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Conference Paper STRC 2018

STRC | 18th Swiss Transport Research Conference
Monte Verità / Ascona, May 16-18, 2018

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Abstract

This paper explores the endowment effects of past travel experience on current choices by introducing interactions of inertia effect and investigates the valuations in inertia effects of different modes in mode shift behavior. A reference preference(RP) and stated preference(SP) survey is conducted to collect data regarding mode shift for commuting using web-scripted technology. Five model specifications are set up for comparisons and the joint RP/SP random parameter logit model is employed for estimation. Substantial and significant interactions of inertia with level-of-service variables were identified indicating the significant influences of inertia effects on travelers' perceptions of attributes in mode choice. Incorporating the interactions of inertia could notably promote the model performance in explaining mode shift behavior and reduce the unobserved heterogeneity in utilities. The interactions between income with cost and in-vehicle crowding with travel time were found. The time multiplier of in-vehicle crowding in bus is found to be larger than that in metro. Moreover, there are substantial and significant differences in the mean values and variances of inertia effects for different modes. Considering mode-specific inertia in modeling could improve the model performance remarkably and ignoring the mode-specific will result in several confounding biases in model estimation. Influencing factors contributing to the heterogeneity in inertia effect of different modes are investigated respectively. Besides, elasticity analysis is conducted to provide several implements yielding shifting car users to public transit. Additionally, the results indicate that the demand estimations would be biased when the interactions of inertia and mode-specific inertia are neglected.

Keywords

Mode shift choice; interaction effects; Mode-specific inertia; Heterogeneity in inertia; demand forecasting

1. Introduction

Increasing private car usages in Chinese metropolis induced a series of transport issues like traffic congestion, air/noise pollution, and parking insufficiency in the last few decades. Promoting the share rate of more sustainable mass public transit(PT) is an evitable tendency to relieve such transportation problems due to the highly-centralized urban structure and large population in the metropolis like Shanghai or Beijing. Many actions have been taken in Shanghai trying to balance the mode structure by shifting car users to public transport system including developing new public transit facilities (e.g. Park and Ride), promoting policies (e.g. discounts for using P&R) and license plate auction). Unfortunately, these policies did not live up to prior expectation and forecasts to shift considerable private car users to PT. For instances, the share rate of private car was continuously increasing from 2009 to 2014 and the established Park and Ride facilities were severely underutilized(SURCTDRI, 2016). One of the possible reasons yielding the failures and biased demand prediction is the insufficiency in modeling travelers' mode shift behavior in forecasting.

Microeconomic theories have commonly been employed to describe mode choice behavior in the context of transportation assuming that the travelers make trade-offs among attributes of available alternatives and select the one with maximum subjective utility. Nevertheless, in some situations like repeated commuting trips without apparent changes over time, people would save their cognitive and processing efforts of gathering information of each possible alternative, and tend to repeat the satisfying past choice again and again without thinking. This is generally called inertia effect in choice(Pendyala, 1999; Simon, 1978; Verplanken et al, 1997). In the field of psychology, inertia effect implies an indisposition to change, a certain stickiness due to human programming, and represents the inevitability of behaving in a certain way indelibly inscribed in the brain(Kowalick, 1998). However, in the context of transportation research, inertia effect measures the influences of past travel experiences on current choice and could represent travelers' tendency to stick with previous choice (i.e. the habitual choice) or the disposition to change(Cantillo et al, 2007; Cherchi & Cirillo, 2014; Cherchi & Manca, 2011; Gärling & Axhausen, 2003; Gardner, 2009; González et al, 2017; Yáñez et al, 2012).

The inertia effect in travel behavior has been discussed in the literature because of its bearing on travel demand forecasting and management strategies(Bradley & Daly, 1991; Cantillo et al, 2007; Cherchi & Cirillo, 2014; Cherchi & Manca, 2011; Cherchi et al, 2013; Daganzo & Sheffi, 1979; Gärling & Axhausen, 2003; Gardner, 2009; González et al, 2017; Goodwin, 1977; Morikawa, 1994; Yáñez et al, 2012). As the inertia effects are explicitly associated with past travel experiences, panel data across different periods are required to suitably incorporate inertia effects in modeling. The inertia effect in certain period was generally measured by specific terms that depend on attributes of the alternative in the previous period. The early relevant work could date back to Ben-Akiva and Morikawa(1990). They considered the inertia effect using state-dependence dummy variables (i.e. one if the choice was used in the past) and put forward a corresponding modelling methodology for mode choice behavior based on mixed stated preference(SP) and revealed preference(RP) data. The proposed state dependence dummy variable was extended by (Morikawa, 1994) and tested by (Bradley & Daly, 1997; Cherchi & de Dios Ortúzar, 2002; Srinivasan & Bhargavi, 2007) using mixed RP/SP data. Afterwards, some researchers proposed and tested several other measurements towards inertia effect like the number of times(Adamowicz, 1994), the level-of-service(LOS) variables of previously chosen choice or differences in LOS variables of the chosen choice and available alternatives (Cherchi, 2010b; Cherchi & Cirillo, 2014; Swait et al, 2004). Their results all confirmed the inertia effects in mode choice, but no agreement regarding the best measurement for inertia effect was reached. More recently, Cantillo et al.(2007) modelled the mode choice behavior in the presence of inertia and serial correlation and discussed the effects of integrating the inertia and serial correlation in specifications. In their work, the inertia effect was defined as a function of the difference between deterministic utilities of the previously used mode and other alternatives. The model was tested by simulated data and a mixed RP and SP databank from Cagliari of Italy. Yáñez et al.(Yáñez et al, 2012) followed the proposed methods and added the shock effects in modeling mode choice behavior. Primarily, they investigated the existence of shock effects and its influence on policy making using a four-wave panel data in Chile. In addition, Cherchi and Manca(2011) compared several measures of inertia effects proposed for both short and long RP panel data, and examined the consistency of inertia effect throughout the different SP scenarios. They indicated that the significance of various measures depended on the investigated context. The adopted model specifications (e.g. considering panel effects and nonlinearity or no) were crucial in properly measuring inertia effect. They also found that the pure inertia effects of past experiences might vary in a series of SP scenarios and they explained the phenomenon by learning and acquiring experience in the sequence SP scenarios. González et al.(González et al, 2017) tested the inertia effects in the university students' mode shift behavior when a new tram was implemented in Tenerife. They followed the method proposed by Cantillo et al.(2007) in model specification and investigated the effects of generic inertia effects on demand estimation.

In the literature, the inertia effect has been regularly modeled by an additive term related to past travels in utilities. However, travelers would develop their own preferences for choices and attributes through past decisions, outcomes and corresponding experiences by trials and adjustments(Garvill et al, 2003; Kitamura & Van Der Hoorn, 1987). This might lead to travelers attach specific values to the previous choice, which called endowment effects in psychology and behavioral economics(Marzilli Ericson & Fuster, 2014). To our best knowledge, no previous study has investigated the potential interactions between inertia effects with other attributes of choice (e.g. LOS variables) to model the cognitive misperceptions towards characteristics of alternatives caused by past travel experiences. Nevertheless, ignoring the travelers' subjective bias in evaluating the attributes may lead to bias in estimations as well as in demand forecasting. Especially, this study introduced and tested the interactions between inertia and LOS variables in modeling to look into the possible cognitive misperception caused by inertia effects. Furthermore, we investigated the impacts of the interactions between inertia and LOS variables on demand estimations.

Moreover, it could be found that most of the empirical studies(Cantillo et al, 2007; Cherchi & Cirillo, 2014; Cherchi & Manca, 2011; Cherchi et al, 2013; González et al, 2017) used generic inertia term for users of different modes in modeling except(Morikawa, 1994; Yáñez et al, 2012). The generic inertia puts a strong homogeneity assumption in inertia effect and might cover the differences in travelers' inertia effects for different modes on account of the instinctive distinctions in experiences of using different modes for commuting. This paper investigated the specific inertia effects for different modes and analyzed their influences on demand estimation. Additionally, we explored the heterogeneity in inertia effect comprehensively. The heterogeneity among travelers was declared to be crucial in modeling serial correlation and inertia effects(Bhat & Castelar, 2002; Hensher & Greene, 2003) and should be addressed in analyzing inertia effects (see discussion in (Cherchi et al, 2013)). Cherchi and Manca(2011) and Cherchi et al. (Cherchi et al, 2013) investigated the systematic heterogeneity(e.g. socio-economic attributes) in inertia term to some extent. However, the generic inertia terms were used and thus the distinctions in heterogeneity among users of different mode were ambiguous. In this study, the heterogeneities in users of different mode were separately analyzed. Potential influencing factors including socioeconomic characteristics (e.g. age, education and income), commuting spatial context(e.g. route, commuting time and distance) and others (e.g. flexible work time and license plate type) were examined. Besides, the impacts of inertia interactions and heterogeneity of inertia on demand forecasting were analyzed to provide implications for transportation policy. The remainder of this paper firstly gives the descriptions of data collection process and then provides the modelling methodology. Afterwards, the analysis results are presented with discussions followed by concluding remarks in the last section.

2.Data Description

The data bank of this study was a mixed dataset of reference preference (RP) and stated preference (SP) regarding commuting collected in 2017 in the context of Shanghai. The survey took advantage of web-scripted technology to generate real-time individually specific SP scenarios depending on individual RP travel information. In the first stage, RP information about the respondent's current commuting trip was collected including the most commonly used commuting mode, travel time, overall cost(ticket, petrol, toll and parking), commuting distance, comfort features, demographic attributes(e.g. gender, age, occupation, education level, income, place of residence, marital status) and other information (e.g. attitudes to public transit or private car, schedule flexibility, perceived controls of using other modes). Information about the availability of other modes for commuting and the level-of-service variables of the available modes, was gather as well. In the second stage, the SP questionnaire was generated immediately using web-scripted code according to the individual RP information, and presented to the same respondent. The SP scenario was a choice between current commuting transport mode and a new hypothetical alternative. Four commuting mode (private car, metro, bus and taxi) were considered. The attributes influencing mode choice in the SP scenarios were travel time, travel cost and in-vehicle crowding levels. The levels of attributes for statistical design of contents in scenarios were set based on the derived information in RP survey and shown in **Table 1** and. The statistical content design refers to D-error efficient design method in (Metrics, 2012) which guarantees orthogonality and utility balance among alternatives. Eighteen scenarios with the best utility balance were selected for each situation and four of them were randomly selected to give out to the respondent. The process of the survey and one example of the scenarios are shown in **Figure 1**. Graphic images instead of word descriptions for different crowding levels were presented in the scenarios to promote understandability(Li & Hensher, 2013). A localized pilot survey was executed in advance to test the validity (e.g.

questions interpretation and understandability) of survey design and renew the prior parameters in design.

Both online surveys and face-to-face interviews were tested to collect data. Nevertheless, the collected data online were not representative as those from face-to-face interviews.

Table 1 Attributes and their levels in SP scenario design

	Alternative	Attributes	Levels
Car/Taxi users	Car/Taxi (original mode)	Travel time	RP_time
		Cost(petrol, parking fare, tolls)	RP_cost + [5,15,25,40]
		Crowding inside car	None
	Metro	Travel time	RP_time × [0.8, 1.1, 1.4]
		Cost (ticket)	[3,4,5,6]
		Crowding inside metro	[Level 1, Level 2, Level 3]
	Bus	Travel time	RP_time × [1, 1.3, 1.6]
		Cost (ticket)	[2,4,6]
		Crowding inside bus	[Level 1, Level 2, Level 3]
Metro users	Metro (original mode)	Travel time	RP_time
		Cost(ticket)	RP_cost + [2,6,10]
		Crowding inside car	RP_crowding level
	Bus	Travel time	RP_time × [0.75, 1, 1.25]
		Cost (ticket)	[2,4,6]
		Crowding inside bus	[Level 1, Level 2, Level 3]
	Car	Travel time	RP_time × [0.7, 0.9, 1.1]
		Cost (petrol, parking fare, tolls)	Cost_pertrol + [5,10,20]
		Crowding inside bus	None
	Taxi	Travel time	RP_time × [0.7, 0.9, 1.1]
		Cost (ticket)	[T1, T2, T3]
		Crowding inside bus	Level 1, Level 2, Level 3
Bus users	Bus (original mode)	Travel time	RP_time
		Cost(ticket)	RP_cost + [2,4,6]
		Crowding inside car	RP_crowding level
	Metro	Travel time	RP_time × [0.75, 1, 1.25]
		Cost (ticket)	[3,4,5,6]
		Crowding inside bus	[Level 1, Level 2, Level 3]
	Car	Travel time	RP_time × [0.6, 0.8, 1]
		Cost (petrol, parking fare, tolls)	Cost_pertrol + [5,10,20]
		Crowding inside bus	None
	Taxi	Travel time	RP_time × [0.7, 0.9, 1.1]
		Cost (ticket)	[T1, T2, T3]
		Crowding inside bus	None

Note: RP_time and RP_cost denote the gathered actual travel time and cost for the respondent's commuting. Crowding Level 1: uncrowded with seats; Level 2: standing in not crowded carriage; Level 3: standing in the very crowded carriage. 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.The levels for the cost of taxi are calculated according to the pricing rules of DiDi company in Shanghai: T1(hitchhiking)=distance*1.6, T2(car sharing with others)=0.8*(distance*2.3+travel time*0.5), T3(taxi without sharing)= (distance*2.3+travel time*0.5. The units for cost and travel time are RMB (1 RMB =0.146 dollar) and minute.

Therefore, investigators were recruited to conduct face-to-face and one-to-one survey for the sake of validity and representativeness of data. The surveys were carried out in public locations (the Hongqiao Transportation Hub and the Bureau of vehicle management) to achieve a wide geographical coverage and to reduce the bias associated with limited respondents. The Hongqiao Transportation Hub is the largest comprehensive transportation junction in Shanghai connecting Hongqiao airport, Hongqiao railway station and Hongqiao public transit center. The Bureau of Vehicle Management is responsible for car license application, driver license application and administration of the traffic violation. The surveys were supported by transport police department to get permission for conducting surveys in the two places. Investigators were trained about how to conduct the survey properly. Respondents were asked to read and understand questions carefully with the assistance of investigators. People over 60 years old were not investigated because of a high probability of retirement. Finally, 1136 valid respondents (9088 observations for SP scenarios) were collected. The sample sizes for private car users, metro users, bus users and taxi users are 55%, 34%, 10% and 1%, respectively. The detailed information of valid respondents is demonstrated in **Table 2**.

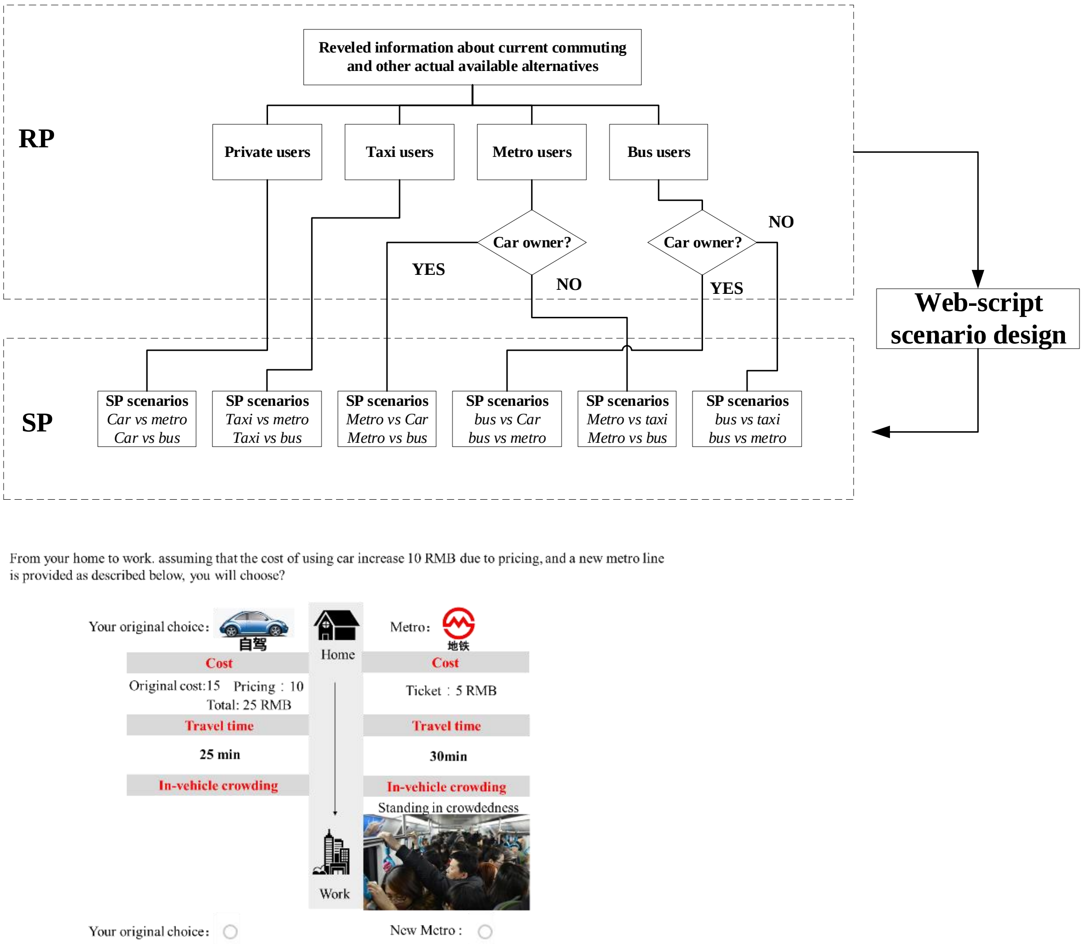

Figure 1 the survey process and example of SP scenarios

Table 2 Statistics of valid respondents

Age	**N**	**%**	**Education**	**N**	**%**	**Monthly Income**	**N**	**%**
<20	7	0.6%	1	250	22.0%	<3000	31	2.7%
20~30	535	47.1%	2	650	57.2%	3000~6000	195	17.2%
30~40	459	40.4%	3	200	17.6%	6000~10000	359	31.6%
40~50	122	10.7%	4	20	1.8%	10000~20000	359	31.6%
50~60	12	1.1%	Skipped	16	1.4%	20000~30000	144	12.7%
						>30000	48	4.2%
License type	**N**	**%**	**Commute time(min)**	**N**	**%**	**Commuting distance(km)**	**N**	**%**
No car	381	33.5%	<30	515	45.4%	<5	169	14.8%
Type 1	533	46.9%	30~60	464	40.9%	5~10	281	24.8%
Type 2	88	7.8%	>60	156	13.8%	10~15	256	22.5%
Type 3	134	11.8%				15~20	173	15.2%
						20~30	151	13.4%
						>30	106	9.3%
Gender	**N**	**%**	**Flexible work time**	**N**	**%**	**Martial status**	**N**	**%**
Male	732	66%	Yes	349	30.7%	Married	490	43.1%
Female	404	34%	No	787	69.3%	Not married	646	56.9%
Occupation	**N**	**%**	**Commute context**	**N**	**%**			
State-owned enterprise	266	23.4%	Suburb	406	35.8%			
Private enterprise	504	44.4%	Urban	303	26.7%			
Individual operation	157	13.8%	Suburb to urban	353	31.1%			
Others	209	18.4%	Urban to suburb	74	6.5%			

Note: Education: 1(below undergraduate), 2(undergraduate), 3(Master), 4(PhD). Only license type 1 can use the express system of Shanghai during peak hours, but type 2 and 3 are not allowed.

3.Model Specification and Estimation

The model specification is built on the random utility theory(McFadden, 1981) assuming that individual would choose the travel mode with highest subjective utility depending on LOS variables, personal attributes, inertia effects and unobservable components. The random parameter logit(RPL) models model as powerful tools to approximate random utility specifications were employed for estimation to account for preference heterogeneity and correlations over different choice situation in estimations(Train, 2009). The panel correlations across RP and SP observations, as well as panel effects among respondents (i.e. individual's homogeneity over observations and heterogeneity among individuals) were considered as well. The modeling of inertia effect use an improved model specification on the basis of works in(Cantillo et al, 2007; Cherchi & Manca, 2011). The utility of alternative j perceived by individual q in SP and RP situations could be expressed by:

$$U_{jq}^{SP} = V_{jq}^{SP} + d_{jq}\phi(I_{jq}^{SP}) + \varepsilon_{jq}^{SP} \qquad \varepsilon_{jq}^{SP} \sim (0, \sigma_{\varepsilon^{SP}}^2) \qquad (1)$$
$$U_{jq}^{RP} = V_{jq}^{RP} + \varepsilon_{jq}^{RP} \qquad \varepsilon_{jq}^{RP} \sim (0, \sigma_{\varepsilon^{RP}}^2) \qquad (2)$$
$$\phi(I_{jq}^{SP}) = (\beta_{Ij}^{SP} + \sigma_{Ijq}^{SP} + \xi_{Ijnq}^{SP} SE_{nq}) * I_{jq}^{SP} \qquad (3)$$

Where V_{jq}^{SP} and V_{jq}^{RP} are the determined segments of utility in SP and RP. $\phi(I_{jq}^{SP})$ presents the inertia effect. d_{jq} is an index that equals one if $\phi(I_{jq}^{SP})$ appears in the utility function of alternative *j*, and zero otherwise. If the value of $\phi(I_{jq}^{SP})$ is positive, it denotes the resistance to change(i.e. inertia); if it is negative, it implies a disposition to change. The ε_{jq}^{SP} and ε_{jq}^{RP} are the error terms with different variances(i.e. $\sigma_{\varepsilon^{SP}}^2 \neq \sigma_{\varepsilon^{RP}}^2$) for SP and RP data, respectively. Eqn. (3) assumes that the inertia effect randomly varies with the personal characteristic SE_{nq} of the individual q . β_{Ij}^{SP} is the mean for inertia effect that might vary over alternative *j* but fixed over individuals and σ_{Ijq}^{SP} is the deviation normally distributed with zero mean. I_{jq}^{SP} is the measurement of inertia effect. As discussed in the introduction, several measures have been proposed in the literature. In this paper, we compared the most popular three measurements to examine their serviceability in our models as shown in Eq.n (4).

$$I_{jq}^{SP} = \begin{cases} Dummy\ variable \\ (U_{jq}^{RP} - U_{kq}^{RP}) \qquad k \neq j \\ U_{jq}^{RP} \end{cases} \qquad (4)$$

The first one is state-dependence dummy variable, which is the most typical measure of inertia(Adamowicz, 1994; Cherchi, 2010a). It equals to 1 if the alternative *j* was chosen in the past and zero otherwise. The second is proposed by (Cantillo et al, 2007) and calculated by the difference in the utility of alternative *j* and other alternative *k* in the RP situation. The last one is the measure applied in(Cherchi & Manca, 2011) and counted by the utility of alternative *j* in the RP situation. Our results show that the dummy variable performs best in terms of model fitness in our dataset and consequently is adopted in this study. In our viewers, the second and third measurements put a strong assumption that the inertia effect is linearly related to the difference of utilities or the utility in RP situation. This may lead to the inadaptability for modeling since the utilities in the RP situation of different respondents vary markedly in scales in our datasets. The detailed formulation of V_{jq}^{SP} and V_{jq}^{RP} are as follows:

$$V_{jq}^{SP} = ASC_j^{SP} + \psi_{jq} + (\beta_{mj}^{SP} + \sigma_{mjq}^{SP} + \xi_{mjnq}^{SP} SE_{nq}) * LOS_{mj}^{SP} + \gamma_{amj}^{SP} LOS_{mj}^{SP} * LOS_{aj}^{SP} + \eta_{mj} LOS_{mj}^{SP} * I_{jq}^{SP} * d_{jq} \qquad (5)$$
$$V_{jq}^{RP} = ASC_j^{RP} + \psi_{jq} + (\beta_{mj}^{RP} + \sigma_{mjq}^{RP} + \xi_{mjnq}^{RP} SE_{nq}) * LOS_{mj}^{RP} \qquad (6)$$

Where ASC_j is the alternative and choice situation specific constants; ψ_{jq} is the parameter accounting for serial correlation between choices in SP and RP situations(Cantillo et al, 2007) It is randomly distributed over the individuals with zero mean, but keep invariant across choice situations. The coefficient of LOS variable m is set to vary randomly (with a mean β_{mj} and standard deviation σ_{mjq}) and systematically as a function of the personal attribute SE_{nq}. The signs of random parameters for LOS variables are constrained to be negative using one-sided triangle distributions(Hensher & Greene, 2003).

We consider the potential nonlinear effects by adding the interaction terms between LOS variables. In particular, we introduced the interactions between inertia effect and LOS variables into the specification to model endowment effect. The γ_{amj}^{SP} and η_{mj} are the corresponding coefficient vectors for the interaction terms. It should be noted herein that when investigating the systematical heterogeneity, the parameters for SE_{nq} in model specification are all dummy variables expect income on account of possible nonlinear relationships. For instance, the parameter of “education (Master or over)” is one if the respondent has an education level of master or over, otherwise zero. The classifications of different group are according to the commonly used principles in various research(Börjesson & Eliasson, 2014; Kouwenhoven et al, 2014) and the recognized classifications in Shanghai(SURCTDRI, 2016). The value for income parameter is the mean income of each group.

The joint estimation of RP and SP dataset needs scaling the utility in the SP situations to make the variances in both datasets equivalent(Adamowicz, 1994; Bhat & Castelar, 2002; Bradley & Daly, 1991). Therefore, the final utility functions can be expressed as:

$$U_{jq}^{SP} = \lambda_{SP}(V_{jq}^{SP} + d_{jq}\phi(I_{jq}^{SP}) + \varepsilon_{jq}^{SP}) \quad (7)$$

$$U_{jq}^{RP} = \lambda_{RP}(V_{jq}^{RP} + \varepsilon_{jq}^{RP}) \quad (8)$$

where $\lambda_{SP}\varepsilon_{jq}^{SP} = \lambda_{RP}\varepsilon_{jq}^{RP}$. It should be noted that the variance of RPL model is the sum of variances of all the random components in the specifications. Let the $\Psi(\sigma^2)$ represent the overall variance of all random parameter except the error term ε_{jq}. The variance of RPL model with scale parameter should be $\lambda^2\Psi(\sigma^2) + \frac{\pi^2}{6\lambda^2}$. Nevertheless, the $\Psi(\sigma^2)$ of the variance matrix Ω could be estimated, so the scale parameter is the only control parameter for obtaining the same variance in the RP and SP datasets(Adamowicz, 1994; Bhat & Castelar, 2002; Cherchi & Manca, 2011). We normalize the model based on the RP data (i.e. λ_{RP} =1). Following the joint estimation of RPL models using maximizing likelihood function(Train, 2009), the integral over all random parameters could be written as:

$$L=\int\left(\prod_{RP}\frac{e^{\lambda_{RP}U_{jq}^{RP}}}{\sum_{j\in RP}e^{\lambda_{RP}U_{jq}^{RP}}}\cdot\prod_{SP}\frac{e^{\lambda_{SP}U_{jq}^{SP}}}{\sum_{j\in SP}e^{\lambda_{SP}U_{jq}^{SP}}}\right)f(\Psi(\sigma_{RP}^2),\Psi(\sigma_{SP}^2)\mid\Omega)d\Psi(\sigma_{RP}^2)d\Psi(\sigma_{SP}^2) \quad (9)$$

Based on the estimated results, we calculated several measurements relevant for transport policy and demand estimation such as the direct elasticity and cross elasticity to investigate the mode-specific inertia and interactions of inertia effects on demand forecasting. The direct elasticity is defined as how responsive changes of the choice probability of alternative *j* to changes in a LOS variable *m* of alternative *j*. The cross elasticity is the corresponding changes of the choice probability of alternative *j* to changes in a LOS variable *m* of another alternative *i*. Since we consider several interactions in the specifications, the direct $E(LOS_{mj},P_{jq})$ and cross elasticity $CE(LOS_{mi},P_{jq})$ could be calculated by Eqn.(10) and Eqn.(11), respectively.

$$E(LOS_{mj},P_{jq})=\frac{\partial P_{jq}\ /\ P_{jq}}{\partial LOS_{mj}\ /\ LOS_{mj}}=\lambda_{SP}(\beta_{mjq}+\gamma_{amj}*LOS_{aj}+\eta_{mj}I_{jq}*d_{jq})*LOS_{mj}(1-P_{jq}) \quad (10)$$

$$CE(LOS_{mi},P_{jq})=\frac{\partial P_{jq}\ /\ P_{jq}}{\partial LOS_{mi}\ /\ LOS_{mi}}=-\lambda_{SP}(\beta_{miq}+\gamma_{ami}*LOS_{ai}+\eta_{mi}I_{iq}*d_{iq})*LOS_{mi}P_{iq} \quad (j\neq i) \quad (11)$$

Where P_{jq} denotes the choice probability of alternative *j* for individual *q*.

4. RESULTS

This section presents the estimated results obtained from the proposed models in the last section. In particular, we tested and compared the results obtained from models with or without the interactions of inertia effects, and using generic or mode-specific inertia for different modes. We specified five different models. The first one **ML1** uses generic inertia for different modes and does not consider the interactions of inertia as the literature did. The second one **ML2** still uses generic inertia, but considers the interactions of inertia. The **ML3** employed mode-specific inertia terms without interaction of inertia and **ML4** takes both mode-specific inertia and interactions of inertia into account. Besides, we estimated a mixed logit model without inertia effects for reference purpose only. The estimation results are summarized in **Table 3**(in Appendix).

For joint RP/SP estimation, it is important to determine use generic or specific coefficients for same parameter of different datasets and different modes(Cherchi & Ortúzar, 2011). The travel cost coefficient and serial correlation term ψ_{jq} were set to be generic for the correlations between RP and SP data. Several combinations of inter-wave (RP and SP) and inter-mode coefficients were examined to search for appropriate specifications. The travel cost coefficient was not found to be different among the modes and hence was specified as generic among modes. Nevertheless, remarked differences between RP and SP datasets for travel time and in-vehicle crowding coefficients were observed and thus specific coefficients for the two variables were specified for different time waves. The travel time coefficients for mass transit(i.e. metro and bus) and private vehicles (car and taxi), as well as in-vehicle crowding coefficients for bus and metro were set to be specific. It should be noted that two dummy variables are used to account for non-linear effects in the comfort variable. We applied three crowding levels in the survey: Crowding Level 1, uncrowded with seats; Level 2, standing in not crowded carriage; Level 3, standing in very crowded carriage. The value of crowding level 2 in utility equals one if the level of crowding was standing in not crowded carriage and zero otherwise. The same goes for in-vehicle crowding level 3. The Level 1 was the “good enough” situation and set as the reference.

Python Biogeme (Bierlaire, 2016) was applied to estimate the models with 500 halton draws. The panel effect among individual was considered for keeping unobserved preference heterogeneity among individuals and preference homogeneity for one individual over a series of choices. The error component models were performed firstly to examine several possible nested structures among modes and serial correlations among RP and SP situations. It turned out that the there is a correlation) between metro and bus. The error component accounting for serial correlations between RP and SP specifications are all significant and positive for car, metro and taxi. This indicates underlying preference homogeneity in different choice situations as demonstrated in (Cantillo et al, 2007).

4.1 Importance of mode-specific inertia and interactions of inertia term

Table 3 shows that the values of Akaike Information Criterion (AIC) for models **ML 1~4** are much smaller than the AIC of the base model and the adjusted ρ^2 of **ML 1~4** are much larger than that of base model. It demonstrates that models considering inertia effects are all remarkably better than the base model in explaining mode shift behavior. Moreover, the likelihood ratio is adopted to compare the performances of **ML1~4**. The test statistic is given by $2*\Delta L$, which is the difference in the log-likelihood of different models and asymptotically distributed as chi-square distribution $\chi^2_{\alpha,k}$. The α and k are the confidence level and the degree of freedom that equals to the difference in the number of parameters in models. To investigate the effects of interactions of inertia on model fitness, we compare the performance of **ML1**(generic inertia without interactions of inertia) and **ML2**(generic inertia with interactions of inertia), as well as **ML3**(mode-specific inertia without interactions of inertia) and **ML4**(mode-specific inertia with interactions of inertia). According to the results in **Table 3**, it turns out that:

$$\begin{aligned} 2*(L_{ML2} - L_{ML1}) &= 2*(-4569.496+4604.756) = 70.52 > \chi^2_{0.99,4} = 13.277 \\ 2*(L_{ML4} - L_{ML3}) &= 2*(-4518.273+4557.972) = 79.40 > \chi^2_{0.99,4} = 13.277 \end{aligned} \quad (12)$$

We can find that the models considering the interactions of inertia outperform those without the interactions of inertia at a confidence level of 99%, no matter the generic or mode-specific inertia is used in the specifications. It implies that interactions of inertia are crucial in explain commuters’ mode shift behavior and should be incorporated in model specification. Moreover, we compare the **ML1** and **ML3,** as well as **ML2** and **ML4** to explore the effects of the mode-specific inertia on model performance. It turns out that:

$$2*(L_{ML3} - L_{ML1}) = 2*(-4557.972+4604.756) = 93.568 > \chi^2_{0.99,15} = 30.578$$
$$2*(L_{ML4} - L_{ML2}) = 2*(-4518.273+4569.496) = 102.446 > \chi^2_{0.99,15} = 30.578$$

No matter considering the interactions of inertia or not, the models using mode-specific inertia are better in describing the mode shift behavior compared to generic inertia according to the results. It indicates that the differences in inertia effects for different mode are noticeable and should be distinguished in modeling. On account of the importance of interactions of inertia and mode-specific inertia, we will mainly demonstrate the results of **ML4** in the following section and compare the **ML4** with **ML1~3** in more details.

4.2 Interactions and endowment effects

Several formulations were tested to consider interactions in modeling. The interactions with personal characteristics for all the LOS variables, interactions with inertia terms for all the LOS variables and interactions between LOS variables were all tested. For the interactions of socioeconomic attributes, we especially tested the possible effects of gender, age, education level and income on coefficients of LOS variables. Finally, we only identified the income effect in the cost parameter of car and others are not significant. The coefficient of the interaction between income and cost of car in **ML4** is positive (0.00156). Since the coefficient of cost is negative, the result indicates that travelers with higher income value the travel cost of car less than others.

For the interactions with inertia for LOS variables, all possible combinations were tested and only interactions that were substantial and significant at a 95% confidence level were kept in the final models. For car users, we identify two significant interactions between inertia effects and LOS variables. The interaction between inertia and cost of car is positive (0.011). It implies that car users underestimate the travel cost of car compared to others. The interaction between inertia and travel time of car is negative (-0.00461) demonstrating that car users value more highly of the travel time of car in comparison to others. For metro users, an interaction effect between inertia and in-vehicle crowding is found. The estimated coefficient of the interaction in **ML 4** is positive and 0.103. It reveals that the metro users comparatively show less aversion to crowding in the metro than others. For bus users, an interaction between inertia and in-vehicle crowding is observed as well. The value of the interaction is negative and -0.113, which means bus users more dislike the in-vehicle crowding in bus compared to others. Based on the above results, we can conclude that there are obvious endowment effects in mode shift behavior. Travelers' past travel experiences indeed have significant impacts on travelers' perceptions of attributes of the mode. It could be easily deduced that considering the interactions or not will influence the estimated value of travel time saving(VTTS) of car for car users and the value of crowding for public transit. Moreover, estimating inertia effect intrinsically requires reference preference data. It is much harder to collect comfort feathers in RP than cost and travel time, so the comfort attributes were usually lacked in RP data as we can see in the literature. The interaction of in-crowding vehicle and inertia effect provide a vital implication that ignoring the in-vehicle crowding in modeling inertia effects of public transit would lead to endogeneity and thus cause bias in estimated values. Therefore, it is necessary to include the interactions of inertia in mode shift in case of bias in estimation.

The scale parameter λ allows heteroscedasticity in RP and SP and is inversely proportional to the unobserved variance $\frac{\pi^2}{6\lambda^2}$. The larger scale parameter is, the smaller unobserved variance is. The estimated scale parameter in **ML 1~4** is significantly different from 1 and large. It is logical since we incorporate interactions and heterogeneity in inertia in SP utility specification and do not include them in RP utility. It is expected that the unobserved variance in SP is much smaller than RP and larger scale parameter would be obtained. More importantly, comparing the estimated scale parameters of **ML4** to **ML3** or **ML2** to **ML1**, it is found that considering the interactions of inertia is very beneficial in explaining unobserved heterogeneity and reducing the unobserved variance in utility.

For interactions between LOS variables, possible interactions were tested and only significant parameters at a 95% confidence level were reserved. Significant interactions between travel time and crowding are found for both metro and bus (except the interaction between crowding level 2 and travel time of metro). The coefficients of the interactions are all negative, indicating that the negative impacts of travel time increase with crowding levels and vice versa. The time multiplier can be calculated to represent the effects of crowding on travel time. The time multiplier is equal to the VTTS under different crowding levels divided by the VTTS under reference condition (i.e. "not crowded with seats available)(Li & Hensher, 2011; Tirachini et al, 2016). Since we used dummies for different crowding levels, the time multipliers of different crowding levels are calculated separately. The time multipliers of crowding level 2 "standing in not crowded carriage" and level 3 "standing in very crowded carriage" for metro are 1 and 1.15, respectively. For bus, the time multipliers for the crowding level 2 and level 3 are 1.24 and 1.33. The time multiplier of same crowding level for bus is larger than that for metro, demonstrating that the interaction effect of crowding to subjective perception of travel time is more remarked in bus than metro. The estimated time multipliers are in line with empirical range(1~3) in literature(Li & Hensher, 2011; Tirachini et al, 2016).

4.3 Mode-specific inertia and heterogeneity in inertia

We examined the difference in travelers' inertia effect of different modes. Since we include interactions of inertia term and systematical heterogeneity of inertia in modeling, a posterior simulation process based on the data sample was conducted to calculate the value of inertia of different modes for respondents with different personal characteristics. Statistical F-test and T-test were employed to compare the differences in mean value and variances of inertia. The results are demonstrated in **Table 4**. Remarkable differences are found in the inertia effects for different modes. The mean values of inertia for car, metro, bus and taxi according to the simulated results are 5.397, -0.231, 1.565 and 4.956, respectively. The inertia of car users is 244% larger than that of bus user. The differences among inertia of car, metro and bus are all statistically significant at a confidence level of 99%. Both the inertia for car and bus are positive on average indicating they are resistant to shift from original mode, while the mean of inertia for metro is negative meaning that metro users have dispositions to change on average. However, large variances are observed for the inertia of the three modes. The sign of inertia of certain mode might change with different respondents. For instance, the minimum value of inertia for car is negative demonstrating some car users tend to change, even though the mean value is much larger than zero. The results of F-tests demonstrate that significant differences exist in the variances of inertia for different modes. For the twelve taxi users, the inertia term is always positive and has a large mean value indicating that taxi users are strongly resistant to change. Though the interview, we found that the reason was that the taxi users generally had special travel characteristics that encourage them to user taxi. For instance, some of them have full subsidy for commuting travel due to special work type and time. Some of them were sick or pregnant and thus not safe to use public transit in peak commuting hours by themselves. However, we would not conclude much and did not investigate the heterogeneity in inertia for taxi on account of the very few respondents.

Table 4. Results of statistical comparison

	Value of Inertia				**Statistical Test**		
	Car	**Metro**	**Bus**	**Taxi**	**Car vs Metro**	**Car vs Bus**	**Metro vs Bus**
Mean	5.397	-0.231	1.565	4.956			
Max	20.906	1.869	4.242	8.390			
Min	-0.619	-2.636	-1.333	1.523			
St.dev.	2.405	0.714	1.460	1.754			
F-value					2527.986***	101.992***	736.195***
T-value					156.086***	52.919***	-27.433***

Note: *** denotes significance at a level of 99%.

The inertia effect measures the effects of past travel choice on current mode shift choice and varies with the travelers' satisfaction with past travel choice(Cherchi & Manca, 2011). It would be influenced by both objective conditions and subjective perceptions. The intrinsically different experiences of using different mode for commuting might account for the significant differences in the inertia effects of different mode. For instance, using the private vehicles like car for commuting is usually more pleasant than using crowded public transit during peak hours. Additionally, when the objective conditions during commuting are similar, travelers' perceptions or satisfaction for the used mode vary with personal characteristics due to travelers' preference heterogeneity. The subjective perceptions may lead to large variances in the inertia of same mode. Due to significant differences in inertia effects of different modes and remarked variances, it is necessary to consider mode-specific inertia and heterogeneity in inertia in modeling shift behavior.

Inspired by above results, we investigated the systematic heterogeneity in inertia effect of different modes. Available influencing factors in the survey including demographic attributes, commuting spatial features (e.g. commuting time and distance) and other factors (e.g. flexible work time, occupation and car license plate type), were examined to explain the variance in inertia terms. We only demonstrated the parameters yielding heterogeneity that were significant at a 95% confidence level in at least one of **ML 1~4** in the results in case of redundancy and negative impacts of nonsignificant parameters in estimations.

For the inertia of car, we identify that flexible work time, license plate type, commuting distance and occupation in SOE are significant personal attributes explaining car users' heterogeneity in inertia. More specifically, the coefficient of “flexible work time”(0.0399), “license plate type 1”(0.189)(this license is allowed to use express system in peak hour) and “commuting distance(>20km)”(0.151) are positive, indicating that car users with any of the three attributes show more stickiness to car in mode shift than others. The coefficient of “occupation in state-own-enterprise(SOE)” (-0.0579) is negative, which implies that car users working in state-own-enterprise show less inertia in mode shift. The influences of license plate type and commuting distance are more substantial than flexible work time and occupation according to the absolute values of the coefficients. For metro users, the found significant parameters that are positively related to the inertia effect are “commuting time(30~60 min)”(0.0454), “flexible work time”(0.0644), “occupation in SOE” (0.0920) and “male”(0.0412). These reveal that metro users who have a commuting time of 30~60 min, have flexible work time, work in SOE or is male, are more resistant to shift from metro to other modes in commuting than others. The coefficient of “education (Master or over)” is negative, meaning that metro users with higher educations have less inertia comparatively. For bus users, travelers who are male, work in SOE or have commuting time of 30~60min or more than 60min are found to be more likely to change previous choice in contrast to others. The absolute values of the coefficients for the four factors range from 0.12 to 0.25. Comparing to the mean inertia of bus(0.404), the influences of the four factors are considerable.

More importantly, we compare the estimation results of the **ML4** to **ML2** and the **ML3** to **ML1** to investigate the differences of using mode-specific inertia and generic inertia in model estimation. Firstly, using generic inertia will confound the remarkable differences of inertia for different mode and equalize the inertia across users of different modes. This will result in overestimation of car users’ willingness to change and metro users’ resistance to change. It also causes obscure effects on the estimated value of bus users’ inertia. Secondly, using generic inertia brings confounding effects among utility of different modes and leads to the non-significance of several interactions. For instance, the interactions for inertia and travel time of car, inertia and in-vehicle crowding of bus, income and cost of car lose their significance in **ML3** compared to **ML4**. Lastly, using generic inertia will confound the distinct systematical heterogeneity of inertia for different modes. Taking the parameter “occupation in SOE” for example, it is positive in **ML3** with generic inertia while it is positive for metro and negative for bus and car in **ML4**. We can summarize that generic inertia term homogenizes the distinctions in travelers’ inertia across different modes, this induces several confounding effects for modeling and causes obvious bias in estimations.

4.4 Elasticities and influences of mode-specific inertia and interactions

Table 5 (in Appendix) demonstrates the direct and cross-elasticities for the car, metro and bus. It should be noted that elasticities are computed by averaging the individual observations and are related to the choice probability of the alternatives in different observations, the mean value of all observations is selected as the representative value. A probability weighted average scheme is conducted to avoid the impacts of extreme values on the estimated mean elasticities(Bierlaire, 2017). The utility for travelers who used different modes in the past are distinct due to incorporation of inertia effects and interactions of inertia.

Therefore, the elasticities of same LOS variable for travelers of different modes differ obviously from each other and should be distinguished. Since we focus on mode shift behavior, we only show the elasticity of an attribute of certain mode for travelers who adopted the mode before. For instance, we show the elasticities of cost of car for car users, but not that for metro users.

For the car, the cost has the smallest direct elasticity (-0.704) followed by average travel time (-0.522). The direct elasticities of cost and travel time are all over -1 meaning that they are not so elastic variables influencing the demand for car. The cross elasticities of attributes of public transit (metro and bus) to car are all very small(0.02~0.25) except the crowding level 2: "standing in not very crowded carriage" (0.409) and level 3: "standing in very crowded carriage" (0.577) of metro. These indicate car users' strong stickiness towards car and resistance to change and imply that it is hard to shift car users to public transit. Nevertheless, increases in cost and travel time of using car from current levels seem to be comparatively efficient in reducing the demand for car and promoting the comfortable level of metro is comparatively attractive for car users than improving other attributes of metro or bus from the current levels. For metro users, the demand of metro is comparatively sensitive to cost(-0.400), travel time(-0.411) and crowding level 3 (-0.305), but very insensitive to crowding level 2. It indicates that increasing the cost, travel time or overcrowding in metro will reduce the demand for metro, while the changes of crowding level 2 show few influences on the demand for metro. For the cross elasticities of metro, the metro users are comparatively sensitive to changes in attributes of bus compared to attributes of car. For bus, the demand is mostly sensitive to crowding level 3(-2.003) followed by crowding level 2(-0.759) and travel time (-0.647) in sequence. The demand for bus is much insensitive to the cost since the bus ticket in Shanghai is very cheap (0.3~1 dollar). For the cross elasticities, the results show the demand for bus is comparatively more sensitive to changes in attributes of metro than those of taxi or car. These indicate that reduction in service qualities like comfort and travel time will decrease the share rate of bus and encourage bus users to shift to other modes.

Summarizing above results, we can find that the cross elasticities of attributes of public transit to car are mostly small and less than 0.4, indicating that supply policies in PT might be not sufficient to attract car. Moreover, the results reveal unfortunate facts that the improvements in services of certain public transport could raise its share rate to some degree, but it does not attract car users remarkedly. The increased demand for this public transport mostly comes from users of other public transit rather than the car users. Only promoting the quality of PT may not live up to the expectations of shifting enough car users to PT. The more efficient measures should be firstly increasing the overall expense of using car to make car users have the intention to change (breaking the inertia) and then promoting the service quality (especially comfort features) of PT at the same time. It should be noted that the phenomenon could be ascribed to the strong inertia of car users and comparatively weaker inertia of metro and bus, besides the correlations between metro and bus. Moreover, it is interesting to find an asymmetry in cross elasticities of metro and bus. The cross elasticities of metro to bus of certain attribute is always larger than that of bus to metro user. It indicates that bus users are more sensitive to changes in attributes of metro than metro users to changes in bus.

The comparison between the results of elasticities from **ML4**, **ML1** and base model leads us to some interesting results about the influences of mode-specific inertia and interaction of inertia on demand estimation. We use the results of **ML4** as the reference, since **ML4** perform best in explaining mode shift behavior as we showed before. Comparing to **ML4**, the **ML1** using generic inertia without interactions of inertia confound the differences inertia effects of different modes and result in several confounding effects in model estimations as we discussed before. This causes diverse and obscure impacts on demand forecasting. For example, the direct elasticity of cost of car decrease 21% from -0.704 in **ML4** to -0.849 in **ML1**, which demonstrates that the **ML1** overestimates the reduced demand for car when the cost of car increases. This could be explained by ignoring the positive interactions between inertia and cost of car, and the underestimation of inertia for car using generic inertia compared to mode-specific inertia. However, the direct elasticity of travel time of car increases 35% from -0.522 in **ML4** to -0.338 in **ML1**, indicating that the **ML1** underestimates the reduced demand for car when the travel time of car worsen in contrast to **ML4**. Furthermore, the **ML1** underrates the cross elasticities of cost and travel time of metro to car, and overrates the cross elasticities of travel time of bus and crowding levels of PT to car. For metro, the **ML1** compared to **ML 4** underestimates the reduced demand for metro when the cost and travel time of metro worsen and the cross elasticities of metro to attributes of bus and taxi. When **ML1** is used, the reduced demand for bus while the attributes of bus worsen is underestimated in comparison to **ML4**. The cross elasticities of bus to cost and travel time of metro are undervalued and the cross elasticities of bus to crowding levels of metro are overestimated.

Comparing the elasticities from **ML4** and the base model, we can summarize that ignoring the inertia effects in estimation will lead to the overestimations towards reduction in demand for car and metro when the attributes of metro and car worsen or the attributes of other mode improve. The changes in elasticities of bus are obscure and not uniform across different attributes. In brief, we can conclude that ignoring the mode-specific inertia and interactions of inertia will cause obvious bias in demand estimations of mode shift and the effects are obviously confounding rather than systematical.

5. Concluding remarks

In this paper, we have investigated the interactions of inertia effects to level-of-service (LOS) variables in mode shift behavior to describe the cognitive misperception caused by past travel experiences on current mode choice (i.e. endowment effects). Interactions between LOS variables and interactions of demographic attributes with LOS variables were examined as well. The differences in the inertia effects for different modes as well as systematic heterogeneity in inertia effects were explored especially. To accomplish these, comprehensive surveys were conducted to collect a mixed RP/SP databank regarding mode shift behavior using web-scripted technology. A joint RP and SP random parameter logit method was used in estimation to account for the preference heterogeneity and panel correlation effects. Based on the estimated results, we analyzed the influences of mode-specific inertia effects and interactions of inertia on model performance and demand forecasting. The main findings could be summarized as follows:

There are substantial and significant interactions between inertia terms and LOS variables. The interactions indicate endowment effects of past travel experience on current mode shift choice. The found interactions indicate that car users undervalue the cost of car and overestimate the travel time of car compared to others. Metro users were found to underrate the in-vehicle crowding in metro than others and bus users value more highly of in-vehicle crowding in bus than others. Incorporating the interactions of inertia in modeling can remarkably promote the model performance in explaining mode shift choice and reduce the unobserved error components in utilities efficiently. The interactions between in-vehicle crowding and travel time are modeled using time multiplier. Travelers show more aversion to the in-vehicle crowding of bus to the same crowding in metro. The time multiplier of same crowding level for bus is larger than that for metro.

We found substantial and significant differences in the inertia effects of different modes which might even have different signs. The car users show very strong inertia compared to public transit users. The differences in inertia effects of different mode should be distinguished in modeling. Large variances in inertia effects were observed indicating the importance to consider heterogeneity in inertia effects. There are significant distinctions in the variances of inertia effects of different modes. Incorporating mode-specific inertia compared to generic inertia can significantly improve the model performance. Moreover, using generic inertia instead of mode-specific inertia will underestimate the inertia of car users and overestimate the inertia of metro users. The generic inertia confounds the remarked differences in inertia effects of different mode and consequently leads to several bias in estimations.

The factors contributing to the heterogeneity in inertia effects were investigated. The flexible work time, license plate type, commuting distance and occupation were significantly influencing factor towards inertia for car. Commuting time, education level, flexible work time, occupation and gender affect the inertia for metro. Commuting time, gender and occupation are the explaining factors for heterogeneity in inertia for bus. These values are useful to predict inertia of different groups.

Mode-specific inertia and interactions of inertia effects have substantial impacts on demand estimations. Compared to model without inertia effects, ignoring the mode-specific inertia and interactions inertia will lead to overestimating car and metro users' willingness to change in mode shift. Compared to model with generic inertia without interactions of inertia, the impacts are confounding as we discussed before since the generic inertia homogenizes the inertia of different mode. The results highlight the importance to consider mode-specific inertia and interactions of inertia in case of bias in demand estimations. Furthermore, the elasticity analysis implies that transport policies from public transport supply perspective like improving the service quality could be insufficient to reduce the car dependency due to the strong inertia of car. An asymmetry in cross elasticities between metro and bus was found.

For future work, more explorations regarding the influences of latent factors like attitudes and social network on travelers' inertia effects in mode shift behavior will be conducted. Taking advantage of the mixed dataset, it is also very interesting to set up model specifications to consider other crucial reasons of unwillingness to change (e.g. risk aversion and bounded rationality) in mode shift behavior.

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7. Appendix

Table 3 Estimated results

	Base model Without inertia effect		ML1 Generic inertia without interaction of inerita		ML2 Generic inertia and interaction of inerita		ML3 Mode-specific inertia without interaction of inerita		ML4 Mode-specific inertia and interaction of inerita	
Parameters	**Value**	**t-stat.**	**Value**	**t-stat.**	**Value**	**t-stat.**	**Value**	**t-stat.**	**Value**	**t-stat.**
Cost(mean)	-0.0265	-4.05	-0.0319	-4.79	-0.0228	-3.77	-0.0342	-4.72	-0.0261	-4.04
Cost(st.dev.)	0.0265	4.05	0.0319	4.79	0.0228	3.77	0.0342	4.72	0.0261	4.04
Travel time_car_SP (mean)	-0.0129	-3.89	-0.00900	-4.25	-0.00365	-3.23	-0.0118	-4.17	-0.00476	-3.48
Travel time_car_SP (st.dev)	0.0129	3.89	0.00900	4.25	0.00365	3.23	0.0118	4.17	0.00476	3.48
Travel time_PT_SP (mean)	-0.0113	-3.95	-0.00875	-4.58	-0.00469	-3.58	-0.00895	-4.44	-0.00603	-3.93
Travel time_PT_SP (st.dev)	0.0113	3.95	0.00875	4.58	0.00469	3.58	0.00895	4.44	0.00603	3.93
Crowd2_metro_SP(mean)	-0.215	-3.85	-0.238	-4.25	-0.104	-3.23	-0.256	-4.18	-0.127	-3.43
Crowd2_metro_SP(st.dev.)	0.215	3.85	0.238	4.25	0.104	-3.23	0.256	4.18	0.127	3.43
Crowd3_metro_SP(mean)	-0.414	-3.90	-0.389	-4.25	-0.223	-3.42	-0.363	-4.13	-0.241	-3.71
Crowd3_metro_SP(st.dev.)	0.414	3.90	0.389	4.25	0.223	3.42	0.363	4.13	0.241	3.71
Crowd2_bus_SP(mean)	-0.0786	-2.10	-0.0797	-2.14	-0.0345	-1.60	-0.106	-2.43	-0.0427	-1.97
Crowd2_bus_SP(st.dev.)	0.0786	2.10	0.0797	2.14	0.0345	1.60	0.106	2.43	0.0427	1.97
Crowd3_bus_SP(mean)	-0.138	-2.82	-0.196	-3.47	-0.119	-3.07	-0.244	-3.57	-0.133	-3.14
Crowd3_bus_SP(st.dev.)	0.138	2.82	0.196	3.47	0.119	3.07	0.244	3.57	0.133	3.14
Error component metro&bus	0.124	2.69	0.164	2.35	0.102	2.26	0.173	2.88	0.093	2.43
ASC_car_SP	0.411	3.89	0.282	3.43	0.165	2.90	0.346	3.01	0.184	2.61
ASC_metro_SP	0.315	3.97	0.391	4.44	0.247	3.60	0.492	4.45	0.308	3.86
ASC_taxi_SP	-0.0327	-1.01	-0.143	-2.27	-0.0438	-1.25	-0.101	-1.59	-0.0710	-1.87

Travel time_car_RP (mean)	-0.0237	-3.71	-0.0290	-3.76	-0.0248	-3.87	-0.0312	-3.58	-0.0253	-3.47
Travel time_car_RP (st.dev)	0.0237	3.71	0.0290	3.76	0.0248	3.87	0.0312	3.58	0.0253	3.47
Travel time_PT_RP (mean)	-0.0246	-3.21	-0.0307	-3.13	-0.0223	-3.02	-0.0327	-3.00	-0.0245	-2.77
Travel time_PT_RP (st.dev)	0.0246	3.21	0.0307	3.13	0.0223	3.02	0.0327	3.00	0.0245	2.77
Crowd2_metro_RP(mean)	-0.466	-1.54	-0.537	-1.71	-0.489	-1.64	-0.641	-2.01	-0.532	-1.94
Crowd2_metro_RP(st.dev.)	0.466	1.54	0.537	1.71	0.489	1.64	0.641	2.01	0.532	1.94
Crowd3_metro_RP(mean)	-0.600	-2.17	-0.762	-2.65	-0.695	-2.51	-0.855	-2.90	-0.756	-2.68
Crowd3_metro_RP(st.dev.)	0.600	2.17	0.762	2.65	0.695	2.51	0.855	2.90	0.756	2.68
Crowd2_bus_RP(mean)	-0.414	-1.08	-0.470	-1.16	-0.421	-1.06	-0.466	-1.14	-0.449	-1.42
Crowd3_bus_RP(mean)	-0.425	-1.04	-0.496	-1.07	-0.452	-2.11	-0.525	-2.01	-0.457	-2.11
ASC_car_RP	2.69	6.96	2.81	7.55	2.84	7.99	2.84	7.47	2.80	7.76
ASC_metro_RP	1.78	5.54	1.90	5.47	1.85	5.55	1.95	5.55	1.89	5.55
ASC_taxi_RP	9.14	14.57	10.3	15.07	10.5	16.52	11.3	17.12	10.8	17.55
Inertia_car(mean)							0.171	2.31	0.124	2.90
Inertia_car(st.dev.)							0.0966	1.74	0.116	3.09
Inertia_metro(mean)							-0.246	-2.73	-0.178	-2.50
Inertia_metro(st.dev.)							0.0322	0.52	-0.0474	-1.91
Inertia_bus(mean)							0.514	3.78	0.404	3.23
Inertia_bus(st.dev.)							0.126	2.23	0.0825	2.26
Inertia_taxi(mean)							0.902	3.64	0.472	3.22
Inertia_taxi(st.dev.)							0.499	2.25	0.167	2.34
Generic inertia(mean)			0.129	3.17	0.142	3.23				
Generic inertia(st.dev)			0.0777	1.99	0.0504	2.37				
Interactions(SP)										
Income&cost(car)			0.00614	4.47	0.000276	0.86	0.00599	4.52	0.00156	3.08
Crowd3_metro&travel time(metro)			-0.00157	-1.94	-0.000363	-0.75	-0.00219	-2.30	-0.000901	-2.59
Crowd2_bus&travel time(bus)			-0.00243	-3.01	-0.00152	-2.76	-0.0027	-3.12	-0.00144	-2.55
Crowd3_bus&travel time(bus)			-0.0028	-2.58	-0.00172	-2.48	-0.00266	-2.32	-0.00197	-2.49

Inertia_car&cost(car)			0.0108	3.70			0.0110	3.88
Inertia_car&travel time(car)			-0.00158	-1.70			-0.00461	-2.66
Inertia_metro&crowd(metro)			-0.0983	-2.41			0.103	2.09
Inertia_bus&crowd(bus)			0.0453	1.01			-0.113	-2.60
Heterogeneity in inertia								
Generic								
Age(>50)	0.123	0.82	0.0270	0.38				
Education(Master or over)	-0.113	-2.53	-0.0828	-2.73				
Flexible work time	0.125	2.85	0.0264	1.30				
License plate type 1(car)	0.288	4.01	0.0892	3.02				
Occupation in SOE	0.0433	1.29	0.0295	0.95				
Car								
Flexible work time					0.240	3.17	0.0399	2.13
License plate type 1					0.237	3.27	0.189	3.38
Commuting distance(>20km)					0.154	2.77	0.151	2.29
Occupation in SOE					-0.0101	-0.18	-0.0579	-2.53
Metro								
Commuting time(30~60min)					0.0890	2.53	0.0454	2.29
Commuting time(>60min)					0.0933	1.30	0.0329	0.75
Education(Master or over)					-0.162	-1.98	-0.106	-2.09
Flexible work time					0.155	2.51	0.0644	1.97
Occupation in SOE					0.153	2.35	0.0920	2.29
Male					0.0790	1.70	0.0412	2.41
Bus								
Commuting time(30~60min)					-0.288	-2.40	-0.175	-2.31
Commuting time(>60min)					-0.445	-2.63	-0.258	-2.32
Male					-0.114	-1.16	-0.120	-1.99
Occupation in SOE					-0.140	-2.31	-0.123	-2.34
Serial correlations of RP and								

SP										
Error component_car			0.383	4.32	0.230	3.62	0.408	4.32	0.228	3.72
Error component_metro			0.339	4.65	0.202	3.67	0.363	4.57	0.214	3.89
Error component_taxi			0.410	4.16	0.235	3.20	0.461	4.10	0.279	3.73
Scale parameter(SP to RP)	6.37	3.36	6.93	3.98	12.0	3.34	6.21	3.89	10.5	3.57
Model fit										
Final log-likelihood	-6753.876		-4604.756		-4569.496		-4557.972		-4518.273	
No. of parameters	24		35		39		50		54	
Adjusted ρ^2	0.247		0.313		0.317		0.317		0.329	
AIC	10164.827		9279.500		9216.991		9217.944		9146.547	

Note: AIC is the Akaike Information Criterion. AIC =-2 * log-likelihood + 2 K, where K is the number of parameters. The smaller AIC indicates a better model fit. SOE denotes the state-owned enterprise. St.dev. means standard deviation. The t-stat. in the table is robust t-value reported by Pythonbiogeme. The t-statistic corresponding to the scale parameter is computed with respect to a value of 1 rather than 0.

Table 5. Direct and cross elasticity of different models

	ML4: mode-specific inertia and interactions of inertia			ML1: generic inertia without interactions of inertia						Base model : No inertia effects					
Parameters	**Car**	**Metro**	**Bus**	**Car**		**Metro**		**Bus**		**Car**		**Metro**		**Bus**	
Cost(car)	**-0.704**	0.064	0.210	**-0.849**	*-21%*	0.064	*-0%*	0.135	*-36%*	**-0.985**	-40%	0.091	42%	0.117	-45%
Travel time(car)	**-0.522**	0.031	0.069	**-0.338**	*35%*	0.047	*52%*	0.070	*1%*	**-0.838**	-60%	0.107	242%	0.115	67%
Cost(metro)	0.115	**-0.400**	0.133	0.090	*-22%*	**-0.267**	*33%*	0.082	*-39%*	0.114	-2%	**-0.401**	0%	0.128	-3%
Travel time(metro)	0.247	**-0.411**	0.281	0.230	*-7%*	**-0.348**	*15%*	0.242	*-14%*	0.408	65%	**-0.673**	-64%	0.433	54%
Crowding level 2(metro)	0.409	**-0.026**	0.639	0.439	*7%*	**-0.090**	*-250%*	0.792	*24%*	0.519	27%	**-0.319**	-1143%	0.672	5%
Crowding level 3(metro)	0.577	**-0.305**	0.832	0.731	*27%*	**-0.302**	*1%*	0.919	*10%*	0.712	23%	**-0.615**	-101%	0.701	-16%
Cost(bus)	0.029	0.045	**-0.146**	0.027	*-8%*	0.029	*-35%*	**-0.108**	*26%*	0.051	74%	0.079	76%	**-0.113**	23%
Travel time(bus)	0.191	0.237	**-0.647**	0.205	*7%*	0.185	*-22%*	**-0.606**	*6%*	0.515	169%	0.672	184%	**-0.929**	-44%
Crowding level 2(bus)	0.026	0.156	**-0.759**	0.138	*439%*	0.145	*-7%*	**-0.571**	*25%*	0.219	754%	0.269	72%	**-0.239**	69%
Crowding level 3(bus)	0.037	0.346	**-2.003**	0.229	*525%*	0.280	*-19%*	**-1.842**	*8%*	0.397	981%	0.503	45%	**-0.875**	56%
Cost(taxi)		0.149	0.360			0.091	*-39%*	0.387	*7%*			0.152	2%	0.228	-37%
Travel time(taxi)		0.073	0.130			0.069	*-6%*	0.201	*54%*			0.172	135%	0.221	69%

Note： The elasticities of crowding levels for metro and bus are arc elasticities since they are dummy variables in estimation. Others are point elasticity. The change percentage of elasticities for ML1 and base model compared to ML4 are shown in grey background.