Modeling Travel Shift Behavior: a Case Study in Shanghai

Jieyu Fan, College of Transportation Engineering, Tongji University
Kun Gao, Institute for Transport Planning and Systems (IVT), ETH Zürich
Kay W Axhausen, Institute for Transport Planning and Systems (IVT), ETH Zürich
Lijun Sun, College of Transportation Engineering, Tongji University

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Jieyu Fan	Kun Gao	Kay W. Axhausen	Lijun Sun
Tongji University	Institute for Transport Planning and Systems (IVT) ETH Zürich Zürich	Institute for Transport Planning and Systems (IVT) ETH Zürich Zürich	College of Transportation Engineering, Tongji University
+86 18801791260 fanjieyu@tongji.edu.cn	+41 787376788 gaok@ethz.ch	+ 41 446333943 axhausen@ivt.baug.ethz.ch	+86 13801983997 ljsun@tongji.edu.cn

Abstract

This paper conducted a comparison study of mode shift behavior based on computer-aided SP surveys trying to distinguish the differences in conceptions of preference and inertia. The results show that same respondents have remarkably different choice behavior in mode shift context and another mode choice scenarios. The results indicate that there exists obvious inertia in mode shift from car to public transit besides preference for car. The inertia in mode shift should be modeled as an inherently independent component in utility function rather than interpreted as the effects of past travel experience on mode preference. It is found that same respondents have different values of travel time in different mode choice contexts. The results are beneficial for accurate modeling of inertia in mode shift behaviors.

Keywords

Travel shift choice; Inertia; Preference; Values of travel time savings; Discrete choice model

1. INTRODUCTION

Mode choice behavior has been traditionally modelled using microeconomic theories based on the assumption that the individual selects the one with maximum expected utility after trade-offs between all available alternatives (called "Ideal Maximization"). Recently, increasing literatures declare that travelers might not perform as perfect utility maximizers in actual situations, especially in repeated travel contexts like commuting trips. Commuting trips mainly take place during certain period and repeat again and again over time. The repeated travel context leads to potential inertia component in the process of mode choice decision[1]. Commuters would not spare much extra vigor to search the best choice among alternatives every day and tend to reuse the satisfying past selection in stable travel context[2, 3], namely "inertia" or "habitual travel". It is generally claimed that inertia measures the effect of experienced preferences in previous periods on the current choice. Faced with new alternatives, the inertia represents the inclination to stick with past choice or disposition to change[4, 5]. In literatures, the effects of inertia in mode choice are commonly modelled by incorporating an inertia term besides preference in the utility function. The inertia term could be lagged dummy variables representing previous travel experience[6], a function of related variables ψ(e.g. the Level of service variables [7-9] or utility of past alternatives [4]) or changes in ψ variables[10, 11]. In these modeling methods, some researchers reckon that the inertia should be regarded as an independent component in utility, which is essentially and theoretically different from the preference term. However, others argue that the inertia term could be interpreted as the increase in preference for original travel choice that is caused by satisfying past travel experience The interpretation seems fair enough since in the viewpoint of utility specification, the inertia term indeed could be regarded as the incremental part of preference term and measures the effects of past experiences on current preferences in mode choice. It is very hard to distinguish the differences of the two conceptions ("inertia" and "preference") in the modeling equations since they have similar mathematic properties in the utility functions and have substitutability in the mathematic process of model estimations. The existing literatures mix the notations of "inertia" and "preference". Theoretically, "preference" and "inertia" are distinct conceptions. Preference denotes a strong favor of something, but inertia represents resistance to change from current state. Even though a lot of studies consider inertia in modeling choice, few works have been conducted to explore whether there are essential differences in the two conceptions in transportation contexts and to identify whether we should treat the inertia term differently from preference or it is fair enough to interpret the inertia as the impacts of past travel experiences on preference. The primary objective of this paper is to address the problem that whether the inertia is an essential independent component influencing travelers' mode choice that is different from preference intrinsically or it could be treated as the effects of past travel experiences on current preference for modes.

2 METHODOLOGY

2.1 Survey Design and Data Collection

A comparison study based on computer-aided stated preference survey was conducted. The surveys are specific for commuters who commute by private cars. At the beginning of the survey, revealed information of the respondent's current commuting trips was collected including the attributes (travel time, cost and comfort levels) of usually used mode and available alternatives (e.g. metro and bus) , demographic attributes and commuting context features (e.g. commuting distance, convenient access to public transit etc.). Then, mode shift scenarios are timely generated and presented to the respondent. In the mode shift scenario, one alternative is the respondent's original choice and other alternatives are hypothetical new public transit(metro and bus) that are available to the respondent in reality. The respondent was informed that the cost of commuting by car increases due to congestion pricing and assuming that new public transit services (metro and bus) are provided, whether they are willing to shift to the assumptive new public transit alternatives. The assumptive new public transit are generally better than actual public transit services that are available to the respondent. Details about the level settings are shown in **Table 1.**

After mode shift scenarios, some questions measuring psychological factors (e.g. awareness of environmental protection) were asked. Afterwards, the same respondent was given another SP scenarios (called new job scenarios). In new job scenarios, the respondent was informed that assuming that the respondent had a new job and the workplace changed to a brand new location and there were three assumptive alternatives (car, metro and bus) for work. The respondent was asked which mode he/she would choose. The scenarios are also generated timely based on the revealed information of travel time. The respondents are classified into three group according to actual mean travel time: short-time commuting, medium-time commuting, long-time commuting. Corresponding scenarios are generated for different groups. Details about the level settings of scenarios for new job scenarios are shown in **Table 2.** An example of the scenarios is shown in **Figure 1.**

The idea is that if the inertia could be explained as the effects of past travel experiences on preference, the respondent's preference for car should keep constant and the respondent will perform similar affection to car in the two different scenarios; if the inertia term in mode shift is essentially different from preference, the respondent will show different affections to car in mode shift scenario and in new job scenarios.

The statistical contents of scenarios are generated based on the D-error efficient design methods referring to the manual of specialized software for designing discrete choice instruments **Ngene**. 18 scenarios with the best utility balance were selected for each situation. Four mode shift scenarios and five new job scenarios were randomly chosen and presented to each respondent. A pilot survey was executed to test the validity (e.g. questions interpretation and understandability) of survey design. The data from pilot survey was used to provide prior information (e.g. preset parameters) for the formal SP scenarios design.

Investigators were recruited to conduct face-to-face and one-to-one surveys. With the assistance of traffic police departments, face-to-face surveys were carried out in two working halls of the Bureau of vehicle management in Shanghai. All the respondents are commuters who commutes by cars. Finally, 295 effective questionnaires (1180 observations for mode shift scenarios and 1475 observations for new job scenarios) were collected after filtering. Summary of all respondents are summarized in **Table 3**.

Table 1: Attributes and Levels Used in the Design of Mode Shift Scenarios

Alternative	Attributes	Levels
Car (original mode)	Travel time	RP_time(car)
	Cost (oil, parking fare, tolls)	RP_cost(car)+[5,15,25,40]RMB
	Crowding inside car	None
Metro	Travel time	RP_time(car)×[0.8, 1.1, 1.4]
	Cost (ticket)	3,4,5,6 RMB
	Crowding inside metro	Level 1, Level 2, Level 3
Bus	Travel time	RP_time(car)×[1, 1.3, 1.6]
	Cost (ticket)	2 RMB
	Crowding inside bus	Level 1, Level 2, Level 3

Note: RP_time(car) and RP_cost(car) denote the collected actual mean travel time and cost of commuting by car. Cost of metro is constrained by its travel time (TT) in design, when TT=<25, the cost=3; when 25<TT<35, cost=4; when 35<TT<45, cost=5; when TT>45, cost=6. Crowding Level 1: uncrowded with seats; Level 2: standing in not crowded carriage; Level 3: standing in very crowded carriage; 1 RMB =0.146 dollar.

Table 2: Attributes and Levels Used in the Design of New Job Scenarios

Alternative	Attributes	Levels
	Short-time commuting	
Car	Travel time	10,20,30min
	Cost(oil, parking fare, tolls)	5,15,25 RMB
	Crowding inside car	None
Metro	Travel time	15,25,35min
	Cost (ticket)	3,4 RMB
	Crowding inside metro	Level 1, Level 2, Level 3
Bus	Travel time	15,25,35min
	Cost (ticket)	2 RMB
	Crowding inside bus	Level 1, Level 2, Level 3
	Medium-time commuting	
Car	Travel time	20,30,40min
	Cost(oil, parking fare, tolls)	10,20,30 RMB
	Crowding inside car	None
Metro	Travel time	25,35,45min
	Cost (ticket)	3,4,5RMB
	Crowding inside metro	Level 1, Level 2, Level 3
Bus	Tavel time	25,35,45min
	Cost (ticket)	2 RMB

	Crowding inside bus	Level 1, Level 2, Level 3
	Long-time commuting	
Car	Travel time	30,40,50min
	Cost(oil, parking fare, tolls)	15,25,35 RMB
	Crowding inside car	None
Metro	Travel time	35,45,55min
	Cost (ticket)	4,5,6 RMB
	Crowding inside metro	Level 1, Level 2, Level 3
Bus	Travel time	40,50,60min
	Cost (ticket)	2 RMB
	Crowding inside bus	Level 1, Level 2, Level 3

Note: Cost of metro is constrained by its travel time (TT) in design, when TT=<25, the cost=3; when 25<TT<35, cost=4; when 35<TT<45, cost=5; when TT>45, cost=6. Crowding Level 1: uncrowded with seats; Level 2: standing in not crowded carriage; Level 3: standing in very crowded carriage.

Figure 1: An example of the SP choice scenario

Table 3: Descriptions about Attributes of Effective Respondents

Personal attributes	**Statistics**
Age	*Less than 30 years old (41%), 30~40(40%), 40~50(13%), more than 50 years old (3%), skipped(3%)*
Education level	*Level 1:Lower than undergraduate (27%), Level 2: Undergraduate(38%), Level 3: Master(29%), Level 4: Doctor(2%), skipped(4%).*
Monthly income(RMB) *(1 RMB =0.152 dollar)*	*Less than 3000(5%), 3000~6000(22%), 6000~10000(36%), 10000~20000(20%), more than 20000(12%), skipped(5%).*
Gender	*Male(56%), female (44%)*
Commuting time	*Less than 25min (short commuting time, 31%),25~55 min(48%), more than 55min(long commuting time, 25%)*
Commuting distance	*Less than 10km (short commuting distance,39%),10~20km(40%), over 20km(long commuting distance, 21%)*

2.2 Model Specifications and Estimation

The utility U_{jq} of alternative *j* perceived by individual *q* could be expressed by

$$U_{jq} = \sum_k \alpha_{qk} x_{jk} + P_{jq} + \varepsilon_{jq}$$

where x_{jk} is a vector of explanatory variables including cost, average travel time and in-vehicle crowding. The α_{qk} is corresponding estimated parameters. Three crowding levels were set in the survey. In the estimation, the crowding level "*uncrowded with seats*" was regarded as the base level and two dummies (CR1 and CR2) are defined in utility function to denote the situations of crowding level 2 ("*standing in not crowded carriage*") and crowding level 3 ("*standing in very crowded carriage*") respectively. P_{jq} stands for individual *q*'s affection towards alternative *j*. ε_{qj} is the random error term.

Random Parameter Logit (RPL) was used to fit the stated choice data. **Nlogit 5.0** [12] was employed to complete the data analyses. An error component model was performed firstly to examine possible nested structures (e.g. bus and metro). No significant correlation between modes was found. The panel data process was performed in estimation to ensure the unobserved preference heterogeneity among individuals and preference homogeneity of one individual over a series of choices [13]. 1000 random Halton draws were used to ensure the accuracy of results referring to Bhat[14]. To avoid the unexpected sign caused by the spread of the distribution, constrained triangular distribution (expressed as $\beta_i = \beta + \sigma{*}v_i$ where v_i complies to standard triangular distribution ranging from -1 to 1 and σ is constrained to be equal to β), are used to constrain the signs of estimated parameters for cost, travel time and crowding levels. The P_{jq} is set to be truncated normal distributions[12].

3 RESULTS AND FINDINGS

Table 4 demonstrates the estimated results. All the estimated parameters are all significant at the 99% confidence level. The term P_{jq} for bus is set to be fixed and equal to zero in case of constant traps in the estimation process[12]. The respondents' predilection for car compared to bus and metro could be expressed by the estimated P_{CAR} and (P_{CAR}- P_{METRO}) respectively. **Nlogit 5.0** is able to provide the individual-specific estimated parameters of each respondent. This enable us to conduct paired comparison for one respondent's same parameter in the mode choice scenario and new job scenario. Due to the different scales in utility function of the two scenarios, it is not feasible to directly compared the estimated results. However, we could use the marginal utility of cost or travel time as baseline to standardize the respondents' predilection for car. $M_{car2bus}(C)$ and $M_{car2bus}(T)$ are defined to measure the respondents' predilection for car compared to bus and are equal to P_{CAR}/C and P_{CAR}/T respectively where C and T are the estimated parameters of cost and travel time. $M_{car2metro}(C)$ and $M_{car2metro}(T)$ are for predilection for car compared to metro and are equal to $(P_{CAR}\text{-}P_{METRO})/C$ and $(P_{CAR}\text{-}P_{METRO})/T$ respectively. The parametric paired T-test and nonparametric test Wilcoxon Test are employed to identify the differences in mean values and distributions. The results are shown in **Table 5**.

The results are straightforward. No matter using the cost or travel time as the baseline, the same respondent's predilection for car compared to bus in mode shift scenarios is significantly larger than that in new job scenarios. The relative differences are 62.1% and 142.9% separately when the baselines are cost and travel time respectively. For the respondent's predilection for car compared to metro, same discipline could be found. The same respondent's affection for car compared to metro in mode shift scenarios is statistically significantly larger than that in new job scenarios.

If the inertia is the effects of past experiences on preference for car, the respondent will perform similar preferences for car in the two different scenarios. Nevertheless, it is found that predilections for car compared to public transit in mode shift are much larger, which indicates that there exist other components in mode shift besides preference. These results provide direct evidence of existence of inertia (indisposition to change) in mode shift behavior. More importantly, it implies that the inertia in mode choice should not be just interpreted as the effects of past travel choice on preference, but should be an independent component in modeling mode shift behavior, which inherently differs from the preference term. The difference between values of predilection for car in mode shift scenario and new job scenario could be regarded as the value of inertia, which measures the scale of resistance to change in mode shift.

Another interesting finding is that the same respondents show different value of travel time savings (VTTS) in different choice scenarios. In the mode shift scenarios, the VTTS is 32.7 RMB/hour on average with a standard deviation (SD) of 10.8. The VTTS in new job scenarios is 52.4 RMB/hour on average with a SD of 12.3 and is 60.2% larger than that in mode shift scenarios. The distributions of VTTS in the two scenarios are demonstrated in **Figure 2**. The results of paired T-test and Kolmogorov-Smirnov test both show that the differences in VTTS of different scenarios are significant. The results indicate travelers have different willing-to-pay(WTPs) for travel time savings in different mode choice context and implies that it is necessary to distinguish the WTPs in mode shift behavior from new mode choice situations in forecasting models.

A controversial topic in modeling mode choice behavior is that whether individual travel choice is habitual shaped by past travel experiences or rationally maximizing the utility in most time. Dual process theory proposed by Chaiken and Trope[15] might shed light on the question. Dual process theory indicates that there are two parts in human's decision process. One part is quick empirical thinking which is based on abundant past experiences and close to instinctive reaction. It takes less time and vigor. Another part is deliberation thinking which is based on logical thinking and deliberation. It takes more time and vigor. The two parts in dual process run at the same time, but one might comparatively dominate another in certain context. Travelers tend to quick empirical thinking in the mode shift context and are partial to deliberation thinking in new choice contexts.

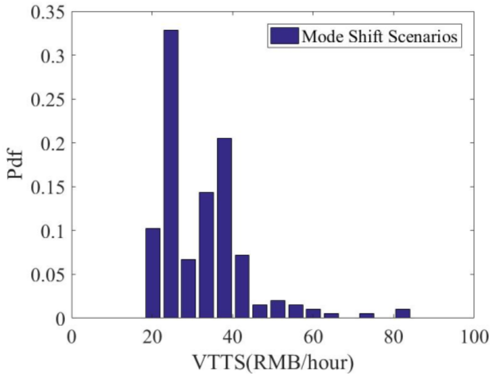
Table 4. Estimation Results

		Car users			Metro users		
Attributes		**Value**	**z**	**p**	**Value**	**z**	**p**
Cost		-0.13459	-11.12	<0.001	-0.3393	-10.62	<0.001
Cost(SD)		0.13459	11.12	<0.001	0.3393	10.62	<0.001
Travel time		-0.08298	-11.92	<0.001	-0.08631	-9.68	<0.001
Travel time(SD)		0.08298	11.92	<0.001	0.08631	9.68	<0.001
Crowding level1(metro)		-0.94281	-4.36	<0.001	-0.87471	-3.34	<0.001
Crowding level1(metro)(SD)		0.94281	4.36	<0.001	0.87471	3.34	<0.001
Crowding level2(metro)		-2.52863	-12.11	<0.001	-2.06870	-6.48	<0.001
Crowding level2((metro)(SD)		2.52863	-12.11	<0.001	2.06870	6.48	<0.001
Crowding level1(bus)		-1.33389	-4.73	<0.001	-0.88762	-3.70	<0.001
Crowding level1((bus)(SD)		1.33389	4.73	<0.001	0.88762	3.70	<0.001
Crowding level2(bus)		-1.68780	-5.78	<0.001	-1.4662	-5.23	<0.001
Crowding level2(bus)(SD)		1.68780	5.78	<0.001	1.4662	5.23	<0.001
Mode shift scenarios	P_{CAR}	3.72558	10.69	<0.001	2.59868	3.87	<0.001
	P_{CAR} (SD)	2.45622	8.44	<0.001	3.34488	4.53	<0.001
	P_{METRO}	1.98478	6.74	<0.001	3.12625	6.93	<0.001
	P_{METRO} (SD)	2.72452	7.37	<0.001	2.07154	7.60	<0.001
	P_{TAXI}	-	-	-	1.35668	2.29	.0219
	P_{TAXI}(SD)	-	-	-	2.55355	3.58	<0.001
Mode Choice scenarios	P_{CAR}	2.55432	10.21	<0.001	2.44696	5.10	<0.001
	P_{CAR} (SD)	2.52863	9.23	<0.001	1.46629	5.23	<0.001
	P_{METRO}	2.02550	12.11	<0.001	2.27483	7.38	<0.001
	P_{METRO} (SD)	1.37501	5.16	<0.001	1.92313	7.86	<0.001
	P_{TAXI}				0.05784	0.10	0.9169
	P_{TAXI}(SD)				1.88047	2.94	0.003
P_{BUS}		0(fixed)	-	-	0(fixed)	-	-
Log likelihood function		-1421.02932			-1043.74682		
McFadden Pseudo R-squared		0.684			0.757		

Table 5 Statistical Comparison Results

		Mean	difference	95% confidence level intervals		Paired T-test (two tails)		Paired Wilcoxon Test	
				Low	Up	T-value	P-value	Z-value	P-value
Car users	P_car(MSS) P_car(MSC)	3.8398 2.8309	1.00897	0.75203	1.26591	7.745	.000	6.876	.000
	P_metro(MSS) P_metro(MSC)	1.9632 2.0577	-0.09448	-0.32768	0.138723	-0.799	.425	-0.910	.363
Metro users	P_car(MSS) P_car(MSC)	2.5605 2.5084	0.0519	-0.16008	0.26420	0.485	.629	0.581	.561
	P_metro(MSS) P_metro(MSC)	3.1360 2.3241	0.81192	0.55505	1.06878	6.243	.000	6.053	.000

Note: MS denotes the results in mode shift scenarios. NB denotes the results of new job scenarios



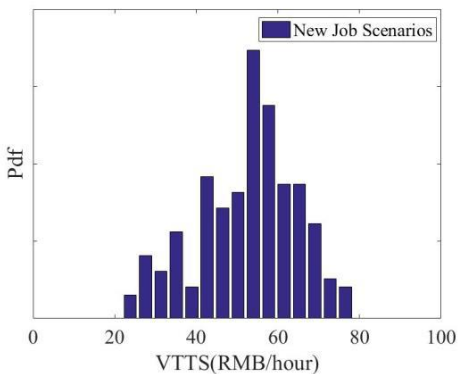


Figure 2: The distributions of VTTS in two different scenarios

4 Concluding remarks

This paper conducted a comparison study of mode shift behavior based on computer-aided SP surveys trying to distinguish the differences in conceptions of preference and inertia. The results show that same respondents have remarkably different choice behavior in mode shift context and another mode choice scenarios. The results indicate that there exists obvious inertia in mode shift from car to public transit besides preference for car. The inertia in mode shift should be modeled as an inherently independent component in utility function rather than interpreted as the effects of past travel experience on mode preference. It is found that same respondents have different values of travel time in different mode choice contexts. The results are beneficial for accurate modeling of inertia in mode shift behaviors.

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