Personal social networks, neighborhood social environments and activity-travel behavior

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Personal Social Networks, Neighborhood Social Environments
and Activity-travel Behavior

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A thesis submitted in partial fulfilment of the requirements
for the degree of
Doctor of Philosophy

Principal Supervisor: Prof. WANG Donggen

Hong Kong Baptist University

April 2015
Declaration

I hereby declare that this thesis represents my own work which has been done after registration for the degree of PhD at Hong Kong Baptist University, and has not been previously included in a thesis, dissertation submitted to this or other institution for a degree, diploma or other qualification.

Signature:

Date: April 2015
Abstract

Rapidly rising levels of car ownership in newly developed economies and increasing travel demand worldwide over the past several decades have intensified the negative externalities of transportation, such as traffic congestion and air pollution. To develop policies that mitigate these problems through managing and controlling travel demand, it is important to have a comprehensive understanding of the determinants of individuals’ activity-travel behavior. A considerable amount of research has been conducted around the impact of the built environment on travel behavior. As well, over the past decade, the social contexts of travel have gradually been recognized as important explanatory factors of activity-travel behavior. Thus, the link between social contexts and activity-travel behavior has become a much discussed research topic recently. This study aims to contribute to this growing literature by investigating three important but under-explored areas related to the connection between social contexts and activity-travel behavior: 1) how social network attributes influence the choice of companions for conducting daily activities and travel; 2) how personal social networks and neighborhood social environments influence activity location choices and time use; and 3) how the dynamics of social networks and changes in residential social environments induce activity-travel behavior changes as a result of home relocation.

This study adopts a longitudinal design and uses both cross-sectional data and longitudinal panel data. Multivariate modelling approaches including Structure Equation Modelling (SEM), multilevel logistic regression and a doubly censored Tobit model are employed. Findings from this study show that social network variables are significant determinants in explaining individuals’ engagements in joint/solo activities/travel and choices of companions for joint activities. Social network attributes and neighborhood
social environments are also found to significantly influence individuals’ choices between in- and out-of-neighborhood locations for activities and time use. The study also demonstrates that changes in travel after residential relocation are induced by changes both in the built and social environments as well as the geography of social networks. These findings contribute to the knowledge about the social contexts of activity-travel behavior.
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Chapter 1 Introduction

1.1 Introduction

Over the past few decades, the vehicle ownership rate and overall travel demand have rapidly increased worldwide (Dargay et al., 2007; Millard-Ball and Schipper, 2011). The trend of increasing vehicle use is expected to continue into the future. Specifically, vehicle ownership in 2002 is predicted to increase 2.5 times by 2030 (Dargay et al., 2007). China is projected to have the fastest growth in vehicles of any country, with 2002 rates of vehicle ownership estimated to increase nearly twenty times by 2030 (Dargay et al., 2007). Total travel demand worldwide is also expected to grow. One prediction suggests that it will climb from 23 billion km in 1990 to 105 billion km by 2050 (Schafer and Victor, 2000). While increases in vehicle ownership and overall travel demand contribute to the development of the economy and modern society, they also introduce serious negative externalities, such as traffic congestion, air pollution, and releases of carbon, which exacerbates global warming. For designing effective policy schemes that can manage urban travel and reduce the negative externalities associated with travel, it is important to understand the underlying mechanism of individuals’ activity-travel behavior. As such, activity-travel behavior has become one of the most important topics for both academics and policy makers.

Research on travel behavior has evolved over time. Early research focused directly on “trips” without considering the reasons for the trips and the interdependences between them. In the 1970s, researchers began to realize the limitations of the traditional trip-based approach for capturing individuals’ responses to public policies (e.g., travel demand management policy such as congestion pricing) (Pinjari and Bhat, 2011). Consequently, the development of an activity-based approach began to gain substantial research attention and has now
become the dominant approach used in travel studies. Unlike the trip-based approach, the activity-based approach considers travel as a derived demand to perform activities and focuses on “activity participation behavior” (Bhat and Koppelman, 1999). Numerous activity-based model frameworks have been developed for modelling and predicting activity-travel behavior (Axhausen and Gärling, 1992; Pinjari and Bhat, 2011). Additionally, over the past few decades, much progress has been made in understanding activity-travel generation and scheduling in time and space, as well as interpersonal interactions in activity-travel decisions (Bhat and Koppelman, 1999; Pinjari and Bhat, 2011).

One important research method is collecting empirical data to investigate individuals’ activity-travel patterns and the factors that influence individuals’ activity-travel behavior. The built environment/urban form, one of the factors related to activity-travel behavior, has received much research attention over the past few decades due, in part, to the usefulness of research findings for public policies (see reviews: e.g., Ewing and Cervero, 2010, 2001; Stead and Marshall, 2001; van Wee, 2002). Results from studies on the built environment seem to consistently suggest that while controlling for socio-demographics and sometimes individuals’ travel-related attitudes and preferences, high-density and mixed land use are associated with shorter travel distances, less car use and more walking and cycling (e.g., Bagley and Mokhtarian, 2002; Boarnet and Crane, 2001; Cao et al., 2009; Ewing and Cervero, 2010; van Wee, 2002). These academic findings have led to major urban policy initiatives such as the Smart Growth strategies and Compact City policies aimed at reducing car use and motorized travel demand (Daniels and Daniels, 2001; Dieleman and Wegener, 2003).

A significant research frontier in transportation in the past decade is the social context of activity-travel behavior. Individuals are not isolated actors within a physical space but are instead members of social networks consisting of family members, relatives, friends, and colleagues. In recent years, leisure or social
activities and travel to meet others have consumed a substantial and increasing portion of daily activity-travel behavior (Larsen et al., 2006; Urry, 2003). The decisions about undertaking these activities and travel cannot simply be explained by the spatial contexts and socio-demographics. Because individuals conduct the social activities with their social network members, individuals’ social networks should be incorporated in studies to understand their social activity-travel behavior (Carrasco et al., 2008a). Researchers have also argued that social network members shape a person’s mental map and social network geography and thus may influence individuals’ activity-travel behavior (Axhausen, 2008).

Additionally, the neighborhoods where people live have both physical dimensions and social dimensions (Wang and Lin, 2013). Studies in sociology and other fields suggest that the neighborhood social environments where people live can influence individuals’ behavior by shaping norms, enforcing social control, providing opportunities or constraints to engage in certain behaviors and reducing or producing stress (Berkman and Kawachi, 2000). Therefore, to better understand individuals’ activity-travel decisions, it is important to consider the social contexts in which individuals live, such as their social networks and neighborhood social environments (Axhausen, 2008; Van Acker et al., 2010).

Exploring the social contexts of activity-travel behavior also has significant policy implications. For example, transportation policies aimed at increasing accessibility should not only consider access to facilities and places but also to individuals’ social network members so that social interactions can be facilitated (Carrasco and Miller, 2009). Policies that encourage network members to live closer to one another or that facilitate people’s social interactions with others living in the same neighborhood or nearby may reduce motorized travel demand.

During the past decade, researchers have paid significant attention to the social contexts of activity-travel behavior and made considerable progress in understanding activity-travel behavior. Numerous studies have examined the
linkages between personal social network attributes (e.g., size and composition) and social activity-travel generation and scheduling (e.g., Carrasco and Miller, 2006, 2009; Larsen et al., 2006; Moore et al., 2013; Tillema et al., 2010; Van den Berg et al., 2013, 2012a). The role of the geographical distance between network members in their social interactions has also been well documented (e.g., Larsen et al., 2006; Mok et al., 2010; Van den Berg et al., 2009). Studies have investigated the impacts of neighborhood social environments on activity participation and travel (e.g., Clark and Scott, 2013; McDonald, 2007; Wang and Lin, 2013). Nevertheless, many important questions related to activity-travel behavior remain unanswered. In particular, what are the impacts of personal social networks on overall activity-travel behavior, not only the impacts on social activities and travel? How does the spatial distribution of personal social networks generally affect activity-travel behavior? And how do the dynamics of personal social networks and neighborhood social environments influence individuals’ activity-travel behavior? This study contributes to advancing this rapidly growing literature.

1.2 Research objectives

The overall research objective of this study is to enrich the knowledge about the impact of social contexts, particularly personal social networks and neighborhood social environments, on activity-travel behavior. Specifically, this research has the following three objectives:

1) To examine the influence of personal social networks on general activity-travel behavior, extending beyond previous studies, which have mostly focused only on social activities and travel;

2) To explore the implications of the spatial distribution of personal social
networks for activity-travel behavior; and

3) To investigate how the dynamics of personal social networks and neighborhood social environments induce changes in activity-travel behavior.

1.3 Contribution to the literature

This dissertation contributes to the literature in several ways. It enriches the literature about the social contexts of activity-travel behavior in general. This study also specifically investigates the influence of social network attributes on activity-travel behavior in terms of “with whom” activities and travel are conducted. Moreover, this research examines the implications of the spatial distribution of social networks for activity location choices and time use. Additionally, this study analyzes the changes in activity-travel behavior in response to the dynamics of social networks and neighborhood social environments after home relocation.

1.4 Outline of the thesis

This dissertation is organized as follows. After the introductory chapter, the next chapter reviews the relevant literature on social networks, neighborhood social environments and activity-travel behavior. The review includes: 1) social networks and social activity-travel behavior; 2) social network geographies and social interactions; 3) neighborhood social environments and activity-travel behavior; and 4) dynamics of social networks, neighborhood social environments and activity-travel behavior. After that, research gaps that future studies should explore are discussed.

Chapter 3 discusses the research framework and methodology underpinning this study. The chapter begins with a theoretical discussion about why and how social
networks and neighborhood social environments may influence individuals’ activity-travel behavior. Then research hypotheses and the research framework are presented. This is followed by descriptions of the data collection and multivariate modelling approaches adopted in data analysis.

Chapter 4 is devoted to investigating how individuals’ personal social network attributes influence their engagements in joint/solo activities/travel and choice of companion for joint activities/travel. The data are analyzed using the Structure Equations Model. Chi-square difference tests are first used to assess the importance of the social network variables in explaining joint/solo activity-travel behavior and companion choices. After that, this chapter estimates the final model and discuss the modelling results.

Chapter 5 investigates how social network attributes and the social environments of the residential neighborhood influence individuals’ choices between in- and out-of-neighborhood locations for discretionary activities and time allocation. This chapter first uses a multilevel logistic model to estimate the influence of personal social networks and neighborhood social environments on the choice between in- and out-of-neighborhood locations for discretionary activities. Then, a doubly censored Tobit model is estimated to test the impact of social network variables and neighborhood social environments on the time allocation between in- and out-of-neighborhood discretionary activities.

Chapter 6 analyzes how changes in social networks and neighborhood social environments associated with residential relocation induce changes in travel, controlling for changes in the built environment and socio-demographics. Descriptive analysis of changes in social networks and neighborhood social environments, as well as car ownership and travel behavior are first presented. Then contribution of the dynamics of social networks and neighborhood social environments to explaining changes in travel are tested using Chi-square
difference tests. After that, the structure equations modelling results are discussed.

The final chapter of this dissertation is concluding remarks based on the empirical analyses. Chapter 7 first presents a summary of the main findings in this research. After that, this chapter discusses policy implications, limitations and recommendations for future research.
Chapter 2 Social contexts of activity-travel behavior: the state of the art

This chapter includes an extended review of the relevant literature to provide the academic background and justification for this study. It begins with a discussion of the existing literature on personal social networks and activity-travel behavior. Then, the literature on social network geographies and social interaction is examined followed by a review of the literature on neighborhood social environments and activity-travel behavior. Previous studies investigating the dynamics of social networks, neighborhood social environments and activity-travel behavior are discussed afterward. Lastly, this chapter identifies the research gaps that future studies should explore.

Travel is a derived demand from performing out-of-home activities distributed in space and time (Axhausen and Gärling, 1992; Bhat and Koppelman, 1999). To better understand travel, the behavior contexts that constrain or facilitate performing activities in certain locations at given times must be studied first (Axhausen and Gärling, 1992; Bhat and Koppelman, 1999; Pinjari and Bhat, 2011). These behavior contexts consist of all the factors that influence why, how, when, where and with whom activities are conducted (Pinjari and Bhat, 2011). These factors include social contexts such as personal social networks and neighborhood social environments (Miller, 2005; Neutens et al., 2011; Van Acker et al., 2010).

2.1 Personal social networks and activity-travel behavior

Personal social networks are “a set of actors (nodes) and a set of relationships connecting pairs of these actors” (Tindall and Wellman, 2001: 266). In this dissertation, these actors refer specifically to people. The core objective of
analyzing personal social networks is “to understand how social structures facilitate and constrain opportunities, behaviors, and cognitions” (Tindall and Wellman, 2001: 266).

Previous travel studies explained individuals’ activity-travel behavior mainly with factors including individuals’ socio-demographics (e.g., Hanson, 1982; Lu and Pas, 1999), the built environment/urban form (e.g., Boarnet and Crane, 2001; Ewing and Cervero, 2010; van Wee, 2002), lifestyle (e.g., Collantes and Mokhtarian, 2007; Kitamura, 2009; Salomon and Ben-Akiva, 1983), travel time and travel cost (e.g., Akar et al., 2011; Gunn, 2001) and lifecycle events, such as residential relocations and job changes (e.g., Oakil et al., 2014; Scheiner and Holz-Rau, 2013a; Sharmeen et al., 2013). The absence of a social dimension of activity-travel behavior in the literature was recognized a decade ago when researchers began calling for more studies to incorporate social dimensions in activity-travel behavior analysis (Axhausen, 2002; Axhausen, 2003; Harvey and Taylor, 2000).

Researchers pointed out the importance of examining the impact of the social dimensions on travel. Harvey and Taylor (2000) argued that individuals have a fundamental need for social interactions, and low social interactions at the workplace may lead people to pursue social interactions elsewhere, thus generating travel. Axhausen (2002) noted that individuals’ daily lives revolve around friends, family, work, school and shopping, and travel models need to consider the social structures of daily life. Urry (2003) attributed the large and increasing scale of social travel in recent years to the increasingly “networked” social life, which involves the combination of increasing distance and intermittent co-presence. Daily activity-travel behavior, especially social activities and travel, are embedded within individuals’ social networks; therefore, researchers argue that personal social networks and their spatial arrangements generate and determine individuals’ activity-travel behavior (Axhausen, 2008; Ohnmacht,
The recognition of the effects of the social aspects on travel has led to an emergence of an increasing body of literature examining the connections between social networks and social activity-travel behavior (Carrasco and Miller, 2006; Dugundji et al., 2011; Van den Berg et al., 2012a).

2.1.1 Social networks and social activity-travel generation

Numerous studies have examined the role of personal social networks in the generation of social activities and travel. A few of these studies have adopted the simulation approach. Páez and Scott (2007) simulated the influence of social contacts on the decision about whether to telecommute. Hackney and Axhausen (2006) presented a multi-agent simulation to study the interdependence between social network and travel behavior. Arentze and Timmermans (2008) developed a micro-simulation model to study the coevolution of the social network and social contacts based on the assumption that the utilities that individuals derive from social interactions are determined by the dynamic social and information needs and the similarities between the individuals involved.

While some studies have used the simulation approach, the majority of the existing literature examining social networks and social activity-travel behavior use empirical data. Carrasco and Miller (2006) applied the social network framework to investigate the effects of individuals’ social network attributes on their propensity to perform social activities, which is measured as the number of people with whom individuals perform social activities. Using the same dataset, Carrasco and Miller (2009) further examined the relevance of personal social networks to explain social activity-travel generation behavior in terms of the frequency of social interactions between social network members. Results from their studies suggest that incorporating personal social networks into an activity-travel behavior model framework improves the understanding of social
activity-travel generation. Carrasco and Miller (2006, 2009) contributed several findings on how social network size, composition etc. influences social activities. In particular, they found that having a large number of social network members significantly increases an individual’s propensity to perform social activities. In addition, the higher the proportion there is of certain types of people in egos’ social networks, the more the egos are willing to have frequent social activities with those types of people. They also found that the distance between individuals negatively relates to the frequency of social activities between them and that higher network densities positively relate to frequent social activities.

Other studies have also examined the impact of social networks on generating social activities and travel. Van den Berg et al. (2013) simultaneously considered the effects of land-use variables, social networks, the use of information and technology (ICT) and socio-demographics on social activity-travel generation. Findings from their studies show that social network size has positive effects on the number of social trips by different modes as well as the social travel distance, indicating that social networks generate social activities and travel. Using data collected with an iterative recruitment method, Silvis and Niemeier (2006) examined how social networks influence social travel behavior. Their results suggest that people are willing to travel longer distances for social activities than other types of activities, and a larger social network size leads to more social trips and more visits to other locations. Carrasco et al. (2008b) introduced a new framework with two concepts—agency and social accessibility—to understand the relationships between social networks, ICT use and travel. Agency is defined as an individual’s propensity to initiate social activity, and social accessibility is their capacity to initiate that activity. The empirical analysis found that individuals having a larger social network size and less fragmented network are typically more active in initiating social interactions with their network members.

Several studies have narrowly examined social networks for their influence on
people’s participation in clubs, the differences in social networks among ethnic groups, and the linkage between car ownership and social capital. Focusing on club activities, Van den Berg et al. (2012) analyzed the interrelationship between social network size and involvement in clubs or voluntary associations and found that having a large social network helps people become club or association members and then more frequently go to club activities. In return, frequent club or association activities increase the personal social network size as well. Ettema and Kwan (2010) compared the influence of social networks on participation in social and recreation activity between ethnic groups in the Netherlands and found that compared to native Dutch, ethnic minorities rely more on interactions with social ties for engagement in social activities. Carrasco and Cid-Aguayo (2012) studied the role of car ownership and receiving emotional and material support from social networks and found that car ownership does not directly influence the frequency of social interactions.

2.1.2 Social networks and social activity-travel scheduling

Apart from social activity-travel generation, research has also examined the effects of social network attributes on activity duration. Habib et al. (2008) and Habib and Carrasco (2011) examined the relationships between “with whom” social activities are performed and the start time and duration of social activity episodes. They found that the social activity start time and duration are mainly determined by “with whom” people socialize rather than the travel time or distances; meanwhile, travel times positively relate to longer durations and later start times. Van den Berg et al. (2012b) applied the latent class hazard model to examine the factors that explain the duration of social activities and found that the features of the social activities and the relationships between the people socializing are significant determinants.
Research has found that social network characteristics have other effects on the scheduling of social activities. Moore et al. (2013) analyzed the relevance of personal social network attributes in understanding the social activity duration, distance and number of participants, with a specific focus of the role of the social networks’ structure and the spatiality of all participants of activities. They found that inclusion of social network density, gender and age similarity and the social closeness of the people involved in social activities offer better explanations for the social activity duration and distance than a traditional framework with only socio-demographics. Deutsch and Goulias (2013) applied latent class cluster analysis to explore the connection between social network composition and the different roles individuals played within different social networks in the decision-making about where to participate in activities. Ettema and Zwartbol (2013) reported the relevance of the residential locations of the respondent and his/her friend on their location choices for two-person leisure trips.

2.2 Social network geographies and social interactions

Because people socialize with their social network members either through physically being together or through some other means of communication, it is important to incorporate the geographies of social network members to understand social interactions and travel (Axhausen, 2008; Ohnmacht, 2009). Social networks are, in general, becoming more spatially dispersed than ever before (Axhausen, 2003; Hazelzet and Wissink, 2012). As a consequence, travel distances between social network members have largely increased since the 1950s (Cass et al., 2005). In agrarian societies, social networks were rooted in communities where “everybody-knows-everybody” and where strong social relations existed within the community and contacts with those outside of the community were limited (Axhausen, 2003). With the development of industrialization, urbanism and urban sprawl, neighborhoods have largely been changed. The dispersion of work,
residences and recreation has undermined the role of the neighborhood as the main source of social relations. People’s social networks and activities are now much more widely distributed, which has led to a “loss of community” and crisis of social cohesion (Hazelzet and Wissink, 2012).

Recognizing the relevance of the geographies of social networks in understanding social activity-travel behavior, several studies have explored social network geographies. Using data from a large survey in Zürich, Frei and Axhausen (2007) analyzed the size and spatial distribution of social networks and found that for young, well educated people with a low or middle incomes, social networks tend to be more spatially distributed. Arguing that the home locations of social networks are key elements for understanding where social activities are performed, Carrasco et al. (2008b) examined the factors explaining home distances between the egos and alters and found that both the egos’ attributes and ego-alter ties affect the spatial patterns of personal social networks. Kowald et al. (2013) examined and compared the factors influencing home distance patterns of social networks in Canada, Switzerland, the Netherlands and Chile. They found that the ego-alter home distance distribution follows the power law distribution for all datasets but with varying degrees of decay. Ohnmacht (2009) studied the spatial distribution of strong ties and found that young people with higher education actively participate in clubs and are more likely to have at least one nonlocal strong relationship.

Another important topic that has received much attention is the impact of the physical distance between social network members on their social interactions. Based on 24 interviews, Larsen et al. (2006) analyzed the impact of social network geographies on social interaction and travel. They found that nearby strong ties are crucial to young people’s social lives, and that social interaction, especially face-to-face contact, decreases regularly with the increasing distance between the respondents and their social network members. Using a large survey in Zürich, Frei and Axhausen (2008) examined the effects of physical distance on
the frequency of social interactions by different means between respondents and their social networks and found that the frequency of face-to-face meetings decreases quickly with an increase in distance. They also observed that the frequency of phoning and SMS messaging fell slightly with distance. Similar results were also found by Tillema et al. (2010), who reported that both the frequency of face-to-face meetings and electronic communications are positively related to the social network size and tie strength but are negatively related to an increase in the geographical distance between social network members. Carrasco and Miller (2009) and Van den Berg et al. (2009) also reported negative effects of the geographical distances between individuals on their interact frequency for social activities, especially through face-to-face encounters.

Using data collected in 2005 and 1978 in Toronto, Mok et al. (2010) compared the role of distance in interpersonal social interactions between social network members pre- and post-internet. They found that the frequency of face-to-face contact among socially close friends and relatives has hardly changed between the 1970s and the 2000s. They argued that distance still matters in the internet age and face-to-face meetings remain strongly tied to social network members living within short distances. Sharmeen et al. (2014b) provided further evidence to support this statement by investigating whether changes in the geographical distance between an ego and alter induces changes in the frequency of meetings. Results from their study show that social activity frequency between the ego and alter increases when the home distance between the ego-alter becomes closer and the frequency decreases when the distance become farther.

### 2.3 Neighborhood social environments and activity-travel behavior

Compared to social networks, the impact of neighborhood social environments on activity-travel behavior thus far has received much less research attention in the
field of transportation. Neighborhood social environments in this context refer to the social dimension of residential environments, such as income inequality, safety, social cohesion and neighborhood relations (McNeill et al., 2006; Sampson et al., 2002). The concept of neighborhood social environments is a complement to the physical dimension of one’s neighborhood environment or the built environment.

Only a few transportation studies have examined the impacts of neighborhood social environments on activity-travel behavior. McDonald (2007) studied the linkage between the neighborhood social environment and children’s school trip mode choice. They found neighborhood social cohesion significantly influences children’s decisions to walk to school. They argued that ignoring the neighborhood social environment may lead to a mis-estimate the relationships between the environment and travel choice. Wang and Lin (2013) simultaneously considered the impacts of both the physical and social dimensions of residential neighborhoods on individuals’ decisions about daily time allocation and activity engagement. Focusing on walking behavior as a mode of transport, Clark and Scott (2013) examined how the neighborhood social environment influences walking behavior and found that having trust in neighbors and friends who are role models significantly increased walking activities. Páez and Whalen (2010) found that active travel is significantly associated with living in a neighborhood with lots of activity and a sense of community. Some scholars also include neighborhood social factors as part of the built environments in their studies. Handy and his colleagues (2005) measured neighborhood safety and socializing as part of the neighborhood built environment in their Northern California studies. Findings from their studies suggest that safer neighborhoods with more socializing tend to increase the amount of walking (Handy et al., 2005) but have no effect on car ownership (Cao et al., 2006) and driving behavior (Handy et al., 2005).

Although the effects of neighborhood social environments on activity-travel
behavior have not received much attention in the field of transportation, many studies in other fields such as public health and sociology have focused on how neighborhood social environments influence physical activities (McNeill et al., 2006; Ball, 2006; Trost et al., 2002). For example, Cradock et al. (2009) examined how neighborhood social cohesion influenced young people’s participation in physical activities and found that living in a neighborhood with higher social cohesion is directly associated with more frequent participation in physical activity by youth. Franzini et al. (2009) reported a positive association between a favorable social environment and children’s overall physical activity. Mendes de Leon et al. (2009) studied the influence of neighborhood safety on the walking behavior of the elderly and found that older adults living in more socially cohesive neighborhoods engage in more walking activities. However, Caspi et al. (2013) investigated the influence of community social capital, perceived safety and disorder on the walking behavior of low-income housing residents and argued that neighborhood social environments are not likely to be the most important determinants of walking behavior for low-income people.

2.4 Dynamics of social networks, neighborhood social environments and activity-travel behavior

Individuals’ activity-travel patterns are quite dynamic in both the short term and long term (e.g., Kang and Scott, 2010; Nurul Habib et al., 2008; Scheiner and Holz-Rau, 2013a; Sharmeen et al., 2013). Understanding the dynamics of activity participation and travel over time can provide valuable insight in modelling and predicting urban travel demand (Roorda and Ruiz, 2008). Hence, modelling the dynamics of activity-travel behavior in response to changes in demographics and environments has become a research frontier in transportation research.

The long-term dynamics of activity-travel behavior have received much research
attention in recent years. Numerous studies link life cycle events with long-term activity-travel behavior dynamics and have argued that key life cycle events such as residential relocation, marriage/divorce, and job changes may break people’s habitual activity-travel patterns and act as the key triggers inducing significant changes in individuals’ activity-travel behavior (e.g., Oakil et al., 2013; Prillwitz et al., 2007; Scheiner and Holz-Rau, 2013, 2012; Sharmeen et al., 2014a, 2014b). Additionally, many studies have explained the long-term dynamics of activity-travel behavior with changes in socio-demographics and residential built environments (Cao et al., 2007; Golob, 1990; Krizek, 2003; Prillwitz et al., 2007; Scheiner and Holz-Rau, 2013a, 2013b).

Similar to activity-travel patterns, personal social networks are quite dynamic as well, particularly in response to life cycle events, such as residential relocation, getting married/divorced, or changing jobs (Oishi, 2010; Sharmeen et al., 2014a, 2014b). Due to those life cycle events, individuals may not only acquire new friends/neighbors, but they may also lose some friends from their old social networks. At the same time, the spatial distribution of individuals’ social networks is subject to change over time too and significant changes may occur especially after lifecycle events like residential relocation. Therefore, the dynamics of social networks may lead to changes in activity-travel behavior, indicating the relevance of incorporating social networks dynamics in understanding the dynamics of activity-travel behavior over time.

Highlighting the importance of social networks, a few studies have very recently incorporated social network dynamics in understanding the dynamics of activity-travel behavior. Sharmeen et al. (2010) made a distinction between the spatial and a-spatial dimension of social networks and how they influence travel. They contended that the spatial dimensions (e.g., social support, place attachment and face-to-face interactions) are more likely to influence long-term mobility, such as residential mobility, whereas the a-spatial dimension (e.g., information
exchange and virtual interaction) largely determines the short- and medium-term mobility, such as daily activity and travel. Based on this proposition, they argued that the dynamics of social networks tend to influence both long-term mobility and short-term activity-travel behavior. Sharmeen et al. (2014b) explored the dynamics of activity and travel needs in response to the dynamics of social networks and life-cycle events. They found that life-cycle events induce significant social network dynamics (measured as number of ties gained or lost) and activity and travel dynamics are significantly influenced by the life-cycle events and social network dynamics. Sharmeen et al. (2014a) investigated the dynamics of the frequency of face-to-face social interactions and reported that social activity frequency between network members are significantly determined by their interaction history and changes in home distances. Though significant effects are found for changes in the geographical distance between social contacts, only 1-2% of overall ties in their sample changed their home distances, which makes their results less conclusive.

Neighborhood social environments also vary from neighborhood to neighborhood and from one time period to the next. From an individual’s perspective, significant changes may occur in his/her neighborhood social environment especially after home relocation. Dawkins (2006) contended that neighborhood-level social ties may significantly influence households’ decisions to choose to live in a particular neighborhood or move away from the neighborhood. While the significance of neighborhood social environments for activity and travel has been subject of an increasing number of studies in recent years, to the best of the author’s knowledge, hardly any studies have developed a dynamic view by focusing on how people respond to changes in neighborhood social environments. One exception is a study by Aditjandra et al. (2012) who reported that moving to a safer neighborhood tends to increase car ownership, whereas moving to a neighborhood with more socializing is associated with less private car driving.
2.5 Research gaps

Although the impact of personal social networks/neighborhood social environments on activity-travel behavior has received much attention and made considerable progress in the past decade, many research gaps still need exploration. As discussed above, previous studies have mostly focused on social activity-travel behavior, and very few studies have examined the influence of personal social networks on general activity-travel behavior, such as individuals’ joint/solo activity-travel and companion choices behavior etc. Personal social networks may not only influence social activity-travel behavior but may also influence other general activity-travel behavior due to activity scheduling (Cullen and Godson, 1975) and information exchange (Sharmeen et al., 2010) etc. Future studies should explore these research areas.

The above literature review also shows that very few studies have examined the effects of the spatial distribution of social networks on activity-travel behavior. Here, the spatial distribution of social networks refers more to the geographies of the overall social network members rather than the distance between social relations. The implication of the spatial distribution of social networks for activity-travel behavior like activity location choices also needs more exploration.

The effects of neighborhood social environments on activity-travel behavior have started gaining attention in recent years. However, many important aspects of the influences of neighborhood social environments on activity-travel behavior have not been examined, such as their effects on the choices of locations for activities and time use, travel mode choices, car ownership etc. Therefore, more studies are needed to better understand the significance of neighborhood social environments in explaining activity-travel behavior.

Personal social networks, neighborhood social environments and activity-travel
behavior are all dynamic over the long term. Advancing a dynamic view to understand activity-travel behavior is a new research frontier in travel studies. A limited number of studies have incorporated the dynamics of personal social networks and neighborhood social environments in understanding the dynamics of activity-travel behavior, and this topic deserves future attention.

2.6 Summary

Over the past decade, the relationships between personal social networks and social activity-travel behavior have been the subject of an increasing number of studies. Much research has examined the role of social network attributes like size and composition to understand the generation and scheduling of social activity-travel behavior. The significance of social network geographies has been recognized, and several studies have investigated the spatial pattern of personal social networks. Numerous studies have examined the influence of the distance between social network members on their social interactions. Moreover, the relationships between the neighborhood social environment and activity-travel behavior have begun attracting attention. Additionally, a few studies have very recently paid attention to the dynamics of social networks and activity-travel behavior. Overall, the existing literature has underscored the importance of personal social networks and neighborhood social environments in understanding individuals’ activity-travel behavior.

Despite this, much research is still needed to thoroughly understand the role of social contexts in activity-travel behavior. For example, very few studies have examined the specific impacts of social networks on general activity-travel behavior, such as the activity/travel companion choices. Limited attention has been devoted to the implications of the spatial distribution of social networks on activity-travel behavior, including activity location choices. Also, little research
has examined the influence of the dynamics of social network and neighborhood social environments on activity-travel behavior. This study thus aims to fill these research gaps with three empirical case studies that contribute to this growing knowledge about social contexts and activity-travel behavior. In the next chapter, the author will discuss the research framework, research design and data analysis.
Chapter 3 Research framework and methodology

This chapter describes the research framework and methodology adopted in this study. It begins with a theoretical discussion about why and how social networks and neighborhood social environments may influence individuals’ activity-travel behaviors. After that, the conceptual framework underpinning this dissertation is illustrated. The next section discusses the research design and data collection. Data analysis and multivariate modelling approaches are introduced in the final section.

3.1 Theoretical framework

3.1.1 Theoretical consideration

Some key questions related to activity and travel behavior include why and how social networks and neighborhood social environments influence individuals’ behaviors. Answers to these questions are important for understanding the effects of social contexts on activity-travel behavior.

Personal social networks

Findings from studies in sociology and other fields indicate that social networks can generate social or joint activities in the following ways: 1) people may perform social activities with their social network members to maintain and develop social relations and social capital; 2) people may conduct social/joint activities with their social network members to satisfy their fundamental need for belongingness (or desire for attachments/companionship); and 3) social network members may provide others company to fulfill obligations or be altruistic. Additionally, social network members may also shape one’s mental map and in

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1 Some contents in this section have been published (see Lin and Wang (2014)).
turn exert influence on people’s activity-travel behaviors. Lastly, the scheduling of social/joint activity may also exert significant influence on the scheduling of other activities and travel before and after.

First, both individuals and organizations need to perform social/joint activities to exchange information and more importantly maintain and develop social networks and social capital. For both enterprises and individuals, social networks and social capital, apart from knowledge or information, are essential to their development and success. For example, strong social relations and trust between the employees within the same company and between employees in different companies was found to significantly improve the performance of enterprises (e.g., Fink and Kessler, 2010; Westlund and Adam, 2010). Individuals’ career successes in terms of salary, promotion and career satisfaction, apart from other factors, tend to be significantly influenced by their social relations and the embedded social capital because social networks and social capital tend to provide individuals with greater access to information, resources and career sponsors (Seibert et al., 2001). Though having different focuses, the “weak tie theory” (Granovetter, 1973), “strong tie theory” (Bian, 1997) and “social capital theory” (Lin, 1999; Lin et al., 1981) all highlight the importance of individuals’ social networks to their occupational or career successes. While the development of information and commutation technology (ICT) largely facilitates interaction and communication between people, social activities like holding face-to-face business meetings, conferences and social gatherings still provide the best opportunities for sustaining and developing social relations and social capital. Some even argue that in this information age, the social function of these face-to-face meetings and conferences surpasses their practical function of information sharing because information can now travel the world in seconds (e.g., Larsen et al., 2006; Weber and Chan, 2003).
Second, people have a fundamental desire for interpersonal attachments or companionship and a need for belongingness (Baumeister and Leary, 1995). Maslow (1968) ranked “needs for love and belongingness” in the middle of his human needs pyramid, after physiological needs including hunger, safety and other basic needs are satisfied. To satisfy such desires or needs, individuals may perform social/joint activities with their social network members to build and maintain at least a minimal level of long-term, stable and positive interpersonal relationships (Baumeister and Leary, 1995). It is acknowledged that sufficient companionship can reduce stress and the feelings of loneliness and can enhance social satisfaction, which in turn can significantly improve people’s physical health and psychological wellbeing (e.g., Rook, 1987; Sorkin et al., 2002). Insufficient social contacts or lack of attachments, however, can lead individuals to suffer from loneliness and social isolation, which have been well documented to be associated with a variety of adverse effects on individuals’ physical health and psychological wellbeing (e.g., Baumeister and Leary, 1995; Penninx et al., 1999; Sorkin et al., 2002).

Third, people may also perform social/joint activities with others passively by providing company out of obligation or altruism. Rights and obligations always go hand in hand, as people enjoy the benefits from the social networks, they also may have a moral obligation to help or provide social support to their social networks. Most people have a hierarchy of moral obligations, with stronger moral obligations to help or provide social support to their family members, lovers and relatives and with less strong obligations to provide social support to friends and acquaintances (Nock et al., 2008; Rossi and Rossi, 1990). Altruism, which is a traditional virtue in many cultures, is the motivation stemming from a concern for the welfare of others and the actions taken to help them (Batson, C.D. and Powell, 2003). Altruism tends to have a similar hierarchical structure as moral obligations, meaning that people are more altruistic towards people with whom they have strong relationships (such as family members and other close kinship) than others.
(Foster et al., 2006). Therefore, when people are asked by their social network members to accompany them on activities, such as shopping and personal errands, they typically will do so if they are available. The response is likely triggered from either obligation or altruism.

In addition, studies also suggest that social network members shape a person’s mental map and social network geography and thus influence individuals’ activity-travel behavior (Axhausen, 2008). A mental map is a person’s spatial knowledge about locations, districts and paths, as well as the separation and connection between locations in either time or distance. Social network members’ homes, workplaces, holiday locations, and their regular meeting places (Axhausen, 2008), and the exchanges of activity-travel information between social network members (Sharmeen et al., 2010) shape an individual’s mental map and social network geography. Numerous studies have acknowledged the importance of individuals’ mental maps (Hannes et al., 2012, 2008) and social network geography (Ohnmacht, 2009) in explaining people’s daily activities and travel. In this manner, social networks affect activity-travel behavior.

Lastly, personal social networks may also influence individuals’ activity-travel behaviors indirectly through the scheduling of social activities (Cullen and Godson, 1975). Activities are subject to various space-time constraints and the scheduling of activities and travel within a given period of time are highly interdependent from one another (Akar et al., 2011; Doherty and Axhausen, 1999). Cullen and Godson (1975) contended that social activities or meetings have priority over other activities and are usually rigidly constrained in time and space. Therefore, social activities are usually scheduled in advance and then act as “pegs” around which other activities are scheduled according to their flexibility rating and the estimated duration and travel time. As such, the scheduling of the social/joint activities with social network members may thus significantly
influence certain aspects of the scheduling of other activities/travel before and after, such as their location choices, duration and so on.

**Neighborhood social environments**

The neighborhood social environment where people live can influence individuals’ behaviors by shaping social norms, enforcing social control, providing opportunities or constraints for engaging in certain behaviors (Berkman and Kawachi, 2000). Firstly, socially cohesive and trusting neighborhoods may reinforce positive social norms that facilitate healthy behaviors and enforce social control that restricts or contains behaviors, such as fighting and excessive drinking (Berkman and Kawachi; 2000). Role model effects may be taken as an example. Role models are people who participate in certain activities (e.g. physical activities, travel mode choice) and whose participation encourages others to follow (Clark and Scott, 2013). Secondly, people who live in cohesive and trusting neighborhoods tend to feel safe, which facilitates leisure activities in the neighborhood. It is found that individuals who live in neighborhoods with risky conditions (e.g., high crime and neighborhood disorder) tend to engage in less physical activity than those living in safer neighborhoods (Seefeldt et al., 2002). Thirdly, a cohesive and trusting neighborhood tends to enhance the social interactions among neighbors. This provides opportunities for people to perform social or joint activities with their neighbors. As such, the characteristics of the neighborhood social environment influence individuals’ activity-travel behavior.

### 3.1.2 Research framework

Figure 3.1 presents the research framework of this dissertation. The core theme of this study is to enrich the literature on the impact of social contexts, specifically personal social networks and neighborhood social environments, on individuals’ activity-travel behavior. Based on the research gaps identified, this study
examines three under-explored topics: 1) the impact of personal social networks on joint/solo activity/travel engagement and companion choices, 2) the impact of personal social networks and neighborhood social environments on the location choices for activities and time use, and 3) linkages between the dynamics of these social contexts and activity-travel dynamics after home relocation. The theoretical discussion and previous empirical evidence indicate that personal social networks and neighborhood social environments provide social opportunities as well as constraints to individuals’ activity-travel behavior and significantly determine individuals’ activity-travel patterns. Based on previous academic research, the author assumes that the characteristics of personal social networks may significantly influence individuals’ engagement in joint/solo activity-travel behavior and the choices of activity/travel companions. This study also hypothesizes that personal social networks and their spatial distribution and neighborhood social environments may significantly influence individuals’ choices of different locations for activities and time use. Moreover, this study expects that changes in personal social networks and neighborhood social environments after relocation may significantly explain changes in activity-travel after a residential move. Numerous previous studies have also documented the significance of individual and spatial factors in explaining individuals’ activity-travel behavior (e.g. Akar et al., 2011; Cao et al., 2007; Lu and Pas, 1999; Srinivasan and Bhat, 2008). To better verify this study’s hypotheses, these factors are controlled in the models as well.
3.2 Research design and data

One approach to study the social contexts and activity-travel behavior is through simulation (e.g., Arentze and Timmermans, 2008; Hackney et al., 2006; Páez and Scott, 2007). Another approach is by collecting empirical data. This study and most previous studies have adopted this approach to examine the relationships between social contexts and activity-travel. Partly due to financial and practical limitations, most previous empirical data collections have used cross-sectional designs (Carrasco and Cid-Aguayo, 2012; Kowald et al., 2010). Longitudinal panel data have advantages over cross-sectional data. A major advantage is that longitudinal data can provide both between person variance (differences between individuals) and within person variance (changes in individuals over time) whereas cross-sectional data provide only between person variance. Longitudinal data therefore enable researchers to explore how the subject changes over time. Additionally, longitudinal design has the capability to control the unobserved
time-invariant factors (Johnson, 2005) and provide more convincing evidence for causal impacts. This study adopts a longitudinal design to collect both cross-sectional and longitudinal panel data, which makes it possible to examine not only the connections between social contexts, specifically personal social networks and neighborhood social environments, and activity-travel behavior in a cross-sectional manner but also how personal social networks, neighborhood social environments and activity-travel are correlated and change over time.

3.2.1 Data collection and measures

Personal social networks

Social networks can be distinguished between “whole” social networks and “ego-centric” social networks (Scott, 2013). Previous studies analyzing social networks and activity-travel have collected ego-centric social network data (Carrasco et al., 2008a; Van den Berg et al., 2009; Kowald and Axhausen, 2012). In accordance with previous studies, this study also uses ego-centric social network data to examine the effects of personal social networks on activity-travel because collecting data for “whole” networks in cities with large populations is often impractical. Ego-centric social networks focus on the respondents (also called egos) and the people (also called alters) who have relationships with the respondents (Carrasco et al., 2008a). A respondent’s ego-centric social network is thus made up of a set of people connected to the respondent, such as his/her family members, relatives, friends, and colleagues.

Personal social networks can be characterized by structural information (e.g., size and composition) and functional contents. The size and composition of social networks are typically used to measure the social network structure (Carrasco and Miller, 2009; Deutsch and Goulia, 2013; Scott, 2013). Social network size refers to the number of social network members (or alters) and the social network
composition is measured as the proportion of similar alters who have the same role or closeness with respect to the ego in the network (Carrasco and Miller, 2009). The spatial distribution of social networks is also a significant indicator of the social network structure and may significantly influence activity-travel (Ohnmacht, 2009). Nevertheless, previous research has paid very little attention to this aspect. Social support is normally used to capture the functional contents of personal social networks (House et al., 1988; van der Poel, 1993). Social support refers to “a generalized resource available from one's social network that helped one to deal with everyday problems or more serious crises” (Walker et al., 1994).

Three major types of social support, namely, emotional support, instrumental support and social companionship are usually distinguished (Lee et al., 2005; van der Poel, 1993; Veiel, 1985; Wellman and Wortley, 1990; Wills, 1985). Emotional support is defined as emotional assistance, such as “giving advice with important decisions” or “help during depression” (Höllinger and Haller, 1990; van der Poel, 1993); instrumental support refers to supplying material or practical assistance, such as “financial aid,” “help with housework” or “help during sickness” (Lee et al., 2005; Schweizer et al., 1998; Veiel, 1985). Social companionship is concerned with the sharing of social activities, such as “going out together” or “participating together in an organization” (Schweizer et al., 1998; Wellman and Wortley, 1990; Wills, 1985).

To collect data on social network attributes, questions on both structural and functional contents of respondents’ ego-centric social networks can be included. Two approaches are typically used to collect the structural information about ego-centric social networks (Kowald and Axhausen, 2012): 1) eliciting members from one’s core network using the so-called “name generator” (Carrasco et al., 2008a) and 2) asking respondents to recall or record all contacts they have made through different means in a given timeframe (Fu, 2007; Milardo et al., 1983; van der Poel, 1993). The second approach (contact diary) was adopted in our survey. Referring to functional contents, questions measuring who and how many of them
provide the respondent emotional support, instrumental support and social companionship respectively can be used (Lee et al., 2005).

**Neighborhood social environments**

Neighborhood social environments may be characterized in different ways. From a social resource perspective, previous studies suggest using variables measuring neighborhood socioeconomic composition to characterize the neighborhood social environment (McDonald, 2007; Morenoff, 2003). These variables are usually aggregated socio-demographic data, such as the unemployment rate, income, racial composition and the percentage of people living below the poverty threshold. (Brooks-Gunn et al., 1993; Estabrooks et al., 2003; Franzini et al., 2010; Sampson et al., 2002). Neighborhood socioeconomic compositions capture the characteristics of the neighborhood social structure and community resources, which have a strong impact on individuals’ social life and behavior (Blau, 1982; Sampson et al., 2002). Apart from neighborhood socioeconomic composition, the neighborhood social environment can also be differentiated by directly measuring neighborhood safety, social cohesion and trust (McDonald, 2007; Mendes de Leon et al., 2009). These concepts are mostly measured through Likert-scale questions. Examples of such statements are those used in California Health Interview Survey (CHIS) and the Canada National Longitudinal Survey of Children and Youth (NLSCY). In the CHIS, respondents were asked to respond from strongly disagree to strongly agree on statements such as “people in my neighborhood are willing to help each other”, “people in this neighborhood can be trusted” and “you can count on adults in this neighborhood to watch out that children are safe and don’t get in trouble” (UCLA Center for Health Policy Research, 2013). Although the wording was slightly different, the statements used in the NLSCY are similar to those in the CHIS. Examples of such questions include “people around here are willing to help their neighbors”, “when I’m away from home, I know that my neighbors will keep their eyes open for possible trouble”, “it is safe for children to play outside
during the day” and “if there is a problem around here, the neighbors get together to deal with it” (Statistics Canada, 2009). In our survey, the direct measurement approach is adopted.

**Activity-travel diary**

Similar to many other activity-travel studies (e.g., Lu and Pas, 1999; Wang et al., 2012; Kwan, 2000), data on activity-travel behavior in this study were collected using activity-travel diaries. The trip-diary approach to collect data for a travel study has a long history and was widely used in the 1980s (Stopher and Greaves, 2007). In a travel diary, respondents are usually asked to report all their trips taken in the diary day and some contextual information for each trip, such as the origin and destination, travel mode, start and ending time, and purposes (Stopher, 1992). Along with the development of an activity-based approach in travel behavior research, the focus of using a diary in data collection gradually shifted from trips to activities. Instead of asking what trip was made first and later some other information about the trip, an activity-based travel diary first asks what did you do, which is then followed by additional questions (Stopher and Greaves, 2007). In an activity-travel diary, respondents are usually required to recall and report all their activities (both in-home and out-of-home activities) continuously in a time frame, typically a day or several days (Harvey, 2003). Trips are treated as just separate activities. The contextual information collected for each activity or travel episode often includes but is not limited to the starting and ending time, activity type or travel mode, location, activity companions, what else they were doing and so on. Activity-travel diaries may present in two forms— with closed intervals and with open intervals. In a closed interval diary, the whole time is divided into numerous time blocks, but in an open interval diary, there is no explicit time structure. It is suggested that an open interval diary works well in face-to-face interviews, but a closed interval diary works better for self-completion surveys (e.g., mail out/mail back surveys) because it is more structured (Harvey, 2003). Referring to activity
coding, there is no widely accepted activity coding scheme. In an activity-travel diary, dozens of specific activity types are often distinguished and gathered into several main groups. For example, in a 2003 CHASE (Computerized Household Activity Scheduling Elicitor) survey, 66 specific activity types were differentiated and organized into nine main groups (Doherty et al., 2004).

3.2.2 Surveys

Survey in Beijing

The major data source for this study comes from the two-wave household activity-travel diary survey in Beijing. The two-wave survey is financially sponsored by the Research Grants Council of the Hong Kong Special Administrative Region (Grant No. HKBU244610). The project is a longitudinal study of home relocation and activity-travel behavior change. The author of this dissertation is a main research team member for this project and participated in the entire data collection process from questionnaire design to data cleaning and data analysis. The author specifically contributed to the design of questions about personal social networks and neighborhood social environments.

The first wave of data collection was conducted from November 2011 to June 2012, and the second wave of data collection was conducted from April 2013 to August 2013. The respondents of the survey were home movers, and thus the sample for the first wave of our survey targeted households who were planning to move within 3 to 6 months. The respondents were recruited using a multi-stage stratified sampling method to ensure that the samples were in proportion to the total transaction volumes of the three types of home movers (renters, new property buyers and second-hand home buyers) in each urban district of Beijing. The survey covers the main 12 urban districts of Beijing (Figure 3.1) and excludes the Huairou district, Pinggu district, Miyun county and Yanqing county because
they are largely rural. The samples were randomly approached in Real Estate Exchange Centers, large furniture Markets and Home Depots specializing in decoration services and through cold calling and street interviews. All household members above 11 years of age were required to complete the survey. A token of 50-100 RMB (or about 8-16 US Dollars) was provided for each successfully interviewed household. In total, 467 households with 1,243 individuals were recruited and successfully completed interviews in the first wave of data collection. The second wave of data collection was implemented after the respondents moved into their new homes. We made numerous attempts to approach all respondents who participated in the first wave and ended with 229 households and 587 respondents who took part in the second wave of data collection. Among the 587 respondents, 537 of them participated in both waves of data collection and formed the longitudinal panel data. Table 3.2 presents the sample profile of this survey.

![The map of Beijing](image)

**Figure 3.2. The map of Beijing**

### Table 3.1 Sample profile of Beijing household activity-travel survey

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35
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<td>Housing tenure</td>
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<td></td>
</tr>
<tr>
<td>Owner</td>
<td>266</td>
<td>182</td>
</tr>
<tr>
<td>Renter and others</td>
<td>201</td>
<td>47</td>
</tr>
<tr>
<td>Monthly household income</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;=5,999</td>
<td>65</td>
<td>35</td>
</tr>
<tr>
<td>6,000-9,999</td>
<td>143</td>
<td>77</td>
</tr>
<tr>
<td>10,000-19,999</td>
<td>205</td>
<td>87</td>
</tr>
<tr>
<td>&gt;=20,000</td>
<td>53</td>
<td>30</td>
</tr>
<tr>
<td>Presence of child(ren)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Have child(ren) under 12</td>
<td>96</td>
<td>46</td>
</tr>
<tr>
<td>No child(ren) under 12</td>
<td>371</td>
<td>183</td>
</tr>
<tr>
<td>Housing type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial housing</td>
<td>248</td>
<td>145</td>
</tr>
<tr>
<td>Non-commercial housing</td>
<td>219</td>
<td>84</td>
</tr>
</tbody>
</table>

In this two-wave household activity-travel diary survey, information collected and relevant to this study includes an activity-travel diary, household and personal socio-demographics, social network information and information on the
neighborhood built environment and social environment. In the activity-travel diary, respondents were asked to report all in- and out-of-home activities and travel episodes from the previous day (24h). For each activity or travel episode, information collected included starting and ending time, activity type or travel mode, activity location, and companionship. We differentiated 5 major types of out-of-home activities (which were further subdivided into 24 subtypes): work/school, shopping, entertainment, personal affairs and social activities and 9 types of in-home activities. As for travel episodes, we differentiated 11 types of travel modes. For each activity, 16 types of activity locations and 9 types of companions were provided from which respondents could select.

This survey adopted the “contact diary” approach to collect the structural information about personal social networks. Specifically, we requested respondents to report the number of social contacts made (in terms of the number of people) through all means including face-to-face, phone calls, and email, in the past week. Social contacts are differentiated 1) between family members/relatives and friends and acquaintances and 2) between those living in Beijing and those living outside Beijing. To capture the spatial ordering of personal social networks, information on the social contacts living in the same neighborhood or within walking distance was also collected. We requested that respondents report all the people they frequently contacted who lived in the same neighborhood or within walking distance. In addition, respondents were also required to report the number of family/relatives, friends and acquaintances from whom they get instrumental support, emotional support and social companionship.

Data on neighborhood social environments were collected using a direct measuring approach. Specifically, household heads were asked to respond on a 5-point Likert-scale from “strongly disagree” to “strongly agree” to several statements describing their neighborhoods including “safety of walking,” “safety of playing outdoors for kids,” “similarity in economic status,” “similarity in
socio-demographics (e.g., social class, age),” “interaction among neighbors,” “trust among neighbors” and “mutual help among neighbors.” These statements are similar to those used in the California Health Interview Survey (CHIS) and the Canada National Longitudinal Survey of Children and Youth (NLSCY).

**Hong Kong data**

In examining the influences of personal social networks on activity/travel companion choices, this study uses data from an activity-travel diary survey conducted in Hong Kong from July to November 2010. This survey is also financially supported by the Research Grants Council of the Hong Kong Special Administrative Region (Grant No. HKBU244508). The author did not participate in this survey. In the survey, a total of 1,500 respondents were randomly recruited through “cold calls” to telephone numbers randomly selected from a database with about 300,000 telephone numbers. The 1,500 respondents who were willing to participate in the survey were asked to fill in a questionnaire online, independently or assisted by our research staff through the telephone. A token of a cash coupon of 50 Hong Kong dollars (or about 6.4 US Dollars) was offered for a successfully completed questionnaire. A total of 770 respondents successfully completed the questionnaires.

The sample in this survey is largely representative of the Hong Kong population in general. Table 3.1 presents the sample profile of the survey. Compared with the general population of Hong Kong (CSDHK, 2012), the percentages in the sample were similar to the general population in terms of employment status, housing types, monthly household income distributions and car ownership. However, the survey over-represents well-educated groups (51.3% vs. 27.0%) and slightly over-represents females (58.3% vs. 53.4%) compared to the general population. On the other hand, people aged 60 or older are underrepresented (2.8% vs. 19.1%), and married individuals are also underrepresented (35.3% vs. 57.8%) in the
survey sample.

Table 3.2 Sample profile of Hong Kong activity-travel diary data

<table>
<thead>
<tr>
<th>Socio-demographics</th>
<th>Classification</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male</td>
<td>321</td>
<td>41.7%</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>449</td>
<td>58.3%</td>
</tr>
<tr>
<td>Age</td>
<td>&lt;19</td>
<td>96</td>
<td>12.5%</td>
</tr>
<tr>
<td></td>
<td>19-39</td>
<td>396</td>
<td>51.4%</td>
</tr>
<tr>
<td></td>
<td>40-59</td>
<td>256</td>
<td>33.2%</td>
</tr>
<tr>
<td></td>
<td>&gt;59</td>
<td>22</td>
<td>2.8%</td>
</tr>
<tr>
<td>Marital status</td>
<td>Married</td>
<td>272</td>
<td>35.3%</td>
</tr>
<tr>
<td></td>
<td>Others</td>
<td>498</td>
<td>64.7%</td>
</tr>
<tr>
<td>Educational attainment</td>
<td>Secondary &amp; below</td>
<td>283</td>
<td>36.8%</td>
</tr>
<tr>
<td></td>
<td>Postsecondary</td>
<td>92</td>
<td>11.9%</td>
</tr>
<tr>
<td></td>
<td>Undergraduate &amp; above</td>
<td>395</td>
<td>51.3%</td>
</tr>
<tr>
<td>Employment status</td>
<td>Employed/self-employed</td>
<td>457</td>
<td>59.4%</td>
</tr>
<tr>
<td></td>
<td>Others</td>
<td>313</td>
<td>40.6%</td>
</tr>
<tr>
<td>Studentship status</td>
<td>Student</td>
<td>212</td>
<td>27.5%</td>
</tr>
<tr>
<td></td>
<td>Not a student</td>
<td>558</td>
<td>72.5%</td>
</tr>
<tr>
<td>Monthly household income (HKD)</td>
<td>&lt;20,000</td>
<td>289</td>
<td>37.5%</td>
</tr>
<tr>
<td></td>
<td>20,000-49,999</td>
<td>352</td>
<td>45.7%</td>
</tr>
<tr>
<td></td>
<td>&gt;50,000</td>
<td>129</td>
<td>16.8%</td>
</tr>
<tr>
<td>Child presence</td>
<td>Presence of child(ren) under 12 in household</td>
<td>139</td>
<td>18.1%</td>
</tr>
<tr>
<td></td>
<td>No presence of child(ren) under 12 in household</td>
<td>631</td>
<td>81.9%</td>
</tr>
<tr>
<td>Elderly presence</td>
<td>Presence of elderly age 65 or above in household</td>
<td>173</td>
<td>22.5%</td>
</tr>
<tr>
<td></td>
<td>No elderly age 65 or above in household</td>
<td>597</td>
<td>77.5%</td>
</tr>
<tr>
<td>Household car ownership</td>
<td>Have car(s) in household</td>
<td>145</td>
<td>18.8%</td>
</tr>
<tr>
<td></td>
<td>No car(s) in household</td>
<td>625</td>
<td>81.2%</td>
</tr>
<tr>
<td>Housing type</td>
<td>Public housing</td>
<td>384</td>
<td>49.9%</td>
</tr>
<tr>
<td></td>
<td>Private housing</td>
<td>386</td>
<td>50.1%</td>
</tr>
</tbody>
</table>

Information collected in three parts of the survey questionnaire is relevant to this study, including an activity-travel diary, individual and household
socio-demographics and information on personal social networks. In the activity-travel diary part, respondents are required to recall and report all their activities and trips in the previous working day (24 hours). For each activity or travel episode, information collected includes starting and ending times, activity type, location and activity companions. Five major types of out-of-home activities (work/school, shopping, entertainment, personal affairs and religious/social/community activities) were differentiated, which were further divided into 14 subtypes. Six types of activity companions were provided for respondents to choose from: family members, partners/lovers, friends, online friends, acquaintances and no companions.

To collect data on social network attributes, questions on the structure and functional content of respondents’ personal social networks were included. Respondents were required to report their major sources of emotional support, instrumental support and social companionship. These sources could be family members/relatives, friends or acquaintances. This survey also adopted the “contact diary” approach to collect structural information about social networks. Specifically, respondents were requested to report the number of social contacts made through all means, including face-to-face, phone calls and email, in the past week. With who social contacts were made was differentiated between family members, lovers/partners, friends, online friends and acquaintances.

3.3 Data analysis and multivariate modeling approaches

The major statistical models used in this dissertation to analyze the data are Structure Equation Models (SEMs). SEMs are employed to examine the influences of social contexts on both joint/solo activity-travel behavior and changes in travel after relocation. Apart from SEM, when investigating the choices of location for activity participation and time use in Chapter 5, a two-level
logistic regression model with random intercepts and a two-limit Tobit model are also formulated.

### 3.3.1 Structure Equation Modeling (SEM)

The use of SEM in travel behavior research can be traced back to the 1980s (Golob, 2003). SEM is a modelling technique that can simultaneously estimate complex relationships among a set of variables that are either observed variables or latent (unobserved) variables. A general structural equation model (which involves both observed and latent variables) can be considered as a combination of factor analysis models (referred to as measurement models) and regression analysis models (referred to as structural models) (Narayanan, 2012). Compared with other statistical techniques, SEM models have several advantages. First, SEM allows multiple relationships between variables to be estimated simultaneously; second, SEM illustrates both direct and indirect effects, which are convenient for testing the activity-travel behavior framework; in addition, SEM allows for testing the reciprocal relationships between variables (Aditjandra et al., 2012; Hair et al., 2010). With the development of user-friendly software packages such as AMOS, the use of SEM in travel behavior research has expanded rapidly in recent years. Some examples of travel behavior research using SEM include Aditjandra et al. (2012), Cao et al. (2007), Carrasco and Miller (2006), Sharmeen et al. (2014a), Van den Berg et al. (2013), Wang and Lin (2013), Wang et al. (2011) and so on.

According to Mueller (1996), for a general structural equation model, the structural part linking the latent constructs can be expressed as

$$
\eta = \mathbf{B}\eta + \mathbf{G}\xi + \zeta
$$

(3.1)
where

\[ \eta = (\text{NE} \times 1) \text{ column vector of endogenous latent constructs (NE is the number of endogenous latent constructs)}; \]
\[ \xi = (\text{NK} \times 1) \text{ column vector of exogenous latent constructs (NK is the number of exogenous latent constructs)}; \]
\[ \mathbf{B} = (\text{NE} \times \text{NK}) \text{ matrix of structural coefficients representing the effects of the endogenous latent constructs on one another}; \]
\[ \mathbf{\Gamma} = (\text{NE} \times \text{NK}) \text{ matrix of structural coefficients representing the effects of exogenous latent constructs on endogenous latent constructs}; \]
\[ \zeta = (\text{NE} \times 1) \text{ column vector of error terms associated with the endogenous latent constructs}. \]

The corresponding measurement models specify how the observed variables define the latent constructs. They can be represented by

\[ \mathbf{X} = \Lambda_x \xi + \delta \]  
\[ \mathbf{Y} = \Lambda_y \eta + \epsilon \]

where

\[ \mathbf{X} = (\text{NX} \times 1) \text{ column vector of observed exogenous variables of latent constructs } \xi \text{ measured as deviations from their means (NX is the number of observed exogenous variables)}; \]
\[ \mathbf{Y} = (\text{NY} \times 1) \text{ column vector of observed endogenous variables of latent constructs } \eta \text{ measured as deviations from their means (NY is the number of observed exogenous variables)}; \]
\[ \Lambda_x = (\text{NX} \times \text{NK}) \text{ matrix of regression coefficients from exogenous latent constructs to their indicator variables}; \]
\[ \Lambda_y = (\text{NY} \times \text{NE}) \text{ matrix of regression coefficients from endogenous latent constructs to their indicator variables}; \]
\[ \delta = (\text{NX} \times 1) \text{ column vector of measurement error terms of the indicator variables}; \]
and $\varepsilon = (NY \times 1)$ column vector of measurement error terms of the observed variables.

In addition to the four coefficient matrices $B$, $\Gamma$, $\Lambda_x$ and $\Lambda_y$, another four variance/covariance matrices $\Phi$, $\Psi$, $\Theta_\delta$ and $\Theta_\varepsilon$ need to be specified and used together to determine the SEM. $\Phi$ is a $(NK \times NK)$ variance/covariance matrix of the latent exogenous constructs; $\Psi$ is a $(NE \times NE)$ variance/covariance matrix of error terms related to latent endogenous constructs; $\Theta_\delta$ is a $(NX \times NX)$ variance/covariance matrix of measurement error terms of the observed exogenous indicators; and $\Theta_\varepsilon$ is a $(NY \times NY)$ variance/covariance matrix of measurement error of the observed endogenous variables.

One specific case of structural equation models is the so-called path analysis model where all the variables involved are observed variables. In the path analysis model, the matrix form of a general SEM is reduced to

$$Y = BY + \Gamma X + \zeta$$  \hspace{1cm} (3.4)

where $Y$, $X$, $B$, $\Gamma$ and $\zeta$ are defined as in equations (3.1), (3.2) and (3.3).

As for path model, $\Lambda_x = I$, $\Lambda_y = I$, $\Theta_\delta = 0$ and $\Theta_\varepsilon = 0$. And the matrices of $B$, $\Gamma$, $\Phi$, and $\Psi$ together define the specific SEM.

**Parameter estimation**

In this section, the author describes the process of how SEM is estimated, but for detailed information, readers are referred to Mueller (1996). First, let $\Sigma$ represent the population covariance matrix of observed variables $X$ and $Y$, and $S$ represent the sample covariance matrix, which is the sample estimate of $\Sigma$. Then define $\Sigma(\theta)$ as the model-implied covariance matrix where $\theta$ represents the vector of all
parameters estimated, which includes both the coefficient matrices and the covariance matrices of residuals. $\Sigma(\theta)$ can be expressed as a function of the eight basic matrices mentioned above: $B$, $\Gamma$, $\Lambda_x$, $\Lambda_y$, $\Phi$, $\Psi$, $\Theta_\delta$ and $\Theta_\varepsilon$. The ultimate goal of parameter estimation is to find the best $\theta$ so that the reproduced model-implied covariance matrix $\Sigma(\theta)$ is as “close” as possible to the population covariance matrix $\Sigma$. The strategy used to find the best $\theta$ is by iteratively inserting improved estimates of $\theta$ until the minimal difference between $\Sigma(\theta)$ and $\Sigma$ is achieved based on a particular criterion. The difference between $\Sigma(\theta)$ and $\Sigma$ is measured by a fit function $F(S, \Sigma(\theta))$, which varies by the approach used to estimate the parameters.

Several methods are available to estimate the parameters, such as maximum likelihood (ML), generalized least squares (GLS), and the Asymptotically Distribution Free (ADF) method. The major distinction between these estimation techniques lies in their underlying assumptions about the distribution of data used and in the fit function utilized during the iteration process. Among these estimation techniques, the maximum likelihood (ML) estimation is the most widely used method. The fit function of the ML estimator can be expressed as

$$F_{ML}[S, \Sigma(\theta)] = \ln|\Sigma(\theta)| - \ln|S| + \text{tr}[S \Sigma(\theta)^{-1}] - (NX + NY) \quad (3.5)$$

where $\text{tr}[S \Sigma(\theta)^{-1}]$ refers to the trace of the matrix $(S \Sigma(\theta)^{-1})$, it simply is the sum of the diagonal elements of the matrix $(S \Sigma(\theta)^{-1})$.

The estimator of maximum likelihood assumes multivariate normal distribution of the data set. However, in practice, failure to meet the multivariate normality assumption to some extent is often the case (e.g., Byrne, 2010; Van den Berg et al., 2013, 2012a). Despite this, the maximum likelihood estimation is still widely used because it is considered to be fairly robust against the violations of multivariate normality (Golob, 2003). In addition, the bootstrapping procedure can also be used to accommodate the violation of multivariate normality (Byrne, 2010). Using
the bootstrap technique, numerous subsamples are created by repeatedly randomly selecting cases from the original sample data with replacement. With the bootstrapping subsamples and the sampling distribution, the estimation of intervals, such as standard errors and confidence intervals, can become more accurate (Zhu, 1997) and the accuracy of the parameter estimates can also be improved.

**Recursive model vs. non-recursive model**

SEM models can be differentiated between recursive models and non-recursive models. For SEM, if only unidirectional relationships are hypothesized among variables, it is called a recursive model. In practice, variables in social science studies are often reciprocally related. Therefore, it is quite unrealistic for recursive models to only assume unidirectional relationships among variables. In such cases, models that allow reciprocal relationships among variables may provide a better understanding of the practice. SEM models that allow reciprocal relationships among variables are called non-recursive SEM models (Berry, 1985; Heise, 1975).

Compared to recursive models, the identification problems of non-recursive models are often important issues that need to be considered. For general recursive models, meeting the following three criteria are believed to be sufficient for identification: 1) the number of parameters $p$ to be estimated in the eight basic matrices ($\mathbf{B}$, $\mathbf{\Gamma}$, $\Lambda_X$, $\Lambda_Y$, $\Phi$, $\Psi$, $\Theta_\delta$ and $\Theta_\epsilon$) does not exceed the number of available variances and covariance among the $(NX + NY)$ observed variables $c$, where $c$ is equal to $(NX + NY)(NX + NY + 1)/2$; 2) a measurement unit is assigned to each latent construct; and 3) if a latent construct has only one indicator, the assumption is that the indicator variable is measured without error (Mueller, 1996). While for a non-recursive model, in addition to the above-mentioned three guidelines, additional rules need to be met. In non-recursive models, the number of parameters to be estimated in the equations involving reciprocal relationships is
usually greater than the amount of information provided by the related observed variables, which are, therefore, under-identified (Berry, 1985). To identify a non-recursive model that contains under-identified equations, some constraints must be added to the under-identified equations that involved reciprocal paths. One strategy is to set some paths equal to zero or assume equality or having a known ratio for the reciprocal effects (Berry, 1985). Another widely used approach is by designating some variables as “instruments” (Heise, 1975; Schaubroeck, 1990; Schooler et al., 1999). An instrumental variable helps identify a non-recursive equation by being allowed to have an effect (either directly or through an intervening variable that has no direct effect on dependent variable) on independent variables but no direct effect on the dependent variable of that equation (Heise, 1975). Finally, some restrictions on the distributions of the error terms of the related variables may also help identify the non-recursive models (Berry, 1985).

**Measures of Goodness-of-fit**

The Goodness-of-fit of SEM assesses the similarity of the reproduced covariance matrix base on the specified SEM model to the observed covariance matrix, indicating how well the theoretical framework tested reflects reality (Hair et al., 2010). Dozens of indices are available to measure the goodness-of-fit of SEM. Table 3.3 shows a list of widely used indices measuring the goodness-of-fit of SEM and their cut-off values for a good model.

<table>
<thead>
<tr>
<th>Model fit indices</th>
<th>Description</th>
<th>Cut-off value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$</td>
<td>Chi-square value; $\chi^2 = (N-1)(S-\Sigma(0))$; measure of discrepancy between the observed and model-implied covariance matrices. The $\chi^2$ increases as sample size increases</td>
<td>$p&gt;0.05$</td>
</tr>
</tbody>
</table>
increases. Smaller values indicate better model fit.

$\chi^2$/df A relative $\chi^2$ statistic corrected for degrees of freedom; values smaller than 5 are acceptable and less than 3 indicate a good fit.

GFI Goodness-of-Fit Index (GFI); measures the proportion of sample covariance explained by the fitted model; values vary between 0 and 1 and higher value means a better fit.

RMSEA Root Mean Square Error or Approximation (RMSEA); values not exceed 0.08 indicate an acceptable fit and less than 0.05 means a good fit.

CFI Comparative Fit Index (CFI); assessing the improvement of the hypothesized model compared to the null model; values greater than 0.90 indicate a good fit and the higher the value the better the fit.

NFI Normed Fit Index (NFI); measured as the proportion of the $\chi^2$ value of the hypothesized model over that of the null model; values closer to 1 indicate a good fit.

IFI Incremental Fit Index (IFI); the incremental improvement of the hypothesized model over the null model; values closer to 1 indicate a good fit.

*References: Bollen and Long (1993); Byrne (2010); Hair et al. (2010); Van Acker and Witlox (2010).

3.3.2 Multi-level logistic regression model

To investigate the role of social contexts on individuals’ choices between in- and out-of-neighborhood locations for activities, a multi-level logistic regression model is employed in Chapter 5. Logistic regression is a kind of regression analysis specifically used for predicting the outcome of dichotomous or
categorical dependent variables. A simple multivariate logistic regression equation can be expressed as

$$ logit(P_i) = \log\left(\frac{P_i}{1-P_i}\right) = \gamma_0 + \sum_{h=1} \gamma_h x_{hi} \tag{3.6} $$

where $P_i$ is the probability for event $i$ to happen and $\gamma_0$ represents the intercept coefficient. $x_{hi}$ is the $h$-th explanatory variable and $\gamma_h$ is the corresponding fixed coefficient. When all observations are sampled independently, such a simple multivariate logistic regression model in equation 3.6 can provide an efficient explanation of the happening of the event $i$. However, when the data have a multi-level structure or include repeated measures from one subject, a standard logistic regression is no longer efficient to explain the data because it cannot deal with the within group associations involved in the data. In such cases, a multilevel model structure is needed (Snijders and Bosker, 2012). In this study, repeated measures were included in the data because one respondent may perform several activities; therefore, this study formulated a two-level logistic model (upper level: individual; lower level: activity episode) with random intercepts at the upper level. The mathematical form of the model is:

$$ logit(P_{ij}) = \log\left(\frac{P_{ij}}{1-P_{ij}}\right) = \gamma_0 + \sum_{h=1}^r \gamma_h x_{hij} + U_{0j} \tag{3.7} $$

where $P_{ij}$ is the probability of performing activity $i$ out-of-neighborhood by individual $j$ and $x_{hij}$ is the $h$-th explanatory variable and $\gamma_h$ is the corresponding fixed coefficient. The random group-dependent deviation $U_{0j}$ is included to account for the within group association. $U_{0j}$ is assumed to have zero mean and variance $\tau_0^2$. For more detailed information on multilevel modeling, readers are referred to Snijders and Bosker (2012).
3.3.3 Doubly censored Tobit model for analyzing time allocation to two types of activities

Time allocation for daily activities involves discreteness because some types of activities, such as out-of-neighborhood activities, may not be performed at all (Kitamura, 1984). To address this discreteness, previous studies have employed a discrete-continuous type of modeling framework, such as a doubly censored or a two-limit Tobit model (Kitamura, 1984; Kitamura et al., 1996; Yamamoto and Kitamura, 1999). In accordance with these studies, a two-limit Tobit model is adopted to investigate the connections between social contexts and individuals’ time allocation for in- and out-of-neighborhood discretionary activities in Chapter 5.

For a given amount of discretionary time available for in- and out-of-neighborhood activities, there are three possible time use patterns: 1) engaging in both in-and out-of-neighborhood activities, 2) engaging in only in-neighborhood activities, and 3) engaging in only out-of-neighborhood activities. With \( t_1 \), \( t_2 \) as time allocation to in- and out-of-neighborhood discretionary activities, respectively, the author can then defines the dependent variable as \( ln(t_2/t_1) \). The variable \( ln(t_2/t_1) \) is defined only when both in- and out-of-neighborhood discretionary activities are performed, and when only one type of activity is engaged, \( ln(t_2/t_1) \) will be either positive infinity or negative infinity, which is undefined. However, for the total discretionary time available for two types of activities, the dependent variable \( ln(t_2/t_1) \) has its lower and upper limits, which can be calculated based on the total available time \( T \) (Kitamura et al., 1996; Yamamoto and Kitamura, 1999). Then, the discrete-continuous time allocation behavior can be formulated as the following two-limit Tobit model:

\[
y_i' = \ln(t_{2i}/t_{1i}) = \beta'x_i + \varepsilon_i
\]
\[ y_i = \begin{cases} 
\ln \theta_{1i}, & \text{if } y_i \leq \ln \theta_{1i} \\
y_i^*, & \text{if } \ln \theta_{1i} \leq y_i^* \leq \ln \theta_{2i} \\
\ln \theta_{2i}, & \text{if } y_i \geq \ln \theta_{2i} 
\end{cases} \]  
(3.8)

\[ \varepsilon_i \sim N(0, \sigma^2) \]

The upper and lower limits of \( y^* \) for individual \( I \) are \( \ln \theta_{1i} \) and \( \ln \theta_{2i} \), respectively. The thresholds of \( \ln \theta_{1i} \) and \( \ln \theta_{2i} \) for individual \( i \) are calculated by solving the following two equations:

\[ \ln T_i + \theta_{1i} \ln \theta_{1i} - (1+ \theta_{1i}) * \ln (1+ \theta_{1i}) = 0 \]  
(3.9)

\[ \theta_{2i} \ln T_i + \theta_{2i} \ln \theta_{2i} - (1+ \theta_{2i}) * \ln (1+ \theta_{2i}) = 0 \]  
(3.10)

where \( T_i \) is the total time available for discretionary activities for individual \( i \) (Kitamura et al., 1996). For details about the doubly censored Tobit model in addressing allocation of time to two kinds of activities, readers are referred to Kitamura (1984), Kitamura et al. (1996) and Yamamoto and Kitamura (1999).

### 3.4 Summary

This chapter provided a detailed account of the research framework and methodology. The theoretical foundation for this study is built upon the discussion of why and how social networks and neighborhood social environments may influence individuals’ activity-travel behavior. Based on this background, the hypotheses of this research are proposed. This study assumes that social network attributes and neighborhood social environments may significantly influence individuals’ joint/solo activity-travel and companion choice behavior and choices of different locations for activities and time use; and the dynamics of social networks and neighborhood social environments after relocation significantly induce changes in travel. Data collection and measures of social networks and the neighborhood social environment are also discussed in this chapter. The two activity-travel diary surveys that provide the data for this study are also introduced.
The major multivariate modelling technique adopted in this study to test the hypotheses is Structure Equations Modelling (SEM). The influence of social networks on individuals’ joint/solo activity-travel and companion choice behavior, as well as the influence of the dynamics of social networks and neighborhood social environments on changes in travel are examined using SEMs. Apart from SEM, a multilevel logistic model and a doubly censored Tobit model are also formulated to investigate the impacts of social networks and neighborhood social environments on individuals’ location choices for activities and time use. The empirical modelling results will be presented in the following chapters.
Chapter 4 Social networks and joint/solo activity-travel and companion choice behavior²

4.1 Introduction

As have been discussed before, previous studies examining the impact of social networks have mainly focused on social activities and travel, and very few studies have investigated the influence of social networks on general activity-travel behavior. This chapter aims to make a contribution to this gap with an empirical case study investigating the impacts of personal social networks on individuals’ engagements in joint/solo activities/travel and choice of activities/travel companions.

Individuals may perform daily activities and travel independently or jointly with others. It is estimated that more than 50% of individuals’ daily out-of-home activities and travel are conducted jointly with others (Srinivasan and Bhat, 2008). Individuals’ decisions about undertaking daily activities independently or jointly, as well as with whom joint activities are performed are very important aspects of activity-travel behavior (Gliebe and Koppelman, 2005; Srinivasan and Bhat, 2008). Decisions about undertaking joint activities significantly shape the activity-travel patterns of the individuals involved. To conduct joint activities and travel with others, the individuals involved need to comply with the coupling constraints suggested by Hägerstrand in his time geography framework (Hägerstrand, 1970). It is believed that understanding the underlying mechanism of the decision making of joint activities and companion choices will generate more insight into individuals’ daily activity-travel behavior (e.g., Gliebe and Koppelman, 2002; Vovsha et al., 2003).

² The main body of this chapter has been published (see Lin and Wang (2014)).
Much research has studied individuals’ engagement in joint activities/travel. The interactions between household adult members in the decisions about engagement in solo and joint activities has been explored and modelled (Gliebe and Koppelman, 2002; Golob and McNally, 1997; Scott and Kanaroglou, 2002). Numerous studies have examined the role of socio-demographics and the built environment on individuals’ engagement in joint activities/travel and their choice of companions (e.g., Fan and Khattak, 2009; Sharmeen and Ettema, 2010; Srinivasan and Bhat, 2008). However, we have little knowledge about the role of individuals’ social networks in decisions about engagement in joint activities/travel and the choice of activity/travel companions.

As Axhausen (2008) suggests, instead of exclusively focusing on an individual’s socio-demographics, values, lifestyles, and attitudes, one should also include personal social network attributes as an explanatory factor of travel behavior. Using activity-travel diary data collected in Hong Kong in 2010, this study employs a structure equations model to examine the interrelationships between social network attributes, decisions between solo and joint activities and the choice of companions in the case of joint activities. The rest of the chapter is organized as follows. The next section discusses the previous literature about joint/solo activity-travel behavior and companion choice. Section 4.3 presents the conceptual model for this study. Section 4.4 explains the data and definitions of the variables. In section 4.5, the empirical findings based on modelling results are presented and discussed. Concluding remarks are presented in the final section.

4.2 Previous research on joint/solo activity-travel behavior

Numerous empirical studies have been carried out to examine individuals’ decisions about joint/solo activity-travel behavior. Several studies have modelled the interactions between household adult members, especially household heads, in
the decision making about undertaking joint or solo activities and travel (Gliebe and Koppelman, 2005; Gliebe and Koppelman, 2002; Golob and McNally, 1997; Scott and Kanaroglou, 2002). Using the American Time Use Survey data, Srinivasan and Bhat (2008) explored the characteristics of joint activity participants and examined how socio-demographics and activity attributes influence individuals’ choices of activity/travel companions. Some important empirical findings concerning joint activity behavior include the following. First, joint activities tend to have a longer duration than solo activities and are more likely to take place during certain time periods of weekdays. Second, there is significant variation in the activity characteristics for joint activities with different purposes, type of companions, and days of the week. Lastly, individuals’ socio-economic statuses, activity purposes as well as timing of joint activities are found to be significant determinants of the choice of activity/travel companions (Srinivasan and Bhat, 2008). Using the same dataset, Kapur and Bhat (2007) employed a multiple discrete-continuous extreme value model to examine how household and individual’s socio-economic characteristics (e.g., gender, education level, age, employment status, household size, and the presence of children in the household) influence adults’ weekend time allocation to out-of-home discretionary activities by different types of companions. Their results are mostly within expectations. For example, females are found to be more family-centric and more likely to undertake out-of-home discretionary activities with family members than males, and young adults tend to have a higher probability of performing joint out-of-home discretionary activities with friends and family than other adults.

Apart from household and personal social demographics, the effects of spatial setting on individuals’ engagement in joint and solo activities and choice of activity/travel companions have also been examined. Fan and Khattak (2009) studied how the residential built environments influence individuals’ decisions about conducting solo activities versus joint activities with household members.
They found that people living closer to department stores are more likely to conduct solo shopping activities with shorter durations on weekdays than those living farther away from department stores; on the other hand, people living closer to parks may have more joint out-of-home discretionary activities. By including multiple types of companions, Sharmeen and Ettema (2010) investigated the influence of the urban form and accessibility of facilities on the choice of companions for social and leisure activities. Results from their study suggest that better access to facilities might induce more joint engagements in social, shopping and sports/recreation activities in general. But for different types of activities, the effects of spatial and socio-demographic variables on the choice of activity companions tend to be different. For example, easy access to facilities tends to increase the amount of social activities with family/household members but does not increase the number of social activities with friends. Farber and Páez (2011) also examined the effects of land use and mobility on engagement in social activities and argued that the increasing spatial dispersion of activity opportunities and traffic congestion limits the opportunity for individuals to participate in social activities.

In summary, numerous studies have examined the influences of individuals’ socio-demographics and the residential built environment on individuals’ decision making about joint/solo activity participation and companion choices. The existing literature about joint/solo activities and companion choices provide much insight into the behavior of joint/solo engagements in activity/travel and the choice of activity/travel companions. However, hardly any study has analyzed the role of personal social networks in individuals’ decisions about engagements in joint/solo activities and choices of activity/travel companions. The existing literature thus needs to be extended along this line.
4.3 Conceptual framework

The theoretical discussion of why and how personal social networks may influence individuals’ activity-travel behavior suggests that individuals with different social network features, such as size and composition, may behave differently in their daily joint/solo activity-travel behavior. For example, the motivation to maintain and develop social relations suggests that individuals with larger social networks may need to undertake more social/joint activities and thus more travel to maintain social relations with their social network members. Further, since individuals may perform social/joint activities to satisfy their needs for belongingness or desire for attachments, the group of people they are more mentally attached to or from whom they get more social support may influence their choices about with whom to undertake social/joint activities. Moreover, the hierarchy structure of the obligation and altruism people feel toward different members of their social network indicates that people may be more likely to provide companionship to their family members, lovers or relatives than to friends and acquaintances, suggesting that the composition of the social network may be an important determinant of joint activity decisions and companionship choices.

Figure 4.1 illustrates the hypothesized connections between social network attributes and the decisions about joint/solo activities and travel as well as the choice of companions. Specifically, this research assumes that social network size, social network composition and sources of social support would significantly affect individuals’ engagements in solo or joint activities and the choices of “with whom” joint activities are performed. The effects of the social network attributes on people’s engagements in joint or solo travel episodes and their choice of companions for joint travel episodes are also hypothesized. This study also assumes that there are interaction effects between activities with different companionship types and between travel episodes with different companionship types. Because travel is induced from undertaking activities (Axhausen and
Gärling, 1992; Kitamura, 1988) and people may travel together to perform joint activities, this study assumes that the decisions about “with whom” to conduct activities may significantly induce similar decisions about associated travel for other activities. Besides, previous sociological studies have documented the linkages between individuals’ socio-demographics and the characteristics of their personal social networks; for example, people with higher income and higher educational levels tend to have more social network members (Campbell et al., 1986; Fischer, 1982; Huang and Tausig, 1990). Thus, this research hypothesizes that individuals’ socio-demographics are important determinants of their social network characteristics. Finally, previous studies have documented the significance of personal socio-demographics in individuals’ decisions between solo and joint activities and their companionship choice for joint activities (Sharmeena and Ettema, 2010; Srinivasan and Bhat, 2008); therefore, socio-demographic characteristics are included in the model as control variables so that the effects of social network attributes can be correctly evaluated.

Figure 4. 1. The conceptual framework for analyzing choices of activity/travel companions

*The dashed arrow represents the link that was included in the hypothesized
conceptual model but not in the final model.

4.4 Data, variables and descriptive analysis

Data
The data used for this empirical analysis comes from the questionnaire survey conducted in Hong Kong. The questionnaire items relevant to the present case study include an activity-travel diary, personal social networks and respondents’ socio-demographics and household characteristics. Data on the structure of respondents’ personal social networks was collected using the “contact diary” approach (Fu, 2007; Milardo et al., 1983; van der Poel, 1993). Given the fact that activity companions may involve not only core network members, but also acquaintances, such as people in the same clubs or voluntary associations (Van den Berg et al., 2012a), the author believes the “contact diary” is the appropriate mechanism to collect information about the structure of social networks. Section 3.2.2 provides detailed information about sampling, implementation and sample profiles from this survey.

Variables
A total of 23 variables (12 endogenous variables and 11 exogenous variables) are selected to operationalize the conceptual model presented in figure 4.1. Among the 12 endogenous variables, six of them measure personal social network attributes including source of social support, network size and composition. The other six endogenous variables measure activity-travel behavior with different companionships. The 11 exogenous variables measure individuals’ socio-demographics. Tables 4.1 and 4.2 list the definitions and descriptive statistics of the endogenous and exogenous variables, respectively.
As table 4.1 shows, the sources of social supports are measured with three dummy variables, including the major sources of emotional support, the major sources of instrumental support and the major sources of social companionship. The sources are from either family members/relatives or friends/acquaintances. Another three variables measure the size and composition of personal social networks. Social network sizes are measured by two variables identifying the amount of contact through all means in the past week with family members/relatives and with friends/acquaintances. Personal social network composition is measured as the number of contacts with family members/relatives over the total number of contacts in the past week.

Given that almost all of the in-home activities are performed with family members or alone and do not directly result in travel, and work episodes are mostly pursued alone since colleagues in the workplace are not counted as companions (Srinivasan and Bhat, 2008), this study specifically focuses on the out-of-home, non-work activity-travel behavior. Six variables are selected to characterize the activity-travel participation with different kinds of companions. This study differentiates three types of companions: family members/relatives, friends/acquaintances and no companions (solo). Accordingly, three variables measuring the frequency of activities performed jointly with family members/relatives, friends/acquaintances and solo are defined. Similarly, three variables measuring the frequency of travel episodes for these three types of companions are also defined. Table 4.1 presents the mean and standard deviation of these variables.

This study also included 11 socio-demographic variables as exogenous variables. They include age, gender, educational attainment, car ownership, presence of children or the elderly, household income, household size, household car ownership, household type and student status. Descriptive statistics of these variables are presented in table 4.2.
Descriptive analysis

As table 4.1 shows, about 72.9% respondents reported that the major source of emotional support comes from family members/relatives, but only 28.8% of respondents reported family members/relatives as their major social companionship source. About 71.2% of respondents receive their major social companionship from their friends/acquaintances. On the other hand, both family members/relatives and friends/acquaintances seem to be equally important sources of instrumental support.

With respect to the social network size, table 4.1 shows that the average network size of the sample is approximately 21, which is very similar to that reported by studies using the “name generator” approach (e.g., Carrasco and Cid-Aguayo, 2012; Kowald and Axhausen, 2012; Van den Berg et al., 2013). As for the social network composition, the average percentage of contacts with family members/relatives in the past week is 36%, which is smaller than the shares of families/relatives in the social networks reported by the studies using the “name generator” approach, which identified 43% as reported by Van den Berg et al. (2009), 50% by Van den Berg et al. (2012a) and 43.5% by Carrasco and Cid-Aguayo (2012).

Referring to the variables measuring activity-travel behavior with different companions, the table shows that the average total number of out-of-home activities is about 1.35, which is much lower than 3.3 reported by a study based on the American Time Use Survey (ATUS) (Srinivasan and Bhat, 2005). However, the percentage of joint out-of-home activities in the sample is quite similar to that of the ATUS (80.7% vs. 72.4%). As for the travel episodes, both the average number of travel episodes and the percentage of joint travel episodes in the sample are fewer than that of the ATUS (1.82 vs. 4.13 and 26.9% vs. 51.4%),
respectively). This discrepancy may be caused by the differences in car ownership between Hong Kong and the United States. The higher car ownership in the United States compared with Hong Kong is more conducive to joint travel and trip making.

Table 4. 1. Endogenous variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable Name</th>
<th>Description</th>
<th>Mean</th>
<th>St. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social network attributes</td>
<td>Source of emotional support</td>
<td>Major source of emotional support (1 for family members/relatives, 0 for friends/acquaintances)</td>
<td>72.9%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Source of instrumental support</td>
<td>Major source of material/informational support (1 for family members/relatives, 0 for friends/acquaintances)</td>
<td>51.9%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Source of social companionship</td>
<td>Major source of social companionship (1 for family members/relatives, 0 for friends/acquaintances)</td>
<td>28.8%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Contacts with family/relatives</td>
<td>Number of family members/relatives contacted in the past week via different ways</td>
<td>5.52</td>
<td>6.07</td>
</tr>
<tr>
<td></td>
<td>Contacts with friends/acquaintances</td>
<td>Number of friends/acquaintances contacted in the past week via different ways</td>
<td>15.29</td>
<td>24.52</td>
</tr>
<tr>
<td></td>
<td>Share of family/relatives over total contacts</td>
<td>Percentage of contacts with family members/relatives in total number of contacts in the past week</td>
<td>0.36</td>
<td>0.24</td>
</tr>
<tr>
<td>Out-of-home non-work activities by types of</td>
<td>Joint-family/relatives</td>
<td>Number of joint out-of-home, non-work activities companied by family members/relatives</td>
<td>0.50</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td>Joint-friends/acq</td>
<td>Number of joint out-of-home,</td>
<td>0.59</td>
<td>0.89</td>
</tr>
<tr>
<td>Travel episodes by types of companions</td>
<td>Solo activities</td>
<td>Companions</td>
<td>Number of solo out-of-home, non-work activities</td>
<td>0.26</td>
</tr>
<tr>
<td>----------------------------------------</td>
<td>----------------</td>
<td>------------</td>
<td>-----------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>Travel-family/relatives</td>
<td>Number of travel episodes with family members/relatives</td>
<td>0.32</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td>Travel-friends/acquaintances</td>
<td>Number of travel episodes with friends/acquaintances</td>
<td>0.17</td>
<td>0.51</td>
<td></td>
</tr>
<tr>
<td>Travel-solo</td>
<td>Number of travel episodes without company</td>
<td>1.33</td>
<td>1.09</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.2. Exogenous variables

<table>
<thead>
<tr>
<th>Socio-demographics</th>
<th>Description</th>
<th>Mean</th>
<th>St. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>1 (11-18); 2 (19-29); 3 (30-39); 4 (40-49); 5 (50-59); 6 (60-69); 7 (70 &amp; +)</td>
<td>2.93</td>
<td>1.35</td>
</tr>
<tr>
<td>Gender</td>
<td>1 (male); 0 (female)</td>
<td>41.7%</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>1 (primary); 2 (secondary); 3 (postsecondary); 4 (undergraduate); 5 (postgraduate or higher)</td>
<td>3.20</td>
<td>1.05</td>
</tr>
<tr>
<td>Employment status</td>
<td>1 if employed/self-employed; 0 otherwise</td>
<td>59.4%</td>
<td></td>
</tr>
<tr>
<td>Student status</td>
<td>1 if student; 0 otherwise</td>
<td>27.5%</td>
<td></td>
</tr>
<tr>
<td>Presence of child(ren)</td>
<td>1 for the presence of child(ren) of age 0-12 years old in the household; 0 otherwise</td>
<td>18.1%</td>
<td></td>
</tr>
<tr>
<td>Presence of elderly</td>
<td>1 for the presence of the elderly of age 65 or above in the household; 0 otherwise</td>
<td>22.5%</td>
<td></td>
</tr>
<tr>
<td>Monthly household income</td>
<td>Monthly household gross income in Hong Kong dollars: 1 (&lt;9,999); 2 (10,000-19,999); 3 (20,000-29,999); ... 11 (&gt;100,000)</td>
<td>3.61</td>
<td>2.22</td>
</tr>
<tr>
<td>Household size</td>
<td>Number of household members</td>
<td>3.71</td>
<td>1.20</td>
</tr>
</tbody>
</table>
Household car ownership | 1 if yes; 0 otherwise | 18.8%
Housing type | 1 for public/home ownership housing; 0 for others | 49.9%

4.5 Modeling results and research findings

The conceptual model presented in figure 4.1 is operationalized as a structural equation model (SEM) or more specifically a path model. To identify the interrelationships between activities with different types of companions as well as between travels with different types of companions in both directions, the model is specified as a non-recursive structural equation model by allowing reciprocal effects between activities with different kinds of companions and between travels with different kinds of companions. Non-recursive structural equation models often have identification problems, which are also present in this study’s models. To avoid the identification problem in estimating non-recursive models, as the author have discussed before, one may impose constraints on some reciprocal paths (e.g., setting some paths to zero or assuming the reciprocal effects are equal or have a known proportion) in the under-identified equations or designate some exogenous variables as “instruments” (Heise, 1975; Schaubroeck, 1990; Schooler et al., 1999). In this case study, the author adopts the second approach and designates the exogenous variable “Household size” as an “instrument,” which is assumed to have direct effects on joint activities with family members/relatives, but no direct effects on solo activities and joint activities with friends/acquaintances.

The software package of AMOS (version 17.0) is used to estimate the models. This study employs a maximum likelihood (ML) estimator to estimate the model coefficients (Byrne, 2010). Maximum likelihood estimation is the most widely used estimator because it is considered to be fairly robust. The maximum
likelihood method requires multivariate normality. Like data used in many other studies, the data used here, however, slightly violate the multivariate normality assumption (e.g., Aditjandra et al., 2012; Cao et al., 2007; Van den Berg et al., 2013, 2012). The bootstrapping procedure is used in this study as an aid to cope with this problem (Byrne, 2010). This study allows the exogenous variables to correlate, as do residuals of social network variables. This study selected several of the most widely used indicators to assess the goodness-of-fit of SEM models, including the $\chi^2$ value, the ratio of $\chi^2$ over degrees of freedom, the Goodness-of-fit Index (GFI), the Comparative Fit Index (CFI), the Normed Fit Index (NFI) and the Root Mean Square Error of Approximation (RMSEA).

4.5.1 Test the contribution of social network variables to the model fit

To verify the major hypothesis that social network attributes significantly determine the decisions on joint/solo activity engagements and activity companion choices, this study first conducts Chi-square difference tests to compare several nested models to test the contribution of social network attributes to the model fit. Three models were developed. Previous studies have established the association between socio-demographic variables and decisions on joint activities and choices of companions (Srinivasan and Bhat, 2008). The first model (referred to as the Base model) follows the existing literature and includes only the 11 social-demographic variables and the 6 variables on activity/travel engagements with 3 different types of companionships. The second model (Model 1) included the direct effects of social network variables on the three variables measuring joint/solo activity engagements and activity companion choices. The third model (Model 2) adds the direct effects of social network variables on the three travel variables to Model 1.
Table 4.3 presents the goodness-of-fit indicators of the three models. Comparing the goodness-of-fit indicators of all three models with the cut-off values for a good model discussed earlier, we can tell that all three models fit the data reasonably well; Model 1 has the best goodness-of-fit. Chi-square difference tests were conducted to compare the three different models in a pairwise way (Anderson and Gerbing, 1988; Mayer and Gavin, 2005). This study first compares Model 1 with the Base model and then compares Model 2 with the Model 1. The results are presented in the first row of table 4.3. The Chi-square difference tests between Model 1 and the Base model show that Model 1 significantly improves the Base model by reducing the 60.363 Chi-square value of the Base model at the cost of 12 degrees of freedom (i.e., $\Delta \chi^2(12) = 60.363$) and the p-value is less than 0.001. This result suggests that the inclusion of social network variables significantly improves the explanatory power of the Base model, and therefore, it is important to consider the characteristics of individuals’ social networks in examining their joint-activity participation and companion choice behavior. However, the Chi-square difference tests between Model 2 and Model 1 suggest that Model 2 does not significantly improve the performance of Model 1. With a cost of 12 degrees of freedom, Model 2 only outperforms Model 1 by a Chi-square value of 11.141 and the significance level is greater than 0.10. This result shows that including paths from social network variables to travel variables with different types of companions does not contribute to the explanatory power of the model.

With parsimony preferred, the author concludes that Model 1 is the model that fits the data the best, and therefore, Model 1 is chose as the final model. The detailed final model results are listed in tables 4.4 and 4.5. Table 4.4 presents the direct and total effects of social network and socio-demographic variables on activity and travel episode variables; table 4.5 shows the direct effects of socio-demographic variables on social network variables. Figure 4.2 further illustrates the direct
effects between the endogenous variables. In the following sub-sections, this study discusses these detailed modeling results.

Table 4. 3. Goodness-of-fit indicators of different model specifications

<table>
<thead>
<tr>
<th></th>
<th>Base model</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \chi^2 (df), (p)$</td>
<td>60.363 (12), (p&lt;0.001)</td>
<td>11.141 (12), (p&gt;0.10)</td>
<td></td>
</tr>
<tr>
<td>$\chi^2 (p)$</td>
<td>232.107 (p=0.000)</td>
<td>171.744 (p=0.000)</td>
<td>160.603 (p=0.000)</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>83</td>
<td>71</td>
<td>59</td>
</tr>
<tr>
<td>$\chi^2/df$</td>
<td>2.795</td>
<td>2.419</td>
<td>2.760</td>
</tr>
<tr>
<td>GFI</td>
<td>0.975</td>
<td>0.981</td>
<td>0.983</td>
</tr>
<tr>
<td>CFI</td>
<td>0.953</td>
<td>0.968</td>
<td>0.968</td>
</tr>
<tr>
<td>NFI</td>
<td>0.932</td>
<td>0.950</td>
<td>0.953</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.048</td>
<td>0.043</td>
<td>0.047</td>
</tr>
</tbody>
</table>

Note: The base model does not include social network variables; Model 1 includes social network variables with direct links to only activity episodes; Model 2 includes social network variables with direct links to both activity and travel episodes.

4.5.2 Social network attributes and joint/solo activity-travel participation and companion choices

Mostly supporting the hypothesis, the modeling results presented in table 4.4 and figure 4.2 shows that five out of the six social network variables are significant determinants of joint/solo activity participation and choices of companions. The analysis finds the source of emotional support to be a significant factor explaining the choice of activity companions: emotional support from family members/relatives has a positive effect on the joint activities with family members/relatives and a negative effect on the activities with friends/acquaintances, suggesting that people who get their emotional support
mainly from their family members/relatives tend to perform more joint activities with their family members/relatives than their friends/acquaintances. This finding is within expectations and consistent with Carrasco and Miller (2009) who found that emotional closeness is positively related to the frequency of social interactions. A possible explanation for this finding is the fundamental human motivation of the need to belong (Baumeister and Leary, 1995). To satisfy the needs of belongingness or attachment, people who get emotional support mainly from their family members/relatives are more attached to them, and therefore, are more likely to perform joint activities with them. The major source of social companionship is found to significantly influence the choice of activity companion. The positive sign of joint activities with family members/relatives and negative sign of joint activities with friends/acquaintances indicate that individuals with family members/relatives as the major source of social companionship are more likely to undertake joint activities with their family members/relatives and less likely to perform activities solely or jointly with friends/acquaintances. This finding was expected and is intuitive. It is also supported by the observation that a considerable share of activities is for social, recreational or leisure purposes (Axhausen, 2008). The findings suggest that the major source of instrumental support is not a significant determinant of individuals’ decisions about choice of activity companion. This is likely because, as Carrasco and Cid-Aguayo (2012) noted, instrumental support (especially material support) usually comes from family members/relatives, and individuals normally conduct in-home joint activities with family members (e.g., Fujii et al., 1999). This study, however, focuses on out-of-home activities.

The results find that the numbers of social contacts with family members/relatives and friends/acquaintances in the past week are both significant variables explaining individuals’ choices of activity companions. Table 4.4 and figure 4.2 show that the number of contacts with family members/relatives has a positive and very significant impact on the number of joint activities with family
members/relatives; similarly, the number of contacts with friends/acquaintances is positively and significantly related to the number of joint activities with friends/acquaintances. These findings indicate that the more family members/relatives were contacted within the past week, the more joint activities people may have performed with their family members/relatives. Also, the more friends/acquaintances were contacted with in the past week, the more joint activities with friends/acquaintances were induced. In other words, social contacts generate joint activities. This is consistent with findings from other studies (e.g., Tillema et al., 2010; Van den Berg et al., 2013). Finally, social network compositions are also found to significantly influence the choice of activity companions. The significant negative coefficient to joint activities with friends/acquaintances suggests that a higher share of the contacts with family members/relatives out of the total number of contacts significantly reduces the chance of undertaking joint activities with friends/acquaintances. This finding is reasonable and understandable. A similar result is also reported by Van den Berg et al. (2012a) who found that having a larger share of relatives in one’s social network is negatively related to the frequency of going to association activities where friends/acquaintances are usually met.
### Table 4.4: Effects of social network and socio-demographic variables on activity and travel episode variables

<table>
<thead>
<tr>
<th></th>
<th>Activity episodes</th>
<th>Travel episodes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Joint-family/relatives</td>
<td>Joint-friends/acquaintances</td>
</tr>
<tr>
<td>Joint-family/relatives</td>
<td>(-0.338)</td>
<td>-0.115 (-0.036)</td>
</tr>
<tr>
<td>Joint - friends/acquaintances</td>
<td>(-0.005)</td>
<td>0.177 (0.177)</td>
</tr>
<tr>
<td>Solo activities</td>
<td>1.029 (0.681)</td>
<td>-0.124 (-0.160)</td>
</tr>
<tr>
<td>Travel - family/relatives</td>
<td>(-0.087)</td>
<td>(-0.516) (-0.512)</td>
</tr>
<tr>
<td>Travel - friends/acquaintances</td>
<td>(-0.029)</td>
<td>(-0.189) (-0.173)</td>
</tr>
<tr>
<td>Travel-solo</td>
<td>0.170 (0.155)</td>
<td>(-0.087)</td>
</tr>
<tr>
<td>Source of emotional support (family/relatives)</td>
<td>0.175 (0.116)</td>
<td>-0.166 (-0.172)</td>
</tr>
<tr>
<td>Source of instrumental support (family/relatives)</td>
<td>0.010 (0.007)</td>
<td>0.084 (0.083)</td>
</tr>
<tr>
<td>Source of social companionship (family/relatives)</td>
<td>0.348 (0.231)</td>
<td>-0.130 (-0.143)</td>
</tr>
<tr>
<td>Contacts with family/relatives</td>
<td>0.015 (0.014)</td>
<td>(-0.002)</td>
</tr>
<tr>
<td>Contacts with friends/acquaintances</td>
<td>(0.000)</td>
<td>0.003 (0.003)</td>
</tr>
<tr>
<td>Share of family/relatives over total contacts (%)</td>
<td>0.099 (0.065)</td>
<td>-0.224 (-0.227)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.033 (0.064)</td>
<td>-0.033 (-0.077)</td>
</tr>
<tr>
<td>Gender (male)</td>
<td>-0.090 (-0.065)</td>
<td>-0.031 (-0.030)</td>
</tr>
<tr>
<td></td>
<td>Education level</td>
<td>Employment status</td>
</tr>
<tr>
<td>---------------------------------------</td>
<td>---------------------</td>
<td>-------------------</td>
</tr>
<tr>
<td></td>
<td>0.045 (0.076) ^a</td>
<td>-0.173 (0.363) ^a</td>
</tr>
<tr>
<td></td>
<td>0.028 (0.017)</td>
<td>-0.202 (-0.164) b</td>
</tr>
<tr>
<td></td>
<td>0.056 (0.020)</td>
<td>-0.385 (-0.201) a</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.315 (-0.345) a</td>
</tr>
<tr>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: (1) ^a significantly different from zero at p<0.01; ^b significantly different from zero at p<0.05; ^c significantly different from zero at p<0.10.

(2) Both direct and total effects are listed and total effects are in parentheses. All effects are unstandardized.
As table 4.4 shows, though indirectly, the influence of social network attributes on joint travel as well as the choice of travel companions are mostly significant and show similar patterns to the activity patterns. The source of emotional support is found to have a positive effect on joint travel with family members/relatives and a negative effect on joint travel with friends/acquaintances, suggesting that people having emotional support mainly from family members/relatives tend to engage in more joint travel with family members/relatives and less in joint travel with friends/acquaintances than those who have emotional support mainly from friends/acquaintances. Similarly, the analysis finds a positive effect of joint travel with family members/relatives and negative effects of joint travel with friends/acquaintances and solo travel, indicating that people with family members/relatives as the main source of social companionship are more likely to travel with family members/relatives and less likely to travel with friends/acquaintances or alone than those with friends/acquaintances as their main source of social companionship. The number of contacts with family
members/relatives (friends/acquaintances) in the past week is found to be a positive factor influencing the frequency of joint trips with family members/relatives (friends/acquaintances). Within expectations, the number of contacts with family/relatives over total contacts is also negatively related to joint travel with friends/acquaintances. Finally, having family members/relatives as the major source of instrumental support is similarly found not to be a significant variable in explaining joint travel behavior.

4.5.3 Interaction effects between activity and travel companion choices

The first six rows of table 4.4 and figure 4.2 indicate that significant interaction effects exist between the activities with different types of companions and travel episodes with different types of companions, as well as between activity companions and travel companions. Supporting the hypothesis, significant interaction effects are found among the three choices of activity companions: “solo,” “with family members/relatives” and “with friends/acquaintances.” Undertaking activities jointly with family members/relatives significantly reduces the number of joint activities with friends/acquaintances and the number of solo activities. This is largely caused by individuals’ time constraints. The findings suggest that there are no significant effects of performing joint activities with friends/acquaintances on performing joint activities with family members/relatives or solo activities. A possible explanation is that joint activities with friends/acquaintances are mostly for leisure or are oriented toward socializing and discretionary activities, whilst solo activities or activities with family members/relatives are more likely to be functional and mandatory (e.g., personal or for household maintenance). People, however, do not usually end functional and mandatory activities for discretionary activities. Further, it is interesting to note that engaging in solo activities is found to significantly reduce the opportunity to perform joint activities with friends/acquaintances. But it significantly increases the chances of conducting joint activities with family members/relatives. This may be partly because
people are usually more obligated to provide companionship to their family members/relatives than to their friends/acquaintances.

Regarding the interaction effects between travel episodes with different types of companions, the results find significant interaction effects between joint travel with family members/relatives and traveling alone, as well as between joint travel with friends/acquaintances and traveling alone. The negative signs indicate that traveling jointly with family members/relatives or friends/acquaintances would significantly reduce the chance of traveling alone. These substitution effects are easy to understand because people can either choose to travel with others or travel alone. Additionally, similar to that of solo activities and joint activities with family members/relatives, there are significant positive effects from solo travel to joint travel with family members/relatives, suggesting that traveling alone would increase the opportunity for joint travel with family members/relatives. Moreover, no significant effects are found between traveling jointly with family members/relatives and traveling jointly with friends/acquaintances, indicating that no interaction effects between the choices of companions for joint travel exist. Lastly, no significant effects are found for solo travel on joint travel with friends/acquaintances.

Significant interactions are also found for activity companions and travel episode companions. As expected, the number of joint activities with family members/relatives has a significant and positive effect on the number of joint travel episodes with family members/relatives; the number of joint activities with friends/acquaintances significantly and positively affects the number of joint travel episodes with friends/acquaintances; and the number of solo activities significantly and positively determines the number of solo travel episodes. These findings imply that in most cases, people travel together to perform joint activities (or travel together after performing joint activities). Judging from the magnitude of the coefficients, we can tell that the activities carried out jointly with family members/relatives are more likely to induce joint travel with family members/relatives than the activities
conducted jointly with friends/acquaintances. This makes sense because family members/relatives are mostly those who are living together and are more likely to travel together to/from the destination for joint activities.

4.5.4 Effects of socio-demographics on joint/solo activity-travel participation and companion choice

Previous studies have reported that socio-demographic characteristics like age, educational attainment, employment status, and the presence of children in the household are significant explanatory factors of joint activity-travel behavior and companion choices (e.g., Carrasco and Miller, 2009; Scott and Kanaroglou, 2002; Srinivasan and Bhat, 2008; Van den Berg et al., 2013). The present study provides further evidence in this regard. Results in table 4.4 suggest that most socio-demographic variables are significant factors explaining companion choices for activities and travel episodes. Specifically, age is found to have positive effects on joint activities with family members/relatives and solo activities, but negative effects on joint activities and travel with friends/acquaintances, implying that, compared with older people, younger people are more likely to undertake joint activities and travel with friends/acquaintances, while also being less likely to perform joint activities with family members/relatives or solo activities. The negative effect of age on joint activities with friends/acquaintances is consistent with the findings by Van den Berg et al. (2012a) that the younger people are, the more likely they are to go to association or club activities where friends/acquaintances are usually met. Educational attainment appears to have a significant and positive impact on joint activities with family members/relatives, suggesting that individuals with higher educational attainments tend to perform more joint activities with their family members/relatives. Similar results are also reported by Kapur and Bhat (2007). As for employment status, as expected, all three effects on activities with different types of companions are found to be negative, indicating that compared with unemployed individuals, employed
people engage in fewer activities, regardless of whether they are with family members/relatives, with friends/acquaintances or on their own. This is in agreement with findings of previous studies (e.g., Lu and Pas, 1999). Unlike the findings of Srinivasan and Bhat (2008), employed persons are found to undertake more solo travel and less joint travel with their family members/relatives than unemployed people. These results are understandable because for employed persons, daily commuting trips are usually solo. Also, employed persons tend to have more time constraints so they conduct fewer joint activities with their family members/relatives compared with unemployed people. Regarding the influence of student status on the choices of activity companions, the results find that students are less likely to perform activities with family members/relatives or on their own. These results also do not align with those of Srinivasan and Bhat (2008) who found students are more likely to conduct joint activities either with family members/relatives or friends/acquaintances when compared with other groups. The potential reason for the divergent findings could be that “study” episodes are not counted in this research, but they are counted in Srinivasan and Bhat (2008) as solo activities. With respect to the influence of with whom students travel, the finding in this study is in agreement with that of Srinivasan and Bhat (2008) that students tend to undertake more solo travel and less joint travel with their family members/relatives compared to other groups.

Consistent with findings of previous studies, the presence of children in a household is found to exert significant influence on individuals’ joint activity-travel behavior (Scott and Kanaaroglou, 2002; Srinivasan and Bhat, 2008). Compared with people whose households do not include children, individuals with the presence of children in their household seem to tend to have more joint activities and travel with family members/relatives and fewer joint activities with friends/acquaintances as well as solo activities/travel. This is probably due to the fact that the adult members of the household spend time with their children doing activities or need to bring their children with them when performing other activities. As for the presence of elderly people in the household, the analysis found that individuals with elderly people in
their household appear to be more likely to perform solo activities and solo travel when compared with those without the presence of elderly people in the household. The results found only significant (and positive) impacts on joint travel with family members/relatives for household income, but no significant effects on other activities or travel. Similarly, household car ownership is found to have only significant (and negative) impacts on joint travel with friends/acquaintances, but not on others. Finally, no significant effects are found for household size and housing type on individuals’ engagements in joint activity-travel and companion choice behavior.

### 4.5.5 Effects of socio-demographics on social network attributes

The model estimates of the effects of socio-demographics on social network attributes are listed in table 4.5. Supporting the hypotheses, individuals’ socio-demographics are found to be significant determinants of their social network attributes. Specifically, the results found older people and the presence of children in households significantly increase the chance of having family members/relatives as the major source of emotional support. However, the presence of elderly people in households decreases the probability that individuals seek emotional support from family members/relatives. Regarding the major sources of instrumental support, results suggest that males, people with a higher educational levels and employed people are less likely to have their family members/relatives as their major sources of instrumental support than females, people with lower educational levels and people who are unemployed. Individuals living in larger households and with higher incomes are more likely to seek instrumental support from their family members/relatives for obvious reasons. With respect to the major source of social companionship, this analysis finds that for older people, family members/relatives are more likely to be the major sources of social companionship. The analysis observes a positive effect on the major source of social companionship for the presence of children in the household and a negative effect for the presence of elderly people in the household, implying that presence of
children in the household increases the chance of having social companionship from family members/relatives whereas the presence of elderly people in the household has the opposite effect. The analysis also finds that household car ownership increases the chance of having family members/relatives as the major source of social companionship.

Referring to the number of family members/relatives contacted in the past week, as expected, the presence of children and household size are found to have positive effects whereas males and people living in public housing have negative effects. These results suggest that people in households with children or who have larger families tend to have more contacts with family members/relatives whereas males and people living in public housing tend to have fewer contacts with family members/relatives. As for contacts with friends/acquaintances, age is found to have a negative effect, implying that younger individuals tend to have more contacts with friends/acquaintances than older people. Finally, age, the presence of children and household size are found to be positively related with the number of contacts with family members/relatives over the total number of contacts, indicating that older people, people with children in the household and people living in larger households are more likely to contact their family members/relatives than others. The analysis also finds a negative effect for the presence of the elderly in the household on the number of contacts with family members/relatives over the total number of contacts.

Table 4.5. Direct effects of socio-demographic variables on social network variables

<table>
<thead>
<tr>
<th>Source of emotional support (family/relatives)</th>
<th>Source of instrumental support (family/relatives)</th>
<th>Source of social companionship (family/relatives)</th>
<th>Contacts with family/relatives</th>
<th>Contacts with friends/acquaintances</th>
<th>Share of family/relatives over total contacts (%)</th>
</tr>
</thead>
</table>

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### Table

<table>
<thead>
<tr>
<th></th>
<th>Value 1</th>
<th>Value 2</th>
<th>Value 3</th>
<th>Value 4</th>
<th>Value 5</th>
<th>Value 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.068</td>
<td>0.009</td>
<td>0.047</td>
<td>0.109</td>
<td>-2.180</td>
<td>0.029</td>
</tr>
<tr>
<td>Gender (male)</td>
<td>-0.029</td>
<td>-0.072</td>
<td>-0.050</td>
<td>-1.266</td>
<td>0.169</td>
<td>-0.020</td>
</tr>
<tr>
<td>Education level</td>
<td>-0.010</td>
<td>-0.028</td>
<td>0.030</td>
<td>0.214</td>
<td>0.674</td>
<td>0.013</td>
</tr>
<tr>
<td>Employment status (Employed)</td>
<td>0.016</td>
<td>-0.194</td>
<td>0.012</td>
<td>0.482</td>
<td>0.770</td>
<td>0.044</td>
</tr>
<tr>
<td>Student</td>
<td>-0.096</td>
<td>0.029</td>
<td>-0.078</td>
<td>-0.708</td>
<td>-0.344</td>
<td>-0.022</td>
</tr>
<tr>
<td>Child presence</td>
<td>0.126</td>
<td>0.032</td>
<td>0.123</td>
<td>1.939</td>
<td>2.163</td>
<td>0.041</td>
</tr>
<tr>
<td>Elderly presence</td>
<td>-0.069</td>
<td>-0.004</td>
<td>-0.092</td>
<td>0.322</td>
<td>1.944</td>
<td>-0.037</td>
</tr>
<tr>
<td>Monthly household income</td>
<td>0.005</td>
<td>0.019</td>
<td>0.005</td>
<td>-0.007</td>
<td>-0.102</td>
<td>0.005</td>
</tr>
<tr>
<td>Household size</td>
<td>-0.002</td>
<td>0.029</td>
<td>-0.008</td>
<td>0.417</td>
<td>-0.911</td>
<td>0.022</td>
</tr>
<tr>
<td>Household car ownership (Yes)</td>
<td>0.052</td>
<td>-0.039</td>
<td>0.073</td>
<td>0.275</td>
<td>0.633</td>
<td>-0.012</td>
</tr>
<tr>
<td>House type (public)</td>
<td>0.016</td>
<td>-0.049</td>
<td>0.005</td>
<td>-0.971</td>
<td>-0.645</td>
<td>-0.016</td>
</tr>
</tbody>
</table>

*Significantly different from zero at *p*<0.01; *Significantly different from zero at *p*<0.05; *Significantly different from zero at *p*<0.10.*

### 4.6 Discussion and conclusion

Individuals’ engagement in daily activities and travel jointly or alone, as well as with whom in the joint travel is conducted is a very important aspect of activity-travel behavior (Srinivasan and Bhat, 2008). The rapidly growing literature on the social contexts of activities and travel has verified the relevance and importance of social networks in understanding and analyzing social activity-travel behavior. However,
hardly any study has analyzed the role of personal social networks in individuals’ overall activity-travel behavior. This chapter tries to fill in this gap by examining how personal social network attributes influence individuals’ decisions on engagement in joint/solo activities/travel and choices of activity/travel companion.

The empirical results in this study highlight the significance of social network attributes in explaining joint engagement in activities and travel and the choice of companions. The analysis found that the sources of emotional support and social companionship are significant determinants of the choice of activity companions. Individuals whose emotional support and social companionship mainly come from family members/relatives (friends/acquaintances) tend to undertake more joint activities with their family members/relatives (friends/acquaintances). This indicates the importance of emotional support and social companionship in explaining joint activity-travel behavior, while no significant impacts are found for the source of instrumental support. The size of social networks is also found to significantly determine the participation in joint/solo activities and the choices of companions. More family members/relatives (friends/acquaintances) contacted induces more joint activities with family members/relatives (friends/acquaintances). The analysis present here also reveals the significant influence of social network composition on the choices of companions for joint activities. Though indirectly, individuals’ social networks are found to be significant predictors of joint/solo travel and the choices of travel companions. The analysis found significant interactions between joint activities and travel with different types of companions.

The findings from this study have important policy implications. The interconnectedness of activity patterns of socially networked people suggests that instead of treating people as individual trip makers, transportation policies may need to take into account individuals’ social networks and joint activity-travel behavior patterns. For example, the effectiveness of carpooling policies may be improved if individuals’ social networks are considered in policy design. On the other hand, given
that joint activities are crucial to the development of individuals’ social networks and wellbeing, when designing transportation policies, the objectives should not only focus on access to facilities and places, but also access to socially connected people so that joint activities can be facilitated (Carrasco and Miller, 2009; Fujii et al., 1999).

The present study has several limitations and should be extended in the future in several different ways. First, activities are jointly considered as a whole in this study but future studies may need to differentiate activities by type (e.g., shopping, going out for meals, association activities, and socializing, etc.) so that further insight into joint activities can be generated. Second, the research findings of the present study may be consolidated in future studies by collecting multiple-day, activity-travel diary data, which will provide richer information on joint activity-travel behavior than the single-day activity diary data used in this study. Third, findings of this and previous studies (e.g., Larsen et al., 2006; Sharmeen et al., n.d.; Srinivasan and Bhat, 2008) suggest that the spatial setting of facilities, the residential environments, together with individuals’ social networks and socio-demographics all influence their decisions on engaging in joint activities and with whom to conduct these activities. If data are available, future studies should consider all factors simultaneously for a more integral and profound understanding of joint activity-travel behavior. Finally, though in many aspects the Hong Kong sample is largely representative of Hong Kong population, the sample underrepresents the elderly and the married while over-represents the well-educated. Since social networks and social supports of elderly and married people tend to be more family/relatives oriented than others, the results presented in this study thus may slightly under-estimate the influences of family/relatives on Hong Kong people’s choices of activity-travel companions. While for well-educated people, previous studies suggest that well-educated tend to have more opportunities for contacting themselves with their friends/acquaintances (Lee et al., 2005) and therefore this study may slightly over-estimate the impacts of friends/acquaintances on individuals’ activity-travel companion choice for Hong Kong people.
Overall, this empirical study enriches the literature on the importance of personal social networks in activity-travel behavior with empirical evidence on the influence of social network attributes on individuals’ joint/solo activity-travel and companion choice behavior. This chapter also contributes to the literature on joint activities; it sheds light on the importance of incorporating the social network variables into the analysis and modeling joint activity-travel behavior.
Chapter 5 Tradeoffs between in- and out-of-residential neighborhood locations for discretionary activities and time use: Do social contexts matter?

5.1 Introduction

The implications of the spatial distribution of social networks on activity-travel behavior have not received much research attention in previous studies. There are also not many studies examining how neighborhood social environments influence activity-travel behavior. This chapter provides further insight in these respects by exploring how social network attributes and neighborhood social environments influence individuals’ choices of different locations for activities and time use.

Where activities are performed has significant implications for the generation of the associated travel. Numerous studies have investigated the effects of household and personal socio-economic characteristics, the built environment and activity attributes on where daily activities are conducted and the time spent on such activities (e.g., Akar et al., 2011; Bhat and Gossen, 2004; Lu and Pas, 1999; Yamamoto and Kitamura, 1999). However, the influence of social contexts, particularly social networks, and the neighborhood social environment on individuals’ decisions about engagement in and time allocation to activities in different locations have received little research attention. This is much to the author’s surprise given the rapidly growing literature on the significance of personal social networks and neighborhood social environments in explaining individuals’ activity-travel behavior.

Using data from the activity-travel diary survey conducted in Beijing, China in 2013, this chapter examines if and how personal social networks and the social environment of the residential neighborhood impact the choice between in- and out-of-neighborhood locations for discretionary activities and time allocation.
Numerous studies have examined the tradeoffs between in-home and out-of-home activities and their implications for daily trip making (e.g., Akar et al., 2011; Bhat and Gossen, 2004; Yamamoto and Kitamura, 1999). This study argues that the choice between in- and out-of-neighborhood activities may also have significant implications for trip-making behavior. The author believes that the underlying motivations for in- and out-of-neighborhood activities may be significantly different. For example, activities in the neighborhood or in the vicinity of the neighborhood may have higher frequencies than similar activities out of the neighborhood because less effort is required to reach the activity location; similarly, activities in the neighborhood are less likely to induce motorized trips than those away from the neighborhood because of the shorter travel distances.

Understanding the tradeoffs between in- and out-of-neighborhood activities may add to the literature on the division between in-home and out-of-home activities (Akar et al., 2011; Yamamoto and Kitamura, 1999). Out-of-home activities include in- and out-of-neighborhood activities, but the former type is more likely to derive non-motorized travel and less likely to generate motorized travel than the latter. Motorized travel is discouraged due to their severe externalities, such as air pollution, traffic congestion, etc. (Cao and Huang, 2013). However, non-motorized travel is believed to have significant health and wellbeing benefits and should be encouraged (De Nazelle et al., 2011).

This case study focuses on discretionary activities because they are responsible for a substantial and growing portion of urban travel (Mokhtarian et al., 2006; Van den Berg et al., 2012a; Ohnmacht, 2009), and they have the most flexibility in terms of where, when and with whom they are performed compared to subsistence and maintenance activities (Kitamura et al., 1996; Mokhtarian et al., 2006). Two statistical models are formulated in this chapter: a multilevel logistic regression model to examine the activity location choice and a doubly censored Tobit model to study time allocation between in- and out-of-neighborhood activities.
The rest of the chapter is organized as follows. The next section introduces the data and defines the variables used in the models. Section 5.3 presents and discusses the empirical results. The last section discusses the research findings and concludes the empirical study.

5.2 Previous studies on locations choice for activities and time use

Since travel is derived from performing activities, where individuals conduct activities and spend their time in daily life is essential to understanding activity-travel behavior. Much research attention in the past few decades has been devoted to understanding activity location. For example, numerous studies have examined the destination choice for shopping trips (e.g., Arentze and Timmermans, 2005; Barnard, 1987; Horni et al., 2009; Koppelman and Hauser, 1978; Scott and He, 2012), recreational activities (e.g., Bhat et al., 1998; Pozsgay and Bhat, 2001; Scarpa and Thiene, 2005; Sivakumar and Bhat, 2007) and work trips (Simpson, 1987; Waddell et al., 2007).

One aspect of destination or location choice that has received much research attention is the substitution or tradeoffs between in-home and out-of-home activities because only out-of-home activities generate trips. Using data from the 2000 San Francisco Bay Area Travel Survey, Bhat and Gossen (2004) developed a mixed logit model to analyze the influence of socio-demographics, land-use and activity attributes on the choice between in-home and out-of-home for recreational activities. They found that household and personal socio-economic characteristics and activity characteristics have a significant influence on the decision to pursue out-of-home recreational activities. However, no significant effects are found for land use variables. Focusing on activity and schedule attributes and travel characteristics, Akar et al. (2011) studied how these factors influence individuals’ choices between in-home and out-of-home for discretionary activities. Four types of discretionary activities are distinguished,
namely: active, passive, eating and social interaction. The study reveals that social, active and eating activities are more likely to be pursued outside the home than passive activities; out-of-home activities are more likely to be followed or preceded by other out-of-home activities; and the chance of undertaking an out-of-home discretionary activity increases as the travel time and cost decreases.

Numerous studies have investigated the time allocation between in-home and out-of-home activities. Kitamura et al. (1996) proposed a doubly censored Tobit model to study individuals’ time allocation for in-home and out-of-home discretionary activities. They found that the work schedule, commuting time and socio-economic attributes significantly impact time allocation to in-home and out-of-home activities. People who have longer commute times are more likely to pursue in-home discretionary activities; the elderly and larger households also tend to spend a larger fraction of time on in-home discretionary activities. However, no significant effects were found for factors like gender, income and the number of vehicles owned. Using the same data set, Yamamoto and Kitamura (1999) extended Kitamura et al. (1996)’s work to examine time allocation to in-home versus out-of-home discretionary activities on working days and non-working days. The study confirmed the major findings of the previous study and further revealed a significant correlation between working and non-working days in the time allocation patterns. However, neither socio-demographic variables nor work-related variables explain the variation of time allocation between working and non-working days. By assuming a pre-determined amount of total weekly discretionary time, Bhat and Misra (1999) studied the allocation of total weekly leisure time to four categories of activities: in-home weekday, in-home weekend, out-of-home weekday and out-of-home weekend. They reported that, among the socio-demographics and work-related variables, age and working hours are the most important factors that shape individuals’ weekly discretionary time allocation. Meloni et al. (2004) developed a Nested-Tobit model to examine how individuals allocate their discretionary time between in-home and out-of-home activities and between activities and trips. Similar to other studies,
socio-demographics and activity variables were included as explanatory variables. Empirical results revealed that activity variables (e.g. time spent for mandatory non-work activities) have substantial power to explain individuals’ decisions about the tradeoffs between discretionary in-home and out-of-home activities.

Some more recent studies have included built environments/land use variables in the analysis of in-home vs. out-of-home tradeoffs. Bhat (2005) formulated a multiple discrete-continuous extreme value (MDCEV) model to analyze individuals’ time use in different types of discretionary activities (in-home social, in-home recreational, out-of-home social, out-of-home recreational and out-of-home shopping). Apart from personal and household socio-demographics and employment characteristics, a set of household location variables (e.g., land-use mix diversity, residential density, area type) was included as explanatory variables. Results, however, show that none of these household location variables are significant. Using structure equation modelling, Wang and Lin (2013) examined the effects of built environments and social environments on individuals’ daily activity-travel behavior and reported that built environment variables significantly influence individuals’ time use for in-home and out-of-home recreation activities. For instance, respondents living in a built environment with a high percentage of public rental housing, high density and good accessibility tend to allocate less time to in-home recreation activities and more time to out-of-home recreational activities.

The studies reviewed above show that the existing literature has well documented the influence of household and personal socio-demographic characteristics, the features of activities and the built environment variables on where daily activities are conducted and time is spent. The influence of social contexts, including personal social networks and residential neighborhood social environments, however, has not received much attention. Based on the previous discussion of the importance of personal social networks and neighborhood social environments in explaining activity-travel behavior, it is reasonable to assume that personal social networks, especially network size and
spatial distribution, and neighborhood social environments may significantly influence individuals’ choices of where to conduct daily activities, specifically discretionary activities, and for how long to carry out these activities. This theme deserves more research attention in the future.

5.3 Data and variables

Data
The data used in this study comes from the second wave of data collection in a two-wave household activity-travel diary survey in Beijing. Section 3.2.2 provides detailed information about this survey, including sampling, survey implementation, sample profiles information, etc. The 229 households or 587 respondents who participated in the second wave of data collection formed the sample of this empirical analysis. Because 72 of these respondents were not engaged in any discretionary activities on the diary day, the final sample includes 515 individuals.

The items related to this empirical analysis include an activity-travel diary, household and personal socio-demographics, and information on personal social networks and neighborhood social environments. Travel behavior studies have traditionally classified daily activities into three categories: 1) subsistence or work-related, 2) maintenance (e.g., sleeping, shopping, eating and other personal affairs) and 3) discretionary or leisure activities (e.g., Reichman, 1976; Lu and Pas, 1999; Wang and Lin, 2013). This study focuses on discretionary or leisure activities. Specifically, the discretionary activities examined in this study include watching TV/movies, hosting visitors, sports/exercise, window-shopping, sightseeing, visiting others, attending social activities/gatherings, among others.

Variables
A total of 21 explanatory variables are included in the location choice and time
allocation models presented in the next sections. Among them are five variables measuring personal social networks, two variables measuring neighborhood social environments, seven variables measuring activity attributes and seven variables measuring personal and household socio-demographics. Table 5.2 presents the definitions and descriptive statistics of these explanatory variables.

As table 5.2 shows, the five variables measuring personal social network size and spatial distribution are: 1) the number of frequently contacted family members/relatives living in the same neighborhood; 2) the number of frequently contacted friends/acquaintances living in the same neighborhood; 3) the number of family members/relatives living in Beijing contacted last week; 4) the number of friends/acquaintances living in Beijing contacted last week3 and 5) the spatial composition of social networks, measured as the ratio of social contacts living in the same neighborhood over the total number of people living in Beijing contacted last week. As for the spatial composition of social networks, in four cases the respondents did not contact anyone living in Beijing last week so the ratio is undefined. In these cases, the population mean is used instead.

The two variables measuring neighborhood social environments are derived from the seven statements on the perceived neighborhood social environments using exploratory factor analysis (EFA) (see table 5.1). The first factor, which is named “neighborhood safety,” has factor loadings of 0.891 and 0.772 from the two statements: “safety of walking” and “safety for kids to play outdoors,” respectively. The second factor, “neighborhood social cohesion,” has factor loadings ranging from 0.598 to 0.838 from the other five statements.

Table 5.1. Factors for neighborhood social environment

<table>
<thead>
<tr>
<th>Factor</th>
<th>Statement</th>
<th>Loading*</th>
</tr>
</thead>
</table>

3 In measuring social network attributes, social networks contacted last week living in Beijing do not include those frequently contacted social networks living in the same neighborhood.
Safety
- Safe to walk in neighborhood: 0.891
- Safe for kids to play outdoors in neighborhood: 0.772

Social cohesion
- People in this neighborhood have similar economic status: 0.598
- People in this neighborhood have similar socio-demographics (e.g., social class, age): 0.621
- People in this neighborhood interact a lot: 0.808
- People in this neighborhood can be trusted: 0.838
- People in this neighborhood are willing to help each other: 0.808

* Factor loadings after quatimax rotation, represents the degree of association between the statement and the factor

Following methods used in previous studies (Passmore and French, 2001; Srinivasan and Bhat, 2008; Akar et al., 2011), this study grouped the various discretionary activities into three categories: passive leisure, active leisure and social interaction. Passive leisure refers to the spectator type of activities, which include watching TV/listening music at home, watching movies in a movie theater, etc.; active leisure includes sports, sightseeing and other physical activities; and social interaction encompasses hosting family members/relatives, hosting friends/acquaintances, visiting others and social gathering/activities. Passive leisure is the reference category, and active leisure and social interaction are defined as dummy variables. Activity timings are measured by two dummy variables that characterize the start times of the activity: afternoon and evening. This study also included two variables in the model to measure activity companionship and activity duration.

Seven socio-demographic variables including gender, age, employment status, household income, child presence, household car ownership and home location defined by within which ring road one lives are also included as control variables.

Table 5.2. Explanatory variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable name</th>
<th>Description</th>
<th>Mean</th>
<th>St. dev</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social network attributes</td>
<td>Contacts with family/relatives living in BJ</td>
<td>Number of family members/relatives living in Beijing contacted last week</td>
<td>6.6</td>
<td>4.3</td>
</tr>
<tr>
<td>--------------------------</td>
<td>------------------------------------------</td>
<td>------------------------------------------------------------------------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td></td>
<td>Contacts with friends/acquaintances living in BJ</td>
<td>Number of friends/acquaintances living in Beijing contacted last week</td>
<td>17.5</td>
<td>19.2</td>
</tr>
<tr>
<td>Spatial composition of social networks</td>
<td>Spatial composition of social networks</td>
<td>Ratio of neighborhood social contacts last week over Beijing social contacts last week</td>
<td>0.66</td>
<td>0.68</td>
</tr>
<tr>
<td>Social environments</td>
<td>Neighborhood safety</td>
<td>Factor score of neighborhood safety based on the exploratory factor analysis</td>
<td>0</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>Neighborhood social cohesion</td>
<td>Factor score of neighborhood social cohesion based on the exploratory factor analysis</td>
<td>0</td>
<td>1.0</td>
</tr>
<tr>
<td>Activity features</td>
<td>Companionship</td>
<td>1 if the activity conducted jointly with others; 0 otherwise</td>
<td>58.8%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Activity duration</td>
<td>In 10 minute increments</td>
<td>11.9</td>
<td>6.9</td>
</tr>
<tr>
<td></td>
<td>Active Leisure</td>
<td>1 if the activity is for active leisure; 0 otherwise</td>
<td>17.1%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Social interaction</td>
<td>1 if the activity is for social interaction; 0 otherwise</td>
<td>7.0%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Afternoon</td>
<td>1 if the activity starts in the afternoon; 0 otherwise</td>
<td>27.8%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Evening</td>
<td>1 if the activity starts in the evening; 0 otherwise</td>
<td>49.4%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Time for mandatory activities</td>
<td>Total time spent on subsistence and maintenance activities (hours)</td>
<td>17.8</td>
<td>2.7</td>
</tr>
<tr>
<td>Social demographics</td>
<td>1 (male); 0 (female)</td>
<td>46.4%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------------------------------------------</td>
<td>----------------------</td>
<td>-------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>1 (12-18); 2 (19-29); 3 (30-39); 4 (40-49); 5 (50-59); 6 (60-69); 7 (70+&amp;+)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>1 (12-18); 2 (19-29); 3 (30-39); 4 (40-49); 5 (50-59); 6 (60-69); 7 (70+&amp;+)</td>
<td>1.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment status</td>
<td>1 if employed/self-employed; 0 otherwise</td>
<td>60.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Child presence</td>
<td>age 12 or younger in the household; 0 otherwise</td>
<td>25.6%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household Income</td>
<td>Monthly household disposable income in RMB: 1 (&lt;=1,999); 2 (2,000-3,999); 3 (4,000-5,999); ... 11 (35,000-39,999); 12 (&gt;=40,000)</td>
<td>5.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household car ownership</td>
<td>1 if yes; 0 otherwise</td>
<td>56.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home location</td>
<td>Residential location in terms of within which ring road of Beijing</td>
<td>4.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.4 Location choice between in- or out-of-neighborhood locations for discretionary activities: A multilevel logistic model

In this section, the author develops a multilevel logistic model to investigate the effects of personal social networks and neighborhood social environments on individuals’ decisions about the tradeoffs between in- and out-of-neighborhood locations for discretionary activities. The location of discretionary activities in this study is distinguished between in-neighborhood and out-of-neighborhood. Previous studies have used two main ways to define neighborhoods. One is by using the census tracts or equivalent administrative units as proxies for neighborhoods (Cao et al., 2007; Guo and Bhat, 2007). The limitation of this approach is that the boundaries of administrative units do not necessarily match the boundaries of neighborhoods and thus may lead to incorrect urban policy (Bhat and Guo, 2007; Coulton et al., 2001).
Another way of defining neighborhood is using buffers around respondents’ homes as a proxy (Prins et al., 2011). Previous studies typically have used 0.5 miles (around 800 meters) or 1 mile (around 1600 meters) as the buffer distance based on the rationale that this is a reasonable distance to walk (e.g., Colabianchi et al., 2007; Norman et al., 2006). This study adopts the second approach to define neighborhoods by using a 20-minute walking distance or 10-minute biking distance (around 1 mile) as the buffer distance.

5.4.1 Model development and estimation

Because the dependent variable discretionary activity location is defined as a dichotomous variable, a logistic regression model is an appropriate modeling tool. As have been discussed in section 3.3.2, given the fact that an individual may perform several discretionary activities, and thus, repeated observations from the same individual are included in the data, a multilevel model structure is thus needed. Specifically, a two-level logistic model (upper level: individual; lower level: activity episode) with random intercepts at the upper level is formulated in this study.

A total of 1,187 discretionary activities are reported by the 515 respondents in the sample. The number of activities conducted by an individual ranges from 1 to 7, with a mean of 2.3 activities. The model is calibrated with the 1,187 observations. To examine the influence of personal social networks and the neighborhood social environment on discretionary activity location choice, all five social network variables and two neighborhood social environment variables listed in table 5.2 are included in the model as explanatory variables. This study included the other variables listed in table 5.2, such as activity features and socio-demographics, as control variables. The model is estimated using Stata 12 with the estimation method of maximum likelihood. The results are presented in table 5.3.
Apart from the two-level random intercept logistic model, the author also estimates a simple logistic model with the same explanatory variables. A log-likelihood ratio test is conducted to compare these two models to confirm this study’s choice of model structure. The log-likelihood ratio test yields a Chi-square value of 23.06 with 1 degree of freedom, which is statistically significant at the 0.000 level. This means the two-level logistic model significantly improves the explanatory power of the simple logistic model. Additionally, the individual-dependent deviation of the random intercept is 3.270, which is also significant at the 0.05 level, indicating that significant correlations between the location choices for discretionary activities exist for the same individual. Thus, the two-level random intercept logistic model is chosen as the final model. The model has a log-likelihood value of -142.632 and is statistically significant at the 0.001 level. Table 5.3 presents the two-level logistic model results. The following subsections discuss the detailed modeling results.

### Table 5.3. Two-level logistic model for discretionary activity location choice

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Coefficients</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.504</td>
<td>3.493</td>
</tr>
<tr>
<td><strong>Social networks attributes</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family/relatives in the neighborhood</td>
<td>0.638***</td>
<td>0.246</td>
</tr>
<tr>
<td>Friends/acquaintances in the neighborhood</td>
<td>-0.256***</td>
<td>0.081</td>
</tr>
<tr>
<td>Contacts with family/relatives living in BJ</td>
<td>-0.048</td>
<td>0.121</td>
</tr>
<tr>
<td>Contacts with friends/acquaintances living in BJ</td>
<td>0.027</td>
<td>0.021</td>
</tr>
<tr>
<td><strong>Spatial composition of social network</strong></td>
<td>-0.117</td>
<td>0.852</td>
</tr>
<tr>
<td><strong>Neighborhood social environments</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood safety</td>
<td>-1.010**</td>
<td>0.469</td>
</tr>
<tr>
<td>Neighborhood social cohesion</td>
<td>-0.620*</td>
<td>0.360</td>
</tr>
<tr>
<td><strong>Activity features</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duration (in 10 min increments)</td>
<td>0.155**</td>
<td>0.054</td>
</tr>
</tbody>
</table>
Companionship (1 for companioned) 2.011** 0.9862
Active leisure 6.641*** 1.531
Social leisure 7.757*** 1.650
Afternoon -1.179* 0.644
Evening -4.798*** 1.252
Time for mandatory activities (hours) -0.483** 0.196

**Socio-demographics**
Gender (male=1) -1.082 0.741
Age -0.638* 0.338
Employed 3.694*** 1.290
Car ownership 0.246 0.815
Child presence 0.554 0.844
Household income -0.025 0.214
Home location 0.127 0.259

**Random effect**
S.D. SE
Intercept standard deviation (individual level) 3.270 0.840

Notes: Dependent variable: ‘1’ for out-of-neighborhood; ***significantly different from zero at p<0.01; ** significantly different from zero at p<0.05; * significantly different from zero at p<0.10.

5.4.2 Effects of social networks and the neighborhood social environment

As table 5.3 shows, supporting the hypothesis, the analysis finds personal social network attributes are significant determinants of the choice between in-and out-of-neighborhood locations for discretionary activities. Specifically, as expected, the effect of “friends/acquaintances in the neighborhood” on the choice of out-of-neighborhood for discretionary activities is negative and significant; suggesting that more frequent contact with friends/acquaintances living in the same neighborhood significantly reduces the probability of an individual conducting
discretionary activities out of the neighborhood. This is understandable. First, having more friends/acquaintances living in the same neighborhood means that there might be more social interactions like hosting/visiting/meeting with friends/acquaintances in the neighborhood due to the spatial proximity. Second, since joint activities like eating out/sports/exercise with friends/acquaintances need to comply with the necessary space-time conditions of proximity in space and synchronicity in time (Miller, 2005; Neutens et al., 2010), more friends/acquaintances in the neighborhood make these conditions easy to meet and thus may induce more joint discretionary activities in the neighborhood. Moreover, having more friends/acquaintances living in the same neighborhood may also enhance individuals’ senses of belonging to the neighborhood (Unger and Wandersman, 1985), which in turn generates more discretionary activities, like leisure walking in the neighborhood (Wood et al., 2010).

In contrast, the effect for “family members/relatives in the neighborhood” on the choice of out-of-neighborhood for discretionary activity appears to be significant and positive, suggesting that having more family members/relatives living in the same neighborhood tends to increase the chance of performing discretionary activities out of the neighborhood. One possible explanation is that more family members/relatives living in the same neighborhood may induce more joint out-of-neighborhood discretionary activities, such as window shopping and cultural activities, due to the ease of coordination (Sharmeen and Ettema, 2010; Srinivasan and Bhat, 2008). This argument is also supported by Kapur and Bhat (2007) who reported that around half of the out-of-home discretionary activities are performed with family members. Though not significant, the number of friends/acquaintances living in Beijing contacted last week positively contributes to the choice of out-of-neighborhood locations for discretionary activities. This is logical because maintaining or developing social relationships with more friends/acquaintances living in Beijing requires more joint activities with them. This result supports the arguments made in other studies and the empirical study in Chapter 4 that social networks generate social activities and travel (e.g., Tillema et al., 2010; Van den Berg et al., 2012a)
Table 5.3 shows that the number of family members/relatives living in Beijing contacted last week seems not to be a significant determinant of activity location choice. This may partly be attributed to the substitution effects of Information and Communication technologies (ICT) (Kwan et al., 2007) because the social contact information used in this study covers contacts through ICT means. Another possible reason is related to the hindering effects of distance for conducting frequent social activities (Larsen et al., 2006; Tillema et al., 2010). Though not significant, the variable on spatial composition of the social network has a negative effect on the choice of going out-of-neighborhood for the discretionary activity, which seems to suggest that spatially concentrated social networks, or a higher proportion of social network members living in the same neighborhood or within walking distance, may reduce the probability of individuals to conduct out-of-neighborhood discretionary activities. This point deserves further investigation.

Supporting the hypothesis, the two neighborhood social environment variables both appear to be significant determinants of discretionary activity location choices. Neighborhood safety has a negative coefficient, which means that people living in a safe neighborhood are more likely to perform the in-neighborhood discretionary activities. This result is consistent with findings from other studies that neighborhood safety is positively associated with physical activities/leisure walking in the neighborhood (e.g., Molnar et al., 2004; Fisher et al., 2004). Similarly, neighborhood social cohesion seems to increase the probability of conducting in-neighborhood discretionary activities. This supports findings from previous studies (e.g., Fisher et al., 2004).

5.4.3 Effects of activity attributes

Table 5.3 shows that the type, companionship, duration and starting time of activities
are significant predictors of where such activities are performed: in-neighborhood or out-of-neighborhood. Aligned with the findings of Akar et al. (2011), activity type is found to be an important indicator of discretionary activity location choice. Compared with passive leisure, active leisure and social interactions are much more likely to be conducted out-of-neighborhood. The results also find activity timing to be an important determinant of location choice of in- or out-of-neighborhood for discretionary activities. Compared with morning discretionary activities, those conducted in the afternoon and evening are more likely to be in-neighborhood activities. These results are partly consistent with Bhat and Gossen (2004) who found that out-of-home discretionary activities are less likely to be performed in the evening than in the morning but are equally likely to be performed in the morning and in the afternoon. Moreover, the results also found that long duration discretionary activities are more likely to be conducted outside the neighborhood. This is supported by findings from Moore et al. (2013) and Van den Berg et al. (2012b) who found that the home-activity distance is positively related to the duration of social activities. In addition, joint discretionary activities are found to be more likely performed out of the neighborhood than solo discretionary activities. This result is in line with results from Srinivasan and Bhat (2005) who reported that a higher proportion of out-of-home leisure are conducted jointly compared with in-home leisure activities. Lastly, with respect to time constraints, consistent with previous studies (e.g., Akar et al., 2011), the analysis found significant negative effects of the total time spent on mandatory activities, indicating that the more time available for people to conduct discretionary activities, the more likely they will choose to go out of the neighborhood for such activities.

5.4.4 Effects of socio-demographics

Referring to the individual and household characteristics, consistent with the findings of Akar et al. (2011) and Bhat and Gossen (2004), the analysis finds the elderly are
less likely than other age groups to perform out-of-neighborhood discretionary activities. The mobility constraints of the elderly may be the major reason for this result. As expected, compared with unemployed individuals, employed individuals are found to have a much higher propensity to perform out-of-neighborhood discretionary activities. This may be partly due to the need for employed persons to participate in social activities to maintain and develop relationships with their colleagues or business partners, as suggested in Chapter 4 of this dissertation.

The analysis does not find significant effects for residential location on discretionary activity location choice. In other words, the choice between in- or out-of-neighborhood locations for discretionary activities appears not to be influenced by the individual home location, which is defined by within which ring road of Beijing the home is located. This result is similar to Bhat and Gossen (2004) who reported that land use tends not to be a significant determinant in individuals’ choice between in-home and out-of-home locations for discretionary activities. Nevertheless, whether this result is real or is related to the measurement of home location requires investigation in future studies.

5.5 Time allocation between in- and out-of-neighborhood discretionary activities:

A doubly censored Tobit model

Next, this study examines the effects of personal social networks and neighborhood social environments on individuals’ time allocations for in- and out-of-neighborhood discretionary activities. As been discussed in section 3.3.3, previous studies have developed a discrete-continuous type of modeling system such as a doubly censored or two-limit Tobit model to analyze time allocation to two types of activities (Kitamura, 1984; Kitamura et al., 1996; Yamamoto and Kitamura (1999). In accordance with these studies, the two-limit Tobit model is adopted here.
The 515 respondents in the final sample are used to calibrate the model. The estimator of maximum likelihood is used to estimate the Tobit model. Table 5.4 presents the modeling results. The likelihood ratio test and Pseudo R² demonstrate that the model is statistically very significant.

Regarding the effects of personal social networks and the neighborhood social environment on individuals’ discretionary activity time allocation, only the number of frequently contacted friends/acquaintances living in the neighborhood is found to be a significant indicator. The number of frequently contacted friends/acquaintances living in the same neighborhood has a negative impact on the time allocated to out-of-neighborhood discretionary activities relative to that of in-neighborhood activities, implying that people with more frequent contact with friends/acquaintances living in the same neighborhood tend to allocate a larger fraction of leisure time to in-neighborhood activities. This finding is consistent with the logistic model result presented in table 5.3. However, as shown in table 5.4, no significant effects are found for other social network variables. As for the neighborhood social environment, neither neighborhood safety nor cohesion seems to significantly impact the tradeoffs between in- and out-of-neighborhood locations for discretionary time use. Future studies may be required to confirm the lack of significance of these variables.

Turning to the socio-demographics, significant negative effects are found for males and the elderly, indicating that males and the elderly tend to spend a larger portion of discretionary time performing in-neighborhood activities than females and younger individuals. These results are consistent with the logistic model results and with findings from other studies (Bhat and Misra, 1999; Bhat, 2005; Yamamoto and Kitamura, 1999). Being employed is found to have a positive effect, implying that employed individuals tend to allocate a larger fraction of discretionary time to out-of-neighborhood activities. Car-ownership appears to have a positive coefficient, suggesting that people with a household car are more likely to allocate a larger fraction of discretionary time to out-of-neighborhood activities. This can be attributed
to the high mobility and flexibility that having a car provides. The effects of time constraints are very significant. The negative coefficient for total time spent on mandatory activities indicates that the less time one has available for discretionary activities, the smaller the fraction of time that person will allocate to out-of-neighborhood activities. Again, this is congruent with the results of the logistic model. Similar to the result of the logistic model, no significant effects are found for home location.

Table 5.4. Two-limit Tobit models of time allocation to in- and out-of-neighborhood discretionary activities

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Coefficient</th>
<th>T-stats</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>13.531***</td>
<td>5.53</td>
</tr>
<tr>
<td>Social networks attribute</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family/relatives in the neighborhood</td>
<td>0.232</td>
<td>1.48</td>
</tr>
<tr>
<td>Friends/acquaintances in the neighborhood</td>
<td>-0.137***</td>
<td>-2.91</td>
</tr>
<tr>
<td>Contacts with family/relatives contacted with in BJ</td>
<td>-0.024</td>
<td>-0.30</td>
</tr>
<tr>
<td>Contacts with friends/acquaintances living in BJ</td>
<td>0.003</td>
<td>0.22</td>
</tr>
<tr>
<td>Spatial composition of social network</td>
<td>-0.830</td>
<td>-1.16</td>
</tr>
<tr>
<td>Neighborhood social environments</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood safety</td>
<td>-0.309</td>
<td>-1.09</td>
</tr>
<tr>
<td>Neighborhood social cohesion</td>
<td>-0.219</td>
<td>-0.91</td>
</tr>
<tr>
<td>Socio-demographics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender (male)</td>
<td>-1.103**</td>
<td>-2.21</td>
</tr>
<tr>
<td>Age</td>
<td>-0.598***</td>
<td>-2.76</td>
</tr>
<tr>
<td>Employed</td>
<td>1.084*</td>
<td>1.65</td>
</tr>
<tr>
<td>Car-ownership</td>
<td>0.946*</td>
<td>1.66</td>
</tr>
<tr>
<td>Household income</td>
<td>0.101</td>
<td>0.65</td>
</tr>
<tr>
<td>Child preference</td>
<td>-0.522</td>
<td>-0.89</td>
</tr>
<tr>
<td>Time for mandatory activities</td>
<td>-0.955***</td>
<td>-8.15</td>
</tr>
</tbody>
</table>
### Home location

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log likelihood</td>
<td>-303.168</td>
<td></td>
</tr>
<tr>
<td>The likelihood ratio chi-square (16)</td>
<td>132.76***</td>
<td></td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.179</td>
<td></td>
</tr>
</tbody>
</table>

Notes: ***significantly different from zero at p<0.01; ** significantly different from zero at p<0.05; * significantly different from zero at p<0.10.

### 5.6 Discussions and conclusions

Location choices for activities and time use have long been an important topic in activity-travel behavior studies (Akar et al., 2011; Pinjari et al., 2009). Previous studies have paid little attention to the implication of the spatial distribution of social networks, the neighborhood social environments for activity-travel behavior. This chapter attempts to contribute to this gap by examining how personal social networks and neighborhood social environments influence individuals’ tradeoffs between in- and out-of-neighborhood discretionary activities and time use. Instead of a choice between in- and out-of-home locations usually used in previous studies, the location choice pattern in this study is defined by between in- and out-of-neighborhood. This substitution pattern has significant transportation implications because out-of-neighborhood activities are more likely to generate motorized travel than in-neighborhood activities.

The results presented in this chapter highlight the importance of personal social networks and neighborhood social environments in explaining individuals’ tradeoffs between in- and out-of-neighborhood locations for activities and time use. The analysis finds that the spatial ordering of social networks in terms of the social network members living in the same neighborhood or within walking distance are very significantly determinant. People who have more frequent contact with friends/acquaintances living in the same neighborhood appear to be more likely to
conduct and allocate a larger fraction of time to discretionary activities in the neighborhood rather than out of the neighborhood. On the other hand, individuals having more family members/relatives living in the same neighborhood tend to have a higher propensity to participate in out-of-neighborhood discretionary activities. The analysis also reveals significant effects of the number of social contacts with people living in the same city. More friends/acquaintances living in Beijing contacted within the past week induces more discretionary activities out of the neighborhood. With respect to neighborhood social environments, the results of this analysis show that people living in neighborhoods with better safety and social cohesion are more likely to participate in in-neighborhood discretionary activities.

Overall, this empirical analysis enriches the growing literature on the effects of personal social networks and neighborhood social environments on activity-travel behavior with empirical evidence of their impacts on individuals’ choice of in- and out-of-neighborhood locations for discretionary activities. The attribute of spatial distribution of social networks is considered. This analysis also contributes to the knowledge about activity-location choices by analyzing the effects of social contexts. The findings in this study have significant policy implications concerning motorized trip generation. First, the finding that more social contact with friends/acquaintances living in the same neighborhood enhances the chance of performing in-neighborhood discretionary activities suggests that policy measures targeted toward improving neighborhoods to facilitate social contact between neighbors may help reduce motorized trips. Examples of such policies include those enhancing voluntary neighborhood associations or clubs, which may help individuals develop and maintain social networks with neighbors (Van den Berg et al., 2012a) and in turn increase in-neighborhood discretionary activities and reduce the need for motorized travel. Moreover, the impacts of neighborhood safety and social cohesion suggest that policies aimed at improving the neighborhood social environment may also act as an instrument to help to reduce motorized trips. Different from previous studies that suggest discouraging out-of-home activities will reduce travel demand (Gärling and
Schuitema, 2007), this study argues that out-of-home but in-neighborhood activities should be encouraged because these activities have significant health benefits but do not induce motorized travel.

The present study may be extended in the future in several directions. First, given the significant implication of the location pattern of in- and out-of-neighborhood for motorized trip generation, more understanding about this substitution pattern is needed. Second, several studies have suggested substitution relationships between discretionary activities on working and non-working days for employed individuals (e.g., Bhat and Misra, 1999; Yamamoto and Kitamura, 1999). Thus if multiday activity-daily data are available for analysis, understanding of the tradeoffs between in- and out-of-neighborhood activities may be improved. Moreover, whether the spatial composition of social networks has a significant impact on the location choice of discretionary activities needs more exploration in the future studies. Lastly, the analysis finds significant impacts of neighborhood safety and social cohesion in the location choice model but not in the time allocation model. What causes this inconsistency needs more exploration in future studies.
Chapter 6 Social contexts, residential relocation and changes in travel

6.1 Introduction

A limited amount of research literature has examined how dynamics of social contexts impact activity-travel behavior. This chapter intends to contribute empirical evidence to this literature by using real panel data collected in Beijing to examine how changes in social networks and the neighborhood social environment after relocation induce changes in travel.

Changes in travel after a residential move have been the subject of a growing number of studies in recent years. Throughout an individual’s life course, a residential relocation is one of the key events that induces significant changes in travel over the long term (e.g., Oakil et al., 2013; Prillwitz et al., 2007; Scheiner and Holz-Rau, 2013a; Sharmeen et al., 2014a). Many studies have explored the importance of the associated changes in residence location and other built environment characteristics after a residential move for explaining changes in travel, after taking socio-demographics and their changes into account (e.g., Aditjandra et al., 2012; Buchanan and Barnett, 2006; Krizek, 2003; Prillwitz et al., 2007; Scheiner and Holz-Rau, 2013a). However, not much research has investigated the connections between the associated changes in social contexts such as personal social networks and neighborhood social environments, after relocation and changes in travel behavior. After a residential move, individuals may not only gain or lose some social networks (e.g., friends/neighbors), but the spatial distribution of the individuals’ social network members may also change significantly (Oishi, 2010; Sharmeen et al., 2014b). In addition, after moving, not only the built environments but also the neighborhood social environments may change significantly. Given the importance of personal social networks and the social environment in explaining activity-travel behavior, this
study would like to argue that changes in travel after a residential move may not only be induced by changes in the built environments associated with the move, but may also be triggered by changes in the social contexts.

The rest of this chapter is organized as follows. The next section reviews previous studies on residential relocation and changes in travel. Section 6.3 discusses the methodology used in this case study and presents the conceptual model underpinning this study. Section 6.4 describes the data and variables used in this case study. Descriptive analyses of the changes in the built environment, social environment and personal social networks, as well as changes in travel are also presented in this section. Model results are shown and discussed in section 6.5. The final section includes a discussion and concluding remarks based on the model results.

6.2 Previous studies on residential relocation and changes in travel

Residential relocation is one of the key events in an individual’s life cycle that induces significant changes in travel over the long term (e.g., Oakil et al., 2013; Prillwitz et al., 2007; Scheiner and Holz-Rau, 2013a; Sharmeen et al., 2014a). Generally, activity-travel patterns are assumed to be relatively habitual and stable when behavior environments remain unchanged. Residential relocation, which usually represents a change in the behavior contexts, is therefore believed to have at least the potential to change individuals’ activity-travel patterns (Prillwitz et al., 2007). The changes in activity-travel after a residential move have been the subject in a growing number of studies in recent years. Numerous studies have examined how travel changes in response to residential location changes. Næss (2005) investigated the changes in travel patterns in Copenhagen after residential relocation. Næss found that changes in the amount of travel due to residential moves are significantly related to the changes in the distance between residences and downtown Copenhagen after a move. Moving away from downtown was reported to significantly increase the amount of travel.
whereas moving closer to the city center reduced the amount of travel. For those who have not changed the distance to the city center significantly after moving, no significant changes in the amounts of travel were observed. From a mobility biographies perspective, Prillwitz et al. investigated the impacts of residential relocation characteristics on changes in the commuting distance (Prillwitz et al., 2007) and car ownership (Prillwitz et al., 2006). They found that moving from a regional core to a non-core area significantly increases the daily commuting distance. Car ownership, however, was found to be significantly linked to moving from a regional core to a regional core area. Yang (2006) examined the impacts of relocation patterns on commuting time and modal choice in transitional China where the job and home site relationship before housing reform (both the home and workplace located in the same work unit compound) significantly differ from western countries. Yang (2006) found that the further people move away from their previous dwelling, the more the commuting time lengthens and the share of non-motorized modes decreases. Compared to the “neutral” mover, residential relocation increases commuting time more for the “reluctant” mover and less for the “affirmative” mover.

Several studies concerned about the influence of urban sprawl on changes in travel have focused on the effects of moving to a suburban area. Burnley et al. (1997) reported that most of the individuals who moved from the urban center to the outer suburbs experience a substantial increase in commuting time and a significant decrease in contacts with friends and relatives. Buchanan and Barnett (2006) explored how moving to a peripheral neighborhood changes individuals’ travel distance for different trip purposes and how it affects the modal split in Christchurch, New Zealand. They found residential relocation to a suburban neighborhood results in a substantial increase in travel distances for work/education and shopping, and a small increase in travel distances for recreation. There is, however, little change in the travel modal split, which remains heavily dependent on the car. Focusing on the moderating role of proximity to metro station, Robert and Jennifer (2008) examined the effects of residential relocation to the suburbs on commuting behavior and modal choice in
Shanghai, China. Their results showed that, on average, both commuting time and cost significantly increase after individuals move to the suburbs. However, moving near a suburban rail station significantly moderates the increasing effects of relocation on both commuting time and cost. They also found that moving near a metro station advances the changes of commute-mode from non-motorized travel and bus transit to rail commuting.

Another strand of research on residential relocation and travel changes paid more attention to the associations between the changes in the built environments and socio-demographics after moving and the changes in urban travel. Krizek (2003) investigated the linkage between changes in neighborhood-scale urban form and changes in urban travel for residential movers, controlling for socio-demographics and their changes. Their findings show that a decrease in the commuting distance after moving lowers the vehicle miles traveled while increasing the number of tours; an increase in neighborhood accessibility and regional accessibility after relocation decreases in the total distance traveled and the number of trips per tour but increases in the number of tours. However, changes in urban form attributes did not seem to trigger changes in the mode split. Additionally, significant effects of changes in socio-demographics on changes in travel were also reported. With the aim of establishing a causal link between the built environment and travel behavior, Cao et al. (2007) employed a structure equation modelling approach to examine the associations between changes in neighborhood accessibility, spaciousness and attractiveness after a residential move and changes in car ownership, driving and walking behavior, after taking socio-demographics, residential preference and travel attitudes into account. They reported that a reduction in driving is mostly a result of the increase in accessibility and walking may increase with the enhancements of neighborhood attractiveness. Arguing that results from the U.S. may not transferrable to Britain due to the difference in land-use patterns and policies, Aditjandra et al. (2012) replicated Cao et al. (2007)’s study using a British dataset. Similar to the findings of Cao et al. (2007), their study found that changes in car ownership are significantly influenced by
changes in neighborhood characteristics, such as shopping accessibility and safety; however, changes in socio-demographics after a move seem to be the main contributors. Moreover, they also found changes in neighborhood attributes, such as travel accessibility and socializing, tend to induce changes in driving. Using a mobility biography approach, Scheiner and Holz-Rau (2013b) examined how changes in the built environment and changes in the socio-demographics associated with a residential move determine changes in the mode of travel used. They found changes in socio-demographics and changes in the built environment go along with relocation to induce substantial changes in the use of a car, public transport, bicycles and walking, and thus they argue that residential relocation should be considered a key event in an individual’s mobility biography. Some studies have also taken a public health perspective and have investigated the association between changes in the built environment and changes in walking behavior after residential relocation. For example, Giles-Corti et al. (2013) reported significant relationships between changes in the neighborhood walking environment and changes in transport-related walking and recreational walking following relocation, after controlling for socio-demographics and residential self-selection. They also found a partial mediation role for changes in perceived neighborhood attractiveness in the observed associations between the built environment and recreational walking.

In conclusion, previous studies have provided much insight for understanding the relationships between residential relocation, changes in the built environments and changes in individuals’ activity-travel behavior. However, few studies have explored the relationships between changes in social contexts, particularly personal social networks and neighborhood social environments and changes in activity-travel behavior after residential relocation. Future studies can extent the existing literature along this line.
6.3 Methodology and conceptual framework

The two basic approaches for analyzing longitudinal data are the lagged dependent variable model and the change score model (Johnson, 2005). Though both methods can be used to analyze the dynamics of outcomes, each method has a different emphasis. The lagged dependent variable model focuses on predicting final outcomes while the change score model focuses on predicting the changes in outcomes between waves. In addition, the lagged dependent variable model allows cross-lagged and reciprocal effects to be estimated, but this is not allowed in a change score model (Johnson, 2005; Mokhtarian and Meenakshisundaram, 1999; Weigl et al., 2010). Finally, the change score approach has the ability to control the effects of unobserved, time-invariant variables, which is the main advantage of the change score approach in obtaining the least biased coefficients (Allison, 1994; Johnson, 2005). In analyzing how travel changes after residential moves, the change score approach is commonly used in previous studies (e.g., Krizek, 2003; Prillwitz et al., 2007). For this case study, the main focus is on explaining the changes in travel between the post-move and pre-move and thus the change score method is the appropriate method to use.

Figure 6.1 illustrates the conceptual framework underpinning this empirical study. The existing literature has well documented the significant impact of the residential built environment on travel (e.g., Ewing and Cervero, 2010, 2001; Stead and Marshall, 2001). The importance of social contexts has been verified by increasing literature on personal social networks and social activity-travel behavior (e.g., Carrasco and Miller, 2009; Dugundji et al., 2011; Van den Berg et al., 2013), as well as on neighborhood social environments and activity-travel behavior (e.g., Joh et al., 2011; McDonald, 2007; Wang and Lin, 2013). The significant linkages between changes in the built environments and changes in travel after a move are also examined by several previous studies on residential relocation and travel changes (e.g., Cao et al., 2007; Krizek, 2003; Yang, 2006). Building on this academic background, it is plausible for us to hypothesize that both changes in the built environments, the social environments
and personal social networks trigger changes in household car ownership and changes in daily travel time by car, public transit and non-motorized modes. One may argue that, changes in car ownership and changes in daily travel may also lead to changes in personal social networks. Nevertheless, the analysis in Chapter 4 suggests car ownership has no impact on personal social networks; meanwhile, Carrasco and Cid-Aguayo (2012) also suggest that car ownership does not lead to more social interaction. I, therefore, only assume undirectional effects from changes in personal social networks on changes in car ownership after relocation. As for changes in daily travel behavior, since the structured information of social networks is measured by the number of social contacts within the past week, it is reasonable for us to only assume undirectional impacts from personal social networks to daily travel behavior.

Changes in car ownership are well documented in previous studies to be significant indicators of changes in driving, public transit use and walking/biking (e.g., Cao et al., 2007; Scheiner and Holz-Rau, 2013). It was thus hypothesized that changes in daily travel time by car, public transit and non-motorized travel mode are influenced by changes in household car ownership. Interaction effects between changes in car travel time, public transit travel time and non-motorized travel time are assumed too. Initially, the author assumed reciprocal effects among changes in travel time by different modes. However, only unidirectional effects are found to be significant in the trial estimations of the model. Therefore, with parsimony preferred, the interaction effects between changes in car travel time, public transit travel time and non-motorized travel time are hypothesized to be unidirectional. Specially, this case study assumes that changes in car travel time impact changes in public transit travel time and non-motorized travel time; changes in public transit travel time impact changes in non-motorized travel time.

In addition, previous literature reported the significance of the base value of socio-demographics and their changes in explaining changes in neighborhood characteristics, car ownership and travel after a residential move (Aditjandra et al.,
2012; Cao et al., 2007; Krizek, 2003). Following the literature, household and personal socio-demographics and their changes are included in the framework as exogenous variables.

![Conceptual framework for analyzing changes in travel after home relocation](image)

Figure 6.1: The conceptual framework for analyzing changes in travel after home relocation

### 6.4 Data, variables and descriptive analyses

#### 6.4.1 Data

The data used in this case study is panel data (before home relocation and after home relocation) collected in a two-wave household activity-travel diary survey in Beijing, China. In total, 537 respondents from 229 households participated in both waves of data collection and formed the samples for the present case study. The data items collected in both waves related to the present case study include: 1) an activity-travel diary, 2) information on personal social networks, residential built environments and social environments, and 3) personal and household socio-demographics. Section
3.2.2 provides detailed information about the survey.

6.4.2 Variables

A total of 11 endogenous variables and 20 exogenous variables were selected in this study. All the variables used are measures of changes except the eight pre-move socio-demographic variables. Among the 11 endogenous variables, three measure changes in built environments, two measure changes in personal social networks, one measures changes in residential social environments, and five measure changes in travel. The 20 exogenous variables include eight pre-move socio-demographic variables and four variables measuring changes in socio-demographics, as well as eight indicator variables for the two latent constructs. All the “change” variables are measured by taking the differences between the values at post-move and pre-move. Tables 6.1 and 6.2 list the definitions and descriptive statistics of the endogenous and exogenous variables, respectively.

Table 6.1. Endogenous variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable name</th>
<th>Description</th>
<th>Mean / %</th>
<th>St.dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Changes in spatial contexts</td>
<td>Move to suburbs</td>
<td>1 if moving from city center to suburbs; 0 otherwise</td>
<td>24.0%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Move to city center</td>
<td>1 if moving from suburbs to city center; 0 otherwise</td>
<td>13.0%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Changes in accessibility</td>
<td>Latent construct of changes in perceived residential accessibility</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Changes in social networks (SN)</td>
<td>Changes in SN-in</td>
<td>Changes in the number of frequent social contacts living in the same neighborhood or within walking distance</td>
<td>-2.32</td>
<td>12.24</td>
</tr>
<tr>
<td></td>
<td>Changes in</td>
<td>Changes in the number of</td>
<td>-10.35</td>
<td>39.06</td>
</tr>
<tr>
<td>Changes in neighborhood social environment</td>
<td>Changes in social environment</td>
<td>Latent construct of changes in perceived neighborhood social environment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>-------------------------------</td>
<td>---------------------------------------------------------------------------------</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>Car acquisition</td>
<td>1 if no car in the household before move while have car(s) after move; 0 otherwise.</td>
<td>23.3%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car disposal</td>
<td>1 if have car in the household before move while no car after move; 0 otherwise</td>
<td>8.6%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changes in non-motorized travel time</td>
<td>Changes in non-motorized travel time in the survey day</td>
<td>5.74 49.58</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changes in public transit travel time</td>
<td>Changes in public transit travel time in the survey day</td>
<td>12.69 76.35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changes in car travel time</td>
<td>Changes in private car travel time in the survey day</td>
<td>5.61 48.03</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As table 6.1 shows, two variables are used to measure changes in personal social networks, including changes in the number of frequent social contacts living in the same neighborhood or within walking distance and changes in the number of social networks contacted within the past week. Changes in the neighborhood social environment are defined as a latent variable with five indicator variables of changes in the values on five statements about the neighborhood social environment. The five statements are about “safe to walk,” “safe for kids to play outdoors,” “similar in economic status,” “similar in socio-demographics (e.g., social class)” and “interaction among neighbors”. Changes in the built environment after a move are also included in this study to control their influence. Changes in residential location and changes in accessibility are reported to be the most important spatial factors in explaining
changes in travel after relocation (e.g., Cao, Mokhtarian, & Handy, 2007; Krizek, 2003; Næss, 2005). Referring to previous studies, two dummy variables of “move to suburbs”, “move to city center” and a latent variable of “changes in accessibility” are selected in this study to measure the changes in the built environment after a move. Changes in perceived accessibility are also defined as a latent construct with three indicators including “changes in accessibility to the city center or shopping mall”, “changes in availability of facilities nearby” and “changes in convenience of public service”. All three indicators were also collected using a 5-Point Likert-scale measure. Five variables are used to measure changes in travel. Among them, two dummy variables “car acquisition” and “car disposal” measure changes in car ownership and the other three measure changes in daily travel time by different modes.

Table 6.2. Exogenous variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable name</th>
<th>Description</th>
<th>Mean/ %</th>
<th>St. dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household and personal socio-demographics (Base: pre-move)</td>
<td>Gender</td>
<td>1(male); 0(female)</td>
<td>46.9%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age</td>
<td>1(12-18); 2(19-29); 3(30-39); 4(40-49); 5(50-59); 6(60-69); 7(70&amp;+)</td>
<td>3.79</td>
<td>1.46</td>
</tr>
<tr>
<td></td>
<td>Education</td>
<td>1(primary); 2(secondary); 3(postsecondary); 4(undergraduate); 5(postgraduate or higher)</td>
<td>3.81</td>
<td>1.17</td>
</tr>
<tr>
<td>Employment status</td>
<td>Employment status</td>
<td>Employment status: 1 if employed or self-employed; 0 otherwise</td>
<td>65.7%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Household income</td>
<td>Monthly household disposable income in RMB: 1(&lt;=1,999); 2(2,000-3,999); 3(4,000-5,999); … 11(35,000-39,999); 12(&gt;=40,000)</td>
<td>5.93</td>
<td>1.74</td>
</tr>
<tr>
<td></td>
<td>Household size</td>
<td>Number of household members living in the house</td>
<td>3.33</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td>Car ownership</td>
<td>Household car ownership: 1 if have</td>
<td>42.5%</td>
<td></td>
</tr>
</tbody>
</table>
### Home location
- Car: 1 if unemployed before move while employed after move; 0 otherwise
- Home location in terms of within which ring road of Beijing: 3.98, 1.65

### Changes in socio-demographics after move

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Get job</td>
<td>1 if unemployed before move while employed after move; 0 otherwise</td>
<td>3.54%</td>
</tr>
<tr>
<td>Lose job</td>
<td>1 if employed before move while unemployed after move; 0 otherwise</td>
<td>4.67%</td>
</tr>
<tr>
<td>Changes in household size</td>
<td>Changes in the number of household size</td>
<td>-0.14, 0.94</td>
</tr>
<tr>
<td>Changes in household income</td>
<td>Changes in monthly household disposable income</td>
<td>-0.23, 2.02</td>
</tr>
</tbody>
</table>

### Indicators of latent variable “changes in perceived accessibility”

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Changes in accessibility to city center or shopping mall</td>
<td>Changes in values on statement: easy access to city center or shopping mall</td>
<td>0.25, 1.17</td>
</tr>
<tr>
<td>Changes in availability of facilities nearby</td>
<td>Changes in values on statement: lots of amenities (e.g. library, sports facilities) available nearby</td>
<td>0.56, 1.36</td>
</tr>
<tr>
<td>Changes in convenience of public service</td>
<td>Changes in values on statement: easy to travel by public transit (bus or metro)</td>
<td>0.22, 1.10</td>
</tr>
</tbody>
</table>

### Indicators of latent variable “changes in neighborhood social environment”

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Changes in safety of walking</td>
<td>Changes in values on statement: safe to walk in this neighborhood</td>
<td>0.44, 1.36</td>
</tr>
<tr>
<td>Changes in safety of playing outdoors for kids</td>
<td>Changes in values on statement: safe for kids to play outdoors in this neighborhood</td>
<td>0.57, 1.68</td>
</tr>
<tr>
<td>Changes in similarity in economic status</td>
<td>Changes in values on statement: people in this neighborhood have similar economic status</td>
<td>0.29, 1.21</td>
</tr>
<tr>
<td>Changes in similarity in socio-demograph</td>
<td>Changes in values on statement: people in this neighborhood have similar socio-demographics (e.g.</td>
<td>0.36, 1.29</td>
</tr>
</tbody>
</table>
A total of 12 socio-demographic variables are included in the model as control variables. Findings from previous studies suggest that both the base values of socio-demographics and their changes are significant indicators of changes in neighborhood characteristics and travel (e.g., Krizek, 2003; Prillwitz et al., 2006; Scheiner & Holz-Rau, 2013). This case study, therefore, controlled eight pre-move socio-demographic variables including age, gender, educational attainment, employment status, household income, household size, household car ownership and ring road location of the home. In addition, four variables that capture changes in socio-demographics are also controlled. These include two dummy variables for “get job” and “lose job”, a variable for changes in household size and a variable for changes in household income.

### 6.4.3 Descriptive analysis

This section simply describes how the spatial contexts, social contexts and travel behaviors change after residential relocations. As suggested by previous literature, the fourth ring road in Beijing can be regarded as the boundary that distinguishes the central city and the suburban area (Ding, 2004; Gu and Shen, 2003; Han, 2004). Table 6.3 presents the contingency table of the residential location pattern at both pre- and post-move. As we can see, 22.7% of the households moved from the city center to a suburban area while only 12.7% moved from the suburbs to the city center. As well, 32.8% of households relocated their residences within the central city and the rest of the 31.9% moved within the suburban area. This relocation pattern is consistent with the undergoing suburbanization process in Beijing (Feng et al., 2008; Li and Siu, 2001; Yang, 2006).
Table 6.3 Contingency table of residential relocation pattern

<table>
<thead>
<tr>
<th></th>
<th>Post-move: city center</th>
<th>Post-move: suburban area</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-move: city center</td>
<td>75 (32.8%)</td>
<td>52 (22.7%)</td>
<td>127 (55.5%)</td>
</tr>
<tr>
<td>(within 4th ring road)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-move: suburban</td>
<td>29 (12.7%)</td>
<td>73 (31.9%)</td>
<td>102 (44.5%)</td>
</tr>
<tr>
<td>area (outside 4th ring</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>road)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>104 (45.4%)</td>
<td>125 (54.6%)</td>
<td>229 (100%)</td>
</tr>
</tbody>
</table>

Referring to the perceived residential accessibility and neighborhood social environment, table 6.4 shows that all the means of the scores on related statements increased significantly after the move indicating an improvement in the perceived neighborhood accessibility and neighborhood social environments in general for home movers. This argument is also supported by the fact that much higher proportions of households reported improvements in neighborhood accessibility and the social environment after moving, whilst only much smaller proportions of households thought their current neighborhood accessibility and social environments are worse than the accessibility and social environments in the pre-move neighborhood (see the last two columns in table 6.4). These results are reasonable because pursuing a better living environment is typically one of the most important reasons for housing relocation (Yang, 2006). Turning to the personal social networks, both the average number of frequent social contacts living in the same neighborhood and the average number of overall social contacts within the past week are found to significantly decrease after a residential move. The analysis also found that more than half of respondents experienced a decrease in the number of frequent social contacts living in the same neighborhood and in the number of social contacts within the past week. Additionally, only 26.8% of respondents have more frequent social contacts living in the same neighborhood and 38.4% have contacted more people within the past week after a move. These results are consistent with Burnley, Murphy, & Jenner.
(1997) who reported that much higher proportions of home movers had reduced levels of contact with their friends and relatives whilst only small proportions saw more friends and relatives after relocation.

Table 6.4. Changes in behavior contexts and travel after relocation

<table>
<thead>
<tr>
<th></th>
<th>Pre-move</th>
<th>Post-move</th>
<th>T</th>
<th>p</th>
<th>% increase</th>
<th>% decrease</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accessibility</strong> (N=229)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Easy access to the city center or a large shopping mall</td>
<td>3.88</td>
<td>4.17</td>
<td>3.70</td>
<td>0.000</td>
<td>40.2%</td>
<td>24.5%</td>
</tr>
<tr>
<td>Lots of amenities (e.g. library, sports facilities) available nearby</td>
<td>3.12</td>
<td>3.67</td>
<td>5.88</td>
<td>0.000</td>
<td>50.2%</td>
<td>22.7%</td>
</tr>
<tr>
<td>Easy to travel by public transit (bus or metro)</td>
<td>4.13</td>
<td>4.34</td>
<td>2.71</td>
<td>0.007</td>
<td>35.4%</td>
<td>26.6%</td>
</tr>
<tr>
<td><strong>Social environment</strong> (N=229)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Safe to walk in the neighborhood</td>
<td>3.33</td>
<td>3.76</td>
<td>4.88</td>
<td>0.000</td>
<td>45.4%</td>
<td>26.2%</td>
</tr>
<tr>
<td>Safe for kids to play outdoors in the neighborhood</td>
<td>2.96</td>
<td>3.51</td>
<td>4.94</td>
<td>0.000</td>
<td>53.3%</td>
<td>27.1%</td>
</tr>
<tr>
<td>People in the neighborhood have similar economic status</td>
<td>3.49</td>
<td>3.73</td>
<td>2.97</td>
<td>0.003</td>
<td>36.7%</td>
<td>28.4%</td>
</tr>
<tr>
<td>People in the neighborhood have similar socio-demographics (e.g. social class, age)</td>
<td>3.41</td>
<td>3.81</td>
<td>4.70</td>
<td>0.000</td>
<td>46.7%</td>
<td>25.8%</td>
</tr>
<tr>
<td>People in the neighborhood interact a lot</td>
<td>3.19</td>
<td>3.47</td>
<td>2.66</td>
<td>0.008</td>
<td>41.5%</td>
<td>29.3%</td>
</tr>
<tr>
<td><strong>Personal social networks (N=537)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequent social contacts in neighborhood</td>
<td>13.95</td>
<td>11.63</td>
<td>-4.3</td>
<td>0.000</td>
<td>26.8%</td>
<td>54.0%</td>
</tr>
</tbody>
</table>
Social contacts in the past week 37.63 27.28 -6.1 0.000 38.4% 60.1%

Daily travel behavior (N=537)
Non-motorized travel time (mins) 33.17 38.91 2.68 0.008 56.1% 35.0%
Public transit travel time (mins) 34.02 46.71 3.85 0.000 33.9% 23.6%
Car travel time (mins) 14.9 20.5 2.71 0.007 17.3% 13.2%

Significant changes in travel are also observed. In term of household car ownership (Table 6.5), the proportions of households who have car(s) increased from 38.4% at pre-move to 53.3% after move. A total of 31.4% of households experienced changes in car ownership. Among them, 23.1% of households changed from having no car to being a car owner and 8.3% of households disposed of their cars. As for daily travel behavior (Table 6.4), average travel times by all three modes increased after the move. Similarly, more people travel longer distances after the move than they did pre-move whereas fewer respondents travel shorter distances after relocation for all three modes.

Table 6.5. Contingency table of changes in household car ownership

<table>
<thead>
<tr>
<th></th>
<th>Post-move: have car(s)</th>
<th>Post-move: no car</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-move: have car(s)</td>
<td>69 (30.1%)</td>
<td>19 (8.3%)</td>
<td>88 (38.4%)</td>
</tr>
<tr>
<td>Pre-move: no car</td>
<td>53 (23.1%)</td>
<td>88 (38.4%)</td>
<td>141 (61.6%)</td>
</tr>
<tr>
<td>Total</td>
<td>122 (53.3%)</td>
<td>107 (46.7%)</td>
<td>229 (100%)</td>
</tr>
</tbody>
</table>

6.5 Modelling results and research findings

A structure equation modelling (SEM) approach is employed in this study to operationalize the conceptual model presented in figure 6.1. The maximum likelihood (ML) approach, which is the most commonly used estimator, is used to estimate the SEM model using AMOS (version 20.0) (Byrne, 2010). Our data, like data used in
many other studies (e.g., Aditjandra et al., 2012; Cao et al., 2007; Van den Berg et al., 2013, 2012), slightly violate the multivariate normality assumption. A bootstrapping procedure is thus used as an aid to address the non-normal data in this study (Byrne, 2010). Error terms of exogenous variables are allowed to correlate.

Several widely used indexes are chosen to assess the goodness-of-fit of the models, including the Chi-square value, the ratio of $\chi^2$ over degrees of freedom, the Goodness-of-Fit Index (GFI), the Comparative Fit Index (CFI), the Incremental Fit Index (IFI) and the Root Mean Square Error of Approximation (RMSEA) (Byrne, 2010; Hair et al., 2010). As mentioned in section 3.3.1, for a model with good fit, the ratio of $\chi^2$ over degrees of freedom needs to be smaller than 5.0; GFI, CIF and IFI need to be larger than 0.9 and RMSEA needs to be smaller than 0.08.

6.5.1 Test the contribution of the social context variables to model fit

To substantiate the major hypothesis that changes in social contexts associated with a residential move significantly determine changes in household car ownership and daily travel behavior, three models were developed and compared. Previous studies have established the significant linkage between socio-demographic variables and changes in car ownership and travel (e.g., Cao et al., 2007; Krizek, 2003; Prillwitz et al., 2006). Following the literature, the first model (Base model) only considers the effects of the 12 socio-demographic variables on the five variables measuring changes in car ownership and daily travel. Previous literature suggests that changes in built environments are significant triggers of changes in car ownership and daily travel after a residential move (e.g., Cao et al., 2007; Krizek, 2003; Naess, 2005). Accordingly, the second model (Model 1) takes into account both changes in the built environments and socio-demographic variables in explaining changes in household car ownership and daily travel after a residential move. Finally, based on Model 1, the third model (Model 2) adds the direct effects of changes in social environments and
social networks on changes in household car ownership and daily travel. Model 2 includes all the paths hypothesized in the conceptual model.

Table 6.6 presents the goodness-of-fit indicators of the three modes. Judging from these goodness-of-fit indicators, we can tell that all three models are acceptable and Model 2 fits the data the best. This study conducted Chi-square difference tests (Anderson and Gerbing, 1988; Mayer and Gavin, 2005) to compare Model 1 and the Base model, as well as Model 2 and Model 1. The results of the Chi-square difference tests are shown in the first row of table 6.6. The Chi-square difference tests between Model 1 and the Base model suggest that Model 1 significantly improves the Base model by reducing the Chi-square value of the Base Model to 29.752 at the cost of 15 degrees of freedom (i.e., $\Delta \chi^2(15)=29.752$) and a $p$ value is smaller than 0.05. This result is consistent with previous studies and confirms the importance of changes in the built environments for explaining changes in travel after relocation (e.g., Cao et al., 2007; Krizek, 2003; Næss, 2005). Moving to the comparison between Model 2 and Model 1, the Chi-square difference tests show that Model 2 significantly outperforms Model 1 with a 67.162 Chi-square value at a loss of 15 degrees of freedom (i.e., $\Delta \chi^2(15)=67.162$) and a $p$-value smaller than 0.001. This result indicates that inclusion of the effects of changes in social context adds explanatory power to the models, and it is thus important to include changes in social environments and social network variables in explaining changes in travel after relocation.

| Table 6.6. Goodness-of-fit indicators of different model specifications |
|-------------------------|------------------------|------------------------|
|                        | Base model             | Model 1                | Model 2 (final model) |
| $\Delta \chi^2(df),(p)$ | 29.752(15), (0.01<p<0.05) | 67.162(15), (p<0.001)  |
| $\chi^2(p)$            | 493.437(p=0.000)       | 463.685(p=0.000)       | 396.523(p=0.000)     |
| Degree of freedom      | 225                    | 210                    | 195                   |
| $\chi^2/df$            | 2.193                  | 2.208                  | 2.033                 |
| GFI                    | 0.942                  | 0.946                  | 0.953                 |
The above analysis suggests that Model 2 is the model that fits the data the best and thus is chosen as the final model. The coefficient estimations of the final model are presented in figure 6.2, tables 6.7 and 6.8. Figure 6.2 presents the measurement model results. Table 6.7 shows the direct and total effects of endogenous and exogenous variables on changes in household car ownership and daily travel time by different modes, whereas table 6.8 lists the direct effects of exogenous socio-demographic variables on changes in social environments, personal social networks and built environments. The explanation and discussion of model results is provided in the following sections.

6.5.2 Measurement model

The model used in this analysis involves two latent constructs defined as changes in the social environment and changes in accessibility. As figure 6.2 shows, all the five variables measuring changes in the social environment and the three variables measuring changes in accessibility are significant indicators of their corresponding latent construct. All the loadings for a latent construct of changes in the social environment are positive. This indicates that the latent construct of changes in the social environment tends to have a high positive value for large improvements in perceived safety of walking and playing outdoors for kids (neighborhood safety), and substantial increases in a perceived similarity in economic status and socio-demographics, and interactions among neighbors (social cohesion) after a move. As for the latent construct of changes in accessibility, similarly, the positive loadings suggest that a large positive value on the construct of changes in accessibility is associated with large improvements in the perceived accessibility to the city center or
shopping mall, perceived availability of facilities nearby and perceived convenience of public transit services after relocation.

![Diagram](image.png)

* significantly different from zero at \( p < 0.01; \)

Figure 6.2. Measurement models

### 6.5.3 Changes in social contexts and changes in travel

As table 6.7 shows, partially supporting the hypothesis, changes in personal social networks are found to be significant determinants of changes in travel time by different modes. Specifically, changes in social contacts living in the same neighborhood negatively relate to changes in public transit time, suggesting that individuals who have more social contacts living in the same neighborhood after a move are more likely to reduce their public transit travel times. This result is consistent with findings in Chapter 5 that people with more
friends/neighbors/acquaintances living in the same neighborhood are more likely to perform their discretionary activities in the neighborhood and thus may use public transit less. Moreover, table 6.7 also shows that changes in the number of social contacts within the past week is positively associated with changes in public transit travel time whereas it is negatively associated with changes in car travel time and changes in non-motorized travel time. These results are statistically significant, suggesting that an increase in overall social contacts within the past week after a move tends to induce more public transit travel, while not increasing more car and non-motorized travel. No significant relationships are found between changes in social networks and changes in car ownership. These results are logically consistent with findings in Chapter 4 and Carrasco and Cid-Aguayo (2012) who argue that having a car does not lead to more social interaction and social support. Findings here seem to suggest the opposite direction of this argument that developing and maintaining more social contacts does not necessarily contribute to car ownership and car use.

As for the latent construct of changes in the social environment, the analysis also finds it to be a significant determinant for both changes in car ownership and changes in daily travel. In particular, people who move to neighborhoods with improved social environments—in other words neighborhoods that are safer and more cohesive—are found to be less likely to acquire a car and more likely to dispose of their car. This finding is not consistent with findings in a British context (Aditjandra et al., 2012) in which those moving to safer neighborhoods (usually a suburban community) were more likely to acquire an additional car. The negative total effect from changes in the social environment to changes in car travel times indicates that an improved social environment tends to reduce car use. This finding is partially consistent with Aditjandra et al. (2012) who found that social factors (highly related to interactions among neighbors) significantly reduce driving behavior. Though not statistically significant, the total effects of changes in the social environment on changes in public transit times and changes in non-motorized travel times are positive, suggesting that
improvements in the social environment may increase public transit use and non-motorized travel. The author hope future studies can verify these relationships.

6.5.4 Changes in the built environment and changes in travel

Table 6.7 shows that as expected, changes in the built environment are important triggers of changes in car ownership and daily travel. Specifically, the results found households moving from a suburban area to the city center are less likely to dispose of their car whereas those moving from the city center to a suburban area are more likely to dispose of their car. This may relate to the fact that those who move from a suburban area into the city center are usually wealthy households since housing prices in central city of Beijing on average are much higher than prices in the suburban area (Han, 2004). For rich people, a car is considered not only a mobility tool but also a symbol of social status (Wang and Lin, 2014), and thus, it is thus understandable that households moving into the city center from a suburban area would be less likely to dispose of their car. While reasons for the positive correlation between moving from the city center to a suburban area and car disposal are not available yet. In addition, within expectations, moving from the city center to a suburban area significantly increases public transit time and non-motorized travel time, whereas moving from suburban area to city center tends to significantly reduce car travel time and public transit travel time. These findings are consistent with Næss (2005) who reported that moving to a suburb increases the amount of travel and moving downtown reduces the amount of travel. These findings are also in line with the well-established notion that suburban residents usually travel more than downtown residents (Stead and Marshall, 2001).

Changes in accessibility are found to be positively related to changes in car travel time and negatively associated with changes in non-motorized travel time. This indicates that when accessibility improves after relocation, individuals are typically
increasing their car use while decreasing their non-motorized travel. This result seems reasonable and consistent with some studies (e.g., Rajamani et al., 2003) because improvements in accessibility may lead people to go out more often and thus lead to more car use. However, there are also some other studies that state the opposite that accessibility has negative effects on driving (e.g., Aditjandra et al., 2012; Cao et al., 2007; Kockelman, 1997). More case studies in different contexts are therefore needed in the future to verify their relationships. As suggested by previous studies that longitudinal designs offer more convincing evidence for causality (e.g., Mokhtarian and Cao, 2008); therefore, findings from this case study also provide further evidence in the debate about the causal relationships between the built environment and travel behavior.

6.5.5 Interactions between car ownership and changes in daily travel by different modes

As table 6.7 shows, changes in car ownership are significant determinants of changes in car travel time, public transit travel time and non-motorized travel time. As expected, acquisition of a car by a household significantly increases car travel time while decreasing public transit travel time, suggesting that when a car is available, it is highly likely that residents will abandon public transit and will instead choose to travel by car. The analysis also finds that car disposal significantly reduces car use while increasing the use of public transit. These results are easy to understand and in accordance with previous studies (e.g., Scheiner and Holz-Rau, 2013).

Interactions between changes in travel times by car, public transit and non-motorized modes are also found to be significant. Changes in car travel time are negatively associated with changes in public transit travel time and non-motorized travel time, suggesting the existence of significant substitution effects between car use and the other two travel modes. However, no significant effects are found between changes in
public transit travel time and non-motorized travel time. A potential explanation may be that the positive complementation effects offset the negative substitution effects because people need to travel to the public transit station by either walking or cycling.

6.5.6 Socio-demographics and changes in travel

The model also estimates the impact of socio-demographics on changes in car ownership and daily travel (Table 6.7). Mostly within expectations, people who are well-educated, are employed, have a high household income, come from a large family, and do not have car in the household are found to be more likely to acquire a car after moving to new neighborhood. Young people are less likely to acquire a car, possibly because of financial constraints. These results mostly align with those found by Oakil et al. (2013) and Prillwitz et al. (2006). Consistent with Aditjandra et al. (2012) and Cao et al. (2007), who reported positive associations between changes in household income and household size and changes in car ownership, this analysis also found that people who get a job after moving or who have an increase in household size and household income are more likely to acquire a car. As for disposing of a car, consistent with expectations, people from wealthy families or from large families are less likely to dispose of their cars. Similar to the findings of Oakil et al. (2013), this analysis found that losing a job after moving increases the probability of disposing of a car whereas getting a job after moving decreases the probability of car disposal. Increases in household size are also positively related to car disposal. In addition, household cars are less likely to be disposed of when there are increases in household income after a move.

Turning to the changes in car travel time, males, people who are employed, people from a large family, and downtown residents are found to have a higher probability of using a car more after a move. Consistent with expectations, getting a job and increasing in household income after a move are positively associated with increases
in car travel time, whereas losing a job after moving significantly reduces car travel
time. As for changes in public transit travel time, this analysis found that the elderly,
people who are well-educated, people who are employed, and suburban residents are
more likely to travel less by public transit after they move to new residences. Model
results also show that increases in household size are associated with increases in
travel time by public transit while increases in household income are related to
decreases in travel time by public transit after a move. Finally, males, people who are
employed, and suburban residents are less likely to increase their non-motorized
travel after moving whereas well-educated people and those who lost their job after
moving have a higher probability of walking or cycling more after moving. These
results highly support the notions that both the base values of socio-demographics and
their changes significantly influence the changes in travel (e.g., Cao et al., 2007;
Krizek, 2003; Scheiner and Holz-Rau, 2013b).
Table 6.7. Direct and total effects of changes in car ownership and daily travel behaviour

<table>
<thead>
<tr>
<th></th>
<th>Car acquisition</th>
<th>Car disposal</th>
<th>Changes in car travel time</th>
<th>Changes in public transit travel time</th>
<th>Changes in non-motorized travel time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Changes in SN-in</td>
<td>0.000(0.000)</td>
<td>0.000(0.000)</td>
<td>-0.041(-0.024)</td>
<td>-0.303^a (-0.301^a)</td>
<td>-0.068(-0.061)</td>
</tr>
<tr>
<td>Changes in SN-all</td>
<td>0.000(0.000)</td>
<td>0.001 (0.001)</td>
<td>-0.051^b (-0.069^b)</td>
<td>0.101^b (0.139^a)</td>
<td>-0.066 (-0.062^a)</td>
</tr>
<tr>
<td>Changes in social environment</td>
<td>-0.111^a (-0.111^a)</td>
<td>0.084^a (0.084^a)</td>
<td>-1.294(-6.843^a)</td>
<td>-5.572 (1.766)</td>
<td>2.150(1.872)</td>
</tr>
<tr>
<td>Move to suburb</td>
<td>0.029(0.029)</td>
<td>0.020^c (0.020^c)</td>
<td>3.024(2.907)</td>
<td>24.010^a (21.972^a)</td>
<td>9.573^a (9.046^a)</td>
</tr>
<tr>
<td>Move to city center</td>
<td>0.035(0.036)</td>
<td>-0.068^a (-0.068^a)</td>
<td>-6.984 (-3.666)</td>
<td>-10.774^b (-10.581^b)</td>
<td>4.305(5.678)</td>
</tr>
<tr>
<td>Changes in accessibility</td>
<td>-0.037 (-0.037)</td>
<td>0.014(0.014)</td>
<td>8.059^a (6.717^b)</td>
<td>-0.106(-2.405)</td>
<td>-13.210^a (-14.399^a)</td>
</tr>
<tr>
<td>Car acquisition</td>
<td>21.836^a (21.836^a)</td>
<td>-26.610^a (-37.762^a)</td>
<td>2.009(-1.133)</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>----------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
<td></td>
</tr>
<tr>
<td>Car disposal</td>
<td>-37.342</td>
<td>-37.342</td>
<td>10.574</td>
<td>-12.098</td>
<td></td>
</tr>
<tr>
<td>Changes in car travel time</td>
<td>-0.511</td>
<td>-0.511</td>
<td>-0.139</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changes in public transit</td>
<td></td>
<td></td>
<td></td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>travel time</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>0.007</td>
<td>0.002</td>
<td>7.516</td>
<td>-0.306</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.027</td>
<td>0.018</td>
<td>-0.053</td>
<td>-5.418</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>0.025</td>
<td>-0.009</td>
<td>-0.180</td>
<td>-3.638</td>
<td></td>
</tr>
<tr>
<td>Employment status</td>
<td>0.076</td>
<td>0.020</td>
<td>9.870</td>
<td>-8.440</td>
<td></td>
</tr>
<tr>
<td>Household income</td>
<td>0.031</td>
<td>-0.022</td>
<td>-0.038</td>
<td>2.478</td>
<td></td>
</tr>
<tr>
<td>Household size</td>
<td>0.031</td>
<td>-0.032</td>
<td>2.353</td>
<td>5.702</td>
<td></td>
</tr>
<tr>
<td>Car ownership</td>
<td>-0.425</td>
<td>0.235</td>
<td>-2.337</td>
<td>-19.933</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Home location</td>
<td>Get a job</td>
<td>Lose a job</td>
<td>Changes in household size</td>
<td>Changes in household income</td>
</tr>
<tr>
<td>------------------------------------</td>
<td>------------------------</td>
<td>--------------------------</td>
<td>--------------------------</td>
<td>----------------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td></td>
<td>-0.008(-0.011(^c))</td>
<td>0.010(^b) (0.001)</td>
<td>-1.783(^b) (-1.864(^a))</td>
<td>-4.765(^a) (-7.577(^a))</td>
<td>0.501(-1.731(^b))</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.136(^a) (0.120(^a))</td>
<td>-0.051(^b) (-0.049(^a))</td>
<td>12.375(^b) (19.519(^a))</td>
<td>2.383(-10.601)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-2.230(-4.870)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.047(-0.056)</td>
<td>0.099(^a) (0.106(^a))</td>
<td>-14.329(^a) (-20.666(^a))</td>
<td>-17.516(^b) (-5.820)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>13.152(^b) (14.678(^a))</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.058(^a) (0.057(^a))</td>
<td>0.014(^a) (0.015(^a))</td>
<td>-0.757(-0.059)</td>
<td>7.481(^a) (6.204(^a))</td>
<td>1.556(1.111)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.050(^a) (0.051(^a))</td>
<td>-0.021(^a) (-0.023(^a))</td>
<td>0.152(1.947(^b))</td>
<td>0.878(-2.058(^b))</td>
<td>-1.995 (-1.027)</td>
</tr>
</tbody>
</table>

Notes: (1)\(^a\) significantly different from zero at \(p<0.01\); \(^b\) significantly different from zero at \(p<0.05\); \(^c\) significantly different from zero at \(p<0.10\).

(2) Both direct and total effects are listed and total effects are in parentheses. All effects are unstandardized.
6.5.7 Determinants of changes in the built environment and social contexts

Table 6.8 presents the effects of the socio-demographics on changes in the built environment and social contexts. Consistent with the residential self-selection hypothesis (Cao et al., 2009; Mokhtarian and Cao, 2008), the analysis found significant effects between the base values and changes in socio-demographics on changes in the built environment after relocation. The analysis also found significant associations between the base values and changes in socio-demographics on changes in the social environment and personal social networks, suggesting that people may not only consider the built environment, but also the social environment and social networks when making relocation decisions. In particular, the elderly and people who are employed are found to be positively associated with moving from the city center to a suburban area. Car owners are less likely to move from either the city center to a suburban area or from a suburban area to the city center, possibly because they want to keep their travel habits. The model results also find that large families and increases in household size are positively related to relocation to the city center. Furthermore, increases in household income are found to positively associated with moving from the suburbs to the city center and from the city center to suburban areas. As for impacts on changes in accessibility, effects are found to be negative for age, education, household income and changes in household income while positive for male, those getting a job and changes in household size.

Moving also changes personal social networks. The analysis found elderly, well-educated and rich people are more likely to suffer from a decrease in the social contacts who live in the same neighborhood after they move into new neighborhoods. The analysis also found people who are employed, wealthy people, car owners and suburban residents are more likely to suffer from a decrease in overall social contacts after relocation. While people with large
families seem to have higher probabilities of having increases in both social contacts living in the same neighborhood and overall social contacts in the past week. Compared with downtown residents, suburban residents are more likely to have increases in social contacts living in the same neighborhood but decreases in overall social contacts after relocation. Rather than a positive effect, car ownership is found to have a negative effect on changes in overall social contacts after a move, indicating that having a car does not necessarily provide an advantage in developing and maintaining social networks, similar to the findings by Carrasco and Cid-Aguayo (2012). As expected, getting a job after moving is negatively related to changes in social contacts living in the same neighborhood and overall social contacts in the past week whereas losing a job after a move has positive effects for both. One reason for this may be the trade-offs between social networks and jobs when making relocation decisions. For those who weigh social networks over their jobs, they may sacrifice their job to move to a preferred neighborhood to facilitate their social interactions, such as having more social contacts living nearby. While for those who weigh their jobs over social networks, they may consider the job opportunities around the new neighborhoods more even if they would have a decrease in social contacts living in the same neighborhood and a decrease in overall social contacts in the past week. Consistent with expectations, the analysis found increases in household size are related to increases in overall social contacts in the past week whereas increases in household income are associated with decreases in overall social contacts in the past week. Referring to changes in the social environment, large families, car owners and suburban residents are found to be less likely to have improvements in the social environment after moving. Losing a job is positively related to changes in the social environment, which suggests that people who lose a job after moving are more likely to have improvements in their social environment. A potential explanation may be that people sacrifice their jobs for a better social environment when making relocation decisions. These results highly suggest that people may not only
choose the built environment, but also the social environment and social networks when making relocation decisions. This may suggest that, similar to the residential self-selection issues in relationships between the built environment and travel behavior, the self-selection of the social environment and social networks may also need to be considered when examining the causal relationships between the social environment, social networks and travel behavior.

Table 6.8. Determinants of changes in social and spatial contexts

<table>
<thead>
<tr>
<th></th>
<th>Changes in SN-in</th>
<th>Changes in SN-all</th>
<th>Changes in social environment</th>
<th>Move to suburbs</th>
<th>Move to city center</th>
<th>Changes in accessibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>-0.739</td>
<td>0.672</td>
<td>0.008</td>
<td>0.024</td>
<td>-0.002</td>
<td>0.047^b</td>
</tr>
<tr>
<td>Age</td>
<td>-1.013^a</td>
<td>-0.033</td>
<td>-0.003</td>
<td>-0.044^a</td>
<td>0.003</td>
<td>-0.026^b</td>
</tr>
<tr>
<td>Education</td>
<td>-0.929^a</td>
<td>-1.379</td>
<td>-0.003</td>
<td>-0.007</td>
<td>-0.011</td>
<td>-0.063^a</td>
</tr>
<tr>
<td>Employment status</td>
<td>-0.465</td>
<td>-12.550^a</td>
<td>-0.004</td>
<td>-0.090^a</td>
<td>0.032</td>
<td>-0.017</td>
</tr>
<tr>
<td>Household income</td>
<td>-0.728^a</td>
<td>-3.781^a</td>
<td>-0.001</td>
<td>0.005</td>
<td>0.006</td>
<td>-0.070^a</td>
</tr>
<tr>
<td>Household size</td>
<td>2.263^a</td>
<td>2.754^a</td>
<td>-0.034^a</td>
<td>0.009</td>
<td>0.031^a</td>
<td>0.003</td>
</tr>
<tr>
<td>Car ownership</td>
<td>0.545</td>
<td>-8.188^a</td>
<td>-0.047^a</td>
<td>-0.060^a</td>
<td>-0.050^a</td>
<td>0.050</td>
</tr>
<tr>
<td>Home location</td>
<td>1.325^a</td>
<td>-1.738^a</td>
<td>-0.021^a</td>
<td>-0.110^a</td>
<td>0.087^a</td>
<td>0.132^a</td>
</tr>
<tr>
<td>Get job</td>
<td>-6.442^a</td>
<td>-16.117^a</td>
<td>0.051</td>
<td>0.018</td>
<td>-0.022</td>
<td>0.183^c</td>
</tr>
<tr>
<td>Lose job</td>
<td>1.619^b</td>
<td>6.577^b</td>
<td>0.122^b</td>
<td>0.000</td>
<td>0.090^b</td>
<td>0.003</td>
</tr>
</tbody>
</table>

135
| Changes in household size | 0.156 | 2.191 \(^b\) | 0.009 | 0.009 | 0.025 \(^a\) | 0.035 \(^b\) |
| Changes in household income | 0.253 | -3.385 \(^a\) | 0.007 | 0.011 \(^b\) | 0.012 \(^a\) | -0.037 \(^a\) |

Notes: (1) \(^a\) significantly different from zero at \(p<0.01\); \(^b\) significantly different from zero at \(p<0.05\); \(^c\) significantly different from zero at \(p<0.10\) (2) All effects are unstandardized.

### 6.6 Discussion and conclusion

Changes in travel after residential relocation are essential to understanding the dynamics of travel demand over time (Scheiner and Holz-Rau, 2013b; Sharmeen et al., 2014b). Since few studies have incorporated the dynamics of social contexts in understanding the dynamics of activity-travel behavior, this chapter aims to make a contribution to this gap with an empirical study. Using panel data, this study examines the linkages between changes in social contexts, specifically neighborhood social environments and personal social networks, after a residential move and changes in travel, after controlling for changes in the built environment and socio-demographics.

The findings of the empirical study underscore the importance of changes in the social environment and personal social networks in explaining changes in travel after moving. In particular, the analysis found changes in the social environment to be significant determinants of changes in car ownership and changes in car travel time. Improvements in the social environment (safer and more cohesive) tend to significantly reduce the probabilities of car acquisition while increasing the probabilities of car disposal. Improvements in the social environment also significantly reduce car use. Changes in personal social networks after a move are also found to be significant determinants of changes in travel. Increases in
the number of social contacts living in the same neighborhood tend to reduce their public transit use. Increases in the number of overall social contacts, however, tend to increase public transit use and decrease car travel time and non-motorized travel time. In addition, this analysis also found significant impacts of changes in the built environment on changes in travel, providing extra evidence for the debate about the causality between the built environment and travel behavior.

This study argues that changes in travel after relocation are not only induced by changes in the built environment associated with a residential move, but are also triggered by changes in the social environment and changes in personal social networks after relocation. The present case study enriches the literature on the social contexts of activity-travel behavior by incorporating the dynamics of the social environment and personal social networks in understanding changes in car ownership and travel behavior after a residential move. Furthermore, this study is one of the few applications using real panel data to examine residential relocations and changes in travel. In terms of policy implications, findings from this research demonstrate the importance of policies aimed at improving the neighborhood social environment. Findings from this study suggest that policies aimed at influencing travel behavior should take the social environment into consideration rather than focus solely on physical urban planning (Wang and Lin, 2013). Furthermore, the significance of dynamics of social networks on changes in travel implies that future policy formulation or evaluation should also assess their impact on personal social networks within which travel behavior is embedded (Sharmeen et al., 2014b).

One major limitation of this study is the use of single-day activity-diary data, even though it has been widely used in travel studies. Previous studies have documented the day-to-day variability in activity-travel patterns and have suggested that multi-day samples produce less biased estimates than single-day
samples (Bhat et al., 2005; Kang and Scott, 2010; Nurul Habib et al., 2008). Given this, if multi-day activity-travel diary panel data had been available for analysis, we might have had a more comprehensive understanding about residential relocation and changes in travel behavior. Additionally, the social environment in this study is characterized only by perceived measurements, and the information was collected only for heads of households instead of all family members. Future research efforts could expand on the study by including both objective measurements (socio-demographic compositions) and perceived measurements for all respondents, if data are available. Lastly, a life-course or mobility biography approach highlights the importance of residential relocation as one of the key events that induces changes in travelling (Scheiner and Holz-Rau, 2013a, 2007; Sharmeen et al., 2014b). Findings from this study suggest that the influence of residential relocation on changes in travel are not equal for all respondents, but rather the influences are multidimensional and vary according to changes in the built environment, the social environment and social networks. Future studies may need to differentiate the characteristics of relocation to generate more insight into life-cycle events and changes in travel.
Chapter 7 Conclusion

7.1 Summary of findings

The social contexts of activity-travel behavior provide important perspectives for understanding and analyzing activity-travel behavior. This topic, however, has only very recently received more research attention. This thesis is dedicated to the effects of social contexts particularly personal social networks and neighborhood social environments on activity-travel behavior and contributes to this rapidly growing literature. Through an extended review of literature, this research finds many important questions related to the social contexts of activity-travel behavior remain unanswered. In particular, what are the influences of personal networks on overall activity-travel behavior, extending beyond social activities and travel? How do the spatial distribution of personal social networks and the neighborhood social environments influence activity-travel behavior? And how do the dynamics of personal social networks and neighborhood social environments induce changes in individuals’ activities and travel? To answer these questions, three case studies are conducted in this research.

The first case study examines how social network attributes influence individuals’ engagements in joint or solo activities/travel and choices of companions for joint activities/travel. The empirical results underscore the importance of social network attributes in explaining individuals’ decisions about engagements in joint or solo activities/travel and their choices of companions. The results of chi-square difference tests of competing models show that the inclusion of social network variables significantly improves the explanatory power and the goodness-of-fit of the models of joint activities/travel and companions choices. The final SEM model results show that the sources of emotional support and social companionship, social network size and
composition are significant determinants of joint/solo activity engagements and choices of activity companions, while no significant impacts are found for the source of instrumental support. Specifically, individuals whose emotional support and social companionship mainly come from family members/relatives (friends/acquaintances) tend to perform more joint activities with their family members/relatives (friends/acquaintances). More contact with family members/relatives (friends/acquaintances) triggers more joint activities with family members/relatives (friends/acquaintances). Individuals’ social networks are found to indirectly significantly influence the engagements in joint/solo travel and the choices of travel companions. This analysis also found significant interactions between joint activities and travel with different types of companions.

The second case study investigates how personal social networks and the residential social environment influence individuals’ choices between in- and out-of-neighborhood locations for discretionary activities and time allocation. Model results highlight the importance of personal social networks and the neighborhood social environment in explaining individuals’ tradeoffs between in- and out-of-neighborhood locations for discretionary activities and time use. Specifically, more frequent contacts with friends/acquaintances living in the same neighborhood or within walking distance tend to lead individuals to conduct and allocate a larger fraction of time to discretionary activities in the neighborhood rather than out of the neighborhood. At the same time, people with more family members/relatives living in the same neighborhood appear to be more likely to participate in out-of-neighborhood discretionary activities. This study also found that contacting more friends/acquaintances living in Beijing within the past week tends to induce more discretionary activities out of the neighborhood. With respect to the neighborhood social environment, people living in safer and more socially cohesive neighborhoods are found to be more likely to participate in in-neighborhood discretionary activities. No significant
effects are found for the neighborhood social environment variables in the model about time allocation.

The third case study explores how changes in social networks and neighborhood social environments associated with residential relocations induce changes in travel, in addition to changes in the built environment and socio-demographics. Supporting the hypothesis, the empirical results demonstrate that changes in the social environment and personal social networks are significant determinants in explaining changes in car ownership and daily travel after moving. Specifically, people who move to a neighborhood with a better social environment are much less likely to acquire a car and more likely to dispose of a car. Improvements in social environments tend to significantly reduce car use. People with increases in the number of social contacts living in the same neighborhood after moving are found to be more likely to reduce their public transit use. Increases in the total number of social contacts, however, tend to be associated with increases in public transit use.

Overall, this thesis enriches the literature on the social contexts of activity-travel behavior with empirical studies on the impacts of personal social networks and/or neighborhood social environments on joint/solo activities/travel and companion choices, location choices for activity and time use, as well as travel changes after relocation. This study highlights the importance of incorporating personal social networks and neighborhood social environments in understanding and analyzing activity-travel behavior. Moreover, this study also 1) improves the understanding of joint activity-travel behavior and companion choice; 2) enriches knowledge about the choice of different locations for activities and time use and 3) improves the understanding of residential relocation and changes in travel. Lastly, this study adds to the limited number of cases that have adopted real panel data to analyze residential relocation and changes in travel.
7.2 Policy implications

The findings from this study have some important policy implications. In general, findings from this study suggest that personal social networks and neighborhood social environments significantly influence individuals’ activity-travel behavior. In this sense, transportation policy design should take social networks and the neighborhood social environments into consideration rather than focus solely on physical urban planning. Specifically, this study demonstrates there are significant connections between social networks and joint activity engagements and companion choices. Given the importance of joint activities for developing social capital and wellbeing, public and transportation policies that advance accessibility should not only focus on access to facilities and places, but also access to socially connected people so that joint activities between them can be facilitated. For an example, when allocate public housings, government may provide some incentives to encourage the tenants to choose to live near their closed social contacts.

Next, this study examines the implications of the spatial distribution of social networks on activity-travel behavior. More social contact with friends/acquaintances living in the same neighborhood is found to lead to more in-neighborhood discretionary activities, implying that policy measures targeted toward facilitating social interactions between neighbors may reduce people’s need for motorized trips. An example of such policies include those enhancing voluntary neighborhood associations or clubs, which may help individuals develop and maintain social networks with neighbors (Van den Berg et al., 2012a) and in turn increase in-neighborhood discretionary activities and reduce the need for motorized travel.

Moreover, the neighborhood social environment (e.g., safety and social cohesion) is found to significantly influence individuals’ activity-travel behavior,
suggesting that policies aimed at improving the neighborhood social environment may also help reduce motorized trips. Building up community center - where facilities such as community library, children’s playground and ping-pong tables etc. are provided - to promote community activities and interactions may be an example of such policies. This study also finds the significance of the influence of the dynamics of social networks and the neighborhood social environments on changes in travel, implying that future policy formulation or evaluation should also assess the impact on personal social networks and the neighborhood social environments within which travel behavior is embedded.

In terms of travel demand modeling, the significance of social contexts of activity-travel behavior in generation of non-motorized and motorized travel implies that incorporating the social contexts into the modelling practice may significantly improve the efficiency of travel demand modelling. For an example, community based social contexts may be collected by randomly sampling dozens of residents in each community and then be incorporated into the modelling system to model and forecast the urban travel demand.

7.3 Limitations and recommendations for future research

This dissertation has several limitations and leaves several questions for future exploration. First, similar to data used in many other studies, the sample data used in this dissertation are from single-day activity-diaries. As noted earlier, compared to single-day data, multi-day activity-diary sample data provide richer information and produce less biased estimates (Bhat et al., 2005; Kang and Scott, 2010; Nurul Habib et al., 2008). Therefore, it would be useful to consolidate this study’s findings with multi-day activity diary sample data if such data become available. Second, only perceived neighborhood social environments are
included in this study. The deficiency of objective neighborhood social environments prevents this dissertation from fully capturing the influences of neighborhood social environments on discretionary activity location choices and changes in travel after relocation. Third, personal, ego-centric social networks collected for this dissertation were categorized based on the type of relationship, but the information about the emotional closeness between the ego and each alter are missing. Therefore, future studies should incorporate emotional closeness information to provide a more comprehensive understanding of social networks and activity-travel behavior.

In addition to the directions suggested above, each empirical study in this dissertation can also be extended along different lines. Referring to the empirical study about the impacts of social networks attributes on joint activities/travel engagements and companion choices, future studies may differentiate joint activities by types (e.g., shopping, going out for meals, association activities, and socializing) so that further insight into joint activities can be generated. Additionally, if data are available, future studies may simultaneously consider all the factors that may influence joint activity-travel decisions, including the spatial setting of facilities, the residential environments, individuals’ social networks and socio-demographics, to obtain a more integral and profound understanding of joint activity-travel behavior. With respect to the empirical case on the influences of social contexts on activity location choices between in- and out-of-neighborhood, this study found neighborhood safety and social cohesion to be significant determinants in the location choice model but not in the time allocation model. Future studies are therefore needed to explore the reasons for this inconsistency. Moreover, whether the spatial composition of social networks has a significant impact on the location choice of discretionary activities also deserves attention in future studies. Finally, turning to the case study about the importance of changes in social contexts and changes in travel after relocation, the findings suggest that the influence of residential
relocations on changes in travel are different among people with different changes in the built environment, social environment and social networks. Future studies using a mobility biography approach may need to differentiate different types of relocation to generate more insight on life-cycle events and changes in travel.
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