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Understanding peak avoidance commuting by subway: an empirical study in Beijing

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ABSTRACT

Congestion is a major problem for peak-hour commuters in the Beijing subway system, as it leads to long queuing times and overcrowded vehicles. This paper explores to what extent peak travel can be reduced by providing incentives for peak avoidance. In a stated preference study, travellers' responses to two financial and two non-financial incentives were measured, and factors increasing or limiting the response were identified. Our results suggest that all four incentives can be reasonably effective tools and the financial incentives seem to have a slightly stronger effect than the services and credit-for-gifts-based scenarios. Ordered logit models indicate that various factors influence people's receptiveness of incentives for peak avoidance which relate to the ease of change or presence of alternatives and receptiveness to incentives. Both theoretical and policy implications are concluded that the proposed factors and incentive system can help solving the subway congestion in Beijing.

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Subway peak-hour avoidance; ordered logit model; Beijing; incentives

1. Introduction

Daily transportation is a key factor for the functioning of cities, as it allows citizens to reach relevant destinations and thereby facilitates participation in necessary and pleasant activities. In megacities in the Global South, however, transportation systems are under pressure, due to the size and density of these cities, as a result of which demand exceeds the combined capacity of road networks and public transport facilities (Gao and Kenworthy 2017; Laseinde and Mpofu 2017; Pojani and Stead 2017). Case in point is the Chinese capital Beijing, with a population of 22 million, which has witnessed tremendous growth in the past decades. While population growth in itself leads to a higher demand for travel, this is exacerbated by the fact that commute distances increase, due to an increasingly specialised job market and an increased distance between jobs and houses as a result of local spatial planning decisions (Zhao, Lü, and de Roo 2010; Chai, Yan, and Liu 2011).

The increased demand for commute travel results in strongly increasing congestion, not only in road traffic, but also in the Beijing subway system. Demand for subway travel in Beijing is high, not only as competing travel modes, such as car, suffer from high congestion levels, but also due to the low price. The price of using the subway has been set a very low flat rate of 2 Yuan per trip between October 2007 and September 2014. Since then, a distance-based fare, ranging between 3 and 6 Yuan is used, which is still very affordable compared to other travel modes. Occupancy rates of the Beijing subway are as high as 135% (Zhang, Fujii, and Managi 2014). The high demand for subway travel leads not only to crowded trains, but also to queues in stations that may lead to waiting times up to 40 minutes (20 minutes to get into the station and another 20 minutes for boarding), and 76

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stations are forced to regularly restricting passenger flows using division guiderails during commuting peaks. Under these circumstances, Beijing has started a pilot pricing strategy including a 30% ticket fare reduction on 16 stations of the Batong and Changping Lines for travellers departing before 7:00 a.m. from December 2015 and a 50% reduction from December, 2016. However, this strategy has proven to be inefficient to persuade subway commuters to avoid the peak. Hence, it is highly important to develop policies to diminish congestion in the Beijing subway system, to decrease waiting times, increase comfort and seat availability and maintain accessibility. In particular, fewer subway trips should be made during the peak period, either by choosing alternative travel modes, or by making subway trips in the off-peak periods.

A policy that has received attention over the last decade is the use of incentives to persuade travellers to avoid the peak (Zhu, Yue, and Mandayam 2015), implying that travellers receive monetary or other incentives if they do not travel in the peak period. However, existing studies on peak avoidance behaviour are predominantly focused on road commuting (see the literature part for more details). We argue that subway commuting is different from road commuting in terms of both the cost structure and flexibility. Those differences may lead to different responses to an incentive system of subway peak avoidance. As far as we know, Zhang, Fujii, and Managi (2014) is the only study which discussed the effect of incentives system to stimulate peak avoidance in the context of subway congestion, but including only a limited set of incentives.

This paper extends the insight into the effect of different incentives on peak-hour avoidance in Beijing metro, by analysing a wider and more comprehensive set of influential factors. Using a stated preference approach, the effects of different incentive systems, including monetary incentives and non-monetary incentives such as extra services and earning credits which can be converted into gifts, are studied. In addition, the effect of personal and commute trip characteristics on metro commuters' response to each type of reward are studied, which has not been systematically studied before.

This paper is organised as follows. Section 2 is devoted to literature review, while Section 3 discusses the survey design, data collection and participants. Section 4 analyses the results, including description of responses and ordered logit (OL) models to investigate the factors influencing peak avoidance. Section 5 provides a further discussion of the estimation results and Section 6 is devoted to the theoretical implications of the findings. Policy implications are also discussed in Section 7 and finally the conclusion is drawn in Section 8.

2. Literature review

2.1. Commuters' travel behaviour

Given that commuting involves repeated trips to a given destination, commuters' travel decisions concerns mode choice and trip timing choice. With respect to trip timing choice, Abkowitz (1981) found that personal characteristics (age, income and profession), work flexibility, commuting mode, traffic service level, work-starting time and uncertain effects of different arrival time all have influences on commuting decisions to different extent. Small (1982) describes departure time choice of the commute trip as a trade-off between travel time and so-called schedule delay. Schedule delay implies arriving too early or too late at the work place, relative to work start time, or an individual preferred arrival time. Small found late arrival to be more negative than early arrival, but the extent of disutility depends on factors such as household type, job type and travel mode. Hamed and Olaywah (2000) found that work-time flexibility played a decisive role in commuters' departure time, and that those with flexible work times were more likely to travel outside the peak and had greater tolerance for schedule delays.

From the perspective of departure and arrival times rather than work-starting time, Saleh and Farrell (2005) measured work-time flexibility while taking into consideration the influence of factors such as family obligations or activities on the flexibility of departure time. They found that the availability to an individual of alternative departure times/arrival times depends on the individual's level of flexibility, which could be influenced by various factors include socio-economic, work schedule or activities/commitments regularly carried out by an individual (family status), etc.

With respect to mode choice, Lai and Chen (2011) explored factors that motivate private car users to turn to public transportation based on a technology acceptance model, theory of planned behaviour and habits, finding that the three variables of planned behaviour theory and habits would affect residents' commuting mode change. Abou-Zeid and Ben-Akiva (2012) investigated the influential factors that enabled commuters to shift their commuting mode, including demographic features, commuting features, traffic policies, experimental condition, psychological factors and social influence. They found that commuters who shifted from private cars to public transport were usually more sensitive to costs and had better attitude towards and cognition of public transport, but those who persisted in original commuting mode had a strong positive attitude toward the car.

It can be concluded from the literature review that a variety of factors including personality traits, household composition, work flexibility, attitudes and social norms will influence commuters' departure time and mode choice. However, peak avoidance behaviour is more complicated than weighing among different travel modes. Instead, it requires trading off between the switching cost of behavioural change and the benefits of peak avoidance.

2.2. Peak avoidance

Literature regarding peak avoidance in commuting is summarised in Table 1. One approach that has been considered worldwide to relieve congestion is to stimulate peak avoidance behaviour. Given that ridership is concentrated in the morning and evening rush hour, spreading the demand more evenly over time would reduce congestion (Zhu, Yue, and Mandayam 2015). To this end, those who have the opportunity should be persuaded to travel before or after the peak or use alternative modes. Providing rewards for peak avoidance has been tested to achieve peak avoidance. One motivation for providing rewards is that in contrast to pricing mechanisms that make travelling in the peak more expensive, a positive stimulus, and various scholars report the effectiveness of rewards in establishing behaviour change in general (Kreps 1997; Berridge 2001).

In addition, it avoids problems associated with pricing policies, such as social equity (Giuliano 1994). According to the pricing mechanism, the person commuting through peak hours have to pay higher fares. If the benefits are distributed inappropriately across the social groups, this will

Table 1. Literature regarding peak avoidance commuting.

Article	Research objectives	Incentives	District	Transport mode
Ben-Elia and Ettema (2011a, 2011b)	Commuters' behaviour using rewards instead of road pricing	- Rewards - Credits for a smart phone	Hague, the Netherlands	Car
Zhang, Fujii, and Managi (2014)	Impact of incentives on commuters' travel behaviour	- Fare (before and after) - Time and congestion - Fast food and free Wi-Fi	Beijing, China	Subway
Leblanc and Walker (2013)	Impacts of different incentives on travellers' commuting choice	- Cash, lottery, donation, credit to Apple store, HOV pass, parking	Bay area, U.S.A.	Car
Bhat and Sardesai (2006)	Impact of stop-making and travel time reliability on commute mode choice	- Fare - Travel time variation - Child care	Austin, U.S.A.	Multi-mode
Douglas and Karpouzis (2006)	Willingness to pay to reduce rail overcrowding	- Seats	Australia	Train

Note: HOV, high-occupancy vehicle lane.

cause further issue about fairness and public acceptability (Eriksson, Garvill, and Nordlund 2006) People may consider it as unfair to charge those who have fixed work schedule and have to departure during peak hours with higher travel fare, thus less likely to accept the pricing policy. Actually, public acceptance is widely recognised as a major barrier to widespread adoption of related policies. With respect to economic efficiency, pricing policy needs to consider the effectiveness in reallocating passenger traffic volumes to maximise social welfare (Viegas 2001; Min, Ahn, and Lambert 2015).

In the context of car congestion in the morning peak in the Netherlands, Ben-Elia and Ettema (2011a, 2011b) report based on an experiment with 340 participants that providing a reward of 3 EURO per avoidance led to a reduction of peak travel among participants of 47%, and that increasing the reward to 7 EURO had limited additional effect. An alternative reward, where participants received credits to acquire a smart phone had a similar impact. Leblanc and Walker (2013) tested the effect of incentives such as cash money, lottery tickets, donations to charity, credit to Apple store, high-occupancy vehicle lane pass and free parking on commute decisions and found that travellers are much more sensitive to charges than to rewards. Bhat and Sardesai (2006) tested the effect of offering child care services near commuter rail stations but did not find this to have a significant effect. Douglas and Karpouzis (2006) found that seat availability is also an important incentives for passengers choose to avoid peaks.

In the context of Beijing subway congestion, Zhang, Fujii, and Managi (2014) describe a stated preference study to investigate the effects of various rewards, which include free drinks, coupons for breakfast and free Wi-Fi. These rewards are offered in combination with price decrease and hypothetical waiting time reductions. The authors reported that about 60% of the participants would avoid the peak by travelling earlier in response to the proposed incentives. In addition, they find that commuters' response is influenced by their work-time flexibility. However, the factors considered in this studied are limited to personal characteristics and the reward system. However, other possible factors such as attitude, preferences, accessibilities, alternative traffic modes, space flexibility, previous experience and technology factors of information availability may also influence peak avoidance behaviour. Hence, studying a wider set of factors influencing the response to rewards in peak avoidance is warranted.

3. Survey design, data collection and participants

3.1. Survey design

Data was collected by a survey among current users of the Beijing subway. The survey included questions regarding the commuter's personal and household situation, such as age, gender, education level, occupation, household composition, income, car ownership. In addition, questions were asked regarding commuters' commute behaviour, such as departure time, preferred departure and arrival time, travel time and waiting time, commuting distance, accessibility of workplace and subway stations, subway commuting frequency, work flexibility and household responsibility, access to and use of travel information, awareness of price levels, experience with peak avoidance and availability of alternative travel modes. Finally, the survey introduced four hypothetical incentives to be earned when avoiding the use of the subway during peak hours.

- Price mark-up of 50% in the peak hour, setting penalties for rush-hour commuting.
- Price reduction of 50% in non-peak hour, giving rewards to low peak commuting.
- Extra services during the non-peak: the extra service includes services of free Wi-Fi, coupons for food and beverage, free transfer tickets for bus.
- Credits: the credits for gifts encourage commuters to participate in rush-hour avoidance and accumulate credits in exchange for cell phone.

Respondents were asked to indicate how likely they were to avoid the peak under each incentive or pricing measure on a 5-point scale ranging from 'highly unlikely' to 'highly likely'. The range of peak hours are defined based on the accumulated survey data.

3.2. Data collection

The target population for this study is frequent Beijing subway commuters. Since this population shows the typical behaviour characteristics of Beijing subway users during peak hours, we focused our research on these frequent commuters with previous screening questions to filter out occasionally travellers and tourists. Therefore, only respondents who reported currently living and working in Beijing with full-time or part-time internship or job and also with daily experience of commuting by subway in Beijing were invited to fill in the questionnaire.

Commuting population is targeted as the primary study population since commuting population is the major reason for the existence of peak hours. Modern societies are organised to permit most people to work at the same time, or go to school at the same time, for efficiency purposes (Downs 2005). Furthermore, in the context of Beijing subway, due to the severe road traffic congestion, commuters have to travel by subway instead of other commuting modes, which further deteriorate the congestion of subway. Therefore, the commuting population constitutes the most concentrated part of peak-hour travellers. Secondly, although other groups may also travel during the peak hours, they are either less sensitive to the rewarding policy or have other objectives, thus may automatically change their behaviour considering the terrible travel experience. For example, tourists' travel demand is also important, however, the discount or other policy information is not always available to them. Therefore, currently we will focus on the behaviour analysis of the relatively rigid demand of commuters.

Both face-to-face and web-based methods were used to solicit respondents for this research. The web-based survey was deployed through the biggest professional survey website in China (http://www.Sojump.com/). A total of 764 Beijing residents were solicited via e-mail, Wechat or phone, each of who registered as Sojump.com panel participants. Among the 764 participants, 631 questionnaires are complete and usable.

Regarding the off-line survey, face-to-face interviews were used to solicit respondents at shopping malls in subway terminals, subway stations and so on, where subway commuters often appear. We put more focus on the main district area where peak-hour subway congestion is most severe, and randomly picked up four stations from the busiest subway stations of Beijing metropolitan area, which are Huilongguan, Xizhimen, Dongzhimen and Shangdi station. Among 259 participants, 189 questionnaires are usable. In total, 1103 potential participants were pre-screened and solicited, of which 1023 individuals participated to complete the survey. From the 1023 participants, 820 surveys were complete and usable.

3.3. Sample description and analysis

Participant descriptive statistics can be found in Table 2. As can be verified from these statistics the sample shows a well-educated population of relatively low-income earnings, most of which are young and single. These descriptive are typical for the commuting population of Beijing. Since a minority has children, there is for most no need to consider the problem of picking up children for most of the participants, thus subway commuting is more appealing to them compared with congested road traffic of vehicles.

3.3.1. Travel behaviour aspects

More than 60% of the participants travel from home to work place at least four times a week. The main purpose of the travel during the morning peak is work related. 14.76% of the participants also own more than one car. Travel times and time use aspects are also indicated in Table 3 and Figure 1.

Table 3 indicates that the median of departure time from home is 7:00–7:30 with more than 60% of participants' departure from home between 7:00 and 8:00. Two hundred and ninety-seven respondents (36.22%) stated they occasionally used other transport modes for the commuter trip. Of those, 21.71% uses bus, 53.64% uses private car, taxi or car-hailing services and 24.65% respondents choose bikes or walking.

Table 2. Basic information of sample.

Basic Information	Types	Options	Frequency	Proportion (%)
Individual information	Gender	Male	348	42.44
		Female	472	57.56
	Age	Under 20 years old	61	7.44
		20–30 years old	511	62.32
		30–40 years old	181	22.07
		40–50 years old	51	6.22
		Above 50 years old	16	1.95
	Education status	High school	26	3.17
		Associate degree	35	4.27
		Bachelor degree	468	57.07
		Master degree	265	32.32
		Doctor degree or above ababove above above	26	3.17
	Income	Students without internship income income inincome ilninternship income) internship income)	156	19.02
		Students with internship income incomincome)	186	22.68
		less than ¥30,000	46	5.61
		¥30,000–80,000	119	14.51
		¥80,000–120,000	121	14.76
		¥120,000–200,000	92	11.22
		¥200,000–30,000	54	6.59
		More than ¥300,000	46	5.61
Household information	Household composition	Married with kids	186	22.68
		Married without kids	86	10.49
		Unmarried	507	61.83
		Single with kids	10	1.22
		Others	31	3.78

Commuting distance and convenience are stated as follows:

- 65.24% of the respondents need to transfer at least once and 21.22% need to transfer more than twice during the commuting trips;
- only 5.61% of the respondents travel less than 2 km for one-way commuting, hence, the respondents have to travel a long distance every day, with mostly including at least one transfer, leading to complicated commuting experience.

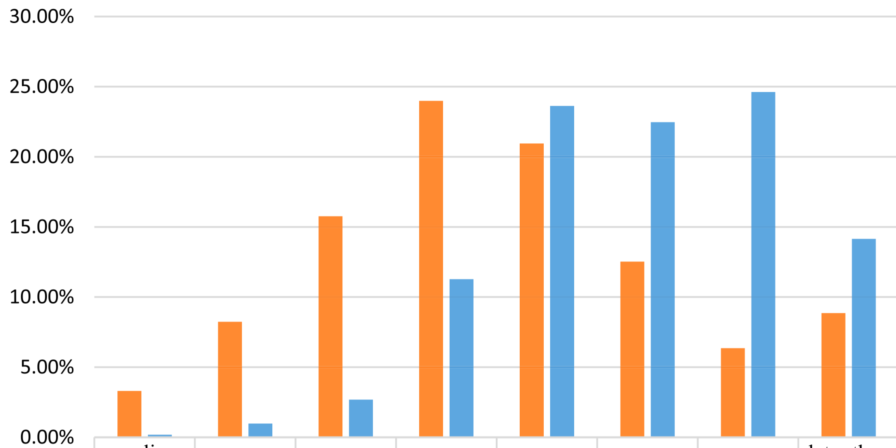
3.3.2. Work schedule flexibility and constraints to behaviour change

Only 7.2% of the respondents stated their employers permitted them to work at home. Others clearly stated they cannot work except their workplace, thus tele-working is currently not an available option to most of the people. 84.9% stated they cannot start their work later under any circumstances, this implies that delaying start of work is also not a realistic option, only 15.1% stated they have flexible working time schedule.

41.2% of the participants are students, who commonly use subway to school, 21.0% of the participants worked in the services industry, while 0.9% worked in agriculture; 7.1% worked in

Table 3. Tavel and commuting expericen statistics.

Attribute	Median	Mean	Standard deviation
Travel time	8:30	8:35	1.21 (mins)
Departure time	7:00–7:30	–	–
Average travel time on subway	–	39.98 (mins)	24.37 (mins)
Average time spend waiting on the platform	–	6.21 (mins)	5.72 (mins)
Average delay in entering the subway station due to congestion	–	11.97 (mins)	8 (mins)
Average ticket price for one-way commuting	–	4.97 (Yuan)	2.56 (Yuan)
Average time spend from home to subway station	–	14.43 (mins)	9.24 (mins)
Average time spend from workplace to subway station	–	12.14 (mins)	8.85 (mins)



	earlier than 6:00	6:00-6:30	6:30-7:00	7:00-7:30	7:30-8:00	8:00-8:30	8:30-9:00	later than 9:00
departure time	3.31%	8.24%	15.76%	23.99%	20.95%	12.53%	6.36%	8.86%
arrival time	0.18%	0.98%	2.69%	11.28%	23.63%	22.47%	24.62%	14.15%

Figure 1. Distributions for arrival and departure time.

manufacturing industry; 3.6% worked in commerce; 14.4% worked in public official; and 11.0% worked in other sectors.

Six per cent mentioned they have to drop-off their kids at school or kindergarten. Other factors may also influence their daily behaviour of subway commuting, 15.4% of the respondents have more than one place to live, thus alternative commuting choices are possible for them. Weather conditions may also alter their commuting choices. 65.6% stated they prefer to commute using subway over other travel modes in bad weather such as rain, snow and smog. Considering heavily congested road traffic in Beijing during morning and evening peak, 63.8% respondents stated subway as their first choice to commute while only 38.5% respondents selected private car as their first choice to commute. This is reasonable, as growing traffic congestion makes the car less convenient, flexible and reliable. In order to be punctual for work, subway is then the more reliable choice.

With respect to traffic information access, 49.6% stated they will actively acquire instant traffic information about congestion and ticket discounts every day, while only 27.2% of the respondents actually noticed the 50.0% price mark-down programme at off-peak time for the Batong and Changping subway line which already lasted for a year. This implies that the propaganda of traffic information to public should be further improved.

Apart from descriptive statistics of the propensity to avoid the peak in different scenarios, OL models were estimated of the probability of avoiding the peak under each of the four scenarios (mark-up in rush-hour model, mark-down in low peak model, extra service model and credits for gifts model), as the response scale of the response variable is ordinal. Explanatory variables include personal characteristics, household characteristics, commute characteristics and use of traffic information. The four models were estimated separately, resulting in a different set of significant explanatory variables for each model. All models are based on 820 observations. The four models were estimated using a stepwise procedure, in which significant variables are added sequentially.

4. OL model

Since our dependent variable in the regression model is five-level of willingness degree to participating peak avoidance, normal logit regression is not enough to properly estimate the escalating level of willingness in the response categories. Therefore, the OL (McCullagh 1980) is adapted here assuming that responses on this ordinal scale are related to a latent continuous variable (U_{iq}) indicating willingness to avoid the peak. The OL model is based on the cumulative probabilities of the response variable. In particular, the logit of each cumulative probability is assumed to be a linear function of the covariates with constant coefficients across response categories.

Concretely in our case, suppose the willingness to avoid rush hour can be categorised into five levels: highly impossible ($Q = 1$), relatively impossible ($Q = 2$), possible ($Q = 3$), relatively possible ($Q = 4$) and highly possible ($Q = 5$). Then the latent willingness is linked to the response variable based on threshold variables U_{iq} as follows.

$$Q = \begin{cases} 1, & 0 < U_{iq} \leq \mu_1 \\ 2, & \mu_1 < U_{iq} \leq \mu_2 \\ & \dots \\ 5, & \mu_4 < U_{iq} < \infty \end{cases}. \tag{1}$$

When describing behaviour choices, the utility function consists of explained part (V_{iq}) and an unexplained part (ε_{iq}):

$$U_{iq} = V_{iq} + \varepsilon_{iq}\,. \tag{2}$$

In this equation, i represents decision makers, and q represents one of the observed choices. Moreover, $V_{iq} = \beta^T X_{iq}$ is the observable part of utility, β^T is a vector of estimated coefficients and X_{iq} is a vector of specific variables, which includes the characteristic of decisions' subject (i) and object (q).

$$\begin{aligned} P_{iq} &= Pr(\mu_n < U_{iq} < \mu_{n+1}) = Pr(\mu_n < V_{iq} + \varepsilon_{iq} < \mu_{n+1}) \\ &= Pr(\mu_n - V_{iq} < \varepsilon_{iq} < \mu_{n+1} - V_{iq}) = F_{\varepsilon_{iq}}(\mu_n - \beta^T X_{iq}) - F_{\varepsilon_{iq}}(\mu_{n+1} - \beta^T X_{iq}). \end{aligned} \tag{3}$$

$F_{\varepsilon_{iq}}$ is cumulative distribution function of ε_{iq}. Suppose ε_{iq} is distributed logistic, then the familiar OL model can be obtained:

$$P_{iq} = Pr(\mu_n < U_{iq} < \mu_{n+1}) = \frac{\exp(\mu_n - \beta^T X_{iq})}{1 + \exp(\mu_n - \beta^T X_{iq})} - \frac{\exp(\mu_{n+1} - \beta^T X_{iq})}{1 + \exp(\mu_{n+1} - \beta^T X_{iq})}, \tag{4}$$

$$P_{i1} + P_{i2} + P_{i3} + P_{i4} + P_{i5} = Pr(0 < U_{iq} < \infty) = 1. \tag{5}$$

Then, cumulative logistic function can be obtained:

$$P(y \leq j) = P_{i0} + P_{i1} + P_{i2} + \dots + P_{ij} = F[\mu_j - \beta^T X_{iq}], \tag{6}$$

$$\ln\left[\frac{P(y \leq j)}{1 - P(y \leq j)}\right] = \mu_j - \beta^T X_{iq}, \quad j = 1,\ 2,\ 3,\ 4,\ 5. \tag{7}$$

The coefficient β remains constant, while μ_j varies from situation to situation. By using Maximum Likelihood method, Likelihood function can be formed. Thus, β and μ_j are estimated to meet the condition in which L has maximal value.

5. Results

5.1. Descriptive statistics

The main focus of the survey was the future likelihood of participating in peak-hour avoidance with subway using proper reward or penalty system. The respondents were asked to rank their preference on a scale of 1–5 with 1 being highly impossible and 5 being highly possible to avoid peak. The distribution was as shown in Figure 1: the price increase in the mark-up scenario made both the policy's supporters and opponents exhibit more distinct attitudes with the biggest proportion of highly possible (25%) and highly impossible (14.39%) replies.

As shown in Figure 2, although it is relatively effective to mark-up the price during peak hour (biggest proportion of highly possible), some participants apparently consider the price rise as unfair and feel dissatisfied about it and intentionally choose the highly impossible option. Hence, commuters' acceptance should be carefully considered when implementing mark-up scenarios.

The mark-down scenario which decreases the ticket price in the off-peak period also has the proper effect with the second biggest proportion of highly possible (24.51%) replies. The second biggest proportion of highly impossible (12.20%) replies shows up in the 'credits for gifts' scenario. The smallest proportion of highly possible replies (11%) is observed for the extra service scenario. In conclusion, monetary incentives (price increase or decrease) have the biggest effect and extra service the least.

The explanatory variables are carefully chosen from literature studies and survey results. The definitions of the explanatory variables in the utility function appear in the Table 4. The factors of alternatives in the table is added to study the influence of alternative traffic mode thus better serve our aims to understand subway commuters' behaviour; the series of factors with the format of Time: home to metro and Distance: work to mall here are intended to measure commuters' space and time elasticity under the circumstances of subway as discussed in Section 1.

The preferences are reflected by Time_startwork as shown in Table 4. Notice that each traveller has different preferred time to start the work of a day. Therefore, we discretized the preferred start work time into eight periods and represent them as dummy variables in the estimation model. For example, Time_startwork = 1 refers to prefer to start work before 6:00 a.m.; while the Time_startwork = 2 means prefer to start work between 6:00 and 6:30 a.m. likewise, Time_startwork = 3, 4, 5, 6, 7, 8 refers to preferred start work period of 6:30–7:00 a.m., 7:00–7:30 a.m., 7:30–8:00 a.m., 8:00–8:30 a.m., 8:30–9:00 a.m., after 9:00 a.m., correspondingly.

Other factors considering family status (whether have to pickup child during commute), information difficulty, whether have several places to live (sole residence), previous peak avoidance experiences, whether student or not, are considered carefully in this study.

All models have 820 individuals' observations out of the 1023 available observations. When questionnaires had missing values or if the responder refused to answer some questions, the corresponding observation was deleted.

5.2. Model results

As mentioned above, the choice variable in the survey was the likelihood to avoid the peak hour under the four indifferent incentives. Therefore, four OL models were estimated. They were

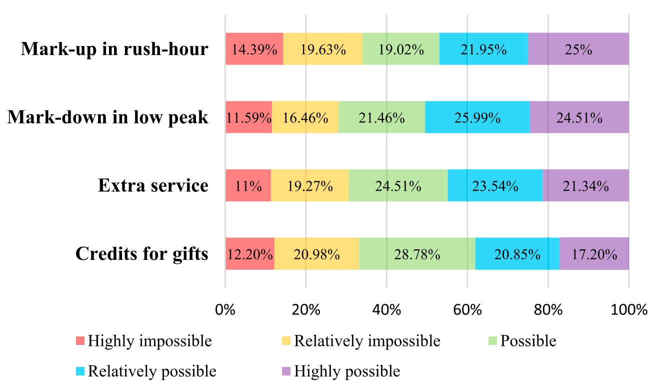


Figure 2. Responses to each of the four reward/penalty systems.

Table 4. Definitions of the explanatory variables.

Name	Data format	Description	Name	Data format	Description
Student	True or False	Whether a student or not	Distance	Continuous	Distance from work to home
Frequency	Discrete	Frequency of commute by subway each week	Stop	Continuous	how many metro stops for each trip
Time: work to metro	Continuous	Average time from work to subway station	Distance: work to mall	Continuous	Distance from work to shopping mall
Time: home to metro	Continuous	Average time from work to subway station	Distance: work to metro	Continuous	Distance from work to subway station
Time: wait for arrival	Continuous	Average time spend waiting for trains' arrival	Sole residence	True or false	Whether have multiple living places
Time delay	Continuous	Average time delay caused by subway peak hour	Information difficulty	Discrete	Difficulty levels to get real time traffic information
Salary level	Discrete	Different salary levels from low to high	Avoidance experience	True or false	Whether had peak avoidance experience
Married without kids	True or false	Whether married but without kids	Pickup child	True or false	Whether have family duties to pickup child
Alternative: taxi	True or false	Whether can use taxi (sharing cars)	Can work at home	True or false	Whether work at home
Alternative: private car	True or false	Whether has a private car	Time_startwork	Discrete	The time period travellers prefer to start their work with
Alternative: bicycle	True or false	Whether can ride bicycle to commute	Ticket fare	Continuous	Ticket fare price
Alternative: bus	True or false	Whether can use bus	Gender	Male or female	Male or Female
Educational level	Discrete	Education level	Age	Continuous	Age
Family status	Dummy	Single, married, divorced, etc.	Job types	Dummy	Job types, totally 9

mark-up in rush-hour model, mark-down in low peak model, extra service model and credits for gifts model respectively. These four models were estimated separately, resulting in a different set of significant explanatory variables for each model.

The thresholds for the ordered categories were estimated according to the ranking in the survey: from 1 (Highly impossible to avoid peak) to 5 (Highly possible to avoid peak). The four models were estimated in a sequential manner. The significant variables are added sequentially and the non-significant ones are excluded automatically. As shown in Table 5, proper numbers of variables are significant.

In Table 5, the Nagelkerke R-square values for the Mark-up, Mark-down, Extra Service, and Credit for gift models were 0.15, 0.16, 0.18, and 0.14 respectively, which are acceptable in terms of explanatory power. All models are significant according to a Chi-square test, with $a = 0.001$.

As shown in Table 5, across all four incentives, it turns out that shorter distance, longer delay, not having to pickup or drop-off a child, having more than one place to live, prior experience with peak avoidance, being a student have a positive effect on peak avoidance and particular preferred work start times have a positive impact on peak avoidance. A shorter distance to work may imply that alternative travel modes such as cycling or the bus are more realistic alternatives, making it easier to avoid the peak by choosing another mode. Also, a shorter distance, if it translates into a shorter travel time, will make the implications of travelling before the peak less problematic. Having to pickup/drop-off a child is likely related to less flexibility in changing departure time, as schools have strict time regimes. Prior experience with peak avoidance may imply that it is more feasible to avoid the peak, but also more knowledge about alternative options or a greater willingness to experiment with alternative behaviours.

As shown in the estimation results, the preferred start work time does not have linear effect on rush-hour avoidance. Travellers preferring to start work in the beginning of the peak and end of the peak are more willing to change their behaviour to adapt to the rush-hour avoidance than those in the middle of

Table 5. Model estimation results.

	Mark-up		Mark-down		Extra service		Credit for gift	
Variance	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value
Student	0.46	.03	0.58	.01	0.43	.01	0.48	.05
Time_startwork = 2[a]	1.52	.01	1.58	.01	0.89	.08	–	–
Time_startwork = 3[a]	–	–	–	–	–	–	0.79	.08
Time_startwork = 6[a]	–	–	0.34	.09	0.50	.02	–	–
Time_startwork = 7[a]	–	–	0.49	.00	0.46	.01	0.43	.01
Distance	−0.03	.00	−0.017	.00	−0.29	.00	−0.82	.02
Distance: work to mall	–	–	0.14	.04	–	–	–	–
Time: work to metro	0.02	.06	–	–	0.02	.03	–	–
Time: home to metro	–	–	−0.01	.09	–	–	–	–
Time: wait for arrival	–	–	–	–	0.03	.03	0.02	.09
Time delay	0.01	.02	0.02	.01	0.02	.01	0.02	.01
Alternative: private car	–	–	−0.36	.06	–	–	–	–
Alternative: bicycle	–	–	–	–	–	–	−0.50	0.05
Can work at home	–	–	–	–	0.52	.05	–	–
Ticket fare	–	–	–	–	–	–	0.02	.1
Sole residence	−0.32	.09	−0.54	.01	–	–	−0.52	.01
Salary level	–	–	–	–	−0.09	.03	−0.07	.08
Married without kids	0.48	.08	–	–	–	–	–	–
Pickup child	−0.57	.05	−0.54	.06	–	–	–	–
Information difficulty	−0.25	.04	–	–	–	–	−0.28	.02
Avoidance experience	0.43	.00	0.58	.00	0.75	.00	0.47	.00

[a] Time_startwork refers to the time period travellers prefer to start their work with, here time interval is 30 minutes and 2, 3, 6 and 7 refers to the time period of 6:00–6:30 a.m.; 6:30–7:00 a.m.; 8:00–8:30 a.m.; and 8:30–9:00 a.m., correspondingly.

the peak since their changing cost is limited. As for the travellers who preferred to leave before 6:00 a.m. every day (Time_startwork = 1), they may have already sacrificed too much of their sleep time which made their changing cost expensive comparing with the incentives.

Regarding distance, longer distance from workplace to a shopping mall has a significant positive effect in the mark-down model. From an urban space perspective, these commuters' demand for non-work activities (such as shopping, have a meal, etc.) is difficult to satisfy when their workplace is far away from malls, therefore, they may be forced to leave their work earlier thus tends to avoid the evening peak of the subway.

Regarding travel time, when commuters need to travel longer from their workplace to the subway station during the evening peak, they are more likely to avoid the peak in the mark-up and extra service model. This may be because a longer travel time to the subway station results in a later arrival at the station making it more likely to travel outside the peak.

A longer time from home to the subway station has a negative effect in the mark-down model. A possible reason is that in the mark-down scenario, ticket price discount is considered as gain for travellers, but a long travel time between home and subway station is a clear cost. As it is complicated for travellers to figure out the net effect by trading off gains against costs, they may want to avoid this mental burden and not engage in peak avoiding. This effect is known as the cognitive miser effect (Orbell and Dawes 1991).

A longer time to wait for the train's arrival makes travellers more likely to avoid the peak in the extra service and credit for gift model. Apparently, waiting time is a strong disincentive (Whelan and Crockett 2008), making travellers more willing to consider alternatives such as off-peak travel that avoid these disincentives.

Longer time delay caused by subway peak hour here refers to the total time waiting for entering a subway train, which includes the time spend queuing up at the entrance and at the platform of the subway. The longer time travellers spend waiting for subway usually implies more congested subway traffic, which encourages them to participate in rush-hour avoidance.

Additionally, when private car is available as an alternative, people's tendency to participate rush-hour avoidance is declining in the mark-down model. The alternative option of bicycle has a significant negative effect in gift model on rush-hour avoidance. Since changing mode is also a way of peak avoidance, someone may anticipate that providing alternatives will increasing commuters' tendency to peak avoidance, it is interesting to notice that the result suggest otherwise. Possible explanation for private car decrease people's peak avoidance tendency should consider the background of severe road traffic congestion in Beijing (Zhu, Yue, and Mandayam 2015). After experiencing more than one-hour road traffic congestion during the peak hours, it is reasonable for commuters to become more persistence with the subway mode. And as described in Section 3.3, more than 94% of the Beijing commuters have to travel more than 2 km for one-way commuting, bicycle can hardly be considered as a proper major commuting mode, but it is very suitable as a supplementary travel tool, for example, some one can ride a bicycle to go to a subway station. Actually, bicycle serves very well when combined with subway, therefore the alternative option of bicycle increase the people's tendency to use subway since travellers can ride bike to subway station conveniently without wasting time to wait for a public transfer bus or walk for a long time. As a result, the alternative mode of bike decreases commuters' tendency to avoid peak hours by changing mode. In general, the negative effect of alternative modes seems to indicate that commuters with a mode alternative would rather stick to their own schedule, when incentives are not so attractive to them.

The possibility to work from home increases the possibility of choosing rush-hour avoidance in the extra service model. This is logical, as working from home the full day or part of the day (Lyons and Haddad 2008) is a concrete alternative for peak-hour commuting.

Ticket fare came out positively significant in the gift model, which is different from the estimations of the other models. The reason may be that in the gift incentive model, commuters have to accumulate credits for a long period in exchange for a cell phone while others have one-to-one correspondence. Therefore, it is important to figure out the cost and gains. Higher ticket fare implies more credits and faster accumulation in the current credit system, thus increase the possibility for rush-hour avoidance.

Sole residence (having only one residential location) also has significant negative effect on people's rush-hour avoidance. This makes sense, since people who have different places to live can be more flexible to choose rush-hour avoidance, for instance because at least one of the residential locations offers access to work by alternative modes such as active travel.

It is interesting to notice that the salary level variable was negatively significant in non-monetary models of extra service and credit for gift. Possible explanation is that lower salary people are more sensitive to those small gifts and free services.

Travellers who have difficulties to obtain rush-hour avoidance information were reluctant to participate in rush-hour avoidance in mark-up model and credits for gift model. Likely, they find it more difficult to figure out alternative travel options that facilitate peak avoidance.

It is noticed that household constraints such as marriage and picking up kids also shows significant effects. These results matched our expectation. Married people are more sensitive to the price penalty since they have to support a family, thus they are more inclined to rush-hour avoidance when married without kids. However, when they have a child to pickup or drop-off, their flexibility to travel at other times decreases, implying a lower likelihood of peak avoidance.

6. Discussion

This paper has discussed the potential effects of various financial and non-financial incentives on peak avoidance probability in the Beijing subway system, using a stated preference survey. Our results suggest that all four incentives can be reasonably effective tools to reduce subway use in the peak period. The percentage of respondents that would with high possibility avoid the peak ranges between 17.2% and 25%. The share being relatively of highly possible to avoid the peak ranges from 38.1% to 50.5%. Overall, the financial incentives seem to have a slightly stronger effect than the services and credit-for-gifts-based scenarios. However, attentions should be paid to that a stated choice experiment basically measures people's intention to change behaviour. Various studies

(Sniehotta, Scholz, and Schwarzer 2005) have shown that factors such as lack of planning, limited maintenance, self-efficacy and limited action control lead to intentions not being translated into behaviour.

The OL models indicate that various factors influence people's receptiveness of incentives for peak avoidance. By and large, effects may relate to the ease of change or presence of alternatives (preferred work start times, travel distance, multiple residences), receptiveness to incentives (salary, fare, having a family). In most cases it is not evident why a particular factor has an effect on responsiveness to one type of incentive and not another type. We assume that this may be due to randomness in the models, and regard the outcomes as general indications of factors influencing responsiveness to incentives in the context of peak avoidance.

Different from existing literature (Zhang, Fujii, and Managi 2014), which concluded that free meal is more effective than monetary incentives, our conclusions suggested that even under the current circumstances of low fare system in Beijing, where the effect of the price adjustment is restricted, the price adjustment is still the most efficient mean to influence commuters' behaviour. Results from the empirical studies imply that the conduction of both mark-up the price in peak and mark-down the price during non-peak may be the better way to help solving the problem.

6.1. Theoretical implications

The high demand for subway travel during peaks in metropolitan areas like Beijing not only leads to crowded trains, but also builds queues in stations that may cost up to 40 minutes waiting time per traveller, yielding severe economic and social cost, not to mention the safety issue that attracts increasing concerns of the public. Under such circumstances, it is highly important to study the key factors which influence the subway commuters' peak avoidance, and thus help develop policies which will effectively encourage people to avoid the peaks. However, the current studies of peak avoidance in subway system are limited due to the vagueness about the difference of peak avoidance behaviour between subway and road traffic system.

This paper clarifies the main difference as follows: firstly, the major objective is not to encourage people to choose other traffic modes, but to reduce the traffic demand, especially during the peak hours, distribute them more evenly across the time span. Therefore, the influence of alternative traffic modes is discussed.

Secondly, the cost structure of subway traffic is different from the road traffic of private car, clearly signalling the monetary cost by fare system. Therefore, the commuters of subway system are comparatively more sensitive to this part of cost. Based on this difference, this paper divided the monetary incentives to mark-up and mark-down scenarios and further analysis the reaction of commuters. Results suggested that commuters are more sensitive to mark-up the price and the most effective way is to combine both the mark-up and mark-down price mechanism.

Thirdly, different from the road traffic of public bus which has more flexible location of stations and lines, the infrastructure of subway system is relatively fixed after being built. Existing studies (Zhang, Fujii, and Managi 2014) did not mention these factors, while the accessibility by subway of live and working place of commuters and the space flexibility (measured by elasticity) are carefully discussed in this paper. A lot of distance and time related factors which reflect time and space elasticity are proven to be significant, further policies could be set based on our conclusions.

Fourthly, other influences such as psychological factors of attitude, preferences, previous experience and technology factors of information availability are also not mentioned in the existing study (Zhang, Fujii, and Managi 2014). This paper filled this gap and found out that preferences, previous experience and information availability do influence people's decision on participation rush-hour avoidance of subway.

Theoretically speaking, Spitsmijden (Ben-Elia and Ettema 2011b), peak avoidance in Dutch, is the largest systematic effort to date to study the potential of rewards as a policy means to change commuter behaviour. However, most of the Sptsmijden study focused on road traffic and rush-hour driving, which is quite different from subway peak-hour behaviours in terms of major objectives, cost structure, and flexibility as summarised above. Focusing on behavioural analysis of subway commuters, this study supplements the peak avoidance behavioural theory to date by incorporating more comprehensive incentives on peak avoidance and analysing more influential factors. Therefore, the proposed paper extends the insights into the effect of different rewards on peak-hour avoidance in Beijing metro, and the results can provide further understanding of subway peak avoidance behaviour.

Previous studies already gained certain extent of insight into the effectiveness of road pricing and rewarding schemes in terms of affecting the behaviours of car drivers (Ben-Elia and Ettema 2011a, 2011b). However, the comparative potential of each policy is affected by several characteristics and context, some of which can be controlled, while others cannot. One of the interesting conclusion is that in road traffic, the reward measure appears to be more effective in persuading people to avoid the peak hours, which would suggest that rewarding them may be more effective than punishing (i.e. charging) them. However, in the context of subway peak avoidance, results suggest otherwise and the mark-up the price seems to be the most effective policy, which is also in accordance with behavioural psychology (Kahneman, Knetsch, and Thaler 1991). People are more sensitive to loss than gains, therefore, due to the loss aversion tendency, the disutility of giving up an object is greater that the utility associated with acquiring it, therefore, people consider the mark-up price as a kind of loss and tries harder to avoid it than gain the price discount, this explain why mark-up is more effective than mark-down the fare price. The result further suggested that the combination of mark-up and mark-down policy will amplify the reference-point effect (He and Yu 2006), which making the gap between the peak-hour fare and non-peak-hour fare more prominent, thus increase the tendency to avoid the peak.

Regarding the chosen alternatives to peak-hour travel, the results also suggest differently than other previous studies: And as described in Section 5.2, cars bicycle serves very well when combined with subway, therefore the alternative option of bicycle in fact increase the people's tendency to use subway since travellers can ride bike to subway station conveniently without wasting time to wait for a public transfer bus or walk for a long time. As a result, the alternative mode of bike decreases commuters' tendency to avoid peak hours by changing mode. In general, the negative effect of alternative modes seems to indicate that commuters with a mode alternative would rather stick to their own subway schedule, this is natural, since subway is the relatively more punctual traffic mode when compare with congested road traffic condition in Beijing.

6.2. Practical implications

Peak-hour congestion in public transport is a major problem in megacities in developing countries, which requires attention of policy-makers. Our results suggest that providing incentives can be a promising way to reduce congestion, by making travellers avoid the peak. Depending on the type of incentive 17–25% of travellers indicate that they would certainly avoid the peak, and 38–51% state this would be rather possible. Reductions of 15–25% would lead to a very substantial reduction of congestion and strongly contribute to the comfort and reliability of subway use. A point of concern is to what extent travellers will avoid the peak by using other travel modes, and contribute to congestion on the road or in buses. The type of response was beyond the scope of this study, but definitely needs attention in future work.

Our study furthermore suggests that peak avoidance can be stimulated by reducing constraints that travellers face when trying to avoid the peak and increase the availability of alternatives. First, since 45% of the trips has a distance less than 10 km, bicycle may be a reasonable option for many, but this requires the presence of safe and comfortable cycling trajectories, which necessitates investments in dedicated infrastructure, bicycle parking facilities and probably availability of bicycle share systems. Another way to stimulate peak avoidance would be by loosening fixed time regimes that force people to travel during the morning peak. As about 40% of travellers in our survey were students and they likely make up a large part of the travellers' population, college hours may be set such that peak travel is avoided. For workers, it is observed that even in a high educated sample, options for working from home and flexible working hours are limited. This may be related to cultural norms, but increasing flexibility might contribute to peak avoidance.

Different than the conclusion of (Zhang, Fujii, and Managi 2014), even when the strength of price incentive mechanism is restricted due to the low-ticket fare setting in Beijing, proper price setting can still induce travellers' behaviour effectively, since they are so sensitive to the price change. Price can be a powerful tool if it is used wisely, for example, the combination of mark-up and mark-down is a good solution, since the extra income from mark-up during the peak hour can compensate the loss which subway companies suffered with the mark-down discount during the off-peak, and the mark-down discount during the non-peak will also increase the public acceptance of the mark-up system.

Finally, given the fact that difficulties with accessing traffic information reduce peak avoidance, policies could be developed to improve information provision to travellers regarding both the existence of incentives and alternative travel options.

7. Conclusion

This study explored the effect of different rewards on peak-hour avoidance in Beijing metro, and analysed the influence of a comprehensive factors set. Using a stated preference approach, the effects of different incentive system, including monetary incentive, non-monetary incentives such as extra services and earning credits which can be converted into gifts, are also studied with OL model. And the ordinal estimation feature of OL model can measure the commuters' intentions ranging from 'highly impossible' to 'highly possible' under different incentives systems, which provides better understandings about how these factors gradually influence the travel behaviour. Especially, the effects of elasticity and accessibility on metro commuters' response to each type of reward are carefully studied, which have not been systematically studied before. Based on the empirical results, some policy implications are discussed including effective price incentive systems, improvement of information availability and loosing fixed work-time regime.

While this study extends the insight into the effect of incentives on peak avoidance in the subway in Beijing, more research is needed to properly assess the potential impact of incentives. First, a wider range of incentives can be tested, including monetary incentives of different sizes, but also additional services or credit schemes. This will be important to find the most efficient level of incentives needed to achieve a substantial amount of peak avoidance. Second, since the stated preference survey measures intention rather than behaviour, it would be important to conduct experiments with incentives, in order to test the actual effect on travellers' behaviour and to test the efficiency of the tool in reducing congestion. Third, it is also interesting to test the full-combination effect of multiple incentive systems by adding more data and setting other scenario experiments. And finally, the behavioural analysis of groups with different travel purposes should be studied for better understanding of the whole picture of peak-hour travellers.

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