Curb Parking Pricing of City Center Incorporating Threshold

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ABSTRACT
Curb parking pricing is a frequently used measure to manage parking demand which could release pressure of curb parking and take full use of road idle resources. How to make a reasonable price for curb parking to balance its demand and supply is troublesome for metropolises like Shanghai. This paper tries to solve this problem from the view of parkers’ choice behavior, meanwhile a research focal in this paper is parking price cutoff, which is the minimum or maximum acceptable level that a decision maker namely parker here sets for an attribute, once attribute value of a choice exceeds the acceptable range, parker may never choose this choice. Discrete choice models incorporating parking price cutoff were compared with conventional models without cutoff to analyze the implication of cutoff on parking type choice behavior, and a multiple linear regression with all independent variables significant was used to further reveal the relationship between the number of cutoff violation, namely although curb parking price exceeds parker’s acceptable range but he still choose curb parking, and individual characteristics. Results show, the precision of models with cutoff are better, and variables such as parking price, searching time and walking time have great influence on parking type choice, which is very meaningful for parking planners and policy makers to manage parking behavior. Besides, people with different age, driving year and parking experience may have diverse tolerance about parking price threshold stated by themselves. Finally, a pricing scheme is put forward to reduce occupancy rate of curb parking to 85% based on parking pricing models with and without cutoffs, indicating not accounting for price cutoff, when present, produces misleading results and might cause an upward bias.

Keywords: curb parking pricing; cutoff; discrete choice; pricing scheme
1 INTRODUCTION

If curb park and garage park are perfect alternatives to each other, curb parking price should be equal to garage parking to achieve the goal of eliminating cruising (1, 2), but they can never be perfect alternatives because of spatial difference (3). More specifically, for approximately 30 percent of the traffic is cruising for parking from studies of 11 international cities (4), and the average time to find a curb parking space is between 3.5min and 14min (1), which have shown that curb park is preferred by drivers over garage park because of its flexibility, convenience, conservation of land, low cost of construction and maintenance. However, curb parking spaces occupy public road resources with the function of taking full advantage of road idle resources, which makes curb parking exclusive, so how to balance its occupancy rate and its function is important (5). Consequently, Shoup proposed that 85% occupancy rate was apposite for curb park, with price raise needed when its occupancy rate exceeded 85%, guaranteeing users could find parking spaces any time (4). Whereas parking data collection is difficult for most cities in China, it is hard to make a reasonable parking price without adverse impact on the transportation system and other systems of a city (6). We are committed to address this issue in Shanghai, and following is a rough introduction of parking situation in Shanghai.

According to Shanghai curb parking duration statistics data from 2008 to 2012, the ratio of parking duration with less than 1 hour, between 1 and 2 hours, more than 2 hours are 69%~73%, 18%~23% and 7%~13% respectively with increasing trend of average parking duration. This leads to daytime berth average turnover rate is only 3.09 times per day for one berth, which means turnover of curb parking spaces is very low (5). Based on this reality, curb parking price badly needs adjustment especially for key areas in which curb parking resource is more scarce, so we attempt to propose a reasonable parking pricing scheme to guide a portion of vehicles to change their main parking address from curb parks to garage parks to reach the goal of 85% occupancy rate, meanwhile we take parking price cutoff (cutoff is the minimum or maximum acceptable level that a decision maker namely parker here sets for an attribute, once attribute value exceeds the acceptable range, parker may never choose this choice) into consideration to avoid bias in price adjustment.

2 LITERATURE REVIEW

For the time being, scholars have dedicated much energy to parking issues, and mathematical programming (7), discrete choice model (DCM) (8-10), linear regression model (11), average pricing method (12), game theory (13), models built by authors themselves (3, 14, 15) are mainstream analytical tools to analyze parking issues. Especially, establishing DCM to study parking type choice behavior is gradually becoming popular, while the most commonly used models are basic DCMs. As we can see, Multinomial Logit (MNL) (16-18) and Nested Logit (NL) (19-21) have a major position in parking type choice research, lately researchers have started to pay attention to more advanced models such as Mixed Multinomial Logit (MMNL) (9, 22) to reveal heterogeneity in parkers’ choice. In view of DCMs used in parking issues have been summarized in paper (9) and (23), we recommend readers to consult the two papers to acquaint DCMs’ application in this field. As far as we can tell, few researches have
been made to use DCMs to adjust parking price, but as the second best measure for solving traffic congestion after congestion charging because of its relatively simple implementation (24, 25), it is important to explore the relationship between price and occupancy rate. Admittedly, establishing parking type choice behavior model by DCMs to study effects of parking price change on occupancy rate is a good alternative, for occupancy rate is the quantity indicator of parking choice for all parkers at the same time, what’s more, the sample size is smaller and easier for collection. However, the exact mechanism of parking price’s effect on parking behavior still stays in the primary stage without considering different parkers’ affordability for parking price. So it is necessary to study the influence of parking price threshold on parking type choice behavior, the relation between the number of threshold violation and parkers’ socio-economic characteristics, where an attribute cutoff is the minimum or maximum acceptable level that an individual sets for an attribute (26), and our study is helpful to fill these defects.

The structure of the paper is as follows: Section 3 describes two different kind parking behavior analysis models, the survey methodology and elementary statistical analysis of data is presented in Section 4, Section 5 gives how to construct parking choice models incorporating price cutoff, in which different models are compared, furthermore the relationship between threshold violation number and individual characteristics is analyzed, which means that a parker still choose curb parking when the price of curb parking has already exceeded the highest price he can accept, based on Section 5, a rational parking pricing scheme is proposed in Section 6, Section 7 includes the conclusions drawn from the research and avenues for further research.

3 MODEL SPECIFICATIONS INCORPORATING CUTOFF

3.1 Conventional Model
The basic idea of DCM is that a decision maker namely parker in this context would obtain a certain level of utility which depends on many influence factors from each alternative, that is, the utility function associated with parker \( n \) choosing alternative \( i \) can be written as:

\[
U_n = \mu(p(d), d, \alpha, \beta, \epsilon_n) = V_n + \epsilon_n
\]  

where \( V_n \) is often called representative utility and typically assumed to be linear in parameters; \( \epsilon_n \) captures the factors that affect utility but are not included in \( V_n \), which is postulated to follow Independently and Identically Distributed (IID) extreme value type I distribution under logit model framework; \( i = c, g \) represent curb and garage parking respectively; \( p_i \) is parking cost for alternative \( i \) with duration \( d \); \( \alpha \) refers to the other attributes that characterize alternative \( i \) except cost; \( \beta \) denotes characteristics of parker \( n \). Furthermore, parker’s behavior follows the assumption of utility-maximizing:

\[
P_n = P(U_n > U_{nj}, j \neq i)
\]  

where \( j = c, g \). To better understand parker’s heterogeneity during decision process, MNL and MMNL are used to estimate parameters for comparison.

3.1.1 MNL
By considering simultaneous formulas of Eq. (1) and Eq. (2) and assumption for \( \varepsilon_u \), the probability formula of MNL is:

\[
P_{ui} = \frac{e^{\varepsilon_u}}{\sum_{j=1}^{2} e^{\varepsilon_j}} = \frac{\exp[\theta X_u]}{\sum_{j=1}^{2} \exp[\theta X_{uj}]} \tag{3}
\]

where \( \theta \) is parameter matrix to be estimated; \( X_u \) is variable matrix. For simplicity, we generally assume observed utility is the linear combination of attributes. Since the probability has a closed form expression, it can be readily solved by maximum likelihood estimation.

3.1.2 MMNL

Unlike MNL, which supposes decision makers’ tastes are homogenous, coefficients of some variables in MMNL can be defined as random, capable of accommodating heterogeneity in parkers’ taste and potential correlation structure of repeated observations made by the same parker:

\[
\theta_{ni} = \theta_i + \sigma_n v_{ni}
\tag{4}
\]

in which \( \theta_i \) is the population mean taste for attribute \( i \); \( v_{ni} \) represents individual specific heterogeneity, with mean zero and standard deviation one. Due to no closed form expression existing for probability of MMNL, variables’ estimation relies on a simulated approximation:

\[
P_{ni} = \frac{1}{R} \sum_{r=1}^{R} \frac{\exp[\theta_r X_u]}{\sum_{j=1}^{2} \exp[\theta_r X_{uj}]} \tag{5}
\]

where \( \theta_r \) is the \( r \)th draw of \( \theta \); \( R \) is sampling times; \( P_{ni} \) is the probability of parker \( n \) choosing mode \( i \).

3.2 Logit Model Incorporating Attribute Cutoff

The aim of this paper is to investigate threshold through models mentioned below by nonlinear utility function, therefore particular attention is given to attribute cutoff. It is reasonable to think that an alternative with an increase above a certain value in one attribute or more is at times considered completely unacceptable and lead to the rejection, no matter how highly compensated by other attributes (26). Given the potential bias that can be caused by ignoring cutoff, this omission may lead to overestimating the role attributes play in some particular situation such as parking price adjustment for demand balance between curb and garage parks. Even so, several studies have sought to account for cutoff (mainly exogenous) during decision process within discrete choice framework, which can be divided into three categories: (1) dummy variable method (27); (2) MNL with piecewise linear utility function (this method was proposed by Swait, hereafter it refers to MNLS) (28); (3) CMNL (Constrained MNL) (29). And threshold is divided into three categories by Cantillo and Ortuzar (30): i) thresholds as inertia, habit or reluctance to change; ii) thresholds defined as minimum perceptible changes; iii) thresholds as mechanisms of acceptance or rejection of alternatives. Numerous
researches have proven that the third threshold appears to be more important for model accuracy. For no clear evidence indicating exogenous cutoff is superior to the endogenous case and vice versa, so we herein only consider exogenous cutoff stated by respondents themselves for convenience. We criticize dummy variable method can’t deal with the issue of different magnitude of exceeding attribute cutoff, which means the utility decrement for one unit exceeding attribute cutoff is the same as two or other units, so it is abandoned here. While the latter two both have particular strengths and weakness, such as easy to apply and non-differentiable for the second, differentiable and needs own programming for the third. In virtue of these reasons, meanwhile few applications have up to that point investigated the cutoff issue in parking type choice, it is meaningful to use two models to study parking price cutoff.

3.2.1 MNLS
MNLS incorporates cutoff by piecewise linear function into decision process without changing the nature of DCMs fundamentally, for this reason it has no impact on parameter estimation and software application compared with conventional MNL. The model is defined as:

\[
\max U = \delta_{i} \left( \sum_{k=1}^{K} \beta_{k} x_{ik} + \sum_{k=1}^{K} v_{i} \cdot \kappa_{ik} + \sum_{k=1}^{K} w_{i} \cdot \lambda_{ik} + \epsilon_{i} \right) \\
\text{s.t. } \sum_{i \in C} \delta_{i} = 1
\]

(6)

where \( i \) is alternative; \( n \) is decision maker; \( \delta_{i} \) is the dummy variable of choice indicator; \( k \) is the \( k \)th attribute of alternative (the number of attributes is \( K \)); \( \beta_{k}, v_{i}, \) and \( w_{i} \) are parameters to be estimated; \( x_{ik} \) is the \( k \)th attribute of alternative \( i \) faced by decision maker \( n \); \( \kappa_{ik} \) and \( \lambda_{ik} \) are lower and upper cutoffs for \( x_{ik} \) respectively; and penalty for exceeding cutoffs in the objective function is reflected via quantities \( v_{i} \) \((\leq 0)\) and \( w_{i} \) \((\leq 0)\).

3.2.2 CMNL
CMNL proposed by Martinez et al. (29) can handle both endogenous and exogenous cutoff issues, having following definition:

\[
U_{ai} = \sum_{k=1}^{K} \beta_{k} x_{ik} + \frac{1}{\mu} \ln \phi_{ai} + \epsilon_{ai} \\
\ln \phi_{ai} = \ln \left( \prod_{k=1}^{K} \phi_{aik} \phi_{aki} \right) = \sum_{k=1}^{K} \ln \phi_{aik} + \ln \phi_{aki} \\
\phi_{aik} = \frac{1}{1 + \exp \left( \frac{w_{i} (a_{ai} - Z_{ai}^a + \rho_{a})}{\eta_{a}} \right)} = \begin{cases} 1 & \text{if } (a_{ai} - Z_{ai}) \to -\infty \\ \eta_{a} & \text{if } a_{ai} = Z_{ai} \\ \end{cases} \\
\phi_{aki} = \frac{1}{1 + \exp \left( \frac{w_{i} (b_{ai} - Z_{ai}^b + \rho_{b})}{\eta_{b}} \right)} = \begin{cases} 1 & \text{if } (b_{ai} - Z_{ai}) \to \infty \\ \eta_{b} & \text{if } b_{ai} = Z_{ai} \\ \end{cases}
\]

(7)
where $\phi_{ki}^L$ and $\phi_{ki}^U$ represent the lower and upper cutoffs of $k$-th attribute of alternative $i$ for decision maker $n$ respectively; $\rho_k = \frac{1}{\eta_k} \cdot \ln \left( \frac{1-\eta_k}{\eta_k} \right)$, in which $\eta_k$ is cutoff tolerance; $\beta$ and $\gamma$ ($\gamma \geq 0$) are parameters to be estimated; $a$ and $b$ are attribute values; $Z$ is cutoff; definitions of the other variables are the same as chapter 3.2.1. The utility function used below is a simplified version, namely $\rho_k$ is omitted.

3.2.3 Difference between models

Some comparisons need to be done before using these models to research parking choice behavior, which will help readers to understand the difference between MNLS and CMNL. The main difference which is clearly showed by two charts above is reflected around the origin, where exists a “kink” for MNLS, namely MNLS is more suitable for the situation that cutoff is a point for utility’s enormous decrement after reaching the cutoff point, while CMNL is more suitable for the situation that cutoff is an interval because of utility’s gradual change around the cutoff point. As far as we know, no research on the comparison of these two models are made, maybe to some extent our study can give readers a little enlightenment to this point, and we think the latter maybe better intuitively.

4 SURVEY AND STATISTICAL ANALYSIS

4.1 Influence Factors Selection

Before the survey started, knowing which factor has a direct influence on choosing parking type choice is crucial for the depth analysis of parking type choice behavior, hence we aggregate 23 literatures involving parking type choice behavior study and its related factors (9, 16-23). TABLE 1 below shows most researches have been taken the first two factors into
consideration in parking type choice behavior study, namely egress time/ walking time/ walking distance and parking fee/ parking charge, nearly half have considered capacity con-
straint factors such as occupancy rate/ chance of free space/ number of spaces. It should be expected that, because of substantial differences existing in study areas and researchers’ cognitions, scholars have yet to reach anything close to a consensus regarding effects of remaining factors to parking type choice behavior. With this brief historical perspective behind us, this paper ultimately chooses search time (the time cost on a vehicle cruising for parking), parking operation time (the time cost from vehicle arrives at park entrance to finish parking), walking time (the time cost on walking from parking place to parker’s destination), probability of finding an empty parking space, parking cost and parkers’ characteristics as main influence factors of parking behavior according to trial survey and inquirer.

<table>
<thead>
<tr>
<th>Influence factor</th>
<th>Frequency</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(occurrence number/ total)</td>
<td>(%)</td>
</tr>
<tr>
<td>Egress time/ Walking time/ Walking distance</td>
<td>22/23</td>
<td>95.65</td>
</tr>
<tr>
<td>Parking fee/ Parking charge</td>
<td>19/23</td>
<td>82.61</td>
</tr>
<tr>
<td>Occupancy rate/ Chance of free space/ Number of spaces</td>
<td>9/23</td>
<td>39.13</td>
</tr>
<tr>
<td>Distance from home/ Travel time</td>
<td>7/23</td>
<td>30.43</td>
</tr>
<tr>
<td>Type of parking</td>
<td>6/23</td>
<td>26.09</td>
</tr>
<tr>
<td>Distance area entrance - parking</td>
<td>5/23</td>
<td>21.74</td>
</tr>
<tr>
<td>Search time</td>
<td>5/23</td>
<td>21.74</td>
</tr>
<tr>
<td>Parking time restriction/ Maximum parking duration</td>
<td>4/23</td>
<td>17.39</td>
</tr>
<tr>
<td>Expected fine illegal parking</td>
<td>3/23</td>
<td>13.04</td>
</tr>
<tr>
<td>Security</td>
<td>2/23</td>
<td>8.70</td>
</tr>
</tbody>
</table>

Note: Each factor may have other expressions instead, here we only list some for simplicity.

### 4.2 Questionnaire Design

The questionnaire is made up of three parts: (1) parking information and price cutoff enquiry; (2) SP (stated preference) choice; (3) detailed personal information. In particular, to reveal parkers’ choice behavioral preferences and avoid parameter estimation problem, design of hypothetical scenarios draws the method proposed by Dell’Olio et al. (8), which allows variable value has small fluctuation around its mean, such that the same SP scenario has a slight difference for each respondent. For example, if the search time of A and B are both 3 + 1.5(2εi - 1) min, while randomly generated εi may be different for A and B, assuming 0.2 and 0.3 respectively, search time is then 2.1 min for A and 2.4 min for B. In the previous trial survey, we find it is hard for parkers to make decisions with five variables’ value all different, so parking cost and parking operation time are determined as fixed variables in orthogonal design. Meanwhile, in order to solve the problem of too many hypothetical scenarios in orthogonal design, one of the remaining variables is selected to add into orthogonal design each time. Apart from parking cost having five levels, the other variables have only three levels, so we can get \( C_3^3 \times 25 = 75 \) hypothetical scenarios (25 is the hypothetical scenario number for or-
to orthogonal design). To ease burden on each respondent, only five scenarios are set in each questionnaire.

4.3 Data Collection
The data was obtained by a face-to-face survey in appointed parks around People’s Square from 8:00 to 18:00 on July 26th and 27th, 2013, including ten curb and six garage parks. First, we asked questions about personal information and parking situation, such as personal income (RMB/month, 1RMB≈0.163$), sex (1=female, 0=male), age (year), driving year (year), reimbursement (1=yes, 0=no), parking experience (1=always park in curb/garage parks, 0=seldom park in curb/garage parks), search time (min), parking operation time (min), walking time (min), cost (RMB) and parking duration (hour); parker’s highest acceptable parking price was then asked; finally choice data of hypothetical scenarios were collected. Survey shows the fact that garage parks are not fully utilized, especially for Xinshijie, Shijibada and Hongxiang Machinery, with almost half or more parking spaces idle. While Curb parks’ average occupancy rate is considerably high which is up to 93.2%, without any doubt, garage parking spaces are enough for curb parkers to transfer in surveyed areas.

4.4 Statistical Analysis of Data
A total of 180 questionnaires are recovered, including 106 valid questionnaires, namely 106 sets RP data and 530 sets SP data. Compared with parkers of garage parking, average parking duration and walking time for parkers of curb parking is shorter; curb parks having shorter research time is not incomprehensible, although curb parking space is scarce in Shanghai, parkers still have chances to park in surrounding curb parks when their first preferred curb parking space is full, which leads to the average search time of curb parks less than garage parks for shorter distance between curb parks and easier to search; as expected, because of curb parking having advantages except parking cost and probability of finding an empty parking space, parkers’ affordability for curb parking cost is 16.10 RMB/h, higher than garage parking which is only 13.47 RMB/h.

5 RESULTS AND DISCUSSION

5.1 RP/SP Data Fusion
Given the possible scale difference between RP and SP data, it is inappropriate to fuse them directly, so calculating inclusive values of Nested Logit Model with degenerated branches is necessary for determining whether more complex models are needed(31). If inclusive values of alternatives have no significant difference, MNL is then enough for further study. As we can see, inclusive values of four choice branches including curb parking RP, curb parking SP, garage parking RP and garage parking SP are calculated, and T-test of inclusive values are all not significant, indicating there is no big difference between RP and SP data, so does curb and garage parking data, which means MNL is appropriate for the fusion of RP and SP data.

5.2 Utility Function Construction
Taking into account that people with different ages have different sensitivity to walking distance, we construct utility function mainly based on variables and this interaction term. Re-
calling the two alternatives under study, the utility functions of MNL(8), MMNL(8) (the utility function of MMNL is the same as MNL’s), MMNL(9) (MMNLC is the abbreviation of MMNL with cutoff) and CMNL (10) are as follows:

\[
U_{n} = \theta_{n} PT_{n} + \theta_{n} ST_{n} + \theta_{n} OT_{n} + \theta_{n} WT_{n} + \theta_{n} PE_{n} + \theta_{n} PFES_{n} + \theta_{n} COST_{n} + \theta_{n} PFES_{n} + \theta_{n} COST_{n} + \theta_{n} PE_{n} + \theta_{n} PT_{n} + \theta_{n} ST_{n} + \theta_{n} OT_{n} + \theta_{n} WT_{n} + \theta_{n} PE_{n} + \theta_{n} PFES_{n} + \theta_{n} COST_{n} + \theta_{n} COST_{n} + \theta_{n} PFES_{n} + \theta_{n} COST_{n} - \theta_{n} \ln(1 + \gamma COST_{n}) + \theta_{n} PE_{n} + \theta_{n} PFES_{n} + \theta_{n} COST_{n} - \theta_{n} \ln(1 + \gamma COST_{n}) + \theta_{n} PE_{n} + \theta_{n} PFES_{n} + \theta_{n} COST_{n} - \theta_{n} \ln(1 + \gamma COST_{n}) + \theta_{n} PE_{n} + \theta_{n} PFES_{n} + \theta_{n} COST_{n} - \theta_{n} \ln(1 + \gamma COST_{n}) + \theta_{n} PE_{n} + \theta_{n} PFES_{n} + \theta_{n} COST_{n} - \theta_{n} \ln(1 + \gamma COST_{n}),
\]

where \( AW = AGE \times WT \) is the interaction term, the corresponding variable name of each code in equation (8-10) is given in TABLE 2.

### 5.3 Parameter Estimation Result

According to utility functions constructed above, we estimate parameters of four models. The results are summarized in TABLE 2, which allow us to quantify the advantages offered by models incorporating cutoff.

### TABLE 2 Parameters Estimation Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Code</th>
<th>MNL</th>
<th>MMNL</th>
<th>MMNLC</th>
<th>CMNL</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Parking attributes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Search time</td>
<td>ST</td>
<td>-0.06669**(-2.12)</td>
<td>-0.06870**(-2.12)</td>
<td>-0.06550**(-2.02)</td>
<td>-0.07021**(-2.18)</td>
</tr>
<tr>
<td>Parking operation time</td>
<td>OT</td>
<td>-0.07774(-1.39)</td>
<td>-0.08048(-1.40)</td>
<td>-0.08242(-1.44)</td>
<td>-0.05807(-1.05)</td>
</tr>
<tr>
<td>Walking time</td>
<td>WT</td>
<td>-0.10153(-1.86)</td>
<td>-0.10505(-1.86)</td>
<td>-0.10561(-1.88)</td>
<td>-0.10038(-1.80)</td>
</tr>
<tr>
<td>Probability of finding an empty parking</td>
<td>PFES</td>
<td>1.51928**(2.39)</td>
<td>1.54432**(2.39)</td>
<td>1.51989**(2.35)</td>
<td>1.53151**(2.39)</td>
</tr>
<tr>
<td><strong>Parker characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parking experience</td>
<td>PE</td>
<td>0.42705**(1.99)</td>
<td>0.43788**(2.00)</td>
<td>0.44134**(2.02)</td>
<td>0.47404**(2.21)</td>
</tr>
<tr>
<td>Sex</td>
<td>SEX</td>
<td>-0.29023(-1.26)</td>
<td>-0.30601(-1.31)</td>
<td>-0.32542(-1.39)</td>
<td>-0.44165(-1.21)</td>
</tr>
<tr>
<td>Age</td>
<td>AGE</td>
<td>0.02782**(2.39)</td>
<td>0.02763**(2.32)</td>
<td>0.02918**(2.45)</td>
<td>0.02659**(2.42)</td>
</tr>
<tr>
<td>Income</td>
<td>INC</td>
<td>1.42\times10^{-5}(1.51)</td>
<td>1.46\times10^{-5}(1.52)</td>
<td>1.30\times10^{-5}(1.35)</td>
<td>9.36\times10^{-6}(1.00)</td>
</tr>
<tr>
<td>Reimbursement</td>
<td>AFR</td>
<td>0.31009(1.43)</td>
<td>0.31766(1.44)</td>
<td>0.28652(1.29)</td>
<td>0.33656(1.55)</td>
</tr>
<tr>
<td><strong>Interaction term</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age \times Walking time</td>
<td>AW</td>
<td>-0.00231**(-2.12)</td>
<td>-0.00225**(-2.03)</td>
<td>-0.00220**(-1.99)</td>
<td>-0.00256**(-2.30)</td>
</tr>
<tr>
<td><strong>Standard deviation (spread) of random parameter</strong></td>
<td></td>
<td>-0.05577**(-4.82)</td>
<td>T:0.04419**(-3.11)</td>
<td>-0.11972**(-5.01)</td>
<td>-0.66880(-0.59)</td>
</tr>
<tr>
<td><strong>Constant term</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant term</td>
<td>ASC</td>
<td>-0.78642(-0.93)</td>
<td>-0.66523(-1.20)</td>
<td>-0.76469(-1.09)</td>
<td>-0.66880(-0.59)</td>
</tr>
<tr>
<td><strong>Penalty coefficient</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Penalty ( \gamma )</td>
<td></td>
<td>0.46910**(*2.71)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The coefficients in TABLE 2 show the effect of explanatory variables on the marginal utility of parking mode. The signs of all significant variables in models are as expected, and magnitudes of estimators have no big difference. We obtain improvements in model fit when moving from MNL to MMNL, CMNL and MMNLC, with high levels of random taste heterogeneity for parking price coefficients, where selected statistical distribution for random parameters of MMNL and MMNLC associated to parking cost and its cutoff is a constrained triangular distribution, which means the spread is constrained to be half of the mean here. Besides, some variables have no significant influence on parking mode choice behavior such as parking operation time, sex, income and reimbursement. No significance for parking operation time can be explained as parking is very convenient for parkers in most parking spaces, but we have no idea about why income and reimbursement are not significant, what should be checked further, because we originally thought these two factors should affect parking behavior to some extent. As for sex, we have reasons to believe that women are more concerned about parking cost for housekeeping considerations or money saving, but the fact proves we are wrong at least it is not the truth in Shanghai. These results have implications about how to improve garage parking service quality to attract parkers especially long parking duration parkers to park in garage parks and what the real factors influencing parkers’ choice are. Comparison of penalty magnitudes with corresponding attribute weights shows that the former outweigh the latter in magnitude. For instance, the mean coefficient for parking cost is -0.08839 below the upper cutoff, whereas the penalty parameter is -0.23944. This shows parkers’ aversion to parking cost that they deem excessive to some extent. Meanwhile variances of random parameters are significant at the 99% level, indicating parkers’ diverse acceptable level of parking cost.

5.4 Model Comparison

According to Prediction Success Indices (PSI) (32) which are summarized in TABLE 3, we find MMNL is superior to MNL, with MMNLC and CMNL the best two models. A test on non-nested choice models is then applied which is based on AIC (see TABLE 3) (33). Suppose there are two non-nested models 1 and 2, the former has \( k_1 \) variables, while the latter has \( k_2 \) variables to explain the same choice situation. Without loss of generality, we suppose \( k_1 \geq k_2 \). The probability that pseudo-\( \rho^2 \) for model 1 will be greater than that for model 2 is
asymptotically bounded by a function given in Eq. (11):

\[
\Pr\left(|\rho_1^2 - \rho_2^2| \geq Z \right) \leq \Phi\left(-\sqrt{2Z \cdot L(e) + (K_1 - K_2)}\right)
\]

(11)

where \( Z \) is the difference of pseudo \( \rho^2 \) between model 1 and model 2, which is assumed larger than 0; \( \Phi \) is the standard normal Cumulative Distribution Function (CDF), and resulting probability is the probability that model 1 is superior to model 2.

### TABLE 3 Model Comparison

<table>
<thead>
<tr>
<th>Model 1</th>
<th>PSI</th>
<th>Model 2</th>
<th>MMNL</th>
<th>MMNLC</th>
<th>CMNL</th>
</tr>
</thead>
<tbody>
<tr>
<td>MNL</td>
<td>0.0353</td>
<td>-2.2514/0.0122</td>
<td>-3.9837/0.0000</td>
<td>-4.1237/0.0000</td>
<td></td>
</tr>
<tr>
<td>MMNL</td>
<td>0.0378</td>
<td>N.A.</td>
<td>-3.2865/0.0005</td>
<td>-3.4548/0.0003</td>
<td></td>
</tr>
<tr>
<td>MMNLC</td>
<td>0.0389</td>
<td>N.A.</td>
<td>N.A.</td>
<td>-1.0651/0.1434</td>
<td></td>
</tr>
<tr>
<td>CMNL</td>
<td>0.0387</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
<td></td>
</tr>
</tbody>
</table>

Note: the former term is \( \Phi(\bullet) \) of Eq. (11); the latter term is the corresponding \( \Phi(\bullet) \), namely the probability that model 1 is better.

As discussed above, it can be concluded that MMNL, MMNLC and CMNL are all superior to MNL, and the latter two models namely MMNLC and CMNL which have no significant difference in goodness of fit are both better than MMNL.

### 5.5 The Relationship between Individual Characteristics and Cutoff Violation

To investigate the intrinsic link between individual characteristics and the number of violating parking price cutoff, a multiple linear regression model is estimated to determine whether a particular group is more sensitive to price cutoff in their decision process, where dependent variable is the number of parking price cutoff respondents violate in SP scenarios. Here backward selection regression is used to exclude non-significant variables, moreover, using correlation test to determine whether these variables are indeed to be excluded. Results are presented in TABLE 4:

### TABLE 4 Results of Multiple Linear Regression Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Dev.</th>
<th>t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>excluded</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>excluded</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.059</td>
<td>0.021</td>
<td>2.828***</td>
</tr>
<tr>
<td>Driving year</td>
<td>-0.072</td>
<td>0.025</td>
<td>-2.923***</td>
</tr>
<tr>
<td>Parking experience 1</td>
<td>-0.619</td>
<td>0.357</td>
<td>-1.736*</td>
</tr>
<tr>
<td>Parking experience 2</td>
<td>-0.668</td>
<td>0.282</td>
<td>-2.371**</td>
</tr>
<tr>
<td>Constant</td>
<td>2.148</td>
<td>0.678</td>
<td>3.168***</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.154</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.121</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observation number</td>
<td>318</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The fact that coefficient of age is positive shows older people are more insensitive to price cutoff than young people because older people have less money stress and do not like
walking long distance for health reasons, so they would rather pay more to park in curb park which is closer to the destination. In terms of driving year, unexperienced drivers are more likely to ignore cutoff during parking process for they are less informed and have less acquaintance about driving and parking like price change, and drivers who have preferences about parking type tend to be unacceptable to enormous price change, because they hate change which can be reflected from their stable parking mode preferences. Moreover, other variables such as sex and income have no impact on the number of cutoff violation. Given such results, it may help us to understand which group is more willing to break threshold defined by parkers themselves. Special care must be taken of constant, its significance means more individual characteristics or other socio-demographic statistics are helpful to the depth understanding of cutoff violation, and here only a first glimpse is provided.

6 PRICING

With regard to average occupancy rate of curb parking space, it is 93.20% in surveyed area which means raising curb parking price to reduce this indicator to 85% is necessary. Resting on parameter estimation result of MMNL and choice probability of curb parking RP data, namely 4.34% of curb parkers needs to be transferred to garage parking space (52.9% respondents choose curb parking in RP situation, so the amount needs to be transferred is $52.9\% \times (93.2\% - 85\%) = 4.34\%$), and curb parking choice probability ratio of parking rate before and after adjustment can be expressed as:

$$\frac{\hat{p}_c}{\hat{p}_c} = \frac{1}{R \sum_{i=1}^{R} \sum_{n=1}^{N} \exp \left[ \sum \theta' \left( X_{cn} - X_{cn} \right) + \theta' \left( F_{cn} - F_{cn} \right) \right]}$$

(12)

where $\hat{p}_c$ is the current probability of curb parking; $\hat{p}_c$ means the probability of curb parking after rate adjustment; $R$ is sampling times of random parameter; $n$ indicates parker; $\theta$ is estimator matrix of parameters except price; $\theta_{pr}$ represents the $r$th draw of price parameter estimator; $X_{cn}$ and $X_{cn}$ are variable matrix of curb and garage parking respectively except price; $F_{cn}$ stands for garage parking price; $F_{cn}$ indicates curb parking price before rate adjustment; $F_{cn}$ denotes curb parking price after rate adjustment, $F_{cn} = (\text{COST}_{cn} \text{ COSTT}_{cn})$; $\text{COST}$ is price variable; $\text{COSTT}$ is price threshold variable; $\varphi$ is the probability of curb parking needs to be transferred.
FIGURE 2 Utility Difference Between Models with and without Cutoff.

FIGURE 2 shows the difference between MNL, MMNLC and CMNL intuitively. For convenience of description, the price cutoff is set as 10 RMB/h. One point needs to be noted is that all models have similar utility changing trend before reaching the cutoff point, that is, the ability of three models to explain the choice behavior are identical, while the situation is quite different after that point, namely MNL (models without cutoff) is easy to underestimate the utility change after reaching the cutoff point, which will overestimate the price increment to reach target of 85% occupancy rate. According to Eq. (12), decrement of curb parking probability induced by increasing curb parking price is calculated:

### TABLE 5 Curb Parking Rate Increment to Reach the Goal of 85% Occupancy Rate (RMB/h)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>MNL</th>
<th>MMNL</th>
<th>MMNLC</th>
<th>CMNL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average occupancy rate</td>
<td>1.896</td>
<td>1.788</td>
<td>1.202</td>
<td>1.186</td>
</tr>
<tr>
<td>Occupancy rate of peak hour</td>
<td>3.684</td>
<td>3.496</td>
<td>2.344</td>
<td>2.312</td>
</tr>
</tbody>
</table>

No matter what kind of scenario we study, the fact that the rate increment obtained from model without cutoff is almost half time bigger than the value obtained from models with cutoff, indicating ignoring cutoff will cause an upward bias. This phenomenon is logical and easy to explain: parkers are more inimical to the rate increment when it exceeds the threshold which is regarded as a “watershed” of decision behavior, namely the penalty of violating threshold is more severe with a larger coefficient. To cope with this issue, it is necessary to consider cutoff to get a more accurate price adjustment scheme.

### 7 SUMMARY AND CONCLUSIONS

This paper has investigated the issue of parking type choice incorporating price cutoff and proposed reasonable parking price adjustment scheme. At the beginning, a simple statistical analysis of parking type choice influence factors which are chosen according to existing research and parkers’ characteristics is done before the formal study. After that, we have contrasted two types of models to identify cutoff issue, with one based on the model proposed by Swait and further extended into MMNL framework, while the other one drawn from Martinez’ research with a slight simplification. Both models show that cutoff does have an important
influence on parkers’ decision-making. However, there is a little bit inconsistency between
two models in terms of parameter estimation. Results show that marginal utilities of attributes
in parking type choice are not constant over the whole range of values presented, and signifi-
cant improvement (see PSI and non-nested choice model test) can be made by introducing
cutoff variables.

In relation to the point about identifying the group who is more likely to violate cutoff, a
multiple regression model is undertaken to check the relationship between the number of vi-
olating cutoff stated by parkers and their characteristics, and the results provide conclusive
evidence to suggest that age, driving year and parking experience play an important role in
tolerance degree of cutoff for parking price. Curb parking rate increment is then calculated by
four models to achieve the goal of 85% occupancy rate. Results provide some implications
for policy makers about parking price increment which may overestimated by models without
cutoff.

This paper focuses on the impact of parking price and its threshold on parking mode
choice, while weakens other factors’ research such as the influence of parking information
and trip purpose on parking mode choice behavior, and this is a promising research topic. In
ongoing research, further investigation of occupancy rate for different time periods to propose
a more reasonable and flexible parking pricing scheme along with time is encouraged, which
could contribute to the maximizing use of parking space resources.

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