Modelling Heterogeneity in Behavioral Response to Peak-avoidance Policy Utilizing Naturalistic Data of Beijing Subway Travelers

Yu Wang

Department of economics

School of Economics and Management, Beijing Jiaotong University, No.3 of Shangyuancun, Haidian District, Beijing 100044, China

E-mail: 18113016@bjtu.edu.cn

Yacan Wang (Corresponding author)

Department of economics

School of Economics and Management, Beijing Jiaotong University, No.3 of Shangyuancun, Haidian District, Beijing 100044, China

E-mail: ycwang@bjtu.edu.cn

Charisma Choudhury

Institute for Transport Studies and School of Civil Engineering

University of Leeds, Leeds, LS2 9JT, UK

E-mail: C.F.Choudhury@leeds.ac.uk

Highlights:

- This paper contributes to the understanding of the taste heterogeneity of travelers to pre-peak discount pricing strategy.
- Naturalistic data from smart card data users in Beijing before and after a policy intervention is used in this regard.
- Four groups of travelers with heterogeneous characteristics are classified by constructing a latent class model.
- Different targeted policy recommendations for each group of travelers are proposed in order to improve the policy effect.

Abstract:

Studies of travelers' response behavior to transportation demand management is receiving substantial attention among researchers and transport operators in recent years. While previous studies in this area have generally assumed that the sensitivity of travelers to different factors is homogeneous and relies on survey responses, which may be prone to self-reporting errors and/or subject to behavioral incongruence. Relying on naturalistic data, this paper aims to investigate the behavioral response to pre-peak discount pricing strategy in the context of the Beijing subway with a special focus on the heterogeneity among the travelers. Anonymous smart card data from 5946 travelers before and after the introduction of a peak avoidance policy in Beijing are used to construct a latent class choice model to capture the sensitivity to different factors and the associated taste heterogeneity of travelers. Given the passive nature of the data, the model can offer more realistic outputs. The results indicate that there is substantial heterogeneity in travelers' responses to the peak avoidance policy, and that they can be probabilistically allocated to four latent classes. For all classes of travelers, the decision to shift their departure to off-peak is affected by the monetary saving, the required change in departure time and the frequency of travel, but in different magnitudes. In particular, only two classes of travelers (who exhibit lower standard-deviation in pre-intervention departure time) show significant sensitivity to price changes indicating that the discount policies are more likely to be effective for these groups. The rest of travelers are largely price insensitive – warranting the need for non-monetary incentives as opposed to fare discounts. To the best of our knowledge, this study is the first to innovatively apply the LCC framework to analyze travelers' heterogeneous behavior using large-scale smart card data without socio-demographic information. The findings can provide guidance to the subway authority in devising differential peak avoidance policies targeted for different groups of users, which are likely to be more effective than the current 'one size fits all' approach.

Keywords: peak avoidance choice, latent class choice model, smart card data, heterogeneous behavioral response, targeted policy

1 Introduction

Public transportation, subways in particular, are crucial components of an efficient mega-city around the world. Unfortunately, the subway systems are under much pressure. Demand levels higher than the capacity are yielding immense congestion costs and leading to loss of social welfare in the subway similar to those of the road transport sector (Tirachini et al., 2013). The city selected as the case study is the Chinese capital Beijing which with its population of 22 million and high growth rate over the past few decades is a megacity getting worldwide interest. The increased demand for commute travel results in strongly increasing congestion in subway system (Wang et al., 2018). Beijing subway has an average occupancy rate of 135% and as many as 4-5 travelers crowded into one square meter of standing space during rush hours (Zhang et al., 2014). Beijing can be regarded as a microcosm of big cities suffering from similar public transport crowding issues around the world (Wei, 2012). To reduce congestion, cities' managers have tried measures to encourage subway travelers to avoid traveling during the peak hours. Among these, fare discounts have been the most common and have to some extent been effective in spreading peak traffic across different urban rail transit systems. The Beijing Subway launched a pricing strategy to promote peak avoidance in December 2015. As a part of this policy, travelers can enjoy a 30% discount on the fare if they depart from selected stations on the Changping Line and Batong Line before 7 a.m. Similar discounts or differential pricing have also been implemented in other big cities, examples including the 'Travel early travel free' project in Singapore (Pluntke & Prabhakar, 2013; Yang & Lim, 2018), the 'Early bird' project in Hong Kong (Halvorsen et al., 2016), and 'Free before 7' project in New Zealand (Currie, 2009), etc. Meanwhile, additional measures, including advertising, incentivizing employers to allow flexible work schedules, and providing real-time information on subway crowding levels, have also been adopted, either in isolation or as complementary to differential pricing policies (Yang & Lim, 2018).

Travelers' travel responses to peak avoidance policies are complex and influenced by various external factors (such as incentives) and travelers' own attributes (such as commuting and social demographic characteristics). Previous studies on travelers' peak avoidance decisions have generally assumed that the sensitivity of travelers to different factors is homogeneous (Ben-Elia & Ettema, 2011a, b; Zhang et al., 2014; Wang et al., 2018). Consequently, such models result in 'one size fits all' policy recommendations. However, the homogeneity assumption ignores the fact that there are different types of subway travelers (Zou et al., 2018; Halvorsen et al., 2019), who are likely to have different sensitivities towards the incentives, leading to substantial taste heterogeneity.

On a parallel stream, several studies have acknowledged the systematic heterogeneity among the travelers and segmented them based on observed socio-demographics. However, these studies have relied on stated preference (SP) surveys (Zhang et al., 2014; Wang et al., 2018). Although the SP approach provides responses on a large set of hypothetical scenarios at a low cost, it is criticized for its lack of realism, hypothetical bias, and behavioral incongruence, which may lead to errors and bias in the responses (Dixit et al., 2017). These limitations call into question the applicability of the results of these studies to policy making.

To fill these gaps, this study investigates the behavioral response to peak avoidance policy using naturalistic data with a special focus on modeling the taste heterogeneity of the travelers. In order to achieve this goal, smart card data generated from the automatic fare collection system of the Beijing Subway have been used. Smart card data from before and after the implementation of the discount fare policy have been used to develop latent class choice (LCC) models (Ben-Akiva et al. 2002) of peak avoidance, where the travelers are probabilistically segmented into different classes according to their travel attributes. The results of the LCC model can be used to formulate targeted policy measures replacing the 'one size fits all' approach.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 presents the data. Section 4 describes the model construction. Section 5 analyzes the estimation results. Section 6 presents the discussion and implications of the study. Finally, Section 7 summarizes the paper and sets the agenda for future research directions.

2 Literature review

2.1 Modelling peak-avoidance behavior

In order to attenuate the travel demand during rush hours, many countries and regions have tried to use traffic demand management policies to encourage travelers to change their preferred travel routine (Taylor et al., 1997). In terms of the policy perspective, previous researchers have explored the influence of various incentives and penalties on individuals' peak avoidance behavior. Leblanc et al. (2013) tested the potential response to seven plans for peak avoidance implemented thus far, including providing High Occupancy Vehicle passes, Apple credits, cash, lottery tickets, donations, and congestion charges. Combining an SP survey with a nested Logit model, they found that the willingness of commuters to change their behaviors varies across incentives. Ben-Elia and Ettema (2011a) explored different levels and types of rewards applied in the Netherlands to encourage drivers to avoid driving at peak hours. Their results suggest that rewards can be effective tools in changing commuting behavior. In Beijing, Zhang (2014) conducted an SP survey among Beijing subway commuters and found that schemes such as providing snack discount coupons, flexible work schedules, and fare concessions are the most effective in encouraging peak avoidance behavior. In addition to investigating policies, previous studies have examined other explanatory factors, including socio-demographic attributes, flexibility of work hours, attitudes towards commuting alternatives, travel information, carriage environment, and weather factors (Peer & Verhoef, 2016; Basu et al., 2012; Wardman & Whelan et al., 2011). Moreover, based on evaluation results, previous studies have provided suggestions regarding ways to make peak avoidance policies more convincing and effective. Discussion angles include the degree of incentives (Halvorsen et al., 2019), temporal coverage (Yang & Lim, 2018; Peer & Verhoef, 2016), spatial coverage (Zou et al., 2018), policy promotion (Greene-Roesel et al., 2018), and policy mix (Zhang et al., 2014). However, these policy recommendations are often of a 'one size fits all' type. In the context of energy consumption, Knittel and Stolper (2019) find that selecting targeted groups using machine learning techniques to formulate targeted policies can improve the effectiveness and efficiency of policies. To the best of our knowledge, previous transport studies that use naturalistic data have not looked at this aspect.

Modeling traveler responses to peak avoidance policies has been an important focus in these studies. Conventional choice models, such as the multivariate logit model (Ben-Elia & Ettema, 2011a, 2011b), multivariate probit model (Zhang et al., 2014), and binary logit model (Halvorsen et al., 2019) have been used to maximize the utility of choosing peak avoidance by incorporating individual socioeconomic characteristics and mode attributes (Ben-Akiva et al., 1999). However, the naturalistic data sources are typically anonymous and do not have information about the sociodemographic characteristics of the travelers. Among previous studies evaluating subway peak avoidance policies using smartcard data, only Halvorsen et al. (2019) and Wang et al. (2018) have considered the heterogeneity of travelers and classified subclasses through K-means. However, these two papers did not construct choice models to explore the heterogeneous behavioral responses of different groups, which has left the behavior mechanism unexplored.

In order to device targeted policy measures, it is essential to capture the way in which the heterogeneity among travelers leads to differences insensitivity toward different influencing factors (Walker & Li, 2007). Among various approaches to incorporating the taste heterogeneity among travelers, the latent class choice model (LCC) is a widely used and powerful method (Gopinath, 1995; Magidson, 2003). LCC captures unobserved preference heterogeneity by assuming that dividing the travelers into a discrete number of classes can sufficiently represent the taste variation (Shen et al., 2006; Greene & Hensher, 2003). The LCC approach has been applied in various transportation contexts: trip scheduling preferences (Peer & Verhoef, 2016), travel mode choice behavior (Vij et al., 2013), attitude consideration (Hess et al., 2013), and driving behavior (Choudhury et al., 2008, Braitman & Braitman, 2017). Based on the LCC specification, these papers drew constructive conclusions regarding the latent heterogeneity in preferred choices.

2.2. Behavior modeling using Smart Card data

The widespread application of smart cards in recent years offers new possibilities to observe and record travelers' behaviors. Automated fare collection (AFC) systems help researchers to better estimate, predict, and validate transport theories and models (Vlahogianni et al., 2015). In subway AFC systems, trip records such as date, enter/exit time, and enter/exit station numbers, are recorded when travelers swipe their cards on a card reader. Smart card data have been widely used to estimate travel attributes, such as the origin–destination (OD) matrix (Munizaga et al., 2010; Alsger et al., 2015), travel mode identification (Long et al., 2012), travelers' route choice mode (Ma et al., 2017; Jánošíková et al., 2014), trip purposes (Lee & Hickman, 2014; Alsger et al., 2018) and traveler flow on different routes (Tavassoli et al., 2018). Compared with the traditional dataset, this new data source has advantages in terms of accuracy, continuity, large-scale application, and cost efficiency (Zhao et al., 2018; Zhang et al., 2017; Kieu et al., 2015; Liu et al., 2019).

However, smart card data are usually anonymous and do not include socioeconomic attributes (e.g., gender, age, career, income, etc.) or detailed travel information (e.g., trip purposes, access and egress modes, etc.) (Bagchi et al., 2005; Anda et al., 2017; Jain et al., 2014). To overcome these limitations, many researchers have attempted to mine indirect and latent information from smart card data, such as journey time reliability (Rahbar et al., 2017), job and housing dynamics (Huang et al., 2018), traveler classification (Halvorsen et al., 2019) and policy response (Zou et al., 2018), etc. (see Zannat and Choudhury 2019 for a comprehensive review).

Smart card data have also been used to capture the change in travelers' behavior in response to subway peak avoidance policy (Yang & Lim, 2018; Zou et al., 2018). However, Zou et al. (2018) only estimated the retiming elasticity of different travelers and did not construct a choice model to analyze the tradeoff among different factors influencing the travelers' behavior. Yang and Lim (2018), on the other hand, have used the method of choice modeling, but without considering taste heterogeneity. Hence, this paper fills a research gap. To the best of our knowledge, this study is the first to use the LCC framework to analyze large-scale smart card data and can offer more realistic outputs, given the massive passive nature of the data.

3 Data

3.1 Smart card data

The discount pricing strategy was implemented on December 28, 2015 and provided a 30% discount for travelers who checked in before 7:00 a.m. This policy was piloted at 16 stations on the Batong Line and Changping Line on weekdays. Data from 20 working days, before and after the policy's implementation, are used in the analyses. As smart card data does not include demographic variables, this study selects the data from travelers whose most frequent origin station is Zhuxinzhuang station, in order to better control for income and other unobserved socio-demographic variables (Huang et al., 2018). Zhuxinzhuang station is located on the Changping Line, as shown in Figure 1.

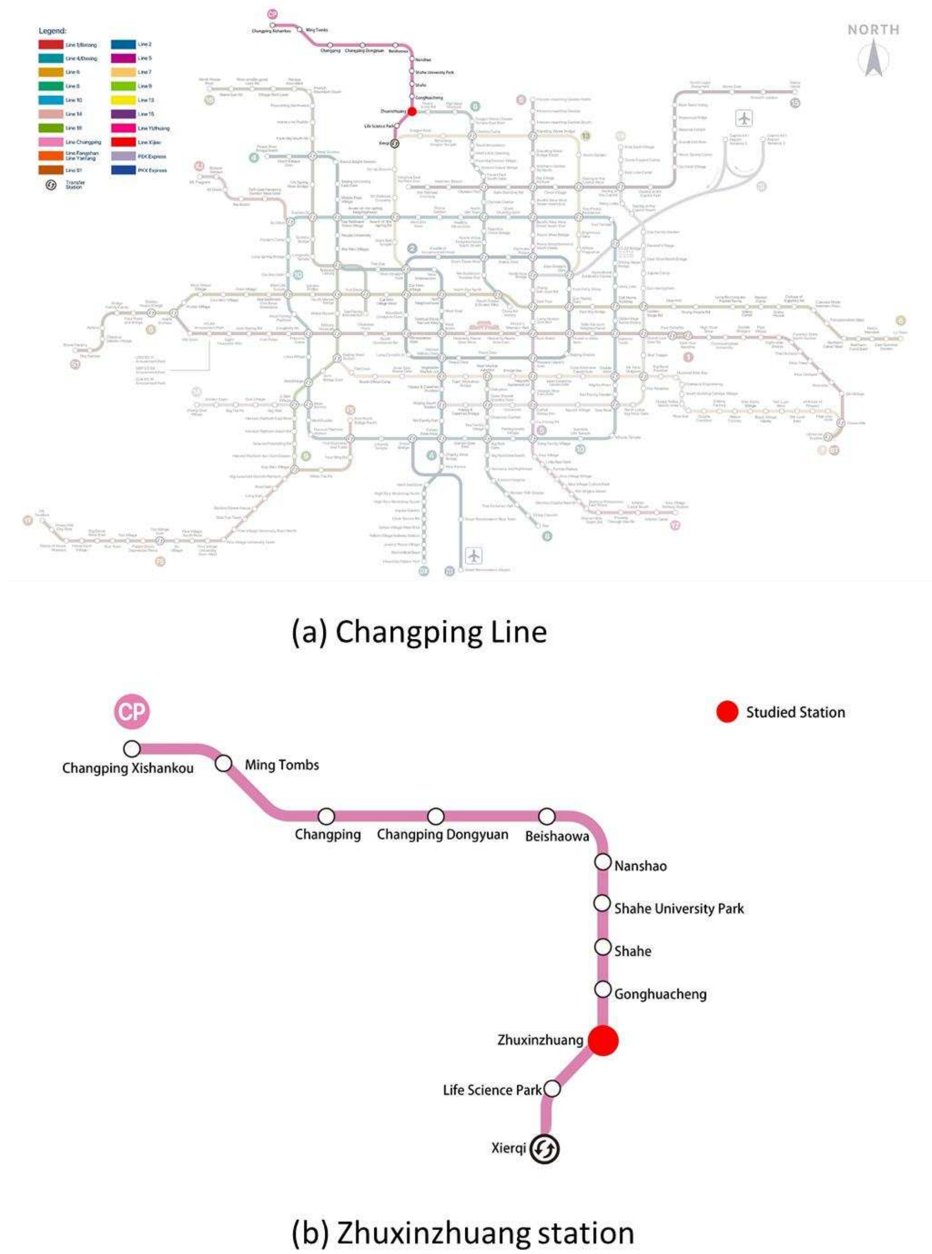

Figure 1. Studied station of this paper-Zhuxinzhuang station[1]

The dataset included 738680 observed trip records from 19843 unique smart cards. Given our interest in habitual travelers traveling during peak hours before the introduction of the policy, only the following types of travelers have been used in our analyses: (a) those who travel at least one day a week (b) those who have departure times between 7:00 a.m. and 9:00 a.m. before the

[1] The map is based on: https://www.bjsubway.com/station/xltzs/

implementation of the policy. After applying these two screening criteria, 437168 trips from 5946 peak-hour travelers are retained.

As shown in Table 1, the smart card database includes 5 fields: card ID, check-in time, origin station ID, check-out time, and destination station ID. As an example, the first card user (1000751085xxxxx) entered station 9429 at 08:52, and exited from station 0103 at 10:37 on November 30, 2015. On December 1, 2015, the traveler entered and exited from the same pair of stations at 08:21 and 10:08, respectively. With one-to-one correspondence between smart cards and travelers, we can track the travel behavior of a specific traveler over time.

Table 1. An excerpt from smart card data

Card ID	Check-in time	Origin station	Check-out time	Destination station
1000751085xxxxxx	20151130085200	9429	103707	0103
1000751085xxxxxx	20151201082100	9429	100826	0103
…	…	…	…	...
1000751017 xxxxxx	20151130081100	9429	95601	0104
…	…	…	…	…

3.2 Identification of variables

The key variable of interest to the policymakers is whether a traveler moves forward his/her departure time from peak hours to pre-peak. If a traveler's median departure time falls into the peak hours before the policy (t_1) and shifts to pre-peak hours afterward (t_2), the traveler is regarded as a 'shifted traveler'. In other words, a shifted traveler (y=1) is defined as follows:

$$y = \begin{cases} 1, t_1 > 7:00am, t_2 < 7:00am \\ 0, else \end{cases} \tag{3}$$

Among the 5946 travelers, 212 travelers shifted from peak to pre-peak. Hence, the rate of shifting is approximately 3.6%. The median value of each traveler's pre-policy departure time is treated as his/her preferred departure time (Peer & Verhoef, 2016).

The candidate explanatory variables used in the model are shown in Table 2.

Table 2. Variable definition

	Variables	Description	Range	Categorical representation in the model (if applicable)
Trip characteristics	Monetary saving	The fare savings associated with pre-peak travel.	0.9-2.7 RMB	-
	The required change in departure time	The amount of time a traveler would have to shift his/her departure time from the preferred departure time to avail the discounted fare.	0-120 minutes	-
	Travel frequency	Average of number of days using subway in morning per week before the policy.	1- 5 times/week	-
Temporal travel characteristics	Trip duration	Median duration time in subway of the period before the policy.	0-120 minutes	1: 0-20 min 2: 20-40 min 3: 40-60 min 4: > 60 min
	Standard deviation of the first-trip departure times	Standard deviation of the first-trip start time - a measures the stability of the start time before the policy.	0-120 minutes	1: 0-30 min 2: 30-60 min 3: >60 min
Spatial travel characteristics	The number of traveled OD pairs	The number of unique OD pairs traveled before the policy – smaller values denote higher spatial stability.	1-5 pairs	1: 1 pair 2: >1 pair
	Ticket fare	Median ticket price of the period before the policy.	3-9 RMB	1: 3,4 RMB 2: 5 RMB 3: 6 RMB 4: >6 RMB

It should be noted that Beijing's subway fare is distance-based and that the trip duration is related to the travel distance to some extent. However, travelers with the same fare or travel distance can have different travel duration depending on routes and/or congestion levels, due to differences in transfer time and queuing time during boarding. As a result, we keep both trip duration and ticket fare. In addition, in order to facilitate the calculation, we regard 5:00 a.m. as 0, and the value increases by 1 for every 1 minute increase in departure time.

4 Model structure

A traveler's decision to switch from peak to off-peak is likely to be affected by travel time, travel cost, frequency, reliability (i.e., standard deviation of travel time), crowding level, required shift from the original departure time, etc. (Peer & Verhoef, 2016; Wang et al., 2018). The sensitivity to these factors, however, is likely to vary substantially among travelers with different travel patterns (e.g., regular vs. irregular, long vs. short distance travelers, etc.), as well as with socio-demographic characteristics. This prompted us to test the applicability of latent class choice (LCC) models, which acknowledge that (a) there are unobserved (latent) groupings among the decision makers and the members of each latent class have similar sensitivity towards an attribute and that (b) the group memberships can be probabilistically inferred from the data (Ben-Akiva et al. 2002). Although the socio-demographic characteristics of the travelers are unobserved in the anonymous smart card data, the travel patterns can be inferred given the panel nature and used as indicators of the class membership. It may be noted that while traditional clustering methods can be used to divide the travelers into different classes deterministically, LCC offers probabilistic class assignment and joint estimation of the class membership utilities and the choice utilities, which leads to more efficient estimates (Hess, 2014). The details of the LCC model structure are presented below.

The LCC model consists mainly of two sub-models, a class-membership model and a class-specific choice model, as shown in Figure 2.

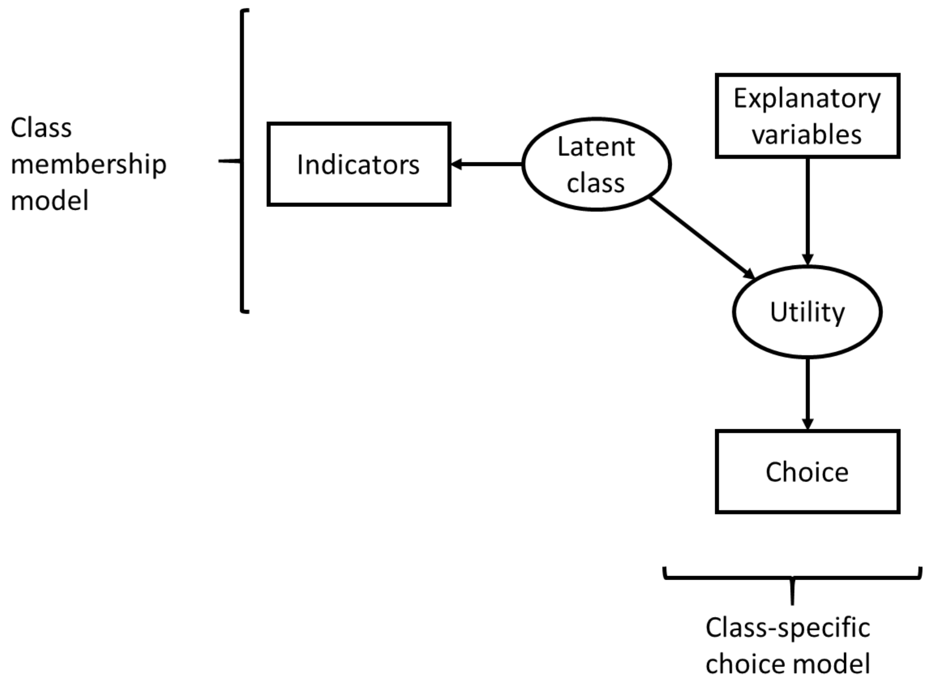

Figure 2. Latent class choice model

The class-specific choice model represents the choice behavior of each class and varies across latent classes. The conditional probability of observing a choice *i* by a traveler *n* belonging to class c_n (y_{in}) can be expressed as follows：

$$P(y_{in}|c_n, X_{in}) = \frac{\exp(\beta_{c_n} X_{in}|c_n)}{\sum_j \exp(\beta_{c_n} X_{jn}|c_n)} \tag{1}$$

where traveler *n* belongs to latent class c_n , X_{in} represents the explanatory variables associated with alternative *i* and traveler *n* , β_{c_n} and represents the coefficients corresponding to c_n.

The unconditional probability of observing a choice *i* by an individual *n* can hence be deduced from the following:

$$P(y_{in}|X_{in}, I_n) = \sum_{c=1}^{\mathrm{C}} P(c_n|I_n) P(y_{in}|c_n, X_{in}) \tag{2}$$

where I_n represents the explanatory variables and/or indicators associated with the class membership, and C denotes the total number of classes.

Assuming that the observations of different travelers are independent and the correlation among decisions by the same traveler is captured by the class membership component, the log-likelihood function for all observed travelers is given by:

$$LL = \sum_{n=1}^{N} lnP(y_{in}|X_{in}, I_n) \tag{3}$$

Parameters of the class-membership model $P(c_n|I_n)$ and class-specific choice model $P(y_{in}|c_n, X_{in})$ are estimated simultaneously by maximizing this function using Latent Gold software.

5 Results

The number of classes in the LCC model has been determined empirically without any prior hypotheses. The goodness-of-fit values and the associated conclusions regarding class membership are presented first, followed by a detailed estimation of the basic model (no latent class) and the final model (with latent classes).

5.1 Determining the number of classes

The number of classes is not predetermined but is determined empirically based on goodness-of-fit statistics as well as the behavioral intuitiveness and statistical significance of the model parameters (Walker & Li, 2007). With the same specifications as the number of classes, models with 1–5 classes are estimated. Among the variables in Table 2, the trip duration, standard deviation of the first-trip start times, the number of traveled OD pairs, and ticket fare have been tested as indicators of traveler classification. Monetary savings, the required change in departure time, and travel frequency are used as explanatory variables in the choice component[2].

In Table 3, the goodness-of-fit of the models, such as BIC, AIC, and log-likelihood, provides the basis for selecting the appropriate number of latent classes. In general, the lower the AIC and BIC, the better the model according to the statistics (Walker & Li, 2007). The results indicate that models with classification are preferred over the model without classification. Based on the BIC, the 2-class model has the best performance. However, AIC suggests that the 4-class model is superior. Considering the behavioral intuitiveness and statistical significance of the model

[2] 'Ticket fare' and 'Travel frequency' have been tested both for class membership and choice component and retained in the components based on the coefficient signs and statistical significance.

parameters, the results of the 4-class model provide a more meaningful behavioral interpretation in terms of capturing travelers' heterogeneity. Therefore, the 4-class model is selected in this study. In the following sections, we discuss the details of the 4-class model.

Table 3. Overview of model estimation results

Number of classes	LL	BIC(LL)	AIC(LL)
1	-641.156	1617.074	1290.312
2	-590.710	**1317.074**	1267.421
3	-569.409	1337.850	1240.818
4	-560.534	1520.847	**1213.085**
5	-549.114	1619.656	1218.228

5.2 Class-specific choice model without latent class

The class-specific choice model without latent class, which is treated as the base model, is shown in Table 4.

Table 4. Class-specific choice model without latent class

Variables	Basic model	
	Coefficient	z-value
Monetary saving	1.100*	1.782
Required change in departure time	-1.549***	-21.012
Travel frequency	-0.700***	-2.888
Intercept	2.129***	3.996

Note: * indicates |z|>=2.58, ** indicates 1.96<=|z|<2.58, and * indicates 1.64<=|z|<1.96**

Estimated coefficients indicate that monetary saving, the required change in departure time, and travel frequency affect peak avoidance choice behavior. The greater the fare savings from choosing peak avoidance, the more travelers tend to depart before 7:00 a.m. Then, the required change in departure time negatively influences travelers' choices. That is, the higher the required change, the lower is the probability of shifting. Moreover, travelers with larger travel frequencies have lower probabilities of changing their behavior. These results are in line with expectations.

5.3 Latent class choice model

5.3.1 Class-membership model

The estimation results show that the proportions of classes 1–4 are approximately 33.9%, 32.5%, 23.3%, and 10.3%, respectively. Coefficients vary significantly between different categories, and each class consists of travelers with different travel characteristics. The detailed results of the 4-class model are shown in Table 5, which helps us to explore the different behavioral responses across different classes of travelers.

Table 5. Class-membership model estimation results

Classification	**Class 1**		**Class 2**		**Class 3**		**Class 4**	
Class size	0.3392		0.3248		0.2332		0.1029	
Indexes	**Coefficient**	**z-value**	**Coefficient**	**z-value**	**Coefficient**	**z-value**	**Coefficient**	**z-value**
Standard deviation of the first-trip start times								
1	-0.3219	-0.5722	-0.1127	-0.1954	1.0466	1.0394	-0.612	-0.5329
2	0.3282	0.4293	0.0125	0.0157	2.2126**	2.0266	-2.5533	-1.3905
3	-0.0063	-0.0069	0.1002	0.1076	-3.2592*	-1.7825	3.1653***	2.697
Trip duration								
1	1.5478	1.5626	0.1455	0.1177	-2.0944	-1.2584	0.4011	0.4642
2	0.616	0.6219	0.609	0.5521	-1.1015	-1.0463	-0.1235	-0.2038
3	1.1659	1.0122	-2.7814	-1.2144	1.4574	1.063	0.1581	0.1663
4	-3.3297**	-2.1553	2.0269	1.3696	1.7384	1.1227	-0.4357	-0.3495
Ticket fare								
1	-0.7012	-0.6855	-1.4593*	-1.836	3.3352*	1.8634	-1.1748	-1.1639
2	-0.3828	-0.455	0.898	0.9136	-0.467	-0.6515	-0.0482	-0.0813
3	-0.5135	-0.6283	0.6704	0.8255	-0.8438	-1.0764	0.687	1.3797
4	1.5975	0.7479	-0.1092	-0.1006	-2.0243	-1.7654	0.536	0.629
The number of traveled OD pairs								
1	0.0618	0.4048	0.1592	0.9616	0.446**	2.256	-0.225	-1.4594

Note: * indicates |z|>=2.58, ** indicates 1.96<=|z|<2.58, and * indicates 1.64<=|z|<1.96**

Figure 3 and Figure 4 show the descriptive statistics of the classification indicators and travel characteristics of the four different classes, respectively, to further highlight the differences between the classes.

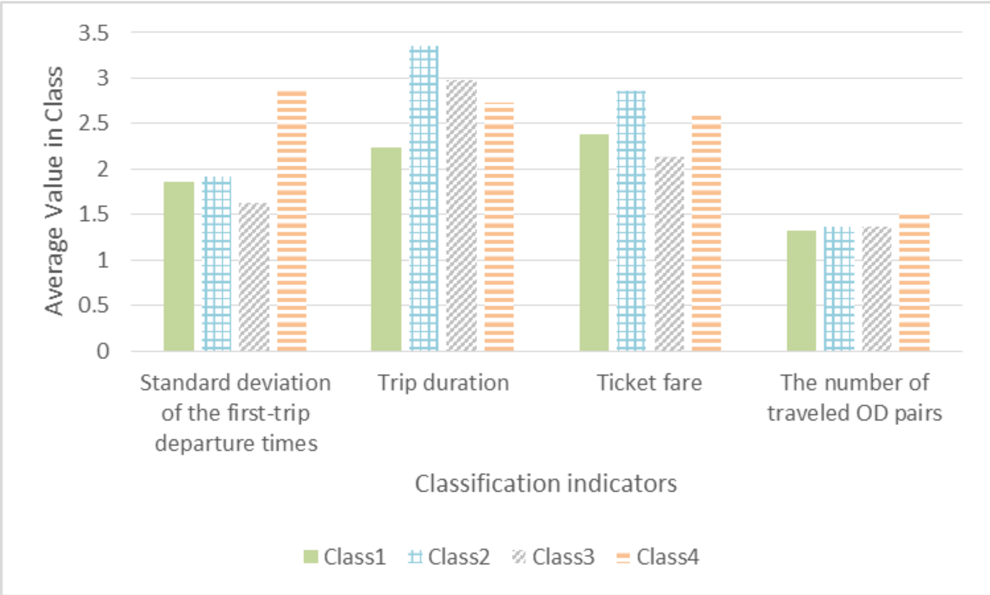

Figure 3. Latent classes profiling-Weighted average value of indicators

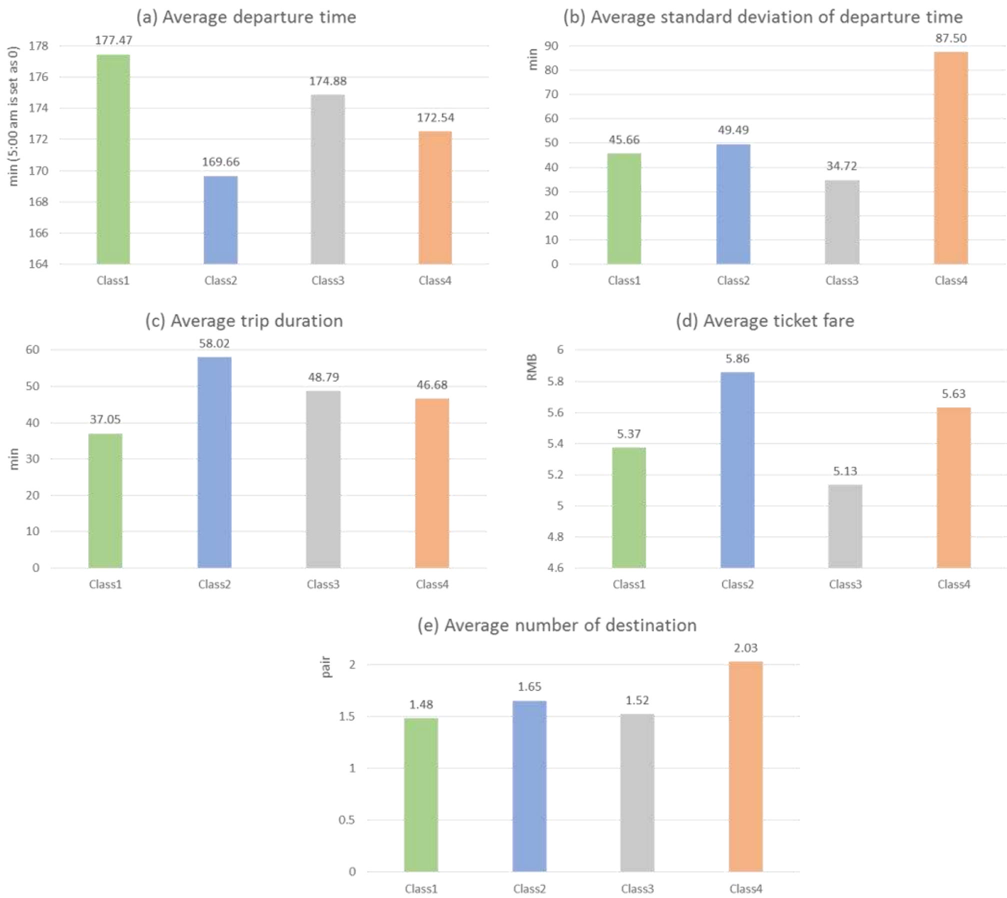

Figure 4. Latent classes profiling- Weighted average value of the traveling characteristics

According to the results of the class-membership model, variable distributions and the traveling characteristics of each classification group, different types of travelers that correspond to each group are identified.

(1) *Class 1. Short-distance, low variation travelers.* This group of travelers' commuting time in the subway is generally no more than 1 hour; the departure time is fixed with low time flexibility, and the destination station is fixed. Moreover, they spend the least time traveling in the subway system. Correspondingly, their average departure time is the latest.

(2) *Class 2. Long-distance, low variation travelers.* The travelers in class 2 are similar to those in class 1, with some differences. They have the longest travel duration and largest average ticket fare. Correspondingly, their average departure time is the earliest.

(3) *Class 3. Multi-transfer, low variation travelers*. Compared with the first group, these travelers have lower ticket fares and longer duration of travel. This suggests that they spend more time in the process of subway transfer or waiting for a train. Their departure times are the most fixed.

(4) *Class 4. Flexible, high variation travelers.* The most distinctive feature of this group of travelers is that they have lower temporal and spatial stability than the other 3 groups.

5.3.2 Class-specific choice model

The estimated results of the class-specific choice model with 4 classes are shown in Table 6. The differences in the magnitude and statistical significance (confirmed by the Wald test) of the estimates confirm the hypothesis regarding significant taste heterogeneity across classes.

Table 6. Class-specific choice model with latent class

Variables	Class 1		Class 2		Class 3		Class 4		Wald	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value	Value	P-value
Monetary saving	19.4162***	3.2641	9.3635**	1.97	5.2297	1.3948	0.4682	0.181	16.16***	0.001
The required change in departure time	-1.6336***	-4.5104	-1.5457***	-4.3599	-5.0792***	-4.1574	-2.9868***	-5.0472	10.57**	0.014
Travel frequency	0.3358	0.3041	-0.3709	-1.426	1.322	0.6932	-2.7185***	-3.8119	9.99**	0.019
Intercept	-10.9827***	-2.6674	6.3442*	1.9589	7.1084*	1.7156	12.1047***	3.9363	24.54***	1.9e-5

Note: * indicates |z|>=2.58, ** indicates 1.96<=|z|<2.58, and * indicates 1.64<=|z|<1.96**

Among the variables, monetary saving and the required change in departure time have the greatest influence on class 1 and class 3, respectively, while class 4 is the most sensitive to travel frequency and least sensitive to monetary saving.

5.4 Inference of the results: plotting the changes in choice probabilities

In order to provide a visual representation of the nonlinear effects of monetary saving and the required change in departure time on travelers' travel time choice, we plotted the probabilities of choosing peak avoidance against the different levels of money-saving and required change in departure time separately. The majority of respondents, regardless of class, have a travel frequency of four days per week which is controlled (unchanged) in our analysis. The fare savings associated with pre-peak travel are controlled to 1.5 yuan (average discount available) when we consider the effect of the required change in departure time. Moreover, the required change in departure time for travelers is maintained at 40 min (the highest peak of sample traveler flow appeared at 7:40 a.m.), when we test the effect of monetary saving.

Figure 5 shows the probability of choosing peak avoidance for class 1 and class 2 as a function of the amount of monetary saving. The results of class 3 and class 4 are not shown in this graph because they are very insensitive to such savings; the amount of savings required for these classes to switch to off-peak travel is much larger than the maximum ticket price. This shows how challenging it is to persuade subway users who belong to class 3 and class 4 to avoid rush hour consciously through ticket discount policies.

However, the discount policy does affect travelers from class 1 and class 2, which covers more than half of the total respondents. It may be noted, however, that the intuitive notion of ‘more monetary saving, higher peak avoidance probability’, is not entirely valid. The probability only changes in a specific price range. For class 1, this range is from 3.5 yuan to 4 yuan. When the amount of monetary saving does not reach 3.5 yuan, their travel time will not change even though the amount of monetary saving increases. Meanwhile, their probability of avoiding rush hour is equal to 1 for 4 yuan and hence discounts beyond 4 yuan will not result in any further shift. Similarly, the sensitive price range for class 2 is from 4.5 yuan to 5.5 yuan. This finding has important policy implications.

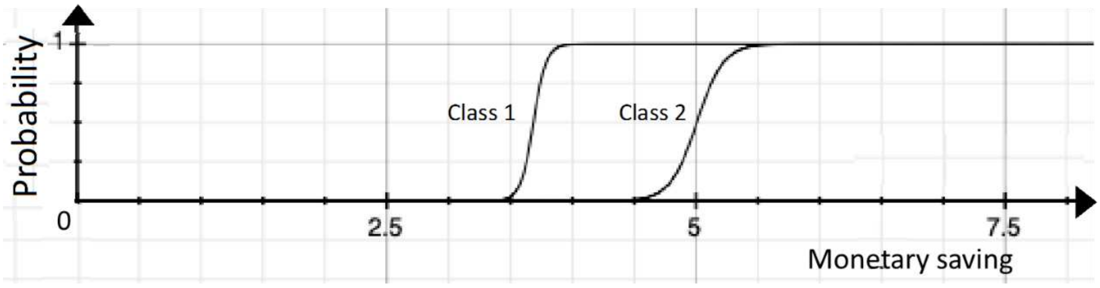

Figure 5. Individual effect of monetary saving

Figure 6 shows the peak avoidance probability for each class as a function of the required change in departure time. Similar to the effect of monetary saving, the peak avoidance probability of each class only changes within a specific range. In general, travelers from class 4 and class 3 have the probability of avoiding rush hour only when the gap between the discount time and their usual time of departure does not exceed 6 minutes. This strict requirement may also mean that it is difficult for travelers from class 3 and class 4 to avoid peak time. Relative to this, travelers in class 1 and class 2 have higher flexibility in terms of departing early. In class 2, especially, a discount policy that starts 20 min before travelers' usual departure time can change their travel behavior.

Figure 6. Individual effect of the required change in departure time

In addition, in order to provide a visual representation of the correlation between monetary saving and required change in departure time, we plotted the equal probability curves for each class. Figure 7 shows the equal probability curves for the peak avoidance probability of 20%. This result is in line with the information of Figure 5 and Figure 6. The marginal rate of substitution of monetary savings for the required change in departure time is quite low for class 3 and class 4. This illustrates that travelers of these classes are not are not easily influenced by ticket discounts. A policy that requires a smaller change in departure time can have a larger effect. For class 1 and class 2, the MRS value is much higher. For class 1, the effect of no required change in departure time equals 0.2 yuan of monetary saving. With an increase in the required change in departure time, the two variables as considered almost equally important. For class 2, the required change in departure weighs more in the decision to avoid peak hours.

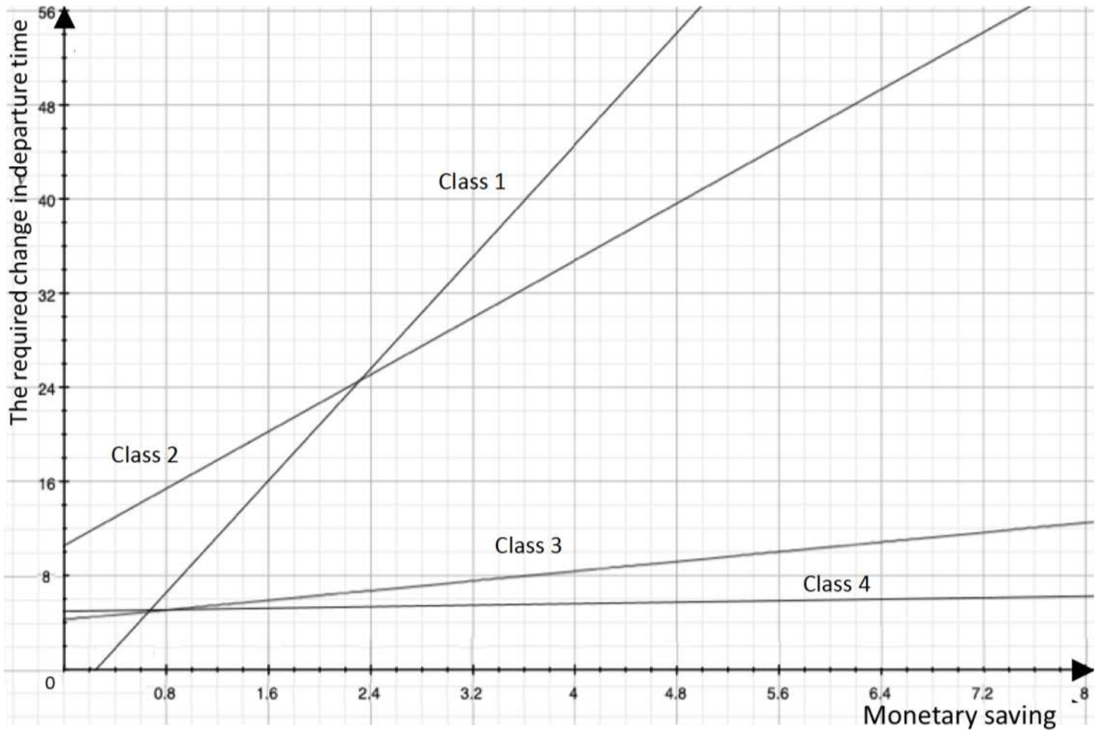

Figure 7. Equal probability curve (20% probability of peak avoidance)

6 Discussion and implications

Beijing subway fare discount policy and the availability of smart card data provide a good opportunity for us to study the heterogeneity of travelers and how to design a targeted peak avoidance policy based on real-life conditions. The behavioral characteristics of travelers mined from the original data are more reliable and authentic compared to self-reported data, which helps us identify the heterogeneity of travelers. We will discuss the results in the following two aspects: behavior and policy.

From the perspective of behavior, the results reveal a heterogeneous impact of policy and commuting factors depending on the type of traveler. Previous studies on peak avoidance using naturalistic data have not focused on this aspect. By predicting the latent classes of travelers, the results of this study not only demonstrates the influence of the heterogeneity of the traveler behavior, but also quantifies the source of the heterogeneity.

From the results, it can be seen that the travelers of class 1 and class 2 are relatively more sensitive to money and less sensitive to time, and they are most likely to accept the discounted fares to change their departure times. Their travel characteristics are consistent with the most common office workers: the departure time is regular, and the travel destination has a very small standard deviation. Although the smart data lacks demographic variables, we can infer some latent information indirectly. The subway station used in the analyses is located near the 6th ring road[3] in Beijing and far from the city center. Previous studies have shown that the income of common office workers living in this location is relatively lower than those living near the city center who have a more suitable job-housing balance (Huang et al., 2018). Meanwhile, travelers with lower incomes tend to have lower value of time (Börjesson et al., 2012). Therefore, they are more sensitive to incentives of monetary saving, and less sensitive to the required change in departure time (Peer & Verhoef, 2016). This is consistent with the result of road peak-avoidance (Ben-Elia & Ettema, 2011b).

The travelers of class 3 also meet the characteristics of office workers but is different from the first and second types of travelers. The salient characteristic of the third group is a short commute (lowest fares), but with a long duration of travel, indicating multiple transfers during the subway commute congested travel routes that lead to time spent getting through crowds (Wu & Huang, 2009). As their journey is the most complicated and uncertain, their departure time is the most fixed, and they are the most sensitive to the required change in departure time among the four types of travelers

[3] Beijing's network of arterials is in hub-and-spoke structure, including six main ring roads that are fed by nine more freeways. The larger the number of ring road, the farther away from the city center.

(Ettema & Timmermans, 2006). It is difficult for such travelers to change their behavior under existing policies, as shown in Figure 5.

The class 4 is relatively flexible in terms of travel and is the smallest group out of the four. Their departure times are the least stable and they have the most varied travel destinations. Interestingly, in previous research, high peak avoidance willingness is always associated with high time flexibility (Zhang et al., 2014; Peer & Verhoef, 2016). However, in this case, it is difficult to persuade the fourth group to choose to change their behavior, as shown in section 5.4. It may be noted that such constraints regarding time flexibility are often not well captured in SP surveys, denoting the high risk of biased estimates on SP-based peak-avoidance analyses. On the other hand, considering the high flexibility, there may be a high representation of travelers with relatively high incomes and flexible jobs in this group. This would help explain why they are the most insensitive to little monetary savings and are more sensitive to time. Moreover, a higher travel frequency is negatively correlated with a switch in departure time in response to the policy. Such travelers are less willing to change their previous habits.

The results and discussion above indicate that the subway authority could improve the current simple fare discount policy. Bamford (1987) points out that transport policies that target specific travelers are likely to be more effective than generic strategies. Based on travelers' heterogeneous taste, giving each individual a specific targeted incentive may be the most effective in theory, but infeasible in practice. Instead, the targeted method can be approached through the use of more homogeneous groups to increase the efficiency and effectiveness of the treatment. The policy suggestions listed below can account for different traveler characteristics by targeting certain groups to ease the inconvenience of a change in behavior.

The travelers of class 1 and class 2 have the highest proportion and are the main target population of the policy. For them, monetary incentives are attractive. However, the actual discount amount is not considered sufficient because of how low the fares are to begin with. In our case, the first and second types of travelers need a discount of approximately 5 yuan to change their behavior. One option would be to increase existing discounts. Referring to the "Travel early travel free" in Singapore, the discount scheme can even change to free fare for peak avoidance. The advantage of the free fare policy is that short-term large-scale incentives may have a persistent effect after the policy is cancelled (Yang & Lim, 2018; Peer & Verhoef, 2016). The disadvantage is that such incentives increase the financial burden for the subway operators. Moreover, travelers whose original departure time is before 7:00 a.m. can enjoy the discount without any behavior change. This leads to inefficiencies in the cost-benefits analysis. Another solution would be the application of other forms of monetary incentives. For example, in other scenarios, a lottery with the same expected value is more effective than a fixed amount of money reward (Halpern et al., 2011). Setting up a lottery with a large monetary prize with low probability of winning, could be a more attractive incentive to price sensitive travelers. In addition, incentives should be structured to reward behavior change rather than pre-existing behavior, such as by establishing a behavior baseline (e.g., travel in peak hours) and rewarding change from that baseline (e.g., shift from peak hours to off-peak hours). This would allow policymakers to increase the rewards for those targeted, using the same financial budget.

For the travelers of class 3, the greatest resistance to behavior change may arise from uncertainty. Sending customized travel information would therefore be an option regarding this group. The negative effects of travel time uncertainty can be reduced by providing travelers with travel time information, allowing them to better estimate their expected travel time and thereby reduce re-scheduling costs (Ettema & Timmermans, 2006). For those who have many transfers and relatively long transit times, the subway operator can provide targeted trip reports based on their historical trip data, informing travelers of their current travel conditions and possible changes after peak avoidance, which would help the travelers to achieve a better trade-off. Meanwhile, based on big data analysis and increasingly popular travel apps, targeted information intervention becomes possible at a low cost.

The class 4 is not sensitive to monetary incentives. Current forms of incentives are therefore insufficient to persuade them to change behavior, as shown in Figure 5 and Figure 6. One consideration is that policymakers can ignore these travelers because of the low proportion. However, as these travelers have the greatest time flexibility, they are actually the travelers who have the ability to re-schedule their departure times. The next step is to find the right form of intervention to motivate them. Beyond monetary incentives, other forms of interventions, such as social norms and information, are all worth exploring the policy potential.

It may be noted that in addition to the factors considered, in future research, it is important to further consider the temporal and spatial heterogeneity and develop differentiated strategies. In particular, as the longer required change in departure time prevents travelers from switching, the optimum departure windows can be different depending on the travel times (including transfer times) from a station to the city center to help reduce the required change in departure time. In addition, since the results indicate, the composition of demand (i.e. the proportion of the four traveler classes) is important for the effectiveness of the fare-discount policy, based on the proportion of the four classes of travelers, targeted measures can be designed for different stations. For instance, discount policies may have potential high effect in stations located far away from city center which serve large number of travelers of class 2. Thus, policy makers can design the discount policy based on these departure stations. In contrast, for travelers in stations close to the city center, such discounted fares may not be as effective. Then, the policy makers should consider taking other measures instead.

7 Conclusion and further research

This paper has explored travelers' heterogeneous behavioral responses to the Beijing peak avoidance policy using smart card data. Considering the heterogeneity of travelers, a latent class choice model is applied to segment travelers into four groups, and the elasticities of different traveler types are also obtained. From a policy perspective. According to the above analysis results, different travelers indeed respond to the discount policy and change their behaviors to a certain degree. Based on the behavioral implications mined from the results, different targeted policy recommendations for each group of travelers are proposed in order to achieve better impacts.

The results of the paper are applicable to Beijing - which is regarded as a microcosm of the other big cities in China and the rest of the world. Further, the innovative application of the LCC framework to analyze travelers' heterogeneous behavior using large-scale smart card data (without socio-demographic information) can be useful in analyzing peak-avoidance behavior in other mega-cities struggling with excessive crowding during the peak.

No research is without limitations. Limited by smart card data, this study cannot account for demographic variables in the model. In the analysis process, these variables are controlled only by selecting data from a single site, which may make the conclusion less solid to some extent. In future studies, more diverse case areas and data are needed. SP survey data and built environment data around the stations should be considered together with the smart card data to investigate the behavior in a wider window. Meanwhile, limited by the acceptability of the dataset, this study only considers the short-term effect of the policy. Finally, in practice, whether the differentiated targeted policies can achieve better results and lead to better welfare (as expected) requires future research – potentially a field experiment to validate the findings.

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Declarations of interest

The authors declared that they have no conflicts of interest to this work.

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