Generation Gaps in Activity and Travel Behavior

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THESIS

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SUMMARY

The United States is experiencing a rapid increase in seniors (i.e. 65 years old or higher) population. According to Census Bureau estimates, seniors' population is expected to increase by 104.2% from 2000 to 2030, which translates into 72.1 million elderly people. The main reason for this considerable increase in seniors' population is the entrance of baby boomers into elderly age since the beginning of 2011. Baby Boomers are the generation who were born between 1946 and 1965 and represent the peak of births rate in the U.S. since 1930. This rapid and sudden increase in seniors' population has become a serious concern in the United States because of the potential social and economic effects that an increasing elderly population can have on socioeconomic systems. Elderly people have their own specific needs that must be addressed in the coming years.

Review of literature showed that the seniors' activity-travel modeling lacks appropriate tools, to deal with the complex nature of activity-travel behavior. Current studies, mostly, employed conventional analytical tools to study differences between seniors' and non-seniors' travel behavior. As a result, the role of actual effective factors in observed travel behavior is mostly overlooked in the current studies.

This study outlines innovative econometric tool box that will address some of the technical and conceptual hurdles that have challenged past travel behavior modeling efforts. The tool box developed in this dissertation includes: 1) Mixed copula-based discrete-continuous joint model; 2) Random Regret Minimization versus Random utility Maximization for travel mode choice; 3) Nested logit model for modeling stop-go behavior of drivers in dilemma zone of a signalized

intersection; and 4) Latent segmentation AFT-based model for shopping activity participation. All these models demonstrate the use of advanced behavioral-based modeling approaches for forecasting travel behavior of seniors at disaggregate individual level.

1. INTRODUCTION

The United States is experiencing a rapid increase in seniors (i.e. 65 years old or higher) population. According to Census Bureau estimates, seniors' population is expected to increase by 104.2% from 2000 to 2030, which translates into 72.1 million elderly people in 2030. The main reason for this considerable increase in seniors' population is the entrance of baby boomers into elderly age since the beginning of 2011 (Wan et al., 2005). Baby Boomers are the generation who were born between 1946 and 1965 and represent the peak of births rate in the U.S. since 1930 (Jones et al., 2003; National Center for Health Statistics, 1994; Mohammadian et al., 2013).

This rapid and sudden increase in seniors' population has become a public alarm in the United States because of the potential social and economic effects that an increasing elderly population can have on socioeconomic systems. Elderly people have their own specific needs that must be addressed in the coming years. Mohammadian and Bekhor emphasized on the point that the travel patterns of special population groups, including seniors, need to be "closely" studied (Mohammadian and Bekhor, 2008). In 2002, the Transportation Research Board of the National Academies identified the aging population as a critical phenomenon in the 21st century. Hilderbrand (2003) addressed "the current lack of a detailed description of elderly travel characteristics and behaviors" as a deficiency in the area of transportation planning. Therefore, it is crucial to understand the dynamics of elderly activity-travel behavior and their potential effects on the transportation system to better identify and meet their transportation requirements (Mohammadian et al., 2013).

Activity-travel behavior is a complex and dynamic process compounded of routine, preplanned, and impulsive activities (or decisions). These activities or decisions can be interdependent or completely independent. They might also vary inter-personally, intra-personally, temporally and spatially. Understanding this process needs advanced tools that can deal with the complex nature of travel behavior at individual level. Travel mode choice, number of daily trip, time-of-day choice, and traveled distance are the most studied attributes of seniors travel patterns. There are still many aspects of their travel behavior that need to be studied. For example, the fact that seniors are not time-pressed and benefit from a flexible schedule has not well been reflected in the modeling of their travel behavior, specifically their activity participation.

This dissertation develops a toolbox involving novel econometric tools that can be used by advanced travel demand modelers for not only seniors, but also other age groups. This study attempts to shed light on some less researched aspects of seniors' travel behavior including activity planning, activity generation, travel mode choice, activity type choice, activity duration, and time-of-day choice by developing innovative and advanced models that can better explain differences between seniors and non-seniors. Two main data sources are used for this purpose including 1) Urban Travel Route and Activity Choice Survey (UTRACS) which is a GPS-based survey collected in the Greater Chicago Area over a one year period 2009-2010; and 2) Chicago Metropolitan Agency for Planning (CMAP) Travel Tracker Survey which is a cross-sectional travel and activity survey with more than 10,000 participated households, collected during January 2007 - February 2008.

However, this dissertation is not limited only to the exploration of activity-travel behavior of elderly people. It also studies and analyzes the driving behavior of different age groups. Driving behavior of elderly people and its impacts on traffic safety is one of the most addressed issues in previous studies about seniors' travel behavior. In 2010, older drivers were 16% of all licensed drivers in the U.S., which showed a 2% increase since 2001 (National Highway's Traffic Safety Administration, 2012; Mohammadian et al., 2013). In the United States, 17% of the traffic fatalities and 8% of the injured people in 2010 were elderly people (NHTSA 2012). In this study, driver's reaction of to the yellow light at the dilemma zone of signalized intersections is studied and modeled with a novel technique that distinguishes potentially hazardous reactions from safe decisions. Data source for this purpose comes from a study conducted in the University of Iowa National Advanced Driving Simulator (NADS) to examine driver's reaction to the yellow light of a signalized intersection.

The developed models are used to examine a set of hypotheses including 1) Activity participation of seniors differs from non-seniors due to their flexible scheduling. Seniors have much less mandatory activities to do than non-seniors that give them more flexibility to participate in other activities; 2) Unobserved heterogeneity in different components of activity-travel behavior of both age groups is significant. This dissertation examines presence of unobserved heterogeneity for activity participation, activity type, and activity duration choice of each age group separately; 3) Activity type choice as discrete variable and activity duration as continuous variable are interrelated. The dependency structure between these two decisions is examined through a joint discrete-continuous model; 4) Other alternatives to Random Utility Models (RUM) may better explain difference in discrete decisions made by seniors and non-seniors. In this dissertation Random Regret Minimization model is compared with Random Utility Model for the case of mode choice to see which of these decision rules can explain mode choice behavior of seniors versus non-seniors.

The remainder of this dissertation is structured as follows: First, literature review is presented in Chapter 2. Then, Chapter 3 presents the objectives of the dissertation and research gaps that need to be addressed. In Chapter 3 the data sources including UTRACS, CMAP, and NADS are introduced and their specifications are discussed. Chapter 4 presents descriptive analysis on some facets of seniors travel behavior. Then in Chapter 5 a latent segmentation hazard-based model for activity generation is presented. Chapter 6 formulates a new model driver’s reaction to yellow light of a signalized intersection. In Chapter 7 framework and application of a mixed copula-based joint model is introduced. Chapter 8 compares Random Regret Minimization and Random Utility Maximization discrete decision rules for travel mode choice behavior. Finally, the thesis concludes by presenting a summary of the work, the major contribution, and future directions of the study.

2. LITERATURE REVIEW

2.1. Importance of Elderly Population

Public health, medical care, diet, and economic circumstance are among the factors influencing life expectancy. In developed countries, with better public health and stronger economies, life expectancy has significantly increased in recent decades. This increase in life expectancy and an accelerating decrease in birth rates have resulted in a higher proportion of elderly population in developed countries (Mohammadian et al., 2013).

The United States, like many other nations, is experiencing more elderly people. The United States has the third-fastest-growing proportion of senior citizens among developed countries, after Japan and the European Union (Turner et al. 1998). Increasing life expectancy is one reason for accelerating growth in the American elderly population. Figure 2.1 shows how life expectancy at birth has changed from 1970 to 2010. Over that 40-year period, life expectancy has gradually increased from 70.8 to 78.7 years (Mohammadian et al., 2013).

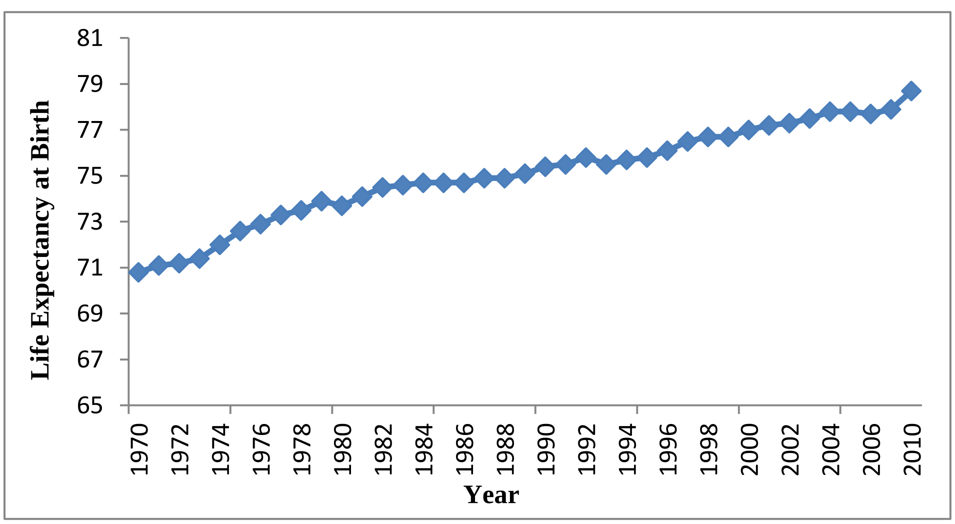

Figure 2.1. Life expectancy at birth in the United States, 1970 to 2010 (National Center for Health Statistics 2012)

The aging of the postwar "baby boom" generation is another important contributor to accelerating growth in the American elderly population (U.S. Census Bureau 2009). The term "baby boomer" refers to people born between 1946 and 1965. Baby boomers, as illustrated in Figure 2.2, represent the peak rate of U.S. births dating back to 1930 (Jones and Hoffmann 2003; National Center for Health Statistics 1994). The oldest baby boomers started joining elderly population in 2011, resulting in a considerable increase in the elderly population (Wan et al. 2005; Mohammadian et al., 2013).

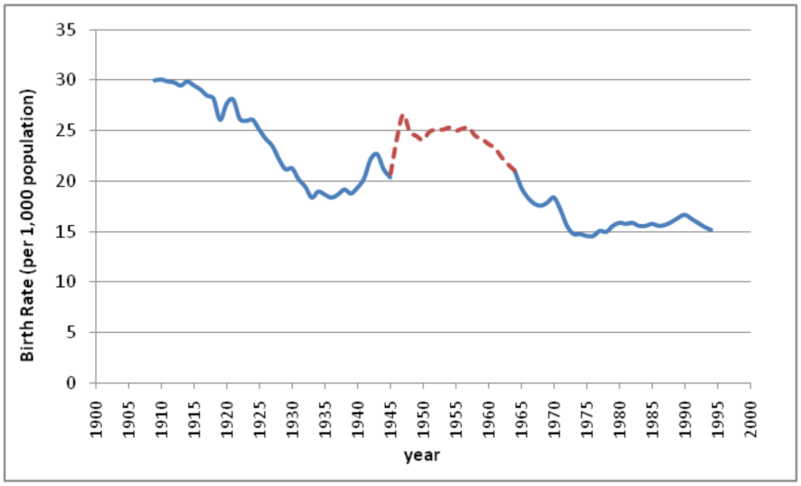

Figure 2.2. U.S. Birth Rate Plot; The dotted line indicates baby boomers' birth rate (National Center for Health Statistics 1994).

In 2010, there were nearly 40.3 million senior (elderly) people across the United States. This represents more than 13% of that year's population. According to Census Bureau estimates, the number of elderly people is expected to increase 104.2% from 2000 to 2030. This translates into 72.1 million elderly in 2030. Meanwhile, the total population is estimated to increase 29.2%. This translates into an additional 33.5 million seniors in the United States by 2030, compared with 2010. This increase has become a serious concern in the United States because of the potential social and economic effects that an increasing elderly population can have on socioeconomic systems (Mohammadian et al., 2013).

These increases in the older American population will affect this country's transportation system. It is therefore crucial to understand the dynamics of seniors' activity-travel behavior and its potential effects on the transportation system to better identify and meet seniors' transportation needs. Senior lifestyles are very different from that of younger people. Unlike younger people, elderly individuals rarely perform the basic home–work–home travel pattern. Instead, they have very different daily activity-travel patterns. Elderly people also often have mobility restrictions that make their travel needs more complicated (Mohammadian et al., 2013).

2.2. Activity-Travel Studies

In the 1970s, several researchers studied elderly peoples' activity-travel behavior and its relationship with the transportation system, when the aging phenomenon was not a critical issue (Bell and Olsen 1974; Hanson 1977; Stirner 1978). In 2002, the National Academies' Transportation Research Board (TRB) listed aging as a critical phenomenon in the 21st century (Pisarki 2003). Since then, aging has become an important research topic. Many studies have investigated seniors' activity-travel behavior and compared these differences with those of the non-elderly (Mohammadian et al., 2013; Giuliano et al. 2003; Mercado and Páez 2009; Páez et al. 2007).

Driving is the most frequent travel mode among elderly Americans (Collia et al. 2003). They drive more than young people (Rosenbloom 2003) and do not use public transit very often

(Collia et al. 2003). Rosenbloom (2003) partly explained the elderly's preference for driving by indicating that most elderly people (79%) live in suburban and rural areas, where public transit or other alternative modes are limited.

Most elderly people travel within suburban areas (Mohammadian et al. 2007) where public transit is frequently unavailable or not appropriate for their typical travel purposes (Collia et al. 2003). In the same context, Giuliano et al. (2003) explored the relationships between elderly peoples' travel patterns and their residences, using the 1995 Nationwide Personal Transportation Survey. The authors found a strong relationship between land use and senior travel patterns. They also analyzed the effects of different land use strategies on elderly mobility. Xinyu et al. (2008) and Hough et al. (2008) also explored the effects of urban design on elderly mobility.

Although walking is a healthy transportation mode for all ages (Yaffe et al. 2001), for a large number of the elderly with mobility restrictions, walking is not the preferred travel mode. People age 65 or over comprise 19.3% of all pedestrian fatalities (NHTSA 2012). However, studies showed that general improvements in the transit system, such as increasing service frequency and providing real-time notices or booklets on transit information and the schedule, are highly appealing to the elderly and would increase their transit ridership (Mohammadian et al. 2007). Paratransit is another public transit alternative that is more convenient but also more costly. Owing to its high operational costs, this service is only available for elderly people with severe disabilities (Rosenbloom 2001).

In Sweden, "community buses" (Stahl 1992) are another public transit alternative for elderly people. They use small buses with low-height floors on fixed routes designed to better serve seniors’ origins and destinations. The community buses more successfully served the older population in Sweden than transit and paratransit services (McLarry et al. 1993). However, community bus implementation in Madison, Wisconsin was unsuccessful because it could not cover a diverse range of destinations, given the city’s sprawl (Rosenbloom 2001).

Collia et al. (2003) used 2001 NHTS data to compare the average number of trips for elderly and non-elderly people. They showed that older individuals take 3.4 trips per day on average, compared with 4.4 trips per day on average for young individuals. They also discovered that gender differences are important factors in travel behavior. Typically, adult men travel more than adult women and have a lower tendency to use public transit (Collia et al. 2003). The same behavior was observed among the elderly, with older men traveling 27 miles per day on average and older women traveling 10 miles per day on average (Collia et al. 2003). However, they found that the distance traveled decreases significantly as age advances. For men, the distance traveled decreases from 42 miles for young men to 27 miles per day for older men, while for women it decreases from 25 miles for young women to 10 miles per day for older women (Collia et al. 2003).

In another study, Mercado and Páez (2009) used data from Canada’s Hamilton Census Metropolitan Area (CMA) to examine what determined the average distance different age groups traveled. They showed travel distance decreased as age increased. Gender, employment constraints, and household characteristics were other significant factors for distance traveled. They also showed that elderly people drove considerably less. Páez et al. (2007) used mixed-ordered probit models to analyze trip generations of different age groups, including elderly people. Newbold et al. (2005) conducted a generational analysis on Canada's elderly population. They used the 1986, 1992, and 1998 General Social Survey databases and found tangible changes over time in elderly travel behavior.

Several studies have investigated elderly travelers' tour-based characteristics. These studies showed the number of tours decreasing significantly as age increases (Golob and Hensher 2007; Mercado and Páez 2009). Golob and Hensher (2007) also compared the number of tours for different modes. They found that the number of auto-driver tours decreases more significantly as people age, in comparison with auto-passenger or transit tours (Golob and Hensher 2007). The number of auto-driver tours peaks between ages 40 and 44 and considerably decreases as people age. This results in an increase in the use of auto-passenger or transit modes in tours (Golob and Hensher 2007). It implies that elderly peoples' loss of driving ability reduces the number of tours, rather than a decline in the desire to perform these activities. Mercado and Páez (2009) argued that older individuals prefer independent and affordable travel modes like public transit rather than dependent modes, such as accepting a ride from family or friends. In another study, Frignani et al. (2011) compared the decision-making and tour formation processes of elderly and non-elderly people and found substantial differences in the activity-travel behavior of the elderly and the non-elderly. They used the Urban Travel Route and Activity Choice Survey (UTRACS) (Frignani et al. 2010) data as their database. This database provided very detailed information on travel activity planning horizons and flexibilities for these age groups. All the facts and findings on the travel behavior differences between elderly and non-elderly people and the social and safety issues associated with the increasing number of elderly, show the importance of providing attractive alternative transportation to fulfill elderly peoples' activity-travel needs (Mohammadian et al., 2013).

Seniors' lifestyle and characteristics have changed over time. The elderly population today has a more active lifestyle, enjoys better health, and lives longer than past generations. Their active life style today results in more out-of-home activity participation. In total, seniors' vehicle trips increased 77% over a period of 12 years from 1983 to 1995, which translates into a 98% increase in miles driven and a 40% increase in driving time (Rosenbloom 2001). However, transit ridership among elderly people declined over the same period and, according to Rosenbloom (2001), will likely continue decreasing. These significant changes in seniors' behavior over time indicates that future generations of seniors might not have the same lifestyle and behavior as those in the past, which should be considered and studied carefully for any long-term planning.

In the same context and considering the ongoing trends, Arentze et al. (2008) used the microsimulation model ALBATROSS to investigate possible alterations in activity-travel behavior of future elderly populations, (Arentze and Timmermans 2003; Mohammadian et al., 2013). Their findings implied that future elderly populations would conduct more out-of-home social and leisure activities. They also found that future seniors would work longer and increasingly choose to live in suburban areas. Their findings would result in an increase in kilometers traveled as a mobility indicator and possible growth in transit ridership among the Dutch elderly.

Other studies exploring the elderly populations' relationship with the transportation system have focused on elderly activity-travel choice. These studies have tried to define separate models for seniors (Hilderband 2003; Chang and Wu 2005; Van den Berg et al. 2010). Highly capable activity- and tour-based models have provided the basis for separately capturing and integrating different homogenous population groups' travel behavior. These models are composed of diverse sub-models and try to approach real daily travel behavior. Some efforts in modeling aspects of elderly travel behavior are moving in this direction (Mohammadian et al., 2013).

Chang and Wu (2005) used a multinomial logit model (MNL) to illuminate the travel mode choice behavior of elderly Taiwanese. They found that age, gender, and living environment are significant factors in elderly people's mode-choice decisions. Van den Berg et al. (2010) studied elderly citizens' travel demand in the Netherlands, to model number of trips, travel mode, and travel distance. They used paper-and-pencil and social-activity diary data collected for two days. Su et al. (2009) examined elderly peoples' mode choice behavior for shopping trips. They ran multinomial logit and nested logit models on the London Area Travel Survey. Their analysis revealed that most elderly people relied on the auto-passenger mode for shopping trips. Mercado and Newbold (2009) also focused on the development of an elderly mode-choice model. Hibino et al. (2007) and Roorda et al. (2009) also investigated factors influencing elderly travel demand. Some studies have shown that categorizing the elderly population into more homogenous subpopulations with unique specifications can provide more accurate output on elderly travel behavior (Mohammadian et al., 2013; Karimi et al. 2012; Hilderband 2003; Wachs 1979; Meyer 1981). Generally, seniors are categorized in two major ways: lifestyle or age.

2.3. Traffic Safety

Elderly driving behavior and the impacts on traffic safety is one of the issues most often addressed in previous studies about seniors' travel behavior. In 2010, older drivers were 16% of all licensed drivers in America, a 2% increase since 2001 (NHTSA 2012). The increased convenience of driving as a result of technological advances, individual's inclinations to maintain their choice travel mode, the elderly population's improving health conditions, and more disposable income are several factors contributing to the increasing share of elderly drivers (Alsnih and Hensher 2003).

Previous studies indicated that increased reaction time, loss of visual and hearing abilities, increased mobility constraints, and decreased cognitive capacity are among the most frequent factors negatively affecting elderly peoples' driving ability (McGwin et al. 2000; Lyman et al. 2001; Dobbs 2005). Rate of side-impact and angle collisions at intersections is relatively high in elderly drivers (Robertson and Vanlaar 2008). They also have a higher fatality rate (Rosenbloom 2003). In the United States, 17% of the traffic fatalities and 8% of the injured people in 2010 were elderly citizens (NHTSA 2012).

3. RESEARCH GAPS AND OBJECTIVES

The remarkable increase in seniors' population and their important influence on socio-economic systems such as transportation systems provide sufficient motivation to develop reliable tools to study, analyze, and model seniors' travel behavior. However, as the review of current studies revealed, the amount of attention dedicated to seniors travel demand forecasting has been insufficient. From the modeling perspective, mode choice, number of daily trip, time-of-day choice, and traveled distance are the most studied attributes of seniors travel patterns. However, there is still significant research gap in terms of understanding elderly activity-travel decision-making process at individual level. Many of the current studies about elderly travel behavior lack robust and suitable modeling techniques. In the literature review, two approaches for modeling seniors' travel behavior have been found. In the first approach, one model is developed for both seniors and non-seniors. In this approach a variable representing age, either dummy or continuous form, is added to the list of descriptive variables. In the second approach, two separate models are developed for each group of seniors and non-seniors. In this approach the modeling structure is the same but list of descriptive variables and estimated parameters may be different. The study by Chang and Wu (2005) is of this group of modeling in which a multinomial logit model (MNL) for travel mode choice behavior of seniors and non-seniors was developed. However none of these two approaches can truly capture the differences in the decision-making process between seniors and non-seniors. For example, a dependable activity generation model should be able to capture the differences between seniors with flexible schedule and non-seniors with tight schedule (Mohammadian et al., 2013). The fact that seniors because of less mandatory activities are less time pressed and have more flexibility in comparison with non-seniors must be reflected in their modeling structure. Another case is finding a suitable paradigm of discrete decision rules for seniors. In most of travel demand studies, Random Utility Maximization (RUM) models (e.g. logit and probit) are the "standard" discrete choice models, are utilized in practice and research. These models assume that people choose the alternative that gives them the highest benefit (utility) that is a challenging assumption. In the recent years, there has been an increasing attention toward parallel paradigms such as random regret minimization (RRM) models that look into decision making process from a different prospective (Chorus et al. 2008 and 2010). RRM models assume that people choose the alternative that gives the minimum regrets. Regret is defined as the feeling that one experience when the chosen alternative performs worse that one or more of non-chosen alternatives. It has been shown that RRM models can justify decision making behaviors that are not explainable with RUM model. Ignoring unobserved heterogeneity across the elderly population is another missing part in modeling of seniors' travel behavior puzzle. While a recent study by Yang et al. (2013) found significant heterogeneity exists across seniors' travel behavior, it has been ignored or treated poorly in the developed models. Hence, the main objective of this proposal is to develop suitable and robust models for activity participation, mode choice, activity duration, activity type, and driving behavior to address some of the outstanding issues discussed above. These models work on the very disaggregate level and tries to treat several seniors' activity-travel attributes that have been practically ignored or simplified in previous studies.

4. DATA SETS

Three major data sources are employed for conducting the proposed dissertation: 1) UTRACS, 2) CMAP Travel Tracker, 3) NADS driving simulator. All these datasets are discussed in this chapter. However, a more detailed description is provided about the UTRACS dataset which is the main data source used in this study.

4.1. UTRACS

Collecting data about travel activity and attributes has become easier and more interesting due to the development of cell phone and global-positioning system (GPS technology (Wolf et al. 2001; Wolf 2006). GPS-based travel surveys have many advantages including creating maps for activity-travel patterns to help respondents recall their activity-travel when answering survey questions (Bachu et al. 2001; Clark and Doherty 2009; Mohammadian et al., 2013).

The Urban Travel Route and Activity Choice Survey (UTRACS) is an automated GPS-based, prompted-recall survey collected in Chicago Area over a one year period 2009-2010. A total of 112 respondents living in 101 households in the Chicago area participated in the survey. This survey asked respondents about details of their activities and trips and their perceived constraints on those decisions. It also collected information from the activity-travel diaries that respondents kept for this study (Mohammadian et al., 2013).

The survey respondent sample included half elderly and half non-elderly households. The study team asked individuals to participate in the survey for 14 days. These respondents daily answered the survey questions about their activity-travel patterns, planning perspectives, travel attributes, etc. The collected data contribute to an understanding of elderly activity-travel behavior and decision-making processes and allow for analysis of the differences in elderly and non-elderly travel behavior (Mohammadian et al., 2013).

As mentioned before, a total of 112 respondents living in 101 households participated in the survey. Fifty-four percent of these participants were seniors. Details for 2,401 trips and 2,622 activities from the seniors and 2,938 trips and 3,419 activities from the younger respondents were collected. Table 4.1 displays descriptive statistics of UTRACS (Mohammadian et al., 2013).

Table 4.1. Descriptive table of UTRACS

Variable	Elderly	Non-elderly
Household Size (Average)	1.88	2.88
Vehicle Availability		
No vehicle	4.08%	3.92%
1 or more vehicles	95.92%	96.08%
Household Income		
$34,999 or less	19.51%	19.57%
$35,000 to 49,999	17.07%	15.22%
$50,000 to 74,999	21.95%	8.70%
$75,000 to 99,999	26.83%	19.57%
More than $100,000	14.63%	36.96%
Race		
White	81.48%	82.46%
Black/African American	16.67%	10.53%
Other	1.85%	7.02%
Gender		
Male	38.89%	34.48%
Female	61.11%	65.52%
TOTAL NUMBER OF RESPONDENTS	51	59

Source: Frignani et al., 2011.

4.2. CMAP's Travel Tracker Survey

CMAP conducted a cross-sectional activity-travel survey for northeastern part of Illinois. The data sample represents details of activity-travel participation of more than 10,000 households between January 2007 and February 2008. Table 4.2 shows some descriptive statistics of CMAP's travel tracker survey.

Table 4.2. Descriptive table of CMAP's Travel Tracker Survey

Variable	Value
Household Size	
1	27.50%
2	29.20%
3	15.70%
4	15.00%
5	7.90%
6	3.50%
7	0.90%
8	0.40%
No. of Vehicles	
0	12.10%
1	34.10%
2	39.20%
3	10.30%
4+	4.30%
Household Income	
$34,999 or less	22.90%
$35,000 to 49,999	13.50%
$50,000 to 74,999	17.50%
$75,000 to 99,999	14.40%
More than $100,000	22.40%
Trip Rate (trips per HH per day)	9.58
Total No. of HH	10,552

Source: CMAP's Travel Tracker Survey Summary.

4.3. NADS' Data

The NADS dataset comes from a study conducted to examine the impacts of cell telephone use on driving behavior of three age groups. The University of Iowa National Advanced Driving Simulator (NADS) conducted this study, where 49 participants were asked to drive through a signalized intersection while engaged in one of three secondary tasks. The traffic signal would change from green to yellow to red to green again. There were three secondary task conditions consist of Baseline (no phone call), Outgoing call, and Incoming Call. This data sample was released for the 2014 TRB's Data contest. Table 4.3 displays some descriptive statistics of NADS' data sample.

Table 4.3. Descriptive table of NADS' data sample

Variable	Value
Age Group	
Young	36.7%
Middle Age	34.7%
Old	28.6%
Gender	
Female	53.1%
Male	46.9%
Speed at Turning Yellow to Red	
Less than 20 MPH	31.7%
20 to 39 MPH	22.9%
Greater than 39 MPH	45.4%
Speed at Turning Green to Yellow	
Less than 30 MPH	1.4%
30 to 44 MPH	62.5%
Greater than 44 MPH	36.1%
Distance from Stop Line at Turning Green to Yellow	
Less than 175 ft	16.8%
175 to 224 ft	49.8%
Greater than 224 ft	33.3%
Total No. of Participants	49

5. BEFORE AND AFTER 65

There are many yet unknown facets of seniors' travel behavior that need to be studied. In this section time-of-day choice behavior, activity duration, and planning time horizons of elderly people are investigated and compared to non-elderly people. The focus is on the two adjacent 10-year age groups of elderly and non-elderly people. The young-old elderly (65-74) and pre-retirement non-seniors (55-64) who will become elderly over the next decade have been selected (Mohammadian et al., 2013; Karimi et al. 2012).

For this analysis, the UTRACS data are used. Table 5.1 shows the descriptive statistics of both young-old elderly (65-74) and pre-retirement non-seniors (55-64) in the UTRACS data (Mohammadian et al., 2013; Karimi et al. 2012).

Table 5.1. Sample description of *young-old* elderly and pre-retirement non-elderly cohorts

Variable	*Young-Old* Elderly (65-74)	Pre-retirement age group (55-64)
Household Size (Average)	1.91	2.35
Vehicle Availability		
No vehicle	2.94%	0.00%
1 or more vehicles	97.06%	100.00%
Household Income		
$34,999 or less	19.23%	18.75%
$35,000 to 49,999	15.38%	31.25%
$50,000 to 74,999	15.38%	18.75%
$75,000 to 99,999	30.77%	12.50%
More than $100,000	19.23%	18.75%
Race		
White	86.11%	77.27%
Black/African American	11.11%	22.73%
Other	2.78%	0.00%
Gender		
Male	38.89%	22.73%
Female	61.11%	77.27%
TOTAL NUMBER OF RESPONDENTS	34	22

Elderly individuals executed 2,706 activities out of 6,041 total activities, and 1,656 of these activities were performed by the young-old elderly. 52% of young-old elderly activities were performed by females, who constitute 60% of the respondents. From 3,335 activities performed by non-elderly people, pre-retirement age group executed 893 activities. 72% of non-seniors' activities were performed by females, who constitute 75% of respondents (Mohammadian et al., 2013; Karimi et al. 2012).

5.1. Methodology

An explanatory analysis is performed on young-old seniors' and pre-retirement non-seniors' travel activities. The initial focus of this analysis is on time-of-day choice, activity duration, and planning time horizons to explore travel behavior differences between young-old seniors and pre-retirement age group. The comparison between these two groups opens avenues to understanding their behavioral differences. By providing different non-parametric probability density plots of activity duration, start time choice, activity type, and planning time horizons, a schematic analysis on how travel behaviors evolve over time as middle-aged people age can be seen.

The unpaired t-test and Fisher test (F-test) are used to examine statistical differences between corresponding for each age group. For the null hypothesis of the F-test it is assumed that the variances of the two samples are statistically equal. Similarly, the null hypothesis in two-sample t-test considers that mean of two samples are statistically identical.

5.2. Explanatory Analysis

The travel behaviors of these two age groups are discussed in four parts: Activity duration vs. activity type, time-of-day choice vs. activity type, activity duration vs. planning time horizons, and time-of-day choice vs. planning time horizons.

5.2.1. Activity duration vs. activity type

Eleven activity classifications in the survey are bundled into five aggregate categories based on their similarities as shown in Table 5.2. Henceforth, the analyses presented in this paper are constructed across these five activity categories. As it can be discerned in Table 5.2, older people are less involved in mandatory activities, but they are busy with other types of activities. This intuitive finding justifies the general public expectation that as people reach retirement, they become engaged in more flexible and non-mandatory activities shopping activities. This activity type switch has a significant impact on other activity attributes such as mode choice, activity duration, time of day choice, etc. Services, errands and pick-up or drop-off activities constitute the smallest portion of activities for both groups. This is followed by the personal, religious and health care activities. It is interesting to note that over time the frequency of performing these activities and their importance in day-to-day life remains almost unchanged as middle-aged individuals become seniors (Mohammadian et al., 2013; Karimi et al. 2012).

Table 5.2. The Share and Definition of Different Activity Types for *young-old* seniors and pre-retirement age group

Definition	*Young-old* seniors	Pre-retirement age group
Work/School/Volunteer	8.0%	29.9%
Personal/Religious/Healthcare	16.9%	14.3%
Services (Auto service, etc.)/Errands/Pick up or drop off	9.6%	7.1%
Discretionary	30.7%	23.9%
Shopping	34.8%	24.9%

The first schematic analysis among the previously mentioned four categories explores activity duration across different activity types in the weekend and weekdays for both age group. Figure

5.1 pictures the non-parametric probability density functions of activity duration calculated by dividing the total number of executed activities of a specific activity type in a 30-minute batch by the total number of all executed activity types during weekdays or weekends.

The general pattern of all four diagrams in Figure 5.1 shows that as the activity duration increases from 0 to 30 minutes, the probability of executing the activity also increases. After that, the probability steadily decreases. However, mandatory trips do not follow this pattern, and have rather a smoother shape with very small peaks, especially for young-old seniors on weekends. The probability of activity execution is very high during the first hour duration, and declines as the activity duration increases. The probability of becoming involve in an activity with short duration is very high during the weekdays while during weekends people are more willing to participate in longer duration activities. Activity types included in the service category are more important for seniors while mandatory activities are obviously more critical for pre-retirement age group (Mohammadian et al., 2013; Karimi et al. 2012).

Table 5.3 presents the statistical tests for corresponding plots in Figure 5.1. Numbers displayed in the table represent p-value for null hypothesis. As explained before, the null hypothesis for the t-test assumes that both samples' means are equal. Similarly, for the F-test, the null hypothesis assumes that the variances of both samples are the same. These tests examine the meaningful statistical differences in activity durations of both age groups in weekdays and weekends. For example, these tests reveal that elderly group has statistically similar behavior in choosing shopping activity duration in weekdays and weekends. Due to the low number of observations, Personal/Religious/Healthcare and Services/Errands/Pick Up and Drop Off activity types are combined and then compared to each other, except for the comparison case of weekday's activities for elderly vs. non-elderly. Therefore, there are five rows for the third column in which weekday's activities of elderly and non-elderly are compared together, while other categories have four rows (Mohammadian et al., 2013; Karimi et al. 2012).

Table 5.3. Statistical tests on plots presented in Figure 4.1. (p-values for the null hypothesis)

<table>
<tr><th rowspan="2">Group of Activity Types</th><th colspan="2">Elderly (weekends vs. weekdays)</th><th colspan="2">Non-elderly (weekends vs. weekdays)</th><th colspan="2">Weekdays (elderly vs. non-elderly)</th><th colspan="2">Weekends (elderly vs. non-elderly)</th></tr>
<tr><th>F-test</th><th>t-test</th><th>F-test</th><th>t-test</th><th>F-test</th><th>t-test</th><th>F-test</th><th>t-test</th></tr>
<tr><td>Work/School/Volunteer</td><td>-[1]</td><td>-[1]</td><td>-[1]</td><td>-[1]</td><td>0.30</td><td>0.54</td><td>-[1]</td><td>-[1]</td></tr>
<tr><td>Personal/Religious/Healthcare</td><td rowspan="2">0.01</td><td rowspan="2">0.04</td><td rowspan="2">0.00</td><td rowspan="2">0.01</td><td>0.02</td><td>0.86</td><td rowspan="2">0.08</td><td rowspan="2">0.06</td></tr>
<tr><td>Services/Errands/PickDrop</td><td>0.12</td><td>0.75</td></tr>
<tr><td>Discretionary</td><td>0.51</td><td>0.70</td><td>0.48</td><td>0.85</td><td>0.02</td><td>0.96</td><td>0.12</td><td>0.93</td></tr>
<tr><td>Shopping</td><td>0.01</td><td>0.42</td><td>0.00</td><td>0.05</td><td>0.01</td><td>0.29</td><td>0.00</td><td>0.15</td></tr>
</table>

1- Number of activities are smaller than 30

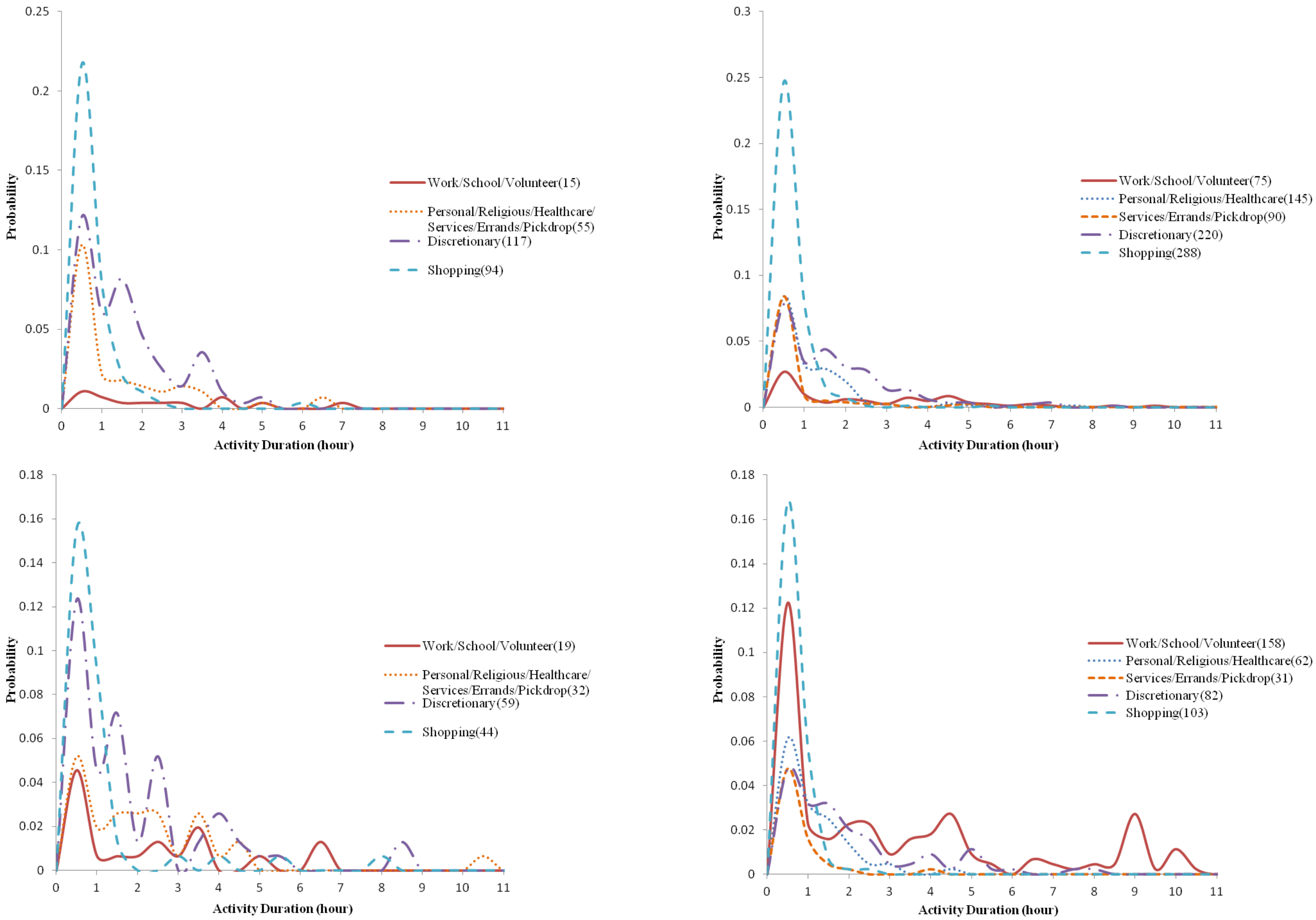

Figure 5.1. Activity duration probability plots for different activity types. Left top: a : *young-old* seniors on weekends, right top: b : *young-old* seniors on weekdays, left bottom: c : non-seniors on weekends, right bottom: d : non-seniors on weekdays.

5.2.2. Time-of-day choice vs. activity type

Activity start time is of great importance and value in activity based models and even conventional four-step models (Hensher and Button, 2000). Thus, this section examines whether there is a distinct difference between young-old seniors and pre-retirement people regarding the time-of-day choice. In Figure 5.2, probability density plots of different activity types across a range of activity start times for both age groups for weekends and weekdays are separately depicted. Two-hour bins are used to calculate probabilities. From the comparison of Figure 5.1 and 5.2, it can be gleaned that while young-old seniors and non-seniors have similar behavior regarding activity duration, these two groups are completely different regarding the time-of-day choice for their activities (Mohammadian et al., 2013; Karimi et al. 2012).

Figure 5.2(b) shows the time-of-day choice behavior of young-old seniors during weekdays. The general pattern of some activities is very similar to one another, meaning that young-old seniors perform these activities consecutively. The probability density function (pdf) curve of the services/errands/pick up and drop off activities almost matches with the pdf curve of the work/school/volunteer activities, while the pdf curve of the personal/religious/healthcare activities stands very close to the pdf curve of discretionary activities. Only shopping activity stands alone with no pdf curve match among all the other four curves.

For seniors, the probability of participating in a discretionary activity is higher than other activities before 10:00 AM,, while the chance of shopping is dominant over other activities after this time, until 6:00 PM. If all plots in Figure 5.2(b) are summed together, it can roughly be said that morning and afternoon peak hours for young-old seniors are at noon and 4:00 PM.

Therefore, seniors are more likely to be seen on streets around these two peak hours. This finding should be of interest to firms providing services to this specific age group.

Figure 5.2(d) displays the time-of-day choice behavior for non-seniors on weekdays. As it can be seen from the figure, the pdf curve for work/school/volunteer activities stands above the other activity types. This is more apparent in the morning hours. After 12:00 PM, the probability of performing a shopping activity steadily increases till 4:00 PM, while work/school/volunteer remains the dominant activity. After 6:00 PM, the probability of performing shopping and discretionary activities stays higher than others. Except for the shopping and work/school/volunteer activities, other activities do not show a prominent peak point during the day. These activities have a higher probability of being executed between 12:00 PM and 6:00 PM.

Figures 5.2(a) and 5.2(c) shows the pdf curves of activities during weekends for both age groups. As the figures illustrate, the plots of the discretionary and shopping activities remain on top of other activities which shows the higher probability of execution for these two activity types. Shapes of these two activity types are similar to each other which indicate that people execute them consecutively.

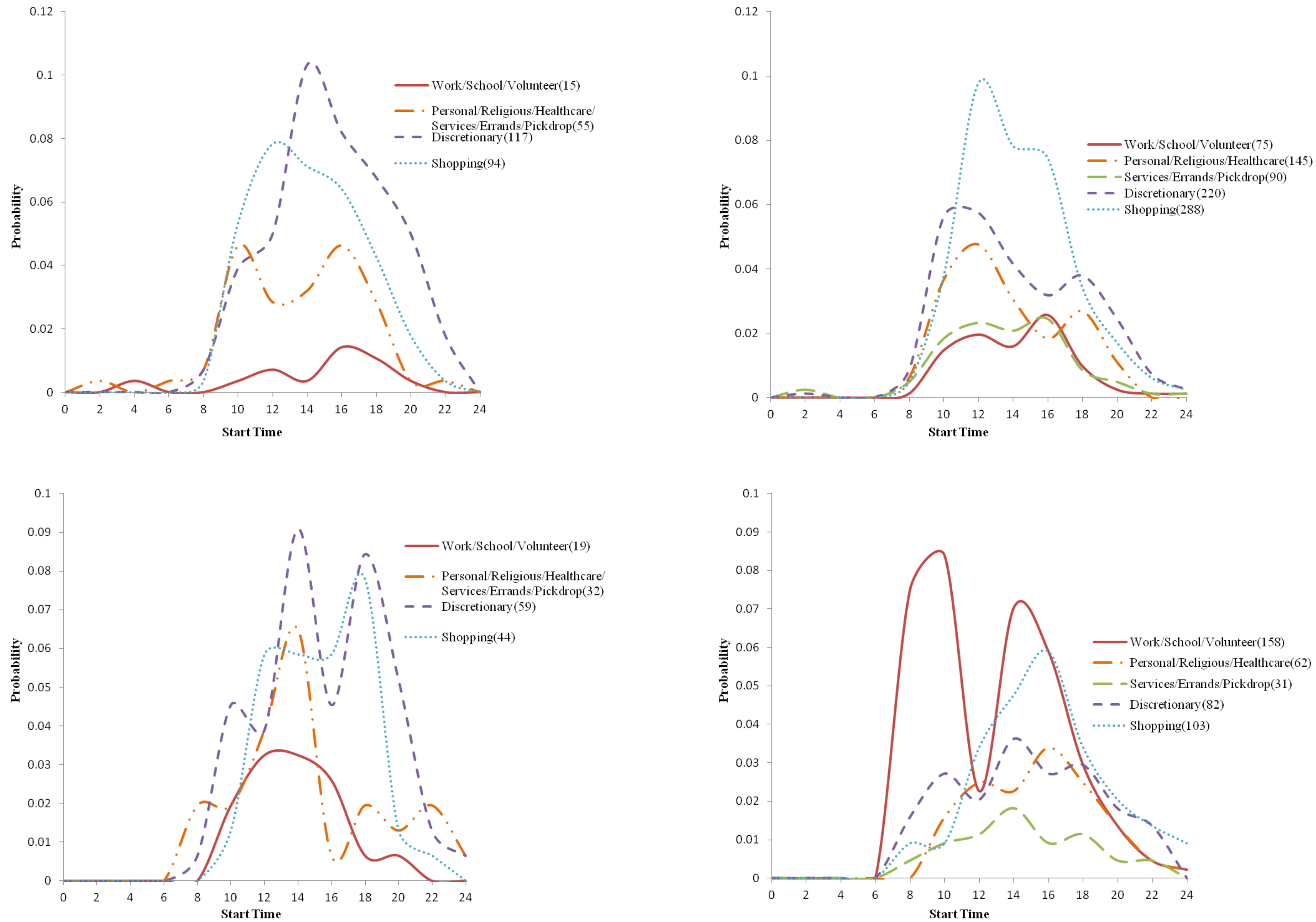

Figure 5.2. Probability plots of chosen time-of-day for different activity types. Left top: a : *young-old* seniors on weekends, right top: b : *young-old* seniors on weekdays, left bottom: c : non-seniors on weekends, right bottom: d : non-seniors on weekdays.

Table 5.4 presents the statistical tests on corresponding plots in Figure 5.2. It can be seen that in the most cases, the null hypothesis of the F-test is rejected (p-value greater than 0.05). This indicates that young-old elderly and non-seniors show very dissimilar behavior regarding the time-of-day choice for their activities.

Table 5.4. Statistical tests on plots presented in Figure 4.2. (p-values for the null hypothesis)

Group of Activity Type	Elderly (weekends vs. weekdays)		Non-elderly (weekends vs. weekdays)		Weekdays (elderly vs. non-elderly)		Weekends (elderly vs. non-elderly)	
	F-test	t-test	F-test	t-test	F-test	t-test	F-test	t-test
Work/School/Volunteer	-[1]	-[1]	-[1]	-[1]	0.02	0.01	-[1]	-[1]
Personal/Religious/Healthcare	0.56	0.85	0.12	0.37	0.66	0.01	0.29	0.28
Services/Errands/PickDrop					0.79	0.12		
Discretionary	0.10	0.01	0.51	0.28	0.50	0.10	0.28	0.73
Shopping	0.53	0.96	0.04	0.37	0.01	0.01	0.45	0.06

1- Number of activities are smaller than 30

5.2.3. Activity Duration vs. Planning Time Horizons

Planning time horizon is an important variable in modeling activity scheduling of pre-planned activities (Mohammadian and Doherty, 2008; Akar et al., 2009). It is defined as the duration between the decision to partake in and the actual performance of an activity. During this period, the decision maker may resolve possible conflicts with other activities and evaluate the importance of the activity compared to other potential activities. Table 5.5 shows the classifications that are used in the planning time horizons analysis in this paper. As Table 5.5 illustrates, the main difference between young-old seniors and non-seniors, regarding their planning time horizons, is related to the routine activities. This observation from Table 5.5 confirms the conclusion in the previous section, which states that non-seniors are more involved in mandatory activities than young-old seniors (Mohammadian et al., 2013; Karimi et al. 2012).

Table 5.5. The share of different planning time horizons for *young-old* seniors and non-seniors

Definition	*Young-old* seniors	Non-seniors
planned less than 1 hr before the activity performance	37.9%	37.3%
planned same day of the activity performance	23.7%	19.6%
planned previous day of the activity performance	7.6%	6.1%
planned 2 days ago or more of the activity performance	15.4%	11.8%
routine activity	15.4%	25.2%

Planning time horizon has a very close connection with activity duration. Therefore, to see how duration of an activity can affect the planning time horizon, the probabilities of different planning time horizons over activity duration is displayed in Figure 5.3. It can be concluded that people impulsively plan for their short activities if "less than 1 hour" and "same day" planning time horizons are assumed as indicators of impulsive activities. .

In Figure 5.3, the steeper the slope of the curves, the more sensitive the planning time horizon would be to the activity duration. Therefore, activities which have been pre-planned in the previous day, 2 days ago or more are less sensitive to the activity duration. In contrast, activities with "less than 1 hour" and "same day" planning time horizons show high sensitivity to the activity duration, especially for durations of less than 1.5 hours. The pre-planning process doesn't show sensitivity to the activity duration for durations greater than 1.5 hours. Comparison between Figures 5.3(a) and 5.3(b) shows that the major disparity between young-old seniors and non-seniors is related to the routine activities. Surprisingly for other time horizons, the curves show very similar patterns for both age groups which means that young-old seniors and non-seniors have similar planning behavior.

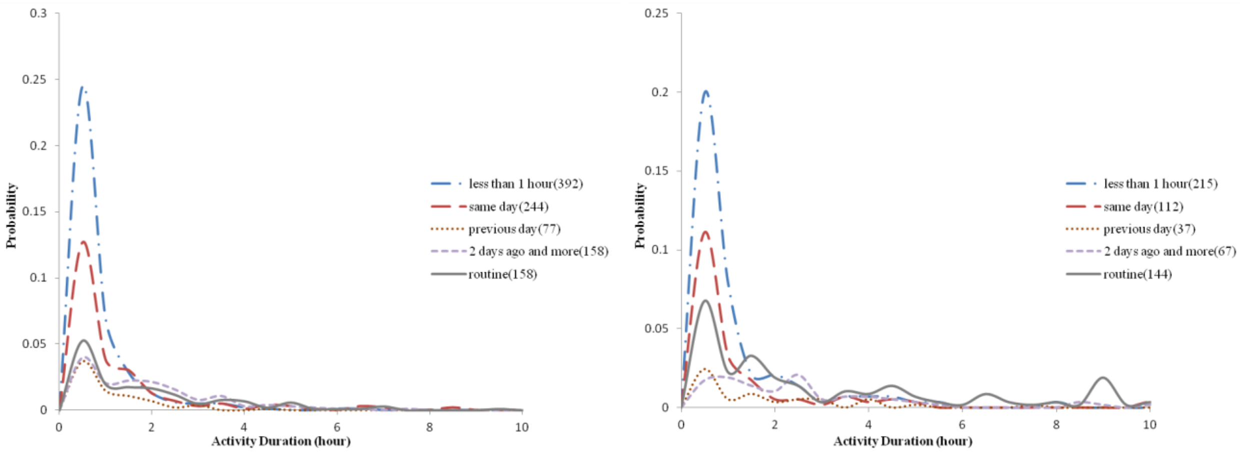

Figure 5.3. Probability plots of activity duration for different planning time horizons. Left: a: *young-old* seniors, right: b: non-seniors.

Table 5.6 presents the statistical tests on corresponding plots in Figure 5.3. It can be seen that p-values of the null hypothesis (equality of means and variances) is small for the routine activities and for the preplanned activities which are planned one or more days before execution. This means that both of these young-old elderly and pre-retirement non-seniors show similar behavior in their preplanning process. For impulsive activities there is a significant disparity either on variance or mean values.

Table 5.6. Statistical tests on plots presented in Figure 4.3. (p-values for the null hypothesis)

Planning Time Horizons	F-test	t-test
planned less than 1 hr before the activity performance	0.79	0.06
planned same day of the activity performance	0.08	0.96
planned previous day of the activity performance	0.01	0.03
planned 2 days ago or more of the activity performance	0.29	0.10
routine activity	0.01	0.01

5.2.4. Time-of-day choice vs. planning time horizons

As with activity duration, there is a strong interconnection between activity start time and planning time horizons. It is understandable that if an activity is planned in the early morning at rush hour, it is treated differently than a similar activity which could be completed during off peak hours. In Figure 5.4, the probability density function curves of different planning time horizons over the chosen time-of-day are plotted. Young-old seniors in Figure 5.4(a) show less sensitivity to the time-of-day choice for their pre-planned activities (previous day or more) than they show to the time-of-day choice for their impulsive activities. For the impulsive activities, they show a greater tendency to execute their activities during the [11:00-13:00] and [14:00-16:00] periods. In Figure 5.4(b), it can be seen that non-seniors' morning activities are highly correlated with routine activities. During the afternoon and evening, they perform a major part of their activities impulsively, especially between 1:00 PM and 7:00 PM (Mohammadian et al., 2013; Karimi et al. 2012).

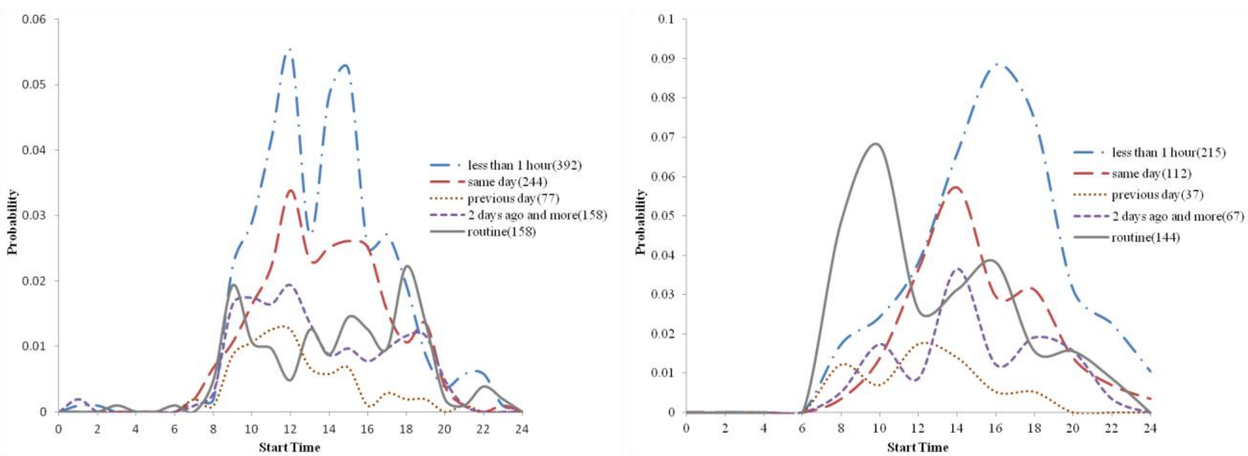

Figure 5.4. Probability plots of chosen time-of-day for different planning time horizons: Left: a: *young-old* seniors, right: b: non-seniors.

The statistical tests presented in Table 5.7 indicate that the means of the corresponding plots are statistically equal, except for the "previous day" planning horizon. However, dispersions of the plots are statistically different, based on the F-test results. Interestingly, in contrast to the previous part, both age groups display similar behaviors regarding the time-of-day choice for their impulsive activities.

Table 5.7. Statistical tests on plots presented in Figure 4.4. (p-values for the null hypothesis)

Planning Time Horizons	F-test	t-test
planned less than 1 hr before the activity performance	0.02	0.01
planned same day of the activity performance	0.39	0.03
planned previous day of the activity performance	0.45	0.62
planned 2 days ago or more of the activity performance	0.69	0.03
routine activity	0.92	0.01

6. ACTIVITY GENERATION MODEL

A key component of any activity-travel study is the analysis of out-of-home activity participation that has different elements such as purpose, start time, and duration. Depending on the modeling framework (i.e. activity-based model and four-step model), different techniques has been developed for forecasting each of those elements, varying from crosstab analysis to advanced joint models. However, this obvious fact that seniors in comparison with non-seniors perform less mandatory activities and consecutively have a more flexible schedule has been ignored or treated insufficiently in the modeling of their travel behavior. This is specifically noticeable in the modeling of seniors' activity participation which is also the focus of this section. To address this issue, a latent segmentation duration model is proposed in this section which can well reflect the effects of seniors' flexible schedule on their activity participation. This model estimates degree of regularity in activity participation at individual level by endogenously dividing travelers into erratic and regular travelers. Regular travelers are defined as time-pressed individuals whose limited schedules result in more regular activity participation patterns. Erratic travelers are defined as people who participate in activities randomly on irregular bases. Since information on being regular or erratic travelers is unknown to us, a latent segmentation model that can endogenously divide travelers into erratic or regular group was employed. The study focuses on shopping participation; however it can well be extended and applied to other activity types.

Seniors spend a considerable amount of their time being engaged in shopping activities. It has been shown that seniors assign around one third of their out-of-home available time to shopping activities which is 1.5 times more than that of non-seniors (Frignani et al., 2011). While the generation of out-of-home activities and their attributes (including location, duration and sequencing) have been explored exclusively in the past decade (Misra and Bhat, 2000; Pendyala et al., 2002; Bowman and Ben-Akiva, 2001; Arentze and Timmermans, 2004), only a handful of earlier studies (Kim and Park, 1997; Schönfelder and Axhausen, 2000; Bhat et al., 2004) focused on the analysis of shopping participation, especially for the elderly cohort. The duration between shopping activities (inter-shopping duration) is one of the most important and least studied attributes of maintenance activities of individuals in the context of travel-activity analysis. The inter-shopping duration models are used for the generation of shopping activities in state-of-the-art activity-based modeling frameworks.

Those studies that explored inter-shopping duration commonly used a proportional hazard-based (PH) framework to model inter-shopping duration. Unquestionably, PH models are the most employed approaches in the context of survival analysis. Like other statistical models, PH models are estimated based on some restrictive assumptions which need to be validated. Proportionality assumption is the most prominent assumption in the PH modeling approach which presumes that the hazard ratio is independent of time. Models presented by Kim and Park (1997), Schönfelder and Axhausen (2000), and Bhat et al. (2004) are based on the proportionality assumption and can be applied when this assumption is valid.

Hazard-based models can be divided into two classes: Non-parametric and parametric models. In contrast to non-parametric hazard based models that make no assumption about distribution of survival time, parametric hazard models assumes that survival time is distributed based on a well-known distribution (e.g., Weibull, Exponential, Gompertz, etc).

Cox's (1972) PH model is the most famous hazard based model that has been used in different fields of research. The model makes no assumption concerning the distribution form of survival time and is estimated based on the partial likelihood approach. However, when there are many tied failure times, this approach becomes cumbersome.

Moreover, accommodating unobserved heterogeneity within the Cox partial likelihood structure requires multiple integrals, as many as the number of observations. Previous attempts for modeling the inter-shopping duration used Cox's PH model, fully parametric PH model, and non-parametric PH model (see Kim and Park, 1997; Schönfelder and Axhausen, 2000; Bhat et al., 2004). Bhat et al. (2004) and Kim and Park (1997) utilized a latent variable or latent segmentation approach in their mixed PH structure to endogenously recognize erratic shoppers from regular shoppers. Results of these studies showed that endogenously dividing shoppers into two groups can significantly improve model's performance.

Kim and Park (1997) divided shoppers into two homogenous groups: random or erratic shoppers and routine or regular shoppers. The latent variable was used to balance the weight of erratic and regular shoppers in the final likelihood function. They found that erratic shoppers constitute 68% of total shoppers. Later, Bhat et al. (2004) improved the model presented by Kim et al. They implemented a non-parametric baseline hazard instead of a parametric function. They also used a latent segmentation approach based on a binary logit structure to endogenously categorize people into erratic (random) or regular (routine) shoppers based on individuals' socioeconomic characteristics.

Major drawback of previous studies is that their models do not account for the cases where proportionality assumption is not valid. There are some tests available that can be used to check this assumption. In the case that this assumption is not valid, non-proportional models like Accelerated Failure Time (AFT) models can be used as alternative approaches.

In this section, the UTRACS data which provide precise information on intra-personal variation over time are used to analyze the shopping participation of seniors and compare it with the non-seniors' behavior. Also, a latent segmentation duration modeling framework is developed to explore the effects of seniors' flexible schedule on their shopping activity participation. In Table 6.1, distribution of inter-shopping duration for seniors and non-seniors in the UTRACS data are presented. It can be seen that both age groups have almost similar distributions. Nonetheless, seniors tend to execute shopping activities more frequently than non-seniors.

Table 6.1. Distribution of Inter-shopping Duration For Seniors And Non-seniors

Inter-shopping duration (day)	Non-Seniors	Seniors
1	61.5%	66.3%
2	15.0%	13.6%
3	8.3%	8.5%
4	4.8%	4.2%
5	4.5%	2.9%
6	2.8%	1.3%
7+	3.3%	3.1%

6.1. Checking the Proportionality Assumption

Proportionality assumption is one of the critical assumptions considered in PH models. It means that hazard ratio of two individuals are constant over time. Proportionality assumption is valid only if covariates used in the model are time independent. Generally there are two tests developed by Grammsch and Therneau (1994) to check the proportionality assumption. The first method suggests adding some time-dependent variables to the original model. If these new variables are statistically significant, then it can be concluded that the proportionality assumption does not apply for the given covariate in the given data. Time-dependent variables can be obtained from the product of a variable of interest and logarithm of survival time. Also, Grammsch and Therneau (1994) used the absolute value of the summed Schoenfeld residuals and designed a global test for proportionality assumption. To run these two tests, a Cox's PH model is developed on the UTRACS data set. There is no need to make an assumption for the baseline hazard when developing a Cox's PH model. In other words, Cox's PH proportionality assumption test is independent of the form of the baseline hazard function.

Table 6.2 presents the final results of the best fitted Cox proportional hazard using the UTRACS data. Table 6.3 shows the validation analysis of the proportionality assumption. At the top of Table 6.3, the PH model is re-estimated with time dependent variables. Four variables including "Total activities", "HHSIZE", "HHTYPE_MC", and "HHTYPE_MNC" were found to be statistically significant meaning that they are time dependent. Therefore, if a PH model is developed with this set of variables, it violates the proportionality assumption and the estimated coefficients might be spurious. Also, in part (b) of Table 6.3, the proportionality assumption for all defined time-dependent covariates is tested simultaneously. Once again a significant result indicates that the proportionality assumption is violated. So it can be inferred that proportionality assumption is not valid for the data set in this study, unless the set of explanatory variables is shrunk to a small set.

Table 6.2. Cox PH Model Results on Inter-shopping Duration of Non-routine Shoppers

Variable	Definition	Estimate	Hazard Ratio	Mean	Standard Deviation
Total activities	Average of total activities performed on two previous inter-shopping episode	-0.266***	0.767	2.828	2.907
Jointactivity	1 if shopping activity is performed jointly by other person(s), 0 otherwise	0.245***	1.278	0.409	0.492
Flexible _Start	1 if start time of shopping activity is flexible, 0 otherwise	-0.170***	0.844	0.425	0.495
HHSIZE	Household size	-0.084***	0.919	2.456	1.240
HHTYPE_MC	1 if household type is married with children, 0 otherwise	0.186*	1.205	0.358	0.480
HHTYPE_MNC	1 if household type is married without children, 0 otherwise	0.229***	1.257	0.357	0.479
Employed	1 if a person is employed, 0 otherwise	0.223***	1.25	0.882	0.323

**Level of confidence greater than 85% ** Level of confidence greater than 90% ***Level of confidence greater than95%*

Table 6.3. Proportionality Assumption Checking On

a) covariates separately

Variable	Estimate	Level of Confidence
Total activities	-0.951	<.0001
Jointactivity	0.206	0.0131
Flexible _Start	-0.135	0.1017
HHSIZE	-0.315	<.0001
HHTYPE_MC	0.694	<.0001
HHTYPE_MNC	0.598	<.0001
Employed	0.229	0.0888
Total activities_time	0.192	**<.0001**
Jointactivity_time	0.004	0.8918
Flexible _Start_time	0.001	0.9608
HHSIZE_time	0.096	**<.0001**
HHTYPE_MC_time	-0.205	**<.0001**
HHTYPE_MNC_time	-0.114	**0.0018**
Employed_time	0.011	0.7867

b) covariates all in once

Label	Level of Confidence	DF	Level of Confidence	Wald Chi-Square
Proportionality_test	<.0001	7	<.0001	383.2

6.2. The PROPOSED MODEL

A latent segmentation AFT-based duration model is developed in this study. Since there is no information available to show if a shopper is regular or erratic, latent segmentation approach is employed to endogenously distinguish regular shoppers from erratic shoppers. Through this approach probability of being a regular or erratic shopper is obtained from a binary logit model that is developed over individual-related characteristics.

6.2.1. AFT Models

Accelerated Failure Time (AFT), discussed by Kalbfleisch (1980), has the following formulation for each observation i:

$$ln(T_i) = \mu + \beta' x_i + \sigma\,\varepsilon_i \tag{6.1}$$

where T_i is the survival time of observation i; ε is the error term; x is the vector of covariates; β′ is the transposed vector of corresponding coefficients to be estimated; σ is the scale parameter; μ is the shape parameter; and ln(.) is the natural logarithm function. In AFT model, in contradictory to PH model, the effects of covariates are directly measured on survival time t and not on a conditional probability. This would make interpretation of the results much easier. Due to the fact that the error terms ε are directly correlated to the logarithm of survival time T in the AFT model, for each distribution of error terms ε, there is a related distribution of survival times T.

There are five parametric AFT models comprising, Exponential, Weibull, Log-logistic, Log-normal, and Gamma AFT models. These models are named after distribution of their survival times not the error terms. It is possible to estimate vector of β non-parametrically (i.e., without making assumption on distribution of error term) with Han's Maximum Rank Correlation estimator; however this approach does not provide information about the hazard function.

The survival function of T_i can be expressed from survival function of ε_i :

$$S_i(t) = Prob(T_i > t) = Prob(\ln(T_i) > \ln(t)) = Prob\,(\mu + \beta' x_i + \sigma\,\varepsilon_i > \ln(t))$$

$$= Prob\left(\varepsilon_i > \frac{\ln(t) - \mu - \beta' x_i}{\sigma}\right) = S_{\varepsilon_i}\left(\frac{\ln(t) - \mu - \beta' x_i}{\sigma}\right) \tag{6.2}$$

Therefore, $\lambda_i(t)$, hazard function of AFT model, can be obtained from $S_i(t)$:

$$\lambda_i(t) = \frac{-S'_i(t)}{S_i(t)} \tag{6.3}$$

where $S'_i(t)$ is the first derivative of $S_i(t)$.

Hazard function of Exponential AFT model is independent from time and its baseline hazard is a constant number. Other types of AFT model have a time-dependent hazard function; however their shapes of hazard function is different from each other. Shape of hazard function of Weibull model is monotone, but for Log-normal, Log-logistic, and Gamma models is variable. In other words, Weibull model holds proportionality property, but Log-normal, Log-logistic, and Gamma models are non-proportional models.

6.2.2. Regular Shoppers' Model

Regular shoppers in contrast to erratic shoppers are time-pressed and have a limited schedule that forces them to choose almost a fixed inter-shopping duration. Therefore, a time-dependent baseline hazard is assumed for this group of shoppers. All AFT models but the Exponential model have time dependent hazard functions. Since we are developing a model for the case that proportionality assumption does not apply, Weibull model is excluded from the analysis. In this study we assume that inter-shopping durations follows a Log-logistic distribution. Log-logistic AFT model with scale parameter σ has the following survivor and probability density functions for person i:

$$S(t_i|x_i) = \left[1 + t_i^{1/\sigma}\, e^{\left(\frac{-\mu - \beta' x_i}{\sigma}\right)}\right]^{-1} \tag{6.4}$$

$$f(t_i|x_i) = \frac{t_i^{\left(\frac{1}{\sigma}-1\right)} e^{\left(\frac{-\mu-\beta' x_i}{\sigma}\right)}}{\sigma\left[1+t_i^{1/\sigma}\, e^{\left(\frac{-\mu-\beta' x_i}{\sigma}\right)}\right]^2} \tag{6.5}$$

The conditional likelihood that person i being a regular shopper with m_i durations in which the last observation is right censored can be obtained as follows:

$$L_{i,regular} = \left[\prod_{j=1}^{m_i-1} f\left(t_j|x_j\right)_{regular}\right] S\left(t_{m_i}|x_{m_i}\right)_{regular} \tag{6.6}$$

6.2.3. Erratic Shoppers' Model

As noted earlier, erratic shoppers are defined as individuals who do their shopping activity irregularly. Hazard function for this group of shoppers is assumed constant over time (i.e., independent from time). Among all AFT models, only Exponential AFT model represent such specification:

$$S(t_i|x_i) = e^{\left\{-t_i\, e^{(-\alpha' x_i-\rho)}\right\}} \tag{6.7}$$

$$f(t_i|x_i) = e^{(-\alpha' x_i-\rho)} e^{\left\{-t_i\, e^{(-\alpha' x_i-\rho)}\right\}} \tag{6.8}$$

where ρ is the shape parameter in AFT model, and α is the vector of coefficients to be estimated. The conditional likelihood function that the person i to be an erratic shopper with m_i durations in which last observation is right censored can be obtained as follows:

$$L_{i,erratic} = \left[\prod_{j=1}^{m_i-1} f\left(t_j|x_j\right)_{erratic}\right] S\left(t_{m_i}|x_{m_i}\right)_{erratic} \tag{6.9}$$

6.2.4. Latent Segmentation

Similar to Bhat et al. (2004), since there is no information showing that shopper i is regular or erratic, the latent segmentation approach is employed to classify erratic (random) and regular shoppers. The probability of shopper i being regular can be estimated by a binary logit model:

$$Prob_{\,i,regular} = \frac{e^{\gamma' z_i}}{1+e^{\gamma' z_i}} \tag{6.10}$$

where z_i is a vector of covariates representing individual characteristics of shopper i and γ is the vector of coefficients. The likelihood function of shopper i to choose inter-shopping duration t_i unconditional on being regular or erratic shopper can be obtained by combining $L_{i,erratic}$ and $L_{i,regular}$:

$$L_i = \left(1 - Prob_{i,regular}\right) * L_{i,erratic} + Prob_{i,regular} * L_{i,regular} \tag{6.11}$$

where

L_i: Unconditional likelihood function of person i

$L_{i,erratic}$: Conditional likelihood of individual i being erratic shopper

$L_{it,regular}$: Conditional likelihood of individual i being regular shopper

$Prob_{i,regular}$: Probability that person i to be a regular shopper; and $\left(1 - P_{i,regular}\right)$ shows the probability that person i to be an erratic shopper.

6.3. Model Estimation

Parameters of the proposed model are estimated by Maximizing the Likelihood Estimator (MLE). The log-likelihood function can be written as follows:

$$LL = \sum_{i=1}^{N} \log L_i \tag{6.12}$$

where N is total number of individuals. This log-likelihood function is estimated by SAS software's interactive matrix language (IML). The vector of parameters β, μ, and σ from duration model of regular shoppers; the vector of α and ρ from duration model of erratic shoppers; and the vector of γ from the latent segmentation model are parameters that need to be estimated.

6.4. Results

For the non-elderly group, the log-likelihood value of the proposed model is -800.53. Also, the likelihood value for the model in which all shoppers are assumed regular is -864.03 and for the model that all shoppers are assumed erratic is -866.34. Running the likelihood ratio test on both pure regular and pure erratic model with latent segmentation indicates that not all shoppers are either erratic or regular shoppers (p-value for both cases is smaller than 0.00).

For elderly group, the log-likelihood value of the proposed model is -860.32. Also, the likelihood value for the model in which all shoppers are assumed regular is -926.41 and for the model in which all shoppers are assumed erratic is -864.91. Running likelihood ratio test of pure regular model with latent segmentation model indicates that elderly shoppers do not show regularity in term of shopping participation (p-value for this case is smaller than 0.00). However, running this test on pure erratic model with latent segmentation shows that all elderly shoppers are statistically erratic shoppers (p-value for this case is 0.515). In other words, inter-shopping duration of elderly people can be modeled with pure erratic model. This result can be justified with the fact that elderly group includes people with fewer shares of mandatory activities (work/school activities) and as a result, shoppers in this group are less time pressed with a more flexible schedule.

As discussed earlier, inter-shopping durations are direct results of AFT model formulation. Employing Equation (6.1), average inter-shopping duration for each age group is calculated. For non-elderly group, average inter-shopping duration of regular segment is equal to 9.86 days and for erratic segment is equal to 1.70 days. For non-elderly group, these values are equal to 1.72 days and 1.89 days respectively for regular and erratic segment. It can be concluded that average value of inter-shopping durations of regular and erratic segment is almost the same for elderly group. In contrast to elderly group, non-elderly regular shoppers choose 5.8 times longer inter-shopping duration than that of non-elderly erratic shoppers on average. The next section discusses the effects of covariates in both age groups. As discussed above, all elderly people are statistically erratic shoppers and for this group of shoppers the result of pure erratic model is presented. However for non-elderly group the result of latent segmentation model is discussed.

6.4.1. Covariate Effects

A combination of variables representing household, personal, and activity characteristics is used in the estimated models. Table 6.4 displays definition of variables and their mean and standard deviation values in the sample.

Table 6.4. Variables used n the model

Variables	Definition	Non-Elderly group		Elderly group	
		Mean Value	Standard Deviation	Mean Value	Standard Deviation
Total activities	Average of total activities performed on two previous inter-shopping episodes	2.74	3.35	2.91	2.44
Jointactivity	1 if shopping activity is performed jointly by other person(s), 0 otherwise	0.39	0.49	0.43	0.50
Education	1 If shopper is holding college degree or higher, 0 otherwise	0.66	0.48	0.64	0.48
logHHINCperSize	Ln (Annual household income per household size)	3.13	0.53	3.56	0.59
HHSIZE	Household size	3.08	1.43	1.82	0.58
HHTYPE_MC	1 if household type is married with children, 0 otherwise	0.52	0.50	0.24	0.43
HHTYPE_LA	1 if person lives alone, 0 otherwise	0.14	0.35	0.13	0.34
HHTYPE_SC	1 if household type is single with children, 0 otherwise	0.10	0.30	0.02	0.15
Female	1 if a person is female, 0 otherwise	0.60	0.50	0.58	0.50
INTERNET_Frequently	1 if a person uses internet frequently, 0 otherwise	0.92	0.27	--	--

Table 6.5 and Table 6.6 present the results of estimated inter-shopping duration models for non-elderly and elderly shoppers. AFT model formulation makes interpretation of covariate effects easier than other hazard models. Inter-shopping durations is the direct output of Equation (6.1). It should be noted that positive coefficients increase inter-shopping duration (i.e., decrease frequency of shopping activities).

For non-senior shoppers, higher income and bigger household size result in shorter regular inert-shopping durations and longer random inter-shopping durations. It can be due to the fact that families with these characteristics have limited schedule and more number of items in their shopping baskets. Therefore, they prefer shorter regular inter-shopping durations. Their limited schedule does not allow them to participate in random shopping frequently. People with higher education tend to choose longer regular inter-shopping durations and do more random shopping activities. “HHtype_LA” has the same effect on both segments. Perhaps due to the reason that shopping activity for those people who live alone is more like a leisure activity. Estimated coefficient for erratic segment is much bigger than Regular segment which means that people who live alone mostly tend to choose short random inter-shopping duration. “Total activities” between two shopping activities can increase the inter-shopping duration in both Regular and Erratic segments. “Total activities” covariate is a candidate of how busy the schedule of a person would look like. The bigger value of this covariate the busier the schedule. Therefore, this covariate shows that increase in the number of a person’s activities postpones shopping activities of that person.

For elderly group, negative sign of “Joint Activity” indicates that participating in the shopping activities with companies decreases the inter-shopping duration. This can be due to this reason that seniors seize each opportunity to socialize with other people. Higher income seniors perform shopping activities more frequently than lower income households. Also, “HHtype_SC” and “HHtype_MC” indicates that seniors with children perform more shopping activities. “Total activities” has the same effect as it showed for non-elderly group.

Table 6.5 Intershopping duration model results of non-elderly people

Variable	Regular shopper segment		Erratic shopper segment	
	Parameter	t-stat	Parameter	t-stat
Total activities	0.280	13.32	0.109	4.94
Education	0.221	2.54	-0.296	-1.63
logHHINCperSize	-0.435	-5.48	0.292	0.95
HHsize	-0.279	-6.18	0.151	2.31
HHtype_LA	-0.294	-2.28	-0.884	-1.58
Constant	-0.316	-0.28	2.431	6.98
Scale Parameter	0.561	20.63	--	--

Table 6.6 Intershopping Duration Model of Elderly People

Variable	pure erratic shopper model	
	Parameter	t-stat
Total activities	0.263	9.68
Joint Activity	-0.324	-2.94
logHHINCperSize	-0.251	-3.00
HHtype_SC	-0.336	-0.82
HHtype_MC	-0.205	-1.82
Constant	1.310	4.36

6.4.2. Segmentation Model

As discussed earlier, all elderly shoppers are essentially erratic shoppers. Therefore, in this section only segmentation model results of non-elderly group are presented. Table 6.7 provides the results of the binary logit model that was used to endogenously divide non-elderly shoppers in two groups of regular and erratic shoppers. Base category for the binary logit model is the erratic shopper group. Being female, having higher education, and frequently using the internet can increase the chance of being a regular shopper; while living in a bigger household increases the chance of being an erratic shopper.

Table 6.7 Segmentation Model For Non-elderly People

Variable	Parameter	t-stat
HHsize	-0.703	-2.11
Female	0.766	0.89
Education	0.882	0.97
INTERNET_Frequently	1.986	1.23
Constant	-0.103	-0.06

Size of the erratic and regular shopper segments can be calculated as follows:

$$S_{i,regular} = \frac{\sum_{i=1}^{N} Prob_{\ i,regular}}{\sum_{i=1}^{N} Prob_{\ i,regular} + \sum_{i=1}^{N} Prob_{\ i,erratic}} = \frac{\sum_{i=1}^{N} Prob_{\ i,regular}}{N} \quad (6.13)$$

$$S_{i,erratic} = \frac{\sum_{i=1}^{N} Prob_{\ i,erratic}}{N} \quad (6.14)$$

It is shown that 62% of non-elderly people are regular shoppers and 38% of them are erratic shoppers. This result is totally different in comparison with the results obtained for elderly people where 100% of them are erratic shoppers.

7. DRIVING BEHAVIOUR OF SENIORS

Elderly driving behavior and its impacts on traffic safety is one of the most addressed issues in previous studies about seniors' travel behavior. In 2010, older drivers were 16% of all licensed drivers in the U.S., which showed a 2% increase since 2001 (National Highway's Traffic Safety Administration, 2012). In the United States, 17% of the traffic fatalities and 8% of the injured people in 2010 were elderly people (NHTSA 2012). Understanding seniors' driving behavior is a key to Analysis of seniors' traffic accidents. Driving behavior includes all the decisions made during driving such as speed, level of respect to traffic signs, reaction to control devices, and lane changing. In this section drivers' reaction to yellow light at dilemma zone of a signalized intersection is explored.

Dilemma zone at signalized intersections is defined as a zone where drivers in response to the traffic signal changing from green to yellow decide either to proceed through the intersection or to stop. Drivers' decision to stop or go can result in rear end or angle crashes. In previous studies, the dominant approach to model driver's stop-go behavior at dilemma zone of signalized intersections is the straightforward logistic regression model. This approach, which is also known as binary logit model, was used to model the probability that a driver decides to stop or go *(*Rakha et al., 2008; Radwan et al., 2005; Abdel-Aty et al., 2009; Elmitiny et al., 2010*)*. Analysis of stop-go behavior is not limited to logistic regression and there are few studies that employed alternative techniques to logistic regression to model stop-go decision. Elmitiny et al. (2010) applied decision tree model to explore drivers' stop-go decision. Hurwitz et al. (2012)

modeled stop-go decision at high-speed signalized intersections by constructing a fuzzy logic model.

Previous efforts on modeling the stop-go behavior have restricted the drivers' decisions into two groups: the decision to go and the decision to stop. This classification disregards the safety of the decision that was made. In other words, it does not consider if the stop or go was a safe or hazardous decision. This type of classification assumes that all drivers in each group have similar dilemma zone behavior and treats them equally. Thus, it cannot distinguish safe and hazardous stop-go decisions within each group.

For example, while some drivers in the Go group pass through the intersection safely on the yellow light, there are some drivers in this group who underestimate their distance to intersection and run the red light. This hazardous decision can result in angle crash which is among the most dangerous accidents at signalized intersections. Same is the case with the Stop group where some drivers stop safely with a low deceleration rate and some who can pass through the intersection on the yellow light may decide to stop suddenly which can cause rear to end crashes. Therefore dividing drivers into only two groups of stop and go may result in ignoring different levels of risk that they put on themselves and other drivers. In other words, current models cannot address behavioral differences between drivers who stop with safe and controlled deceleration with drivers who stop with an abrupt and hazardous brake. This conclusion is also valid for the drivers who run the red light, meaning that models that consider these drivers in one group cannot capture the behavioral differences between drivers who safely pass through the intersection in the yellow light and the drivers who run the red light.

In contrast to the previous efforts, this paper proposes a nested logit modeling structure with four alternative decisions to replicate the dilemma zone driver behavior at signalized intersections. Stop decisions are divided into two alternatives: Safe Stop with a deceleration rate less than 20 ft/Sec^2 and Hazardous or Sudden Stop decisions with a deceleration rate more than 20 ft/Sec^2 that can cause rear end crash. These two alternatives of stop decision are kept in one nest called *Stop*. Similarly, passing through decisions are divided into two alternatives: Safe Go where drivers pass through the intersection when the light is still yellow and Hazardous Go which means running the red light which can result in angle crash. These two alternatives of go decision are kept in one nest called *Go*. Using the proposed structure, the developed model can capture the behavioral differences of drivers in each decision group and distinguish between safe and hazardous stop and go.

The data used in this study comes from University of Iowa National Advanced Driving Simulator (NADS) in which a driving simulator was used to examine the impacts of cell phone use and individual characteristics on driving performance and specifically dilemma zone behavior of drivers at signalized intersections. The data set includes very detailed information on drivers' reaction to the yellow light.

7.1. Proposed Methodology

Data sample for this analysis comes from a study conducted in the University of Iowa National Advanced Driving Simulator (NADS) to examine driver's reaction to the yellow light of a signalized intersection. To deeply understand drivers' behavior at the dilemma zone, drivers are classified into four groups (instead of two) as follows.

1) Safe Stop: Drivers who stop with maximum deceleration less than 20 ft/s2

2) Hazardous Stop: Drivers who stop with maximum deceleration greater than 20 ft/s2

3) Safe Go: Drivers who pass through the yellow light

4) Hazardous Go: Drivers who run the red light

The deceleration rate of 20 ft/s2, which is selected as the classification threshold, is the average value of maximum decelerations of drivers who decided to stop during the simulation. Table 7.1 displays distribution of drivers' decisions over different age groups. It is obvious that older participants have displayed different driving behavior from other age cohorts especially in term of Hazardous Go and Safe Stop decisions. Their tendency to run the red light is almost as twice as it is for the young and middle-age groups. There is also a considerable difference between driving behavior of females and males. Female participants display a much safer driving behavior than males. Hazardous decisions made by males are about 1.5 times of females.

Table 7.1 Distribution of drivers' decisions across their personal characteristics.

Variable	Hazardous Go	Safe Go	Hazardous Stop	Safe Stop	Total
Age Group					
Young	11.8%	21.8%	28.0%	38.3%	37%
Middle-age	9.6%	25.1%	28.4%	37.0%	35%
Old	20.4%	22.8%	28.8%	28.0%	29%
Gender					
Female	10.8%	29.6%	21.4%	38.2%	48%
Male	15.9%	17.5%	34.7%	31.9%	52%

The Nested Logit (NL) model with the structure shown in Figure 7.1 is utilized to model driver's decision in response to yellow light. The NL model that belongs to the family of discrete choice models can predict probability of making any of the four decisions while taking into account personal characteristics and driving conditions. In contrast to the standard logit model, the NL model can capture correlation between similar alternatives and classify similar subsets of alternatives into hierarchies or nests. Each nest is considered as a complex alternative that competes with other choices. Therefore, the NL model can provide more precise results compared to the standard logit model in this case. As it can be seen in Figure 1, for the case of this study the Safe Stop and Hazardous Stop are considered similar subsets of stop alternative and classified in one (Stop) nest and Safe Go and Hazardous Go are considered correlated subsets of the Go alternative and classified in another nest.

For the nested structure shown in Figure 7.1, the probability that driver n makes decision i from the nest Stop is obtained using the following Equation.

$$P_{i\,n} = \frac{e^{\frac{\beta' x_i}{\theta_S}}\left(e^{\frac{\beta' x_i}{\theta_S}} + e^{\frac{\alpha' x_i}{\theta_S}}\right)^{\theta_{S-1}}}{\left(e^{\frac{\beta' x_i}{\theta_S}} + e^{\frac{\alpha' x_i}{\theta_S}}\right)^{\theta_S} + \left(e^{\frac{\gamma' x_i}{\theta_G}} + e^{\frac{\rho' x_i}{\theta_G}}\right)^{\theta_G}} \qquad (7.1)$$

where x_i is the vector of characteristics of driver i and driving condition (explanatory variables); β and α are vectors of coefficients to be estimated for alternatives in the Stop nest; γ and ρ are vectors of coefficients to be estimated for alternatives in the Go nest; θ_S and θ_G are the nest parameters for the Stop and Go nests respectively. They determine if the subsets of alternatives in one nest are correlated and how significant is their correlation. There will be no detected correlation between subsets of alternatives in each nest if the nest parameters θ_S and θ_G are estimated to be equal to one. In this case the nested logit structure will collapse to the standard logit model.

Another advantage of NL model is that the probability function has a closed form which makes the model's estimation and application very straightforward. More discussion on NL models can be found in (Train, 2003).

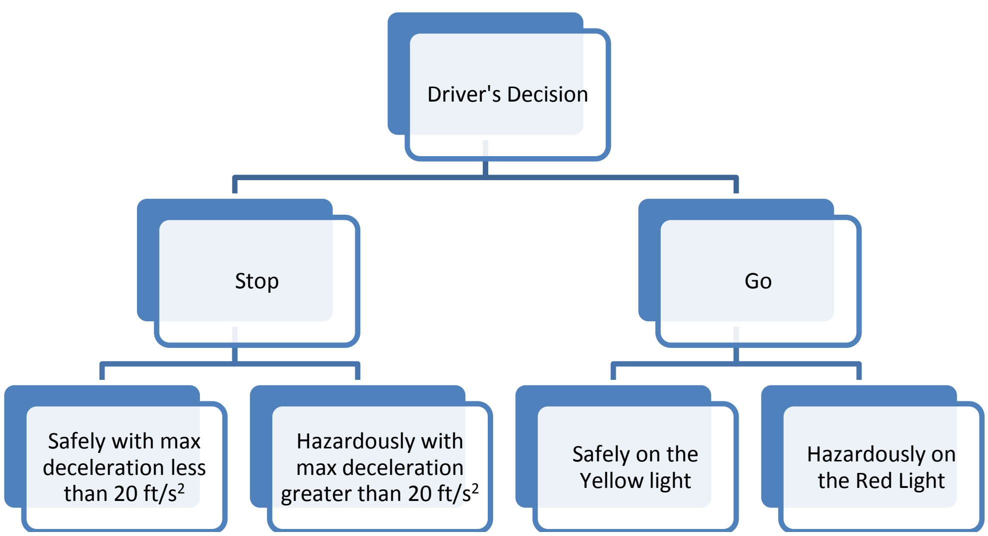

Figure 7.1 The nested logit structure for drivers' stop-go decision at dilemma zone.

7.2. Model Estimation and Results

The log-likelihood function for individual n with the set of observations $\mathrm{M_n}$, which is equal to 18 in this study, takes the following form:

$$LL_n = \sum_{\mathrm{j=1}}^{M_n} \sum_{\mathrm{i=1}}^{\mathrm{I}} r_{i\,n} \times P_{i\,n} \tag{7.2}$$

Where dummy variable $\mathrm{r_{i\,n}}$ takes the value of 1 if and only if driver n makes decision i and value of zero otherwise. The model parameters are using maximum likelihood estimator. The log-likelihood function can be written as follows:

$$LL = \sum_{n=1}^{N} \log L_p \tag{7.3}$$

where N is the total number of drivers participated in the simulation trial. The parameters to be estimated include vectors of coefficients β, α, γ, and ρ and nest parameters θ_{S} and θ_{G}. The proposed model is estimated with Biogeme software which is an open source freeware designed for the estimation of discrete choice models (8 and 9; biogeme.epfl.ch).

Table 7.2 displays sample statistics and definition of explanatory variables used in the model. The provided data set gives very restricted information about participant characteristics (limited only to gender and age group). More information on personal (i.e. race, marital status, education, and income) and household (i.e. household size, number of cars, household income, and household type) characteristics could be very helpful to have a better and more precise model.

Table 7.2 Sample statistics and definition of variables used in the final model.

Variables	**Definition**	**Mean Value**	**Standard Deviation**
Individual Characteristics			
Age Group			
Young	1 if driver is young (18-25 years), 0 otherwise	0.37	0.48
Middle-age	1 if driver is middle-aged (30-45 years), 0 otherwise	0.35	0.48
Old	1 if driver is old (50-60 years), 0 otherwise	0.28	0.45
Female	1 if driver is female, 0 otherwise	0.47	0.50
Driving Attributes			
Velocity (mph)	Driver's velocity when the light turns from green to yellow	42.67	4.91
Distance (ft)	Driver's distance from stop line when the light turns from green to yellow (	205.34	33.14
Distance/Velocity (Sec)	Driver's distance from stop line when the light turns from green to yellow divided by driver's velocity,	3.28	0.38
Cell Phone Status			
Handset	1 if the secondary task condition is handset, 0 otherwise	0.32	0.47
Baseline	1 if the call status is "baseline", 0 otherwise	0.34	0.48

Table 7.3 presents model estimation results at convergence. The model was estimated at highly disaggregated personal (driver) level. Based on t-stat values, many variables were tested and insignificant variables have been removed from the final estimate. The table shows only significant variables used in final estimation. Both nest parameters are statistically significant and less than one which implies that there is meaningful correlation between subset alternatives and confirms the proposed nested structure in Figure 1. Adjusted rho-square value shows that included covariates have improved model's fit by 20.4% which is very good for the case of this study with a small sample size. In addition, the likelihood ratio test on the proposed model and null model indicates that added covariates to the proposed model can significantly enhance model's fit. The likelihood ratio test takes on a value of 507.38, greater than χ^2 statistic with 20 degrees of freedom at 99% level of significant (37.57).

Table 7.3 Model Estimates (The Alternative *Stop with deceleration < 20* is the base alternative)

	Nest STOP				Nest GO			
	Safe		Hazardous		Safe		Hazardous	
Variables	**parameter**	**t-stat**	**parameter**	**t-stat**	**parameter**	**t-stat**	**parameter**	**t-stat**
Constant	-	-	-3.17	-2.38	1.66	0.94	-2.24	-2.58
Age Group								
Young	-	-	-	-	-0.344	-1.74	-0.796	-3.00
Middle-age	-	-	-	-	-	-	-0.914	-3.12
Old	-	-	0.407	1.80	0.436	1.94	-	-
Female	-	-	-0.424	-2.05	0.408	2.19	-0.380	-1.31
Velocity (mph)	-	-	0.250	2.41	0.107	3.59	0.0471	2.26
Distance (ft)	-	-	-0.0369	-2.32	-	-	-	-
Distance/Velocity (Sec)	-	-	-	-	-2.15	-2.97	-	-
Handset	-	-	-	-	-	-	0.325	1.92
Baseline	-	-	-	-	0.293	1.65	-	-
Nest Parameter	0.66 (t-stat = 2.28)				0.51 (t-stat = 2.73)			
LogLikelihood	-892.78							
Null LogLikelihood	-1146.47							
Ratio test	507.38							
Adjusted Rho-square	0.204							

Since the negative (positive) sign of an alternative's covariate decreases (increases) the chance of that alternative to be selected, the following results can be obtained from Table 2 when traffic light turns from green to yellow:

- Talking on the phone with handset increases the chance of running the red light
- Generally, young and middle-age drivers show less tendency to cross the intersection at the dilemma zone
- Older people show more tendencies either to pass on the yellow light or to make a sudden brake
- Being female reduces the probability of making sudden brake and running the red light.
- Being female increases the chance of crossing intersection on the yellow light
- High velocity has a significant effect on both making a sudden brake and crossing the intersection
- Drivers with longer distance from the intersection shows smaller propensity to make a sudden brake than drivers with shorter distance from the stop line

- Drivers with higher speed show higher tendency to cross the intersection at the dilemma zone

To test the model's performance in predicting drivers' decision, measures of fit at both aggregate and disaggregate levels are examined. Due to the small size of the data sample, train and test data are kept the same and there is no hold up sample for validation purpose. At aggregate level, distribution (share) of the four alternatives is compared to what the proposed model predicts separately for different sub-samples including young, middle-aged, and old age groups, males, and females. Table 7.4 presents this comparison. It can be seen that the model has predicted alternatives' share for each sub-sample pretty well.

Table 7.4 Comparison between predicted and in-data shares for different subsamples.

Decision	Young		Middle-aged		Old		Female		Male	
	Predicted	In-data Share	Predicted	In-data Share	Predicted	In-data Share	Predicted	In-data Share	Predicted	In-data Share
Hazardous Go	11%	10%	8%	9%	8%	9%	9%	9%	15%	15%
Safe Go	19%	20%	24%	24%	24%	24%	28%	28%	16%	16%
Hazardous Stop	31%	30%	27%	29%	27%	29%	22%	23%	36%	36%
Safe Stop	39%	40%	40%	38%	40%	38%	41%	41%	33%	33%

At disaggregate level, the probability that chosen decision has the highest predicted propensity is computed. In 52% of cases, the model could correctly predict the highest probability for the chosen decision. It could be higher if the sample size was bigger and there were more information available on personal and household characteristics.

8. MIXED JOINT DISCRET-CONTINUOUS MODEL OF NON-MANDATORY OUT-OF-HOME ACTIVITY TYPE and ACTIVITY DURATION

8.1. Introduction

There has been considerable focus on the modeling of the relationship between inter-related aspects of activity-travel behavior, motivated by the possibility that these models can result in a more realistic and precise prediction of travel demand. Discrete-continuous Joint modeling techniques have been widely used in travel behavior analysis to investigate casual relationship between inter-related discrete choice and its continuous outcome (i.e. the activity type and the episode duration). The continuous choice is called the "outcome" of the discrete decision to imply that it is only observed if the discrete decision has been made (self-selection).

In travel behavior analysis research, Lee's technique (1983) and copula-based models have been the two dominant approaches for discrete-continuous joint models. In Lee's (1983) approach, error terms of discrete and continuous choice equations are transformed into normal variables. Then, these transformed variables are jointly coupled with a bivariate normal distribution. Some recent examples of this approach's application in the travel behavior analysis are Bhat (1997), Habib et al. (2008 and 2009), and Habib (2009). Bhat (1997) formulated a discrete-discrete joint model of number of stops (ordered probit model) and work mode choice (multinomial logit model) for work commutes. A discrete-continuous model developed by Habib et al. (2008) that examined the inter-relationship between "with whom" (multinomial logit model) and start time/duration of social activities (parametric accelerated failure time model). Lee's approach is not limited to two choices and can be extended to more number of decisions. Habib et al. (2009) employed Lee's (1983) approach successively to formulate a trivariate joint model of start time, duration, and mode choice decisions. Although Lee's (1983) approach has been very popular in discrete-continuous joint modeling, it's assumption on dependency structure between error terms can be restrictive. The dependency structure in this approach is assumed to be symmetrical and linear, which results in being inflexible; not always an appropriate assumption.

Bhat and Eluru (2009) introduced the copula-based approach into travel behavior modeling that, in contrast to Lee's approach, can provide a flexible dependency structure between error terms. Copula is a function that generates joint probability of random variables with pre-defined marginal distributions. A rich set of copula classes have been generated (Nelsen, 2006). This variety in type allows researchers to find the most appropriate dependency structure between the random variables in the model development procedure.

In the past few years, copula-based joint models have been extensively used in the travel behavior analysis. Spissu et al. (2009) developed a copula-based joint model to inspect connection between vehicle type choice and traveled distance. Comparison of obtained results with previous joint modeling approaches showed a better goodness-of-fit for copula-based model. Sener et al. (2010) presented a copula-based model to analyze the physical activity participation of individuals (in terms of the number of daily "episodes" of physical activity during a weekend day) of all members of a family jointly. Studies presented by Eluru et al.

(2010a), Sener and Bhat (2010), Bhat and Sener (2009), Eluru et al. (2010b) and Born et al. (2014) show diverse applications of copula for travel behavior analysis.

All these studies have well established the benefits of employing copula-based approach in the joint modeling problems. However there are still some deficiencies in terms of accommodating more detailed modeling aspects in the formulation and structure development. One common shortage in the previous efforts is that they are based on the homogeneity assumption, where heterogeneity is ignored and is assumed to be unobservable in individuals' choice process (P. Leszczyc and Bass, 1998). Unobserved preference heterogeneity is normally introduced in the econometric models by adding more stochastic terms into the choice indices. Failure in accounting for the unobserved heterogeneity can cause bias in estimates of covariate effects.

This chapter of dissertation extends previous efforts on copula-based joint modeling by incorporating unobserved heterogeneity into a copula-based discrete-continuous joint modeling. To the best of the authors' knowledge, the proposed model is the first in the transportation literature to capture the heterogeneity effects in a joint copula-based structure. The heterogeneity is examined using two separate scenarios: 1) Incorporating unobserved heterogeneity into marginal distributions 2) Incorporating unobserved heterogeneity into copula parameter. Mixed and non-mixed copula models are examined for activity type choice as the discrete decision and episode duration as the continuous variable. The focus of the study is on weekday non-mandatory out-of-home activities.

8.2. Model Structure and Estimation

This section discusses the proposed structure of the mixed copula-based discrete-continuous joint model in which non-mandatory activity type is considered the discrete choice and episode duration is considered the continuous outcome. In the first scenario, random parameter is added to the marginal distributions; and in the second scenario, the random parameter is added only to the copula parameter. At the end of the section, estimation procedure of the proposed models is presented.

8.2.1. Scenario 1: Unobserved Heterogeneity Added to the Marginal Distributions

The discrete choice component takes the form of a mixed generalized extreme value model and the continuous component is modeled with a non-parametric mixed proportional hazard duration model. The joint model has discrete and continuous components that are coupled with a copula function. First, the discrete choice component and its modeling structure are discussed.

Let LU_{pi} be the latent utility that individual p gains by choosing a discrete alternative i:

$$LU_{pi} = \beta' x_{pi} + \eta_p + \varepsilon_{pi} \tag{8.1}$$

where x_{pi} represents the independent covariates; β is the coefficients to be estimated; ε_{pi} is the error term with an Extreme Value Type I (Gumbel) distribution; and η_p is the individual-specific random effect that captures unobserved heterogeneity. η_p is assumed to follow normal distribution with mean of zero and standard error of σ_η. Individual p chooses the alternative i if and only if the acquired latent utility from the alternative i is greater than latent utility of any other alternative in a choice set of J alternatives:

$$LU_{pi} > \max_{\substack{j=1,2,\ldots,J \\ j\neq i}} LU_{pj} \tag{8.2}$$

If ν_{pi} is defined as

$$\nu_{pi} = \varepsilon_{pi} - \left\{ \max_{\substack{j=1,2,\ldots,J \\ j\neq i}} LU_{pj} \right\} \tag{8.3}$$

Then, from equations (8.1), (8.2), and (8.3) it can be concluded that individual p chooses alternative i if and only if:

$$\nu_{pi} + \beta' x_{pi} + \eta_p > 0 \Leftrightarrow r_{pi} = 1 \tag{8.4}$$

where r_{pi} is a binary variable.

Based on the definition of ν_{pi} in Equation (8.3), $F(.|\eta_p)$ the cumulative distribution function (CDF) of ν_{pi} conditional on η_p can be obtained from distributional assumption on the ε_{pi} as written below:

$$F\left(\nu \middle| \eta_p\right) = Prob\left(\nu_{pi} < \nu \middle| \eta_p\right) = \frac{\sum_{j\neq i} \exp\left(\beta' x_{pj} + \eta_p\right)}{\exp(-\nu) + \sum_{j\neq i} \exp\left(\beta' x_{pj} + \eta_p\right)} \tag{8.5}$$

Non-parametric Mixed Proportional Hazard (MPH) model is employed in this study to model the choice of activity duration as the continuous component. Non-parametric form of proportional hazard model is a suitable choice for the case that time is divided into discrete intervals which is the case of this study. Based on the MPH model, the hazard function that individual p performs activity i at time duration t takes the following form:

$$\lambda_{pi}(t) = \lambda_{0i}(t) \exp(-\alpha' z_{pi} - \mu_p) \tag{8.6}$$

Where $\lambda_{0i}(t)$ is the baseline hazard for activity type i at time duration t; z_{pi} is the vector of covariates; α represents the coefficients to be estimated; and μ_p is individual-specific random effect that captures unobserved heterogeneity. μ_p is assumed to follow normal distribution with mean of zero and standard error of σ_μ.The equivalent form of Equation (8.6) can be written as (Bhat, 1996):

$$d_i(t) = \ln\left[\int_{s=0}^{t} \lambda_{0i}(s)\, ds\right] = \alpha' z_{pi} + \mu_p + \omega_{pi} \qquad (8.7)$$

where ω_{pi} is the error term that has an extreme value distribution with the following CDF function:

$$G(.) = 1 - \exp(-\exp(.)) \qquad (8.8)$$

$d_i(t)$ in Equation (8.7) is not observable and the researcher can only observe activity duration in the form of discrete spells. Since $\ln\left[\int_{s=0}^{t} \lambda_{0i}(s)\, ds\right]$ is a monotonically increasing function with time, for any $t_1 < t_2$ it can be concluded that $d_i(t_1) < d_i(t_2)$. Let T_k be pre-determined cutoff pints that divide continuous duration time into K $(k = 1,2, \dots, K)$ time spells. The duration time t that individual p has assigned to activity type i is equivalent to time spell k when $T_{k-1} < t \leq T_k$. Then from Equation (8.7) it can be concluded that individual p chooses time spell k for activity type i when

$$\delta_{i,k-1} < \alpha' z_{pi} + \mu_p + \omega_{pi} \leq \delta_{i,k} \qquad (8.9)$$

where $\delta_{i,k} = \ln\left[\int_{s=0}^{T_k} \lambda_{0i}(s)\, ds\right]$, $\delta_{i,0} = -\infty$ and $\delta_{i,K} = +\infty$.

Summarizing above discussion, the probability that individual p chooses perform activity type i with time duration spell k conditional on $\eta_p$and $\mu_p$can be written as:

$$
\begin{aligned}
Prob\ \left(r_{pi}=1, t_{pi}=k|\eta_p,\mu_p\right) &= Prob\ \left(\nu_{pi}+\beta^{'}x_{pi}+\eta_p>0, \delta_{i,k-1}<\alpha^{'}z_{pi}+\mu_p+\omega_{pi}<\delta_{i,k}\right)\\
&= Prob\ \left(\nu_{pi}>-\beta^{'}x_{pi}-\eta_p, \delta_{i,k-1}-\alpha^{'}z_{pi}-\mu_p<\omega_{pi}<\delta_{i,k}-\alpha^{'}z_{pi}-\mu_p\right)\\
&= Prob\ \left(\delta_{i,k-1}-\alpha^{'}z_{pi}-\mu_p<\omega_{pi}<\delta_{i,k}-\alpha^{'}z_{pi}-\mu_p\right)\\
&- Prob\ \left(\nu_{pi}<-\beta^{'}x_{pi}-\eta_p, \delta_{i,k-1}-\alpha^{'}z_{pi}-\mu_p<\omega_{pi}<\delta_{i,k}-\alpha^{'}z_{pi}-\mu_p\right)\\
&= G\left(\delta_{i,k}-\alpha^{'}z_{pi}-\mu_p\right)-G\left(\delta_{i,k-1}-\alpha^{'}z_{pi}-\mu_p\right)\\
&- \Big[Prob\ \left(\nu_{pi}<-\beta^{'}x_{pi}-\eta_p, \omega_{pi}<\delta_{i,k}-\alpha^{'}z_{pi}-\mu_p\right)\\
&- Prob\ \left(\nu_{pi}<-\beta^{'}x_{pi}-\eta_p, \omega_{pi}<\delta_{i,k-1}-\alpha^{'}z_{pi}-\mu_p\right)\Big] \qquad (8.10)
\end{aligned}
$$

It’s time for copula to play its role in Equation (8.10). As mentioned earlier, copula is a connector that provides a dependence structure among random variables with pre-specified marginal distribution. Consider a uniformly distributed random vector (U_1, U_2, …, U_m) over [0, 1]. Then,

$$C_\theta(u_1, u_2, \ldots, u_m) = \Pr(U_1<u_1, U_2<u_2, \ldots, U_m<u_m) \qquad (8.11)$$

is the m-dimensional copula of random variables U_1, U_2, ..., and U_m. θ is the copula parameter which shows how random variables are inter-related. Employing copula, one can generate joint multivariate distribution functions with pre-defined marginal distributions. Consider a random vector (V_1, V_2, …, V_m) with pre-defined marginal distribution of ($F_1(\vartheta_1)$, $F_2(\vartheta_2)$, …, $F_m(\vartheta_m)$). Then joint multivariate distribution can be generated as

$$J(\vartheta_1, \vartheta_2, \ldots, \vartheta_m) = \Pr(V_1<\vartheta_1, V_2<\vartheta_2, \ldots, V_m<\vartheta_m) = \Pr(U_1<F_1(\vartheta_1),\ U_2<F_2(\vartheta_2), \ldots, U_m<F_m(\vartheta_m)) = C_\theta(F_1(\vartheta_1), F_2(\vartheta_2), \ldots, F_m(\vartheta_m)) \qquad (8.12)$$

Hence, Equation (10) can be written as follows:

$$
\begin{aligned}
&Prob\left(r_{pi}=1,t_{pi}=k|\eta_p,\mu_p\right)= \\
&\qquad = G\left(\delta_{i,k}-\alpha' z_{pi}-\mu_p\right)-G\left(\delta_{i,k-1}-\alpha' z_{pi}-\mu_p\right) \\
&\qquad -\left\{C_\theta\left[F\left(-\beta' x_{pi}\middle|\eta_p\right),G\left(\delta_{i,k}-\alpha' z_{pi}-\mu_p\right)\right]\right. \\
&\qquad \left.-C_\theta\left[F\left(-\beta' x_{pi}\middle|\eta_p\right),G\left(\delta_{i,k-1}-\alpha' z_{pi}-\mu_p\right)\right]\right\} \qquad (8.13)
\end{aligned}
$$

Finally, the unconditional likelihood function for individual p with N_p observations can be formulated as follows:

$$L_p=\int_{\mu_p=-\infty}^{+\infty}\left\{\int_{\eta_p=-\infty}^{+\infty}\left[\prod_{m=1}^{N_p}Prob\left(r_{p\,j_m}=1,t_{pj_m}=k_m|\eta_p,\mu_p\right)\right]dN(\eta_p|\sigma_\eta)\right\}dN(\mu_p|\sigma_\mu) \qquad (8.14)$$

where j_m and k_m are respectively activity type and time duration of observation m and $N(.)$ is cumulative normal distribution function.

8.2.2. Scenario 2: Unobserved Heterogeneity Added to the Copula Parameters

In this scenario, random parameters μ_p and η_p are dropped from equations (8.1) and (8.6); and random parameter is only added to the copula parameter as follows:

$$\theta_p=\theta+\varphi_p \qquad (8.15)$$

where φ_p is assumed to follow normal distribution with mean of zero and standard error of σ_φ.

Therefore, the joint probability in Equation (8.13) turns to be:

$$
\begin{aligned}
&Prob\left(r_{pi}=1,t_{pi}=k|\varphi_p\right) \\
&\qquad = G\left(\delta_{i,k}-\alpha' z_{pi}\right)-G\left(\delta_{i,k-1}-\alpha' z_{pi}\right) \\
&\qquad -\left\{C_{\theta_p}\left[F(-\beta' x_{pi}),G\left(\delta_{i,k}-\alpha' z_{pi}\right)\right]-C_{\theta_p}\left[F(-\beta' x_{pi}),G\left(\delta_{i,k-1}-\alpha' z_{pi}\right)\right]\right\} \qquad (8.16)
\end{aligned}
$$

The unconditional likelihood function for individual p with N_p observations can be formulated as written below:

$$L_p=\int_{\varphi_p=-\infty}^{+\infty}\left[\prod_{m=1}^{N_p}Prob\left(r_{p\,j_m}=1,t_{pj_m}=k_m|\varphi_p\right)\right]dN(\varphi_p|\sigma_\varphi) \qquad (8.17)$$

For both scenarios the log-likelihood function takes the following form:

$$LL = \sum_{p=1}^{P} \log L_p \tag{8.18}$$

where P is the total number of partcipants in the sample. This log-likelihood function is maximized using NLMIXED procedure of SAS econometrics software. Adaptive Gauss-Hermite quadrature method is employed for approximating the integral of the likelihood over the random effects μ_p, η_p, and τ_p. The parameters to be estimated include β vector and σ_η of discrete component; α vector, σ_μ, and $\delta_{i,k}$ ($k = 1,2,\dots,K$ and $i = 1,2,\dots,I$) of continuous component; and copula parameter θ and σ_φ as its standard error.

8.3. Data

The data used for the purpose of this study is a sample randomly selected from the Chicago Metropolitan Agency for Planning (CMAP) Travel Tracker Survey collected in the Greater Chicago Area in 2007-2008. More than 10,000 households participated in the survey, providing a total of 160,000 activities on the assigned travel day(s). The focus of the study is on weekday out-of-home non-mandatory activities that are divided into the following four groups:

- Personal such as religious, healthcare, and civic activities.
- Services such as pickup, drop off, and errands
- Discretionary such as dining out, visiting friends, and entertainments
- Shopping such as grocery shopping

There are totally 36,344 weekday non-mandatory out-of-home activities in the CMAP data set. A sample of 5,000 activities from 1,642 individuals that follows almost the same age distribution in the CMAP data set is derived for the purpose of this study. The activity duration is divided into seven time spells (minutes) including [0-10], [10-20], [20-30], [30-45], [45-60], [60-90], and [90+]. Table 8.1 displays sample characteristics over activity types and duration intervals.

Table 8.1. Sample Characteristics

	Activity Type				**Activity Duration Spell (minutes)**							Average
	Personal	Services	Discretionary	Shopping	[0-10]	[10-20]	[20-30]	[30-45]	[45-60]	[60-90]	[90+]	
Individual Characteristics												
Gender												
Female	21.6%	34.2%	13.6%	30.6%	38.3%	12.3%	9.1%	11.2%	8.6%	9.7%	10.8%	58.3%
Male	21.2%	31.7%	20.4%	26.7%	38.7%	14.2%	10.7%	9.1%	8.6%	9.1%	9.8%	41.7%
Age												
Age 18-24	20.7%	37.9%	22.4%	19.0%	53.4%	3.4%	10.3%	6.9%	8.6%	10.3%	6.9%	3.5%
Age 25-34	16.6%	33.7%	18.2%	31.5%	38.7%	13.8%	8.3%	10.5%	8.8%	8.3%	11.6%	11.0%
Age 35-44	14.8%	45.4%	17.0%	22.9%	49.8%	14.8%	7.4%	8.5%	8.1%	5.9%	5.5%	16.5%
Age 45-54	16.4%	40.0%	15.3%	28.3%	49.4%	14.5%	6.8%	9.1%	6.8%	7.0%	6.5%	23.4%
Age 55-64	23.1%	26.3%	18.6%	32.0%	32.9%	12.0%	14.4%	10.5%	9.3%	9.6%	11.4%	20.3%
Age 65 and more	31.5%	23.2%	13.8%	31.5%	23.2%	12.6%	10.9%	12.8%	9.9%	14.3%	16.2%	25.2%
Education												
High School and lower	24.1%	28.6%	13.9%	33.4%	33.1%	9.3%	12.5%	12.2%	8.5%	12.2%	12.2%	21.9%
Some College	27.5%	32.8%	12.7%	27.1%	38.9%	13.5%	10.0%	12.7%	7.9%	6.1%	10.9%	14.2%
Associate	21.8%	30.3%	11.8%	36.1%	40.3%	13.4%	5.0%	11.8%	6.7%	7.6%	15.1%	7.4%
Bachelor	18.6%	34.8%	16.9%	29.7%	42.6%	14.0%	7.8%	10.2%	9.3%	7.8%	8.4%	28.0%
Graduate	19.3%	36.0%	20.4%	24.3%	38.2%	14.5%	10.8%	7.2%	8.9%	11.1%	9.3%	28.6%
Race												
White	20.6%	33.7%	17.5%	28.2%	39.4%	13.0%	9.7%	10.1%	8.7%	9.5%	9.5%	85.9%
Black	29.6%	26.6%	10.6%	33.2%	33.2%	12.1%	9.0%	11.1%	7.5%	10.6%	16.6%	12.1%
Other	6.1%	48.5%	6.1%	39.4%	33.3%	21.2%	15.2%	12.1%	9.1%	0.0%	9.1%	2.0%
Household Characteristics												
Number of Vehicles												
0 vehicles	42.9%	14.3%	9.5%	33.3%	15.5%	13.1%	13.1%	8.3%	13.1%	17.9%	19.0%	5.1%
1 vehicles	23.0%	28.8%	16.5%	31.7%	35.9%	15.0%	9.4%	10.2%	8.1%	9.8%	11.5%	29.2%
2 vehicles	18.8%	35.2%	17.2%	28.8%	38.9%	14.5%	9.7%	10.5%	8.9%	8.0%	9.4%	47.1%
3 vehicles and more	19.9%	39.9%	16.3%	23.9%	47.7%	6.5%	9.5%	10.5%	7.2%	10.1%	8.5%	18.6%
Annual Income												
Under $20,000	33.3%	26.3%	5.1%	35.4%	29.3%	10.1%	10.1%	10.1%	7.1%	18.2%	15.2%	6.0%
$20,000-35,000	31.4%	21.2%	9.5%	38.0%	27.7%	9.5%	14.6%	10.2%	10.9%	9.5%	17.5%	8.3%
$35,000-50,000	19.7%	29.5%	17.5%	33.3%	33.9%	13.1%	10.4%	10.4%	11.5%	8.7%	12.0%	11.1%
$50,000-60,000	27.1%	24.3%	15.0%	33.6%	29.0%	17.8%	11.2%	15.0%	8.4%	8.4%	10.3%	6.5%
$60,000-75,000	15.6%	30.7%	20.1%	33.5%	36.9%	16.2%	11.2%	9.5%	8.9%	7.8%	9.5%	10.9%
$75,000-100,000	24.8%	35.8%	15.2%	24.1%	44.7%	12.1%	9.9%	9.9%	5.3%	8.2%	9.9%	17.2%
more than $100,000	15.8%	39.4%	20.0%	24.8%	44.4%	13.0%	8.0%	8.4%	10.4%	8.4%	7.4%	30.5%
Residential Location												
Rural	20.5%	35.4%	16.2%	27.9%	37.0%	12.8%	11.4%	10.4%	6.9%	11.4%	10.1%	22.9%
Dense Rural	21.8%	32.0%	16.6%	29.7%	39.8%	10.8%	7.6%	12.4%	11.3%	8.7%	9.4%	26.5%
Suburban	22.2%	36.2%	14.2%	27.3%	40.8%	13.3%	9.9%	9.5%	7.4%	8.5%	10.6%	32.1%
Urban	22.0%	25.2%	19.7%	33.0%	31.7%	16.5%	9.6%	10.6%	8.7%	11.5%	11.5%	13.3%
Dense Urban	17.4%	30.2%	22.1%	30.2%	41.9%	16.3%	12.8%	3.5%	9.3%	4.7%	11.6%	5.2%

Table 8.2 displays joint distribution of activity types versus episode duration spells. It is obvious that the distributions of episode duration follow different patterns across different group of activities. For example, while Personal activity displays a u-shape probability distribution over duration spells, Services activity follows a distribution similar to exponential.

Table 8.2. Distribution of Episode Duration across Activity Types

Activity Type	Activity Duration (minutes)							Total
	[0-10]	[10-20]	[20-30]	[30-45]	[45-60]	[60-90]	[90+]	
Personal	169 (19.5%)	76 (8.8%)	81 (9.3%)	104 (12.0%)	86 (9.9%)	141 (16.3%)	210 (24.2%)	**867 (17.3%)**
Services	1218 (74.0%)	251 (15.2%)	67 (4.1%)	37 (2.2%)	20 (1.2%)	26 (1.6%)	27 (1.6%)	**1646 (32.9%)**
Discretionary	207 (26.1%)	58 (7.3%)	56 (7.1%)	90 (11.4%)	130 (16.4%)	130 (16.4%)	121 (15.3%)	**792 (15.8%)**
Shopping	351 (20.7%)	379 (22.4%)	300 (17.7%)	271 (16.0%)	173 (10.2%)	134 (7.9%)	87 (5.1%)	**1695 (33.9%)**
Total	**1945 (38.9%)**	**764 (15.3%)**	**504 (10.1%)**	**502 (10.0%)**	**409 (8.2%)**	**431 (8.6%)**	**445 (8.9%)**	**5000 (100.0%)**

8.4. Estimation Results

8.4.1. Overall Results

As discussed before, there is a diverse range of copulas that allow testing different dependency structure between two or more variables. The focus of this study is on the Archimedean class of copulas for two main reasons: First, this class of copulas has a closed form function that makes estimation procedure much easier and faster than other copula models; second, a diverse set of dependency structures is offered with the Archimedean copulas. Nelsen (2006) lists at least 22 Archimedean copulas from which four copulas including Gumbel, Clayton, Frank, and Joe are chosen to test the dependency structure between the choice of activity type as the discrete decision and the episode duration as its continuous outcome. Overall results are summarized in Table 8.3 for non-seniors and Table 8.4 for seniors.

Table 8.3. Overall Results of Tested Models for non-seniors

Model	**Result**
<u>**Independent Model**</u>	
Non-mixed	Converged with a log-likelihood value of -9954 and the Bayesian Information Criterion (BIC) value of 20204
Mixed	Converged with a log-likelihood value of -9939 and the BIC value of 20140 (Note: Both σ_μ was statistically insignificant meaning the mixed proportional hazard model collapsed to the proportional hazard model);
<u>**Non-mixed copula model**</u>	
Joe	Collapsed to the independent model (θ=1)
Clayton	Collapsed to the independent model ($\theta \rightarrow 0$)
Gumbel	Collapsed to the independent model (θ=1)
Frank	Converged with a log-likelihood value of -9400 and the BIC value of 19038. (Copula parameter estimated to be -11.6 which translates to a value of Kendall's τ =-0.71)
<u>**Mixed Frank model**</u>	
Unobserved heterogeneity incorporated in the copula parameter	Collapsed to the non-mixed Frank model (φ_p was statistically insignificant);
Unobserved heterogeneity incorporated in the marginal distributions	Converged with a log-likelihood value of - 9382 and the BIC value of 18977. Copula parameter estimated to be -11.6 which translates to a value of Kendall's τ =-0.71 (Note: σ_μ was statistically insignificant meaning the mixed proportional hazard model collapsed to the proportional hazard model)

Table 8.4. Overall Results of Tested Models for seniors

Model	Result
<u>Independent Model</u>	
Non-mixed	Converged with a log-likelihood value of -3647 and the Bayesian Information Criterion (BIC) value of 7559
Mixed	Converged with a log-likelihood value of -3633 and the BIC value of 7501 (Note: Both σ_μ and σ_η were statistically significant);
<u>Non-mixed copula model</u>	
Joe	Collapsed to the independent model (θ=1)
Clayton	Collapsed to the independent model ($\theta \rightarrow 0$)
Gumbel	Collapsed to the independent model (θ=1)
Frank	Converged with a log-likelihood value of -3339 and the BIC value of 6915. (Copula parameter estimated to be -21.7 which translates to a value of Kendall's τ =-0.83)
<u>Mixed Frank model</u>	
Unobserved heterogeneity incorporated in the copula parameter	Collapsed to the non-mixed Frank model (φ_p was statistically insignificant);
Unobserved heterogeneity incorporated in the marginal distributions	Collapsed to the non-mixed Frank model (σ_μ and σ_η were statistically insignificant)

The Kendall's τ is computed using the estimated copula parameter. The Kendall's τ which lies between -1 and 1, measures the degree of dependence between random variables. Two random variables are independent when the tau is zero and perfectly dependent when absolute value of tau is 1. Joe, Clayton, and Gumbel model collapsed to the independent model. It happened because of the non-comprehensive dependence structure that these copula functions posses. The range of Kendall's τ in these non-comprehensive copulas is between 0 and 1 meaning that these copulas cannot account for negative dependence between random variables. The only Archimedean copula that can account for negative dependence is Frank copula. The results above show that there is a very strong negative dependence between error terms of discrete and continuous equations and that's why Joe, Clayton, and Gumbel copulas have collapsed to the independent model. Kendall's τ gets the value of -0.71 for non-seniors and -0.83 for seniors which shows a strong central dependence and very weak tail dependence between error terms of discrete and continuous choice equations. In other words, it shows weak correlation at high and low values of the error terms (Figure 8.1).

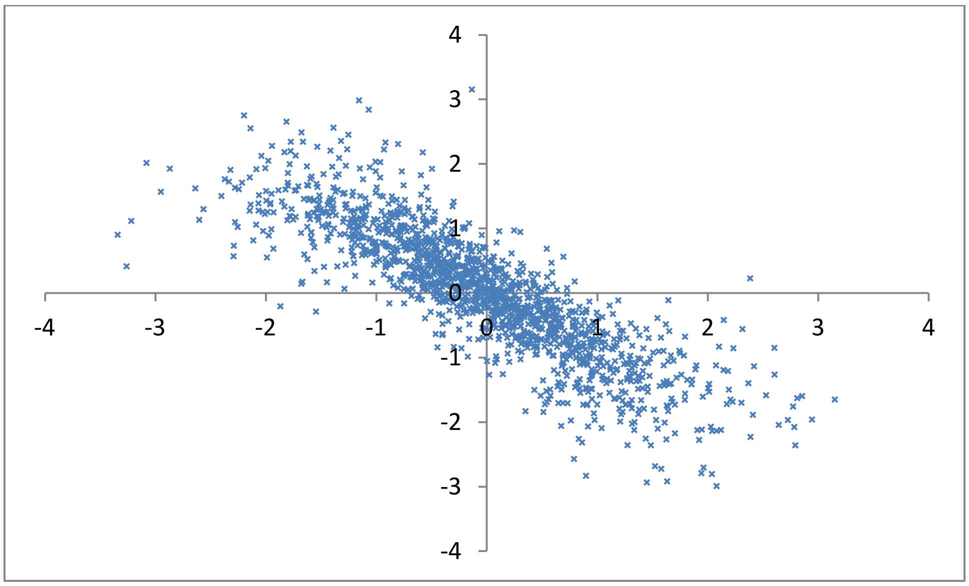

Figure 8.1. Frank Copula with τ=-0.71 and θ=-11.6

The Bayesian Information Criterion (BIC) is employed to find the model that gives the best fit. The model with lower BIC provides a better fit. Based on the reported BIC values, the models are ranked as follows (the collapsed models are not reported):

For non-seniors:

1. Mixed Frank model with unobserved heterogeneity incorporated in the marginal distributions (BIC=18977);
2. Non-mixed Frank copula model (BIC=19038);

3. Mixed independent model (BIC=20140);
4. Non-mixed independent model (BIC=20204).

For seniors:

1. Non-mixed Frank copula model (BIC=6519);
2. Mixed independent model (BIC=7501);
3. Non-mixed independent model (BIC=7559).

In continue, the focus will be on the best-fitted model for each age group.

8.4.2. Estimation Results for Non-Seniors

Descriptive statistics of variables used in the mixed Frank model is presented in Table 8.5. The model is composed of a wide range of variables representing personal and household characteristic, location attributes, temporal aspects of the activity participation, and tour formation attributes.

Table 8.5. Definition of Variables Used in the Mixed Frank Model for non-senior age group

Variable	Variable	Mean	Std. Dev.
Household Characteristics			
Number of household student	Number of students in household	0.95	1.16
Income less than $20,000	1 if household income is less than $20,000, 0 otherwise	0.05	0.22
Individual Characteristics			
License	1 if individual holds a valid driver license, 0 otherwise	0.96	0.20
Age (Ln)	Natural logarithm of individual age in years	3.80	0.27
Male	1 if individual is male, 0 otherwise	0.36	0.48
Location Attributes			
Suburban[1]	1 if household lives in a suburban neighborhood, 0 otherwise	0.32	0.47
Trip-Making Temporal Attributes			
Start time			
between 9:00 and 12:00	1 if an activity type is performed between 9 and 12, 0 otherwise	0.20	0.40
between 12:00 and 15:00	1 if an activity type is performed between 12 and 15, 0 otherwise	0.25	0.43
between 15:00 and 18:00	1 if an activity type is performed between 15 and 18, 0 otherwise	0.23	0.42
between 18:00 and 21:00	1 if an activity type is performed between 18 and 21, 0 otherwise	0.15	0.36
Tour Formation Attributes			
Tour Size	Number of out of home activities in tour. Tour is defined as a sequence of activities began at home and ended at home.	3.21	2.01
Main Trip	1 if trip made to performed activity has the longest duration in the tour, 0 otherwise	0.44	0.50

- **Discrete Component**

In the mixed Frank copula the choice of activity type is modeled as the discrete component using mixed multinomial logit structure. σ_η, the standard error of random parameter η_p, is estimated to be 0.451 with a significant t-stat value equal to 4.88 which underlines the presence of

[1] In CMAP Travel Tracker Survey, Chicago Area is divided into five regions defined by an index calculated using population density, job density, and level of transit service available. These five regions are Rural, Dense Rural, Suburban, Urban, and Dense Urban.

unobserved heterogeneity in the choice of activity type. The estimated parameter σ_{μ}, the standard error of random parameter μ, was statistically insignificant. Hence, random parameter μ_p was dropped from Equation (8.7). Table 8.6 presents the estimation results for the choice of activity type.

Table 8.6. Discrete Component of Mixed Frank Copula Model Estimates: Choice of Activity Type
(Personal activity is the base utility)

Variable	Service		Discretionary		Shopping	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	1.57	3.33	1.42	2.44	0.82	10.72
Household Characteristics						
Number of household student	0.17	6.72	-	-	-	-
Income less than $20,000	-	-	-	-	-0.32	-1.37
Individual Characteristics						
License	0.82	4.31	-	-	-	-
Age (Ln)	-0.34	-3.02	-0.33	-2.18	-	-
Male	-	-	0.21	2.50	-	-
Location Attributes						
Suburban	0.09	1.53	-	-	-	-
Trip-Making Temporal Attributes						
Start time						
between 12:00 and 15:00	-0.32	-4.36	-	-	-	-
between 15:00 and 18:00	-	-	-	-	0.21	3.12
between 18:00 and 21:00	-0.43	-4.89	-	-	-	-

Generally, positive (negative) coefficient under each activity type increases (decreases) probability of participation in that activity. Number of household student increases the probability of performing Service activities. This is probably due to this reason that students needs to be picked up or dropped off. The propensity of participating in the shopping activities is lower for households with lower income (less than $20,000), which is most possibly because they have less expendable money. Being male increases the chance of participation in the Discretionary activities. Households residing in the suburban neighborhoods perform more Service activities. It's probably due to the insufficient public transportation systems in the suburban areas that force residents to participate more in pick-up/drop-off activities. As age goes up, probability of participation in the Service and Discretionary activities goes down. The probability of doing shopping increases between 3 pm to 6 pm. The probability of performing service activities decreases between 12 pm to 3 pm and 6 pm to 9 pm.

- **Continuous Component**

The choice of activity duration is modeled as the continuous decision using non-parametric proportional hazard modeling approach. Table 8.7 presents the estimation results of the model. To estimate $\delta_{i,k}$, the cutoff points that divide activity duration into seven time spells, it was assumed that they are the same for all activity types: $\delta_{i,k} = \delta_k \; \forall i$. However, a threshold shift parameter is estimated for each activity type to take into account the differences in the cutoff point values. Shift parameter for Shopping activity is assumed (normalized) to be zero. An estimated positive (negative) shift parameter for an activity type means that the relevant activity has longer (shorter) duration than the Shopping activity. Positive (negative) coefficients increase (decrease) duration of the activity. Being male increases the chance of choosing longer duration for activities. As tour sizes increases activity duration decreases. That's because time is limited and individual has other activities to perform. Individuals tend to put more time for the activity that has the longest trip in the tour.

Table 8.7. Continuous Component of Mixed Frank Copula Model Estimates: Choice of Activity Duration (Non-parametric proportional hazard model)

Variable	Coeff.	t-stat
Threshold Parameters (δ_k)		
10 minutes	-2.73	-11.54
20 minutes	-2.24	-9.47
30 minutes	-1.94	-8.20
45 minutes	-1.63	-6.87
60 minutes	-1.31	-5.49
90 minutes	-0.71	-2.97
Shift Parameters		
Personal	-0.01	-4.15
Services	-1.49	-27.97
Discretionary	0.50	9.35
Individual Characteristics		
Male	-0.06	-1.88
Trip-Making Temporal Attributes		
Start time		
between 9:00 and 12:00	0.13	3.19
between 12:00 and 15:00	0.10	2.54
Tour Formation Attributes		
Tour Size	-0.03	-2.98
Main Trip	0.17	4.67
Copula Parameter	-11.6	-18.36

8.4.3. Estimation Results for seniors

Descriptive statistics of variables used in the Frank model is presented in Table 8.8. The model is composed of a wide range of variables representing personal and household characteristic, location attributes, temporal aspects of the activity participation, and tour formation attributes.

Table 8.8. Definition of Variables Used in the Mixed Frank Model

Variable	Variable	Mean	Std. Dev.
Household Characteristics			
Income less than $20,000	1 if household income is less than $20,000, 0 otherwise	0.08	0.27
Individual Characteristics			
License	1 if individual holds a valid driver license, 0 otherwise	0.94	0.24
Age (Ln)	Natural logarithm of individual age in years	4.29	0.09
Male	1 if individual is male, 0 otherwise	0.42	0.49
Bachelor Degree	1 if individual is holding bachelor degree, 0 otherwise	0.18	0.39
Location Attributes			
Suburban[1]	1 if household lives in a suburban neighborhood, 0 otherwise	0.36	0.48
Dense Rural	1 if household lives in a dense rural neighborhood, 0 otherwise	0.24	0.43
Cook County	1 if household reside in Cook County, 0 otherwise	0.65	0.48
Trip-Making Temporal Attributes			
Start time			
between 15:00 and 18:00	1 if an activity type is performed between 15 and 18, 0 otherwise	0.18	0.38
between 18:00 and 21:00	1 if an activity type is performed between 18 and 21, 0 otherwise	0.08	0.27
Tour Formation Attributes			
Tour Size	Number of out of home activities in tour. Tour is defined as a sequence of activities began at home and ended at home.	3.02	1.91
Main Trip	1 if trip made to performed activity has the longest duration in the tour, 0 otherwise	0.48	0.50

[1] In CMAP Travel Tracker Survey, Chicago Area is divided into five regions defined by an index calculated using population density, job density, and level of transit service available. These five regions are Rural, Dense Rural, Suburban, Urban, and Dense Urban.

- **Discrete Component**

In the Frank copula the choice of activity type is modeled as the discrete component using multinomial logit structure. σ_η, the standard error of random parameter η_p, was statistically insignificant. Hence, random parameter η_p was dropped from Equation (8.5). Table 8.9 presents the estimation results for the choice of activity type.

Table 8.9. Discrete Component of Frank Copula Model Estimates for Seniors: Choice of Activity Type (Personal activity is the base utility)

Variable	Service		Discretionary		Shopping	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	6.92	2.90	-0.43	-3.41	0.69	8.58
Household Characteristics						
Income less than $20,000	-	-	-0.49	-1.47	-	-
Individual Characteristics						
Age (Ln)	-1.56	-2.82	-	-	-	-
Male	-	-	0.22	1.75	-	-
Location Attributes						
Suburban	0.28	2.96	-	-	-	-
Trip-Making Temporal Attributes						
Start time						
between 15:00 and 18:00	-	-	0.22	1.31	0.16	1.52
between 18:00 and 21:00	-0.28	-1.37	-	-	-	-

Again, positive (negative) coefficient under each activity type increases (decreases) probability of participation in that activity. The propensity of participating in the Discretionary activities is lower for households with lower income (less than $20,000), which is most possibly because they have less expendable money. Being male increases the chance of participation in the Discretionary activities. Households residing in the suburban neighborhoods perform more Service activities. It's probably due to the insufficient public transportation systems in the suburban areas that force residents to participate more in pick-up/drop-off activities. As age goes up, probability of participation in the Service activities goes down. The probability of doing shopping increases between 3 pm to 6 pm. Finally, the probability of performing service activities decreases between 6 pm to 9 pm.

- **Continuous Component**

The choice of activity duration is modeled as the continuous decision using non-parametric proportional hazard modeling approach. Table 8.10 presents the estimation results of the model. Positive (negative) coefficients increase (decrease) duration of the activity. Older elderly people tend to choose longer activity duration than younger seniors. Being male increases the chance of choosing shorter duration for activities. As tour size increases activity duration decreases. That's because time is limited and individual has other activities to perform. Individuals tend to put more time for the activity that has the longest trip in the tour.

Table 8.10. Continuous Component of Frank Copula Model Estimates for Seniors: Choice of Activity Duration (Non-parametric proportional hazard model)

Variable	**Coeff.**	**t-stat**
Threshold Parameters (δ_k)		
10 minutes	-2.38	-15.42
20 minutes	-1.87	-12.53
30 minutes	-1.53	-10.44
45 minutes	-1.21	-8.31
60 minutes	-0.97	-6.67
90 minutes	-0.30	-1.97
Shift Parameters		
Personal	0.90	9.48
Services	-0.29	-2.73
Discretionary	1.23	11.53
Individual Characteristics		
Age (Ln)	0.13	3.09
Bachelor Degree	-0.07	-1.16
License	-0.22	-2.19
Male	-0.14	-3.16
Location Attributes		
Dense Rural	-0.08	-1.50
Cook County	0.07	1.53
Tour Formation Attributes		
Tour Size	-0.03	-2.08
Main Trip	0.19	3.69
Copula Parameter	-21.7	-7.94

9. REGRET MINIMIZATION VS. UTILITY MAXIMIZATION FOR MODELING TRAVEL MODE CHOICE BEHAVIOR

Random utility maximization (RUM) model (e.g. logit and probit models) is the dominant decision rule used in discrete choice analysis (Train, 2003). RUM models have been extensively used to predict discrete decisions such as travel mode, route choice, trip purpose, and destination. RUM models are based on this assumption that people choose alternative that give them the highest propensity or utility. However, there are some studies showing that the way people make their decision is inconsistent this assumption (Kahneman and Tversky, 1979). Hence, in the recent years there has been an attention toward other discrete decision rules that such as Random Regret Minimization (RRM) that looks into decision making process from a different perspective (Chorus et al., 2008; Chorus, 2010). The regret is described as the feeling an individual experiences when the selected alternative performs worse than other available alternatives. The RRM model assumes that people choose the alternative that gives the minimum regret. During the past few years, many studies have discussed advantages and disadvantages of using RRM model in comparison with RUM model for different applications in travel behavior analysis. Also, there are few studies that have underscored beneficiation of combining RRM and RUM instead of using sole RUM or RRM (Hess et al., 2012; Hess and Stathopoulos, 2014).

This chapter of dissertation compares RRM model with multinomial logit (MNL) model for the case of travel mode choice of seniors and non-seniors to see which of these decision rules can provide a better fit. The models can explain to what degree seniors try to minimize their regret and maximize their utility and how it is different among non-seniors.

9.1. Methodology

As stated earlier, the main objective of this chapter is to compare two popular discrete decision rules for travel mode choice behavior of seniors and non-seniors:

- **RRM**

Based on Regret Theory (Bell, 1982; Loomes & Sugden, 1982), Chorus et al. (2008) formulated RRM model as written below:

$$RR_i = R_i + \varepsilon_i = max_{i \neq j}\{R_{ij}\} + \varepsilon_i = max_{i \neq j}\left\{\sum_{k=1,\ldots,K} max\{0, \beta_k(x_{jk} - x_{ik})\}\right\} + \varepsilon_i \tag{10.1}$$

where RR_i is the random regret of alternative i; R_i is the observable regret of alternative i; R_{ij} is the regret associated with alternative i when it is compared with alternative j; x is the vector of covariates; β represents the coefficients; and ε is the error term. Assuming that ε has an Extreme Value Type I (Gumbel) distribution, then the probability of alternative i can be computed as the well-know Equation (10.2):

$$P_i = \frac{\exp(-R_i)}{\sum_j \exp(-R_j)} \tag{10.2}$$

It should be noted that minimizing regret R_i is mathematically equal to maximizing $-R_i$. The Equation (10.2) is very similar to MNL model, however there is big difference. RRM in contrast to MNL model does not hold IIA property. That is sourcing from the way the regret is computed. Regret associated to any alternative is gained by pair-wise comparison against other alternatives. In RUM, utility of each alternative represents attributes of that alternative only. The following example adapted from Chorus et 1. (2008) can better explain difference between RRM and

RUM. Consider a route choice between cities A and B with three available routes: route #1 = {2 hr travel time, $40 travel cost}, route #2 = {3 hr travel time, $30 travel cost}, and route #3 = {4 hr travel time, $20 travel cost}. Assuming, for simplicity, that each $10 in travel cost and each 1 hour in travel time cause -1 utility. Therefore, utility associated with each route option is the same and equal to -6. Then, based on logit model, the probability of choosing each alternative is equal to 1/3. However, the story is different for RRM model as computed below:

$$R_{12} = \max(0, -3+2) + \max\,(0, -3+4) = 0 + 1 = 1$$

$$R_{13} = \max(0, -4+2) + \max\,(0, -2+4) = 0 + 2 = 2$$

$$\Rightarrow\; R_1 = \max(R_{12}, R_{13}) = 2$$

$$R_{21} = \max(0, -2+3) + \max\,(0, -4+3) = 1 + 0 = 1$$

$$R_{23} = \max(0, -4+3) + \max\,(0, -2+3) = 0 + 1 = 1$$

$$\Rightarrow\; R_2 = \max(R_{12}, R_{13}) = 1$$

$$R_{31} = \max(0, -2+4) + \max\,(0, -4+2) = 2 + 0 = 2$$

$$R_{32} = \max(0, -3+4) + \max\,(0, -3+2) = 1 + 0 = 1$$

$$\Rightarrow\; R_3 = \max(R_{31}, R_{32}) = 2$$

$$P_1 = \frac{\exp\,(-R_1)}{\sum_j \exp\,(-R_j)} = \frac{\exp\,(-2)}{\exp(-2) + \exp(-1) + \exp\,(-2)} = 21\%\,, P_2 = 58\%\,, P_3 = 21\%$$

This example clearly demonstrates how well RRM model can capture compromise effect, meaning that RRM gives the highest probability to the alternative with the average value across different attributes. In the example, travel time and cost of route #2 are average values of other two alternatives.

- **RUM**

Different models of RUM family have been used and discussed in previous chapters of this dissertation. MNL model as a member of RUM family is employed to model travel mode choice. Based on this model, probability of choosing alternative i is estimated from the following equation:

$$P_i = \frac{\exp\,(\beta\, x_i)}{\sum_j \exp\,(\beta\, x_j)} \tag{10.3}$$

where x is the vector of covariates and β is the vector of coefficients.

9.2. Model Estimation

For both models the log-likelihood function can be written as follows:

$$LL = \sum_{n=1}^{N} \sum_{i=1}^{I} (\log P_{ni} * \delta_{ni}) \tag{10.4}$$

where N is the total number of individuals in the sample; I is the total number of available travel mode alternatives. δ_{ni} is equal to 1 if and only if individual *n* chooses alternative *i*; 0 otherwise. This log-likelihood function is maximized using NLMIXED procedure of SAS econometrics software.

The data used for the purpose of this chapter of dissertation is a sample randomly drawn from the UTRACS. The UTRACS has captured a significant amount of data on the respondents' activity-travel behavior (Frignani et al. 2010; Auld et al. 2009). One important survey aspect was focused on using GPS traces to identify the respondents' tour formation behavior. The core component of the tour formation process is the within-tour mode-choice modeling component. Factors that influence the choice of a specific mode (e.g. transit) are identified within this component.

In total, elderly and non-elderly respondents registered 625 and 788 tours respectively. Out of these numbers, elderly and non-elderly people completed 276 and 224 non-mandatory complex tours, respectively. Table 9.1 shows the distribution of the main mode of non-mandatory complex tours. This table shows that the elderly are less auto-dependent than non-elderly people for non-work tours. Table 9.2 gives some statistics of the variables used in the final models. The explanatory variables are a combination of individual, household, and travel mode characteristics.

Table 9.1. Distribution of Main Travel Mode

		Elderly	**Non-elderly**
Main Mode	Auto	87%	93%
	Transit	7%	3%
	Non-motorized	6%	4%

Table 9.2. Descriptive Statistics of Variables Used in the Model

Variable	Definition	Lower value		Upper value		Average		Standard deviation	
		Seniors	Non-seniors	Seniors	Non-seniors	Seniors	Non-seniors	Seniors	Non-seniors
Travel Mode Characteristics									
$Cost$	Travel costs in U.S. dollars	\$0.1	—	\$18.75	—	\$2.17	—	\$2.10	—
$TravelTime$	Travel time in hours	0.05	0.06	2.50	1.91	0.39	0.31	0.37	0.27
Household Characteristics									
$NCar$	Number of cars in household	0	0	4	2	2.24	1.42	1.03	0.62
$HHSize$	Household size	1	—	5	—	1.83	—	0.63	—
Ave_Income	1, if household income is between \$50,000 and \$100,000; 0, otherwise	0	0	1	1	0.44	0.32	0.50	0.46
$Married\_NoChildren$	1, if household is married without children; 0, otherwise	0	0	1	1	0.13	0.48	0.34	0.50
Low_Income	1, if household income is under \$50,000; 0, otherwise	0	—	1	—	0.26	—	0.44	—
Individual Characteristics									
$Alone$	1, if person is traveling alone; 0, otherwise	0	0	1	1	0.44	0.42	0.50	0.49
$NoFamily$	1, if person lives alone; 0, otherwise	0	0	1	1	0.10	0.12	0.32	0.32
$Degree$	1, if the person holds a college degree; 0, otherwise	0	—	1	—	.068	—	0.47	—

9.3. Estimation Results

- **Overall Results**

Tables 9.3 and 9.4 present the estimation results for the non-elderly and elderly groups. For both age groups, MNL outperforms RRM model at aggregate level with about 0.10 higher rho-square values. Coefficient of travel time is the main difference between MNL and RRM models. While this coefficient in the MNL model is a significant large negative value, in the RRM model it is statistically equal to zero. My investigation showed that it is happening because in the data sample travel time values of auto is smaller than transit and travel time values of transit is smaller than non-motorized, over all records. This results in $Regret_{Auto}=0 < Regret_{Transit} < Regret_{Non\text{-}motorized}$ which is valid over all records. Hence, the way travel time attribute affects on the regret function can be taken into account mainly by constants.

Table 9.3. Estimation Results for Non-Elderly People

Variable	MNL			RRM		
	Auto	**Transit**	**Non-motorized**	**Auto**	**Transit**	**Non-motorized**
Constant	1.98 (2.64)	— —	4.88 (1.38)	3.86 (5.51)	— —	5.15 (4.59)
Cost	–0.709 (–1.69)	–0.709 (–1.69)	— —	–0.56 (–1.99)	–0.56 (–1.99)	— —
TravelTime	–13.1 (–2.98)	–13.1 (–2.98)	–13.1 (–2.98)	0.01 (0.33)	0.01 (0.33)	0.01 (0.33)
NCar	— —	— —	–1.57 (–2.12)	— —	— —	–2.07 (–2.76)
Alone	1.51 (1.66)	— —	— —	-0.19 (-0.29)	— —	— —
Average_HHincome	— —	— —	2.10 (1.54)	— —	— —	2.46 (1.75)
NoFamily	— —	2.97 (2.50)	— —	— —	2.56 (2.74)	— —
Log-likelihood Rho-square	-24.81 0.792			-38.28 0.68		

Table 9.4. Estimation Results for Elderly People

Variable	MNL			RRM		
	Auto	**Transit**	**Non-motorized**	**Auto**	**Transit**	**Non-motorized**
$Constant$	— —	1.35 (1.56)	2.08 (1.77)	— —	1.18 (1.55)	0.99 (1.06)
$TravelTime$	–4.35 (–2.88)	–4.35 (–2.88)	–4.35 (–2.88)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
$NCar$	— —	-2.44 (-3.75)	— —	— —	-2.82 (-4.27)	— —
$Alone$	— —	— —	1.26 (1.59)	— —	— —	0.19 (0.30)
$HHSize$	— —	— —	–2.19 (–2.79)	— —	— —	–1.37 (–2.30)
$Married\_NoChildren$	–1.10 (–1.92)	— —	— —	–0.63 (–1.28)	— —	— —
$Degree$	— —	–1.06 (–1.44)	— —	— —	–0.93 (–1.38)	— —
Log-likelihood Rho-square	-52.51 0.66			-58.21 0.62		

To further compare the models' power of prediction in mode choice, measures of fit at both aggregate and disaggregate levels are examined. Due to the small size of the data sample, train and test data are kept the same and there is no hold up sample for validation purpose. At aggregate level, distribution (share) of the four alternatives is compared to what the models predicts separately. Table 9.5 presents this comparison. It can be seen that the models provides a very good prediction at aggregate level for both age groups.

Table 9.5 Comparison between predicted and in-data shares.

Travel Mode	Elderly			Non-elderly		
	In-data share	**MNL**	**RRM**	**In-data share**	**MNL**	**RRM**
Auto	87%	89%	88%	93%	93%	94%
Transit	7%	6%	6%	3%	3%	3%
Non-motorized	6%	5%	6%	4%	4%	3%

At disaggregate level, the probability that chosen decision has the highest predicted propensity is computed. For elderly people, both RRM and MNL for 92% of observations predicted the highest probability for the really chosen mode. For non-elderly people, this percentage is 95% and 96% for RRM and MNL models, respectively. Another way to examine power of prediction at disaggregate level is to compute percentage of observations that the models could predict probability greater than 75% for the chosen travel mode. Following this measure, the computation showed that MNL and RRM models predicted 92% and 85% for elderly group; and 92% and 91% for non-elderly group.

Another interesting result is the degree of regret minimization (utility maximization) among elderly and non-elderly people. The degree is computed by comparing the log-likelihood value that MNL and RRM models predicted for each observation:

$\text{Degree}_{\text{RegretMinimization}} = 1\text{-Degree}_{\text{utilityMaximization}}$ and $0 \leq \text{Degree} \leq 1$.

The computation results showed that degree of regret minimization is 53% for elderly people and 52% for non-elderly group. In other words, travelers equivalently try to minimize their regrets and maximize their utility when deciding on travel mode.

- **Covariate Effects**

  Some key findings regarding estimated parameters are summarized as follows.
  For the non-elderly group, it was found that

  - A higher number of cars reduces the propensity for using a non-motorized mode.
  - Individuals with an average income level of $50,000 to $100,000 are more likely to choose a non-motorized mode.

- Being alone increases the likelihood of selecting the transit mode, perhaps because people who live alone have more free time.

For the elderly group, is was found that

- A higher number of cars reduces the propensity for choosing transit.
- Bigger households are less likely to choose non-motorized modes.
- Holding a college degree decreases the propensity for choosing transit.
- Traveling alone increases the likelihood of choosing a non-motorized mode.

CONCLUSIONS

The United States is experiencing a rapid increase in seniors population. According to Census Bureau estimates, seniors' population is expected to increase by 104.2% from 2000 to 2030, which translates into 72.1 million elderly people in 2030. The remarkable increase in seniors' population and their important influence on socio-economic systems such as transportation system provide sufficient motivation to develop reliable tools to study, analyze, and model seniors' travel behavior. However, as the review of current studies revealed, the amount of attention dedicated to seniors travel demand forecasting has been insufficient. This dissertation developed a tool box of advanced econometric techniques for modeling activity-travel behavior of elderly people. This dissertation extended previous research on seniors' activity-travel behavior by developing advanced econometric models that are capable to deal with complexities inherited in the nature of travel behavior. Each model shed light on some less studied aspects of travel behavior of seniors and non-seniors.

In Chapter 5 a descriptive analysis of activity-travel behavior of two consecutive age groups, after and before 65, was presented. The analysis on pre-retirement (55-65) and young-old elderly (65-75) as two homogenous age groups revealed that while behavior of choice of activity duration is almost the same for different activity groups, their time-of-day choice behavior is significantly different, which must be considered in the activity-based models. The analysis also showed that activity duration is strongly sensitive to the type of activity. This sensitivity is higher for durations less than 2 hours. For all presented activity types except work/school/volunteer activity, both age groups showed very similar sensitivities to change in activity duration. In contrast to the duration of activity, both age groups display completely dissimilar behaviors in the choice of a start time for activities. This is because the baby boomers' activity plan is highly affected by mandatory activities (work/school/volunteer). This pattern is opposite for young-old seniors, of which mandatory activities have the smallest share. Both age groups execute a major part of their activities impulsively. Young-old seniors and pre-retirement age group pre-plan 61.6% and 56.9% of their activities on "less than 1 hour" and "same day" planning time horizons. The analysis on planning time horizons also revealed that for specific activity duration, the chance of a specific time horizon to be selected by both groups is almost the same.

In Chapter 6 a new activity generation model with focus on shopping activities was developed. A latent segmentation duration model was formulated that can well reflect seniors' flexible schedule into their activity participation. The model estimates degree of regularity in activity participation at individual level by endogenously dividing travelers into erratic and regular travelers. The proposed model was estimated for two age groups of seniors and non-seniors. The results indicated that all elderly people are erratic shoppers. In non-elderly group, 62% of shoppers were regular and 38% of them were erratic shoppers. The considerable difference between these two age groups can be attributed to the fact that elderly people have much less share of mandatory activities (e.g., work/school) in their schedule and therefore are much less time pressed and more flexible. The covariate effects were also analyzed. For non-senior shoppers, higher income and bigger household size result in smaller regular inert-shopping durations and bigger random shopping durations. Non-senior shoppers with higher education tend to choose longer regular inter-shopping durations and engage in more random shopping activities. Non-senior shoppers who live alone do more random shopping activities, perhaps due to the reason that shopping activity for them is more like a hobby. For elderly group, participating in shopping activities with companies decreases inter-shopping duration, perhaps due to the reason that seniors seize each opportunity to socialize with other people. It was also shown that seniors with higher income perform shopping activities more frequently.

Chapter 7 developed an innovative technique to model driver's reaction to yellow light. To the best of my knowledge, this chapter is the first to analyze stop-go behavior at dilemma zone of a signalized intersection using a nested logit model. The main reason to employ a nested logit model is that neither all the decisions to stop are safe nor are all the decisions to go hazardous. The nested logit structure allows separating hazardous and safe behaviors in either stop or go decisions. This classification could provide more information on driver's reaction to yellow light at the dilemma zone. The model was estimated over data coming from University of Iowa National Advanced Driving Simulator (NADS). The results confirmed that the proposed nested structure works well for modeling the stop-go behavior. Also, the model results showed that personal characteristics including age, cell phone usage, driving conditions, speed and distance from the stops line when traffic light turns yellow have significant effect on drivers' stop-go behavior.

Chapter 8 extended previous efforts on copula-based joint modeling by formulating a mixed copula-based discrete-continuous joint modeling framework for two separate scenarios: 1)

Incorporating unobserved heterogeneity into marginal distributions; 2) Incorporating unobserved heterogeneity into copula parameter. Mixed and non-mixed copula models were examined for weekday non-mandatory out-of-home activity type choice as the discrete decision and episode duration as the continuous outcome. Gumbel, Clayton, Frank, and Joe from Archimedean class were chosen to test the dependency structure between the choice of activity type as the discrete decision and the episode duration. For non-seniors, the results underlined superior fit of mixed model to non-mixed version. Incorporating unobserved heterogeneity could significantly improve model's goodness-of-fit. . Mixed Frank model with incorporated unobserved heterogeneity in marginal distribution of discrete choice provides the best fit and outperforms other non-mixed and mixed copula models. Joe, Clayton, and Gumbel model collapsed to the independent model. The results showed that there is a very strong negative dependence between error terms of discrete and continuous equations and that's why Joe, Clayton, and Gumbel copulas have collapsed to the independent model. It happened because of the non-comprehensive dependence structure that these copula functions posses. Kendall's τ gets the value of -0.71 for both mixed and non-mixed Frank copula models which show a strong central dependence and very weak tail dependence between error terms of discrete and continuous choice equations. For senior age group, non-mixed Frank model outperformed other models. Kendall's τ for elderly people estimated to be -0.83 which is strong enough deal with unobserved heterogeneity alone and that is probably why random parameters added to discrete and continuous equations turned to be insignificant. For both age groups, the model also signified effects of a wide range of variables representing personal and household characteristic, residential location, temporal aspects of the activity participation, and tour characteristics on weekday non-mandatory out-of-home activity participation.

Chapter 9 compared travel mode choice behavior of seniors and non-seniors through two well known discrete decision rules: Random Regret Minimization (RRM) and Random Utility Maximization (RUM). The main goals of the study were to determine 1) which discrete decision rule can better explain travel mode choice behavior 2) degree of regret minimization (utility maximization) among seniors and non-seniors. For both age groups, RUM outperforms RRM At aggregate level. However, at disaggregate level RRM did better than RUM. In almost 52% of observations the RRM could estimate a greater value of log-likelihood than RUM. In average, the results showed that both age groups have an equal degree of regret minimization and utility maximization for travel mode choice.

This dissertation develops innovative and advanced techniques to better understand some aspects of seniors' activity-travel behavior. Developing such advanced tools is a must to deal with complex nature of activity-travel behavior. Each chapter of this dissertation looks from a different perspective at activity-travel behavior and provides a first-hand analysis that can better explain *why* and *how* seniors and non-seniors different activity-travel behavior. This dissertation is a collection of first-hand studies and techniques including: Incorporating random parameters in structure of a copula-based discrete-continuous joint model to deal with unobserved heterogeneity; Examining two famous discrete decision rules, RRM and RUM, for travel mode choice behavior of seniors and non-seniors; Latent segmentation AFT-based model for shopping activity participation; Nested-logit model for drivers' reaction to yellow light of a signalized intersection; Descriptive analysis of activity-travel behavior of two consecutive age groups after and before 65

10.3. Future Direction

This dissertation is a step toward improving the existing analysis tools for activity-travel behavior of seniors. There are some aspects of the seniors' activity-travel behavior that require further exploration and improvement:

1. Examining Heteroskedastisity in structure of discrete-continuous joint model. All current joint models are based on homoskedsticity assumption meaning that the error terms has equal variance.
2. All current joint models are utilizing Random Utility Maximizations for either discrete or continuous equation. Developing a joint model based on other discrete decision rules can be an interesting subject of research.
3. Different class of Copula models: The copula-based joint model just examined few class of copulas. There are many more copula classes that may provide better fit and explanation for interaction between discrete and continuous variables.
4. Data sets coming from driving simulators have different observations (runs) from each participant. Running a nested logit kernel model that can capture correlation among repeated observations from an individual is highly recommended.

5. Decision Rules: This study is limited to RUM and RRM discrete decision rules. There are other decision rules such as Elimination by Aspect (EBA) that are based on different theories and assumptions.
6. Social Network: Social networks simply means a set of nodes (e.g. friends, family members, relatives, colleagues) and the links between nodes (e.g. relationship). Understanding the role of social network in activity-travel behavior of seniors versus non-seniors has not yet been studied well.

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Ye, X., R.M. Pendyala, G. Giovanni (2007). An exploration of the relationship between mode choice and complexity of trip chaining patterns. *Transportation Research Part B* 41 (1), 96-113.

Behzad Karimi

Curriculum Vitae

EDUCATION

Ph.D. **University of Illinois at Chicago** January 2015
Transportation Engineering Program
Adviser: Prof. Kouros Mohammadian.
Thesis: Generation Gaps in Activity and Travel Behavior

M.S. **Sharif University of Technology, Tehran, Iran** November 2006
Transportation Engineering Program
Adviser: Prof. Yousef Shafahi
Thesis: A New Location Model for Emergency Medical Services

B.S. **Azad University, Mashhad, Iran** September 2004
Civil Engineering

RESEARCH EXPERIENCE

Graduate Research Assistant spring 2011-January 2015
Department of Civil & Materials Engineering
University of Illinois at Chicago

Adviser: Prof. Kouros Mohammadian

- Illinois Statewide Passenger and Freight Travel Demand Model, Illinois Department of Transportation (2013-2015)
- Modeling Seniors' Activity-Travel Behavior, Illinois Center for Transportation (2011-2013)
- Ridership Estimation Study for the IDOT 220 High-Speed Rail Preliminary Feasibility Study, Illinois Department of Transportation (2011-2012)

TEACHING EXPERIENCE

Teaching Assistant *CME408: Traffic Engineering and Design* Fall 2010
Department of Civil & Materials Eng.
University of Illinois at Chicago

Guest Lecturer *CME508:Travel Demand Modeling* Fall 2013
Department of Civil & Materials Eng.
University of Illinois at Chicago

- Discrete choice analysis with focus on mode choice
- Estimating logit model in Excel without macro
  http://bkarimiv.wix.com/transportvision

Guest Lecturer *CME503: Advanced Travel Demand Analysis* Fall 2014
Department of Civil & Materials Eng.
University of Illinois at Chicago

- Advanced discrete choice analysis with SAS and Biogeme
- Big data visualization with D3

WORK EXPERIENCE

Traffic Engineer Oct 06-Aug10

R.T.A. Traffic Engineering Consulting Co., Tehran, Iran

- Traffic Improvement Program (TIP) for Andishe New Town, Miane, Behshahr, and RobatKarim;
- Design of traffic signs and pavement markings for Miane, Behshahr, RobatKarim and Ahwaz;
- Design of bicycle network for Qzavin, Andishe New Town, Urmia;
- Design of educational traffic park for Qods, RobatKarim and Namin;
- Safety Improvement Plan for three major highways in Tehran;

HONORS & AWARDS

- Best Student Paper of Transportation Research Board (TRB) 2014 Data Competition: Driver's Reaction to Yellow Light at Dilemma Zone of a Signalized Intersection. (http://trbstats.weebly.com/2014-trb-data-competition.html). The paper is under review for a special issue of the Accident Analysis & Prevention Journal.
- Half-tuition scholarship (2800 CHF) for 2014 Discrete Choice Analysis Course, EPFL. (http://transp-or.epfl.ch/dca/index.php)

JOURNAL PUBLICATIONS AND PEER REVIEWED CONFERENCE PROCEEDINGS

- **Passenger Transportation**

1- **Karimi B**., Z. Pourabdollahi (2015) Driver's Reaction to Yellow Light at Dilemma Zone of a Signalized Intersection, Under review in Accident Analysis & Prevention Journal, 2015.

2- **Karimi B**., Z. Pourabdollahi, A. Mohammadian, R. Shabanpour (2015) A Mixed Copula-based Joint Model of Non-Mandatory Out-of-home Activity Type and Activity Duration, Forthcoming in the proceeding of the 94th Annual Meeting of Transportation Research Board, January 2015.

3- Auld J., **B. Karimi**, Z. Pourabdollahi, A. Mohammadian, and K. Kawamura (2015) A Stated-Preference Intercept Survey of Long-Distance Mode Choice for Estimating High-Speed Rail Demand, Accepted for presentation in the 10th International Conference on Transport Survey Methods, November 2014.

4- **Karimi B.**, T. Rashidi, A. Mohammadian, (2013). A latent segmentation AFT-based duration model. The International Choice Modeling Conference, Sydney, July 2013.

5- **Karimi B.**, Z. Pourabdollahi, A. Mohammadian, (2013) A nested logit-based latent segmentation model for examining rhythms of long-distance trips in Illinois, In the proceeding of the 93rd Annual Meeting of Transportation Research Board, January 2014.

6- **Karimi B.**, Y. Shafahi, A. Mohammadian, K. Sturm, (2013), A Multi-Objective, Stochastic, and Capacity-Constrained Static Location Model for Ambulances, In the proceeding of the 92nd Annual Meeting of Transportation Research Board, January 2013.

7- **Karimi B.**, Z. pourabdollahi, A. Mohammadian, (2013). The Random Subspace Proportional Hazard (RSPH) Model for Inter-shopping Duration. The International Choice Modeling Conference, Sydney, July 2013.

8- **Karimi B.**, T. Rashidi, A. Mohammadian, K. Sturm, (2012). A log-normal accelerated failure time (AFT) model for inter-shopping duration of maintenance shopping activities of non-routine elderly shoppers. In the proceeding of the 91st Annual Meeting of Transportation Research Board, January 2012.

9- **Karimi B.**, T. Rashidi, A. Mohammadian, K. Sturm, (2012), Young-old elderly and baby boomers: An explanatory analysis on activity duration, time-of-day choice, and planning time horizons. Transportation Research Record: Journal of the Transportation Research Board (2322):1, pp 51-59.

- **Freight Transportation**

10- Pourabdollahi Z., **B. Karimi**, and A. Mohammadian (2013), Joint Model of Freight Mode and Shipment Size Choice, Transportation Research Record: Journal of the Transportation Research Board (2378):1, pp 84-91.

11- Pourabdollahi Z., M. Javanmardi, **B. Karimi**, A. Mohammadian, K. Kawamura (2013), Mode and Shipment Size Choice Models in the FAME Simulation Framework, In the proceeding of the 92nd Annual Meeting of Transportation Research Board, January 2013.

12- Ko S., **B. Karimi**, and A. Mohammadian, (2013) Scenario Analysis of Containerized Freight Distribution into the Midwest Region in Response to Capacity Expansions, In the proceeding of the 93rd Annual Meeting of Transportation Research Board, January 2014.

13- Pourabdollahi Z., **B. Karimi**, A. Mohammadian (2013), Shipping Chain Choices in Long Distance Supply Chains: Descriptive Analysis and a Decision Tree Model, In the proceeding of the 93rd Annual Meeting of Transportation Research Board, January 2014.

14- Ko S., **B. Karimi**, and A. Mohammadian, (2013) U.S. Containerized Import Freight Network with Peripheral Capacity Expansions: A Review, In the proceeding of the 93rd Annual Meeting of Transportation Research Board, January 2014.

OTHER PRESENTATIONS

15- **Karimi B.**, Z. Pourabdollahi, A. Mohammadian (2014) GABATOV: a galaxy-shaped behavioral activity- travel modeling visualizer. 29thAnnual Transport Chicago Conference. June 2014.

16- Pourabdollahi, Z., **B. Karimi**, A. Mohammadian, and K. Kawamura, (2013) An Optimization Model of Warehouse Location and Retailer Allocation, Student Freight Symposium, The University of Memphis Intermodal Freight Transportation Institute, 4-6, February 2013.

17- Ko S., **B. Karimi**, and A. Mohammadian, (2013) Analysis of Changes in Freight Distribution from Major Capacity Expansion Projects, 2013 INFORMS Annual Meeting, Minneapolis, October 2013.

18- **Karimi B.**, A. Mohammadian, (2012). Elderly and non-Elderly People: Differences in Tour-based Travel Mode Choice Behavior. The Aging, Mobility and Quality of Life (AMQoL) Conference, Ann Arbor, June 2013.

19- **Karimi B.**, A. Mohammadian, (2012). An Explanatory Analysis of Activity Planning and Travel Scheduling Process of Elderly and non-Elderly People. The Aging, Mobility and Quality of Life (AMQoL) Conference, Ann Arbor, June 2013.