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Commuting Behavior Changes at Different Stages of Localized COVID-19 Outbreak: Evidence from Nanjing, China

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Abstract: Commuting behaviors have been changed by the COVID-19 pandemic. To investigate the impacts at different stages of sudden and localized COVID-19 outbreak, this paper carries out an online survey to obtain data, targeting the residents in Nanjing China, where there had been COVID-19 outbreaks and proposes a sequential analysis method to calculate the complexity of commuting behavior changes. The Tobit model is used to explore the factors that influence the complexity of commuting behavior changes. Results show that commuters using public transportation drop significantly when sudden outbreaks occur, with 43.5% of them switching to private cars or working from home. The number of residents working from home increases by 14 times. While an outbreak gradually subsides, commuting modes tend to recover, but does not immediately return to the state before the outbreak. Regression model results indicate that commuters aged 40–60 tend to maintain their commuting habits, while younger workers are more flexible on their commuting options. Middle-income commuters, or those living in low-risk areas or near a subway within 800 m prefer to change commuting modes, opting for what they perceive to be safer ways to commute. For commuters living in medium- or high-risk areas and those who are living with people who have non-green health codes, they tend to adjust their commuting modes in real time based on the color change in the health codes and the risk level of the areas they live. The research findings contribute to our understanding of commuting behaviors and targeted management needs during local outbreaks, and can help the government formulate a comprehensive and more effective pandemic prevention policy.

Keywords: commuting; mode shift; sequential analysis; turbulence; localized COVID-19 outbreak

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1. Introduction

On 30 January 2020, the WHO declared that the COVID-19 outbreak is a public health emergency of international concern and, in March 2020, defined it as a pandemic. As of 30 September 2022, there have been 614,385,693 confirmed cases of COVID-19 across the globe, including 6,522,600 deaths [1]. The pandemic greatly changed people's travel behaviors [2–4]. In 2021, although the pandemic is generally under control, small-scale outbreaks occur from time to time in China [5]. If a sudden and localized outbreak occurs, restrictions come and residents' daily travels are affected [6]. As we enter the post epidemic era, the society is moving into a new normal of productive life and economy. However, it is necessary to explore commuting behavior during the epidemic period, which can provide coping strategies for possible similar health events in the future [7].

Commuting is an essential part of urban daily life. It describes the travel between an individual's residential place and workplace. Substantial variations are observed concerning individual commuting behaviors during the COVID-19 pandemic [8,9]. Commuting was a matter of habit rather than forethought, yet many commuters have to rethink their habits due to the concerns with the virus [10]. Early empirical evidence suggested that COVID-19 would reduce urban traffic volumes [11]. Restrictions on residents' travel due to the pandemic caused them to change their everyday travel behaviors [12]. When outbreaks occur, people tend to take more preventive measures and travel less to medium- or high-risk areas [13]. At the same time, there has been an increase in the use of telework and virtual meetings, which caused a great reduction in commuting and business trips [14]. The shift from physical commuting to working from home led to an even greater drop in mobility [15].

Some studies focused on the changes in commuting modes and commuting frequency in the post-pandemic era. However, few studies have investigated the impacts on commuting behaviors at different stages of localized COVID-19 outbreak. This study focuses on the changes in commuting frequency and commuting patterns at different COVID-19 outbreak stages, from the beginning of an outbreak to the gradual subsiding. Specifically, a sequential analysis method is proposed to calculate the complexity of commuting behaviors and the Tobit model is used to explore the factors that influence the complexity of commuting behaviors. Understanding residents' travel patterns and the complexity of their trips is essential in transportation planning, public health, and many other areas [16]. The measurement of commuting travel complexity during sudden COVID-19 outbreaks improves our understanding of commuting behaviors and facilitates user segmentation and targeted demand management. Analyzing the complexity of commuting modes and finding the key influencing factors is also of great significance for the government to formulate transportation and pandemic prevention policies to cope with such complex commuting changes.

The main contributions of this paper are as follows:

Exploring the impacts of pandemic on commuting behavior changes at different stages of sudden and localized COVID-19 outbreak.

From a new perspective, sequence analysis is used to calculate the complexity of commuting behavior changes during localized outbreaks.

Establishing a Tobit regression model to analyze the influential factors associated with the complexity of residents' commuting behaviors during localized outbreaks.

In Section 2, a literature review of the impacts of COVID-19 on commuting behaviors and influential factors of commuting behaviors is provided. Section 3 describes the data collection effort. In Section 4, the basic frameworks of Sequence analysis and Tobit regression used in the study are described. In Section 5, the effects of the COVID-19 pandemic on commuting behavior changes are discussed, and the results of the regression model are analyzed. Conclusions and suggestions for future research are summarized in the last part of the paper.

2. Literature Review

A brief review that focuses on the impacts of the COVID-19 pandemic on commuting behaviors and the factors influencing commuting behaviors is provided below.

2.1. Impacts of COVID-19 on Commuting Behaviors

People's travel behaviors have changed in response to the threats of COVID-19 and related guidelines and restrictions that are still active [17,18]. The COVID-19 pandemic led to a reduction in the number of trips and a change in mode choice [19,20]. The proportion of commuting trips has declined during the pandemic [21]. However, Bh and TM, [22] found that in India, the majority of their survey respondents were willing to reduce their trips for recreation and essential trips but in addition to work. During the COVID-19 pandemic, commuters have a strong sense of self-protection. They do not think buses, subways, and taxis are secure enough [23]. Yıldırım et al. [24] concluded that one of the most adopted preventive behaviors during COVID-19 was the avoidance of public transportation, which further led to a significant reduction in the number of trips on all kind of public transportation during the pandemic period and maintained at a low level for a long time [18]. Dingil and Esztergár-Kiss [25] found that after the COVID-19 pandemic, the majority of workers are willing to change their primary commuting mode. Public transit users are more likely to change their commuting modes than car users, motorcycle users, and people that walk. Some empirical evidence and information worldwide indicated that people are also resorting more to active transport since the outbreak of COVID-19 [26,27]. Advani et al. [28] suggested that there is a good opportunity to facilitate the switch to non-motorized transport (e.g., walking and cycling) if suitable infrastructure is provided in the post-pandemic era. Nikiforiadis et al. [29] found that non-motorized transportation modes are now more likely to become desirable alternatives to public transportation modes during and after the pandemic. The pandemic has also increased the average trip time of bike-sharing [30]. However, COVID-19 does not affect significantly the number of residents using shared bike for their trips [29]. The COVID-19 pandemic has increased the proportion of work-from-home jobs [31]. De Haas et al. [27] found that nearly half of employees encountered work environment changes, such as workplace or working hour changes during the lockdown period. Astroza et al. [32] found that the majority of workers increased the amount of hours working from home and have more remote meetings. In addition, 27% of home-workers expect to work from home more often in the future. Beck and Hensher, [33] found that nearly half of employees have started to spend more and more time working from home, and the majority of these employees report positive experiences.

2.2. Influencing Factors of Commuting Behaviors on the Impact of COVID-19

Based on previous studies on the impact of COVID-19 on commuting behaviors, several interesting conclusions have been drawn, such as the following: with the implementation of preventive measures, travel frequency has dropped significantly [34]; differences in factors such as gender, education level, lifestyle, number of positive cases, and travel restrictions have an impact on travel choice and travel behavior [35,36]; and lockdown and travel restrictions have a significant impact on people's commuting trips [37]. Hadjidemetriou et al. [38] investigated the impact of government control measures on human mobility reduction. As the government announced more measures, the mobility of people gradually declined and stabilized at around 80% after the lockdown was imposed. The travel restriction policy forces most residents to work remotely [39]. Hensher et al. [40] suggested that gender and age are related to travel frequency change during the lockdown. Men commute more times per week than women, and the number of weekly car trips increases with age. Anwari et al. [41] used ordered logistic regression to find that men are more likely than women to continue to work outside the home when the pandemic started. In addition, there is a relationship between the working-from-home mode and commuting travel. If commuters work from home for more than 4 or 5 days, the number of weekly car trips will decrease. Beck et al. [26] found that high-income families drive more to and from work each week. By contrast, higher-income households commute less by public transport. The number of residents commuting by car increased as restrictions eased. Regions with higher income and more white and Asian residents suffer a more significant decrease in shared bike trips during the pandemic [42,43]. Studies have shown that gender, education level, employment status, and occupation are all important factors affecting working from home [12]. Kogus et al. [44] used multinomial logistic modeling to find that socio-demographic, work-related, and personality traits have a significant effect on commuting/telecommuting trends and frequency. Shibayama et al. [45] found that among those who continued to commute but switched commuting modes from public transport to others, and COVID-19 infection concern on public transport was the most frequently cited reason. Zhao et al. [46] used a binary logistic regression model to find that subway and e-bike commuters were more likely to work from home than active commuters. However, in the post-pandemic period, the risk level did not have a significant impact on residents' public transport trips, while awareness of the pandemic and travel susceptibility had a significant impact on public transport trips [47]. The increased perception of risk in the workplace did not significantly reduce travel [13]. Astroza et al. [32] found that income has a certain impact on whether employees need to work at home. A total of 77% of employees from low-income families have to work outside, while 80% of employees from high-income families work from home. Zhou et al. [48] research has shown that risk awareness and interventions are the main drivers for people to change the way they travel.

2.3. Research Gaps

Recent research examines the interaction between COVID-19 outbreaks and changes in commuting modes. However, few studies have explored the changes in commuting modes at different stages of sudden and localized COVID-19 outbreak. In addition, few studies specified an indicator to quantitatively examine commuting behavior changes at different stages of localized COVID-19 outbreak. When exploring the influencing factors, recent research explores mainly the impacts of personal attributes and pandemic prevention policies on commuting behaviors. Few studies explore the impact of health codes and risk areas on commuting behaviors. In exploring the factors affecting commuting behavior, scholars often use the logit model, which is suitable for discrete dependent variables, especially for binary problems. The Tobit model is used to deal with continuous but constrained dependent variables, such as the serial turbulence values of the time series. Using an online survey, this paper reveals the commuting modes changes. Then, a sequential analysis method is proposed to calculate the complexity of commuting behaviors and the Tobit model is used to explore the factors that influence the complexity of commuting behaviors.

3. Data

On 20 July 2021, in Nanjing Lukou Airport, Delta strain carriers were found, and the prevention and control of the localized COVID-19 outbreak in Nanjing entered a stage of comprehensive strictness. From July 20 to August 9, the strain spread rapidly, and large-scale outbreaks occurred in the main city and surrounding areas. As of 24:00 on 9 August, Nanjing had reported a total of 235 local confirmed cases, and a total of 26 cases had been discharged [49]. Figure 1 shows the changes in new cases and accumulated confirmed cases (including recovered cases and cases treated in hospital) during the outbreak in Nanjing, China.

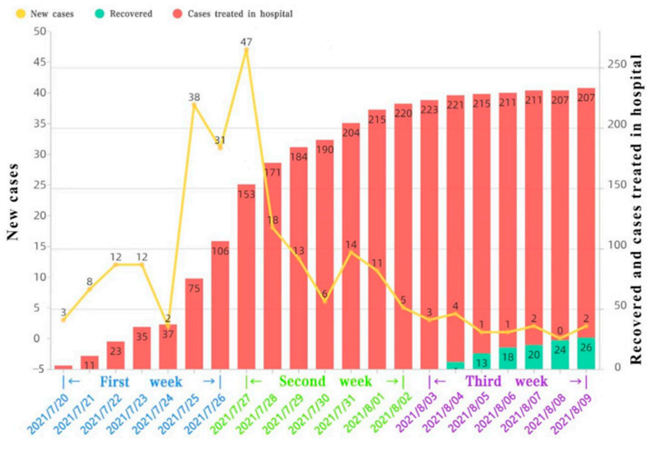

Figure 1. Changes in new cases and accumulated confirmed cases.

It took three weeks for the outbreak to subside. The first week (20 July 2021–26 July 2021) was the starting phase of the outbreak, during which the number of cases increased rapidly. The second week (27 July 2021–2 August 2021) was the mitigation phase of the outbreak. During this period, the number of cases continued to increase, with the highest number of new cases recorded on the first day of this period, but then the daily number of new cases began to decline significantly. In the third week (3 August 2021–9 August 2021), the outbreak was under control, during which the daily number of new cases was close to zero. Especially at this phase, the number of people being cured starts to increase.

The outbreak in Nanjing has changed the way residents travel and work. During this time, traffic tightened and some subway and bus stops were closed and residents' commuting and other travel patterns may change to a large extent.

"Questionnaire Star" is one of the largest online survey platforms in China and has the advantages of simplicity and ease of use, rich functionality, data security, and multi-channel sharing [50]. With reference to the data collection procedure, for security reasons, and in combination with the data collection methods of previous studies, this research released formal questionnaires on "Questionnaire Star" [51,52]. The area scope was limited to Nanjing, and the survey time was from 11 August 2021 to 25 August 2021. Respondents were asked to recall their commuting patterns before the sudden outbreak (from 13 to 19 July 2021) and during the outbreak period (three weeks from 20 July to 9 August 2021). To ensure the quality of the questionnaire, the minimum answer time for each questionnaire was set at 270 s. In addition, a reward strategy was introduced that respondents would receive USD 1.42 (RMB 10) if respondents completed the questionnaire and passed a logical secondary screening. The questionnaire system reminds participants of incomplete questions in real time to prevent respondents from missing questions while answering. Incomplete questionnaires cannot be submitted to the system to ensure the completeness of each questionnaire.

The questionnaire includes two parts: personal information and residents' commuting behavior survey. The personal information includes the sociodemographic characteristics of Nanjing commuters, including age, gender, income, education level, occupation, family members, driving license, car ownership, bike ownership, electric bike ownership, and whether there is a subway station within 800 m of the residence (800 m is an acceptable walking distance for residents to travel and is the most effective buffer to measure the environment around a subway station). In particular, COVID-19 pandemic-related observation variables were specifically considered, including vaccination, regional risk type (respondents responded based on regional risk levels as determined by local public health authorities), frequency of nucleic acid testing (NAT), and personal health code status. Among them, the personal health code status, which is generated after the background review based on data submitted online by citizens, can be used as an electronic voucher for entry and exit to public places and transportation systems during the epidemic period [53]. In the second part, we divide the sudden and localized outbreak in Nanjing into four stages, one week a stage, and then record the main commuting mode choice that residents choose each week, as well as their weekly commuting frequency. Detailed survey questions are presented in Appendix A.

4. Methodologies

The purpose of this paper is to focus on how residents' commuting behaviors have changed at different stages of the localized COVID-19 outbreak and to explore the factors that influence changes in commuting behaviors. The method of sequence analysis is briefly introduced to obtain the evaluation index of the complexity of residents' commuting behaviors, and then the Tobit regression model is briefly illustrated.

4.1. Sequence Analysis

Sequence analysis is used to measure residents' commuting behavior changes. A sequence is defined as a series of time points at which a subject can move from one discrete "state" to another [54]. These states are calibrated based on commuting modes of residents and corresponding commuting days of each mode before and during the sudden outbreak. The commuting modes include walking (W), private bike (PB), electric bicycle (EB), bus (B), subway (S), private car (PC), taxi and ride-hailing (T&RH), shared bike (SB), working from home (WFH), and others (O). In this research, residents' major weekly commuting modes are stretched according to corresponding frequency to form a sequence.

For example, consider a resident's commuting mode sequence as (S,5)-(W,3)-(WFH,3)-(W,5), which means that the commuter mainly used subway for commuting for 5 days before the outbreak. Then, this commuter mainly used walking for commuting 3 days in the first week of the outbreak. In the second week of the outbreak, he worked from home for 3 days. In the third week of the outbreak, he walked again for 5 days, and the frequency of commuting this week returned to the level before the outbreak. This sequence contains the following subsequences: the full sequence itself ((S,5)-(W,3)-(WFH,3)-(W,5)), subsequences of the type S-W-WFH, W-WFH-W, S-W and W-WFH, discontinuous subsequences like S-WFH-W (which skips the commuting mode "walking"), single activities S, W, and WFH, and an empty sequence. Enumerating all these subsequences yields 14 possible combinations that represent the precedence of activities in the S-W-WFH-W sequence.

Turbulence of sequence is calculated as a measure of the extent to which commuter travel patterns have changed at different stages of the localized COVID-19 outbreak. For a given sequence of activities, turbulence is a measure of variability and schedule complexity in relation to distinct commuting modes, the order of these commuting modes, and the variance of the durations (days for each commuting mode) of these commuting modes. It can be useful to measure fragmentation in commuting behaviors at different stages of the outbreak. Turbulence captures the order of activity participation, duration, as well as the variance within the sequence of commuting modes by a person weighted by the possible maximum of the combination of duration in each sequence and is sensitive to the number of subsequences and the differences in durations. This is a summative metric that captures the changes in each resident's commuting behaviors at different stages of the outbreak. The calculation formula of sequence turbulence is Equation (1) [55].

$$T(x) = log_2(\phi(x)\frac{s^2_{t_i,max}(x)+1}{s^2_{t_i}(x)+1}) \tag{1}$$

where

x = the sequence of commuting mode,
$\phi(x)$ = the number of distinct subsequences in sequence x,
t_i = duration in each distinct state, used to compute the mean consecutive time and variance below (i = 1, number of distinct episodes),
$s^2_{t_i}\ (x)$ = variance of the state duration for the x sequence, and
$s^2_{t_i\ ,max}(x)$ = the maximum value that the variance can take given the total duration of the sequence x.

$$s^2_{t_i\ ,max}(x) = (n-1)(1-\bar{t})^2 \tag{2}$$

where n is length of distinct state sequence and $\bar{t}$ is mean consecutive time spent in the distinct states. Turbulence uses the number of distinct subsequences in a given sequence and the number of consecutive time points spent in a given state [56].

Table 1 provides a few examples of sequences with respective lasting days for each commuting mode, counts of subsequences, and the value of turbulence. Person 1 used shared bike (SB, 20) for commuting before and throughout the localized COVID-19 outbreak, and the value of turbulence is 1. The number of distinct subsequences is two (i.e., the empty sequence and the sequence itself). Person 2, 3, and 4 record only one change in commuting mode during the outbreak compared with the mode before the outbreak. All three people have 4 subsequences, but the sequence turbulence is different. It can also be found from Persons 5, 6, and 7 that when the commuting mode of a person is changed frequently in the whole period and the commuting frequency does not change much, the turbulence of this person tends to be greater.

Turbulence of 1 indicates that the commuting pattern of a person remains the same before and throughout the outbreak. The turbulence value is greater when the commuting mode changes and the commuting frequency between the two contiguous phases does not change much. A higher turbulence value means that the commuting behavior changes more during this period.

Table 1. Examples of sequences and turbulence.

	(Commuting Mode, Commuting Days for Each Week)	Pattern	Number of Subsequences	Turbulence $T(x)$
Person 1	(SB,5)-(SB,5)-(SB,5)-(SB,5)	SB	2	1
Person 2	(EB,6)-(PC,5)-(PC,4)-(PC,3)	EB-PC	4	4.47
Person 3	(S,6)-(PC,6)-(PC,6)-(PC,6)	S-PC	4	3.72
Person 4	(S,5)-(S,5)-(WFH,5)-(WFH,5)	S-WFH	4	8.36
Person 5	(B,6)-(B,6)-(S,6)-(T&RH,6)	B-S-T&RH	8	6.46
Person 6	(B,7)-(T&RH,2)-(PC,7)-(EB,5)	B-T&RH-PC-EB	16	7.41
Person 7	(S,5)-(PC,5)-(WFH,5)-(PC,5)	S-PC-WFH-PC	14	9.42

Note: W = walk, PB = private bike, EB = electric bicycle, B = bus, S = subway, PC = private car, T&RH = taxi and ride-hailing, SB = shared bike, WFH = work from home, O = other.

4.2. Tobit Regression

In order to explore the relationship between the complexity of commuting behavior changes and sociodemographic characteristics and COVID-19-related variables, turbulence, as an indicator measuring the complexity of commuting behavior changes, is used as the dependent variable, and sociodemographic characteristics and pandemic related variables are used as independent variables. Figure 2 shows a histogram of the turbulence. It can be seen that 228 (51.4%) people exhibit a turbulence of 1, which means many observations are at a specific left censored limit value of the dependent variable.

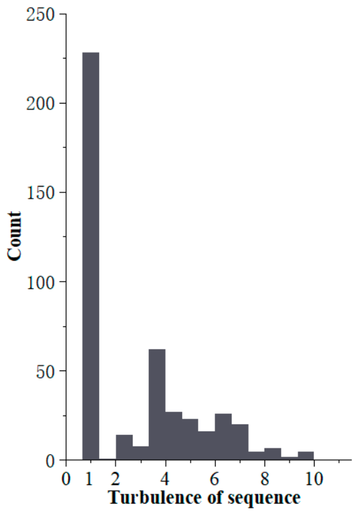

Figure 2. Histograms of the turbulence.

Previous studies have proven that standard ordinary least squares estimation would lead to serious specification errors when the dependent variable does not meet the assumption of normality and observations are stacked at a certain point [57]. The Tobit model has been widely used as an alternative method to model the left-censored data [58,59]. The Tobit model is a non-linear regression model that accounts for the "piling up" of observations at a value of the dependent variable. For turbulence, the value was one. A Tobit model with a left-censored limit of one takes the following forms and the specification of Tobit models is given using an index function in Equations (3) and (4):

$$Y_i^* = \beta X_i' + \varepsilon_i\ ,\ i = 1, 2, \cdots N \tag{3}$$

$$Y_i = \begin{cases} Y_i^*\ if\ Y_i^* > 1 \\ 1\ if\ Y_i^* \leq 1 \end{cases} \tag{4}$$

where Y_i^* is latent variables generated by the classical linear regression model, which is observed only when it is greater than one, N is the total number of observations, Y_i is used to calculate the turbulence value of i, β is a vector of estimable parameters, X_i' is a vector of explanatory variables, and ε_i is the normally and independently distributed error term with mean zero and constant variance $\sigma_\varepsilon{}^2$.

The corresponding log likelihood function of a Tobit model over one observation ($Y_i = 1$) and more than one observation ($Y_i = Y_i^*$) is expressed as

$$L(Y_i \mid \beta, \sigma_\varepsilon) = \prod_{Y_i=1}\left[1 - \Phi\left(\frac{\beta X_i'}{\sigma_\varepsilon}\right)\right]\prod_{Y_i>1}\left(\sigma_\varepsilon^{-1}\right)exp\left[-\frac{1}{2\sigma_\varepsilon^2}\left(Y_i - \beta X_i'\right)^2\right] \tag{5}$$

The posterior distribution $f(\beta, \sigma_\varepsilon \mid Y_i)$ can be estimated using the Bayes theorem as

$$f(\beta, \sigma_\varepsilon \mid Y_i) \propto L(Y_i \mid \beta, \sigma_\varepsilon)\pi(\beta)\pi(\sigma_\varepsilon) \tag{6}$$

where $\pi(\beta)$ is the prior distribution of β, and $\pi(\sigma_\varepsilon)$ is the prior distribution of σ_ε.

Tobit model parameters do not directly correspond to changes in the dependent variable brought about by changes in independent variables. According to Greene [60], the marginal effect on the intensity of turbulence due to changes in the explanatory variable is given as follows:

$$\frac{\partial E[\frac{Y_i}{X_i}]}{\partial x_i} = \beta \times Prob[y_i^* > 1] \tag{7}$$

5. Results and Discussion

This section explores changes in residents' commuting behaviors at different stages of the localized COVID-19 outbreak and explores the factors that affect the degree of change in commuting behaviors. Specifically, Section 5.1 performs descriptive statistics on our sample. Section 5.2 explores the impact of different stages of an outbreak on commuting frequency and commuting modes. Section 5.3 analyzes the results of the Tobit regression model.

5.1. Descriptive Statistics

The purpose of this survey is to explore the impacts of localized COVID-19 outbreak on commuting behaviors at different stages of the outbreaks. Ultimately, 444 valid questionnaires were obtained. In terms of the age of the respondents, about 81.3% of the respondents are concentrated under the age of 40, with 18–25- and 31–40-year-olds occupying the majority position. Males account for 51.6%, close to the average level of Nanjing (51%) in 2021 [61]. In terms of education, more than 75% of the respondents have a bachelor's degree or above, which is related to Nanjing's sufficient educational resources and high education penetration rate. The number of individuals with annual salary of less than RMB 80,000 (less than USD 12,346) and RMB 80,000–160,000 (USD 12,346–24,692) is about the same, both of which are about 45%. Only a small portion (11.3%) of people are high-paid with an annual salary of more than RMB 160,000 (more than USD 24,692). The vast majority of commuters (92.6%) and commuters' family members (93.9%) have maintained a green health code throughout the outbreak. Only a minority of commuters (7.4%) and commuters' family members (6.1%) have non-green health codes. The regional risk type indicates the severity of the outbreak in the location of the residents, the higher the regional risk, the more likely people in that area are to become infected [62]. In China, when an epidemic occurs in a certain area, the government take rapid blockade measures or policy restrictions for medium- and high-risk residential communities in the region [51]. In 2021, China has implemented a vaccination campaign and large-scale NAT and screening will be carried out when the outbreak occurs [63]. Residents will follow government policy to receive vaccinations, so the following table shows a high vaccination rate. Detailed socio-demographic statistics are presented in Table 2.

Table 2. Demographic characteristics.

Variable	Levels	Percentage (%)
Gender	Male	51.6
	Female	48.4
Age	<18	4.7
	18–25	24.3
	26–30	21.6
	31–40	30.7
	41–50	11.9
	51–60	6.8
Income (RMB)	0–80,000	45.0
	80,000–160,000	43.7
	>160,000	11.3
Education	Primary school and below	0.7
	Secondary school	6.1
	High school	17.8
	Undergraduate	63.7
	Above undergraduate	11.7
Occupation	Student	19.6
	Enterprise employees	57.0
	Institutional employees	13.3
	Freelancer	7.0
	Self-employed	3.1
Vaccination	Not vaccinated	12.8
	Vaccinated	87.2
Family member	1	9.2
	2	13.7
	3	34.7
	4	23.2
	5	11.7
	6	7.4
Risk type	Risk-free area	46.2
	Low-risk area	45.3
	Medium-risk area	7.2
	High-risk areas	1.4
Nucleic acid test (NAT)	1	18.5
	2	9.9
	3	16.0
	4	14.6
	5	12.2
	6	10.8
	7	11.7
	8	12.6
Driving license	Yes	74.8
	No	25.2
Whether there is a subway station within 800 meters of the residence	Yes	48.6
	No	51.4
Car ownership	Yes	73.2
	No	26.8
Bike ownership	Yes	35.4
	No	64.6
Electric bike ownership	Yes	63.5
	No	36.5
Health code situation since the outbreak	Always green	92.6
	There was a non-green code	7.4
Family health codes since the outbreak	Living alone	11.5
	Cohabitants are always green codes	82.4
	Cohabitants have yellow codes	5.4
	Cohabitants have red codes	0.7

5.2. Impact of Localized COVID-19 Outbreak on Overall Commuting Behaviors

Commuting behaviors can be explored by comparing the changes in commuting frequency before and after the localized COVID-19 outbreak. Figure 3 summarizes the weekly commuting frequency before the outbreak and during the three-week outbreak. It is important to note that the number of commuters with zero weekly commuting trips continued to increase in the three weeks of the outbreak. In the first two weeks after the outbreak (the worst half of the month), the number of people who can maintain high-frequency (e.g., five, six or seven times a week) commuting continues to decline, and 30.1% of them cannot maintain high commuting frequency. In the third week after the outbreak, when the outbreak was under control, the number of commuters with higher commuting frequency began to pick up. However, it did not return to the level before the outbreak immediately, showing only a slow recovery trend. Liu et al. [64] reached a similar conclusion that commuters' job strength would drop significantly after outbreaks. When the outbreak eases, only some commuters return to normal levels.

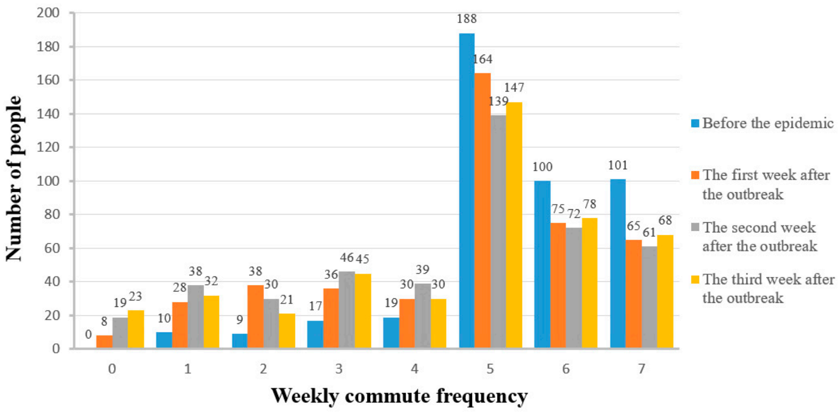

Figure 3. Changes in commuting frequency at different stages of the outbreak.

The commuting modes of residents at various stages before and after the localized COVID-19 outbreak are counted, from which we can see the conversion methods of commuting modes in each stage. The modal shift dynamics of commuting following the localized outbreak are shown in the Sankey diagram in Figures 4–6.

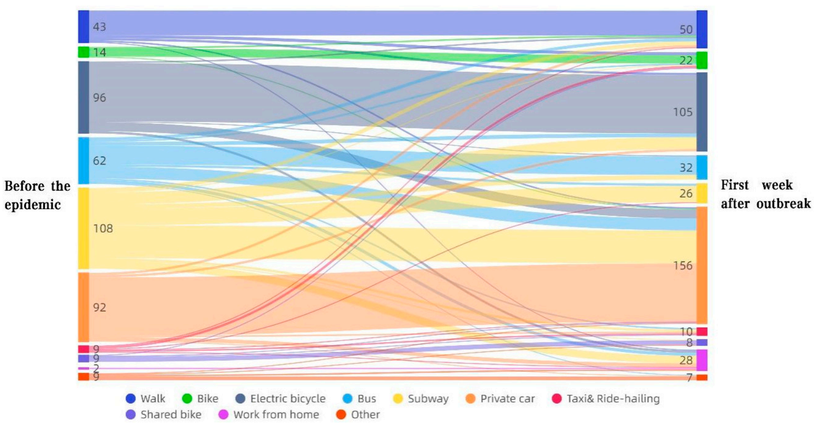

Figure 4. Mode shifts in commuting in the first week before and after the outbreak.

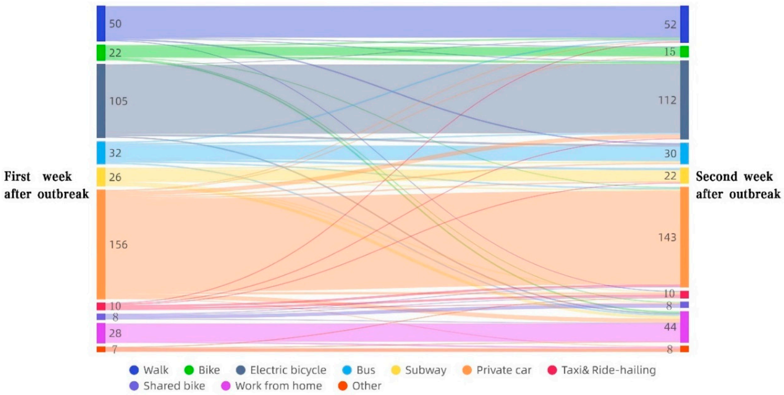

Figure 5. Mode shifts in commuting in the first and second weeks after the outbreak.

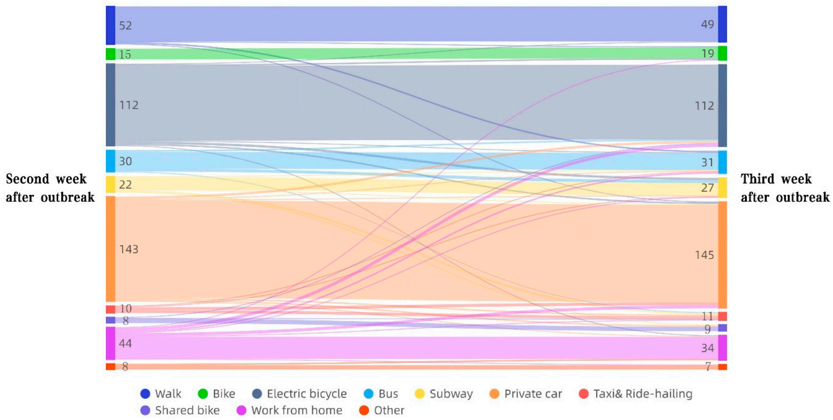

Figure 6. Mode shifts in commuting in the second and third weeks after the outbreak.

For each phase, a Sankey diagram is constructed showing commuting patterns in the previous period on the left and commuting patterns in the following period on the right. The thickness of each line represents the percentage of modal shift, with colors to distinguish different types of commuting modes. Figure 4 shows the changes in commuting patterns of residents before the outbreak and in the first week after the outbreak. In general, people tend to avoid public transport during an outbreak [24,65–67]. Before the outbreak, the majority of commuters (38.3%) used public transport as their primary commuting mode. In the first week after the outbreak, a sharp drop in public transport use was observed, with only 13.1% of commuters using public transport and 43.5% of commuters who used public transportation primarily to work before the outbreak switching to private cars or working from home in the first week after the outbreak. As explained in previous studies, the outbreak led to a shift in residents' commuting modes from public to private transportation [68–70]. The use of private cars increased from 20.1% before the outbreak to 34.2% in the first week after the outbreak. This is reasonable because people tend to rely on private vehicles more as it is safer compared to public transport or other alternatives [71,72]. Very few people worked from home before the outbreak, but in first the week after the outbreak, the number of residents working from home increased 14 times. A higher number of people working from home is considered to have a high potential to contribute to a more sustainable mobility in the future [10]. Working from home greatly reduces the probability of physical contacts and avoids cross-infection. More than 85% of commuters who chose to drive a private car, cycle or walk before the localized COVID-19 outbreak continued to do so during the pandemic. This is consistent with the findings of Cai's study [68].

Figure 5 shows the changes in commuting patterns in the first and second week after the outbreak. The number of commuters using public transportation continues to decline. These commuters who used to rely on public transportation are turning to private commuting modes such as walking, private cars, working from home and shared bikes.

Molloy et al. [18] also proved that public transport trips maintained a low level for a long time, which is complemented by the increase in the use of other transport modes such as private vehicles, non-motorized vehicles (e.g., bike and electric bicycle), and walking. Similarly, Paul et al. [73] showed that the COVID-19 pandemic has also prompted commuters to reduce their use of public transportation and increase their use of cars and active modes. The number of residents working from home increased by 57.1%. Astroza et al. [32] also made a similar finding that an increasing number of people began to work from home during the COVID-19 pandemic.

Figure 6 shows the changes in commuting patterns in the second and third weeks after the COVID-19 outbreak. Since the outbreak has been brought under control in the third week, work gradually began returning to normal. Unlike the first three phases, the number of residents using public transportation began to increase in this phase, but did not return to the levels before the outbreak. Currie et al. [74] found similar results that the use of public transport, which has fallen sharply during the pandemic, will gradually recover after the pandemic. But it will not return to pre-outbreak levels. In addition, the number of residents working from home decreased significantly. These residents mainly changed to their electric bicycles, private cars and buses. More than 90% of car commuters continue to commute by private car. Harrington DM et al. [75] came to a similar conclusion that the majority of car commuters would continue to travel by car after the restrictions were lifted.

The results also show that commuters' shared bike usage has barely changed over the four periods, which means COVID-19 does not significantly affect the number of people using shared bike for their trips. Nikiforiadis et al. [29] found a similar conclusion that the COVID-19 pandemic has not affected the number of shared bike trips, and for some residents it even becomes more attractive. For those who previously commuted by private cars and those who were already registered users of a shared bike system, shared bike is a preferable mobility option.

5.3. Tobit Regression Model Results

In this section, the Tobit regression model results are examined to measure the impact of different variables on these measures of fragmentation. Before calibrating the Tobit regression model, in order to check whether there are significant relationships among the independent variables, we performed independence tests on all independent variables in the regression model. Pearson's chi-square was used for two independent variables with only two categories. When the value is greater than 0.5, it indicates that there is a strong correlation between independent variables [76]. The results showed that all Pearson's Chi-squares were less than 0.5, so there was no multicollinearity problem in our data. Table 3 shows the Tobit model regression results.

The marginal utility of people aged 40–60 is negative and significant, reflecting that young employees are more flexible in commuting choices after the COVID-19 outbreak. At the same time, it also reflects that older employees are more inclined to maintain the original commuting habits after the outbreak. When they change, this group of people may significantly reduce their commuting frequency throughout the outbreak. Pawar et al. [77] and Gao et al. [7] found a similar conclusion that age significantly affects changes in commuting behaviors in the post-pandemic era.

Results showed that people with a subway station around their home are more likely to change their commuting mode than those without a subway station around their home. This may be because residents often take subway to work when there is a subway station nearby because of its convenience. But after the outbreak, taking subway, a public transportation, may cause cross-infection. Therefore, to protect themselves from the virus, people tend to change their commuting mode. As can be seen from the previous section, when the pandemic comes, commuters often avoid public transportation and switch to private transportation such as private cars or electric bikes.

Table 3. Tobit regression models.

Category	Sub-Category	Coefficient	Marginal Effects	t Value
Age group	<25	——	——	——
	25–40	−0.780	−0.314	−1.19
	40–60	−1.611	−0.610	−1.98 **
Gender	Female	——	——	——
	Male	−0.517	−0.199	−1.15
Family member	Number of household members	−0.231	−0.089	−1.20
Income	Less than 80,000¥	——	——	——
	80,000–160,000¥	1.589	0.618	2.64 ***
	More than 160,000¥	0.078	0.027	0.09
Education level	Low	——	——	——
	Medium	0.034	0.012	0.03
	High	0.407	0.154	0.42
Profession	Student	——	——	——
	Unit staff	−0.520	−0.200	−0.68
	Freelancers	0.913	0.390	0.96
Driving license ownership	No	——	——	——
	Yes	−0.187	−0.072	−0.30
Car ownership	No	——	——	——
	Yes	0.492	0.186	0.89
Bike ownership	No	——	——	——
	Yes	0.496	0.193	1.04
Electric bike ownership	No	——	——	——
	Yes	−0.093	−0.036	−0.19
Subway	There is no subway station within 800 m of the residential place	——	——	——
	There is a subway station within 800 m of the residential place	0.877	0.337	1.99 **
Vaccination	Vaccinated	——	——	——
	Not vaccinated	−0.829	−0.304	−1.23
NAT	The total number of nucleic acid tests since the outbreak	0.031	0.012	0.31
Residence risk zone	Risk free area	——	——	——
	Low-risk area	0.815	0.883	1.76 *
	Medium-or high-risk areas	2.133	0.305	2.69 ***
Health code situation since the outbreak	Alwas green code	——	——	——
	Have a non-green code	−0.951	−0.345	−0.95
Family health codes since the outbreak	Living alone	——	——	——

Table 3. *Cont.*

Category	Sub-Category	Coefficient	Marginal Effects	t Value
	Cohabitants always have green health codes	0.928	0.330	1.13
	Cohabitants have non-green health codes	3.342	1.428	2.79 ***
Observations			444	
Left-censored observations (1 turbulence)			228	
Uncensored observations			216	
Log likelihood at zero			−864.15	
Log likelihood at convergence			−752.11	
Akaike information criterion (AIC)			1552.22	
Bayesian information criterion (BIC)			1650.52	

Note: * Statistically significant at the 10% level (i.e., $p < 0.10$). ** Statistically significant at the 5% level (i.e., $p < 0.05$). *** Statistically significant at the 1% level (i.e., $p < 0.01$). —— Reference category within sociodemographic characteristics and COVID-19 pandemic-related variables sub-categories.

In terms of the impact of the resident's income on the changes in commuting behaviors, it can be seen that residents' income has an impact on both commuting frequency and commuting mode [68,77]. The variable of annual income between RMB 80,000 and 160,000 has a strong positive effect on changes in commuting patterns. This group of people tends to change their commuting patterns when the outbreak occurs suddenly, and then switches their commuting patterns back to normal after the outbreak subsides. Public transport is the backbone in urban areas. These services are especially important for middle-income commuters to their daily transit needs [26]. The arrival of the localized COVID-19 outbreak has forced middle-income residents to give up public transportation for safety. But when the outbreak starts to recover, they tend to switch back to public transportation.

Compared with residents who live in non-risk areas, residents living in risk areas have some impact on commuting patterns and frequency. The medium- or high-risk area is significant and has the second largest marginal utility. This reflects that commuters living in medium- or high-risk areas may change their commuting modes frequently during these four periods. The risk of infection is higher in these areas, so commuting requirements tend to be strict. The commuters will appropriately reduce their commuting frequency after the outbreak. For residents living in low-risk areas, because there is still a risk possibility, even after the outbreak, residents will make appropriate changes to their commuting modes to ensure their own safety. This may be due to the fact that restrictions on activities are more stringent in areas of medium- or high-risk areas, whereas restrictions are merely recommended in areas of low risk [78].

The red, yellow, and green-colored health code apps have been credited as an effective tool for the COVID-19 response in China [79]. A red health code indicates a mandatory quarantine. A yellow health code indicates self-isolation. When the health code is green, there are no restrictions on travels [80]. Therefore, health codes also affect commuting behaviors. An interesting finding show that people living together who have a non-green code are most affected on changes in commuting behavior. This indicates that these commuters tend to change their commuting modes each week in the three weeks following the outbreak. However, there is little effect on their weekly commuting frequency, which remains the same. When cohabitants have non-green health codes, commuters may feel they are at risk of infection, so they may choose to commute in less exposed ways. As the color of the health code will change with the pandemic situation in the region, commuters may adjust their commuting modes according to the health code color change in cohabitants.

6. Conclusions and Recommendations

In this paper, a new method was developed to explore commuting behavior changes at the localized COVID-19 outbreak in the post-pandemic era. The main purpose is to examine the changes in the commuting frequency and mode of each resident at different stages of the outbreak. By comparing the weekly commuting frequency in the past four weeks, we found that commuters will try to reduce the number of commutes after the outbreak. And because some factories would be temporarily closed, the commuting frequency will be 0. After the outbreak subsides, the commuting frequency does not return to pre-outbreak levels immediately, but shows a slow recovery trend. During the outbreak, the number of people using public transport drops significantly. These commuters switch to private transportation for fewer physical contacts with others. The number of residents working from home increases 14 times. When the outbreak eases, the number of people using public transportation begins to increase, and the number of people working from home begins to decrease, but the overall commuting pattern has not changed much, compared to the pattern before the outbreak. The outbreak hardly affects the commuting modes of shared bikes. When the outbreak eases, shared-bike usage quickly returns to the usual level.

A sequence is formed by extending the main weekly commuting modes dependent upon commuting frequency. We use turbulence as a measure of complexity in commuting sequences. We correlate the values of turbulence with the sociodemographic characteristics of the commuters and COVID-19-related variables analyzed here. Commuters aged 40–60 tend to be more inclined to maintain their commuting habits after the outbreak, while young workers tend to be more flexible in their choice of commuting modes when the outbreak occurs. Commuting behaviors are highly fragmented during this period for those living in medium- or high-risk areas and those living together with people who have non-green health codes. They change their commuting modes frequently, but their weekly commuting frequency tends to remain the same. For commuters in low-risk areas, they also adjust their commuting modes for safety reasons.

The outcomes of this study provide insights on the design of future interventions aimed at providing safer commuting. They can help transport authorities understand individual commuting behaviors and gradually relieve pressure on transport infrastructure during the lockdown lifting process. Considering the commuting differences in different age groups, it is necessary to provide correct and objective guidance for people of different ages. Young workers, in particular, need to raise their awareness of the virus and their perception of personal risks. Different nucleic acid testing policies and intervention policies should be implemented for people in different risk areas, especially to strengthen the frequency of nucleic acid testing for people in high-risk areas. Screening infected people as quickly as possible curbs the spread of the virus. Governments and businesses should encourage employees to work from home and adopt flexible working hours. In the longer term, if this trend in working from home is to be encouraged to last beyond the COVID-19 time horizon, this would suggest that we can reduce commuting for work purposes while at the same time improve the environment, but without a negative impact on employment outcomes [81]. In addition, flexible working hours can reduce daily passenger peaks, thereby reducing the risk of infection during commuting.

This study has several limitations. Firstly, it exclusively examined commuting pattern changes during different phases of the localized COVID-19 outbreak, neglecting non-commuting behaviors. Secondly, the sample size is limited, encompassing data from only Nanjing. In future research, cross-regional analyses should be considered to provide insight into the variability of behavioral patterns and to assess the role of psychological variables in commuting pattern variation.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Part I: Personal Attributes Survey

1. Age?: [single question]
○<18 ○18~25 ○26~30 ○31~40 ○41~50 ○51~60 ○>60
2. Number of family members (including self) [single question]
○1 ○2 ○3 ○4 ○5 ○>5
3. Gender?: [single question]
○Male ○Female
4. Occupation? [single question]
○Student
○Enterprise employees
○Institutional employees
○Freelancer
○Self-employed
5. Income before tax (RMB)? [single question]
○0–80,000
○80,000–160,000
○>160,000
6. Educational background? [single question]
○Primary school and below
○Secondary school
○High school
○Undergraduate
○Above undergraduate
7. Have a driver's licence? [single question]
○Yes
○No
8. Household vehicle ownership? [multiple-choice question]
☐Car
☐Bike
☐Electric bike
☐None
9. Whether there is a subway station within 800 m of the residence? [single question]
○Yes
○No
11. Have you been vaccinated? [single question]
○Yes
○No
12. Total number of nucleic acid tests you have taken since this outbreak? [single question]
○Always green
○The health code has had a yellow code
○The health code has had a red code
15. Health code situation since the outbreak? [single question]
○Always green
○The health code has had a yellow code
○The health code has had a red code
16. Family health codes since the outbreak? [single question]
○Living alone
○Cohabitants are always green codes
○Cohabitants have yellow codes
○Cohabitants have red codes
17. Type of place of residence since this outbreak? [single question]
○Risk-free area
○Low-risk area
○Medium-risk area
○High-risk areas

Part II: Survey of travel behavior of the population during the epidemic.

The number of days per week you commuted to travel (e.g., to work, school) during the period before and after the outbreak: [matrix single-choice question].

	0	1	2	3	4	5	6	7
Before this outbreak	○	○	○	○	○	○	○	○
First week after outbreak	○	○	○	○	○	○	○	○
Second week after outbreak	○	○	○	○	○	○	○	○
Third week after outbreak	○	○	○	○	○	○	○	○

The main mode of transport you chose for commuting (e.g., to work, school) during the period before and after the outbreak: [matrix single-choice question]

	walking	private bike	electric bicycle	bus	subway	private car	taxi&ride-hailing	shared bike	working from home	others
Before this outbreak	○	○	○	○	○	○	○	○	○	○
First week after outbreak	○	○	○	○	○	○	○	○	○	○
Second week after outbreak	○	○	○	○	○	○	○	○	○	○
Third week after outbreak	○	○	○	○	○	○	○	○	○	○

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