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Which Is More Effective in Guiding Households to Choose Bus Travel–A Transit Subsidy Policy or Discount Policy?

TIANCHAO GUAN [1,2], **AND TONGFEI LI** [3]
[1]Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, Beijing Jiaotong University, Beijing 100044, China
[2]State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing 100044, China
[3]Beijing Key Laboratory of Traffic Engineering, Beijing University of Technology, Beijing 100124, China

Corresponding author: Tianchao Guan (14114195@bjtu.edu.cn)

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ABSTRACT The continuous increase in the number of private cars has caused an imbalance in the travel of cars and buses. This phenomenon has become a bottleneck restricting urban transportation economy and sustainable development. This paper examines the effectiveness of policy options in motivating travelers to choose buses instead of cars. Using of reference dependence describes mode choice behaviors with two attributes under different public transit policies in uncertain conditions. At the same time, we also consider using the bus fare concession strategy to guide the traveler to reasonably choose the bus travel, and establish a bi-level programming model to optimize the bus fare proportions. Among them, the lower-level planning considers the two attributes impact of traffic policy on travelers' decision to bus travel. Using the upper-level planning, the optimal fare preferential proportion for different policy decisions is decided considering the lowest total system cost. The study highlights that the transit subsidy policy can be employed to guide travelers to choose bus travel preferentially. Model effectiveness is verified using numerical examples. The model is indispensable for the implementation of future traffic demand management strategies.

INDEX TERMS Bus travel, reference dependence, transit discount policy, transit subsidy policy.

I. INTRODUCTION

Traffic demand management has been employed to address to release traffic congestion problems since the 1960s. Traffic demand management aims to alleviate traffic congestion by influencing households' travel behavior through various policies, regulations, and modernized information equipment. While, with the development of the economy and the improvement of family living standards, we have concluded that the travel demand for private cars has gradually increased. Taking Beijing as an example, the capital of China, it experienced exponential growth in the total number of private cars ownership, from 5.591 million in 2014 to 6.084 million in 2018 [1]. This phenomenon has caused the imbalance between buses and private cars and has become a bottleneck restricting urban transportation economy and sustainable development. Likewise, it also brings new questions and challenges, especially to managers who advocate bus travel. In principle, the manager sometimes ignores the traveler's choice behavior when implementing the traffic policy, which leads to the failure to achieve the expected results. If we want to achieve the expected results, managers need to analyze the impact of this policy on the traveler's choice behavior. In practice, travel choices are also affected by a variety of uncertainties, such as transportation policies, travel purposes, travel distance, travelers' age, income, and travel expenses, etc. In the choice, there may be no completely rational behavior for travelers. So, reference [2] first proposed the expected utility theory (EUT) or random utility theory (RUT) to discuss the choice behavior. They generally believe that travelers are fully aware of the probability of each mode choice occurring. They also assume that travelers are

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TABLE 1. Research related to choose behavior.

Contents	Author	Year	Main results
Research on the influence of loss avoidance attribute	Thaler [19]	1980	It demonstrates that consumer choice behavior has loss avoidance.
	Knetsch [20]	1989	There is an essential difference between the price and the asking price considered loss avoidance.
	Tversky & Kahneman [15]	1991	Review and comment on evidence of loss avoidance.
	Bell & Latin [20]	2000	The loss avoidance behavior of consumers in the choice of price attributes does not exist.
	Wang Wei et al [22]	2013	Travel time stochastic user equilibrium based on loss avoidance.
	Bao Yue et al [24]	2014	User Equilibrium of tradeable credit based on loss avoidance.
Research on the influence of reference point attributes	Johnson et al [25]	1996	Reference points are important for recruiters.
	Swenson et al [26]	1996	The reference point plays a pivotal role in brand marketing of marketing strategy.
	Ordonez [27]	1998	Product price-quality impact reference price.
	Cuijpers et al [28]	2001	The reference point has a certain influence on external decision-making policies for production decision-makers.
	Kopple & Joan [29]	2003	External price information and external price present U-shaped relationship.
	De Borger & Fougera et al [34]	2008	The impact of reference points on path selection behavior is analyzed in detail.
	Avineri E et.al [32,33]	2009	The influence of reference points on the stochastic network equilibrium is analyzed.
	Xu Hong li et al [35]	2015a	The influence of the reference point on the distribution of the congestion toll road network is analyzed.
	Wang Wei et al [23]	2015	Impact of reference points on the bottleneck model of multi-stage charging.
	Xu Hongli et al [36]	2015b	The influence of reference points on the path choice behavior of day-to-day.
	Li Tongfei et.al [37]	2017	The influence of reference points on the choice behavior of residents.

based on the choice of minimum travel cost or maximum travel utility. However, this basic assumption was verified by behavioral economists and empirical economists using experimental methods to verify its irrationality [3]–[6]. Subsequently, reference [7]–[13] also proved that travelers are differences in personal cognitive and logical reasoning. It will be impossible to understand the exact probability of each choice. And it is necessary to have a reference point in the choice. So, reference [14], [16] and other scholars combined the personal perception characteristics and the reference point to propose prospect theory (PT) and cumulative prospect theory (CPT). However, as travelers increase and become familiar with the travel environment, reference dependencies will gradually diminish for travelers. Likewise, travelers also mistakenly underestimate the probability of a large probability event or overestimate the probability of a small probability event. In order to avoid the dependence on the travel environment and the error of travel probability estimation, reference [15], [17], [18] proposed the reference dependence theory (RDT).

There are two basic attributes of loss avoidance and a reference point in RDT. The reference point attribute pays more attention to the traveler's choice preferences, ignoring the opportunity cost loss and risk attitudes. Rarely, the loss avoidance attribute can better explain the opportunity cost loss and risk attitudes. In addition, RDT can describe both uncertain and deterministic scenarios and is more universal. Therefore, when the two attributes are determined, the result of the mode choice will be determined. TABLE 1 lists the related studies of two attributes of RDT at home and abroad.

TABLE 2. Contributions to literatures.

Citation	Transportation Modes	Transportation Policies	The Attributes of RDT	Solutions
Reference [14,15,22,24]	No	No	Loss avoidance	Analytical
Reference [38-40]	Two modes	No	No	Numerical
Reference [23,34-37]	No	No	Reference point	Analytical
Reference [41-43]	Two modes	Subsidy policy	No	Analytical& Numerical
This paper	Two modes	Two policies	Two attributes	Analytical & Numerical

As can be seen from TABLE 1, the two attributes are widely used in various fields. Most of these studies only focus on one of the two attributes which in path selection, residential choice, road toll, road network design. Furthermore, existing research pays more attention to the network and ignores the impact of travel policy on choice behavior. Reasonable travel policies are of great significance in guiding bus travel. On the one hand, managers who advocate bus travel can accurately obtain the behavior characteristics of travelers for global control. On the other hand, travelers can reasonably arrange their own travel through transportation policies to avoid unnecessary travel. In this study, we characterize two attributes of RDT and traffic policy to reveal the choice behavior in a continuum model framework. We compare the effectiveness of the two policies through traveler's choice behavior and provide theoretical support for the effective implementation of the policies.

TABLE 2 summarizes the differences among the related studies together with these papers' contributions.

The paper proceeds as-is: the next section, the paper presents a basic model for travelers based on transit subsidy and discount policy. Section 3 describes a bi-level program and the solution algorithms apply in the model. Finally, numerous studies and conclusions are discussed in Section 4 and Section 5.

II. BASIC CHOICE MODEL CONSIDERED TRANSPORTATION POLICIES

In this section, we propose a model with two transportation modes to illustrate which policy is more effective for bus travel, which is a modification of the stylized behavioral economics model [14], [15], [22], [23], [30], [31]. In this model, two traffic policies are considered, namely, the bus fare subsidy policy and bus fare discount policy. Travelers are willing to choose the best mode to travel to maximize their utility within their travel budget. Managers are more interested in knowing which policies are more effective in guiding travelers to choose buses. To facilitate the presentation of basic ideas without loss of generality, Section 2.1 lists some of the basic assumptions and symbols employed in this paper.

A. ASSUMPTIONS AND SYMBOLS

In this model, we assume that total travel demand is random and the total travel demand distribution is a normal distribution with a mean of x and variance of cvx. And, the travel demand distribution for each mode can also be expressed as $X_i^j \sim N\left(x_i^j, \left(cv_i^j \cdot x_i^j\right)^2\right)$. Among them, x_i^j is mean and cv_i^j is variance. Furthermore, we take the expectation on both sides of $X = \sum_{i,j} X_i^j$ and get $x = \sum_{i,j} x_i^j$. Then, it is reasonable to satisfy the condition $\left(cv_A^j \cdot x_A^j\right)^2 + \left(cv_T^j \cdot x_T^j\right)^2 = (cvx \cdot x)^2$. If $cv_A^j = cv_T^j$, we also can get $cv_A^j = cv_T^j = \frac{cvx \cdot x}{\sqrt{\left(x_A^j\right)^2 + \left(x_T^j\right)^2}}$ [22], [23], [44], [45]. Meanwhile, the other symbols associated with this model and their interpretations are shown in TABLE 3 of Appendix B. Additionally, the following basic assumptions are made:

A1. All the travelers are assumed to be homogeneous, implying that their travel budget level, risk attitude, and travel utility are identical. The objective of travelers is to maximize its own travel utility by choosing a travel mode under the transit subsidy policy or the discount policy within their travel budget (see, e.g. [46]–[50]).

A2. There are only two transportation modes and not affect each other. The capacity of the bus is large enough and the passenger crowding discomfort in buses is considered. The crowding effect in buses is modeled using a discomfort cost function [22], [23], [37], [45], [51]–[54].

B. BENCHMARK MODEL BASED ON RDT IN DIFFERENT TRAFFIC POLICIES

The discount policy is that households who choose to travel by bus every time will definitely receive travel discounts, otherwise they will not. And the travel budget does not change. In turn, the subsidy policy is that households who choose to travel by bus have already received a one-time travel subsidy, and the travel budget will be reduced by $\delta_S P_T$ [55], [56]. The travel concessions received for each bus travel are only a prorated share of the one-time travel subsidy. For example, we compare the discount policy to the bank's demand deposits and compare the discount proportion to the interest rate of the current deposit. As long as you choose to travel by bus, you will get an interest in the current deposit. Otherwise, there will be no interest. Similarly, we compare the subsidy policy to a bank's time deposit and the subsidy proportion as the interest rate of the time deposit. The 'gain' for bus travel is calculated as the interest of time deposits ($\frac{1}{1+\delta_S}$). The former has the characteristics of high flexibility but low-interest rates, and the latter has the advantage of high-interest rates, but the flexibility is poor. In general, households will choose the higher interest rates and ignore those that can bring benefits in the short term. Based on this, the proportion of subsidy policy will be higher than the discount policy. It can be expressed as $\delta_S \geq \delta_D \geq 0$. Behavioral financiers use the myopia loss aversion (MLA) to explain the phenomenon of such different benefits [56]–[58]. At this point, it is good to explain the travel behavior of travelers affected by different policies. Next, the paper will explain one by one.

1) TRAVEL COST IN DIFFERENT TRAFFIC POLICIES

Travel costs for choosing a bus include 3 parts: time cost, monetary cost (only bus fares are considered), and congestion costs. The time cost mainly includes bus travel time and average waiting time. Congestion costs are presented in a congestion cost function and are a quadratic functional form of the number of bus travelers. A congestion cost function can be given by equation (1). The travel cost of the bus under the discount policy can be indicated by equation (2). Equation (3) expresses the travel cost of the bus under subsidy policy.

$$C_T^j\left(X_T^j\right) = a\left(X_T^j\right)^2 + bX_T^j \tag{1}$$

$$\begin{aligned} g_T^D\left(X_T^D\right) &= (1-\delta_D)P_T + T_T \\ &= (1-\delta_D)P_T + \alpha_1\left(t_T + C_T + t_T^W\right) \\ &= (1-\delta_D)P_T + \alpha_1\left(t_T + a\left(X_T^D\right)^2 + bX_T^D + \frac{1}{2f}\right) \end{aligned} \tag{2}$$

$$\begin{aligned} g_T^S\left(X_T^S\right) &= \frac{1}{1+\delta_S}P_T + T_T \\ &= \frac{1}{1+\delta_S}P_T + \alpha_1\left(t_T + C_T + t_T^W\right) \\ &= \frac{1}{1+\delta_S}P_T + \alpha_1\left(t_T + a\left(X_T^S\right)^2 + bX_T^S + \frac{1}{2f}\right) \end{aligned} \tag{3}$$

According to assumptions, the mean and variance of the bus travel cost under the discount policy can be expressed using equations (4) and (5), respectively. Similarly, the mean and variance of the bus travel cost under the subsidy policy can be expressed using equations (6) and (7) respectively.

$$\begin{aligned} &E\left(g_T^D\left(X_T^D\right)\right) \\ &= (1-\delta_D)P_T + \alpha_1\left(t_T + E\left(C_T^D\left(X_T^D\right)\right) + t_T^W\right) \\ &= (1-\delta_D)P_T + \alpha_1\left(t_T + \frac{1}{2f}\right) + \alpha_1 E\left(a\left(X_T^D\right)^2 + bX_T^D\right) \\ &= \delta_D P_T + \alpha_1\left(t_T + \frac{1}{2f}\right) + \alpha_1\left(a\left(\left(x_T^D\right)^2 + \left(cv_T^D\cdot x_T^D\right)^2\right) + bx_T^D\right) \end{aligned} \tag{4}$$

$$\begin{aligned} &Var\left(g_T^D\left(X_T^D\right)\right) \\ &= \alpha_1^2\left(cv_T^D\cdot x_T^D\right)^2\left(4a\left(x_T^D\right)^2 + 2a^2\left(cv_T^D\cdot x_T^D\right)^2 + 4abx_T^D + b^2\right) \end{aligned} \tag{5}$$

$$\begin{aligned} &E\left(g_T^S\left(X_T^S\right)\right) \\ &= \frac{1}{1+\delta_S}P_T + \alpha_1\left(t_T + E\left(C_T^S\left(X_T^S\right)\right) + t_T^W\right) \\ &= \frac{1}{1+\delta_S}P_T + \alpha_1\left(t_T + \frac{1}{2f}\right) + \alpha_1 E\left(a\left(X_T^S\right)^2 + bX_T^S\right) \\ &= \frac{1}{1+\delta_S}P_T + \alpha_1\left(t_T + \frac{1}{2f}\right) + \alpha_1\left(a\left(\left(x_T^S\right)^2 + \left(cv_T^S\cdot x_T^S\right)^2\right) + bx_T^S\right) \end{aligned} \tag{6}$$

$$\begin{aligned} &Var\left(g_T^S\left(X_T^S\right)\right) \\ &= \alpha_1^2\left(cv_T^S\cdot x_T^S\right)^2\left(4a\left(x_T^S\right)^2 + 2a^2\left(cv_T^S\cdot x_T^S\right)^2 + 4abx_T^S + b^2\right) \end{aligned} \tag{7}$$

Then, the travel cost of choosing a private car to travel includes time cost and monetary cost. The monetary cost mainly includes fixed costs such as fuel consumption and depreciation of private car travel. The time cost is represented by the classical BPR function. Therefore, the travel cost of choosing a private car to travel can be expressed using equation (8). Furthermore, the mean and variance of the related car travel cost can be respectively expressed using the form of equations (9) and (10).

$$\begin{aligned} g_A^j\left(X_A^j\right) &= P_A + T_A^j = P_A + \alpha_2 T_A^j\left(X_A^j\right) \\ &= P_A + \alpha_2 t_A^0\left[1 + m\left(\frac{X_A^j}{C_A}\right)^n\right] \end{aligned} \tag{8}$$

$$E\left(g_A^j\left(X_A^j\right)\right) = P_A + E\left(T_A^j\left(X_A^j\right)\right) \tag{9}$$

$$Var\left(g_A^j\left(X_A^j\right)\right) = \alpha_2^2 Var\left(T_A^j\left(X_A^j\right)\right) \tag{10}$$

The mean and variance of the car travel cost can be expressed in the form equations (11) to (12).

$$\begin{aligned} &E\left(g_A^j\left(X_A^j\right)\right) \\ &= P_A + t_A^0 + t_A^0\frac{m}{C_A^n}\sum_{l=0,l=even}^{n}\binom{n}{l}\left(cv_A^j\cdot x_A^j\right)^l\left(x_A^j\right)^{n-l}(l-1)!! \end{aligned} \tag{11}$$

$$\begin{aligned} &Var\left(g_A^j\left(X_A^j\right)\right) \\ &= \alpha_2^2\left(t_A^0\frac{m}{C_A^n}\right)^2 \\ &\times\left(\begin{aligned} &\sum_{l=0,l=even}^{2n}\binom{2n}{l}\left(cv_A^j\cdot x_A^j\right)^l\left(x_A^j\right)^{2n-l}(l-1)!! \\ &-\left(\sum_{l=0,l=even}^{n}\binom{n}{l}\left(cv_A^j\cdot x_A^j\right)^l\left(x_A^j\right)^{n-l}(l-1)!!\right)^2 \end{aligned}\right) \end{aligned} \tag{12}$$

We know that the travel cost of the two modes is also in accordance with the normal distribution, thus, the following relationship can be expressed equations (13) and (14). The calculation process is described in Appendix A. Therefore, the probability density can be obtained from the normal distribution probability density function, as shown in equations

(15) and (16).

$$g_T^j \sim N\left(E\left(g_T^j\left(X_T^j\right)\right),\quad Var\left(g_T^j\left(X_T^j\right)\right)\right) \tag{13}$$

$$g_A^j \sim N\left(E\left(g_A^j\left(X_A^j\right)\right),\quad Var\left(g_A^j\left(X_A^j\right)\right)\right) \tag{14}$$

$$f\left(g_T^j\left(X_T^j\right)\right) = \frac{1}{\sqrt{2\pi}\sqrt{Var\left(g_T^j\left(X_T^j\right)\right)}}\exp \times\left[-\frac{\left(g_T^j\left(X_T^j\right)-E\left(g_T^j\left(X_T^j\right)\right)\right)^2}{2Var\left(g_T^j\left(X_T^j\right)\right)}\right] \tag{15}$$

$$f\left(g_A^j\left(X_A^j\right)\right) = \frac{1}{\sqrt{2\pi}\sqrt{Var\left(g_A^j\left(X_A^j\right)\right)}}\exp \times\left[-\frac{\left(g_A^j\left(X_A^j\right)-E\left(g_A^j\left(X_A^j\right)\right)\right)^2}{2Var\left(g_A^j\left(X_A^j\right)\right)}\right] \tag{16}$$

2) TRAVEL UTILITY IN DIFFERENT TRAFFIC POLICIES

Travel utility is a comprehensive evaluation indicator that describes the household's choice behavior. It can not only distinguish the travel costs but more importantly, it can also reflect the satisfaction of the traveler. So, we can use equations (17) and (18) to describe the travel utility of different modes under different policies. While we introduced the 'reference point' to explain how travelers distinguish between different modes of travel. The 'reference point' changes the selection criteria are based on the maximum travel utility. The choice of travel mode is based on the reference point, and the 'loss' and 'gain' of the travelers are also for the reference point. This approach highlights the traveler's preferences while avoiding the errors caused by the estimated probabilities. This paper selects the expected travel utility of the alternative travel model as a reference point, and more researchers cited this [37], [45], [59]–[61]. In reality, the choice of travel mode should consider the influence of external 'risk'. So, we have added the concept of 'loss avoidance' which describes the traveler's attitude towards risk. The gain-loss utility function reflects the choice of mode that is influenced by both a reference point, risk, and loss avoidance, representing the equation (19).

$$U_i^D\left(X_i^D\right) = I - \int_{g_i^D(0)}^{g_i^D(X_i^D)} g_i^D\left(X_i^D\right) f\left(g_i^D\left(X_i^D\right)\right)dx \tag{17}$$

$$U_i^S\left(X_i^S\right) = \left(I - \delta_S P_T\right) - \int_{g_i^S(0)}^{g_i^{S}!!(X_i^D)} g_i^S\left(X_i^S\right) f\left(g_i^S\left(X_i^S\right)\right)dx \tag{18}$$

$$U_{iR}^j\left(X_i^j\right) = \begin{cases} \left(U_A^j\left(X_A^j\right) - U_T^j\left(X_T^j\right)\right)^{\theta_1^j}, & U_T^j\left(X_T^j\right) \le U_A^j\left(X_A^j\right) \\ -\eta^j\left(U_T^j\left(X_T^j\right) - U_A^j\left(X_A^j\right)\right)^{\theta_2^j}, & U_T^j\left(X_T^j\right) > U_A^j\left(X_A^j\right) \end{cases} \tag{19}$$

In summary, we use equations (20) and (21) to present travel utility based on a reference point, risk and loss avoidance under different travel policies.

$$\overline{U}_i^D = I - \left(\int_{g_i^D(0)}^{g_i^D(X_i^D)} U_i^D\left(X_i^D\right) f\left(g_i^D\left(X_i^D\right)\right)dx + \int_{g_i^D(0)}^{g_i^D(X_i^D)} U_{iR}^D\left(X_{iR}^D\right) f\left(g_i^D\left(X_i^D\right)\right)dx\right) \tag{20}$$

$$\overline{U}_i^S = \left(I - \delta_S P_T\right) - \left(\int_{g_i^S(0)}^{g_i^S(X_i^S)} U_i^S\left(X_i^S\right) f\left(g_i^S\left(X_i^S\right)\right)dx + \int_{g_i^S(0)}^{g_i^S(X_i^S)} U_{iR}^S\left(X_{iR}^S\right) f\left(g_i^S\left(X_i^S\right)\right)dx\right) \tag{21}$$

3) TRAVEL MODE CHOICE IN DIFFERENT TRAFFIC POLICIES

Travelers have different cognitions of understanding of road conditions and are affected by uncertainties such as weather, policies, and congestion. Moreover, there are errors in estimating. Therefore, the utility of each mode of transport is shown by equation (22), which ε is the cognitive bias. It is assumed that ε obeys the same and independent Gumbel distribution. The sharing rate of travel mode is the classic Logit discrete selection model, such as equation (23).

$$\widetilde{U}_i^j = \overline{U}_i^j + \varepsilon \quad i = T \text{ or } A\ j = D \text{ or } S \tag{22}$$

$$p_i^j = \frac{\exp \widetilde{U}_i^j}{\sum_{i,j}\exp \widetilde{U}_i^j} \quad i = T \text{ or } A\ j = D \text{ or } S \tag{23}$$

III. OPTIMAL BUS FARE PROPORTIONS CONSIDERED TRANSPORTATION POLICIES

A. A BI-LEVEL PLANNING FOR THE OPTIMAL BUS FARE PROPORTIONS

As managers who advocate bus travel, they are more concerned with finding effective public transport policies (discount policies or subsidy policies). However, managers often ignore traveler travel preferences. Then, travelers only pay attention to the modes which are suit for them and do not care about the effectiveness of the policy. Therefore, this paper establishes a bi-level program model to resolve the gap between managers and travelers. The manager minimizes the

TABLE 3. Symbols employed in the model.

Symbols	Explanation
i	Travel mode (T indicates bus travel and A means private car travel)
j	Traffic policy (D represents the bus discount policy and S represents the bus subsidy policy.)
X	The total travel demand
X_i^j	The travel demand for travel mode i under j traffic policy
f	Bus frequency
I	Travel budget
t_T	Travel time in bus travel
t_T^W	The average waiting time in bus travel
P_i	The fixed cost in the i $\left(i=T \quad or \quad A\right)$ travel mode
T_i	The time cost in the i $\left(i=T \quad or \quad A\right)$ travel mode
δ_D	Bus fare discount proportion
δ_S	Bus fare subsidy proportion
C_T	Congestion cost of bus
α_1	Value of time in the bus
α_2	Value of time in the car
C_A	Road capacity
t_A^0	Zero-time overflow
a,b	Bus congestion cost function parameters
m,n	Private car travel time function parameters
η^j	Loss avoidance coefficient of reference point
θ_1^j	Risk avoidance coefficient of reference point based on 'gain'
θ_2^j	Risk avoidance coefficient of reference point based on 'loss'
p_i^j	Probability of choice in different modes under different policies

mean of total cost by adjusting the optimal bus fare proportion in the upper-level planning. We can express it with equations (24) and (25). The bus sharing rate of the traveler changes due to the variety in bus fare proportion in the low-level planning. It can be portrayed as a reference dependence choice model from the equation (26).

$$\min_{\delta_j} Z^j \tag{24}$$

$$s.t\ \underline{\delta_j} \leq \delta_j < \overline{\delta_j} \quad j = D\ or\ S \tag{25}$$

While, $\underline{\delta_j}$ and $\overline{\delta_j}$ respectively indicate the minimum and maximum value of the bus fare proportion when the $j\,(D\ or\ S)$ type policy is implemented.

$$X_i^j = p_i^j X \quad i = T\ or\ A\ j = D\ or\ S \tag{26}$$

While X indicates the total travel demand and X_i^j respects for the travel demand for travel mode i under j traffic policy. Expecting both sides of equation (26) simultaneously, there is

$$x_i^j = p_i^j x \quad i = T\ or\ A\ j = D\ or\ S \tag{27}$$

Then, $p_i^j\,(i = T\ \ or\ \ A\ j = D\ \ or\ \ S)$ in the equation (27) can be calculated by the equation (22).

Furthermore, the mean of total system cost in different policy implementations can be expressed as follows.

$$Z^j = E\left(X_T^j g_T^j\left(X_T^j\right) + X_A^j g_A^j\left(X_A^j\right)\right) \quad j = D\ or\ S \tag{28}$$

Substituting the equations (4) to (7), (11), (12), (15), and (16) into the above equation (28), the expression of the total social utility under the j-type policy can be obtained.

$$Z^j = x_T^j E\left(g_T^j\left(X_T^j\right)\right) + x_A^j E\left(g_A^j\left(X_A^j\right)\right) \quad j = D\ or\ S \tag{29}$$

Therefore, this optimization model can be expressed as follows:

$$U \quad \min_{\delta_j} \overset{j}{Z} = x_T^j E\left(g_T^j\left(X_T^j\right)\right) + x_A^j E\left(g_A^j\left(X_A^j\right)\right) \quad j = D\ or\ S$$

$$s.t\ \underline{\delta_j} \leq \delta_j < \overline{\delta_j} \quad j = D\ or\ S$$
$$L \quad x_i^j = p_i^j x \quad i = T\ or\ A\ j = D\ or\ S \tag{30}$$

B. CALCULATION PROCESS

Generally speaking, the bi-level programming problem is an NP-hard problem (Non-deterministic Polynomial), and there is no polynomial solving algorithm. Therefore, the solution to the bi-level programming problem is complex and the global optimal solution cannot be obtained. Then, heuristic algorithms are often used to solve such problems. This paper uses the integrated method of successive average (MSA) genetic algorithm (GA) to solve the problem [22], [23], [37]. Solving the underlying plan to use the MSA method to obtain the number of households who choose to travel by bus. The specific steps are as follows:

Step 1, Initialize. Let $N = 1$ and set the initial flow X_i^N. Making use of equations (2) and (3) to calculate the initial cost of selecting a bus under the discount policy and subsidy policy, and use equation (8) to calculate the initial travel cost of the private car. Utilize $g_i^{j,N}$ to indicate.

Step 2, Calculate travel utility. Use the above equations (17) to (22) to calculate the travel utility of different modes under the discount or subsidy policy $\widetilde{U}_i^{j,N}$.

Step 3, Look for the iteration direction. According to the reference-dependent utility calculated in step 2, the additional flow y_i^n is obtained by the all-all allocation method.

Step 4, $X_i^{N+1} = \left(1 - \frac{1}{M}\right) X_i^N + \frac{1}{M} y_i^N$ Where the iteration step is $\frac{1}{M}$. Set $N = N + 1$ and return to step 2.

Step 5, Convergence judgment. If $\left|\overline{U}_i^{j,N+1} - \overline{U}_i^{j,N}\right| \leq 10^{-3}$ or $M \leq M_{\max}$ is satisfied, the algorithm is terminated. M is the maximum number of iterations.

Based on the genetic algorithm to calculate the optimal proportion of policy implementation of the upper layer planning, the calculation steps are as follows:

Step 1, Initialize. Determine crossover probability y_c and mutation probability y_e, the number of chromosomes S in the population and the largest evolutionary algebra Y. At the same time, set the evolution algebra to 0, i.e. $L = 0$.

Step 2, The fitness function is determined according to equation (24), and the form of the fitness function selected here is $F(\delta_j) = -\left(x_T^j E\left(g_T^j\left(X_T^j\right)\right) + x_A^j E\left(g_A^j\left(X_A^j\right)\right)\right)$. Where δ_j is the decision variable and is actually encoded. It is possible to obtain a set δ_j that satisfies the equation (25) and set $L = 1$.

Step 3, Fitness matching. The set δ_j obtained in step 2 is substituted into the model with the above, and the corresponding travel demand x_T^j and x_A^j is obtained by the lower layer plan solved by the MSA. This requirement is substituted into the fitness function and the chromosomes are sorted from good to bad according to their corresponding fitness. If $L = Y$, get the optimal solution δ_j^*, otherwise return to step 4.

Step 4, Population update. The next round of populations is updated based on the elite model and the betting round selection model.

TABLE 4. Parameters in case.

Parameter	Value
t_T	20min
C_A	60veh/min
α_1	0.4
α_2	0.1
a	0.005
b	0.25
t_A^0	15min
f	12/h
P_T	6/CNY
P_A	10/CNY
$\underline{\delta_j} / \overline{\delta_j}$	0/1
y_c / y_e	0.7/0.05
S	50
Y	1000

Step 5, Cross. The updated chromosomes are re-randomly assigned to the $\frac{S}{2}$ pair. Suppose there are pairs of chromosomes y_{v1} and y_{v2}, and there is any random number κ between [0, 1]. If the condition is met $\kappa < p_c$, the rules of equation (31) are cross-operated for y_{v1} and y_{v2}, otherwise, no intersection is performed. Where $\tau\tau \in [0, 1]$ represents the degree of intersection between chromosomes.

$$\begin{cases} y'_{v1} = \tau y_{v1} + (1 - \tau)\, y_{v2} \\ y'_{v2} = \tau y_{v2} + (1 - \tau)\, y_{v1} \end{cases} \tag{31}$$

Step 6, Variation. Same as the rule of the intersection, if the condition $\kappa < p_e$ is satisfied, it will be mutated according to rule $y_v = y_v + e \cdot K$, otherwise it will not be mutated. While e represents a small positive number and K represents a random disturbance term. However, it should be noted that each mutation operation must ensure that it is a feasible solution, otherwise, it needs to be re-mutated.

Step 7, Go back to step 3.

IV. CASE STUDY

In this subsection, an example is provided to illustrate the properties of the proposed model and its applications. Considering the combination of risk aversion and loss avoidance, the trends of the total system cost, bus travel, optimal proportion, and travel utility of the two policies are compared. The relevant parameters in case are shown in Table 4 [22], [23], [37], [45]. In the following analysis, unless specifically stated otherwise, the input data are identical to those of the base case.

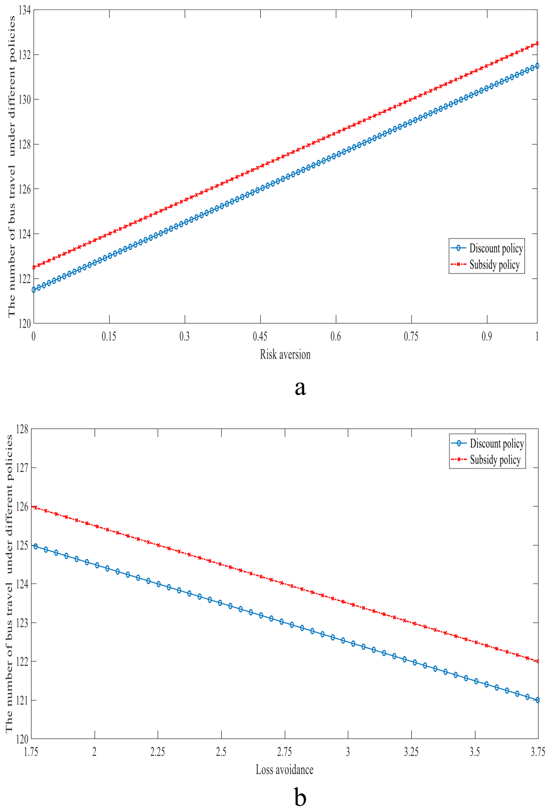

FIGURE 1. **The number of travelers considered one of the attributes in RDT.**

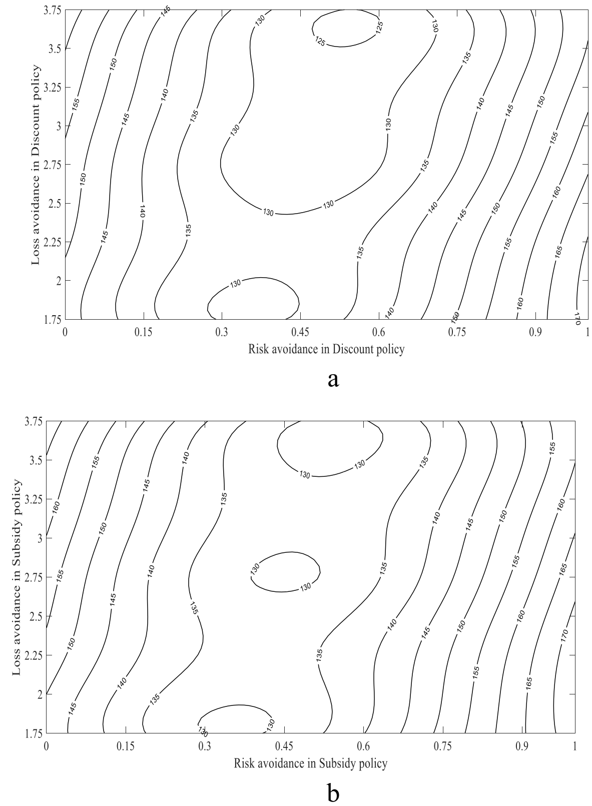

FIGURE 2. **The number of travelers varies under different policies.**

A. THE IMPACT ON BUS TRAVEL

We assume a fixed bus fare proportion ($\delta_j = 0.3$) and analyze the changes in the number of bus travel. FIGURE 1. indicates the changes in bus travel only considering one of the attributes in RDT [23], [45]. The increase in the number of bus travel as the risk increases is due to the traveler's pursuit of risk in Figure 1-a. However, in Figure 1-b, the decrease in the number of bus travel as the loss increases is due to the fact that travelers treat 'losses' more sensitively than 'gains'. It can be seen that if we only consider one of the attributes in RDT, it will lead to an increase or decrease in the single trend of bus travel. Furthermore, the agglomeration or dispersion of bus travel is also generated. In order to avoid this phenomenon, we need to consider both attributes at the same time. FIGURE 2. shows the changes in the number of bus travel considered risk aversion and loss avoidance. The number of travelers decreases first and then increases. The risk aversion range is between 0 and 0.45, and the number of travelers will continue to decrease affected by the increase in loss avoidance. The risk aversion range is between 0.45 and 1, and the number of travelers will continue to increase affected by the increase in loss avoidance. While the number of travelers under the discount policy (Figure 2-a) is lower than the number of travelers under the subsidy policy (Figure 2-b). This is because the congestion factor in the bus and both the two attributes are considered in the model. Travelers are more willing to accept the form of subsidy policy.

B. THE IMPACT ON TOTAL SYSTEM COST

The total system cost can also reflect the effectiveness of the policy from the perspective of cost. If there is the same bus travel, then we can conclude that the lower the total system cost, the better the policy. The total system cost changes the same as the number of bus travel in FIGURE 1. FIGURE 3 shows that the total cost of the system tends to decrease first and then increase. This is because when the risk aversion is relatively low, the 'gain' of the traveler is much higher than the 'loss', which also reveals the cause of Figure 3-a. Although there is a 'loss' within the acceptable range for travelers, the total system cost will increase. However, increasing risks will increase the 'loss' of travelers, and travelers' self-interest will lead to a decrease in travel, resulting in a reduction in the total cost of the system (see Figure 3-b). The risk aversion is in the interval 0-0.6, and the total system cost of the discount policy (Figure 4-a) is faster than the total system cost of the subsidy policy (Figure 4-b). However, when the risk aversion factor is in the interval 0.6-1, the situation is reversed. Through Figure 4, we can easily find out that when the bus fare proportion is certain, the total cost of the subsidy policy is lower than the discount policy. Furthermore, the total system cost considering two attributes is lower than considering one attribute by comparing Figures 3 and Figures 4. The risk aversion effectively avoids the occurrence of 'high losses' for travelers, while the loss avoidance controls the possibility of 'high gains'. As the factors of

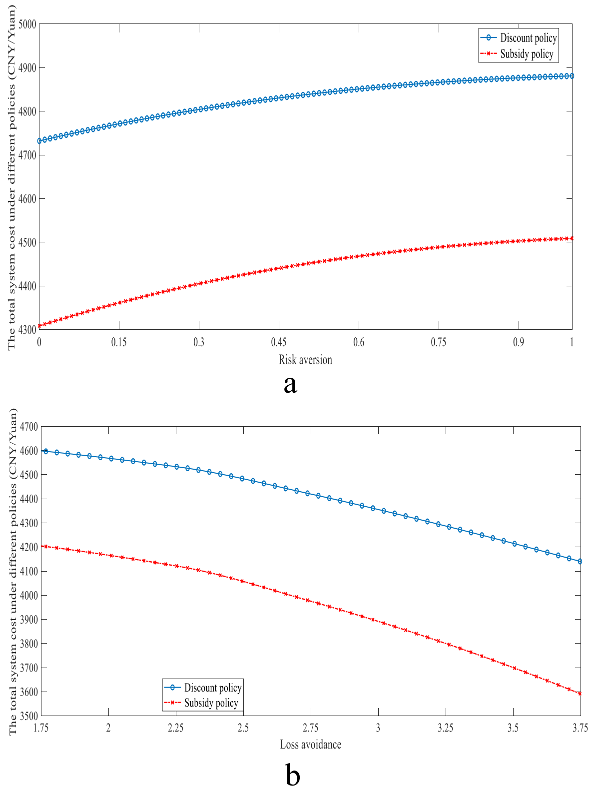

FIGURE 3. The total system cost considered one of the attributes in RDT.

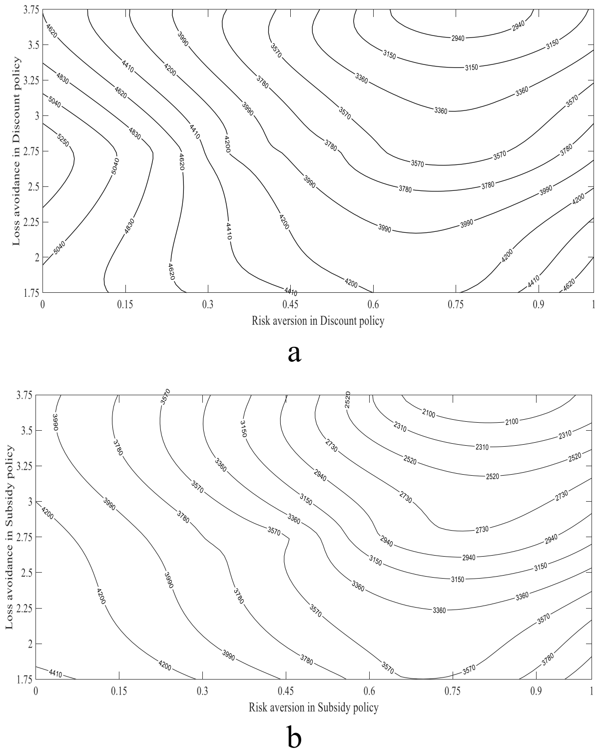

FIGURE 4. Total system cost varies under different policies.

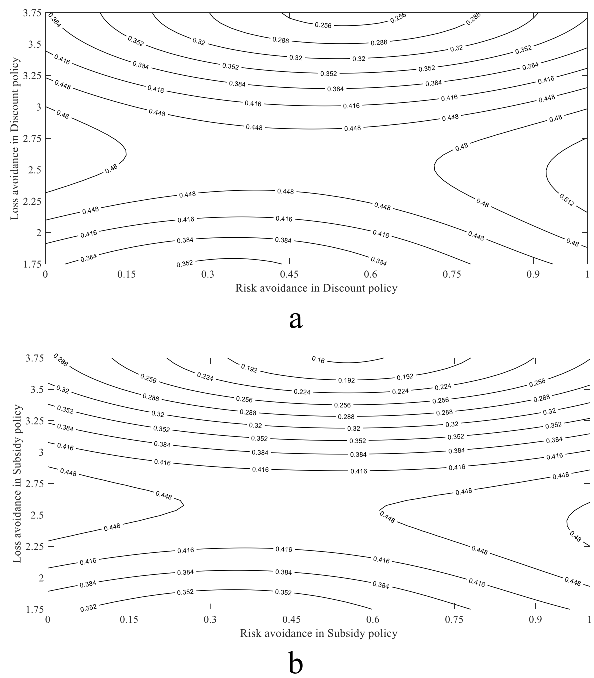

FIGURE 5. The optimal bus fare proportions vary under different policies.

travel decisions increase, the total system cost will become smaller. So, the subsidy policy can reduce the total cost of the system and reduce some unnecessary travel.

C. THE IMPACT ON OPTIMAL BUS FARE PROPORTIONS

If we take the number of bus travel is the same, we can discover the disciplines which considered two attributes. Through the observation of FIGURE 5., it can be easily seen that as the risk continues to increase, the optimal bus fare proportion will first decrease and then increase. When the risk is determined, the optimal bus fare proportion also shows a trend of increasing first and then decreasing with the increase of loss avoidance. In order to achieve the two policies to guide the same traveler to choose a bus, the discount rate under the discount policy (Figure 5-a) is higher than the discount rate under the subsidy policy (Figure 5-b). This is because, under the discount policy, travelers can only enjoy preferential policies if they travel, otherwise they will not receive preferential treatment. However, the subsidy policy is to guide the traveler to reduce unnecessary travel, so the proportion of incentives will be lower than the discount policy. It can also be obtained that the total system cost of the subsidy policy will be lower than the discount policy when guiding the traveler to select the same number of bus travel.

D. THE IMPACT ON TRAVEL UTILITIES

How does the travel utility change when the bus fare proportion changes? FIGURE 6. shows the results of different scenarios after the change in the bus fare proportion under the two policies. With the increasing proportion of concessions, the travel utility of travelers under the two policies also showed a trend of increasing first and then decreasing. In particular, the discount policy is significantly slower than

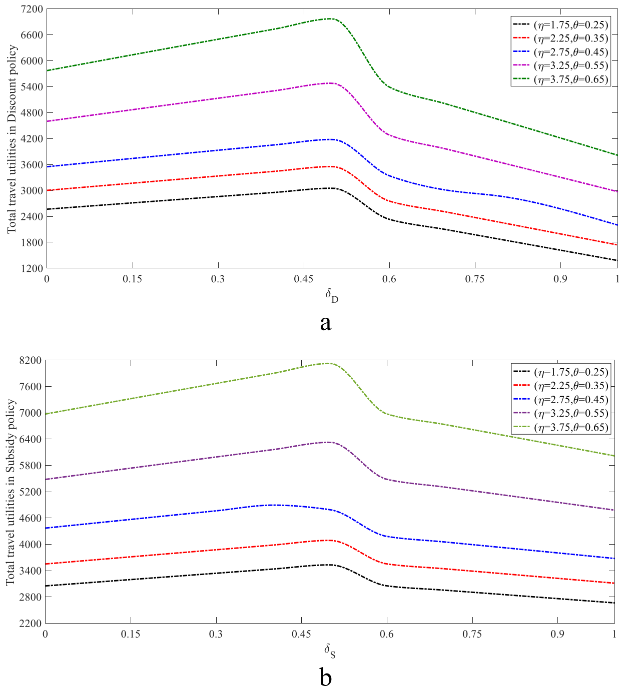

FIGURE 6. The bus fare proportions vary on travel utilities under different policies.

the subsidy policy in the range of 0.5 to 1. The high discount rate under the discount policy has attracted a large number of travelers to choose bus travel. Although the fare concessions are very attractive, the congestion inside the train is hard to ignore. Another reason for this phenomenon is that a sufficiently high percentage of benefits under the subsidy policy will reduce unnecessary travel or convert to a car. In short, the travel effect of travelers under the implementation of the subsidy policy is always higher than the implementation of the discount policy.

V. CONCLUSION

The paper attempts to respond to the call for green transportation by examining the mechanism which will motivate the traveler to choose to travel by buses instead of cars. In the simple dual-mode selection, we assume that the travel demand is uncertain, and the traveler has the characteristics of loss avoidance and reference dependence when choosing the travel mode. This paper uses the reference dependence theory to explain the two basic attributes and sets up the model. The uncertainty of travel costs makes it necessary for travelers to consider the mean and variance of travel costs. At the same time, we also consider using the bus fare concession strategy to guide the traveler to reasonably choose the bus travel, and establish a bi-level programming model to optimize the bus fare proportions. The upper-level planning is aimed at minimizing the average total system cost, and the lower-level planning is the transportation mode selection model, which is solved by a heuristic algorithm. By comparing the effects of travel modes and total travel costs under different policies, the traveler is considering one attribute and considering two attributes. The results of the study show that the subsidy policy is more favorable than the discount policy to guide bus travel by analyzing the number of bus trips affected by two attributes. Similarly, the total social cost will also decrease. While the paper highlights that the subsidy policy plays an important role in guiding the traveler to choose to travel by bus. In order to better illustrate this conclusion, we also analyzed the changes in the optimal fare proportions and travel utilities in considering the impact of two attributes. The model is indispensable for the implementation of future traffic demand management strategies.

In this paper, we clearly know that subsidy policies are of great significance in bus travel. Then, in future research, we will study its impact on urban structure, social welfare, and other urban economies.

APPEDIXES

APPENDIX A

DERIVATION OF MEAN AND VARIANCE

The calculation of the mean and variance of equation (1) is as follows.

$$\begin{aligned} E\left(C_T\left(X_T\right)\right) &= \mathrm{E}\left(a\left(X_T\right)^2+bX_T\right) = aE\left(X_T^2\right)+bE\left(X_T\right) \\ &= a\left(x_T^2+\left(cv_T\cdot x_T\right)^2\right)+bx_T \end{aligned} \tag{A-1}$$

$$\begin{aligned} Var\left(C_T\left(X_T\right)\right) &= Var\left(a\left(X_T\right)^2+bX_T\right) \\ &= \mathrm{E}\left(\left(a\left(X_T\right)^2+bX_T\right)^2\right)-\left(\mathrm{E}\left(a\left(X_T\right)^2+bX_T\right)\right)^2 \\ &= E\left(a^2X_T^4+2abX_T^3+b^2X_T^2\right) \\ &\quad -\left(aE\left(X_T^2\right)+bE\left(X_T\right)\right)^2 \\ &= a^2E\left(X_T^4\right)+2abE\left(X_T^3\right)+b^2E\left(X_T^2\right) \\ &\quad -\left(aE\left(X_T^2\right)+bE\left(X_T\right)\right)^2 \end{aligned} \tag{A-2}$$

In the equation (A-2), there is a mean calculation of nth power, and the calculation process based on the nth power of the normal distribution is as follows.

$$E\left(X_T^2\right) = x_T^2+\left(cv_T\cdot x_T\right)^2 \tag{A-3}$$

$$E\left(X_T^3\right) = x_T^3+3x_T\left(cv_T\cdot x_T\right)^2 \tag{A-4}$$

$$E\left(X_T^4\right) = x_T^4+6x_T^2\left(cv_T\cdot x_T\right)^2+3\left(cv_T\cdot x_T\right)^4 \tag{A-5}$$

Substituting the equations (A-3) to (A-5) into the equation (A-2), and simplification can be obtained.

$$\begin{aligned} Var\left(C_T\left(X_T\right)\right) = \left(cv_T\times x_T\right)^2 \Big(&4ax_T^2+2a^2\left(cv_T\times x_T\right)^2 \\ &+4abx_T+b^2\Big) \end{aligned} \tag{A-6}$$

Substituting the equation (A-1) into the equation (3), and finishing the simplification, the equation (8) is obtained. Substituting the equation (A-6) into the equation (4), and sorting out the form of the equation (9).

$$E\left(T_A\left(X_A\right)\right) = t_A^0 + t_A^0 \frac{m}{C_A^n} \sum_{i=0, i=even}^{n} \binom{n}{i} \left(cv_A \cdot x_A\right)^i \left(x_A\right)^{n-i} (i-1)!! \tag{A-7}$$

$$Var\left(T_A\left(X_A\right)\right) = \left(t_A^0 \frac{m}{C_A^n}\right)^2 \left(\begin{array}{l} \sum_{i=0, i=even}^{2n} \binom{2n}{i} \left(cv_A \cdot x_A\right)^i \left(x_A\right)^{2n-i} (i-1)!! - \\ \left(\sum_{i=0, i=even}^{n} \binom{n}{i} \left(cv_A \cdot x_A\right)^i \left(x_A\right)^{n-i} (i-1)!! \right)^2 \end{array} \right) \tag{A-8}$$

The calculation of the mean and variance $T_A\left(X_A\right)$ is as follows.

Substituting the equations (A-7) and (A-8), as shown at the top of this page, into the equations (6) and (7), respectively, and sorting out the forms of the equations (10) and (11).

APPENDIX B
TABLE 3

See the Table 3.

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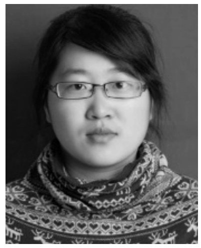

TIANCHAO GUAN received the M.S. degree in system theory from the Shandong University of Science and Technology. She is currently pursuing the Ph.D. degree with the Systems Science Institute, School of Traffic and Transportation, Beijing Jiaotong University. She is currently focused on transportation economics, travel behavior analysis, and traffic policy.

TONGFEI LI received the joint Ph.D. degree from the National University of Singapore, in 2017, and the Ph.D. degree in system science from Beijing Jiaotong University, in 2018. Since 2018, he has been a Lecturer with the Beijing University of Technology. His research interests include transportation and land use, ridesharing, and connected automated vehicle.