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

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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).

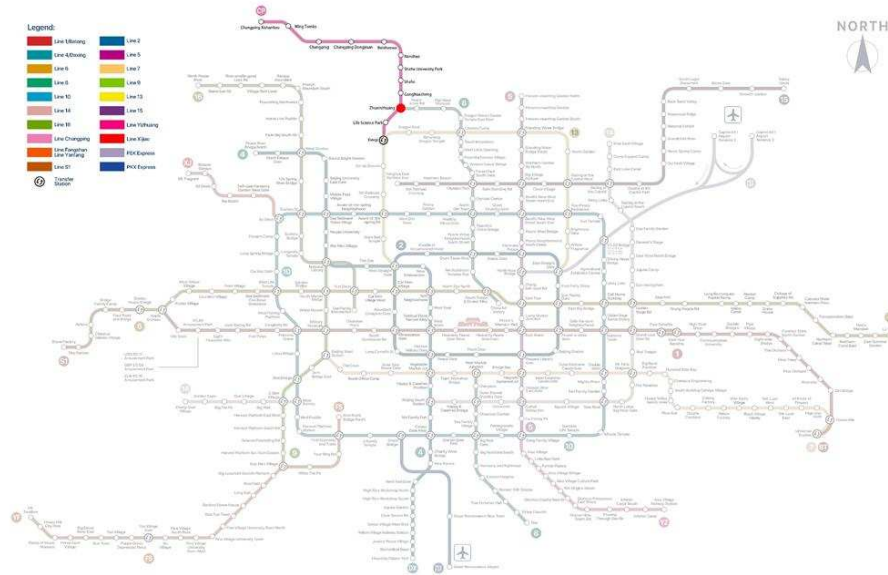
However, smart card data are usually anonymous and do not include socioeconomic attributes (e.g., gender, age, career, income, etc.) or detailed travel information (e.g., trip purposes, access and egress modes, etc.) (Bagchi et al., 2005; Anda et al., 2017; Jain et al., 2014). To overcome these limitations, 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.

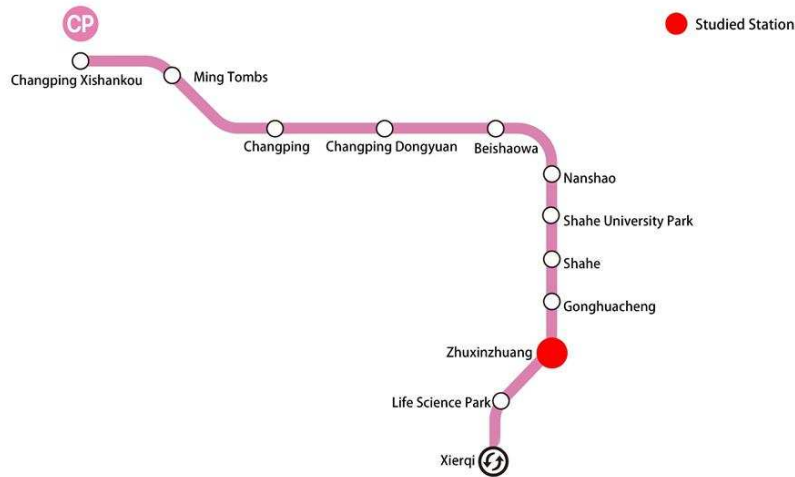
3 Data

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.



(a) Changping Line



(b) Zhuxin Zhuang station

Figure 1. Studied station of this paper-Zhuxin Zhuang station¹

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 (1000751085xxxxxx) 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:

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

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.

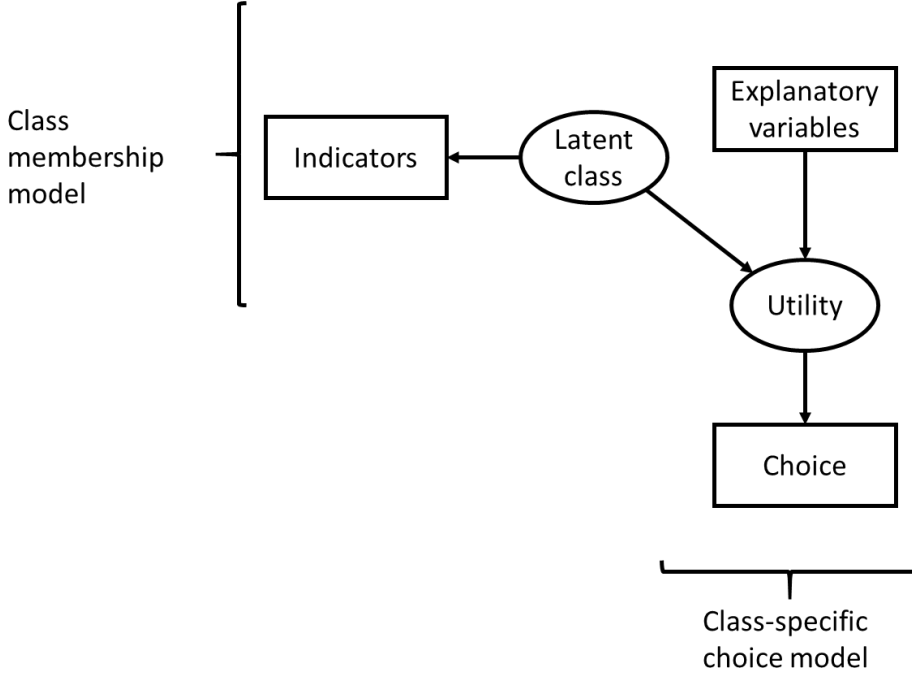


Figure 2. Latent class choice model

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:

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

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:

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

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:

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

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 component².

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 $|z| \geq 2.58$, ** indicates $1.96 \leq |z| < 2.58$, and * indicates $1.64 \leq |z| < 1.96$

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%,

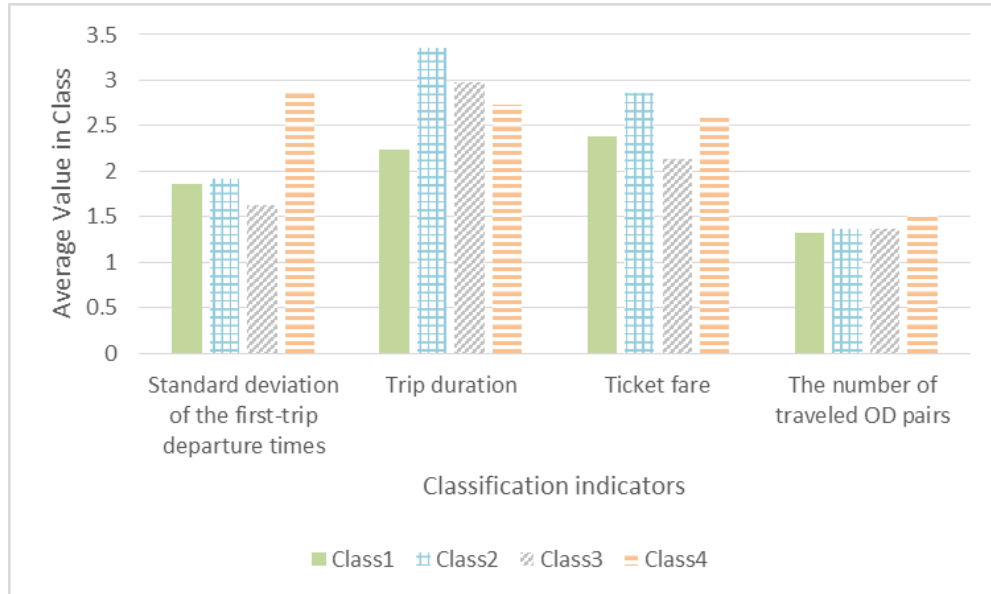
32.5%, 23.3%, and 10.3%, respectively. Coefficients vary significantly between different categories, and each class consists of travelers with different travel characteristics. The detailed results of the 4-class model are shown in Table 5, which helps us to explore the different behavioral responses 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 $|z| \geq 2.58$, ** indicates $1.96 \leq |z| < 2.58$, and * indicates $1.64 \leq |z| < 1.96$

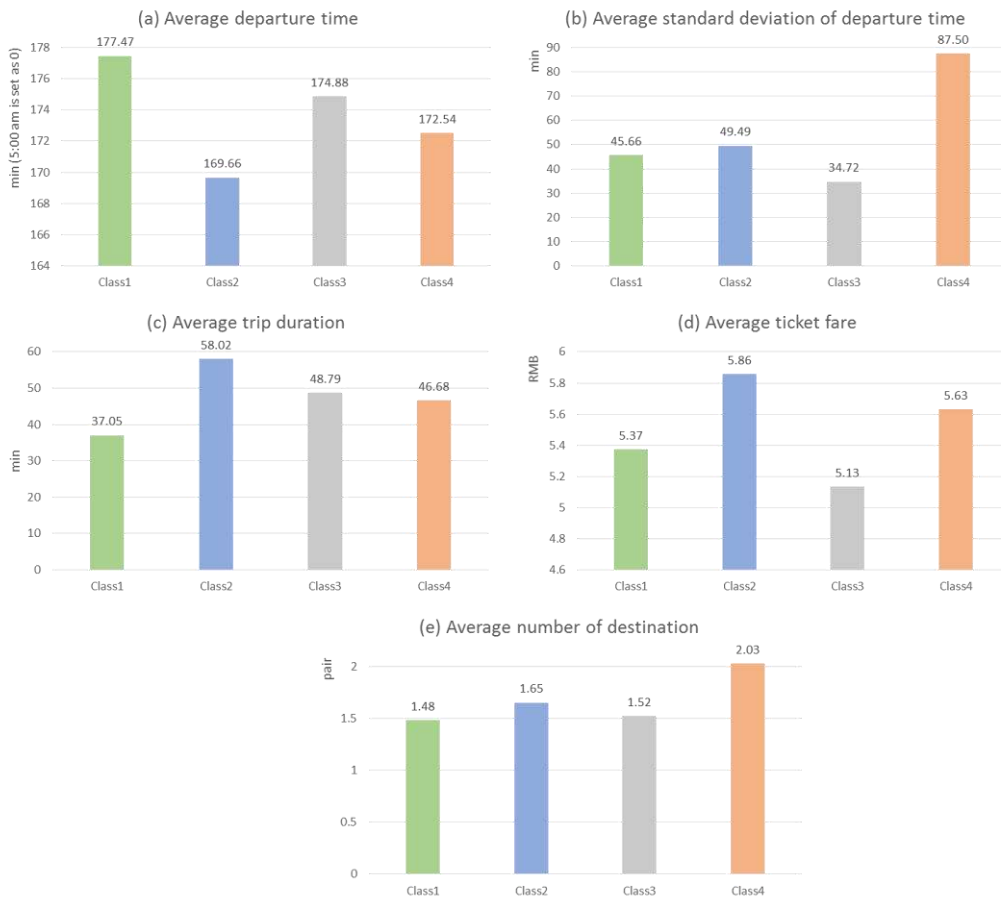
311 Figure 3 and Figure 4 show the descriptive statistics of the classification indicators
 312 and travel characteristics of the four different classes, respectively, to further highlight
 313 the differences between the classes.



314

315

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



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317

318

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

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

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

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

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

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

338 5.3.2 Class-specific choice model

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

343 **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

344 Note: *** indicates $|z| \geq 2.58$, ** indicates $1.96 \leq |z| < 2.58$, and * indicates $1.64 \leq |z| < 1.96$
345 Among the variables, monetary saving and the required change in departure time
346 have the greatest influence on class 1 and class 3, respectively, while class 4 is the most
347 sensitive to travel frequency and least sensitive to monetary saving.

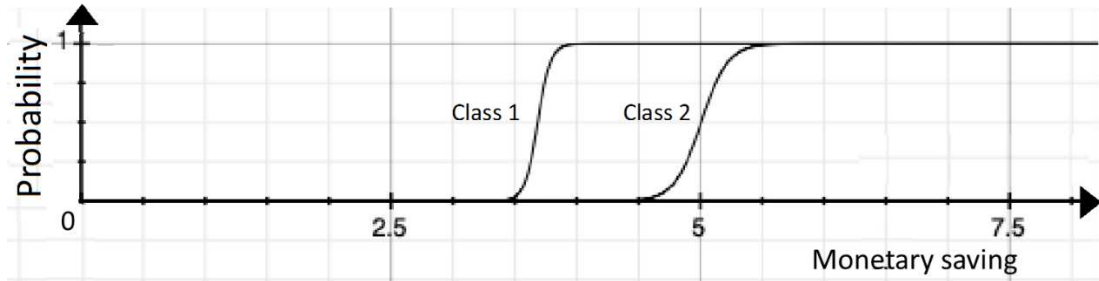
348 5.4 Inference of the results: plotting the changes in choice probabilities

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

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

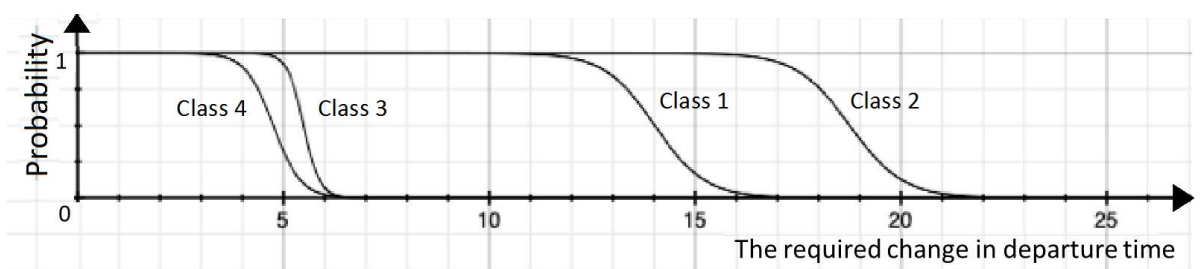
366 However, the discount policy does affect travelers from class 1 and class 2, which
367 covers more than half of the total respondents. It may be noted, however, that the
368 intuitive notion of 'more monetary saving, higher peak avoidance probability', is not
369 entirely valid. The probability only changes in a specific price range. For class 1, this
370 range is from 3.5 yuan to 4 yuan. When the amount of monetary saving does not reach
371 3.5 yuan, their travel time will not change even though the amount of monetary saving
372 increases. Meanwhile, their probability of avoiding rush hour is equal to 1 for 4 yuan

373 and hence discounts beyond 4 yuan will not result in any further shift. Similarly, the
 374 sensitive price range for class 2 is from 4.5 yuan to 5.5 yuan. This finding has important
 375 policy implications.



376
 377 **Figure 5. Individual effect of monetary saving**

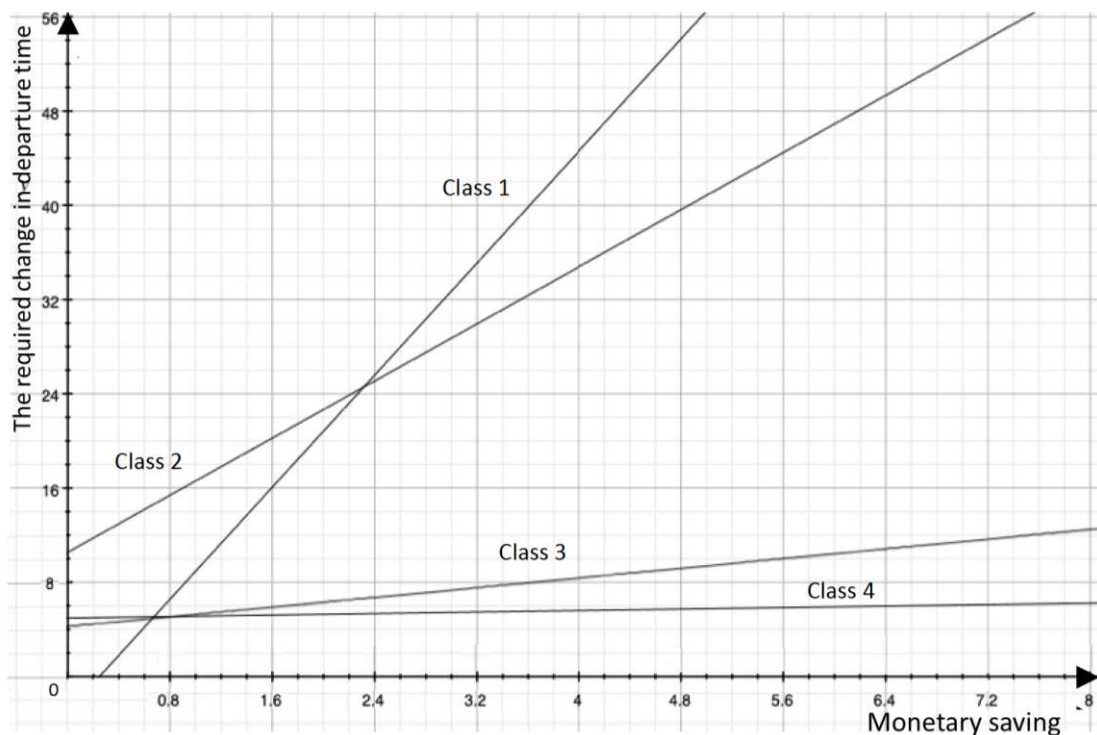
378 Figure 6 shows the peak avoidance probability for each class as a function of the
 379 required change in departure time. Similar to the effect of monetary saving, the peak
 380 avoidance probability of each class only changes within a specific range. In general,
 381 travelers from class 4 and class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



388
 389 **Figure 6. Individual effect of the required change in departure time**

390 In addition, in order to provide a visual representation of the correlation between
 391 monetary saving and required change in departure time, we plotted the equal probability
 392 curves for each class. Figure 7 shows the equal probability curves for the peak
 393 avoidance probability of 20%. This result is in line with the information of Figure 5 and
 394 Figure 6. The marginal rate of substitution of monetary savings for the required change

395 in departure time is quite low for class 3 and class 4. This illustrates that travelers of
396 these classes are not are not easily influenced by ticket discounts. A policy that requires
397 a smaller change in departure time can have a larger effect. For class 1 and class 2, the
398 MRS value is much higher. For class 1, the effect of no required change in departure
399 time equals 0.2 yuan of monetary saving. With an increase in the required change in
400 departure time, the two variables as considered almost equally important. For class 2,
401 the required change in departure weighs more in the decision to avoid peak hours.



402

403

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

404 **6 Discussion and implications**

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

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

417 From the results, it can be seen that the travelers of class 1 and class 2 are relatively
418 more sensitive to money and less sensitive to time, and they are most likely to accept
419 the discounted fares to change their departure times. Their travel characteristics are
420 consistent with the most common office workers: the departure time is regular, and the
421 travel destination has a very small standard deviation. Although the smart data lacks
422 demographic variables, we can infer some latent information indirectly. The subway
423 station used in the analyses is located near the 6th ring road³ in Beijing and far from the
424 city center. Previous studies have shown that the income of common office workers
425 living in this location is relatively lower than those living near the city center who have
426 a more suitable job-housing balance (Huang et al., 2018). Meanwhile, travelers with
427 lower incomes tend to have lower value of time (Börjesson et al., 2012). Therefore, they
428 are more sensitive to incentives of monetary saving, and less sensitive to the required
429 change in departure time (Peer & Verhoef, 2016). This is consistent with the result of
430 road peak-avoidance (Ben-Elia & Ettema, 2011b).

431 The travelers of class 3 also meet the characteristics of office workers but is
432 different from the first and second types of travelers. The salient characteristic of the
433 third group is a short commute (lowest fares), but with a long duration of travel,
434 indicating multiple transfers during the subway commute congested travel routes that
435 lead to time spent getting through crowds (Wu & Huang, 2009). As their journey is the
436 most complicated and uncertain, their departure time is the most fixed, and they are the
437 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.

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

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

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

462 The travelers of class 1 and class 2 have the highest proportion and are the main
463 target population of the policy. For them, monetary incentives are attractive. However,
464 the actual discount amount is not considered sufficient because of how low the fares are
465 to begin with. In our case, the first and second types of travelers need a discount of
466 approximately 5 yuan to change their behavior. One option would be to increase
467 existing discounts. Referring to the "Travel early travel free" in Singapore, the discount

468 scheme can even change to free fare for peak avoidance. The advantage of the free fare
469 policy is that short-term large-scale incentives may have a persistent effect after the
470 policy is cancelled (Yang & Lim, 2018; Peer & Verhoef, 2016). The disadvantage is
471 that such incentives increase the financial burden for the subway operators. Moreover,
472 travelers whose original departure time is before 7:00 a.m. can enjoy the discount
473 without any behavior change. This leads to inefficiencies in the cost-benefits analysis.
474 Another solution would be the application of other forms of monetary incentives. For
475 example, in other scenarios, a lottery with the same expected value is more effective
476 than a fixed amount of money reward (Halpern et al., 2011). Setting up a lottery with a
477 large monetary prize with low probability of winning, could be a more attractive
478 incentive to price sensitive travelers. In addition, incentives should be structured to
479 reward behavior change rather than pre-existing behavior, such as by establishing a
480 behavior baseline (e.g., travel in peak hours) and rewarding change from that baseline
481 (e.g., shift from peak hours to off-peak hours). This would allow policymakers to
482 increase the rewards for those targeted, using the same financial budget.

483 For the travelers of class 3, the greatest resistance to behavior change may arise
484 from uncertainty. Sending customized travel information would therefore be an option
485 regarding this group. The negative effects of travel time uncertainty can be reduced by
486 providing travelers with travel time information, allowing them to better estimate their
487 expected travel time and thereby reduce re-scheduling costs (Ettema & Timmermans,
488 2006). For those who have many transfers and relatively long transit times, the subway
489 operator can provide targeted trip reports based on their historical trip data, informing
490 travelers of their current travel conditions and possible changes after peak avoidance,
491 which would help the travelers to achieve a better trade-off. Meanwhile, based on big
492 data analysis and increasingly popular travel apps, targeted information intervention
493 becomes possible at a low cost.

494 The class 4 is not sensitive to monetary incentives. Current forms of incentives are
495 therefore insufficient to persuade them to change behavior, as shown in Figure 5 and
496 Figure 6. One consideration is that policymakers can ignore these travelers because of
497 the low proportion. However, as these travelers have the greatest time flexibility, they

498 are actually the travelers who have the ability to re-schedule their departure times. The
499 next step is to find the right form of intervention to motivate them. Beyond monetary
500 incentives, other forms of interventions, such as social norms and information, are all
501 worth exploring the policy potential.

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

516 **7 Conclusion and further research**

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

525 impacts.

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

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

542

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551 **Declarations of interest**

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

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