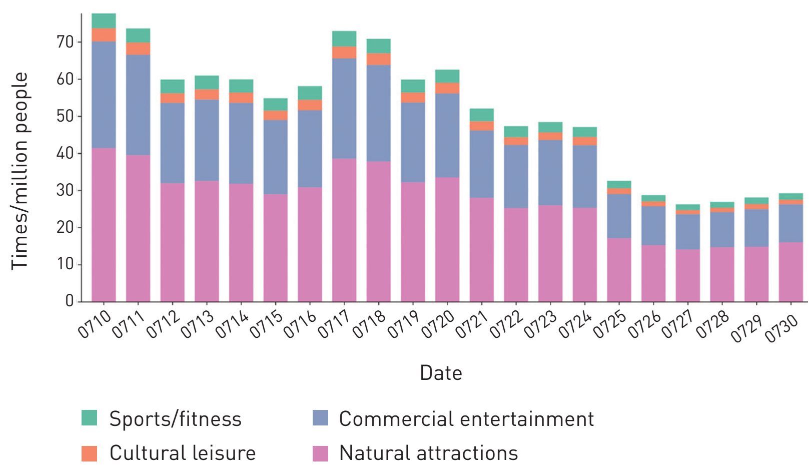

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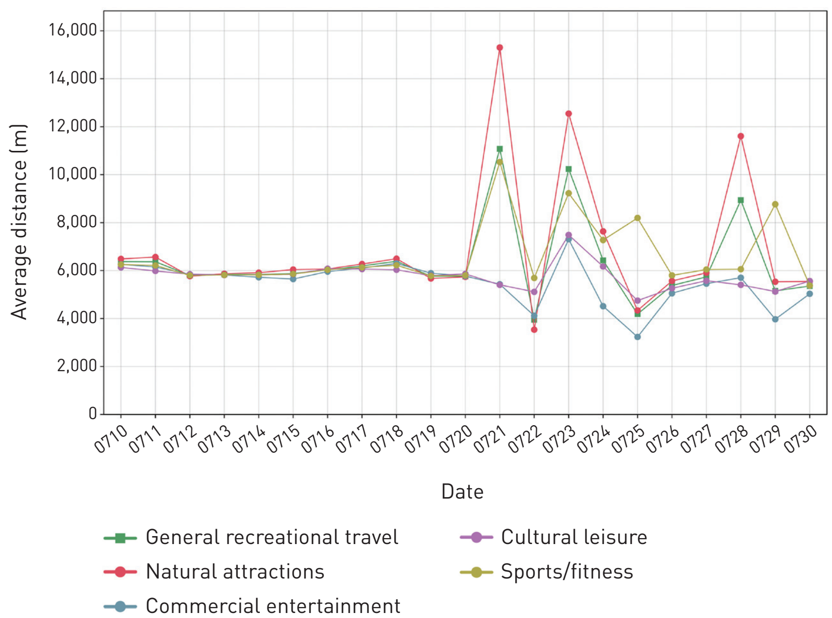

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significantly, especially rapidly in the early few days until July 25; then the decrease was slowing down and reached the bottom on July 27 (28 times/million people), and began to increase slightly. In addition, before the outbreak, the recreational travel frequency at weekends (July 17 to 18) was obviously higher than that on workdays, but such a “recreational travel peak” disappeared after the outbreak (Fig. 2).

Furtherly, although the outbreak decreased the travel frequency of each type of recreational AOI, their proportions little changed, which indicates that for residents the type of recreational AOIs did not impact their recreational travel choices alternatively (Fig. 3).

3.1.2 Changes of Average Travel Distance

Before the outbreak (July 10 to 19), residents’ general average travel distance was 6,046 m and the average travel distance to each type of recreational AOI was around 6,000 m. After the outbreak (July 21 to 30), the general average recreational travel distance had increased to 6,644 m. Specifically, the travels to natural attractions and sports/fitness AOIs saw greater changes in average distance, reaching 15,302 m and 10,527 m as the peak, respectively, while those to culture leisure and commercial entertainment AOIs changed slightly.

Meanwhile, the fluctuation trend of average distances of general recreational travels and to each recreational AOI type all varied significantly. For example, the average distance of general recreational travel was around 11,000 m on July 21, while dramatically dropping down to around 4,000 m on July 22 without a clear pattern (Fig. 4).

3.2 Impacts of Hierarchical Control Policies on General Recreational Travels

3.2.1 Baseline Regression Results of Controlled Zones and Uncontrolled Zones

According to regression results of the 20 controlled zones and 95 uncontrolled zones (Table 5), the impact of control policies on travel frequency was significantly negative at the 0.1% level,

2. Day-by-day changes of recreational travel frequencies
3. Proportions of travel frequencies to the four types of recreational AOIs
4. Day-by-day changes of average travel distance. Here the daily average distance of “general recreational travel” equals the average value of the total distance of all recreational travels divided by the total times of all recreational travels recorded in that day; and the daily average distance to a certain type of recreational AOI equals the average value of the total distance to this type of AOI divided by the total travel times of this type of AOI in that day.

Table 5: Regression summary on with and without control policy vs. travel frequency and average travel distance

Variable	Travel frequency	Average travel distance
With/without control policy	–0.555*** (0.0846)	0.00382 (0.0313)
Group dummy variable	–0.0662 (0.0734)	0.111*** (0.0347)
Time dummy variable	–0.231*** (0.0563)	–0.108*** (0.0184)
Number of the four types of recreational AOIs within sub-district	0.0364*** (0.00228)	0.00780*** (0.000964)
Permanent resident population	2.40e–05*** (1.09e–06)	–1.28e–05*** (4.17e–07)
Average minimum distance to the four types of recreational AOIs	–7.92e–05*** (1.95e–06)	3.09e–05*** (7.67e–07)
Constant	7.264*** (0.0600)	10.23*** (0.0205)
Observation	2,389	2,389
Goodness-of-fit (R^2)	0.643	0.685

NOTES
1. * means p < 0.05; ** means p < 0.01; and *** means p < 0.001.
2. Standard errors are shown in parentheses.

Table 6: Regression summary on high- and moderate-risk control policy vs. travel frequency and average travel distance

Variable	Travel frequency	Average travel distance
High-/moderate-risk control policy	–1.126*** (–0.23)	–0.309*** (–0.116)
Group dummy variable	1.672*** (–0.108)	0.333*** (–0.0551)
Time dummy variable	–0.550*** (–0.0991)	–0.125*** (–0.0439)
Number of the four types of recreational AOIs within sub-district	0.0353*** (–0.00378)	0.00269* (–0.0016)
Permanent resident population	2.51e–05*** (–2.76e–06)	–1.64e–05*** (–1.18e–06)
Average minimum distance to the four types of recreational AOIs	–9.42e–05*** (–5.06e–06)	2.94e–05*** (–2.89e–06)
Constant	7.434*** (–0.154)	10.52*** (–0.0806)
Observation	419	419
Goodness-of-fit (R^2)	0.767	0.711

NOTES
1. * means p < 0.05; ** means p < 0.01; and *** means p < 0.001.
2. Standard errors are shown in parentheses.

suggesting that the policies taken since July 20 did significantly decrease the recreational travel frequency of people who lived in risk zones. In terms of the average travel distance, the impact was insignificant in general, suggesting that the policies had no significant positive or negative impact on residents' recreational travels who lived in risk zones.

3.2.2 Baseline Regression Results of High- and Moderate-Risk Controlled Zones

After expanding the sample size of high-risk controlled zones to 21 with PSM method, a regression analysis with the 19 moderate-risk controlled zones was conducted (Table 6). The results showed that the impact of control level on recreational travel frequency was significantly negative at the 0.1% level, indicating that the varied control levels in high- and moderate-risk controlled zones after July 20 led to significant differences on the recreational travel frequency of residents living in corresponding zones—the higher control level, the lower recreational travel frequency. In terms of the average travel distance, the impact of control level was significantly negative at the 0.1% level,

Table 7: Regression summary on high-risk and no control policy vs. travel frequency and average travel distance

Variable	Travel frequency	Average travel distance
High-risk/no control policy	–1.445*** (–0.214)	–0.327*** (–0.108)
Group dummy variable	1.245*** (–0.0556)	0.454*** (–0.0205)
Time dummy variable	–0.231*** (–0.0563)	–0.108*** (–0.0184)
Number of the four types of recreational AOIs within sub-district	0.0356*** (–0.00328)	0.00737*** (–0.00142)
Permanent resident population	2.34e–05*** (–1.23e–06)	–1.22e–05*** (–4.86e–07)
Average minimum distance (m) to the four types of recreational AOIs	–7.77e–05*** (–2.14e–06)	3.08e–05*** (–7.77e–07)
Constant	7.369*** (–0.071)	10.27*** (–0.025)
Observation	1,991	1,991
Goodness-of-fit (R^2)	0.625	0.695

NOTES

1. * means $p < 0.05$; ** means $p < 0.01$; and *** means $p < 0.001$.
2. Standard errors are shown in parentheses.

indicating that higher control level would significantly reduce recreational travel distance. In sum, the effectiveness of different control levels varied on residents' recreational travel frequency and distance.

3.2.3 Baseline Regression Results of High-Risk Controlled Zones and Uncontrolled Zones

Similarly, after expanding the sample size of high-risk controlled zones to 21, a regression analysis was performed with the 95 uncontrolled zones (Table 7), and the results showed that the impact of high control level on recreational travel frequency was significantly negative at the 0.1% level, suggesting a significant impact of control policy in high-risk controlled zones. In terms of travel distance, the impact of high control level was significantly negative at the 0.1% level, indicating that the average recreational travel distance of residents living in high-risk controlled zones would be significantly reduced by the policies.

3.3 Impacts of Hierarchical Control Policies on Travel Behaviors to Different Recreational AOI Types

3.3.1 Baseline Regression Results of Controlled Zones and Uncontrolled Zones

Analysis on controlled and uncontrolled zones (Table 8) showed that except travels to sports/fitness AOIs, control policies had significantly negative impacts on the travel frequency to the other three AOI types at the 0.1% level. Specifically, according to the coefficients, the control policies had the most significant impact on the travel frequency to natural attractions and cultural leisure AOIs, followed by commercial entertainment AOIs, and a minor impact on sports/fitness ones. In terms of average travel distance, the control policies had no significant impacts on none of the four AOI types, which is consistent with the analysis results of general recreational travel above. The results mean that residents living in controlled zones would primarily reduce their recreational travels to natural attractions and cultural leisure AOIs.

3.3.2 Baseline Regression Results of High- and Moderate-Risk Controlled Zones

According to analysis on high- and moderate-risk controlled zones (Table 9), for travel frequency, both control levels had significantly negative impacts on all the travels to the four types of recreational AOIs. According to the specific coefficients, the control policies had a minor negative impact on the travel frequency to commercial entertainment AOIs while a greater impact on those to cultural leisure and sports/fitness AOIs. For the average travel distance, the high control level had significantly negative impact on those to natural attractions and commercial entertainment AOIs, but no significant impact on those to cultural leisure and sports/fitness AOIs.

In conclusion, for both two types of controlled zones, stricter control policy would significantly reduce the travel frequencies to cultural leisure and sports/fitness AOIs, but had no significant impact on the average travel distances to such destinations. In contrast, stricter control policy would reduce both travel frequencies and average distances to natural attractions and

Table 8: Regression summary on with and without control policy vs. travel frequency and average travel distance to the four types of recreational AOIs

Variable	Natural attractions		Commercial entertainment		Cultural leisure		Sports/fitness	
	Travel frequency	Average travel distance	Travel frequency	Average travel distance	Travel frequency	Average travel distance	Travel frequency	Average travel distance
With/without control policy	−0.435*** (−0.117)	−0.0063 (−0.048)	−0.315*** (−0.113)	−0.0309 (−0.0416)	−0.387*** (−0.123)	−0.0408 (−0.0458)	−0.258** (−0.122)	−0.0659 (−0.0502)
Group dummy variable	−0.0794 (−0.0752)	0.118*** (−0.0338)	−0.0434 (−0.0744)	0.0999*** (−0.0302)	−0.0672 (−0.0893)	0.135*** (−0.0336)	−0.0953 (−0.085)	0.191*** (−0.0386)
Time dummy variable	−0.203*** (−0.0568)	−0.0659*** (−0.0184)	−0.229*** (−0.0558)	−0.0568*** (−0.0178)	−0.044 (−0.054)	−0.0794*** (−0.0204)	−0.163*** (−0.0557)	−0.0617*** (−0.0231)
Number of the four types of recreational AOIs within sub-district	0.0363*** (−0.00234)	0.00263*** (−0.00091)	0.0358*** (−0.00234)	0.00324*** (−0.00099)	0.0179*** (−0.00271)	0.00716*** (−0.00101)	0.0228*** (−0.0025)	0.00556*** (−0.0017)
Permanent resident population	2.58e−05*** (−1.09e−06)	−1.64e−05*** (−4.84e−07)	2.22e−05*** (−1.07e−06)	−1.30e−05*** (−4.41e−07)	1.87e−05*** (−1.09e−06)	−1.27e−05*** (−4.58e−07)	1.42e−05*** (−1.10e−06)	−6.92e−06*** (−4.62e−07)
Average minimum distance to the four types of recreational AOIs	−7.81e−05*** (−2.02e−06)	3.45e−05*** (−7.20e−07)	−7.92e−05*** (−1.91e−06)	3.54e−05*** (−6.90e−07)	−7.95e−05*** (−2.44e−06)	4.28e−05*** (−9.09e−07)	−8.06e−05*** (−1.95e−06)	3.78e−05*** (−1.03e−06)
Constant	6.712*** (−0.0678)	8.938*** (−0.0229)	6.386*** (−0.0662)	8.850*** (−0.0222)	4.506*** (−0.0723)	8.816*** (−0.026)	4.881*** (−0.0674)	8.717*** (−0.0338)
Observations	2,384	2,385	2,376	2,376	2,082	2,082	2,183	2,184
Goodness-of-fit (R^2)	0.642	0.754	0.645	0.759	0.588	0.746	0.581	0.617

NOTES

1. * means $p < 0.05$; ** means $p < 0.01$; and *** means $p < 0.001$.
2. Standard errors are shown in parentheses.

commercial entertainment AOIs, suggesting that residents in high-risk controlled zones preferred to visit recreational places nearby.

3.3.3 Baseline Regression Results of High-Risk Controlled Zones and Uncontrolled Zones

According to analysis on high-risk controlled zones and uncontrolled zones (Table 10), the high control level had significantly negative impacts on the travel frequencies to all types of recreational AOIs, and the coefficients showed that the travel frequencies to cultural leisure and sports/fitness AOIs were more negatively impacted. Also, the high control level had a greater impact on the average travel distances to natural attractions and commercial entertainment AOIs, but no significant impact on those to cultural leisure and sports/fitness ones.

Table 9: Regression summary on high- and moderate-risk control policies vs. travel frequency and average travel distance to the four types of recreational AOIs

Variable	Natural attractions		Commercial entertainment		Cultural leisure		Sports/fitness	
	Travel frequency	Average travel distance	Travel frequency	Average travel distance	Travel frequency	Average travel distance	Travel frequency	Average travel distance
High-/moderate-risk control policy	−1.380*** (−0.273)	−0.291*** (−0.0864)	−0.834*** (−0.196)	−0.516*** (−0.116)	−1.871*** (−0.378)	−0.0635 (−0.068)	−1.883*** (−0.39)	−0.0857 (−0.114)
Group dummy variable	1.683*** (−0.117)	0.262*** (−0.0552)	1.701*** (−0.106)	0.178*** (−0.0452)	2.346*** (−0.298)	−0.209** (−0.0902)	1.580*** (−0.167)	0.124* (−0.0631)
Time dummy variable	−0.572*** (−0.102)	−0.0576 (−0.0466)	−0.507*** (−0.0981)	−0.061 (−0.0386)	−0.387*** (−0.102)	−0.102** (−0.0411)	−0.368*** (−0.107)	−0.103** (−0.044)
Number of the four types of recreational AOIs within sub-district	0.0339*** (−0.00388)	0.00235 (−0.00169)	0.0375*** (−0.00379)	0.00458*** (−0.00142)	0.0193*** (−0.00451)	0.00710*** (−0.00137)	0.0265*** (−0.00368)	0.00752*** (−0.00156)
Permanent resident population	2.53e−05*** (−0.00000286)	−1.82e−05*** (−0.0000013)	2.42e−05*** (−0.00000272)	−1.40e−05*** (−0.00000107)	1.78e−05*** (−0.00000372)	−1.17e−05*** (−0.00000107)	2.17e−05*** (−0.00000278)	−1.13e−05*** (−0.00000107)
Average minimum distance to the four types of recreational AOIs	−9.61e−05*** (−0.00000549)	3.39e−05*** (−0.00000304)	−9.28e−05*** (−0.00000482)	3.83e−05*** (−0.00000216)	−0.000127*** (−0.0000157)	5.78e−05*** (−0.0000045)	−9.45e−05*** (−0.00000757)	4.53e−05*** (−0.00000305)
Constant	6.838*** (−0.16)	9.080*** (−0.0851)	6.385*** (−0.155)	8.894*** (−0.0663)	4.832*** (−0.269)	8.782*** (−0.0764)	4.720*** (−0.181)	8.833*** (−0.075)
Observation	419	419	418	418	375	375	397	397
Goodness-of-fit (R^2)	0.762	0.732	0.767	0.789	0.713	0.794	0.681	0.754

NOTES

1. * means p < 0.05; ** means p < 0.01; and *** means p < 0.001.
2. Standard errors are shown in parentheses.

In conclusion, compared with uncontrolled zones, the high control level had significant impacts on the travel behaviors to the four types of recreational AOIs. It would significantly reduce the travel frequencies to cultural leisure and sports/fitness AOIs, but less impact the average travel distances to them. This means that high control level would reduce residents' demand of recreational travel to cultural leisure and sports/fitness AOIs, which was probably due to the lockdown of the two types of destinations. In contrast, for natural attractions and commercial entertainment AOIs, the average travel distances were significantly impacted but the frequencies were not, suggesting that visiting these two types of recreational AOIs were non-substitutable for residents living in high-risk controlled zones, and they would turn to visit such AOIs nearby homes.

Table 10: Regression summary on high-risk and no control policy vs. travel frequency and average travel distance to the four types of recreational AOIs

Variable	Natural attractions		Commercial entertainment		Cultural leisure		Sports/fitness	
	Travel frequency	Average travel distance	Travel frequency	Average travel distance	Travel frequency	Average travel distance	Travel frequency	Average travel distance
High-risk/no control policy	−1.750*** (−0.258)	−0.283*** (−0.0745)	−1.113*** (−0.177)	−0.520*** (−0.11)	−2.217*** (−0.365)	−0.0849 (−0.0575)	−2.091*** (−0.377)	−0.126 (−0.107)
Group dummy variable	1.208*** (−0.0574)	0.394*** (−0.0201)	1.316*** (−0.0591)	0.347*** (−0.0238)	1.263*** (−0.0812)	0.211*** (−0.0265)	1.022*** (−0.0865)	0.547*** (−0.0364)
Time dummy variable	−0.202*** (−0.0568)	−0.0659*** (−0.0184)	−0.228*** (−0.0558)	−0.0569*** (−0.0178)	−0.0409 (−0.0539)	−0.0805*** (−0.0204)	−0.161*** (−0.0557)	−0.0628*** (−0.023)
Number of the four types of recreational AOIs within sub-district	0.0360*** (−0.00331)	0.00182 (−0.00127)	0.0341*** (−0.00331)	0.00209 (−0.00146)	0.0131*** (−0.00401)	0.00871*** (−0.00146)	0.0231*** (−0.0037)	0.00247 (−0.00254)
Permanent resident population	2.55e−05*** (−0.00000123)	−1.58e−05*** (−0.000000552)	2.18e−05*** (−0.00000123)	−1.25e−05*** (−0.000000515)	1.80e−05*** (−0.00000125)	−1.26e−05*** (−0.000000531)	1.20e−05*** (−0.00000127)	−4.98e−06*** (−0.000000475)
Average minimum distance to the four types of recreational AOIs	−7.60e−05*** (−0.00000221)	3.45e−05*** (−0.000000711)	−7.79e−05*** (−0.0000021)	3.50e−05*** (−0.000000738)	−7.66e−05*** (−0.00000245)	4.17e−05*** (−0.00000093)	−7.90e−05*** (−0.00000207)	3.67e−05*** (−0.00000109)
Constant	6.683*** (−0.0728)	8.939*** (−0.0237)	6.383*** (−0.071)	8.861*** (−0.024)	4.521*** (−0.0777)	8.816*** (−0.028)	4.881*** (−0.0721)	8.741*** (−0.0383)
Observation	1,986	1,987	1,979	1,979	1,725	1,725	1,806	1,807
Goodness-of-fit (R^2)	0.621	0.763	0.624	0.756	0.582	0.746	0.57	0.603

NOTES
1. * means $p < 0.05$; ** means $p < 0.01$; and *** means $p < 0.001$.
2. Standard errors are shown in parentheses.

4 Conclusions and Discussion

In public health emergencies especially pandemic infectious diseases, applying control policies in certain zones is common and effective[44]~[46], which meanwhile will directly impact citizens' travel behaviors. Through the analyses on temporal variation of residents' recreational travel behaviors before and after a public health emergency in Nanjing in July 2021 and considering it with the implementation of the hierarchical control policies, this research probes into the impact of public health emergencies on residents' recreational behaviors and draws the following conclusions. On the one hand, the control policies would largely impact residents' travel choices, significantly decrease their travel frequencies to recreational AOIs, and increase the average travel distance (especially to natural attractions and sports/fitness AOIs). On the other hand, the control policies would have different impacts on people's recreational travel behaviors: stricter control level would lead to lower travel frequency, but without a clear pattern of the average travel distance; compared with moderate-risk controlled zones, the average travel distance in high-risk controlled zones decreased. For the travel behaviors to the four types of recreational AOIs, the increase of control level will decrease the travel frequencies, especially on that to cultural leisure and sports/fitness AOIs; as to average travel distance, the increase of control level would significantly reduce those to natural attractions and commercial entertainment AOIs, but have no significant effect on those to the other two types.

4.1 Changes of Travel Behavior Pattern

Since the official report on the first day of the outbreak, the frequency and average distance of general recreational travels in Nanjing had seen obvious variation, which conformed the transmission characteristics of public health emergencies: the transmission of disease[13][14] would make people re-assess and control[30][32] the risk of their daily travel behaviors and they often actively reduce those of high risk[16][17]. When their risk perception and travel motivation change[26][27], they would alter their choice for recreational travels. In this research, the significant decrease of travel frequencies of general recreational travels and to each recreational AOI types might be due to some residents regarding recreational travels as "unnecessary" and reducing them to avoid infection risk. People tend to reduce visit to popular recreational destinations[47] (which means a higher possibility of crowding) to avoid infection risk[30][32]. In terms of average travel distance (e.g., the distance from residence to destination), residents with high recreational demands would rather choose AOIs further away from home with fewer visits and lower infection risk, which was especially significant in the increase of those to natural attractions and sports/fitness AOIs. The results also can support relevant former research findings[18][23][48].

4.2 Effectiveness of Hierarchical Control Policies

Given the transmission pattern of COVID-19, zoning intervention measures to avoid crowding have been adopted during the peak of the pandemic worldwide[49][50]. Under different control policies, residents living in controlled zones would largely change their travel behaviors and patterns. In this research, it was found that varied control levels would have significant impacts on the travel frequencies to the four types of recreational AOIs. With the increase of control level (stricter behavioral restriction and protective quarantine), citizens reduced their recreational travels and turned to visit the recreational destinations nearby, which are generally in line with some existing studies[3][7][22]. On the other hand, for the specific degree of impact on the travels to four types of recreational AOIs, the research results show that the increase of control level had a minor impact on the travel frequencies to natural attractions and commercial entertainment AOIs, but a significant decrease on average travel distances to them; travels to cultural leisure and sports/fitness AOIs saw significant decreases in the frequency while no significant impacts on the average distance. It is different from the results of average distance for general recreational travels in Nanjing, suggesting that different control policies indeed show varied effectiveness in the corresponding controlled zones. Meanwhile, some studies indicate that the use frequency of urban natural attractions spaces and outdoor sports places would increase during the control[19][47], not consistent with findings above. One reason might be that this research selected recreational destinations only from AOI data and failed to cover all the sites or venues for every kind of recreational activity; another possible reason is that different cultural and regional backgrounds would lead to different effectiveness of control policies.

4.3 Implications to Planning and Policy-Making

In public health emergencies, urban residents' common recreational activities have been reduced due to the changed risk perception and the restrictions by control policies[24]. The findings of this research, as a response, provides a reference for cities regarding how to ensure citizens' physical and mental health while controlling the transmission of disease during public health emergencies. From the perspective of urban planning, people's travel distance is deeply related to urban land use pattern[51][52]. There have been abundant studies concerning the distance between public facilities (such as green spaces and commercial/service sites) and residential areas[53][54], to better meet residents' daily recreational needs. In face of public health emergencies, the panic for the epidemic makes residents prefer recreational places with fewer visits and lower infection risk[55], which results in a longer travel distance. Combined with the results of this paper, the distance between public recreational spaces and residential areas should be considered more carefully, and the number of natural attractions and sports/fitness sites (such as street-side green space and community squares) adjacent to residential areas should be increased to meet residents' basic recreational demands even under high-risk control level, so as to enhance cities' resilience against public health emergencies. The volume and size of available sites are also important to keep proper visit intensity, thus indirectly regulating people's social distance and reducing the risk of disease transmission[12].

In policy-making, control policies such as the lockdown on risk residences and recreational areas by the government of Nanjing did prevent the virus transmission, but may also have negative influence on people's mental health with increased anxiety, depression, loneliness, etc.[47]. During the outbreak in this research, residents' travel was largely confined by control policies and the government's enforcement of the closure of all types of recreational places (outdoor urban parks, scenic areas, commercial pedestrian streets, cultural entertainment places, sports and fitness sites, etc.), which resulted in the decrease of residents' recreational travel frequency in controlled zones, thus somewhat affecting their physical and mental health. Therefore, in the future the control policies for risk areas should be more flexible to meet residents' daily use needs for parks, scenic areas, squares, pedestrian streets, and other outdoor spaces to carry out recreational activities. This can not only save the cost of dealing with public health emergencies and help record people's travel tracks, but also minimize the disturbance to residents' normal life in non-risk areas.

There are also some deficiencies in this research. First, in screening recreational places, taking urban AOI as the data source cannot fully cover all the actual recreational sites used by urban residents. Second, in public health emergencies, the differences between impacts of active risk avoidance and passive behavior confinement on recreational travels still need to be further explored. Last, it expects in-depth studies of how to guide residents to adjust their daily activities and improve the planning practice of urban renewal under the impact of public health emergencies.

ELECTRONIC SUPPLEMENTARY MATERIAL

Supplementary material is available in the online version of this article at https://doi.org/10.15302/J-LAF-1-020076.

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突发公共卫生事件对城市居民广义游憩行为的影响——以中国南京市2021年7月新型冠状病毒（COVID-19）感染事件为例

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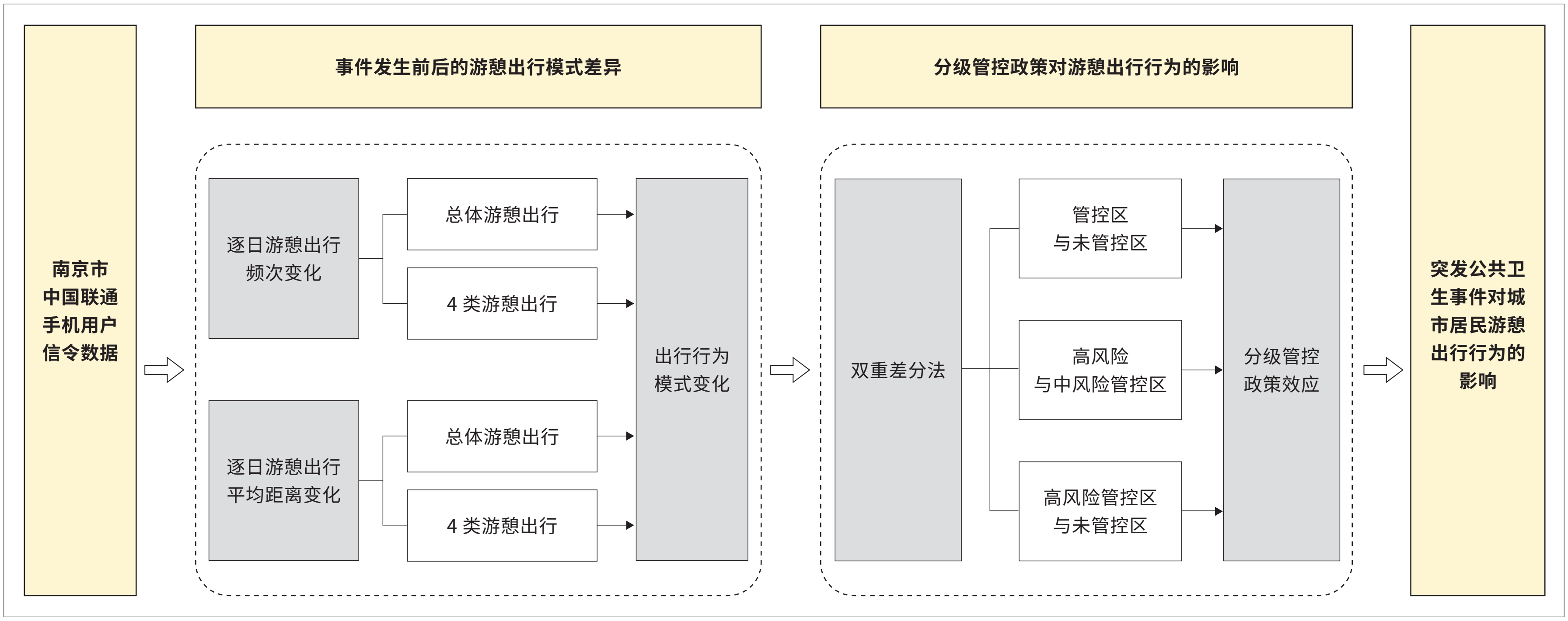
图文摘要



文章亮点

- 突发公共卫生事件会造成居民游憩出行频次下降、游憩出行距离增加
- 分级管控政策对于不同类型的游憩行为影响程度存在差异
- 自然生态类和商业娱乐类游憩出行受管控政策影响较大
- 本研究可为城市更新及韧性城市建设中公共游憩空间的合理布局提供参考

关键词

突发公共卫生事件；
广义游憩行为；
出行频次；
出行距离；
分级管控；
城市游憩空间规划

摘要

为探究突发公共卫生事件对城市居民广义游憩行为的影响，本研究以2021年7月江苏省南京市的新型冠状病毒（COVID-19）感染事件为例，利用手机信令数据，分析事件前后城市居民游憩行为的空间分布和时序变化特征，并通过双重差分法探究分级疫情管控政策对游憩行为的影响。研究发现：本轮感染事件发生后，居民

的游憩出行频次明显减少、出行平均距离有所增加；所有4类游憩目的地（自然生态类、商业娱乐类、文化休闲类、体育健身类）的出行频次在事件后均有所减少；在出行平均距离方面，指向自然生态类和体育健身类游憩目的地的出行平均距离呈现增加趋势，指向文化休闲类和商业娱乐类游憩目的地的出行平均距离则在事件后呈现一定程度的减少趋势。研究结果表明，分级管控政策对于不同类型的游憩行为影响程度各异。研究探讨了突发公共卫生事件下城市居民广义游憩行为的时空模式和机制，可为城市游憩空间规划提供参考。

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1 引言

突发公共卫生事件是指突然发生，造成或者可能造成社会公众健康严重损害的重大传染病疫情、群体性不明原因疾病、重大食物中毒和职业中毒，以及其他严重影响公众健康的事件[1]。从14～15世纪的黑死病，到19世纪的霍乱乃至21世纪的非典型性肺炎（SARS）和甲型H1N1流感等，一系列历史事实与模型模拟结果均表明，在突发公共卫生事件中，人们的出行态度、意愿、行为等[2]-[4]均会发生变化。

广义的游憩行为是一种重要的出行类型，具体包括休息、交往、锻炼、娱乐、购物、观光、旅游等[5][6]。因其“非必要活动”的基本特征，在突发公共卫生事件中往往首当其冲[7][8]。鉴于游憩空间在现代城市中的重要地位[9]，这种影响涉及自然生态、体育健身、文化休闲、商业娱乐等各类城市广义游憩空间[10][11]，因而具有深刻的城市规划意涵。厘清广义游憩行为受突发公共卫生事件影响的机制，对于强化城市的抗灾韧性具有重要意义[12]。

自2019年12月以来，新型冠状病毒（COVID-19）感染成为了全球关注的突发公共卫生事件之一。避免发生规模性疫情区域居民的大规模流动和聚集被推荐为有效的公共卫生干预措施[13][14]。因此，除居民自发进行的规避感染风险[15]-[17]的行为之外，政府也会对这类区域人员的流动进行一定的管控[18][19]。这些措施可能对居民的正常生活秩序及生活方式造成冲击[20]-[23]，对城市居民的游憩行为产生负面影响[24][25]。然而，在突发公共卫生事件的背景下，适当的游憩活动可对人们的身心健康产生积极影响[26][27]，可减轻因疫情隔离而增加的精神压力、焦虑和孤独感，提高主观幸福感[28][29]。因此，广泛的人员流动管控固然具有控制疾病传播的效果，但其对居民游憩行为的负面影响亦不可忽视。特别地，从城市规划的角度来看，上述问题也向城市游憩空间的布局和管理也提出了挑战。研究发现，不同类别游憩场所的感染风险和健康指数①均会影响人们的游憩行为选择[30]-[32]，人们会根据风险程度、社会规范、权威建议、身心益处等因素选择出行行为[33]-[36]，因此厘清其中关联的时空机制具有重要意义。然而，当前基于游憩行为变化分析突发公共卫生事件对居民游憩出行影响的研究仍尚不充分。

本研究以江苏省南京市2021年7月的新型冠状病毒感染事件为案例，探讨突发公共卫生事件发生前后城市居民游憩行为的时序变化特征，以及当地政府所采取的分级管控政策对居民游憩行为的影响。这次事件持续约1个月时间，其间当地政府基于城市内部各地区的疫情态势，出台了一系列在空间上有差异的管控政策，在不同程度上导致了居民出行行为的变化，因此是研究突发公共卫生事件对城市居民广义游憩行为之影响的良好案例。具体而言，本文提出以下研究问题：1）突发公共卫生事件发生前后居民的游憩出行行为发生了怎样的变化？2）突发公共卫生事件发生后，分级管控政策对游憩出行行为产生了怎样的影响？通过回答上述研究问题，本文旨在为城市游憩场所的规划布局提供参考。

2 数据与方法

2.1 研究时空范围

选取南京市11个市辖区（玄武区、秦淮区、建邺区、鼓楼区、浦口区、栖霞区、雨花台区、江宁区、六合区、溧水区、高淳区）为研究区域。由于本次研究仅可获取南京市7月整月的联通智慧足迹数据，结合数据可获取性限制和感染事件的发生时间，本次研究时间范围确定为感染事件突发的时间点（7月20日）前后各10天，即2021年7月10～30日，以便于对照分析感染事件前后的数据。同时，考虑到不同年龄层的人群具有不同的游憩行为模式[37]，而青年人的手机使用频率较高，数据可用

① 此处“感染风险”指游憩场所本身的密闭性等与疾病传播介质相关的因素。“健康指数”指游憩场所本身是否曾有过病例。

性较强，且是城市游憩场所的主要使用人群，研究其游憩行为的变化对城市游憩场所的规划布局具有较高的参考价值，故本研究参照世界卫生组织2021年对年龄分期的划定，将研究对象确定为常住南京市的青年（18~45岁）人群②。

2.2 研究框架

本研究主要分为三个阶段。第一阶段为数据获取与处理，数据包括南京市2021年7月整月政府通报的每日新增病例数目、每日病例总数、疫情管控区域变化情况，以及手机信令数据和兴趣面（Area of Interest，AOI）数据；并通过预处理，依据管控等级与游憩目的地类别将地点数据分类，提取手机信令数据中的游憩出行频次与出行平均距离作为表征游憩的行为数据。第二阶段为时空特征变化分析，以描述性统计分析为主，以天为时间单位，从游憩出行频次与出行平均距离两个维度来刻画游憩行为的时序变化特征。在此基础上展开第三阶段的研究，使用双重差分法探究分级管控政策对于居民游憩行为的影响。

2.3 数据获取与预处理

研究的开展需要采集地理信息、疫情信息及居民出行信息三个维度的数据。本文分别从百度开放平台、南京市卫生健康委员会新闻发布平台与极智分析平台获取了南京市游憩空间AOI数据、疫情发展情况数据及能够反映居民出行情况的手机信令数据。

2.3.1 地理数据

AOI数据是按地理实体划分的区域数据，本研究采用AOI数据作为研究所用地点标识。研究者从百度开放平台上下载了2021年南京市AOI数据，筛选出城市公园、绿地、广场，以及科学、教育、文化、体育、购物、商务、娱乐场所等可进行游憩行为的AOI数据，同时参考相关学者分类体系[5][6][11]，将上述数据整合集聚为自然生态类、商业娱乐类、文化休闲类、体育健身类四种主要游憩空间类型，结果如表1所示。另外筛选出居住小区、公寓、社区等居住区AOI数据。

2.3.2 疫情数据

2021年7月10~19日，南京无新增本土病例；7月20日，新增本土确诊病例9例；一周后（7月27日）每日新增病例数达到峰值，直至8月13日全市无新增病例（图1）。

在本次事件中，南京市疾病预防控制单位依据疫情逐日发展情况，对南京市全域制定了分级管控政策，动态调整相关区域的管控等级。研究者获取并梳理了2021年7月间南京市本土疫情发展情况，同时整理每日新闻通报中涉及的风险点位。以街道（含乡镇、开发区、林场等）内现存各管控等级风险点位③的数量为依据，将各街道划分为未管控区、中风险管控区和高风险管控区三个风险等级（表2）——前后共有20个街道因疫情风险受到管控，占南京市街道总数的17.39%（表3）。

2.3.3 居住出行数据

极智分析平台开放了中国联通南京市手机用户的全量信令数据，并通过DAAS（Data as a Service）在线数据分析平台，基于原始信令数据处理生成了用户出行点位、驻留信息等方面的信息。本研究首先筛选出本

表 1：游憩目的地 AOI 数据重分类结果

游憩目的地类型	数量	覆盖实体
自然生态类	567	包括城市公园、植物园、动物园、自然风景名胜区等旅游景点
商业娱乐类	371	包括百货商场、购物中心、商业街等购物场所
文化休闲类	41	包括人文风景名胜区、博物馆、图书馆、展览馆、高等院校、文化宫等文化场所
体育健身类	62	包括城市广场、体育公园、健身中心、运动场馆等运动健身场所

表 2：区域风险等级及管控区划分情况

风险等级	对应管控区	划分标准
Risk0	未管控区	0 个风险点位
Risk1	中风险管控区	≥ 1 个中风险点位，且不存在高风险点位
Risk2	高风险管控区	≥ 1 个高风险点位

② 本研究认为，青年人群的游憩出行行为的变化对于城市全体居民的整体游憩出行情况有较好的代表性，主要原因为：1）基于对所获取数据的初步分析，18~45 岁青年在研究的所有样本中占比较大，超过 70%；2）相较于未成年人及出行模式较为固定的中老年人，青年人群选择游憩出行行为的自由度较高。

③ 如点位处于中（高）险区，即表示为“中（高）风险区”。

表 3：风险街道数量逐日变化统计

日期	Risk0 街道数量	Risk1 街道数量	Risk2 街道数量	存在风险的街道占比
07-20	115	0	0	—
07-21	113	2	0	1.74%
07-22	113	2	0	1.74%
07-23	111	3	1	3.48%
07-24	111	3	1	3.48%
07-25	108	6	1	6.09%
07-26	104	10	1	9.57%
07-27	100	14	1	13.04%
07-28	97	17	1	15.65%
07-29	95	19	1	17.39%
07-30	95	19	1	17.39%

研究时间范围内居住在南京市且年龄符合要求的样本。随后通过网格标号及经纬度信息将用户出行的起始点位与居住区AOI数据相关联，终点点位与游憩空间AOI数据相关联，并筛选出在游憩类终点驻留10分钟至16小时的用户出行数据，作为研究数据。最后，将上述数据进行聚合处理，输出用户游憩出行频次与出行平均距离数据。

2.4 研究方法：双重差分法

本研究采用双重差分法（Difference-in-Differences，DID）研究分级管控政策对游憩出行的影响。双重差分法近年常被用于产业、环境、经济等政策效果评估领域[38]~[40]，其理论框架建立在“自然实验”（natural experiment）的基础上[41]，通过一个反事实假设来评估政策发生和不发生两种情况下被描述变量的变化，通常包括冲击事件、实验组、控制组和时期四个要素[42]。

将7月20日南京颁布疫情管控政策作为政策冲击时间，描述时间范围为7月10~30日，将南京市不同等级风险区居民的出行频次与距离作为被描述变量，并选取常住人口数量、街道内4类游憩AOI数量及居住区AOI距离4类游憩AOI最近距离平均值作为控制变量[5]（表4），以南京市115个街道作为空间限定，根据管控等级划分3对实验组与对照组：1）已划定为管控区的区域（Risk1、Risk2）作为实验组，未管控区（Risk0）为对照组；2）高风险管控区（Risk2）作为实验组，中风险管控区（Risk1）为对照组；3）高风险管控区（Risk2）作为实验组，未管控区（Risk0）为对照组。最终得出居住区不同等级的管控政策对人群游憩出行行为产生的影响。公式如下：

$$\gamma_{i,t} = \alpha + \mu_i + \lambda_t + \theta D_{i,t} + \beta X_{i,t} + \varepsilon_{i,t} \quad (1)$$

式中，$\gamma_{i,t}$ 表示因变量，即响应变量；i（i=1，…，N）表示个体；t（t=1，…，T）表示时间；μ_i 表示街道固定效应；λ_t 表示时间固定效应；θ 表示处理效应；$D_{i,t}$表示因个体而异的处理期虚拟变量，若个体i在第t期接受处理，代表进入处理期，则此后时期均取值为1，否则取值

为0；β表示控制变量的系数；$X_{i,t}$表示随时间和个体变化的控制变量；$\varepsilon_{i,t}$表示模型误差项；α为常数。

研究基于STATA平台进行DID实验，由于DID有效性须具备随机事件和随机分组两个前提条件，而高风险管控区样本量较少，因此，本研究并不完全满足DID方法的使用条件。为减少实验误差，在针对以高风险管控区作为实验组的两组分析中，采用倾向得分匹配—双重差分法（PSM-DID）。首先基于萨沙·O. 贝克尔和安德烈·市野对倾向得分匹配法[43]的介绍，将高风险管控区样本数扩展至和中风险管控区及未管控区样本数同一量级，在满足平衡性要求的前提下再使用DID方法进行政策效应评估，这样可有效避免内生性干扰，分离出尽可能纯粹的政策效应。

3 研究结果

3.1 事件发生前后全域游憩出行差异

3.1.1 游憩出行频次变化情况

对事件发生前后居民游憩出行频次进行统计分析，研究结果显示，自7月20日疫情发生后，各类游憩目的地的出行频次均显著下降，且在初期下降趋势较快，自7月25日始下降趋势逐渐减缓，7月27日起变化趋于平缓（总计约28次/万人），此后有轻微上升趋势。此外，在本次疫情发生前，周末（7月17～18日）游憩出行频次显著高于工作日，呈现出“游憩小高峰”的特征；但在疫情发生后，周末（7月24～25日）出游“高峰”特征不再显著（图2）。

同时，由针对4类游憩出行的频次进行结构变化分析可知，尽管疫情突发后4类游憩行为的出行频次均有所下降，但与事件发生前出行频次的占比无明显差异，可见4类游憩行为之间不存在选择上的相互替代关系（图3）。

3.1.2 游憩出行平均距离变化情况

对事件发生前后居民各类游憩出行行为的出行平均距离进行统计分析，研究结果显示，疫情突发前（7月10～19日），居民总体游憩行为的出行平均距离为6 046m，各类游憩出行的总体平均距离均稳定在6 000m左右。疫情发生后（7月21～30日），居民总体游憩行为的出行平均距离增加至6 644m；在4类游憩出行行为中，自然生态类和体育健身类游憩出行平均距离变化较为显著，自然生态类游憩出行平均距离最高值达15 302m，体育健身类游憩出行最高值达10 527m。商业娱乐类和文化休闲类游憩出行的平均距离整体变化较小。

同时，总体游憩出行及每类游憩出行平均距离的逐日差异均较大。总体游憩出行平均距离在7月21日增加至11 000m，7月22日骤降至4 000m，无明确变化规律（图4）。

3.2 分级管控政策对整体游憩出行行为的影响

3.2.1 管控区与未管控区基准回归结果

从20个管控区与95个未管控区的样本回归结果（表5）来看，疫情管控政策对出行频次的影响在0.1%的水平上显著，且呈现负相关，说明7月20日后因突发疫情所采取的政策导致了居住在有风险地区的居民游憩出行频次的明显下降。就出行平均距离的回归结果来看，影响总体不显

表 4：双重差分法变量类型与数据来源

变量类型	指标	数据来源
响应变量	出行频次	极智分析平台
	出行平均距离	
解释变量	管控政策	南京市卫生健康委员会新闻发布平台等新闻渠道
控制变量	常住人口数量	WorldPop 网站
	街道内 4 类游憩 AOI 数量	百度地图开放平台
	居住区 AOI 距离 4 类游憩 AOI 的最近距离平均值	

表 5：加入控制变量后有无管控政策对出行频次与出行平均距离的回归结果

变量	出行频次	出行平均距离
有无管控政策	–0.555*** （0.0846）	0.00382 （0.0313）
组别虚拟变量	–0.0662 （0.0734）	0.111*** （0.0347）
时间虚拟变量	–0.231*** （0.0563）	–0.108*** （0.0184）
街道内 4 类游憩 AOI 数量	0.0364*** （0.00228）	0.00780*** （0.000964）
常住人口数量	2.40e–05*** （1.09e–06）	–1.28e–05*** （4.17e–07）
居住区 AOI 距离游憩 AOI 的最近距离平均值	–7.92e–05*** （1.95e–06）	3.09e–05*** （7.67e–07）
常数	7.264*** （0.0600）	10.23*** （0.0205）
观测值	2,389	2,389
拟合优度 R^2	0.643	0.685

注
1. * 代表 p<0.05；** 代表 p<0.01；*** 代表 p<0.001。
2. 括号内为标准误。

表 6：加入控制变量后高等级与中等级管控政策对出行频次与出行平均距离的回归结果

变量	出行频次	出行平均距离
高等级或中等级管控政策	–1.126*** （–0.23）	–0.309*** （–0.116）
组别虚拟变量	1.672*** （–0.108）	0.333*** （–0.0551）
时间虚拟变量	–0.550*** （–0.0991）	–0.125*** （–0.0439）
街道内 4 类游憩类型 AOI 数量	0.0353*** （–0.00378）	0.00269* （–0.0016）
常住人口数量	2.51e–05*** （–2.76e–06）	–1.64e–05*** （–1.18e–06）
居住区 AOI 距离游憩 AOI 的最近距离平均值	–9.42e–05*** （–5.06e–06）	2.94e–05*** （–2.89e–06）
常数	7.434*** （–0.154）	10.52*** （–0.0806）
观测值	419	419
拟合优度 R^2	0.767	0.711

注
1. * 代表 p<0.05；** 代表 p<0.01；*** 代表 p<0.001。
2. 括号内为标准误。

著，说明受到疫情管控的相应区域内居民的游憩出行距离无明显正向或反向影响。

3.2.2 高风险与中风险管控区基准回归结果

通过PSM方法将高风险管控区样本量扩充为21个后，与19个中风险管控区的样本作回归分析（表6），结果表明：疫情管控政策等级对居民游憩出行频次的影响在0.1%的水平上显著，且呈现负相关，说明7月20日后高风险、中风险管控区的不同等级的管控政策，使这两类区域内居民的游憩出行频次产生了十分显著的差异，管控政策等级越高，游憩出行频次越低。就出行平均距离的回归结果来看，疫情管控政策的影响在0.1%的水平上显著，且呈现负相关，表明更高等级的管控政策会显著减少居民的游憩出行距离。因此，同为管控区域，中风险和高风险区域的管控政策效力确实存在不同。

3.2.3 高风险管控区与未管控区基准回归结果

通过PSM方法将高风险管控区样本量扩充为21个后，与95个未管控

区的样本作回归分析（表7），结果表明：高等级管控政策对居民游憩出行频次的影响在0.1%的水平上显著，且呈现负相关，说明处于高风险管控区人群的游憩出行频次受管控政策影响明显。就出行距离的回归结果来看，高等级管控政策对居民出行平均距离的影响在0.1%的水平上显著，且呈现负相关，表明高等级管控政策会使区域内居民的游憩出行平均距离显著减少。

3.3 分级管控政策对不同类型游憩出行行为的影响差异

3.3.1 管控区与未管控区基准回归结果

根据管控区与未管控区分析结果（表8），管控政策对4类游憩目的地的出行频次均有显著负向影响，除体育健身类出行外，均在0.1%水平上显著。从不同游憩出行行为的具体回归系数上看，有无管控政策对自然生态类和文化休闲类游憩出行频次影响程度最大，商业娱乐类次之，体育健身类游憩频次影响程度较小。在出行平均距离方面，管控政策对4类游憩目的地的出行平均距离均无显著的正向或负向影响，与前文对整体游憩出行影响的分析结果一致。可见处在风险管控范围内的居民会首先减少自然生态类和文化休闲类游憩出行行为。

3.3.2 高风险与中风险管控区基准回归结果

根据高风险与中风险管控区分析结果（表9），在出行频次方面，中、高等级管控政策对4类游憩行为出行频次均产生了明显负向影响。从不同游憩出行行为的具体系数上看，不同等级的管控政策对商业娱乐类游憩出行频次的负面影响较小，对文化休闲类与体育健身类出行的频次影响较大。在出行平均距离方面，管控政策等级的提高对自然生态类与商业娱乐类出行的平均距离产生了明显负向影响，但对文化休闲类与体育健身类游憩出行的平均距离无明显影响。

综上所述，同为管控区域，更严格的管控政策会大大降低文化休闲类和体育健身类出行的频次，但对这两类游憩出行平均距离影响不大；相对地，更严格的管控政策会降低自然生态类和商业娱乐类出行频次及出行平均距离，可见高风险区域的居民会倾向于就近选择游憩场所。

3.3.3 高风险管控区与未管控区基准回归结果

根据高风险管控区与未管控区对比结果（表10），高风险区域管控政策对4种游憩出行的频次均有显著负面影响，但通过比较系数发现，文化休闲类与体育健身类游憩出行频次受高等级管控政策的负面影响较大；在出行平均距离方面，自然生态类和商业娱乐类游憩出行平均距离受高等级管控政策影响较大，文化休闲类和体育健身类游憩出行平均距离受高等级管控政策的影响则不显著。

综上所述，相较于未管控区，高等级的管控政策会对4类游憩行为产生较为明显的影响。高等级管控政策实施，会大大降低文化休闲类和体育健身类游憩出行频次，但对这两类出行平均距离影响不大，可见高等级管控政策会降低居民进行文化休闲类和体育健身类游憩出行的需求，这也与这两类游憩场所大多会进行封控管理有关；相应地，高等级管控政策实施会使自然生态类和商业娱乐类游憩出行平均距离下降，但对这两类出行频次影响较小，可见这两类游憩出行对高风险管控区的居民来说具有一定的不可替代性，有相应需求的居民会去探寻居住区附近的游憩场所。

表 7：加入控制变量后高风险与未管控政策对出行频次与出行平均距离的回归结果

变量	出行频次	出行平均距离
高风险或无管控政策	−1.445*** (−0.214)	−0.327*** (−0.108)
组别虚拟变量	1.245*** (−0.0556)	0.454*** (−0.0205)
时间虚拟变量	−0.231*** (−0.0563)	−0.108*** (−0.0184)
街道内四类游憩类型 AOI 数量	0.0356*** (−0.00328)	0.00737*** (−0.00142)
常住人口数量	2.34e−05*** (−1.23e−06)	−1.22e−05*** (−4.86e−07)
居住区 AOI 距离游憩 AOI 的最近距离平均值	−7.77e−05*** (−2.14e−06)	3.08e−05*** (−7.77e−07)
常数	7.369*** (−0.071)	10.27*** (−0.025)
观测值	1,991	1,991
拟合优度 R^2	0.625	0.695

注

1. * 代表 $p<0.05$；** 代表 $p<0.01$；*** 代表 $p<0.001$。
2. 括号内为标准误。

表 8：加入控制变量后有无管控政策对 4 类游憩出行频次与距离的回归结果

变量	自然生态类		商业娱乐类		文化休闲类		体育健身类	
	出行频次	出行平均距离	出行频次	出行平均距离	出行频次	出行平均距离	出行频次	出行平均距离
有无管控政策	−0.435*** (−0.117)	−0.0063 (−0.048)	−0.315*** (−0.113)	−0.0309 (−0.0416)	−0.387*** (−0.123)	−0.0408 (−0.0458)	−0.258** (−0.122)	−0.0659 (−0.0502)
组别虚拟变量	−0.0794 (−0.0752)	0.118*** (−0.0338)	−0.0434 (−0.0744)	0.0999*** (−0.0302)	−0.0672 (−0.0893)	0.135*** (−0.0336)	−0.0953 (−0.085)	0.191*** (−0.0386)
时间虚拟变量	−0.203*** (−0.0568)	−0.0659*** (−0.0184)	−0.229*** (−0.0558)	−0.0568*** (−0.0178)	−0.044 (−0.054)	−0.0794*** (−0.0204)	−0.163*** (−0.0557)	−0.0617*** (−0.0231)
街道内 4 类游憩 AOI 数量	0.0363*** (−0.00234)	0.00263*** (−0.00091)	0.0358*** (−0.00234)	0.00324*** (−0.00099)	0.0179*** (−0.00271)	0.00716*** (−0.00101)	0.0228*** (−0.0025)	0.00556*** (−0.0017)
常住人口数量	2.58e−05*** (−1.09e−06)	−1.64e−05*** (−4.84e−07)	2.22e−05*** (−1.07e−06)	−1.30e−05*** (−4.41e−07)	1.87e−05*** (−1.09e−06)	−1.27e−05*** (−4.58e−07)	1.42e−05*** (−1.10e−06)	−6.92e−06*** (−4.62e−07)
居住区 AOI 距游憩 AOI 最近距离平均值	−7.81e−05*** (−2.02e−06)	3.45e−05*** (−7.20e−07)	−7.92e−05*** (−1.91e−06)	3.54e−05*** (−6.90e−07)	−7.95e−05*** (−2.44e−06)	4.28e−05*** (−9.09e−07)	−8.06e−05*** (−1.95e−06)	3.78e−05*** (−1.03e−06)
常数	6.712*** (−0.0678)	8.938*** (−0.0229)	6.386*** (−0.0662)	8.850*** (−0.0222)	4.506*** (−0.0723)	8.816*** (−0.026)	4.881*** (−0.0674)	8.717*** (−0.0338)
观测值	2,384	2,385	2,376	2,376	2,082	2,082	2,183	2,184
拟合优度 R^2	0.642	0.754	0.645	0.759	0.588	0.746	0.581	0.617

注

1. * 代表 p<0.05；** 代表 p<0.01；*** 代表 p<0.001。
2. 括号内为标准误。

4 结论与讨论

在突发公共卫生事件中，特别是在各类传染病流行的情况下，基于确定的地理区域进行管控干预是常规且有效的做法[44]-[46]，对地理区域的管控会直接影响居民的特定出行行为。研究通过分析2021年7月南京市突发公共卫生事件发生前后居民游憩出行行为的时序变化特征，结合政府分级管控政策的实施情况，探究突发公共卫生事件对居民游憩行为的影响，得出以下结论：一方面，突发的公共卫生事件所导致的管控措施在很大程度上会影响居民的出行选择，造成全域居民游憩出行频次明显下降，平均距离有所增加，自然生态类和体育健身类游憩出行平均距离增加较为明显。另一方面，分级管控政策会对不同政策管控区域内居民的游憩出行产生不同的影响——管控等级越高，游憩出行频次越低；但出行距离的变化不规则，当管控等级由中风险提升到高风险时，管控区域内居民出行的平均距离会相应减少。对4种不同游憩出行行为而言，管控政策等级的提高会导致4种游憩出行频次均有一定下降，其中随着管控等级的提高，相应区域范围内居民的文化休闲类和体育健身类游憩出行

表 9：加入控制变量后高等级与中等级管控政策对 4 类游憩出行频次与距离的回归结果

变量	自然生态类		商业娱乐类		文化休闲类		体育健身类	
	出行频次	出行平均距离	出行频次	出行平均距离	出行频次	出行平均距离	出行频次	出行平均距离
高等级或中等级管控政策	−1.380*** (−0.273)	−0.291*** (−0.0864)	−0.834*** (−0.196)	−0.516*** (−0.116)	−1.871*** (−0.378)	−0.0635 (−0.068)	−1.883*** (−0.39)	−0.0857 (−0.114)
组别虚拟变量	1.683*** (−0.117)	0.262*** (−0.0552)	1.701*** (−0.106)	0.178*** (−0.0452)	2.346*** (−0.298)	−0.209** (−0.0902)	1.580*** (−0.167)	0.124* (−0.0631)
时间虚拟变量	−0.572*** (−0.102)	−0.0576 (−0.0466)	−0.507*** (−0.0981)	−0.061 (−0.0386)	−0.387*** (−0.102)	−0.102** (−0.0411)	−0.368*** (−0.107)	−0.103** (−0.044)
街道内 4 类游憩 AOI 数量	0.0339*** (−0.00388)	0.00235 (−0.00169)	0.0375*** (−0.00379)	0.00458*** (−0.00142)	0.0193*** (−0.00451)	0.00710*** (−0.00137)	0.0265*** (−0.00368)	0.00752*** (−0.00156)
常住人口数量	2.53e−05*** (−0.00000286)	−1.82e−05*** (−0.0000013)	2.42e−05*** (−0.00000272)	−1.40e−05*** (−0.00000107)	1.78e−05*** (−0.00000372)	−1.17e−05*** (−0.00000107)	2.17e−05*** (−0.00000278)	−1.13e−05*** (−0.00000107)
居住区 AOI 距游憩 AOI 最近距离平均值	−9.61e−05*** (−0.00000549)	3.39e−05*** (−0.00000304)	−9.28e−05*** (−0.00000482)	3.83e−05*** (−0.00000216)	−0.000127*** (−0.0000157)	5.78e−05*** (−0.0000045)	−9.45e−05*** (−0.00000757)	4.53e−05*** (−0.00000305)
常数	6.838*** (−0.16)	9.080*** (−0.0851)	6.385*** (−0.155)	8.894*** (−0.0663)	4.832*** (−0.269)	8.782*** (−0.0764)	4.720*** (−0.181)	8.833*** (−0.075)
观测值	419	419	418	418	375	375	397	397
拟合优度 R^2	0.762	0.732	0.767	0.789	0.713	0.794	0.681	0.754

注
1. * 代表 p<0.05；** 代表 p<0.01；*** 代表 p<0.001。
2. 括号内为标准误。

频次下降更为明显；在出行平均距离方面，管控风险的变化对自然生态类、商业娱乐类的平均距离会产生明显影响，更高等级的管控政策，会使这两类游憩出行平均距离显著下降，但对文化休闲类与体育健身类的出行平均距离无显著影响。

4.1 出行行为变化模式

自疫情第一天官方通报后，南京市居民总体游憩出行的频次和平均距离较事件发生前均产生了明显的变化，这和突发公共卫生事件的传播特征有关。在突发公共卫生事件中，基于疫情传播的特征[13][14]，居民会对日常出行行为的风险进行把控[30][32]，主动减少高风险行为[16][17]。对游憩出行而言，居民的风险感知和出行动机都会发生变化[26][27]，这些因素会影响居民游憩出行行为的选择。结合本研究结果，疫情突发后，南京市全域居民总体游憩出行频次及各类型游憩出行频次均明显下降，可能原因是将游憩行为作为“非必要”出行的居民会选择不出行，减少感染风险，同时，居民会将平日较热门（群体聚集可能性高）的游憩场所视为高风险目的地[30][32]，选择不再或减少去往这类场所[47]。在出行平均

表 10：加入控制变量后高等级管控政策与无管控政策对 4 类游憩出行频次与距离的回归结果

变量	自然生态类		商业娱乐类		文化休闲类		体育健身类	
	出行频次	出行平均距离	出行频次	出行平均距离	出行频次	出行平均距离	出行频次	出行平均距离
高等级或无管控政策	–1.750*** （–0.258）	–0.283*** （–0.0745）	–1.113*** （–0.177）	–0.520*** （–0.11）	–2.217*** （–0.365）	–0.0849 （–0.0575）	–2.091*** （–0.377）	–0.126 （–0.107）
组别虚拟变量	1.208*** （–0.0574）	0.394*** （–0.0201）	1.316*** （–0.0591）	0.347*** （–0.0238）	1.263*** （–0.0812）	0.211*** （–0.0265）	1.022*** （–0.0865）	0.547*** （–0.0364）
时间虚拟变量	–0.202*** （–0.0568）	–0.0659*** （–0.0184）	–0.228*** （–0.0558）	–0.0569*** （–0.0178）	–0.0409 （–0.0539）	–0.0805*** （–0.0204）	–0.161*** （–0.0557）	–0.0628*** （–0.023）
街道内 4 类游憩 AOI 数量	0.0360*** （–0.00331）	0.00182 （–0.00127）	0.0341*** （–0.00331）	0.00209 （–0.00146）	0.0131*** （–0.00401）	0.00871*** （–0.00146）	0.0231*** （–0.0037）	0.00247 （–0.00254）
常住人口数量	2.55e–05*** （–0.00000123）	–1.58e–05*** （–0.000000552）	2.18e–05*** （–0.00000123）	–1.25e–05*** （–0.000000515）	1.80e–05*** （–0.00000125）	–1.26e–05*** （–0.000000531）	1.20e–05*** （–0.00000127）	–4.98e–06*** （–0.000000475）
居住区 AOI 距游憩 AOI 最近距离平均值	–7.60e–05*** （–0.00000221）	3.45e–05*** （–0.000000711）	–7.79e–05*** （–0.0000021）	3.50e–05*** （–0.000000738）	–7.66e–05*** （–0.00000245）	4.17e–05*** （–0.00000093）	–7.90e–05*** （–0.00000207）	3.67e–05*** （–0.00000109）
常数	6.683*** （–0.0728）	8.939*** （–0.0237）	6.383*** （–0.071）	8.861*** （–0.024）	4.521*** （–0.0777）	8.816*** （–0.028）	4.881*** （–0.0721）	8.741*** （–0.0383）
观测值	1,986	1,987	1,979	1,979	1,725	1,725	1,806	1,807
拟合优度 R^2	0.621	0.763	0.624	0.756	0.582	0.746	0.57	0.603

注

1. * 代表 p<0.05；** 代表 p<0.01；*** 代表 p<0.001。
2. 括号内为标准误。

距离（即出行目的地距离居住地的远近）方面，对游憩行为具有较高需求的居民可能会选择距离较远、人流量较少、感染风险较低的区域，尤其就自然生态类和体育健身类游憩出行行为而言，其在疫情突发后部分日期的出行平均距离增加十分明显，这一点可以补充前人的相关研究结果[18][23][48]。

4.2 分级管控政策效应

鉴于新型冠状病毒的传播特点，国内外在流行高峰期均采取了一定的基于地理空间的限制人群出行的干预措施[49][50]。处在风险管控区内的居民会因为政策的变化被迫改变出行行为，与以往的出行模式差异较大。本研究发现，不同风险等级的管控政策会对4类游憩的出行频次产生明显影响，随着管控等级的提高，居民会遵守政策规定的行为限制和保护隔离要求，减少游憩出行，同时选择就近生活圈范围内的游憩场所满足必要需求，这些发现与现有部分研究基本一致[3][7][22]。另一方面，关于4类游憩出行的受影响程度差异，本研究结果表明，管控等级的提高对自然生态类和商业娱乐类游憩的出行频次影响较小，出行平均距离会明显

下降；而文化休闲类和体育健身类游憩的出行频次降低十分明显，出行平均距离变化不明显。此结论和前文总体游憩出行平均距离的结果有所差异，也可见管控政策实施区域居民的游憩出行行为确实会因为政策的实施呈现较为不一样的结果。同时，有研究表明，疫情管控期间人们对城市自然生态空间及户外运动场所的使用频率会增加[19][47]，这种差异可能是由于本研究仅从AOI数据中筛选游憩目的地，未能涵盖所有可进行特定游憩活动的场所；同时，不同的文化和区域背景会导致管控政策的实施效力有所差别，使得本研究的结果与先前的研究有所不同。

4.3 规划与政策意涵

在突发公共卫生事件后，由于风险感知变化及政策管控的限制，居民的传统游憩行为难以得到充分实现[24]，本研究结果为城市应对突发公共卫生事件提供了重要参考，可在控制疾病传播的同时在一定程度上为保障居民的身心健康提供策略。从城市规划角度出发，人群出行距离与城市用地布局关系密切[51][52]。已有众多研究关注绿地、商业服务场所等公共设施与居住区的距离[53][54]，以期更好地满足居民日常游憩需要。在突发公共卫生事件中，对疫情的恐慌使得居民更倾向于前往人流量少的场所开展游憩活动[55]，并期望避开周边的风险点位，由此导致了更远的出行距离。结合本文研究结果，为增强城市应对突发公共卫生事件的韧性，在城市规划中应考虑公共游憩空间与居住区的距离，尤其应增加居住区附近自然生态类和体育健身类游憩空间，如街边绿地、社区广场等，保证居民在封控范围内也可就近进行户外休闲活动，满足高等级管控范围内居民的基本游憩行为。同时应注重其规模，将单位时间内可承载的人流密度控制在合理范围内，从而间接保障社交距离，减少疫情传播的风险[12]。

在政策制定方面，为阻止疫情的传播扩散，南京市封控了具有疫情传播风险的居住区与游憩场所，即不仅限制了人群流动，还对游憩出行目的地进行了管控。面对传染病类的突发公共卫生事件，进行社会隔离的做法已被证明对减少病毒的传播有效，但可能会对人们的心理健康造成负面影响，如导致焦虑、抑郁和孤独感的增加[47]。本次突发感染事件发生期间，政府采取的封控政策强力限制了居民的出行，同时对游憩场所的强制关闭也影响了居民的出行行为，部分户外的城市公园、景区、商业步行街、文化娱乐场所、体育健身场地等均禁止居民进入，这大大限制了居民的活动范围，从而导致风险管控区域居民的游憩出行频次减少，这在一定程度上会影响居民的身心健康。因此，针对突发的公共卫生事件，风险区域的管控政策或可更加灵活，可对公园、风景区、广场、步行街等户外活动空间适当放宽或解除封闭限制，鼓励居民就近在户外进行游憩行为，一方面可以降低突发公共卫生事件应对成本，便于人口流动统计，同时也可以尽可能满足无涉疫风险人群的游憩需求，进而减少对居民生活的影响。

本研究可丰富对城市居民游憩行为的认知及突发公共卫生事件下居民行为变化特征的相关探索，但仍存在一定不足。首先，在居民游憩出行目的地的选择上，以城市AOI作为数据来源，并不能完全覆盖城市居民的所有游憩出行目的地；其次，在突发公共卫生事件中，居民主动性的风险规避和被动的行为限制对游憩出行的影响差异仍需进一步探究；最后，如何在重大突发公共卫生事件背景下引导居民调整日常生活安排及城市更新规划实践，还有待进一步深入研究。

补充材料

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图 1. 南京市 2021 年 7、8 月病例数变化逐日统计图
图 2. 游憩出行频次逐日变化
图 3. 4 类游憩出行频次结构统计
图 4. 游憩出行平均距离逐日变化。每日的总体游憩出行平均距离指当日游憩出行总距离 / 当日游憩出行总频次。每日某一类游憩出行平均距离指当日该类游憩出行总距离 / 当日该类游憩出行总频次。