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Research Article

Assessing the Impacts of Stay-in-Place Policy of COVID-19 Pandemic during the Chinese Spring Festival: A Stated Preference Approach

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This paper aims to investigate Chinese people's willingness to stay in the city where they work when the Spring Festival meets the COVID-19 pandemic. Specifically, a stated choice experiment about intercity travel including three homecoming trips (i.e., trips carried by conventional railway, high-speed railways, and private car) and the option "stay in place" was designed. Respondents were requested to choose the most preferred alternative in the context of the current situation of the COVID-19 pandemic and relevant policies. Based on the data collected from 800 respondents, a latent class mixed logit model was developed and estimated to capture the potential correlations within alternatives and respondents and the preference heterogeneity between respondents. Two latent classes were identified, one of which paid more attention to epidemic prevention policies while the other cared more about the characteristics of homecoming trips. Results show that people's willingness to stay in the city of work is largely dependent on epidemic prevention policies in their hometowns and decisions of social network members.

1. Introduction

The Spring Festival is one of the most important holidays for Chinese people. As a tradition, it has been an important moment at the end of the lunar year for all Chinese people for family reunion. However, it is often the case that people work in a different city that is far away from their hometown, particularly because of the large country size, which makes the regular short visit almost impossible. For some people, the Spring Festival becomes be the only feasible period to visit to their hometowns and stay relatively long with their families, and therefore create a huge intercity travel demand. Statistics show that around 3 billion trips induced by the so-called Spring Festival travel need to start 15 days before the Chinese New Year and last 40 days [1]. Such a phenomenon is very unique in the world and is also a good reflection of Chinese traditional culture.

However, the outbreak of the COVID-19 pandemic that happened at the end of 2019 made a great impact on this tradition. Started from Wuhan, the COVID-19 spread rapidly to other places of China. To cut off its diffusion, many cities were put on lockdown, and people had to stay at home and were not allowed to get out even for grocery shopping (food and daily supplies were unified, allocated and delivered by special volunteers). This policy turned out to be very helpful in preventing the spread of COVID-19 but was also seen as extremely damaging people's mobility needs. In the Spring Festival travel rush of 2020, only 1.5 billion trips were generated, accounting for 50% of the trip demand of the previous years (see Figure 1).

After a national-level fight against COVID-19, the pandemic was finally under control. Although it is not completely wiped out, the Chinese government got rich experiences and generated effective strategies to deal with its sudden outbreak. However, the COVID-19 pandemic has

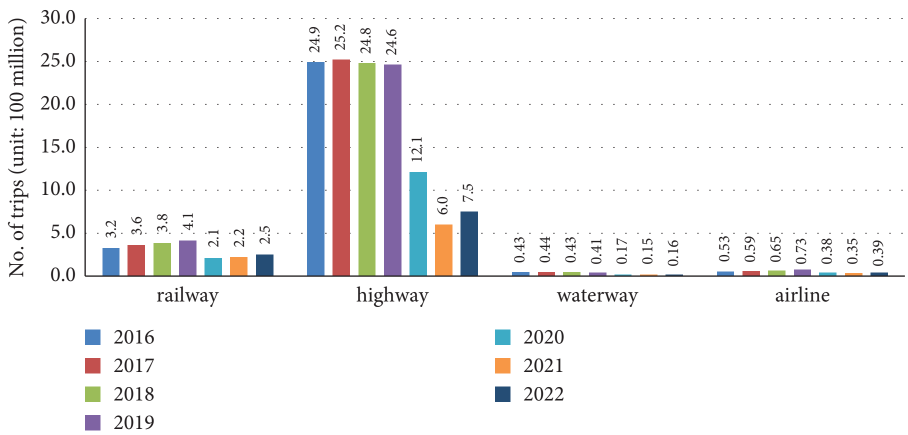

Figure 1: Number of trips in the Spring Festival travel rush for the latest 5 years.

been lasting for over two years and influenced the Spring Festival travel rush again in the years of 2021 and 2022. On the one hand, the pandemic was largely under control and its severity was much lower than it was in the Spring Festival of 2020. Therefore, the lockdown policy was not suitable anymore. On the other hand, small-scale outbreak still happened in some cities. Therefore, suitable policies must be proposed to prevent the spread of COVID-19. Under this background, staying in the place where people work for the Spring Festivals of 2021 and 2022 has been implemented in Chinese cities.

Basically, the stay-in-place policy is not compulsive, and the government intends to encourage people to stay in the cities of work in order to prevent the potential resurgence of the COVID-19 pandemic in China. In addition, the government proposed some complementary policies (such as subsidy) to encourage local enterprises to persuade their employees to stay and celebrate the Spring Festival with colleagues. Nevertheless, two questions remained to be answered: what policies are effective in persuading people to stay in place, and what kinds of people comply with the stay-in-place policy? Given the fact that the COVID-19 pandemic is still lasting, these two questions seem important for the prevention policies in the next Spring Festival or towards other potential pandemics in the future.

This paper tries to answer the above two questions using a stated preference approach. Specifically, a stated choice experiment about intercity travel was designed in which respondents were requested to choose one out of three hypothetical ways to come back to hometowns or to choose "stay in place" based on the hypothetical status of the COVID-19 pandemic and under the stay-in-place policies. Meanwhile, a latent class mixed logit model was developed and estimated to evaluate the effects of various policies on people in different sociodemographic groups. In addition, this paper also tries to investigate the difference of the people's choices regarding homecoming train trips before and during the COVID-19 pandemic.

The remainder of the paper is structured as follows. Section 2 gives a brief literature review about intercity travel mode choice analysis and the impact of the COVID-19 pandemic on travel demand. Section 3 presents the details of the stated choice experiment and the survey. Section 4 introduces the specifications of the latent class mixed logit model. Section 5 gives the model estimation results and corresponding analyses. Section 6 discusses the conclusions and summarizes the paper.

2. Literature Review

2.1. Intercity Travel Mode Choice Analysis. Since this paper aims to investigate the choice behavior of people who live and work in a city that differs from their hometown, it is necessary to review the studies focus on mode choice behavior of intercity travel to show which determinants influence people mode choice behavior for intercity travel before the COVID-19 pandemic.

The first determinant for intercity travel mode choice is travel cost. Evidences can be found everywhere in the literature (e.g., [2–5]). This is reasonable and theoretically necessary as Train [6] shows that ignoring the monetary attribute can cause the issue of endogeneity. However, some variations regarding this attribute can also be found. For instance, instead of measuring the impact of travel cost directly, Srinivasan et al. [4] introduced the ratio of travel cost and household income into the model, which was confirmed to significantly and negatively influence people's intercity travel mode choice. By doing so, the people's heterogeneous preferences toward travel cost can be measured. Another instance is Lin et al. [7] who investigated the impact of road toll discount on intercity travel mode choice during the Spring Festival in China.

The second determinant for intercity travel mode choice is travel time. However, different studies may define travel time in different ways. Bhat [2] introduced the attributes in-vehicle time and out-of-vehicle time into a mixed logit model and found different significant effects on passengers' intercity mode choice behavior. Similarly, Lee et al. [3] also differentiated between in-vehicle and out-of-vehicle time. However, they specified out-of-vehicle time as access/egress time. Both in-vehicle time and access/egress time are confirmed to significantly influence passengers' intercity mode choice. Besides total travel time, Srinivasan et al. [4] also investigated the effect of airline inspection and boarding time on passengers' choice toward air mode. Regarding air mode, transfer time (sometimes is reflected by number of transfer) of an itinerary is an attribute that commonly adopted in the literature (e.g., [8–10]).

Similar to the case of intracity travel, trip purpose can also be a determinant for passengers' mode choice in the context of intercity travel. For instance, Li et al. [11] categorized travel purposes as mandatory and optional (i.e., leisure) and found that compared to the train, leisure passengers prefer HSRs or airplanes more than passengers for mandatory travel. Meanwhile, seat type is found to significantly influence passengers choosing trains and air mode. For instance, Pan [1] concludes that passengers prefer train trips with bunks the most, followed by hard seat and standing-only seat in sequence. This conclusion is reasonable as seat type is related to the comfort of the travel mode and intercity travel is usually a middle/long distance travel in which comfort is normally important [11]. In addition, departure or arrival time of train and air modes is also confirmed to be significant in some studies (e.g., [12, 13]).

At last, passengers' heterogeneous preferences toward intercity travel mode are also of great interest among the community. Specifically, passengers' sociodemographic characteristics such as gender, age, education level, occupation, and income are normally introduced into the model to capture potential heterogeneous preferences. Ren et al. [14] presented evidences of significant influence of passengers' gender, age, education level, and income on their behavior of choosing HSR when traveling between Chengdu and Chongqing in China. Similar, Hess et al. [15] found significant influence of passengers' gender and age, as well as occupation and district on intercity travel choice in US. Other studies about passengers' heterogeneous preferences can be found in the literature. Basically, the conclusions from the literature are not extremely consistent since of the differences of travel context and backgrounds of economy, culture, and society.

2.2. Impact of the COVID-19 Pandemic on Travel Demand. Since the end of 2019, COVID-19 suddenly spreads all over the world. Many cross-country studies were carried out to investigate the effects of factors, one of which can be policies (e.g., [16–18]). In transportation community, various policies were also proposed to constrain passengers' travel demands to cut off the spread of COVID-19. In such context, people's mobility is significantly damaged. A widely acknowledged conclusion is that passengers' travel demands experienced a severe reduction. Take the travel demands during the Chinese Spring Festival as an instance. Figure 1 shows that before the outbreak of the COVID-19 pandemic, the annual travel demand in this particular period almost reaches 3 billion. However, in 2020, only 1.5 billion trips were generated, accounting for 50% of the previous years. Even though the demand increases gradually in the past two years, it seems to have barely recovered to its previous level during the normalized prevention and control period.

In addition to the reduction of total travel demand, there are some specific conclusions about the change of passengers' preferences toward different travel modes. Studies comparing passengers' preferences toward public and private travel modes conclude that after experiencing the hit of the COVID-19 pandemic, people are likely to drive a private car rather than to take a bus to complete a trip (e.g., [19–21]). More specifically, people have become less sensitive to the ticket fare of public travel mode (e.g., bus and metro) compared to that before the COVID-19 pandemic, and this sensitivity is recovering gradually [22]. The shift of preference toward public transport is reasonable and imaginable, as public transport indicates crowded and open space, which means passengers may be infected by COVID-19. Therefore, this preference shift is in fact rooted in passengers' fear of COVID-19.

On the other hand, with the development of the pandemic, the rate of fatality and pathogenicity of COVID-19 is decreased. Therefore, policies for normalized prevention and control were proposed in succession. There policies can also affect passengers' travel demand. For instance, Hensher and his colleagues paid their most attention on the impact of COVID-19 pandemic on working from home (e.g., [23–25], as they stated that the COVID-19 pandemic offers a great opportunity for researchers to investigate people's willingness and attitudes toward working from home. Basically, they believe that the growing popularity of working from home, which is proven to some extent through the forced policy of staying at home under the COVID-19 pandemic, must become an important feature of peoples' travel choice behavior during COVID-19 after all restrictions are removed.

2.3. Conclusions from the Literature Review. When passengers choose a mode of transportation for daily travel, there are common attributes that they have to consider, such as travel time and travel cost (or ticket fare). However, studies confirmed that after experiencing the hit of the COVID-19 pandemic, these attributes can become less important. Meanwhile, in order to win the fight against COVID-19, many policies for epidemic prevention and control are being proposed, which usually have a negative influence on peoples' mobility. The question that to which extent the policies affect people's mobility is of great interest for transport researchers.

The stay-in-place policy during Chinese Spring Festival is a policy to advocate staying in the cites people work instead of coming back to their hometown to celebrate the Spring Festival, by which to cut off the intercity travel demand and further reduce the wide-spread of COVID-19 in the particular period. After reviewing the literature, we find the stay-in-place policy can significantly influence passengers' intercity travel, but there are still rare studies focusing on this policy. In this sense, this paper aims to investigate Chinese people's willingness to stay in the city where they work when the Spring Festival meets the COVID-19 pandemic to finally explore how and to what extent the stay-in-place policy affects intercity travel.

3. Data Collection

3.1. Questionnaire. In order to investigate how Chinese people celebrate the Spring Festival during the COVID-19 pandemic, a questionnaire based on a stated choice experiment was adopted. In addition, people's sociodemographic characteristics were also collected. The following describe the details of the questionnaire.

In terms of the stated choice experiment, short or medium trips are considered, where private cars could be an available option. To complete such trips, railway and self-driving are believed suitable. Therefore, in the experiment, a choice set contains four alternatives: conventional railway, high-speed railway, private car, and stay in place. High-speed railway indicates the trains whose numbers starting with "*G*" or "*D*," while conventional railway refers to the trains whose numbers starting with other letters (such as "*T*" or "*K*").

The alternative-specific attributes include arrival time, travel time, ticket fare, and seat class of railway, and road charging and fuel consumption for private cars. Given the difference between the performance of conventional and high-speed railways and private cars, the levels of attributes were also alternative-specific, except for arrival time. The descriptions of each attribute and corresponding levels are found in Table 1. Meanwhile, the information of departure time for railway is also given in stated choice tasks as such information can be easily found in the national railway ticket booking system. Specifically, the departure time is calculated by the travel time and the arrival time. The punctuality or delay of railway is not included for two reasons. One is that such information is actually difficult to get in the ticket booking system. Although it is a common sense that the delay of conventional railway is larger than that of high-speed railway, usually travelers do not know the exact numbers. The other reason is that the previous study [1] confirms that the delay of railway has no significant impact, which may be caused by the fact that the Spring Festival travel rush is actually featured by large delays.

As this study mainly focuses on the influence of the COVID-19 pandemic and relevant policies, some context attributes should be considered. In this regard, six context attributes are considered: decisions of social network members, quarantine policy in hometown or the city of work, confirmed cases in hometown or the city of work, and subsidy for staying in place. The descriptions of each attribute and corresponding levels are found in Table 1. The attribute quarantine policy in hometown or the city of work represents the current prevention policy. Note that the national holiday of Spring Festival officially starts from the last day of Chinese year (the Chinese New Year's Eve) and lasts 7 days. Therefore, the attribute level "home quarantine" or "quarantine in hotels" for 14 days means practically people cannot come back to their hometowns. The attribute confirmed cases in hometown or the city of work reflects the current status of the COVID-19 pandemic. The attribute subsidy for staying in place is a special stay-in-place policy to make up for people's emotional losses. Note that decisions from social network are not directly related to the stay-in-place policy. However, it is believed that such an attribute could provide potential practical implications for the stay-in-place policy.

A simultaneous orthogonal design (orthogonal design is to generate an orthogonal table where a column indicate an attribute of a certain alternative and a row indicates a profile/choice task presented to respondents; and by saying "simultaneous," it means orthogonality is held across alternatives in a choice set), which combines the alternative-specific and context attributes was implemented using the R package "support.CEs" [26]. Finally, 96 profiles (choice sets) were generated, which were further grouped into 12 blocks. Therefore, each respondent was required to complete 8 sequential choice tasks. Figure 2 shows an example of the stated choice tasks, in which respondents were requested to choose the preferred one from three transportation modes for homecoming or choose to stay in place after evaluating the whole choice context.

In addition, to model the property of heterogeneity among respondents, information about respondents' sociodemographic characteristics is needed. In detail, such information contains: age, gender, marital status, the city of hometown, and the city of work, location of family (urban or rural area). Note that the information about respondents' income and occupation was not included, as suggested by the survey company that respondents in the panel are sensitive to such information and the inclusion of corresponding questions would dramatically decrease the percentage of valid samples and increase the monetary and time costs.

3.2. Survey. The data were collected using an online survey questionnaire between July 5th in 2021 and July 8th in 2021, in China. The URL of the online questionnaire was randomly sent to respondents in a panel of a commercial online-survey company. Finally, 825 respondents were contacted of which 800 were deemed as valid. However, it was found that 232 respondents reported that the city of work and the hometown were actually the same, which was believed not suitable for model estimation as the stay-in-place policy may have less influence on such a group. Nevertheless, it could be used for model prediction to test the predictive power of the model. Hereafter, the observations for model estimation were labeled as "estimation sample" and those for model prediction were labeled as "prediction sample."

The descriptive statistics of respondents' sociodemographic characteristics are presented in Figure 3. In terms of respondents' gender, female takes 60.7% in estimation sample and 54.7% in prediction sample. In terms of respondents' age, most respondents are younger than 40 years old. People who are younger than 25, between 25~30 and 31~40 are roughly equally distributed in both samples. The only difference is that, in the prediction sample, the number of respondents aged between 25~30 are relatively lower. In terms of respondents' marital status, around half of the respondents are single in both samples, followed by those who are married and have kids and those who are married without children. In terms of the location of the respondents' families, over half of the respondents' families locate in rural area in the estimation sample, while the corresponding number is only 33.2% in the prediction sample. One thing should be noted that, as of the huge population spatial heterogeneity in China, statement saying the study analysis is representative to China is hasty. In this sense, give the relatively

Table 1: Attributes and corresponding levels.

Attributes	Description	Levels
Alternative-specific attribute		
Arrival time (railway)	The time moment that trains arrives at the destination station for conventional or high-speed railway	2:00 AM, 8:00 AM, 14:00 PM, and 20:00 PM
Travel time (conventional railway)	The ticket fare for the homecoming trips using conventional railway	3 hours, 4 hours, 5 hours, and 6 hours
Travel time (high-speed railway)	The ticket fare for the homecoming trips using high-speed railway	1 hours, 1.5 hours, 2 hours, and 2.5 hours
Ticket fare* (conventional railway)	The ticket fare for the homecoming trips using conventional railway (RMB)	¥50, ¥70, ¥90, and ¥110
Ticket fare* (high-speed railway)	The ticket fare for the homecoming trips using high-speed railway (RMB)	¥150, ¥200, ¥250, and ¥300
Road charging* (private car)	Charging on the road for the homecoming trips using private car (RMB)	¥0, ¥150, ¥200, and ¥250
Fuel consumption* (private car)	The cost of fuel consumption for the homecoming trips using private car (RMB)	¥160, ¥180, ¥200, and ¥220
Seat class (conventional railway)	The class or type of the seat for the homecoming trips using conventional railway	Standing-room only, hard seat, hard berth, and soft berth
Seat class (high-speed railway)	The class or type of the seat for the homecoming trips using high-speed railway	Standing-room only, 2nd class seat, 1st class seat, and business class
Context attribute		
Decisions from social networks	How many people in the social networks decide to stay in place	All, most, a few, and none
Quarantine policies in hometown	What are the current quarantine policies in hometown	No quarantine policies, no quarantine needed with valid negative test reports, home quarantine for 14 days, quarantined in hotels for 14 days
Quarantine policies in the city of work	What are the current quarantine policies in the city of work	No quarantine policies, no quarantine needed with valid negative test reports, home quarantine for 14 days, quarantined in hotels for 14 days
Confirmed cases in hometown	Whether there are confirmed cases in hometown currently	Yes and no
Confirmed cases in the city of work	Whether there are confirmed cases in the city of work currently	Yes and no
Subsidy for staying in place*	How much subsidy one would get if staying in place (RMB)	¥1000, ¥2000, ¥3000, and ¥4000

*In the moment that the survey was carried out (July 5th~8th, 2021), the exchange rate between CNY and USD was around 1 : 6.5.

small sample size of the current study (i.e., 6400 observations from 800 respondents), the objective of this study is to investigate the general effects of the stay-in-place policy rather than predict its effects of polices.

To sum up, the descriptive statistics of gender, age, and marital status in estimation and prediction samples are similar. However, Figure 3 shows that the respondents in the prediction sample seem relatively older than those in the estimation sample. In terms of the location of respondents' families, the difference between estimation and prediction samples is considerably large.

4. Model

4.1. Mixed Logit Model. The model used in this study is developed from a traditional multinomial logit model [27, 28], which assumes that the pure random terms in the utilities of choice alternatives follow an IID Gumbel distribution. However, the independent-distribution assumption is too rigorous to be against reality in most cases. Therefore, some advanced models were proposed in the literature, such as the nested logit model [29], the probit model [30], and the error component model [6]. As the conventional and high-speed railways in the stated choice experiment both belong to the national railway system, it is reasonable to assume that a correlation exists between the two. This study follows Train [6] and adopts the error component model to capture such a potential correlation. Therefore, the utilities of each alternative could be described as follows:

$$U_{nt}^{CR} = \beta_0^{CR} + \sum_k \beta_k^{CR} \cdot x_{ntk}^{CR} + \epsilon^{RAIL} + \varepsilon_{nt}^{CR}, \quad (1)$$

$$U_{nt}^{HS} = \beta_0^{HS} + \sum_k \beta_k^{HS} \cdot x_{ntk}^{HS} + \epsilon^{RAIL} + \varepsilon_{nt}^{HS}, \quad (2)$$

$$U_{nt}^{PC} = \beta_0^{PC} + \sum_k \beta_k^{PC} \cdot x_{ntk}^{PC} + \varepsilon_{nt}^{PC}, \quad (3)$$

$$U_{nt}^{\mathrm{STAY}} = \beta_0^{\mathrm{STAY}} + \sum_c \beta_c^{\mathrm{STAY}} \cdot q_{ntc}^{\mathrm{STAY}} + \varepsilon_{nt}^{\mathrm{STAY}}, \quad (4)$$

where U_{nt}^{CR}, U_{nt}^{HS}, U_{nt}^{PC}, and U_{nt}^{STAY} indicate respondent n's utilities for alternatives conventional railway, high-speed

Please recall the Spring Festival of 2021. The COVID-19 epidemic rebounded to some degree, therefore the government proposed the policies of staying in place in Spring Festival. The followings describe the hypothetical status of the COVID-19 epidemic and some details of the stay-in-place policies. In addition, the followings list 3 hypothetical ways to go home, from which please choose the preferred one or choose "stay in place" based on the given information.

Note:

a) The presented alternatives may not satisfy you or reflect your real situation, and in this case please choose the optimal one after comparison;
b) There may be other attributes that you want to know to make a choice, in this case please make a choice based on the information that we present and assume other missing information are all the same across the train trips.

Decisions from Social Networks	Most of them plan to stay in place in Spring Festival			
Quarantine Policies in Hometown	No Quarantine Policies			
Quarantine Policies in the City of Work	No Quarantine Policies			
Confirmed Cases in Hometown	Yes			
Confirmed Cases in the City of Work	Yes			
Subsidy for Staying in Place (¥)	4000			
Travel Mode	Conventional Railway	High-Speed Railway	Private Car	Stay in Place
Departure Time	7:00	19:00	---	---
Arrival Time	11:00	20:30	---	---
Travel Time (Hour)	4	1.5	4	---
Ticket Fare (¥)	110	300	---	---
Road Charging (¥)	---	---	150	---
Fuel Consumption (¥)	---	---	180	---
Seat Class	Soft Berth	Second Class	---	---
Your Choice	☐	☐	☐	☐

Figure 2: An example of the stated choice tasks (translated from Chinese).

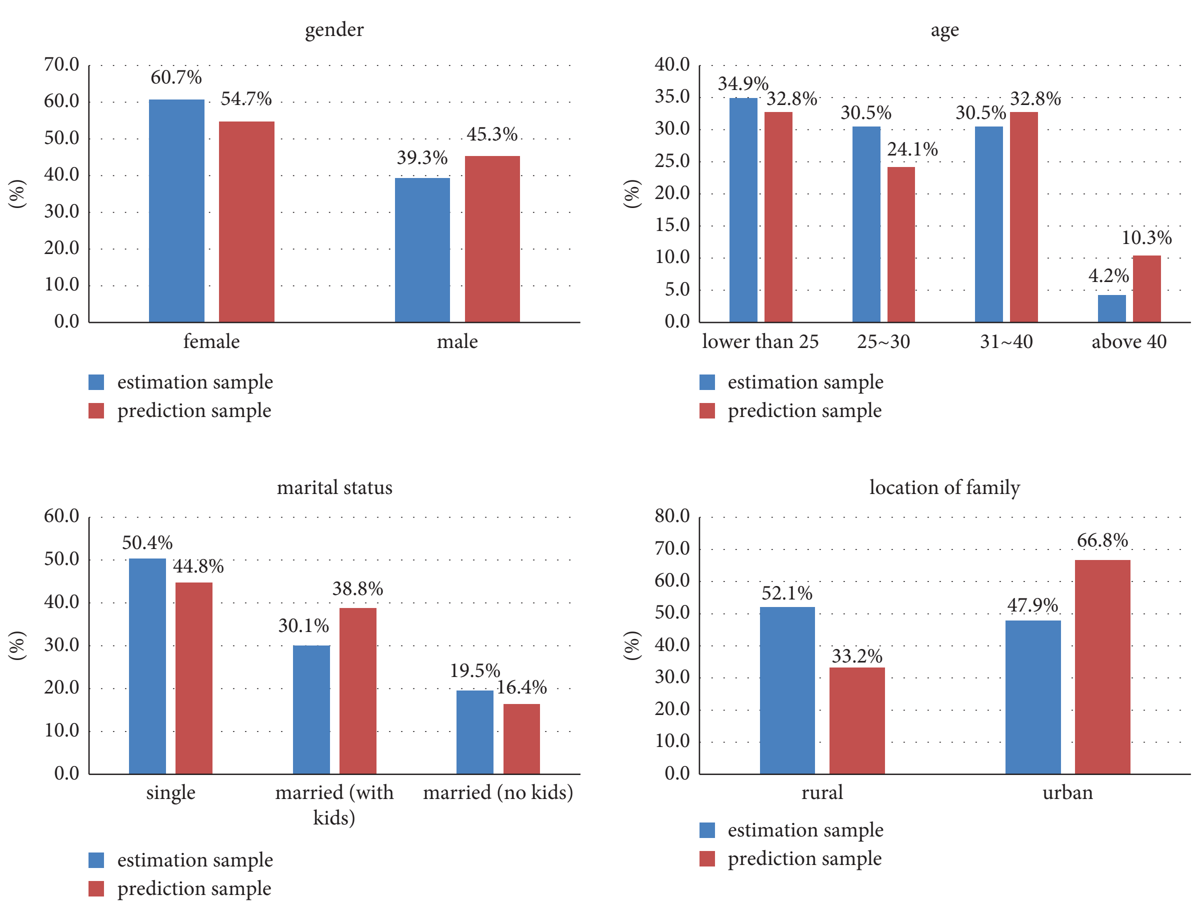

Figure 3: Descriptive statistics of respondents' sociodemographic characteristics.

railway, private car, and stay in place, respectively, in choice task t; ε_{nt}^{CR}, ε_{nt}^{HS}, ε_{nt}^{PC}, and $\varepsilon_{nt}^{\text{STAY}}$ are the pure error terms of corresponding alternatives' utilities which follow IID Gumbel distributions as stated above; ϵ^{RAIL} is the error component shared by conventional and high-speed railway indicating potential correlation, which is normally distributed with 0 mean and standard deviation σ^{RAIL}; x_{ntk}^{CR}, x_{ntk}^{HS}, and x_{ntk}^{PC} are alternative-specific attributes of conventional railways, high-speed railway and private car, respectively, in choice task t; β_k^{CR}, β_k^{HS}, and β_k^{PC} are corresponding taste parameters to be estimated; q_{ntc}^{STAY} indicates context attributes which represent the current status of the COVID-19 pandemic or the stay-in-place policy, and β_c^{STAY} is the corresponding parameter to be estimated.

Meanwhile, since one respondent was requested to answer multiple stated choice tasks in the survey, correlation may also exist in the choice tasks answered by the same respondents (i.e., intrarespondent homogeneity), which is normally labeled as panel effect in the literature [6]. To capture the potential panel effect, extra random terms, denoted as ξ^{CT}, ξ^{HS}, ξ^{PC}, and ξ^{STAY}, should be introduced to the utility functions. Therefore, equations (1)–(4) are modified as follows:

$$\begin{aligned}
U_{nt}^{CR} &= \beta_0^{CR} + \sum_k \beta_k^{CR} \cdot x_{ntk}^{CR} + \epsilon^{\text{RAIL}} + \xi^{CT} + \varepsilon_{nt}^{CR},\\
U_{nt}^{HS} &= \beta_0^{HS} + \sum_k \beta_k^{HS} \cdot x_{ntk}^{HS} + \epsilon^{\text{RAIL}} + \xi^{HS} + \varepsilon_{nt}^{HS},\\
U_{nt}^{PC} &= \beta_0^{PC} + \sum_k \beta_k^{PC} \cdot x_{ntk}^{PC} + \xi^{PC} + \varepsilon_{nt}^{PC},\\
U_{nt}^{\text{STAY}} &= \beta_0^{\text{STAY}} + \sum_c \beta_c^{\text{STAY}} \cdot z_{ntc}^{\text{STAY}} + \xi^{\text{STAY}} + \varepsilon_{nt}^{\text{STAY}}.
\end{aligned} \tag{5}$$

Note that four extra random terms are introduced for the four alternatives. For the sake of simplicity, it is assumed that they follow IID normal distributions with a zero mean and standard deviation σ^{PE} although studies (e.g., [31, 32]) argue that an identical distribution is necessarily the case. In addition, note that the error component model with panel effect still falls in the scope of mixed logit model. For the sake of simplicity, the model described above is labeled as mixed logit model hereafter.

4.2. Latent Class Mixed Logit Model. Travelers' preference heterogeneity is a topic of interest in the transportation community. Many studies in transportation (e.g., [33–35]) have confirmed its existence. In order to capture such a property, a latent class model framework was adopted in this study. Theoretically, the mixed logit model (specifically, the random parameter logit model) also has the ability to capture travelers' heterogeneous preferences [36]. However, it received some criticisms recently. For instance, it needs to decide the specific distributions of the random parameters in advance by trial-and-error method, which is extremely time-consuming. Besides, Shen [37] found that latent class models in general have better goodness of fit than mixed logit models.

The latent class model assumes that there are multiple latent classes among the sample, which could be related to the sociodemographic characteristics of the sample. Individuals show identical preferences in a same class but various preferences across different classes, through which the heterogeneous preferences could be measured. However, an individual does not have to belong to a class for sure. Instead, an individual belongs to a certain latent class with a membership probability. Therefore, the probability of the respondent n choosing a specific alternative j could be described as follows:

$$P_{nt}^{j} = \sum_s P_{ns} \cdot P_{nts}^{j}, \tag{6}$$

where P_{nt}^{j} denotes the probability of respondent n choosing alternative j in choice task t; P_{ns} denotes the membership probability of respondent n belonging to the latent class s; P_{nts}^{j} denotes the probability of respondent n choosing alternative j in choice task t conditioning on respondent n belongs to the latent class s.

As stated above, the membership probability P_{ns} could be represented by the respondent n's sociodemographic characteristics. Thus, a logit expression could be used for membership probabilities:

$$P_{ns} = \frac{\exp\left(\sum_l \alpha_l^s \cdot z_{nl} + \varsigma^s\right)}{\sum_{s'} \exp \sum_l \alpha_l^{s'} \cdot z_{nl} + \varsigma^{s'}}, \tag{7}$$

where z_{nl} denotes sociodemographic characteristics l of respondent n; α_l^s is the parameter to be estimated for the l^{th} sociodemographic attribute *in* class s; and ς^s is the constant of latent class s.

A maximum likelihood estimation approach could be used for model estimation. However, since it contains a mixed logit model segment (therefore, this model is labeled as latent class mixed logit model hereafter), which results in integration in choice probabilities, simulation is needed for model estimation [6]. The simulated likelihood function could be given as follows:

$$LL = \sum_n \sum_r \frac{1}{R} \left(\prod_t \prod_j P_{nt}^{j,r} y_{nt}^{j} \right), \tag{8}$$

where $j \in \{CT, HS, PC, \text{STAY}\}$; LL denotes the log-likelihood; y_{nt}^{j} is a dummy variable, which equals 1 if the respondent n chooses alternative j in choice task t, 0 otherwise; $P_{nt}^{j,r}$ is the simulation of P_{nt}^{j}, indicating the respondent n' choice probability of alternative j in choice task t conditioning on a vector of random draws from certain distributions; and R is the number of random draws to mimic the distributions of random terms.

5. Results

The models were estimated using the R package "maxLik" [38]. The attributes arrival time, seat class for both conventional and high-speed railways, decision from social networks, quarantine policies in hometown and the city of work, and confirmed cases in hometown and the city of work are regarded as categorical variables, and therefore effects coded [39]. Other attributes like travel time and ticket price for both conventional and high-speed railways, road charging and fuel consumption for private car, and subsidy for staying in place are introduced in the utility functions as continuous variables. Regarding the simulations of distributions of random terms measuring the potential correlation between conventional and high-speed railways and panel effects, sequences with 100 scrambled Halton draws based on different prime numbers [40, 41] were adopted. The alternative "stay in place" was set as the reference, which means the parameter β_0^{STAY} in equation (4) was fixed as 0 in model estimation.

5.1. Analyses of Latent Classes. When estimating a latent class model, the first thing that needs to be done is to determine the number of latent classes. Various goodness of fit indices for the models with different numbers of latent classes are presented in Table 2. The convergent log-likelihoods and adjusted Rho-squared increase with the number of latent classes, which confirms the existence of heterogeneous preferences. Besides, to determine the optimal number of latent classes, the AIC (i.e., Akaike information criterion) and BIC (i.e., Bayesian Information Criterion) indices are adopted. The lowest values of AIC and BIC are found in the models with 3-class and 2-class, respectively. However, regarding AIC, the difference between 1-class and 2-class models are remarkably larger than the difference between 2-class and 3-class models. Therefore, the 2-class model is deemed as the optimal in this study. The final results with 2 latent classes are presented in Table 3, in which completely insignificant attributes are removed. The adjusted Rho-squared is 0.307, which is deemed satisfactory [42, 43].

When looking into the estimated parameters for alternative-specific and context-specific attributes in the two latent classes, one can get an impression that the respondents in one class are more sensitive to the quarantine and stay-in-place policies, while those in the other class care more about how they can come back home and are much less sensitive to policies, which implies that respondents in the latter class are more likely to celebrate the Spring Festival with families. In this sense, the former is labeled as "COVID-19-care" class and the latter is labeled as "trip-care" class. In terms of the membership of each latent class, the significant constant indicates that generally most respondents (accounting for 71.98%) are allocated in the trip-care class, which means whether they would come back to their hometown mainly depends on the characteristics of homecoming trips. Nevertheless, the results also show that the allocation varies across respondents' sociodemographic characteristics. First, the older the respondents are, the higher of the probability they belong to the trip-care class, which indicates that they are less influenced by quarantine and stay-in-play policies. The underlying reasons could be that the middle-aged people may leave their older parent(s) in their hometowns and coming back to stay with their parent(s) during the Spring Festival is more likely to be their first thought. Second, people who are married are more likely to be in the COVID-19-care class. The underlying reason may be that married people have higher responsibilities for the family and have to consider the risk of family members being infected. Additionally, married people with or without children show no statistically different preferences (the t value equals 0.11). Meanwhile, results do not show any significant impacts of gender and location of family.

5.2. Analyses of Alternative-Specific Attributes. In case of the effects of alternative-specific attributes, respondents in two latent classes reveal considerably different preferences. Respondents in the COVID-19-care class show only significant preferences toward ticket fare and seat class for conventional and high-speed railways. Respondents in the trip-care class show significant preferences toward travel time for conventional and high-speed railways and private cars, and ticket fare and seat class for conventional and high-speed railways. Specifically, several conclusions can be drawn.

First, the arrival time of train trips is not statistically significant for both latent classes, which is against the conclusion in a previous study [1], conducted before the COVID-19 pandemic, which stated that trips arriving during daytime was always preferred. Given the impact of the COVID-19 pandemic, people may also consider, in addition to the (in)convenience of their following trips, the crowdedness in the train stations when arriving. The insignificance of arrival time may be the result of the tradeoff between these two considerations. Second, travel time has significantly negative influences for the respondents in the trip-care class but not for those in COVID-19-care class, which again supports the definition of the two latent classes. Besides, respondents in the trip-care class are more sensitive to travel time of conventional railway, following by high-speed railway and private car. This may be because taking railway means exposing in public space where is often crowded in Spring Festival travel rush (especially for conventional railway) means taking risks of being infected by COVID-19. Third, the ticket fare for conventional and high-speed railways is both statistically significant. However, when comparing preferences of respondents in different latent classes, the results show that the trip-care class is more sensitive. Further, comparison between conventional and high-speed railways shows that respondents are more sensitive to the ticket price of conventional railway, which is again inconsistent with the conclusion made by Pan [1]. The reason may be that high-speed trains provide people more comfortable and less crowded environment, which could reduce the probability of being infected by COVID-19 during the trips. Fourthly, the road charging and fuel consumption of the alternative private car are not statistically significant. A potential reason could be that respondents who prefer to a private car may have a high level of income. However, income data and occupation are not available, thus the above inference cannot be further examined in this study. One thing that should be noted is that the parameter of fuel consumption was actually statistically significant when all respondents were allocated in a single class. However, this attribute is not statistically significant in the 2-class model, which provides evidence of inappropriateness of simply using a 1-class model that makes researchers misunderstand the respondents' choice preferences. Finally, the seat class of conventional and high-speed railways is also statistically significant.

Table 2: Goodness of fit for the latent class models.

Number of classes	Number of parameters	Convergent log-likelihood	Adj. Rho-squared	AIC	BIC
1	25	−4453.321	0.289	8957.042	9117.581
2	55	−4310.362	0.307	8730.725	9083.911
3	85	−4274.184	0.308	8718.368	9264.201

Regarding the alternative-specific constants, a conclusion can be drawn that if all prevention policies are removed, there is a great probability that people in COVID-19-care class will come back to their hometown even though confirmed cases of COVID-19 are reported in their hometown. This conclusion is largely different from the analysis of policy of working-from-home, as studies (e.g., [23–25]) find that the growing popularity of working from home must become an important feature of peoples' travel choice behavior during COVID-19 after all restrictions are removed. The reason may lie in the Chinese traditional culture, which largely emphasize the importance of family reunion in lives.

Results of the correlation between conventional and high-speed railways, although show different estimates for the two latent classes, indicate that the two kinds of railways are actually highly correlated: the estimates of the standard deviation of the error components are 3.23 and 6.32 with respect to the COVID-19-care and trip-care classes, respectively. In addition, the results also show significant panel effects, indicating the existence of intrarespondent homogeneity.

5.3. Analyses of Context Attributes. In terms of context attributes, the influences vary in different latent classes. Respondents in the COVID-19-care class are significantly influenced by the subsidy for staying in place, the quarantine policy in their hometown, and decisions from social networks, while respondents in the trip-care class are only significantly influenced by confirmed cases in their hometown. Specifically, some conclusions could be made as follows.

First, the quarantine policy and confirmed cases in the city of work did not significantly influence respondents' choice behavior, which is reasonable and imaginable. As the topic of this study is whether Chinese people would come back to hometown in the Spring Festival, which is less relevant to the situations happened in the city of work. In addition, although the quarantine policy in the city of work may affect people's returning trips, the quarantine policy is actually changing and unpredictable depending on the latest status of the COVID-19 pandemic. Second, subsidy for staying in place has statistically significant impact on the respondents in the COVID-19-care class, who would be more likely to stay in the city of work if they get more subsidies. Third, the quarantine policy in hometown could significantly influence the choice of staying in place for respondents in the COVID-19-care class. No quarantine policies would of course stimulate people to come back home. It is also the case that those respondents do not need to be quarantined if they have valid negative tests, although the magnitude is lower. Respondents are more likely to stay in the city of work if they have to be quarantined in hometowns either in their own family houses or hotels, although the magnitude of home quarantine is relatively lower. Fourth, decisions from social networks also have a significant impact on the choice decision for respondents in COVID-19-care class. In detail, the more the people from social networks choose to stay in place, the higher the willingness of those respondents to stay in place, which is consistent with most conclusions about social influence on choice behavior (e.g., [44–46]). Finally, the results show that whether there are confirmed cases in the hometown significantly influences the choices of respondents in the trip-care class. Specifically, those respondents are more willing to stay in the city of work if confirmed cases are reported in their hometowns.

5.4. Policy Analyses. One of the aims of this study is to investigate how epidemic prevention policies affect peoples' willingness to stay in the city of work during the Spring Festival. Therefore, this subsection examines the variation of alternatives' market shares caused by different epidemic prevention policies. However, before analyzing the effects of different prevention policies, it is necessary to verify the prediction performance of the model.

The verification of the prediction performance of the model is divided into two steps. First of all, the market shares of each alternative regarding the estimation sample are calculated and further compared with the observed shares. However, as the model is estimated based on a sample, a good match between the observed and predicted marked shares is needed. Therefore, the market shares of each alternative regarding the prediction sample is also calculated and compared with the corresponding observed shares. The results are presented in Table 4. One can see that the difference between observed and predicted shares with respect to the estimation sample is less than 2%, and the average of the difference equals 0.89%, which is considerably low. With respect to the prediction sample, the difference between observed and predicted shares with respect to the estimation sample is relatively large but still less than 5%, and the average of the difference equals 4.05%. Given the fact that the respondents in these two samples have different sociodemographic characteristics, especially in age and location of family, such a difference of share is acceptable. To sum up, the model can predict the alternatives' market shares well for estimation as well as prediction samples. Namely, it has high prediction performance.

Table 5 presents the results of variation regarding alternatives' market shares based on different epidemic prevention policies, which include increasing the ticket fare of railway and subsidy for staying in place, changing the quarantine policy in hometown and changing the share of staying in place in social

Table 3: Estimation results of the final model.

	Estimate	Std. error	p values	Estimate	Std. error	p.values
Panel effect	1.800611	0.104454	0.0001***			
	COVID-19-care class			Trip-care class		
Alternative-specific constant						
Conventional railway	7.997449	2.219578	0.0003***	1.092724	0.902121	0.2258
High-speed railway	9.841382	2.280200	0.0001***	−1.747842	1.096703	0.1110
Private car	4.064016	1.955903	0.0377**	−0.916661	0.746893	0.2197
Stay in place	0.000000			0.000000		
Alternative-specific attribute						
Travel time						
Conventional railway	0.004029	0.126532	0.9746	−1.040597	0.158513	0.0001***
High-speed railway	−0.033325	0.231755	0.8857	−0.974192	0.317450	0.0021***
Private car	0.212808	0.217407	0.3277	−0.463382	0.122272	0.0002***
Ticket fare						
Conventional railway	−0.011552	0.005766	0.0451**	−0.033681	0.007371	0.0001***
High-speed railway	−0.004431	0.002220	0.0459**	−0.011583	0.002940	0.0001***
Seat class (conventional railway)						
Hard berth	0.039716			0.533920		
Hard seat	0.002715	0.223989	0.9903	−0.156376	0.257217	0.5432
Soft berth	0.357021	0.217251	0.1003	0.402044	0.258284	0.1196
Standing-room only	−0.399452	0.232867	0.0863*	−0.779588	0.269298	0.0038***
Seat class (high-speed railway)						
First class	−0.291001			0.576797		
Second class	1.057980	0.240335	0.0001 ***	0.073848	0.270726	0.7850
Business class	0.248026	0.208970	0.2353	0.110066	0.258180	0.6699
Standing-room only	−1.015005	0.214643	0.0001 ***	−0.760711	0.296179	0.0102**
Context attribute						
Subsidy	0.001376	0.000551	0.0126**	0.000133	0.000113	0.2412
Confirmed cases in hometown						
Yes	−0.627689			0.421307		
No	0.627689	0.643440	0.3293	−0.421307	0.134650	0.0018***
Quarantine policy in hometown						
No quarantine policies	−5.013357			−0.236481		
No quarantine needed with valid negative test reports	−0.639765	1.345637	0.6345	0.021119	0.179377	0.9063
Home quarantine for 14 days	2.156989	1.026747	0.0357**	0.237127	0.177920	0.1826
Quarantined in hotels for 14 days	3.496133	1.066590	0.0010 ***	−0.021765	0.196350	0.9117
Decisions from social networks						
All stay in place	2.631740			−0.138801		
Most stay in place	0.819895	0.763138	0.2827	0.260562	0.177990	0.1432
A few stay in place	−1.883353	0.681702	0.0057***	0.042470	0.173286	0.8064
None stay in place	−1.568282	0.748591	0.0362**	−0.164231	0.177038	0.3536
Std. deviation of error component between conventional and high-speed railway	3.228615	1.001238	0.0013 ***	6.322326	1.018145	0.0001***
Latent class membership						
Age						
Above 40				0.563990		
31~40				0.490777	0.126844	0.0001***
25~30				−0.364855	0.111166	0.0010***
Lower than 25				−0.689912	0.146704	0.0001***
Marital status						
Single				0.447999		
Married (with kids)				−0.232936	0.093271	0.0125**
Married (no kids)				−0.215063	0.100966	0.0332**
Constant				0.943526	0.110246	0.0001***
No. of observations			4544			
No. of respondents			568			
No. of scrambled Halton draws			100			
Initial loglikelihood			−6299.322			
Final loglikelihood			−4310.362			
Rho-squared			0.3157			
Adj. Rho-squared			0.3070			

***p value <0.01; **p value <0.05; *p value <0.1.

Table 4: Predictions for estimation and prediction samples using the final model.

	Estimation samples			Prediction samples		
	Observed (%)	Predicted (%)	Abs. difference (%)	Observed (%)	Predicted (%)	Abs. difference (%)
Conventional railway	13.56	14.22	0.66	9.75	14.14	4.39
High-speed railway	23.04	24.15	1.11	20.10	23.81	3.71
Private car	8.49	8.27	0.22	12.07	8.25	3.82
Stay in place	54.91	53.36	1.55	58.08	53.80	4.28

Table 5: Policy analysis based on the final model.

	Conventional railway (%)	High-speed railway (%)	Private car (%)	Stay in place (%)
Subsidy for staying in place	−0.17	−0.32	−0.18	0.67
Ticket fare for conventional railway	−0.93	0.52	0.08	0.33
Ticket fare for high-speed railway	0.54	−1.05	0.12	0.39
Ticket fare for conventional and high-speed railways	−0.41	−0.53	0.19	0.75
Decisions from social networks				
All stay in place	−0.83	−2.05	−0.54	3.42
Most stay in place	−0.60	−0.94	−0.91	2.45
A few stay in place	0.38	0.88	0.41	−1.67
None stay in place	0.59	1.04	0.89	−2.52
Quarantine policy in hometown				
No quarantine policies	0.86	1.47	1.48	−3.81
No quarantine needed with valid negative test reports	0.11	0.27	0.14	−0.52
Home quarantine for 14 days	−1.03	−1.90	−1.39	4.32
Quarantined in hotels for 14 days	−1.35	−2.96	−1.33	5.64

networks. In terms of the monetary policies, effects of being increased by 10% are examined. The results show that the change in the probability of respondents choosing staying in place in the Spring Festival is relatively small. The largest variation (0.75% increasing) is caused by a 10% increasing of ticket fare of conventional and high-speed railways; the second largest (0.67% increasing) is caused by a 10% increasing of subsidy for staying in place. The influence of 10% increasing of ticket fare of conventional or high-speed railway only is smallest. If one kind of railway becomes more expensive, respondents are more likely to choose other travel modes to come back to hometown rather than staying in place. In terms of the quarantine policy in hometown and decisions from social networks, the results of all respondents facing with a same attribute level are compared with the results of respondents who cannot get such information (i.e., the average of the attribute utility). The results from Table 5 show that the influence of quarantine policy in hometown is the highest. If respondents needed to be quarantined in a hotel or at home for 14 days, the probability of choosing to stay in place increased by 5.64% or 4.32%, respectively. Instead, if the respondents could come back to their hometowns freely with no conditions or with valid negative test reports, the probability of choosing to stay in place decreased by 3.81% or 0.52%, respectively. Regarding the social influence, the probability of choosing to stay in place increased by 3.42% or 2.45%, respectively, if all or most of the social network members choose to stay in place, while the probability of choosing to stay in place decreased by 2.52% or 1.67%, respectively, if none or only a few social network members choose to stay in place.

6. Summary and Conclusions

This study investigates Chinese people's willingness to stay in the city of work in the Spring Festival when the COVID-19 pandemic occurs. A stated choice experiment was adopted to collect data, in which respondents were requested to choose the preferred alternative from a choice set that consisted of three hypothetical homecoming trips and the option of staying in place, in the context of the current status of the COVID-19 pandemic and relevant prevention policies. A latent class mixed logit model was applied and estimated; in which two latent classes were identified in the sense that one paid more attention to epidemic prevention policies while the other cared more about the characteristics of homecoming trips.

The estimation results provide many interesting findings about the impact of the COVID-19 pandemic on Chinese people's choice behavior in Spring Festival. First, the COVID-19 pandemic does influence people's homecoming trips, which leads to preference heterogeneity among people. However, most people still pay attention to the trip-related attributes and COVID-19 pandemic can only show its significant effect to some degree. Second, age and marital status are found to have significant impacts on the influence of epidemic prevention policies or the characteristics of homecoming trips when making decisions. Third, the quarantine policy in people's hometowns has the greatest impact on their willingness to stay, followed by the number of social network members who choose to stay in place. In addition, policies such as increasing the subsidy for staying in place or the ticket fare of railway have minor impacts on the travel decisions. Fourth, when all prevention policies are removed, people who are significantly affected by the COVID-19 pandemic and related policies will come back to their hometown even though confirmed cases of COVID-19 are still reported in their hometown.

Moreover, this study also provides some practical implications for government. First of all, the results show that whether people would like to comply with the epidemic prevention policies when considering coming back home or not is largely dependent on people's sociodemographic characteristics. Therefore, the government could propose some special policies targeting particularly to specific sociodemographic groups. For instance, government could encourage enterprises to propose a tiered subsidy policy for younger or single employees if they are not going to come back home in the Spring Festival. Second, the results show that people are more likely to conform to the choices from their social network members. Government or enterprises could encourage people to be volunteers who choose to stay in place, which would make others in their social networks follow their choices. Moreover, government could broadcast some stories or news regarding the benefits of staying in the city of work and celebrate the Spring Festival with colleagues or friends in social or mass medias to spread the positive contributions of not spreading virus. Third, the government could also make strict quarantine policies not only for preventing people coming back to their hometowns but also preventing the sudden outbreak due to potential loopholes in the epidemic prevention system.

Some shortcomings should be noticed. First, the sample size used in this study is relatively small and may harm its representativeness. Second, some attributes about COVID-19 pandemic are ignored as the situation of the COVID-19 pandemic changes very quickly. In addition to improving the current study from above aspects, some further works need to be done in the future. First, the COVID-19 pandemic may not only influence people's preferences but also their attitude toward certain travel modes, as transportation system is believed as a way of contributing to the diffusion of COVID-19, especially the railway or the public transit system which is featured by high capacity. How and to what extent that the COVID-19 pandemic affects people's attitudes is a topic of great interest in the future. Second, people who do not come back to their hometowns in the Spring Festival may still need to come back in other time, e.g., as already happened in the Labor Day of 2021 in China. In this sense, the COVID-19 policies do not prevent people coming back but only postpone it. Who decide to come to home in other holidays of a year and how the government should deal with this situation are questions to be answered. Third, the COVID-19 pandemic has been lasting for over two years and some new and unexpected situations have come out. How people's travel choice behavior changes in response to the new situations are worth to be studied. However, carefully finding the good balance to keep travelers against infection and to warrant travelers' mobility need may be the biggest challenge in the future.

Data Availability

Data are available upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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