Job-housing co-dependent mobility decisions in life trajectories

Job-Housing Co-Dependent Mobility Decisions in Life Trajectories

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Jia Guo

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Introduction

1.1 Background and motivation

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 utility for travelers of a particular socio-economic profile and that travelers choose the transportation mode that maximizes their utility. Sometimes, taste variation is incorporated 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 train, prevailing models predicted a shift in transportation mode choice towards the train. In reality, however, a substantial share of the workers decided to move further away from their workplace to enjoy large, relatively cheap housing, located in a more rural area without increasing their habitual commuting 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. Ignoring the larger residential and job context, these transportation mode choice models may lead to an inflation of the importance of transportation-related variables. Consequently, results may be misleading and suggest ill-founded policy recommendations.

To complement this single-domain oriented research, recently the view has been advocated that individuals and households consider different choice dimensions jointly, implying that various choice dimensions/domains are strongly co-dependent (e.g., Bhat and Guo, 2007; Eluru, et al., 2009; Pinjari, et al., 2011; Paleti, et al., 2012). Rather than maximizing the utility of each choice domain separately and independently, it is more realistic to assume that individuals and households consider these choice domains jointly. Although the co-dependencies between residential choice, job choice, and commuting transportation mode choice have been widely acknowledged, most studies on multi-dimensional choice behavior have focused on two dimensions only (e.g., Paleti, et al., 2012). Studies focusing on more dimensions are relatively rare.

1.2 Aim and objectives

The aim of this PhD study is to better understand the co-dependencies between residence, job and travel mobility decision. We present different models of residence, job and travel mobility decision that consider the interdependency of different domains. In addition, because individuals' preferences are heterogeneous in nature, both observed and unobserved preference heterogeneity are investigated in the context of these co-dependent mobility choices. Moreover, as these domain choices tend to be related to different life stages, we extend the life course modeling approach to better understand these interdependencies in the context of long-term decision processes. The life course approach acknowledges that life events may lead to a reconsideration of ones' current state in different life domains and possibly to decisions changing the current states. For instance, several studies found that child birth plays an important role in various life course mobility decisions due to the fact that an increase in the number of household members may create the need for a bigger house, or an additional or larger car (e.g., Dieleman and Mulder, 2002; Warner and Sharp, 2015). Similarly, commuting mode changes are primarily driven by job change and residential relocation (Clark, et al., 2016).

A limitation of many life course studies is the use of a static model specification. Most studies only capture a snapshot of behavior but ignore that the co-dependencies between life events themselves may change over time. Until recently, an emerging body of studies on the dynamics in household and mobility decisions suggests that the co-dependencies between decisions on different dimensions may stretch across multiple years. Long-term mobility decisions are not instantaneous decisions but may need time to adapt. Specifically, people may adapt their preference not only based on their current state, but also their historical experiences and future expectations. Therefore, a dynamic life course analysis is introduced in this study to examine the temporal interdependencies between various life domains.

Lastly, research has conventionally viewed individuals as the decision-making unit, ignoring decision roles of other family members. Because family members share various household resources, long-term mobility decisions such as residential mobility and car ownership change are often a decision made jointly by multiple household members. However, both theoretical and empirical analyses of household mobility decisions remain very limited in number. Thus, in order to fill this research gap, this study examines interdependencies between various life events and mobility decisions from both an individual and household level.

1.3 Organization of the thesis

The thesis is organized into eight chapters. Following this introductory chapter, Chapter 2 summarizes existing theories and reviews the relevant literature. First, it reviews the literature on multidimensional choice behavior related to residence, job and travel mobility decision. Second, it reviews the life course approach. Lastly, to investigate intra-household interactions between various mobility decisions, the household decision making process is reviewed.

Chapter 3 explains the survey design. A stated choice experiment and a retrospective survey are implemented in this study. This chapter provides the details of the design and administration of the overall survey design used to collect the data. Features of the questionnaire, properties of the stated choice experiment, the choice of study area, and respondent recruitment are explained and motivated in this chapter.

Chapter 4 reports the results of the analyses based on discrete choice models. To investigate the behavior of people in the context of multidimensional decisions about residence, job and transportation mode, three discrete choice models are discussed in this chapter: a mixed logit model, an error component mixed logit model, and a latent class model.

Chapter 5 discusses how residential mobility change, job change and car ownership change are interrelated, and influenced by the occurrence of key life events such as marriage and child birth. Clearly, attitudes and lifestyle preferences play an important role in shaping the decision-making processes. These lifestyle preferences and attitudes constitute unobserved factors that simultaneously affect choices in different life domains. Considering this, based on the retrospective data, a simultaneous equations model is formulated to estimate the effects of both observed and unobserved factors influencing various mobility decisions in different life domains.

To understand the interdependencies among various life domains and the timing of these decisions, as two main methods, hazard models and Bayesians network approach have been applied. However, a limitation of the existing approaches is the time-invariant nature of the causal structure between life trajectory events. In light of this limitation, a dynamic Bayesian network is introduced in Chapter 6. While Chapter 6 is based on individual trajectories, Chapter 7 examines temporal interdependencies between various life course mobility decisions at the household level.

The last chapter summarizes the main conclusions of this study, discusses their implications for transportation and urban policy, and provides recommendations for future research.

2

Literature Review

In this chapter, we will review the literature on the choices of various life domains in residence, job and travel mobility decision. First, we review the literature on multidimensional choice behavior related to residence, job and travel mobility decision. Then, we briefly review the life course approach because this approach constitutes an integral framework, taking temporal effects into account. In this context, individuals/households make their decisions not only based on their current state but also consider their previous experiences and future expectations. Lastly, because many long terms decisions in dual-earner households tend to be household decisions involving more than one family member, the literature on household decision making process is briefly summarized.

2.1 Multidimensional choice of residence, job and travel mobility decision

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, considering trip characteristics. Thus, these models involve a uni-dimensional choice problem. Consequently, any predictions based on these models are necessarily refined to the uni-dimensional domain captured by the model. This is not a problem if the management or policy issue concerns transportation mode choice, 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.

During the last decades, many studies have emphasized the interdependencies between 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 job 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, 2013b). In turn, commuting mode preferences also influence residential and/or job location choice. For example, commuters who use public transportation may find the egress time important and consciously choose to live/work near a transit station (Bhat and Guo, 2007). By contrast, people living in sprawling areas rely more on cars to conduct their daily activities (Khattak and Rodriguez, 2005; Schwanen and Mokhtarian, 2005a; 2005b). Additionally, increasing travel time may trigger people to reconsider and possibly change their residence or job. Ettema (2010) pointed out that an excessive commute distance may prompt the relocation process and trigger people to move to a new dwelling; Similarity, Rashidi, et al. (2011) found that longer commuting time or activity duration may accelerate relocation decisions. This emphasis on interdependency has led to the joint choice modeling of residential/job location and commuting behavior (e.g., Kim, et al., 2003; Ng, 2008).

Although the interdependencies between residential and job choice and travel mobility decision has been acknowledged in the literature, most studies considered only two dimensions. Studies focusing on all three dimensions are relatively scare. 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 job 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 econometric model system that simultaneously considers six different choice dimensions: residential location, job location, commute distance, household vehicle ownership, commuting mode and number of stops of commute trips. Similarly, using multinomial discrete choice model, Vietnam, Tran, et al. (2016) jointly modelled the choices of residence, workplace, and commuting modes in Hanoi and confirmed significant interdependencies between these choice dimensions.

Although these multidimensional choice models consider long-term decisions and short-term decisions as a single integrated choice, unfortunately, only a limited number of variables were chosen in the multidimensional choice model, which may oversimplify the choice problem and make it difficult to depict the decision-making process in the real world.

2.2 Life course approach

The life course approach, which originates in sociology and psychology field has introduced into the mobility research since 1980s, whereas the life events have been recognized a central role for a variety of economic and demographic triggers of mobility decisions (Elder, 1994, 1998). According to the life course approach, life events cover several domains (household, employment, education and residence). These events run in parallel and are associated as events in a particular domain. This may lead people to reconsider their status in that domain and other life domains.

Over the past decades, research examining various mobility decisions has been enriched by applying the life course approach. Empirically, research based on the life course approach has unfolded along two lines. First, a substantial body of research has demonstrated that changes in household composition trigger residential/job relocation and/or mobility tools possession choice. For example, Rossi (1980), as one of the earliest studies, argued that changes in family size may render the current dwelling inadequate, thus creating dissatisfaction with the current dwelling. Habib et al. (2011) examined the effects of household structure change on job mobility decisions, and found that an increase in household size may increase household member propensity to change job. Similarly, using the German Socioeconomic Panel data, Prillwitz et al. (2006) confirmed the key role of marriage and child birth on car ownership decisions. Similar findings were reported elsewhere in the literature (e.g., Verhoeven, et al., 2005; Lanzendorf, 2010; Beige and Axhausen, 2012).

Second, another stream of research has analyzed the impact of residential move and/or job relocation on mobility tools possession choice. For instance, Prillwitz et al. (2006) found that there is significant car ownership growth because of the residential change, suggesting that a change in residential location could be a main cause of transportation mode choice. Additional evidence about change in car ownership conditioned on residential relocation has been reported in other studies (e.g., Prillwitz et al., 2006; Choocharukul et al., 2007; Kim, 2008; Scheiner and Holz-Rau, 2013a). In addition, several studies have investigated the impact of a change in job location on car ownership decisions. As an example, Lanzendorf (2010) concluded that a new job may stimulate individuals/households to purchase a car to save commuting time without changing their place of residence. Similar findings were reported in Prillwitz et al. (2006), Habib et al. (2011), Rashidi et al. (2011), and Yang et al. (2017) to name a few.

In fact, most long-term mobility decisions are not instantaneous decisions. Earlier decisions may cause individuals to reconsider their current behavior, but in some cases with a time lag (Yamamoto, 2008; Fatmi and Habib, 2016). In other words, people may need time to adapt, which implies a lagged response to the changing needs. Similarly, long-term decisions may also depend on individuals' anticipation of certain life events such as expected marriage and child birth (Oakil, et al., 2014; Yu, et al., 2017).

Empirically, to incorporate the temporal dependencies between various life domains, two different types of modelling approaches have been applied. The first one is hazard-based modeling. These models predict the interval times of life course events and their transitions as a function of the time elapsed since the last occurrence of the event and a set of covariates. For example, using a hazard model, Beige and Axhausen (2008) utilized a hazard model to compare different durations of residence, education, employment, and ownership of mobility tools. A major limitation is that these models cannot fully capture the complex direct and indirect relationship between the life course events and mobility decisions.

The second is known as the Bayesian network. A Bayesian network (BN) offers some advantages over econometric approaches in analyzing complex interdependencies among a set of variables. First, a BN has the ability to deal with uncertain and complex relationships hidden in the data. Especially in the context of life course mobility decisions in which state changes in one domain can lead to the changes in other domains, the BN approach has a clear advantage to find the complex interdependencies. Second, a BN can incorporate different types of information, including empirical data, theoretical relationships, and expert knowledge. It is an ideal representation for combining prior research knowledge and data (Heckerman, 1995). When testing a proposed theory using a BN, one does not have to rely only on statistical evidence that may be biased, particularly for small samples.

Bayesian networks, however, have some disadvantages. The most important of these is the treatment of time, which is an important dimension in detecting the temporal dependencies among different life domains. The problem is that Bayesian networks were not designed to explicitly model temporal relationships. To incorporate time element into the model, two types of Temporal Event Bayesian network models contribute to modeling the temporal effects, Temporal Nodes Bayesian Network (TNBN) and Network of Probabilistic Events in Discrete Time (NPEDT). TNBN is composed of a set of temporal nodes, which represents an event or a state change. For each node, time is discretized in a finite number of intervals. Verhoeven, et al. (2007) applied a TNBN to model and simulate the effects of life trajectory events on transportation mode choice decisions. Similar to TNBN approach where each variable represents an event that can occur only once, NPEDT differs from TNBNs in the temporal intervals. While TNBNs assumes the interval of each temporal node is relative to its parent nodes, NPEDT assumes that time is absolute and each value of a variable represents the instant at which a certain event may occur, without a dependency on its parent nodes. Based on this approach, Oakil, et al. (2011) found evidence of 1-year lagged effects of change in employment status on the probability to move house. Similarly, birth of the first child was found to have a 2-year lagged effect on residential relocation. In another work, Oakil, et al. (2014) built a framework investigating residential relocation, employer change and change in car ownership level and temporal dependencies among these long-term decisions and other household decisions. Similarly, using the NPEDT, Wang, et al. (2018) confirmed that interdependencies exist among the long-term and mid-term life domains, and evidenced the reactive and proactive behavior of individuals and households in the context of various life events over the life course.

As for the treatment of time, these studies either treat the probability of a state of certain nodes at the previous year as an independent node or transform two events at different times as one event (e.g. defined as increase or decrease), regardless of the contextual dependencies with other nodes which should be incorporated at the same (previous) time slice. In addition, treating the dynamic dependency in this static way may involve extra complexity in network structure learning. To improve the modeling process, a dynamic Bayesian network approach may be applied.

2.3 Household decision process

Although the life course approach provides a better understanding of the interdependencies in long-term decision processes, individuals are conventionally assumed to be the decision-making unit. However, because household members physically share household resources, long-term decisions affect all household members. Moreover, especially if both partners have a job, the decision-making process is much more complicated under such circumstances because both partners have to decide jointly about their choice of residence and their choice of jobs. Long-term decisions, hence, tend to be made at the household level (Timmermans, et al., 1992; Borgers and Timmermans, 1993; Roorda, et al., 2009; Timmermans and Zhang, 2009).

Taking household as the decision unit, Scheiner (2014) studied changes in travel mode specific trip rates after life course events. Significant effects were found for some key events, and some effects differed distinctly between men and women, suggesting that men and women are differently affected by life course events. Similarly, Oakil (2016) provided empirical evidences that life events such as birth of the first child, residential relocation and job change only significantly affect women's decisions to get full-access to a car.

Although some studies focused on specific aspects, intra-household analyses in long-term mobility decisions remain very limited in the existing literature; this study contributes to provide a theoretical and empirical framework of intra-household interactions on various household mobility decisions.

2.4 Conclusions

Residential and job choice are critical in understanding individuals' activity-travel behavior. The modeling and prediction of transportation mode choice depends on other choice dimensions. However, this review of the literature suggests that few studies have reported individuals' preferences for the interdependent choice of house, job and transportation mode. Ignoring the effects of residential and job choice on transportation mode decisions may lead to biased estimation results and therefore misleading policy recommendations or assessment of policy impacts. In order to address the relative paucity of this kind of research, multidimensional choice model needs to be further developed.

Life course approach provides a rich framework to study these decision processes. Existing studies that investigated the temporal effects between life events and long-term mobility decisions tend to oversimplify the decision process over a life trajectory. The interrelations between various mobility decisions need to be examined further from a dynamic perspective. Moreover, relative to the individuals' perspective, the literature of household decision makings on these mobility decisions is relatively scarce. Household level studies would be an important addition to the state-of-the art.

3

Survey Design and Data Collection

3.1 Introduction

The aim of this PhD thesis is to analyze the co-dependency of long-term residential and job decisions and short-term travel behavior using a variety of different models. In order to analyze these choices in different life domains, a stated choice experiment was developed. In addition, to allow a life course analysis, a retrospective survey that recorded demographic transitions, housing and job careers was administered.

The next sections will outline how these different parts of the survey were developed in order to collect data about the various concepts introduced in the last chapter. Next, the field work is discussed. The chapter ends with a summary and conclusions.

3.2 Survey design

The questionnaire was developed and conducted through a platform (Pauline questionnaire system) that has been developed by our group to generate Internet-based questionnaires. The questionnaire requirements for this study consist of two segments: a stated choice experiment and a retrospective survey, which are further explained below.

Table 3.1 Attributes and attribute levels of residence, job and transportation mode

Name	Attribute	Attribute level
Residence	Tenure	Rent, Buy
	Cost (yuan/ month)	500, 1600, 2200, 3800
	Size (m²)	30, 65, 90, 125
	Distance to the metro station	-75%, -25%, 25%, 75% variation from the current
	Distance to the bus stop	-75%, -25%, 25%, 75% variation from the current
	Distance to shopping mall	-75%, -25%, 25%, 75% variation from the current
	Home location	Central of the city, Surrounding area
Job	Working type	Government, Institution, Enterprise, Self-employed
	Flexibility	Yes, No
	Salary (yuan/year)	30k, 80k, 130k, 200k
	Work environment	Very good, Good, Poor, Very poor
	Colleague relationship	Very good, Good, Poor, Very poor
	Easy to find a similar or not	Yes, No
	Job location	Central of the city, Surrounding area
Transportation mode		
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% variation from the current
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% variation from the current
	Have seats or not	Yes, No
Bike	Travel time (min)	9, 54, 84, 120
Walk	Travel time (min)	30, 144, 252, 360

	Current Situation	Move House					Change Job				
Tenure	Buy	Rent					Your current house				
Cost (yuan/month)	3800	500									
Size (m²)	80	65									
Distance to the metro station (km)	3	3.75									
Distance to the bus station (km)	1	0.25									
Distance to the shopping mall (km)	2	2.5									
Home location	Central of the city	Central of the city									
Work type	Government	Your current job					Self-employed				
Flexibility	Yes						No				
Salary (yuan/year)	8w						18w				
Work environment	Not good						Good				
Colleague relationship	Good						Poor				
Easy to find a similar job or not	Yes						No				
Job location	Central City						Surrounding area				
Transportation mode	Bus	Car	Metro	Bus	Bike	Walk	Car	Metro	Bus	Bike	Walk
Travel Cost (yuan/time)	1	1.4	2	1			7	2	1		
Travel time (min)	40	4.5	5	8	9	30	18	20	29	54	144
Out-of-vehicle time(min)	5		10	5				20	5		
Congestion time (min)	10	7.5		7.5			17.5		7.5		
Have seats or not	No		Yes	Yes				Yes	No		
Your choice											

Figure 3.1 The pivot choice design

3.2.1 Stated choice experiment design and implementation

A stated choice experiment was designed to measure the preferences for multi-dimensional residential choice, job choice and travel mobility decision. A stated choice experiment was chosen because it gives researchers more control over the variation of attribute levels, making the approach more appropriate for theoretical studies.

Attributes that potentially influence the choice of resident, job and transportation mode were selected based on the results of literature review. The examination of the relevant literature suggests that residential choice is primarily affected by tenure, monthly costs, housing size, distance to metro station, bus stop, shopping center and the location of the dwelling (e.g., Louviere and Timmermans, 1990; Timmermans, et al., 1992; Bagley, et al., 2002; Walker and Li, 2007; Balbontin, et al., 2015). Similarly, based on the existing literature, job situations were represented in terms of type of work, flexibility of the work schedule, income, work environment, relationship with co-workers, easy to find a similar job and job location (Timmermans, et al., 1992; Tran, et al., 2016). Commuting mode behavior is based on travel costs, travel time, out-of-vehicle time, congestion time and having seats or not (Van Ommeren, et al., 1999; Bagley, et al., 2002). Hence, the experiment involves a total of (7+7+5) =19 attributes.

Some researchers have expressed concern about the administration of such complex experiments with so many attributes and have advocated the use of simple experiments with a very small number of attributes. In contrast, our contention is that, as a guiding principle, experiments should capture the complexity of real-world decision-making. A technical problem is that when modelling multi-dimensional choice phenomena, choice sets may explode in size due to the large number of selected attributes. To limit the problem, we separately generated home-job profiles and mobility profiles and randomly paired these profiles. For the home-job design, five attributes were systematically varied in terms of two levels, while another ten attributes had four levels. In the mobility experimental design, five transportation modes were included and shown to respondents. These modes include car, metro, bus, bike and walk. Table 3.1 lists the attributes and their levels used in the experimental design.

The choice profiles were generated using a Bayesian D-efficient optimal design by Ngene. The objective of producing efficient designs is to minimize the asymptotic standard errors obtained from models estimated from data collected from sampled individuals (Rose, et al., 2008). Prior expectations of the size and sign of the effects of selected attributes are provided based on the findings of previous research to increase the efficiency of the designs. If no previous research existed, parameters are assumed.

Moreover, instead of all respondents facing the same choice situations, we developed a pivoted-efficient design, which presents changes relative to the respondents' current situation (Hensher, et al., 2015). We created this optimal stated choice experiment using five selected variables (distance to the bus station, metro station and shopping center from home; congestion time of car and bus) as the pivoting attributes. We pivoted these five attributes (-75%, -25%, 25%, 75% difference from the current) around personally experienced values, thus representing more realistic hypothetical profiles specific for each respondent.

The inclusion of attributes such as travel times in stated choice experiments tends to be challenging. The design of experiments typically independently varies the attributes levels of the choice alternatives. Consequently, this procedure may result in highly unrealistic travel time differences between modes. For example, the bus may be substantially faster than the private car. It may lead respondents to doubt the professionalism of the research and credibility of the survey. In part, such unrealistic differences may be explained away by pointing at dedicated bus lanes and similar traffic control measures. Nevertheless, such explanations introduce other latent attributes, the effect of which is unknown.

Table 3.2 Conditions of travel time of different transportation modes

Condition	Car	Metro	Bus	Bike	Walk
Short-distance	4.5	5	8	9	30
Medium 1-distance	18	20	29	54	144
Medium 2-distance	31.5	35	50	84	252
Long-distance	45	50	71	120	360

To avoid this problem, a different procedure was applied in the present study. Rather than independently varying travel times across transportation models, a vector of travel times for the different modes was systematically varied. This vector reflects underlying speed differences between transportation modes. Four levels and hence four vectors were used. We first assumed four distance categories with constant intervals: 5, 20, 35, 50 km. Then, these distances were converted into travel times by dividing them by the typical speeds of the different transportation modes for the study area. Small variations around the speeds were assumed: (1) the travel times of the bus was assumed less than proportional to the travel times of the car because the number of stops tends to be less for the longer trips by bus; (2) the travel times by bike and walking were assumed disproportionally higher due to increasing fatigue. Note that the different speeds destroy the equation intervals of distance. This is not considered an issue because we created a D-optimal rather than an orthogonal fractional factorial design anyhow.

Table 3.2 displays the four vectors (conditions) that were used in the experimental design. Note that for some conditions, the travel times by bike and especially walking become very high and therefore probably prohibitive to choose the corresponding transportation mode. We argue this is a non-issue as the estimated models will predict approximately zero choice probabilities for the concerned transportation modes under these circumstances. If the selected algorithm would not converge, the usual technical tricks can be applied to solve non-convergence.

To be more specific, we developed two designs, one for the long-term residential and job dimension, and the other for the short-term transportation mode dimension. Each design has 128 profiles. By pairing these profiles between two designs, we generated the combination of paired profiles in the sense that each paired profile represents a choice set. Each respondent received eight choice sets that were randomly selected from the full list of paired profiles, which means each respondent needed to finish the choice experiments eight times. In total, 3,208 observations were available from 401 effective interviews.

We created the full set of multidimensional attribute profiles, covering the residential, job and commute mode choice. As shown in Figure 3.1, 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 may become aware of a new job opportunity and/or 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 moving house or changing job, they should also indicate which transportation mode they would choose for the commute trip.

Although the survey was administered on a face-to-face basis, we used a stand-alone version of the Web-based survey system. The system offers many features not available in commercial software, particularly with respect to stated preference and choice experiments. Because different interviewers conducted the interviews, relatively strict controls were maintained in the process. For each variable, a range of feasible responses was defined. If a respondent violated the specified range, the respondent was asked whether the answer was correct and given the opportunity to change the response. In addition, except for some variables such as income that are known to lead to missing values, respondents could only continue with the questionnaire if they provided a response to every question. Finally, logical relationships between different variables were specified and answers were checked for consistency and feasibility. Again, if an answer did not satisfy the conditions we imposed, the inconsistency was signaled to the respondent, who was then asked to provide a new answer.

The relatively strict controls also served as a data cleaning tool. The set of collected data automatically satisfies all data range constraints and conditions on the allowed interdependencies of the data. Although we did not quantify the number of activations of the controls, debriefing of the volunteers gave the impression it was not activated many times, except in those cases where respondents simply forgot answering a question or made mistakes in using the platform. Despite the automated controls, a set of analysis was completed, including identifying and deleting respondents with invariant response patterns. Ultimately, 401 out of 450 were used in the analyses.

	Married	*Divorce*	*Birth of Child*
First time	Make a choice ▾	Make a choice ▾	Make a choice ▾
Second time	Make a choice ▾	Make a choice ▾	Make a choice ▾
Third time	Make a choice ▾	Make a choice ▾	Make a choice ▾

Please fill in your current and historical residential information.

	Current	Previous h1	Previous h2	Previous h3	Previous h4	Previous h5
Residential location	Make a cho ▾	Make a cho ▾	Make a cho ▾	Make a cho ▾	Make a choi ▾	Make a choi ▾
When do you move to this house	Make a cho ▾	Make a cho ▾	Make a cho ▾	Make a cho ▾	Make a choi ▾	Make a choi ▾

Please fill in your current and historical work information.

	Current	Previous w1	Previous w2	Previous w3	Previous w4	Previous w5
Work Location	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Job starting year	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Type of work contract	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Type of company	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Work status	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Salary	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾

Figure 3.2 Historical mobility decisions

Please indicate the travel environment of your partner's historical work.

	Current	Previous w1	Previous w2	Previous w3	Previous w4	Previous w5
Mode	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Travel time	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾

Please fill in the current and historical work information of your partner.

	Current	Previous w1	Previous w2	Previous w3	Previous w4	Previous w5
Work Location	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Work starting year	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Work status	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Type of work contract	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Type of company	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾
Salary	Make a cl ▾	Make a cl ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾	Make a ct ▾

Figure 3.3 Partner's historical job mobility decisions

3.2.2 Retrospective survey

For testing the temporal causal relationships, longitudinal data are needed. Although panel data is the best option for the purpose of the study, obtaining enough information about long-term behavioral changes in a panel survey is both time and resource consuming. Thus, as an alternative to the panel survey, a retrospective approach was used, which asked respondents to recall their historical mobility decisions. Previous studies (e.g., Verhoeven, et al., 2005; Beige and Axhausen, 2008; Oakil, et al., 2014) based on retrospective surveys indicate that retrospective surveys can provide reliable information about the temporal events as long as respondents tend not to easy forget the measured events. We contend that demographic events, housing and job history have such a pregnant impact on people’s life that they can relatively recall these events and provide reliable and valid responses.

Respondents were asked to provide a wide range of longitudinal information of their life course events. The retrospective data was collected from five different sections: 1) information of household members. Questions asked concern age, gender, highest education, etc.; 2) household structure biography (i.e., get married and child birth); 3) historical residential mobility (i.e., the year move, historical residential location, etc.); 4) historical employment mobility (i.e., the year of changing job, historical annual salary and job locations); and 5) historical car ownership change and corresponding historical commuting time. Figure 3.2 shows the organization and structure of the retrospective survey.

A web-based retrospective survey was designed and implemented with the assistance of interviewers. Respondents were asked to continue only if they provided the detailed information of all mobility decisions in the past. A potential problem of retrospective data is that richer life experiences may take substantial time. Thus, in order to reduce respondent burden, respondents were asked to provide information about the life events for only the last five times it occurred. In many cases, this maximum of five still covers the full trajectory of life events in a particular domain, particularly for younger respondents.

3.3 Data collection

The survey was conducted in Shenyang, China, between September and November, 2016. Shenyang has a total area of 3495 km2 and 8.3 million people. As the capital city of Liaoning province, Shenyang is an important industrial city and a hub for transportation and commercial activities. The city is located in the northeast of China, covering five main districts in the central city (Heping, Shenhe, Huanggu, Dadong, Tiexi) and four districts in the surrounding areas (Hunnan, Yuhong, Shenbei, Sujiatun). The surrounded four districts are relatively newly developed areas. The location of nine districts is shown in Figure 3.4. Population densities of the nine districts are shown in Table 3.3. The interviews were conducted in the nine districts based on a spatially stratified sample. Considering the aim of this study, we only interviewed respondents who have a job.

Volunteers assisted respondents to complete the questionnaire. These were mainly master students and trained to provide good instructions to respondents. First, after a general introduction about the aims and objectives of the study, and the methodology used, they were asked to complete the questionnaire themselves and identify questions they did not understand. This step also served as another pilot of the survey. The original questionnaire was designed in English by the authors. Several rounds of improvements were made until a final survey instrument that did not create obvious problems was developed. This version was then translated into Mandarin, and the student volunteers served as the trial respondents to check the wording, flow and explanations of the questionnaire. Their feedback was discussed within the group of volunteer interviewees, and final changes were made. Individual interviewees were monitored during the data collection process and further instructions and feedback were given on a daily basis, if necessary.

Respondents were given small gifts of appreciation as the survey was 24 web pages long and its completion took over 50 minutes. The response rate is about 16%, which is satisfactory, considering the length of the survey.

Table 3.3 Population density of nine districts

District	Heping	Shenhe	Huanggu	Dadong	Tiexi
Population	651,557	711,914	818,015	681,607	908,652
Area (km2)	59	60	66	100	286
Population density (person/ km2)	10,952	11,961	12,360	6,807	3,177
District	Hunnan	Yuhong	Shenbei	Sujiatun	
Population	333,563	445,834	320,337	427,158	
Area (km2)	734	499	884	782	
Population density (person/ km2)	455	893	362	546	

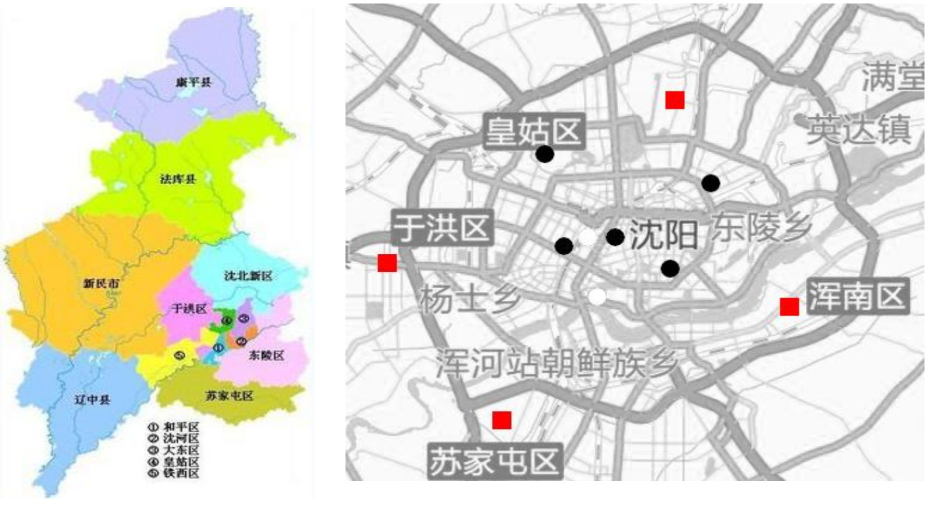

Figure 3.4 Survey area in the Shenyang city

3.4 Conclusions

In this chapter, the design and administration of the survey was presented. The survey aims at collecting data on people's preferences when they jointly consider various key variables influencing residential, job and transportation mode choice for commute trips and on key life events and mobility decisions. The data collection was implemented in Shenyang, China, from September to November 2016. Respondents were selected at random from five main districts in the central city and four other districts in the surrounding area. It was a successful experiment and the response rate is satisfactory, considering the length of the survey.

4

Co-Dependent Choice of Residence, Job and Travel Mobility Decision[1]

4.1 Introduction

Individuals' travel mobility decision highly depends on the choice of where to live and where to work. An examination of the literature reveals that existing studies mainly focus on two choice dimensions only. In an attempt to modeling people's co-dependent choices concerning residence location, job and transportation mode, we assume that individuals/households attempt to find the combination of these three dimensions that maximizes their utility.

However, individuals' preferences are heterogeneous in nature, and the needs and preferences differ between respondents. Hence, in this chapter, preference heterogeneity in the described multi-dimensional choice behavior will be investigated.

[1] *This chapter is based on the articles:*
Guo J., Feng T., Timmermans H.T.P. (2020). Modeling co-dependent choice of workplace, residence and commuting mode using an error component mixed logit model, Transportation: Vol. 47, 911-933.
Guo J., Feng T., Timmermans H.T.P. (2020). Co-dependent workplace, residence and commuting mode choice: results of a multi-dimensional mixed logit model with panel effects, Cities: Vol. 96, 102448.

To specify heterogeneity, first, we consider a range of demographic variables, to examine differences in sensitivity due to observed household/individual factors. We estimate covariate-dependent effects to account for heterogeneity around the mean of taste parameter distributions. Second, a latent class model is formulated to account for individuals' preference heterogeneity. Lastly, 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 parameterization 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 socio-demographic characteristics (gender, income and numbers of workers in the households).

The remainder of this chapter is structured as follows. In the following sections, the data analysis regarding a subset of samples will be presented first. Results of the model estimation are presented in the next section. Various sources of observed and unobserved heterogeneity in the multidimensional choice behavior are reported afterwards. Finally, the chapter is concluded by summarizing the major conclusions and illustrating the future research directions.

4.2 Data analysis

The data used for this chapter is obtained from the multidimensional stated choice experiment. In our questionnaire, respondents were asked to report their current residential situation, job, and travel behavior, as well as personal and household socio-demographic characteristics. In total, 401 out of 450 valid data were used. The descriptive statistics of the main socio-demographic variables and other characteristics of respondents are reported in Table 4.1.

It shows that 63.8% of the respondents reside in the central city and 36.2% in the surrounding areas. Similarly, regarding job location, 65.3% are employed in the central city, 34.7% work in the surrounding areas and other cities. 48.6% of the respondents is male, 51.4% is female. People participating in the survey are younger than average. Owing to the purpose of our research, only respondents having a job were taken considered, which explains this finding.

Table 4.1 Descriptive analysis of the survey attributes

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
Living area	Central city	256	63.8
	Surrounding area	145	36.2
Type of work unit	Government	35	8.7
	Public institutions	74	18.5
	Joint venture, private firms	201	50.1
	Self-employed	91	22.7
Working area	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

The distribution of marital status shows that singles represent 36.2% of the sample, while couples without children make up only 9.5%. It suggests that 50% of the respondents has one or more children. The mean annual income is 60,000 RMB with a standard deviation of 39,000 RMB. Additionally, of the 401 surveyed respondents, 240 belong to a dual worker household, while 161 belong to a single-worker household. As for commuting, about 58% of the respondents mentioned they do not have a car in their household. Public transportation is the dominant travel mode, 65 and 96 cases for metro and bus respectively. 26.4% of the respondents driving to work for their current job, while the percentage of slow traffic (bike and walk) still remains at a high rate in our sample (25.4%).

4.3 Methods and results

Before estimating the model, all attributes were effect-coded. We first estimated a basic Multinomial Logit model and then a mixed logit model and a latent class model to uncover the unobserved heterogeneity of the taste variation. Finally, an error component mixed logit model was developed to estimate the unobserved heterogeneity through the selected taste parameters and the choice dependent heteroscedasticity in error component variance.

4.3.1 Capturing taste variations through mixed logit model

We first estimated a basic Multinomial Logit model and then a Mixed Logit model, assuming a normal distribution for five selected variables. Three residential attributes and two job attributes were selected to define the unobserved heterogeneity of the selected random parameters. Alternative-specific constants were set in our model, unobserved heterogeneity of these constants was also taken into account. Furthermore, to uncover the unobserved heterogeneity, socio-demographic attributes were introduced. Potentially, there are many interaction effects, but only those interaction effects that were significant were included in the final specification of the model. The reported estimates are based on these 500 draws.

In our experiment, each participate responds to the choice 8 times. 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.

Estimation results are presented in Table 4.2. The overall fit of the multinomial logit model is good (McFadden's rho squared is 0.560, adjusted rho squared is 0.539). The adjusted rho squared for the basic multinomial logit model is 0.488. Moreover, most main and interaction effects are significant.

Interpretation of the residential choice component

The coefficients for the residential attributes lead to some interesting interpretations. Effects of tenure and housing size are significant, which implies that people prefer to buy their own house with large space, suggesting that buying house with large space gives people more security and stability. Moreover, it is found that standard deviations of these two variables are significant, indicating that significant unobserved factors influence individuals/households' sensitivity of residential decision making. Furthermore, the results show that old people are generally reluctant to rent house and more likely to live in a very large house but more reluctant to live in a very small house. Housing ownership is generally the largest part of the household's wealth. It shows that older people prefer owning a property, considering it an asset for the future. Similarly, the results show that households with one or more children are more likely to consider buying a house rather than renting one, relative to households without children. These results are in line with the life course analyses, which indicates that buying a house is closely linked to marriage and the birth of children (Kulu, 2008; Feijten, et al., 2008; Wang, et al, 2018). Results also suggest that people prefer to live in the central city rather than in the surrounding area. Life in city centers differs from residential environments in the surrounding areas notably in the sense that cities have a high level of amenities. For instance, city centers create more opportunities for work and offer a wide range of facilities for leisure activities and social interaction. This makes the city center an attractive place to live. However, city centers have a high density of buildings and consequently make the city a crowded place, while surrounding areas tend to have more spacious and greener living environments. In addition, the interactions are insignificant; indicating that marital status in this study is not influencing taste variation. Moreover, although not all levels of distance to the metro station, bus station and shopping mall are significant, the estimation results still indicate that people tend to prefer living in an area close to these public facilities.

Interpretation of the job choice component

In terms of the job domain, our results indicate that people prefer to work in public institutions and government rather than in private firms or be self-employed. The reason may be that, in Shenyang city, stability is one of the main factors for individuals to choose job type. As expected, income has a positive impact on people's job choices. Moreover, the results show that males more strongly consider high income than females.

Table 4.2 Estimation results of MNL model and mixed logit model

		MNL		MMNL	
Variable	Description	Estimate	S.E.	Estimate	S.E.
Random parameters					
Tenure	Buy 1; Rent -1	1.07***	.14	1.79***	.24
Housing size	Small	-1.44***	.19	-2.03***	.30
	Medium 1	-.13	.13	-.31	.13
	Medium 2	.26**	.13	.61***	.00
	Large	1.31***	.14	1.72***	.24
Home location	Central 1; Surrounding area -1	.17**	.07	.26**	.12
Salary	Low	-1.70***	.10	-2.83***	.21
	Medium 1	-.51***	.08	-.61***	.00
	Medium 1	.86***	.10	1.21***	.00
	High	1.35***	.10	2.24***	.19
Job location	Central 1; Surrounding area -1	.07	.06	.08	.09
Constant 1	Move house: by car	-2.41***	.19	-3.45***	.34
Constant 2	Move house: by metro	-2.91***	.21	-4.25***	.11
Constant 3	Move house: by bus	-3.38***	.23	-4.45***	.40
Constant 4	Move house: by bike	-4.10***	.27	-5.35***	.44
Constant 5	Move house: by walk	-3.91***	.25	-5.18***	.41
Constant 6	Change job: by car	-1.68***	.14	-2.46***	.25
Constant 7	Change job: by metro	-2.04***	.16	-2.81***	.27
Constant 8	Change job: by bus	-2.92***	.18	-3.68***	.27
Constant 9	Change job: by bike	-3.35***	.19	-4.56***	.33
Constant 10	Change job: by walk	-3.28***	.18	-4.30***	.31
Non-random parameters					
Housing price	Low	.81***	.11	1.35***	.17
	Medium 1	.04	.11	-.09	.16
	Medium 2	.06	.11	-.09	.15
	High	-.91***	.15	-1.18***	.21
Distance to metro station	Small	.36***	.14	.23	.21
	Medium 1	.25**	.12	.30	.19
	Medium 2	-.22	.14	-.18	.22
	Large	-.38**	.19	-.65	.32
Distance to bus stop	Small	.48***	.19	.66**	.28
	Medium 1	.63***	.19	.89***	.27

	Medium 2	-.33	.26	-.45	.36
	Large	-.78**	.36	-1.10	.51
Distance to shopping mall	Small	-.05	.18	-.15	.27
	Medium 1	.22	.16	.21	.24
	Medium 2	.19	.17	.53*	.28
	Large	-.36	.27	-.60	.41
Working type	Government	.42***	.09	.61***	.13
	Institution	.21***	.08	.32***	.12
	Company	-.18***	.07	-.29***	.11
	Self-employed	-.45***	.08	-.64***	.14
Flexible working time	Yes 1; No -1	-.01	.04	-.02	.07
Working environment	Very poor	-.78***	.11	-1.17***	.15
	Poor	-.10	.09	-.23*	.13
	Good	.41***	.07	.64***	.12
	Very good	.47***	.08	.76***	.14
Colleague relationship	Very poor	-.90***	.11	-1.30***	.16
	Poor	-.46***	.10	-.59***	.14
	Good	.68***	.08	.87***	.12
	Very good	.68***	.08	1.03***	.13
Easy to change job	Yes 1; No -1	-.05	.04	-.18	.07
Cost-car	Low	-.26	.28	-.04	.46
	Medium 1	.09	.20	-.11	.32
	Medium 2	.31	.21	.37	.37
	High	-.14	.22	-.22	.37
Travel time-car	Low	.03	.19	.05	.34
	Medium 1	.34**	.16	.59**	.28
	Medium 2	-.13	.18	-.04	.34
	High	-.30	.26	-.61	.45
Congestion time-car	Low	.37***	.10	.43***	.13
	Medium 1	-.07	.10	.00	.14
	Medium 2	-.14	.10	-.11	.15
	High	-.16	.11	-.32***	.16
Cost-metro	Low 1; High -1	.44***	.13	.58***	.20
Travel time-metro	Low	-.23**	.22	-.08	.33
	Medium 1	.21*	.11	.11	.15
	Medium 2	.22**	.11	.27*	.16
	High	-.20	.11	-1.23	.15

Out-of-vehicle time-metro	Low	.64***	.09	.91***	.12
	Medium 1	.13	.10	.18	.13
	Medium 2	-.16	.11	-.14	.14
	High	-.62***	.13	-.95***	.16
Have seats or not-metro	No 1; Yes -1	-.04	.06	-.11	.08
Cost-bus	Low 1; High -1	.23**	.09	.39***	.13
Travel time-bus	Low	.21	.17	.21	.22
	Medium 1	.83***	.12	.99***	.17
	Medium 2	.27**	.13	.51***	.18
	High	-1.31***	.22	-1.71***	.30
Out-of-vehicle time-bus	Low	.40***	.12	.41***	.16
	Medium 1	-.07	.11	-.02	.15
	Medium 2	-.08	.12	.05	.16
	High	-.25**	.13	-.44***	.18
Congestion time-bus	Low	.30**	.15	.33*	.22
	Medium 1	.07	.13	-.22	.16
	Medium 2	-.27**	.13	-.28	.18
	High	-.10	.13	.17	.17
Have seats or not-bus	No 1; Yes -1	-.07	.07	-.08	.09
Travel time-bike	Low	1.81***	.15	2.81***	.23
	Medium 1	.52**	.21	.46*	.279
	Medium 2	-1.14***	.36	-1.55***	.51
	High	-1.19***	.34	-1.72***	.57
Travel time-walk	Low	1.72***	.12	2.80***	.21
	Medium 1	-.40	.28	-.65	.41
	Medium 2	-.53*	.28	-.82**	.41
	High	-.78***	.28	-1.32***	.42
Interaction effects					
Age	<40 1, Older than 40 -1	.18**	.09	.15	.15
Gender	Male 1; Female -1	.12*	.07	.22**	.11
Marital status 1	Couple with children	-.08	.09	-.18	.16
Marital status 2	Couple without children	-.09	.12	-.23	.21
Tenure * Age		-.25**	.12	-.43**	.18
Tenure * Marital status 1		-.12	.13	-.35*	.20
Tenure * Marital status 2		.28	.17	.48*	.28
Housing size 1 * Age		.51***	.18	.35	.28
Housing size 2 * Age		-.35***	.13	-.34*	.20

Housing size 3 * Age	.13	.12	.12	.19
Housing size 4 * Age	-.29**	.12	-.13*	.19
Home location * Marital status 1	.02	.09	-.08	.14
Home location * Marital status 2	.05	.126	.08	.19
Salary 1 * Age	-.13	.09	-.24	.18
Salary 2 * Age	.03	.08	.26*	.14
Salary 3 * Age	-.12	.09	-.12	.13
Salary 4 * Age	.22**	.10	.10	.16
Salary 1 * Gender	.04	.07	.00	.14
Salary 2 * Gender	-.24***	.07	-.44***	.13
Standard deviation of the random parameters				
Tenure			.52***	.20
Housing size 1			.87***	.28
Housing size 2			1.27***	.18
Housing size 3			.58***	.20
Housing size 4			1.52***	.34
Home location			.48***	.15
Salary 1			1.69***	.15
Salary 2			1.14***	.15
Salary 3			.48**	.22
Salary 4			1.11***	.19
Job location			.02	.20
Constant 1 (Move house by car)			1.31***	.19
Constant 2 (Move house by metro)			1.25***	.27
Constant 3 (Move house by bus)			1.30***	.39
Constant 4 (Move house by bike)			.84	.54
Constant 5 (Move house by walk)			.59	.43
Constant 6 (Move house by car)			2.15***	.17
Constant 7 (Change job by metro)			1.50***	.16
Constant 8 (Change job by bus)			.81***	.17
Constant 9 (Change job by bike)			1.14***	.19
Constant 10 (Change job by walk)			1.25***	.38
Rho2	0.505		0.560	
Rho2 adjusted	0.488		0.539	

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

Table 4.3 Value of time of different transportation modes

Mode	Car	Metro	Bus
VoT (CNY / hour)	27.96	18.48	17.23
VoT (€/ hour)	3.78	2.49	2.33

Similarly, a job with a very high salary attracts young people more, while jobs with an extremely low salary are less attractive for young people. Moreover, the coefficients of working environment and co-worker relationship indicate that people have a strong preference for a good relationship with co-workers and working environment. It indicates that not only a high salary, but also good harmony with co-workers will influence people's job choice. The coefficient for flexible work time is shown insignificant, which indicates that compared to Western cities, workers in China care less about the working hours flexibility. Lastly, although insignificant, the results show that in general, individuals prefer to work in the central city. The standard deviation of the random coefficient of job location is insignificant, suggesting that there is no significant unobserved variance in the population in the sensitivity of job location in the job choice process. Couples without children are found to be more sensitive to finding a job in the central city.

Interpretation of the travel mobility decision component

As expected, time-related variables indicate excess commute time/congestion time/ out of vehicle time have significant negative influence on the travel mobility decision of different transportation modes. Furthermore, results indicate that sensitivity to travel cost of different transportation modes is not the same. In general, individuals are less sensitive to travel cost when commuting by car. Conversely, opposite effects are found for the public transportation modes. Lastly, taking having seats or not into consideration, although not significant, the negative sign reveals that improvement of comfort on public transportation might attract individuals to metro and/or bus as the commute mode.

Considering the importance of practical relevance of the estimation results, the values of time are calculated (see Table 4.3). The value of commuting time is about 27.96 CNY per hour (3.78 €/ hour) for car, 18.48 CNY per hour (2.49 €/ hour) for metro, and 17.23 CNY per hour (2.33 €/ hour) for bus. Most studies are central to the evaluation of transportation in the context of short-term mobility decisions. In turn, the values of time for all transportation modes in this long-term residential and job mobility context are quite low. The implications are in line with previous research, focusing on long-term mobility decisions (Pérez, et al., 2003; Kim, et al., 2005; Tillema, et al., 2010; Peer, et al., 2015; Dubernet and Axhausen, 2016; Beck, et al., 2017), where commuting time is found less important in the context of long-term decisions.

Comparing the alternative-specific constants, the base utility of the 'keeping the current' alternative has the highest utility compared to the other alternatives. It suggests that the respondents are relatively satisfied with their current situation. Only the job/house exceeds their expectation thresholds, individuals are more likely to consider to change. Findings also show that respondents are less inclined to move house relative to change job. Taken all alternative-specific constants as random parameters, unobserved heterogeneity is shown significant for all base preferences.

In general, coefficients of various dimensions in the MNL and mixed logit model have the same signs. Interestingly, some significant coefficients in the MNL model became insignificant in the mixed logit model. The reduction in the number of parameters may be due to the relative increase in the number of parameters to estimate as well as the introduction of more random parameters.

4.3.2 Capturing taste variation through a latent class model

To examine heterogeneity in preferences, a latent class model was estimated. In order to identify the optimal number of classes, the AIC values for the models without membership specification were calculated. The LCM considered 2 to 5 classes. However, due to the limitation in sample size and relatively large number of attributes, models with more than three classes could not be estimated. Table 4.4 reports the AIC and BIC values for 2 and 3 classes. Although the AIC of the 3-class model is smaller than that of the 2-class model, the difference is small. The model with two classes was therefore chosen for further analysis.

Table 4.4 AIC and BIC value of the base models with different number of classes

Indicators	2 classes	3 classes
AIC	5470.3	5369.3
AIC/N	2.399	2.355
BIC	5505.9	5417.0
BIC/N	2.415	2.376

The results of LCM and MNL are presented in Table 4.5. It confirms that the LCM has a higher goodness-of-fit than the MNL model, where the adjusted Rho-squared increases from 0.484 for the base MNL model to 0.518. On the whole, class 1 contains 56.7% of the cases, while class 2 contains 43.3%. Because the second class is chosen as the reference, positive parameters of the membership variables relate to class 1 while negative parameters relate to class 2.

An important issue when specifying a latent class choice model is the specification of the variables in the class membership. To identify the membership of each class, socio-demographic characteristics were introduced in the membership functions, which included age, gender and income. Results of the estimation (Table 4.5) indicate that income has a significant effect on membership probability at the 95% level, providing evidence that high-income people are more likely to belong to class 2.

Taking a closer look at the differences and similarities between the two classes, we see that the effects of housing-related attributes are homogeneous between the two classes. Both housing price and housing size have a substantial impact on households' residential mobility in the sense that people prefer larger and cheaper houses. In addition, individuals/households in both classes prefer to buy a house to renting one. The taste variation between the two classes is reflected in the factors of the built environment. The effect of 'distance to bus stop' in the first class is larger than that in the second class, which indicates that lower-income households may take shorter trips and are therefore more likely to use buses. Similarly, the results indicate that people in class 1 (mostly lower income) put more weight on locations that provide greater accessibility to shopping malls; it may because that individuals with a higher income buy more often online than individuals with a lower income, which motivates the former make less shopping trips. Moreover, variety of travel modes are used for shopping trips. High-income households are more likely to own and use a private car than low-income households. Consequently, people in class 2 may be less likely to consider the distance to shopping malls. On the other hand, the attribute 'distance to metro station' shows a larger effect in the second class, indicating that housing with good accessibility to a metro station is more important for people in the second class. It is understandable that in contrast with 'distance to metro station', there is a strong evidence that proximity to metro stations can uplift house price (Du and Mulley, 2006), which may cause households with low income being unable to buy such houses.

Table 4.5 Estimation results of the MNL model and the latent class model

		MNL		LCM Class 1		LCM Class 2	
Variable	Description	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Tenure	Buy 1; Rent -1	.78***	.07	.77***	.20	1.02***	.19
Housing price	Low	.79***	.10	.97***	.28	.86**	.34
	Medium 1	.04	.10	.03	.21	.14	.54
	Medium 2	.06	.11	-.05	.25	.07	.80
	High	-.89***	.15	-.95***	.33	-1.08***	.33
Housing size	Small	-1.13***	.14	-1.37***	.45	-1.35**	.62
	Medium 1	-.36***	.10	-.41**	.19	-.27	.31
	Medium 2	.30***	.10	.20	.23	.53	.28
	Large	1.19***	.12	1.58***	.32	1.08***	.28
Distance to metro station	Small	.36***	.13	.31	.27	.82***	.30
	Medium 1	.24**	.12	.44	.32	.25	.24
	Medium 2	-.19	.14	-.57	.36	.15	.35
	Large	-.41**	.18	-.18**	.33	-1.23	.57
Distance to bus stop	Small	.43**	.18	1.11*	.61	-.01	.45
	Medium 1	.55***	.18	.81	.71	.76	.58
	Medium 2	-.31	.25	-.75	.85	-.20	.76
	Large	-.66*	.34	-1.17	1.37	-.54	.98
Distance to shopping mall	Small	-.07	.17	-.44	.67	.36	.51
	Medium 1	.23	.16	.57	.55	-.17	.46
	Medium 2	.20	.17	.32	.45	-.07	.66
	Large	-.36	.26	-.44	1.09	-.12	1.04
Home location	Central 1; Surrounding area -1	.13**	.06	.26	.17	.05	.16
Working type	Government	.40***	.08	.43**	.19	.73***	.22
	Institution	.26***	.08	.18	.18	.28	.19
	Company	-.20***	.07	-.08	.12	-.42**	.17
	Self-employed	-.47***	.08	-.53***	.15	-.59**	.19
Flexible working time	Yes 1; No -1	-.02	.04	-.13	.20	.06	.10
Salary	Low	-1.64***	.09	-2.15***	.26	-2.58***	.29
	Medium 1	-.52***	.08	.19**	.08	-.66***	.16
	Medium 1	.87***	.09	.91***	.21	1.26***	.21
	High	1.29***	.09	1.11***	.23	1.98***	.26
Working	Very poor	-.79***	.11	-1.05***	.25	-.83***	.27

environment	Poor	-.10	.09	-.15	.15	-.21**	.09
	Good	.40***	.07	.40***	.15	.36*	.20
	Very good	.48***	.08	.79***	.18	.67***	.22
Colleague relationship	Very poor	-.88***	.11	-1.50***	.27	-.68**	.30
	Poor	-.45***	.10	-.53***	.18	-.48*	.27
	Good	.65***	.08	.93***	.16	.64***	.24
	Very good	1.15***	.08	1.10***	.15	.52*	.21
Easy to change job	Yes 1; No -1	-.04	.04	.09	.08	-.20	.20
Job location	Central 1; Surrounding area -1	.05	.04	.01	.09	.09	.12
Cost-car	Low	-.13	.28	-.62	.65	3.12***	.62
	Medium 1	.07	.19	.56	.58	-1.24***	.42
	Medium 2	.22	.21	.22	.78	-.58*	.35
	High	-.16	.21	-.16	.65	-1.30***	.54
Travel time-car	Low	.14	.19	.20	.55	1.15**	.48
	Medium 1	.34**	.15	.14	.56	1.55***	.29
	Medium 2	-.04	.18	-.01	.52	1.05***	.29
	High	-.44*	.26	-.33	.58	-3.75***	.63
Congestion time-car	Low	.40***	.09	.71**	.32	.40*	.22
	Medium 1	-.08	.10	.43	.40	.35*	.18
	Medium 2	-.11	.10	.54*	.28	-.38	.26
	High	-.21**	.10	-1.67***	.42	-.37*	.20
Cost by metro	Low 1; High -1	.39***	.13	.11	.21	-.49	.50
Travel time-metro	Low	.21**	.11	.39**	.19	.82**	.32
	Medium 1	.20*	.11	.00	.21	.19	.37
	Medium 2	-.17	.10	.19*	.19	-.39	.27
	High	-.25	.22	-.58*	.31	-.62	.83
Out-of-vehicle time-metro	Low	.59***	.09	.28	.19	1.11***	.27
	Medium 1	.13	.01	.11	.20	.30	.24
	Medium 2	-.16	.11	-.07	.19	-.36	.52
	High	-.56***	.12	-.33	.20	-1.04**	.48
Have seats-metro	No 1; Yes -1	-.03	.06	-.00	.11	-.03	.16
Cost-bus	Low 1; High -1	.25***	.09	.29*	.17	-.22	.34
Travel time-bus	Low	.14	.17	-.02	.26	.20	.92
	Medium 1	.78***	.12	.66***	.20	1.39***	.48
	Medium 2	.29**	.13	.22	.22	.11	.69
	High	-1.22***	.21	-.85**	.34	-1.71**	.95

Out-of-vehicle time-bus	Low	.42***	.11	.60***	.18	.11	.44
	Medium 1	-.10	.11	-.28	.20	.29	.42
	Medium 2	-.10	.12	-.01	.19	-.12	.45
	High	-.22*	.13	-.31	.21	-.29	.48
Congestion time-bus	Low	.31**	.15	.22	.22	.91	.82
	Medium 1	.09	.13	.13	.23	-.26	.50
	Medium 2	-.26**	.13	-.31	.22	-.32	.50
	High	-.15	.13	-.04	.23	-.33	.69
Have seats- bus	No 1; Yes -1	-.06	.07	-.08	.14	-.05	.27
Travel time-bike	Low	1.78***	.15	2.07***	.33	2.05***	.52
	Medium 1	.48**	.20	.60	31	-.54	1.51
	Medium 2	-1.12***	.35	-1.53	1.65	-.40	1.64
	High	-1.14***	.34	-1.15	1.41	-1.11	2.71
Travel time-walk	Low	1.69***	.12	2.54***	.38	1.86***	.31
	Medium 1	-.40	.28	-.62	1.47	-.49	1.36
	Medium 2	-.54**	.28	-.95	2.27	-.33	1.82
	High	-.78**	.28	-.97	1.83	-1.04	2.54
Constant 1 (Move house by car)		-2.37***	.17	-3.60***	.40	-1.21***	.38
Constant 2 (Move house by metro)		-2.82***	.20	-3.42***	.51	-2.02***	.45
Constant 3 (Move house by bus)		-3.32***	.22	-3.56***	.47	-2.41***	.61
Constant 4 (Move house by bike)		-4.02***	.25	-4.12***	.49	-3.95***	.90
Constant 5 (Move house by walk)		-3.84***	.24	-4.33***	.53	-3.79***	.82
Constant 6 (Change job: by car)		-1.60***	.13	-3.91***	.38	-1.20***	.31
Constant 7 (Change job by metro)		-1.92***	.15	-2.37***	.33	-1.65***	.40
Constant 8 (Change job by bus)		-2.84***	.16	-3.32***	.35	-2.31***	.48
Constant 9 (Change job by bike)		-3.25***	.18	-4.01***	.38	-2.85***	.51
Constant 10 (Change job by walk)		-3.19***	.17	-4.54	.53	-2.52	.45
Rho2		.498			.547		
Rho2 adjusted		.484			.518		
Membership variables (Latent class 1)		**Estimate**			**S.E.**		
Constant		.36*			.21		
Gender (Male 1,Female -1)		-.15			.23		
Age (Young 1, Old -1)		-.47			.29		
Income (Low 1; High -1)		.92***			.26		

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

As for job-related variables, results show that people in the second class with higher income are more concerned about salary. People in the first class favour good co-worker relationships and working environments more than people in the second class. One explanation may be that lower income workers may have lower aspirations about a high salary because these jobs are limited. Moreover, attitudes may induce job self-selection in the sense that people who expect more opportunities for promotion may consciously choose to work with more duties and responsibilities, and thus get better paid.

As for the utility of transportation modes, time-related variables show different effects between the two classes. Some existing studies have confirmed that people with higher income have shorter travel time and prefer to live closer to their work places, while other studies reported the opposite findings and argued that commute distance tends to be positively correlated with earnings. Wealthier people have longer commuting times (Blumenberg, 2004; Sandowa and Westin, 2010), since their desire for a better quality of life and larger houses can be more easily fulfilled by living far from the city center and their workplaces (Dargay and van Ommeren, 2005). In line with the former argument, results of the current study indicate that the second class has larger coefficients for travel time than the first class. This means that people with higher income are more sensitive to travel time than people with lower income. In this regard, once provided by a dream job offer, low-income people may consider accepting it, even if it may take longer time to commute.

Similarly, regarding out-of-vehicle time, results of metro related attributes show that people in class 2 (mostly higher income) consider metro more important than people with lower income. However, an opposite effect is found for the bus mode. In other words, people in class 2 are more sensitive to the distance to metro stations, but less sensitive to the distance to bus stops compared to people in class 1. In addition, travel cost by car is found significant only in the second class, which means that people with higher income may be concerned more with the travel cost by car. However, such difference between the two classes is not found for public transportation modes.

4.3.3 Capturing taste variations through an error component mixed logit model

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 discussed 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 for the work commute. Individuals are assumed to derive from these multidimensional profiles a certain utility. The utility of alternative *i* is assumed to be stochastic and consists of a deterministic utility, V_{nit}, and a random error, ε_{nit}, such that

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

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

$$U_{nit} = \beta_{io} + \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} \beta_k x_{nikt} + \varepsilon_{nit} \tag{2}$$

where, β_k is the parameter for attribute *k*, x_{nit} 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,

$$\beta_{nk} = \bar{\beta}_k + \sigma_k + \sum_{\boldsymbol{m=1}}^{\boldsymbol{M}} \theta_{km} z_{nm} \;, k = 1, \ldots, K \tag{3}$$

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

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

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:

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

Move house:

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

...

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

Change job:

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

...

$$U_{n11t} = \beta_{11o} + \sum_{k=1}^{K} (\bar{\beta}_k + \sigma_k + \sum_{m=1}^{M} \theta_{km} z_{nm}) x_{n11kt} + \lambda_3 Q_{n3} + \varepsilon_{n11t} \tag{5}$$

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

$$\mathrm{Var}[Q_{nl}] = [\lambda_l \exp \sum_{m=1}^{M} \tau_{lm} z_{nm}]^2 \tag{6}$$

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

The conditional choice probabilities then take on the logit form:

$$p_{nt}(i|\boldsymbol{Q}_n) = \frac{\exp(\beta_{io} + \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}}(\bar{\beta}_k + \sigma_k + \sum_{\boldsymbol{m=1}}^{\boldsymbol{M}} \theta_{km}\, z_{nm}\,)\, x_{nikt} + \lambda_l Q_{nl}\,)}{\sum_{i=1}^{I} \exp(\beta_{io} + \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}}(\bar{\beta}_k + \sigma_k + \sum_{\boldsymbol{m=1}}^{\boldsymbol{M}} \theta_{km}\, z_{nm}\,)\, x_{nikt} + \lambda_l Q_{nl}\,)} \tag{7}$$

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

$$p_{\,nit} = \int_{\boldsymbol{E}_n} (p_{nt}(i|\boldsymbol{Q}_n) f(\boldsymbol{Q}_{nl}))\, d\boldsymbol{Q}_{nl} \tag{8}$$

Integrating the taste variation of random parameter β_{nk}, the unconditional choice in equation (7) denotes as

$$p_{\,nit} = \int_{\boldsymbol{Q}_{nl}} \int_{\boldsymbol{\beta}_n} \left((P_{nit}|\boldsymbol{Q}_{nl}, \boldsymbol{\beta}_n)\, f(\boldsymbol{Q}_{nl}, \boldsymbol{\beta}_n|\boldsymbol{z}_n)\right) d\boldsymbol{Q}_{nl}\, d\boldsymbol{\beta}_n \tag{9}$$

In our experiment, respondents provide multiple responses. Thus, we estimated these panel effects. Consequently, the full log-likelihood function can be written as follows

$$LL = \sum_{n=1}^{N} \log \int_{\boldsymbol{Q}_{nl}} \int_{\boldsymbol{\beta}_n} \prod_{t=1}^{T} \left((P_{nit}\middle|\boldsymbol{Q}_{nl}, \boldsymbol{\beta}_n)\, f\left(\boldsymbol{Q}_{nl}, \boldsymbol{\beta}_n\middle|\boldsymbol{z}_n\right)\right)\, d\boldsymbol{Q}_{nl}\, d\boldsymbol{\beta}_n \tag{10}$$

Table 4.7 presents the results of the error component mixed logit model. 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 modelling residential and job location choice behavior is a primary concern for urban planners, policymakers, and researchers (Schirmer, et al., 2014; Dubernet and Axhausen, 2016). Thus, residential and job location were selected as the random attributes. In addition, not only the main effects but also several socio-demographic interaction effects were estimated.

Nlogit software was used to estimate the error component mixed logit model. Both random variables and error components were assumed to be normally distributed. To get stable estimates, 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 largely improve the estimates. Overall, the estimated error component logit model has a good fit. The error component model improves the adjusted Rho-squared from 0.495 for the base random parameter model to 0.53.

Results in Table 4.7 indicate that parameter signs for both the error component mixed logit model and the 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 most taste parameters in the error component model have the same direction as in the base multinomial logit model and mixed logit model, we discuss the results by focusing mainly on the 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 job 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 socio-demographics. Because the number of parameters relative to sample size does not allow estimating too many interaction effects, after exploring different combinations of socio-demographic variables, as listed in Table 4.7, 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, the number of workers in the household shows a significant effect on the heterogeneity of moving house. Specifically, results indicate that households with 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 results show 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.

Table 4.7 Estimation results of the MNL and error components mixed logit model

		MNL		ECL	
Variable	Description	Estimate	S.E.	Estimate	S.E.
Random parameter					
Home location	Central 1; Surrounding area-1	.23**	.09	.11	.14
Job location	Central 1; Surrounding area -1	.09	.07	.09	.10
Non-Random parameters					
Tenure	Buy 1; Rent -1	.94***	.09	1.36***	.18
Housing cost	Low	.97***	.12	1.26***	.22
	Medium 1	-.04	.12	.03	.21
	Medium 2	-.04	.12	-.13	.22
	High	-.89***	.17	-1.15***	.23
Housing size	Small	-1.37***	.17	-2.15**	.46
	Medium 1	-.38***	.12	-.52**	.21
	Medium 2	.39***	.12	.60***	.21
	Large	1.36***	.14	2.07***	.30
Distance to metro station	Small	.40**	.16	.20	.32
	Medium 1	.17	.14	.48	.30
	Medium 2	-.22	.16	-.24	.33
	Large	-.34	.21	-.45	.53
Distance to bus stop	Small	.43**	.21	.60	.40
	Medium 1	.62***	.21	.77*	.44
	Medium 2	-.38	.28	-.45	.52
	Large	-.67*	.41	-.92	.83
Distance to shopping mall	Small	.09	.20	.01	.46
	Medium 1	.23	.18	.27	.40
	Medium 2	.30	.19	.50	.45
	Large	-.62	.30	-.78	.88
Work type	Government	.45***	.10	.55***	.15
	Institution	.27***	.09	.29**	.15
	Company	-.23***	.08	-.27**	.14
	Self-employed	-.48***	.09	.57***	.14
Flexible working time	Yes 1; No -1	-.02	.05	-.05	.08
Salary	Low	-1.87***	.11	-2.88***	.21
	Medium 1	-.58***	.09	-.36***	.13
	Medium 1	1.01***	.10	1.38***	.13

	High	1.44***	.11	1.85***	.15
Work environment	Very poor	-.91***	.12	-1.11***	.19
	Poor	-.14	.10	-.27*	.14
	Good	.45***	.09	.61***	.15
	Very good	.59***	.09	.77***	.14
Colleague relationship	Very poor	-1.09***	.13	-1.36***	.18
	Poor	-.49***	.11	-.66***	.16
	Good	.81***	.09	.99***	.15
	Very good	.76***	.09	1.04***	.14
Easy to change job	Yes 1; No -1	-.04	.05	-.04	.09
Cost-car	Low	-.06	.33	-.01	.64
	Medium 1	.14	.22	-.12	.49
	Medium 1	.19	.24	.44	.58
	High	-.27	.25	-.32	.58
Travel time-car	Low	.18	.22	.13	.56
	Medium 1	.31*	.19	.49	.47
	Medium 1	-.02	.22	-.27	.54
	High	-.48	.32	-.35	.64
Congestion time-car	Low	.40***	.10	.40***	.13
	Medium 1	-.05	.11	-.01	.15
	Medium 1	-.11	.11	-.07	.15
	High	-.25**	.12	-.32	.18
Cost-metro	Low 1; High -1	.22*	.12	.23	.27
Travel time-metro	Low	.28**	.12	.58**	.23
	Medium 1	.20	.12	.60**	.26
	Medium 1	-.21	.12	.06	.17
	High	-.27	.25	-1.23*	.65
Out-of-vehicle time-metro	Low	.66***	.10	.76***	.13
	Medium 1	.14	.10	.09	.15
	Medium 1	-.17	.11	-.19	.17
	High	-.63***	.13	-.66***	.18
Have seats or not-metro	No 1; Yes -1	-.05	.06	-.10	.09
Cost by bus	Low 1; High -1	.28***	.10	.26	.18
Travel time-bus	Low	.14	.18	.07	.25
	Medium 1	.88***	.13	1.12***	.22
	Medium 1	.33**	.14	.51*	.25
	High	-1.35***	.23	-1.7***	.39

Out-of-vehicle time-bus	Low	.43***	.12	.54***	.19
	Medium 1	.09	.12	.10	.23
	Medium 1	-.07	.13	-.16	.22
	High	-.45*	.14	-.47*	.24
Congestion time-bus	Low	.32*	.17	.16	.28
	Medium 1	.11	.14	.26	.22
	Medium 1	-.29**	.14	-.24	.22
	High	-.14	.14	-.18	.26
Have seats or not-bus	No 1; Yes -1	-.05	.08	-.16	.13
Travel time-bike	Low	2.02***	.17	2.80***	.45
	Medium 1	.56**	.23	.66	.48
	Medium 1	-1.27***	.401	-1.84	1.89
	High	-1.31***	.379	-1.62	1.39
Travel time-walk	Low	1.91***	.14	1.19***	.14
	Medium 1	-.41	.30	-.18	.26
	Medium 1	-.61**	.30	-.40	.30
	High	-.90***	.31	-.61*	.30
Constant 1	Move house by car	-2.50***	.19	-2.96***	.38
Constant 2	Move house by metro	-3.00***	.22	-3.19***	.50
Constant 3	Move house by bus	-3.51***	.24	-4.15***	.43
Constant 4	Move house by bike	-4.32***	.28	-5.28***	.60
Constant 5	Move house by walk	-4.12***	.26	-5.54***	.66
Constant 6	Change job by car	-1.64***	.15	-2.12***	. 31
Constant 7	Change job by metro	-1.99***	.17	-2.23***	.37
Constant 8	Change job by bus	-2.91***	.18	-3.55***	.36
Constant 9	Change job by bike	-3.41***	.20	-4.37***	.45
Constant 10	Change job by walk	-3.34***	.19	-4.73***	.59
Heterogeneity around mean					
Home location: number of workers		-.01	.08	-.02	.13
Job location: number of workers		-.16**	.07	-.13	.10
Standard deviation of random parameters					
Home location	Central 1; Surrounding area -1	.68***	.12	.01	.62
Job location	Central 1; Surrounding area -1	.82***	.08	.49**	.19
Error components for alternatives and nests of alternatives parameters					
Standard deviation--Current				.32	.40
Standard deviation--Move house				2.08***	.48

Standard deviation--Change job			2.12***	.31
Heterogeneity around standard deviation of error components effect				
Current	Gender		.10	.15
	Income		.36	.34
	Numbers of workers		.13	.17
Move house	Gender		-.20	.14
	Income		-.43**	.18
	Numbers of workers		. 29*	.15
Change job	Gender		-.04	.11
	Income		-.30**	.14
	Numbers of workers		.30**	.14
Rho^2		0.51	0.55	
Rho^2 adjusted		0.450	0.53	

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

4.4 Conclusions and discussion

This chapter is based on the contention that individuals and households in response to dramatic change in their decision context maximize the combined utility of housing, job and commuting trips as opposed to maximizing their utility of one of these domains, treating the other dimensions as given, as many models assume. To support this contention, a stated choice experiment was designed to mimic the multidimensional choice behavior of interest. Furthermore, because a considerable amount of observed and unobserved preference heterogeneity normally exists in multi-dimensional choice behavior, this study investigated the heterogeneous behavior of people in the context of co-dependent decisions about residence, job and transportation modes using the data collected from a pivoted stated choice experiment. A mixed logit model, a latent class model and an error component model were estimated to identify the taste variation.

Results of mixed logit model estimation show that different choice dimensions considered in this paper are interrelated, both through directly observed relationships and through correlations across unobserved factors (error terms) affecting multiple choice dimensions. In terms of the housing dimension, tenure, size, price, distance to the bus stop and location were found to be important characteristics that help explaining the residential mobility choice process. In general, the old generation and households with one or more children are more likely to consider buying their own house rather than renting one. Moreover, relative to young people, old residents prefer larger houses instead of small houses. In terms of the job dimension, salary, job type, co-worker relationships and work environment were found to be the significant factors in the job mobility choice process. In general, males are more likely to choose jobs with a high salary (have the better paying jobs). Similarly, a job with a very high salary attracts young people more, while an extremely low salary makes young people more reluctant to accept it. Relative to other households, couples with no children prefer jobs in the central city. In case of the commute mode dimension, estimation results show significant presence of time-related factors affecting travel mobility dimension. Moreover, effects of commute cost on various transportation modes differ. Specifically, results indicate that public transportation modes are sensitive to commute cost but the car mode is not.

Results of the latent class model show that people with lower income are less likely to change their current house and/or job than people with higher income. In this regard, policies such as supplying affordable housing for low-income households or training working skills for non-professional workers will provide more alternative choices and increase their aspirations to find a better a house/job. Moreover, by exploring heterogeneity among individuals, results show that people with lower income have a higher probability to use public transportation for commuting than private cars, while a reverse effect is found for people with higher income. Increasing the accessibility of public transportation (especially for metro) in new areas would attract lower-income households more to the public transport system. Likewise, in terms of slow modes, results indicate that people with a lower income are more likely to cycle than walk, while a reserve effect is found for people with higher income. Thus, building bicycle-friendly environments may encourage people to commute more by bicycle.

Results of the error component mixed logit model show that not only the random parameters but also the variances associated with the long-term alternative-specific error components are significant. Results of the specified error components for the long-term decisions indicate that unobserved heterogeneity exists in transportation mode choice, dependent upon moving house and changing job decisions that are not fully captured by the alternative-specific attributes of different transportation modes.

Although the co-dependency of multidimensional long-term mobility choices has been addressed in this chapter, it should be noted that most long-term decisions are not static considering the various change over life courses. It still needs to further investigate the long-term mobility decisions from a longitudinal perspective. As a natural extension, the temporal interdependencies between different long-term mobility decisions will be examined in the next chapter.

5

Simultaneous Mobility Decisions

5.1 Introduction

To complement the dominant single-domain research in transportation, different models for the co-dependent choice of various life domains were proposed and estimated in previous chapters. Although the multidimensionality was considered in these choice models, the interdependencies between different mobility decisions were not examined. Therefore, the analysis reported in this chapter is motivated by the desire to better understand the temporal interdependencies between residential choice, job choice and car ownership change decision.

Moreover, there is a growing body of studies indicating that changes in the demographic profile of individuals/households, such as change in household composition, may trigger households to reconsider their status in each domain (Clark, et al., 2003; Lanzendorf, 2010; Prillwitz, et al., 2006; Habib, et al., 2011; Oakil, et al., 2014; Zhao and Zhang, 2018). Consequently, incorporating life trajectory choices in the choice of car ownership is expected to provide a better understanding of the underlying decision processes.

During the last decades, many studies have indicated that qualitative views and desires (value orientations, individual-specific attitudes and lifestyle preferences) may simultaneously influence various long-term decisions. Whereas some authors try to measure these concepts, others (e.g., Paleti, et al., 2012) argue they are difficult to quantify directly. Thus, simultaneously considering choices in various life dimensions increases the needs of controlling for these unknown factors and their correlation among different decision processes (Michielin and Mulder, 2008). For instance, Manaugh, et al. (2010) argued that commuting behavior is correlated with socio-demographic characteristics and unobserved factors (e.g., lifestyle, environmental concerns, perception of risk related to road accidents, etc.). These unobserved factors then affect both car travel distance and home-job location choice. Similarly, Eluru, et al. (2011) and Pinjari, et al. (2011) proposed integrated multi-dimensional choice models that tie together long-term location choices and short-term activity-travel choices, and suggested that the only way to accurately reflect their impacts and capture the 'bundling' of choices is to model the choice dimensions together in a joint modelling equation framework that accounts for correlated unobserved effects.

Furthermore, it is assumed that most life course events have lasting effects on future decision-making, since these decisions involve investment of time and money (Beige and Axhausen, 2017). To understand how current states, past decisions and future expectations influence individual decisions, a life course approach will be introduced into this chapter to investigate the life course decisions from a long-term perspective.

Thus, following this stream of research, the objective of this chapter is threefold. First, it will look into the interdependencies between the decisions to change residence, job and car ownership. Second, to reflect the impacts of unobserved factors on the various mobility decisions, a simultaneous equation model is built and discussed in this chapter. Third, since most long-term mobility decisions are in adjustment to past events and/or in anticipation of future events, the concurrent, lagged and lead effects are incorporated in the model.

The remainder of this chapter first provides a short review of the relevant literature. Section 5.3 describes the characteristics of the retrospective data used in the analysis. Next, the simultaneous equation model is presented, while model estimation results and interpretations are presented in Section 5.5. Finally, conclusions are presented in the last section.

5.2 Literature review

A growing body of studies in life course approach indicates that qualitative views and desires, such as individual attitudes and lifestyle references, may simultaneously influence various long-term decisions, which increases the need of controlling for unobserved factors and their correlation among different decision-making processes. For instance, Kan (2000) developed an econometric model to study the intricate relationship between residential mobility and tenure choice. Four variables (current tenure choice, actual mobility, mobility expectation, and previous tenure mode) are modeled as a simultaneous equation system. It assumes that a tenure choice decision is observed only if there is a move, the decision depends on previous tenure status, and the tenure mode and future length of stay are determined simultaneously. Based on the Florida subsample of the 2009 National Household Travel Survey of the United States, Kortum, et al. (2012) applied a simultaneous equation model to explore the primary reason for moving. The results showed significant unobserved heterogeneity in the sensitivity to surroundings simultaneously affect the choice of residential locations and the decision to move.

In transportation, commuting behavior is often treated a simultaneous decision with other choice dimensions (Bhat and Guo, 2007; Eluru, et al., 2009; Manaugh, et al. 2010; Pinjari, et al., 2011; Tu Tran, et al., 2016), whereas the unobserved factors have been examined using simultaneous equation models. For example, Plaut (2006) developed a seemingly unrelated regression model to estimate commuting distance and time simultaneously. Based on an Origin-Destination Survey in Montreal, Canada, Manaugh, et al. (2010) suggested that unobserved factors (life style, environmental concerns, perception of risk concerned with accidents on roads, etc.) are found to simultaneously influence both travel distance and home-job location choice. In addition, based on the data set from the San Francisco Bay Area, Pinjari, et al. (2011) presented an integrated simultaneous multi-dimensional choice model of residential location, car ownership, bicycle ownership, and commute tour mode choices. The significant magnitude of common unobserved factors was found across multiple choice dimensions. Thus, ignoring any of these effects could result in biased estimation of other effects. More recently, Tran, et al. (2016) proposed a joint equation modeling framework for the choice of residential location, job location, and commuting mode. It was found that the effects of common unobserved factors on residential location, job location and commuting mode choices are all existed in different magnitudes.

In addition, evidences in favor of life course approach proposed that, most life course mobility decisions are choices of lifestyles. Lifestyle refers to an individual’s way of living and is influenced by his or her outlook of life and motivations, including opinions, beliefs, interests and attitudes (Van Acker, et al., 2010), which may influence the choices in different life domains simultaneously. Although researchers have recognized the importance of lifestyles and attitudes in life course analysis, to the best to our knowledge, there are little research which incorporates the effects of such factors on the choice of various long-term decisions. To fill this research gap and being in line with the life course approach, multiple long-term mobility decisions are modeled jointly whereas the unobserved common factors are assumed simultaneously impact residential, job and car ownership change.

5.3 Data Analysis

Longitudinal data was collected to analyze the complex temporal interdependencies among various long-term mobility decisions and life events. In addition to describing their socio-demographic profile, respondents were asked to provide data pertaining to their longitudinal mobility decisions, including household events (marriage and child birth), housing and employment mobility decisions, and car ownership change. After checking the integrity and accuracy of the retrospective data, data of 414 respondents were used in this analysis.

Table 5.1 Descriptive statistics of life events and different mobility decisions

Life events and mobility decisions		# of Cases	Percentage (%)
Marriage	Getting married before	266	64.3
	Never marriage	148	35.7
Child birth	Birthing child before	232	56.0
	Never have child	182	44.0
Move house	Never moved house	94	22.7
	Move house once	180	43.5
	Move house two times	97	23.2
	Move house three times	31	7.5
	Move house more than three times	13	3.1
Change job	Never changed job	166	40.1
	Change job once	140	33.8
	Change job two times	77	18.6
	Chang job three times	21	5.1
	Change job more than three times	10	2.4
Car ownership change	Never have cars	174	42.0
	Have cars but never change	163	39.4
	Chang cars once	60	14.5
	Change cars more than once	17	4.1

The descriptive statistics of the life events and mobility decisions in different life domains are summarized in Table 5.1. In 2016, about 35.7% people were married, while 44% of the households had no child; 56% of the households had one or more child. As for residential mobility decisions, 22.7% of the sample never moved house, 43.5% moved once, 23.2% moved twice, while only 10% people moved more than two times. In terms of job change, almost 60% of the respondents experienced employment relocation, with 33.8% changing once, 18.6% changing twice, and 7.5% changing more than two times. Regarding car ownership change, more than 42.0% of the respondent never owned a car (174 respondents), nearly 39.2% owned one but never changed, 14.5% changed once, while only 4.1% changed at least once.

5.4 Conceptual considerations and model estimation

5.4.1 Conceptual considerations

The purpose of this analysis is to uncover the interdependencies between different long-term mobility decisions. Three life choice dimensions in residence, job and car ownership are considered. In this study, residential change denotes renting/purchasing the first apartment/house and/or moving to a new place; Job change denotes getting the first job or changing to a new job; car ownership change denotes purchasing or replacing cars. Household structure change includes getting married and the birth of a child.

According to the existing literature, we assume the long-term decisions of residential and job mobility are directly influenced by household structure. Residential mobility decision is influenced by job mobility decision, and the reverse effect also exists. In terms of car ownership change, besides household structure change, both residential and job mobility choices are considered as important determinants. The interdependencies between various life events and mobility decisions in different life domains are shown in Figure 5.1. Second, we included lagged and lead effects in the model. Lastly, we assume that the effects of unobserved factors such as attitudes and lifestyles preferences may simultaneously influence different mobility decisions.

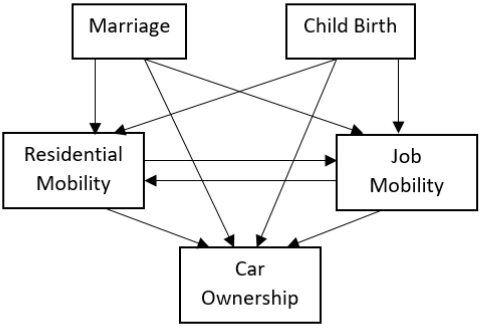

Figure 5.1 Interdependencies between various long-term mobility decisions

5.4.2 Model specification and estimation

Here, we use a simultaneous equation model to capture three binary responses. Different from treating each mobility decision independently, the simultaneous equation systems allow the error terms to be correlated across equations. This makes it possible to formulate model specifications that account for complex observed and unobserved interrelationships that exist among multiple dependent variables. The general specification for a multivariate probit model is,

$$\boldsymbol{y}_{D\_t0} = \boldsymbol{c}_D + \boldsymbol{\beta}_D\boldsymbol{x} + \boldsymbol{\gamma}_{hDt}\boldsymbol{w}_{ht} + \boldsymbol{\gamma}_{mDt}\boldsymbol{w}_{mt} + \boldsymbol{\varepsilon}_r \quad (1)$$

where $\boldsymbol{y}_{D\_t0}$ denotes the binary response of various mobility decisions in the current year t_0, which $\boldsymbol{y}_{D\_t0}$ = 1 if a mobility decision *D* at time t_0 is made, and 0 otherwise. $\boldsymbol{c}_D$ denote the constant of mobility decisions *D* at time t_0; $\boldsymbol{x}$ is a vector of socio-demographic characteristics with the coefficient vector $\boldsymbol{\beta}_D$; while $\boldsymbol{w}_{ht}$ denotes household structure change, including marriage and child birth at time *t*, where t refers to the time earlier or latter then or same as the current year t_0; $\boldsymbol{w}_{mt}$ denotes a mobility decision m at time *t* related to residence, job and car ownership change, which influence the targeted mobility decision *D* at time t_0. Similarly, as a dummy variable, both $\boldsymbol{w}_{ht}$= 1 and $\boldsymbol{w}_{mt}$ = 1 if mobility decisions are made at time *t*, and 0 otherwise. $\boldsymbol{\gamma}_{hDt}$ and $\boldsymbol{r}_{mDt}$ are vectors of coefficients to be estimated. $\boldsymbol{\varepsilon}_D$ is a multivariate normally distributed error term, representing the unobserved components of mobility decision *D*.

More specifically, three equations represent the mobility decisions. For each decision, temporal effects are considered. Thus, the simultaneous equation model can be written as follows,

$$\boldsymbol{y}_{r\_t0} = \boldsymbol{c}_r + \boldsymbol{\beta}_r \boldsymbol{x} + \boldsymbol{\gamma}_{hrt} \boldsymbol{w}_{ht} + \boldsymbol{\gamma}_{rrt} \boldsymbol{w}_{rt} + \boldsymbol{\gamma}_{jrt} \boldsymbol{w}_{jt} + \boldsymbol{\varepsilon}_r \tag{2}$$

$$\boldsymbol{y}_{j\_t0} = \boldsymbol{c}_j + \boldsymbol{\beta}_j \boldsymbol{x} + \boldsymbol{\gamma}_{hjt} \boldsymbol{w}_{ht} + \boldsymbol{\gamma}_{rjt} \boldsymbol{w}_{rt} + \boldsymbol{\gamma}_{jjt} \boldsymbol{w}_{jt} + \boldsymbol{\varepsilon}_j \tag{3}$$

$$\boldsymbol{y}_{c\_t0} = \boldsymbol{c}_c + \boldsymbol{\beta}_c \boldsymbol{x} + \boldsymbol{\gamma}_{hct} \boldsymbol{w}_{ht} + \boldsymbol{\gamma}_{rct} \boldsymbol{w}_{rt} + \boldsymbol{\gamma}_{jct} \boldsymbol{w}_{jt} + \boldsymbol{\gamma}_{cct} \boldsymbol{w}_{ct} + \boldsymbol{\varepsilon}_c \tag{4}$$

In the equations above, $\boldsymbol{y}_{r\_t0}$, $\boldsymbol{y}_{j\_t0}$ and $\boldsymbol{y}_{c\_t0}$ denote the binary response of residence, job and car ownership change at time t_0, respectively. $\boldsymbol{c}_r$, $\boldsymbol{c}_j$, and $\boldsymbol{c}_c$ are the constants. $\boldsymbol{x}$ are vectors of social-demographic attributes with corresponding coefficient vectors $\boldsymbol{\beta}_r$, $\boldsymbol{\beta}_j$, and $\boldsymbol{\beta}_c$ for residence, job, and car ownership change, respectively. The timing influences on different mobility choice are also considered, including the concurrent, lagged and lead effects. $\boldsymbol{w}_{ht}$, $\boldsymbol{w}_{rt}$, $\boldsymbol{w}_{jt}$ and $\boldsymbol{w}_{ct}$ are vectors of time-dependent attributes. To be more specific, for residential and job mobility decisions at time t_0, household structure change ($\boldsymbol{w}_{ht}$), residential mobility decisions ($\boldsymbol{w}_{rt}$) and job mobility decisions ($\boldsymbol{w}_{jt}$) at time t are assumed influencing moving house and changing job at time t_0; In terms of car ownership change at time t_0, not only household structure change, residential and job mobility decisions at time t_0 are assumed to have an influence, but also car ownership change ($\boldsymbol{w}_{ct}$) at different time are assumed trigging individuals or households change their car ownership at time t_0. $\boldsymbol{\gamma}_{hrt}$, $\boldsymbol{\gamma}_{rrt}$, $\boldsymbol{\gamma}_{jrt}$, $\boldsymbol{\gamma}_{hjt}$, $\boldsymbol{\gamma}_{rjt}$, $\boldsymbol{\gamma}_{jjt}$, $\boldsymbol{\gamma}_{hct}$, $\boldsymbol{\gamma}_{rct}$, $\boldsymbol{\gamma}_{jct}$ and $\boldsymbol{\gamma}_{cct}$ are vectors of coefficients to be estimated. ε_r, ε_j, and ε_c are error terms representing the unobserved components of moving house, changing job and car ownership. The unobserved components are all assumed to be normally distributed with mean 0 and variance-covariance matrix V { $\varepsilon_r, \varepsilon_j, \varepsilon_c$} ~ N (0, V). The variance covariance matrix is given by:

$$V = \begin{pmatrix} 1 & \rho_{rj} & \rho_{rc} \\ \rho_{jr} & 1 & \rho_{jc} \\ \rho_{cr} & \rho_{cj} & 1 \end{pmatrix}$$

The off-diagonal elements in the covariate matrix represent the unobserved correlation between the stochastic components of three choice dimensions.

5.5 Results and discussion

Table 5.2 presents the estimated coefficients of the simultaneous equation model. The log likelihood at the optimal value is -1429.14, while the initial log likelihood is -1592.32. The McFadden's rho-squared values is 0.102. Results indicate that although effects are different for different time slices, various mobility decisions are shown to be influenced by social-demographic characteristics and different life events. Moreover, error correlations between all three life domains are statistically significant, which indicates that one choice dimension is not exogenous to the other life choice, but is endogenous to the system as a whole.

5.5.1 Personal characteristics

Turning to the socio-demographic characteristics, the results indicate that people at different life stages have different willingness to move house, change job and/or change cars. Specifically, the results indicate that young people change job more frequently than old people. This is understandable because young people may need to change a job to explore their career goals, while older people are more possible to settle down into a steady career and prefer not to change jobs frequently. In contrast, it appears that individuals/households are more likely to plan to move up the housing ladder with age. For many movers, residential relocation denotes an opportunity to improve ones' living environment (better educational institution, hospital, etc.). In terms of car ownership change, age is an important factor influencing the decisions of buying/changing cars in a household. Looking at different age groups, the results show that people aged at 25-40 are more prone to buy/change cars compared to other groups of people.

In addition, results show that compared with the high salary group, people with low salary are less inclined to change job. One reason is that people with a fair and stable salary are more likely to pursue a better one when they go through a job ladder. Looking at the influence of income on car ownership change, the results show that, compared with other groups, individuals with very high salary are more incline to buy/change cars.

5.5.2 Household structure change

Household structure changes are found having different impacts on various mobility decisions. Based on the life course approach, rather than studying the instantaneous effects, both the lagged and lead effects are addressed in this research. In terms of the residential mobility decisions, although coefficients at all time instances are not statistically significant, the signs indicate both marriage and child birth may positively influence individuals'/households' moving house decision. For instance, household structure change may induce housing characteristics (i.e. numbers of bedrooms) no longer meet their needs, such a mismatch may induce families change their house to achieve a better fit. Additionally, the results show that marriage and child birth are shown having different magnitude of effects on residential mobility decisions. Specifically, it shows that child birth in general has a larger effect on residential mobility than marriage. Taking a closer look at different temporal effects, the concurrent effect of marriage on residential mobility decisions are shown to be higher than both the lagged and lead effects. However, a reverse effect was found between child birth and residential mobility decisions where the concurrent effect is shown much smaller than other temporal effects. This is perhaps because life course events like a child birth may cause much mental/monetary/time cost and consequently, families need time to adapt to buy/change a house. In addition, household structure change (job change and getting married) is found to negatively influence job mobility decisions which means people are less likely to change job in occurrence of household structure change.

Lastly, with respect to the effects of household structure change on car ownership change, a body of research found that marriage or child birth may positively influence household car purchase in response to the increased household size (e.g. Verhoeven, et al., 2005; Beige and Axhausen, 2012). However, in this study, household structure change does not show a statistically significant effect on car ownership mobility decision.

5.5.3 Mobility decisions in different life domains

With respect to the bi-directional relationships between residential and job change, in line with our hypothesis, it shows that a job change may lead to a change to residential relocation. Similarly, residential mobility is shown positively associated with job mobility. It confirms the interplay between job and residential mobility decisions, because mobility decision in one life domain can affect mobility decision in other life domain.

Looking at all temporal effects, it is found that bi-direction relationships between residential and job change both have the bigger concurrent effects than the lagged/lead effects. In terms of the 1-year and 2-year lagged effects, residential relocation is found to be positively affected by job change. This finding indicates that job change of one or more household members may trigger the residential relocation in the next 1 or 2 years. In contrast, 1 and 2-year lead effects of job change are found negatively affecting the likelihood of moving house, which means that individuals/households are prone not to relocate when they have the expectation to change jobs in the near future. In case of the temporal effects of residential relocation on job mobility decisions, a residential change in the next 1 and/or 2 years may increase the likelihood of changing job.

Regarding car ownership change, we analyzed the temporal effects of residential and job change on car ownership change. It shows that car ownership decision is greatly affected by residential mobility than job mobility. This suggests that individuals/households may be more likely to consider changing their travel behavior in face of a residential relocation rather than changing a job. Furthermore, effects at different time vary in size. Both lagged and lead effects of residential mobility are shown larger than the immediate effect on car ownership change; conversely, job mobility is shown largely increasing the likelihood to buy or change cars in the same year. This may be due to that residential mobility and car ownership change are costly, thus households need time to balance their goals. However, a workplace change may cause the change of travel time which increases the needs of households to buy/change cars directly. Regarding the changing frequency in a certain period of time, as expected, the negative signs of the parameters within each life domain shows that people prefer not to make a transition within 2 years regarding moving house, changing job or car ownership.

Table 5.2 Estimation results

	Move house		Change job		Car ownership change	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Age1(<25)	-.08	.08	.85***	.10	-.04	.10
Age2 (25-40)	.04	.07	.04	.10	.15**	.07
Age3 (41-55)	.01	.09	-.35***	.12	-.20**	.10
Income (low)	.01	.07	-.01	.08	-.06	.08
Income (medium1)	.08	.07	-.16*	.08	-.11	.08
Income (medium2)	-.09	.09	.14	.10	-.09	.10

Marriage (t-2)	-.38	.28	-.41	.28	.10	.22
Marriage (t-1)	.37	.24	-.02	.24	-.12	.26
Marriage (t0)	1.04***	.21	-.36	.27	.03	.26
Marriage (t+1)	.35	.25	.03	.22	.28	.23
Marriage (t+2)	-.02	.25	-.57**	.28	-1.50	1.54
Child birth (t-2)	.54***	.16	.08	.19	-.26	.24
Child birth (t-1)	.61***	.19	-.17	.22	.13	.20
Child birth (t0)	.13	.23	-.36	.24	-.03	.23
Child birth (t+1)	.33	.21	-.50*	.26	.23	.23
Child birth (t+2)	.27	.22	-.43*	.26	.38*	.22
Move house (t-2)	-.73***	.23	-.29	.23	.25	.16
Move house (t-1)	-.99***	.28	.02	.17	.32**	.15
Move house (t0)	--	--	.71***	.18	.08	.22
Move house (t+1)	-.44***	.14	.37***	.12	.32***	.12
Move house (t+2)	-.12	.12	.16	.13	.31***	.12
Change job (t-2)	.11	.15	-.26***	.15	.04	.15
Change job (t-1)	.21	.15	-.58***	.17	-.06	.16
Change job (t0)	.80***	.21	--	--	.44**	.20
Change job (t+1)	-.10	.19	-.49**	.21	.13	.17
Change job (t+2)	-.34*	.19	.14	.16	-.24	.20
Car ownership change (t-2)	--	--	--	--	-.60**	.23
Car ownership change (t-1)	--	--	--	--	-.67***	.22
Car ownership change (t0)	--	--	--	--	--	--
Car ownership change (t+1)	--	--	--	--	-.57***	.19
Car ownership change (t+2)	--	--	--	--	-.67***	.21
Constant	-1.52***	.08	-1.60***	.10	-1.40***	.09
Error correlations						
Correlation error correlations--move house with job change					-.26**	.02
Correlation error correlations--move house with car ownership change					.13*	.08
Correlation error correlations--Job change with car ownership change					-.14**	.05
LL(β)					-1429.14	
LL(0)					-1592.32	
Rho-square					.102	

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

5.5.4 Common error components among multiple long-term mobility decisions

In this particular study, all error correlations are found to be statistically significant, indicating that the validity of the assumption that various mobility decisions should be modeled jointly. The interpretation of the error correlations is that unobserved attributes that affect one dimension are correlated with the unobserved attributes that affect other dimensions. In this regard, one choice dimension is not exogenous to the other life choice, but is endogenous to the system as a whole.

In addition, correlation of unobserved variables between residential and job change is higher than other two bundles (change of car ownership and residence, change of job and car ownership). Additionally, it shows that residential change is positively correlated with unobserved factors that contribute to car ownership change, while correlations between job mobility and other two mobility decisions are both negative. The positive sign of the parameter (0.13) suggests that unobserved factors that motivate individuals/households to relocate are likely to contribute to purchase/change cars. Conversely, there are negative covariances (-0.26 and -0.14), reflecting a negative disposition across the job mobility decision and other mobility decisions.

5.6 Conclusions and discussion

By explicitly dealing with the endogeneity issue among various mobility decisions, this chapter analyzed the temporal dependencies between various life choices using retrospective survey data. In an attempt to consider the common error components in residential mobility, job mobility and car ownership change, a simultaneous equation model was applied.

Results of the analyses identified the household structure change and various life course mobility decisions may influence the long-term mobility decisions. It is found that household structure change turns out to be an important factor for long-term residential and job mobility decisions. More specifically, both marriage and child birth are significant determinants for moving house, whereas child birth has a larger effect on residential mobility than getting marriage. Conversely, household structure change was found to negatively influence individuals' changing job. With respect to the household structure change effect on car ownership change, the findings indicate that both marriage and child birth have small and insignificant influences on car ownership change. Additionally, two-way relationships between residential and job mobility are found, with the concurrent effect larger than the lagged/lead effects. The findings also suggest that the correlated unobserved factors simultaneously affect the decision to move house/job and the decision of purchasing/changing cars, which clearly points to the need to associate various life course decisions in a simultaneous system.

6

Temporal Dependencies in Mobility Decisions over the Life Course[2]

6.1 Introduction

In Chapter 5, a simultaneous equation model was used to examine the concurrent, lagged and lead effects between various life events and mobility decisions. A limitation of the approach is the time-invariant nature of the causal structure of life trajectory events. In light of this consideration, a dynamic Bayesian network (DBN) is introduced in this chapter. Under the formalism of a DBN, initially, a causal model for a single time instance is built. Then, a copy of this model is generated for each time instance belonging to the temporal range of interest. Finally, links between nodes in adjacent networks are introduced. In this way, a DBN obeys the Markov property, with links connecting either nodes within the same time slice or between adjacent networks, and the value of each variable represents the state of a real-world property at each time instance. Therefore, DBNs are more appropriate to model the interdependencies

[2] *This chapter is based on the article:*
Guo J., Feng T., Timmermans H.T.P. (2019). Time-varying dependencies among mobility decisions and key life course events: An application of dynamic Bayesian decision networks, Transportation Research Part A, Vol 130, 82-92.

between various life domains in the real-world, since they explicitly represent the state of the system at each time instance.

From the beginning of the 1990s, there are numerous studies focusing on the choice of workplace and place of residence. Some studies have investigated how decisions about job and residential locations are mutually influential (Gordon, et al., 1991; Abraham and Hunt, 1999). Although the interdependency between residential and job mobility decisions was examined in the previous chapter, the interaction between job location and residential location was not included in the analysis. Therefore, this chapter will explore whether people have the intention to move home closer to their workplace and vice versa.

Thus, the aim of this chapter is two-fold. First, it looks into the interdependencies between various long-term events: household events, residential choice, job choice and car ownership change. Second, as an extension of the time-invariant models, this chapter examines the complex temporal dependencies by developing a dynamic Bayesian network. The network creates an instance of each random variable for each point in time. Thus, concurrent, lagged and lead effects between various life course domains are examined in this research.

The remainder of this chapter is organized as follows: The next section presents the integrated framework. Following that, the Dynamic Bayesian network approach is presented. A brief description of the survey data is given in Section 6.3. Next, estimation results are discussed in Section 6.4. Conclusions and suggestions for future research are presented in the last section.

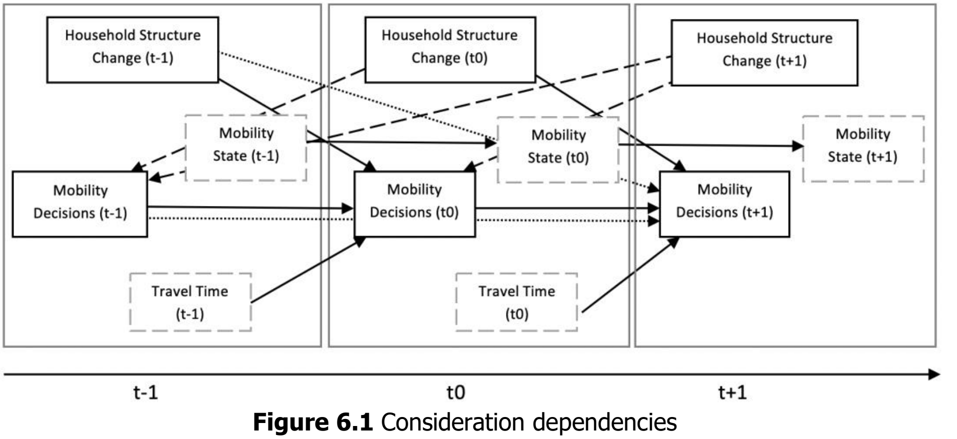

Figure 6.1 Consideration dependencies

6.2 Dynamic Bayesian networks

6.2.1 Conceptual considerations

The aim of this chapter is to uncover the interdependencies among long-term mobility decisions under the influence of various life course events. Based on the literature and available data, the life course events considered include change in household structure, residential change, job change and car change. Household structure change includes getting married and the birth of a child; residential mobility includes renting/purchasing the first apartment or house and moving house; changing job includes getting the first job and change of job; car change includes purchasing and/or replacing a car, regardless of buying the first/additional cars or going from one car to a different car. Besides, the influence of commuting time and socio-demographic characteristics on behavioral change is considered.

Decisions made during the current year are assumed to be influenced by past events, events in the same year and future events. Thus, the proposed Bayesian network examines concurrent, lagged and lead effects among various time-dependent events as illustrated in Fig. 6.1, where only the connections between different time instances are presented: the current (t0), previous (t-1) and future (t+1) situations. The rounded dot dashed lines present the one-year and two-year effects of future household structure change on current mobility decisions (lead/anticipation effects). Black bold lines represent the one-year effects of previous mobility decisions on current mobility decisions (lagged effects). Similarly, two-year lagged effects between household structure change and mobility decisions are shown by long dashed lines.

6.2.2 Model specification

Bayesian networks are attractive to flexibly examine the interdependency relationships between various life course domains. BNs belong to the family of probabilistic graphical models. They consist of a set of nodes and a set of arcs that form a directed acyclic graph (DAG). Each node represents a domain variable, whereas directed arrows between variables indicate dependence between them given that the values of their parents are known. Let $\mathbf{X} = \{X_1, X_2, \dots, X_n\}$ denote a set of random variables, while $\mathbf{Pa}\ (X_i)$ denote the parent node of X_i in the DAG. The conditional probability distribution of X_i is denoted by $P(X_i|Pa\ (X_i))$. Then, the joint probability distribution can be represented as follows

$$P\ (X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P\ (X_i | \boldsymbol{Pa}\ (X_i)) \tag{1}$$

Any probability of interest can be computed from this joint probability distribution.

While Bayesian networks are powerful models for examining the interdependencies between various household long-term decisions, the Bayesian Networks were originally not designed to explicitly model temporal relationships; they are static models. As a temporal extension of a Bayesian network, dynamic Bayesian network has been developed to introduce a temporal dimension to BNs. Therefore, this chapter represents an extension of previous work on life trajectory decisions using static Bayesian networks (e.g. Verhoeven, et al., 2005; Wang, et al., 2018). It offers an appropriate approach to explore the dynamic dependencies between various life course domains into an integrated model, in which the state of a variable at one time instance depends on one or more states at other time instances.

DBNs can be defined as a pair of BNs $(B, B_{\rightarrow})$, where B represents the initial distribution $P(X_t)$ and $B_{\rightarrow}$ is a two-slice temporal Bayes net, which contains an instance of each variable at time $m+m'$ and m. The probability of node *i* over two time slices is defined as,

$$P\left(X_{m+m'}^{i} | X_{m}^{i}\right) = \prod_{t=m}^{m+m'} P\left(X_t^i | \boldsymbol{Pa}\ (X_t^i)\right) \tag{2}$$

Where X_t^i is the *i*th node at time instance *t*, and $\boldsymbol{Pa}\ (X_t^i)$ is the set of parent nodes X_t^i, $t \in [m', m]$.

6.2.3 Learning

Similar to a BN, a useful property of DBNs is their ability to learn from observations. Learning a DBN involves two steps: finding the network structure (structure learning), and finding the parameters that best describe the data, given a network structure (parameter learning).

6.2.3.1 Structure learning

Structure learning aims to figure out a proper DAG, and confirm the association relationship between nodes. DBNs consider not only the dependencies between variables at one time instance but also the dependencies existing between several time instances. The dependent and causal directions between time nodes can be determined based on the mutual information between a pair of nodes. Structure learning of DBNs remains an active research field with several algorithms being proposed (Murphy, 2003). Even though the MCMC (Markov chain Monte Carlo) and Structural EM algorithms (Expectation Maximization) can be applied in dynamic Bayesian network structure learning, their applicability in the current study is limited due to too many nodes and number of time slices. In this regard, based on *a priori* knowledge, some constraints were enforced to reduce the degrees of freedom in learning the structure of the network. That is, semi-structure learning is adopted in the current study, where the structure within the same time slice is learned from the data, while the temporal dependency structure between different time instances is constructed based on a priori knowledge.

Considering the complexity of the structural learning process in DBNs, especially in treating the constrained casual relationships between different time instances, the network structure was learned automatically from the data only for the base network. The temporal dependency was determined in accordance with the conceptual framework. More specifically, a Bayesian search algorithm was used for structure learning for a single time instance. For a more detailed explanation on the search algorithm, readers are referred to Cooper and Herkovits (1992) and Heckerman (1995). In addition, some constraints were set to simplify structure learning and deny some unreasonable causal relationships learned from the data in the first instance of time. Setting these constraints will not affect the validity of the analysis.

1) Age, as a socio-demographic characteristic, is closely related to longer-term decisions. For example, older people are less likely to move house than younger people. Similarly, family structure change, residential and job mobility, as well as car ownership change might be all influenced by the age of individuals. On the other hand, it is impossible that any life course events influence age. Thus, such effects are unidirectional between state/events and age.
2) Family structure change (getting married and child birth) may affect change of residence, job, and car ownership, while the opposite process is less likely to happen. Therefore, the effects of mobility decisions on family structure change are ignored in this study.

As discussed above, the network structure can be extracted from empirical data or simply derived from domain knowledge. Due to limited computational power, the dependencies between life course events across different time instances are based on the literature. First, family structure change is assumed to have both forward and backward effects on mobility decisions. Second, residential and job mobility decisions are assumed to have concurrent/lagged/lead effects on car ownership change. Third, in terms of the residential/job location change, the current location choice is assumed to be a major factor influencing future location choice. Moreover, considering that residences and workers might relocate or purchase a car to avoid excess commuting time, travel time is assumed to affect various mobility decisions.

6.2.3.2 Parameter learning

With the given network structure, parameter learning entails finding the optimal parameters for a given network structure and determining the conditional probability distribution of each observation variable. Parameter learning in DBN is similar to learning in BN, except that parameters must be tied across time-slices. The expectation Maximization (EM) algorithm is capable of learning parameters from datasets that contain missing values. Thus, the EM algorithm was adopted in this study.

Because longitudinal data cover a long period of time, some life course events data are missing. The EM algorithm solves this problem by iterating between an Expectation step (E-step) and a Maximization step (M-step). Each E-step estimates expectations over the hidden variables. Next, parameters are updated in the M-step using the expectations of the hidden variables obtained in the E-step. The updated model is then used in the next E-step to obtain more accurate estimates of the hidden variables. In this way, estimated parameters are improved in every iteration and eventually converge to an optimum.

6.3 Data

In order to test the concurrent, lagged and lead effects between different mobility decisions and life events, data which were collected through the retrospective survey were used. This chapter uses data from four dimensions, family structure biography, residential history, job history, and car ownership biography. The sample size adopted in this chapter is the same as in Chapter 5. Data of 414 respondents are used in this analysis.

6.4 Results and analysis

6.4.1 Results of structure learning

The Bayesian search algorithm was used in the structure learning process within one time slice. The prior link probability was set at the default value of 0.001 for the structure learning process. The learned causal dependencies between the variables within one time-slice are shown in Figure 6.2. Household mobility decisions include two life course events within households: getting married (marry) and child birth (birth); life course mobility decisions include three life domains: residential mobility (changeH), job mobility (changeW), and car ownership change (changeC). Residential location and workplace are represented as locationH and locationW, respectively. As expected, family structure change is closely associated with other life course mobility decisions. The results clearly present a direct concurrent relationship between car ownership change and residential and job change, which is in line with previous studies. Moreover, life course mobility decisions have concurrent effects on state variables, i.e. travel time (tt). Lastly, the socio-demographic variable 'age' is directly linked with various life course mobility decisions.

The causal relationships with temporal dependencies are presented in Figure 6.3. Orange numbers in rectangles represent one and two years lagged effects between various mobility decisions, while green numbers represent previous location choice influencing people's future location choice. In the unrolling structure of the DBN model, the same network is copied to each time instance. Here, the lead effects between life course events and various mobility decisions are added manually to the unrolling structure network. In total, five time slices are constructed based on five years of continuous data.

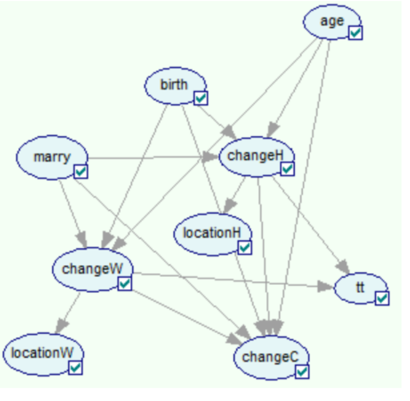

Fig 6.2 Structure of concurrent effects

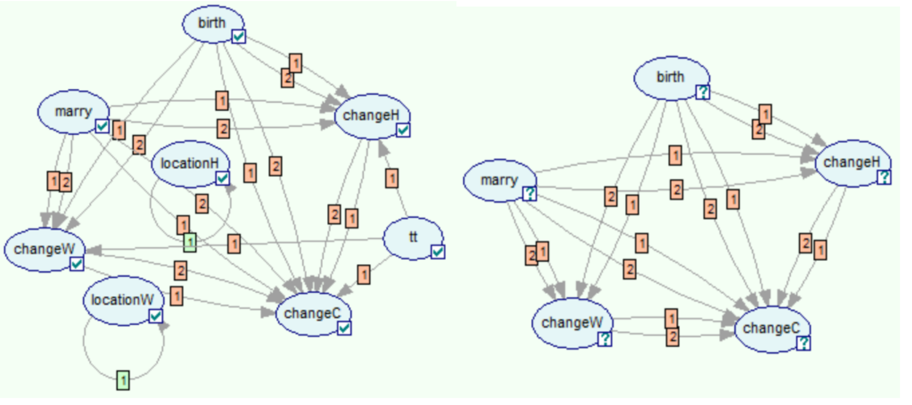

Fig 6.3 Structure of lagged effects (left) and lead effects (right)

6.4.2 Results of parameter learning

Based on the network structure presented above, the EM algorithm was used to estimate the conditional probability tables (CPTs) for each time node based on the retrospective data. Bayesian networks can portray the direct and indirect dynamic effects between the nodes of interest based on provided evidence, and compare the change in probabilities with and without an event. The evidence means that the probability of a state of a certain node is known or instantiated. When providing evidence for certain nodes, the probability of the states of others nodes may be updated depending on their structural connection. To analyze the positive or negative causal effects between different mobility decisions and states given evidence for other nodes, both the updated probability and the relative probability differences are calculated. The relative probability differences are defined as the difference between the updated and prior probability divided by the prior value. Assume the prior probability of a certain state of a variable x is p_0, the updated probability is p', the relative probability difference p_{diff} is calculated as follows,

$$p_{diff} = \frac{p_0 - p'}{p_0} \tag{3}$$

The relative probability difference can be negative or positive, which means that the probability of the predicted event decreases or increases given the evidence of certain variables/events. A value close to 0 means that the predicted event is not influenced by the given variables/events.

The conditional probabilities in DBN reflect the effects of state variables between time slices. The relevant conditional probability tables, which describe the temporal interdependencies between different life domains, are shown in the following sections.

6.4.2.1 Mobility decisions change for different age categories

Taking age as the parent node, both the updated probability and the relative probability differences of various mobility changes (shown in parentheses) are presented in Table 6.1. It is found that age has a direct impact on residential and job mobility decisions as well as car ownership change. As a socio-demographic variable, 'age' was categorized into four categories: under 25, 25-34, 35-50, and over 50. For the category age under 25, the probability of change is positive for all mobility decisions, indicating that young people are more likely to change their current residence, job and car ownership. The biggest relative probability difference among these mobility decisions is for the job domain, which suggests that the probability of changing job is bigger for younger generations. In contrast, people aged 25-34 and 35-50 are more likely to have a stable life and are less likely to change their current status. Our results indicate that people aged over 50 also change residence, job and car. The reason may be that, compared to those aged 25-50, people aged over 50 may have more money and time, thus having the capability and willingness to choose their favorable house/job or to buy a new car. However, the size of change is much smaller than that of young people, which suggests that young people (aged under 25) are instable in both the labor and housing market, and change more frequently than other age groups. This result is consistent with the findings of other studies, including Habib, et al. (2011), which also found that younger people are more likely to change job than older people.

6.4.2.2 Mobility decisions change given different levels of family structure change

Given family structure change as the parent node, the updated probability and the relative probability differences of various mobility are presented in Table 6.2. Here, '*t*' indicates the year when a certain event occurred; '*t*-1, *t*-2' indicate one-year and two-years ahead of the event, and '*t*+1, *t*+2' indicate one-year and two-year later than the event. It shows that various life course mobility decisions are strongly influenced by family structure change. This finding emphasizes the importance of family structure change as a trigger of people's relocation and car ownership change.

Table 6.1 Conditional probability distribution of various mobility decisions for different age categories

Age	Residential mobility	Job mobility	Car ownership change
No evidence	8%	9%	13%
<25	19% (141.7%)	38% (322.2%)	33% (153.3%)
26-34	7% (-9.1%)	11% (22.2%)	12% (-6.7%)
35-50	7% (-9.1%)	7% (-22.2%)	12% (-6.7%)
>50	10% (25.0 %)	11% (22.2%)	19% (46.7%)

Table 6.2 Transition probability of various mobility change given evidence of life events

Family structure change		Residential mobility (*t*)	Job mobility (*t*)	Car ownership change (*t*)
No change		8%	9%	13%
	t-2	17% (112.5%)	14% (55.6%)	37% (184.6%)
	t-1	18% (125.0%)	24% (166.7%)	36% (176.9%)
Getting married	*t*	41% (412.5%)	21% (133.3%)	37% (184.6%)
	t+1	19% (125.0%)	23% (155.6%)	30% (130.8%)
	t+2	17% (112.5%)	21% (133.3%)	31% (138.5%)
	t-2	20% (150.0%)	18% (100.0%)	29% (123.1%)
	t-1	23% (187.5%)	17% (88.9%)	28% (115.4%)
Child birth	*t*	16% (100.0%)	15% (66.7%)	31% (138.5%)
	t+1	24% (200.0%)	17% (88.9%)	32% (146.2%)
	t+2	18% (125.0%)	17% (88.9%)	30% (130.8%)

The conditional probability table shows that both marriage and child birth have a positive effect on residential mobility decisions, which is consistent with existing findings. However, effects differ in size at different time instances. In general, child birth has larger effects on residential mobility than getting married. Obviously, the birth of a child implies new responsibilities. As a consequence, household may be more likely to find a larger house in response to the increase in household size. The biggest probability change occurs for getting married at time t (dramatic increase from 8% to 41%), which indicates that the concurrent effect of getting married is larger than both the lagged and lead effects. However, a reverse effect was found between child birth and residential mobility, with lagged and lead effects both being larger than the concurrent effects. This means people are more likely to move house in the year of marriage, but less likely when a child is born. This is understandable considering that arrangements for having a child and moving house in the same year may not be easy. Additionally, the comparison between probabilities change across different time slices shows that one-year temporal effects are in general larger than two-year temporal effects for both lagged and lead effects.

In terms of job mobility, concurrent, lead, and one-year lagged effects (*t*-1) of a child are found in general smaller than the effects of getting married. In addition, the comparison between different time instances shows that both lagged and lead effects of having a child (17%) are larger than the effect at time *t* (15%). However, the same effects are not found for getting married.

Table 6.3 Transition probability of car ownership change given evidence of residential and work change

Mobility decision		Car ownership change (*t*)
No change		13%
Residential mobility	*t*-2	29% (123.1%)
	t-1	29% (123.1%)
	t	31% (138.5%)
	t+1	19% (46.2%)
	t+2	17% (30.8%)
Job mobility	*t*-2	27% (107.7%)
	t-1	30% (130.8%)
	t	28% (115.4%)
	t+1	19% (46.2%)
	t+2	16% (23.1%)

Table 6.4 Transition probability of residential/work location at time t given location at time t-1 and mobility decisions

		Residential location (*t*)	Job location (*t*)
Mobility decisions		Change home	Change job
No evidence		62%	69%
Residential location (*t*-1)	Job location (*t*-1)	(central city)	(central city)
Central city	central city	73% (17.7%)	88% (27.5%)
Central city	surrounding area of the city	68% (9.7%)	75% (8.7%)
Surrounding area of the city	central city	60% (-3.2%)	47% (-31.9%)
Surrounding area of the city	surrounding area of the city	21% (-66.1%)	22% (-68.1%)

Table 6.5 Transition probability of commuting time at time *t* given commuting time at time *t*-1 and various mobility decisions

Mobility decisions		Residential mobility(*t*)		Job mobility (*t*)		Car ownership change (*t*)	
	No evidence	8%		9%		13%	
Commuting time (*t*-1)	<20 min	8%	(0.00%)	8%	(-11.10%)	12%	(-6.67%)
	20-40 min	7%	(-16.67%)	10%	(11.10%)	12%	(-6.67%)
	41-60 min	9%	(8.33%)	10%	(11.10%)	14%	(6.67%)
	>60 min	9%	(16.67%)	10%	(11.10%)	14%	(6.67%)

6.4.2.3 Mobility decisions change given different levels of commuting time

Considering the role of commuting time in different mobility decisions, Table 6.5 presents the probability change of various mobility decisions at time *t* given evidence of commuting time at time *t* -1. Commuting time is categorized into four levels: less than 20 minutes, 20-40 minutes, 41-60 minutes, and longer than one hour. Results show that commuting time is a factor influencing people to change residence, job and car ownership. In general, the longer the commuting time, the higher the probability people move house, change job or car. More specifically, the probability of moving house or changing car increases when commuting time is longer than 40 minutes. For changing job, the probability increases when commuting time exceeds 40 minutes. It indicates that longer commuting time increases the probability of changing job. This conclusion is in line with the previous findings by Habib, et al., (2011). However, it should be noted that, compared with the results of various life course mobility decisions, effects of commuting time are relatively small. This probably indicates that these long-term decisions are more dependent on anticipated life course events than on travel-related attributes like commuting time.

6.5 Conclusions and discussion

Research on long-term mobility decisions has received increasing interest lately. People hold a series of aspirations related to different life domains. In an attempt to better understand the decision-making process, this chapter proposed an integrated framework to comprehensively explore the interdependencies between various life domains. In addition, because people have different needs at different life stages, interdependencies between life events and mobility decisions may change over time. To incorporate the time dimension into life course analysis, a dynamic Bayesian network was estimated.

The model results evidence the existence of concurrent and temporal interdependencies between different mobility decisions. Both getting married and child birth are found to increase the probability of residential/job/car ownership change. Likewise, both residence and job relocation are found to have positive effects on car ownership change, indicating that either moving house or changing job may increase people' needs to purchase/replace a car.

In terms of the relevance of long-term policy interventions, people's mobility decisions over the life course cannot be ignored. Results also show that temporal one-year effects are larger than two-year effects for both lagged and lead effects.

Despite the relevance of the approach, a limitation of the current analysis is its focus on the individual as the decision-making unit. However, in reality, it is more likely that life trajectory decisions of households, who physically share resources such as house, income and cars (Roorda, et al., 2009; Timmermans and Zhang, 2009), are made at the household level. To contribute to the further development of the relatively thin line of research on household decision-making, temporal interdependencies between various life course mobility decisions for household members are examined in the next chapter.

7

Temporal Dependencies in Mobility Decisions: A Household-level Analysis[3]

7.1 Introduction

In the previous two chapters, a life course approach has been introduced to examine the interdependencies between key life events, long-term mobility decisions such as residential move, job change and change in vehicle possession. However, to deepen the understanding of the temporal interdependencies between different life domains, further analyses are necessary. The previous two chapters were conducted based on individuals, without considering the possible influence of other household members. However, as members in a household physically share various household resources, some of these long-term decisions affect them equally, while job change affects them differently because their job location likely differs. Thus, as a natural extension to the previous chapter, this chapter contributes to the literature by modelling long-term

[3] *This chapter is based on the article:*
Guo J., Feng T., Zhang, J., Timmermans H.T.P. (2020). Temporal interdependencies in mobility decisions over the life course: a household-level analysis using dynamic Bayesian networks, JournalJournal of Transport Geography, Vol 82.

mobility of dual-earner households, looking into the temporal dependencies between various life domains: child birth, residential change, job change, and car ownership change. Moreover, gender analyses will be conducted in this chapter. We analyze to what extent child birth affects life trajectories in other domains of wives and husbands, and how the status of wives and husbands affects household decisions.

The remainder of this paper is organized as follows. Section 7.2 presents the structure of the integrated model that explicitly incorporates time-dependent dependencies within and between different life domains, using households as the observed decision-making unit. Section 7.3 discusses the retrospective survey that was used to collect the life trajectory data of households. The model results are presented and interpreted in Section 7.4. Finally, concluding remarks are made regarding results, policy implications and future research.

7.2 Methodology

7.2.1 Background

Long-term decisions such as residential and job choice are high involvement decisions that have long-term repercussions on people's daily life. These decisions tend to co-depend on past and future decisions across different life domains. The aim of this chapter is to uncover these dynamic interdependencies between household long-term mobility decisions in various life domains. In particular, we focus on residential mobility (moving house), job mobility (changing job) and car ownership mobility (change in car possession). We use one year as the time unit. If any event occurs more than once in a single year, we take the last event into account. For example, if individuals reported they changed job three times within one year, we take the state of the last event as input to the Bayesian decision network.

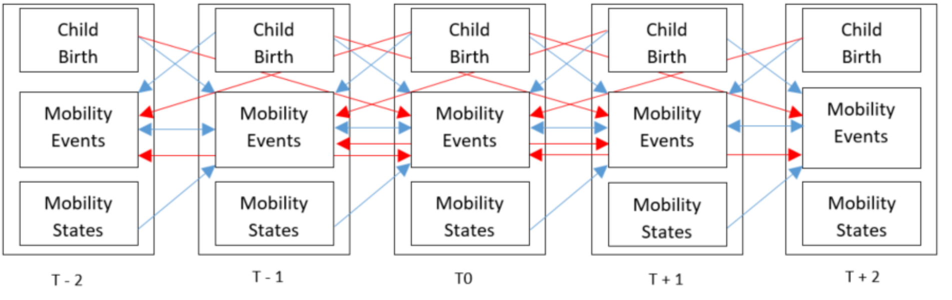

Figure 7.1 Network structure

7.2.2 Network structure

The network structure is shown in Figure 7.1. As discussed, the framework includes dynamics, time dependence, and interrelationships between long-term decisions. With respect to temporal interdependencies between different long-term mobility decisions, it is assumed that child birth may have both 1 and 2 years lagged and lead effects on the long-term mobility decisions. Thus, for example, mobility events such as residential and job relocation may have lagged, concurrent and lead effects on car ownership change. Lastly, mobility states such as income and commuting time are assumed to have direct impacts on various long-term mobility decisions. For example, people may take different actions such as changing job, moving house, and purchasing/changing cars to avoid excessive commuting time.

7.2.3 Learning

Given a dataset, developing a DBN requires two steps: learning the network structure and estimating the parameters of the learned network structure. A semi-structure learning process was adopted in this study. A more detailed explanation of the learning process is discussed in section 6.2.3.

Moreover, to simplify the network structure and avoid unrealistic relationships, plausible constraints were set. In particular, child birth may affect residential change, job change for both wives and husbands, and car ownership change. However, the reversed effects are not allowed. Thus, unidirectional effects were set between child birth and various long-term decisions.

7.3 Data analysis

7.3.1 Data collection

In order to analyze the temporal effects between various life course household mobility decisions, retrospective life course data were used in this research. Except for socio-demographic information of each household member, data about life course events were collected. In particular, the following events were included in the data collection: child birth, residential moves, car ownership change and job change of each spouse. In addition, because these were assumed to be important influential variables, annual income/and commuting time of both spouses were collected. A single respondent provided the data of both spouses. This may be less ideal, but arranging interviews with two spouses would have been much more demanding and not worthwhile. In order to reduce respondent burden, respondents were asked to provide information about the life events for only the last five times it occurred. In many cases, this maximum of five still covers the full trajectory of life events in a particular domain, particularly for younger respondents.

Considering the aim of the study, we restricted our sample to respondents belonging to dual earner households. Ultimately, 266 respondents were used in the analyses. The response rate is 16%, which is satisfactory, considering the unannounced contacting of possible respondents, the high percentage of non-eligible respondents.

7.3.2 Sample description

As shown in Table 7.1, the sample consists of 138 (51.9%) females and 128 (48.1%) males. The average age is 38.2, while on average are younger than their husbands. Average household size is 3.2 persons. 12.8% of the couples have no children; 5.6% have two children, while the remaining 81.6% has one child. These statistics indicate that some households involved three generations.

Table 7.1 Sample description

Variable	Classification	# of Cases	Percentage (%)
Gender	Female	138	51.9
	Male	128	48.1
Age	<35	97	36.5
(Wife)	35-50	128	48.1
	>50	41	15.4
(Husband)	<35	66	24.8
	35-50	152	57.1
	>50	48	18.0
Marital Status	Couple with no child	34	12.8
	Couple with one child	217	81.6
	Couple with two children	15	5.6

Table 7.2 presents the descriptive statistics for the main life course events. 22.9% of the respondents never changed residence; 41.4% changed only once, 25.2% changed twice and only about 10.5% moved house more than 2 times. In case of car ownership change, 33.5% of the respondents never had a car in their household; 43.2% had one car but never changed; 14.4% reported to have changed cars once, while the remaining 5.7% changed cars more than once in the past. Moreover, data of job change were collected for both spouses. As shown in Table 7.1, wives changed job less often than husbands.

Table 7.2 Descriptive statistics of the life course events

Variable	Classification	# of Cases	Percentage (%)
Residential change	Never moved house	61	22.9
	Moved house once	110	41.4
	Moved house twice	67	25.2
	Moved house three times	19	7.1
	Moved house more than three times	9	3.4
Job change	Never moved job	78	29.3
(Wife)	Moved job once	156	46.2
	Moved job twice	46	17.3
	Moved job three times	14	5.3
	Moved job more than three times	5	1.9
(Husband)	Never moved job	54	20.3
	Moved job once	130	48.9
	Moved job twice	58	21.8
	Moved job three times	18	6.8
	Moved job more than three times	6	2.3
Car ownership change	Never had any cars	89	33.5
	Always had the same vehicle	115	43.2
	Change cars once	47	14.4
	Change cars twice	14	5.3
	Change cars more than two times	1	0.4

7.4 Results and analysis

7.4.1 Results of structure learning

The Bayesian search algorithm was used in the structure learning process within one time slice. The prior link probability was set as the default value 0.001 for the structure learning process. The learned structure network for the one-time slice is shown in Figure 7.2 (left). Concurrent effects between various household mobility decisions are shown as two aspects. First, as we expected, child birth has direct effects on various household mobility decisions such as residential change, car ownership change, and job change for both husband and wife. Second, the learned structure network indicates that moving house and changing job for both wife and husband have direct effects on household car ownership change. Lagged and lead causal relationship between various household mobility decisions discussed in section 7.3 are represented in Figure 7.2 (right) and 7.3 respectively. 1-year temporal effects are shown by the blue lines, while 2-year temporal effects are shown by red lines.

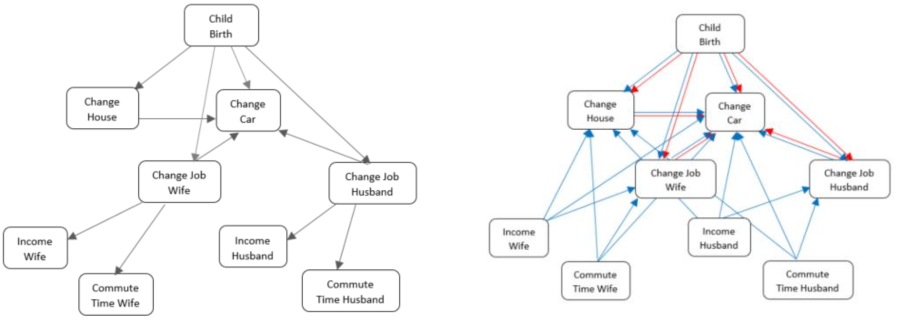

Figure 7.2 Learned network structure of concurrent effects (left) and lagged effects (right)

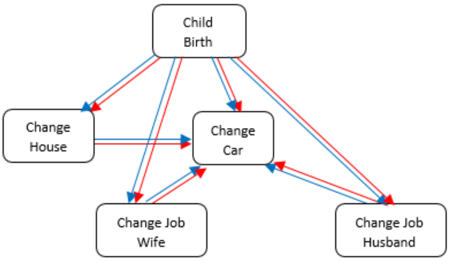

Figure 7.3 Network structure of lead effects

7.4.2 Results of parameter learning

Based on the network structure shown in Figure 7.1, the EM algorithm was applied to estimate the time-dependent conditional probability tables (CPTs) for all nodes and time slices. In this paper, both the updated conditional probability and relative probability differences are calculated.

7.4.2.1 Household mobility decisions given child birth

The effects of child birth on different household mobility decisions are presented in Tables 7.3 and 7.4. Tables 7.3 and 7.4 show that child birth positively influences different mobility decisions in households. However, the effects differ in size for different decisions. Looking at the conditional probability table, the effects on residential change and car ownership change are much stronger than the effect on job change for both wife and husband in dual-worker households. The birth of a child implies new responsibilities. Consequently, household are more likely to find a larger house/change car in response to an increase in household size.

Table 7.3 Conditional probability and probability difference (in parentheses) of residential mobility and car ownership change given different levels of child birth

Mobility decisions	Residential mobility	Car ownership change
No child birth	9%	13%
t-2	19% (111%)	24% (85%)
t-1	20% (122%)	30% (131%)
t	17% (89%)	32% (146%)
t+1	27% (200%)	30% (131%)
t+2	24% (167%)	28% (115%)

Table 7.4 Conditional probability and probability difference (in parentheses) of job mobility given different levels of child birth

Mobility decisions	Job mobility (Wife)	Work mobility (Husband)
No child birth	10%	9%
t-2	18% (80%)	13% (44%)
t-1	12% (20%)	12% (33%)
t	13% (30%)	12% (33%)
t+1	12% (20%)	12% (33%)
t+2	14% (40%)	11% (22%)

In addition, the temporal effects of child birth are shown to differ in size between the long-term mobility decisions in different life domains. Specifically, results show that both the 1-year lagged and lead effect are much bigger than the 2-years temporal effects. In addition, the lead effects (t+1/t+2) are in general larger than the lagged effects (t-1/t-2), suggesting that residential change/car ownership change is more likely to occur in anticipation of a household structure change in the current study.

However, a reverse result is found for car ownership. A child birth increases the probability of a change in car ownership mostly in the same year. The two-year lag effect is much smaller than the 2-year lead effect, while the one-year lead and lag effects are the same. It suggests that child birth tends to immediately increase people's mobility needs and hence their tendency of purchasing an (additional) car.

In case of changing job, results show that both the lagged and lead effect as well as the concurrent effect of child birth on changing job for both wife and husband are much smaller than the effects on other life course mobility decisions. It means that childbirth tends to primarily increase the need for a larger dwelling and/or a more convenient transportation option. Although the set of responsibilities of both wife and husband may increase due to a new-born baby, there is no strong evidence that household members will change their job. Moreover, a noticeable finding is that both the 2-year lagged and lead effects for the wife are bigger than the 1-year and concurrent effects, indicating that wives need more time to change job before/after giving birth to a child as a similar result is not found for husbands.

7.4.2.2 Car ownership change given residential and job change

Tables 7.5 and 7.6 show the results of the relative probability differences given evidence of various household mobility decisions. The lagged, lead and concurrent effects of residential and job change for both wife and husband are found to positively influence car ownership change. In general, concurrent effects are stronger than lagged and lead effects on car ownership change.

Taking a closer look at the different temporal effects on various mobility decisions, results show that the conditional probability of car ownership change is nearly double the prior probability. Moreover, the updated CPTs show that concurrent and lagged effects are slightly larger than the lead effects. Only minor differences are found between wife and husband. However, when both wife and husband change their job, the probability for households buying or changing car increases dramatically.

Table 7.5 Conditional probability and probability difference (in parentheses) of car ownership change given different levels of residential mobility

Mobility decision	Car ownership change
No change	13%
t-2	28% (115%)
t-1	28% (115%)
t	30% (131%)
t+1	25% (92%)
t+2	25% (92%)

Table 7.6 Conditional probability and probability difference (in parentheses) of car ownership change given different levels of job mobility

Mobility decision	Car ownership change		
No change		13%	
	Wife	Husband	Both wife and husband
t-2	20% (54%)	21% (62%)	35% (169%)
t-1	21% (62%)	22% (69%)	39% (200%)
t	23% (77%)	23% (77%)	38% (192%)
t+1	21% (62%)	22% (70%)	36% (177%)
t+2	21% (62%)	21% (62%)	34% (162%)

7.4.2.3 Household mobility decisions given wife and husband's commuting time

Our conceptual model assumed that commuting times of household members may influence long-term residential change, job change and car ownership change. Several interesting findings are found in this analysis (shown in Tables 7.7, 7.8 and 7.9). First, as expected, wife and husband's commuting times differently influence household residential change and car ownership change. In case husbands have excessive commuting times (more than 1 hour) while wives have a relative long commuting time (40-60 minutes), residential change and car ownership change increase to 14% and 18%, respectively. However, when the wife has more than 1 hour travel time, while the husband has 40-60 minutes commuting time, the probability of change is small (only 5% and 12%, respectively). This means that the probability of residential change and car ownership change increase when wife and husband both face relative long commuting times. However, the magnitude of this effect varies between household members.

Table 7.7 Conditional probability and relative probability differences (in parentheses) of residential mobility at time *t* given commuting time at time *t* -1 of the spouses

Mobility decision		Residential mobility
No change		9%
Wife	Husband	
< 20 min	< 20 min	11% (26%)
	20-40 min	9% (0%)
	41-60 min	11% (21%)
	>60 min	14% (53%)
20-40 min	< 20 min	8% (-11%)
	20-40 min	6% (-32%)
	41-60 min	7% (-21%)
	>60 min	10% (5%)
41-60 min	< 20 min	10% (16%)
	20-40 min	10% (11%)
	41-60 min	12% (32%)
	>60 min	14% (58%)
>60 min	< 20 min	14% (58%)
	20-40 min	10% (5%)
	41-60 min	10% (5%)
	>60 min	13% (42%)

Second, in dual-earner household, the probability of moving house dramatically increases if the residential location is very close to one worker but quite far away from the other worker's job location. For example, as shown in Table 7.8, in case the commuting time is less than 20 minutes for the wife and more than one hour for the husband respectively, the probability of moving house is increased to 14%. Similar results can be found for car ownership mobility change. Lastly, if at least one household member has a relatively short commuting time (20-40 minutes), the probability to move house and change cars are relatively low.

Given different levels of commuting time for wife and husband, results show that excessive commuting times do increase the probability of job change. However, this effect differs between wives and husbands. As shown in Table 7.9, wives are more sensitive to long commuting times (more than 40 minutes) than husbands, and consequently more likely to change job. In this regard, wives and husbands may take different actions when faced with excessive commuting times. In case only husbands face an excessive commuting time, dual-worker households have a larger probability to move to a new house or switch to a more convenient transportation mode (53% and 35% increase of probability, respectively). However, if only the wife is facing an excessive commuting time, they are more likely to change job instead of moving house or changing car ownership.

Table 7.8 Conditional probability and relative probability differences (in parentheses) of car ownership change at time *t* given different levels commuting time at time *t* -1 of the spouses

Mobility decision		Car ownership change
No change		13%
Wife	Husband	
< 20 min	< 20 min	15% (12%)
	20-40 min	14% (8%)
	41-60 min	16% (20%)
	>60 min	18% (35%)
20-40 min	< 20 min	11% (-20%)
	20-40 min	10% (-27%)
	41-60 min	11% (-15%)
	>60 min	14% (4%)
41-60 min	< 20 min	15% (15%)
	20-40 min	14% (8%)
	41-60 min	15% (15%)
	>60 min	18% (35%)
>60 min	< 20 min	16% (23%)
	20-40 min	13% (0%)
	41-60 min	15% (12%)
	>60 min	18% (35%)

Table 7.9 Conditional probability and relative probability differences (in parentheses) of job mobility at time *t* given different levels commuting time at time *t* -1 of the spouses

Mobility decision	Job mobility (Wife)	Job mobility (Husband)
No change	10%	
< 20 min	4% (-56%)	6% (-38%)
20-40 min	9% (-11%)	8% (-25%)
41-60 min	12% (22%)	9% (-13%)
>60 min	14% (37%)	13% (34%)

Table 7.10 Conditional probability and relative probability differences (in parentheses) of residential mobility at time *t* given different levels of annual income at time *t* -1 of the spouses

Mobility decision		Residential mobility
No change		9%
Wife	Husband	
<40,000 yuan	<40,000 yuan	8% (-11%)
	50,000-80,000 yuan	7% (-21%)
	90,000-150,000 yuan	11% (21%)
	>150,000 yuan	14% (58%)
50,000-80,000 yuan	<40,000 yuan	8% (-11%)
	50,000-80,000 yuan	6% (-32%)
	90,000-150,000 yuan	9% (0%)
	>150,000 yuan	12% (32%)
90,000-150,000 yuan	<40,000 yuan	15% (68%)
	50,000-80,000 yuan	13% (42%)
	90,000-150,000 yuan	16% (74%)
	>150,000 yuan	19% (116%)
>150,000 yuan	<40,000 yuan	17% (90%)
	50,000-80,000 yuan	16% (79%)
	90,000-150,000 yuan	19% (116%)
	>150,000 yuan	22% (147%)

7.4.2.4 Household mobility decisions given wife and husband's annual income

The difference in probabilities of various life course mobility decisions given different levels of annual income for both wife and husband are shown in Tables 7.10, 7.11 and 7.12. Results show that households with a high income have a larger probability to move house and change car. The probability of moving house and of changing car for both wives and husbands with the highest annual income (more than 150,000 yuan/year) are 8.7 times and 3.4 times higher than for households with the lowest annual income (less than 40,000 yuan/year for both wife and husband). Another notable finding is that the wife's income plays an important role in various household mobility decisions. Households with the wife having the lowest annual income (less than 40,000 yuan/year) and the husband having the highest annual income (more than 150,000 yuan/year) have a 14% probability of moving house. On the other hand, the probability of moving house for households with the same total annual income but different contribution between members (i.e. wife has the highest and husband has the lowest annual income) is 17%. Similar results are found for car ownership change.

Table 7.11 Conditional probability and relative probability differences (in parentheses) of car ownership change at time *t* given different levels of annual income at time *t* -1 of the spouses

Mobility decision		Car ownership change
No change		13%
Wife	Husband	
<40,000 yuan	<40,000 yuan	13% (-4%)
	50,000-80,000 yuan	11% (-15%)
	90,000-150,000 yuan	14% (10%)
	>150,000 yuan	17% (31%)
50,000-80,000 yuan	<40,000 yuan	12% (-8%)
	50,000-80,000 yuan	10% (-23%)
	90,000-150,000 yuan	12% (-8%)
	>150,000 yuan	10% (-23%)
90,000-150,000 yuan	<40,000 yuan	19% (46%)
	50,000-80,000 yuan	16% (19%)
	90,000-150,000 yuan	19% (46%)
	>150,000 yuan	22% (69%)
>150,000 yuan	<40,000 yuan	21% (62%)
	50,000-80,000 yuan	19% (46%)
	90,000-150,000 yuan	23% (73%)
	>150,000 yuan	24% (85%)

Table 7.12 Conditional probability and relative probability differences (in parentheses) of job mobility at time *t* given different levels of annual income at time *t* -1 of the spouses

Mobility decision	Job mobility (Wife)	Job mobility (Husband)
No change	10%	9%
<40,000 yuan	17% (67%)	10% (8%)
50,000-80,000 yuan	9% (67%)	7% (25%)
90,000-150,000 yuan	8% (-22%)	3% (-63%)
>150,000 yuan	12% (22%)	2% (-75%)

Likewise, wife and husband's income have a direct influence on the decision of changing job. In general, the probability of changing job is relatively high for people with a relatively low income. Income has a different effect on the decision to change job for wives and husbands. When both household members have the lowest annual income (less than 40,000 yuan/year), wives have a larger probability of changing job (67% vs. 8% respectively). When having a high-paid job (150,000 yuan/year), the probability for husbands to change job is lower than for wives.

7.5 Conclusions and discussion

Life course analysis is a rich approach to analyze and model the interdependencies among a set of lifetime events. In contributing to this emerging field of study in transportation research, this chapter reports the main findings of a dynamic Bayesian Network derived from life trajectories of dual-earner households, considering lagged, concurrent and lead effects, in part separately for husbands and wives. Four life course domains (child birth, residential change, job change for both wife and husband, and car ownership change) are incorporated. In addition, commuting time and income of husband and wife are taken into consideration, in order to examine their potential influence on various household mobility decisions.

The model results point at some interesting findings. First, it suggests that wives need more time to change job before/after giving birth to a child. Second, the lagged, lead and concurrent effects of residential and job change for both wife and husband are found to positively influence car ownership change. Moreover, in case of the influence of changing job on car ownership change, only minor differences are found between husbands and wives. However, when both wife and husband change their job, the probability of buying or changing car increases dramatically.

These findings illustrate the richness of the suggested approach. Findings of this analysis in part confirm findings of earlier studies, mostly conducted in a European context. In addition, the differential effects complement earlier findings in life trajectory analysis, where the vast majority of studies did not involve households. Despite the convincing results, a caveat should be mentioned. Although time has been treated explicitly and some causal relationships have been constrained in the model, still Bayesian networks rely on observed co-occurrences in the data.

8

Conclusions and Discussions

Residential and job choice 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. Ignoring the effects of any long-term key events may lead to biased estimation results and therefore misleading policy recommendations or assessment of policy impacts. This PhD study therefore contributes to address an underdeveloped area of research on modeling the choice of multiple dimensions. The key assumption is that individuals and households consider different choice dimensions jointly.

This study provides insightful implication for urban planning and transportation study. First, transportation planners should realize that the decision on transportation may be considered jointly with other life domains. The results of our analyses have provided evidence that in the long-term decision context, travel behavior such as travel time appears to play a less important role. Second, people react differently to changes in life domains. Both observed and unobserved heterogeneities were observed. To the best of our knowledge, this is the first time to investigate heterogeneous preferences in the context of co-dependent mobility choices across different life domains. The results could provide useful information for planners and policy makers regarding the importance of dwelling and job market supplement of various segments of the population.

In addition, to broad our view from static to dynamic, this thesis develops an integrated framework for modelling the temporally interdependent choices related to residential change, job change and car purchasing decisions. According to our results, the proposed framework coincides with the life-oriented approach where the timing in mobility decisions play an important role. Individuals/households make their decisions based on their past experiences and future expectations. In terms of the dynamic interdependencies, concurrent and lagged effects were found larger than the lead effects, indicating that in general the probability of people taking an action to change before a triggering event is smaller than that after these events happen. Results also show that one-year lagged and lead effects are larger than two-year effects. Thus, this study sheds light on better understanding the mechanisms underlying long-term mobility decisions in response to various life course events.

Lastly, because people in a household physically share resources, most long-term decisions are household as opposed to individual decisions. In order to examine the potential influence of various household mobility decisions on wives and husbands, and how status of wives and husbands affects household decisions, a gender analysis of dynamics in life course decisions was conducted at the household level. The research contributes to the literature by providing insights into life course approach from a household perspective. To the best of our knowledge, this is the first time such a life course analysis is conducted at the households' level. Results added to the interpretability of the life course research findings in dual-earner households.

This PhD research addressed an underdeveloped area of research on modeling the co-dependent choice of multi-dimensional long-term mobility. As the complement to the single-domain oriented research, we jointly consider various key variables of different domains by presenting an integrated model between long-term residence choice, job choice, and short-term commute mode choices. However, there are still some rooms for extensions in further studies.

First, the current study is built based on the assumption that people will not change transportation modes only nor both houses or job 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.

Second, in the current study, we did not further examine to what extent the current situation influences the multidimensional choice decision. Individuals climb a ladder of a nicer house or job close to their expectation. Normally, people considered residential and job relocation carefully for process of moving house and changing job can be costly. Residential relocation may involve necessitate expenditure on selling their current house, removal old/purchase new furniture and redecoration of the new home. It also takes time to familiarize with the new working environment and colleagues. Furthermore, if people relocate to a remote area and lead to longer commute budget (both time and money), the process may involve family members changing job or children changing schools by force. In this context, if requisite gap (between the new residence/job and the current one) is not greater than the cost of changing, people do not consider move to the new house or change a new job. In other words, if the utility difference is too small, people will decline to change. Thus, in the future research, we plan to further examine to what extent the current situation influences the multidimensional choice decision.

Third, variance proportions explained by error terms in residential mobility, job mobility and car ownership change suggest that correlated unobserved factors simultaneously affect the decisions to move house, change job and the preferences to purchasing or changing cars, which clearly points to the need of incorporating various life course decisions in a simultaneous framework. In the future, more surveys and analyses are needed to capture the subjective factors such as attitudes and lifestyle preferences.

Fourth, related to the life-oriented approach, we have found that various life domains are interdependent. While future research may extend this analysis into different directions. If a larger sample can be obtained, the network can be realistically expanded with additional lifetime events, such as divorce, retirement, children enroll in school, etc. Further refinement can be obtained by including the aspects of daily activity-travel behavior. Moreover, rather than examining the mobility histories of dual-earner households, other household types can be studied.

Finally, this study brings insight into the case of Shenyang city in China, which is relatively larger in size and population than many western cities. Some conclusions drawn may be generalized for other cities with a similar context in their policy decision making. More case studies in different cities need to be carried out in future.

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Summary

Job-housing Co-dependent Mobility Decisions in Life Trajectories

An effective instrument of urban planning to alleviate congestion is to create a job-housing balance, which depends on the co-localisation of housing and labour. 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).

To mimic the complexity of the decision-making process under investigation in the real world, a stated choice experiment was designed to mimic the multidimensional choice behavior of interest. Instead of creating an experimental design that is the same for all respondents, we generated an efficient design in which attribute values were pivoted based on the real-world data of individual respondents.

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. Considering the aim of the study, we only interviewed respondents who had a job.

Based on data collected in Shenyang, China, a Mixed Multinomial Logit (MMNL) model with panel effects, which allows for unobserved heterogeneity in individual preferences, was estimated to capture the effects of different residential, work and commuting attributes on the multidimensional choice, accounting for the panel nature of the data. Our findings indicate that, 1) Housing tenure, size, price, distance to the

bus stop, housing location are important housing characteristics that help explaining the residential mobility choice process. Salary, work type, co-worker relationships and work environment are significant factors in the job mobility choice process. 2) Time-related factors influence commute mode choice. Choice of public transportation modes is sensitive to commuting costs while car mode choice is not. 3) People are relatively satisfied with their current situation and do not frequently make changes. Furthermore, people are less inclined to move house relative to changing job. 4) Unobserved heterogeneity and demographic characters both affect the multiple dimensions of choices.

Moreover, a latent class model was adopted to account for individuals' preference heterogeneity which assume a finite mixture of the latent groups to explore preference heterogeneity. Results based on a two-class model show that income is the main variable explaining class membership. The results of the heterogeneous behavior indicate that people with lower income are less likely to change their current house and/or job than people with higher income. In addition, people with lower income prefer public transportation modes over private cars. In terms of slow modes, people with lower income are more likely to cycling than walking. While these effects are shown reversely for people with higher income. These findings could provide useful information for planners and policy makers regarding the importance of dwelling and job market supplement of various segments of the population.

Third, to allow for the possibility that unobserved preferences for transportation models depend on long-term choice behavior, specific error components are identified and the variance of these error components is estimated through parameterization of their heteroscedasticity. Thus, we estimate an error component mixed logit model to identify random and systematic long-term choice specific heterogeneity. 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.

From a behavioral perspective, people's long-term mobility decisions may depend on their current situation, past experiences and/or future plans. Consequently, models of long-term mobility decisions should take lagged, concurrent and/or lead effects into account. In turn, long-term mobility decisions may be the consequence of particular events in other life domains. Contributing to the literature on long-term mobility analysis, this study develops an integrated framework for modeling the dynamic, interdependent choices related to residential move, job changes and mobility tools transactions. Using retrospective life trajectory data collected through a Web-based survey, a dynamic Bayesian network model is estimated. Results show that different life domains are highly interdependent. Concurrent, as well as lagged and lead effects of various mobility decisions are observed.

In addition, because people in multi-earner households share resources, most long-term decisions are made by more than one household member. Thus, to contribute to the further development of the relatively thin line of research in transportation studies, a dynamic Bayesian network approach is proposed from a household perspective. Results show that the effects of child birth are much larger on residential and car ownership change than on job change for both household heads in dual-earner households. Moreover, the probability of residential and car ownership change increases when both spouses have relatively long commuting times. In case only the husband faces an excessive commuting time, households have a larger probability of moving house or purchasing an additional car. By contrast, in case only the wife faces an excessive commuting time, she is more likely to change job rather than the household taking particular actions to adjust to the problematic situation.

Curriculum Vitae

Jia Guo was born on June, 1987 in Shenyang, China. She completed her bachelor and master degree in Urban Planning and Design at Shenyang Architectural University in 2011 and 2015, respectively. After obtaining her master's degree, she joined the Urban Planning and Transportation Group of the Department of Built Environment at TU/e and started working on her PhD project. Her primary research interests include travel behavior analysis, transportation planning, residential location choice, and household long-term decisions.

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I have got plenty of support along this journey. I would even wonder whether I can manage to go this long and accomplish my dissertation without all the help. First of all, I want to express my sincere thanks to my supervisor Prof. Harry Timmermans, who inspired this thesis, shared his expertise and ideas as well as gave me critical comments and advices. Working with him gives me a deep understanding about what makes a good researcher and I also found my role model for future career. Besides working, his attitudes towards life, optimism and great leadership also deeply influenced me.

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Living abroad for four years is a challenging but beautiful journey. Thanks to all my friends, who made me enjoy my time in the Netherlands. I have received lots of encouragement and friendship, and turned my PhD study into a wonderful experience. I will remember your support and help in work and life during these years forever. Thank you for all the great moments. I am grateful to you all!

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Jia Guo

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Publication List

Journal papers

Guo, J., Feng, T. and Timmermans, H.J.P. 2018. Modeling Co-dependent Choice of Workplace, Residence and Commuting Mode using An Error Component Mixed Logit Model. Transportation, Vol. 47, 911-933.

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Guo, J., Feng, T., Zhang, J. and Timmermans, H.J.P. 2019. Temporal Interdependencies in Mobility Decisions over the Life Course: A Family-Based Analysis Using Dynamic Bayesian Networks. 98th Annual Meeting of the Transportation Research Board (TRB), Washington DC, USA.

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