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Factor Analysis of Customized Bus Attraction to Commuters with Different Travel Modes

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Abstract: The customized bus (CB) is an innovative and environmental supplementary mode of public transport, providing demand-responsive and user-oriented service to specific passenger groups with similar travel demands, especially commuters, based on online reservations. However, sufficient travel demand is essential for the successful operation of CB. The purpose of this study is to analyze the factors influencing the attraction of CB to commuters, which is tied to the ordered mode shift decisions, do no transfer to CB, remain undecided, and transfer to CB. A combination of revealed preference (RP) survey and stated preference (SP) survey is conducted among commuters in Beijing through online and offline questionnaire, collecting 1304 valid commuting demands. The ordered logit (OL) model and two-level mixed-effect ordered logit (MEOL) model are used to estimate the variable effects and the difference in five commute modes, including car, taxi, bus, rail, bus + rail, is considered. Common variables significantly influencing the transfer decision in all groups are specified in models, including familiarity to CB, seat availability, and gender. Meanwhile, travel cost, travel time, and transfer time of the current travel mode have positive effects on the attraction of CB. In addition, car ownership and accessibility to bus stations also influence the attraction of CB to certain group commuters. This paper can provide references to CB operators for formulating differentiation strategies and attracting more passengers in Beijing.

Keywords: customized bus; commuting mode; travel demand; ordered logit model

1. Introduction

1.1. Background

Many cities around the world, especially large cities, are trying out a multitude of transportation policy and investment alternatives with the aim of alleviating traffic congestion and traffic-related environmental pollution caused by the increase in car ownership. At the same time, commuting travels show heavy reliance on the private cars because of the dispersion of jobs and amenities as a result of the rapid population growth and the improvement of urbanization. Commuting is a widespread social activity that ensure residents' normal work and life, and constitutes a considerable share of total household trip-making [1]. As a result, it becomes particularly important to introduce alternatives for commuters. Public transportation has long been considered to build environmentally and socially sustainable and livable cities [2,3]. Nevertheless, it sometimes cannot provide satisfactory service because of the inefficient facilities and more and more diverse and characteristic travel demands of commuters. So far, a new innovative mode of public transport services named customized bus (CB) has been launched and rapidly promoted benefit from the development of information and tele-communication technology [1].

CB is a novel mode of demand responsive transport [4], providing advanced, attractive, and user-oriented service to specific passenger groups with similar travel demand pattern, especially commuters [5]. Passengers submit their precise origins, destinations, and departure time through interactive online information platform, such as Internet websites and smartphone apps. CB operators then design candidate bus routes by aggregating similar travel demands. The final routes will be scheduled definitely if recruiting enough potential passengers. So CB belongs to demand-responsive service, wherein the travel demand is collected using modern technologies. The route network, timetable, vehicle type, and schedule of CB are flexible during planning stage with the participation of passengers, and finally reach a balance between users and operators. Once a CB route is launched, it has the characteristics of fixed stops, fixed vehicles, fixed timetables, fixed prices, fixed passengers, yet flexible route segments. CB service is a complement of public transport system between conventional buses and taxis in terms of the degree of user participation in operational planning activities, the level of services, and operating cost [6]. It is more comfortable, convenient, and reliable than conventional public transport service and more efficient, cost-effective, and environmentally friendly than private cars and taxis. The goal of the service is to increase vehicle seat capacity utilization and decrease the number of vehicles on road, leading to traffic congestion reduction and environmental friendliness.

1.2. Literature Review

As early as the 1970s, subscription bus, which is somewhat similar to CB, appeared in the European and American cities between suburbs and downtown, mainly serving commuters. Kirby and Bhatt proposed guidelines on recruiting passengers, network planning, operating, and dispatching, and so forth of this service based on detailed analysis of ten case studies. The authors also identified seven main characteristics that were assumed to be important for the successful operation of such subscription bus service [7,8]. McCall analyzed the history and evolution of COM-BUS, a subscription commuter-bus-service system operated in Ventura, Los Angeles, and Orange Country, California [9]. Shaheen et al. reviewed the development of car-sharing and summarized the advantages of somewhat similar transport service. They first pointed out that the development tendency of subscription bus service in the future was the continuous expansion of service areas and more advanced booking technologies [10]. In recent years, new programs using online information platforms have been developed for better matching between commuters and service providers [11,12]. Chan and Shaheen divided the evolution of ridesharing into five phases and characterized the recent phase as the incorporation of the Internet, mobile phones, and social networking into ridesharing services [13]. Foldes and Csiszar developed an information management method for combined ride-sourcing, in which the vehicles are shared between passengers, passengers and packages, or packages [14]. The focus of this paper is to customized the bus service with the help of modern technologies.

CB started relatively late in China, but it springs up like the mushrooms. Since CB was first introduced in Qingdao in August 2013 [15], more than 40 cities, like Beijing, Jinan, and Tianjin, either operate a CB service or have one under construction as a green supplement to public transport, mainly serving commuting demand, because of the great potential for meeting the ever-increasing and diversified commuting mobility needs of large population and the improvement of the commuting experience. Xu et al. discussed the definition, key service elements, advantage, and potential applications of CB service in China, concluding that the development of CB can significantly improve and enhance a city's public transportation system [16]. Liu and Ceder provided a systematic examination and analysis of the current state of CB practices in China and described the detailed operation-planning progress of CB for the first time. This report offers a valuable reference for policy-makers, academic researchers, PT practitioners, and others worldwide [5]. More and more researchers pay attention to the scientific and systematic methodologies for planning and designing problems of CB service, including routes and timetable optimization, as it is a new successfully transport mode for which the existing models for conventional buses are not suitable [17–19]. Though CB serves as a good alternative to commuters for reducing urban traffic congestion, improving the efficiency of road resource use and

alleviating pollution gas emission problems, a sufficient travel demand with relatively stable origin, destination and travel time is necessary to ensure the operating of CB. The purpose of this study is to understand the factors influencing the attraction of CB service to commuters with different travel modes and then make targeted policies encouraging more commuters making decisions to switch from the current travel mode to CB.

The multinomial logit (MNL) model is the most commonly used choice model because of its simple mathematical structure and ease of estimation. To relax the restriction that the distribution of error terms is independent and identical over alternatives in MNL, the nested logit (NL) model and cross-nested (CNL) model were developed to analyze and predict travel choice decisions [20,21]. Many existing studies analyzed the factors influencing residents' mode choice concerning all modes available including CB based on the questionnaire surveys using discrete choice models [22–25]. Besides, Nalmpantis et al. revealed that utility, as well as feasibility and innovativeness were promising criterions to make public transport more attractive [26]. Tsafarakis et al. also concentrated on differences in user preferences along with public transport innovations in European cities [27]. But when concerning the mode shift behavior between the current habitual travel mode and the objective travel mode, there was few references. Travelers, especially commuters, always get accustomed to their current travel mode for regular trips without changes in the residents and workplace, or in government policy environment in general. As CB service is a fresh mode for most people, there is high probability for them to choose one from the current travel mode and new CB system. If CB is attractive enough, one would transfer to it, otherwise he or she would not. It looks as if a binary logit model is suitable, but sometimes the attraction of CB is uncertain and traveler cannot make a clear decision whether to transfer or not. In this situation, with more than two choices are discrete and ordinal, estimating and forecasting with the MNL model may discard the sequence information conveyed by the ordinal responses. Thus, the ordered logit (OL) model is employed, providing appropriate means to exploit the ordering information. The OL model was generally adopted to examine driver injury severity, traffic accident severity, health status, and so on [28,29]. To the best of our knowledge, it is new to use OL model estimating the attraction of a travel mode with outcomes being individual transport mode shift decision.

Since revealed preference (RP) survey reflects the actual mode choice of travelers and stated preference (SP) survey get the preferences of travelers on alternatives that do not exist or that people are not yet familiar with, a combined estimation of RP/SP data is an effective method for researchers to capture the complex travel behavior and perception, then forecasting travel demand for new transport services more accurately [30,31].

The remainder of this paper is organized as follows. In the methodology section, conceptual model and the empirical approach are presented. We describe the RP/SP survey and make simple statistics on the data in the data and influencing factors section. The presentation of the results and discussion will follow. Finally, in the last section brief conclusions are summarized.

2. Methodology

2.1. Ordered Logit Model

The ordered logit (OL) model is built based on a continuous latent variable which is unobserved but can be converted to three or more observed indicator variables through a series of cut points. The greater the value, the stronger the indicator. Let A_i denotes the latent variable for individual i and is defined as follows:

$$A_i = \beta X_i + \varepsilon_i = Z_i + \varepsilon_i \tag{1}$$

where Z_i denotes the systematic utility function and ε_i denotes the random disturbance term that are not included in the systematic component. X_i is a vector of independent variables and β is a vector of unknown parameters associated with X_i. In the parameterization used in this paper, no constant

appears because its effect is absorbed into the cut points. The latent variable A_i is tied to the ordered variable Y_i by the observation rule as shown in the following formula:

$$Y_i = m \; if \; u_{m-1} < A_i \le u_m, \; m = 1, \, 2, \ldots, M \tag{2}$$

where u_m represent the thresholds with an ascending order: $u_1 < u_2 < \ldots < u_{M-1}$. They are also unknown parameters to be estimated. Besides, u_0 and u_M are defined as $-\infty$ and $+\infty$ respectively. The probability function can be written as follows:

$$Pr(Y_i = m) = Pr(u_{m-1} < Z_i + \varepsilon_i \le u_m) = Pr(u_{m-1} - Z_i < \varepsilon_i \le u_m - Z_i) \tag{3}$$

In the OL model, ε_i is subjected to the logistic distribution. The standard logistic cumulative distribution function is as follows:

$$Pr(X \le x) = \frac{e^x}{1 + e^x} = \frac{1}{1 + e^{-x}} \tag{4}$$

Then the probability function in formula (3) can further be written as

$$P_{im} = Pr(Y_i = m) = \frac{1}{1 + exp(Z_i - u_m)} - \frac{1}{1 + exp(Z_i - u_{m-1})} \tag{5}$$

The unknown parameters in formula (5) include cut points u_m and coefficients β in the systematic utility function Z_i. The parameter estimating approach is maximum likelihood method and the likelihood is the product of all the observation probability.

2.2. Multilevel Mixed-Effects Ordered Logit Model

Multilevel mixed-effects ordered logit (MEOL) model considers fixed effects of explanatory variables and random effects which may contains many level of nested clusters. In the absence of random effects, MEOL model reduces to OL model. For simplicity, the following two-level MEOL model is considered for the latent variable A_{ij}, which denotes the utility of individual i in cluster j.

$$A_{ij} = \alpha_j C_{ij} + \beta X_{ij} + \varepsilon_{ij} = W_{ij} + \varepsilon_{ij} \tag{6}$$

where X_{ij} is a vector of independent variables for the fixed effects at individual level with coefficients β. C_{ij} is a vector of independent variables at cluster level corresponding to the random effects α_j, which are J realizations from a multivariate normal distribution. The random effects are not directly estimated as model parameters but are instead summarized according to the variance components. The errors ε_{ij} are subjected to the logistic distribution. Similar to OL model, the relationship between latent variable A_{ij} and observing outcome Y_{ij} is as follows:

$$Y_{ij} = m \; if \; v_{m-1} < A_{ij} \le v_m, \; m = 1, \, 2, \ldots, M \tag{7}$$

where the definition of cut points v_m are the same as u_m. Corresponding to formula (3) and (5), the probability function is

$$
\begin{aligned}
P_{ij} = Pr\left(Y_{ij} = m \middle| v, \alpha_j\right) &= Pr\left(v_{m-1} < W_{ij} + \varepsilon_{ij} \le v_m\right) \\
&= Pr\left(v_{m-1} - W_{ij} < \varepsilon_{ij} \le v_m - W_{ij}\right) \\
&= \frac{1}{1 + exp\left(W_{ij} - v_m\right)} - \frac{1}{1 + exp\left(W_{ij} - v_{m-1}\right)}
\end{aligned}
\tag{8}
$$

For cluster j, consisting of $i = 1, 2, \ldots, n_j$ observations, the conditional distribution of $y_j = \left(Y_{1j}, \ldots, Y_{n_jj}\right)\prime$ given a set of cluster-level random effects α_j is

$$f\left(y_j|v, \alpha_j\right) = \prod_{i=1}^{n_j} P_{ij}^{I_m(Y_{ij})} = exp \sum_{i=1}^{n_j} \left\{I_m\left(Y_{ij}\right)lnP_{ij}\right\}$$
$$I_m\left(Y_{ij}\right) = \left\{ \begin{array}{l} 1, \text{ if } Y_{ij} = m \\ 0, \text{ otherwise} \end{array} \right.$$

(9)

where the likelihood contribution for the jth is obtained by integrating α_j out of the joint density $f\left(y_j, \alpha_j\right)$. And the likelihood for the entire dataset is simply the sum of the contributions of all the clusters.

3. Data and Influencing Factors

3.1. RP/SP Survey

Beijing is the second earliest city operating customized buses (CB) in China, only less than one month later than Qingdao in 2013. In this study, a two-step combined survey of revealed preference (RP) survey and stated preference (SP) survey for commuters was conducted through online and offline methods in Beijing, and 888 individuals participated in this survey.

First, the RP survey was designed to collect three parts of information. The first part is the individual characteristics of commuters, including gender, age, education, job, and income. The second part investigated commuters' car ownership, the convenience to a bus or subway station and the familiarity with CB service. The last part collected the commuting characteristics of respondents. In the current mode option, seven main commute modes were considered: (1) car; (2) taxi; (3) bus; (4) rail; (5) bus + rail, a combination of bus and rail; (6) biking or walking; (7) others. Commute time, commute cost, and transfer numbers were also collected in this part. It needs to be pointed out that commute distance was discarded in this survey although it is an important feature representing the commuting characteristics. This is because travel distance and travel time are highly correlated and existing studies usually prefer to use travel time instead of travel distance since respondents are found to be more sensitive to travel time duration than to distances [24,32].

The purpose of SP survey step was to collect the mode shift decisions of commuters from the current travel modes to customized bus. Because the travel distance of biking or walking commuters were too short to enjoy the customized bus service and only few people travelling by other modes, respondents using the first five commute modes were required to complete the SP survey. In this way, 652 valid questionnaires were further selected for this study. Two hypothetical scenarios, one seat and no seat, were designed and respondents were asked to make a decision under each scenario. Eventually, database with 1304 commuter demands were collected to analyze the influencing factors of transfer behaviors.

3.2. Data Description

Based on the RP data, the descriptive statistics and variables definition are summarized and visually represented in Table 1. In the sample, there are slightly more men commuters than women commuters. Most of them are less than fifty years old, have a bachelor's degree, work in enterprises and institutions, and have a middle income. These feature distributions accord with the social pattern. A large portion of sample commuters have no car but a bus or subway station near their residences, additionally never heard of CB service. It is noteworthy the nearly half of the commuters who do not need to transfer contain car and taxi commuters, so that most of the public transport commuters need to transfer once or twice.

Table 1. Descriptive statistics and variables definition about revealed preference (RP) data.

Variable	Type	Value	Frequency	Percent
Gender	Female	0	286	43.87
	Male	1	366	56.13
Age	≤25	1	226	34.66
	26~50	2	387	59.36
	>50	3	39	5.98
Education	High school or below	1	30	4.60
	College degree	2	399	61.20
	Master or above	3	223	34.20
Job	Others	0	238	36.50
	Enterprises and institutions	1	414	63.50
Income per month (RMB)	<5000	1	65	9.97
	5000~12,000	2	311	47.70
	12,001~20,000	3	245	37.58
	>20,000	4	31	4.75
Car ownership	No car	1	394	60.43
	One car	2	222	34.05
	Two or more cars	3	36	5.52
Station within 500m of the residence	No	0	138	21.17
	Yes	1	514	78.83
Familiarity with CB	Never heard	1	335	51.38
	Know about it	2	204	31.29
	Experienced	3	113	17.33
Commute mode	Car	1	113	17.33
	Taxi	2	77	11.81
	Bus	3	187	28.68
	Rail	4	121	18.56
	Bus + rail	5	154	23.62
Commute time (min)	Float	-	-	-
Commute cost (RMB)	Float	-	-	-
Transfer number	0	0	290	44.48
	1	1	173	26.53
	2	2	127	19.48
	3	3	44	6.75
	4 or more	4	18	2.76

The SP survey designs two scenarios, each of which consists of three SP choices including do not transfer to CB, remain undecided, and transfer to CB. If the CB service is attractive enough for one commuter, he or she would transfer to CB, on the contrary, he or she would not transfer if there is weak attraction. The frequency and proportion of transfer decisions are displayed in Table 2. About half of the sample commuters do not transfer to CB if there is no seat, while want to transfer if there is one.

Table 2. Frequency and proportion of choices under two scenarios in stated preference (SP) survey.

Choices	No Seat		One Seat	
	Frequency	Percent	Frequency	Percent
Do not transfer to CB	483	54.82	107	12.15
Remain undecided	185	21.00	363	41.20
Transfer to CB	213	24.18	411	46.65

Combining RP data with SP data, choices of commuters with different travel modes can be seen in Figure 1. When there is no seat in CB, a large proportion of commuters choose not to transfer whatever the travel mode is used. The number of commuters choosing remain undecided and transfer increases when CB provides one seat; furthermore, more commuters are willing to transfer under this scenario except for bus commuters. It can be preliminarily supposed, from Table 2 and Figure 1, seat is an important factors influencing commuters' decisions.
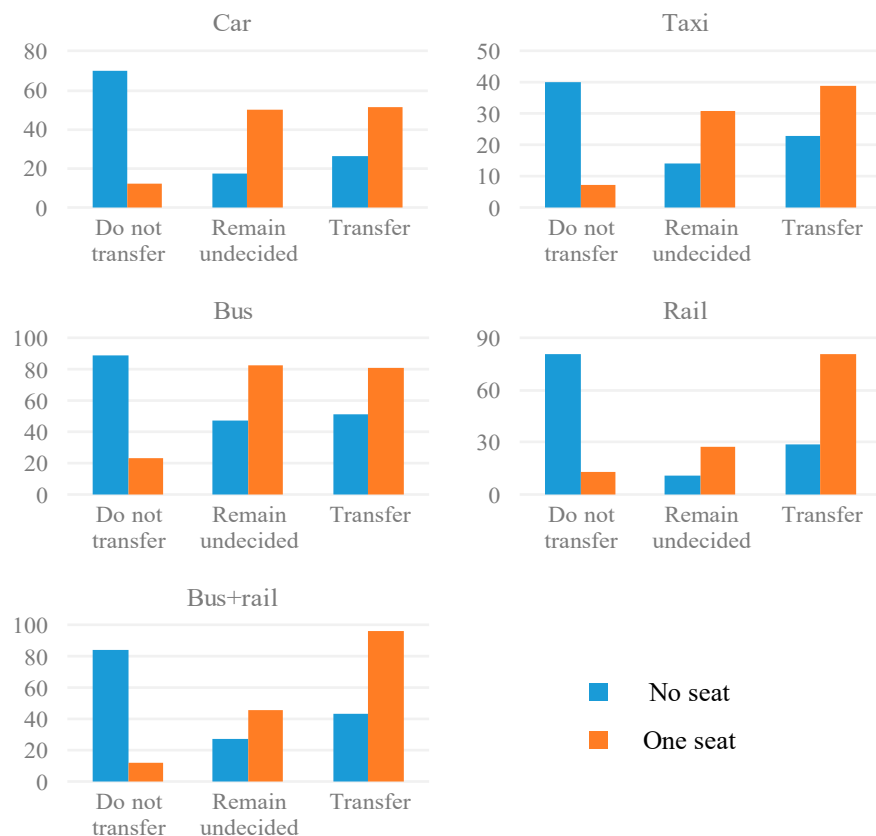
Figure 1. Number of commuters for each option.

4. Empirical Study

4.1. Model Structure

The purpose of this study is to analyze the influence of explanatory variables on transfer probabilities from the current commute mode to customized bus. Using the methodology described in Section 2, the latent variable (A_i and A_{ij}) in this study is the attraction of CB service to commuters. Commuters choose one of the three ordered decisions, taking on the value 1, 2, or 3, according to the attractiveness of CB, which are do not transfer, remain undecided, and transfer. The explanatory variables of fixed effects are divided into three categories, individual characteristics, commuting characteristics, and CB-related information. Considering different travel modes provide particular services and bring different experience to commuters, attitudes and habits may be somewhat similar among individuals using the same commute mode, but are different from other groups. So a random intercept effects for commute modes is specified in the two-level MEOL model, indicating individuals are nested in mode. Figure 2 illustrates the conceptual models.
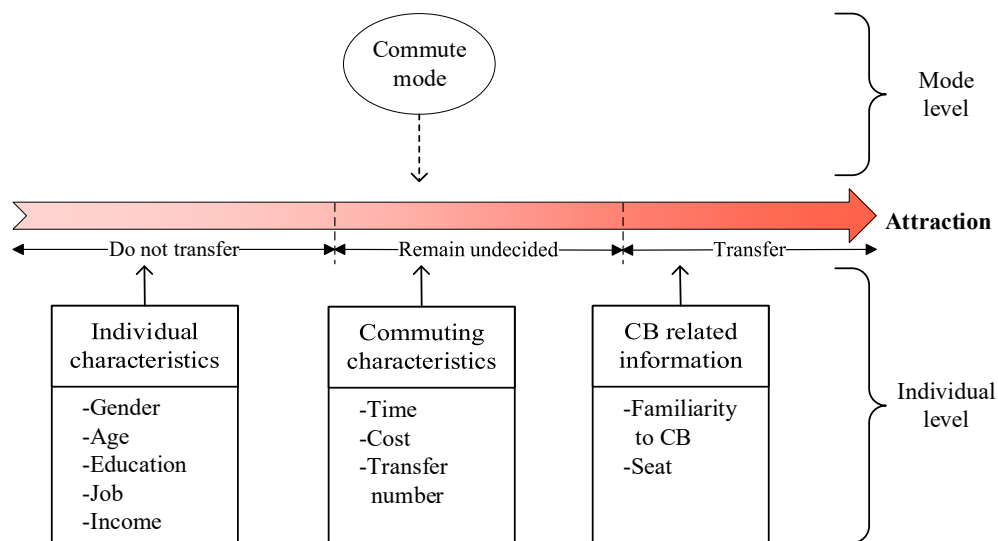
Figure 2. Conceptual models for the attraction of customized bus (CB) service.

4.2. Estimation Results

Using the RP and SP data, the estimated coefficients and cut points of the two models are displayed in Table 3, also showing the goodness of fit and the significant level. The likelihood ratio test means MEOL model versus OL model. The parameters are standardized so that the independent variable does not contain a constant term, which are absorbed into the cut points.

Table 3. Estimation results of ordered logit (OL) model and mixed-effect ordered logit (MEOL) model.

Variables	OL Model		MEOL Model	
	Coef.	Z-stat.	Coef.	Z-stat.
Gender	0.686 ***	5.83	0.696 ***	5.86
Age	0.254 **	2.00	0.263 **	2.03
Education	−0.017	−0.16	0.029	0.27
Job	0.019	0.12	0.012	0.08
Income	−0.420 ***	−4.69	-0.419 ***	-4.61
Time	0.351 ***	5.69	0.347 ***	5.44
Cost	0.203 ***	4.95	0.220 ***	4.54
Transfer number	0.189 ***	2.65	0.335 ***	3.84
Familiarity to CB	0.479 ***	5.33	0.525 ***	5.73
Seat	1.905 ***	15.88	1.932 ***	15.96
/cut1	2.480	–	2.800	-
/cut2	4.007	–	4.354	-
Mode				
Var(_cons)	–	–	0.130	-
Goodness of fit				
Number of observations	1304		1304	
Log-likelihood	−1168.8468		−1161.2334	
Chi2	495.30		378.19	
Prob > Chi2	0.00		0.00	
Pseudo R2	0.175		-	
Likelihood-ratio test				
LR chi2(1)		15.23		
Prob > Chi2		0.00		

Note: ***, ** represent 1%, 5% significance.

4.3. Mode Difference Estimation

It is obvious that commute modes have great influence on commuters' mode shift decisions, leading us to consider whether the coefficients of explanatory variables vary with different modes. Using subsamples for each commute mode, five OL models are constructed and estimated respectively. Car ownership is added as an explanatory variable and travel number is removed when estimating coefficients of car commuters, because car ownership reflects the convenience for them and the transfer numbers tend to be zero. As for public transport commuters, containing bus, rail, bus + rail commuters, station within 500 m of the residence is taken into account, representing whether there are good public transport facilities. Estimation results and significance levels are presented in Table 4. All models have passed the goodness of fit test at a high level so that the test index are not listed in the table.

Table 4. Estimation results of each commute modes.

Variables	Coefficients	Z-Statistics
Car		
Gender	0.792 ***	2.73
Age	0.426	1.08
Education	−0.394	−1.52
Job	0.007	0.02
Income	−0.497 **	−2.20
Time	0.447 **	2.29
Cost	0.183 *	1.86
Familiarity to CB	0.702 ***	2.72
Seat	2.013 ***	6.89
Car ownership	−0.834 **	−2.22
Taxi		
Gender	0.736 **	2.08
Age	0.593	1.42
Education	0.486	1.34
Job	−0.681	−1.38
Income	−0.617 **	−2.29
Time	0.658 ***	3.04
Cost	0.218 *	1.76
Transfer number	−0.194	−0.41
Familiarity to CB	0.953 ***	2.83
Seat	1.767 ***	5.06
Bus		
Gender	0.492 **	2.30
Age	−0.042	−0.20
Education	0.133	0.63
Job	0.263	0.95
Income	−0.300	−1.46
Time	0.207 **	2.06
Cost	0.368 ***	2.63
Transfer number	0.311 **	2.23
Familiarity to CB	0.400 **	2.11
Seat	1.359 ***	6.42
Station within 500 m of the residence	−0.470*	−1.71
Rail		
Gender	1.000 ***	2.97
Age	0.582	1.36
Education	−0.145	−0.48
Job	0.080	0.17
Income	−0.523 **	−2.13
Time	0.478 **	2.19

Table 4. *Cont.*

Variables	Coefficients	Z-Statistics
Cost	0.394 **	2.12
Transfer number	0.435 **	2.02
Familiarity to CB	0.505 **	2.25
Seat	3.097 ***	8.57
Station within 500 m of the residence	−0.446	−1.12
Bus + rail		
Gender	0.532 *	1.95
Age	0.535 *	1.74
Education	0.259	1.08
Job	−0.255	−0.68
Income	−0.319	−1.57
Time	0.290 **	2.06
Cost	0.281 **	2.10
Transfer number	0.388 **	2.02
Familiarity to CB	0.433 **	2.32
Seat	2.218 ***	8.44
Station within 500 m of the residence	−0.638 *	−1.95

Note: ***, **, *represent 1%, 5%, 10% significance.

4.4. Discussion

See Table 3, the coefficient estimates of time, cost and transfer number had significant positive signs as expected. It is undoubted that the attraction of CB service increases when commute time, commute cost, or transfer time of the current travel mode rise, resulting in stronger willingness of commuters to travel by CB. The coefficient of gender is significantly positive, implying that men are more likely to make a commute mode shift than women, all things being equal. Notice that, the absolute value of coefficient, 0.686 in OL model, only means the attraction of CB to men is 0.686 larger than to women. The comparison of transfer probability between men and women should make further efforts. Other coefficient values are the same. Income negatively affects the transfer probability. On the contrary, age has a positive effects. Commuters who know about CB or had ever experienced CB may have much more willingness to use it, which is a valuable information for operators of CB. Absolutely, seat is the most advantageous factor for the attractiveness of CB service comparing with any other public transport modes unsurprisingly. In the MEOL model, variance component at the mode level, and coefficients at the individual level are estimated. The signs and significant level of coefficients of explanatory variables are the same with that in OL model and can be interpreted in the same way. The reported likelihood-ratio test shows that there is enough variability between commute modes to favor a MEOL model over a standard OL model.

Before discussing peculiarities in each group, common phenomenon among all groups are first presented, to some extent have similarities with the results above. (1) CB is more attractive to men than women. This is probably because a large number of women have to transport children to schools during their commuting. The current commute modes, especially car mode, make women more accustomed and convenient. Direct access of CB from home to work may not satisfy their travel demands. (2) The influences of age, education, and job on the attraction of CB service are not obvious, with the exception of age in bus + rail commuters. The majority of respondents have bachelor's degree or above, maybe they are much alike in perception and acceptance of new things, so that the education background of commuters make no difference to their mode shift decisions. Meanwhile, young people and middle-aged people have the same attitudes toward CB service, so does the employees of enterprises and institutions and employees of non-enterprises and institutions. (3) Commuters' familiarity to CB positively affects the attraction of CB. Commuters are always skeptical about unfamiliar travel mode but are more willing to try it once they understand the advantages and make a comparison with the

current mode. Besides, the impact is greater for car and taxi commuters, of which the coefficients are 0.702 and 0.953. CB belongs to public transport, affecting the bus, rail, and bus + rail commuters a little less. (4) The coefficients of seat had the expected signs and were significantly different from zero at the 1% level in all groups. We can draw a conclusion that comfort is one of the greatest strengths of CB from the absolute high coefficient value in addition.

Some peculiar and notable phenomenon in certain groups are then discovered as follows. (1) For car commuters, the coefficient of car ownership is significantly negative, indicating that commuters owing two or more cars have less probability to transfer to CB than commuters owing one car with other characteristics unchanged. In other words, the probability of using CB for commuting decreases if he or she, who commutes by car, buys one more car. (2) For bus and bus + rail commuters, if there is a station within 500 m of their residences, the attraction of CB significantly decreases at the 10% level because it is convenient to use the current commute modes. But for rail commuters, the impact of station is not significant. So whether there is a station near residence is not a particularly important factor influencing the mode shift decisions of public transport commuters. (3) The coefficients of income have negative signs and are significantly different from zero at the 5% level in car, taxi, and rail commuter groups. As commute cost of these travel modes are a little higher than bus, and commuters with higher income are relatively insensitive to cost factor, resulting in less probability of transfer to CB among high income commuters using high cost travel modes. (4) Increase in travel time and travel cost of the current commute modes have positive effects on the attraction of CB as a result of the competitive relationship between the two modes. But the influence of cost in car and taxi commuter groups is small as the coefficients are 0.183 and 0.218 respectively and are significant at the 10% level. The reason of this phenomenon is the high cost and high income of commuters using cars and taxis. This group of commuters may face higher time cost relatively speaking and one yuan increase in travel cost only has little impact on them, which is not worth mentioning. (5) Transfer number of current commute mode also has significant positive effect on the attraction of CB, except for that in taxi commuter group. The uneven sample distribution can explain this irrational coefficient. Usually speaking, taxi commuters need no transfer because of the one-stop service of taxis. But in our sample, 13 of the 77 commuters need to transfer once for some unknown reasons, leading to the strange coefficient value, which is meaningless and can be ignored.

5. Summary and Conclusions

Based on the combined RP and SP data collected from a questionnaire survey for commuters in Beijing through online and offline questionnaire, this study attempts to analyze the factors influencing the commuters' mode shift choices from the current commute mode to CB mode by applying standard and mixed-effects ordered logit model. The proposed models have estimated potential influencing factors from three aspects, including individual characteristics, commuting characteristics, and CB-related information. Five commute modes, which are car, taxi, bus, rail, and bus + rail, were taken into account because of the features and targeted passengers of CB. The attractiveness of CB service is segmented into three parts by two thresholds appearing as ordered discrete responses of commuters, do not transfer to CB, remain undecided, and transfer to CB.

The estimation results of models predict that one person one seat service makes the greatest contribution to the attractiveness of CB. In addition, familiarity to CB has the strongest association with mode shift decisions, the more commuters know about CB, the greater willingness to accept the relatively new mode. This puts forward suggestions of a wider popularization, even a trial experience service can be provided if possible, for CB operators to attract more target passengers. Moreover, female commuters show less tendency to transfer to CB than male commuters. Regarding the current commute modes, car and taxi commuters with higher income are more sensitive to time rather than to cost, whereas public transport commuters tend to have a high requirement against convenience, including easy access to the transport and less transfer numbers. The government and CB operators can

develop differentiation strategies for different groups of commuters based on the impacts of influencing factors so as to encourage more commuters to transfer to CB.

Future research would focus on the expansion of sample to consider the possible differences among cities because of the specific city cultures and features. In addition, some latent factors, such as user expectations toward mobility service, user attitude to environmental protection and safety concern, could be explored to achieve more accurate models. Finally, larger sample scale and the application of a random approach would be introduced into our survey.

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