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EFFECT OF ATTRIBUTE PERCEPTIONS ON MODE CHOICE BEHAVIOR IN A TRANSIT MARKET

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Abstract: Random utility models are often used to model traveler mode choice behavior in the demand analysis of a transit system. Transit operators might base their policy and operations planning on these estimates. The choice probability of these models is expressed in terms of utility for all transit modes, which is in turn associated with the characteristics or attribute values perceived by each traveler. In practice, however, often observed or published attribute values (e.g., fare) rather than perceived attribute values are used to estimate the utility. In reality, perception biases of the actual attribute values are likely to happen due to lack of convenient access to information. Fare and travel time, for example, are often not precisely known to all travelers. Therefore, there are variations in the perceived transit service attributes among travelers. How these perception variations affect the choice behavior is not generally understood. Will the provision of perfect information, and therefore the removal of these biases in attribute perceptions, be beneficial to travelers, operators and the overall system? This study conducts some simulation experiments to explore these issues.

Key Words: Mode choice, random utility models, attribute perceptions, bias, simulation

1. INTRODUCTION

Mode choice problem has been extensively studied and finds many real-life applications in the transportation industry. In demand analysis, this problem relates the choice behavior of travelers to the characteristics and level of service of different transport modes. The result of which provides the overall market shares of the transport modes, which are often used for transit system planning and operations. For example, rail service will only be provided if it would capture an adequate market share to offset the huge cost of infrastructure development and support its daily operations. In a competitive market, each private transit operator keeps alert of travelers' choices and therefore its market share, because these translate directly into revenue and hence profits.

As a result, accurate traveler choice prediction is always desired. Various discrete choice models, especially the random utility models (RUMs), play an important role in such prediction and more sophisticated models are being developed. For example, the restrictive independence assumption in logit model can be relaxed to different extent in nested logit (NL) model, generalized nested logit (GNL) models, or probit models for different computational requirements (e.g. McFadden, 1974; Ben-Akiva and Lerman, 1985; Willimas, 1977; Wen and Koppleman, 2001). On the other hand, others observe that taste variation exists in the population such that dissimilar evaluation of the characteristics and level of

services may lead to different choice behavior. Random coefficient models (RCM), or mixed logit (ML) models, with different utility coefficients across individuals on attributes is developed to capture the taste heterogeneity (e.g. Bhat, 2000; Munizaga *et. al.*, 2000). This approach is more consistent with the reality of choice behavior: each individual associates a utility value to each available mode according to his or her own scale, and he or she chooses a mode based on these values. In other words, choice is made at individual level and so should the discrete choice model. In random coefficient models, for example, the utility coefficient for time for each individual is not assumed to be the same but is assumed to follow a distribution among the population.

These advanced models have addressed part of the stochastic nature of utility by the introduction of alternative model structure and the inclusion of taste variation. However, there still remain other sources of variations that are usually overlooked. Among these, perceived values of the characteristics and level of service, like taste variation, can be different across individuals. In some cases, there may be a definite bias, or misperception, on a particular characteristic. For example, the bus fare of a leisure service in rural area may not be known to all; each traveler thus assesses his or her utility value of this service based on his or her perceived fare, which would vary across people. Besides, a consistent overestimation or underestimation of the fare may well be the case. Similarly, as in the case of taste variation, the choice behavior should be modeled at the individual level by using each individual's perceived attribute values in the utility function. Unfortunately, as is generally the case, the perceived attribute values are generally unobservable to the analyst. Both random coefficient and attribute perception will in effect lead to varying utility values at the individual level. Conceptually, taste variation is an indication of innate personality while attribute perception is related to the quality of information available. Taste variation is something hard to change in the short run. As for attribute perception, transit operators can manage to adjust the quality of their service information, through promotion or advanced traveler information system, as a strategy so as to capture market share.

This paper will investigate the effect of attribute perception on the mode choice behavior in a transit market. Attribute perception is reflected by the quality of information made available. Both travelers and transit operators will be considered. The existence and conditions of win-win situation, if any, will also be studied. In section 2, we provide a brief review of mode choice model and describe the approach that is used in this study. We then report and discuss our simulation results in section 3. In last section, we will conclude the paper.

2. MODE CHOICE WITH ATTRIBUTE PERCEPTIONS

Discrete choice models are commonly used to model mode choice behavior. Among these, the random utility models (RUMs) receive the utmost popularity to simulate the choice of an individual among available alternatives. Each individual is assumed to be rational, to associate a utility value to each alternative, and to choose the alternative that exhibits the maximum utility. The utility is random and can be decomposed into a systematic component and a random error term:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

where U_{ni} is the utility individual n associate to alternative i in the choice set $\mathbf{C}$, V_{ni} and ε_{ni}

are the systematical and random components respectively such that $E(U_{ni}) = V_{ni}$ and $E(\varepsilon_{ni}) = 0$. In RUMs, hence, individual n chooses alternative i if $U_{ni} > U_{nj}$, $\forall j \in \mathbf{C}, i \neq j$. The systematic utility is a function of the attribute values of different alternatives and socioeconomic characteristics of the decision-maker. In most applications, linear-in-parameter utility function is specified (Ben-Akiva and Lerman, 1985) as

$$V_{ni} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_i + \boldsymbol{\gamma}_i'\mathbf{z}_n \tag{2}$$

where $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}_i$ vectors of utility coefficient, $\mathbf{x}_i$ is the attribute vector of alternative i, $\mathbf{z}_n$ is the socioeconomic vector of individual n, and α_i is the alternative-specific constant.

Different choices of distribution for ε_{ni} will lead to different choice models. For example, logit model is obtained if all ε_{ni}'s are i.i.d. Gumbel, which has a closed form of the choice probability:

$$P_n(i) = \frac{\exp(V_{ni})}{\sum_{j \in \mathbf{C}} \exp(V_{nj})} \tag{3}$$

Probit model is obtained if ε_{ni}'s are multivariate normal. When each error term can be decomposed into an i.i.d. Gumbel variate and another random error term of any distribution, then it is a mixed logit model (Train, 2003). Random coefficient model can also be interpreted as a logit model wherein the utility coefficient $\boldsymbol{\beta}$ is not constant across individuals but be individual-specific, i.e. to replace $\boldsymbol{\beta}$ with $\boldsymbol{\beta}_n$ in (2). The alternative-specific constant α_i is generally assumed to be the same for every decision-maker for estimation reasons; the coefficient $\boldsymbol{\gamma}_i$ can be individual-specific and be treated in the same way as $\boldsymbol{\beta}$, but it is not considered here to ease notational complication. All $\boldsymbol{\beta}_n$'s are not known a priori but are assumed a common mixing distribution with density $f(\boldsymbol{\beta})$ of the underlying population. Therefore, the choice probability of a RCM takes the form

$$P_n(i) = \int \frac{\exp(V_{ni})}{\sum_{j \in \mathbf{C}} \exp(V_{nj})} f(\boldsymbol{\beta}) d\boldsymbol{\beta} \tag{4}$$

All these and other discrete choice models are different from one another in terms of their specifications of the error term or the utility coefficient. Even though specification of utility in (2) can be relaxed such that $\mathbf{x}_i$ is replaced by individual-specific vector $\mathbf{x}_{ni}$ to represent the variation of attribute perception in the population, this is not common because of the following reasons. Firstly, it is not practical to retrieve information in such details in a survey with limited resources or when there are many alternatives in the choice set. Secondly, as the perceived values is not known, it is generally treated by absorbing the biases of attributes into the unobservable error term ε_{ni}; thus it reduces to a standard model using the true attribute value vector $\mathbf{x}_i$. However, there can be a consistent overestimate or underestimate of the attribute values and the expected bias may not be zero in both cases. To absorb the bias into

the error term would result in $E(\varepsilon_{ni}) \neq 0$, which is assumed when decomposing utility in (1). Some may argue that this bias can be handled by adjusting the alternative-specific constant by an amount equal to the expected bias. Though this approach may result in a similar forecast as if the perception is modeled explicitly, it may lead to different statistical test results of the calibrated coefficients and possibly different model specifications.

In this study, we address these issues by considering individual perceptions on attribute values. Since we do not have information on all perceived attributes for each traveler, we assume the attribute perception follow a distribution $\mathbf{X}_{ni} \sim F_{\mathbf{X}}$. Hence $\mathbf{X}_{ni}$ enters the utility equation (2) as a random variable. As a result, the choice probability of the discrete choice model should consider all possible realizations of $\mathbf{x}_{ni}$. For example, the logit model with attribute perception takes a similar form as RCM:

$$P_n(i) = \int \frac{\exp\left(V_{ni}\left(\mathbf{x}_{ni}\right)\right)}{\sum_{j \in \mathbf{C}} \exp\left(V_{nj}\left(\mathbf{x}_{nj}\right)\right)} dF_{\mathbf{X}}\left(\mathbf{x}_{nk}, \forall k \in \mathbf{C}\right) \tag{5}$$

Extensions to other discrete choice models like probit, NL, ML as well as RCM etc., are similar and straightforward.

We formally define the bias as the difference of the expected $\mathbf{X}_{ni}$ less the true attribute level. The rationale behind such definition is best shown with an illustration. Consider only with one attribute – fare, which is actually \$5. Without perfect information, a traveler may overestimate the fare (say at \$6) or underestimate it (say at \$4). It would be the case that some travelers overestimate the fare while the others underestimate it. In our current study, we denote each traveler's perceived fare by a random variable X with the corresponding distribution F_X. To describe such distribution, we need some statistics such as mean and variance of F_X. With reference to the true attribute level x_0 (i.e. x_0=\$5 in the illustration), we can write the perceived fare as

$$X = x_0 + B \tag{6}$$

where B is another random variable for the misperception of attribute level. Collectively among all travelers, we denote the mean of such misperception as the bias of the attribute in the population, which is equal to

$$E(B) = E(X) - x_0 \tag{7}$$

as it is in the above definition. As a result, $E(B) > 0$ stands for, on average among all travelers, an overestimated fare. In a similar manner, the opposite holds. Moreover, a specific value of bias is associated with the perception in the unit of the concerned attribute. For instance, in our illustration, a zero bias stands for $E(B) = 0$, or F_X is distributed with the true attribute level x_0 (\$5) as its mean; while a bias of two, i.e. $E(B) = 2$, indicates F_X has a mean two units higher than the true attribute level x_0, or \$7. Thus, generalizing to more than one attribute, a positive bias refers to an overestimation while a negative bias corresponds to

an underestimation. The uncertainty is then measured by the variance of $\mathbf{X}_{ni}$. In this study, we express the quality of information in terms of the bias $E(\mathbf{B})$ and variance of $\mathbf{X}_{ni}$; and in the special case of perfect information $E(\mathbf{B}) = \mathbf{0}$ with null variance, that is, the distribution $F_{\mathbf{X}}$ is indeed degenerated.

3. SIMULATION STUDIES

3.1 Simulation Methodology

The discrete choice model with attribute perception in the last section is used to study the mode choice behavior. Many types of kernel can be used for study; we have chosen the simplest form of logit-kernel, as shown in (5). Other advanced models are not chosen as the kernel because of the complexity to separate the effect of attribute perception from other features such as taste variation. A universal choice set is also assumed in the study.

We perform the studies in the following ways. For different extents of attribute perception, we specify a family of distribution $F_{\mathbf{X}}$ for the perceived attribute vector $\mathbf{X}_{ni}$. We investigate two aspects of the attribute perception. Firstly, we are interested in the existence of a definite bias in the perceived characteristics or level-of-service, i.e. $E(\mathbf{B}) \neq \mathbf{0}$. This can be either a consistent overestimate or underestimate of the attributes in the population. However, the case of zero bias is also included for the purpose of comparison as in the usual case when attribute perception is not considered. In the study, the bias is included by specifying the mean of $F_{\mathbf{X}}$ being equal to the sum of true attribute value and the bias similar to (6). Secondly, we are also interested in the variation of the attribute perception among individuals. This is modeled as the variance and coefficient of variation (c.o.v.) of $F_{\mathbf{X}}$. A higher c.o.v. represents a state of more disagreement among individuals. This can be the case of an unfamiliar mode (e.g. unknown fare) or a less reliable service (e.g. travel time with possible congestion).

The logit-kernel model with attribute perception in (5) predicts the aggregate choice probability of each mode. It does not have a closed form and is often estimated by simulation. In this study, we simulate the result at the individual level. That is, instead of expressing one's choice as a probability according to (5), the utility vector of each individual is simulated and the mode with the maximum utility is chosen with probability one. This resembles the data collected in a survey when each respondent is asked for only the chosen alternative in a revealed or stated preference survey. The data is simulated in a way consistent to (5).

Specifically, we generate data on attribute perceptions $\mathbf{x}_{ni}$, socioeconomic characteristics $\mathbf{z}_n$ and disturbance terms ε_{ni} from respective distributions in each simulation. For example, in the m-th simulation, $\mathbf{x}_{ni}^{(m)}$ is randomly drawn from its distribution $F_{\mathbf{X}_i}$, i.e. $\mathbf{x}_{ni}^{(m)} = F_{\mathbf{X}_i}^{-1}(u_{mni})$ where $u_{mni} \in [0,1]$ is a standard uniform random variable. The $\mathbf{z}_n^{(m)}$'s are obtained in the same manner. As for the logit-kernel chosen in this study, ε_{ni} is i.i.d. Gumbel with density given by $f(\varepsilon_{ni}) = \exp(-\exp(-\varepsilon_{ni}))$, the simulated $\varepsilon_{ni}^{(m)} = -\ln(-\ln u'_{mni})$ where u'_{mni} is an independent standard uniform random variable. The same procedures apply to every alternative $i \in \mathbf{C}$ and

each individual n. We then have generated a full data set $S_m = \left(\mathbf{x}_{ni}^{(m)}, \mathbf{z}_n^{(m)}, \varepsilon_{ni}^{(m)}; \forall n, \forall i \in \mathbf{C}\right)$ in the end. With S_m, we can directly compute the perceived utility from (1) and (2):

$$U_{ni}^{(m)} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_i^{(m)} + \boldsymbol{\gamma}_i'\mathbf{z}_n^{(m)} + \varepsilon_{ni}^{(m)} \tag{8}$$

for all alternatives, and identify the final choice of individual n as $I_n = \arg\max_i \left\{U_{ni}^{(m)}, i \in \mathbf{C}\right\}$ with the maximum perceived utility. By denoting the simulated choice indicator $\delta_{ni}^{(m)} = 1\left\{U_{ni}^{(m)} > U_{nj}^{(m)}, \forall j \in \mathbf{C}, i \neq j\right\}$, we have:

$$\lim_{M\to\infty} \frac{1}{M}\sum_{m=1}^{M} \delta_{ni}^{(m)} = P_n(i), \tag{9}$$

meaning that the simulation approach is a consistent estimation of the expression in (5). Moreover, the current simulation approach allows us to examine the possible magnitude of the bias of each individual.

3.2 Simulation Cases

In the case studies, we consider four modes – A, B, C and D. For each mode, the attribute vector $\mathbf{x}_i$ consists of two characteristics, travel time and fare, as shown in Table 1. The time and fare of these modes are assumed as they are to screen out any dominated option. In addition, the socioeconomic characteristics of each individual are also generated: age is drawn from a uniform distribution between 10 and 60, gender from a half-half split, and income to the nearest thousand is evenly distributed between 8,000 and 12,000. The alternative-specific constants and utility coefficients assumed in the choice behavioral model is tabulated in Table 2. Since it is a hypothetical case study, the exact type of transit mode does not matter in the behavioral model given the information in Tables 1 and 2. Nonetheless, one can consider that modes A and B are different bus services; mode C is a streetcar service;

Table 1. True Characteristics of All Modes

Mode	**A**	**B**	**C**	**D**
Time	15	20	18	10
Fare	10	8	9	15

Table 2. Alternative-Specific Constants and Utility Coefficients

Mode	α_i	$\boldsymbol{\beta}$		$\boldsymbol{\gamma}_i$		
		Time	Fare	Age	Gender	Income
A	-			-	-	-
B	0.188	-0.204	-0.252	0	0	0.000037
C	0.275			-0.045	0.24	0.000018
D	0.425			-0.06	0.14	0.000042

and mode D is a subway. Female, with dummy gender indicator being 1, favours newer rail-based transit modes C and D, and older people favours traditional bus services.

The perceived attribute vector $\mathbf{X}_{ni}$ is assumed to follow a lognormal distribution. A family of the distribution is considered with different magnitudes of biases and coefficient of variations. We examine the influence on the actual travel time and fare payment of the system, along with the average perception of these attributes by the travelers. The indirect utility of the system is also measured by the expected maximum utility (EMU) term. Breakdown of the market shares is also recorded. In the simulation case study, all four modes are subjected to the issue of quality of information. Travelers impose both biases and variations to the attributes of all modes. In order to streamline the analysis and discussion, we limit ourselves to consider that all modes, whichever applicable, are subjected to the same magnitude of bias and c.o.v. at the same time.

3.3 Simulation Results

We examine different magnitudes of the biases first. Figure 1 shows the market share of each mode when the variation is small (i.e. c.o.v. = 0.1) and when the bias is between zero and two (the same for both travel times and fares of all modes). When the bias is zero and the variation is small, it is approximately the choice probability given by the logit model with the true attribute values. Indeed numerical results not reported here show that the difference in market share with perfect information is less than 0.5%. From Figure 1, it shows as the bias increases across the individuals for all modes, some modes (e.g. A and B) would lose market shares to other modes (e.g. C and D). This appears contradictory to the belief that the equal biases on all modes should be compensated as only differences in utility values matter in RUMs. However, as the perceived attribute values are random among individuals, the same average perception biases for all modes does not imply that one has equal perception on the alternatives unless there is no variation between decision-makers, i.e. when c.o.v. is zero. This is also the reason why we obtain wavy curves in the figure. In the meantime, at higher

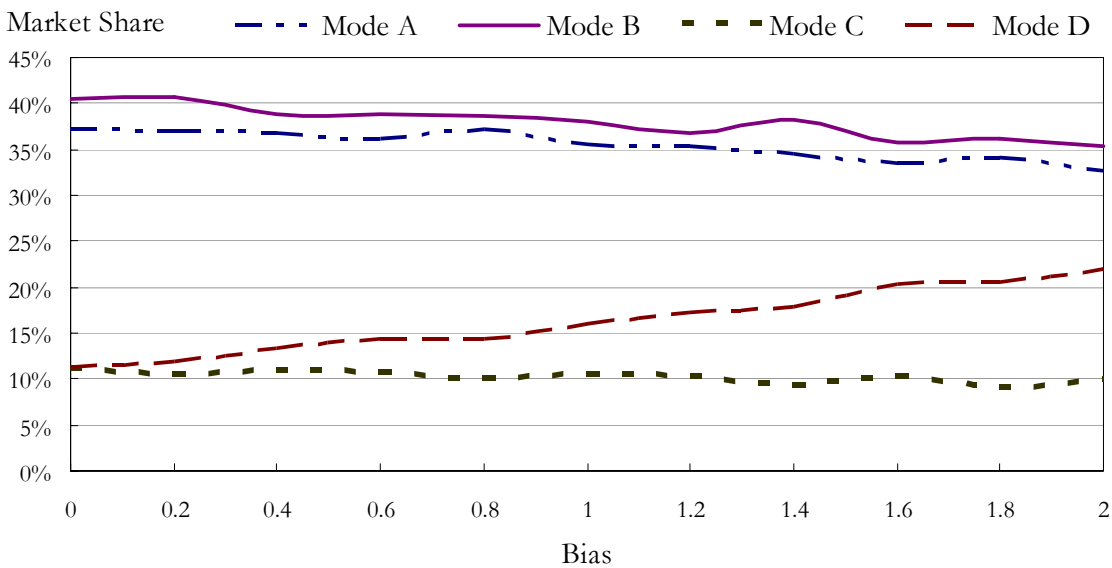

Figure 1. Market Share by Transit Modes at Various Biases (C.O.V. = 0.1)

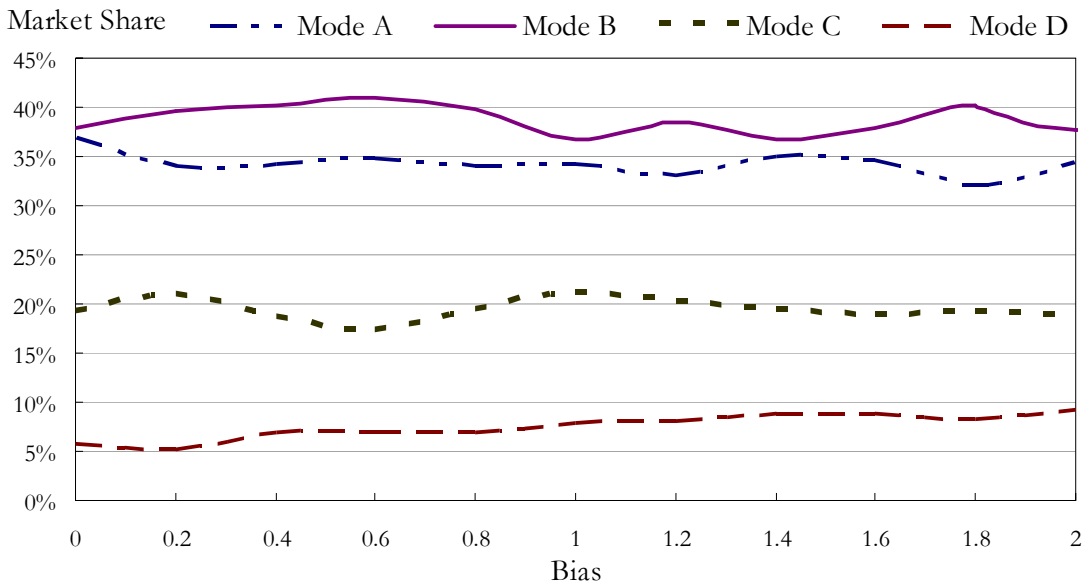

Figure 2. Market Share by Transit Modes at Various Biases (C.O.V. = 0.9)

bias and fixed c.o.v., the variation of an attribute value is actually larger. Therefore, one should anticipate that part of the substantial increase in market share by Mode D is contributed by the more uncertain situation on the transit characteristics and level of service.

However, the conjecture that Mode D always benefits from uncertainty is probably wrong. Figure 2 shows the same graph as in Figure 1 except with a larger variation, c.o.v. = 0.9. One should note the generally flat, though wavy, curves. It shows that at high uncertainty, the effect of an equal bias to all modes is not too significant as the biases gradually increase. Nonetheless, if one compares Figure 2 with Figure 1, and especially the case of perfect information at the left-end on Figure 1, one should note that Mode C roughly doubles its market share in this highly uncertain situation. Mode D, on the other hand, cannot maintain its market share obtained under the perfect information situation. It actually loses patrons at this uncertain environment. One interesting point is also observed: there may be some transit modes (Modes A and B) that maintain relatively stable market shares at various levels of bias and c.o.v.

Table 3 summarizes some of simulation results in scenario 1. The top panel corresponds to a situation when the variation is relatively small, while the middle and lowest panels show the case of medium and high variations. From the table, we observe similar trends at different variation levels. The actual mean travel time (fare) of travelers decreases (increases) with the biases. Interestingly, the perceived mean travel time of travelers shows an opposite trend; it increased with the biases. On the other hand, the perceived mean fare follows the same trend as the actual mean fare, which increases with the biases. The EMU drops in all cases. The mean biases become larger, or less negative, with the bias, though it never is the same as in the assumed bias.

It is helpful to make cross-reference to Figure 1 when we discuss these results. With a larger bias, there is a net shift from Modes A and B to Modes C and D, which have relatively shorter travel time, hence the drop in mean actual travel time. By the same token, the increase in

Table 3. Influence of Attribute Perception in Scenario 1

Bias	c.o.v.	Mean actual		Mean perceived		EMU	Mean Bias	
		Time	Fare	Time	Fare		Time	Fare
0	0.1	16.92	9.57	16.60	9.48	0.0111	-0.32	-0.09
0.2		16.83	9.65	16.71	9.71	0.0101	-0.12	0.06
0.4		16.74	9.71	16.78	9.99	0.0094	0.05	0.28
0.6		16.60	9.81	16.83	10.20	0.0086	0.23	0.39
0.8		16.39	9.91	16.66	10.53	0.0080	0.27	0.61
1.0		16.47	9.91	16.99	10.64	0.0074	0.52	0.73
1.2		16.40	9.96	17.05	10.82	0.0069	0.64	0.86
1.4		16.23	10.08	16.97	11.14	0.0064	0.74	1.06
1.6		16.03	10.23	17.03	11.44	0.0060	1.00	1.20
1.8		15.98	10.28	17.03	11.55	0.0056	1.04	1.28
2.0		15.80	10.41	17.02	11.83	0.0052	1.22	1.41
0	0.5	17.01	9.45	12.69	7.91	0.0358	-4.32	-1.54
0.2		16.97	9.51	12.67	8.13	0.0334	-4.30	-1.38
0.4		17.02	9.51	13.08	8.28	0.0299	-3.94	-1.22
0.6		17.10	9.48	13.38	8.44	0.0287	-3.71	-1.04
0.8		17.00	9.51	13.32	8.68	0.0281	-3.68	-0.84
1.0		16.76	9.69	13.16	8.84	0.0261	-3.60	-0.85
1.2		16.93	9.54	13.40	8.94	0.0251	-3.52	-0.60
1.4		16.72	9.72	13.27	9.38	0.0228	-3.45	-0.34
1.6		16.73	9.73	13.50	9.13	0.0237	-3.23	-0.60
1.8		16.61	9.84	13.44	9.53	0.0203	-3.16	-0.31
2.0		16.64	9.80	13.74	9.71	0.0189	-2.90	-0.08
0	0.9	17.16	9.35	10.21	6.34	0.0951	-6.96	-3.01
0.2		17.41	9.24	10.00	6.35	0.0941	-7.41	-2.89
0.4		17.22	9.37	10.24	6.56	0.0954	-6.97	-2.81
0.6		17.33	9.29	10.39	6.61	0.0886	-6.95	-2.68
0.8		17.10	9.42	10.30	7.02	0.0834	-6.80	-2.40
1.0		17.03	9.49	10.18	7.05	0.0789	-6.84	-2.44
1.2		17.17	9.39	10.61	7.27	0.0737	-6.57	-2.12
1.4		16.86	9.59	10.25	7.42	0.0770	-6.61	-2.16
1.6		17.04	9.48	10.27	7.37	0.0742	-6.77	-2.11
1.8		17.29	9.35	10.60	7.37	0.0727	-6.69	-1.98
2.0		16.97	9.54	10.79	7.68	0.0683	-6.18	-1.85

mean actual fare is a result of travelers shifting to more expensive transit modes. At small variations, the perceived attribute values center closely to the actual mean plus a positive bias, thus resulting in the consistent overestimates of time and fare. Therefore, in the top panel of Table 3, the perceived means of travel time and fare are both higher than the actual means. And the EMU drops with the bias down the column.

At higher variations (c.o.v.), the attribute values of individuals have much larger shifts from their actual values. The utility maximization principle of the choice model picks the mode

with the highest (or least negative) utility given the realized random biases. The mode happens to have received the most favorable bias (in most cases a negative shift) is picked. That is, the biases are always considered in an optimistic manner. The end result is that the perceived means of travel time and fare are consistently lower than their actual means, as observed in the middle and bottom panels of Table 3. This result is also confirmed by the negative mean bias observed in the middle and bottom panels, which corresponds to an underestimation of the attribute values, and by the increasing EMU with biases in these two panels. The high variations in perceived attribute values fool travelers into thinking that their choices are good, despite the contrary. Had they known better, they would not have chosen what they have.

On last point is that although not considered in this study, the EMU value may be used as the representative utility in the demand curve. Therefore, it raises an interesting observation that poor quality of information would induce more travel demand, because some rational utility-maximizing travelers are misled to travel as a result of their own underestimation of time and fare in situations short of quality service information.

4 CONCLUDING REMARKS

Mode choice forms an important part of transportation demand analysis. Transit operators largely base their policy and operations planning on these estimates. Random utility models express the choice probability of any specific mode of an individual as a function of all modes' indirect utility values. The individual utility of a mode is in turn derived from its perceived level-of-service characteristics. In practice, however, we seldom have access to the perceived level-of-service characteristics of all modes of each individual; as a result, the individual-specific attribute perception is often absorbed into the unobserved error term in these models. Observed or published attribute values are instead used to estimate the utility function. Moreover, the effect of the quality of information to traveler choice behavior is not precisely understood. Is it always beneficial to provide information of higher quality, or even perfect information, on all transit services?

In this paper, individual perception is modeled explicitly to study these issues. The consistent misperception is specified as biases, and the uncertainty among travelers are expressed as the variance or coefficient of variation. Simulations of perceived attributes for different biases and variations are performed. Attribute perception is found to be an important factor in modifying travelers' choice toward a particular transit mode. In particular, based on our simulation case study, we draw the following two interesting observations:

1. Higher expected maximum utility (EMU), which reflects an increased satisfaction of the transit system, is achieved at higher c.o.v. or variations. In other words, travelers consider and take advantage of the uncertain information in an optimistic manner. They feel that they are making better choices, and hence a higher EMU, even though the actual travel times and fares of their choices are worse than choices they would have made under the situation with perfect information – the happy fool scenario.

2. The quality of information to be provided has a large influence on travelers' choices and therefore the market shares of transit services. However, it appears to be difficult to manipulate the kind of information to be provided so as to optimize one's market share. Some general trends of the impact of information provision, however, can be observed.

To this end, it is found that lack of information is not always an evil to travelers, operators and the system, neither is perfect information always desirable. However, the findings of this paper are based on a limited simulation case study. There remains a lot to be done and extended in order to get a better understanding of this interesting problem.

It is the aim of this paper to acknowledge the usually overlooked phenomenon of attribute misperception of decision-makers, partly due to its hidden nature to transport analysts, and the potential problems of lower quality demand analysis thereof. We wanted to show, and have established, the importance of such consideration in this paper by showing how travelers behave and decide their choices with different quality of information. Therefore, we purposefully studied in a setting where the only uncertainty comes from the unknown attribute misperception but not from the accuracy of model specification and bias estimation. These additional considerations are nonetheless central in extending the current findings. Just as much scrutiny is needed for the estimation of utility parameters for different model specifications (such as logit, probit, NL, GEV, etc.), bias estimation should be dealt with closely with the underlying bias mechanism. This is beyond the scope of this paper, but we will focus on the estimation issue in another subsequent study.

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