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Research Article

Commuter Departure Time Choice Considering Parking Space Shortage and Commuter's Bounded Rationality

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In order to better understand how commuters decide departure time considering parking space shortage and commuters' bounded rationality, the reference point hypothesis of prospect theory is applied in the departure time decision-making. Commuter personal perception differences, the road congestion situation, destination parking status, and other factors were also analysed in the influence of commuter departure time choice. Based on prospect theory, an experiment was designed to investigate the intention of the commuter departure time choice. The experiment results show that the commuter's travel satisfaction and the departure time choice of the next trip are related to the parking space residual status after the commuter arrives at the destination. The satisfaction degree of the commuter is reduced, with the decrease of the remaining parking spaces. If the commuter is satisfied with the travel result, the commuter's departure time of next trip tends to be later. In the case of illegal parking, different penalty measures may lead to different decisions of next departure time choice. A commuter tends to depart earlier when more severe punishment for illegal parking is enforced. The research results can reveal to some degree the travellers' departure time choice behaviour when they face the risk of no parking spaces and provide a theoretical and practical support for parking management and car travelling decision.

1. Introduction

Along with economic development and urbanization, the amount of private cars in China has rapidly increased, which leads to hard parking, traffic congestion, emissions, and other transportation problems [1, 2]. One-third of the traffic congestion is created by cars searching for parking lots [1]. Therefore, it is of significant importance to promote urban sustainable transportation through controlling car ownership and use as well as improving the public transport accessibility. However, in the absence of other alternative travel modes for car-driving travelers, and when the parking supply near the destination is insufficient, it is necessary to properly select the departure time according to the parking space supply situation, that is, to ensure that there is a parking space and not to arrive too early [3]. The departure time decisions of commuters are of importance to the analysis of traffic control and to the study of peak-period traffic congestion [3, 4].

A variety of literature has focused on the departure time decisions of commuters especially the auto travelers. Thorhauge [5] analyzed the peak morning traffic data of Copenhagen and found that arriving at the company on time occupied a large proportion of the travel purpose, shorter travel time also had a significant impact on the departure time choice, and different travel purposes led to different choices. Paleti et al. established a time value model for departure time choice [6]. The analysis of the travel data of Jerusalem residents shows that, not only economic factors, travel purposes have an impact on time value, but different travel model scenarios also have an impact on time value [6].

Actually, the travel choices of travelers may be influenced by factors such as personal habits and perceived limitations of life; individual commuter behavior is not completely rational, but bounded rational for an acceptable outcome [7]. Studies by Mahmassani et al. [7] show that when the

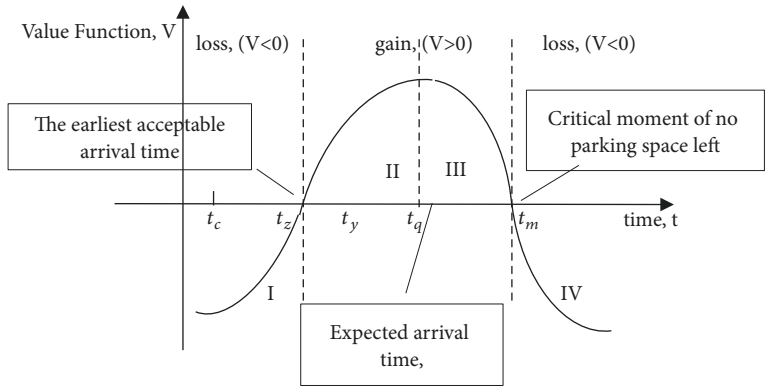

Figure 1: Value function of departure time choice.

traveler's choice behavior is within a satisfactory time range (indifference band) for acceptable results, the traveler's next trip will not change the departure time; otherwise, it will change. This satisfactory arrival time range is an important basis for the traveler to choose the departure time. In the perspective of bounded rationality, Xiong [8] established a departure time choice model considering road pricing and uncertainty. Based on this model, the dynamic evolution characteristics of road networks were analyzed. De Moraes [9] compared the expected utility theory, prospect theory, and regret theory. The results show that prospect theory is more suitable for predicting travel choice behavior than expected utility theory, and regret theory is the opposite. Zhang et al. [10] established a departure time and route choice model based on multiple reference points. The departure time and travel route choice data of 1872 travelers considering dynamic travel information was obtained through the survey in May 2008 in Beijing, and the model validation was tested. In addition, studies [11] have shown that the traveler's perception of travel time is a time interval rather than a certain value, and the traveler chooses the departure time based on this time interval.

In summary, the existing research focused on the factors affecting travelers' departure time in the perspective of bounded rationality. However, these studies do not involve the choice behaviors under specific conditions such as the destination parking space supply situation and if auto drivers cannot stop in the legal parking space will be subject to penalties, and so on. In reality, with the development of the economy, the problem of insufficient parking space and hard parking has become a serious issue in urban transportation. However, the existing research of departure time choice has not considered the above factor, resulting in the inconsistency between existing research and actual life.

Based on the prospect theory, this paper considers the actual situation of the commuter's perception error of travel time and constructs the departure time choice model for the commuter who may be worried that the parking space is insufficient and illegal parking will be punished. The research results can provide suggestions and guidance for the relevant policies, help to alleviate traffic congestion, and promote the sustainable development of urban transportation.

2. Research Methodology

In view of the research questions proposed above, Stated Preference (SP) survey is carried out to obtain the departure time choice behavior data considering road traffic congestion status, destination parking space supply status, and different penalty measures. According to the survey data, a commuters' departure time choice model is established.

2.1. Prospect Theory. Individual decision-making is divided into two phases in prospect theory: the editing phase and the evaluation phase. In the editing phase, decision-maker organizes and analyzes the results of various options; then, in the evaluation phase, the decision-maker evaluates the results obtained in the editing phase and selects the highest value plan (the largest prospect value) as the implementation plan.

According to the theoretical framework of the prospect theory, and based on the previous research [4, 12, 13], two reference points will be set in the paper, a segmented value function of departure time choice of auto commuter is postulated as shown in Figure 1. The first reference point is the commuter's acceptable earliest arrival time, and the second point is the critical moment when all the parking spaces are occupied and there are no legal parking spaces left at the destination. When the commuter's predicted arrival time is between the two reference points (the earliest arrival time and the critical time when the parking space is insufficient), the travel result is considered to be profitable, and the commuter will not change his/her departure time in the next trip. When the traveler's predicted arrival time is outside the range of the two reference points, the travel result is considered to be lost, and the commuter will consider adjusting the departure time for the next trip.

In Figure 1, t_c is the commuter's chosen departure time; t_z is the earliest acceptable arrival time of commuter; t_q is the commuter's preferred arrival time (PAT); t_m is the critical moment when all the parking spaces are occupied. In addition, t_y is the commuter's predicted arrival time based on the travel routes given by the experiment, and $t_y = t_c + \theta_r t_f$, where t_f is the travel time at free flow speed and θ_r is traffic congestion factor.

It can be seen that t_z and t_m are two reference points and t_q is the expected arrival time which is a pseudo reference

point. When the commuter arrives before t_z ($t_y < t_z$), it is considered a loss, and the value function is negative. When the traveller arrives between t_z and t_m ($t_z < t_y < t_m$), it is considered to be profitable, and the value function is positive; when the traveller arrives later than t_m ($t_y > t_m$), it is considered to be loss, and the value is less than 0. If $t_y < t_q$, it is defined as early arrive; if $t_y > t_q$, it is defined as late arrive. Area I means $t_y < t_z$, area II means $t_z < t_y < t_q$, $t_q < t_y < t_m$ is area III, and $t_y > t_m$ means area IV. Areas II and III are symmetrical or asymmetrical depending on the value of t_q.

2.2. Model Construction. According to the previous theoretical analysis [4, 12, 13], the model is a segmentation model containing two reference points. At the same time, consider the characteristics of the traveller's perception error of the predicted travel time. In real life, the traveller's perception of the predicted travel time varies from person to person, not a certain value, but fluctuating up and down on the basis of this value. Factors such as road congestion, the time of searching for parking spaces in the parking lot, and status of left parking spaces at the destination are also considered. The model formula is expressed as follows:

$$V(t) = \begin{cases} V_1(t) = \beta_1 \left(t_z - t_y\right)^{\alpha_1} + \varepsilon_1, & t_y \le t_z \\ V_2(t) = \beta_2 \left(t_y - t_z\right)^{\alpha_2} + \varepsilon_2, & t_z < t_y \le t_q \\ V_3(t) = \beta_3 \left(t_m - t_y\right)^{\alpha_3} + \varepsilon_3, & t_q \le t_y < t_m \\ V_4(t) = \beta_4 \left(t_z - t_y\right)^{\alpha_4} + \varepsilon_4, & t_y \ge t_m \end{cases} \quad (1)$$

where β_i ($i = 1, 2, 3, 4$) are the weighting factors of the values of the traveller's gain or loss. In the loss area, the greater the absolute value, the higher the sensitivity to loss; in the income area, the greater the absolute value, the higher the sensitivity to the return. And, in the loss area, $\beta_i < 0$; in the income area, $\beta_i > 0$. α_i ($i = 1, 2, 3, 4$) are risk pursuit coefficients, which have a value range of (0,1), and the larger the value, the more the risk pursued. ε_i ($i = 1, 2, 3, 4$) are the travellers' perception errors of the path travel time, and they obey the double exponential distribution, and the expected value of ε is zero.

According to formula (1), if the value function $v_i(t) > 0$ when the traveller arrives, that is, when the traveller's arrival time lies in area II or area III, the traveller's travel value is profitable, and the next trip does not change the departure time. Its probability is expressed as follows according to statistical knowledge:

$$P(V_2 > 0) = \exp\left(-\exp\left(\omega_2\left(\beta_2\left(t_y - t_z\right)^{\alpha_2} + \eta_2\right)\right)\right) \quad (2)$$

$$P(V_3 > 0) = \exp\left(-\exp\left(\omega_3\left(\beta_3\left(t_m - t_y\right)^{\alpha_3} + \eta_3\right)\right)\right) \quad (3)$$

Similarly, when the traveller's arrival time is in area I or IV, the value function is negative, and the travel result is loss. The traveller will change the departure time on the next trip. The probability is expressed as follows:

$$P(V_1 < 0) = \exp\left(-\exp\left(\omega_1\left(\beta_1\left(t_z - t_y\right)^{\alpha_1} + \eta_1\right)\right)\right) \quad (4)$$

$$P(V_4 < 0) = \exp\left(-\exp\left(\omega_4\left(\beta_4\left(t_y - t_m\right)^{\alpha_4} + \eta_4\right)\right)\right) \quad (5)$$

In (2)-(3), ω_i and η_i are the parameters of ε_i obeying the double exponential distribution; that is, ε_i obey the double exponential distribution with the parameter (ω_i, η_i). η_i is the most frequent value; the expected value of ε_i is $E(\varepsilon_i) = \mu_i + Y/\omega_i$, where Y is the Euler-Mascheroni constant (≈0.577) [14].

3. Survey and Data Analysis

3.1. Survey Design. The travel behaviors of commuters are investigated by questionnaire through the scenario experiment in the paper. The survey contents mainly include the personal characteristics of the travelers (age, gender, income, etc.), social attributes (occupation), and the intention of travelers to choose the departure time in a given scenario.

Scenarios assume that urban commuters need to drive from home to work every day, and the travel path is fixed. The company's working time starts at 9:00 am; there are 150 parking spaces in the parking lot near the company, but the parking demand on the working day exceeds 150. The departure time selection information that needs to be investigated mainly includes the following: (1) the departure time selected according to the above scenario; (2) expected time to arrive at the company parking lot; (3) whether there are changes to the departure time when it is told there is a car entering the parking lot and there is no parking space; (4) whether to change the expected time to arrive at the parking lot if it is told there are some cars entering the parking lot and at what time there are no parking spaces; (5) acceptable earliest arrival time; (6) acceptable latest arrival time. At the same time, the survey conducted a scenario design for the situation where there was no parking space after traveler arrives at the destination. The experimental scenarios and problems contain the following: (1) Suppose there are no parking space when you arrive at the parking lot, and you will be fined 200 yuan for illegal parking. How long will you depart in advance for such punishment? (2) Suppose there will be no parking space when you arrive at the parking lot, and the illegal parking will be towed away. For such punishment, how long will you depart in advance for the next time?

During the experiment, the respondents were provided with a path prediction time from 6:00-9:00 in the interval of 20 minutes. The walking time from the parking lot to the company is negligible, considering that the road congestion condition changes with time, therefore, the path predictive time corresponding to different departure time periods is different, and the general trend is that the path travel time is gradually increased and then gradually decreases after reaching the apex.

The earlier the traveler arrives at the parking lot, the more the parking spaces remain in the parking lot, and the shorter the searching time is. On the contrary, the fewer remaining parking spaces, the longer time for search parking space. Participants select the departure time according to the given situation and fill in the relevant questions. After the selection is completed and according to the selection results of all the subjects, the participant is informed that the selection is stopped when the remaining parking space is 0, and then the next round of testing is performed.

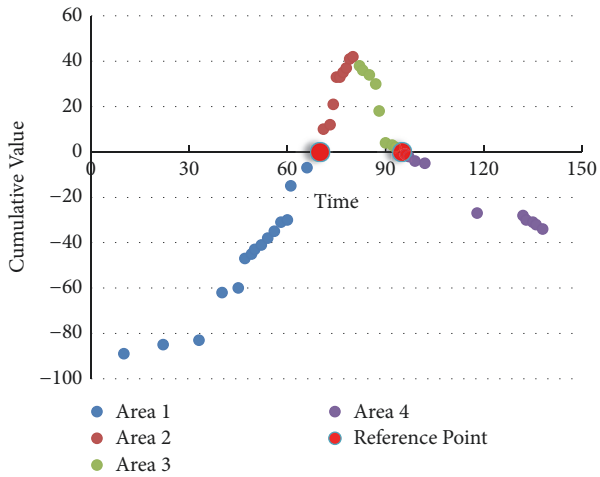

Figure 2: Cumulative value distribution of departure time decision.

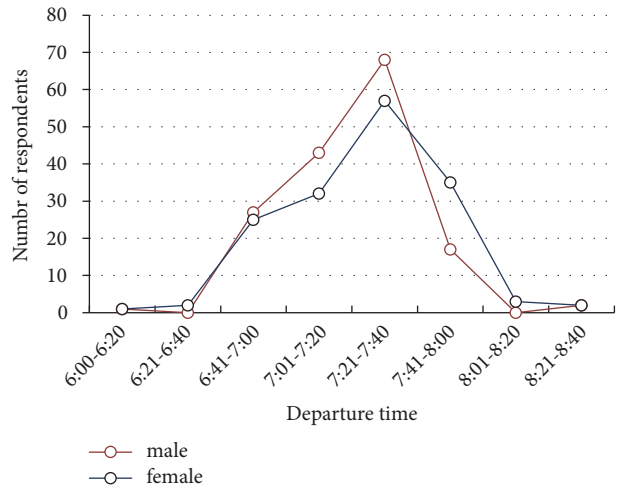

Figure 3: Departure time preference of different genders.

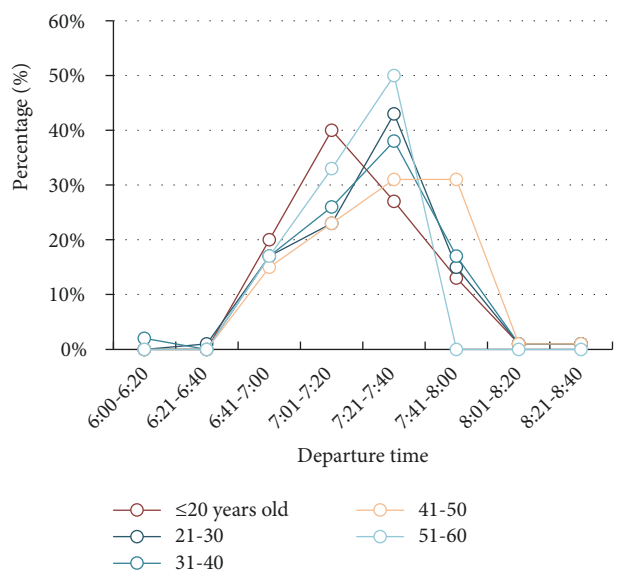

Figure 4: Departure time preference of commuters at different ages.

The purpose of this survey is to collect effective information such as characteristics and tendencies of commuters' departure time choice, personal attributes, and factors affecting the departure time choice. The survey recovered 346 samples and 311 valid samples. The ratio of male to female is 1.6:1.5, which is consistent with the statistical characteristics of small samples.

3.2. Survey Data Analysis

3.2.1. Value Function Analysis. Firstly, the value function and the concavity are examined by simple graphs. The concavity and convexity of the value function are tested according to the cumulative distribution curve of the traveler whether or not change the willingness of the departure time.

Areas I and IV in Figure 2 are lost areas, in which travelers change departure time in the next trip. The income area (area II and area III) shows the data that the traveler does not change the departure time for the next trip and the traveler does not change the departure time also indicating that travel result is profitable and satisfied for the trip. Figure 2 shows the cumulative values of all the respondents, and each point represents one respondent's cumulative value. The abscissa is the relative time between the arrival time and the reference point corresponding to the departure time of the traveler, and the ordinate is the cumulative value. In order to better understand and analyze the departure time choice behavior, the cumulative values of region I and region IV are taken as negative values. Although the cumulative distribution curve is not exactly equivalent to the value function curve, the probability that the traveler will change the departure time in next trip is linearly related to the value function of the traveler's arrival time. The cumulative distribution curve of arrival time is consistent with the concavo-convex change trend of the value function in theory [4].

As can be seen from Figure 2, the loss area (area I and area IV) curves are convex, and the income areas (area II and area III) curves are concave. The data curves are consistent with the value function form of the prospect theory [4, 12, 13].

3.2.2. Preference Analysis of Departure Time Choice. Seen from Figure 3, both male and female commuters peaked between 7:21 and 7:40, and there are more women than men during the time range. The number of female commuters is higher than male commuters before 7:40, and there are more male commuters after 7:40. This shows that female commuters are more inclined to depart earlier than male commuters.

In Figure 4, the abscissa is the departure time period. In order to facilitate the preference analysis of the commuter departure time of different age groups, the percentage of the total commuters in different departure periods is taken as the ordinate. Seen from Figure 4 that, among the commuters of different ages, the departure time choices of the 21-60 age group commuters peak in the 7:21-7:40 period, while the commuters under the age of 20 reach the peak within 7:01-7:20 period. Other than that, there is no significant difference in the departure time choices for commuters of different ages.

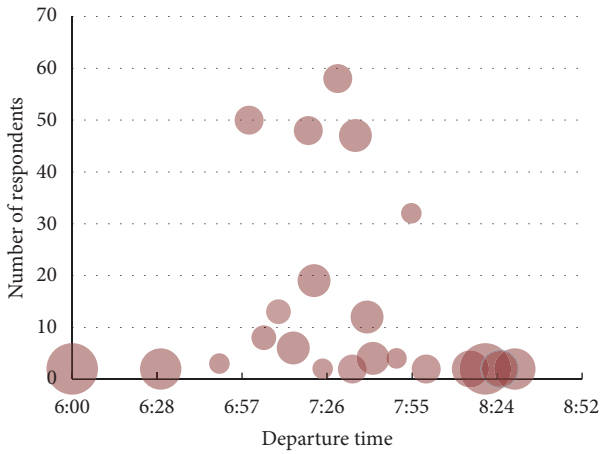

Figure 5: Cumulative distribution of departure time decision.

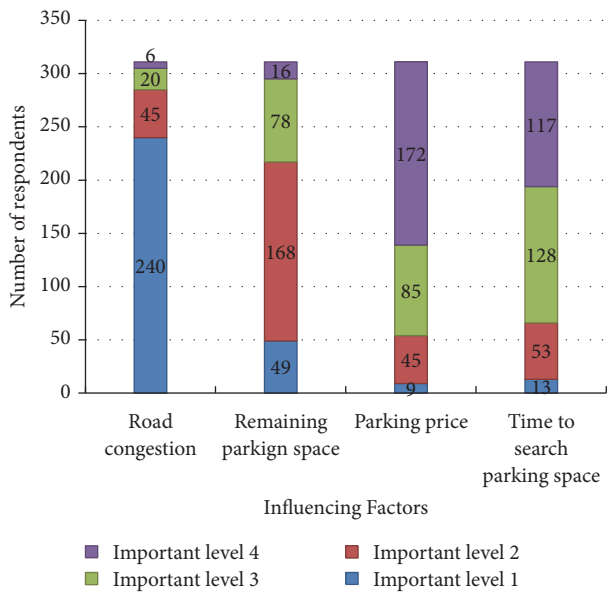

Figure 6: Importance levels of factors that affect departure time.

In Figure 5, the size of the scatter plot represents the average income level of the commuters. As can be seen from the figure, the departure time of most auto commuters is concentrated in the 6:41-8:00 period, during which there is no significant difference in commuters' income. The commuters who choose to depart before 6:41 and after 8:00 have significantly higher income than the commuters who depart in the time range of 6:41-8:00.

3.2.3. Influencing Factors Analysis of Departure Time. In Figure 6, the key factors of road congestion, the status of remaining parking spaces, parking price, and the searching time for a parking space are selected for analyzing the impacts on departure time choice behavior.

In the questionnaire, the auto commuter needs to rank the factors that affect the choice of the commuter's departure time. It is defaulted that the importance level 1> importance level 2 > importance level 3 > importance level 4. In Figure 6,

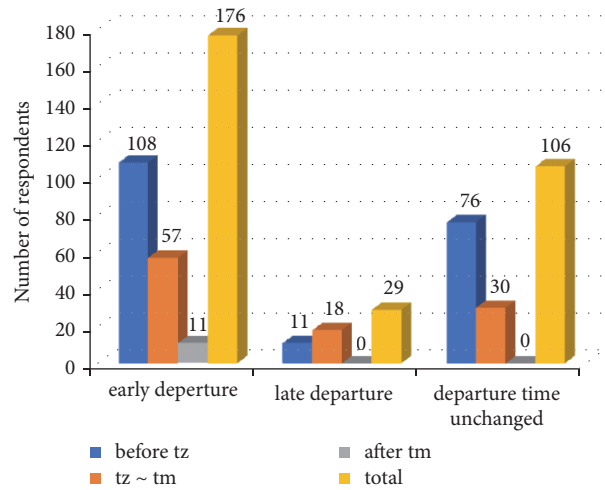

Figure 7: The impact of insufficient parking spaces on expected arrival time.

a statistical analysis is performed on the number of people selected for each factor's importance. Taking the factor of road congestion status for an example, most participants select importance 1 that means the "road congestion status" is the most important factor for commuter departure time choice and the others are sorted in order.

As can be seen from Figure 6, the ranking results of the factors affecting the commuter's departure time choice are as follows: congestion status > parking space remaining > parking search time > parking price. The ranking results of commuters of different genders are consistent with the results of Figure 6. However, among the auto commuters of different income levels, the commuters with the monthly income level 6000-8000 and more than 10000 RMB rank the influencing factors as follows: congestion status > parking space remaining > parking charge price > parking search time, which is intuitively different from Figure 6 because people with higher income would care less about parking fees. Perhaps the sample size and survey respondents lead to some deviations. The commuters of other monthly income levels have the same ranking results of influencing factors as Figure 6.

In Figure 7, the expected arrival time of experimenters is segmented and integrated. The integration period is as follows: before t_z (the earliest acceptable arrival time), between t_z and t_m (the critical moment when all the parking spaces are occupied), and after t_m. The commuter fills in his/her expected arrival time according to the experimental scenario, and when all the commuters have chosen, they will be informed of the time when there is no parking space left. The commuter decides whether the departure time of the next trip will be earlier or later or remain unchanged based on the selected departure time and the critical moment without parking space left.

It can be seen from Figure 7 that when considering the shortage of parking spaces, the number of commuters who expect the earlier arrival time in the next trip is the most, and the departure time is the same (before t_m) among the

Table 1: Calibration results of model parameters.

Reference point	β_1	β_2	β_3	β_4
8:25-8:45	- 0.177	0.394	0.392	-0.360
8:25-8:50	- 0.177	0.390	0.322	-0.300
8:25-8:55	- 0.177	0.234	0.267	-0.360
T=2.061		$\rho^2 = 0.299$		

Note: the sample size is 311.

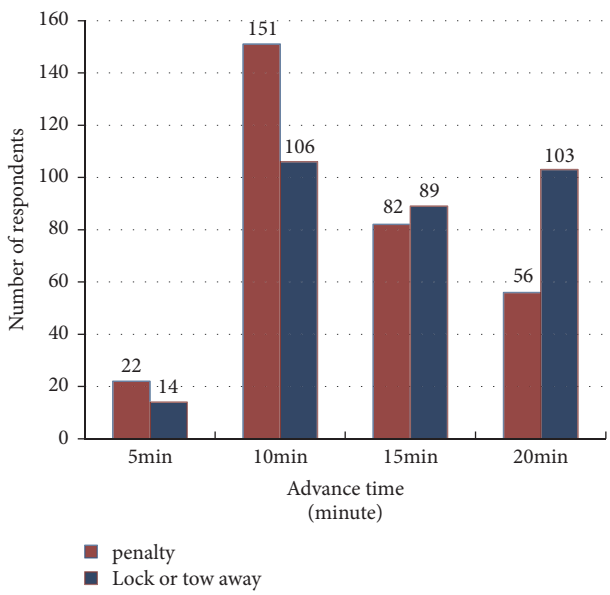

Figure 8: The effect of punishment on the department time.

commuters who keep the expected arrival time unchanged next trip or expect later arrival time. That is, when the commuter considers that the parking space is insufficient, the expected arrival time is advanced to avoid the risk of no parking space.

3.2.4. Impacts of Penalty Measures on Departure Time. If there are no parking spaces near the destination in real life, auto commuters often have the luck and choose to park illegally. This experiment sets 2 scenarios.

Scenario 1. If there is no parking space this time, the illegal parking will be fined and how early will the auto commuter depart next trip?

Scenario 2. If there is no parking space for this trip, the penalty is to lock or tow the illegal parking car and how early will the commuter depart next trip?

As can be seen from Figure 8, more auto commuters choose to depart 5 or 10 minutes earlier next time if the punitive measure is penalty. While more commuters choose to depart 15 or 20 minutes earlier next time, if the punitive measure is locking and towing the illegal-parking car. It is obvious that when the penalty level increases, commuters tend to choose earlier departure time to avoid penalty risk.

4. Model Calibration and Discussion

The model parameters β_i are calibrated using the maximum likelihood estimation method [14]. β_i in loss area indicates the commuter's sensitivity to loss and indicates the commuter's sensitivity to revenue in the income area. The commuter's preferences can be understood by the calibration results of β_i. Many studies use the calibration results ($\alpha_i = 0.88$) of Kahneman and Tversky [12]. At the same time, the selection of reference points refers to the previous research and the scenario hypothesis of this paper, which are taken as follows: 8:25-8:45, 8:25-8:50, and 8:25-8:55, where 8:25 is the earliest acceptable arrival time of the commuter; 8:45, 8:50, and 8:55 are the critical moments when all the parking spaces are occupied. Actually, the commuter's departure time is influenced by the arrival time, the remaining parking spaces at the destination, and the searching time of finding a parking space. The fewer the remaining parking spaces at the time of arrival, the greater the cost that the commuter may pay, and the commuter will consider an earlier departure next time based on the risk of loss.

This paper takes three sets of reference points to analyze the travel behaviors of commuters. The change of the reference point indicates the change of the parking space supply rate at the destination; that is, the later the critical time of the parking space is insufficient, the higher the supply rate of the remaining parking space at the destination is; the earlier the critical time, the lower the parking space supply rate, and the tighter the parking space is. The calibration results are shown in Table 1.

According to the prospect theory, when the value function is positive, the travel result is in the income area, and the value of β is greater than 0; similarly, when the value function is negative, the value of β is less than 0.

Seen from Table 1, $\beta_2 > 0$ and $\beta_3 > 0$ indicate that the value function is positive between the two reference points, and the travel result is profitable. Similarly, $\beta_1 < 0$ and $\beta_4 < 0$ indicate the travel result is lost. The analysis results are consistent with the theoretical principles of the prospect theory [4, 12, 13]. As the reference point changes, β_1 does not change, indicating that the commuter's sensitivity to the loss of early arrival has not changed.

When the reference point is 8:25-8:45, it is obvious $\beta_2 > \beta_3$, and it means that the commuter prefers to earlier arrival, but the difference is not significant, indicating that this tendency is not obvious. When the reference point is 8:25-8:50, we have $\beta_2 > \beta_3$ and the difference is significant, indicating that the commuter tends to avoid the risk of no parking space left by earlier arrival, and this tendency is obvious. When

the reference point is 8:25-8:55, the parameters results show that $\beta_2 < \beta_3$ and indicate that commuters are more likely to arrive later. As the critical time of all the parking spaces are occupied, the values of β_2 and β_3 are gradually reduced, and the sensitivity of the commuter to the income value in the area is gradually reduced. Also, auto commuters tend to be early arrival and then gradually tend to be later arrival. β_4 has the same value when the reference points are 8:25-8:45 and 8:25-8:55, and its value is smaller when the reference point is 8:25-8:50. That is, the commuters with reference points of 8:25-8:45 and 8:25-8:55 are more sensitive to late arrivals without parking spaces than when the reference point is 8:25-8:50.

5. Conclusions

(i) The commuter departure time choice changes with the parking space supply rate. The sensitivity to the loss of early arrival does not change with the parking space supply rate; in the early arrival income area and the late arrival income area, as the parking space supply rate decreases, the travel income sensitivity of the auto commuter decreases. At the same time, commuters tend to change from early arrival to late arrival.

(ii) After arriving at the destination without parking spaces, penalties will cause commuters to change the departure time of the next trip. The heavier the punishment, the more likely the commuter will depart earlier next time.

(iii) The two most important factors affecting the commuter's departure time choice are road congestion and remaining parking space status.

(iv) The research results can reveal to some degree the travellers' departure time choice behaviour when they face the risk of no parking spaces and provide a theoretical and practical support for parking management and car travelling decision.

(v) There are still some problems that need to be further studied and solved in this paper. For example, whether the illegal parking punishment measures will lead auto commuters to choose other travel modes should be considered in the future. The model in this paper does not consider the commuter's dependence on the predicted travel time and the learning process, and the model based on this process needs further study.

Data Availability

The survey data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

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

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