Modeling co-dependent choice of workplace, residence and commuting mode using an error component mixed logit model

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Abstract

This paper develops an error component mixed logit model to analyze the multi-dimensional residential, work and transportation mode choice. It expands previous studies based on life-trajectory theory which predominantly only considered two life domains. In contributing to this emerging field of research, we design an integrated pivoted stated choice experiment considering the multi-dimensional choice of job, residence and transportation mode for the journey to work. The results of the estimated error component mixed logit model with panel effects indicate that most selected attributes of the residential environment, job profile and transportation mode are significantly related to individual differences in multidimensional choices. Moreover, the estimation of various sources of unobserved heterogeneity signals significant unobserved heterogeneity in selected taste parameters, and choice dependent heteroscedasticity in error component variance.

Keywords Co-dependent location · Multidimensional choice · Pivoted stated choice experiment · Error component logit model · Panel data · Heterogeneity

Introduction

The transportation literature is well endowed with models of transportation mode choice (e.g. Quarmby 1967; Meyer et al. 1978; Grava 2003; Rodriguez and Joo 2004; Meixell and Norbis 2008; Heinen et al. 2013). The most common way of modeling transportation mode choice is to assume that a set of vehicle and trip attributes generates a certain amount of

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utility for travellers of a particular socio-economic profile who are assumed to choose the transportation mode that maximizes their utility. Sometimes, taste variation is allowed by assuming the taste parameters exhibit a particular distribution (e.g., Bhat 2000; Paulssen et al. 2014).

This common restriction to vehicle and trip attributes has some important limitations. When some time ago, major transit oriented development projects in the Netherlands decreased travel times by public transportation, prevailing models predicted a shift in transportation mode choice to the train. In reality, however, a substantial share of the workers decided to move further away from their workplace to enjoy a larger, relatively cheap house, located in a more rural area without increasing their commute travel times. The transportation mode choice models did and could not predict this response to the development scheme, simply because the transportation mode choice model lacked the relevant variables and the necessary larger perspective.

The point is that life trajectories are critical in understanding daily activity-travel patterns and underlying decisions. People hold a series of aspirations related to different life domains, among which job and housing careers constitute key domains. The decision to move to the next stage in the careers that make up the life trajectories is often made if certain constraints (e.g. budget, travel time constraints) are lifted or if changes in other careers increase the need for change in the domain of interest. The example above illustrates that as travel times constraints are relaxed, some households will take the opportunity to move closer to the ultimate life trajectory housing aspirations by moving house without the need to deal with longer travel time commutes.

Recently, the view has re-emerged that people's decisions with respect to different life-domains should be treated as a 'bundle' choice. In that sense, the job (location) choice, residential choice, commuting times, transportation mode choice and underlying vehicle possession are strongly interdependent. Rather than maximizing the utility of each of these choice facets separately and independently, it is more realistic to assume that individuals/households consider the multidimensionality and maximize the utility of the multidimensional profile (or apply another choice mechanism to the multidimensional profile), against the background of their life-course trajectories. Because we do not observe people moving house or changing jobs many times, we should account for some possible inertia in response times.

To date, relatively little work has been reported about people's preferences for interdependent long-term residential, job choice, and short-term commuting transportation mode choice. Moreover, existing work tends to be based on retrospective survey data. While such data reflect real historical events and decisions, a disadvantage is that the data controls the researcher rather than the researcher controlling the data (properties). Thus, it would be relevant to complement these studies with studies based on stated choice data to obtain a more fundamental understanding of multidimensional choice behavior as it relates to the choice of job, residence and transportation mode for the commute trip.

Thus, the objective of this study is twofold. First, based on the contention that individuals and households consider these three dimensions, a stated choice experiment was designed to mimic the multidimensional choice behavior of interest and estimate a model of multidimensional choice concerned with residence, job and transportation mode for the commute trip. Second, this study further examines various sources of unobserved heterogeneity in the multidimensional choice behavior addressed in this study.

The remainder of this paper is organized as follows: In "[Literature review](#)" section, we review the literature on the multidimensional choice behavior related to housing, job and transportation. "[Survey and experimental design](#)" section presents the stated choice

experiment that is based on a pivoted D-efficient design. A brief description of the data is also presented in this section. Next, the multi-dimensional choice model based on the error component mixed logit model is presented in “[Model formulation](#)” section. Then, the results of the model estimation are presented in “[Analysis and results](#)” section. Conclusions and a discussion of future research directions are presented in the last section.

Literature review

The transportation literature is extremely rich of transportation mode choice models. The vast majority of these models assume that individuals maximize the utility they derive from the attributes of the transportation mode and trip characteristics. In the context of the topic of this paper, these models thus involve a unidimensional choice problem. Consequently, any predictions, based on these models, are necessarily refined to vehicle and trip characteristics. This is not a problem if the management or policy issue concerns vehicles and trip attributes, and does not affect space–time prisms of individuals. However, if the policy would open up new opportunities, individuals may reconsider the intricate relationship between residence, job and transportation mode.

As argued in Van der Waerden and Timmermans (2003), other key life domains, such as residential and work relocation, may induce changes in travel behavior. During the last decades, many studies have emphasized the simultaneous nature of the choice of residential mobility and commuting mode (e.g., Desalvo and Huq 2005; Bhat and Guo 2007; Salon 2009; Pinjari et al. 2011; Guerra 2015). As an example, Handy et al. (2005) found significant changes in travel mode and car travel distances after residential relocation. In the work domain, key events such as first-time entry into the labor market, job change, income change and retirement were found to influence travel mobility change (e.g., Dargay 2001; Dargay and Hanly 2007; Scheiner and Holz-Rau 2013). In turn, commuting mode preference also influences residential and/or work location choice. For example, commuters by public transportation may find the egress time important and consciously choose to live/work near a transit station (Bhat and Guo 2007). People living in sprawling areas rely more on cars to conduct their daily activities (Khattak and Rodriguez 2005; Schwanen and Mokhtarian 2005a, b). Additionally, increasing travel time may trigger people to reconsider and possibly change their residence or job. Ettema (2010) pointed out that excess commute distance may prompt the relocation process and trigger people move to a new dwelling; likewise, longer commuting time or activity duration may accelerate relocation decisions (Rashidi et al. 2011). This emphasis on the interdependency has led to the joint choice modeling of residential/work location and commuting behavior (e.g., Kim et al. 2003; Ng 2008).

However, although the interdependency between residential and job choice decisions and transportation mode choice has been acknowledged, most empirical studies considered only two choice dimensions. Literature on the joint choice of all three dimensions is relatively scarce. Several decades ago, Lerman (1976) developed a multinomial logit model that combined multiple dimensions (residential location, automobile ownership, and commute mode choice). Rich and Nielsen (2001) presented a micro-econometric model for forecasting long-term travel demand considering residential location, house type and choice of work location. Salon (2006) explored the relationship between the transportation and land use system in New York City by modeling a multinomial logit model of the joint choices of residential location, car ownership, and commute mode of New Yorkers.

Likewise, using data from the San Francisco Bay Area, Pinjari et al. (2011) formulated a joint model of residential location, car ownership, bicycle ownership, and commute tour mode choice. They found that these aspects are interrelated and one choice dimension is not exogenous to the others, but endogenous to the system as a whole. In another publication, Paleti et al. (2012) developed an integrated joint model of six different choice dimensions: residential location, work location, commute distance, household vehicle ownership, commuting mode and number of stops of commute trips.

Although these simultaneous choice models consider long-term decisions and short-term decisions as an integrated choice, unfortunately, only few attributes were taken into account. Consequently, these studies perhaps oversimplified the choice problem. Thus, for the purpose of our research, we selected relatively many influential factors to mimic the complexity of the interdependency of residential, job and work commute transportation mode choice in reality.

Furthermore, because a considerable amount of observed and unobserved preference heterogeneity normally exists in multi-dimensional choice behavior, several error components are added to the conventional multidimensional multinomial logit model. The current study contributes to the literature in further understanding the joint decision of long-term mobility regarding house, job and transportation using the data collected through a stated choice experiment. First, we assume that taste differences in part depend on observed socio-demographic variables and in part reflect pure error. To incorporate this assumption, we estimate covariate-dependent effects to account for heterogeneity around the mean of taste parameter distributions, following Train (2003), and Hensher and Greene (2003). Second, to allow for the possibility that unobserved preferences for transportation modes depend on long-term choice behavior, long-term choice specific error components are identified and the variance of these error components is estimated through parameterisation of their heteroscedasticity (Hensher and Greene 2003). Thus, we estimate an error component mixed logit model to identify random and systematic long-term choice specific heterogeneity. As an extension of the standard mixed logit model, this error component approach includes parameter estimates for latent error component effects (Greene and Hensher 2007). Specifically, the error component consists of IID and non-IID components, and the non-IID component part associates the unobserved variance nests with sociodemographic characteristics (gender, income and numbers of workers in the households).

Survey and experimental design

Experimental design

A stated preference experiment was designed to measure the preferences for multi-dimensional residential choice, job choice and transportation mode choice behavior. In total, nineteen attributes were selected for the choice experiment (Table 1). Several transportation researchers have expressed concerns about such a large number of attributes. While we do not wish to deny that large experimental design may induce unreliable responses, simple designs with just a few attributes may oversimplify the nature of the choice problem and therefore be less useful. The aim of the experimental design should be to mimic the complexity of the decision-making process under investigation in the real world, while controlling as much as possible for experimental artifacts that may jeopardize the reliability and validity of the experiment.

Table 1 Attributes of house, job and transportation mode

Name	Attribute	Attribute level
Residence	Tenure	Rent, Buy
	Cost (yuan/ month)	500, 1600, 2200, 3800
	Size (m ²)	30, 65, 90, 125
	Distance to metro station	– 75%, – 25%, 25%, 75% change from the current situation
	Distance to bus stop	– 75%, – 25%, 25%, 75% change from the current situation
	Distance to shopping mall	– 75%, – 25%, 25%, 75% change from the current situation
Work	Home location	Central city, Surrounding area
	Work type	Government, Institution, Enterprise, Self-employed
	Flexibility	Yes, No
	Salary (yuan/year)	30 k, 80 k, 130 k, 200 k
	Work environment	Very good, Good, Poor, Very poor
	Colleague relationship	Very good, Good, Poor, Very poor
	Easy to find a similar job	Yes, No
<i>Transportation mode</i>	Work location	Central city, Surrounding area
Car	Travel cost (yuan)	1.4, 7, 12.6, 21
	Travel time (min)	4.5, 18, 31.5, 45
	Congestion time (min)	– 75%, – 25%, 25%, 75% change from the current situation
Metro	Travel cost (yuan)	2, 4
	Travel time (min)	5, 20, 35, 50
	Out-of-vehicle time (min)	10, 20, 30, 40
	Have seats or not	Yes, No
Bus	Travel cost (yuan)	1, 2
	Travel time (min)	8, 29, 50, 71
	Out-of-vehicle time (min)	5, 10, 15, 20
	Congestion time (min)	– 75%, – 25%, 25%, 75% change from the current situation
Bike	Have seats or not	Yes, No
	Travel time (min)	9, 54, 84, 120
Walk	Travel time (min)	30, 144, 252, 360

Without specifying a particular causality in the dynamics, we told respondents that new job and residential opportunities occur regularly and that properties of work commute trips may change. They were informed that we were interested if under such circumstances, they would change their current house or job and which transportation mode they would then choose. Respondents were explained before making a choice so that they can take into account residential, work and transportation modes simultaneously in the choice experiment.

It should be noted that the single choice of transportation mode given residential and job attributes was not considered, neither the case of changing house and job

simultaneously. The former, discussed already in a large body of transportation literature, is not the focus of the current study. However, we specifically examine the long-term mobility decision and treat the transportation mode choice a bundled decision with changing house or changing job. Changing transportation mode only given a certain situation of residence and job is considered a short-term decision. The latter option (changing both house and job), on the other hand, may require much mental processing from the people and the response could be unreliable without giving a proper setting of life contexts. Moreover, including these two options could make the choice experiment over complicated. Thus, the choice of changing transportation mode only and the option of changing both residential and work mobility were not considered.

The attributes included in the experiment were mainly drawn from the relevant literature in urban geography, urban sociology, and transportation (e.g., Louviere and Timmermans 1990; Timmermans et al. 1992; Van Ommeren 1999; Bagley et al. 2002; Walker and Li 2007; Ettema 2010; Schirmer et al. 2014; Balbontin et al. 2015; Tran et al. 2016). For the residential dimension, 2 two-level attributes and 5 four-level attributes were considered. These attributes include various attributes of the house (rent or buy, monthly costs, house size), location and neighbourhood characteristics (accessibility of metro station, bus station, shopping center), and residential location (city vs suburban). For the work dimension 2 two-level and 5 four-level attributes were used in the experiment: work type, flexibility of the work schedule, income, work environment, relationship with co-workers, the ease of finding a similar job and job location. The transportation mode dimension included five attributes: travel cost, travel time, out-of-vehicle time, congestion time and having seats or not. The attributes and their levels are shown in Table 1.

In order to better capture the effects of the selected attributes, we created a pivoted stated choice experimental design, which generates change relative to the current status of the respondents. Pivoting allows estimating choice models that include constraints on the choice probabilities and explicitly consider changes in attribute levels. Five attributes (distance to the metro station, bus station and shopping centre; congestion time by auto and bus) were considered as the pivoted attributes. Four levels (−75%, −25%, 25%, 75% difference) were set using the personally experienced situation as the reference. Consequently, the hypothetical profiles are more realistic to specific respondents.

Because the profiles depend on the current situation of the respondents, they need to be generated during the survey completion process. Therefore, we used a Web-based survey system (Pauline, designed by our group), which offers many features especially related to the design and implementation of stated choice experiments. We dealt with the large numbers of attributes by designing two separate experiments; one for the residence-work dimension and another for the transportation dimension, and randomly paired these two designs. The first design involved a $4^9 \times 2^5$ design and the second design involved a combination design (car: $4^3 \times 2$, metro: $4^2 \times 2^2$, bus: $4^3 \times 2^2$, bike and walk 4^1). Each design involved 128 profiles, which were randomly paired, creating $128 \times 128 = 16,384$ choice sets. Eight profiles were selected at random for each respondent.

As shown in Fig. 1, the choice task includes eleven labelled alternatives: three long term decisions (status quo, move house or change job), and for the latter two options, the choice among five transportation modes. Respondents were told that at any moment in time they more become aware of a new job opportunity and a vacant house. They were asked whether they would change job, move house or do not take any action if faced with these options. If they move house or change job, they should also indicate which transportation mode they would choose for the commute trip.

	Current Situation	Move House						Change Job				
Tenure	Buy	Rent						Your current house				
Cost (yuan/month)	3800	600										
Size (m²)	80	65										
Distance to the metro station (km)	0.3	2.0										
Distance to the bus stop (km)	0.2	1.0										
Distance to the shopping mall (km)	2	1.25										
Home Location	Central City	Central City										
Type of company	Government	Your current job						Self-employed				
Flexibility	Yes							No				
Salary (yuan/year)	8w							18w				
Working environment	Not good							Good				
Co-worker Relationship	Good							Not good				
Easy to find a similar job	Yes							No				
Work Location	Central City							Surrounding Area				
Travel Mode	Bus	Car	Metro	Bus	Bike	Walk	Car	Metro	Bus	Bike	Walk	
Cost (yuan/time)	1	10	2	4			40	4	1			
Travel Time (min)	40	7.5	7.5	15	7.5	20	30	30	25	30	5	
Out-of Time (min)	5		40	40				20	40			
Congestion Time (min)	20	7.5		7.5			7.5		22.5			
Have seats or not	No		Yes	No				No	Yes			
Your Choice:								√				

Fig. 1 The pivoted stated choice design

Data analysis

The data was collected in Shenyang, China, in 2016. Respondents were selected at random from five main districts in the central city and four other districts in the surrounding, new development areas. In our survey, respondents were asked to report their current residential situation, work characteristics, and travel behaviour, as well as personal and household socio-demographic characteristics. Considering the aim of the study, we only interviewed respondents who had a job. The sample consists of 401 respondents and 3208 observations for model estimation.

Table 2 presents the descriptive statistics of the main socio-demographic variables and other characteristics of the sample. It shows that gender is almost equally distributed. More than half of the respondents live alone (54.4%); 63.8% live in the city center, while 36.2% live in the suburbs. Similarly, 65.3% of the respondents are employed in the central city, 34.7% work in the suburbs or other cities. As for commuting, 52% of the respondents have at least one car in their household. However, public transportation still dominates the transportation modes in our survey. 26.4% of the respondents drives to work, while 24.4% uses slow mode (bicycle or walk), implying that almost half of the respondents depend on/use public transportation.

Model formulation

To reflect the structure of the collected data, and incorporate different sources of heterogeneity, we formulated an error component mixed logit model. The model follows the principles of the approach suggested in Greene and Hensher (2007). Assume that individual n faces the choice among multidimensional alternatives in choice situation t . The multidimensionality of the alternatives relates to the residential environment, job and a set of transportation modes focusing on the work commute. Individuals are assumed to derive from these multidimensional profiles a certain utility. The utility of alternative

Table 2 Socio-demographic characteristics of respondents

Variable	Classification	# of cases	Percentage
Gender	Male	195	48.6
	Female	206	51.4
Age	18–40	281	70.0
	> 40	120	30.0
Marital status	Couple with children	145	36.2
	Couple without children	38	9.5
	Single	218	54.4
Number of workers	Dual-earn workers	240	59.9
	Single worker	161	40.1
Annual income	< 60,000	243	60.6
	≥ 60,000	158	39.4
Tenure	Buy	337	84.0
	Rent	64	16.0
Home location	Central city	256	63.8
	Surrounding area	145	36.2
Work type	Government	35	8.7
	Public institutions	74	18.5
	Joint venture, private firms	201	50.1
	Self-employed	91	22.7
Work location	Central city	262	65.3
	Surrounding area	139	34.7
Commute mode	Car	106	26.4
	Metro	65	16.2
	Bus	96	23.9
	Shuttle	32	8.0
	Bike	75	18.7
	Walk	27	6.7

i is assumed to be stochastic and consists of a deterministic utility, V_{nit} , and a random error, ϵ_{nit} , such that

$$U_{nit} = V_{nit} + \epsilon_{nit} \quad (1)$$

The deterministic utility is assumed to be a linear function of observed attributes. Hence, the utility function may be expressed as

$$U_{nit} = \beta_{io} + \sum_{k=1}^K \beta_k x_{nikt} + \epsilon_{nit} \quad (2)$$

where β_k is the parameter for attribute k , x_{nikt} is an explanatory variable, related to attributes of the residence, job or transportation modes for commuting, and ϵ_{nit} is a random IID Gumbel distributed error term. We assume that individuals choose the multidimensional alternative that maximizes their utility.

We introduce various sources of preference heterogeneity in the model. First, we assume that people differ in terms of taste parameters β_k . In part, the unobserved heterogeneity in taste

parameters can be accounted for by differences in socio-demographics, and in part there is pure error. Thus,

$$\beta_{nk} = \bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm}, k = 1, \dots, K \quad (3)$$

where $\bar{\beta}_k$ is the mean of the random parameter of attribute k , z_{nm} is the m th sociodemographic characteristic of individual n , θ_{km} is a parameter to be estimated, and σ_k denotes the standard deviation of random parameter β_{nk} . Then, the utility expression becomes

$$U_{nit} = \beta_{io} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{nikt} + \epsilon_{nit} \quad (4)$$

Our experiment induced respondents to choose among three long-term life trajectory decisions, i.e. status quo (keep current), move house or change job. To allow for the possibility that unobserved heterogeneity underlying the choice of these long-term decisions may affect preferences for transportation modes, we additionally allow for three additional error components in each nested alternative, defined by the outcome of the long-term decision. The error components, Q_{n1} , Q_{n2} and Q_{n3} , denote the grouped error component of keep current, move house and change job. Thus, the utility function becomes

Status quo:

$$U_{n1t} = \beta_{1o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n1kt} + \lambda_1 Q_{n1} + \epsilon_{n1t}$$

Move house :

$$U_{n2t} = \beta_{2o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n2kt} + \lambda_2 Q_{n2} + \epsilon_{n2t}$$

...

$$U_{n6t} = \beta_{6o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n6kt} + \lambda_2 Q_{n2} + \epsilon_{n6t} \quad (5)$$

...

Change job :

$$U_{n7t} = \beta_{7o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n7kt} + \lambda_3 Q_{n3} + \epsilon_{n7t}$$

...

$$U_{n11t} = \beta_{11o} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm} \right) x_{n11kt} + \lambda_3 Q_{n3} + \epsilon_{n11t}$$

We assume that these error components Q_{nl} are independent and follow a standard normal distribution, with $Q_{nl} \sim N[0, 1]$. λ_l is a parameter to be estimated for the error component l .

Finally, we specify the variance heterogeneity of the error component as

$$\text{Var}[Q_{nl}] = \left[\lambda_l \exp \sum_{m=1}^M \tau_{lm} z_{nm} \right]^2 \quad (6)$$

where τ_{lm} is a parameter that needs to be estimated.

The conditional choice probabilities then take on the logit form:

$$p_{nit}(i|Q_n) = \frac{\exp\left(\beta_{io} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm}\right) x_{nikt} + \lambda_l Q_{nl}\right)}{\sum_{i=1}^I \exp\left(\beta_{io} + \sum_{k=1}^K \left(\bar{\beta}_k + \sigma_k + \sum_{m=1}^M \theta_{km} z_{nm}\right) x_{nikt} + \lambda_l Q_{nl}\right)} \quad (7)$$

Conditioned on the error components, the unconditional probability of a choice for alternative i for individual n is

$$p_{nit} = \int_{E_n} (p_{nit}(i|Q_n) f(Q_{nl})) dQ_{nl} \quad (8)$$

Integrate the taste variation of random parameter β_{nk} , the unconditional choice in Eq. (7) denotes as

$$p_{nit} = \int_{Q_{nl}} \int_{\beta_n} ((P_{nit}|Q_{nl}, \beta_n) f(Q_{nl}, \beta_n | z_n)) dQ_{nl} d\beta_n \quad (9)$$

In our experiment, respondents provide responses. If we ignore the repeated measurement nature of the data, biased parameter estimates may be produced. Furthermore, the model will underestimate the standard errors of the parameters, thus t-values will be inflated. In turn, this may lead researchers to falsely decide some effects are significant for the current sample size. Thus, we estimated these panel effects. Consequently, the full log-likelihood function can be written as follows

$$LL = \sum_{n=1}^N \log \int_{Q_{nl}} \int_{\beta_n} \prod_{t=1}^T ((P_{nit}|Q_{nl}, \beta_n) f(Q_{nl}, \beta_n | z_n)) dQ_{nl} d\beta_n$$

Analysis and results

Table 3 presents the results of the error component mixed logit model (Model 2) and the base model with random parameters only (Model 1). Because we have a large number of attributes, it is unrealistic for the given sample size to estimate random effects for all attributes. From a behavioral point of view, understanding and modeling residential and work location choice behavior is a primary concern for urban planners, policymakers, and researchers (Schirmer et al. 2014; Dubernet and Axhausen 2016). Thus, residential and

Table 3 Estimation results

Variable	Description	Model 1			Model 2		
		Coefficient	Standard Error	Prob. z > Z	Coefficient	Standard Error	Prob. z > Z
<i>Random parameters</i>							
Home location	(Central 1; Surrounding area-1)	.226**	.091	.013	.111	.135	.411
Work location	(Central 1; Surrounding area -1)	.085	.074	.248	.086	.103	.400
<i>Non-Random parameters</i>							
Change of residence							
Tenure	(Buy 1; Rent -1)	.942***	.088	.000	1.362***	.177	.000
Housing cost	(Low)	.970***	.124	.000	1.256***	.220	.000
	(Medium 1)	-.038	.117	.749	.032	.207	.876
	(Medium 2)	-.044	.118	.713	-.134	.224	.549
	(High)	-.888***	.166	.000	-1.154***	.227	.000
Housing size	(Small)	-1.370***	.170	.000	-2.147**	.456	.000
	(Medium 1)	-.375***	.115	.001	-.516**	.206	.012
	(Medium 2)	.385***	.115	.001	.597***	.210	.004
	(Large)	1.360***	.137	.000	2.066***	.299	.000
Distance to metro station	(Small)	.396**	.155	.011	.202	.320	.528
	(Medium 1)	.166	.138	.231	.484	.295	.101
	(Medium 2)	-.219	.161	.173	-.238	.330	.470
	(Large)	-.343	.212	.112	-.448	.532	.400
Distance to bus stop	(Small)	.431**	.208	.038	.597	.397	.132
	(Medium 1)	.617***	.209	.003	.774*	.440	.079
	(Medium 2)	-.374	.284	.188	-.447	.518	.388
	(Large)	-.674*	.411	.098	-.924	.830	.240
Distance to shopping mall	(Small)	.085	.196	.666	.010	.455	.983
	(Medium 1)	.232	.182	.201	.273	.402	.497
	(Medium 2)	.302	.188	.109	.496	.446	.266

Table 3 (continued)

Variable	Description	Model 1			Model 2		
		Coefficient	Standard Error	Prob. > z	Coefficient	Standard Error	Prob. > z
<i>Change of job</i> Work type	(Large)	-.619	.295	.119	-.779	.871	.544
	Government	.446***	.097	.000	.553***	.150	.000
	Institution	.266***	.093	.004	.289***	.145	.047
	Company	-.234***	.081	.004	-.269***	.135	.047
Flexibility Salary	Self-employed	-.478***	.092	.000	.573***	.135	.000
	Flexibility working time (Yes 1; No - 1)	-.019	.048	.697	-.052	.084	.543
	(Low)	-1.870***	.107	.000	-2.879***	.212	.000
	(Medium 1)	-.581***	.088	.000	-.356***	.132	.007
Work environment	(Medium 1)	1.011***	.103	.000	1.383***	.134	.000
	(High)	1.440***	.109	.000	1.852***	.154	.000
	Very poor	-.906***	.121	.000	-1.108***	.186	.000
	Poor	-.135	.099	.171	-.274*	.142	.054
Colleague relationship	Good	.450***	.086	.000	.609***	.150	.000
	Very good	.591***	.092	.000	.773***	.137	.000
	Very poor	-1.086***	.129	.000	-1.361***	.179	.000
	Poor	-.491***	.109	.000	-.664***	.162	.000
Easy to find a similar <i>Travel Mobility</i>	Good	.814***	.093	.000	.987***	.150	.000
	Very good	.763***	.092	.000	1.038***	.137	.000
	Easy to change work or not (Yes 1; No -1)	-.038	.049	.435	-.040	.085	.641
	(Low)	-.058	.333	.861	-.008	.634	.989
Cost by car	(Medium 1)	.139	.224	.535	-.116	.487	.811

Table 3 (continued)

Variable	Description	Model 1			Model 2		
		Coefficient	Standard Error	Prob. > z > Z	Coefficient	Standard Error	Prob. > z > Z
Travel time by car	(Medium 2)	.189	.243	.437	.444	.575	.440
	(High)	-.270	.249	.377	-.320	.583	.510
	(Low)	.183	.222	.427	.130	.564	.713
	(Medium 1)	.314*	.189	.096	.488	.469	.298
	(Medium 2)	-.021	.217	.924	-.270	.544	.619
Congestion time by car	(High)	-.476	.315	.130	-.348	.642	.588
	(Low)	.401***	.099	.000	.401***	.128	.002
	(Medium 1)	-.048	.109	.661	-.008	.148	.958
	(Medium 2)	-.106	.108	.328	-.073	.150	.627
	(High)	-.247**	.115	.025	-.320	.183	.118
Cost by metro	(Low 1; High - 1)	.221*	.115	.054	.232	.267	.384
	(Low)	.281**	.121	.020	.575**	.232	.013
	(Medium 1)	.196	.123	.109	.596**	.256	.020
	(Medium 2)	-.207	.115	.947	.059	.171	.502
	(High)	-.270	.254	.288	-1.230*	.645	.057
Out-of-vehicle time by metro	(Low)	.660***	.098	.000	.755***	.133	.000
	(Medium 1)	.143	.103	.161	.094	.147	.521
	(Medium 2)	-.170	.111	.126	-.185	.165	.263
	(High)	-.633***	.129	.000	-.664***	.184	.000
	(No 1; Yes - 1)	-.048	.061	.432	-.095	.091	.299
Have seats or not by metro	(Low 1; High - 1)	.275***	.101	.007	.255	.180	.157
	(Low)	.144	.183	.431	.067	.254	.792
	(Medium 1)	.878***	.134	.000	1.124***	.216	.000
	(Medium 2)	.330**	.143	.021	.507*	.252	.045
	(High)						

Table 3 (continued)

Variable	Description	Model 1			Model 2		
		Coefficient	Standard Error	Prob. > z > Z	Coefficient	Standard Error	Prob. > z > Z
Out-of-vehicle time by bus	(High)	−1.352***	.229	.000	−1.698***	.392	.000
	(Low)	.432***	.124	.000	.539***	.186	.004
	(Medium 1)	.090	.121	.456	.097	.228	.671
	(Medium 2)	−.071	.132	.591	−.163	.215	.450
	(High)	−.451*	.144	.052	−.473*	.240	.076
Congestion time by bus	(Low)	.317*	.165	.053	.161	.284	.337
	(Medium 1)	.111	.144	.438	.262	.220	.233
	(Medium 2)	−.291**	.135	.031	−.239	.215	.265
	(High)	−.137	.140	.327	−.184	.263	.483
	(No 1; Yes −1)	−.045	.075	.555	−.160	.131	.223
Have seats or not by bus Travel time by bike	(Low)	2.017***	.169	.000	2.798***	.447	.000
	(Medium 1)	.564**	.228	.013	.660	.482	.171
	(Medium 2)	−1.268***	.401	.002	−1.838	1.893	.331
	(High)	−1.313***	.379	.001	−1.620	1.393	.234
	(Low)	1.914***	.138	.000	1.193***	.138	.000
Travel time by walk	(Medium 1)	−.405	.304	.182	−.184	.262	.483
	(Medium 2)	−.610**	.304	.045	−.402	.304	.186
	(High)	−.899***	.306	.005	−.610*	.304	.045
	Move house: by car	−2.495***	.192	.000	−2.961***	.376	.000
	Move house: by metro	−3.000***	.222	.000	−3.186***	.498	.000
Contant 1	Move house: by bus	−3.505***	.235	.000	−4.147***	.425	.000
Contant 2	Move house: by bike	−4.324***	.280	.000	−5.280***	.596	.000
Contant 3	Move house: by walk	−4.122***	.260	.000	−5.543***	.655	.000
Contant 4	Change job: by car	−1.640***	.145	.000	−2.123***	.312	.000
Contant 5							
Contant 6							

Table 3 (continued)

Variable	Description	Model 1		Model 2	
		Coefficient	Standard Error	Coefficient	Standard Error
Contant 7	Change job: by metro	−1.994***	.170	−2.229***	.371
Contant 8	Change job: by bus	−2.912***	.182	−3.549***	.355
Contant 9	Change job: by bike	−3.414***	.203	−4.368***	.450
Contant 10	Change job: by walk	−3.339***	.187	−4.727***	.586
<i>Heterogeneity around mean</i>					
Home location: number of workers		−.005	.081	−.018	.130
Work location: number of workers		−.157**	.071	−.130	.097
<i>Standard deviation of random parameters</i>					
Home location	(Central 1; Surrounding area − 1)	.679***	.116	.014	.617
Work location	(Central 1; Surrounding area − 1)	.822***	.082	.487***	.194
<i>Error components for alternatives and nests of alternatives parameters</i>					
Standard deviation	Current			.321	.396
Standard deviation	Move house			2.075***	.481
Standard deviation	Change job			2.119***	.306
<i>Heterogeneity around standard deviation of error components effect</i>					
Gender	Current			.103	.152
Income	Current			.356	.344
Numbers of workers	Current			.127	.166
Gender	Move house			−.202	.143
Income	Move house			−.433***	.181
Numbers of workers	Move house			.285*	.151
Gender	Change job			−.035	.114
Income	Change job			−.297***	.136

Table 3 (continued)

Variable	Description	Model 1		Model 2	
		Coefficient	Standard Error	Coefficient	Standard Error
Numbers of workers	Change job				
$LL(\beta)$				.301**	.137
$LL(0)$					.028
Rho^2					– 2474.46
Rho^2 adjusted					– 5467.20
					0.547
					0.531

***, **, * means significance at 1%, 5% and 10% level

work location were selected as the random attributes. In addition, not only the main effects but also several socio-demographic interaction effects were estimated in this study.

Nlogit software was used to estimate the error component mixed logit model. Both random variables and error components were assumed with a normal distribution. To get a stable estimate, we systematically checked the convergence of the parameter estimates from 100 to 5000 random Halton draws. The final estimates reported in this study are based on 500 Halton draws since increasing the number of draws did not improve the estimates.

Overall, the estimated error component logit model has a good fit. The log-likelihood (*LL*) increased from -5467.20 to -2474.46 . The error component model improves the adjusted *Rho*-squared from 0.495 for the base random parameter model to 0.531.

Results in Table 3 indicate that parameter signs for both the error component mixed logit model and base random parameter model are almost the same. Additionally, compared with the base random parameter mixed logit model, attributes were found less statistically significant for the error component mixed logit model. Since the error component mixed logit model performs better than the base mixed logit model, we discuss the results by focusing mainly on the error component model.

Change of residence

Overall, in the majority of situations respondents indicate to keep their current residence, suggesting that that everything else being equal, individuals/households prefer not to move house. This is as expected as that the process of changing residence is relatively costly and takes a lot of effort (buying and selling house, removal of furniture, and redecoration of the new home, etc.). Moreover, once settled and satisfied with their housing situation, individuals/households tend not to move any longer (Fischer and Malmberg 2001). Only if the increase in benefits from a new residence outweighs the cost of relocating, a household is expected to relocate. Moreover, compared to changing jobs, the threshold to move house is relatively high which indicates that, as a long-term decision, people consider residential relocation more carefully and less easy. In addition, all housing-related attributes (tenure, monthly costs, housing size) are statistically significant for the moving house decision, while the effects of location and neighborhood-related attributes on the relocate decision are relatively small.

According to the results, the signs of the housing-related variables are consistent with the preceding expectations. Tenure is found to have a significant influence on the utility of residential relocation, the positive sign indicating that people prefer to buy their own house rather than rent one. Moreover, extreme high/low sales prices or rental costs have a substantial impact on a household's decision to move. In other words, extremely high housing cost, subject to their budget constraint, may cause owners and tenants to move house. Effects of house size are compelling, as well, supporting the previous literature and confirming that households prefer to have more living space when relocating.

For the built environment factors, previous studies have evaluated how accessibility affects location choice. As reported in several studies, proximity to local public transport stops (bus, tram, subway) is of relevance to residents. For example, Van de Vyvere et al. (1998) reported a positive effect of proximity to bus stops. In addition, other studies found that households prefer locations that provide greater accessibility to shopping (Bhat and Guo 2004). In line with the previous findings, our results show that the distance to bus stop has a significant effect on residential location decision. In addition, some studies showed that households prefer not to reside in the centre of cities (Kim et al. 2003; Vega

and Reynolds-Feighan 2009, etc.), while other studies reported the opposite findings (Bhat and Guo 2004; Pinjari et al. 2007). This difference may be due to the fact that the effect of residential location differs between population groups. For instance, Zondag and Pieters (2005) differentiated between household types in the Netherlands and reported that single-earner households favour urban living, while households with children prefer to live in sub-urban environments. In the current study, we found that central city is more attractive than the surrounding areas. The negative sign of the interaction between residential location and numbers of workers in the household suggests that households with more than one worker have a higher preference to work in the central city. However, these estimates are not statistically significant.

Change of job

Here also, the vast majority of the choices result in keeping the current job. People prefer not to change job frequently may due to the mental costs (i.e. the necessity to learn a new job, familiarize oneself with new colleagues and the new institution, etc.) associated with changing jobs. However, compared to moving house, the relative low alternative-specific constant indicates that the cost of changing job is relatively small.

For the variable job type, the results show that individuals prefer government and public institutions to company and self-employed. This is understandable because government organizations and public institutions generally display a relative high degree of job security, a good work-family balance, and a fair and stable wage (Lewis and Frank 2002). As important predictors of job choice, the effects of a high salary, good co-worker relationship and work environment are significant. This means people consider not only salary, but also work environment and harmony in colleague communications. Company policies, which enhance the work relationships and improve the work environment, reduce the chance of changing job.

In case of other influential attributes, little compelling evidence is found that ‘having flexible working hours’ and ‘easy to find a similar job or not’ plays a role in job change. Similarly, the geographic location factor does not seem an influential factor in job decision-making. Moreover, we estimated the effect of numbers of workers on work location preference. The negative sign suggests that households with more than one worker care more about working in the central city. However, this effect is not statistically significant.

Travel mobility

As for transportation mode preferences, time-related variables representing an increase in commuting time, congestion time and out-of-vehicle time influence the likelihood of mobility change. Many previous studies reported that excessive commuting time has a significant negative impact on the utility of different transportation modes for the journey to work (e.g., Guo and Bhat 2007; Zhou and Kockelman 2008; Habib and Miller 2009; Lee and Waddell 2010). As expected, according to our results, commuting time is negatively associated with mobility change, suggesting that individuals generally try to locate close to work. Differentiating in commuting time by car, public transport and non-motorized modes, commuting time is shown as an influential factor but with a different level of significance. For the public transportation and non-motorized modes, we observe a significant impact on choice probability, while the commuting time for the car mode is not significant. Such findings may be useful to city planners and policy makers to encourage people working or living in close proximity

to avoid excess commuting time. A long commuting time by public and slow transportation modes may increase motorization and lead to a higher propensity of car ownership. In addition, although not all attributes are significant, results pertaining to congestion time and out-of-vehicle time of different transportation modes suggest these two factors influence people's choice behavior. From a policy point of view, these results indicate the importance of improving accessibility of bus stops and metro stations and reducing congestion time for public transportation modes.

The value of travel time (VoT) is often used in applied transport studies. In most cases, VoT is estimated in the context of short-term decisions such as route and mode choice. In longer term settings which involve changes in residential or employment locations, people may trade-off between the travel time and travel cost. In the context of co-dependent choices, we calculated the values of time as shown in Table 4. The estimated value of travel time is 27.84 CNY per hour (or 3.76 €/h) for car, 2.22 CNY per hour (0.3 €/h) for metro and 15.36 CNY per hour (2.1 €/h) for bus. Although these values are smaller than the average of the studies on short-term decisions, they are in line with previous research based on the long-term context (Pérez et al. 2003; Kim et al. 2005; Tillema et al. 2010; Peer et al. 2015; Dubernet and Axhausen 2016; Beck et al. 2017). Furthermore, as indicated by a relatively lower value of time, the travel time appears to play a less important role in the context of long-term decisions.

Estimates of the alternative-specific constants indicate that respondents on average prefer private transport over than other commuting modes. Furthermore, metro is more attractive than bus. Preferences for slow modes (bicycle and walk) are similar. Moreover, results show that nonlinear effects are found for several travel-related attributes, such as cost by car, travel time and congestion time by bus.

Explanation of error components

Results of the three alternative-specific error components (keep current, move house or change job) show that the standard deviation of moving house and changing job are statistically significant. It suggests that unobserved heterogeneity exists in preferences for transportation modes, dependent upon moving house and changing work decisions that are not fully captured by the alternative-specific parameter estimates of the attributes of the different transportation modes. This evidence indicates that a 'nested structure' exists in the process of transportation mode choice when people decide to move house and change job. Furthermore, we allowed for heteroscedasticity in the variance of the error components as a function of sociodemographics. Because the number of parameters relative to sample size does not invite estimating too many interaction effects, after exploring different combinations of socio-demographic variables, as listed in Table 3, gender, income and numbers of workers in the households were taken into consideration.

In case of moving house, the negative value of income indicates that as income decreases, the standard deviation of the error component decreases as well, leading to a reduction in preference heterogeneity from these unobserved effects for individuals with higher salary when they decide to move house. Moreover, number of workers in the household shows a significant effect on the heterogeneity of moving house. Specifically, results indicate that households with

Table 4 Value of time of different transportation modes

Mode	Car	Metro	Bus
VoT (CNY/h)	27.84	2.22	15.36

single workers are more heterogeneous when they decide to move house. Similarly, as to job choice, income and numbers of workers in the household have a significant influence on preference heterogeneity for this long-term decision. Our result shows that as the income and/or number of workers increases, the standard deviation of the error component decreases, implying a reduction in preference heterogeneity in these unobserved effects.

Conclusions and discussion

Life-trajectories are critical in understanding individuals' activity-travel behavior. The modeling and prediction of transportation mode choice depends on long-term life choices. However, few studies have reported individuals' preferences for the interdependent choice of house, job and transportation mode. Ignoring the effects of any long-term key life events may lead to biased estimation results and therefore misleading policy recommendations or assessment of policy impacts.

In order to fill this research gap, this study estimated a multi-dimensional choice model related to residential, job and transportation mode choice for commute trips using a pivoted stated choice experiment. In addition to estimating the part-worth utilities of the attribute levels defining the three choice dimensions, the estimated error components mixed logit model allows estimating the effects of various sources of observed and unobserved heterogeneity on the utility of the multi-dimensional choice profiles and the corresponding choice probabilities.

Results show that not only the random parameters but also the variances associated with the long-term alternative-specific error components are significant. The specified error components for the long-term decisions are significant, indicating that unobserved heterogeneity exists between relocation and transportation mode choice, which is not fully captured by the alternative specific attributes of transportation modes.

Although significant interdependencies between different life domains have been found in this study, it still needs to further investigate the long-term mobility decisions from a longitudinal perspective. Most life course decisions are dynamic in nature, one mobility decision may increase the need/desire of mobility decision in other life domain. As a nature extension to the current study, more long-term life events as well as the duration for life course mobility decisions might be taken into consideration. Moreover, in order to avoid the choice experiment is over complex, the model in the current study is built based on the assumption that people will not change transportation modes only nor both houses or jobs simultaneously, but either change house or change job. We acknowledge that this assumption may not be strictly hold in actual situations since people may unavoidably change transportation mode only, and in rare cases both house and job with or without a time lag. It might be necessary to study exclusive choice options especially when the focus is more on the aspect of market shares.

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Compliance with ethical standards

Conflict of interest The authors declared that they have no conflict of interest.

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