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Understanding Dynamics of Travel Behavior with Inverse Reinforcement Learning and Hidden Markov Model

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Understanding Dynamics of Travel Behavior with Inverse Reinforcement Learning and Hidden Markov Model

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Committee in charge:

Professor Joan Walker, Chair
Professor Mark Hansen
Professor Pravin Varaiya

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Abstract

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Mengqiao Yu

Doctor of Philosophy in Engineering – Civil Environmental Engineering

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Professor Joan Walker, Chair

We are in an era of rapid urbanization, technological advances, transportation transformation, and increasingly big data and computation power. We have witnessed how shared transportation (Uber, Lyft, Lime, Bird, etc) intrudes into daily lives in just a few years, how online shopping, including same-day grocery delivery, has changed day-to-day travel trajectories, and how the emerging work-from-home lifestyle would fundamentally change people's location choices. At the same time, large-scale data becomes more accessible than ever; so does the computation power needed to process such data. It is therefore a good time to retrospect existing paradigms of dynamic behavior models and keep exploring the potentials and new opportunities.

While studies on long-term travel behavior, such as residential location choice and working location choice, have been the emphasis of a substantial body of prior work, most empirical studies adopt a static approach to behavior modeling. For the small body of work that allows for dynamic behavior modeling, only backward-looking behavior, i.e., time-dependency, is incorporated, and the role of forward-looking behavior, i.e. by considering future expectations in sequential decision-making, has long been neglected. This is with good reasons: the estimation of a truly dynamic choice model is extraordinarily difficult due to (a) computational tractability associated with big data and large-scale dynamic programming to accommodate forward-looking and (b) scarcity of longitudinal data on long-term travel behaviors, such as residential moving trajectories. Yet long-term travel behavior is inherently dynamic, and this has led to concerns that estimates from static models may be biased.

In economics, dynamic discrete choice models (DDCM) have been used to model many aspects of transportation behaviors; however, this approach has several limitations, including its assumptions of optimal human behavior, conditional independence, extreme value distribution, etc. In the recent decade, advances in artificial intelligence, especially in inverse reinforcement learning (IRL), have inspired new approaches to solving complex dynamic behav-

ioral problems. In particular, IRL can circumvent several assumptions common in DDCM, while still reconstructing problems and estimating models in a tractable way. ***However, the research worlds of economics and of artificial intelligence rarely reference each other; one objective of this dissertation is to bridge these two disciplines to address the challenging problem of modeling large-scale long-term forward-looking travel behavior.***

We do not necessarily need the forward-looking assumption in all situations. In practice, for short-term and medium-term behavior trajectories, such as mode choice, car usage and car ownership, the backward-looking assumption can be sufficient. This is because these choices are associated with much lower costs both financially and psychologically and the impact of future expectations can be trivial. There is a rich amount of literature on backward-looking dynamic models, including studies on identifying policy and environment triggers that shift travel behavior ([83]), studies that investigate the role of key life events on travel behavior change ([66, 12, 88, 32, 69, 58]), and studies on lifestyle analysis which treat lifestyle transition as a higher-level orientation of behavioral change ([67, 87, 100, 107, 109, 35]. ***However, most frameworks on backward-looking dynamic modeling concentrate on analysis of single-dimensional choice and ignore the interdependence and multi-dimensionality of travel behaviors. Furthermore, few prior work consolidates all these dynamics components in a single framework to analyze the joint effect of different sources of triggers. Therefore, another objective of this dissertation is to develop a unified modeling framework that accounts for time-varying economic and policy context (external dynamics), life events (internal dynamics), lifestyle, and multi-dimensional interrelated choices.***

The first component of this dissertation formulates a mathematical framework for representing long-term travel behaviors as sequential actions under the Inverse Reinforcement Learning (IRL) framework, which aims to address the forward-looking limitation. In the proposed framework, the individual observes the environment and takes action (i.e., move to a new location or not) accordingly by evaluating action-dependent future rewards received from the environment. The reward can be a function of built-in environment attributes, which shares a similar concept with the utility function in discrete choice models. Three highlights of the first component of this work are presented below:

- In the classic IRL setting within the domain of artificial intelligence, the agents (usually robots) are often assumed to have homogeneous behavior and do not own any internal dynamics associated with the agents. Our work extends the IRL framework to accommodate heterogeneous household behavioral dynamics, and derives its corresponding learning algorithm to estimate the parameters associated with the attributes.
- We provide an in-depth theoretical comparison between Dynamic Discrete Choice Model (DDCM) in economics and IRL in artificial intelligence from different aspects, including terminologies, assumptions, and model structures.

- To validate the existence of forward-looking behavior and the methodological feasibility of the proposed framework, we use a large-scale infused data set of household relocation trajectories in Texas over a 7-year period (2005-2011).
- The empirical results are three-fold. First, all households have a positive preference to locate in areas with higher degree of land-use mix, higher accessibility to jobs, and lower employment density. Our model also shows that low-income households focus more on current needs and are less forward-looking compared with households with higher income level. And low-income households present less willingness to pay for neighborhood amenities such as land-use mix and accessibility to jobs. In terms of goodness of fit, our proposed model outperforms the DDCM model (for high-income and low-income households), backward-looking model and the static model.

The second component of this work addresses the limitation on backward-looking models. The HMM framework has gained increasing attention in the transportation arena (in applications from car ownership to mode choice) due to its latent hierarchical structure, favorable model performance, and intuitive interpretation. Highlights of this component are as follows:

- We extend the framework of heterogeneous Hidden Markov Model (HMM) from single-dimensional discrete choice to multi-dimensional discrete and continuous choices, and derive its recursive parameter learning algorithm. Building on this framework, we propose a unified model that conjoins lifestyle, life events, external environment, and multi-dimensional travel behavior dynamics.
- We evaluate the feasibility and robustness of the proposed methodology via a case study: a retrospective survey in the San Francisco Bay Area consisting of 830 households.
- To fully explore the potentials of the proposed framework, we provide trend analysis of car ownership and mode use based on estimation results, and conduct sensitivity analysis of changes in fuel price and unemployment rate.
- We identify four latent lifestyles: auto-oriented-2-car group with rare use of other travel modes, auto-oriented-1-car group with rare use of other travel modes, multi-modals group that own at least one car, and auto-free group that have the lowest car ownership and car usage. The results demonstrate how life events, policies, and the economic environment influence people on lifestyle transitions.

In sum, this dissertation provides building blocks to evolve the field of dynamic behavior modeling by incorporating advances in artificial intelligence. Throughout this dissertation, when providing theoretical improvements building on each mathematical framework, we ground each methodology with case studies. Empirical results have shown our methodologies can effectively help quantify the triggers that prompt individuals and households to change their travel behavior, better predict the trend of future mobility, and help transportation planning and policy-making.

To my mom, dad, and Tianhao

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One of the most fortunate things in my life is to be a PhD student in Berkeley. The say that it takes a village to raise a child and indeed, it is so true for me. I feel grateful to have the privilege of working with so many smart, knowledgeable, kind, and interesting professors and peers I have met at Cal with whom I have learned, laughed, struggled, and most importantly, grown.

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Chapter 1

Introduction

"I think you should always bear in mind that entropy is not on your side."

(Elon Musk)

I grew up in China in the period of astonishing economic growth and urbanization; we called it the era of "reform and opening up". Since the mid-1980s, most municipalities, including my hometown, have substantially increased spending in city planning, road construction, public transit service, metro system, etc. The resulting expansion in infrastructure and city services stimulated a huge increase in travel demand along with the zenith of vehicle adoption and an overly burdened public transport system. From my childhood to adolescence, my parents transitioned from inflating bike tires every week to visiting gas stations every month. We moved several times - from a small and closed-knit community, a 15-minute walk to my school and my parents' work place, to a CBD area with a convenient public transportation system and general living environment. As a witness to how the world's largest transportation system came to be, I was deeply obsessed with asking questions about its transformation. How did these changes happen? How to quantify each factor that played a role in this historical period, including government investment, housing market, global and local economics, social system? And should we also treat it as a natural process of life transitions along generations? How to make trend predictions in the future? As China has a such a big population, which means tons of data, are we capable of handling such a big amount of data? All these questions motivated me to initiate this work in my graduate school. I may not have found answers to all the them, but fortunately I found some.

1.1 Dynamics of Travel Behavior

While vehicle technology advances, such as electrification, have the potential to increase efficiency and reduce energy consumption in the transportation system, these advances alone are not sufficient to increase the overall system sustainability. Any potential shifts in transportation system efficiency and performance will depend critically on individual travel-related behaviors and choices, including use of efficient travel modes and shifts in patterns of vehicle-dependence.

Modeling long-term dynamics and understanding the conditions of these critical behavioral shifts are a recurrent research question and topic of interest for policy makers.[1] Shifting long-term travel behaviors requires a gradual adjustment of personal needs and adaption to environmental changes, and might require years, or even generations, to reach the desired outcome. Travel behaviors are deeply habitual. They may be flexible at some points but less flexible after certain choices have been made, such as whether or not to purchase a vehicle or where to live. For example, choosing whether to drive or use public transit is a fundamentally different choice for households owning multiple vehicles versus those owning one or none, and similarly for those living in suburbs far away from their destination versus those living in the city center with immediate access to alternative transportation.

Travel trends have been evolving in recent years, especially with respect to the prevalence of using multiple lower-emission modes to replace personal vehicle trips (multimodality) in western countries. In Germany, [65] reveals a rise in multimodality and a decrease in vehicle ownership and use among young adults (aged 18-29 years) since 1990. [23] investigates the prevalence of multimodality in the United States between 2001 and 2009, and observes a significant shift away from personal vehicle use towards multimodal vehicle use (combining occasional car use with occasional use of other modes) as well as exclusive walking-bicycling-public transport use. [56] provides evidence of similar shifts in mode use in Britain.

Under the long-term context, behavior dynamics, especially those that may trigger changes in travel habits and behaviors, are an important topic at all times. To identify triggers that shift travel behavior, a traditional focus of the literature has been on how changes to the external environment (policies, economics, societal, and cultural factors) result in households adjusting travel-related behavior. For example, using nine years of U.S. Consumer Expenditure Survey (CES) data, [83] finds that households would reduce vehicle miles traveled (VMT) in the year following an increase in gasoline price.

Another more recent facet of the literature employing "mobility biography" approaches emphasizes the role of internal dynamics (change of life-cycle, life stages, key life events, etc.). The life events analyzed include shifts in residential location, employment, and household structure (e.g., having children or living with a partner). While most of these studies have observed a strong relationship between life event and travel behavior change, [88] concludes that life events are only loosely associated with changes in mode use.

The concept of lifestyles, related to but distinct from the concepts of life-cycle phases or life events, has been increasingly recognized in the literature as important to travel behavior choices and outcomes. Studies in lifestyles recognize that travel behavior is driven by more than objective constraints (e.g., built environment and socioeconomic characteristics) traditionally used in classic travel demand models. As [67] points out, lifestyles can be un-

[1] We emphasize 'long-term' in the scope of this paper to differentiate from studies focused on short-term dynamics, which usually refer to within-day and day-to-day activity-based behavior [111].

derstood as a social construct that determines how individuals identify with a social group and manifests itself in all facets of everyday lives, such as consumption habits and tastes (e.g., furniture, clothes, favorite television programs or newspapers) and leisure activities. Lifestyle therefore determines the dynamics of travel behavior as a higher-level orientation ([87]). More specifically, some recent empirical studies have demonstrated the existence of modality style as a subset of lifestyle that influences mode choice behavior ([100, 107, 109, 35]).

All the above-mentioned components (a sequence of choices, external dynamics, internal dynamics, and higher-level lifestyle transitions) are comprised of the concept of behavior dynamics we are interested in. However, I would like to point out two sets of concepts that are highly correlated with the behavior dynamics but have long been neglected in long-term travel behavior modeling. One is related with the multi-dimensionality of human behaviors, and the other one is related with the character of decision-makers. These two will be discussed in the following two sections.

1.2 Single-Dimensional Choice vs A Bundle of Choices

We are encountering an era of rapid urbanization, technological change and transportation transformability (shared transport, electrical car, etc), which reshapes the demand for jobs, housing, energy, transportation infrastructure, and social services and brings the long existing problems, including greenhouse gas emission, climate change and traffic congestion, back to agenda. In recent years, policy makers are more inclined towards developing smart cities that promote sustainable mobility and multi modality. In transport and land use public policy arenas, they often try to encourage certain types of travel-related behaviors, such as less driving, more public transit, walking, biking, living closer to work, purchasing and using alternative-fueled vehicles, etc.

Such a sustainable goal encourages individuals and households to collectively adjust their travel behaviors in varied dimensions. In the transportation field, it has been well recognized that people indeed make a bundle of choices together. That is to say, consumer choices and decisions, from longer-term to shorter-term, such as residential and work location, vehicle ownership and usage (e.g., VMT), and mode choice, are all interdependent. For example, a household that moves from an urban to a suburban area might add a vehicle to improve access to more dispersed activities, and once owning a vehicle, they may start to use it exclusively, regardless of the availability of alternatives. A growing body of literature has demonstrated that ignoring this interdependence can yield inconsistent model results that either over- or under-estimate the true impact of explanatory factors ([18, 80, 17]).

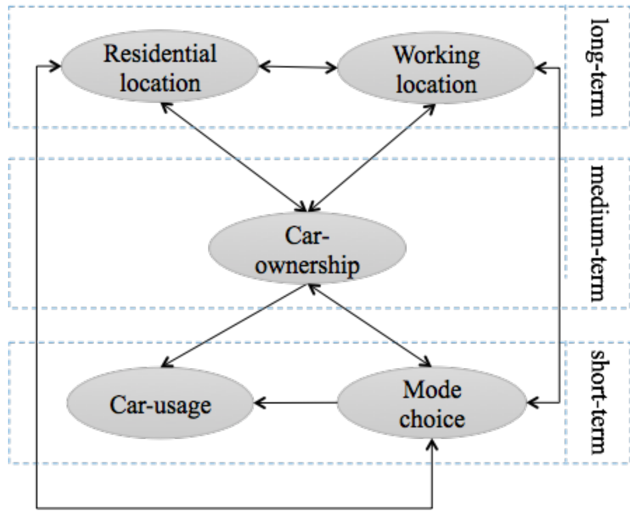


Figure 1.1: Multi-dimensional travel behaviors

1.3 Forward-Looking vs Backward-Looking

Unlike shorter term travel behavior, such as mode choice or even car ownership, changing residential location incurs much higher costs both financially and psychologically. As a result, in response to these internal and external dynamics discussed in Section 1.1, households often plan more carefully and weigh their past living experiences and/or future expectations. Individuals and households that only connect past experience with their current decision are often referred to as **"backward-looking"**, "shortsighted", or "myopic" agents, while those that take into account effects of future expectations in their current decisions are considered "**forward-looking**" or "foresighted" agents. **One is not necessarily better than the other. The choice on modeling either the foresighted people or not depends on the decision-making problem researchers deal with.**

One's past experience plays a critical role in decision making as a result of strong inertia, i.e. reluctance to move away from current residential locations or move to an unfamiliar environment ([42, 26, 21, 108]). This inertia is even stronger when moving away from a community that may lead to some loss of social and sentimental ties [81]. Along with past experience, the importance of incorporating forward-looking behavior has been gradually recognized in recent years, and many studies have found that excluding this factor leads to biased estimation [98]. As [20] finds using California housing data from 1990-2008, a model that does not consider future expectations can underestimate households' willingness to pay for a lower violent crime rate by 21 percent. [10] also highlights that, by ignoring forward-looking agents, estimated neighborhood preferences may be biased towards areas with high population makeup of whites, low violent crime, and low air pollution.

1.4 Dissertation Organization

This dissertation is structured in the following manner:

- Chapter 2 reviews the key model frameworks of forward-looking dynamic models in different arenas. We first introduce the Markov Decision Process (MDP), which is fundamental to modeling how people make sequential decisions. We clearly define its corresponding concepts to avoid terminology confusion since we will follow with two model frameworks based on MDP from different domains. The two frameworks are Dynamic Discrete Choice Model (DDCM) from economics and Inverse Reinforcement Learning (IRL) from artificial intelligence. We provide an in-depth comparison between these models from problem statement, assumptions, model structures, and estimation function.

- Chapter 3 recognizes the limitations discussed in Chapter 2 and formulates an IRL-based model framework for long-term residential choice behavior. We derive a recursive learning algorithm to estimate the parameters associated with the attributes. We use an infused data set of household relocation trajectories in Texas over a 7-year period (2005-2011). We describe how to extract approximately one million movement trajectories between 2005-2011 using the vehicle registration records provided by the Texas Department of Motor Vehicles. Based on empirical results we analyze whether high-income and low-income groups have different forward-looking behaviors and compare their estimated willingness to pay for mix land use and accessibility to jobs.

- Chapter 4 reviews the key model frameworks of backward-looking dynamic models in different arenas. We first present the history, strengths, and limitations of Structural Equation Model (SEM) in economics and then introduce another thread of research built on Hidden Markov Model (HMM) in machine learning. We also provide a review for static latent class choice model in economics since it explicitly accommodates the latent lifestyle component in model structure which shares a similar concept with the hidden state in HMM.

- Chapter 5 presents the model structure of the heterogeneous Hidden Markov Model with joint choices and derives the corresponding estimation algorithm. We apply this methodology to the dynamic analysis of mobility styles in the San Francisco Bay Area, using data from a retrospective survey. We then present the estimation results and conduct further analyses on how people transition between mobility styles as a result of changes in life stages, policies and the economic environment.

- Chapter 6 summarizes the work presented herein and proposes future research directions. We conclude with final thoughts on the strengths and limitations of model frameworks rooted in machine learning and artificial intelligence and how we should be prepared for big data and large-scale problem set in the transportation arena.

1.5 Summary of Contributions

This dissertation focuses on complementing dynamic travel behavior models using longitudinal data, both in the forward-looking setting and the backward-looking one. This dissertation presents a comprehensive review of the current dynamic models in the field of economics, machine learning and artificial intelligence. On one hand the author conducts an in-depth comparison between the key model frameworks from these two different worlds; on the other hand, the author aims to build the bridge across domains and develop a consolidated model framework. Moreover, this dissertation also provides the low cost recurring learning algorithms that can be applied in real-world large-scale longitudinal data set. The model frameworks developed in this dissertation demonstrated its power in providing policy implications and trend analysis using different data sets. The contributions of the dissertation are six-fold.

As for forward-looking model framework, this dissertation explores the potentials and feasibility of applying Inverse Reinforcement Learning to model households' long-term sequential decision making process.

- In the classic Inverse Reinforcement Learning setting such as [112]'s work in the artificial intelligence world, the agents (usually robots) are often assumed to have homogeneous behavior and do not own any internal dynamics. Our first contribution is extending the IRL framework to accommodate heterogeneous household behaviors and dynamics.

- Second, this work pioneers an in-depth comparison between IRL approach and the dynamic discrete choice model (DDCM) in economics (a traditional framework to deal with dynamics) from four perspective: terminologies, assumptions, model structures, and empirical results. Such a comparison aims to build connections between the two domains and shed light on the differences and similarities of these two approaches.

- Third, the existence of forward-looking behaviors in residential location choice and its distinction between different households have long been neglected. In this paper, we show that households with different income levels have different forward-looking behaviors. Medium- and high-income households reveal a greater consideration of future expectations (i.e., exhibit behavior consistent with less discounting of future outcomes) than low-income ones.

- Fourth, this dissertation provides a maximum-entropy based recursive learning algorithm to estimate the proposed model framework and validate its feasibility and robustness with large-scale (around 5 million) longitudinal moving trajectories data set.

As for backward-looking model framework, this dissertation extends the HMM and LCCM model framework and provides its recurring estimation method.

- Fifth, this dissertation proposes an unified model framework using a heterogeneous Hidden Markov Model with joint choices (both discrete and continuous) that dynamically account for life events, time-varying economic and policy context, lifestyle and mobility style, and multi-dimensional behaviors dynamics.

- Sixth, this dissertation provides a comprehensive analysis of four different mobility styles and corresponding differences in travel behavior based on a case study in San Francisco Bay Area.

- Seventh, this dissertation furthers the understanding of mobility styles by providing trend analysis across different age groups and conducting sensitivity analysis for two key external factors (6-month average fuel price and annual unemployment rate).

Chapter 2

Literature Review: Forward-Looking Models

"A man may plant a tree for a number of reasons. Perhaps he likes trees. Perhaps he wants shelter. Or perhaps he knows that someday he may need the firewood."

(Joanne Harris)

2.1 Overview

In the static framework, choice modeling is restricted to the assumption that people are not affected by the past and future states when choosing their preferred alternative(s) in the present. However, as discussed in Section 1, this dissertation is particularly interested in exploring the behavior change towards travel behavior over the life-course. Thus, how to account for the impact of past experience and future expectations by introducing dynamics of travel behavior is a foremost task. In this section, we summarize those studies whose dynamic model framework satisfies three requirements.

- First, the model accommodates longitudinal data with a panel of respondents contacted at least three times (waves). We found many studies that only address household dynamics using a before-after analysis, for example using only two waves of survey responses or collecting retrospective data of travel behavior changes before and after a given life event [e.g., 95, 11, 36]. While useful for some applications, these models are too simplistic for our purposes, as they cannot fully capture the long-term dynamics or be applied to longitudinal data with more than two waves.

- Second, the model should account for the serial correlation or time-dependency between different waves. That is, if the model treats each wave of data to be independent, we exclude it from our discussion.

- Third, the model should accommodate individual-level dynamic variables that exhibit significant change over days, months, or years, i.e., both short-term dynamics and long-term dynamics.

As we discussed in 1.3, decision-makers can either be treated as foresighted (forward-looking) or shortsighted (backward-looking) depending on the situations they are faced with and the assumptions the researchers are making. Different model frameworks are thus developed based on different needs. In this section, we will conduct a literature review targeting both types of decision makers. We first introduce the common ground of most forward-looking dynamic frameworks: the Markov Decision Process in 2.2, which is fundamental to modeling how people make sequential decisions. We then explicitly analyze the common assumptions and the model structure of dynamic discrete choice model (DDCM) from economics arena in 2.3, followed by a literature review of inverse reinforcement learning (IRL) framework from artificial intelligence world.

2.2 Markov Decision Process

Modeling sequential decisions of forward-looking agents as Markovian processes is a natural choice since it can (1) simplify the decision-making process in an environment known to the decision maker due to its Markov property; and (2) provide a convenient way to compute expected future rewards based on dynamic programming by decomposing the original problem into sub-problems in a recursive manner via the Bellman equation [13]. Although some human behaviors such as the habits of web users have been demonstrated not to satisfy an MDP [27], assuming travel behaviors follow a Markovian process is a common practice [16].

Building on the MDP framework, two important strands of research have been conducted to estimate the reward function in order to understand agents' preferences. One is known as dynamic discrete choice modeling (DDCM) in the economics arena, and the other comes from the field of artificial intelligence under the name of inverse reinforcement learning (IRL). Although these two approaches rarely reference each other and are developed independently in separate fields, we find it useful to connect them and compare their performance in solving the long-term dynamic residence location choice behavior problem. Before we dive into the theoretical differences between these two approaches, we here provide a high-level summary of how MDP is used in modeling forward-looking travel behavior. As mentioned above, there are not many studies using sequential decision making processes to understand residential location choice, although some literature exists using such a process to understand other travel behaviors.

An MDP can be defined as $(S, A, T, \gamma, R, s_0)$ where, the environment is represented as a state space S, and during each time period the decision maker may choose an action a_t from a set of actions A available in the current state s_t. The state s_t is represented by discrete or continuous state variables based on the problem setting. For instance, s_t represents the accumulated mileage of the bus engine at time t in [86]'s paper and a_t represents replacing the bus engine or not at time t. Upon selection of an action, the process responds with a transition into a new state s_{t+1} based on the transition function $T = P_{a_t}(s_t, s_{t+1})$, respecting the first-order Markov Property. The backward-looking behavior is reflected in the transition function by correlating the past experience with the current. Concurrently, the agent also receives a corresponding reward from the environment $R_{a_t}(s_t)$ in the current time period. This reward function might also be characterized as $R(s_t, s_{t+1})$ or $R(s_t)$, depending on exactly how the problem is formulated. γ is the time discount factor, and s_0 represents the initial state of the agent. The main objective of an MDP is to find an optimal policy π where, for any state s, π specifies an action $a = \pi(s)$ that maximizes the expected accumulative rewards over a finite/infinite time horizon:

$$V^{\pi}(s) = \mathbb{E}[\sum_t \gamma^t R_{a_t}(s_t)|s_0 = s] \tag{2.1}$$

The policy can either be deterministic or stochastic, and most travel behavior studies adopt the stochastic form, that is, it outputs a probability distribution over actions. Equation 2.1 is also called a value function. It incorporates future expectations into the current reward function, and the forward-looking behavior is manifested by the value of γ. Larger γ implies more consideration of the future. Equation 2.1 can be computed recursively by the Bellman equation in Equation 2.2. And the optimal policy can be expressed in terms of the value function as Equation 2.3.

$$V^{\pi}(s) = R_{\pi(s)}(s) + \gamma \sum_{s'} P_{\pi(s)}(s, s')V^{\pi}(s') \tag{2.2}$$

$$\pi(s) \in \arg\max_{a \in A} \sum_{s' \in S} P_a(s)(R_a(s) + \gamma V^{\pi}(s')) \tag{2.3}$$

To fully understand residence location choice behaviors, our interest is not limited to finding the policy itself as it would be when solving a standard MDP problem, we are also interested in interrogating the reward function, which reveals decision makers' preferences towards features of the environment related to their choice alternatives. DDCM and IRL are two model frameworks built on MDP to solve such a problem. In the next section we will discuss the fundamental differences between these two approaches, and list their pros and cons.

2.3 Dynamic Discrete Choice Model (DDCM)

The dynamic discrete choice model (DDCM) originated in economics, and was first proposed in [86]'s seminal paper from a bus engine replacement problem. Following Rust's model, a standard setup for a dynamic discrete choice model can be defined as a tuple $(X, \mathcal{E}, A, T, \gamma, R, s_0)$. Different from a basic MDP $(S, A, T, \gamma, R, s_0)$, the state space S in DDCM is now represented by two types of variables: observed state variables $x_t \in X$ and unobserved state variables $\epsilon_t \in \mathcal{E}$. In each time period, the decision maker observed x_t and ϵ_t when taking action a_t, whereas researchers can only observe x_t and a_t. The state variables evolve as a Markov transition process T, namely $p(x_{t+1}, \epsilon_{t+1}|x_t, \epsilon_t, a_t)$, which can either be assumed known to both decision makers and researchers or be parameterized with a transition probability distribution. The single-period reward (also named as payoff or flow utility) is represented by $R(x_t, \epsilon_t)$, and it is usually identified in a linear form of observed and unobserved variables:

$$R(x_t, \epsilon_t) = \beta^T x_t + \epsilon_t \tag{2.4}$$

where β^T is the parameters we want to estimate associated with the observed state variables.

Finally, a rational decision maker is assumed to sequentially choose actions that maximize their expected sum of current and discounted future utility, denoted as $\mathbb{E}[\sum_{\tau=t}^{T} \gamma^{\tau-t} r_t | s_0]$. The problem is expressed as maximizing the likelihood function:

$$\max \quad \mathcal{L}(a_1, s_1, \ldots, a_T, s_T) \tag{2.5}$$

The introduction of unobserved state variables $\mathcal{E}$ to the MDP is the essence of DDCMs. Different assumptions on the distributions of unobserved variables can lead to various representations of the likelihood function as in Equation 2.5 and associated estimation method [38, 3]. This thread of literature is also known as *structural estimation of Markov Decision Process*. We here summarize some standard assumptions in the DDCM literature.

- *Assumption AS (Additive Separability).* The single-period reward function is additively separable in observable and unobservable components, that is:

$$R_t = R_{a_t}(x_t, \epsilon_t) = R_{a_t}(x_t) + R(\epsilon_t) \tag{2.6}$$

- *Assumption CI (Conditional Independence).* The transition probability can be decomposed as in Equation 2.7, which embodies two restrictions: (a) The unobservables ϵ_t are independently and identically distributed (IID) over agents and over time. This precludes autocorrelation of unobserved state variables and permanent unobserved heterogeneity [97, 73]; and (b) observed variables x_t evolve independently of unobserved variables.

$$p(x_{t+1}, \epsilon_{t+1}|a_t, x_t, \epsilon_t) = p(x_{t+1}|a_t, x_t) g(\epsilon_{t+1}|x_{t+1}) \tag{2.7}$$

- *Assumption DIS (Discrete support of X).* The observed state variable x_t is discrete and finite.

- *Assumption EV (Extreme Value distribution of $\mathcal{E}$).* The unobserved state variable ϵ_t is independent across alternatives and has an Extreme Value Type I distribution. Similarly with the application of Extreme Value Type I distributions in discrete choice models, this assumption leads to a convenient analytical expression of the value function, which greatly simplifies the solution of the dynamic programming problem.

- *Assumption OHB (Optimal Human Behavior).* People are assumed to behave in an optimal way in the sense that they maximize the future expected utility over the given time horizon.

Most of these assumptions are fundamental to the derivation of the nested fixed point algorithm in [86]'s paper, and are inherited by most subsequent work. In recent decades, most of the theoretical studies of DDCMs either try to relax these assumptions to push the boundary of structural models [24, 1, 77, 7] or propose different tractable and efficient estimation methods with existing assumptions [4, 6, 57, 5]. However, these assumptions also become the limitations of applying DDCM in practice.

In most real-world applications, people are likely to have better information about their future expectations than the researchers attempting to model their behavior. If they make a decision based on this superior information, then *Assumption CI* typically breaks down. To address this problem, some studies ([2], [59], [77]) explore a more complicated model structure by incorporating a persistent unobserved heterogeneity component and mixture structures. These attempts unavoidably add more computational burden to the estimation, and most of them are proposed as a state of art and rarely demonstrated with a real large-scale data set. *Assumption EV* faces a similar issue: relaxing assumptions implies a sacrifice of estimation complexity, which usually leads to the infeasibility of applying them to a large-scale system, especially in the problem of sequential residential location choice.

Although it is quite common to make *Assumption OHB* in the MDP framework, people often make sub-optimal decisions in reality. The existence and nature of suboptimal human behaviors have been indicated from many perspectives such as medical students matching residency behavior in [85], route planning in [8], mode choice behavior in [45], etc. Notwithstanding, the optimal behavior assumption still prevails in current behavioral studies, and rarely gets further attention. Furthermore, as for the *Assumption DIS*, state variables are usually converted to be discrete so that the state space can be restricted to a small finite dimension to avoid the computational burden in high dimensional cases [14], which implies a loss of state information in this discretization. In a nutshell, in spite of the introduction of unobserved state variables and the fact that the assumptions imposed on them establish the cornerstones of structural estimation of DDCMs, these assumptions also bring out fundamental limitations with respect to validation.

In additional to the theoretical extensions and advanced estimation methods of DDCMs, empirical research has flourished in recent decades, including applications in labor economics ([60, 61]), marketing [7], transportation in vehicle acquisition behavior ([30], [31]), and neighborhood selection [10, 20].

2.4 Inverse Reinforcement Learning (IRL)

Under the paradigm of the MDP framework, there is a growing body of studies from artificial intelligence applying an approach referred to as inverse reinforcement learning (IRL), which also tries to estimate agents' reward functions. More specifically, proposed by [76], IRL refers to the problem of "inferring the reward function of an agent from observations of the agent's behavior, which is assumed to be optimal (or approximately so)." The agents in IRL usually refer to robots, players in games, autonomous vehicles, etc. [91, 63, 47], whereas in DDCM the agents are humans or households.

The typical setting of IRL is based on the structure of a standard MDP problem $(S, A, T, \gamma, R, s_0)$ as shown in Section 2.2. In the early work on IRL, the reward is represented as a linear combination of features:

$$R(s) = \theta^T f(s) \tag{2.8}$$

where $f(s)$ is the feature vector of state s and θ is the corresponding coefficients to be estimated. There is recent work applying nonlinear reward functions in IRL, such as those applying neural network ([105]). However, this approach is not comparable with DDCMs since DDCMs rarely accommodate complicated non-linear reward functions. In this paper, we will only focus on linear reward functions for both IRL and DDCM. Based on Equation 2.8, the value function can be reduced to:

$$\begin{aligned} V^\pi(s) &= \mathbb{E}[\sum_t \gamma^t R_{a_t}(s_t)|s_0 = s] \\ &= \mathbb{E}[\sum_t \gamma^t \theta^T f(s_t)|s_0 = s] \\ &= \theta^T \mathbb{E}[\sum_t \gamma^t f(s_t)|s_0 = s] \\ &= \theta^T \mu(\pi|s_0 = s) \end{aligned} \tag{2.9}$$

where $\mu(\pi|s_0 = s)$ is defined as discounted weighted frequency of state features $f(s)$ under policy π. For an optimal reward function R^*, it needs to satisfy ([76]):

$$\mathbb{E}_{\pi^*}[\sum_t \gamma^t R^*_{a_t}(s_t)|s_0 = s] \geq \mathbb{E}_{\pi}[\sum_t \gamma^t R^*_{a_t}(s_t)|s_0 = s], \forall \pi \tag{2.10}$$

which is now equivalent to:

$$\theta^* \mu(\pi^*|s_0 = s) \geq \theta^* \mu(\pi|s_0 = s), \forall \pi, s \tag{2.11}$$

[1]'s seminal paper then converts it to a margin-based optimization problem:

$$\begin{aligned} & \arg\max_\theta \max_\gamma \gamma \\ s.t. \quad & \theta^* \mu(\pi^*|s_0 = s) \geq \theta^* \mu(\pi|s_0 = s) + \gamma, \forall \pi, s \\ & ||\theta||_2 \leq 1 \end{aligned} \tag{2.12}$$

However, most of these initial efforts on IRL make the same assumption on optimal human behavior (*Assumption OHB*) as in DDCMs. Some recent IRL studies have relaxed this assumption by allowing sub-optimal behaviors, which was first proposed by [112], known as maximum entropy inverse reinforcement learning algorithms (MaxEnt IRL). In MaxEnt IRL, the problem is constructed by maximizing entropy of trajectories with feature matching constraints:

$$\begin{aligned} &\max_{p} \quad p(\tau)\log p(\tau) \\ s.t. \quad &\sum_{\tau} p(\tau)\mu_{\tau} = \bar{\mu} \\ &\sum_{\tau} p(\tau) = 1 \end{aligned} \tag{2.13}$$

where μ_τ is total discounted feature counts for a trajectory τ and $\bar{\mu}$ is the average for all trajectories.

In recent decades, IRL has been widely applied as an emerging alternative estimation methodology to solve an MDP problem, utilizing its power in dealing with large-scale problems in many realistic settings, especially in the transportation area. ([112]) learns drivers' reward function of route choice from global positioning system (GPS) data and successfully estimates the parameters on travel time, travel cost, and safety. [70] adopts a similar approach, analyzing taxi drivers' preferences towards travel time, idle time, and number of passengers.

2.5 Theoretical Comparison: DDCM vs IRL

Based on the above discussion, we contend that IRL differs from DDCMs in several ways. In this subsection, we provide a thorough comparison between DDCM and IRL from the theoretical perspective, shown in Table 2.1.

In IRL, the state S usually represents a concrete and exogenous concept, such as an intersection in the road network, or a pair of coordinates in a game. Each state s, has a vector of features f_s associated with it. In DDCMs, the state space usually is endogenously represented by the state variables (which are f_s in IRL) themselves. Based on the definition of the state space in IRL, the transition function is hence more intuitive while DDCMs usually require a joint distribution of different state variables.

The IRL reward function is only composed of observed features from the environment for the state while DDCMs accommodate unobserved state variables. Furthermore, in DDCMs, the maximum likelihood estimation is supported by making multiple proper assumptions (*Assumption EV, CI, AS*) on these unobserved state variables. IRL circumvents this by constructing other forms of optimization problems, such as maximum margin in [1] and maximum entropy in [112]. Although early IRL studies make the same assumption on optimal human behavior (*Assumption OHB*) as in DDCMs ([76], [1]), recent work has relaxed this assumption by allowing sub-optimal behaviors [112, 105, 22]).

	Rust (1987) [86]	DDCMs	Ziebart et al. (2008) [112]	IRL
Model Setup				
Observed variables/features	X		$f(s)$	
Unobserved variables/features	$\mathcal{E}$		$\times$	
State	$(X, \mathcal{E})$		S	
Action	A			
Reward function	$\beta^T x_t + \epsilon_t$		$\theta^T f(s)$	
Transition function	$p(x_{t+1}, \epsilon_{t+1} \| a_t, x_t, \epsilon_t)$		$p(s_{t+1} \| a_t, x_t)$	
Agent heterogeneity	$\times$	◯	$\times$	$\times$
Assumptions				
Additive Separability	✓	✓	$\times$	$\times$
Conditional Independence	✓	◯	$\times$	$\times$
Discrete support of X	$\times$	◯	✓	◯
EV distribution of E	✓	◯	$\times$	$\times$
Optimal Human Behavior	✓	✓	$\times$	◯
Dynamics				
Internal dynamics	✓	✓	$\times$	$\times$
External dynamics	✓	✓	✓	✓
Estimation				
Optimization problem	Equation 2.5		Equation 2.13	Equation 2.12
Objective	maximum likelihood $\max \mathcal{L}(a_1, s_1, \dots, a_T, s_T)$		maximum entropy $\arg\max_\theta \max_\gamma \gamma$	maximum margin $\max_p p(\tau) \log p(\tau)$
Known transition function	$\times$	$\times$	✓	◯

Table 2.1: Theoretical comparison between DDCM and IRL. ✓ denotes that the assumptions, dynamics, or certain conditions are included or satisfied in a paper while $\times$ has the opposite meaning. ◯ denotes that in one model framework, different papers make different treatments.

Regarding estimation feasibility, most practical applications of DDCMs still rely on making the five assumptions in Table 2.1 in spite of the fact that some of them are invalid in the real world. This is because relaxing any of them requires a complex estimation improvement and more importantly, much higher computation burden as was discussed above. Although IRL has the advantage of fewer assumptions, it has some notable limitations. The agents in IRL models are treated as homogeneous and their characteristics do not change over time, while DDCMs usually incorporate agent heterogeneity and internal dynamics of the agents. Estimation of IRL depends on known transition probabilities from the environment while DDCMs usually allow unknown transition probabilities, which are estimated in the learning process. Some recent studies have extended IRL to include an unknown transition matrix ([43]). However, the validity and feasibility of this approach is still under further investigation and it is not our focus in this paper.

This paper builds on [112]'s work and extends IRL to the transportation setting with two major improvements. First, we consolidate agents' (households') heterogeneity and their internal dynamics into the model. The model framework and estimation algorithm will be discussed in Section 3. Second, to our knowledge, this paper is the first effort to connect forward-looking behavior with transportation dynamics and household dynamics under the dynamic residential choice umbrella. It is important to note that we do not presume one approach is better than the other as each has its own advantages and disadvantages.

Chapter 3

Understanding the Sequential Decision Making of Residential Location with Inverse Reinforcement Learning

> *"I am tomorrow, or some future day, what I establish today. I am today what I established yesterday or some previous day."*
>
> (James Joyce)

Previous studies on residential location choice usually employ traditional discrete choice models with cross-sectional data (i.e., data from a single point in time). However, even more-so than mode choice and other daily activity behavior, residential location is an outcome of long-term deliberation, which reflects both an individual's historical preferences and constraints as well as future expectations. Furthermore, newly available and large-scale longitudinal data sets can provide trajectories of millions of individuals' movement over a long period of time. Given these considerations, modeling residential location choice as a sequential decision-making process may further our understanding of both long-term population movement and how different factors impact these phenomena. In economics, dynamic discrete choice models (DDCM) have been used to model many aspects of transportation behavior such as car ownership; however this approach has several limitations, including the assumptions of optimal human behavior, additive separability, conditional independence, and extreme value distribution. In the recent decade, advances in artificial intelligence, especially the framework of inverse reinforcement learning (IRL), has provided another approach to solve complex dynamic behavioral problems. In particular, IRL can circumvent the multiple assumptions commonly used in DDCM while still reconstructing and estimating the problem in a feasible way. In this section, we formulate a mathematical framework of representing the relocation behavior as sequential actions under the IRL framework, in which the individual observes the environment and takes action (i.e., move or not) accordingly by evaluating the action-dependent future rewards received from their environment. The reward can be a function of built environment attributes, which shares a similar concept as the utility function in discrete choice models. We derive a recursive learning algorithm to estimate the parameters associated with the attributes. We use an infused data set of household relocation trajectories in Texas over a 7-year period (2005-2011).

3.1 Introduction

Decision making around residential location is dynamic in nature, which is reflected in the following ways. First, households have internal dynamics such as education, wealth accumulation, job opportunities/loss, and changes in household structures (new child, marriage, divorce, etc.). These household dynamics, more commonly summarized as changes in life-cycle or life-course, have been observed and widely studied as important triggers to residential moves ([74], [64], [34], [62], [82], [33], [110]). Furthermore, a growing body of literature has revealed that these triggers usually do not happen in the same calendar year as the resulting residential move, but instead have either lead or lagged effects [41]. A lead effect results if people plan ahead and relocate in advance to allow themselves time to gradually adjust, when anticipating trigger events that change household dynamics. For example, the prospect of a firstborn may encourage a family to relocate into a larger dwelling and an education-friendly area before the actual birth [96], [78]. In contrast, a lagged effect results if a residential move takes place after certain events are triggered; for example, [41] observed a one-year lagged effect of residential moves triggered by previous job changes. Due to lead and lagged effects, modeling only a cross-sectional snapshot of residential move trajectories may not capture the accurate relationship between household characteristics and residential preferences [10], [20], [71].

In addition to internal household dynamics, external dynamics are also an important consideration; this is often closely associated with changes in property value, transport accessibility, neighborhood amenities, living quality, land use, etc. When people decide whether to move and where to live, the external dynamics can be seen as a reflection of future life opportunities, and may have a crucial impact on current decision-making. For instance, a household may choose to stay in their current location even though public transit accessibility is low, because they expect a new regional public transit center to be constructed in two years. A similar circumstance happens when people treat housing as a major financial investment, and the expected future appreciation in the value of their home may lessen their sensitivity to housing price and other factors.

Unlike shorter term travel behavior, such as mode choice or even car ownership, changing residential location incurs much higher costs both financially and psychologically. As a result, in response to these internal and external dynamics, households often plan more carefully, and consider their past living experiences and/or future expectations. Households that only connect past experience with their current decision are often referred to as "backward-looking" or "myopic" agents, while those that take into account effects of future expectations in their current decisions are considered "forward-looking" agents. One's past experience plays a critical role in decision making as a result of strong inertia, i.e. reluctance to move away from current residential locations or move to an unfamiliar environment [42], [26], [21], [108]. This inertia is even stronger when moving away from a community leads to loss of social and sentimental ties [81]. Along with past experience, the importance of incorporating forward-looking behavior has been gradually recognized in recent years, and many studies have found that excluding this factor leads to biased estimation [98]. As [20] found using California housing data from 1990-2008, a model that doesn't consider future expectations can underestimate households' willingness to pay to lower violent crime by 21 percent. [10] also highlights that, by ignoring forward-looking agents, estimated neighborhood preferences may be biased towards areas with high percent white, low violent crime, and air pollution.

In summary, decision-making regarding residential location is an inter-temporal reflection of internal and external dynamics, where both backward-looking and forward-looking perspectives are important. However, research on modeling the dynamic nature of residential location choice is limited. Most existing studies focus on only one piece of the dynamics mentioned above, most often the impact of internal dynamics and past experience, while ignoring external dynamics and future expectations. To our knowledge, there are few efforts made that unify both of these dynamics in one framework.

The challenge of building a comprehensive dynamic decision-making model in the residential location choice setting is two-fold. The first challenge arises from the large scale of the problem: thousands of potential locations and moving trajectories to choose from. The scale of the problem poses estimation difficulty even in a traditional static residential choice model, and the dynamic structure further impedes computational feasibility. The second challenge is the scarcity of data on where households relocate over time. The household-level data provided by the Census or National Household Travel Survey is cross-sectional and cannot be transformed into longitudinal data. The small body of studies that explore the residential location dynamic models use either private housing transaction data [20], [10] or micro-simulated data [46].

Although some dynamic models on travel behavior have flourished in recent decades (e.g., [30]), most of them concentrate on small-scale, short- or medium-term behaviors such as car ownership and use [68], [49], [31], or route planning [44]. Some recent work in the economics arena [20], [10] explored households' willingness to pay for neighborhood amenities such as low violent crime in a dynamic setting; however, we are not aware of any studies that apply such complete dynamic models to understand the connection between the transportation system and residential location choice.

This section seeks to advance the understanding of households' residential decision making process by developing a feasible model framework in a dynamic, finite-horizon setting, which can accommodate both backward-looking and forward-looking behavior in response to both internal and external dynamics. To this end, we propose a novel approach adapted from the Inverse Reinforcement Learning (IRL) framework in the field of artificial intelligence.

The contribution of the this piece of work is three-fold.

- In the classic IRL setting such as [112]'s work, the agents (usually robots) are often assumed to have homogeneous behavior and do not own any internal dynamics. Our first contribution is extending the IRL framework to accommodate heterogeneous household behaviors and household dynamics.

- Second, we provide an in-depth comparison between our approach and the dynamic discrete choice model (DDCM) in economics (a traditional framework to deal with dynamics), from three perspective: terminologies, assumptions, and model structures. Such a comparison aims to build the bridge between the economics and artificial intelligence worlds, and shed light on understanding the differences and similarities of these two approaches.

- Finally, the existence of forward-looking behavior in residential location choice and its distinction between different households have long been neglected. In this section, we show that households with different income levels have different forward-looking behavior. Medium- and high-income households reveal a greater consideration of future expectations (i.e., exhibit behavior consistent with less discounting of future outcomes) than low-income ones.

The rest of the section is structured as follows. Section 3.2 describes the data set, which includes moving trajectories in Texas from 2005 to 2011. We also provide some preliminary analysis of the temporal and spatial movement patterns exhibited in these data. In Section 3.3, we propose the sequential decision making model of residential location choice by extending [112]'s work and derive the corresponding estimation algorithm. The estimation results and analysis based on households with different income levels are shown in Section 3.4.

3.2 Data

In this section, we describe a large-scale data set that we have assembled, merging information about households' moving trajectories with location features. The source of movement trajectories comes from Texas Department of Motor Vehicles (DMV) vehicle registration records from 2005 to 2011. As each record is associated with a registration address, owner name, and Vehicle Identification Number (VIN), we are able to track the residential location of each household over multiple years. The location features are acquired by joining the DMV data set with two other public databases as shown in Figure 3.1. Here we discuss these three main sources of data in detail and also provide preliminary analysis.

Source 1: The raw Texas DMV data set contains around 5 million VIN records in 2005 and 9 million VIN records in 2011. The population in Texas is 22.8 million in 2005 and 25.7 million in 2011. For each vehicle registration record, it contains a unique VIN, the full name of the owner, and the registration address, which can reasonably be assumed to be the residential location. Considering that residents are required to renew their vehicle registration every year in Texas, we are capable of reconstructing the households' locations by the following three steps.

- We assume each address represents a household, and pair each household with its vehicle owner name(s) and VIN(s) from the records in 2005. Note that both name and VIN are necessary due to the existence of multiple vehicles being registered to the same full name, and potential transactions that transfer a vehicle to a new owner.
- We trace the location of each household for the subsequent 6 years (2006-2011) and build moving trajectories. In cases involving household reorganization (such as moving out of an existing household, two individuals moving into the same household), we treat the registered owner of each individual vehicle as one household during the 7-year period.
- We remove the trajectories based on two rules: (i) remove vehicles that appear to be in commercial use (e.g., registered to owners with names ending in "INC", "CORPORATION", "ELECTRIC"); (ii) remove households without full 7-year trajectories.

Source 2: The attributes associated with each residential location come from the Environmental Protection Agency's (EPA) Smart Location Database (SLD), a public resource that summarizes several demographic, employment, and built-environment variables for every Census Block Group (CBG) in the United States. In this study, we adopt five attributes that are commonly considered as important factors in most (static or dynamic) residential choice models. They include socio-economic variables represented by "household density" and "employment density", land use diversity variable, "mix land use", measured as an entropy-based index using the 5-tier employment categories presented by [84], transportation infrastructure exemplified by "road network density", and accessibility variable indicated by "jobs within 45 minutes auto travel time". We join the DMV data with SLD by identifying the CBG of each address. The CBG information is obtained by mapping the addresses with the Census Topologically Integrated Geographic Encoding and Referencing (TIGER) database.

Source 3: The American Community Survey (ACS) provides the survey-based period estimates on a wide range of social, economic, and housing characteristics, including housing values. The 1-year and 3-year estimates provide the most current housing values but are only available for geographic locations with populations of more than 65,000. By contrast, ACS 5-year estimates are based on the data collected over the previous 5 years, and with the greatest precision, as they are available for each CBG. In this paper, we extract "median owner-occupied housing values" variable from ACS 5-year estimates as a proxy for the average housing price of each CBG. We join the trajectories from Source 1 with five built environment attributes from Source 2 and housing price from Source 3. The spatial distributions of the relative values are shown in Figure 3.5, and the distribution of relocation frequency by household is presented in Figure 3.2. We also layout the relocation frequencies among four major metropolitan areas in Texas, shown in Figure 3.4.

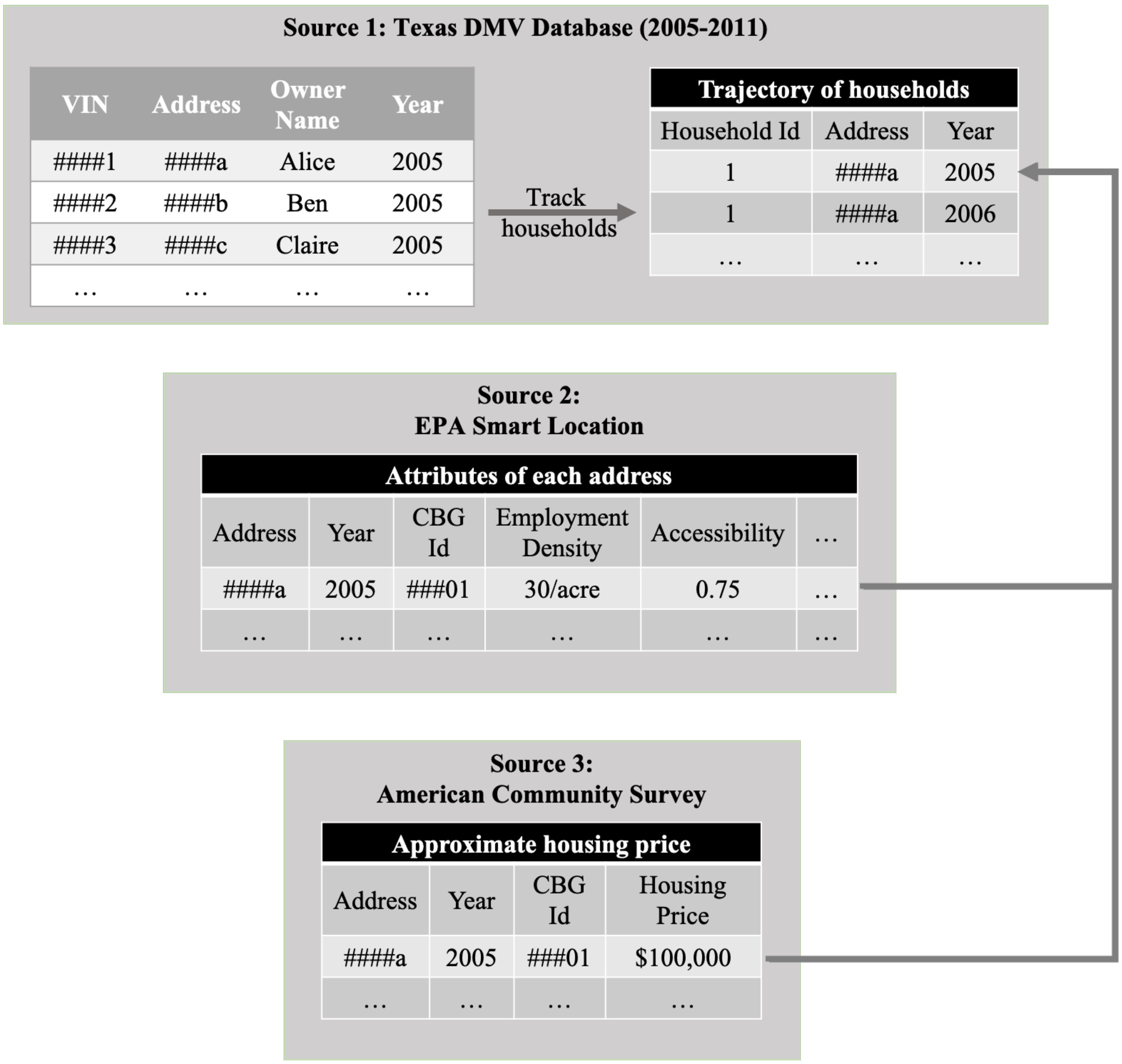


Figure 3.1: Infused data set.

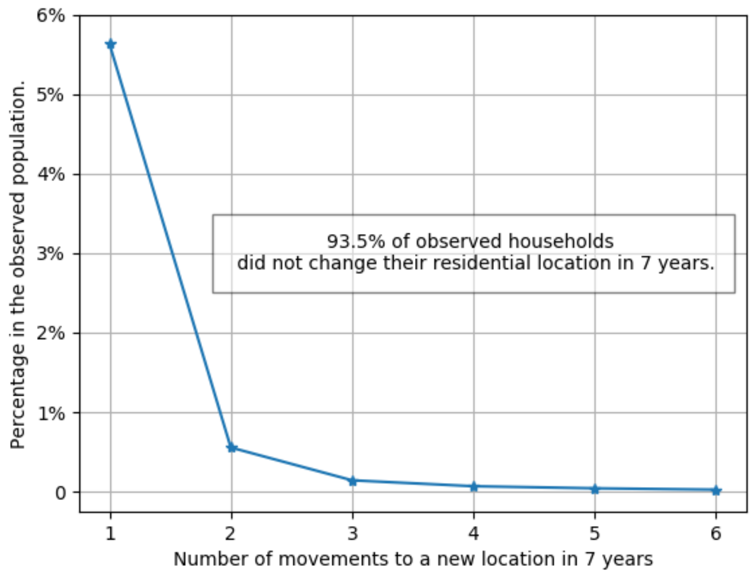
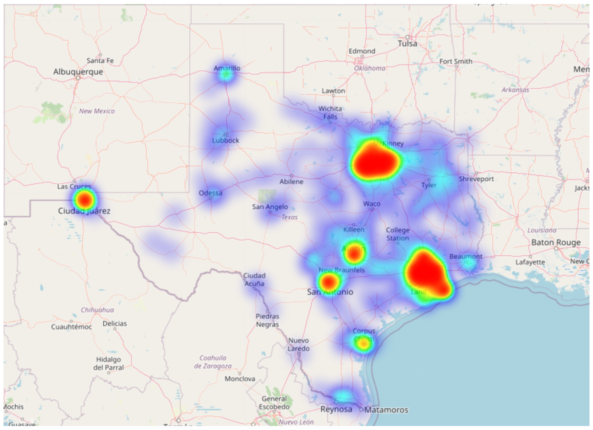


Figure 3.2: Distribution of moving frequencies.

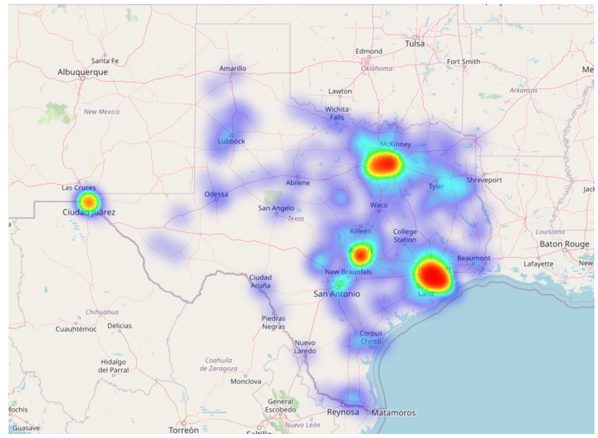
There are 178237 unique households and 1455 CBGs in the dataset. 6.8% of households move more than once in the 7-year period, among whom 80% of them move only once. 70.3 % of the relocations tend to be over a short distance and within the same county. Among relocations to a different county, 65.9% are in the same metropolitan area. This means only 10.1% of household relocation in the data occurred between the major metropolitan areas in Texas.

In Figure 3.4, we provide the relocation patterns between the four biggest metropolitan areas (Dallas–Fort Worth–Arlington, Houston–The Woodlands–Sugar Land, Austin–Round Rock–San Marcos, and San Antonio–New Braunfels) in Texas. Note that not moving, and moving in or from other metropolitan areas, are not reflected in this figure.

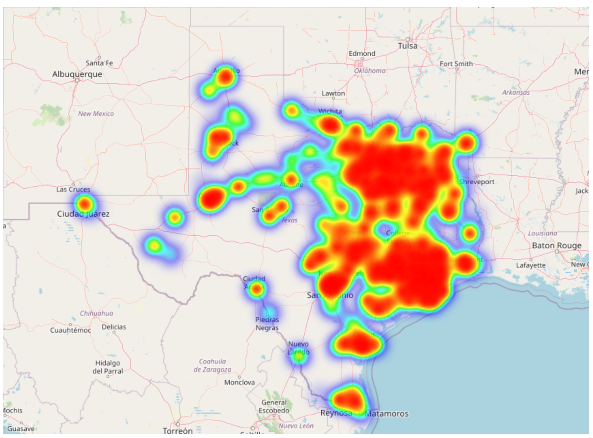
The fused data set has some limitations. First, the data set includes only households that owned at least one registered vehicle; the residential relocation trajectories of the rest of population (mainly low-income) are not reflected. Second, household-level characteristics are not available. Therefore, the results should be interpreted as averaged across the population. Third, people living in a rental property are also treated as one household since it's very challenging to fully differentiate the rentals and the owners from their names and addresses. Moreover, the moving trajectories are limited to those within Texas, with relocation behavior into and out of Texas intentionally excluded in this study. Notwithstanding these limitations, this data set provides rich longitudinal information to construct the sequential decision-making process of a large number of households and capture the marginal value of each attribute of interest.



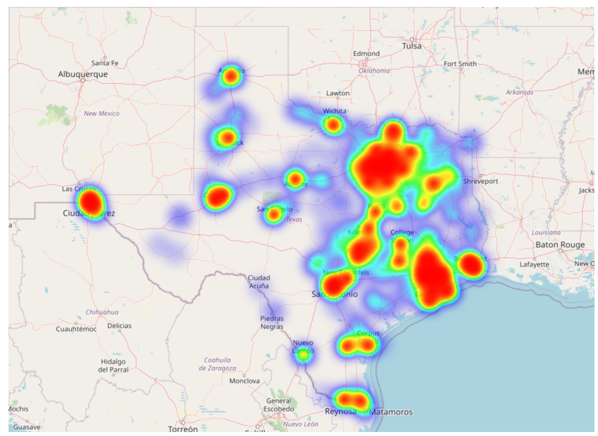
(a) Household density.



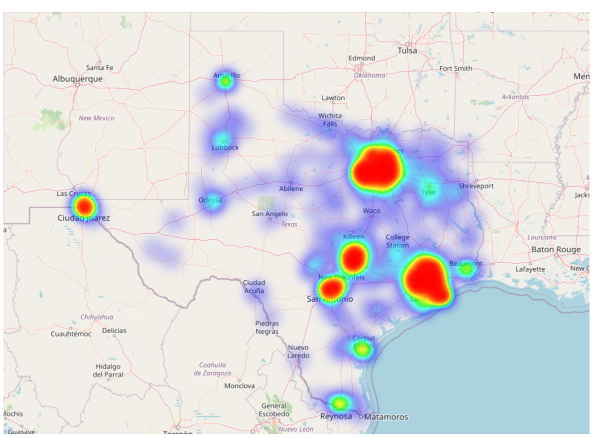
(b) Employment density.



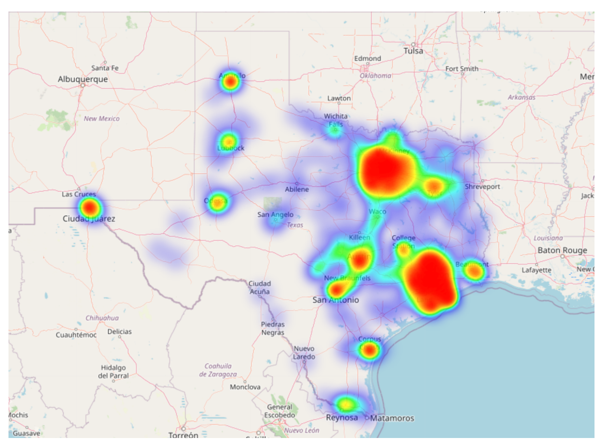
(c) Land-use mix.



(d) Road density.



(e) Accessibility to jobs.



(f) Housing price.

Figure 3.3: Spatial distribution of features in each Census Block Group.(The color represents the relative density or value of each feature, with red areas having higher, and purple areas lower, density or value.)

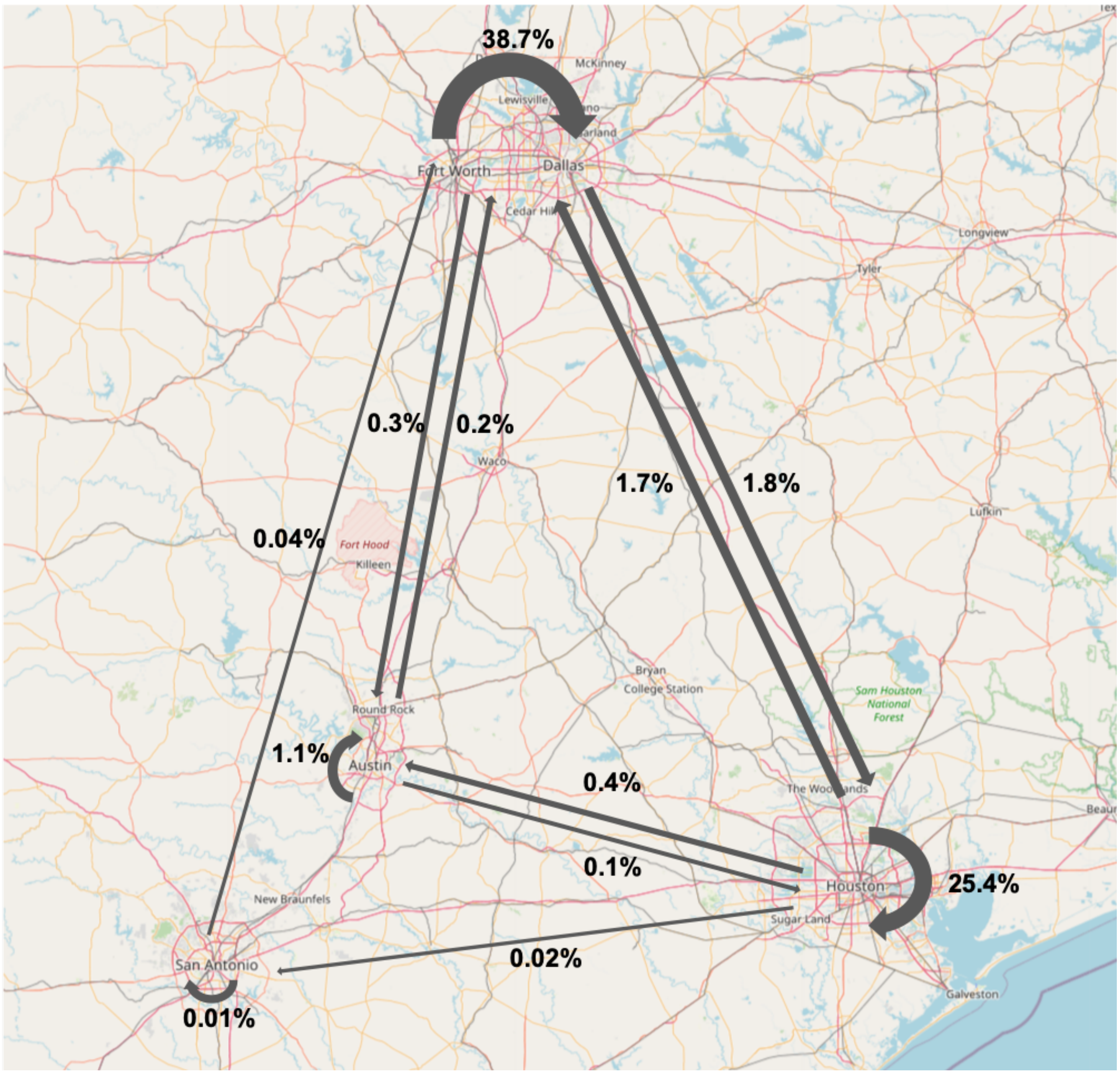


Figure 3.4: Relocation trajectories between 4 (biggest) metropolitan areas in Texas. The circular arrow represents the relocation within same metropolitan area. The number associated with each arrow denotes the percentage of that particular move direction in the total number of relocation trajectories.

3.3 An IRL-Based Model of Sequential Residential Location Choices

When making residential location sequential choices, forward-looking households are attempting to maximize their future rewards during each time period while efficiently optimizing the trade-offs between different features of the residential location such as transport accessibility, employment density, housing price, etc. In this paper, we first describe this decision process of residential location choice as an IRL problem in a finite discrete time horizon in Section 3.3, and then derive the estimation algorithm (i.e., learning the parameters associated with the features) in Section 3.3.

Model structure

In the residential choice setting, its MDP can be defined as $(S, A, T, \gamma, R, s_0)$.

S is a finite set of states representing CBGs. $s_{i,t}$ denotes the CBG the household i chose to dwell in during time period t. s_0 is a set of the starting states of the households' trajectories. The size of the state space is the number of total CBGs in the data set. A is the binary choice set of moving or not. $a_{i,t}$ is the action taken by household i at time period t. A is a finite set whose size is 2, and is shared by all the households. The action naturally controls households' transition between states, i.e, movement between census CBGs. $T = Pr(s_{t+1} = s^{'}|s_t = s, a_t = a)$ is the probability that action a in state s at time t will lead to state $s^{'}$ at time $t+1$. Obviously, if $a = 0$ denoting not moving, then $T = Pr(s_{t+1} = s^{'}|s_t = s, a_t = 0) = 1$; while if $a = 1$ denoting moving, then $T = Pr(s_{t+1} = s^{'}|s_t = s, a_t = 0) \in [0, 1]$. $r_\theta(s_t) \in R$ is the reward received by household i from the environment after transitioning from state s to state $s^{'}$, due to action a. The reward is a function of the features of the new state the household relocates to, including household density, employment density, road density, land-use mix, accessibility to jobs, and housing price. The parameters associated with these features for each household group can be denoted as a vector, θ. We assume the reward function is linear-in-parameter in this study, i.e., $r_\theta(s_t) = \theta^T f(s_t)$. The total reward of a trajectory ξ_i can be factorized as the discounted sum of the rewards along the finite time horizon modeled.

$$R_\theta(\xi_i) = \sum_{t=0}^{T} \gamma^t r_{\xi_i}(s_t|\theta) \tag{3.1}$$

Discount factor: $\gamma \in [0, 1]$ is the discount factor, which determines how much the households care about rewards in the distant future relative to those in the current time period. If $\gamma = 0$, the household will be considered completely myopic and only care about immediate reward. That is to say, a larger γ indicates a more forward-looking behavior.

As was mentioned in Section 3.1 and 2.4, in traditional IRL settings, the agents in MDP (as presented above) are often assumed to have homogeneous behavior and follow the same reward function. Such an assumption is valid and reasonable if the time span is targeting short- or medium-term decisions. However, in the long term, household income level might change over years and household structure might evolve due to marriage, birth of children, a household member going to college, etc. In these scenarios, some households might switch to another demographic group and adjust to a different reward function and future expectations correspondingly. All these considerations introduce the necessity of extending the IRL framework by incorporating (a) population heterogeneity and (b) internal dynamics.

We hence classify households into G groups based on their income level, household size, etc. We assume different groups of households share the same state space and share the same set of potential trajectories since they reside in the same region and are exposed to the same housing market. However, different groups of households may present different transition functions, trade-offs between features, and forward-looking behaviors. Take the gth household group as an example, its MDP is now a tuple of five elements (A, S, T^g, r_{θ^g}, γ^g).

In each time period, a household belonging to household group g may first make a decision a_t to relocate or not. If deciding to relocate, the household would transition to another state s_{t+1} with the transition probability $T^g = Pr(s_{t+1} = s^{'}|s_t = s, a_t = a)$ and receive a reward $r_{\theta^g}(s_t)$. The moving trajectory of household i can be denoted as a sequence of state-action pairs: $\xi_i = \{(s_0, a_0), ..., (s_{\tilde{T}}, a_{\tilde{T}})\}$. To avoid confusion, $\tilde{T}$ here represents the final time step while T denotes transition function.

As discussed in the previous section, forward-looking dynamic models often ignore the possibility that relocation trajectories might sometimes deviate from the optimum, since people are not always making optimal choices. Therefore, to accommodate these sub-optimal decision makers, we approach the problem in a probabilistic way by using the principle of maximum entropy. The following principle of maximum entropy is derived by solving the optimization problem in Equation 2.13 ([112]).

(Principle of maximum entropy): *In a household decision-making process, the probability of choosing one trajectory is exponentially proportional to the discounted sum of its reward at each time period.* This preposition yields the probability of all potential trajectories for each household group as Equation 3.2.

$$p(\xi_i|\theta) = p(\xi_i|\theta^g) = \frac{R_{\theta^g}(\xi_i)}{Z(\theta^g)} \tag{3.2}$$

$$Z(\theta) = Z(\theta^g) = \int \exp R_{\theta^g}(\xi) d\xi \tag{3.3}$$

Back to our objective, by defining the household's movements as a set of transitions in an MDP, we would like to find the reward function that forces the resulting sequential state-action pairs to more closely match the observed relocation trajectories. Therefore, the problem can be stated as follows.

Restatement of the problem: *Given a large amount of household moving trajectories $\xi = \{\xi_i\}_{1:N}$ within a region, our goal is to learn the parameters $\theta = \{\theta^g\}_{1:G}$ associated with the reward functions which maximizes the posterior likelihood of all trajectories shown in*

Equation 3.4.

$$\begin{aligned}\theta^* &= \arg\max_{\theta} \prod_{i=1}^{N} p(\xi_i|\theta) \\ &= \arg\max_{\theta} \sum_{i=1}^{N} \log p(\xi_i|\theta) \\ &= \arg\max_{\theta} \sum_{i=1}^{N} R_\theta(\xi_i) - \sum_{i=1}^{N} \log Z(\theta) \qquad (3.4)\end{aligned}$$

Estimation

Internal and External Dynamics

Before diving into the derivation of the estimation algorithm, we first discuss the treatment of internal dynamics of the households and external dynamics of the environment, which are the two key elements in sequential residential location choices. For the households that evolve into a different group during the observation period, we can split their trajectories based on the transition point(s), that is to say, if household i belongs to g_1 from t_0 to t_c and belongs to g_2 for the rest of time, then we split ξ_i into two independent parts and allocate them to the corresponding trajectory sets: $\xi_{i,0:t_c} \in \xi^{g_1}$, $\xi_{i,t_{c+1}:T} \in \xi^{g_2}$. After reprocessing the trajectories, we convert the original problem (in Equation 3.4) to estimating the model with a new set of trajectories of different lengths of observation.

As for accommodating the external dynamics such as changes in the transportation system, appreciation of housing, etc., we let $f^{(t)}(s_t)$ denote the dynamic feature vector of each state instead of $f(s_t)$. Combining internal and external dynamics, the denotation of the problem remains the same except that ξ_i in Equation 3.5 represents the processed trajectories and N is the total number of new trajectories. And R_θ is now a linear combination of dynamic features.

$$\theta^* = \arg\max_{\theta} \sum_{i=1}^{N} R_\theta(\xi_i) - \sum_{i=1}^{N} \log Z(\theta) \qquad (3.5)$$

Estimation Part I - Gradient Derivation

We adopt the gradient ascent approach to estimate θ, and start our derivation by calculating the gradient of the posterior log likelihood.

Let the right hand side of Equation 3.4 be defined as LL(θ), then its derivative with respect to θ is given by

$$\frac{\partial LL(\theta)}{\partial \theta} = \frac{\partial \sum_{i=1}^{N} R_\theta(\xi_i)}{\partial \theta} - \frac{\partial \sum_{i=1}^{N} \log Z(\theta)}{\partial \theta} \qquad (3.6)$$

Note that there are G sets of θ parameters in total, and we here derive the gradient of the log-likelihood with respect to θ^g in a generalized way. The first item of Equation 3.6 can be reduced to Equation 3.7 where ξ^g represents the set of observed trajectories for household group g.

$$\begin{aligned}\frac{\partial \sum_{i=1}^{N} R_\theta(\xi_i)}{\partial \theta^g} &= \frac{\partial \sum_{\xi_i \in \xi^g} \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} f_{\xi_i}^{(t)}(s_t)^T \theta^g}{\partial \theta^g} \\ &= \sum_{\xi_i \in \xi^g} \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} f_{\xi_i}^{(t)}(s_t) \end{aligned} \tag{3.7}$$

As for the second item, we notice that the value of $\log Z(\theta)$ should be the same for each household group, and it can be reformulated as Equation 3.8.

$$\frac{\partial \sum_{i=1}^{N} \log Z(\theta)}{\partial \theta^g} = \sum_{\xi_i \in \xi^g} N^g \cdot \frac{\partial \log \int \exp R_{\theta^g}(\xi) d\xi}{\partial \theta^g} \tag{3.8}$$

where N^g denotes the number of trajectories for household group g. We then further decompose the problem of estimation over trajectories to individual states (from Equation 3.9 to Equation 3.10).

$$\begin{aligned}\frac{\partial \log \int \exp R_{\theta^g}(\xi) d\xi}{\partial \theta^g} &= \frac{1}{\int \exp R_{\theta^g}(\xi) d\xi} \int \exp R_{\theta^g}(\xi) \frac{\partial R_{\theta^g}(\xi)}{\partial \theta^g} d\xi \\ &= \int \frac{\exp R_{\theta^g}(\xi)}{\int \exp R_{\theta^g}(\xi) d\xi} \cdot \frac{\partial \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} f_{\xi}^{(t)}(s_t)^T \theta^g}{\partial \theta^g} d\xi \\ &= \int p(\xi|\theta^g) \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} f_{\xi}^{(t)}(s_t) d\xi \qquad (3.9) \\ &= \mathbb{E}_{\xi \sim \phi_{\theta^g}} [\sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} f_{\xi}^{(t)}(s_t)] \\ &= \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} \mathbb{E}_{\xi \sim \phi_{\theta^g}} [f_{\xi}^{(t)}(s_t)] \\ &= \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} \sum_{s} P(s_t = s|\theta^g) f^{(t)}(s) \\ &= \sum_{s} \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} P(s_t = s|\theta^g) \cdot f^{(t)}(s) \qquad (3.10) \end{aligned}$$

Substitute Equation 3.10 into Equation 3.8, we have:

$$\begin{aligned}\frac{\partial \sum_{i=1}^{N} \log Z(\theta)}{\partial \theta^g} &= \sum_{\xi_i \in \xi^g} \sum_{s} \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} P(s_t = s|\theta^g)^{(t)}(s) \\ &= \sum_{l=1}^{\max|\xi|} N^l \cdot [\sum_{s} \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} P(s_t = s|\theta^g) \cdot f^{(t)}(s)] \end{aligned} \tag{3.11}$$

where $\max|\xi|$ denotes the maximum length of all the new trajectories and N^l denotes the number of those with length l.

By combining Equation 3.11 and 3.7, we can compute the gradient with respect to θ^g as:

$$\frac{\partial LL(\theta)}{\partial \theta^g} = \sum_{\xi_i \in \xi^g} \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} f_{\xi_i}^{(t)}(s_t) - \sum_{l=1}^{\max|\xi|} N^l \cdot [\sum_{s} \sum_{t=1}^{|\xi_i|} \gamma^{g,(t)} P(s_t = s|\theta^g) \cdot f^{(t)}(s)] \tag{3.12}$$

Theoretically, considering household dynamics doesn't add more complexity to computation time (in linear scale). Neither is considering external environmental dynamics, as the extra calculation happens inside the loop over the time horizon (in Equation 3.10), which is tolerable in the finite time space. Therefore, it is computationally feasible to incorporate both types of dynamics in practice.

The first item in Equation 3.12 can be conveniently obtained by extracting states and feature vectors from gth group of trajectories. Concerning the second item, we abridge $\sum_{t=1}^{T} \gamma^{g,(t)} P(s_t = s|\theta^g)$ as $P(s|\theta^g)$ which can be interpreted as the state visitation frequency under policy ϕ_{θ^g}. And now our estimation goal is to calculate $P(s|\theta^g)$.

Estimation Part II - Recursive learning algorithm

We use $\mu_t(s)$ to denote the discounted probability of living in state s at time period t, i.e., $\mu_t(s) = \gamma^{g,(t)} P(s_t = s|\theta^g)$. Given the household residential MDP framework (A, S, T^g, r_{θ^g}, γ^g), we establish the following forward update formula based on the Markov property ($P(s_{t+1}|a_t, s_0, ..., s_t) = P(s_{t+1}|a_t, s_t)$):

$$\mu_{t+1}(s) = \sum_{a} \sum_{s'} \gamma^g \mu_t(s') \phi_{\theta^g}(a|s') T^g(s|a, s') \tag{3.13}$$

$$\mu_0(s) = P(s_0 = s) = \frac{N_{s_0=s}}{N} \tag{3.14}$$

where $\phi_{\theta^g(a|s')}$ is the optimal policy for MDP(A, S, T^g, r_{θ^g}, γ^g) if θ^g are the parameters associated with the reward function, which can be recovered by value iteration as we discussed in Section 2.2 Equation 2.2 and 2.3. $T^g(s|a, s')$ is the known transition matrix which can be directly computed from the gth household moving trajectories. Note that $T^g(s|a, s')$ can be time-dependent in order to capture the transition dynamics, and we here simplify it as a stable transition matrix. $N_{s_0=s}$, shown in the initialization Equation 3.14, denotes the number of trajectories that start from state s. After the above iteration, we substitute $P(s|\theta^g) = \sum_{t=1}^{T} \mu_t(s)$ into Equation 3.12 to update θ^g.

Algorithm 1: Residential location MDP framework with multiple household groups

Data: $\xi = \{\xi_i = (s_{i,t}, a_{i,t})_{1:|\xi_i|}\}_{1:N}$
Result: $\theta = \{\theta^g\}_{1:G}$, $\phi = \{\phi_{\theta^g}\}_{1:G}$
Initialize θ, $\gamma = \{\gamma^g\}_{1:G}$
for *epoch* $\leftarrow 1$ **to** E **do**
  for $g \leftarrow 1$ **to** G **do**
    ϕ_{θ^g} = `value_iteration`$(A, S, T^g, r_{\theta^g}, \gamma)$; `// Solution of MDP with current` θ^g
    for $s \leftarrow 1$ **to** S **do**
      $P(s|\theta^g) = \sum_{t=1}^{T} \mu_t(s)$; `// Applying Equation 3.13 and 3.14`
    end
    Compute $\frac{\partial LL}{\partial \theta^g}$; `// Applying Equation 3.7, 3.11, and 3.12`
    Update θ^g
  end
end

The summarized estimation procedure is shown in Algorithm 1. We specify E, maximum number of iterations, to be the algorithm stopping criteria, and it can be replaced by other criterion such as the convergence of the final log-likelihood.

Willingness to pay for better neighborhood.

By incorporating the housing price, it is handy to compute the marginal cost of the key features for different household groups, which provides both a calibration matrix for the model performance and a solid understanding of people's housing preference.

Our optimization approach is adapted from the maximum entropy inverse reinforcement learning algorithm ([112]) with several improvements considering the setting of the residential location decision making process. We first extend the learning algorithm for a multi-agent MDP system where different household groups may have different reward functions while sharing the same state and action space, and potential moving trajectories. Furthermore, we incorporate a discount factor in our derivation which is often ignored in previous studies. The derivation is straightforward and we present the revised algorithm without intermediate steps. Equation 3.7 can be transformed as follows:

$$\frac{\partial \sum_{i=1}^{N} R_\theta(\xi_i)}{\partial \theta^g} = \sum_{\xi_i \in \xi^g} \sum_{t=1}^{|\xi_i|} \gamma^t f_{\xi_i}(s_t) \tag{3.15}$$

where $|\xi_i|$ represents the length of current trajectory. Equation 3.10 and 3.11 are revised respectively as the following:

$$\frac{\partial \log \int \exp R_{\theta^g}(\xi) d\xi}{\partial \theta^g} = \sum_s [f(s) \cdot \sum_{t=1}^{|\xi_i|} \gamma^t P(s_t = s|\theta^g)] \tag{3.16}$$

$$\begin{aligned} \frac{\partial \sum_{i=1}^N \log Z(\theta)}{\partial \theta^g} &= \sum_{\xi_i \in \xi^g} \sum_s [f(s) \cdot \sum_{t=1}^{|\xi_i|} \gamma^t P(s_t = s|\theta^g)] \\ &= \sum_{l=1}^{\max|\xi|} [N^l \cdot \sum_s [f(s) \cdot \sum_{t=1}^{l} \gamma^t P(s_t = s|\theta^g)]] \end{aligned} \tag{3.17}$$

where $\max|\xi|$ denotes the maximum length of all the new trajectories and N^l denotes the number of those with length l. The skeleton of the learning algorithm 1 remains the same while we replace the key equations with the above. Furthermore, we can observe from Equation 3.17 that considering the dynamics in household evolution doesn't add more complexity to computation time (in linear scale). Therefore, it is computationally feasible to incorporate household dynamics in practice.

Housing market dynamics.

During the derivation from Equation 3.9 to 3.10, we made an assumption that the feature vector $f(s)$ associated with each state remains the same over time. This holds true in our case since most features associated with the neighborhood built-in environment such as accessibility and land-use mix are not available annually. Therefore, we treat those features as static when applying the proposed model into the data set, which may potentially accelerate the estimation process. However, the assumption of a static feature vector can be easily relaxed in our model estimation by a minor revision of Equation 3.12 into Equation 3.18.

$$\frac{\partial LL(\theta)}{\partial \theta^g} = \sum_{\xi_i \in \xi^g} \sum_{t=1}^{T} \gamma^t f_{\xi_i}^{(t)}(s_t) - N^g \cdot [\sum_s \sum_{t=1}^{T} \gamma^t P(s_t = s|\theta^g) \cdot f^{(t)}(s)] \tag{3.18}$$

$f^{(t)}$ denotes the dynamic feature vector for each state. With this in hand, we can flexibly incorporate the external dynamics caused by changes in the transportation system, land use, appreciation of housing, etc. Theoretically speaking, considering feature dynamics does not add much computational burden in the estimation procedure since the extra calculation happens inside the loop over the time horizon, which is tolerable in the finite time space.

3.4 Results

We apply our methodology to the synthesized data set, and the result section comprises four parts. We begin with examining the forward-looking behaviors of household groups with different income levels. Then we explicitly analyze the estimated parameters associated with the six attributes in the reward function, and validate the model capability of capturing households' residential location preferences using the example of Austin, Texas. Last but not least, we provide a thorough comparison between four types of models: IRL-based model, DDCM, myopic dynamic model, and static model in the residential location choice setting. Finally, we also point out some practical issues regarding this large-scale dynamic residential choice model and how we handle them.

Forward-looking behavior for different groups of households

Considering the household income is not available in the infused dataset, we use the medium family income of the first location (CBG) in each trajectory as an proxy of the household income. We assign households to one of three income groups based on 2005 income quintile data from the Census for Texas; we define the low income households as those that earn below \$36,000 (2nd quintile), and the medium income group as those that earn between \$36,000 and \$91,000 (4th quintile) and the high income group as those that earn above \$91,000. The choice of the 2nd and 4th quintile as the cut-offs is based on a relative balanced percentage of trajectories that belong to each group, shown in Table 3.1. Since γ specified how much the households care about future rewards relative to immediate rewards, the value of the optimal γ^g can reflect the degree of forward-looking behavior for each household group, namely $\gamma = 0$ being completely myopic and $\gamma = 1$ being extremely foresighted. We search the optimal γ^g with increments of 0.05 in the range of [0, 1] based on the final log-likelihood, and the results are shown in Table 3.1.

household group	high income	medium income	low income
% in the data set	25%	59%	16%
optimal discount factor γ^g	0.55	0.60	0.35

Table 3.1: Forward-looking behavior for different household groups

We observe that low-income households present a lower discount factor compared with the other two groups. Low-income households are more likely to rent rather than own[1], and hence they are more likely to relocate more frequently, as mentioned in Section 3.2. Renters may be relatively more flexible and able to move, and therefore more inclined to focus on their current needs. There might be a number of other reasons that contribute to low-income households being more inclined to focus on immediate rewards. For example, low-income households might confront more credit constraints or experience more uncertainty about future outcomes.

[1]According to the 2015 statistics provided by U.S. Census Bureau, homeownership rate for households with family income greater than or equal to the median family income is 78.4% while the rate for households with family income less than the median family income is 48.9%.

Because medium- and high-income households are more likely to be home-owners, their residential location choice is more long-term and therefore presents as more forward-looking within the model, which results in a higher estimated discount factor for their future residential location. An interesting phenomenon is that medium-income households have a slightly higher discount factor than high-income households; we speculate that this may be because high-income households can better afford to relocate, and therefore are not necessarily as locked into choices, making those choices less risky, and therefore do not loom as large in their choice as compared to medium-income households.

(a) High income households (b) Medium income households (c) Low income households

Figure 3.5: Comparison of reward values in Austin for different households. (The color represents the relative reward value within each household group, with red areas having higher, and purple areas lower, rewards.)

Understanding the residential location choice from IRL

The estimated parameters in the reward function are shown in Table 3.2 under the "IRL" heading. To better illustrate the housing preference differences between the three income groups and verify that our model results are consistent with the real world situation, we map our estimated parameters into the city of Austin as an example. The spatial distribution of location rewards for each household group is shown in Figure 3.5.

The estimation results show that for high-income households the most attractive residential locations are in the upper left area of the Figure 3.5a, the Bryker Woods and Old

Western Austin neighborhoods known as the one of the most desirable and affluent places in Austin or even in Texas. These two neighborhoods are close to many activities, iconic Austin landmarks, green spaces, and golf courses, which is consistent with the positive sign of the land use mix estimate. Medium-income households are also attracted to these neighborhoods, though low-income households are not, likely because of their relatively high housing costs.

As for the medium- and low-income households, they both have a strong preference for the lower right areas in the Figures 3.5b and 3.5c, which are the Central East Austin, Riverside, and Pleasant Valley neighborhoods. Since 2000, Austin experienced tremendous growth by adding a large amount of housing units; East Austin has been rapidly gentrifying since that time and has experienced some of the greatest increases in rental and housing prices in all of Austin. Therefore, as a rapidly gentrifying area, East Austin is a popular residential choice for low- and medium-income households, but less so for high-income households. The Riverside and Pleasant Valley neighborhoods are in a similar situation. They also traditionally had a large number of low-cost multifamily housing units, and new developments were persistently constructed after 2000. An interesting area in Figure 3.5b is the upper middle region (identified as the black box), which is only preferred by medium-income households. This area is around the University of Texas; students (at least those with a car) and university employees are more likely to belong to the medium-income category. The example of Austin, Texas justifies the model capability of explaining households' preferences in the dynamic residential location choice problem. We will further investigate each of these parameters in details and compare with other model frameworks in the following section.

Comparison between IRL, DDCM and baseline models

As for model comparison, we provide three types of models: (1) a static residential choice model with a classic nested logit structure, in which the choice is whether to move, and where to move conditional on moving; (2) a myopic model considering only backward-looking behavior by setting $\gamma = 0$ in the IRL-based model, i.e., the only time dependency captured is between the past and the current location; (3) a DDCM model follows the classic structure of [86]'s paper as we presented in Section 2.3: $R(x_t, \epsilon_t) = r_t = \beta^T x_t + \epsilon_t$ where β^T are the parameters we want to estimate, x_t is the vector of six features we observed, and ϵ_t satisfies Assumption AS, CI, and EV. In the DDCM setting, a household is assumed to sequentially choose to relocate to a location that maximizes their expected sum of current and discounted future utility, denoted as $\mathbb{E}[\sum_{\tau=t}^{T} \gamma^{\tau-t} r_t | s_t]$. We adopt nested fixed point algorithm proposed in [86] for estimating this DDCM model.

Because the objective of the four models is to maximize the log-likelihood, we use the final log-likelihood as the model performance metric. Dynamic frameworks (baseline myopic, IRL, and DDCM) show an apparent performance advantage over the static model. By incorporating forward-looking behavior, both IRL and DDCM improve the goodness of fit compared with the baseline myopic model while IRL works better than DDCM for high- and low-income households.

parameters	IRL			DDCM		
	(high)	(medium)	(low)	(high)	(medium)	(low)
household density	0.314	0.138	0.341	0.187	0.137	0.166
employment density	-0.013	-0.040	-0.002	-0.002	-0.005	0.009
road network density	-0.002	-0.011	0.009	-0.056	-0.010	0.105
land-use mix	0.349	0.272	0.255	0.281	0.162	0.114
accessibility to jobs (by car)	0.390	0.243	0.402	0.167	0.180	0.190
housing price	-0.143	-0.236	-0.673	-0.149	-0.277	-0.521
log-likelihood	-17,001	-43,369	-9,483	-17,081	-42,975	-10,596
parameters	Myopic IRL			Static		
	(high)	(medium)	(low)	(high)	(medium)	(low)
household density	0.465	0.005	0.363	0.133	0.068	0.125
employment density	-0.015	-0.047	-0.006	0.009	0.021	0.003
road network density	-0.010	-0.268	0.015	0.014	0.012	0.018
land-use mix	0.244	0.021	0.043	0.034	0.042	0.194
accessibility to jobs (by car)	0.077	0.124	0.641	0.139	0.110	0.026
housing price	-0.398	-0.110	-1.249	-0.506	-0.281	-0.434
log-likelihood	-18,284	-44,355	-11,348	-22,974	-47,974	-16,651

Table 3.2: Estimation results

The signs of six parameters in the static model are consistent with the common findings in previous studies, and a comprehensive review can be found in [89]. All four models show that households have a positive preference towards areas with higher household density. As for employment density, we observe that households prefer high employment density locations only in the static model. Indeed, in the IRL model all the signs for this parameter are negative. A similar phenomenon occurs for road network density, where high- and medium-income households show an inclination for areas with higher road density in the static model, but not in the three dynamic models. One potential reason behind this is the time-dependent structure of the Markovian process in the dynamic models where people show strong inertia to their current living environment and won't move to an area with higher employment or road network density. Therefore, some part of the relationship between location choice and density measures is undermined by the temporal correlation. However, the static model does not address this issue since it is directly estimated using cross-sectional data. For the above discussion, one exception is that for the lower-income households, which presumably prefer dense road networks that may be correlated with likelihood of public transit availability.

For neighborhood amenities and transport-related attributes, namely land-use mix, housing value, and accessibility to work measure, we find the same sign across all four models, and across all three income groups: a consistent positive preference for land use mix and car accessibility to jobs, and a consistent disinclination for housing value (prices). People opt for locations with higher land-use mix, higher accessibility for work, and lower housing price. Not surprisingly, low income households are much more sensitive to housing price compared with the other two groups, which is reasonable since they have a tighter budget to buy or rent a house. High-income households show a strong preference for higher land-use mix, which is demonstrated in our Austin example; however, they don't care about accessibility to jobs as much as the medium- and low-income groups. One exception is that in the IRL model, medium-income groups care less about high accessibility to jobs, which is the opposite case in the DDCM and myopic model results. Until now, we can basically conclude that the two forward-looking models and the myopic backward-looking model have a consistent interpretation for most of the coefficients. There are some minor differences such as the sign of employment density for low-income households.

Value of neighborhood amenities and transportation attributes

To further explore the difference among these models, we compare the estimated value of each attribute across income groups. The estimated values of land-use mix and accessibility to jobs within 45 minutes are provided in Table 3.3. We observe that IRL tends to yield a higher value of land-use mix and value of accessibility to jobs compared with DDCM. Although there is a discrepancy between the two models, they both show that high-income households are willing to pay almost twice as much for better land-use mix residence and accessibility to jobs than medium-income households, and medium-income households would pay 2-3 times more than low-income households for better neighborhood amenities.

household group	high income	medium income	low income
value of land-use mix in $ (IRL)	244,056	115,025	37,890
value of land-use mix $ (DDCM)	188,591	58,483	21,881
value of accessibility to jobs in $ (IRL)	272,727	102,966	59,732
value of accessibility to jobs in $ (DDCM)	112,081	64,982	36,538

Table 3.3: Value of neighborhood amenities

As we point out in Section 2.1, the empirical results don't necessarily mean one methodological approach is better than another. One of the objectives of this paper is to provide another tractable framework to solve the sequential decision making problem of residential location choice. The above analysis indicates that IRL and DDCM share some similarities on interpreting some households' preferences but also exhibit a few differences, including the model performance and willingness to pay for different attributes.

Practical Issues

We here point out two practical issues related with dynamic residential location choice models. One is that relocation is a relatively rare occurrence in reality, which often leads to unbalanced data, as in our case. In other words, the estimation algorithm will put much more emphasis on learning from households that do not relocate, and result in a biased estimation. Therefore, we adopted the SMOTE ([25]) oversampling method to produce balanced data, i.e., more moving trajectories. By applying the SMOTE method, we can generate synthetic moving trajectories and avoid copying the same observations from the original data.

Another common issue related with residential choice models is the endogeneity caused by the correlation between housing value and the unobserved error term; we add a correction for price endogeneity according to the control function method ([54]) to obtain consistent estimates. Note that the estimated correction term is not reflected in the results table for simplicity.

3.5 Conclusion

While residential location choice models have been the emphasis of a substantial body of research, most empirical studies have adopted a static estimation approach. For the small body of studies that allow for dynamic decision-making, only backward-looking behavior, i.e., time-dependency, is incorporated. This is with good reason: the estimation of a truly dynamic residential choice model is extraordinarily difficult due to (a) computational feasibility associated with large-scale dynamic programming and (b) scarcity of long-term household relocation data. Yet residential location choice is inherently dynamic, and this has led to concerns that estimates from static models may be biased. In economics, dynamic discrete choice models (DDCM) have been used to model many aspects of transportation behavior; however this approach has several limitations, including the assumptions of optimal human behavior, conditional independence, extreme value distribution, etc. In the recent decade, advances in artificial intelligence, especially the framework of inverse reinforcement learning (IRL), has provided another approach to solve complex dynamic behavioral problems. In particular, IRL can circumvent the multiple assumptions commonly used in DDCM while still reconstructing and estimating the problem in a feasible way. In this paper, we propose a dynamic model for the sequential decision-making problem of residential location choice under the framework of IRL. We provide a comprehensive comparison between DDCM and IRL, both theoretically and empirically. With an infused data set of household relocations in Texas over a 7-year period, we show that these two forward-looking dynamic frameworks yield some, but not all, consistent results. However, IRL performs better than DDCM for high-income and low-income groups in terms of the model fit, and there is a discrepancy between the estimated willingness to pay for mix land use and accessibility to jobs between the two approaches.

The worlds of economics and artificial intelligence rarely reference each other; this paper aims to bridge these two disciplines to address the difficulty in modeling residential location choice. Needless to say, each approach has its own strengths and weaknesses; our focus is not to conclude which one is preferable, but to provide a novel approach to modeling dynamic behavior relevant to transportation research and show their similarities and differences in solving a real-world long-term large scale problem: residential location choice. This paper can be used as a starting point for more exploratory work, including: establishing a more flexible reward function and transition matrix; efficiently estimating the model with full household internal dynamics and external environment dynamics; and incorporating the concept of lifestyle or other latent variables into the IRL framework, among others.

Chapter 4

Literature Review: Backward-Looking Models

"I think somehow we learn who we really are and then we live with that decision."

(Eleanor Roosevelt)

In backward-looking models, individuals and households usually make a decision in a retrospective way based on their past experience. In the context of classic static travel demand models and behavioral analysis, most backward-looking studies adopted the framework of discrete choice model which is based on Random Utility Maximization (RUM) theory. However, when generalizing the model framework to a dynamic context, we may confront some major challenges in this classic discrete choice model system, including:

- Lack rich longitudinal multi-dimensional data.
- How to explicitly interpret the (causal or correlational) relationship among the multi-dimensional choice system.
- How to represent the interrelated connection between discrete and continuous outcomes.
- How to represent the time-dependency between different time periods.

4.1 Structural Equation Model (SEM)

Static SEM

The static SEM framework incorporates mutual causal effects between different dimensions of travel behavior via the covariance matrix making up the error structure.

Initially, studies on SEM system are aiming to handle the second challenge. For example, to analyze the true effect of the built environment on car ownership by considering self-selection in residence choices, [18] formulated joint mixed multinomial logit-ordered response structure. [79] did a similar study, in which a simultaneous mixed logit model of residential location and mode choice for work tours is developed to examine the self-selection effect.

In recent years, thanks to the availability of voluminous data, more research gradually focus on tackling the third challenge. [40] proposed a joint multiple discrete continuous extreme value (MDCEV) framework that models an individual's choices across the following five choice dimensions: activity type, time of day, mode, destination, and time use allocation. Most recently, [17] formulated a generalized heterogeneous data model (GHDM) that jointly models mixed types of dependent variables, including multiple nominal outcomes, multiple ordinal variables, and multiple count variables, as well as multiple continuous variables, in which the covariance relationships among outcomes are represented through a reduced number of latent factors.

All these studies constitute major contributions to the integrated modeling framework and their using of mixture distributions often provides an excellent fit to the data. However, some common drawbacks of these integrated models are listed here: (1) The mixture distributions of parameters are always assumed to be static, which limits application of these models since transport planners and policy makers are more interested in forecasting market and travel demand in a long run. (2) Many models require the analyst to make an a priori assumption about the mixture distribution for each randomly distributed coefficient. Considering distributional assumptions exert influences of their own on the results, it might be of limited utility to policy makers using these models with predetermined distributions.

Dynamic SEM

As for the forth challenge stated at the beginning of the section, the dynamic SEM framework incorporates both auto-correlation and mutual causal effects between different dimensions of travel behavior via the covariance matrix making up the error structure. [72] first proposes a conceptual framework of dynamic SEM without validating it with real data. Lyon's model was extended by Golob and his collaborators in the subsequent decade; they extended the SEM framework in three ways. First, they brought joint dynamic choice models into the dynamic SEM framework, enabling it to accomodate the dependency of different types of behavior variables. They demonstrate this in the context of vehicle ownership and trip generation as an ordered probit, and travel time by different travel modes as censored continuous variables [53, 50, 99]. Second, they articulated the importance of integrating exogenous variables to mitigate period effects [52, 51]. Third, they provided a practical estimation approach (a combined version of generalized linear model [GLM] and maximum likelihood [ML]) which was lacking in the [72]. In addition to these methodology improvements, they estimated and validated all of their models using real data.

The Dynamic SEM framework continued to progress from the 1980s to the early 2000s, along with further examples of studies applying dynamic SEM to assorted behaviors and identifying practical estimation methods. For example, [29] explored the relationship between activity participation patterns and travel behavior using a dynamic SEM with a nine-wave panel of data collected in the greater Seattle metropolitan area of the U.S. Other examples of dynamic SEM applications include [48], [92], [29], etc.

There are two limitations of the SEM approach with regards to our research objective. First, as [103] stated, the complicated correlation structure of the SEM approach can be seen as a black box, resulting in the cause of the distribution to not be readily apparent and the model results hard to interpret in order to provide policy implications. In particular, the time-dependency and inter-dependency between multidimensional behaviors, essential to dynamic models, are challenging to intuitively explained from form an SEM covariance matrix. Second, although the SEM framework is capable of accounting for correlated attitudes and behavior, a multi-level hierarchical relationship between life events, social events, lifestyle and behaviors cannot be clearly constructed through SEM.

4.2 Latent Class Choice Model (LCCM)

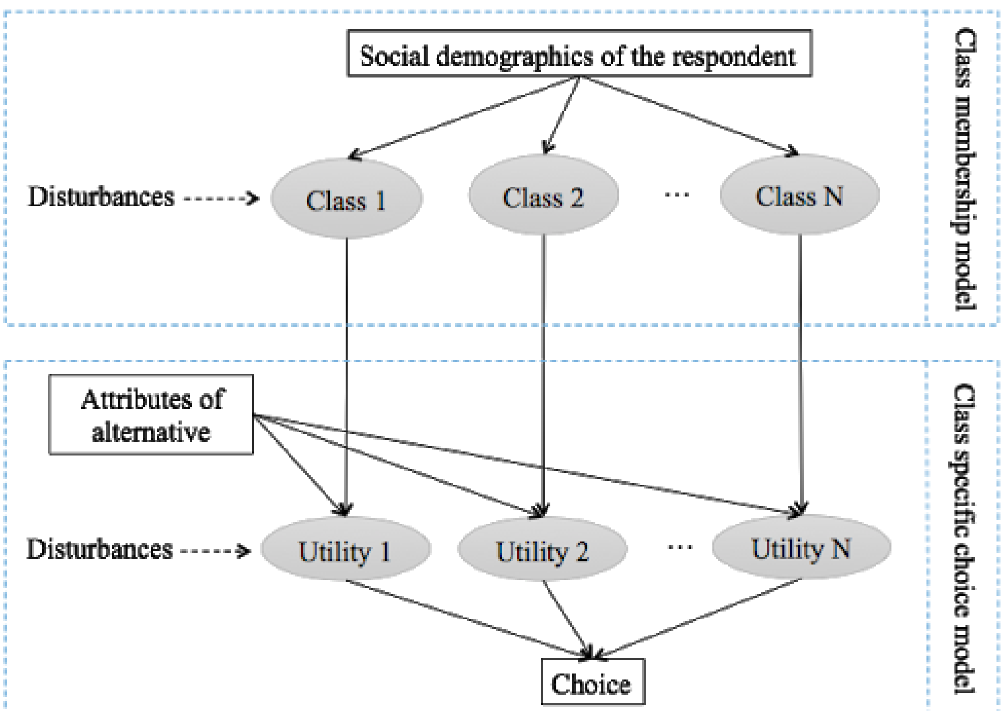


Figure 4.1: LCCM model structure

The framework of LCCM is shown in Figure 5. LCCM constitutes class membership model and class-specific choice models. It is assumed that individuals or households are implicitly categorized into a set of N classes. The underlying assumption of the LCCM postulates that individual-level/household-level behavior depends on observable attributes such as socio- demographics and on latent class that are unobserved by the analyst. Here are some representative work. [102] employed it in residential location choice model and empirical results indicate three latent lifestyle segments: suburban dwellers, urban dwellers, and transit-riders. [101] then extended LCCM with preference endogeneity constructing feedback from the class-specific choice models to the class membership model through consumer surplus. They applied the new model to mode choice data from the Bay Area Travel Survey (BATS) 2000 and find six modality styles. Also, it is demonstrated a better goodness of fit and greater behavioral insights. The LCCM framework have been applied to mamy

4.3 Hidden Markov Model (HMM)

Hidden Markov Model provided another way to model the dynamic travel behavior by accommodating LCCM framework in the dynamic setting. HMM is proposed by Baum and Petrie in [9] where the system being modeled is assumed to be a Markov process with unknown parameters. The property of "state transitioning" in a Markov chain allows the model to capture the dependency between two timestamps and the concept of "latent state" (or "hidden state") in HMM can be aligned with the concept of latent lifestyle or modality style in the LCCM framework.

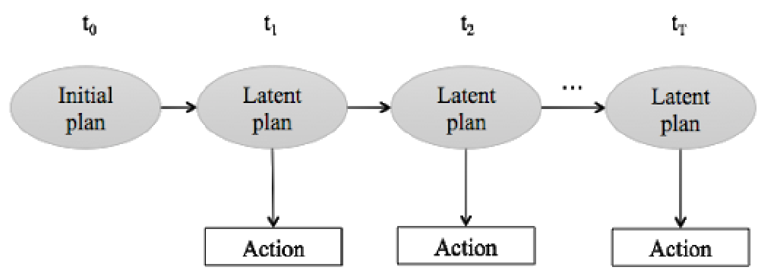


Figure 4.2: First-order planning-action HMM model structure

In recent years, the HMM framework has been gradually adopted in various decision-related applications in transportation. [15] proposed a planning-action model for dynamic contexts where the plan of changing behavior is often unobservant and is treated as latent variables in model estimation using observed actions. [28] applied the planning-action process to study more short-term dynamic plans of driving and route changing behavior. The underlying assumption is that the plan at every time period is determined only by the plan at the previous time period (known as first-order Markov model, shown in Figure 2) and may be affected by the maneuver taken in the previous time period (experience). The concept of latent plan and the proposed framework can be generalized to many other choice behaviors involving dynamically evolving 'hidden' decision layers and latent alternatives, for example, residential location choice, route choice and other travel behaviour models.

[107] further extended HMM framework to heterogeneous one, in which the transition probability model between states from one time period to the other is no longer consistent, but varies over time. Vij (2013) also demonstrated the use of Markov process by treating the Markovian state as a dynamic extension to "latent class" and combined HMM with Latent Class Choice Model (LCCM), a framework discussed in section to analyze mode choice and modality style based on panel data. [106] also proposed a second-order HMM to capture lag effects across two periods of time.

However, most of the current studies that applied LCMM-based and HMM-based models to infer latent lifestyle or mobility style segments all focus on one-dimension of choice behavior alone while ignoring the inter-dependency with other choice behaviors. Moreover, the empirical studies tend to neglect the impacts of key life events and policies on travel behavior in the life course horizon.

In summary, a unified backward-looking dynamic model needs to satisfy at least the following three requirements:

- The model can accommodate several endogenous behavioral variables and build the structure of their contemporaneous interrelationship.

- The model can accommodate lagged effects. Many studies have revealed that the effect of a change in the desirability evaluation on behavior can be lagged from one period to several periods.

- The model can accommodate period effects which accounts for the factors triggering temporal behavior changes of all households. Those factors could range from transport related factors (fuel price, housing price, public transit rate, etc.) to state economy (unemployment rate).

Our work contributes to extending heterogeneous HMM to multi-dimensional travel behaviors and explores the behavior change in association with key life events, as well as policy and economics environments. The methodology, estimation algorithm and case study will be presented in Chapter 5

Chapter 5

Unifying Life Stages, Lifestyle, External Environment, and Multi-Dimensional Behaviors with Hidden Markov Model

"It is our choices that show what we truly are, far more than our abilities."

(J. K. Rowling)

Studying behavior change is fundamental to effective travel demand management as it may help quantify the triggers that prompt individuals and households to change their habits and better predict the trend of future mobility. Under the umbrella of long-term dynamic behavior models, the Hidden Markov Models (HMM) framework has gained increasingly attention in the transportation arena (in applications from car ownership to mode choice) due to its latent hierarchical structure, favorable model performance, and intuitive interpretation. In this section, we extend the single discrete choice HMM framework to joint choices with discrete and continuous types, and derive its recursive parameter learning algorithm. Building on this framework, we propose a unified model that conjoins lifestyle, life events, external environment, and multi-dimensional travel behavior dynamics. We evaluate our method via one case study: a retrospective survey in the San Francisco Bay Area of 830 households. In the final model, we identify four latent lifestyles (auto-oriented-2-car group with rare use of other travel modes, auto-oriented-1-car group with rare use of other travel modes, multi-modals group that own at least one car, and auto-free group that have the lowest car ownership and car usage). The results highlight how life events, policies, and the economic environment might influence people to transition between these lifestyles. To fully explore the potential of the extended joint HMM framework, we provide trend analysis of car ownership and mode use based on estimation results, and conduct sensitivity analysis of changes in fuel price and the unemployment rate.

5.1 Introduction

We are encountering an era of rapid urbanization, technological change and transportation transformability (shared transport, electrical car, etc), which reshapes the demand for jobs, housing, energy, transportation infrastructure, and social services and puts the long existing problems, including greenhouse gas emission, climate change and traffic congestion back to agenda. Policy makers and city planners attempt to influence people to adopt more sustainable travel-related choices, such as less driving, living closer to work, purchasing and using alternative-fueled vehicles, etc. To achieve this sustainable goal, a comprehensive understanding of the people's travel-related behavior is fundamental to make better travel demand prediction and implement effective policies.

Shifting travel behaviors requires a gradual adjustment of personal needs and environmental adaptation, and might require years and even generations to yield the desired outcome. Travel behaviors are deeply habitual. They are flexible at some points but less flexible after certain choices have been made, such as whether or not to purchase a vehicle or where to live–choosing whether to drive versus use public transit is a fundamentally different choice for those with multiple vehicles in a household versus one or none, or for those living in the suburbs far away from their destination versus those living in the city center with immediate access to transportation alternative.

Travel trends have been evolving in recent years, especially with respect to the prevalence of using multiple lower-emission modes to replace personal vehicle trips (multimodality) in western countries. In Germany, [65] reveals a rise in multimodality and a decrease in vehicle ownership and use among young adults (aged 18-29 years) since 1990. [23] investigates the prevalence of multimodality in the United States between 2001 and 2009, and observes a significant shift away from personal vehicle use towards multimodal vehicle use (combining occasional car use with occasional use of other modes) as well as exclusive walking-bicycling-public transport use. [56] provides evidence of similar mode use shifts in Great Britain.

To identify triggers that shift travel behavior, a traditional focus of the literature has been how changes to the external environment dynamics such as change of policies, economics, societal, and cultural factors result in households adjusting travel-related behavior. For example, using nine years of U.S. Consumer Expenditure Survey (CES) data, [83] found that households would reduce vehicle miles traveled (VMT) in the year following an increase in gasoline price.

Some more recent facet of the literature focuses on the triggers of internal dynamics such as the role of key life events on travel behavior change [66, 12, 88, 32, 69, 58]. The life events analyzed include shifts in residential location, employment, and household structure (e.g., having children or living with a partner). Travel behaviors analyzed include vehicle ownership/usage and mode choice. While most of these studies have observed a strong relationship between life event and travel behavior change, [88] concludes that life events are only loosely associated with changes in mode use.

Transportation researchers used to understand travel as a derived demand, whose underlying assumption is that individuals' or households' travel decisions are the result of objective constraints (e.g., the built environment or socioeconomic conditions). In recent decades, some researchers find this to be an oversimplification and begin to understand the use of transportation system in the context of the choice and symbols in the social space of lifestyles. The concept of lifestyle, related to but distinct from the concepts of life-cycle phase or life events, has been gradually recognized in the literature as being important to travel behavior choices and outcomes. Studies on lifestyle recognize that travel behavior is driven by more than objective constraints (e.g., built environment and socioeconomic characteristics) traditionally used in classic travel demand models. As [67] points out, lifestyle can be understood as a social construct that determines an individual identification with a social group and manifests itself in all facets of everyday life, such as consumption habits and the demonstration of tastes (e.g., furniture, clothes, favorite television programs or newspapers) and leisure activities. Lifestyle therefore determines the dynamics of travel behavior as a higher-level orientation [87]. More specifically, some recent empirical studies have demonstrated the existence of modality style as a subset of lifestyle that influences mode choice behavior [100, 107, 109, 35].

Individuals or households usually collectively adjust their travel behavior in varied dimensions. That is to say, consumer choices and decisions, from longer-term to shorter-term, such as residential and work location, vehicle ownership and usage (e.g., VMT), and mode choice, are all interdependent. For example, a household that moves from an urban to a suburban area might add a vehicle to improve access to more dispersed activities, and once they own that vehicle, may start to use it exclusively, regardless of the availability of alternatives. A growing body of literature has demonstrated that ignore this interdependence can yield inconsistent model results that either over- or under-estimate the true impact of explanatory factors [18, 80, 17].

Therefore, to capture a complete picture of travel behavior trends and drivers of behavior change, a model needs to dynamically account for life events, time-varying economic and policy context, lifestyle/mobility style, and multi-dimensional behaviors (including vehicle ownership and mode use patterns). Few studies have consolidated all of these factors into one framework. The objective of this paper is to develop a unified model framework using a heterogeneous Hidden Markov Model with joint choices (both discrete and continuous).

The rest of this section is structured as follows. In Section 5.3, we propose the heterogeneous Hidden Markov Model structure with joint choices, present each component, and derive the corresponding estimation algorithm. Section 5.2 describes a case study where we apply this model to the dynamic analysis of lifestyles in the San Francisco Bay Area, using data from a retrospective survey. We then present the estimation results and conduct further analyses on how people transition between lifestyles as a result of life stages, policies and the economic environment.

5.2 Data

We use survey responses from the WholeTraveler Transportation Behavior Study conducted as a part of the Department of Energy's SMART Mobility Initiative. This survey was conducted in the Spring of 2018 and recruited residence of the San Francisco Bay Area [94, 37, 93]. The invitation to participate in the survey was mailed to a random sample of 60,000 active residential addresses in the nine core Bay Area counties, with the household member over 18 years old with the most recent birthday asked to respond to the survey. The recruitment letter included the web address to access the survey, which could only be responded to online. The survey collected a variety of data, including information on current mode use, vehicle information, mode and travel experience preferences, interest in and adoption of emerging technologies, e-commerce behavior and preferences, as well as a rich set of respondent characteristics including risk and time preferences, personality characteristics, and standard socio-demographic information. The survey additionally had a section in which respondents were requested to fill out a life history calendar. The life history calendar covered key changes in life stages (being in school, employed, living with a partner, with a young child at home) and mobility-related decisions. The mobility-related decisions included: (1) regular mode use–defined as regularly using a given mode at least twice per week on average for the indicated year–including public transit, walk/bike, personal vehicle and ridehailing; and (2) the number of vehicles owned by the household. Data were requested on an annual basis for each respondent starting at age 20 and up to age 50. So, for example, for a respondent that was 45 years old at the time they took the survey, they would have provided 25 years worth of annual responses covering the above-mentioned topics.[1] As shown in Figure 5.2, the respondents would check the box for distinct events (like the year a new child entered the household) or clicked and dragged to fill in a range of years covering life stage states (like being in school, or employed) if he/she satisfies the condition in that particular year.

Data for this analysis are drawn from the 997 respondents who completed the entire WholeTraveler survey, including the life history calendar. From this 997, the sample was further reduced to the 813 respondents for whom was born after 1950 and have a complete life event and travel behavior history since age 20.

The respondents' birth years are nicely distributed between 1950 and 1994; the ratio of each generation is shown in figure 5.1. We assume that the decision-making unit for our analysis is a household and that all the members of a household may share one or more vehicles. Because we cannot assign specific vehicles to individuals in a household, we did not consider individual characteristics, such as gender, in our model.

Figure 5.3a shows the trends in four life stages, primary travel mode used, and number of vehicles, by respondent age (left hand panels) and calendar year (right hand panels), based on the life histories reported by each respondent. The four life stages do not necessarily sum to 100 percent at each age or year, as some households may belong to all four of the

[1]Although the movement of residential and work locations is also a crucial part of lifestyle, unfortunately, we do not have access to the past residential or work locations of these respondents. The survey only asked in which years a significant move occured, but nothing about the type of locations moved to or from.

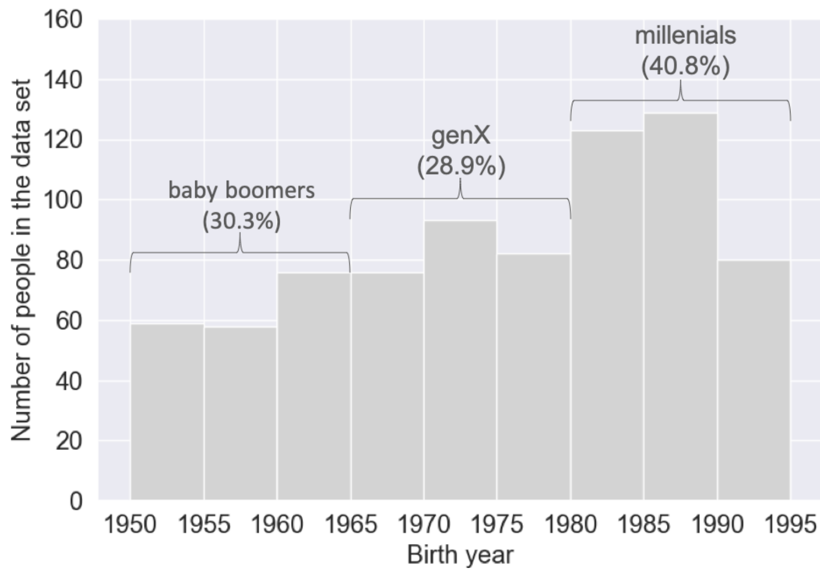
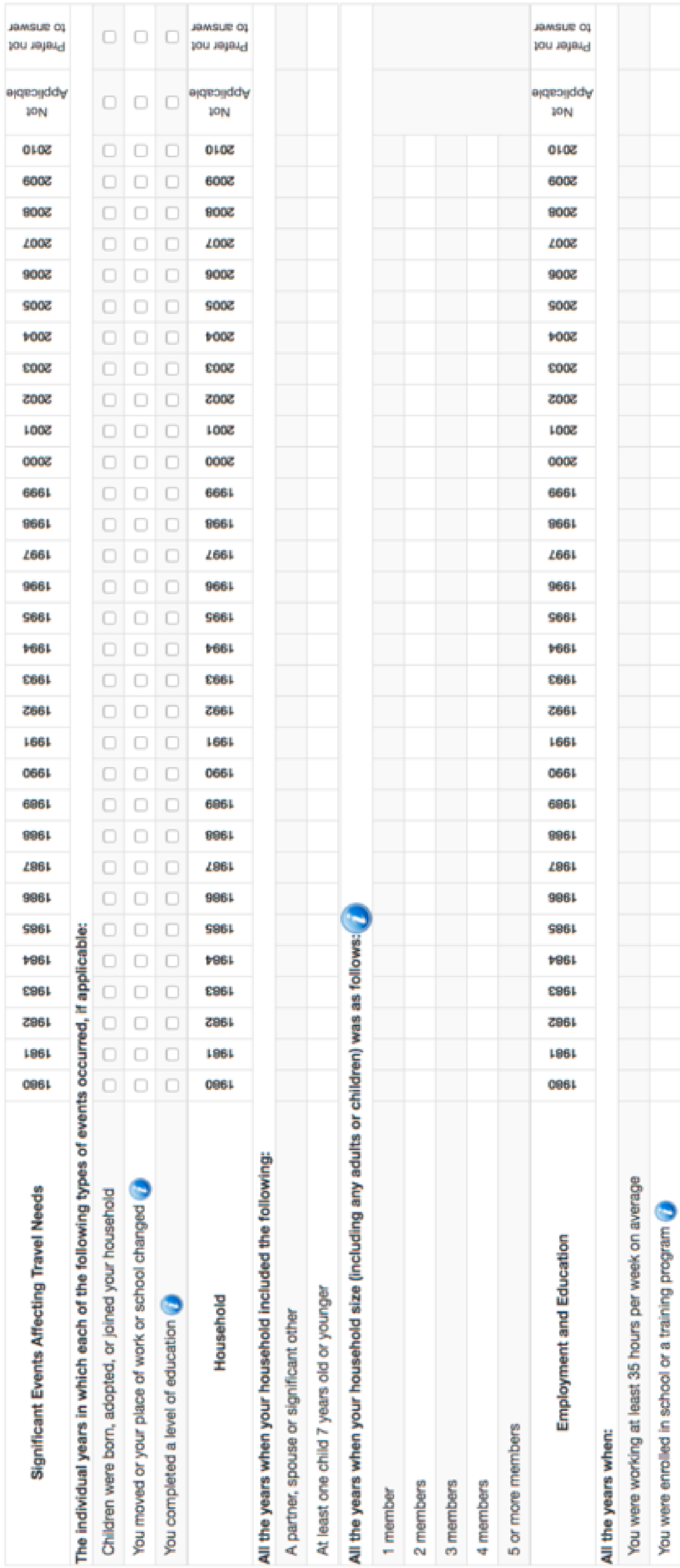


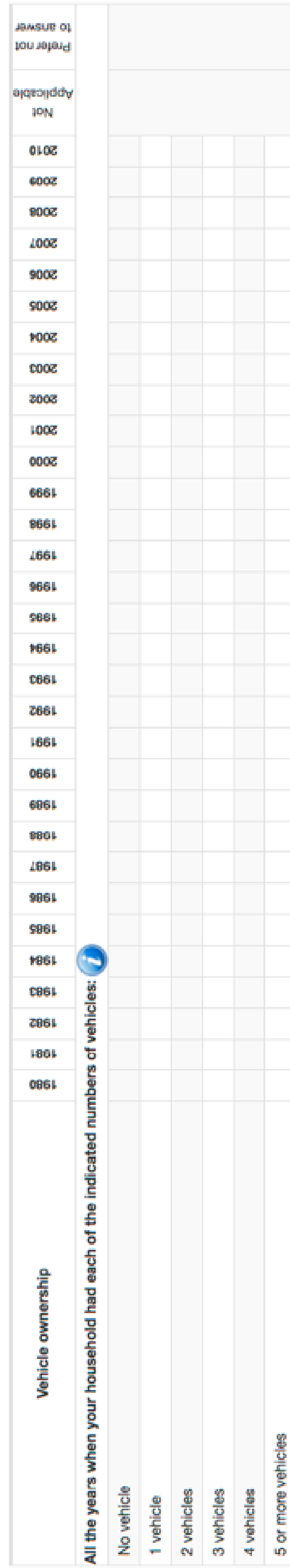
Figure 5.1: Birth year distribution

life stages (with a partner, with a child, employed, and in school). Based on age and year, we also provide the trend of mode use, and number of vehicles, shown in the second and third rows of Figure 5.3. From Figure 5.3a, we observe that the sample reaches its highest employment rate (around 80 percent) at age 32 while the peak points of being with a partner and a young child occurs at around age 34. Also worth mentioning is that our respondents are highly educated, as 31 percent of the respondents are in school at age 25 while the same statistic is about 13 percent in 2018 and 8 percent in 1970 in U.S. based on the American Community Survey (ACS).

The trends of these four life stages over calendar years shown in Figure 5.3b show some potential evidence of underlying patterns responding to macro economic conditions. These patterns have to be interpreted with a grain of salt, as the composition of the sample changes across calendar years, and so trends can be affected by this as well. The underlying relationships between these trends and economic conditions will be more carefully disentangled using appropriate statistics in the modeling. We do observe that, for example, that the percentage of people employed, living with a partner or living with a young child increases from 2010 to 2018, a period of economic recovery and prosperity after the global financial crisis.



(a) key life events



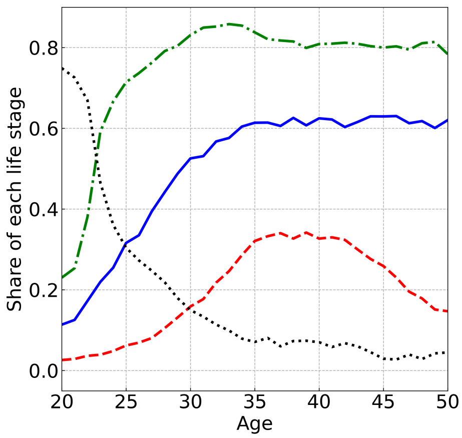
(b) mobility related

Figure 5.2: Example questions in the survey

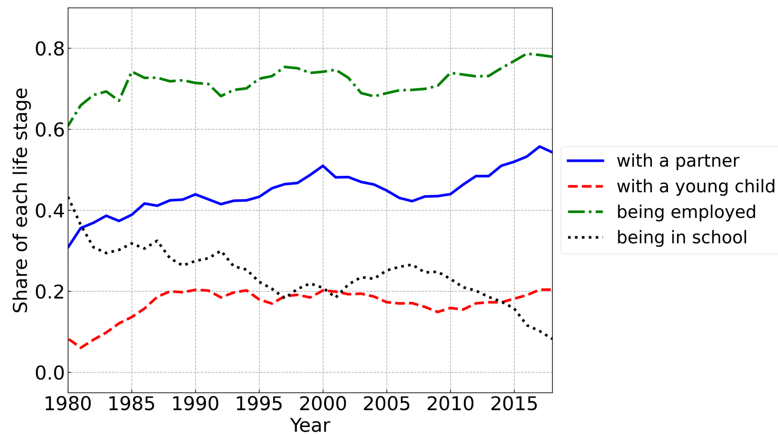
In terms of the primary travel mode used, as shown in Figure 5.3c and 5.3d, people gradually shift from similar fractions of personal vehicles, public transit, and walk/bike (30 to 40 percent each) to only 20 percent using public transit and walk/bike, and 70 percent personal vehicle, by age 50. Note that we here adopt the concept of ”mode use” not ”mode choice” since respondents were asked to indicate which modes they used regularly for their primary commute–defined as at least twice per week on average. They could have therefore selected more than one in a given year, if they walked to work two days per week but drive three days per week, on average, for example. We can clearly observe that people increasingly started to use ride-hail service starting in 2010 when Transportation Network Companies (TNCs) emerged.

An trend of an increasing number of vehicles (in a household) by the age of the respondent is observed. People are more likely to own more vehicles as they age due to increasing income, declining health, or family necessities (transporting children; Figure 5.3e). During economic booms, such as 1992-2000 and 2010-2018, we do observe evidence of a larger number of vehicle per household.

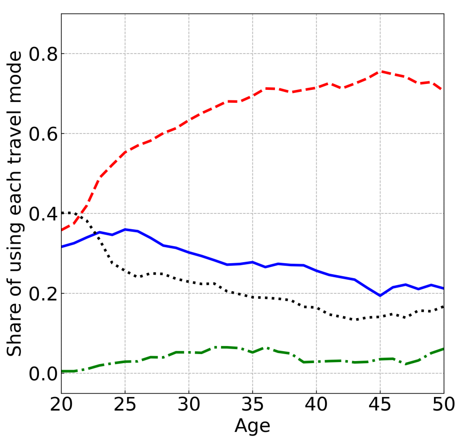
In additional to the impact of key life stages, other social (internet use) and economic (fuel price and unemployment rate) factors, as well as transportation-related policies (such as those affecting fuel price), also play an important role in the evolution of lifestyle. To account for these factors we add (a) annual average fuel price (in 2018 dollars), (b) annual unemployment rate, and (c) annual internet penetration rate to the WholeTraveler survey data. Note that these three variables are nationwide statistics with the consideration that the respondents might have lived in other areas in earlier points of their lives. The final data set we use for analysis therefore includes life cycle trajectories–from age 20 up to age 50–of 813 households and their multi-dimensional travel behaviors (vehicle-ownership and use patterns across four modes) until 2018. This includes four life stages in each year, and three annual external economic/policy environment variables.



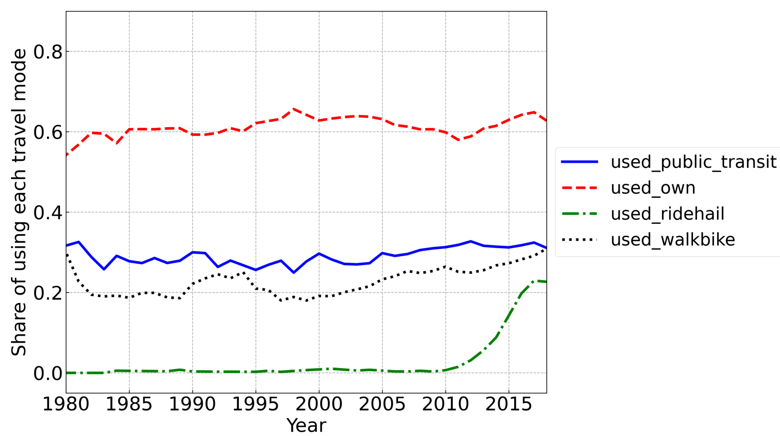
(a) Life stage over age.



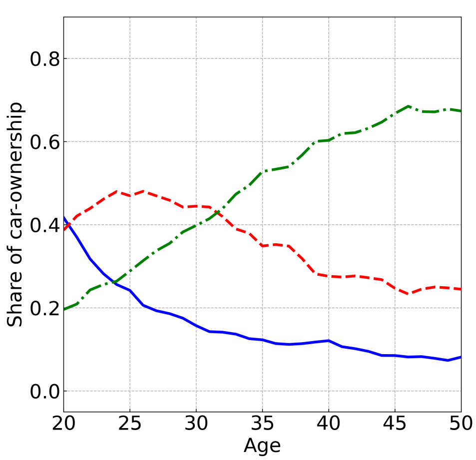
(b) Life stage over year.



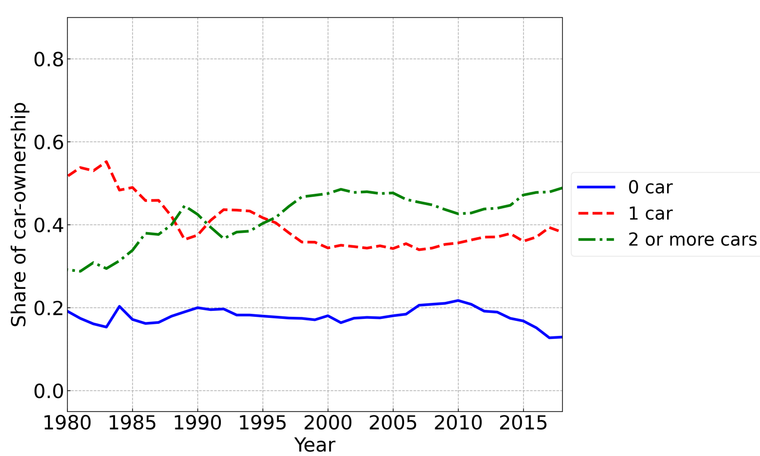
(c) Mode use over age.



(d) Mode use over year.



(e) Number of cars over age.



(f) Number of cars over year.

Figure 5.3: Trend of life stages, mode use, and number of cars over age (20-50) and period (1980-2018). Note that we start from 1980 to make sure at least 20% of samples are included when calculating the shares.

5.3 Methodology

Model Structure

In this study, we develop a probabilistic approach building on HMM to consolidate the dynamics of the three key elements of interest: household lifestyle (specifically we focus on modality style as demonstrated through multi-dimensional short- and medium-term travel behaviors), household life stages, and the economics environment. We demonstrate how different types of policies within these contexts could affect the prevalence of these lifestyles or modality styles. The approach hinges on the following three arguments. First, lifestyle is a higher order orientation of multi-dimensional behaviors, as shown in the hierarchical structure in Figure 5.4. These behaviors can either be short-term, medium-term or long-term. We choose mode choice (short-term) and vehicle ownership (medium-term) as a choice bundle to illustrate the model framework in Figure 5.4. The relationship between lifestyle and multi-dimensional behavior is captured via ***choice models***, which will be further discussed in Section 5.3. Second, lifestyle evolves over time and its evolution can be triggered by: (1) the household dynamics such as changes in life stages, and/or (2) the external environment such as the economy and potential policies like fuel price. This evolutionary process is captured via ***transition models***. The model specification will be explained in Section 5.3. Finally, during the first time period, the households may follow an initial lifestyle distribution, i.e., an ***initial model*** that identifies the probability of belonging to one of x lifestyles at the beginning of each data sequence. More detail on this will be discussed in Section 5.3.

The underlying assumptions for the extended heterogeneous HMM model are:

- Each travel behavior is driven by its corresponding higher-level orientation.
- Correlation exists between each higher-level orientation, that is, travel-related behaviors are assumed to be only conditional on current lifestyle.
- Temporal transition happens on higher-level orientation.

For each individual or household, its lifestyle is unknown; we can only observe the their vehicle ownership and mode choice; their life stage; and their economic and policy environment during each time period. The purpose of our study is to identify the hidden lifestyles via multi-dimensional behaviors and understand the trend of lifestyles over years in response to life stage transitions, policies, and economics. To this end, we develop a heterogeneous HMM model with joint choices as shown in Figure 5.4. The framework is composed of three types of models: a initial model represented by the yellow area, transition models (red area), and choice models (blue area).

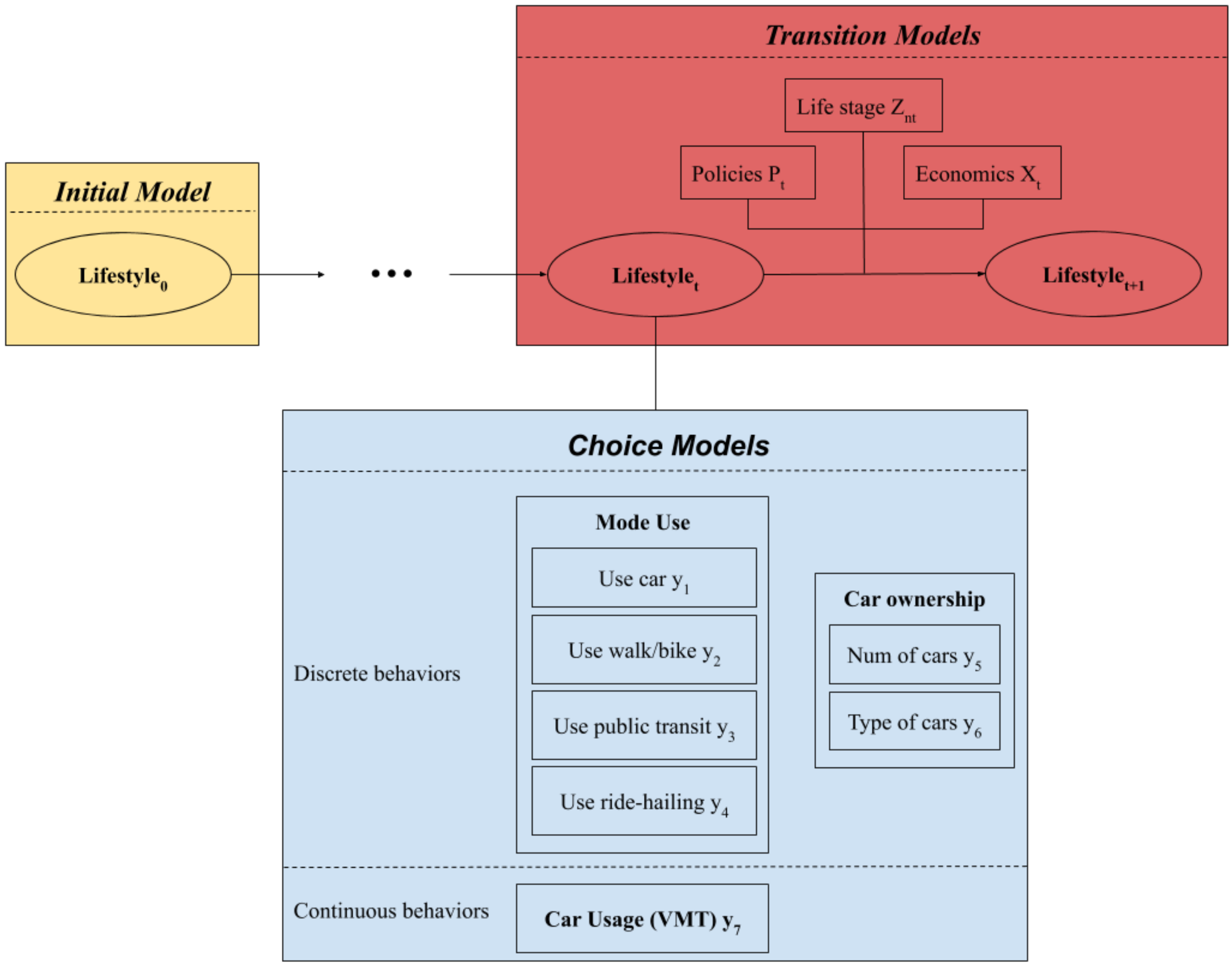


Figure 5.4: Model framework

Initial model

The initial model can be specified as a mulinomial logit model in which the utility functions are expressed as a linear function of individual characteristics, shown in (5.1). These characteristics may include age, household annual income, education level, etc. The Utility of lifestyle i in the initial observation period for individual n is given by

$$U^i_{n0} = {\beta^i_{init}}^T Z_{n0} + \epsilon^i_{n0} \tag{5.1}$$

where Z_{n0} denotes the initial lifestyle style and β^i_{init} denotes the vector of parameters associated with ith lifestyle. ϵ^i_{n0} is a random variable assumed to be i.i.d. Extreme Value across individuals, initial period, and lifestyle. And the probability of household n belonging to lifestyle $q_{n0} = i$ at time $t = 0$ is given by

$$Pr(q_{n0} = i|X_{n0}; \beta_{init}) = \frac{e^{\beta_{init}^{i}{}^{T} Z_{n0}}}{\sum_j e^{\beta_{init}^{j}{}^{T} Z_{n0}}} \tag{5.2}$$

Transition models

Conditional on belonging to lifestyle i at time t, individual n may evolve to other lifestyles or stay at the same depending on the changes in life stage, policies, and the economic environment. Such a decision process is captured in transition models and we formulate them as the form of multinomial logit. Let q_{nt} denote the latent lifestyle of individual n at time t. The utility function of lifestyle j in time period $t+1$ conditional on individual n belonging to lifestyle i in time period t is given by

$$U_{q^j_{n(t+1)}|q^i_{nt}} = \beta^j_{trans,i}[Z_{nt}, X_t, P_t] + \gamma_{q_n(t+1)^j|q^i_{nt}} \tag{5.3}$$

where $\beta^j_{trans,i}$ denotes the coefficients associated with observed triggers (Z_{nt}, X_t, P_t) if transition from lifestyle i to j. $\gamma_{q^j_{n(t+1)}|q^i_{nt}}$ represents the random variable assumed to be i.i.d. Extreme Value across individuals, time periods, and lifestyles. The probability of transitioning from lifestyle i to j can be expressed as

$$Pr(q_{n(t+1)} = j|q_{nt} = i, Z_{nt}, X_t, P_t; \beta_{trans}) = \frac{e^{\beta^j_{trans,i}[Z_{nt}, X_t, P_t]}}{\sum_k e^{\beta^k_{trans,i}[Z_{nt}, X_t, P_t]}} \tag{5.4}$$

where $\beta^j_{trans,i}$ denotes the coefficients associated with observed triggers (Z_{nt}, X_t, P_t) if transition from lifestyle i to j.

Choice models

Choice models are the output of the model framework, where choices, i.e., travel-related behaviors, can vary from discrete to continuous. Under the framework of HMM, travel-related behaviors are assumed to be only conditional on current lifestyle. Different choices are conditionally independent with each other, which also indicates that the correlation between different dimensions of choices is captured in the representative lifestyle (the higher level). The utility function of choosing alternative r for choice y (one dimension of choice) in time period t conditional on individual n belong to lifestyle i given by

$$U_{y^r_{nt}|q^i_{nt}} = \beta^r_{choice,i} A^r_{nt} + \eta_{y^r_{nt}|q^i_{nt}} \tag{5.5}$$

If discrete choice y^1, we assume $\eta_{y^r_{nt}|q^i_{nt}}$ to be i.i.d. Extreme Value across individuals, time periods, choices, alternatives, and lifestyles. The probability of individual n choosing alternative r for discrete choice y^1 in time period t conditional on n belonging to lifestyle i may be expressed in a logit form as shown in Equation (5.6).

$$Pr(y_{nt}^1 = r|q_{nt} = i; \beta_{choice}) = \frac{e^{\beta_{choice,i}^r A_{nt}^r}}{\sum_s e^{\beta_{choice,i}^s A_{nt}^s}} \tag{5.6}$$

where y_{nt}^1 denotes one discrete travel behavior for individual n at time t, A_{nt}^r denotes the attributes associated with alternative j for individual n at time t, and $\beta_{choice,i}^r$ denotes the corresponding coefficients. For example, in the vehicle-ownership model, A_{nt}^r can represent the price of vehicle type r. However, in practice, we prefer not to add so many details to simplify the dynamic framework and treat A_{nt}^r as constant. Then Equation (5.6) can be degenerated into Equation (5.7). The model framework shown in Figure 5.4 is based on Equation (5.7), where A_{nt}^r is assumed to be constant and so normalized to one. In Equation (5.7) $\beta_{choice,i}^r$ now represents the probability of choosing alternative r conditional on lifestyle i.

$$Pr(y_{nt}^1 = j|q_{nt} = i; \beta_{choice}) = \beta_{choice,i}^j \tag{5.7}$$

For continuous travel behavior y^2 such as VMT, we assume $\eta_{y_{nt}^r|q_{nt}^i}$ to be i.i.d. Gaussian across individuals, time periods, choices, alternatives, and lifestyles. The probability is now given by

$$Pr(y_{nt}^2|q_{nt} = i; \beta_{choice}) = \frac{1}{\sqrt{2\pi}\sigma_i^2} e^{-\frac{(y_{nt}^2 - \beta_{choice,i})^2}{2\sigma_i^2}} \tag{5.8}$$

where y_{nt}^2 denotes one continuous travel behavior for individual n at time t, and $\beta_{choice,i}$ and σ_i denote its corresponding coefficient (mean) and standard deviation, conditional on lifestyle i, respectively.

Initial condition problem

Initial condition problem is a common and challenging problem when we deal with individual-level longitudinal data, which first gets attention in [55]. It arises when the initial observations are missing in the panel since the dynamic process started. That is, the first observation we captured in the panel is a choice happened in the middle of this dynamic process, which has already been influenced by the past experience. Since this past experience (which is captured by error components persistent over time) is unobserved by the researchers, the error terms will be correlated with the observed choices and cause endogeneity problem. This may lead to inconsistent parameter estimation and erroneous interpretation of the choice.

Under the Hidden Markov Markov framework, the proposed model framework stated above circumvent the initial condition problem from the following perspectives. First, the error components in the choice models, $\eta_{y_{nt}^r|q_{nt}^i}$ in Equation (5.5), are assumed to be serially independent, which implies that the initial condition is exogenous theoretically. [39] provides a concise proof in Section 5. Second, different studies have explored various approaches to capture unobserved heterogeneity. For example, [75] and [104] parameterize the unobserved heterogeneity by assuming an auxiliary distribution of initial condition and time-varying independent variables. In the proposed heterogeneous HMM model, the specification of initial lifestyle model and transition models play a similar role of allowing for unobserved heterogeneity on initial states and carry over time periods. Equations (5.1) and (5.3) aim to capture the time-varying individual variables through lifestyles. Third, the life trajectory data we collected from the retrospective survey stated in Section 5.2 can be assumed to start from the first observation (age being 20).

Estimation

Based on the model specification, there are three groups of unknown parameters under the proposed framework: initial model parameters (β_{init}), transition model parameters (β_{trans}), and choice model parameters (β_{choice}). The likelihood function for T time stamps, N individuals, and S life styles is thus given by Equation (5.9). We provide one discrete choice and one continuous choice as an example.

$$
\begin{aligned}
L(\beta_{init}, \beta_{trans}, \beta_{choice\_1,\beta_{choice\_2},\beta_{choice\_3}}) = \prod_N \sum_S \{ & Pr(q_{n1}|Z_{n1}, X_{n1}, I_1; \beta_{init}) \cdot \\
& \Pi_{t=1}^{T} Pr(q_{n(t+1)}|q_{nt}, Z_{nt}, X_{nt}, I_t; \beta_{trans}) \cdot \\
& \Pi_{t=1}^{T} Pr(y_{nt}^1|q_{nt}; \beta_{choice}) \cdot Pr(y_{nt}^2|q_{nt}; \beta_{choice}) \}
\end{aligned} \tag{5.9}
$$

An expectation-maximization (EM) algorithm ([19]) is used to maximize the log-likelihood and estimate these parameters. EM algorithms are a widely used approach to estimate standard HMM, and consist of two steps.

$$
\begin{aligned}
Q(\theta', \theta) &= \mathbb{E}_{p(s|y,\theta')[\ln p(y,s|\theta)]} \\
&= \sum_{i=1}^{S} \gamma_{i,1} \ln P(s_1 = i; \theta_{init}) \\
&+ \sum_{t=2}^{T} \sum_i \sum_j \xi_{ij,t} \ln P(s_t = j, s_{t-1} = i; \theta_{trans}) \\
&+ \sum_{t=1}^{T} \sum_i \gamma_{i,t} [\ln P(y_t^1|s_t = i; \theta_{choice,i}^1) + \ln P(y_t^2|s_t = i; \theta_{choice,i}^1) + \ln P(y_t^3|s_t = i; \theta_{choice,i}^1)]
\end{aligned} \tag{5.10}
$$

The E step computes the expected complete log-likelihood (denoted by Equation (5.10)), given the parameters, using forward-backward recursion. The M step updates the parameters by maximizing the expected value. The meaning of each variable is shown in Table 5.1. The estimation algorithm is presented Algorithm 2 and its corresponding code is published online in "https://github.com/MengqiaoYu/DynamicLCCM".

Algorithm 2: Estimate extended HMM with multiple discrete and continuous choices

```
Result: θ_init, θ_trans, θ_choice_1, θ_choice_2, θ_choice_3
Initialization.;
while not converge: |LL_{t+1} − LL_t| < 10^{−5} do
    E step:;
    for each timestamp do
        for each hidden state do
            calculate α_{i,t}, β_{i,t}, γ_{i,t}, ξ_{ij,t} ;
        end
    end
    M step:;
    Update θ_init using equation;
    for each state do
        Update θ_trans using equation ;
        Update θ_choice_1, θ_choice_2, θ_choice_3 using equations ;
    end
    Update LL_{t+1} and LL_t. ;
end
```

	standard HMM	joint choice heterogeneous HMM model
Life events	✓	✓
Policies and economics environment	×	✓
Travel behaviors	Mode Choice	Discrete and Continuous Joint Choice
initial state probability π_i	$\mathrm{P}(s_1 = i)$	
transition probability $\psi_{ij,t}$	$\mathrm{P}(s_t = j \mid s_{t=1} = i)$	
choice probability $\delta_{i,t}$	$\mathrm{P}(y_t \mid s_t = i)$	$\mathrm{P}(y_t^1 \mid s_t = i) \cdot \mathrm{P}(y_t^2 \mid s_t = i) \cdot P(\mathrm{y}_t^3 \mid s_t = i)$
forward variable $\alpha_{i,t}$	$\mathrm{P}(y_1, ..., y_t, s_t = i)$	$\mathrm{P}(\begin{bmatrix} \mathrm{y}_1^1 \\ \mathrm{y}_1^2 \\ \mathrm{y}_1^3 \end{bmatrix}, ..., \begin{bmatrix} y_t^1 \\ y_t^2 \\ y_t^3 \end{bmatrix}, \mathrm{s}_t = i)$
backward variable $\beta_{i,t}$	$\mathrm{P}(\mathrm{y}_{t+1}, ..., y_T \mid s_t = i)$	$\mathrm{P}(\begin{bmatrix} y_{t+1}^1 \\ y_{t+1}^2 \\ y_{t+1}^3 \end{bmatrix}, ..., \begin{bmatrix} y_T^1 \\ y_T^2 \\ y_T^3 \end{bmatrix} \mid s_t = i)$
log-likelihood L	$\mathrm{P}(y_1, ..., y_T)$	$\mathrm{P}(\begin{bmatrix} \mathrm{y}_1^1 \\ \mathrm{y}_1^2 \\ \mathrm{y}_1^3 \end{bmatrix}, ..., \begin{bmatrix} y_T^1 \\ y_T^2 \\ y_T^3 \end{bmatrix})$
state marginal probability $\gamma_{i,t}$	$\mathrm{P}(\mathrm{s}_t = i \mid y_1, ...y_T)$	$\mathrm{P}(\mathrm{s}_t = i \mid \begin{bmatrix} \mathrm{y}_1^1 \\ \mathrm{y}_1^2 \\ \mathrm{y}_1^3 \end{bmatrix}, ..., \begin{bmatrix} y_T^1 \\ y_T^2 \\ y_T^3 \end{bmatrix})$
pairwise state probability $\xi_{ij,t}$	$\mathrm{P}(\mathrm{s}_t = i, s_{t+1} = j \mid y_1, ...y_T)$	$\mathrm{P}(\mathrm{s}_t = i, s_{t+1} = j \mid \begin{bmatrix} \mathrm{y}_1^1 \\ \mathrm{y}_1^2 \\ \mathrm{y}_1^3 \end{bmatrix}, ..., \begin{bmatrix} y_T^1 \\ y_T^2 \\ y_T^3 \end{bmatrix})$

Table 5.1: Highlights of standard HMM and HMM extensions

5.4 Model Set-Up and Results

Model set-up

In our WholeTraveler case study, the three components of the proposed model framework (initial model, transition models, and choice models) are specified according to the data set, which will be discussed in the following subsection.

We have five choice models based on the data we collect in the survey; they are regularly using public transit (binary), using personal vehicle (binary), walking/biking (binary), using ridehailing (binary), and number of vehicles (0, 1, and ≥ 2 vehicles). Since the attributes associated with each choice are not available, we simplify the choice models as Equation 5.7. The values of the coefficients, i.e., constants, are converted into probabilities of choosing alternatives for interpretation convenience. The results of the five choice models are shown as Table 5.2.

For the initial model, we simplify it by setting each utility function as a constant with several considerations. First, all the respondents in the retrospective survey start at age 20 years old, therefore age cannot be added to the initial model. Second, other life stage variables in the data set including marriage, child birth, employment, education nearly has no variance at age 20, and cannot be estimated based on our exploration. After simplification, the initial model may represent the initial probabilities of each lifestyle. The results are shown in Table 5.3.

For the transition models that quantify the evolution between different life styles include four life stage variables, age, generation, and three social and economic environment variables. The four life stages are "in school", "with a partner", "with a young child", and "employed". We differentiate "with a young child" above 30 and over 30 to capture the higher-order relationship between age and life stage. Similar treatment is done to "with a young child". We also add the square of "age" variable and interaction between "age" and "generation". It is worth mentioning that we have tried different transition model specifications such as no interaction term or second order term, and the final specification shown in Table 5.4 and 5.5 is our best model. The best model is determined by both goodness-of-fit and parameter interpretation. As for social and economic variables, we include annual internet percentage, annual unemployment rate, and gas price in 2008 dollars. We cannot add period (i.e., year) into the model since it would be perfectly correlated with age and cohort (i.e, generation). Adding these environment variables can also be regarded as setting instrumental variables of period. We scale each variable for better estimation stability, for example, we divide age by 10, multiply internet penetration rate by 10, and multiply unemployment rate by 100. The estimation results of the transition models are presented in Table 5.4 and 5.5. It includes four sub-models that each is a multinomial logit, and the base of each sub-model is "Auto-Oriented-2-veh" style. Each sub-model represents how the individuals would stay in current lifestyle or transition to other lifestyles conditional on current lifestyle.

The final model yields four lifestyles. ***Note that the lifestyle generated from this WholeTraveler case study is more akin to the concept of mobility style since***

	Auto-oriented-2-veh	Auto-oriented-1-veh	Multimodals	Auto-free
vehicle Ownership Model probability				
0 vehicle	0.001***	0.062***	0.078***	0.421***
1 vehicle	0.001***	0.934***	0.581***	0.343***
$\geq$ 2 vehicles	0.998***	0.004***	0.342***	0.235***
Use Own vehicle probability				
Use	0.981***	0.974***	0.384***	0.004***
Use public transit probability				
Use	0.064***	0.090***	0.476***	0.552***
Use walk/bike probability				
Use	0.005***	0.007***	0.988***	0.369***
Use ride-hail service probability				
Use	0.019***	0.026***	0.079***	0.026***

Table 5.2: Estimation Results (1): Choice Models

	Auto-oriented-2-veh	Auto-oriented-1-veh	Multimodals	Auto-free
probability	0.094***	0.177***	0.086***	0.643***

Table 5.3: Estimation Results (2): Initial Model

the five choices here are highly related with mobility. However, in this paper, we focus more on the flexibility of this model framework, and do not explicitly differentiate these two concepts. We will use lifestyle for the rest of result analysis. A summary of goodness-of-fit measures are shown in Table 5.8. In the following subsections, we will first analyze the multi-dimensional behavior differences between these lifestyles based on Tables 5.2 through 5.5. We also provide detailed discussion on the age and generation composition of each lifestyle, and explicitly investigate the transition mechanism among them. We conduct sensitivity analysis of how the changes in fuel price and unemployment rate might influence the trend of each lifestyle.

Model Results I: Four Lifestyles

The four lifestyles are identified based on a combined interpretation from Table 5.2 to 5.5. We describe them as follows.

Auto-oriented-2-veh. As the name implies, individuals belonging to this lifestyle usually own at least two vehicles and use their own vehicles for as much as 99% of their daily travel. They shun other modes of transport, which can be inferred from the low probabilities of using public transit (0.064), walk/bike (0.005), and ride-hail service (0.019) in the first column of Table 5.2. From the life stage perspective, being in school may motivate them to transition to AO-1-veh since "being in school" parameter is positive and significant of AO-2-veh model (−>AO-1-veh) in Table 5.4. In contrast, the negative signs of "with a

Auto-Oriented-2-veh (AO-2-veh)			
	-> Auto-Free	-> MultiModals	-> AO-1-veh
age (millennial)	-1.489	-0.886	-1.488
age (genX)	-1.924	-1.674**	-1.948*
age (boomer)	-4.953*	-4.733***	-3.731**
age^2$(millennial)$	0.375	0.284*	0.395
age^2$(genX)$	0.376	0.368***	0.393*
age^2$(boomer)$	1.014**	1.018***	0.767***
in school	0.052	0.069	0.056**
with a partner (under30)	-0.108	-0.223	-0.092
with a partner (above30)	-0.419*	-0.381***	-0.506*
with a young child (under30)	-0.118	-0.101	-0.068
with a young child (above30)	-0.202	-0.223*	-0.198
employed	-0.002	-0.014	0.043
internet penetration rate	0.338**	0.41***	0.205***
unemployment rate	-0.473***	-0.535***	-0.427***
gas price	0.038	-0.010	0.122

Table 5.4: Estimation Results (3-1): Transition Models

partner (above 30)" and "with a young child (above 30)" reveal that once a individual falls in this lifestyle, they are less likely to evolve to other lifestyles except when they are married or their children grow up. The impact of age on the transition model is not monotonic since the signs of first-order age and second order age are opposite. To provide a more intuitive interpretation, we plot the trend of each lifestyle over age in Figure 5.5. We will give more trend analysis in the next subsection. Internet penetration rate can be seen as an indicator of time period, and the positive sign of its coefficient implies a trend of owning less vehicles and embracing multi-modals. In response to the increasing fuel price, these auto-oriented-2-veh individuals are inclined to transition to other three lifestyles from Table 5.4, i.e., reduce vehicle use and number of vehicles while increase the use of other transport modes. As the unemployment rate decreases, i.e., the economy gets better, they may also consider other lifestyles; however, the parameters associated with unemployment rate are so negative (-0.473, -0.535, -0.427 in Table 5.4) that the auto-oriented-2-veh individuals still have a high probability of staying in current style. As for gas price, we observe that its coefficients are all small and insignificant. One reason is that the variance of gas price over years is very small (i.e., little fluctuation) after we adjust it for inflation, and the model cannot estimate its impact anymore. Similar phenomenon happens to other three transition models.

Auto-oriented-1-veh. People in this group behave similarly with auto-adherent-2-veh in the heavy use of their own vehicles and rare use of other modes as shown in Table 5.2; the only difference is that they are more likely to own one vehicle but not two or more vehicles. When starting to live with a partner, people in this group are more likely to add a vehicle and

Auto-Oriented-1-veh (AO-1-veh)			
	-> Auto-Free	-> MultiModals	-> AO-1-veh
age (millennial)	0.186	0.673	1.257*
age (genX)	-0.104	0.008	1.415*
age (boomer)	-0.729*	-1.674*	1.136
age^2$(millennial)$	-0.025	-0.13	-0.319*
age^2$(genX)$	0.038*	0.035*	-0.278
age^2$(boomer)$	0.169*	0.397***	-0.236*
in school	0.047	-0.005	0.011
with a partner (under30)	-0.081**	-0.258*	-0.75**
with a partner (above30)	-0.062**	-0.075*	-0.442**
with a young child (under30)	0.001	0.149	-0.248
with a young child (above30)	-0.016	-0.001	-0.059
employed	-0.099*	-0.008	0.067*
internet penetration rate	0.058**	0.361*	-0.097*
unemployment rate	-0.061***	-0.127***	0.291*
gas price	0.011	-0.209	0.018

Table 5.5: Estimation Results (3-2): Transition Models

evolve to auto-oriented-2-veh group (negative and significant coefficients of "with a partner (under30)" and "with a partner (above30)" from Table 5.5). Being employed either reinforces their staying at current lifestyle (single vehicle) or triggers the transition to auto-oriented-2-veh style. However, being in school and having young child in home have little effect (insignificant and small values of coefficients) on their transition models; i.e. they continue to own only one vehicle, and do not use the other travel modes. In terms of the response to environment variables, better economy (reduction in unemployment rate) would drive individuals either to stay in current auto-oriented-1-veh lifestyle or evolve to auto-oriented-2-veh style. The coefficients of internet penetration rate emphasize a similar finding from auto-oriented-2-veh style, i.e., the trend of more multi-modals over time.

Auto-free. Opposite to the two auto-oriented styles, the auto-free individuals rarely use their own vehicle (with 0.004 probability in the last column of Table 5.2) even though 57.8% of them own at least a vehicle and 23.5% with two or more vehicles. And the name of "auto-free" can be interpret as rarely using vehicles. These auto-free people prefer to take public transit (0.552 probability) highest of the four lifestyles, followed by walk/bike (0.37 probability). From Table 5.3, 63% of the people belong to this lifestyle at age 20, and the share gradually declines to 23% until age 46. For all three generations, as the age increases, they present a strong inclination (more negative and significant coefficients in 5.6) to abandon current lifestyle and transition to the other three ones. Being in school, with a young child under 30 and being employed also help accelerate this transition. With a partner under 30 may trigger the transition to AO-1-veh nad AO-2-veh, which implies

Auto-free (AF)			
	-> Auto-Free	-> MultiModals	-> AO-1-veh
age (millennial)	2.718**	0.423	-0.405
age (genX)	2.28***	0.181	-0.38
age (boomer)	2.435***	-1.096*	-0.494*
age$^2(millennial)$	-0.682***	-0.094	0.061
age$^2(genX)$	-0.436***	-0.026*	0.047
age$^2(boomer)$	-0.481***	0.238**	0.056*
in school	-0.147*	0.155*	0.166*
with a partner (under30)	-0.601	-0.432	-0.407**
with a partner (above30)	-0.094	-0.078	-0.06
with a young child (under30)	-0.497*	-0.014	-0.156
with a young child (above30)	0.086	-0.034	-0.126
employed	-0.086**	0.039	0.005
internet penetration rate	-0.208***	0.038*	-0.178**
unemployment rate	0.452***	-0.016*	0.079***
gas price	-0.188	-0.111	-0.007

Table 5.6: Estimation Results (3-3): Transition Models

adding vehicles. The influence of internet penetration rate is the same with the above two lifestyles. In bad economy time when unemployment rate increases, the individuals would be more likely to stay in auto-free style from the big positive and significant value (0.452) in table 5.6.

Multimodals. In the middle of two auto-oriented styles and auto-free are multimodals who own at least one vehicles and would use all travel modes: most likely walk/bike (0.988 probability) followed by public transit (0.476 probability) and personal vehicle (0.384 probability) shown in Table 5.2. Moreover, the multimodals are most likely to use ride-hailing service among the four individual types (0.08 probability). Being with a partner under 30 would provoke them to transition to AO-1-veh and AO-2-veh styles, which means more vehicle use and less public transit. Adding a young child under 30 would push individuals to transition to other lifestyles (-0.079* in table 5.7) while we cannot draw a concrete conclusion of which specific one they switch to due to the insignificance of the coefficients (0.074 and 0.005). Meanwhile, an increase in unemployment rate would reinforce the lifestyle of multimodals and they are more likely to transition to auto-free than AO-1-veh and AO-2-veh in bad economy period.

Model Results II: Model Goodness of Fit

We also pay attention to the model goodness of fit. We use two statistics, log-likelihood and Bayesian Information Criterion (BIC) which penalizes larger number of coefficients ([90]), as

Multimodals (MM)			
	-> Auto-Free	-> MultiModals	-> AO-1-veh
age (millennial)	-0.072	1.198**	0.21
age (genX)	-0.007	1.217**	0.226
age (boomer)	-0.959*	1.893***	-0.597
age^2($millennial$)	-0.004	-0.306***	-0.028*
age^2($genX$)	-0.013*	-0.239***	-0.031*
age^2($boomer$)	0.186**	-0.402***	0.127*
in school	-0.23	-0.053	-0.102
with a partner (under30)	-0.19*	-0.354**	-0.186*
with a partner (above30)	-0.016	0.061	-0.052
with a young child (under30)	0.074	-0.079*	0.005
with a young child (above30)	-0.073	0.093	-0.032
employed	-0.035*	0.08*	0.034
internet penetration rate	0.195	-0.264***	-0.11*
unemployment rate	0.057**	0.351***	0.021***
gas price	-0.225	-0.039	0.034

Table 5.7: Estimation Results (3-4): Transition Models

criteria to evaluate the model performance. We compare the final model with 3-style, 5-style dynamic model, and the 4-style model shows the best BIC and reasonable interpretation results.

	Num of Coef.	log-likelihood	BIC
3-style multi-dimensional dynamic	105	-37201.18	67105.93
4-style multi-dimensional dynamic	196	-34147.67	61608.68
5-style multi-dimensional dynamic	335	-29732.71	61689.77

Table 5.8: Estimation Results (4): Comparison between different models

Model Results III: Trend Analysis

The dynamic model framework empowers us to analyze the evolution of each lifestyle from two key perspectives: age and period. In this subsection, we will present the trend of four lifestyles over age and period based on the prediction results from the estimation tables we just discussed.

Age

Figure 5.5 shows the share of four lifestyles from age 20 to 50. From this figure we can observe that the share of auto-oriented-2-veh in the sampled population gradually increases until age 42 with the share up to 43%, and it sharply goes down after that. Note that such an up-and-down trend is the result of the joint effect of age and life stages. On the contrary, 64% of individuals are auto-free at age 20, with the fraction consistently decreasing until age 45 when it levels off. The share of auto-oriented-1-veh is relatively stable at 20% across all individual ages. The fraction of multi-modal individuals increases slightly from 9% at age 20 to 12% at age 40, then increases substantially to 20 percent by age 50. These trending lines are consistent with our expectation since people in their 30s are the group who rely heavily on vehicles with the constraint of individuals needs (suburban residence and school-age children). Compared with auto-oriented-2-car and auto-free, the share of auto-oriented-1-car and multi-modals are more resilient and stable among the sampled population.

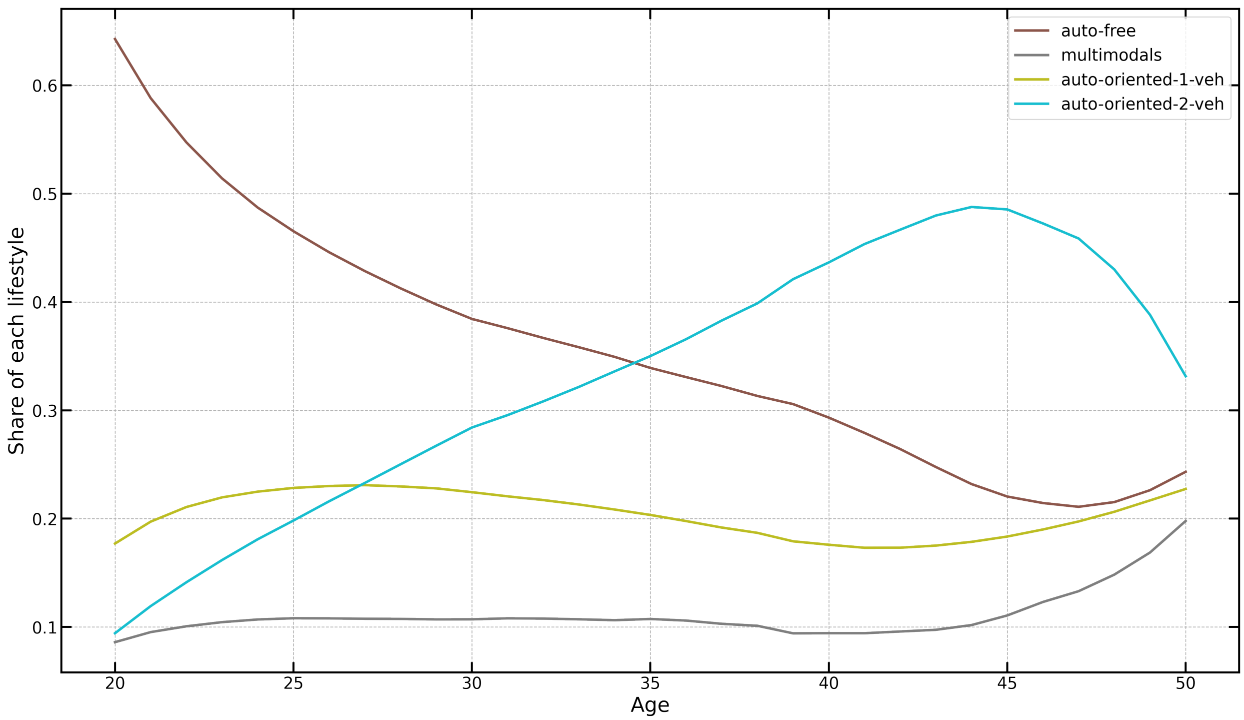


Figure 5.5: Evolution of lifestyles over age

Cohort

As the estimation results imply, the generation, i.e., the cohort effects largely contributes to the transition of classes. Figure 5.6 can help us understand the difference between three generations. One thing deserves to point out is that the proposed model framework resolves the identification problem embedded in age-period-cohort effects by adding instrumental variables such as fuel-price, unemployment rate, internet users rate to replace period variable.

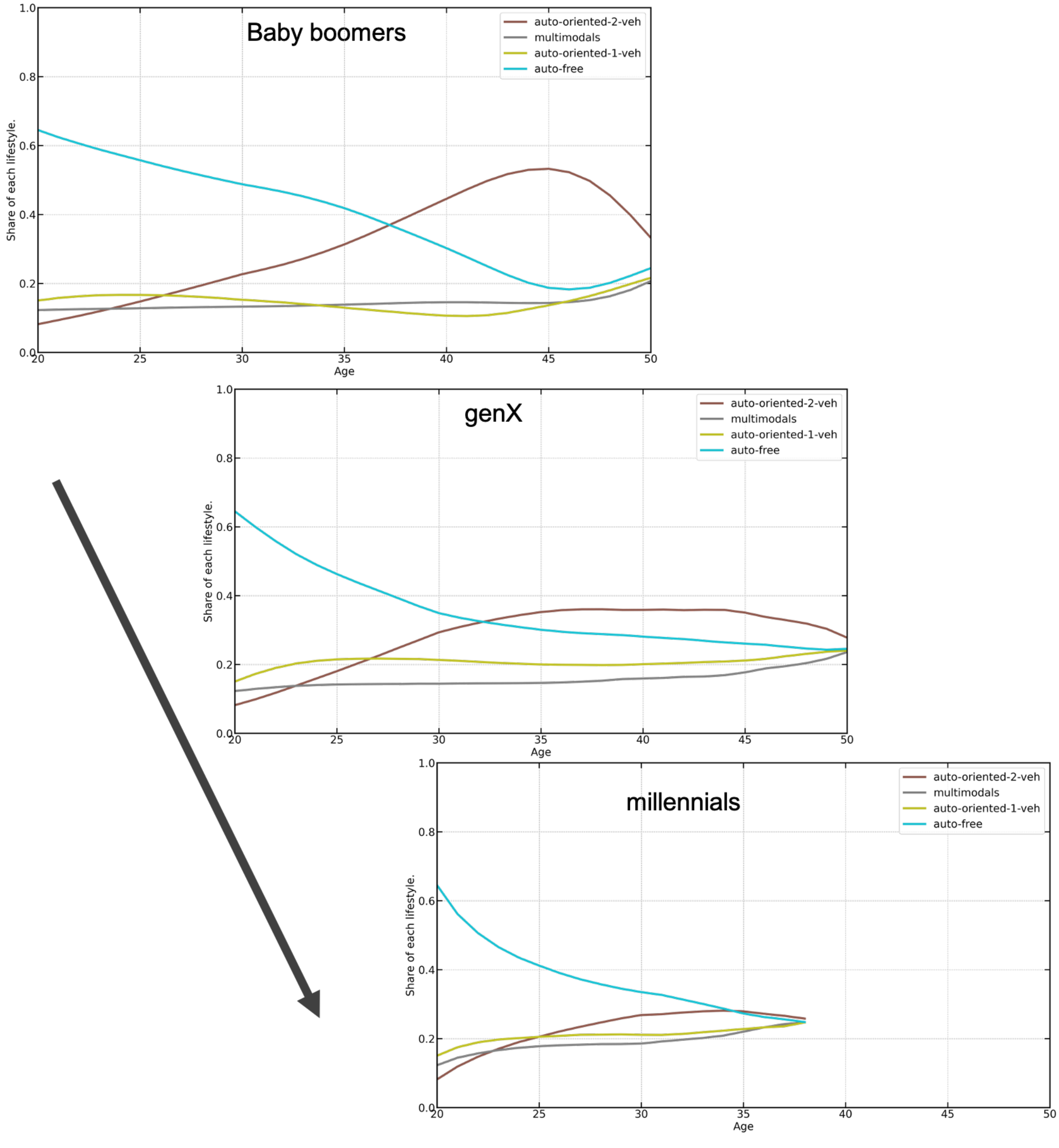


Figure 5.6: Evolution of lifestyles over three generations: baby boomers, genX, and millennial

We observe that GenX individuals are less likely to transition to more than one personal vehicle, and more likely to transition away from vehicle-free, than Baby Boomer individuals, but have roughly the same transition pattern to one personal vehicle and multi-modal lifestyles. Surprisingly, Millenial individuals are much less likely to go vehicle free after age 20 than GenX individuals, and are less likely to transition to more than one personal vehicle, and more likely to transition to only one personal vehicle and multimodal lifestyles at earlier ages than GenX individuals.

Time Period

We also plot the trend of each class from 1971 to 2018 (Figure 5.7).

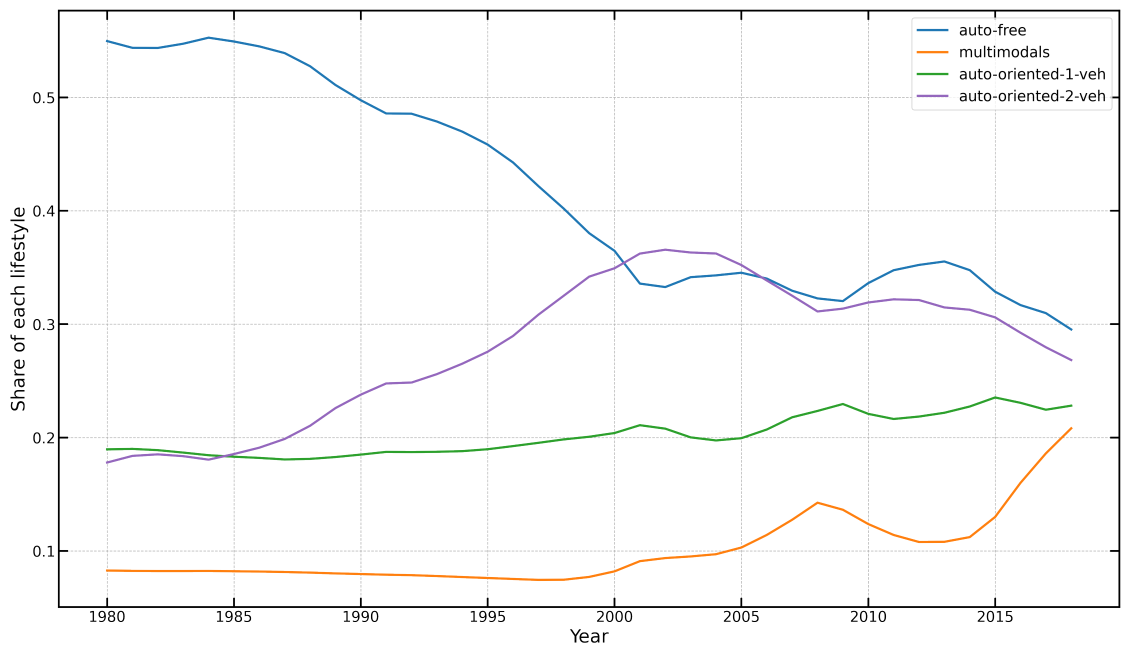


Figure 5.7: Evolution of lifestyles over time period (year)

Generally speaking, before 2000, the share of "auto-free" declines over years while the "auto-oriented-2-veh" style increases, while there is little change in the fraction of "multimodals" and "auto-oriented-1-veh" lifestyles. After 2000, the four lifestyles didn't show a monotonic trend pattern and usually fluctuated within a certain interval respectively. We observe that the up-and-downs along the evolution trends over years are consistent with the several past economic recessions. The 1973 oil crisis, coupled with the 1973–1974 stock market crash led to a stagflation recession in the United States. Therefore, the share of "auto-free" in the population rose and the increasing trend of "auto-oriented-2-veh" reached a plateau. Similar phenomenon happened after 1980 recession. The evolution flows are generally smooth over the years except some particular periods such as the dot come bubble and 2008 economic recession. The signs of unemployment rate, which also implies the economics situation, in the transition model also show that the bull market would stimulate multi-modals and auto-adherents while discourage auto-antagonists.

Figure 5.7 clearly delineates that the trends of four classes began to frequently reshuffle after 2004 compared with the more linear situation before that. The share of individuals with more than one personal vehicle essentially levels off, and the decline in vehicle-free individuals becomes much more gradual, after 2000. The share of individuals with only one personal vehicle begins to increase after 2005, perhaps in response to the economic recession, while the share of multimodal individuals increases from 6% in 2000 to over 20% by 2018, with an unexplained dip between 2009 and 2016. That dip could have been caused by pent-up demand for personal vehicles which was suppressed by the economic recession between 2008 and 2010, while the large increase in multimodal individuals from 12% in 2014 to over 20% by 2018 could have been caused by the increasing use of public transit and ridehail services by these individuals.

Model Results IV: Sensitivity Analysis

To fully explore the policy implications of the proposed model framework, we also conduct sensitivity analysis for policy-related variables.

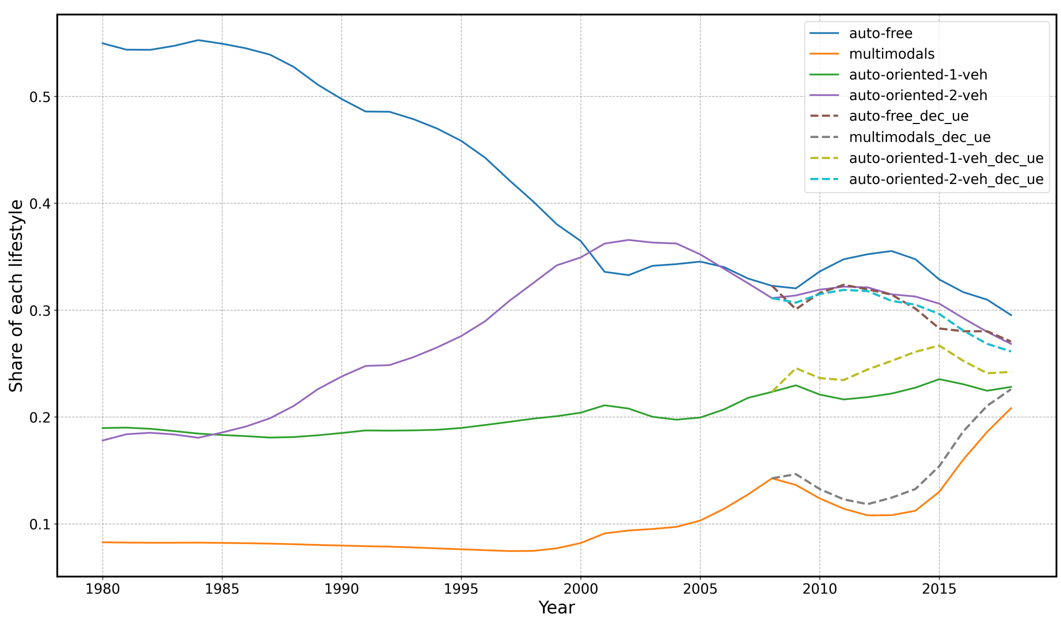


Figure 5.8: Sensitivity analysis of unemployment rate

From model estimation results in Table 5.4 - 5.7, we have concluded that the parameters associated with gas price in all transition functions are not significant so that the sensitive analysis of gas price is also not as useful as the unemployment rate one. Therefore, we conduct sensitivity analysis of annual employment rate only via decreasing it by 20% since 2008. The before-after comparison is shown in Figure 5.8.

From aggregation level, we observe that better economic condition (i.e., lower employment rate) indicates higher share of "multimodals" (from 20.4% to 22.6%) and higher share of "auto-oriented-1-vehicle" lifestyle (from 22.7% to 24.5%) in the 10-year horizon. At the same time, "auto-free" lifestyle is impacted the most by its share decreasing by 3.6% (from 29.7% to 26.1%). Such a finding is reasonable since lower unemployment rate means more earnings per households in average and low-income households would have more money to afford a vehicle. Note that we do not have enough data to support the income information within each lifestyle and all the interpretation is based on our experience and common sense.

Interestingly, "auto-oriented-2-vehicle" lifestyle is quite stable in the 10-year period with its share nearly being at the same level as the one before the change. This implies that better economic condition has little impact on the travel pattern of "auto-oriented-2-vehicle" group which might be mainly from high-income households. And this can be well explained by the definition of this lifestyle: they have already had two or more than two vehicles and heavily rely on them; better economic condition does not contribute to their transition to a more "auto-oriented" and more vehicle lifestyle.

In a nutshell, the sensitivity analysis verifies how the turbulence of economics-related factors or other external variables could influence the trend of each lifestyle. The results also imply that behavioral change, especially the change of lifestyle, is a long-term process that may require years or even generations to achieve gradual adjustment.

5.5 Conclusion

Understanding behavioral changes and distinguishing population groups by their different behavior change in response to external and internal changes have been widely explored and investigated in travel demand management. This section focuses on backward-looking dynamic models by first summarizing several key concepts of existing relevant studies: external dynamics such as economics, policy and transportation infrastructure, internal dynamics such as key life events, and higher-level internal dynamics such as transitions of lifestyle and mobility style.

We then point out two missing blocks of the current backward-looking dynamic framework: (a) lack of multi-dimensional interrelated travel behavior; and (b) lack of a unified model framework that consolidates all of these factors into one system. We extend current single-dimensional heterogeneous Hidden Markov Model to a multi-dimensional one with joint choice (both discrete and continuous) and derive its estimation method to learn the parameters and co-variance matrix.

Our empirical results from a retrospective survey conducted in San Francisco Bay Area highlight three key findings.

- We observe four different lifestyles: "auto-oriented-2-veh" lifestyle represents those who usually own at least two vehicles and use their own vehicles for as much as 99% of their daily travel while they shun other modes of transport; "Auto-oriented-1-veh" people behave similarly with "auto-oriented-2-veh" group in the heavy use of their own vehicles and rare use of other modes but they are more likely to own one vehicle; "Auto-free" lifestyle belongs to those who rarely use their own vehicle even though 57.8% of them own at least a vehicle; "Multimodals" are in the middle of two auto-oriented styles and auto-free style who own at least one vehicle and would use all travel modes.

- In trend analysis, we find that the generation factor plays an important role of lifestyle transitions. For example, millenials are more likely to transition to only one personal vehicle and multimodal lifestyles at earlier ages than GenX individuals; the share of four lifestyles over age shows a "fish-like" shape where "auto-oriented-2-veh" is the back of the fish whose share gradually increases until age 42 and sharply goes down after that. The share of "auto-oriented-1-veh" is relatively more stable and resilient compared with "auto-oriented-2-veh" across all individual ages At 20%. The fraction of multi-modal individuals becomes the abdomen of fish which increases slightly from 9% at age 20 to 12% at age 40, then increases substantially to 20 percent by age 50. The share of "auto-free" style is the tail of the fish which keeps going down as age increases.

- In sensitive analysis, by decreasing annual unemployment rate by 20%, we observe that better economic condition (i.e., lower employment rate) indicates higher share of "multimodals" (from 20.4% to 22.6%) and higher share of "auto-oriented-1-vehicle" lifestyle (from 22.7% to 24.5%) in the 10-year horizon. At the same time, "auto-free" lifestyle is impacted the most by its share decreasing from 29.7% to 26.1%.

Chapter 6

Conclusion

"The only way to make sense out of change is to plunge into it, move with it, and join the dance."

(Alan Watts)

6.1 Findings and Contributions

Travel behaviors world-wide are experiencing a rapid change in recent years. People change their travel patterns in a much faster pace than before in order to adapt to the fast-changing world where Uber/Lyft, shared scooter and bicycle, online shopping, work-from-home, and many other emerging new concepts keep shaping our lives. At the same time, large-scale but potentially less detailed big data becomes more accessible to the public than ever. Our research on dynamic travel behavior analysis needs to take a prompt action, too!

Among it, incorporating dynamics of travel behavior and its property of interrelated multi-dimensionality in travel behavior models are of vital importance for us researchers to understand the trends of population travel pattern and extrapolate their future short-term and long-term choices. At the same time, it also assists transportation planners and policy makers to produce more sustainable behaviors and improves economy, environment, living condition and safety.

To achieve this, this dissertation classifies the dynamic travel behavior models into two categories: forward-looking and backward-looking and the difference between them is whether future expectations are being considered or not in the decision-making process.

As for forward-looking model framework, this dissertation explores the new potentials and feasibility of the Inverse Reinforcement Learning framework from artificial intelligence world to model households' long-term sequential decision making process.

- We extend the IRL framework to accommodate heterogeneous household behaviors and household dynamics.

- We provide an in-depth comparison between IRL approach and the dynamic discrete choice model (DDCM) in economics (a traditional framework to deal with dynamics), from four perspective: terminologies, assumptions, model structures, and empirical results. And the comparison shows that IRL can circumvent the multiple assumptions made in the DDCM framework, including optimal human behavior, conditional independence, and extreme value distribution.
- We develop a maximum-entropy based recursive learning algorithm to estimate the proposed model framework and validated its feasibility and robustness with large-scale (around 5 million) longitudinal moving trajectories data set.
- The empirical results are three-fold. First, all the households have a positive preference to locate in areas with higher degree of land-use mix, higher accessibility to jobs, and lower employment density; our model also shows that low-income households focus more on current needs and are less forward-looking compared with households with higher income level; low-income households present less willingness to pay for neighborhood amenities such as land-use mix and accessibility to jobs.
- In terms of goodness of fit, our proposed model outperforms the DDCM model (for high-income and low-income households), myopic model and the static model.

As for backward-looking model framework, we extend the single discrete choice HMM framework to joint choices with discrete and continuous types, and derive its recursive parameter learning algorithm.

- Building on this framework, we propose a unified model that conjoins lifestyle, life events, external environment, and multi-dimensional travel behavior dynamics.
- We provide a comprehensive analysis of four different mobility styles and their travel behavior differences from a case study in San Francisco Bay Area.
- We identify four latent lifestyles (auto-oriented-2-car group with rare use of other travel modes, auto-oriented-1-car group with rare use of other travel modes, multi-modals group that own at least one car, and auto-free group that have the lowest car ownership and car usage). The results highlight how life events, policies, and the economic environment might influence people to transition between these mobility styles. To fully explore the potential of the extended joint HMM framework, we provide trend analysis of car ownership and mode use based on estimation results, and conduct sensitivity analysis of changes in fuel price and the unemployment rate.

6.2 Future Direction

The worlds of economics and artificial intelligence rarely reference each other. Needless to say, each approach has its own strengths and weaknesses; our focus is not to conclude which one is preferable, but to provide a novel approach to modeling dynamic behavior relevant to transportation research and show their similarities and differences in solving a real-world dynamic travel behavior problem. This work can be used as a starting point for more exploratory work, including:

- Further explore about how to establish a more flexible reward function and transition matrix under the IRL framework.
- Further explore more efficient recursive learning algorithm to estimate the model with full household internal dynamics and external environment dynamics
- How to incorporate the concept of lifestyle or other latent variables into the IRL framework, among others.
- How to conduct a comprehensive comparison between different HMM frameworks, including joint HMM model, isolated HMM model and a static joint latent class choice model.
- Utilize large-scale longitudinal data to validate the feasibility and robustness of the proposed heterogeneous HMM model with joint choices.
- How to incorporate second-order Markov process (i.e., decision at time T is dependent on the hidden states on $T-1$ and $T-2$) into the proposed unified model framework.
- Exploration on combination of short-term backward-looking behavior with long-term forward-looking behavior in one model framework.

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