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Developing Advanced Econometric Frameworks for Modeling Multidimensional Choices: An Application to Integrated Land-Use Activity Based Model Framework

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Developing Advanced Econometric Frameworks for Modeling Multidimensional Choices: An Application to Integrated Land-Use Activity Based Model Framework

by

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Dedication

To my mother Swarajyam, my father Babu Rao, my sister Navatha
and professor B.S. Murthy

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I was fortunate enough to meet great individuals during the course of my doctoral education at Austin. Hence, be prepared for a long list of acknowledgements.

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The overall goal of the dissertation is to contribute to the growing literature on the activity-based framework by focusing on the modeling of choices that are influenced by land-use and travel environment attributes. An accurate characterization of activity-travel patterns requires explicit consideration of the land-use and travel environment (referred to as travel environment from here on). There are two important categories of travel environment influences: *direct* (or *causal*) and *indirect* (or *self-selection*) effects. The direct effect of travel environment refers to how travel environment attributes causally influence travel choices. This direct effect may be captured by including travel environment variables as exogenous variables in travel models. Of course, determining if a travel environment variable has a direct effect on an activity/travel choice of interest is anything but straightforward. This is because of a potential *indirect* effect of the influence of the travel environment, which is not related to a causal effect. That is, the very travel environment attributes experienced by a decision maker (individual or household) is a function of a suite of *a priori* travel related choices made by the decision maker.

The specific emphasis of the current dissertation is on moving away from considering travel environment choices as purely exogenous determinants of activity-travel models, and instead explicitly modeling travel environment decisions jointly along

with activity-travel decisions in an integrated framework. Towards this end, the current dissertation formulates econometric models to analyze multidimensional choices. The multidimensional choice situations examined (and the corresponding model developed) in the research effort include: (1) reason for residential relocation and associated duration of stay (joint multinomial logit model and a grouped logit model), (2) household residential location and daily vehicle miles travelled (Copula based joint binary logit and log-linear regression model), (3) household residential location, vehicle type and usage choices (copula based Generalized Extreme Value and log-linear regression model) and (4) activity type, travel mode, time period of day, activity duration and activity location (joint multiple discrete continuous extreme value (MDCEV) model and multinomial logit model (MNL) with sampling of alternatives). The models developed in the current dissertation are estimated using actual field data from Zurich and San Francisco. A variety of policy exercises are conducted to illustrate the advantages of the econometric models developed. The results from these exercises clearly underline the importance of incorporating the direct and indirect effects of travel environment on these choice scenarios.

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CHAPTER 1 INTRODUCTION

1.1 Auto-oriented travel in the United States

In the United States, a significant number of individuals depend on the auto mode of transportation. This dependency on the auto mode can be attributed to high auto-ownership affordability, inadequate public transportation facilities (in many cities), and excess suburban land-use developments. For instance, the 2009 NHTS data shows that about 91% of US households owned at least one motor vehicle in 2009 (compared to about 80% in the early 1970s; see Pucher and Renne, (2003)). The high auto dependency, in turn, results in high auto travel demand on highways. At the same time, the ability to build additional infrastructure is limited by high capital costs, real-estate constraints and environment considerations. The net result has been that traffic congestion levels in metropolitan areas of United States have risen substantially over the past decade (see Schrank and Lomax, (2005)). The increase in traffic congestion levels not only causes increased travel delays and impacts stress levels of drivers, but also adversely affects the environment as a result of rising air pollution and green house gas emissions.

To be sure, the past few decades have seen considerable progress in automobile technology, leading to a reduction in the amount of pollutants released into the environment and an increase in the mileage per gallon of gasoline used (Foundation for Clean Air Progress (FCAP)). For example, on average, about 20 of today's cars put together produce the same amount of per-mile emissions as one mid-1960s car. In another 10 years, thanks to new automotive and fuel technologies, it is expected that 33 cars will produce the same amount of per-mile emissions as one of mid-1960s model (Air pollution facts, FCAP). However, the advantages of the progress in the automobile industry are offset considerably by the escalated ownership of personal automobiles and their subsequent use for work and non-work trips. The household vehicle miles of travel increased 300% between 1977 and 2001 (relative to a population increase of 30% during the same period; see Polzin *et al.,* (2004)). The increasing vehicle miles traveled has resulted in an increase in the quantity of emissions in recent years. In fact, in many urban regions, the quantity of emissions is very close to the threshold or beyond the threshold of the Environmental Protection Agency (EPA) conformity levels. Of course, these mobile-source emissions in the environment also contribute to global warming (Greene and Shafer, (2003)).

The increasing auto travel, and its adverse environmental impacts, has led, in the past decade, to the serious consideration and implementation of travel demand management (TDM) strategies (for example, promoting car sharing schemes, enhancing existing public transportation services and building new services such as light rail transit). The main objective of these TDM strategies is to encourage the efficient use of transportation resources by influencing travel behavior. TDM strategies offer flexible solutions that can be tailored to meet the specific requirements of a particular urban region. Concomitant with this emphasis on demand management has been the stronger emphasis on analyzing traveler behavior at the individual level rather than using direct statistical projections of aggregate travel demand. In particular, the focus of travel demand modeling has shifted from an underlying trip-based paradigm to an activity-based paradigm, which treats travel as a demand derived from the need to participate in activities dislocated in time and space (see Bhat and Koppelman, (1993)). This activity-based paradigm is discussed in more detail in the rest of this chapter, along with the objectives of this dissertation.

The remainder of this chapter is organized as follows. Section 1.2 provides a brief summary of activity-based travel models, while Section 1.3 presents an overview of a typical activity-based modeling framework. In Section 1.4 we discuss the focus of the current research and outline the importance of land-use and travel environment in modeling activity patterns. Section 1.5 presents the objectives of the dissertation. Section 1.6 outlines the rest of the dissertation.

1.2 Activity-based travel modeling framework

The objective of an activity-based travel modeling framework is to micro-simulate individual activity and travel participation over the course of certain time interval, which usually is a typical weekday. The framework considers travel as a means to pursue activities distributed in time and space. The activity-based modeling framework essentially attempts to replace the statistical travel prediction focus of the traditional trip-based model framework with a more behavioral approach that explicitly recognizes the fundamental role of activity participation as a precursor to travel. In doing so, the activity-based framework offers several advantages from a travel modeling perspective. First, it ensures that there is consistency across the different choices (for example, mode choices, time-of-day choices, and destination choices) assigned to successive trips of an individual. Second, the modeling of daily patterns allows a more accurate analysis of the changes to travel patterns in response to travel demand management strategies and policy initiatives, because of the explicit recognition of the interplay among the several activity participation-related choices of an individual. Third, the activity-based models allow the incorporation of the influence of inter-household interactions on travel. Finally the activity-based framework generally considers a finer resolution of time and space (compared to the traditional trip-based framework), and thus is more suited to providing travel inputs needed for vehicle emissions and air quality modeling.

To better illustrate the advantages of the activity-based modeling framework, consider an employer-based work policy that involves releasing employees early from work in the afternoon to reduce PM peak period traffic. Since there is little to no connection between the prediction of work trips and non-work trips in the trip-based framework, the use of a trip-based approach may lead one to believe that the employer work policy would indeed reduce trips in the PM peak. However, from an activity participation standpoint, it is possible that individuals use the additional time available now in the late afternoon to pursue more non-work activities during evening commute or after returning home. If some of these "new" non-work activity participations are pursued during the peak period, the reduction in peak period trips, as predicted by an activity-based modeling framework, will be lesser than predicted by the trip-based framework. Previous studies have clearly indicated such an "available time" effect on the generation of non-work activities (see Bhat et al., 2004), which implies that the trip-based framework can over-predict the benefit of an "early-release-from-work" policy, while the activity-based framework provides more realistic responses.

Federal transportation agencies and metropolitan organizations (MPOs) in the United States and Europe have started to recognize the advantages of the activity-based framework and are investing substantially in the development and deployment of activity-based models. Examples of urban regions in the United States and Europe that have an operational or research based activity model include (name of the software in parenthesis): Portland (METRO), San Francisco (SF-CHAMP), New York (NY-BPM), Columbus (MORPC), Sacramento (SACSIM), Dallas-Fort-Worth (CEMDAP), Southeast Florida (FAMOS), and Rotterdam (ALBATROSS). A brief review of these models is provided in Table 1.1. Specifically, the table presents details of the development base year, the primary unit of analysis, the core modeling approach, the data sources used, the application status of the software and references. All the frameworks discussed in the table employ microsimulation for generating travel forecasts.

1.3 Conceptual overview of activity-based framework

In this section, we provide a conceptual overview of an activity-based modeling framework. A schematic description provided in Figure 1.1 identifies the following key elements: (1) disaggregate level individual and household attribute generator (DIHG), (2) demographic, land-use and travel environment attribute generator (DLUTEG), (3) activity travel pattern attribute generator (ATPG), and (4) traffic assignment module (TA). The schematic also outlines the base year inputs typically provided for activity-based models, which include information on the aggregate socioeconomics and the activity-travel environment characteristics in the urban study region for the base year, as well as policy actions prescribed for future years.

In the subsequent discussion, we present details of how each of the different elements identified above operate within an iterative procedure to generate activity travel patterns for the forecast year.

1.3.1 Disaggregate level individual and household attribute generator (DIHG)

The activity-based modeling frameworks employ disaggregate level individual and household level information to model activity-travel patterns. The DIHG element is also often referred to as synthetic population generation with the travel demand community. The DIHG generation involves an aggregate dataset that represents the desired or expected marginal distribution of the variables (such as Summary Files (SF) of the U.S. or the Small Area Statistics (SAS) files of the U.K) and a disaggregate dataset that is a collection of records representing a sample of the "real" households and individuals in the population (for example Public-Use Microdata Samples (PUMS) of the U.S. and the Sample of Anonymized Records (SAR) of the U.K). The disaggregate population attributes are generated by selecting records from the disaggregate dataset while ensuring that the marginal distributions from the aggregate dataset match using an Iterative Proportional Fitting (IPF) approach or its variants. The marginal distributions selected for the matching process form the control totals for the synthetic population generation. Typically, researchers employ a sub-set of person (such as age, gender and race) and household (such as head of the household age, and household size) attributes as control variables (see Guo and Bhat 2007 and Xin et al., 2009 for more details on DIHG procedures). The data generated based on these control totals in the DIHG module contains details of all person and household attributes. However, because we employ only some dimensions as control variables in the data generation, the "un-controlled" variable information is typically removed from the data set and re-generated using the DLUTEG element. It is important to note that DIHG procedure is only employed at the beginning of the first iteration. Subsequently, the procedure iterates between DLUTEG, ATPG and TA elements.

1.3.2 Demographic, land-use and travel environment attribute generator (DLUTEG)

Recent literature in travel demand modeling community has emphasized the importance of generating accurate land-use and travel environment attributes for improving activity-based travel forecasting (see Bhat and Guo 2007, Pinjari et al., 2009 for a detailed discussion). The DLUTEG element generates disaggregate level land-use and travel environment information for all individuals in the DIHG synthesized population. The DLUTEG element, typically, consists of two components: (1) base year component and (2) an evolution component.

1.3.2.1 Base year component

The major function of the base year component is to augment the available demographic variables with other relevant variables required for activity travel pattern generation. These variables generally include: study status, labor participation, employment location, employment schedule, employment flexibility at the individual level, household income, residential tenure, housing type, vehicle ownership, and vehicle fleet composition at the househol level[1]. These variables are generated using a series of sequential modules, all embedded within a microsimulation platform. Typically, all the person-related variables are generated first, and appropriately aggregated to compute such household level attributes as household income, number of workers, followed by the generation of other household level attributes (see Eluru et al., 2007).

1.3.2.2 Evolution component

The base year component of the DLUTEG model is adequate if the emphasis is on generating travel patterns solely for the base year. However, the objective of most transportation planning exercises is to forecast forward into a future year, or to examine the travel impact of policy changes related to the transportation system. In such predictive contexts, there is a need to explicitly model how the individuals, households, land-use forms and the travel environment evolve over time. The choices typically modeled in the evolution components include: (1) individual-level evolution and choice models (for

[1] The household residential location determination for the base year is typically made within the DIHG element..

births, deaths, schooling, and employment) (2) household formation models (for living arrangement, divorce, move-ins, and move-outs from a family), (3) household-level long-term choice models (for residential moves, duration of stay, residential housing characteristics, automobile fleet composition, annual automobile usage, information and communication technology adoption, and bicycle ownership) and (4) land-use policies (to represent urban form regulations and firm establishment and relocation decisions). The evolution components also typically employ an *a priori* sequential structure for modeling the choices identified.

To date, a number of demographic and socioeconomic updating modules have been developed in the field of sociology (for example DYNAMOD, DYNACAN, NEDYMAS, and LIFEPATHS). These modules explicitly model demographic processes at a high level of detail. However, they are not well suited for application in the context of an activity-based travel microsimulation system because generating the necessary land-use and transportation system characteristics required for an activity-based travel microsimulator with these models is not straightforward. Examples of population and land-use updating systems that have been developed in the travel demand forecasting community (and with varying levels of detail and sophistication) include TRANUS, MEPLAN, URBANSIM, ILUTE, and CEMSELTS. Table 1.2 provides a brief summary of the aforementioned systems with brief details regarding the base year of development, level of detail of information, choice components modeled, data sources used and references.

1.3.3 Activity travel pattern attribute generator (ATPG)

The third element of the activity based model is the activity travel pattern attribute generator. The ATPG employs the outputs from the DLUTEG element to predict activity travel patterns for the entire population in the urban region. This activity-based micro-simulation effort, in addition to determining the different activities pursued, involves, among other things, modeling activity location, activity duration, individuals participating in the activity, and the travel mode (for out-of-home activities) to the activity[2]. In determining these choices, the ATPG considers a host of factors including: (1) individual socio-demographics (such as age, gender, race, employment status, employment location), (2) household socio-demographics (such as number of household members, number of children, number of employed individuals, household location, and vehicle fleet composition and usage), and (3) the travel environment (level of service (LOS) measures such as travel time to location, accessibility to activity locations, perception of space, time of day, access to vehicles, access to public transportation, and presence of bicycling and walking infrastructure). The information regarding these factors is obtained from the outputs generated from the DIHG and DLUTEG components of the framework. The DLUTEG and ATPG components require LOS measures for the transportation network. For this purpose, an initial set of LOS measures is assumed for the first iteration. These LOS measures are updated based on the LOS measures generated in the traffic assignment (TA) module.

1.3.4 Traffic assignment (TA)

Recent advances in integrating activity based models with advanced assignment methodologies enable us to directly translate, based on continuous time intervals, the activity-travel patterns generated from the ATPG into vehicles on the transportation network. To elaborate, the activity-travel patterns generated are converted into dynamic origin destination (O-D) matrices (see Lin et al., 2008) that are then input to the TA module. Within the TA module, the network assignment undertakes traffic simulation, optimal routing and path assignment to obtain traffic link volumes and speeds. The travel times obtained as outputs from the TA module are appropriately processed and provided as input back to DLUTEG and ATPG element. Then the DLUTEG and ATPG elements

[2] The actual attributes modeled in the ATPG vary based on the implementation instance developed for micro-simulation. For instance, tour models do not explicitly model activity durations in their effort to mimic individuals' activity participation.

are re-run to generate revised outputs. This "within year" iteration is continued until there is little change in the convergence criterion[3].

1.3.5 Iterative procedure

The preceding discussion presented the details of one time-step in the activity-based framework. In the next phase of the activity-based framework in Figure 1.1, the emphasis on moving one step forward in time (usually this step is considered as one year), by updating the population, urban-form, and the land-use markets, using the evolution component of the DLUTEG element (note that the DIHG is used only to generate the disaggregate-level synthetic population for the base-year and is not used beyond the base year). An initial set of transportation system attributes is generated for this next time step based on (a) the population, urban form, and land-use markets for the next time step, (b) the transportation system attributes from the previous year in the simulation, and (c) the future year policy scenarios provided as input. The DLUTEG element outputs are then provided as input into ATPG, which interfaces with a TA element in a series of consistency/equilibrium iterations for the next time step (just as for the base year) to obtain the "one time step" outputs. The loop continues for several time steps forward until the socioeconomics, land-use, and transportation system path/link flows and transportation system level of service are obtained for the forecast year specified by the analyst.

[3] Two possible convergence criteria have been used in literature: (1) O-D matrix convergence and (2) travel time convergence. In the former, the O-D trip tables generated in the current iteration are checked against the O-D trip values generated in the previous iteration. If the O-D matrices are within a certain tolerance, the iterations are terminated and the O-D matrices with the corresponding link volumes and speeds are provided for analysis. The travel time convergence criterion is similar, except that the link travel times predicted in the current iteration are checked against corresponding values in the previous iteration. If these are within a certain tolerance, convergence is assumed to have been reached.

1.4 Focus of current research effort

In the preceding section, we discussed a "blueprint" of an activity-based model framework and briefly summarized how the many elements of the framework interact with one another. The overall goal of the dissertation is to contribute to this growing literature on the activity-based framework by focusing on the modeling of choices that are influenced by land-use and travel environment attributes. These choices fall within the realm of the DLUTEG and ATPG components of the framework of Section 1.3.

1.4.1 Role of land-use and travel environment

An accurate characterization of activity-travel patterns requires explicit consideration of the land-use and travel environment (referred to as travel environment from here on). There are two important categories of travel environment influences: *direct* and *indirect* effects. The direct effect of travel environment refers to how travel environment attributes causally influence travel choices. This direct effect may be captured by including travel environment variables as exogenous variables in travel models. For example, a household's residential location may affect the travel mode choice for activity participation of each of the household members. If the household resides in a suburban region with inadequate public transportation service it is likely that members of the household will pursue activities using the auto mode. This may be captured by incorporating, for instance, residential location-related public transportation accessibility measures in a travel mode choice model. Other similar accessibility measures may include length/density of bicycle (highway) lanes within a mile radius of the household, and accessibility to shopping, recreation or maintenance activities by alternate modes. If such direct measures turn out to be statistically significant predictors of activity-travel choices, the suggestion is that transportation decision-makers may be able to influence activity/travel choices by making appropriate design changes to the travel environment. For instance, the growing environmental and public health concerns have led to studies that attempt to examine if and how altering travel environment (densification of neighborhoods, improving bicycling facilities etc.) results in changes to walking and transit-use behavior.

Of course, determining if a travel environment variable has a direct effect on an activity/travel choice of interest is anything but straightforward. This is because of a potential *indirect* effect of the influence of the travel environment, which is not related to a causal effect. That is, the very travel environment attributes experienced by a decision maker (individual or household) is a function of a suite of *a priori* travel related choices made by the decision maker. For instance, a decision maker who has an intrinsic preference for driving may not mind residing in a suburban region of the metropolitan area with minimal transit accessibility. On the other hand, a decision maker who is "environmentally conscious" might possibly choose to reside in a downtown region of the metropolitan area, so that s/he can use public transportation for a large fraction of her/his travel. In both cases, the decision maker chooses a travel environment that would be conducive to *a priori* travel dispositions. In the context of the above example, if we disregard that residential location is a choice (i.e. if we ignore that decision makers may self-select their residential location), the analysis results may suggest incorrectly that creating dense neighborhoods will substantially reduce vehicular usage (mileage). This is not to say that policies that alter travel environment are generically ineffectual, but that the emphasis needs to be on carefully disentangling the *direct* (or causal) and *indirect* (self-selection) influence of the travel environment on activity/travel choices.

1.4.2 The current study in the context of direct and indirect travel environment effects

The emphasis of the current dissertation is on moving away from considering travel environment choices as purely exogenous determinants of activity-travel models, and instead explicitly modeling travel environment decisions jointly along with activity-travel decisions in an integrated framework. In the example discussed in the previous section, this would mean jointly modeling residential choice decisions along with travel mode choice dimensions, and accommodating the effects of individual pre-dispositions (such as auto-inclination or environment-friendliness) on both residential and travel choices. Once this indirect (or spurious or self-selection) effect is captured, the remaining effect of the travel environment on travel choice may be more realistically considered as the "true" (or direct or causal) effect. Of course, the example provided in the previous section is but one of the many potential joint choices within the gamut of choices in DLUTEG and ATPG. Other possible joint choice situations (within the DLUTEG and ATPG components) likely to manifest *direct* and *indirect* travel environment effects include: (1) reason for residential relocation and associated duration of stay, (2) household residential location and vehicle ownership, (3) household residential location and daily vehicle miles travelled, (4) household residential location, vehicle type and usage choices, (5) activity type, travel mode, time period of day, activity duration and activity location. There is a need to develop econometric models that can potentially model such multidimensional choices (see Pinjari et al., 2007 and Bhat and Guo, 2007 for examples of earlier studies along these lines). In this dissertation, we contribute substantively to the development of such multidimensional choice models of travel environment and activity-travel choices, while also addressing several methodological challenges, in doing so, as discussed next.

1.5 Objectives of the dissertation

Recent research in activity-based models has called for the unification of different streams of research on transportation planning, land-use modeling and activity time-use. This is, at least in part, to disentangle causal (or direct) effects of travel environment variables from spurious (or self-selection or indirect) effects (see Cao et al., 2008, and Pinjari, 2009). The current dissertation contributes to this existing research by (a) developing advanced econometric models for modeling multi-dimensional choices, (b) estimating these models for travel data sets, and (c) undertaking policy analysis.

The specific objectives of the current dissertation are four fold as discussed in more detail below:

The first objective is to contribute substantively to the growing stream of literature on multidimensional choices within an integrated land-use activity-based model framework. Specifically, the multidimensional choice situations examined in the research effort include: (1) reason for residential relocation and associated duration of stay, (2) household residential location and daily vehicle miles travelled, (3) household residential location, vehicle type and usage choices and (4) activity type, travel mode, time period of day, activity duration and activity location.

The second objective is to formulate a suite of econometric models that are applicable to examine the different multi-dimensional choice contexts identified above. Specifically, the econometric models developed, in sequence of the choice contexts mentioned earlier, include: (1) joint multinomial logit model and a grouped logit model, (2) Copula based joint binary logit and log-linear regression model, (3) copula based Generalized Extreme Value and log-linear regression model, and (4) joint multiple discrete continuous extreme value (MDCEV) model and multinomial logit model (MNL) with sampling of alternatives.

The third objective is to apply the multidimensional choice model formulations in an actual field context to understand the direct and indirect effects of travel environment variables on activity-travel choices. We do so by using activity-travel surveys conducted in two urban regions in the world. These correspond to (1) a longitudinal data set derived from a retrospective survey that was administered in the beginning of 2005 to households drawn from a stratified sample of municipalities in the Zurich region of Switzerland and (2) a cross-section two-day retrospective activity survey travel data set derived from the 2000 San Francisco Bay Area Household Travel Survey (BATS). The Zurich dataset is employed for modeling residential moves and duration of stay while the BATS data is employed for the other three multidimensional choices.

The fourth objective is to undertake validation and policy analysis, relevant to the choice context under consideration, to clearly examine the advantages of modeling these choices as multidimensional choices as opposed to considering them as sequential choices.

1.6 Structure of the dissertation

Figure 1.2 presents a schematic representation of the structure of the remainder of the dissertation, which shows how each chapter contributes to the activity-based model components identified in Section 1.3 and how each chapter furthers the objectives of the dissertation. Within each chapter, an exhaustive literature review is conducted to discuss earlier research, identify limitations of earlier research, and position the research effort in the current dissertation within the larger context of the literature.

Chapter 2 examines the household residential relocation decision at the household level, both in terms of the reasons for relocation and in terms of the duration of stay at a given residential location. The joint modeling of the move decision and the stay duration is important because they are simultaneous decisions in the sense of being contemporaneous i.e. the move decision and the stay duration represent a package choice. The model takes the form of a joint multinomial logit model of reason for move and a grouped logit model of residential stay duration preceding the move.

Chapter 3 addresses the following question: Is the effect of the built environment on travel demand causal or merely associative or some combination of the two? Towards this end, a model of residential neighborhood choice and daily household vehicle miles of travel (VMT) is formulated. The dominant approach in the literature to dealing with such self-selection choice situations is to assume a bivariate normality assumption directly on the error terms, or on transformed error terms, in the discrete neighborhood choice and continuous VMT equations. Such an assumption can be restrictive and inappropriate, since the implication is a linear and symmetrical dependency structure between the error terms. In this dissertation, we introduce and apply a flexible approach to sample selection in the context of built environment effects on travel behavior. The approach is based on the concept of a "copula", which is a multivariate functional form for the joint distribution of random variables derived purely from pre-specified parametric marginal distributions of each random variable. The copula-based approach retains a parametric specification for the bivariate dependency, but allows testing of several parametric structures to characterize the dependency.

Chapter 4 focuses on modeling household vehicle fleet composition and usage choices, which include the household vehicle count, vehicle type (classified as small sedan, large sedan, coupe, van, pick-up truck and sports utility vehicle), and annual vehicle usage decisions. However, the framework needs to take into account the impact of residential self-selection effects on vehicle fleet composition and usage. To do so, the chapter presents a joint GEV-based logit regression model of residential location choice, vehicle count by type choice, and vehicle usage (vehicle miles of travel) using a copula based framework that facilitates the estimation of joint equations systems with error dependence structures within a simple and flexible closed-form analytic framework.

Chapter 5 examines activity participation decisions in a unified framework that simultaneously determines activity type choice (generation), time of day choice, mode choice, destination choice, and time use allocation (duration). The unified framework allows us to capture the effects of spatial land use and built environment characteristics on activity generation, an effect often incorporated in a very tedious cascading fashion in earlier literature. The model system formulated constitutes a joint multiple discrete continuous extreme value (MDCEV) – multinomial logit (MNL) model, in which all discrete choices except for destination choice as well as the continuous duration dimension are modeled using the MDCEV, while destination choice is modeled as a MNL (with sampling of alternatives) nested and integrated within the MDCEV model component.

Chapter 6 undertakes validation and policy evaluation exercises for the econometric models developed in Chapters 2 through 5.

Chapter 7 discusses the substantive implications of the policy exercises for informed policy making. The chapter also identifies future directions of research and concludes the dissertation.

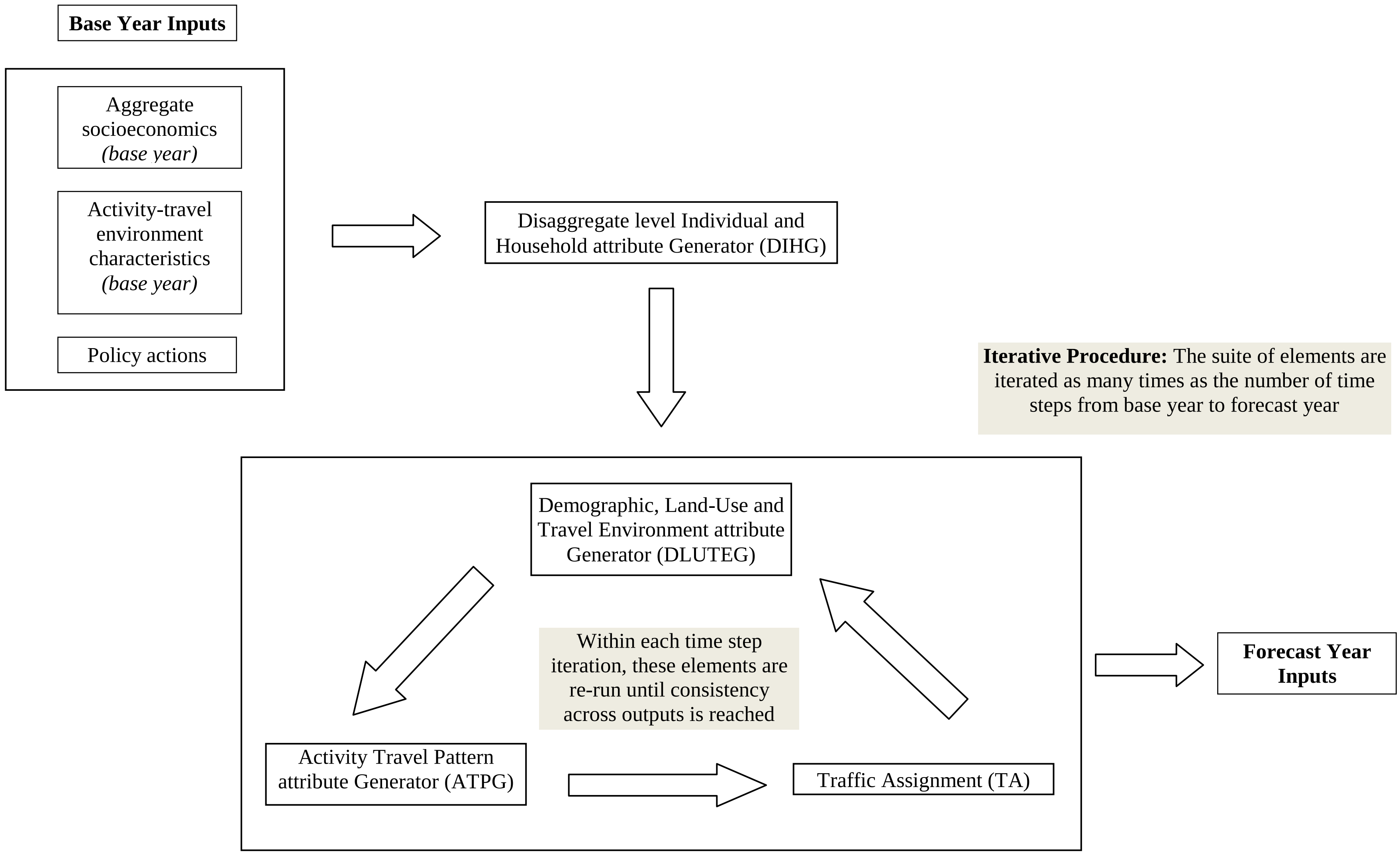


Figure 1.1: Conceptual representation of activity-based modeling framework.

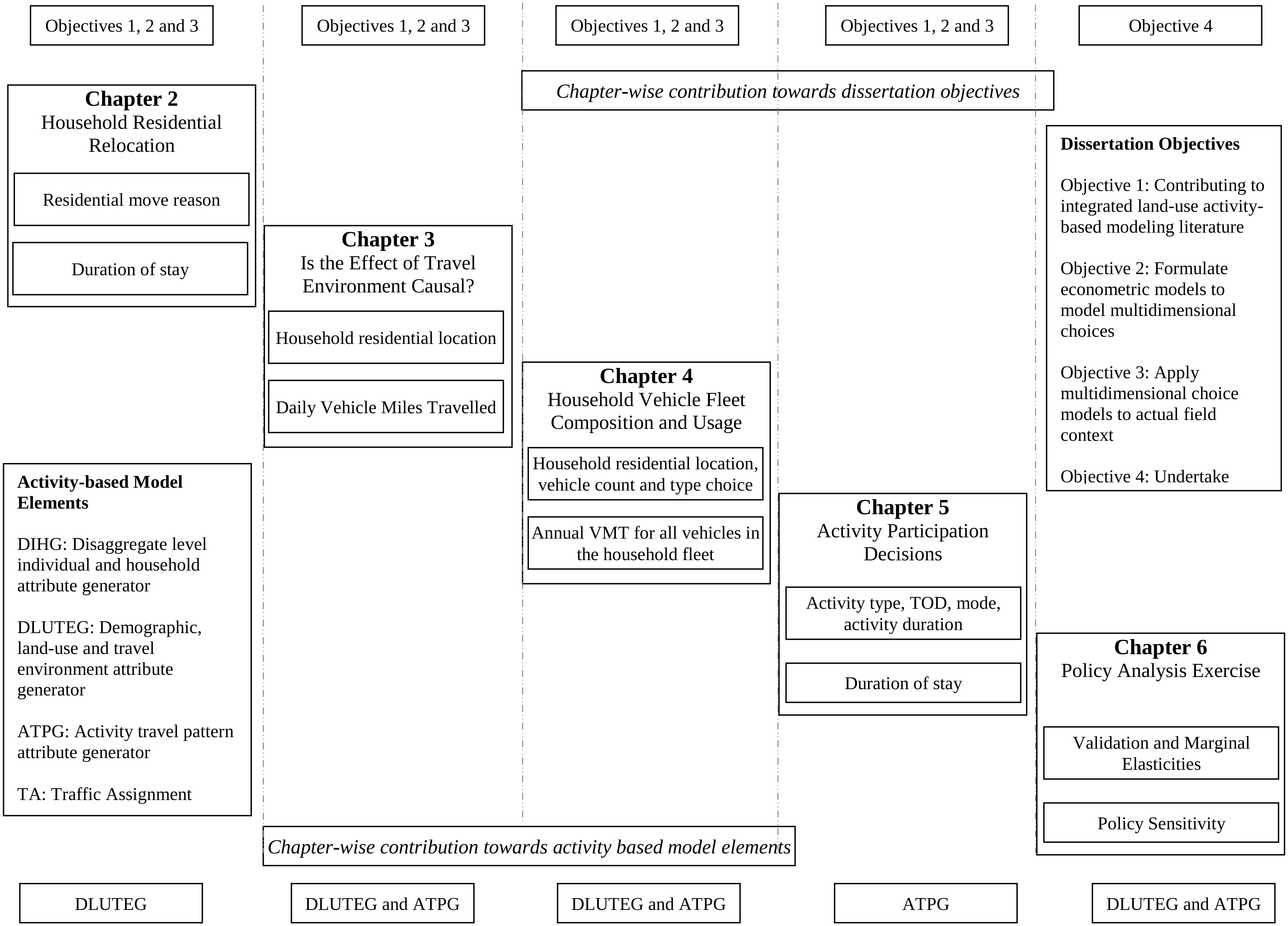


Figure 1.2: A schematic representation of the dissertation

Table 1.1: Activity-based modeling frameworks

Activity-Based Framework	Developme nt Base Year	Primary Unit of Analysis	Core Modeling Approach	Data Sources Used	Application Status Of The Software	References
METRO	1994	Trips	Econometric models	Survey contains 5,000 Households, giving more than 10,000 persons	Never fully calibrated	Bradley *et al*., 1998
SF-CHAMP	1998	Tours	Econometric models	1990 SF Bay Area Household Travel Survey Data of 1100 HHs on SF County, stated preference survey of 609HHs for transit related preferences	Applied for 1998	Cambridge Systematics (2002)
NY-BPM	1997	journeys	Econometric models	1997 Household Travel Survey of about 11,000 households in 28 counties	Applied for 1998 and 2020	Parsons Brinckerhoff (2004)
MORPC	2000	Tours	Econometric models	1999 Household travel survey data of 5,500 HHs in the Columbus region, 1993 on-board transit survey data	Applied for 2000 and 2030	PB Consult (2005)
SACSIM	2000	Tours	Econometric models	Household activity diary survey	Applied for 2000, 2005 and 2032	Bowman and Bradley (2005-2006), Bradley *et al*. (2007)
CEMDAP	2000	Tours	Econometric models	1996 Household travel survey data of 3,500 households in DFW, on-board transit survey data	Applied for 2000, 2030	Bhat *et al*. (2004), Pinjari *et al.* (2006), Pinjari *et al*. (2008)
FAMOS	2000	Tours	Econometric models	2000 Southeast Florida Household Travel Survey that consists of approximately 33,000 trips made by 9,500 people in 5,000 households.	Applied for 2000	Pendyala *et al*., 2005
ALBATROS S	1997	Tours	Decision tree induction	Activity diaries collected for two municipalities in Rotterdam, Netherlands	Applied for 1997	Arentze and Timmermans, 2004

Table 1.2: Demographic, land-use and travel environment attribute generator (DLUTEG) evolution component modules

Activity-Based Framework	Developmen t Base Year	Level of detail	Choice components modeled	Data Sources Used	References
TRANUS	1980s	Aggregate	Household location choice, employment location, real estate measures	Not available	Barra 1989
MEPLAN	1985	Aggregate	Household location choice, employment location, real estate measures	Data corresponding to Cities of Bilbao, (Spain), Dortmund (West Germany) and Leeds (England)	Echenique et al., 1990, Hunt 1993
URBANSIM	2000	Disaggregate	Population updating, employment mobility, employment location, real estate development, land price model	Eugene-Springfield, Oregon metropolitan organization Lane Council of Governments (LCOG) provided the data	Waddell 2002, Waddell et al., 2008
ILUTE	1986	Disaggregate	Population Updating, Housing Supply, Residential Mobility	Canadian Census data, Transportation Tomorrow Surveys, Greater Toronto Area real estate market database etc.	Miller et al., 2004
CEMSELTS	2000	Disaggregate	Population updating	Dallas Fort worth Travel survey, Texas State Data Center, National Vital Statistics, National Survey of Family Growth Data, Census data etc.	Eluru et al., 2007

CHAPTER 2 MODELING HOUSEHOLD RESIDENTIAL RELOCATION DECISIONS

2.1 Background

The traditional mobility-centric, supply-oriented, focus of transportation planning has, in recent years, been expanded to include the objective of promoting sustainable communities and urban areas by integrating transportation planning with land-use planning. This is evident in the movement away from considering land-use attributes and choices as purely exogenous determinants of travel models to explicitly modeling land-use decisions along with travel decisions in an integrated framework. A comprehensive conceptualization of the many decision-makers/agents (for example, households/individuals, businesses, developers, the government, etc.), and the interactions between these agents, involved in such an integrated land use-transportation framework is provided in Waddell et al. 2001. Among these decision-makers/agents are households and individuals, and it is this residential sector of the overall enterprise that is the focus of the current chapter.

Indeed, there has been considerable research recently on the joint consideration of long-term household/individual choices (such as residential relocation decisions, residential location choices, housing tenure and type choices) with short-term travel choices (see, for example, Eliasson and Mattsson 2000, Waddell et al. 2007, and Salon 2006; Pinjari et al. 2008 provide an extensive listing of such studies). This stream of research recognizes the possibility that employment, residential, and travel choices are not independent of each other, and that individuals and households adjust with combinations of short-term travel-related and long-term household-related behavioral responses to land-use and transportation policies. Similarly, short-term travel-related experiences may lead to shifts in long term household choices. For instance, if a worker in a household is living quite far away from her/his workplace, the household may be more likely in the future to relocate to a location closer to work. Of course, such responses and shifts in long-term housing choices are likely to involve a lag effect, which immediately raises the issue of temporal dynamics. It is not surprising, therefore, that comprehensive model systems of urban systems such as ILUTE (Salvini and Miller, 2005) and CEMUS (Eluru et al., 2007) include dynamic population microsimulation modules to "evolve" households and individuals, and their spatial locations, over time (to obtain the synthesized population of households and individuals, and their corresponding residential locations, for future years). These model systems involve several dimensions, including in-migration and out-migration from study area, age, mortality, births, employment choices, living arrangement, household formation and dissolution, and household relocation decisions. In this chapter, we focus on the household relocation decision in particular, including if and when a household will relocate and for what reason.

The remainder of the chapter is organized as follows. The next section presents a review of studies on household relocation. The subsequent section presents the modeling methodology, while the penultimate section offers a brief description of the data set and discusses model estimation results. The final section provides a summary of the chapter.

2.2 Literature review

Residential mobility or relocation is a concept that has been widely researched in various fields including transportation, urban planning, housing policy, regional science, economics, sociology, and geography. Given the vastness and diversity of the literature on this topic, it is impossible to include a comprehensive and exhaustive literature review within the scope of this chapter. The discussion is intended to highlight the primary approaches that researchers have taken to address this issue, and how the proposed approach in this research effort fills a gap in past work.

Some of the work on understanding residential mobility can be traced to the work of Rossi 1955 who characterized residential mobility as a means by which housing consumption patterns adjust over time. In many respects, this characterization remains true today; however, the patterns of residential mobility and the household and personal dynamics that drive such mobility have undergone transitions over the past half-century.

Coupe and Morgan, 1981 suggested that changes in household and personal characteristics are not the only factors that should be considered in household relocation studies. They note that housing choices may be affected by residential history and market factors or forces that are external to the household. Building further on this concept, Clark and Onaka 1983 is a rather unique study that attempted to consider an amalgamation of factors driving residential relocation and mobility processes. They characterize residential mobility as a combination of an adjustment move (adjusting to the market), an induced move (changes in household composition and lifecycle), and a forced move (loss of housing unit or job).

Since these early residential mobility studies, considerable research has been undertaken to address issues related to residential mobility due to the increasing recognition of the importance of this phenomenon from a wide range of perspectives. Residential mobility affects land use patterns, travel demand, housing consumption, housing values and property tax revenues, and urban landscapes, and has therefore been studied by researchers from a variety of disciplines. Previous studies in the non-transportation fields have indicated the following: (1) Most moves are driven by housing-related reasons such as the desire to own a home, upgrade to a nicer home or neighborhood, and get into a home of a more appropriate size (Schachter, 2001, US Census Bureau, 2005), (2) Income, employment status of individuals, age, ethnicity, intensity of social ties, lifecycle stage, and life course events (marriage, divorce, getting a job, birth of a child, change in job, children leaving home) also have a significant effect on residential mobility (see Dieleman 2001, Clark and Huang 2003, Li 2004, Kan 2007), (3) The structure of local housing markets and residential location vis-à-vis employment opportunities play a role in the decision to move (Boheim and Taylor, 2002, der Vlist et al., 2001).

In the field of transportation research, residential mobility has been examined with a specific emphasis on the role of transport costs (in particular, commuting costs), while controlling for household socio-economic and demographic characteristics. The interaction between the household location and the workplace locations of household workers is explicitly identified as a key dimension of interest in these studies (Waddell et al., 2007). Kim et al. 2005 attempt to understand the trade-offs between residential mobility on the one hand and accessibility, neighborhood amenities (built environment), and other socio-economic factors on the other. Clark et al. 2003 is another example where housing mobility decisions are examined with an explicit focus on commuting distance and commuting tolerance. They find that both one- and two-worker households tend to relocate to reduce total commute time of household workers, with a move generally resulting in the female worker shortening commuting distance more than the male worker. van Ommeren et al. 1998 and van Ommeren 1999 analyze the relationship between housing mobility/location and job mobility/location choice in a simultaneous framework. They focus on the role of commuting distance and find that a 10 km increase in commuting distance reduces duration at a home location by about one year.

In virtually all of these studies, there has been an explicit recognition of the need to use longitudinal data to study residential mobility decision processes, a point that has also been stressed by Hollingworth and Miller, 1996 who use a retrospective interviewing technique to obtain historical residential mobility information. Although retrospective surveys covering long periods do raise questions regarding the accuracy of memory recall, they constitute the most appropriate method to collect such information in the absence of a long-term panel survey (which would probably suffer from attrition). Beige and Axhausen 2006 use a retrospective survey of households in Zurich, Switzerland to study the influence of life course events on long-term mobility decisions over a 20 year period. They employ a duration modeling approach to understand the factors affecting the duration of sojourn at a particular location between moves, considering reasons for move as exogenous variables.

2.3 Focus of current chapter

This study constitutes a follow-up to Beige and Axhausen 2006 by jointly modeling the reason for relocation and the duration of stay at a location preceding the relocation, recognizing that the reason for location may itself be an endogenous variable influenced by observed and unobserved variables. Much of the literature has treated the decision to move as a binary choice decision (move/no-move) and modeled this decision as a function of various factors, including the reason to move as an exogenous variable. Other studies have used hazard-based duration models to represent the sojourn at a location between moves, once again treating the reason for a move as an exogenous variable. This study extends these previous studies in three important ways. First, the move decision (whether or not to move and the reason for the move) is treated as an endogenous variable in a multinomial unordered choice modeling framework as opposed to being considered as an exogenous variable. Second, the duration of stay is modeled as a grouped choice, with explicit accounting for the presence of unobserved variables that may simultaneously impact duration of stay and primary reason for move. Modeling the duration of stay as a grouped choice variable recognizes that individuals and households treat the duration of stay at a residential location in terms of time-period ranges as opposed to exact continuous durations. Third, we accommodate heterogeneity (or variation in effect) of exogenous variables (i.e., random coefficients) in both the equation for the move as well as the equation for the duration of stay preceding a re-location. To our knowledge, this is the first application of such a joint unordered choice-grouped choice model system with random coefficients.

The joint modeling of the move decision and the stay duration is important because they are simultaneous decisions in the sense of being contemporaneous – An end of stay duration occurs when a person decides to move out for a certain reason. In this sense, one choice cannot structurally cause the other. Rather, the move decision and the stay duration represent a package choice. Thus, the joint nature of the two decisions arises because the choices are caused or determined by certain common underlying observed and unobserved factors (see Train 1986, page 85). For example, high income households may be more likely to move to upgrade their housing stock, and these same households may also stay for shorter durations in any one residential location. Thus, there is jointness among the choices because of a common underlying observed variable. Similarly, a household's intrinsic (unobserved) preference for change (or quick satiation with current housing attributes or neighborhood characteristics) may make the household more likely to move to seek new housing attributes or a new neighborhood as well as reduce stay durations at any single residential location. The association between the reason to move and the stay duration in this case arises because of a common underlying unobserved preference measure. Ignoring this error correlation due to unobserved factors, and using the reason to move as an exogenous variable in a model of stay duration (or estimating separate stay duration equations for each move reason), will, in general, result in econometrically inconsistent estimates due to classic sample selection problems (see Greene 2000, page 926 for a textbook treatment of this issue). Intuitively speaking, the stay duration sample corresponding to the move reason of seeking new housing attributes will be characterized by short stay durations (because of the common unobserved intrinsic preference for change). If we use this "biased" sample for stay duration modeling, the resulting stay duration estimates will not be appropriate for a randomly picked household. But by modeling both reason for move and the stay duration, and accounting for unobserved error correlation, the estimation effectively accounts for the "bias" due to common unobserved preferences and is able to return unbiased stay duration estimates that will be appropriate for a randomly picked household.

The model system takes the form of a joint unordered discrete choice – grouped discrete choice model system with correlated error structures across the two choice dimensions and random coefficients in each choice dimension. Specifically, the reason for moving is modeled as a mixed multinomial logit (MNL). The duration of stay could be modeled as a continuous variable; however, the data set used in this study and the discrete nature of moving events lends itself more appropriately to the representation of duration of stay as a grouped (ordered) choice variable in this particular study. The mixed grouped logit model formulation is used to represent the duration of stay choice. The data set used in this study is derived from a survey conducted in Zurich, Switzerland that collected detailed information about residential relocations and the primary reason for each relocation event for one individual (aged 18 years or older) in the household over the 20 year period from 1985-2004 (as a result of this individual-level focus, the relocation analysis in the current chapter is conducted at the individual-level rather than a household level. With a sample size of more than 1000 individuals and 2000 move events, the data set is very suitable for the estimation of a model system of the nature proposed in this study. More importantly, it is quite a unique longitudinal data set with a rich history of residential (re)location information. The availability of such data sets is extremely rare in the profession, and this study offers a unique look at the long history of residential location behavior in a large urban context.

2.4 Modeling methodology

This section presents the econometric formulation underlying the modeling methodology adopted in this chapter. The modeling methodology is applicable to any joint choice context involving a multinomial choice and a grouped or ordered choice variable that may share common unobserved variables that influence them.

Let q (q = 1, 2,…, Q) be an index to represent individuals, k (k = 1, 2, 3,…, K) be an index to represent the different move reasons, and j (j = 1, 2, 3,…, J) be an index to represent the duration categories. The index k, for example, includes "Personal reasons", "Education/Employment reasons" or "Accommodation reasons", while index j represents duration categories such as "<2 years", "2-5 years", "5-10 years" and ">10 years". Further, to accommodate the possibility of multiple move records per person, let t (t = 1, 2, 3,…, T) represent the different moving choice occasions for individual q. Then, the equation system for modeling the reason for move and the duration of stay jointly may be written as follows:

$$u^*_{qkt} = (\beta'_k + \gamma'_{qk})x_{qt} + \eta_{qk} + \varepsilon_{qkt}, \text{ move corresponds to reason } k \text{ if } u^*_{qkt} > \max_{\substack{i=1,2,...K \\ k \neq i}} u^*_{qit} \qquad (2.1)$$

$$y^*_{qkt} = (\alpha'_k + \delta'_{qk})x_{qt} \pm \eta_{qk} + \xi_{qkt}, \quad y_{qkt} = j \text{ if } \psi_{kj-1} < y^*_{qtk} < \psi_{kj} \qquad (2.2)$$

The first equation is associated with the utility u^*_{qkt} for an individual q corresponding to the reason to move k at choice occasion t, and x_{qt} is an (M x 1)-column vector of attributes associated with individual q (for example, sex, age, employment status, etc.)

and individual q's choice environment (for example, family type, transportation mode to work, etc.) at the t^{th} choice occasion. β_k represents a corresponding (M x 1)-column vector of mean effects of the elements of x_{qt} for move reason k, while γ_{qk} is another (M x 1)-column vector with its m^{th} element representing unobserved factors specific to individual q and her/his choice environment that moderate the influence of the corresponding m^{th} element of the vector x_{qt} for the k^{th} move reason. η_{qk} captures unobserved individual factors that simultaneously impact stay duration and increase the propensity of moving for a certain reason k. For instance, individuals who have an intrinsic preference to experience different housing accommodations may be the ones who stay short durations at any given residence and also are likely to move out of their residence due to "accommodation reasons". Since we have multiple residential relocation records from individuals, we can estimate the presence of such individual-specific correlation effects between the residential move reason and stay duration preceding the move. ε_{qkt} is an idiosyncratic random error term assumed to be identically and independently standard gumbel distributed across individuals, move reasons, and choice occasions.

The second equation is associated with y^*_{qkt} being the latent (continuous) duration of stay for individual q before moving for reason k at the t^{th} choice occasion. This latent duration y^*_{qkt} is mapped to the actual grouped duration category y_{qkt} by the ψ thresholds ($\psi_{k0} = -\infty$ and $\psi_{kJ} = \infty$) in the usual ordered-response modeling framework. Note that y_{qkt} is observed only if the reason triggering the move (i.e., terminating the duration of stay at a residence) is associated with alternative k. x_{qt} is an (M x 1) column vector of attributes that influences the duration of stay for the q^{th} individual at the t^{th} choice occasion[4]. α_k is a corresponding (M x 1)-column vector of mean effects for category k,

[4]We use the same vector x_{qt} of independent variables in the reason for move and stay duration equations for ease in presentation, though different sets of variables may impact the two decisions.

and δ_{qk} is another (M x 1)-column vector of unobserved factors moderating the influence of attributes in x_{qt} on the duration of stay for individual q if the stay is terminated due to reason k. ξ_{qkt} is an idiosyncratic random error term, assumed identically and independently logistic distributed (across individuals, reasons for move, and choice occasions) with variance λ^2. In the current empirical context, the thresholds ψ are known (corresponding to the boundaries of the grouped categories), allowing us to estimate the variance of ξ_{qkt}.

The $\pm$ sign in front of η_{qk} in the duration category equation indicates that the correlation in unobserved individual factors between the reason to move and the duration of stay may be positive or negative. A positive sign implies that unobserved factors that increase the propensity of a move for a given reason will also increase the duration of stay preceding such a potential move, while a negative sign suggests that unobserved individual factors that increase the propensity of a move for a certain reason will decrease the duration of stay preceding such a potential move. Clearly, one expects, from an intuitive standpoint, that the latter case will hold, as also indicated in the initial discussion of η_{qk} in the context of the first equation. However, one can empirically test the models with both '+' and '−' signs to determine the best empirical result.

To complete the model structure of the system in Equations (2.1) and (2.2), it is necessary to specify the structure for the unobserved vectors γ_{qk}, δ_{qk}, and η_{qk}. In this chapter, it is assumed that the γ_{qk}, δ_{qk}, and η_{qk} elements are independent realizations from normal population distributions; $\gamma_{qkm} \sim N(0, \sigma_{km}^2)$, $\delta_{qkm} \sim N(0, \omega_{km}^2)$, and $\eta_{qk} \sim N(0, \upsilon_k^2)$. With these assumptions, the probability expressions for the reason to move and the duration category choices may be derived. Conditional on γ_{qk} and η_{qk} for each (and all) k, the probability of an individual q choosing to move for reason k at the t^{th} choice occasion is given by:

$$P_{qkt} \mid (\gamma_{q1}, \eta_{q1}, \gamma_{q2}, \eta_{q2}, ...\gamma_{qK}, \eta_{qK}) = \frac{e^{(\beta_k^{'} + \gamma_{qk}^{'}) x_{qt} + \eta_{qk}^{'}}}{\sum_{k=1}^{K} e^{(\beta_k^{'} + \gamma_{qk}^{'}) x_{qt} + \eta_{qk}^{'}}} \qquad (2.3)$$

Similarly, conditional on δ_{qk} and η_{qk}, the probability of an individual *q* choosing to stay for a particular duration category *j* preceding a move for reason *k* at the t^{th} choice occasion is given by:

$$R_{qktj} \mid (\delta_{qk}, \eta_{qk}) = G\left[\frac{\psi_{kj} - \left\{(\alpha_k^{'} + \delta_{qk}^{'}) x_q \pm \eta_{qk}\right\}}{\lambda}\right] - G\left[\frac{\psi_{kj-1} - \left\{(\alpha_k^{'} + \delta_{qk}^{'}) x_q \pm \eta_{qk}\right\}}{\lambda}\right] (2.4)$$

where G(.) is the cumulative distribution of the standard logistic distribution

The parameters to be estimated in the joint model system of Equations (2.1) and (2.2) are the β_k and α_k vectors (for each *k*), the variance parameter λ, and the following standard error terms: σ_{km}, ω_{km}, and υ_k (*m* = 1, 2,…, *M*; *k* = 1, 2,…, *K*). Let Ω represent a vector that includes all these parameters to be estimated. Also, let c_q be a vector that vertically stacks the coefficients γ_{qk}, δ_{qk}, and η_{qk} across all *k* for individual *q*. Let Σ be another vertically stacked vector of standard error terms σ_{km}, ω_{km}, and υ_k for all *k* (*k* = 1, 2,…, *K*) and *m* (*m* = 1, 2,…, *M*), and let $\Omega_{-\Sigma}$ represent a vector of all parameters except the standard error terms. Then, the likelihood function, for a given value of $\Omega_{-\Sigma}$ and error vector c_q, may be written for individual *q* as:

$$L_q(\Omega_{-\Sigma} \mid c_q) = \prod_{k=1}^{K}\prod_{t=1}^{T}\prod_{j=1}^{J}\Big[\Big(P_{qkt} \mid (\gamma_{q1}, \eta_{q1}, \gamma_{q2}, \eta_{q2}, ...\gamma_{qK}, \eta_{qK})\Big)\Big(R_{qktj} \mid \delta_{qk}, \eta_{qk}\Big)\Big]^{d_{qkt} e_{qjt}} \qquad (2.5)$$

where d_{qkt} is a dummy variable taking a value of 1 if individual *q* chooses to move for reason *k* on the t^{th} choice occasion and 0 otherwise, while e_{qjt} is a dummy variable equal to 1 if individual *q* chooses to stay for duration category *j* on the t^{th} choice occasion and 0 otherwise. Finally, the unconditional likelihood function may be computed for individual *q* as:

$$L_q(\Omega) = \int_{c_q} (L_q(\Omega_{-\Sigma}) \mid c_q)\, dF(c_q \mid \Sigma), \qquad (2.6)$$

where F is the multidimensional cumulative normal distribution. The log-likelihood function is

$$\ln L(\Omega) = \sum_q \ln L_q(\Omega). \tag{2.7}$$

The likelihood function in Equation (2.6) involves the evaluation of a multi-dimensional integral of size equal to the number of rows in c_q. We apply Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence to approximate this integral in the likelihood function and maximize the logarithm of the resulting simulated likelihood function across individuals with respect to Ω (see Bhat 2001, 2003).

2.5 Empirical analysis

2.5.1 Data Source

The examination of long term household mobility trends requires the use of longitudinal data to track residential move events and measure durations between moves. This study uses a longitudinal data set derived from a retrospective survey that was administered in the beginning of 2005 to households drawn from a stratified sample of municipalities in the Zurich region of Switzerland. Information about residential relocations and the primary reason for each relocation event for one individual (aged 18 years or older) in the household is recorded for the 20 year period of 1985-2004. For this 20 year period, retrospective information about the personal and familial history, including all data about residential locations and moving events, was collected. In addition, respondents were asked to provide information about changes in vehicle ownership and public transit season ticket holding patterns. Data on the places of education and employment, primary commute mode, and personal income was gathered for the 20 year time-span. More details on the survey may be found in Beige and Axhausen 2006.

2.5.2 Sample preparation

The survey data was extracted and compiled in a format needed to estimate the joint model system proposed in this chapter. Each moving event of each individual was associated with one of the following alternatives, with the final alternative being the "No move" alternative:

- Family reasons only (Fam)
- Education/Employment reasons only (Edu)
- Accommodation (size) related reasons only (Acc)
- Surrounding environment related reasons and proximity to family and friends only (SuVi)
- Any two of the above reasons (Two)
- All of the remaining types/reasons of moves (Oth)
- No move in the 20 year period (NM)

The durations were coded into the following four ordered categories:

- Less than 2 years
- Two years or more, but less than 5 years
- Five years or more, but less than 10 years
- Greater than 10 years

The data set was compiled at the person level to reflect the fact that households undergo transformations over a 20-year time period and that it makes more sense to track individuals over time as opposed to whole households. Only those records that had complete information for the entire 20 year period were included in the final data set for analysis. The final data set includes 1012 individuals and 2590 move records. It is to be noted that the move records do not include the first move that an individual reported in the survey. As the move prior to 1985 is not known, there is no way to calculate the duration of stay prior to the first move reported in the survey. Thus, each move record in the database includes a primary reason for move and a duration category reflecting the duration of stay prior to the reported move event.

A comprehensive descriptive analysis of the data set was undertaken prior to model specification and estimation. A concise descriptive tabulation of key variables is presented in Table 2.1.

2.5.3 Model structures estimated

In this study, three different model structures were estimated to facilitate comparisons and to evaluate the efficacy of employing the correlated joint model system proposed in this chapter. The three models are:

(1) A simple multinomial logit model for reason to move and an independent grouped response model for duration of stay, referred to as the Independent Multinomial Ordered (IMO) model

(2) A random coefficients multinomial logit model for reason to move and an independent random coefficients grouped response model for duration of stay, referred to as the Independent Random Multinomial Ordered (IRMO) model

(3) A random coefficients multinomial logit model for reason to move and a correlated random coefficients grouped response model for duration of stay, referred to as the Correlated Random Multinomial Ordered (CRMO) model.

In the context of the modeling methodology presented earlier in the chapter, the IMO model imposes assumptions that $\sigma_{km} = 0$, $\sigma_{km} = 0$, and $\upsilon_k = 0$ for all k and m. The IRMO model imposes the assumption that $\upsilon_k = 0$ for all k. The final specification of the random coefficients in the reason to move and duration of stay components of the IRMO and CRMO models were obtained after extensive testing. For the sake of brevity, only the CRMO model estimation results are presented in detail in the chapter; however, the IMO and IRMO models will be used as baseline model specifications to evaluate the efficacy of using the CRMO model structure.

2.5.4 CRMO model estimation results

Three primary categories of variables were considered for inclusion in the models. The first category includes individual characteristics such as age, gender, and employment/education status of the person at the time of move. The second category includes household characteristics such as household size, household type (family structure and life cycle stage), household income, and vehicle ownership. Finally, the third category includes commute characteristics including mode of transportation to work and commute distance. Interaction effects among these categories of variables were also considered and tested prior to arriving at the final model specification. The final model specification was driven by intuitive judgment, parsimony in specification, and statistical significance testing.

2.5.4.1 Residential move component

Model estimation results for the reason to move component of the CRMO model are presented in Table 2.2. Consistent with the multinomial logit structure for this model component, there are seven utility equations corresponding to each reason category. One of the alternative specific constants is set to zero and there is at least one base category for the introduction of other variables (in the Table all categories for a particular variable with a '-' indication together form the base i.e. an effective coefficient of zero for interpreting the effects of the variable). Consistent with the descriptive statistical analysis presented in Table 2.1, all other things being equal, family and education/employment reasons are more likely to trigger a move than other reasons as evidenced by the higher alternative specific constants for these two reasons. Another major finding worthy of being highlighted at the outset is that there were no statistically significant unobserved effects in the "reason to move" model.

Among individual characteristics, it is found that females are more likely to move due to family-related or personal reasons. Those in the age bracket of 31-45 years are less likely to move for family-related or education/employment reasons; these effects are more pronounced for those over the age of 45 years. In general, it appears that individuals who have reached a lifecycle stage where they have settled into a household and/or family setting are less likely to move for these specific reasons. Usually families are quite stable in these age ranges; family transitions occur either when individuals are young due to such events as marriage, gaining employment, or birth of a child, or when they are old due to such events as retirement, children growing up and leaving home, death of a spouse, or physical limitations set in. Those who are employed are more likely to move for reasons related to the nature of the accommodation (e.g., desiring to move to a larger home), for multiple reasons (which may include family and education/employment related factors), or for other reasons. Thus, it appears that employed individuals tend to be more inclined to move in comparison to unemployed individuals.

Among household characteristics, it is found that larger households are more likely to not move as evidenced by the positive coefficient associated with household size in the no-move equation. It is likely that larger households are mature, with children, and have stable situations that have them inclined to stay in place for longer durations. In comparison to single-person households, family households are less likely to move for education/employment or surrounding/vicinity related reasons. Again, these households are likely to be in more stable situations in the life cycle and hence more disinclined to move for these reasons. Individuals in non-family households, on the other hand, are more prone to move as evidenced by the negative coefficient associated with this variable in the no-move equation. Individuals in non-family households are less likely to have family-related roots in their current situation, and would therefore be more likely to move as they transition to more stable stages of their lifecycle. The notion of stability and its influence in reducing the likelihood of moving for various reasons is further confirmed by the negative coefficient associated with the home ownership variable. Those living in households who own their home are less likely to move for family, education/employment, and surrounding vicinity-related reasons. In other words, when such households do move, it is likely to be due to accommodation-related reasons or combinations of factors.

Commute characteristics are also found to play an important role in influencing individual residential mobility for various reasons. In comparison to those who commute by car, those who use alternate modes of transportation are more likely to move for various reasons, a finding that is rather noteworthy in the context of transport policy debates. Those who commute by bicycle appear to be most prone to moving for a variety of reasons such as education/employment, accommodation, surrounding vicinity, and a multitude of factors. Those who use public transit are more likely to move for education/employment reasons, surrounding vicinity, and other reasons. In both of these instances, it is possible that the individuals who use these modes of transportation are in neighborhoods or employment situations that are transient or less desirable. Further, those who walk are likely to move for education/employment reasons, but less likely to move for accommodation or surrounding vicinity related reasons. It appears that those who live within a comfortable walking distance from work are pleased with their neighborhood; hence, any move is triggered by an education/employment related reason as opposed to a neighborhood or housing related reason. Finally, if one commutes more than 10 km to work, then the likelihood of not moving reduces; in other words those who commute longer distances are likely to move, presumably to find a more palatable commuting distance.

2.5.4.2 Stay duration component

The stay duration component of the model system is presented in Table 2.3. It is to be noted that there are six possible duration equations that can be estimated, one for each reason to move. After extensive testing and model estimation runs, it was found that there were no significant differences across model coefficients among the different reasons; therefore, virtually all parameters (except for a couple of constants) are identical across the six move reasons.

Among individual characteristics, females are likely to have shorter stay durations across all reasons for moving. It is not immediately clear as to why this is the case and further exploration of the basis for this finding is warranted in future research on this topic. Age exhibits a non-linear effect with the square of age showing a negative effect, but the square of age showing a positive effect. This parabolic relationship means that, as age increases, the duration of stay tends to decrease. However, this tendency peaks at the age of 39 years and reduces with age until individuals are about 75 years old. After the age of 75 years, there is an overall positive impact of age on duration of stay. Thus, it appears that people move when they are young, but the frequency of moving decreases (thus, durations get longer) after the age of 39 until the age of 75 years. After the age of 75, individuals tend to be quite stable in place, contributing to the positive effect on the square of age.

Among household characteristics, individuals in larger households tend to have longer stay durations, consistent with earlier findings that these individuals are less likely to move. However, it is noteworthy that the impact of household size exhibits variability across the population as indicated by the statistically significant standard deviation on the unobserved component associated with household size variable. Thus, this model specification captures unobserved heterogeneity in the population with respect to household size effects. An individual in a non-family household tends have shorter stay durations, while an individual in a household that owns its home tends to have longer stay durations. Individuals in smaller houses (with just one or two rooms) tend to have shorter stay durations as evidenced by the negative coefficient associated with this variable. Presumably, these individuals are more prone to moving frequently as they attempt to upgrade to larger and more spacious homes. Finally, those commuting by public transportation and bicycle tend to have shorter stay durations, consistent with the findings reported in the reason-to-move model. Also, those commuting more than 10 km tend to have shorter stay durations as well, presumably because they move more frequently in search of housing that reduces their commute.

The CRMO model presented in Tables 2.2 and 2.3 clearly shows the importance of capturing the correlation across the move reason and the duration of stay phenomena (see the last row of Table 2.3, which presents the υ_k estimates). In the estimations, we considered both the positive and negative signs on the η_{qk} terms in Equation (2.2) for each (and all) k, and the negative sign for all k provided statistically superior results. Also, the standard error (deviation) estimates were not statistically different in magnitude across the move regimes, and so were constrained to be equal across regimes. The magnitude and significance of the standard deviations of the η_{qk} terms, along with the negative sign on these terms in Equation (2.2), confirms our hypothesis of the presence of a negative correlation due to common unobserved individual elements between the propensity to move and the corresponding duration of stay for each move regime k.

2.5.5 Model assessment

As mentioned earlier, three distinct model systems were estimated. The IMO and IRMO model systems offered nearly identical statistical goodness-of-fit measures. The log-likelihood value at convergence for the IMO model is -7397.9 with 44 parameters, while that for the IRMO model is -7397.1 with 45 parameters. A likelihood ratio test comparison between these models does not reject the hypotheses that these two models are identical with respect to statistical fit. On the other hand, the CRMO model yields a log-likelihood value of -7227.2 with 46 parameters. Likelihood ratio test statistics show that the CRMO offers significantly better goodness-of-fit at any level of significance. This finding further corroborates that accounting for error correlation across the reason-to-move and stay-duration equations results in statistically superior parameter estimates.

2.6 Summary

The current chapter focuses on modeling household residential relocation decisions. In particular, the emphasis is on jointly modeling the reason for residential relocation and the associated duration of stay. The chapter formulates an econometric framework to model these choices in a unified framework. The model in this chapter takes the form of a joint multinomial logit model of reason for move and a grouped logit model of residential stay duration preceding the move. The econometric model formulated is applied for actual data using data drawn from a 2005 retrospective survey in the Zurich region of Switzerland. Several demographic, socio-economic, and commute related variables are found to significantly influence the reason for move and the duration of stay. What is most important in the context of this study is the finding that there are common unobserved factors affecting the reason to move and the duration of stay choices. This simultaneity or endogeneity between the choice processes clearly calls for modeling these two choice dimensions in a joint modeling framework that accommodates error correlation structures. In addition, in the duration of stay model, it was found that the impact of household size exhibited heterogeneity across the sample of individuals considered in this study. Goodness-of-fit measures were significantly superior for the joint correlated model structure, clearly favoring the use of the model framework presented here for modeling residential mobility processes.

Table 2.1: Sample Characteristics

Characteristics	Sample shares
Dependent variable	
Reason for move	
Family reasons only	23.1%
Education/Employment reasons only	20.5%
Accommodation related reasons only	15.5%
Surrounding environment related reasons and Vicinity to family and friends only	7.4%
Two of the above reasons	22.7%
All other reasons for move	8.1%
No move	2.7%
Duration of stay category	
< 2 years	39.2%
2 - 5 years	37.0%
5 - 10 years	14.7%
> 10 years	9.1%
Characteristics	
Gender	
Male	49.8%
Female	50.2%
Average number of moves per person in 20 years	2.6
Sample size	*2590*

Table 2.2: Reason to Move Component of Joint Model

Characteristics \ Alternatives	Fam		Edu		Acc		SuVi		Two		Oth		NM	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	3.010	7.50	3.589	8.87	2.185	5.37	2.290	5.59	2.613	6.50	1.172	2.76	-	-
<u>Individual characteristics</u>														
Gender														
Female	0.332	2.40	-	-	-	-	-	-	-	-	-	-	-	-
Age														
Age 31 - 45 years	-0.261	-2.14	-0.261	-2.14	-	-	-	-	-	-	-	-	-	-
Age > 45 years	-1.234	-6.97	-1.234	-6.97	-	-	-	-	-	-	-	-	-	-
Employed	-	-	-	-	0.260	1.69	-	-	0.201	1.42	0.355	1.82	-	-
<u>Household characteristics</u>														
Household size	-	-	-	-	-	-	-	-	-	-	-	-	0.513	4.11
Household Type (Single person household is base)														
Family household	-	-	-1.397	-10.36	-	-	-1.100	-6.50	-	-	-	-	-	-
Non-family household	-	-	-	-	-	-	-	-	-	-	-	-	-2.095	-1.96
Household tenure (Rent is base)														
Own household	-0.463	-2.70	-1.634	-5.47	-	-	-0.826	-2.68	-	-	-	-	-	-
<u>Commute characteristics</u>														
Mode to work (Car is base)														
Public transportation	-	-	0.314	2.05	-	-	0.195	0.97	-	-	0.363	2.00	-	-
Bicycle	-	-	1.178	4.46	0.963	3.17	0.388	1.01	0.970	3.71	1.054	3.25	-	-
Walk	-	-	0.619	2.64	-0.549	-1.70	-0.937	-2.01	-	-	-	-	-	-
Distance to work														
Above 10 km	-	-	-	-	-	-	-	-	-	-	-	-	-1.249	-3.03

Table 2.3: Duration of Stay Component of Joint Model

Characteristics \ Alternatives	Fam		Edu		Acc		SuVi		Two		Oth	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	4.128	6.84	4.128	6.84	4.526	7.40	4.128	6.84	4.526	7.40	4.128	6.84
<u>Individual characteristics</u>												
Gender	-0.461	-2.60	-0.461	-2.60	-0.461	-2.60	-0.461	-2.60	-0.461	-2.60	-0.461	-2.60
Female												
Age	-0.059	-2.11	-0.059	-2.11	-0.059	-2.11	-0.059	-2.11	-0.059	-2.11	-0.059	-2.11
Age square / 1000	0.783	2.16	0.783	2.16	0.783	2.16	0.783	2.16	0.783	2.16	0.783	2.16
<u>Household characteristics</u>												
Household size	0.567	5.62	0.567	5.62	0.567	5.62	0.567	5.62	0.567	5.62	0.567	5.62
Standard Deviation	0.171	1.67	0.171	1.67	0.171	1.67	0.171	1.67	0.171	1.67	0.171	1.67
Household Type (Single person household is base)												
Non-family household	-1.754	-6.27	-1.754	-6.27	-1.754	-6.27	-1.754	-6.27	-1.754	-6.27	-1.754	-6.27
Number of rooms in the house												
1 - 2 rooms	-0.825	-3.37	-0.825	-3.37	-0.825	-3.37	-0.825	-3.37	-0.825	-3.37	-0.825	-3.37
Household tenure (Rent is base)												
Own household	0.557	2.37	0.557	2.37	0.557	2.37	0.557	2.37	0.557	2.37	0.557	2.37
<u>Commute characteristics</u>												
Mode to work (Car is base)												
Public transportation	-0.442	-2.30	-0.442	-2.30	-0.442	-2.30	-0.442	-2.30	-0.442	-2.30	-0.442	-2.30
Bicycle	-0.624	-2.11	-0.624	-2.11	-0.624	-2.11	-0.624	-2.11	-0.624	-2.11	-0.624	-2.11
Distance to work												
Above 10 km	-0.920	-4.89	-0.920	-4.89	-0.920	-4.89	-0.920	-4.89	-0.920	-4.89	-0.920	-4.89
Variance (λ)	2.112	39.07	2.112	39.07	2.112	39.07	2.112	39.07	2.112	39.07	2.112	39.07
<u>Common Unobserved component</u>												
Standard Deviation (υ_k)	1.109	21.58	1.109	21.58	1.109	21.58	1.109	21.58	1.109	21.58	1.109	21.58

CHAPTER 3 EXAMINING THE INFLUENCE OF BUILT ENVIRONMENT ON TRAVEL DEMAND

3.1 Introduction

There has been considerable interest in the land use-transportation connection in the past decade, motivated by the possibility that land-use and urban form design policies can be used to control, manage, and shape individual traveler behavior and aggregate travel demand. A central issue in this regard is the debate whether any effect of the built environment on travel demand is causal or merely associative (or some combination of the two; see Bhat and Guo, 2007). To explicate this, consider a cross-sectional sample of households, some of whom live in a neo-urbanist neighborhood and others of whom live in a conventional neighborhood. A neo-urbanist neighborhood is one with high population density, high bicycle lane and roadway street density, good land-use mix, and good transit and non-motorized mode accessibility/facilities. A conventional neighborhood is one with relatively low population density, low bicycle lane and roadway street density, primarily single use residential land use, and auto-dependent urban design. Assume that the vehicle miles of travel (VMT) of households living in conventional neighborhoods is higher than the VMT of households residing in neo-urbanist neighborhoods. The question is whether this difference in VMT between households in conventional and neo-urbanist households is due to "true" effects of the built environment, or due to households self-selecting themselves into neighborhoods based on their VMT desires. For instance, it is at least possible (if not likely) that unobserved factors that increase the propensity or desire of a household to reside in a conventional neighborhood (such as overall auto inclination, a predisposition to enjoying travel, safety and security concerns regarding non-auto travel, *etc.*) also lead to the household putting more vehicle miles of travel on personal vehicles. If this self selection is not accounted for, the difference in VMT attributed directly to the variation in the built environment between conventional and neo-urbanist neighborhoods can be misestimated. On the other hand, accommodating for such self-selection effects can aid in identifying the "true" causal effect of the built environment on VMT.

The situation just discussed can be cast in the form of Roy's (1951) endogenous switching model system (see Maddala, 1983; Chapter 9), which takes the following form:

$$\begin{aligned} &r_q^* = \beta' x_q + \varepsilon_q, \quad r_q = 1 \text{ if } r_q^* > 0, \quad r_q = 0 \text{ if } r_q^* \leq 0, \\ &m_{q0}^* = \alpha' z_q + \eta_q, \; m_{q0} = 1[r_q = 0] m_{q0}^* \\ &m_{q1}^* = \gamma' w_q + \xi_q, \; m_{q1} = 1[r_q = 1] m_{q1}^* \end{aligned} \tag{3.1}$$

The notation $1[r_q = 0]$ represents an indicator function taking the value 1 if $r_q = 0$ and 0 otherwise, while the notation $1[r_q = 1]$ represents an indicator function taking the value 1 if $r_q = 1$ and 0 otherwise. The first selection equation represents a binary discrete decision of households to reside in a neo-urbanist built environment neighborhood or a conventional built environment neighborhood. r_q^* in Equation (3.1) is the unobserved propensity to reside in a conventional neighborhood relative to a neo-urbanist neighborhood, which is a function of an (*M* x 1)-column vector x_q of household attributes (including a constant). β represents a corresponding (*M* x 1)-column vector of household attribute effects on the unobserved propensity to reside in a conventional neighborhood relative to a neo-urbanist neighborhood. In the usual structure of a binary choice model, the unobserved propensity r_q^* gets reflected in the actual observed choice r_q (r_q = 1 if the *q*th household chooses to reside in a conventional neighborhood, and r_q = 0 if the *q*th household decides to reside in a neo-urbanist neighborhood). ε_q is usually a standard normal or logistic error tem capturing the effects of unobserved factors on the residential choice decision.

The second and third equations of the system in Equation (3.1) represent the continuous outcome variables of log(vehicle miles of travel) in our empirical context. m_{q0}^* is a latent variable representing the logarithm of miles of travel if a random household *q* were to reside in a neo-urbanist neighborhood, and m_{q1}^* is the corresponding variable if the household q were to reside in a conventional neighborhood. These are related to vectors of household attributes z_q and w_q, respectively, in the usual linear regression fashion, with η_q and ξ_q being random error terms. Of course, we observe m^*_{q0} in the form of m_{q0} only if household q in the sample is observed to live in a neo-urbanist neighborhood. Similarly, we observe m^*_{q1} in the form of m_{q1} only if household q in the sample is observed to live in a conventional neighborhood.

The potential dependence between the error pairs (ε_q, η_q) and (ε_q, ξ_q) has to be expressly recognized in the above system, as discussed earlier from an intuitive standpoint.[5] The classic econometric estimation approach proceeds by using Heckman's or Lee's approaches or their variants (Heckman, 1974, 1976, 1979, 2001, Greene, 1981, Lee, 1982, 1983, Dubin and McFadden, 1984). Heckman's (1974) original approach used a full information maximum likelihood method with bivariate normal distribution assumptions for (ε_q, η_q) and (ε_q, ξ_q). Lee (1983) generalized Heckman's approach by allowing the univariate error terms ε_q, η_q, and ξ_q to be non-normal, using a technique to transform non-normal variables into normal variates, and then adopting a bivariate normal distribution to couple the transformed normal variables. Thus, while maintaining an efficient full-information likelihood approach, Lee's method relaxes the normality assumption on the marginals but still imposes a bivariate normal coupling. In addition to these full-information likelihood methods, there are also two-step and more robust parametric approaches that impose a specific form of linearity between the error term in the discrete choice and the continuous outcome (rather than a pre-specified bivariate joint distribution). These approaches are based on the Heckman method for the binary choice case, which was generalized by Hay (1980) and Dubin and McFadden (1984) for the multinomial case. The approach involves the first step estimation of the discrete choice equation given distributional assumptions on the choice model error terms, followed by

[5] The reader will note that it is not possible to identify any dependence parameters between (η_q, ξ_q) because the vehicle miles of travel is observed in only one of the two regimes for any given household.

the second step estimation of the continuous equation after the introduction of a correction term that is an estimate of the expected value of the continuous equation error term given the discrete choice. However, these two-step methods do not perform well when there is a high degree of collinearity between the explanatory variables in the choice equation and the continuous outcome equation, as is usually the case in empirical applications. This is because the correction term in the second step involves a non-linear function of the discrete choice explanatory variables. But this non-linear function is effectively a linear function for a substantial range, causing identification problems when the set of discrete choice explanatory variables and continuous outcome explanatory variables are about the same. The net result is that the two-step approach can lead to unreliable estimates for the outcome equation (see Leung and Yu, 2000 and Puhani, 2000).

Overall, Lee's full information maximum likelihood approach has seen more application in the literature relative to the other approaches just described because of its simple structure, ease of estimation using a maximum likelihood approach, and its lower vulnerability to the collinearity problem of two-step methods. But Lee's approach is also critically predicated on the bivariate normality assumption on the transformed normal variates in the discrete and continuous equation, which imposes the restriction that the dependence between the transformed discrete and continuous choice error terms is linear and symmetric. There are two ways that one can relax this joint bivariate normal coupling used in Lee's approach. One is to use semi-parametric or non-parametric approaches to characterize the relationship between the discrete and continuous error terms, and the second is to test alternative copula-based bivariate distributional assumptions to couple error terms. Each of these approaches is discussed in turn next.

3.1.1 Semi-Parametric and Non-Parametric Approaches

The potential econometric estimation problems associated with Lee's parametric distribution approach has spawned a whole set of semi-parametric and non-parametric two-step estimation methods to handle sample selection, apparently having beginnings in the semi-parametric work of Heckman and Robb (1985). The general approach in these methods is to first estimate the discrete choice model in a semi-parametric or non-parametric fashion using methods developed by, among others, Cosslett (1983), Ichimura (1993), Matzkin (1992, 1993), and Briesch *et al.* (2002). These estimates then form the basis to develop an index function to generate a correction term in the continuous equation that is an estimate of the expected value of the continuous equation error term given the discrete choice. While in the two-step parametric methods, the index function is defined based on the assumed marginal and joint distributional assumptions, or on an assumed marginal distribution for the discrete choice along with a specific linear form of relationship between the discrete and continuous equation error terms, in the semi- and non-parametric approaches, the index function is approximated by a flexible function of parameters such as the polynomial, Hermitian, or Fourier series expansion methods (see Vella, 1998 and Bourguignon *et al.*, 2007 for good reviews). But, of course, there are "no free lunches". The semi-parametric and non-parametric approaches involve a large number of parameters to estimate, are relatively very inefficient from an econometric estimation standpoint, typically do not allow the testing and inclusion of a rich set of explanatory variables with the usual range of sample sizes available in empirical contexts, and are difficult to implement. Further, the computation of the covariance matrix of parameters for inference is anything but simple in the semi- and non-parametric approaches. The net result is that the semi- and non-parametric approaches have been pretty much confined to the academic realm and have seen little use in actual empirical application.

3.1.2 The Copula Approach

The turn toward semi-parametric and non-parametric approaches to dealing with sample selection was ostensibly because of a sense that replacing Lee's parametric bivariate normal coupling with alternative bivariate couplings would lead to substantial computational burden. However, an approach referred to as the "Copula" approach has recently revived interest in maintaining a Lee-like sample selection framework, while generalizing Lee's framework to adopt and test a whole set of alternative bivariate couplings that can allow non-linear and asymmetric dependencies. A copula is essentially a multivariate functional form for the joint distribution of random variables derived purely from pre-specified parametric marginal distributions of each random variable. The reasons for the interest in the copula approach for sample selection models are several. First, the copula approach does not entail any more computational burden than Lee's approach. Second, the approach allows the analyst to stay within the familiar maximum likelihood framework for estimation and inference, and does not entail any kind of numerical integration or simulation machinery. Third, the approach allows the marginal distributions in the discrete and continuous equations to take on any parametric distribution, just as in Lee's method. Finally, under the copula approach, Lee's coupling method is but one of a suite of different types of couplings that can be tested.

In this chapter, we apply the copula approach to examine built environment effects on vehicle miles of travel (VMT). The rest of this chapter is structured as follows. The next section provides a theoretical overview of the copula approach, and presents several important copula structures. Section 3.3 discusses the use of copulas in sample selection models. Section 3.4 provides an overview of the data sources and sample used for the empirical application. Section 3.5 presents and discusses the modeling results. The final section concludes the chapter by highlighting its findings.

3.2 Overview of the copula approach

3.2.1 <u>Background</u>

The incorporation of dependency effects in econometric models can be greatly facilitated by using a copula approach for modeling joint distributions, so that the resulting model can be in closed-form and can be estimated using direct maximum likelihood techniques (the reader is referred to Trivedi and Zimmer, 2007 or Nelsen, 2006 for extensive reviews of copula theory, approaches, and benefits). The word copula itself was coined by Sklar, 1959 and is derived from the Latin word "copulare", which means to tie, bond, or connect (see Schmidt, 2007). Thus, a copula is a device or function that generates a stochastic dependence relationship (*i.e.*, a multivariate distribution) among random variables with pre-specified marginal distributions. In essence, the copula approach separates the marginal distributions from the dependence structure, so that the dependence structure is entirely unaffected by the marginal distributions assumed. This provides substantial flexibility in correlating random variables, which may not even have the same marginal distributions.

The effectiveness of a copula approach has been recognized in the statistics field for several decades now (see Schweizer and Sklar, 1983, Ch. 6), but it is only recently that copula-based methods have been explicitly recognized and employed in the finance, actuarial science, hydrological modeling, and econometrics fields (see, for example, Embrechts *et al.*, 2002, Cherubini *et al.*, 2004, Frees and Wang, 2005, Genest and Favre, 2007, Grimaldi and Serinaldi, 2006, Smith, 2005, Prieger, 2002, Zimmer and Trivedi, 2006, Cameron *et al.*, 2004, Junker and May, 2005, and Quinn, 2007). The precise definition of a copula is that it is a multivariate distribution function defined over the unit cube linking uniformly distributed marginals. Let C be a K-dimensional copula of uniformly distributed random variables U_1, U_2, U_3, …, U_K with support contained in $[0,1]^K$. Then,

$$C_\theta (u_1, u_2, \ldots, u_K) = \Pr(U_1 < u_1, U_2 < u_2, \ldots, U_K < u_K), \tag{3.2}$$

where θ is a parameter vector of the copula commonly referred to as the dependence parameter vector. A copula, once developed, allows the generation of joint multivariate distribution functions with given marginals. Consider K random variables Y_1, Y_2, Y_3, …, Y_K, each with univariate continuous marginal distribution functions $F_k(y_k) = \Pr(Y_k < y_k)$, k =1, 2, 3, …, K. Then, by the integral transform result, and using the notation $F_k^{-1}(.)$ for the inverse univariate cumulative distribution function, we can write the following expression for each k (k = 1, 2, 3, …, K):

$$F_k(y_k) = \Pr(Y_k < y_k) = \Pr(F_k^{-1}(U_k) < y_k) = \Pr(U_k < F_k(y_k)). \tag{3.3}$$

Then, by Sklar's (1973) theorem, a joint K-dimensional distribution function of the random variables with the continuous marginal distribution functions $F_k(y_k)$ can be generated as follows:

$F(y_1, y_2, \ldots, y_K) = \Pr(Y_1 < y_1, Y_2 < y_2, \ldots, Y_K < y_K) = \Pr(U_1 < F_1(y_1), U_2 < F_2(y_2), \ldots, U_K < F_K(y_K))$

$$= C_\theta (u_1 = F_1(y_1), u_2 = F_2(y_2), \ldots, u_K = F_K(y_K)). \tag{3.4}$$

Conversely, by Sklar's theorem, for any multivariate distribution function with continuous marginal distribution functions, a unique copula can be defined that satisfies the condition in Equation (3.4).

Copulas themselves can be generated in several different ways, including the method of inversion, geometric methods, and algebraic methods (see Nelsen, 2006; Ch. 3). For instance, given a known multivariate distribution $F(y_1, y_2, \ldots, y_K)$ with continuous margins $F_k(y_k)$, the inversion method inverts the relationship in Equation (3.4) to obtain a copula:

$$\begin{aligned} C_\theta (u_1, u_2, \ldots, u_K) &= \Pr(U_1 < u_1, U_2 < u_2, \ldots, U_K < u_K) \\ &= \Pr(Y_1 < F^{-1}{}_1(u_1), Y_2 < F^{-1}{}_2(u_2), \ldots, Y_3 < F^{-1}{}_3(u_3)) \\ &= F(y_1 = F^{-1}{}_1(u_1), y_2 = F^{-1}{}_2(u_2), \ldots, y_K = F^{-1}{}_k(u_k)). \end{aligned} \tag{3.5}$$

Once the copula is developed, one can revert to Equation (3.4) to develop new multivariate distributions with arbitrary univariate margins.

A rich set of copula types have been generated using the inversion and other methods, including the Gaussian copula, the Farlie-Gumbel-Morgenstern (FGM) copula, and the Archimedean class of copulas (including the Clayton, Gumbel, Frank, and Joe copulas). These copulas are discussed later in the context of bivariate distributions. In such bivariate distributions, while θ can be a vector of parameters, it is customary to use a scalar measure of dependence. In the next section, we discuss some copula properties and dependence structure concepts for bivariate copulas, though generalizations to higher dimensions are possible.

3.2.2 Copula Properties and Dependence Structure

Consider any bivariate copula $C_\theta(u_1, u_2)$. Since this is a bivariate cumulative distribution function, the copula should satisfy the well known Fréchet-Hoeffding bounds (see

Kwerel, 1988). Specifically, the Fréchet lower bound $W(u_1, u_2)$ is $\max(u_1 + u_2 - 1, 0)$ and the Fréchet upper bound $M(u_1, u_2)$ is $\min(u_1, u_2)$. Thus,

$$W(u_1, u_2) \leq C_\theta(u_1, u_2) \leq M(u_1, u_2). \tag{3.6}$$

From Sklar's theorem of Equation (3.4), we can also re-write the equation above in terms of Fréchet bounds for the multivariate distribution $F(y_1, y_2)$ generated from the copula $C_\theta(u_1, u_2)$:

$$\max(F_1(y_1) + F_2(y_2) - 1, 0) \leq F(y_1, y_2) \leq \min(F_1(y_1), F_2(y_2)). \tag{3.7}$$

If the copula $C_\theta(u_1, u_2)$ is equal to the lower bound $W(u_1, u_2)$ in Equation (3.6), or equivalently if $F(y_1, y_2)$ is equal to the lower bound in Equation (3.7), then the random variables Y_1 and Y_2 are almost surely decreasing functions of each other and are called "countermonotonic". On the other hand, if the copula $C_\theta(u_1, u_2)$ is equal to the upper bound $M(u_1, u_2)$ in Equation (3.6), or equivalently if $F(y_1, y_2)$ is equal to the upper bound in Equation (3.7), then the random variables Y_1 and Y_2 are almost surely increasing functions of each other and are called "comonotonic". The case when $C_\theta(u_1, u_2) = \Pi = u_1 u_2$, or equivalently $F(y_1, y_2) = F_1(y_1)F_2(y_2)$, corresponds to stochastic independence between Y_1 and Y_2.

Different copulas provide different levels of ability to capture dependence between Y_1 and Y_2 based on the degree to which they cover the interval between the Fréchet-Hoeffding bounds. Comprehensive copulas are those that (1) attain or approach the lower bound W as θ approaches the lower bound of its permissible range, (2) attain or approach the upper bound M as θ approaches its upper bound, and (3) cover the entire domain between W and M (including the product copula case Π as a special or limiting case). Thus, comprehensive copulas parameterize the full range of dependence as opposed to non-comprehensive copulas that are only able to capture dependence in a limited manner. As we discuss later, the Gaussian and Frank copulas are comprehensive in their dependence structure, while the FGM, Clayton, Gumbel, and Joe copulas are not comprehensive.

To better understand the generated dependence structures between the random variables (Y_1, Y_2) based on different copulas, and examine the coverage offered by non-comprehensive copulas, it is useful to construct a scalar dependence measure between Y_1 and Y_2 that satisfies four properties as listed below (see Embrechts *et al.*, 2002):

(1) $\delta(Y_1, Y_2) = \delta(Y_2, Y_1)$

(2) $-1 \leq \delta(Y_1, Y_2) \leq 1$ (3.8)

(3) $\delta(Y_1, Y_2) = 1 \Leftrightarrow (Y_1, Y_2)$ comonotonic; $\delta(Y_1, Y_2) = -1 \Leftrightarrow (Y_1, Y_2)$ countermonotonic

(4) $\delta(Y_1, Y_2) = \delta(G_1(Y_1), G_2(Y_2))$, where G_1 and G_2 are two (possibly different) strictly increasing transformations.

The traditional dependence concept of correlation coefficient ρ (*i.e.*, the Pearson's product-moment correlation coefficient) is a measure of linear dependence between Y_1 and Y_2. It satisfies the first two of the properties discussed above. However, it satisfies the third property only for bivariate elliptical distributions (including the bivariate normal distribution) and adheres to the fourth property only for strictly increasing <u>linear</u> transformations (see Embrechts *et al.*, 2002 for specific examples where the Pearson's correlation coefficient fails the third and fourth properties). In addition, $\rho = 0$ does not necessarily imply independence. A simple example given by Embrechts *et al.*, 2002 is that $\rho(Y_1, Y_2) = 0$ if $Y_1 \sim N$ (0,1) and $Y_2 = Y_1^2$, even though Y_1 and Y_2 are clearly dependent. This is because Cov(Y_1, Y_2) = 0 implies zero correlation, but the stronger condition that Cov($G_1(Y_1)$, ($G_2(Y_2)$) = 0 for any functions G_1 and G_2 is needed for zero dependence. Other limitations of the Pearson's correlation coefficient include that it is not informative for asymmetric distributions (Boyer *et al.*, 1999), effectively goes to zero as one asymptotically heads into tail events just because the joint distribution gets flatter at the tails (Embrechts *et al.*, 2002), and the attainable correlation coefficient values within the [–1, 1] range depend upon the margins $F_1(.)$ and $F_2(.)$.

The limitations of the traditional correlation coefficient have led statisticians to the use of concordance measures to characterize dependence. Basically, two random variables are labeled as being concordant (discordant) if large values of one variable are associated with large (small) values of the other, and small values of one variable are associated with small (large) values of the other. This concordance concept has led to the use of two measures of dependence in the literature: the Kendall's τ and the Spearman's ρ_S.

Kendall's τ measure of dependence between two random variables (Y_1, Y_2) is defined as the probability of concordance minus the probability of discordance. Notationally,

$$\tau(Y_1, Y_2) = P\left((Y_1 - \tilde{Y}_1)(Y_2 - \tilde{Y}_2) > 0\right) - P\left((Y_1 - \tilde{Y}_1)(Y_2 - \tilde{Y}_2) < 0\right), \tag{3.9}$$

where $(\tilde{Y}_1, \tilde{Y}_2)$ is an independent copy of (Y_1, Y_2). The first expression on the right side is the probability of concordance of (Y_1, Y_2) and $(\tilde{Y}_1, \tilde{Y}_2)$, and the second expression on the right side is the probability of discordance of the same two vectors. It is straightforward to show that if $C_\theta(u_1, u_2)$ is the copula for the continuous random variables (Y_1, Y_2), *i.e.*, if $F(y_1, y_2) = C_\theta(u_1 = F_1(y_1),\ u_2 = F_2(y_2))$, then the expression above collapses to the following (see Nelsen, 2006, page 159 for a proof):

$$\tau(Y_1, Y_2) = 4\iint_{[0,1]^2} C_\theta(u_1, u_2)\, dC_\theta(u_1, u_2) - 1 = 4E[C_\theta(U_1, U_2)] - 1, \tag{3.10}$$

where the second expression is the expected value of the function $C_\theta(U_1, U_2)$ of uniformly distributed random variables U_1 and U_2 with a joint distribution function C.

Spearman's ρ_S measure of dependence between two random variables (Y_1, Y_2) is defined as follows. Let $(\tilde{Y}_1, \tilde{Y}_2)$ and $(\breve{Y}_1, \breve{Y}_2)$ be independent copies of (Y_1, Y_2). That is, (Y_1, Y_2), $(\tilde{Y}_1, \tilde{Y}_2)$, and $(\breve{Y}_1, \breve{Y}_2)$ are all independent random vectors, each with a common joint distribution function F(.,.) and margins F_1 and F_2. Then, Spearman's ρ_S is three times the probability of concordance minus the probability of discordance for the two vectors (Y_1, Y_2) and $(\tilde{Y}_1, \breve{Y}_2)$:

$$\rho_S(Y_1, Y_2) = 3\left(P\left((Y_1 - \tilde{Y}_1)(Y_2 - \breve{Y}_2) > 0\right) - P\left((Y_1 - \tilde{Y}_1)(Y_2 - \breve{Y}_2)\right) < 0\right) \tag{3.11}$$

In the above expression, note that the distribution function for (Y_1, Y_2) is F(.,.), while the distribution function of $(\tilde{Y}_1, \breve{Y}_2)$ is $F_1(.)F_2(.)$. because of the independence of

$\tilde{Y}_1$ and $\breve{Y}_2$. The coefficient "3" is a normalization constant, since the expression in parenthesis is bounded in the region [–1/3, 1/3] (see Nelsen, 2006, pg 161). In terms of the copula $C_\theta(u_1,u_2)$ for the continuous random variables (Y_1,Y_2), ρ_S can be simplified to the expression below:

$$\rho_S(Y_1,Y_2)=12\iint_{[0,1]^2} u_1u_2dC_\theta(u_1,u_2)-3=12\iint_{[0,1]^2} C_\theta(u_1,u_2)du_1du_2-3=12E[(U_1U_2)]-3 \tag{3.12}$$

where $U_1=F_1(Y_1)$ and $U_2=F_2(Y_2)$ are uniform random variables with joint distribution function $C_\theta(u_1,u_2)$. Since U_1 and U_2 have a mean of 0.5 and a variance of 1/12, the expression above can be re-written as:

$$\begin{aligned}\rho_S(Y_1,Y_2)&=12E[(U_1U_2)]-3=\frac{E(U_1U_2)-1/4}{1/12}=\frac{E(U_1U_2)-E(U_1)E(U_2)}{\sqrt{Var(U_1)}\sqrt{Var(U_2)}} \\ &=\rho(F_1(Y_1),F_2(Y_2))\end{aligned} \tag{3.13}$$

Thus, the Spearman ρ_S dependence measure for a pair of continuous variables (Y_1,Y_2) is equivalent to the familiar Pearson's correlation coefficient ρ for the grades of Y_1 and Y_2, where the grade of Y_1 is $F_1(Y_1)$ and the grade of Y_2 is $F_2(Y_2)$.

The Kendall's τ and the Spearman's ρ_S measures can be shown to satisfy all the four properties listed in Equation (3.8). In addition, both assume the value of zero under independence and are not dependent on the margins $F_1(.)$ and $F_2(.)$. Hence, these two concordance measures are used to characterize dependence structures in the copula literature, rather than the familiar Pearson's correlation coefficient.

3.2.3 Alternative Copulas

Several copulas have been formulated in the literature, and these copulas can be used to tie random variables together. In the bivariate case, given a particular bivariate copula, a bivariate distribution $F(y_1, y_2)$ can be generated for two random variables Y_1 (with margin F_1) and Y_2 (with margin F_2) using the general expression of Equation (3.4) as:

$$F(y_1, y_2) = C_\theta(u_1 = F_1(y_1), u_2 = F_2(y_2)) \tag{3.14}$$

For given functional forms of the margins, the precise bivariate dependence profile between the variables Y_1 and Y_2 is a function of the copula $C_\theta(u_1, u_2)$ used, and the dependence parameter θ. But, regardless of the margins assumed, the overall nature of the dependence between Y_1 and Y_2 is determined by the copula. Note also that the Kendall's τ and the Spearman's ρ_S measures are functions only of the copula used and the dependence parameter in the copula, and not dependent on the functional forms of the margins. Thus, bounds on the τ and ρ_S measures for any copula will apply to all bivariate distributions derived from that copula. In the rest of this section, we focus on bivariate forms of the Gaussian copula, the Farlie-Gumbel-Morgenstern (FGM) copula, and the Archimedean class of copulas. To visualize the dependence structure for each copula, we follow Nelsen (2006) and Armstrong (2003), and first generate 1000 pairs of uniform random variates from the copula with a specified value of Kendall's τ (see http://www.caee.utexas.edu/prof/bhat/ABSTRACTS/Supp_material.pdf for details of the procedure to generate uniform variates from each copula). Then, we transform these uniform random variates to normal random variates using the integral transform result ($Y_1 = \Phi^{-1}(U_1)$ and $Y_2 = \Phi^{-1}(U_2)$). For each copula, we plot two-way scatter diagrams of the realizations of the normally distributed random variables Y_1 and Y_2. In addition, Table 3.1 provides comprehensive details of each of the copulas.

3.2.3.1 The Gaussian copula

The Gaussian copula is the most familiar of all copulas, and forms the basis for Lee's (1983) sample selection mechanism. The copula belongs to the class of elliptical copulas, since the Gaussian copula is simply the copula of the elliptical bivariate normal distribution (the density contours of elliptical distributions are elliptical with constant eccentricity). The Gaussian copula takes the following form:

$$C_\theta(u_1, u_2) = \Phi_2(\Phi^{-1}(u_1), \Phi^{-1}(u_2), \theta), \quad (3.15)$$

where $\Phi_2(.,.,\theta)$ is the bivariate cumulative distribution function with Pearson's correlation parameter $\theta(-1 \le \theta \le 1)$. The Gaussian copula is comprehensive in that it attains the Fréchet lower and upper bounds, and captures the full range of (negative or positive) dependence between two random variables. However, it also assumes the property of asymptotic independence. That is, regardless of the level of correlation assumed, extreme tail events appear to be independent in each margin just because the density function gets very thin at the tails (see Embrechts *et al.*, 2002). Further, the dependence structure is radially symmetric about the center point in the Gaussian copula. That is, for a given correlation, the level of dependence is equal in the upper and lower tails.[6]

The Kendall's τ and the Spearman's ρ_S measures for the Gaussian copula can be written in terms of the dependence (correlation) parameter θ as $\tau = (2/\pi)\sin^{-1}(\theta)$ and $\rho_S = (6/\pi)\sin^{-1}(\theta/2)$, where $z = \sin^{-1}(\theta) \Rightarrow \sin(z) = \theta$. Thus, τ and ρ_S take on values on [–1, 1]. The Spearman's ρ_S tracks the correlation parameter closely.

A visual scatter plot of realizations from the Gaussian copula-generated distribution for transformed normally distributed margins is shown in Figure (1a). A value of τ = 0.75 is used in the figure. Note that, for the Gaussian copula, the image is essentially the scatter plot of points from a bivariate normal distribution with a correlation parameter θ = 0.9239 (because we are using normal marginals). One can note

[6] Mathematically, the dependence structure of a copula is labeled as "radially symmetric" if the following condition holds: $C_\theta(u_1, u_2) = u_1 + u_2 - 1 + C_\theta(1 - u_1, 1 - u_2)$, where the right side of the expression above is the survival copula (see Nelsen, 2006, page 37). Consider two random variables Y_1 and Y_2 whose marginal distributions are individually symmetric about points *a* and *b*, respectively. Then, the joint distribution *F* of Y_1 and Y_2 will be radially symmetric about points *a* and *b* if and only if the underlying copula from which *F* is derived is radially symmetric.

the familiar elliptical shape with symmetric dependence. As one goes toward the extreme tails, there is more scatter, corresponding to asymptotic independence. The strongest dependence is in the middle of the distribution.

3.2.3.2 The Farlie-Gumbel-Morgenstern (FGM) copula

The FGM copula was first proposed by Morgenstern (1956), and also discussed by Gumbel (1960) and Farlie (1960). It has been well known for some time in Statistics (see Conway, 1979, Kotz *et al.*, 2000; Section 44.13). However, until Prieger (2002), it does not seem to have been used in Econometrics. In the bivariate case, the FGM copula takes the following form:

$$C_\theta(u_1, u_2) = u_1 u_2 [1 + \theta(1 - u_1)(1 - u_2)]. \tag{3.16}$$

For the copula above to be 2-increasing (that is, for any rectangle with vertices in the domain of [0,1] to have a positive volume based on the function), θ must be in [–1, 1]. The presence of the θ term allows the possibility of correlation between the uniform marginals u_1 and u_2. Thus, the FGM copula has a simple analytic form and allows for either negative or positive dependence. Like the Gaussian copula, it also imposes the assumptions of asymptotic independence and radial symmetry in dependence structure.

However, the FGM copula is not comprehensive in coverage, and can accommodate only relatively weak dependence between the marginals. The concordance-based dependence measures for the FGM copula can be shown to be $\tau = \frac{2}{9}\theta$ and $\rho_S = \frac{1}{3}\theta$, and thus these two measures are bounded on $\left[-\frac{2}{9}, \frac{2}{9}\right]$ and $\left[-\frac{1}{3}, \frac{1}{3}\right]$, respectively.

The FGM scatterplot for the normally distributed marginal case is shown in Figure (1b), where Kendall's τ is set to the maximum possible value of 2/9 (corresponding to θ = 1). The weak dependence offered by the FGM copula is obvious from this figure.

3.2.3.3 The Archimedean class of copulas

The Archimedean class of copulas is popular in empirical applications (see Genest and MacKay, 1986 and Nelsen, 2006 for extensive reviews). This class of copulas includes a whole suite of closed-form copulas that cover a wide range of dependency structures, including comprehensive and non-comprehensive copulas, radial symmetry and asymmetry, and asymptotic tail independence and dependence. The class is very flexible, and easy to construct. Further, the asymmetric Archimedean copulas can be flipped to generate additional copulas (see Venter, 2001).

Archimedean copulas are constructed based on an underlying continuous convex decreasing generator function φ from [0, 1] to [0, ∞] with the following properties: $\varphi(1)=0, \varphi'(t)<0,$ and $\varphi''(t)>0$ for all $0<t<1\,(\varphi'(t)=\partial\varphi/\partial t; \varphi''(t)=\partial^2\varphi/\partial^2 t)$. Further, in the discussion here, we will assume that $\varphi(0)=\infty$, so that an inverse φ^{-1} exists. With these preliminaries, we can generate bivariate Archimedean copulas as:

$$C_\theta(u_1,u_2)=\varphi^{-1}[\varphi(u_1)+\varphi(u_2)], \tag{3.17}$$

where the dependence parameter θ is embedded within the generator function. Note that the above expression can also be equivalently written as:

$$\varphi[C_\theta(u_1,u_2)]=[\varphi(u_1)+\varphi(u_2)]. \tag{3.18}$$

Using the differentiation chain rule on the equation above, we obtain the following important result for Archimedean copulas that will be relevant to the sample selection model discussed in the next section:

$$\frac{\partial C_\theta(u_1,u_2)}{\partial u_2}=\frac{\varphi'(u_2)}{\varphi'[C_\theta(u_1,u_2)]},\ \text{where}\ \varphi'(t)=\partial\varphi(t)/\partial t. \tag{3.19}$$

The density function of absolutely continuous Archimedean copulas of the type discussed later in this section may be written as:

$$c_\theta(u_1,u_2)=-\frac{\varphi''\big(C(u_1,u_2)\big)\varphi'(u_1)\,\varphi'(u_2)}{\big[\varphi'\big(C(u_1,u_2)\big)\big]^3}\quad. \tag{3.20}$$

Another useful result for Archimedean copulas is that the expression for Kendall's τ in Equation (3.10) collapses to the following simple form (see Embrechts *et al.*, 2002 for a derivation):

$$\tau = 1 + 4\int_0^1 \frac{\varphi(t)}{\varphi'(t)} dt. \tag{3.21}$$

In the rest of this section, we provide an overview of four different Archimedean copulas: the Clayton, Gumbel, Frank, and Joe copulas.

3.2.3.3.1   <u>The Clayton copula</u>

The Clayton copula has the generator function $\varphi(t) = (1/\theta)(t^{-\theta} - 1)$, giving rise to the following copula function (see Huard *et al.*, 2006):

$$C_\theta(u_1, u_2) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta},\ 0 < \theta < \infty. \tag{3.22}$$

The above copula, proposed by Clayton (1978), cannot account for negative dependence. It attains the Fréchet upper bound as $\theta \to \infty$, but cannot achieve the Fréchet lower bound. Using the Archimedean copula expression in Equation (3.21) for τ, it is easy to see that τ is related to θ by $\tau = \theta/(\theta + 2)$, so that 0 < τ < 1 for the Clayton copula. Independence corresponds to $\theta \to 0$.

The figure corresponding to the Clayton copula for $\tau = 0.75$ indicates asymmetric and positive dependence [see Figure (1c)]. The tight clustering of the points in the left tail, and the fanning out of the points toward the right tail, indicate that the copula is best suited for strong left tail dependence and weak right tail dependence. That is, it is best suited when the random variables are likely to experience low values together (such as loan defaults during a recession). Note that the Gaussian copula cannot replicate such asymmetric and strong tail dependence at one end.

3.2.3.3.2   <u>The Gumbel copula</u>

The Gumbel copula, first discussed by Gumbel (1960) and sometimes also referred to as the Gumbel-Hougaard copula, has a generator function given by $\varphi(t) = (-\ln t)^\theta$. The form of the copula is provided below:

$$C_\theta(u_1,u_2) = \exp\left(-\left[(-\ln u_1)^\theta + (-\ln u_2)^\theta\right]^{1/\theta}\right),\ 1 \le \theta < \infty. \tag{3.23}$$

Like the Clayton copula, the Gumbel copula cannot account for negative dependence, but attains the Fréchet upper bound as $\theta \to \infty$. Kendall's τ is related to θ by $\tau = 1-(1/\theta)$, so that 0 < τ < 1, with independence corresponding to $\theta = 1$.

As can be observed from Figure (1d), the Gumbel copula for $\tau = 0.75$ has a dependence structure that is the reverse of the Clayton copula. Specifically, it is well suited for the case when there is strong right tail dependence (strong correlation at high values) but weak left tail dependence (weak correlation at low values). However, the contrast between the dependence in the two tails of the Gumbel is clearly not as pronounced as in the Clayton.

3.2.3.3.3 <u>The Frank copula</u>

The Frank copula, proposed by Frank (1979), is the only Archimedean copula that is comprehensive in that it attains both the upper and lower Fréchet bounds, thus allowing for positive and negative dependence. It is radially symmetric in its dependence structure and imposes the assumption of asymptotic independence. The generator function is $\varphi(t) = -\ln[(e^{-\theta t}-1)/(e^{-\theta}-1)]$, and the corresponding copula function is given by:

$$C_\theta(u_1,u_2) = -\frac{1}{\theta}\ln\left(1+\frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)}{e^{-\theta}-1}\right),\ -\infty < \theta < \infty. \tag{3.24}$$

Kendall's τ does not have a closed form expression for Frank's copula, but may be written as (see Nelsen, 2006, pg 171):

$$\tau = 1-\frac{4}{\theta}\left[1-D_F(\theta)\right],\ D_F(\theta) = \frac{1}{\theta}\int_{t=0}^{\theta}\frac{t}{e^t-1}dt. \tag{3.25}$$

The range of τ is –1 < τ < 1. Independence is attained in Frank's copula as $\theta \to 0$.

The scatter plot for points from the Frank copula is provided in Figure (1e) for a value of $\tau = 0.75$, which translates to a θ value of 14.14. The points show very strong central dependence (even stronger than the Gaussian copula, as can be noted from the substantial central clustering) and very weak tail dependence (even weaker than the Gaussian copula, as can be noted from the fanning out at the tails). Thus, the Frank copula is suited for very strong central dependency with very weak tail dependency. The Frank copula has been used quite extensively in empirical applications (see Meester and MacKay, 1994; Micocci and Masala, 2003).

3.2.3.3.4 __The Joe copula__

The Joe copula, introduced by Joe (1993, 1997), has a generator function $\varphi(t) = -\ln[1-(1-t)^{\theta}]$ and takes the following copula form:

$$C_{\theta}(u_1,u_2) = 1-\left[(1-u_1)^{\theta}+(1-u_2)^{\theta}-(1-u_1)^{\theta}(1-u_2)^{\theta}\right]^{1/\theta},\ 1\le\theta<\infty. \tag{3.26}$$

The Joe copula is similar to the Clayton copula. It cannot account for negative dependence. It attains the Fréchet upper bound as $\theta\to\infty$, but cannot achieve the Fréchet lower bound. The relationship between τ and θ for Joe's copula does not have a closed form expression, but takes the following form:

$$\tau = 1+\frac{4}{\theta}D_J(\theta), D_J(\theta) = \int_{t=0}^{1}\frac{\left[\ln(1-t^{\theta})\right](1-t^{\theta})}{t^{\theta-1}}dt. \tag{3.27}$$

The range of τ is between 0 and 1, and independence corresponds to $\theta = 1$. Figure (1f) presents the scatter plot for the Joe copula (with $\tau = 0.75$), which indicates that the Joe copula is similar to the Gumbel, but the right tail positive dependence is stronger (as can be observed from the tighter clustering of points in the right tail). In fact, from this standpoint, the Joe copula is closer to being the reverse of the Clayton copula than is the Gumbel.

3.3 Model estimation and measurement of treatment effects

In the current chapter, we introduce copula methods to accommodate residential self-selection in the context of assessing built environments effects on travel choices. To our knowledge, this is the first consideration and application of the copula approach in the urban planning and transportation literature (see Prieger, 2002 and Schmidt, 2003 for the application of copulas in the Economics literature). In the next section, we discuss the maximum likelihood estimation approach for estimating the parameters of Equation system (3.1) with different copulas.

3.3.1 Maximum Likelihood Estimation

Let the univariate standardized marginal cumulative distribution functions of the error terms $(\varepsilon_q, \eta_q, \xi_q)$ in Equation (3.1) be $(F_\varepsilon, F_\eta, F_\xi)$, respectively. Assume that η_q has a scale parameter of σ_η, and ξ_q has a scale parameter of σ_ξ. Also, let the standardized joint distribution of (ε_q, η_q) be $F(.,.)$ with the corresponding copula $C_{\theta_0}(.,.)$, and let the standardized joint distribution of (ε_q, ξ_q) be $G(.,.)$ with the corresponding copula $C_{\theta_1}(.,.)$. Consider a random sample size of Q (q=1,2,…,Q) with observations on $(r_q, m_{q0}, m_{q1}, x_q, z_q, w_q)$. The switching regime model has the following likelihood function (see Appendix A for the derivation).

$$L = \prod_{q=1}^{Q} \left[\frac{1}{\sigma_\eta} \cdot f_\eta\left(\frac{m_{q0} - \alpha' z_q}{\sigma_\eta} \right) \cdot \frac{\partial}{\partial u_{q2}^0} C_{\theta_0}\left(u_{q1}^0, u_{q2}^0\right) \right]^{1-r_q} \times \left[\frac{1}{\sigma_\xi} \cdot f_\xi\left(\frac{m_{q1} - \gamma' w_q}{\sigma_\xi} \right) \left\{ 1 - \frac{\partial}{\partial u_{q2}^1} C_{\theta_1}\left(u_{q1}^1, u_{q2}^1\right) \right\} \right]^{r_q}, \tag{3.28}$$

where $u_{q1}^0 = F_\varepsilon(-\beta' x_q)$, $\quad u_{q2}^0 = F_\eta\left(\frac{m_{q0} - \alpha' z_q}{\sigma_\eta} \right)$, $u_{q1}^1 = u_{q1}^0$, $u_{q2}^1 = F_\xi\left(\frac{m_{q1} - \gamma' w_q}{\sigma_\xi} \right)$.

Any copula function can be used to generate the bivariate dependence between (ε_q, η_q) and (ε_q, ξ_q), and the copulas can be different for these two dependencies (*i.e.*, C_{θ_0} and C_{θ_1} need not be the same). Thus, there is substantial flexibility in specifying the dependence structure, while still staying within the maximum likelihood framework and not needing any simulation machinery. In the current study, we use normal distribution functions for the marginals $F_\varepsilon(.), F_\eta(.)$ and $F_\xi(.)$, and test various different copulas for

C_{θ_0} and C_{θ_1}. In Table 3.2, we provide the expression for $\frac{\partial}{\partial u_2} C_\theta(u_1, u_2)$ for the six copulas discussed in Section 3.2.3. For Archimedean copulas, the expression has the simple form provided in Equation (3.19).

The maximum-likelihood estimation of the sample selection model with different copulas leads to a case of non-nested models. The most widely used approach to select among the competing non-nested copula models is the Bayesian Information Criterion (or BIC; see Quinn, 2007, Genius and Strazzera, 2008, Trivedi and Zimmer, 2007, page 65). The BIC for a given copula model is equal to $-2\ln(L) + K\ln(Q)$, where $\ln(L)$ is the log-likelihood value at convergence, K is the number of parameters, and Q is the number of observations. The copula that results in the lowest BIC value is the preferred copula. But, if all the competing models have the same exogenous variables and a single copula dependence parameter θ, the BIC information selection procedure measure is equivalent to selection based on the largest value of the log-likelihood function at convergence.

3.4 Data

3.4.1 Data sources

The data used for this analysis is drawn from the 2000 San Francisco Bay Area Household Travel Survey (BATS) designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission (MTC). In addition to the 2000 BATS data, several other secondary data sources were used to derive spatial variables characterizing the activity-travel and built environment in the region. These included: (1) Zonal-level land-use/demographic coverage data, obtained from the MTC, (2) GIS layers of sports and fitness centers, parks and gardens, restaurants, recreational businesses, and shopping locations, obtained from the InfoUSA business directory, (3) GIS layers of bicycling facilities, obtained from MTC, and (4) GIS layers of the highway network (interstate, national, state and county highways) and the local roadways network (local, neighborhood, and rural roads), extracted from the Census 2000 Tiger files. From these secondary data sources, a wide variety of built environment variables were developed for the purpose of classifying the residential neighborhoods into neo-urbanist and conventional neighborhoods.

3.4.2 <u>The Dependent Variables</u>

This study uses factor analysis and a clustering technique to define a binary residential location variable that classifies the Traffic Analysis Zones (TAZs) of the Bay Area into neo-urbanist and conventional neighborhoods based on built environment measures. Factor analysis helps in reducing the correlated attributes (or *factors*) that characterize the built environment of a neighborhood into a manageable number of *principal components* (or variables). The clustering technique employs these *principal components* to classify zones into neo-urbanist or conventional neighborhoods. In the current study, we employ the results from Pinjari *et al*. (2008) that identified two principal components to characterize the built environment of a zone - (1) Residential density and transportation/land-use environment, and (2) Accessibility to activity centers. The factors loading on the first component included bicycle lane density, number of zones accessible from the home zone by bicycle, street block density, household population density, and fraction of residential land use in the zone. The factors loading on the second component included bicycle lane density and number of physically active and natural recreation centers in the zone. The two principal components formed the basis for a cluster analysis that categorizes the 1099 zones in the Bay area into neo-urbanist or conventional neighborhoods (see Pinjari *et al*., 2008 for complete details). This binary variable is used as the dependent variable in the selection equation of Equation (3.1).

The continuous outcome dependent variable in each of the neo-urbanist and conventional neighborhood residential location regimes is the household vehicle miles of travel (VMT). This was obtained from the reported odometer readings before and after the two days of the survey for each vehicle in the household. The two-day vehicle-specific VMT was aggregated across all vehicles in the household to obtain a total two-day household VMT, which was subsequently averaged across the two survey days to obtain an average daily household VMT. The logarithm of the average daily household VMT was then used as the dependent variable, after recoding the small share (<5%) of households with a VMT value of zero to one (so that the logarithm of VMT takes a value of zero for these households).

The final estimation sample in our analysis includes 3696 households from 5 counties (San Francisco, San Mateo, Santa Clara, Alameda, and Contra Costa) of the Bay area. Among these households, about 34% of the households reside in neo-urbanist neighborhoods and 66% reside in conventional neighborhoods. The average daily household VMT is about 37 miles for households in neo-urbanist neighborhoods, and 68 miles for households in conventional neighborhoods.

3.5 Empirical analysis

3.5.1 Variables considered

Several categories of variables were considered in the analysis, including household demographics, employment characteristics, and neighborhood characteristics. The neighborhood characteristics considered include population density, employment density, Hansen-type accessibility measures (such as accessibility to employment and accessibility to shopping; see Bhat and Guo, 2007 for the precise functional form), population by ethnicity in the neighborhood, presence/number of schools and physically active centers, and density of bicycle lanes and street blocks. These measures are included in the VMT outcome equation and capture the effect of variations in built environment across zones within each group of neo-urbanist and conventional neighborhoods.

3.5.2 Estimation Results

The empirical analysis involved estimating models with the same structure for (ε_q, η_q) and (ε_q, ξ_q), as well as different copula-based dependency structures. This led to 6 models with the same copula dependency structure (corresponding to the six copulas discussed in Section 3.2.3), and 24 models with different combinations of the six copula dependency structures for (ε_q, η_q) and (ε_q, ξ_q). We also estimated a model that assumed independence between ε_q and η_q, and ε_q and ξ_q.

The Bayesian Information Criterion, which collapses to a comparison of the log-likelihood values across different models, is employed to determine the best copula dependency structure combination. The log-likelihood values for the five best copula dependency structure combinations are: (1) Frank-Frank (-6842.2), (2) Frank-Joe (-6844.2), (3) FGM-Joe (-6851.0), (4) Independent-Joe (-6863.7), and (5) FGM-Gumbel (-6866.2). It is evident that the log-likelihood at convergence of the Frank-Frank and Frank-Joe copula combinations are higher compared to the other copula combinations. Between the Frank-Frank and Frank-Joe copula combinations, the former is slightly better. The log-likelihood value for the structure that assumes independence (*i.e.*, no self-selection effects) is -6878.1. All the five copula-based dependency models reject the independence assumption at any reasonable level of significance, based on likelihood ratio tests, indicating the significant presence of self-selection effects. Interestingly, however, the log-likelihood value at convergence for the classic textbook structure that assumes a Gaussian-Gaussian copula combination is -6877.9, indicating that there is no statistically significant difference between the Gaussian-Gaussian (G-G) and the independence-independence (I-I) copula structures. This is also observed in the estimated bivariate normal correlation parameters, which are -0.020 (t-statistic of 0.18) for the residential choice-neo-urbanist VMT regime error correlation and -0.050 (t-statistic of -0.50) for the residential choice-conventional neighborhood VMT regime error correlation. Clearly, the traditional G-G copula combination indicates the absence of self-selection effects. However, this is simply an artifact of the normal dependency structure, and is indicative of the kind of incorrect results that can be obtained by placing restrictive distributional assumptions.

In the following presentation of the empirical results, we focus our attention on the results of the Independent-Independent (or I-I copula) specification that ignores self-selection effects entirely and the Frank-Frank (or F-F copula) specification that provides the best data fit. Table 3.3 provides the results, which are discussed below.

3.5.2.1 Binary choice component

The results of the binary discrete equation of neighborhood choice provide the effects of variables on the propensity to reside in a conventional neighborhood relative to a neo-urbanist neighborhood. The parameter estimates indicate that younger households (*i.e.*, households whose heads are less than 35 years of age) are less likely to reside in conventional neighborhoods and more likely to reside in neo-urbanist neighborhoods, perhaps because of higher environmental sensitivity and/or higher need to be close to social and recreational activity opportunities (see also Lu and Pas, 1999). Households with children have a preference for conventional neighborhoods, potentially because of a perceived better quality of life/schooling for children in conventional neighborhoods compared to neo-urbanist neighborhoods. Also, as expected, households who own their home and who live in a single family dwelling unit are more likely to reside in conventional neighborhoods.

3.5.2.2 Log(VMT) continuous component for neo-urbanist neighborhood regime

The estimation results corresponding to the natural logarithm of vehicle miles of travel (VMT) in a neo-urbanist neighborhood highlight the significance of the number of household vehicles and number of full-time students. As expected, both of these effects are positive. In particular, log(VMT) increases with number of vehicles in the household and number of students. The effect of number of vehicles is non-linear, with a jump in log(VMT) for an increase from no vehicles to one vehicle, and a lesser impact for an increase from one vehicle to 2 or more vehicles (there were only two households in neo-urbanist neighborhoods with 3 vehicles, so we are unable to estimate impacts of vehicle increases beyond 2 vehicles in neo-urbanist neighborhoods). Interestingly, we did not find any statistically significant effect of employment and neighborhood characteristics, in part because the variability of these characteristics across households in neo-urbanist zones is relatively small.

The copula dependency parameter between the discrete choice residence error term and the log(VMT) error term for neo-urbanist households is highly statistically significant and negative for the F-F model. The θ estimate translates to a Kendall's τ value of -0.26. The negative dependency parameter indicates that a household that has a higher inclination to locate in conventional neighborhoods would travel less than an observationally equivalent "random" household if both these households were located in a neo-urbanist neighborhood (a "random" household, as used above, is one that is indifferent between residing in a neo-urbanist or a conventional neighborhood, based on factors unobserved to the analyst). Equivalently, the implication is that a household that makes the choice to reside in a neo-urbanist neighborhood is likely to travel more than an observationally equivalent random household in a neo-urbanist environment, and much more than if an observationally equivalent household from a conventional neighborhood were relocated to a neo-urbanist neighborhood. This may be attributed to, among other things, such unobserved factors characterizing households inclined to reside in neo-urbanist settings as a higher degree of comfort level driving in dense, one-way street-oriented, parking-loaded, traffic conditions.

The lower travel tendency of a random household in a neo-urbanist neighborhood (relative to a household that expressly chooses to locate in a neo-urbanist neighborhood) is teased out and reflected in the high statistically significant negative constant in the F-F copula model. On the other hand, the I-I model assumes, incorrectly, that the travel of households choosing to reside in neo-urbanist neighborhoods is independent of the choice of residence. The result is an inflation of the VMT generated by a random household if located in a neo-urbanist setting.

3.5.2.3 Log(VMT) continuous component for conventional neighborhood regime

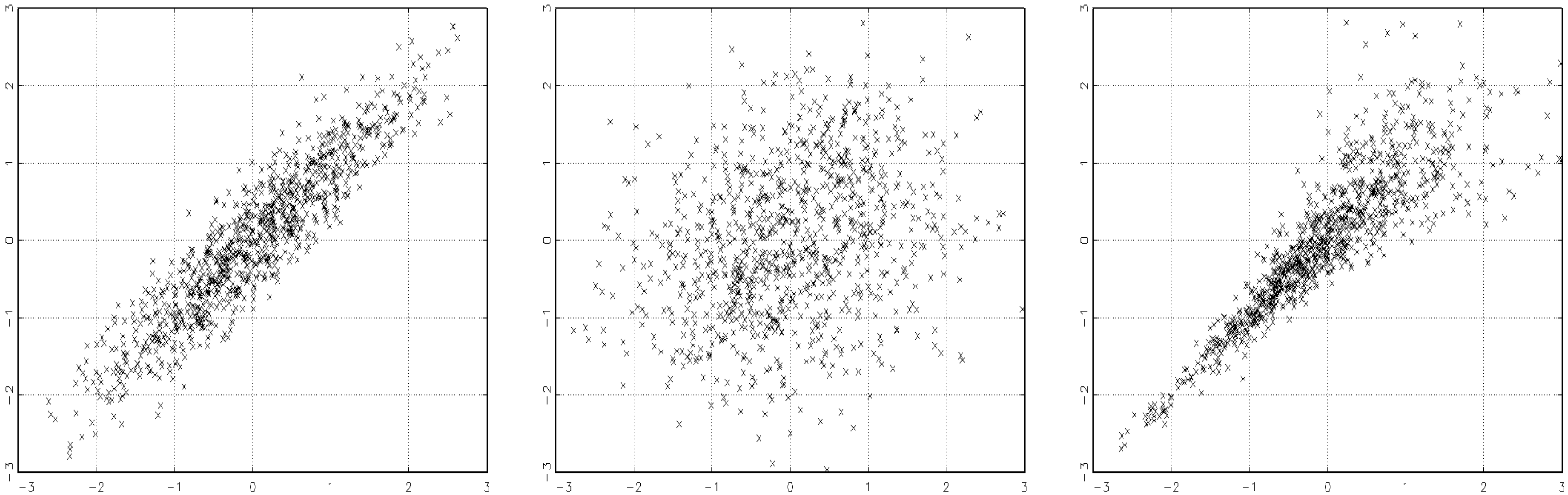
The household socio-demographics that influence vehicle mileage for households in a conventional neighborhood include number of household vehicles, number of full-time students, and number of employed individuals. As expected, the effects of all of these variables are positive. The household vehicle effect is non-linear, with the marginal increase in log(VMT) decreasing with the number of vehicles. In addition, two neighborhood characteristics – density of vehicle lanes and accessibility to shopping – have statistically significant effects on log(VMT) in the conventional neighborhood regime. Both these effects are negative, as expected.

The dependency parameter in this segment for the F-F model is highly statistically significant and positive. The θ estimate translates to a Kendall's τ value of 0.36. The positive dependency indicates that a household that has a higher inclination to locate in conventional neighborhoods is likely to travel more in that setting than an observationally equivalent random household. Again, the I-I model ignores this residential self-selection in the estimation sample, resulting in an over-estimation of the VMT generated by a random household if located in a conventional neighborhood setting (see the higher constant in the I-I model relative to the F-F model corresponding to the conventional neighborhood VMT regime).

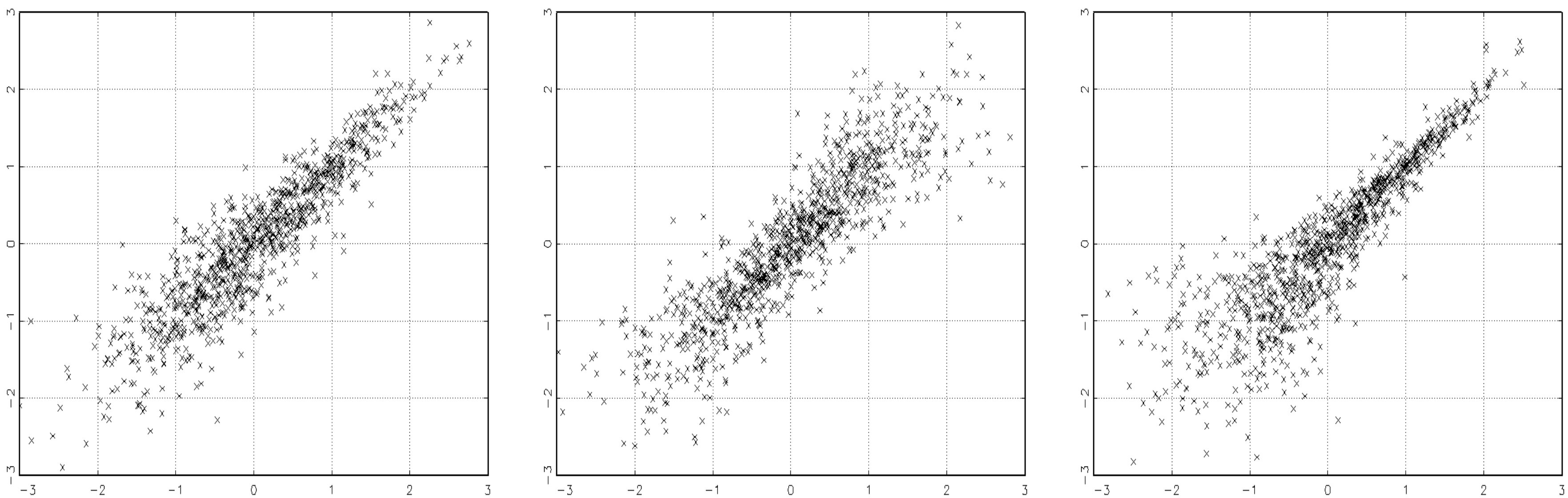
3.6 Summary

In the current study, we apply a copula based approach to model residential neighborhood choice and daily household vehicle miles of travel (VMT) using the 2000 San Francisco Bay Area Household Travel Survey (BATS). The self-selection hypothesis in the current empirical context is that households select their residence locations based on their travel needs, which implies that observed VMT differences between households residing in neo-urbanist and conventional neighborhoods cannot be attributed entirely to built environment variations between the two neighborhoods types. A variety of copula-based models are estimated, including the traditional Gaussian-Gaussian (G-G) copula model. The results indicate that using a bivariate normal dependency structure suggests the absence of residential self-selection effects. However, other copula structures reveal a high and statistically significant level of residential self-selection, highlighting the potentially inappropriate empirical inferences from using incorrect dependency structures. In the current empirical case, we find the Frank-Frank (F-F) copula dependency structure to be the best in terms of data fit based on the Bayesian Information Criterion.

The copula approach used here can be extended to the case of sample selection with a multinomial treatment effect. In the subsequent chapter we extend the copula approach for multinomial context (see also Spizzu *et al*., 2009, for a similar application). It should also have wide applicability in other bivariate/multivariate contexts in the transportation and other fields, including spatial dependence modeling (see Bhat and Sener, 2009).



(1a) (1b) (1c)



(1d) (1e) (1f)

Figure 1 Normal variate copula plots (1a) Gaussian Copula $\tau = 0.75$, $\theta = 0.92$; (1b) FGM Copula $\tau = 0.22$, $\theta = 1.00$; (1c) Clayton Copula $\tau = 0.75$, $\theta = 6.00$; (1d) Gumbel Copula $\tau = 0.75$, $\theta = 4.00$; (1e) Frank Copula $\tau = 0.75$, $\theta = 14.14$; (1f) Joe Copula $\tau = 0.75$, $\theta = 6.79$.

Table 3.1: Characteristics of Alternative Copula Structures

Copula	Dependence Structure Characteristics	Archimedean Generation Function $\psi(t)$	$\psi'(t)$	θ range and value for index	Kendall's τ and range	Spearman's ρ_S and range
Gaussian	Radially symmetric, weak tail dependencies, left and right tail dependencies go to zero at extremes	Not applicable	Not applicable	$-1 \le \theta \le 1$ θ = 0 is independence	$\frac{2}{\pi}\arcsin(\theta)$ $-1 \le \tau \le 1$	$\frac{6}{\pi}\arcsin\left(\frac{\theta}{2}\right)$ $-1 \le \rho_S \le 1$
FGM	Radially symmetric, only moderate dependencies can be accommodated	Not applicable	Not applicable	$-1 \le \theta \le 1$ θ = 0 is independence	$\frac{2}{9}\theta$ $-2/9 \le \tau \le 2/9$	$\frac{1}{3}\theta$ $-1/3 \le \rho_S \le 1/3$
Clayton	Radially asymmetric, strong left tail dependence and weak right tail dependence, right tail dependence goes to zero at right extreme	$\varphi(t) = \frac{1}{\theta}(t^{-\theta} - 1)$	$t^{-\theta-1}$	$0 < \theta < \infty$ θ → 0 is independence	$\frac{\theta}{\theta+2}$ $0 < \tau < 1$	No simple form $0 < \rho_S < 1$
Gumbel	Radially asymmetric, weak left tail dependence, strong right tail dependence, left tail dependence goes to zero at left extreme	$\varphi(t) = (-\ln t)^{\theta}$	$-\frac{\theta}{t}(-\log t)^{\theta-1}$	$1 \le \theta < \infty$ θ = 1 is independence	$1 - \frac{1}{\theta}$ $0 \le \tau < 1$	No simple form $0 \le \rho_S < 1$
Frank	Radially symmetric, very weak tail dependencies (even weaker than Gaussian), left and right tail dependencies go to zero at extremes	$\varphi(t) = -\ln\left[\frac{e^{-\theta t} - 1}{e^{-\theta} - 1}\right]$	$\frac{\theta}{1 - e^{\theta t}}$	$-\infty < \theta < \infty$ θ → 0 is independence	See Equation (3.25) $-1 \le \tau \le 1$	$1 - \frac{12}{\theta}(D_1 \mid \theta) - D_2(\theta)$ * $-1 \le \rho_S \le 1$
Joe	Radially asymmetric, weak left tail dependence and very strong right tail dependence (stronger than Gumbel), left tail dependence goes to zero at left extreme	$\varphi(t) = -\ln[1 - (1-t)^{\theta}]$	$\frac{-\theta(1-t)^{\theta-1}}{1-(1-t)^{\theta}}$	$1 \le \theta < \infty$ θ = 1 is independence	See Equation (3.27) $0 \le \tau < 1$	No simple form $0 \le \rho_S < 1$

$$* D_k(\theta) = \frac{k}{e^k} \int_{t=0}^{\theta} \frac{t^k}{(e^t - 1)} dt$$

Table 3.2: **Expressions for** $\frac{\partial}{\partial u_2} C_\theta(u_1, u_2)$

Copula	Expression
Gaussian Copula	$\Phi\left[\frac{\Phi^{-1}(u_1) - \theta\,\Phi^{-1}(u_2)}{\sqrt{1-\theta^2}}\right]$
FGM Copula	$u_1[1+\theta(1-u_1)(1-2u_2)$
Clayton Copula	$u_2^{-(\theta+1)}(u_1^{-\theta} + u_2^{-\theta} - 1)^{-\left(\frac{1+\theta}{\theta}\right)}$
Gumbel Copula	$u_2^{-1}(-\ln u_2)^{\theta-1} \cdot C_\theta(u_1,u_2)\left[(-\ln u_1)^\theta + (-\ln u_2)^\theta\right]^{\left(\frac{1}{\theta}-1\right)}$
Frank Copula	$1-e^{\theta u_2}(e^{\theta u_1} - e^\theta)\left[e^{\theta u_1}e^{\theta u_2} + e^\theta(1-e^{\theta u_1} - e^{\theta u_2})\right]^{-1} = \left[1-e^{\theta C_\theta(u_1,u_2)}\right](1-e^{\theta u_2})^{-1}$
Joe Copula*	$\bar{u}_2^{\theta-1}(1-\bar{u}_1^\theta)\left[\bar{u}_1^\theta + \bar{u}_2^\theta - \bar{u}_1^\theta, \bar{u}_2^\theta\right]^{\left(\frac{1}{\theta}-1\right)}$

* For Joe's Copula, $\bar{u}_2 = 1-u_2$, $\bar{u}_1 = 1-u_1$

Table 3.3: Estimation Results of the Switching Regime Model

Variables	Independence-Independence Copula		Frank-Frank Copula	
	Parameter	t-stat	Parameter	t-stat
Propensity to choose conventional neighborhood relative to neo-urbanist neighborhood				
Constant	0.201	4.15	0.275	5.72
Age of householder < 35 years	-0.131	-2.35	-0.143	-2.75
Number of children (of age < 16 years) in the household	0.164	4.62	0.161	4.59
Household lives in a single family dwelling unit	0.382	6.79	0.337	6.28
Own household	0.597	10.37	0.497	8.81
Log of vehicle miles of travel in a neo-urbanist neighborhood				
Constant	-0.017	-0.16	-0.638	-5.48
Household vehicle ownership				
Household Vehicles = 1	2.617	21.50	2.744	24.26
Household Vehicles ≥ 2	3.525	25.44	3.518	27.40
Number of full-time students in the household	0.183	2.13	0.112	1.41
Copula dependency parameter (θ)	--	--	-2.472	-6.98
Scale parameter of the continuous component	1.301	40.62	1.348	34.31
Log of vehicle miles of travel in a conventional neighborhood				
Constant	0.379	2.28	0.163	1.08
Household vehicle ownership				
Household Vehicles = 1	3.172	21.77	3.257	25.43
Household Vehicles = 2	3.705	25.32	3.854	29.92
Household Vehicles ≥ 3	3.931	25.92	4.102	30.41
Number of employed individuals in the household	0.229	7.24	0.208	6.66
Number of full-time students in the household	0.104	5.06	0.131	6.27
Density of bicycle lanes	-0.023	-3.08	-0.024	-3.24
Accessibility to shopping (Hansen measure)	-0.024	-7.34	-0.027	-8.19
Copula dependency parameter (θ)	--	--	3.604	7.22
Scale parameter of the continuous component	0.891	75.78	0.920	63.59
Log-likelihood at convergence	-6878.1		-6842.2	

CHAPTER 4 HOUSEHOLD VEHICLE FLEET COMPOSITION AND USAGE CHOICES

4.1 Introduction and literature

This chapter focuses on understanding the effects of land use measures on vehicle ownership by type of vehicle and usage. Understanding the interaction between land use and travel behavior has been of much interest to the profession, with a long history and strand of literature devoted to this subject (*e.g.*, Ewing and Cervero 2001, Lund 2003, Song and Knaap 2003, Bhat and Eluru 2009). There are descriptive studies that compare travel behavior characteristics of households and individuals residing in low density land use configurations against those that reside in higher density mixed land use configurations. There are studies that consider the impacts of residential location characteristics on a host of travel behavior characteristics including, for example, mode choice (Pinjari et al., 2007, Chen et al., 2008), auto ownership (Bhat and Guo, 2007), vehicle miles of travel, activity time use patterns (Pinjari et al., 2009) and amount of non-motorized travel (Pinjari et al., 2008). Thus, the interplay between land use and travel behavior remains a major focus area of research in the profession and continues to be of much interest particularly in the context of developing integrated land use-transport models that effectively model the impacts of alternative land use strategies on travel demand.

In recent years, there has been an explicit recognition in the integrated land use-transport modeling field that the treatment of residential land use characteristics as exogenous factors (variables) in models of vehicle ownership and use (or any travel behavior model) may provide erroneous indications of the true impacts of land use on travel behavior. This is due to the phenomenon referred to as “self-selection” where households or individuals who have a proclivity towards a certain lifestyle may choose or “self-select” to reside in neighborhoods that support their lifestyle preferences. People’s attitudes, preferences, and values, not to mention their socio-economic and demographic characteristics, undoubtedly play a role in shaping behavioral choices (Bhat and Guo

2007, Choo and Mokhtarian 2004, Cao et al., 2006, Handy 2005). If an individual who tends to be environmentally conscious and enjoys a non-motorized travel lifestyle characterized by bicycling and walking chooses to reside in a high-density mixed land use development, it is likely that the residential location choice was influenced by the lifestyle and travel preferences of the individual (as opposed to the travel choices being driven by the land use pattern of the residential location). In other words, residential location choice is endogenous to vehicle ownership choice by vehicle type, vehicle usage decisions, and other travel behavior choices that are made by individuals and households in which they reside.

In light of the key role that vehicle ownership, vehicle type choice, and vehicle usage have played in travel demand analysis over many decades, and in the global climate change debate more recently, there has been considerable research the determinants of vehicle ownership, household fleet composition (vehicle type mix), and vehicle usage (usually measured in vehicle miles of travel). Work in this area has ranged from simple regression or discrete choice models of levels of auto ownership (*e.g.*, Mannering and Winston 1985) and vehicle type choice (Feng et al., 2005, Goldberg 1998, Mohamaddian and Miller 2003) to more sophisticated models of vehicle acquisition, disposal, and replacement (Yamamoto et al., 1999). More recently, there has been considerable work on modeling household fleet composition in terms of the mix of vehicle types owned by a household together with the amount that each vehicle in the household is used. But these models often treat residential location choice variables (land use measures) as exogenous variables that influence vehicle fleet ownership and usage (*e.g.*, Shay and Khattak 2005, Bhat et al., 2009). Further, many of these earlier studies consider the jointness in vehicle type choice and usage for the most recent vehicle or most driven by the household [for example, see Choo and Mokhtarian 2004, Mohammadian and Miller 2003, Spissu *et al*. 2009], or confine their attention to households with two or fewer vehicles [see West 2004]. Overall, there has been relatively little research on treating residential choice as being endogenous in vehicle type and usage decisions, or on examining the entire vehicle fleet composition and usage characteristics of households.

This chapter contributes to the literature on land use and travel demand by explicitly integrating household vehicle ownership, vehicle type, and vehicle usage decisions with residential location decisions of households. Such a joint model can be used to conduct a host of policy analyses aimed at reducing GHG emissions and fuel consumption. The joint model system is estimated on a data set derived from the 2000 San Francisco Bay Area Household Travel Survey (BATS) that has been comprehensively augmented with land use and network level of service attributes. The chapter starts with a presentation of the methodology in the next section. A brief description of the data is offered in the third section. The fourth section presents model estimation results while the fifth section offers a discussion on the simultaneity in the choice processes. Concluding thoughts are offered in the sixth section.

4.2 Modeling methodology

In this section, the model framework to jointly model residential location, vehicle ownership and type choice, and vehicle usage, is discussed first followed by a detailed presentation of the model structure and model estimation procedure.

4.2.1 Model framework

The number of dimensions that need to be modeled in the joint residential choice and vehicle fleet composition/usage system is high, especially because of the consideration of multiple vehicles in the household. One appealing approach to accommodating the high number of dimensions due to multiple vehicles is to consider a multiple discrete-continuous extreme value (MDCEV) based model, as undertaken by Bhat *et al*. 2009. The approach is quite elegant and relatively simple, but, when applied to vehicle fleet composition analysis, is predicated on the assumption that the process of acquiring vehicles is instantaneous and based on "horizontal" choice behavior. The basic supposition is that, at a given instant, individuals choose to purchase the number of vehicles they want to own as well as the vehicle type and use decisions. However, it is more reasonable to assume that the fleet ownership of households is based on repeated choice decisions over time, with the choices made at an earlier occasion influencing future choices. The MDCEV approach is fundamentally at odds with this more realistic process of household vehicle ownership and use. Further, the MDCEV approach ties the discrete and continuous choices in a restrictive framework by having a single stochastic utility function (and therefore, a single error term) that underlies both the discrete and continuous choices. Finally, the MDCEV approach needs to have an exogenous total mileage budget of households for implementation. Bhat *et al*. 2009 develop this budget by aggregating the mileage across all vehicles held by a household and adding non-motorized mode mileage. However, the non-motorized mileage is a relatively negligible fraction of total mileage, effectively imposing the constraint that total motorized vehicle utilization is exogenous, and does not change in response to policies or fuel cost increases (though the MDCEV model allows substitution in vehicle mileage across different vehicle types).

In the current study, a different approach is adopted to accommodate the many dimensions characterizing vehicle fleet/usage decisions. Multiple vehicle ownership and usage dimensions are accommodated by assuming that vehicle fleet and usage decisions are determined through a series of unobserved (to the analyst) repeated discrete-continuous choice occasions [see Hendel 1999 and Dube 2004, who have earlier used a repeated choice framework to handle the purchase and consumption levels of multiple items in a marketing context]. The number of choice occasions in such a “vertical” choice behavior is linked to the number of adults in the household. In particular, since the number of vehicles is never greater than the number of adults in the household plus 1 in the data used in this empirical context, the number of choice occasions is set to be equal to the number of adults plus 1. At each choice occasion, the household may choose not to purchase a vehicle or to acquire a vehicle of a certain type. However, the choice of residential location, vehicle ownership, vehicle type and vehicle utilization are likely to be multiple dimensions of a single choice bundle at each choice occasion. For example, a household that is environmentally conscious may deliberately decide to locate in a neo-urbanist neighborhood, have few cars (as reflected in the choice of zero cars on one or more choice occasions of the household), favor compact vehicles in each choice occasion, and use the chosen vehicles relatively sparingly. This joint nature of the decisions is recognized at each choice occasion by proposing a joint discrete-continuous copula-based framework [the use of a copula framework is a deviation from earlier modeling approaches of repeated discrete-continuous choices, including those of Dube 2004 and Bento *et al*. 2005]. In the framework, the decision of residential choice, and choice of no vehicle purchase or one of several vehicle types, is captured using a GEV-based logit model, while vehicle utilization (as measured by annual vehicle miles of travel or VMT) of the chosen vehicle type is modeled using a continuous regression model. Note that one can use this framework to model any representation of residential choice (such as neo-urbanist versus traditional neighborhoods as in Bhat and Eluru 2009 or multiple residential choice alternatives based on density as in Brownstone and Golob 2009 and any taxonomy of vehicle types. Also important is that the number of vehicles owned by the household is endogenously, even if implicitly, determined as the sum of those choice occasions when the household selects a certain vehicle type. Overall, the proposed approach jointly models residential choice and all vehicle fleet characteristics in a unifying framework.

To implement this framework in estimation, “synthetic” repeated choice occasions for each household are generated based on the number of adults in the household. Appropriate vehicle type choices are assigned to each choice occasion in the estimation sample. For example, consider a household with two adults, and two vehicles – a coupe and a compact sedan. For this household, three choice occasions (2 adults +1) are created with the chosen alternatives for the choice occasions being coupe, compact sedan and “no vehicle”. In the data set used in the empirical analysis part of this study, the temporal sequence of the purchase of the vehicles currently owned is known. Thus, it is possible to capture the impacts of the types of vehicles already owned on the type of vehicle that may be purchased in a subsequent purchase decision. In the example above, if the coupe is the first vehicle purchased and the sedan is the second one purchased, coupe is assigned as the chosen alternative at the first choice occasion, and sedan as the chosen alternative in the second. In the second choice occasion, information that the household has a coupe is used as an explanatory variable. This "mimics" the dynamics of fleet ownership decisions.[7]

4.2.2 <u>Model Structure</u>

4.2.2.1 Joint Residential Location-Vehicle Type Choice Model Component (Discrete Choice Component)

Let q be the index for households, $(q = 1,\ 2,\ ...,\ Q)$ and let i be the index for the possible combinations of residential location alternatives and vehicle type alternatives. For example, if residential location is characterized by two alternatives (residing in a neo-urbanist neighborhood and residing in a traditional neighborhood) and vehicle type is represented by three alternatives (no vehicle purchased, sedan, and coupe; for ease in presentation, the "no vehicle" purchased case will be treated as a vehicle type alternative), there are 6 possible combinations of residential location and vehicle type alternatives, and i = 1, 2, 3, 4, 5, 6. More generally, let i = 1, 2, …, I. Also, let j be the index to represent the vehicle choice occasion $(j = 1, 2, ...J,$ where J is the number of adults in the household q plus 1). With this notation, the residential location-vehicle type discrete choice model component takes the familiar random utility formulation:

$$u^*_{qij} = \beta' x_{qij} + \varepsilon_{qij} \tag{4.1}$$

In the equation above, u^*_{qij} is the latent utility that the q^{th} household derives from choosing alternative i at the j^{th} choice occasion. x_{qij} is a column vector of known

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[7] Note that in the example just provided, one could also assign the chosen alternatives to the choice occasions as follows: coupe in first choice occasion, no vehicle in the second, and sedan in the third. This is in place of coupe in the first, sedan in the second and no vehicle in the third. But both these assignments will give the same results, because the "dynamics" are based on what the household already owns in totality, not what was chosen in the immediately previous choice occasion. Of course, for the first choice occasion, there are no explanatory variables related to the vehicle types already chosen, because there is no information on what the household owned prior to the set of vehicles currently held.

household attributes at choice occasion j (including household demographics, types of vehicles "chosen" before the j^{th} choice occasion, and activity-travel environment characteristics), β is a corresponding coefficient column vector of parameters to be estimated, and ε_{qij} is an idiosyncratic error term assumed to be standard type-1 extreme value distributed. Then, in the usual framework of random utility maximization, household q will choose alternative i at the j^{th} choice occasion if the following condition holds:

$$u^*_{qij} > \max_{s=1,2,\ldots,I,\ s\neq i} u^*_{qsj} \tag{4.2}$$

The condition above can be equivalently written in the form of a series of binary choice formulations for each alternative i [see Lee 1983]. To see this, let R_{qij} be a dichotomous variable that takes the values 0 and 1, with $R_{qij} = 1$ if the i^{th} alternative is chosen by the q^{th} household at the j^{th} choice occasion, and $R_{qij} = 0$ otherwise. Then, one can recast the discrete choice model formulation in Equation (4.2) by substituting $\beta' x_{qij} + \varepsilon_{qij}$ for u^*_{qij} [from Equation (4.1)]:

$$R_{qij} = 1 \text{ if } \beta' x_{qij} > v_{qij},\ (i = 1, 2, \ldots I) \tag{4.3}$$

$$\text{where } v_{qij} = \{\max_{s=1,2,\ldots,I,\ s\neq i} u^*_{qsj}\} - \varepsilon_{qij} \tag{4.4}$$

With the structure in Equation (4.4) and an appropriate Generalized Extreme Value (GEV) distribution assumption on the ε_{qij} terms, the residential location-vehicle type choice probability expressions at each choice occasion j take the usual GEV form [see McFadden 1978]. In the model, it is assumed that the error terms ε_{qij} are independent and identically distributed (IID) across households q and choice occasions j, and that they are identically distributed (but not necessarily independent) across alternatives i.[8] Let $F_{vi}(.)$ be the marginal distribution of v_{qij} implied by the assumed GEV distributional form for the ε_{qij} terms and the relationship in Equation (4.4). This implied distribution is very straightforward to obtain, since it is based on the probability expression for the corresponding discrete choice model. For example, if the ε_{qij} terms are independent across alternative i, then, from Equation (4.3), it must be the case that:

$$F_{vi}(v_{qij} < \beta' x_{qij}) = \frac{\exp(\beta' x_{qij})}{\exp(\beta' x_{qij}) + \sum_{s \neq i} \exp(\beta' x_{qsj})}$$, and therefore

$$F_{vi}(v_{qij} < \beta' x_{qij}) = \frac{\exp(w)}{\exp(w) + \sum_{s \neq i} \exp(\beta' x_{qsj})}$$

If some other GEV form is used for the ε_{qij} terms, then the implied distribution of v_{qij} will take the corresponding GEV probability form.

4.2.2.2 The Vehicle Mileage Model Component

In the current modeling framework, the vehicle mileage model component takes the form of the classic log-linear regression, as shown below:

$$m_{qij}^{*} = \alpha' z_{qij} + \eta_{qij}, \quad m_{qij} = 1[R_{qij} = 1] m_{qij}^{*} \tag{4.5}$$

In the equation above, m_{qij}^{*} is a latent variable representing the logarithm of annual mileage on the vehicle of type i if it had been chosen at the j^{th} choice occasion. This latent vehicle usage variable is mapped to the observed household attributes and the corresponding attribute effects in the form of column vectors z_{qij} and α', respectively, as well as to unobserved factors through a η_{qij} term. On the right hand side of this equation, the notation $1[R_{qij} = 1]$ represents an indicator function taking the value 1 if

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[8] The IID assumptions across households and choice occasions can be relaxed in a conceptually straightforward manner by accommodating mixing distributions. This is left for future research, and focus in the current paper on implementing the fundamental “vertical” choice approach.

household q chooses vehicle type i in the j^{th} choice occasion, and 0 otherwise. That is, m^*_{qij} is observed (in the form of m_{qij}) only if household q is observed to actually acquire a vehicle of type *i* at the j^{th} choice occasion. It is assumed that the η_{qij} error terms are independent and identically distributed (IID) across households *q* and choice occasions *j*, and that they are identically distributed (but not necessarily independent) across alternatives *i*. Further, since the annual mileage for the chosen vehicle is only observed at each choice occasion, any dependence between the η_{qij} terms across alternatives *i* is not identified.

4.2.2.3 The Joint Model: A Copula-based Approach

In this sub-section, the specifications of the individual model components discussed in the previous two subsections are brought together in the following equation system:

$$\begin{aligned} &R_{qij} = 1 \quad \text{if} \quad \beta_i' x_{qij} > v_{qij}, \quad (i = 1, 2, ...I)\ (j = 1, 2, ...J) \\ &m^*_{qij} = \alpha_i' z_{qij} + \eta_{qij}, \quad m_{qij} = 1[R_{qij} = 1]\, m^*_{qij} \end{aligned} \tag{4.6}$$

The type and the extent of the dependency between the stochastic terms v_{qij} and η_{qij} for household q determines the level of dependency between the underlying propensity of vehicle type choice and vehicle usage decisions for the household. In the research effort, as indicated earlier, copula-based methods are used to capture and explore these dependencies (or correlations). In particular, copulas are used to describe the joint distribution of the v_{qij} and η_{qij} terms. In this approach, first, the v_{qij} and η_{qij} terms are transformed into uniform distributions using their inverse cumulative distribution functions. Subsequently, copulas are applied to "couple" the uniformly distributed inverse cumulative distributions into multivariate joint distributions. To explicate, lets assume that the marginal distributions of v_{qij} and η_{qij} be $F_{vi}(.)$ and $F_{\eta i}(.)$, respectively, and let the joint distribution of v_{qij} and η_{qij} be $F_{vi,\eta i}(.,.)$.

Subsequently, consider $F_{vi,\eta i}(y_1, y_2)$, which can be expressed as a joint cumulative probability distribution of uniform [0,1] marginal variables U_1 and U_2 as below:

$$\begin{aligned} F_{vi,\eta i}(y_1, y_2) &= \mathrm{P}(v_{qij} < y_1, \eta_{qij} < y_2) \\ &= \mathrm{P}(F_{vi}^{-1}(U_1) < y_1, F_{\eta i}^{-1}(U_2) < y_2) \qquad (4.7) \\ &= \mathrm{P}(U_1 < F_{vi}(y_1), U_2 < F_{\eta i}(y_2)) \end{aligned}$$

Then, the above joint distribution (of uniform marginal variables) can be generated by a function $C_\theta(.,.)$ such that (Sklar 1973):

$$F_{vi,\eta i}(y_1, y_2) = C_\theta(u_1 = F_{vi}(y_1), u_2 = F_{\eta i}(y_2)) \qquad (4.8)$$

where $C_\theta(.,.)$ is a copula function and θ is a dependency parameter (assumed to be scalar), together characterizing the dependency between v_{qij} and η_{qij}. The joint distribution formed in the above-discussed manner is used to derive the joint residential location, and vehicle ownership and type combination choice, and vehicle mileage probabilities and log-likelihood expressions.

4.2.3 <u>Model estimation</u>

The joint model based on the formulation above has the following log-likelihood expression for a random sample of Q households $(q = 1,\ 2,\ ...,\ Q)$:

$$L = \prod_{q=1}^{Q} \left[\prod_{j=1}^{J} \prod_{i=1}^{I} \left\{ P\left(m_{qij} \,|\, \beta' x_{qij} > v_{qij}\right)^{(R_{qij} * H_{qj})} \times P\left(\beta' x_{qij} > v_{qij}\right)^{R_{qij}} \right\} \right]. \qquad (4.9)$$

where H_{qj} = 1 if it is not the case that the household q chooses no vehicles at choice occasion j, and 0 otherwise.

The conditional distributions in the above expression can be expressed as:

$$
\begin{aligned}
P\left(m_{qij}|\beta' x_{qij}>v_{qij}\right) &= \left[P\left(\beta' x_{qij}>v_{qij}\right)\right]^{-1} \times \frac{\partial}{\partial m_{qi}} F_{vi,\eta i}\left(\beta' x_{qij}, \frac{m_{qij}-\alpha' z_{qij}}{\sigma_{\eta i}}\right) \\
&= \left[P\left(\beta' x_{qij}>v_{qij}\right)\right]^{-1} \times \frac{1}{\sigma_{\eta i}} \times \frac{\partial}{\partial t} F_{vi,\eta i}\left(\beta' x_{qij}, t\right)\Big|_{t=\frac{m_{qij}-\alpha' z_{qij}}{\sigma_{\eta i}}} \\
&= \left[P\left(\beta' x_{qij}>v_{qij}\right)\right]^{-1} \times \frac{1}{\sigma_{\eta i}} \times \frac{\partial C_{\theta i}\left(u^i_{q1}, u^i_{q2}\right)}{\partial u^i_{q2}} f_{\eta i}\left(\frac{m_{qij}-\alpha' z_{qij}}{\sigma_{\eta i}}\right)
\end{aligned}
$$

(4.10)

where $C_{\theta i}(.,.)$ is the copula corresponding to $F_{vi,\eta i}(u^i_{q1}, u^i_{q2})$ with $u^i_{q1} = F_{vi}(\beta'_i x_{qij})$ and $u^i_{q2} = F_{\eta i}\left(\frac{m_{qij}-\alpha'_i z_{qij}}{\sigma_{\eta i}}\right)$, $\frac{\partial C_{\theta i}\left(u^i_{q1}, u^i_{q2}\right)}{\partial u^i_{q2}}$ is the partial derivative of the copula with respect to u^i_{q2} [see Bhat and Eluru (*4*)], $f_{\eta i}$ is the probability density function of η_{qij}, and $\sigma_{\eta i}$ is the scale parameter of η_{qij}.

Substitution of the above conditional distribution expression back into Equation (4.10) provides the following log-likelihood expression for the joint residential location, and vehicle ownership and type combination choice, and vehicle usage model:

$$
L = \prod_{q=1}^{Q} \prod_{j=1}^{J} \prod_{i=1}^{I} \left[\left\{ \frac{1}{\sigma_{\eta i}} \times \frac{\partial C_{\theta i}\left(u^i_{q1}, u^i_{q2}\right)}{\partial u^i_{q2}} f_{\eta i}\left(\frac{m_{qij}-\alpha' z_{qij}}{\sigma_{\eta i}}\right) \right\}^{(R_{qij} * H_{qj})} * P\left(\beta' x_{qij}>v_{qij}\right)^{(1-H_{qj})} \right]
$$

(4.11)

A particular advantage of the copula-based approach is that, in the above log-likelihood expression, several different copula [*i.e.*, $C_{\theta i}(.,.)$] functions can be explored to characterize the dependency between the residential location-vehicle type choice discrete component and the continuous vehicle miles of travel (VMT) component [see Chapter 3 for a review of alternative copula functions available in the literature]. Specifically, the copula approach allows us to test a variety of radially symmetric and asymmetric joint distributions to appropriately accommodate the dependency between choice dimensions.

Another appealing feature is that the copula approach separates the marginal distributions from the dependence structure so that the dependence structure is entirely unaffected by the marginal distributions assumed. Finally, Equation (4.11) has a closed form expression for most of the copulas available in the literature and hence obviates the need to adopt the more computationally intensive simulation-based procedures for parameter estimation. In this study, six different copulas are chosen from the rich set of copulas available. These include the following: (1) Gaussian copula, (2) Farlie-Gumbel-Morgenstern (FGM) copula, (3) Clayton, (4) Gumbel, (5) Frank, and (6) Joe copulas (please refer to the discussion in Chapter 3 for more details on these six copula structures).

To complete the model specification, in this study, it is assumed that the marginal distribution of the η_{qij} terms follows a normal distribution centered at zero with variance $\sigma^2_{\eta i}$. For the ε_{qij} terms, two GEV-based distributional assumptions were explored. The first was independence across alternatives *i*, leading to a multinomial logit (MNL) model for the residential choice-vehicle type choice component of the model system. The second was a nesting structure with residential location choice at the top level and vehicle type choice at the bottom level, to recognize that common unobserved residence location-based effects may increase the sensitivity between certain vehicle types, For example, a household whose individuals are environmentally conscious may decide to reside in neo-urbanist neighborhoods and also purchase coupe or compact sedans as a way of contributing less to environmental pollution).

4.3 Data

The data for this study is drawn from the 2000 San Francisco Bay Area Household Travel Survey (BATS) designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission (MTC).

There are three dependent variables in this study. The first dependent variable is that of residential location neighborhood type. A binary dependent variable, neo-urbanist or conventional, was constructed to characterize the traffic analysis zone (TAZ) of the household residence using a factor analysis and clustering technique. The complete details on the development of the neighborhood characterization is provided in Chapter 3. In brief, two principal components were identified through the factor analysis – one describing residential density and the transportation/land use environment and the second describing accessibility to activity center. The factors loading on the first component included bicycle lane density, number of zones accessible from the home zone by bicycle, street block density, household population density, and fraction of residential land use in the zone. The factors loading on the second component included bicycle lane density and number of physically active and natural recreation centers in the zone. A cluster analysis of the traffic analysis zones based on these two principal components or dimensions helped characterize all zones as either neo-urbanist or conventional.

The second dimension of the discrete dependent variable is the vehicle type. The vehicle types of the vehicles in the dataset were classified into six categories: (1) Coupe, (2) Sports utility vehicle (SUV), (3) Pickup truck, (4) Vans (including minivans), (5) compact sedans (including subcompact sedans) and (6) large sedans (including mid-size sedans and station wagons). In addition to these six alternatives, there exists the "no vehicle" alternative.

The third dependent variable is the logarithm of annual vehicle miles traveled (for each vehicle). This is the continuous choice dimension of interest in this study. Annual vehicle mileage was computed for each vehicle using the odometer readings recorded at the end of the diary period, reported mileage at the time of vehicle possession, the survey year, and the year of possession. The annual vehicle mileage is then:

$$\text{Annual Mileage} = \frac{\text{Mileage recorded at end of survey - Miles on possession}}{\text{Survey year} - \text{Year of possession}} \tag{4.12}$$

4.3.1 <u>Sample characteristics</u>

Only those households with four or fewer vehicles and that provided complete information on all vehicles in the household were included in the final data set used for model estimation. This yielded a final sample of 5,082 households. Of these households, 68.5% reside in conventional neighborhoods; these households report average annual mileage on vehicles equal to 12,023 miles, which is about 600 miles more than that reported by the households in neo-urbanist zones. Table 4.1 offers a summary of the characteristics of the sample used in this study. For both types of neighborhoods, it is found that SUV's are used more than other vehicle types as indicated by the higher vehicle mileage. In both neighborhood types, it is found that sedans account for a larger share of vehicle types than other vehicle types. Other salient characteristics of the sample are that about one-half of the households own only one vehicle, about 40 percent of the households are single-person households, nearly two-thirds own their residence, about one-third have two or more workers, and about three-quarters have no children.

4.4 Empirical analysis

This section presents a detailed discussion on the model estimation results. Models were estimated using a host of explanatory variables including household demographics, land use or built environment variables, and a variety of transportation network and accessibility measures. Bhat and Guo 2007 provide a detailed description of the nature and definition of the various land use and transportation network/accessibility measures used in the model specification. Joint nested logit-regression models of residential location choice, vehicle type choice, and vehicle mileage were estimated using the copula-based framework. The approach accommodates correlations across alternatives and potential self-selection effects on vehicle usage (via the correlation between v_{qij} and η_{qij}). In the model estimation effort, it was found that the correlation across alternatives was statistically insignificant. As a result, GEV-based logit model collapses into a simpler MNL-regression copula structure. The empirical analysis involved estimating models with six different copula structures (Gaussian, FGM, Frank, Clayton, Gumbel, and Joe) for specifying the dependency between the v_{qij} and η_{qij} terms (*4*). Finally, an independent model that ignores the possible dependency between the discrete and continuous choice dimensions was also estimated.

The maximum-likelihood estimation of the models with different copulas leads to a case of non-nested models. The most widely used approach to select among competing non-nested copula models is the Bayesian Information Criterion (BIC) [see Genius and Strazzera 2008, Trivedi and Zimmer 2007]. The BIC for a given copula model is equal to $-2\ln(L)+K\ln(Q)$, where $\ln(L)$ is the log-likelihood value at convergence, K is the number of parameters, and Q is the number of observations. The copula that results in the lowest BIC value is the preferred copula. However, if all of the competing models have the same exogenous variables and the same number of thresholds, as is the case here, the BIC information selection procedure measure is equivalent to selection based on the largest value of the log-likelihood function at convergence.

Among the copula models, it was found that the Frank copula model provides the best data fit with a likelihood value of –37291.3. The corresponding likelihood value for the independent copula model is –38607.1, clearly rejecting the hypothesis of independence between the combined residential location - vehicle type combination choice and vehicle usage equations in favor of the model structure that accommodates correlations between the v_{qij} and η_{qij} terms. The joint model in which the dependency parameters were specified to be Gaussian (*i.e.*, equivalent to Lee's model) yielded a log-likelihood value very close to the independent model log-likelihood. This result clearly underlines the importance of accommodating dependencies using flexible copula structures. In the interest of brevity, only estimation results for the Frank copula model are presented in Table 4.2. The parameters (and the t-statistics in parenthesis beneath the parameters) are presented for the discrete component for the fourteen residential location-vehicle type choice combinations and twelve continuous components separately.[9]

[9] The "no vehicle" alternative would not have any associated mileage component.

4.4.1 Model Estimation Results

This section is devoted to describing the findings reported in Table 4.2.

4.4.1.1 Discrete (MNL) component

The constant terms clearly indicate an overall preference to reside in conventional neighborhoods (as indicated by the higher coefficient for all vehicle types in the conventional neighborhood compared to their counterparts in the neo-urbanist neighborhood). Among the vehicle acquisition choices, the highest propensity is associated with acquiring "no vehicle" suggesting that, for most households, the number of vehicles is less than the number of adults plus 1 implying that every household is likely to have at least one "no vehicle" purchase decision. Among the vehicle types themselves, there is a greater propensity to acquire sedans in comparison to other vehicle types. Vans are least likely to be the vehicle type of choice as evidenced by the high negative constant relative to other vehicle types.

A host of household demographics impact joint residential location-vehicle count and type choice. Larger households are likely to acquire larger vehicles (large sedan, van, pickup truck) or choose not to acquire a vehicle. Households with children also exhibit preference for larger vehicles. Further, a comparison of coefficients across neighborhood types indicates that households with children are likely to prefer living in conventional neighborhoods, a finding earlier reported also by Bhat and Eluru 2009. A higher number of workers is associated with an inclination to acquire pickup truck while higher number of females is associated with a disinclination to acquire a pickup, suggesting gender related differences in vehicle type choice. Those who own a household tend to reside in conventional neighborhoods as opposed to neo-urbanist neighborhoods. Further, they are less likely to opt for a "no vehicle" option indicating a tendency to acquire as many vehicles as the number of adults + 1. This holds true for higher income households who show an inclination to acquire SUV and coupe type vehicles as opposed to other vehicle types, a finding consistent with earlier research [see Choo and Mokhtarian 2004].

Built environment variables significantly impact vehicle type choice. In general, as land use density and land use mix increase, the likelihood of acquiring pickup trucks decreases. This finding is consistent with expectations as one would expect households in such environments to shun the larger pickup truck type vehicles [also see Choo and Mokhtarian 2004 for a similar result]. Further, with the increase in density of non-motorized transport facilities, the likelihood of choosing neo-urbanist neighborhoods and not acquiring a vehicle increases. Transportation accessibility measures also impact joint neighborhood-vehicle type choices. As walk access time to a transit stop increases, the likelihood of owning vehicles of various types increases while enhanced bicycle accessibility reduces the likelihood of owning a pickup truck. Enhanced transit accessibility is associated with acquiring compact and large sedans as opposed to larger pickup trucks, SUVs, or vans.

One of the virtues of the model specification and form adopted in this study is that it allows one to capture household fleet dynamics [see Mannering and Winston 1985 for a discussion on the importance of household fleet dynamics on vehicle type choice]. By considering each vehicle type choice as a choice occasion, and ordering the choices in a chronological manner, one can model the choice of acquiring a vehicle type as a function of the previously held vehicle types in the household. An examination of the last set of variables in Table 4.2 shows that there is considerable household fleet dynamics and history dependency in vehicle type choice. If a household already owns a coupe, then the likelihood that the household will choose a different vehicle (than a coupe) increases across the vehicle types with the SUV vehicle type indicating the highest positive coefficient. Parameters along the diagonal are negative, suggesting that households are less likely to repeat the same vehicle type choice; instead, households are likely to acquire a mix of vehicle types suitable to different types of trips. The presence of a car (of any type) or SUV in the vehicle fleet increases the likelihood of not acquiring a vehicle. The presence of a van in the household reduces the likelihood that the household will acquire another large vehicle (SUV or pickup truck).

To accommodate the influence of vehicle make/model for each vehicle type, a logsum variable was computed from the multinomial logit (MNL) model results presented in Bhat *et al*. 2009. This logsum variable contains information on the vehicle attributes, fuel price, and household characteristics (*i.e.*, household size and income) that affected the choice of vehicle make/model within each vehicle type category, *i.e.*, the logsum variable is employed to capture the utility derived from the different make/model combinations within each vehicle type. In the context of residential location-vehicle type choice, the logsum parameter was not found to be statistically different from one, and is therefore set to one, indicating independence among the utilities of make/model alternatives within each vehicle body type category in vehicle make/model decisions.

4.4.1.2 Regression component

The regression component of the model presented in Table 4.2 shows how various factors influence vehicle usage for the various residential zone-vehicle type choice combinations. The constants indicate that mileage in conventional neighborhoods is higher than that in neo-urbanist neighborhoods for all vehicle types clearly suggesting that there is a neighborhood effect even when controlling for all other factors. The presence of children contributes to higher levels of mileage across virtually all vehicle types, except vans, a somewhat surprising finding given that vans are often the “family” vehicle. However, the coefficients associated with van mileage are not statistically significant. The presence of employed individuals contributes to higher vehicle mileage for all vehicle types (except vans). The finding is consistent with intuitive expectations because employed individuals travel regularly to their work place accruing significant mileage on the vehicle. The presence of senior adults, on the other hand has an opposite effect on vehicle mileage. Senior adults are less likely to be mobile, thus accruing less miles on their vehicles. Higher income levels are generally associated with higher levels of mileage, except for pickup trucks, which may be driven more by lower income blue-collar workers (see Spissu et al. 2009, Brownstone and Golob 2009).

Virtually all built environment measures indicative of density and land use mix contribute negatively to vehicle usage [similar to the findings of Brownstone and Golob 2009]. Similarly, non-motorized transportation accessibility also contributes negatively to vehicle usage. As such, there is a clear finding that land use and built environment does impact vehicular travel demand, even after accounting for residential self-selection effects. Cao *et al*. 2008, in their review of research on the influence of residential self-selection on travel behavior, find that most research efforts lend credence to our finding. The strong presence of unobserved factors is amply demonstrated by the highly statistically significant scale parameters that represent the variance of the error term in the continuous model component.

4.4.2 Model Assessment

This section presents a discussion of the model findings focusing on the simultaneity among choice processes to better understand the nature of the dependency among residential location-vehicle type choices and vehicle usage. This section also presents an application of the model to demonstrate its ability to replicate multi-dimensional choice processes.

In the last row of Table 4.2, it can be found that all dependency parameters are significantly different from zero, lending strong credence to the belief that there is substantial self-selection in the residential location-vehicle count by type-vehicle usage choice processes. The significant dependency parameters suggest that there are non-ignorable unobserved factors that affect both residential location-vehicle ownership and type combination choice and vehicle miles of travel for each type of vehicle. In the interest of parsimony in specification, the parameters are constrained to be equal across the residential location neighborhood types. The dependency parameters can be converted into a measure similar to a correlation coefficient that takes on a value between –1 and 1. This measure is called the Kendall's τ and it is essentially a transformation of the copula dependency parameters such that the τ value is constrained to a range of –1 to 1. It is computed as the probability of concordance minus the probability of discordance.

For the Frank copula, $\tau = 1 - \frac{4}{\theta}\left[1 - \frac{1}{\theta}\int_{t=0}^{\theta} \frac{t}{e^t - 1}dt\right]$ and $-1 < \tau < 1$ [for details, see Chapter 3]. The Kendall's measures of dependency by vehicle type are:

- Coupe: –0.52
- SUV: –0.56
- Pickup truck: –0.55
- Van: –0.61
- Compact sedan: –0.59
- Large sedan: –0.58

All of these values indicate that there is substantial dependency among the choice dimensions due to common unobserved factors. To interpret these dependency parameters further, note that Equation (4.3) can be rewritten as: $R_{qij} = 1$ if $\beta_i' x_{qij} - \nu_{qij} > 0$, and $R_{qij} = 0$ if $\beta_i' x_{qij} - \nu_{qij} < 0$. The error term ν_{qij} enters with a negative sign in the equation. Therefore a negative correlation (or dependency) between this error term and the error term η_{qij} in the vehicle usage equation implies that unobserved factors that increase (decrease) the propensity to choose a residential location-vehicle type *i* also increase (decrease) the usage of that vehicle type. Similarly, a positive correlation between the ν_{qij} and the η_{qij} terms implies that unobserved factors that increase (decrease) the propensity to choose a residential location-vehicle type *i* also decrease (increase) the usage of that vehicle type. Based on intuitive consideration, one can expect the estimated dependency parameters between the ν_{qij} and the η_{qij} terms to be negative, implying that the dependency between vehicle type choice and usage is positive.

In this study, it is indeed found that the dependency parameters are negative suggesting that unobserved factors that make a household more (less) inclined to acquire a certain vehicle type also make the household more (less) inclined to use that vehicle more (*i.e.*, accumulate more miles). As mentioned earlier, it is important to note that the model using Gaussian copula fails to capture these correlations and suggests that there is no self-selection bias. To further emphasize the importance of this finding, in a recent effort to examine the influence of self-selection on vehicle usage, Brownstone and Golob 2009 estimate a joint model of residential density and vehicle usage assuming a Gaussian error dependency structure. They conclude from their model results that there are no statistically significant self-selection impacts on vehicle usage. However, the results from the Frank copula clearly suggest the presence of dependency underscoring the importance of using flexible copula structures in modeling self-selection impacts.

4.5 Summary

There has been substantial interest in the transportation literature on examining the influence of residential neighborhood choice on vehicle count by type and vehicle usage. These choice phenomena are of much interest to the profession given the recent attention being paid to global warming, public health, sustainable development and mobility patterns, and energy independence. The current research proposes a simple, yet effective methodological approach that focuses on incorporating the impact of "self-selection" of individuals in residential location-vehicle ownership and type choice and its influence thereof on vehicle usage. In this chapter, a simultaneous model of residential location choice, vehicle count and type choice, and vehicle usage is presented with a view to capture the potential effects of the presence of common unobserved factors that may jointly impact these choice dimensions. The research effort employs the structure of the copula-based joint GEV-based logit – regression modeling framework to jointly model the choice dimensions. Multiple vehicle ownership and usage dimensions are accommodated by assuming that the current vehicle fleet and its usage are determined through a series of unobserved (to the analyst) repeated discrete-continuous choice occasions. The number of choice occasions is linked to the number of adults in the household. At each choice occasion the household is faced with a choice of acquiring different vehicle types or "acquiring no vehicle". The estimation of such complex multidimensional discrete-continuous model systems that accommodate error correlations or dependencies has proven to be a challenge, both from an analytical and a computational burden perspective.

In this study, a GEV based logit – regression copula-based modeling approach that offers a closed form solution to the evaluation of the likelihood function is employed to overcome the computational and analytical challenges associated with estimating such model systems. In the current study, six different copulas are tested from the rich set of copulas generated in literature including (1) Gaussian copula, (2) Farlie-Gumbel-Morgenstern (FGM) copula, (3) Clayton, (4) Gumbel, (5) Frank, and (6) Joe copulas for the simultaneous model of residential location choice, vehicle ownership and type choice, and vehicle usage. The research effort offers an advanced methodology that can be used to specify, estimate, and apply travel models that simultaneously represent multiple choice dimensions.

The findings in the current study confirm that there are significant common unobserved factors that simultaneously impact residential location choice, vehicle type choice, and vehicle usage. The Frank copula models offers a substantially superior data fit compared to the model that ignores the presence of self-selection impacts. Notably, the Gaussian copula estimation results are not statistically superior to the independent model results. A conventional joint modeling of these choices (assuming normal correlated errors across choice dimensions) would have one conclude that self-selection impacts are negligible in affecting vehicle usage. However, the Frank copula model results support the notion that there are significant self-selection effects in residential location choice and vehicle type choice and usage. People choose neighborhoods and vehicles that support their lifestyle preferences and attitudes and values.

Further, the model system presented in this chapter offers the ability to not only model vehicle fleet composition or holdings, but also the vehicle acquisition process itself as a function of previously held vehicles in the household. This model provides an effective solution to obtain a complete and accurate picture of the land use-vehicle fleet-vehicle use choices of a household while controlling for self-selection effects in these choice processes.

Table 4.1: Sample Characteristics

Dependent variable				
Vehicle type	**Conventional neighborhood**		**Neo-urbanist neighborhood**	
	Sample share (%)	Annual mileage	Sample share (%)	Annual mileage
Coupe	7.8	10319	3.1	9926
SUV	7.6	13555	3.0	12901
Pickup truck	9.6	12005	3.2	11512
Vans	6.2	13252	2.0	12200
Compact sedan	15.4	12257	8.0	11350
Large sedan	24.4	11637	9.6	11369
Overall by neighborhood	71.1	12023	28.9	11439
Number of vehicles				
1			51.8	
2			40.9	
3 or more			7.3	
Household size				
1			39.2	
2			36.1	
3			9.6	
4			11.1	
5 or more			4.0	
Household tenure				
Own			66.6	
Rent			33.4	
Number of Employed individuals				
0			18.9	
1			48.1	
2 or more			33.0	
Number of children				
0			75.7	
1			9.5	
2 or more			14.8	
Sample size			5082	

Table 4.2: Frank Copula Model Results: MNL component

Variable	**MNL** (Dependent variable = Combined Residential location, vehicle count and type)													
	Conventional neighborhood							**Neo-urbanist neighborhood**						
	Coupe	**SUV**	**Pickup Truck**	**Van**	**Comp Sedan**	**Large Sedan**	**No vehicle**	**Coupe**	**SUV**	**Pickup Truck**	**Van**	**Comp Sedan**	**Large Sedan**	**No vehicle**
Constant	-	-0.444 (-3.92)	-1.302 (-6.43)	-2.878 (-12.73)	0.358 (3.61)	0.389 (2.82)	3.145 (17.01)	-0.639 (-6.97)	-0.968 (-7.47)	-2.041 (-9.66)	-3.455 (-15.43)	0.036 (0.32)	-0.143 (-0.98)	2.476 (11.69)
Household demographics														
Household size	-	-	0.377 (5.91)	0.765 (14.92)	-0.192 (-3.26)	0.205 (4.24)	0.259 (4.93)	-	-	0.377 (5.91)	0.765 (14.92)	-0.192 (-3.26)	0.205 (4.24)	0.327 (5.14)
<u>No. of children</u>														
#children ≤ 4 yrs	--	0.504 (5.95)	-	-	0.372 (4.66)	-	-	-0.157 (-4.82)	0.348 (3.83)	-0.157 (-4.82)	-0.157 (-4.82)	0.215 (2.50)	-0.157 (-4.82)	-0.157 (-4.82)
#children 5 - 10 yrs	-	0.417 (5.00)	-	0.238 (3.07)		-	-	-0.154 (-5.15)	0.263 (2.97)	-0.154 (-5.15)	0.084 (1.01)	-0.154 (-5.15)	-0.154 (-5.15)	-0.154 (-5.15)
#children 11 - 15 yrs	-	0.493 (4.93)	-	0.353 (4.22)	0.201 (2.04)	-	-	-0.162 (-4.38)	0.331 (3.11)	-0.162 (-4.38)	0.191 (2.10)	0.039 (0.37)	-0.162 (-4.38)	-0.162 (-4.38)
#employed individuals	-	-	0.355 (7.18)	-	0.237 (4.98)	-0.113 (-2.93)	-	-	-	0.355 (7.18)	-	0.237 (4.98)	-0.113 (-2.93)	-
#females	--	-0.280 (-3.55)	-	-	0.367 (5.82)	0.155 (2.71)	0.153 (2.33)	-	-	-0.280 (-3.55)	-	0.367 (5.82)	0.155 (2.71)	0.166 (2.09)
<u>Annual household income</u>														
35K-90K	-	0.180 (1.89)	-	-	-	-	-	-	0.180 (1.89)	-	-	-	-	-
>90K	-	-	-0.859 (-7.69)	-0.339 (-2.93)	-0.405 (-4.41)	-0.344 (-3.99)	-0.570 (-5.98)	-	-	-0.859 (-7.69)	-0.339 (-2.93)	-0.405 (-4.41)	-0.344 (-3.99)	-0.536 (-5.02)
<u>Household tenure</u>														
Own household	-	0.346 (3.74)	0.534 (6.05)	0.792 (6.77)		0.326 (5.17)	-0.189 (-2.27)	-0.446 (-10.00)	-0.100 (-0.98)	0.087 (0.88)	0.346 (2.76)	-0.446 (-10.00)	-0.121 (-1.57)	-0.446 (-10.00)
Built environment variables														
Employment density	-	-	-0.001 (-1.16)	-	-	-	-	-	-	-0.001 (-1.16)	-	-	-	-
Land use mix (0-1)	-	-	-0.345 (-2.00)	-	-	-	-	-	-	-0.345 (-2.00)	-	-	-	-
Density of bicycle lanes	-	-	-	-	-0.012 (-1.13)		-0.104 (-7.34)	-	-	-	-	-0.012 (-1.13)		0.149 (10.90)

Variable	MNL (Dependent variable = Combined Residential location, vehicle count and type)													
	Conventional neighborhood							**Neo-urbanist neighborhood**						
	Coupe	**SUV**	**Pickup Truck**	**Van**	**Comp Sedan**	**Large Sedan**	**No vehicle**	**Coupe**	**SUV**	**Pickup Truck**	**Van**	**Comp Sedan**	**Large Sedan**	**No vehicle**
Local transportation measures														
Walk access time to in-zone transit stop	-	0.030 (4.32)	-	0.038 (4.68)	-	0.020 (4.03)	0.032 (5.02)	-	-	-	-	-	0.020 (4.03)	-0.036 (-4.51)
No. of zones accessible by bike within 6 miles	-		-0.008(- 4.78)	-	-	-	-0.004 (-2.86)	-	-	-0.008 (-4.78)	-	-	-	0.010 (7.27)
No. of zones accessible by transit within 30 minutes	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Household fleet dynamics														
Presence of coupe	-	1.142 (5.88)	0.466 (2.38)	0.512 (2.09)	0.243 (1.25)	0.501 (2.82)	0.667 (4.21)		1.142 (5.88)	0.466 (2.38)	0.512 (2.09)	0.243 (1.25)	0.501 (2.82)	-
Presence of SUV	-	-	-	-	-	-	0.325 (2.46)	-	-	-	-	-	-	0.325 (2.46)
Presence of Pickup truck	-	-1.733 (-7.30)	-	-	-	-	-		-1.733 (-7.30)	-	-	-	-	-0.291 (-1.97)
Presence of Van	-	-0.474 (-2.27)	-0.372 (-2.13)	-2.033 (-6.20)	-	-	-	-	-0.474 (-2.27)	-0.372 (-2.13)	-2.033 (-6.20)	-	-	-
Presence of compact sedan	-	-	-	-	-	-	0.329 (3.32)	-	-	-	-	-	-	-
Presence of large sedan	-	-	-	-	-	-	0.310 (3.73)	-	-	-	-	-	-	-
Log-sum parameter	1.000	1.000	1.000	1.000	1.000	1.000	-	1.000	1.000	1.000	1.000	1.000	1.000	-

Table 4.2 Frank Copula Model Results: Regression component

	Regression (Dependent variable = LnVMT)											
	Conventional neighborhood						**Neo Neighborhood**					
	Coupe	**SUV**	**Pickup Truck**	**Van**	**Com-Sedan**	**Large Sedan**	**Coupe**	**SUV**	**Pickup Truck**	**Van**	**Com-Sedan**	**Large Sedan**
Constant	7.562 (53.24)	8.246 (80.57)	7.897 (54.67)	7.692 (58.89)	8.077 (128.87)	8.041 (160.66)	7.459 (46.54)	8.142 (79.16)	7.798 (46.13)	7.578 (47.09)	7.985 (104.56)	7.893 (131.50)
Household demographics												
Household size	-0.047 (-1.50)	-0.073 (-1.70)	-0.205 (-3.16)	0.152 (4.64)	-0.059 (-1.67)	-	-0.047 (-1.50)	-0.073 (-1.70)	-0.205 (-3.16)	0.152 (4.64)	-0.059 (-1.67)	-
<u>No. of children in the household</u>												
#children ≤ 4 yrs	-	0.188 (2.69)	0.301 (2.63)	-0.103 (-1.66)	0.091 (1.55)	0.037 (1.93)	-	0.188 (2.69)	0.301 (2.63)	-0.103 (-1.66)	0.091 (1.55)	0.037 (1.93)
#children 5-10 yrs	-	0.144 (2.39)	0.246 (2.90)	-0.077 (-1.36)	0.070 (1.42)	0.037 (1.93)	-	0.144 (2.39)	0.246 (2.90)	-0.077 (-1.36)	0.070 (1.42)	0.037 (1.93)
#children 11-15 yrs	-	0.144 (2.39)	0.246 (2.90)	-	0.070 (1.42)	0.037 (1.93)	-	0.144 (2.39)	0.246 (2.90)	-	0.070 (1.42)	0.037 (1.93)
#employed individuals	0.090 (1.80)	0.068 (1.70)	0.234 (3.75)	-	0.158 (4.42)	0.093 (4.67)	0.090 (1.80)	0.068 (1.70)	0.234 (3.75)	-	0.158 (4.42)	0.093 (4.67)
#senior adults	-0.154 (-2.01)	-	-0.145 (-2.03)	-0.190 (-3.16)	-0.212 (-5.53)	-0.084 (-3.55)	-0.154 (-2.01)		-0.145 (-2.03)	-0.190 (-3.16)	-0.212 (-5.53)	-0.084 (-3.55)
<u>Annual hhld income</u>												
35K-90K	0.330 (3.27)	-	-	0.228 (2.31)	-	0.179 (4.49)	0.330 (3.27)	-	-	0.228 (2.31)	-	0.179 (4.49)
>90K	0.348 (3.08)	0.126 (2.23)	-0.095 (-1.17)	0.306 (2.69)	-	0.179 (4.49)	0.348 (3.08)	0.126 (2.23)	-0.095 (-1.17)	0.306 (2.69)	-	0.179 (4.49)
<u>Household tenure</u>												
Own household	-	-	-0.105 (-1.22)	-	-	-0.023 (-0.71)	-	-	-0.105 (-1.22)	-	-	-0.023 (-0.71)
Built environment variables												
Population density	-	-	-	-	-0.002 (-1.39)	-	-	-	-	-	-0.002 (-1.39)	-
Employment density	-	-	-	-	0.001 (0.90)	-	-	-	-	-	0.001 (0.90)	-
Density of bicycle lanes	-	-0.012 (-1.15)	-	-0.021 (-1.58)	-0.012 (-1.64)	-0.011 (-1.79)		-0.012 (-1.15)		-0.021 (-1.58)	-0.012 (-1.64)	-0.011 (-1.79)
Presence of 4+ physical activity centers	-	-	-	-0.135 (-1.26)	-	-	-	-	-	-0.135 (-1.26)	-	-
Local transportation measures												
No. of zones accessible by bike within 6 miles	-0.002 (-1.47)	-	-0.003 (-2.09)	-0.004 (-3.27)	-0.001 (-1.87)	-0.002 (-4.27)	-0.002 (-1.47)	-	-0.003 (-2.09)	-0.004 (-3.27)	-0.001 (-1.87)	-0.002 (-4.27)
Scale parameter	1.122 (76.99)	0.926 (89.57)	1.303 (60.93)	0.989 (87.89)	1.007 (142.97)	0.953 (157.86)	1.122 (76.99)	0.926 (89.57)	1.303 (60.93)	0.989 (87.89)	1.007 (142.97)	0.953 (157.86)
Copula dependency parameter (θ)	-6.034 (-14.27)	-6.999 (-15.20)	-6.723 (-13.40)	-8.085 (-12.07)	-7.780 (-21.69)	-7.365 (-27.24)	-6.034 (-14.27)	-6.999 (-15.20)	-6.723 (-13.40)	-8.085 (-12.07)	-7.780 (-21.69)	-7.365 (-27.24)

CHAPTER 5 ACTIVITY PARTICIPATION DECISIONS

5.1 Introduction and motivation

Emerging policy issues of interest, including concerns regarding global climate change and the desire to better understand how pricing policies and technological innovations impact travel demand, enhanced understanding of activity-travel behavior dimensions garnered over decades of behavioral research, and advances in microsimulation-based computational approaches have all contributed to a new era in travel demand modeling and forecasting (Pendyala *et al*, 2005; Pinjari *et al*, 2006). This era is characterized by an increasing shift towards activity-based travel demand modeling approaches that explicitly recognize that travel is undertaken to fulfill activity needs and desires dispersed in space and time (Meloni *et al*, 2004). The move towards microsimulation-based approaches facilitates the disaggregate representation of behavioral agents and their interactions, while simultaneously incorporating the ability to analyze policy impacts and address equity concerns at the level of the individual traveler or any sub-market segment of interest (Miller and Roorda, 2003).

Within the scope of this chapter, it is not possible to thoroughly review the developments in activity-based models over the past decade and the gradual implementation of tour-based models in practice in several urban areas in the United States and other parts of the world (see Chapter 1 for review of operational activity-based models). Regardless of the specific model design adopted, it is found that activity and tour-based model systems universally strive to mimic and replicate activity-travel choice processes of individuals. These choice processes include such dimensions as activity type choice, time of day choice, trip chaining or linking choice, joint versus solo activity engagement choice, destination choice, mode choice, activity sequencing decisions, and activity time allocation (duration) decisions. Many of these choice processes are discrete in nature (e.g., activity type choice, time of day period choice, mode and destination choices), while a few may be more continuous in nature (e.g., activity duration). Given the large number of choices that are involved in the behavioral process, many models, particularly the tour-based models in practice, resort to the adoption of deeply nested logit models (Ben-Akiva and Lerman, 1985) where one choice process is nested within another choice process and so on, forming a long chain of inter-connected nests to complete the representation of the behavioral process (Bowman, 1995; Bowman and Bradley, 2006; PB Consult, 2005). As it is virtually impossible to estimate such long chains of nested logit models simultaneously (i.e., in one single step), components of the nested logit model are usually estimated one step (or maybe two steps) at a time and the logsum from one level is carried up to the next higher level, resulting in a sequential estimation and model application approach. Although there are other behavioral model systems that attempt to move away from such deeply nested logit specifications, such as those based on computational process modeling and heuristic approaches (Arentze and Timmermans, 2005), the fact remains that most activity-based model systems break down the behavioral decision process so that one is modeling only one or two choice processes at any step in the model system.

5.1.1 Joint model systems

Although a sequential treatment of choice mechanisms is convenient from a practical model estimation and application standpoint, it is unclear whether such model systems truly replicate behavioral processes. While tour-based and activity-based models in practice can be lauded for their ability to model activity engagement patterns, consider interactions among activities and trips, and microsimulate activity-travel patterns at the level of the individual traveler, the issue arises as to whether these model systems can be challenged and questioned from a behavioral standpoint not unlike the traditional four-step travel modeling process. The four-step travel modeling process has been consistently criticized for its sequential nature of treatment of the travel demand process. To what extent activity and tour-based models in practice overcome this issue is potentially open to debate, although there is no question that even limited information maximum likelihood (LIML) specifications of deeply nested logit models allow one to model correlated choice processes better than was done in the four-step travel modeling process.

While it is arguably true that people have limited cognitive abilities and therefore exercise choices in a limited, sequential way, there is considerable evidence that many choices are made jointly or simultaneously and that there are significant unobserved factors that simultaneously impact multiple choice dimensions (see, for example, Pinjari and Bhat, 2009a). In fact, one could argue that the limited information sequential model specifications have been adopted in the activity-based modeling realm because of the estimation challenges and computational complexity associated with specifying, identifying, and estimating simultaneous equations model systems that represent joint choice processes in which individuals and households are making a "package" of activity-travel choices as a "bundle". In other words, it is conceivable that individual agents are making choices regarding the type of activity to pursue, the mode and destination, and the time allocation to the activity in one swoop, thus motivating the adoption of a "joint" choice model specification in which unobserved factors unknown to the analyst may be simultaneously impacting multiple dimensions of interest (Jara-Diaz *et al*, 2007).

5.1.2 Current research effort

The growing interest in the ability to model multiple choice dimensions simultaneously, where the endogeneity of many choice variables is explicitly recognized in the activity-travel behavior modeling arena, motivates this research effort. Specifically, this chapter presents a joint model system of five choice dimensions:

- Activity type choice
- Activity time of day choice (treated as discrete time intervals)
- Mode choice
- Destination choice
- Activity duration (continuous choice dimension)

These five choice dimensions are of critical interest to any activity-based model system regardless of the model design that might be adopted. Thus, this study aims to specify and estimate a comprehensive econometric model system that jointly models these five choice dimensions in a holistic unifying utility-maximization framework. The model system explicitly includes consideration of built environment attributes including level of service variables and spatial land use characteristics to capture the potential impacts of such variables on the activity generation process, a key area that warrants additional research. Such a model specification provides the ability to examine induced and suppressed demand effects in response to changes in system capacity and level of service.

The modeling methodology adopted in this study builds on previous work by the authors and constitutes a joint multiple discrete continuous extreme value model and multinomial logit model system (Bhat 2005, Bhat et al., 2006, Bhat 2008). The multiple discrete continuous extreme value (MDCEV) model component is used to jointly analyze activity type choice, activity time of day choice, mode choice, and activity duration. Specifically, the MDCEV model is used to represent activity participation (discrete choice) and time use (continuous choice) for different types of activities at different time periods of the day by different travel modes. The activity location choice is modeled using a multinomial logit (MNL) model nested within the MDCEV framework. The model system is estimated for a survey sample drawn from the 2000 San Francisco Bay Area Travel Survey (BATS), a comprehensive database that includes detailed household and personal socio-economic, demographic, and activity-travel information together with a host of secondary transportation level-of-service and land use variables.

The next section presents the modeling methodology in detail. This is followed by a description of the dataset and survey sample. The fourth and fifth sections present model estimation and policy simulation results, while the sixth and final section offers concluding remarks.

5.2 Modeling methodology

This section presents the modeling methodology for the joint MDCEV-MNL model structure. First, the utility structure is presented, second, the econometric model specification is presented, and finally the procedure for sampling of location choice alternatives is discussed. An intuitive behavioral interpretation of the model structure is offered as well.

5.2.1 Utility Structure

Consider the following utility specification for the integrated analysis of individuals' activity time-use, timing, mode choice, and location choice decisions:

$$U(\boldsymbol{x}) = \{\psi_1 \ln x_1\} + \left\{\gamma_2 \psi_2 \ln\left(\frac{x_2}{\gamma_2}+1\right)\right\} + \sum_{ptm=3}^{62}\left\{\gamma_{ptm}\psi_{ptm} \ln\left(\frac{x_{ptm}}{\gamma_{ptm}}+1\right)\right\} \tag{5.1}$$

In the above equation, the first term $\psi_1 \ln x_1$ corresponds to the utility contribution of the total daily time invested (x_1) in all maintenance activities, and the second term corresponds to the utility contribution of the total daily time invested (x_2) in all in-home (IH) discretionary activities. The next set of terms correspond to the utility contribution due to the time investment (x_{ptm}) in out-of-home (OH) discretionary activity episode types (indexed by *ptm*), with each activity episode type defined by its purpose (*p*), timing (*t*), and mode of travel (*m*). In the current empirical context considered in this chapter, there are five OH discretionary activity purposes (volunteering, socializing, recreation, meals, and shopping), six time periods (3am-7am or early morning, 7am-9am or morning, 9am-12noon or late morning, 12noon-4pm or afternoon, 4pm-7pm or evening, and 7pm-3am or night), and two modes of travel (auto, and non-auto), yielding 60 different types of OH discretionary activity episodes (or *ptm* combinations). Thus, there are a total of 62 MDCEV choice alternatives in that one or more of these alternatives may be chosen by an individual through the course of a day.[10] For each of these alternatives, the ψ terms ($\psi_1, \psi_2, \text{and} \psi_{ptm}$) are the baseline utility parameters that control the discrete choice of the alternative. For all alternatives except the first alternative, the γ terms (γ_2 and γ_{ptm}) allow for corner solutions (*i.e.*, the possibility of not choosing the alternative) as well as satiation effects (*i.e.*, diminishing marginal utility with increasing time investment).[11] There is no γ term corresponding to the first alternative (maintenance activity) as it is always chosen by all individuals.

Finally, let each of the 60 OH discretionary activity episode types (*ptm*) be defined (by its purpose-timing-mode (*ptm*) combination) such that an individual participates in no more than one episode of that type in a day. Consequently, if an individual chooses to undertake an activity episode type (*ptm*), it has to be at only one of the several destination alternatives (*l*) available to her/him.

Let the index for the activity destination (or location) be *l*, and let N_{ptm} be the set of destinations available for an activity episode type (*ptm*). Further, for each activity episode type (*ptm*), let ψ_{ptm} be defined as follows (Bhat et al., 2006):

$$\psi_{ptm} = \exp\left(\sum_{l \in N_{ptm}} \delta_{lptm} W_{lptm} \right), \tag{5.2}$$

where, W_{lptm} is the utility perceived by the individual for undertaking the OH discretionary activity episode of purpose *p*, during time period *t*, by traveling on mode *m* to location *l*,

---

[10] Without loss of generality, all individuals can be assumed to participate in maintenance activities. On the other hand, an individual can participate in none, or one, or more of IH discretionary and 5 OH discretionary activity purposes (*p*) identified above. If (s)he chooses to participate in OH discretionary activities, (s)he can do so during one or more of the 6 time periods (*t*), and access the activities using one or more of the 2 travel modes (*m*). Thus, there is multiple discreteness in the choices across the activity purpose, activity timing, and travel mode dimensions.

[11] To distinguish the satiation along OH discretionary activity purpose, activity timing, and travel mode dimensions (and to facilitate estimation), γ_{ptm} (*ptm* = 3,4,…,62) is parameterized as $\gamma_{ptm} = \gamma_p \times \gamma_t \times \gamma_m$, where γ_p, γ_t, γ_m are the estimated dimension-specific satiation parameters.

and δ_{lptm} is a dummy variable taking a value of 1 if the l^{th} location is chosen for that activity episode such that $\sum_{l \in N_{ptm}} (\delta_{lptm}) = 1$ (*i.e.*, only one location is chosen).

With the above definition of ψ_{ptm} and other terms described earlier, the individual is assumed to maximize the utility function $U(\boldsymbol{x})$ in Equation (5.1) subject to $x_1 + x_2 + \sum_{ptm} x_{ptm} = X$; $x_1 > 0,\ x_2 \geq 0,\ x_{ptm} \geq 0\ \forall ptm = 3, 4, ...62.$ Since the individual maximizes $U(\boldsymbol{x})$ and can choose only one location for each activity episode *ptm* type, the functional form of $U(\boldsymbol{x})$ implies that the individual will consider the location that provides the maximum utility for each activity episode *ptm* type in the process of maximizing $U(\boldsymbol{x})$ (see Bhat et al., 2008). That is, $\sum_{l \in N_{ptm}} \delta_{lptm} W_{lptm} = \max_{l \in N_{ptm}} W_{lptm}$, or $\psi_{ptm} = \exp\left(\max_{l \in N_{ptm}} W_{lptm}\right)$ Thus, the individual's utility maximizing problem can be written as:

$$U(\boldsymbol{x}) = \{\psi_1 \ln x_1\} + \left\{\gamma_2 \psi_2 \ln\left(\frac{x_2}{\gamma_2} + 1\right)\right\} + \sum_{ptm} \left\{\gamma_{ptm} \exp\left(\max_{l \in N_{ptm}} W_{lptm}\right) \ln\left(\frac{x_{ptm}}{\gamma_{ptm}} + 1\right)\right\} \tag{5.3}$$

subject to $x_1 + x_2 + \sum_{ptm} x_{ptm} = X$; $x_1 > 0,\ x_2 \geq 0,\ x_{ptm} \geq 0\ \forall ptm.$

The analyst can solve for the optimal values of $x_1, x_2,$ and x_{ptm} by forming the Lagrangian and applying the Kuhn-Tucker (KT) conditions. Specifically, the following KT conditions can be formed (see Bhat, 2008):

$$\begin{aligned} &H_2 = H_1 \ \ if\ x_2 > 0 \\ &H_2 < H_1 \ \ if\ x_2 = 0 \\ &H_{ptm} = H_1 \ \ if\ x_{ptm} > 0 \\ &H_{ptm} < H_1 \ \ if\ x_{ptm} = 0 \end{aligned} \tag{5.4}$$

where,

$H_1 = \ln(\psi_1) - \ln(x_1)$,

$H_2 = \ln(\psi_2) - \ln\left(\dfrac{x_2}{\gamma_2} + 1\right)$, and

$H_{ptm} = \max\limits_{l \in N_{ptm}} W_{lptm} - \ln\left(\dfrac{x_{ptm}}{\gamma_{ptm}} + 1\right)$

5.2.2 Econometric Structure

To complete the model specification, let $\psi_1 = \exp(\beta' z_1 + \varepsilon_1)$ and $\psi_2 = \exp(\beta' z_2 + \varepsilon_2)$, where $\beta' z_1$ and $\beta' z_2$ are the observed baseline utility components of maintenance and IH discretionary activities, respectively, and ε_1 and ε_2 are the corresponding unobserved components assumed to be independent and identically Gumbel distributed. Further, to define ψ_{ptm}, we expand W_{lptm} as:

$$W_{lptm} = \beta' z_{ptm} + \phi' w_{lptm} + \eta_{lptm} \tag{5.5}$$

where, $\beta' z_{ptm}$ is the observed baseline utility corresponding to the activity purpose, timing, and mode of the OH discretionary activity episode *ptm*, $\phi' w_{lptm}$ is the observed utility corresponding to the potential location *l* for the activity episode, and η_{lptm} is the unobserved utility component associated with the location *l* of activity episode *ptm*. Similar to ε_1 and ε_2, the η_{lptm} terms are assumed to be independent and identically distributed (across different activity episode *ptm* types) Gumbel terms. Within each activity episode *ptm* type, however, all the error terms may share common unobserved attributes (specific to the activity episode *ptm* type) generating correlations among the η_{lptm} terms across all potential locations for the activity episode. Thus, for each activity episode *ptm* type, the following distribution of error terms may be used:

$$F(\eta_{1ptm}, \eta_{2ptm}, \ldots, \eta_{Lptm}) = \exp\left\{ -\left[e^{-\eta_{1ptm}/\theta_{ptm}} + e^{-\eta_{2ptm}/\theta_{ptm}} + \ldots + e^{-\eta_{Lptm}/\theta_{ptm}} \right]^{\theta_{ptm}} \right\} \tag{5.6}$$

where the θ_{ptm} is the dissimilarity parameter indicating the level of correlation among the η_{lptm} terms across all the potential locations for the activity episode *ptm* combination. Given this error distribution, using the properties of Gumbel distribution, H_{ptm} in Equation (5.4) can be expressed as:

$$
\begin{aligned}
H_{ptm} &= \max_{l \in N_{ptm}} \left\{ \beta' z_{ptm} + \phi' w_{lptm} + \eta_{lptm} \right\} - \ln\left(\frac{x_{ptm}}{\gamma_{ptm}} + 1 \right) \\
&= \beta' z_{ptm} + \theta_{ptm} \ln \sum_{l \in N_{ptm}} \exp\left(\frac{\phi' w_{lptm}}{\theta_{ptm}} \right) + \zeta_{ptm} - \ln\left(\frac{x_{ptm}}{\gamma_{ptm}} + 1 \right)
\end{aligned} \tag{5.7}
$$

where, ζ_{ptm} is a standard independent and identically distributed (across *ptm*) Gumbel error term. In this equation, $\ln \sum_{l \in N_k} \exp\left(\frac{\phi' w_{lk}}{\theta_k} \right)$ constitutes the logsum term.

Next, following the MDCEV model derivations (see Bhat, 2008), the probability that the individual chooses the first Q out of K (=62) activity purpose-timing-mode alternatives (this may include maintenance as well as the IH discretionary activities without any timing and mode distinctions) for time investments $x_1^*, x_2^*, ..., x_Q^*$ may be written as:

$$
P(x_1^*, x_2^*, ..., x_Q^* 0, 0, ..., 0) = \left[\prod_{k=1}^{Q} r_k \right] \left[\sum_{k=1}^{Q} \frac{1}{r_k} \right] \left[\frac{\prod_{k=1}^{Q} e^{V_k}}{\left(\sum_{h=1}^{K} e^{V_h} \right)^Q} \right] (Q-1)!, \tag{5.8}
$$

where[12]

$$
r_1 = \left(\frac{1}{x_k^*} \right) \text{ and } r_k = \left(\frac{1}{x_k^* + \gamma_k} \right) \forall k > 1
$$

[12] Note that the notation for the subscripts of the choice alternatives has been changed to *k(=1,2,…62)* from *1,2,ptm(=3,4,…62)* for convenience.

$$V_1 = \beta' z_1 - \ln(x_1),$$
$$V_2 = \beta' z_2 - \ln\left(\frac{x_2}{\gamma_2} + 1\right), \text{ and}$$
$$V_k = \beta' z_k + \theta_k \ln \sum_{l \in N_k} \left(\frac{\phi' w_{lk}}{\theta_k}\right) - \ln\left(\frac{x_k}{\gamma_k} + 1\right); \forall k > 2$$

The conditional probability that location *l* will be chosen for an activity episode purpose-timing-mode (*ptm*) combination *k*, given that $x_k^* > 0$, is given by:

$$P(l \mid x_k^* > 0;\ \ l \in N_k) = P\left[\phi' w_{lk} + \eta_{lk} > \phi' w_{l'k} + \eta_{l'k}\ \ \forall\ l' \neq l\right] \tag{5.9}$$

Based on the multivariate Gumbel distribution function for the η_{lk} (or η_{lptm}) terms (l = 1,2,…, L) from Equation (5.6), the above probability expression can be computed using the following standard multinomial logit formula:

$$P(l \mid x_k^* > 0;\ \ l \in N_k) = \frac{\exp\left(\frac{\phi' w_{lk}}{\theta_k}\right)}{\sum_{l' \in N_k} \exp\left(\frac{\phi' w_{l'k}}{\theta_k}\right)} \tag{5.10}$$

Next, the unconditional probability that the individual spends x_1^* amount of time in daily maintenance activities, x_2^* amount of time in daily IH-discretionary activities, x_3^* amount of time in OH discretionary activity episode purpose-timing-mode (*ptm*) combination 3 (*i.e., k* =3) at location *a*, x_4^* amount of time in OH discretionary activity episode purpose-timing-mode (*ptm*) combination 4 (*i.e., k* =4) at location *b*, … and so on, may be written as:

$$\begin{aligned} &P(x_1^*,\ x_2^*,\ x_3^* \text{ at } a,\ x_4^* \text{ at } b, ...,\ x_Q^* \text{ at } q,\ 0,0,0,...0) \\ &= P(x_1^*, x_2^*, ...x_Q^*, 0,0,...0) \times P(a \mid x_3^* > 0) \times P(b \mid x_4^* > 0) ... P(q \mid x_Q^* > 0) \end{aligned} \tag{5.11}$$

5.2.3 <u>Sampling of Location Choice Alternatives</u>

A practical issue with the proposed MDCEV-MNL model (as also with the deeply nested logit approach) is that, since there can be a large number of location choice alternatives at the single discrete choice level (and since multiple single discrete choice models may be invoked), the model estimation can be highly computation intensive. To reduce the computation time, the analyst can include only a smaller sample of the location choice alternatives (with the chosen alternative in the sample) during estimation. According to McFadden (1978), random sampling of alternatives will not compromise the consistency of the location choice model parameters as long as a simple multinomial logit modeling framework is maintained for the location choice as in Equation (5.10).[13] However, sampling the location choice alternatives warrants a correction to the log-sum term $\ln \sum_{l \in N_k} \exp\left(\frac{\phi' w_{lk}}{\theta_k}\right)$ used in the MDCEV component of the joint model (See Equation 5.7). This is because, in this term, the sum of exponentials of the utilities (scaled by the dissimilarity parameter) of all the location choice alternatives $\sum_{l \in N_k} \exp\left(\frac{\phi' w_{lk}}{\theta_k}\right)$ is not equal to the sum of exponentials of the utilities of a sample of those alternatives. This is corrected by incorporating a scaling factor (π_k) that is equal to the total number of available location choice alternatives divided by the number of sampled alternatives. Since location choice alternatives are sampled randomly, and since the random sample varies across individuals and activity purpose-timing-mode (*ptm*) combinations, this scaling factor should help approximate the logsum term reasonably well. That is:

$$\ln\left(\pi_k \sum_{l \in \text{ a random sample of } N_k} \exp\left(\frac{\phi' w_{lk}}{\theta_k}\right)\right) \approx \ln \sum_{l \in N_k} \exp\left(\frac{\phi' w_{lk}}{\theta_k}\right) \tag{5.12}$$

In this study, 30 location choice alternatives are randomly sampled from 1099 potential locations yielding, π_k = 36.63.

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[13] The reader will note here that Equation (10) is derived from a nested extreme value error term distribution as in Equation (6). However, since this distribution assumes the same scale parameter for all location choice alternatives associated with the activity episode *ptm* type, the location choice parameters will be consistent. In essence, as long as the error distributions do not allow different scale parameters across the location choice alternatives associated with an activity episode *ptm* type (*i.e.*, to accommodate spatial correlations, etc.) and no random coefficients are estimated in the location choice model, one can use a random sample of location choice alternatives to consistently estimate the model parameters. See Bierlaire et al. (2008) for more details on sampling related issues with multi-dimensional choice models.

5.2.4 An Intuitive Behavioral Interpretation

The probability expression in Equation (5.11) is a combination of MDCEV and single discrete choice probabilities. Specifically, for each OH discretionary activity episode purpose-timing-mode (*ptm*) combination chosen by an individual, a single discrete choice model of location choice is invoked. The parameters ϕ and θ_k appear in both the MDCEV probability expression (Equation 5.8) as well as the standard discrete choice probability expression for the choice of activity location (Equation 5.10) to create jointness between the multiple discrete-continuous and single discrete choices. Further, the logsum term (see Equation 5.7) appearing in the MDCEV probability expression carries the accessibility of destinations (or potential locations) from the single discrete location choice model to the MDCEV model of time investment by activity purpose, timing, and travel mode. Thus, Equation (5.11) represents a unified and comprehensive model of activity-travel program generation that incorporates the influence of accessibility measures on activity time-use, timing, and mode choices.

The proposed two-level MDCEV-MNL model is an attractive alternative to the deeply nested logit modeling approach available in the literature, where accessibility measures have to propagate up to the activity generation level through multiple levels of a deeply nested logit model. Further, the MDCEV-MNL model provides a seamless way of incorporating time-use (and the impact of accessibility on time-use) into the framework. Specifically, the modeling framework explicitly accommodates the concept that individual's activity time-use (*i.e.*, time allocation) decisions are important and influential components of their activity-travel decision-making (Bhat and Koppelman, 1999). On the other hand, the deeply nested logit approach does not explicitly incorporate activity time-allocation choices into the analysis framework in a straight forward manner. Another appealing feature is that the model recognizes the simultaneity of the activity time-use, timing, mode choice, and location choice decisions within a unified utility maximization framework.

5.3 Data Description

The data set used in this chapter is derived from the 2000 San Francisco Bay Area Travel Survey (BATS), designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission (MTC). The data includes information on: (1) Individual and household socio-demographics for over 15,000 households in the Bay Area, and (2) All activity episodes (including activity type, start and end times of the activity, geo-referenced location of activity participation, and mode of travel to the activity) undertaken by the individuals in all surveyed households for a two-day period.

The travel survey records were augmented extensively with several secondary data items, including land-use characteristics, transportation network level-of-service data, and Census population and housing data. In addition, geo-referenced data on businesses, bicycle facilities, highways and local roads were used to derive spatial variables characterizing the activity-travel environment (ATE) in and around the household locations of the individuals in the data set. Details regarding the data preparation and augmentation processes can be found in Guo and Bhat (2004) and Pinjari et al., (2009).

As mentioned in the previous section, the activity choice dimensions modeled in this research effort include activity type choice, activity time of day choice, travel mode choice, activity location (destination) choice, and activity time use allocation (duration). The MDCEV model component alternatives are formed as combinations of activity type, time of day, and travel mode while the duration of each activity episode constitutes the continuous dependent variable. Finally, the MNL module accommodates the activity location or destination choice. There are: (a) a maintenance activity type, (b) an in-home discretionary activity type, and (c) five out-of-home discretionary activity types, six time periods, and two travel modes, yielding a total of 62 possible MDCEV choice alternatives (2 + 5x6x2 = 62). It is to be noted that the activity timing and travel mode analysis is limited to the five out-of-home discretionary activity types.

In order to control for fundamental differences between workers and non-workers in their activity engagement patterns and choice processes, and in the interest of brevity, the analysis in this chapter was restricted to the sample of 5,360 non-working individuals aged 16 years or above. Descriptive statistics for this sample of individuals are presented in Table 5.1. All 5,360 individuals participate in in-home maintenance for an average duration of nearly 11 hours. Forty percent engage in in-home discretionary activities for an average duration of about 5.5 hours. Note that the average durations are computed over those who actually participate in the activity type. A little over one-half of the sample participated in OH discretionary activities, for an average duration of about 2.5 hours. It is found that the automobile mode is the preferred and dominant mode of travel accounting for nearly 90 percent of all out-of-home discretionary activity engagement. Non-maintenance shopping shows a relatively high participation rate, but lower time allocation (regardless of mode), while activities such as meals, socializing, and recreation show lower participation rates but higher time allocation. Across the top of the table (in the grey shaded row), it is seen that only a very small percent of individuals participate in OH discretionary activities in the early morning, and the percentage steadily rises into the afternoon, and then shows a decline towards the night hours. Activities undertaken in the morning and early morning, however, show the longest average durations relative to those in the afternoon and evening, potentially indicating the effect of time constraints that might get tighter towards the latter half of the day. Overall, this table shows the interplay among the dimensions of activity-travel participation that merit a unified approach towards modeling these behavioral characteristics.

5.4 Empirical analysis

5.4.1 <u>Model specification and estimation</u>

Model estimation was performed using Gauss code written specifically to estimate the joint MDCEV-MNL model system. Although it would have been ideal to estimate a separate destination choice model for each of the 60 OH discretionary activity purpose-timing-mode (*ptm*) combination categories, for this initial effort, a single MNL location choice model was estimated for all discretionary activity *ptm* categories. However, extending the estimation process to incorporate 60 MNL models of destination choice is straightforward by specifying dimension-specific model coefficients; the model specification here is one in which all destination choice model coefficients are restricted to be identical across all activity purpose categories, timing categories, and mode categories. A variety of variables were included in the model specification including household and personal socio-economic and demographic variables, contextual variables such as day of week and season of the year, and a host of spatial variables characterizing the activity-travel environment (ATE) around the household locations, not to mention several transportation network level of service variables. The spatial ATE variables included density measures, activity opportunity and accessibility measures, and population and housing data for the neighborhood (traffic analysis zone). The ATE measures were considered at the level of the traffic analysis zone and at finer spatial resolutions, including within 0.25 mile, 1 mile, and 5 mile radii buffers of the household location (see Guo and Bhat, 2004 and Pinjari *et al*, 2009 for complete details).

5.4.2 Model assessment

In the current research effort, a comparison was made between the joint MDCEV-MNL model that integrates destination choice with activity choices and an independent MDCEV-MNL model that does not incorporate the log-sum parameters in the MDCEV component. The goodness of fit of the two models were compared using the Bayesian Information Criterion (BIC), which is given by the expression $-2 \times \ln(L) + number\ of\ parameters \times \ln(Q)$, where $\ln(L)$ is the log-likelihood value at convergence and Q is the number of observations. The model that results in the lower BIC value is the preferred model. The BIC value for the MDCEV-MNL model (with 103 model parameters) is,150514.2 which is substantially lower than that for the independent MDCEV-MNL model (152334.2 with 102 model parameters). Thus, the BIC clearly favors the MDCEV-MNL model of integrated activity choices and destination choice.

5.4.3 Estimation results

The discussion in this chapter is limited to the results of the joint MDCEV-MNL model. The MDCEV component is specified (and the results are presented) in such a way that the effect of each variable is first identified separately along the activity purpose, activity timing and travel mode dimensions. Subsequently, any interaction effects of the variable over and above the uni-dimensional effects are identified. A blank entry corresponding to the effect of a variable indicates no significant effect of the variable on the integrated choice process. Further, the effects of variables on the baseline utilities have been constrained to be equal if coefficient equality could not be rejected based on statistical tests. Finally, t-statistics are presented in parentheses. The final specification of the MDCEV component of the model is presented in Table 5.2. In the interest of brevity, and considering the large number of alternatives (62), tables showing estimates of baseline preference constants and satiation parameters are not furnished here.

Overall, the model results show indications as expected. Larger household sizes are associated with greater levels of participation in maintenance activities (in and out of home), while single persons are more prone to out-of-home socializing and recreation in the evening. The presence of very young kids motivates activity engagement in the prime period of the day as opposed to early mornings and late nights, although those with school age children are more restricted to pre- and post-school hours. The number of working adults contributes negatively to activity engagement in the middle of the day, presumably due to work constraints. Lower income individuals are more prone to in-home discretionary activities, while higher income individuals are prone to undertake out-of-home activities, consistent with expectations. Higher levels of car ownership contribute negatively to in-home activity participation and non-auto mode use.

Females are more likely to engage in volunteering and maintenance activities, particularly in the midday period, confirming the role of gender differences in activity engagement. Younger individuals are likely to socialize in the evening and night, while older individuals (65+ years) are more likely to volunteer and not undertake night activities. Those who are licensed to drive have a greater propensity for out-of-home activities, while the reverse is true for those physically disabled. Employed individuals engage less in maintenance activities and in-home discretionary activities, even on days that they do not work (this analysis was limited to non-working days for all 5,360 individuals, whether they are employed or not). Fridays are associated with greater out-of-home discretionary activity participation, and night time activities. On rainy days, it is less likely that individuals will eat out using non-auto modes. Population density contributes positively to out-of-home meals, shopping by non-auto mode, possibly because such areas are better served by transit and have better walk and bicycle access to destinations. Overall, the findings are consistent with expectations and consistent with those found earlier by Pinjari and Bhat (2009a).

The estimation results for the destination choice model are presented in Table 5.3. The destination choice model component was estimated with 30 randomly sampled choice alternatives for each location choice decision. The effects of transportation network level of service, built environment, and demographic interaction terms were represented in the final model specification. Auto travel times and costs decrease the utility associated with choosing a destination for any activity type. The presence of bicycle lanes, total employment, the size of the zone, and zonal household income positively impact destination choice for discretionary activities while retain and service employment, increasing fraction of land devoted to residential uses in the zone, and accessibility to passive and natural recreation contribute negatively to destination choice for the activity categories considered in this study. The long list of interaction terms demonstrates how household and personal socio-economic and demographic characteristics play a key role in influencing destination choice for discretionary activities undertaken outside home. In the interest of brevity, a detailed explanation is not provided here, but suffice to say that all of the interaction terms included in the model specification are highly significant and indicate that household socio-economic and demographic characteristics serve to moderate or enhance the likelihood of choosing a certain type of destination for activity engagement. For example, females are more prone to choosing destinations with high density of eat-out centers, as are older people and higher income individuals. Those with kids and in larger households are less prone to choose zones with high household density as destinations, presumably because they prefer more open space and suburban locations to accommodate family activities.

The logsum parameters (θ_{ptm}) estimated for each activity purpose, timing, and travel mode combination were not statistically different from unity. In the final model estimation, all logsum parameters were restricted equal to one. This implies the absence of common unobserved factors across all location choice alternatives specific to an activity type, timing, and mode combination. Note that this finding does not imply independence between the MDCEV and MNL model components; rather the logsum variables tie the two model components together, where as the logsum parameters represent only the presence (or absence) of correlated unobserved factors across destination choice alternatives for each activity type, timing, and mode combination category.

5.5 Summary

This study aims to present a comprehensive unified model system of activity-travel choices that is consistent with microeconomic utility maximization theory of behavior. The activity-travel choice dimensions analyzed in this chapter include activity type choice, time of day choice, mode choice, destination choice, and activity time allocation or duration. All discrete choices, except for activity destination choice, and the continuous choice dimension of activity duration are modeled simultaneously using the multiple discrete continuous extreme value (MDCEV) model form while the destination choice is modeled using a classic multinomial logit model (MNL) component. The model components are tied together within a utility maximization-consistent framework using logsum variables that reflect the accessibility of destinations for each activity type, timing, and mode combination. Model estimation results and the policy simulation analysis showed that the joint model system has merit, offers behaviorally intuitive interpretation, and offers a goodness of fit statistically superior to that offered by an independent model system that treats various choice dimensions separately and sequentially. The model specifications included built environment and transportation network level of service attributes demonstrating the impact of these variables on activity-travel dimensions. The model system is presented for a non-worker sample drawn from the 2000 San Francisco Bay Area Travel Survey (BATS). One of the key empirical findings of this analysis is that the built environment and transportation network level of service attributes of the destinations significantly impact activity time use allocation, an aspect that is often overlooked in the literature.

The model form adopted in this study has key implications for activity-travel demand model development. It appears that the findings reported here support the notion that individuals make several activity-travel choices jointly as a “bundle”, calling for the simultaneous modeling of various choice dimensions in a unifying framework. Activity-travel model systems that purport to simulate the behavior of agents along the time axis may benefit from the adoption of model forms that are able to simultaneously predict multiple choice dimensions as a “bundle”. Ignoring to do so may yield erroneous policy scenario predictions.

Table 5.1: Descriptive Statistics of Activity participation and Time-Use by Activity Purpose, Activity Timing and Travel mode[14]

		ACTIVITY TIMING					
		Early Morning (3am-7am)	**Morning (7am-9am)**	**Late Morning (9am-12pm)**	**Afternoon (12pm-4pm)**	**Evening (4pm-7pm)**	**Night (7pm-3am)**
ACTIVITY PURPOSE and TRAVEL MODE	Number (%) of non-workers participating, and mean duration of participation among those participating	63 (2.3%)[15] 140 min	382 (13.9%) 169 min	1131 (41.1%) 121 min	1257 (45.7%) 97 min	720 (26.2%) 103 min	371 (13.5%) 111 min
Maintenance	5360 (100%) 651 min	--	--	--	--	--	--
IH Discretionary	2133 (39.8%) 341 min	--	--	--	--	--	--
OH Discretionary	2752 (51.3%) 163 min	--	--	--	--	--	--
OH Discretionary Auto mode	2473 (89.9%) 158 min						
Volunteering	396 (14.4%)[16] 149 min	4 (1.0%)[17]	81 (20.5%)	137 (34.6%)	89 (22.5%)	72 (18.2%)	63 (15.9%)
Socializing	508 (18.5%) 128 min	6 (1.2%)	20 (3.9%)	125 (24.6%)	159 (31.3%)	97 (19.1%)	77 (15.2%)
Meals	809 (29.4%) 115 min	13 (1.6%)	90 (11.1%)	206 (25.5%)	270 (33.4%)	223 (27.6%)	84 (10.4%)
Non-Maintenance Shopping	1092 (39.7%) 60 min	4 (0.4%)	46 (4.2%)	372 (34.1%)	571 (52.3%)	175 (16.0%)	53 (4.9%)
Recreation	7 38 (26.8%) 145 min	33 (4.5 %)	116 (15.7%)	256 (34.7%)	200 (27.1%)	115 (15.6%)	88 (11.9%)
OH Discretionary Non Auto mode	432 (15.7%) 134 min						
Volunteering	37 (1.3%) 170 min	2 (5.4%)	9 (24.3%)	10 (27.0%)	8 (21.6%)	3 (8.1%)	6 (16.2%)
Socializing	72 (2.6%) 140 min	0 (0.0%)	3 (4.2%)	19 (4.2%)	27 (37.5%)	21 (29.2%)	4 (5.6%)
Meals	135 (4.9%) 119 min	1 (0.7%)	9 (6.7%)	35 (25.9%)	54 (40.0%)	25 (18.5%)	18 (13.3%)
Non-Maintenance Shopping	132 (4.8%) 59 min	0 (0.0%)	4 (3.0%)	50 (37.9%)	62 (47.0%)	12 (9.1%)	6 (4.5%)
Recreation	131 (4.8%) 136 min	1 (0.8%)	14 (10.7%)	52 (39.7%)	33 (25.2%)	32 (24.4%)	6 (4.6%)

[14] The reader will note here that the average time investments reported in this table are for only those who participated in the corresponding activity purpose or for those who participated in OH discretionary activities during the corresponding time period. Also, the activity participation percentages across all activity purposes (or across all time periods, or modes) may sum to more than 100% because of multiple discreteness (*i.e.*, participation in multiple activity purposes and/or during multiple time periods and/or travel by multiple modes over a day). For example, a non-worker can undertake both OH recreation and OH meal activities on a day.

[15] Percentages in this row are out of the 2752 non-workers who participated in at least one OH discretionary activity during the day.

[16] Percentages in this column, from this row onward, are out of the 2473 non-workers who traveled by auto mode for at least one OH discretionary activity during the day.

[17] Percentages from this row and column onward (within this block of rows) are based on total number of non-workers participating in row activity purpose [(4/396)×100=1.0%].

Table 5.2: The MDCEV Model Results: Baseline Parameter Estimates

	Household (HH) Socio-demographics								
	HH size	Single member HH	Kids of age <5 yrs present	Kids of age 5-15 yrs present	Number of kids of age <15 yrs	# of adults in HH who worked on the day	HH annual income < 45k	HH annual income >100k	# of vehicles in HH
'Activity Purpose' Dimension									
IH and OH Maintenance	0.071 (3.74)	-	-	-	-	-	-	-	-
IH Discretionary	-	-	-	-	-	-	0.168 (2.92)	-	-0.061 (-1.89)
OH Volunteering	-	-	-	-	-	-	-	-	-
OH Socializing	-	0.420 (3.73)	-	-	-	-	-	0.169 (3.61)	-
OH Recreation	-	-	-	-	-	-	-	0.169 (3.61)	-
OH Meals	-	-	-	-	-	-	-	0.169 (3.61)	-
OH Non-Maintenance Shopping	-	-	-	-	-	-	-	0.169 (3.61)	-
'Activity Timing' Dimension									
Early Morning	-	-	-	-	-	-	-	-	-
Morning	-	-	0.125 (1.77)	0.297 (2.10)	-	-	-	-	-
Late Morning	-	-	0.125 (1.77)	-	-	-0.170 (-4.43)	-	-	-
Afternoon	-	-	0.125 (1.77)	-	-	-0.170 (-4.43)	-	-	-
Evening	-	-	0.125 (1.77)	0.428 (3.88)	-	-	-	-	-
Night	-	-	-	-	-	-	-	-	-
'Travel Mode' Dimension									
Auto mode	-	-	-	-	-	-	-	-	-
Non-auto mode	-	-	-	-	-	-	-	-	-1.190 (-31.90)
Interactions									
OH Recreation – Evening	-	0.363 (3.53)	-	-	-	-	-	-	-
OH Recreation – Non-auto	-	-	-	-	-	-	-	0.463 (2.11)	-
OH Meals - Non-auto	-	-	-	-	0.154 (1.17)	-	-	-	-
OH Meals - Non-auto - Evening	-	-	-	-	-0.535 (-1.36)	-	-	-	-

Table 5.2 (Continued) The MDCEV Model Results: Baseline Parameter Estimates

	Individual Socio-demographics						Contextual			ATE attributes			
	Female	**Age < 30 yrs**	**Age > 65 yrs**	**Licensed to drive**	**Physically disabled**	**Employed**	**Friday**	**Fall**	**Rain**	**Retail employment**	**Population density**	**Total employment density**	**Density of highways**
'Activity Purpose' Dimension													
IH and OH Maintenance	0.315 (7.29)	-	-	-	-	-0.173 (-3.59)	-	-	-	-	-	-	-
IH Discretionary	-	-	-	-	-	-0.1263 (-1.98)	-	-0.105 (-1.98)	-	-	-	-	-
OH Volunteering	0.350 (3.46)	-	0.617 (6.51)	0.743 (9.46)	-0.249 (-3.09)	-	-	-	-	-	-	-	-
OH Socializing	-	0.467 (2.70)	-	0.743 (9.46)	-0.249 (-3.09)	-	0.242 (4.31)	-	-	-	-	-	-
OH Recreation	-	-	-	0.743 (9.46)	-0.249 (-3.09)	-	0.357 (4.14)	-	-	-	-	-	-
OH Meals	-	-	-	0.743 (9.46)	-0.249 (-3.09)	-	0.242 (4.31)	-	-	-	-	-	-
OH Non-Maintenance Shopping	-	-	-	0.743 (9.46)	-0.249 (-3.09)	-	0.242 (4.31)	-	-	-	-	-	-
'Activity Timing' Dimension													
Early Morning	-	-	-	-	-	-	-	-	-	-	-	-	-
Morning	-	-	-	-	-	-	-	-	-	-	-	-	-
Late Morning	0.286 (5.10)	-	-	-	-	-	-	-	-	-	-	-	-
Afternoon	0.286 (5.10)	-	-	-	-	-	-	-	-	-	-	-	-
Evening	-	0.308 (1.85)	-	-	-	-	-	-	-	-	-	-	-
Night	-	0.739 (4.78)	-0.482 (-3.70)	-	-	-	0.404 (3.23)	-	-	-	-	-	-
'Travel Mode' Dimension													
Auto mode	-	-	-	-	-	-	-	-	-	-	-	-	-
Non-auto mode	-0.220 (-2.92)	-	-	-	-	-	-	-	-	-	-	-	-
'Interactions'													
OH Non-Maintenance Shopping – Afternoon	-	-	-	-	-	-	-	-	-	-0.001 (-2.59)	-	-	-
OH activity Non-auto - Afternoon (except shopping)	-	-	-	-	-	0.369 (1.91)	-	-	-	-	-	-	-
OH Meals - Non-auto	-	-	-	-	-	-	-	-	-0.263 (-0.85)	-	-	-	-
OH Meals, shopping -Non-auto	-	-	-	-	-	-	-	-	-	-	0.016 (5.43)	-	-
OH Recreation - Non-auto	-	-	-	-	-	-	-	-	-	-	-	0.006 (0.75)	-
OH Social, meals - Non-auto	-	-	-	-	-	-	-	-	-	-	-	-	-0.069 (-0.88)

Table 5.3: MNL Component (Location Choice) Model Estimation Results

Variable	Coefficient	t-stat
LOS Measures		
Auto peak travel time	-0.012	-11.82
Auto peak travel cost	-0.056	-2.59
ATE Attributes		
Density of bicycle lanes	0.129	7.75
Retail employment	-0.005	-5.70
Service employment	-0.005	-4.47
Logarithm of Total employment	0.405	29.06
Fraction of residential land-use	-2.272	-41.69
Logarithm of zonal area	0.056	5.44
Mean zonal household income	0.007	9.19
Accessibility to passive and natural recreation	-0.364	-2.92
<u>Interaction with socio-demographics</u>		
Density of bicycle lanes * age/100	-0.110	-4.84
Density of bicycle lanes * Continuous income x 10^{-5}	0.042	5.46
Density of bicycle lanes * household vehicles	0.025	4.94
Density of eat-out centers * female	0.003	3.26
Density of eat-out centers * Continuous income x 10^{-5}	0.010	13.31
Density of eat-out centers * age/100	0.027	32.64
Density of eat-out centers * household size	0.014	28.96
Density of eat-out centers * Own household	0.002	2.17
Logarithm of household population * age/100	0.102	6.42
Logarithm of household population * household vehicles	0.011	3.32
Household density * No. of kids < 15yrs	-0.006	-1.32
Household density * household size	-0.001	-0.36
Household density * household vehicles	0.009	3.41
Accessibility to employment * household size	-0.003	-6.25
Accessibility to employment * Own household	0.008	15.38

CHAPTER 6 POLICY ANALYSIS

6.1 Background

In Chapters 2 through 5, we have discussed the formulation of econometric models for analyzing multidimensional choices. Specifically, in the current dissertation, we discussed the development of the following econometric frameworks (the choice dimension is indicated in parenthesis): (1) multinomial logit model (reason for move) and a grouped logit model (residential stay duration preceding the move), (2) copula-based binary logit model (residential location) and log-linear regression (VMT), (3) copula-based nested logit model (combination of residential location and vehicle type) and log-linear regression (annual vehicle mileage for each vehicle type) and (4) joint multiple discrete continuous extreme value model (activity type, travel mode, time of day combination as the discrete component and activity duration as continuous component) and multinomial logit model (MNL) with sampling of alternatives (activity location). The preceding chapters, in addition to formulating these models, discuss how these models have been estimated for actual data sets. The results from these exercises provide useful insights on examining the different multinomial choice contexts. In fact, the results presented clearly highlight the importance of incorporating *direct (causal)* and *indirect (self-selection)* effects of travel environment on the choices considered from intuitive and statistical perspectives (see goodness of fit measures for each of the models formulated).

In the current chapter, we undertake a series of policy analysis exercise that further reinforce the importance of accommodating *direct (causal)* and *indirect (self-selection)* effects of travel environment. The rest of the chapter is organized as follows. Section 6.2 through 6.5 presents details of the policy exercises undertaken for each multidimensional choice framework considered in the dissertation and discuss the implication of their results. Section 6.6 concludes the chapter by summarizing the insights across the different choice contexts.

6.2 Household residential relocation decision

In Chapter 2, three different model structures were estimated to facilitate comparisons and to evaluate the efficacy of employing the correlated joint model system proposed for modeling residential location decisions. The three models are:

- A simple multinomial logit model for reason to move and an independent grouped response model for duration of stay, referred to as the Independent Multinomial Ordered (IMO) model
- A random coefficients multinomial logit model for reason to move and an independent random coefficients grouped response model for duration of stay, referred to as the Independent Random Multinomial Ordered (IRMO) model
- A random coefficients multinomial logit model for reason to move and a correlated random coefficients grouped response model for duration of stay, referred to as the Correlated Random Multinomial Ordered (CRMO) model.

6.2.1 <u>Elasticity effects computation</u>

The parameters on the exogenous variables for the CRMO model presented in Tables 6.1 and 6.2 do not directly provide the magnitude of the effects of the variables on the probability of each choice dimension. To better understand the effects of various factors on the reason to move and duration of stay choices, aggregate level elasticity effects were computed. To discuss how we computed elasticities, let us briefly revisit the probability expression from Section 2.4.

The probability of an individual q choosing to move for reason k at the t^{th} choice occasion, conditional on γ_{qk} and η_{qk} for each (and all) k, is given by:

$$P_{qkt} \mid (\gamma_{q1}, \eta_{q1}, \gamma_{q2}, \eta_{q2}, \ldots \gamma_{qK}, \eta_{qK}) = \frac{e^{(\beta_k' + \gamma_{qk}')x_{qt} + \eta_{qk}'}}{\sum_{k=1}^{K} e^{(\beta_k' + \gamma_{qk}')x_{qt} + \eta_{qk}'}} \tag{6.1}$$

Similarly, conditional on δ_{qk} and η_{qk}, the probability of an individual q choosing to stay for a particular duration category j preceding a move for reason k at the t^{th} choice occasion is given by:

$$R_{qktj} \mid (\delta_{qk}, \eta_{qk}) = G\left[\frac{\psi_{kj} - \left\{(\alpha_k^{'} + \delta_{qk}^{'})x_q \pm \eta_{qk}\right\}}{\lambda}\right] - G\left[\frac{\psi_{kj-1} - \left\{(\alpha_k^{'} + \delta_{qk}^{'})x_q \pm \eta_{qk}\right\}}{\lambda}\right] \quad (6.2)$$

where G(.) is the cumulative distribution of the standard logistic distribution

Then the joint probability of individual q choosing to move for reason k at the t^{th} choice occasion and stay for a particular duration j, conditional on γ_{qk}, δ_{qk} and η_{qk} is given by :

$$S_{qktj} \mid (\gamma_{qk}, \delta_{qk}, \eta_{qk}) = \left(P_{qkt} \mid (\gamma_{q1}, \eta_{q1}, \gamma_{q2}, \eta_{q2}, ...\gamma_{qK}, \eta_{qK})\right)\left(R_{qktj} \mid \delta_{qk}, \eta_{qk}\right) \quad (6.3)$$

The unconditional probability is computed as:

$$S_{qktj} = \int_{\gamma_{qk}, \delta_{qk}, \eta_{qk}} \left(P_{qkt} \mid (\gamma_{q1}, \eta_{q1}, \gamma_{q2}, \eta_{q2}, ...\gamma_{qK}, \eta_{qK})\right)\left(R_{qktj} \mid \gamma_{qk}, \eta_{qk}\right) \quad (6.4)$$

The expected aggregate numbers for level reason k and duration of stay j is then computed by summing the above individual-level probability across all individuals Q for each reason and stay duration.

With the preliminaries above, one can compute the aggregate-level "elasticity" of any dummy exogenous variable (all exogenous variables in the model are dummy variables) by changing the value of the variable to one for the subsample of observations for which the variable takes a value of zero and to zero for the subsample of observations for which the variable takes a value of one. We then sum the shifts in expected aggregate shares in the two subsamples after reversing the sign of the shifts in the second subsample, and compute an effective percentage change in expected aggregate shares in the entire sample due to change in the dummy variable from 0 to 1 (see Eluru and Bhat 2008 for example of similar application to compute elasticities). In the current exercise, as the IMO and IRMO models were statistically identical, one set of elasticity values are computed for these two model specifications and another set of elasticity values for the CRMO model specification.

6.2.2 Elasticity effects

A comparison of elasticity measures across these model specifications sheds further light on the importance of considering error correlation structures in simultaneously modeling the reason to move and stay duration. The results for the move reason and duration component are discussed subsequently.

6.2.2.1 Reason to move choice

Elasticity computations for the reason to move choice are shown in Table 6.1. The interpretation of the elasticity values themselves is quite straightforward. For instance, the table suggests that the probability of a female moving for personal family reasons is about 28 percent more than that for males, all else being equal. On the other hand, the probability of males moving for education/employment reasons exceeds that for females by about 7.5 percent. The key finding from this table is that the CRMO model offers elasticity estimates that differ by at least a few percentage points for all exogenous factors considered in the model system. Also, several variables are found to have large impacts on the probability of the reason to move. For example, an individual in a family-household is less likely to move for education/employment reasons by nearly 95 percent. The probability of an individual in a non-family household moving within the 20 year period covered by the survey is less than that for an individual in a family household by nearly 90 percent. Those who commute by walk exhibit a probability of moving for education/employment reasons exceeding that for non-walk commuters by more than 75 percent. However, the probability of their moving for accommodation or surrounding vicinity related reasons is substantially smaller than that for non-walk commuters.

6.2.2.2 Duration of stay choice

In Table 6.2, elasticity computations are provided for the duration of stay choice and the differences between elasticity measures derived from the IMO/IRMO model and those derived from the CRMO model are more striking. It is found that, in comparison to males, females are more likely to stay for less than two years at a single location by nearly 20 percent. In the case of household size, it is interesting to note that the aggregate elasticity value is of a different magnitude and sign for the 2-5 year stay category. While the IMO/IMRO models suggest that the probability of staying 2-5 years at a single location increases with household size, the CRMO model suggests that this probability actually decreases with an increase in household size. Indeed, one would expect that the probability of stay duration being short (2-5 years may be considered a short stay) would decrease with an increase in household size. Similar sign reversals are seen for the variables representing home ownership and number of rooms in the home, in the 2-5 year stay category. This category probably represents a transition point between short-term stays and longer-term stays and hence the model that accounts for the presence of common unobserved factors (error correlations) is offering elasticity measures substantially different than those obtained from models that do not account for such factors. These sign reversals are also seen for commute-related variables, where the IMO/IMRO models suggest that the probability of staying 2-5 years (short stay) is lower for public transportation and walk users. However, the CRMO model suggests that the probability of staying 2-5 years is actually higher, albeit by rather small amounts, for these alternate mode users. The CRMO model suggests greater negative differentials in the longer stay duration category of greater than 10 years. For example, according to the IMO/IRMO model, the probability of bicycle commuters staying more than 10 years at the same location is lower than that for others by 3 percent; the corresponding differential (elasticity) is 5.2 percent in the CRMO model.

6.3 Residential location and VMT

In Chapter 3, we formulated a copula based approach to model residential neighborhood choice and daily household vehicle miles of travel (VMT). The situation can be cast in the form of Roy's (1951) endogenous switching model system (see Maddala, 1983; Chapter 9), which takes the following form:

$$
\begin{aligned}
&r_q^* = \beta' x_q + \varepsilon_q, \quad r_q = 1 \text{ if } r_q^* > 0, \quad r_q = 0 \text{ if } r_q^* \le 0, \\
&m_{q0}^* = \alpha' z_q + \eta_q, \; m_{q0} = 1[r_q = 0] m_{q0}^* \\
&m_{q1}^* = \gamma' w_q + \xi_q, \; m_{q1} = 1[r_q = 1] m_{q1}^*
\end{aligned}
\tag{6.5}
$$

The notation $1[r_q = 0]$ represents an indicator function taking the value 1 if $r_q = 0$ and 0 otherwise, while the notation $1[r_q = 1]$ represents an indicator function taking the value 1 if $r_q = 1$ and 0 otherwise. The first selection equation represents a binary discrete decision of households to reside in a neo-urbanist built environment neighborhood or a conventional built environment neighborhood. r_q^* in Equation (1) is the unobserved propensity to reside in a conventional neighborhood relative to a neo-urbanist neighborhood, which is a function of an (M x 1)-column vector x_q of household attributes (including a constant). β represents a corresponding (M x 1)-column vector of household attribute effects on the unobserved propensity to reside in a conventional neighborhood relative to a neo-urbanist neighborhood. In the usual structure of a binary choice model, the unobserved propensity r_q^* gets reflected in the actual observed choice r_q (r_q = 1 if the qth household chooses to reside in a conventional neighborhood, and r_q = 0 if the qth household decides to reside in a neo-urbanist neighborhood). ε_q is usually a standard normal or logistic error tem capturing the effects of unobserved factors on the residential choice decision.

The second and third equations of the system in Equation (6.5) represent the continuous outcome variables of log(vehicle miles of travel) in our empirical context. m_{q0}^* is a latent variable representing the logarithm of miles of travel if a random household q were to reside in a neo-urbanist neighborhood, and m_{q1}^* is the corresponding variable if the household q were to reside in a conventional neighborhood. These are related to vectors of household attributes z_q and w_q, respectively, in the usual linear regression fashion, with η_q and ξ_q being random error terms. Of course, we observe m_{q0}^*

in the form of m_{q0} only if household q in the sample is observed to live in a neo-urbanist neighborhood. Similarly, we observe m^*_{q1} in the form of m_{q1} only if household q in the sample is observed to live in a conventional neighborhood.

The observed data for each household in the switching model of Equation (6.5) is its chosen residence location and the VMT given the chosen residential location. That is, we observe if $r_q = 0$ or $r_q = 1$ for each q, so that either m_{q0} or m_{q1} is observed for each q. We do not observe the data pair (m_{q0}, m_{q1}) for any household q. However, using the switching model, we would like to assess the impact of the neighborhood on VMT. In the social science terminology, we would like to evaluate the expected gains (*i.e.*, VMT increase) from the receipt of treatment (*i.e.*, residing in a conventional neighborhood). Heckman and Vytlacil, 2000 and Heckman *et al.*, 2001 define a set of measures to study the influence of treatment, two important such measures being Average Treatment Effect (ATE) and the Effect of Treatment on the Treated (TT). We discuss these below, and propose two new measures labeled "Effect of Treatment on the Non-Treated (TNT)" and "Effect of Treatment on the Treated and Non-treated (TTNT)".

6.3.1 <u>Treatment Effects</u>

The ATE measure provides the expected VMT increase for a random household if it were to reside in a conventional neighborhood as opposed to a neo-urbanist neighborhood. The ATE is estimated as:

$$\hat{\text{ATE}} = \frac{1}{Q}\sum_{q=1}^{Q}\Big(\exp(\hat{\gamma}'w_q + \hat{\sigma}_{\xi}^2/2) - \exp(\hat{\alpha}'z_q + \hat{\sigma}_{\eta}^2/2)\Big) \tag{6.6}$$

Heckman and Vytlacil (2000) propose a "Treatment on the Treated" or TT measure that captures the expected VMT increase for a household randomly picked from the pool located in a conventional neighborhood if it were instead located in a neo-urbanist neighborhood (in social science parlance, it is the average impact of "treatment on the treated"; see Heckman and Vytlacil, 2005). The TT measure can be estimated as follows:

$$\hat{\text{TT}} = \left[\frac{1}{Q_{r1}} \sum_{q=1}^{Q} r_q \times \left(\exp(\hat{b}_{q1} + \hat{\sigma}_{\xi}^2 / 2) - \exp(\hat{b}_{q0} + \hat{\sigma}_{\eta}^2 / 2) \right) \right], \tag{6.7}$$

where Q_{r1} is the number of households in the sample residing in conventional neighborhoods, and $\hat{b}_{q0}$ and $\hat{b}_{q1}$ are defined as follows:

$$\hat{b}_{qo} = E(m_{qo} \mid r_q^* > 0) = \left\{1 - F_{\varepsilon}(-\hat{\beta}' x_q)\right\}^{-1} \times \frac{1}{\hat{\sigma}_{\eta}} \times \int_{m_{q0}} m_{qo} \times \left(1 - \frac{\partial C_{\theta_0}(u_{q1}^0, u_{q2}^0)}{\partial u_{q2}^0}\right) \times f_{\eta}\left(\frac{m_{q0} - \hat{\alpha}' z_q}{\hat{\sigma}_{\eta}}\right) dm_{qo},$$

$$\hat{b}_{q1} = E(m_{q1} \mid r_q^* > 0) = \left\{1 - F_{\varepsilon}(-\hat{\beta}' x_q)\right\}^{-1} \times \frac{1}{\hat{\sigma}_{\xi}} \times \int_{m_{q1}} m_{q1} \times \left(1 - \frac{\partial C_{\theta_1}(u_{q1}^1, u_{q2}^1)}{\partial u_{q2}^1}\right) \times f_{\eta}\left(\frac{m_{q1} - \hat{\gamma}' w_q}{\hat{\sigma}_{\xi}}\right) dm_{q1}. \tag{6.8}$$

The expressions above do not have a closed form in the general copula case. However, when a Gaussian copula is used for both the switching regimes, the expressions simplify nicely (see Lee, 1978). In the general copula case, the expressions (and the TT measure) can be computed using numerical integration techniques.

It is straightforward algebra to show that $\hat{b}_{q0} = \hat{\alpha}' z_q$ if there is no dependency in the (ε_q, η_q) terms, and $\hat{b}_{q1} = \hat{\gamma}' w_q$ if there is no dependency between the (ε_q, ξ_q) error terms. Thus, TT collapses to the ATE if the ATE were computed only across those households living in conventional neighborhoods (see the relationship between Equations (33) and (34) after letting $\hat{b}_{q0} = \hat{\alpha}' z_q$ and $\hat{b}_{q1} = \hat{\gamma}' w_q$ in the latter equation). However, in the current empirical setting, it is also of interest to assess the expected VMT increase for a household randomly picked from the pool located in a neo-urbanist neighborhood if it were instead located in a conventional neighborhood (*i.e.*, the "average impact of treatment on the non-treated" or TNT). This may be computed as:

$$\hat{\text{TNT}} = \frac{1}{Q_{r0}} \left[\sum_{q=1}^{Q} (1 - r_q) \times \left(\exp(\hat{h}_{q1} + \hat{\sigma}_{\xi}^2 / 2) - \exp(\hat{h}_{q0} + \hat{\sigma}_{\eta}^2 / 2) \right) \right], \tag{6.9}$$

where Q_{r0} is the number of households in the sample residing in neo-urbanist neighborhoods, and $\hat{h}_{q0}$ and $\hat{h}_{q1}$ are defined as follows:

$$\hat{h}_{q0} = E(m_{q0} \mid r_q^* < 0) = \left\{F_{\varepsilon}(-\hat{\beta}'x_q)\right\}^{-1} \times \frac{1}{\hat{\sigma}_{\eta}} \times \int_{m_{q0}} m_{qo} \times \left(\frac{\partial C_{\theta_0}(u_{q1}^0, u_{q2}^0)}{\partial u_{q2}^0}\right) \times f_{\eta}\left(\frac{m_{q0} - \hat{\alpha}'z_q}{\hat{\sigma}_{\eta}}\right) dm_{qo}, \tag{6.11}$$

$$\hat{h}_{q1} = E(m_{q1} \mid r_q^* < 0) = \left\{F_{\varepsilon}(-\hat{\beta}'x_q)\right\}^{-1} \times \frac{1}{\hat{\sigma}_{\xi}} \times \int_{m_{q1}} m_{q1} \times \left(\frac{\partial C_{\theta_1}(u_{q1}^1, u_{q2}^1)}{\partial u_{q2}^1}\right) \times f_{\eta}\left(\frac{m_{q1} - \hat{\gamma}'w_q}{\hat{\sigma}_{\xi}}\right) dm_{q1}$$

. Finally, we can combine the $\hat{\text{TT}}$ and $\hat{\text{TNT}}$ measures into a single measure that represents the average impact of treatment on the (currently) treated and (currently) non-treated (TTNT). In the current empirical context, it is the expected VMT change for a randomly picked household if it were relocated from its current neighborhood type to the other neighborhood type, measured in the *common direction* of change from a traditional neighborhood to a conventional neighborhood:

$$\hat{\text{TTNT}} = \frac{1}{Q}\left(Q_{r0}\,\hat{\text{TNT}} + Q_{r1}\,\hat{\text{TT}}\right) \tag{6.12}$$

The above measure, in effect, provides the average expected change in VMT if all households were located in a conventional neighborhood relative to if all households were located in a neo-urbanist neighborhood. The relationship between $\hat{\text{TTNT}}$ and ATE should be obvious. Essentially, $\hat{\text{TTNT}}$ includes both the "true" causal effect of neighborhood effects on VMT as well as the "self-selection" effect of households choosing neighborhoods based on their travel desires. The closer $\hat{\text{TTNT}}$ is to ATE, the lesser is the self-selection effect. Of course, in the limit that there is no self-selection, $\hat{\text{TTNT}}$ collapses to the ATE.

6.3.2 <u>Treatment effect results</u>

It is clear from the results presented in Section 3.5 that there are statistically significant residential self-selection effects; that is, households' choice of residence is linked to their VMT. To understand the magnitude of self-selection effects, we present point estimates of the treatment effects in this section. In addition to the point treatment effects, we also estimate large sample standard errors for the treatment effects using 1000 bootstrap draws. This involves drawing from the asymptotic distributions of parameters appearing in the treatment effect, and computing the standard deviation of the simulated treatment effect values.

The results are presented in Table 6.3 for the Independence-Independence (I-I) model and the three copula models with the best data fit, corresponding to the FGM-Joe (FG-J), Frank-Joe (F-J), and the Frank -Frank (F-F) copula models. Of course, the results from the traditional Gaussian-Gaussian (G-G) model are literally identical to the results from the I-I model, since the correlation parameters in the G-G model are small and very insignificant. The results show substantial variation in the treatment measures across models, except for the F-J and F-F models which provide similar results (this is not surprising, since the model parameters and log-likelihood values at convergence for these two models are almost the same, as discussed earlier in Section 3.5.2). According to the I-I model, a randomly selected household will have about the same VMT regardless of whether it is located in a conventional or neo-urbanist neighborhood (see the small and statistically insignificant ATE estimate for the I-I model). On the other hand, the other copula models indicate that there is indeed a statistically significant impact of the built environment on VMT. For instance, the best-fitting F-F model indicates that a randomly picked household will drive about 21 vehicle-miles per day more if in a conventional neighborhood relative to a neo-urbanist neighborhood. The important message here is that ignoring sample selection can lead to an underestimation or an overestimation of built environment effects (the general impression is that ignoring sample selection can only lead to an overestimation of built environment effects). Further, one needs to empirically test alternative copulas to determine which structure provides the best data fit, rather than testing the presence or absence of sample selection using normal dependency structures.

The results also show statistically significant variations in the other treatment effects between the I-I model and the non I-I models. The $\hat{T}T$ and $T\hat{N}T$ measures from the non I-I models reflect, as expected, that a household choosing to locate in a certain kind of neighborhood travels more in its chosen environment relative to an observationally equivalent random household. Thus, if a randomly picked household in a conventional neighborhood were to be relocated to a neo-urbanist neighborhood, the household's VMT is estimated to decrease by about 42 miles. Similarly, if a randomly picked household in a neo-urbanist neighborhood were to be relocated to a conventional neighborhood, the household's VMT is estimated to decrease by about 31 miles. On the other hand, if a randomly picked household that is indifferent to neighborhood type is moved from a conventional to a neo-urbanist neighborhood, the household's VMT is estimated to decrease by about 21 miles (which is, of course, the ATE measure).

The $\widehat{\text{TTNT}}$ measure is a weighted average of the $\widehat{\text{TT}}$ and $\widehat{\text{TNT}}$ measures, and shows that there would be a decrease of about 25 vehicle miles of travel per day if all households in the population (as represented by the estimation sample) were located in a neo-urbanist neighborhood rather than a conventional neighborhood. When compared to the average VMT of 58 miles, the implication is that one may expect a VMT reduction of about 43% by redesigning all neighborhoods to be of the neo-urbanist neighborhood type.[18] Finally, the $\widehat{\text{TTNT}}$ measure for the best F-F copula model shows that about 87% of the VMT difference between households residing in conventional and neo-urbanist neighborhoods is due to "true" built environment effects, while the remainder is due to residential self-selection effects. However, most importantly, it is critical to note that failure to accommodate the self-selection effect leads to a substantial underestimation of the "true" built environment effect (see the ATE for the I-I model of 0.49 miles relative to the ATE for the F-F model of 21.37 miles.

[18] Note that we are simply presenting this figure as a way to provide a magnitude effect of VMT reduction by designing urban environments to be of the neo-urbanist kind. In practice, different neighborhoods may be redesigned to different extents to make them less auto-dependent. Further, in a democratic society, demand will (and should) fuel supply. Thus, as long as there are individuals who prefer to live in a conventional setting, there will be developers to provide that option.

6.4 Household vehicle fleet composition and usage choices

In Chapter 4, a simultaneous model of residential location choice, vehicle count and type choice, and vehicle usage is presented with a view to capture the potential effects of the presence of common unobserved factors that may jointly impact these choice dimensions. The research effort employs the structure of the copula-based joint GEV-based logit – regression modeling framework to jointly model the choice dimensions. To demonstrate the applicability of the model system developed in the Chapter 4, the model results presented in Table 4.2 are employed to predict changes in residential location, vehicle type shares, and vehicle usage.

6.4.1 <u>Policy exercise</u>

In this exercise, changes in the choice dimensions are examined as a function of changes in exogenous factors. In particular, the impacts of changes in household demographics, built environment variables, and local transportation measures are examined in this simple simulation exercise. The specific changes in exogenous factors considered are

- increasing household size,
- number of employed individuals,
- number of females by unity,
- increasing land use mix value of the neighborhood by 25 percent, and
- increasing the number of zones accessible by bicycle within a six mile radius by 50 percent.

The results of the application exercise are presented in Table 6.4. The table shows changes in shares and usage by residential location and vehicle type for the Frank copula model and the model of independence that sets all dependency parameters to zero.

6.4.2 <u>Results</u>

In general, it is found that the sensitivity (changes in shares and usage) provided by the Frank copula model differs from that of the model of independence. While some differences are small, there are some that are quite substantial (*e.g.*, effect of household size increase on usage of van), suggesting that ignoring dependency among choice dimensions could result in serious over- or under-estimation of impacts of changes in exogenous variables.

- Larger household sizes and an increase in number of employed individuals result in a shift towards conventional neighborhoods, although an increase in the number of females results in a shift towards neo-urbanist neighborhoods. Similarly, improvements in land use density and bicycle accessibility result in shifts towards neo-urbanist neighborhoods.
- An increase in the number of employed individuals increases the share of pickup trucks significantly, while resulting in a decrease across all other vehicle types, including the choice of no vehicle purchase. On the other hand, an increase in the number of females reduces the share of all vehicle types, except that for compact and large sedans whose shares increase.
- Increases in household sizes are met with a higher likelihood of not making a vehicle purchase suggesting that households reach a vehicle ownership saturation point beyond which they do not acquire additional vehicles even when an additional person enters the household.
- Built environment and transportation accessibility are associated with a decreased share of pickup trucks and slight increases in shares of all other vehicle types, including the choice of not acquiring a vehicle. In fact, an increase in the number of zones accessible by bicycle results in reduction of all vehicle types leading to an increase in the share of the “no vehicle” alternative.

It is interesting to note that the Frank copula model shows consistently different levels of sensitivity in vehicle usage compared to the model of independence. It is apparent that ignoring unobserved dependency among choice dimensions (*indirect* effects or *self-selection*) may result in biased estimation of the potential impacts (benefits) of enhanced non-motorized transport accessibility.

6.5 Activity participation decisions

In Chapter 5, we presented a joint model system of five choice dimensions, activity type choice, activity time of day choice (treated as discrete time intervals), mode choice, destination choice, and activity duration (continuous choice dimension). Specifically, the MDCEV model is used to represent activity participation (discrete choice) and time use (continuous choice) for different types of activities at different time periods of the day by different travel modes. The activity location choice is modeled using a multinomial logit (MNL) model nested within the MDCEV framework. The major objective of this research effort was to develop a unified model of activity-travel and location choices and time use that would allow one to examine the influence of level of service measures and activity-travel environment (ATE) attributes on these choice dimensions in an integrated manner. To demonstrate the capabilities of the model system presented in Chapter 5, we undertake a series of policy exercises that are discussed subsequently.

6.5.1 Policy exercise details

The econometric model formulated and estimated in Chapter 5 was used to examine the impacts of the following scenarios on activity and time use behavior:

- Doubling travel cost across all time periods
- Doubling travel cost during peak periods
- Doubling travel cost for auto mode
- Doubling travel time across all time periods
- Doubling travel time during peak periods
- Doubling travel time by auto mode

Logsum variables computed using the activity destination choice MNL model were used as explanatory variables in the MDCEV model to predict individual's participation in and time allocation to activities by activity purpose, timing, and mode (see the formulation in Section 5.2.2 for definition of logsum). For each policy scenario, logsum variables were computed for all 60 OH discretionary activity purpose, timing, and mode combinations (for use in the base case prediction), and then updated for the specific timing or travel mode categories for which the policy applied (for the policy case prediction). The prediction using MDCEV was carried out for all individuals in the sample using 1000 replications of the error term draws for each individual. Additional details about the forecasting procedure using the MDCEV model are provided in Pinjari and Bhat (2009b).

6.5.2 Policy exercise results

The forecasts under alternative scenarios are presented in Table 6.5. Specifically, the influence of each policy is reported as an aggregate percent change in the amount of time invested in maintenance activities, in-home discretionary activities, and out-of-home discretionary activities by purpose, time of day, and mode (relative to the base case). The important findings from the policy exercise are highlighted below:

- Increases in travel cost lead to reduced out-of-home activity engagement and slight increases in in-home activity engagement.
- Increases in travel cost during the peak period impact volunteer, eat-meal, and recreation activities more than others, and reduce peak period activity engagement while increasing off-peak activity engagement.
- Increases in auto travel costs and times reduce the use of auto mode for activity engagement and contribute to enhanced mode shares for non-auto modes.
- In general, travel time increases appear to have larger impacts than travel costs, suggesting that individuals are more time-sensitive when making activity-travel choices.
- In terms of the modal impact, it appears that all day travel cost or time increases have a greater impact than a time-specific peak-period travel cost or time increase.
- It appears that individuals are more likely to respond to price and time signals that cover an entire day as opposed to those that are narrower in the time band of influence.

In general, the results provide indications along expected lines. To summarize, the policy simulation results clearly show that the model is effective in capturing the responses of individuals to system changes in a unifying framework.

6.6 Summary

In the current chapter, we present a variety of policy exercises undertaken using the econometric models formulated and estimated in Chapter 2 through 5. In fact, we summarize the results of the wide ranging exercise that includes computing different policy measures including: (a) aggregate elasticicties, (b) treatment effects and (c) response to incremental changes to exogenous variables and (d) sensitivity to policy scenarios. The results, in this chapter, further corroborate the findings from Chapter 2 through 5 that it is important to incorporate the influence of *direct* and *indirect* effects of travel environment on travel demand.

Table 6.1: Elasticity Values for the Move Reason Choice

Characteristics \ Alternatives	Fam		Edu		Acc		SuVi		Two		Oth		NM	
	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO
Individual characteristics														
Gender														
Female	28.2	26.2	-8.4	-7.5	-6.9	-6.5	-6.3	-6.5	-7.4	-6.5	-6.4	-6.5	-6.5	-6.8
Age														
Age 31 - 45 years	-14.0	-13.0	-13.2	-12.5	7.3	7.4	8.0	8.6	7.7	7.4	7.2	7.6	6.9	7.9
Age > 45 years	-69.0	-66.4	-63.1	-63.1	38.0	39.4	40.4	44.8	41.6	40.1	35.8	39.5	33.6	38.6
Employed	-12.8	-10.6	-11.4	-9.6	7.8	10.9	-12.3	-11.7	8.3	5.8	23.4	19.6	-13.0	-13.9
Household characteristics														
Household size	2.9	3.0	2.0	2.3	2.8	3.1	2.2	2.7	3.0	3.0	2.6	3.2	-61.9	-61.3
Household Type (Single person household is base)														
Family household	28.5	27.2	-97.5	-94.4	24.5	25.5	-83.1	-81.0	25.4	24.9	24.2	26.8	22.6	27.3
Non-family household	4.4	4.4	3.1	3.3	4.3	4.6	3.4	4.2	4.5	4.5	3.9	4.9	-90.2	-89.0
Household tenure (Rent is base)														
Own household	-2.1	-8.0	-75.5	-75.5	26.1	31.6	-35.8	-38.6	28.0	31.8	25.3	32.3	21.9	30.7
Commute characteristics														
Mode to work (Car is base)														
Public transportation	-8.8	-8.5	13.5	17.2	-8.4	-8.4	10.7	8.4	-8.7	-8.2	33.9	26.1	-7.4	-8.7
Bicycle	-55.4	-53.3	44.9	45.4	14.4	19.0	-29.8	-32.3	17.8	19.5	42.2	30.2	-50.8	-54.8
Walk	3.5	1.5	73.6	76.6	-41.9	-38.3	-58.1	-60.7	6.9	3.9	6.4	5.0	7.0	7.0
Distance to work														
Above 10 km	3.6	3.4	2.6	2.6	3.7	3.8	3.0	3.5	3.8	3.6	3.5	4.2	-82.1	-81.0

Table 6.2: Elasticity Values for the Duration of Stay Choice

Alternatives / Characteristics	< 2years		2 - 5 years		5 - 10 years		> 10 years	
	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO
Individual characteristics								
Gender								
Female	16.4	19.5	-1.8	1.8	-14.0	-13.5	-2.5	-4.4
Age	0.2	0.2	-0.1	-0.1	0.1	0.0	0.1	0.1
Household characteristics								
Household size	-18.0	-20.5	1.0	-4.3	17.7	16.8	3.3	6.6
Household Type (Single person household is base)								
Non-family household	75.8	83.8	-17.5	-4.6	-47.7	-43.2	-7.7	-11.9
Household tenure (Rent is base)								
Own household	-23.4	-19.3	1.8	-2.5	23.1	14.1	4.7	5.3
Number of rooms in the house								
1 - 2 rooms	28.6	31.4	-5.1	1.1	-24.5	-21.0	-4.3	-6.7
Transportation characteristics								
Mode to work (Car is base)								
Public transportation	14.6	15.7	-2.0	1.4	-13.6	-11.3	-2.5	-3.9
Bicycle	21.5	27.1	-3.4	0.8	-16.9	-16.8	-3.0	-5.2
Distance to work								
Above 10 km	29.4	31.9	-4.9	1.9	-26.9	-22.2	-5.1	-7.6

Table 6.3: Estimates of Treatment Effects in Miles

Copulas	Independence-Independence Copula (I-I)	FGM-Joe Copula (FG-J)	Frank-Joe Copula (F-J)	Frank-Frank Copula (F-F)
$\hat{ATE}$	0.49 (1.75)	10.75 (1.03)	19.99 (4.42)	21.37 (5.21)
$\hat{TT}$	3.04 (1.49)	31.04 (3.30)	42.45 (7.46)	41.76 (8.16)
$\hat{TNT}$	-8.38 (1.38)	-31.55 (10.06)	-33.66 (10.82)	-30.74 (9.55)
$\hat{TTNT}$	0.49 (1.75)	17.07 (0.88)	25.46 (3.03)	25.59 (4.75)

Table 6.4: Model Application

Variables / Sample	Household size increased by 1				No. of employed individuals increased by 1				No. of females increased by 1				Zonal land use mix increased by 25%				No. of zones accessible by bicycle within 6 miles			
	Frank		Independent		Frank		Independent		Frank		Independent		Frank		Independent		Frank		Independent	
	Shares	Usage	Shares	Usage	Shares	Usage	Shares	Usage	Shares	Usage	Shares	Usage	Shares	Usage	Shares	Usage	Shares	Usage	Shares	Usage
Residential neighborhood																				
Conventional	-0.69	-3.35	-0.35	-6.05	0.02	11.53	0.03	12.86	-0.50	0.00	-0.77	0.00	-0.01	0.00	-0.01	0.00	-3.71	-3.00	-3.50	-2.99
Neo-urbanist	1.55	-3.35	0.79	-6.05	-0.03	11.53	-0.07	12.86	1.12	0.00	1.73	0.00	0.03	0.00	0.03	0.00	8.30	-3.00	7.84	-2.99
Vehicle Type																				
Coupe	-18.39	-4.62	-22.02	-7.10	-4.54	9.44	-4.78	12.56	-13.00	0.00	-11.94	0.00	0.22	0.00	0.24	0.00	-2.14	-2.57	-2.37	-2.43
Suv	-19.48	-7.04	-23.19	-9.24	-4.47	7.07	-4.71	5.32	-12.42	0.00	-11.31	0.00	0.23	0.00	0.25	0.00	-1.51	0.00	-1.71	0.00
Pickup	16.85	-18.56	16.27	-20.94	35.20	26.36	37.19	29.60	-33.42	0.00	-33.38	0.00	-2.83	0.00	-3.03	0.00	-9.56	-4.58	-9.27	-3.97
Van	64.98	16.36	67.89	11.24	-4.21	0.00	-4.45	0.00	-11.15	0.00	-10.04	0.00	0.26	0.00	0.28	0.00	-0.42	-5.82	-0.52	-6.45
Compact sedan	-32.86	-5.74	-31.34	-7.31	20.79	17.06	20.07	15.68	25.39	0.00	25.40	0.00	0.23	0.00	0.24	0.00	-2.01	-2.22	-2.21	-1.29
Large sedan	-0.96	0.00	-0.25	0.00	-14.59	9.74	-14.03	11.46	1.96	0.00	0.84	0.00	0.24	0.00	0.25	0.00	-1.24	-3.38	-1.35	-3.74
No vehicle	7.07	-	7.24	-	-4.37	-	-4.63	-	1.83	-	2.01	-	0.22	-	0.24	-	3.67	-	3.85	-

Table 6.5: Policy Simulation Results

Alternatives	Activity Purpose							Activity Timing						Travel Mode	
Scenario details	Maintenance	IH Discretionary	OH Volunteer	OH Social	OH Meals	OH Shopping	OH Recreation	Early Morning	Morning	Late Morning	Afternoon	Evening	Night	Auto	Non-auto
Travel cost measure increased by 100% for all time periods	0.01	0.02	-0.99	-1.00	-0.84	-0.91	-0.93	-0.92	-0.90	-0.92	-0.96	-0.92	-0.87	-1.00	-0.75
Travel cost measure increased by 100% for peak periods	0.00	0.00	-0.58	-0.05	-0.46	0.07	-0.29	1.34	-3.89	1.30	1.26	-3.93	1.34	-0.30	-0.19
Travel cost measure increased by 100% for auto mode	0.01	0.01	-1.16	-1.21	-0.27	-0.31	-0.83	-0.77	-0.75	-0.69	-0.64	-0.68	-0.76	-2.10	2.48
Travel time measure increased by 100% for all time periods	0.04	0.06	-3.36	-3.40	-2.86	-3.09	-3.18	-3.11	-3.07	-3.13	-3.26	-3.13	-2.95	-3.39	-2.57
Travel time measure increased by 100% for peak periods	0.01	0.02	-1.88	-0.15	-1.53	0.22	-0.95	4.41	-12.70	4.22	4.12	-12.83	4.37	-0.99	-0.64
Travel time measure increased by 100% for auto mode	0.03	0.04	-3.85	-3.99	-0.95	-1.05	-2.73	-2.54	-2.51	-2.30	-2.12	-2.27	-2.54	-7.03	8.34

CHAPTER 7 CONCLUSIONS AND DIRECTIONS FOR FURTURE RESEARCH

7.1 Introduction

In the United States, a significant number of individuals depend on the auto mode of transportation. The increasing auto travel, and its adverse environmental impacts (such as traffic congestion and air pollution), has led, in the past decade, to a growing emphasis on analyzing traveler behavior at the individual level rather than using direct statistical projections of aggregate travel demand. In particular, the focus of travel demand modeling has shifted from an underlying trip-based paradigm to an activity-based paradigm, which treats travel as a demand derived from the need to participate in activities dislocated in time and space (see Bhat and Koppelman, (1993)).

The activity-based framework considers travel as a means to pursue activities distributed in time and space. The activity-based modeling framework essentially attempts to replace the statistical travel prediction focus of the traditional trip-based model framework with a more behavioral approach that explicitly recognizes the fundamental role of activity participation as a precursor to travel. Essentially, the objective of an activity-based travel modeling framework is to micro-simulate individual activity and travel participation over the course of certain time interval, which usually is a typical weekday.

It is widely recognized in transportation literature that an accurate characterization of activity-travel patterns requires explicit consideration of the land-use and travel environment. The influence of travel environment on travel behavior can be classified into two categories: direct and indirect effects. The direct effect can be captured by including travel environment related variables as exogenous variables in travel models. However, accommodating only the direct effect in a travel model is far from simple because the very travel environment attributes experienced by a decision maker (individual or household) is a function of a suite of *a priori* travel related choices made by the decision maker. The emphasis of the current dissertation is on recognizing the two categories of travel environment effects and incorporating them within an econometric framework.

The overall objective of the dissertation is to contribute to the growing literature on integrated land-use activity-based model framework by developing econometric models that can accommodate joint modeling of multidimensional choices. In particular, the overall goal is to contribute to the debate on whether the empirically observed association between the built environment and travel behavior-related variables is a true reflection of underlying causality, or simply a spurious correlation attributable to the intervening relationship between the built environment and the characteristics of people who choose to live in particular built environments (or some combination of both these effects). Towards this end, the current research effort contributes to the existing research by (a) developing advanced econometric models for modeling multi-dimensional choices, (b) estimating these models for travel data sets, and (c) undertaking policy analysis.

The current dissertation contributes substantially to integrated land-use activity based modeling literature while simultaneously contributing methodologically by formulating advanced econometric models. Specifically, we examine different modules of an activity based framework. The empirical problems addressed in the dissertation include: (1) reason for residential relocation and associated duration of stay, (2) household residential location and daily vehicle miles travelled, (3) household residential location, vehicle type and usage choices and (4) activity type, travel mode, time period of day, activity duration and activity location.

The rest of the chapter is organized as follows. Section 7.2 through 7.5 discusses the substantive and methodological contributions of the dissertation for each multidimensional choice context examined in the dissertation. Section 7.6 concludes the dissertation by offering directions for future research.

7.2 Household residential relocation decision

The major focus of the research effort presented in Chapter 2 is to understand household residential relocation decisions. The study jointly models the reason for relocation and the duration of stay at a location preceding the relocation, recognizing that the reason for location may itself be an endogenous variable influenced by observed and unobserved variables. The data for the empirical case study is drawn from a longitudinal data set derived from a retrospective survey that was administered in the beginning of 2005 to households drawn from a stratified sample of municipalities in the Zurich region of Switzerland. The most important finding in the context of examining household residential relocation decisions is that there are common unobserved factors affecting the reason to move and the duration of stay choices. Other important findings and recommendations include:

- Several demographic, socio-economic, and commute related variables are found to significantly influence the reason for move and the duration of stay
- The study findings (based on estimation results and aggregate elasticity effects) have implications for housing and labor policy. For example, those who own households have a lower probability of moving for surrounding vicinity related reasons than those renting their units. In other words, it appears that the potential exists for improving existing surrounding vicinity conditions around rental properties so that individuals unable to afford home ownership can enjoy the same level of amenities and environment as those who are able to own their homes.
- From a jobs-housing balance standpoint, having a mix of job opportunities located close to residential neighborhoods may help increase the duration of stay for individuals; reducing commute distance to a value of less than 10 km (in the context of this Zurich based survey sample) fosters longer stay durations.
- From a social standpoint, it appears that women are more prone to moving for personal and family reasons; this may be reflective of the need for social support systems for women who are affected by personal or family turmoil so that they do not necessarily feel compelled to move away.
- From a methodological perspective, the joint multinomial logit model and a grouped logit model is the first instance of such a model developed in econometrics literature.

7.3 Residential location and VMT

In Chapter 3, we apply a copula based approach to model residential neighborhood choice and daily household vehicle miles of travel (VMT) using the 2000 San Francisco Bay Area Household Travel Survey (BATS). The model considers the possibility of households selecting their residence locations based on their travel needs i.e. the observed VMT differences between households residing in neo-urbanist and conventional neighborhoods cannot be attributed entirely to built environment variations between the two neighborhoods types. A variety of copula-based models are estimated, including the traditional Gaussian-Gaussian (G-G) copula model. The results indicate that using a bivariate normal dependency structure suggests the absence of residential self-selection effects. However, other copula structures reveal a high and statistically significant level of residential self-selection, highlighting the potentially inappropriate empirical inferences from using incorrect dependency structures.

Other important findings from the study include:

- The best fit copula model developed in Chapter 3 estimates that self-selection effects constitute about 17% of the VMT difference between neo-urbanist and conventional households, while "true" built environment effects constitute the remaining 83% of the VMT difference.
- The results of this study indicate that, in the empirical context of the current study, failure to accommodate residential self-selection effects can lead to a substantial mis-estimation of the true built environment effects.
- A randomly picked household will drive about 21 vehicle-miles per day more if residing in a conventional neighborhood relative to a neo-urbanist neighborhood.
- If a randomly picked household in a conventional neighborhood were to be relocated to a neo-urbanist neighborhood, the household's VMT is estimated to decrease by about 42 miles.
- From a methodological standpoint, the copula approach introduced in this dissertation happens to be the first instance of the application of copulas models in transportation literature. In fact, this work has led to huge attention within the

transportation community as revealed by a multitude of papers employing copulas (for example see Spissu et al.2009, Eluru et al., 2009, Portogese et al., 2009, Sener and Bhat 2009, Sener et al., 2009, Lamondia and Bhat 2009, Rana et al., 2010)

- Finally, the model results imply that one may expect a VMT reduction of about 43% by redesigning all neighborhoods to be of the neo-urbanist neighborhood type[19].

7.4 Household vehicle fleet composition and usage choices

Chapter 4 proposes a simple, yet effective methodological approach that focuses on incorporating the impact of "self-selection" of individuals in residential location-vehicle ownership and type choice and its influence thereof on vehicle usage. The data for this research effort is drawn from using the 2000 San Francisco Bay Area Household Travel Survey (BATS).

Important findings and policy recommendations from the research effort include:

- The research effort confirms the presence of significant common unobserved factors that simultaneously impact residential location choice, vehicle type choice, and vehicle usage.
- The Gaussian copula estimation results are not statistically superior to the independent model results. A conventional joint modeling of these choices (assuming normal correlated errors across choice dimensions) would have one conclude that self-selection impacts are negligible in affecting vehicle usage.
- The model system presented in this study offers the ability to not only model vehicle fleet composition or holdings, but also the vehicle acquisition process itself as a function of previously held vehicles in the household.

[19] Note that we are simply presenting this figure as a way to provide a magnitude effect of VMT reduction by designing urban environments to be of the neo-urbanist kind. In practice, different neighborhoods may be redesigned to different extents to make them less auto-dependent. Further, in a democratic society, demand will (and should) fuel supply. Thus, as long as there are individuals who prefer to live in a conventional setting, developers will provide that option.

- This model provides an effective solution to obtain a complete and accurate picture of the land use-vehicle fleet-vehicle use choices of a household while controlling for self-selection effects in these choice processes.
- From a methodological stand point, the model developed here extend the copula based multinomial logit – regression models to incorporate correlation across alternatives in the multinomial logit component yielding copula based Generalized Extreme Value – regression model.

7.5 Activity participation decisions

A comprehensive unified model system of activity-travel choices that is consistent with microeconomic utility maximization theory of behavior was proposed in Chapter 5. The activity-travel choice dimensions analyzed in this chapter include activity type choice, time of day choice, mode choice, destination choice, and activity time allocation or duration. The data for this research effort is drawn from using the 2000 San Francisco Bay Area Household Travel Survey (BATS). The model estimation and model application results clearly underline the importance of the joint model system developed in the research effort. The findings reported here clearly support the notion that individuals make several activity-travel choices jointly as a "bundle", calling for the simultaneous modeling of various choice dimensions in a unifying framework.

Other important results from the analysis include:

- Activity-travel model systems that purport to simulate the behavior of agents along the time axis may benefit from the adoption of model forms that are able to simultaneously predict multiple choice dimensions as a "bundle".
- Increases in travel cost lead to reduced out-of-home activity engagement and slight increases in in-home activity engagement.
- travel time increases appear to have larger impacts than travel costs, suggesting that individuals are more time-sensitive when making activity-travel choices

- It appears that individuals are more likely to respond to price and time signals that cover an entire day as opposed to those that are narrower in the time band of influence.
- The methodology developed in this chapter, extends the MDCEV-MNL model formulated by Bhat et al., 2009 to incorporate sampling within the MNL component. Allowing for sampling within the MNL component allows us to incorporate choice situations with large number of alternatives.

7.6 Directions for future research

The preceding sections discuss at length the contributions of the current dissertation to the areas of transportation and econometrics and more specifically to integrated land-use activity-based model frameworks. In the current discussion, we focus on the limitations of the research efforts (Section 7.6.1) and discuss possible extensions for the future (Section 7.6.2).

7.6.1 Limitations

The models estimated in the current study are based on data from a particular urban region. Hence, it is important to examine their transferability to other urban regions prior to generalizing their results. An effort to estimate these models using different datasets will enable us to draw more insights and propose more wide ranging policies. Another aspect often discussed in literature is the availability of data.

The research in transportation (as in any other fields) is limited by availability of data. In particular, two aspects of data have always been found lacking. First, it is often very difficult to obtain longitudinal data in the US. There is only so much an analyst can achieve with cross-sectional data. It is imperative to possess longitudinal data to accommodate for decision maker's inertia and variety seeking behavior. Second, the lack of individual lifestyles and attitudes, neighborhood attributes such as school quality and crime rates, in typical travel data sets. There has been increasing recognition within the transportation community of the importance of individual including attitudes and preferences related question in travel surveys. An example for such a travel survey includes the recent National Household Travel Survey's 2009 travel data extended survey. If we could estimate the models developed in the current dissertation employing longitudinal data with a wealth of information on individual lifestyles, attitudes and neighborhood characteristics it is more likely to enhance the findings.

7.6.2 Research extensions

The primary objective of transportation modeling is to employ the models developed for forecasting. The different modules developed in the dissertation can be embedded within an activity-based framework. The models formulated and estimated will aid existing activity-based frameworks to make incorporate the direct and indirect effects of land-use and travel environment on travel behavior. In figure 1.1, we present how each module can be embedded in an activity-based framework. The household relocation model will be embedded in the DLUTEG component, while the copula-based models from chapters 3 and 4 will contribute to DLUTEG and ATPG components. The activity participation model developed in chapter 5 will fit within the ATPG component. The embedding of these modules within an activity-based framework will require a substantial amount of effort in creating an efficient microsimulation framework that runs through these choices for individuals and households in reasonable time.

The current research effort has chosen four of the many multidimensional choice contexts within the integrated land-use activity-based model framework. There are many other choice contexts that need to be examined as multidimensional choices. Examples of such choices include: residential location and physical activity participation, physical activity participation of all household members modeled jointly (see Sener et al., 2009 for a research effort to address this).

Future efforts should also consider analyzing number of travel tours and trips by purpose, and mileage of individual trips, rather than considering vehicle miles of travel in the aggregate (as considered in Chapter 3 and 4). With the increasing focus on sustainable living, it is important to consider accurate measures of transit and bicycle accessibility in the analysis.

APPENDIX 1

Using the notation in Section 3.1, the likelihood function may be written as:

$$L = \prod_{q=1}^{Q} \left[\left\{ \Pr[m_{q0} \mid r_q^* \le 0] \times \Pr[r_q^* \le 0] \right\}^{1-r_q} \times \left\{ \Pr[m_{q1} \mid r_q^* > 0] \times \Pr[r_q^* > 0] \right\}^{r_q} \right] \qquad \text{(A.1)}$$

The conditional distributions in the expression above can be simplified. Specifically, we have the following:

$$\begin{aligned}
\Pr[m_{q0} \mid r_q^* \le 0] &= \left\{ \Pr[r_q^* \le 0] \right\}^{-1} \times \frac{\partial}{\partial m_{q0}} F\left(-\beta' x_q, \frac{m_{q0} - \alpha' z_q}{\sigma_\eta} \right) \\
&= \left\{ \Pr[r_q^* \le 0] \right\}^{-1} \times \frac{1}{\sigma_\eta} \times \frac{\partial}{\partial t} F\left(-\beta' x_q, t \right) \Big|_{t = \frac{m_{q0} - \alpha' z_q}{\sigma_\eta}} \qquad \text{(A.2)} \\
&= \left\{ \Pr[r_q^* \le 0] \right\}^{-1} \times \frac{1}{\sigma_\eta} \times \frac{\partial C_{\theta_0}(u_{q1}^0, u_{q2}^0)}{\partial u_{q2}^0} \times f_\eta\left(\frac{m_{q0} - \alpha' z_q}{\sigma_\eta} \right)
\end{aligned}$$

where $C_{\theta_0}(.,.)$ is the copula corresponding to F with $u_{q1}^0 = F_\varepsilon(-\beta' x_q)$ and $u_{q2}^0 = F_\eta\left(\frac{m_{q0} - \alpha' z_q}{\sigma_\eta} \right)$.

Similarly, we can write:

$$\begin{aligned}
\Pr[m_{q1} \mid r_q^* > 0] &= \left\{ \Pr[r_q^* > 0] \right\}^{-1} \times \frac{\partial}{\partial m_{q1}} \left[F_\xi\left(\frac{m_{q1} - \gamma' w_q}{\sigma_\xi} \right) - G\left(-\beta' x_q, \frac{m_{q1} - \gamma' w_q}{\sigma_\xi} \right) \right] \\
&= \left\{ \Pr[r_q^* > 0] \right\}^{-1} \times \frac{1}{\sigma_\xi} \times \left[f_\xi\left(\frac{m_{q1} - \gamma' w_q}{\sigma_\xi} \right) - \frac{\partial}{\partial v} G\left(-\beta' x_q, v \right) \Big|_{v = \frac{m_{q1} - \gamma' w_q}{\sigma_\xi}} \right] \qquad \text{(A.3)} \\
&= \left\{ \Pr[r_q^* > 0] \right\}^{-1} \times \frac{1}{\sigma_\xi} \left[f_\xi\left(\frac{m_{q1} - \gamma' w_q}{\sigma_\xi} \right) - \frac{\partial}{\partial u_{q2}^1} C_{\theta_1}(u_{q1}^1, u_{q2}^1) \times f_\xi\left(\frac{m_{q1} - \gamma' w_q}{\sigma_\xi} \right) \right],
\end{aligned}$$

where $C_{\theta_1}(.,.)$ is the copula corresponding to G with $u_{q1}^1 = F_\varepsilon(-\beta' x_q)$ and $u_{q2}^1 = F_\xi\left(\frac{m_{q1} - \gamma' w_q}{\sigma_\xi} \right)$.

Substituting these conditional probabilities back into Equation (A.1) provides the general likelihood function expression for any sample selection model presented in Equation (28) in the text.

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