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From Trend Spotting to Trend Setting: Modeling the Impact of Major Technological and Infrastructural Changes on Travel Demand

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Walker, Joan

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16. ABSTRACT
 Major technological and infrastructural changes are expected to occur over the next decades such as the introduction of autonomous vehicles, advances in information and communication technology, California High Speed Rail, carsharing and ridesharing, etc. However, this evolution has no defined path and we should be cautious with how the future is going to play out. We want the future to consist of sustainable and efficient systems. One critical component in this strategy comprises developing quantitative behavioral analysis tools that focus on modeling and influencing trends of travel behavior to guide transformative mobility and set it on the right track. Moreover, the potential roles of the government and policy are key in shaping and influencing the future. This could be achieved by developing quantitative methods that offer insights to planners and policy-makers on what can be done to influence possible outcomes. In order to tackle and address the general research questions we are interested in, we have addressed three specific components regarding developing the methodological framework:
 1- Projecting membership and market shares of upcoming modes of transport. Developing such a framework will be based on integrating models of technology adoption and discrete choice analysis (Paper #1).
 2- Understanding and predicting structural long-range trends of travel behavior. Developing such a dynamic framework of disaggregate decision-making will require integrating hidden markov models (HMM) with current travel demand models (Paper #2).
 3- While the first two components focus on developing quantitative behavioral analysis tools to guide transformative mobility to ensure a sustainable and efficient system, we also investigate the adoption and diffusion processes in light of economic theory and its pertinent literature.

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EXECUTIVE SUMMARY

INTRODUCTION

This is the final deliverable for UC Connect project “From Trend Spotting to Trend Setting: Modeling the Impact of Major Technological and Infrastructural Changes on Travel Demand” (Contract No. 65A0529). This deliverable entails three components. The first two components comprise two journal articles based on the research performed in the project that will be submitted for publication in the next couple of months. The third component is a brief draft report that begins to lay out basic principles of what we can learn from the literature of technology adoption with respect to autonomous vehicles. The research motivation behind this project comprises defining a methodological framework tailored to address impacts of technological innovation to understand and predict long-range trends in travel behavior.

The behavioral analysis approach builds on urban land use, travel, and activity microsimulation models. These models incorporate a range of individual-level decisions that impact travel, such as residential location choice, auto ownership, and mode choice. The models are based on detailed travel and activity data collected from individuals, and the resulting behavior is specified to be a function of the socio-demographics of the individuals, as well as the transport and land use infrastructure. The models are used to perform “what-if” analyses regarding potential policies, new technologies and services. For example, cities are trying to navigate a range of policies related to new transport services such as Uber and Lyft. These policies impact price and service and therefore also influence use of these services. While these models are used extensively to inform long-run infrastructure investments and policy decisions, existing models and frameworks are not able to address major technology and service changes in the transport system.

PROBLEM STATEMENT

Major technological and infrastructural changes are expected to occur over the next decades such as the introduction of autonomous vehicles, advances in information and communication technology, California High Speed Rail, carsharing and ridesharing, etc. However, this evolution has no defined path and we should be cautious with how the future is going to play out. We want the future to consist of sustainable and efficient systems. One critical component in this strategy comprises developing quantitative behavioral analysis tools that focus on modeling and influencing trends of travel behavior to guide transformative mobility and set it on the right track. Moreover, the potential roles of the government and policy are key in shaping and influencing the future. This could be achieved by developing quantitative methods that offer insights to planners and policy-makers on what can be done to influence possible outcomes.

In order to tackle and address the general research questions we are interested in, we have addressed three specific components regarding developing the methodological framework:

- 1- Projecting membership and market shares of upcoming modes of transport. Developing such a framework will be based on integrating models of technology adoption and discrete choice analysis (Paper #1).

- 2- Understanding and predicting structural long-range trends of travel behavior. Developing such a dynamic framework of disaggregate decision-making will require integrating hidden markov models (HMM) with current travel demand models (Paper #2).
- 3- While the first two components focus on developing quantitative behavioral analysis tools to guide transformative mobility to ensure a sustainable and efficient system, we also investigate the adoption and diffusion processes in light of economic theory and its pertinent literature.

PAPER #1

An Econometric Framework for Modeling and Forecasting the Adoption and Diffusion of New Transportation Services

This paper is motivated by existing work in technology adoption modeling which employs a microeconomic utility-maximizing representation of individuals. This framework is of interest to us as it could be easily integrated with our disaggregate activity-based models. Moreover, we are interested in capturing the impact of social influences and network effect (spatial component) on the adoption process.

The technology adoption model we estimated builds on the formulation of discrete mixture models and specifically Latent Class Choice Models (LCCM) that allow for heterogeneity in the utility of adoption for the various market segments i.e. innovators/early adopters, imitators and non-adopters. We make use of revealed preference (RP) time series data for a one-way car sharing system in a major city in the US. The data contains a complete set of member enrollment ever since the service was launched. Consistent with the technology diffusion literature, our model identifies three latent classes whose utility of adoption have a well-defined set of preferences that are significant and behaviorally consistent.

PRACTICAL IMPLICATIONS

The technology adoption dynamic model predicts the probability that a certain individual will adopt the service at a certain time period, and is explained by social influences, network effect, socio-demographics and level-of-service attributes. The model was calibrated and then used to forecast adoption of the carsharing system for potential investment strategy scenarios. A couple of takeaways from the adoption forecasts were: (1) placing a new station/pod for the carsharing system in coordination with recruiting at a major technology firm induces the highest expected increase in the monthly number of adopters; and (2) there is no significant difference in the expected number of monthly adopters for the downtown region will exist between having a station or on-street parking.

PAPER #2

Integrated Hidden Markov and Discrete Choice Models: Developing a Forecasting Framework for the Transition Matrix Model

Autonomous vehicles on the horizon, not to mention the introduction of newer ways of travel and activity engagement such as ridesharing, carsharing, etc. It is critical to understand and quantify the impacts of this transformative mobility trend on travel behavior, and in particular mode choice

conditional on decision-makers adopting to those new technologies and services. This paper is motivated by existing work that integrates the construct of modality styles in travel demand models. Modality styles are lifestyles built around the use of a travel mode or set of travel modes that people consider when making mode choice decisions (Vij, 2013). In addition to that, dynamic modeling is of interest to us and specifically Hidden Markov Models (Baum and Petrie, 1966) as they provide a structural approach to model the evolution of modality styles over time after a certain shock occurs in the transportation network. As an example, this shock could be brought about by the introduction of a new rail system in the market or a new technology (Uber, Lyft, etc.).

This paper focuses on dynamic modeling to capture how decision-makers make choices relevant to their work trip commutes (mode choice used: auto, metro, bus, etc.). The model identifies various segments of the population that use a certain set of modes for work commute and have different sensitivities to attributes of the travel modes i.e. travel time, travel cost, waiting time, etc. The dataset used comes from Santiago, Chile (Yañez et al., 2010). This panel dataset offers the opportunity to investigate the effects of a sudden change in the transportation network (introduction of Transantiago, complete redesign of the public transportation system in Santiago) on lifestyles, modality styles and travel mode choice behavior.

Our model identifies the following market segments: multimodal segment with a concentration on drivers, bus users, bus-metro users and auto-metro users. The transition probability model identifies how decision-makers can transition from one segment to the other as a function of socio-demographics and the derived consumer surplus from subscribing to a certain market segment (modality style).

PRACTICAL IMPLICATIONS

The key to understanding the future of transformative mobility is not only to study the immediate impact of current policies, services, and nudges; but also how these impacts influence trends and play out over decades and as new technologies and services are introduced. The developed methodology of our dynamic model of modality styles will provide the quantitative tools to do so. The proposed dynamic model can help policy makers assess the influence of a certain policy/investment on the projected market shares of the various modal orientations (and modes of transport) in order to identify the most effective policy that caters for behavior change. Also, this methodological framework shall provide a mechanism to capture and predict structural shifts in trends in overall travel behavior.

PAPER #3

What can the Literature on Technology Adoption Teach Us about Autonomous Vehicles?

In this initial report we begin to investigate how the economic literature on technology adoption can help us understand and predict the expected market penetration rates of autonomous cars in order to guide the diffusion of this new technology. We also highlight some key research questions that should be addressed with autonomous vehicles being on the horizon. In addition to that, the report addresses the potential role required by the government to support this transformative mobility trend. Finally, it is essential to understand the importance of effective policies and investment

strategies, whether on the public or private level, and how they can guide the evolution of the autonomous vehicles market.

CONCLUSION

The developed methodological framework in this research project will provide the means to assess how policies and investment strategies can transform cities to be more efficient and sustainable, provide a higher level of connectivity and improve the economic and environmental health for people. Those models provide key quantitative analysis tools that try to understand how the transportation system performance is going to look like in the future. Planners, policy makers and transportation specialists are eager about the investments in infrastructure and technology that are bound to occur and are interested in assessing how current decisions will play out in the future. This research project shall provide the building blocks to advances in dynamic travel demand modeling to guide transformative mobility and infrastructure investments towards a more sustainable and efficient system.

DELIVERABLES

The two journal publications and the brief report:

- El Zarwi, F., Vij, A., and Walker, J. An Econometric Framework for Modeling and Forecasting the Adoption and Diffusion of New Transportation Services. In preparation for Submission for Transportation Research: Part C.
- El Zarwi, F., Vij, A., and Walker, J. Integrated Discrete Choice and Hidden Markov Models: Developing a Forecasting Framework for the Transition Matrix Model. In preparation for Submission for Transportation Research: Part B.
- Brief report on autonomous vehicles that focuses on what we can learn from the economic technology adoption literature.

These papers are all works in progress that we will submit to archival journals. We ask that Caltrans keep them internal until we provide versions that we have submitted.

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An Econometric Framework for Modeling and Forecasting The Adoption and Diffusion of New Transportation Services

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Feras El Zarwi (corresponding author)
Department of Civil and Environmental Engineering
University of California at Berkeley
116 McLaughlin Hall
Berkeley, CA 94720-1720
ferasz@berkeley.edu
+1 510 529 8357

Akshay Vij
Institute for Choice
University of South Australia
Level 13, 140 Arthur Street
North Sydney, NSW 2060
vij.akshay@gmail.com
+61 08 8302 0817

Joan L. Walker
Department of Civil and Environmental Engineering
University of California at Berkeley
111 McLaughlin Hall
Berkeley, CA 94720-1720
joanwalker@berkeley.edu
+1 510 642 6897

ABSTRACT

Major technological and infrastructural changes over the next decades, such as the introduction of autonomous vehicles, implementation of mileage-based fees, carsharing and ridesharing are expected to have a profound impact on lifestyles and travel behavior. Current travel demand models are unable to predict long-range trends in travel behavior as they do not entail a mechanism that projects membership and market share of new modes of transport (Uber, Lyft, etc). We propose integrating discrete choice and technology adoptions models to address the aforementioned issue. In order to do so, we build on the formulation of discrete mixture models and specifically Latent Class Choice Models (LCCM). We adopted a confirmatory approach to estimating our dynamic LCCM based on findings from the technology diffusion literature across multiple disciplines that focus on defining two distinct types of adopters: innovator/early adopters and imitators. LCCM allow for heterogeneity in the utility of adoption for the various market segments i.e. innovators/early adopters, imitators and non-adopters. We make use of revealed preference (RP) time series data from a one-way carsharing system in a major city in the United States to estimate model parameters. The data entails a complete set of member enrollment for the carsharing service for a time period of 2.5 years after being launched.

Consistent with the technology diffusion literature, our model identifies three latent classes whose utility of adoption have a well-defined set of preferences that are significant and behaviorally consistent. The technology adoption model predicts the probability that a certain individual will adopt the service at a certain time period, and is explained by social influences, network effect, socio-demographics and level-of-service attributes. Results from model estimation depict that an individual is more likely to be a non-adopter, high-income groups and men are more likely to be early adopters. In addition to that, each latent class is characterized by a distinct set of sensitivities for the following covariates: network/spatial effect, socio-demographics, social influences and level-of-service attributes. Finally, the model was calibrated and then used to forecast adoption of the carsharing system for potential investment strategy scenarios. A couple of takeaways from the adoption forecasts were: (1) placing a new station/pod for the carsharing system outside a major technology firm induces the highest expected increase in the monthly number of adopters; and (2) no significant difference in the expected number of monthly adopters for the downtown region will exist between having a station or on-street parking.

Keywords: technology diffusion, dynamics, latent class choice models, social influences, spatial effect, demand forecasting

1. INTRODUCTION

The nonstop growth in population and urban development has impacted societies in one way or another from air pollution to greenhouse gas emission, climate change and traffic congestion. This made policy makers more inclined towards the development of smart cities that promote sustainable mobility and multimodality. As such, major technological and infrastructural changes over the next decades such as the introduction of autonomous vehicles, advances in information and communication technology, California High Speed Rail, carsharing and ridesharing are expected to traverse our societies. This will induce potential paradigm shifts in the cost, speed, safety, convenience and reliability of travel.

Travel demand models are the dominant approach to predict 20-30 year forecasts of traffic volumes and transit ridership across transportation networks. However, current travel demand models are unable to predict long-range trends in travel behavior as they do not entail a mechanism that projects membership and market share of new modes of transport (Uber, Lyft, autonomous vehicles, etc). Our objective is to develop a methodological framework tailored to model the technology diffusion process by focusing on quantifying the effect of the spatial configuration of the new technology and socio-demographic variables. Moreover, we are also interested in capturing the effect of social influences and level-of-service attributes of the new technology on the adoption process. This will help planners and policy makers gain more insight about the projected market shares of upcoming modes of transport for various policies and investment strategies at the public and private levels. Our research is motivated by existing work in technology adoption modeling which employs a microeconomic utility-maximizing representation of individuals. This framework is of interest to us as it could be easily integrated with our disaggregate activity-based models.

This study contributes to the existing body of literature in providing a unique methodology to model the adoption behavior and uptake of new products/technologies by various market segments. Our model caters for the effects of social influences, network effect, socio-demographics and level-of-service attributes of the product on the adoption behavior of each of the market segments. The following framework could be used to predict future market shares of upcoming modes of transport as one specific type of application. The paper is organized as follows: Section 2 provides a literature review of existing technology adoption and diffusion frameworks. Section 3 provides the adopted methodological framework used to model technology adoption and details the framework of the Latent Class Choice Model (LCCM). Section 4 explains the dataset used in the study. Section 5 discusses model results and model applications. Section 6 concludes the findings of the paper.

2. LITERATURE REVIEW

Autonomous vehicles on the horizon, not to mention the transformative mobility trend that is occurring in our transportation system via the introduction of electric vehicles, ridesharing, carsharing, and many other new technologies. The transportation industry has been trying to develop quantitative methods rooted in the technology diffusion literature to try and predict market shares of those upcoming modes of transportation. One study (Li et al., 2015), focused on defining variables that influence ridership of the Taiwan High Speed Rail System (THSR) using econometric time series models and revealed preference (RP) data of monthly ridership from January 2007 till December 2013. Two models were estimated: (1) seasonal autoregressive integrated moving average and (2) first order moving average model to explore the influence of explanatory variables on ridership.

Moreover, studying the market diffusion of electric vehicles has received worldwide attention these past few years. For example, Plötz et al. (2014), estimated an agent-based simulation model of the diffusion process of electric vehicles using real-world driving data that captured heterogeneity among decision-makers, psychological factors and attributes of the new technology. Another study, please refer to Gnann et al. (2015), used an Alternative Automobiles Diffusion and Infrastructure (ALADIN) diffusion model to forecast market penetration of plug-in electric vehicles through simulation techniques. Their proposed methodology incorporated an agent based simulation model that catered for different types of users in addition to their respective decision making processes to make it behaviorally richer. Other studies focused

on using agent based simulation models alone while others integrated them with discrete choice methods to account for a richer behavioral interpretation (Eppstein et al., 2011; Brown, 2013; Zhang et al, 2011). For example in Eppstein et al. (2011), an integrated agent based and consumer choice model was estimated that tried to capture the effect of social interactions and media on the market penetration of plug-in hybrid electric vehicles.

Also, a current developed model focuses on forecasting adoption of electric vehicles using an integrated discrete choice and diffusion models (Jensen, 2014). This model builds on the previous work of Jun and Park (1999) whereby they specify the utility of adopting a certain good at time t as a function of the attributes of the technology, and difference between time t and the time period at which the product was introduced in the market. The parameter associated with the aforementioned second variable in the utility of adoption will account for the effect of the diffusion process. The probability of adoption at a certain time period could be computed using the logit closed form. Following that, the sales of electric vehicles at different time periods could be computed respectively. To forecast the demand of electric vehicles, data was collected from a stated preference (SP) survey conducted in Denmark in 2012 and 2013 for the choice between electric vehicles and internal combustion engines. The specification of the utility of choosing either mode included purchase price, propulsion costs, driving range, emissions, number of battery stations, and characteristic of public charging facilities. The utility equation of choosing an electric vehicle also entailed a parameter that portrays the effect of the diffusion process while assuming that internal combustion engines have reached market saturation. The model was used to forecast market share of electric vehicles for several policy scenarios. Our proposed methodological framework is different as it caters for (1) heterogeneity among decision-makers and in particular among distinct discrete market segments in the population that have different adoption behavior; (2) effect of various socio-economic and demographic variables on the diffusion process; (3) spatial or network effect of the new technology whereby we are interested in assessing how an increase in the size of the network that is covered by the new mode of transportation will impact adoption behavior; and (4) social influences and how that will influence the utility of adoption.

In order to have a deep understanding of the diffusion process tackled in the transportation literature, we need to get a handle on the diffusion literature in a thorough manner. Over the course of the next few paragraphs we will describe the central piece of the framework governed by the model of technology adoption. The adoption and diffusion of new technologies has received attention across multiple disciplines within economics and social sciences over the years. As defined by Rogers (1962), “diffusion is the process by which an innovation is communicated through certain channels over time among the members of a certain social system”. Diffusion models are widely used in the marketing science industry as they capture the dynamics behind the uptake of a new product in addition to forecasting its demand. Diffusion models are popular in a variety of disciplines such as: agriculture (Sunding and Zilberman, 2001; and Ward & Pulido-Velazquez, 2008), consumer durables (Delre et al., 2007; and Schramm et al., 2010), pharmaceutical industry (Desiraju et al., 2004), and the automobile industry and in particular aggregate diffusion patterns of car ownership (Dargay and Gately, 1999). Those models have been estimated and used in forecasting across different cultures such as: United States, France, Spain and many other countries (please refer to Tellis et al., 2003). Forecasting accuracy with diffusion models varies depending on the type of dataset being used, whether it’s homogenous or heterogeneous i.e. from different sources (Meade and Islam, 2006). Improvement with respect to specification of the diffusion models such as incorporating non-parametric parametrization and enhancing flexibility has helped increase forecasting accuracy across multiple disciplines (Meade and Islam, 2006).

The rate and extent of diffusion is a function of the attributes of the innovation, the characteristics of the social system, time, and the available channels for communication (Rogers, 1962). Any innovation may be defined in terms of the relative advantage offered by the innovation over existing alternatives, the degree to which the innovation is consistent with existing needs and values, the measure of difficulty associated

with using the innovation, the extent to which the innovation can be tried on a limited basis, and the ease with which the benefits of the innovation are tangible to others. Differences in social systems may be characterized by the pattern of relationships among members of the system, established norms of what constitutes acceptable and unacceptable behavior, and the degree to which individual agents are able to influence the behavior of others. Communication channels can be broadly classified as either mass media, such as the television, or interpersonal channels that require a direct exchange between two or more individuals.

Rogers (1962) defines the following five classes of adopters that define the uptake of a certain technology across various disciplines: innovators, early adopters, early majority, late majority and laggards. Based on the mathematical formulation of the diffusion model of Bass (1969), adopters can be divided into two distinct groups: innovators and imitators with the latter comprising the remaining four classes of adopters listed above. The technology diffusion literature stresses on the importance of the role of those two different types of adopters in shaping the market penetration rate of a new good or service (please refer to Mansfield, 1961; Mahajan et al., 1990; and Cavusoglu et al, 2014). Innovators are individuals that “decide to adopt an innovation independently of the decisions of other individuals in a social system” while imitators are adopters that “are influenced in the timing of adoption by the pressures of the social system” (Bass, 1969).

The dominant models for technology adoption and diffusion are either disaggregate or aggregate. Throughout the next few paragraphs, we will describe the assumptions and formulations for those two distinct frameworks, and motivate why disaggregate models are a better methodological approach to our research question. Aggregate models of technology diffusion formulate the percentage of the total population that has adopted an innovation at some time period as some function of the characteristics of the population and the attributes of the innovation. The empirical research on aggregate models was pioneered by Griliches (1957), Mansfield (1961), and Bass (1969). The Bass model is well-known in the marketing science literature and it formulates the probability that a certain consumer will make an initial purchase at a given time t given that no purchase has been yet made by that specific consumer denoted as P_t in the equation below as a linear function of the number of previous buyers:

$$P_t = p + \frac{q}{M}Y(t)$$

p : Coefficient of innovation; q : Coefficient of imitation; M : Total potential market for the technology

$Y(t)$: Cumulative number of individuals that adopted the new technology by time t (number of previous buyers)

The term $\frac{q}{M}Y(t)$ reflects the “pressures operating on imitators with an increase in the number of previous buyers” (Bass, 1969) while p reflects the percentage of adopters that are innovators.

Using this formulation, sales of a certain technology/product could be forecasted into the future via a closed form solution. We are interested in the formulation of the Bass model as it identifies the two types of adopters of a new technology in addition to capturing the effect of social influence onto the probability of adoption. The figure below depicts the sales of a product over time (bell-shaped curve, $S(t)$) and cumulative sales over time (“S”-shaped curve, $Y(t)$) according to Bass (1969). The plot below uses a value of 0.005 for the coefficient of innovation p , 0.3 for coefficient of imitation q , and 100 for total potential market M . Those values were chosen arbitrarily to display the shape of the $S(t)$ and $Y(t)$ curves and provide useful insights. It is evident from the “S”-shaped diffusion curve that once a certain good or service is introduced in a market, it exhibits a low adoption rate followed by takeoff whereby the market experiences high adoption rates. After the takeoff period, technology adoption slows down until it reaches market saturation.

Mansfield (1961) on the other hand formulates the cumulative sales of a good/service using a logistic model which is a special case of the Bass model ($p=0$). Extensions of the Bass model and more recent

enhancements to aggregate diffusion models (see for example Kamakura and Balasubramanian, 1988; and Meade & Islam, 2006), have incorporated the effects of price, advertising and other marketing variables into the model parametrization in an attempt to increase forecasting power. Furthermore, aggregate models have been developed to assess the diffusion levels of a certain technology across different countries. A major drawback in these models is the absence of explicit understanding and modeling of utility-maximizing representation of individuals that drives decision-makers to adopt at different times.

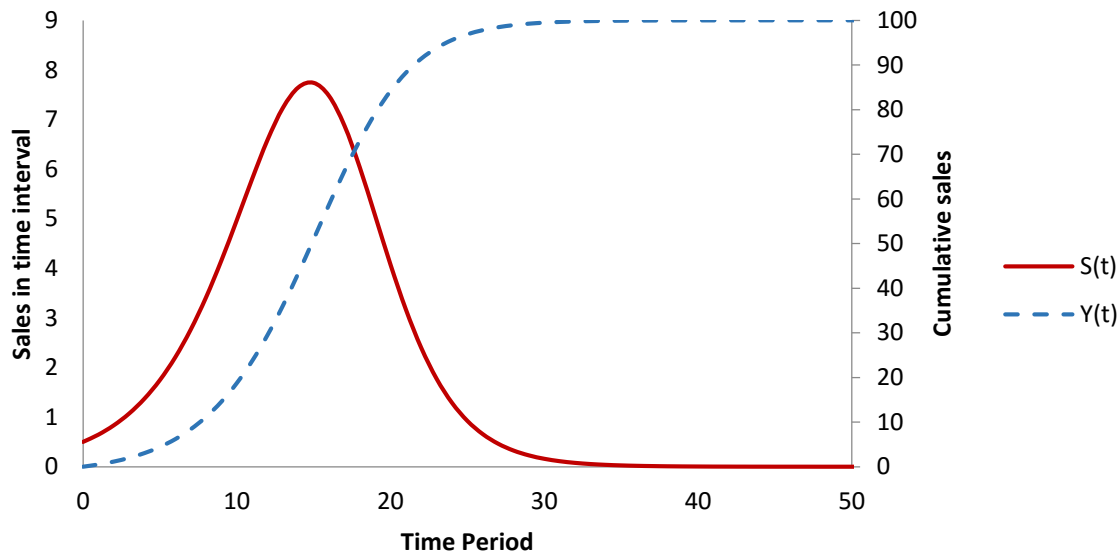


Figure 1: Sales vs. Cumulative Sales over Time

Recently, agent-based modeling and simulation methods are becoming more popular in the technology diffusion discipline as they are estimated on an individual level. This will in turn address some of the shortcomings of aggregate diffusion models and cater for heterogeneity among consumers and explicit social structure (Kiesling et al., 2012; and Schramm et al., 2010).

Disaggregate models of technology adoption on the other hand formulate the probability that an individual or household adopts an innovation as some function of the characteristics of the decision-maker, attributes of the alternative, communication channels (both interpersonal networks and mass media) and time in order to cater for the temporal dimension of the diffusion process. These models have been used to predict the adoption of a wide variety of technologies and innovations that include color televisions, genetically modified crops, irrigation technology, computers, diapers and drill bits (Zilberman et al., 2012). Disaggregate models are of interest to us for the following reasons: (1) they employ a microeconomic utility-maximizing representation of individuals that provides insight into the decision-making process underlying the adoption or non-adoption of different innovations by consumers which is consistent with the framework typically employed by travel demand models; (2) they capture various sources of heterogeneity in the decision-making process; (3) they can be transferable across different geographical, social and cultural contexts with the pertinent model calibration; and (4) they can account for a range of policy variables that can be used to rank policies and investment strategies in terms of maximizing the expected number of adopters of a new technology in future time periods. Moreover, we are interested in understanding how the spatial configuration of a new transportation service and the different socio-demographic variables of decision-makers can influence the adoption behavior. The aforementioned aggregate models cannot cater for those two key variables in their formulation to project future market shares of a new technology in a more representative manner. In addition to that, model application is a key

component in our analysis to provide policy makers and transportation specialists with the means to quantify the expected number of adopters for a set of policies and strategies at the metropolitan levels. Aggregate models do suffer from a limited degree of policy sensitivity and can only account for a narrow range of policy variables which make them less appealing to our analysis.

There are various disaggregate diffusion models, each focusing on different aspects of the decision making process and behavior. One dominant disaggregate adoption model is the threshold model which was first introduced by David (1969) in an attempt to study the technology adoption of grain harvesting machinery and was further explored by Sunding and Zilberman (2001). The threshold model incorporates heterogeneity among decision-makers in the adoption process and could be used in conjunction with discrete choice models (logit or probit) to represent the utility maximization behavior of decision-makers. The sources of heterogeneity that affect the adoption process may include various variables depending on the available data and what the analyst is trying to capture. At every time period, the critical level of each source of heterogeneity in the model is determined. Decision-makers equipped with a value of that source of heterogeneity, say income, that is larger than the critical level at a certain time period will choose to adopt the new technology/product at that time period. The critical level of a source of heterogeneity shall decrease over time which induces more consumers to adopt due to principles of “learning by doing” and “learning by using” (please refer to Sunding and Zilberman, 2001). One application of this consisted of using a disaggregate utility function model of household vehicle choice using the threshold model in its aggregate context with income, household structure, comfort/quality being three critical sources of heterogeneity (Liu, 2010). Advances in the threshold model incorporate dynamic optimization in their analysis, such that a decision-maker is making a trade-off between the expected decrease in price of a certain technology in the future and the current benefits from purchasing it which will dictate the timing of adoption (McWilliams and Zilberman, 1996).

As we are interested in capturing various sources of heterogeneity in the decision-making process, the threshold model does not seem to be a good fit to the methodological framework we want to adopt. As previously mentioned, the literature focuses on two different types of adopters (early adopters and imitators). We are interested in modeling the adoption behavior of those two distinct market segments in addition to the non-adopters market segment that chooses to never adopt a new technology. The formulation of disaggregate utility function of the threshold model can be used as a starting point in the development of our methodological framework of technology adoption for the three different market segments.

3. METHODOLOGICAL FRAMEWORK

The methodological framework we want to develop builds on the aggregate diffusion literature and in particular the concepts of consumer heterogeneity towards the adoption process i.e. innovators versus imitators and social influences as described in the Bass model. We are interested in disaggregate diffusion models as they can be easily integrated with the activity-based travel demand models of interest. Also, with disaggregate models, we can account for the impact of socio-demographics and social influences on the adoption process in addition to spatial effects. By spatial effects we are referring to increasing the relative size of potential destinations that one can reach out to via the new mode of transport. While there have been disaggregate models developed in the literature, they seem to be based on different behavioral assumptions (for example the previously mentioned threshold model) or do not cater for heterogeneity in the specification of the utility of adoption. Most studies in the literature focus on the role of three defined distinct market segments in their analysis that differ in their respective adoption behavior towards a new technology. Those market segments are: innovators/ early adopters, imitators and non-adopters. We will be building on these findings using a disaggregate technology diffusion approach, which is rooted in findings from the aggregate diffusion literature.

The specification we are interested in developing is unique as it tries to model how technology adoption and use is influenced by socio-demographics, attributes of the new technology/service, spatial effect (or network effect) and finally social influences. The aggregate diffusion literature mainly refers to two types

of adopters (innovators and imitators). In order to assess the adoption behavior of a certain population we need to take into account those decision-makers that will choose to never adopt the new technology/service. We are interested in modeling the adoption behavior of each of the following three market segments (innovators/early adopters, imitators, and non-adopters) to try and capture heterogeneity in the adoption behavior of each of those market segments. Innovators or early adopters denote the market segment that determines whether a new technology will pick up in market share or not after being introduced in the market. They define how steep or flat the “S” cumulative diffusion curve (figure 1) can be during the early stages. Innovators comprise the biggest fraction of adopters of a new technology during the initial time periods. Imitators on the other hand come into play as time elapses since the introduction of the new technology. They will determine the rate at which the market will adopt the new product or service and will in turn shape the steepness of the “S” cumulative diffusion curve at later stages in the diffusion process. Non-adopters will define the time period at which the cumulative diffusion curve reaches a plateau. For example, as the number of non-adopters increases the faster the “S” curve attains a plateau.

However, we do not observe what type of a person any given individual is i.e. we do not have information about which market segment each decision-maker belongs to. In order to account for this, discrete mixture models and in particular latent class choice models (LCCM) are found to be the most appropriate framework. Latent class choice models comprise two components: a class membership and a class-specific choice model as depicted in the figure below.

The class-specific choice model formulates the probability of technology adoption of a certain individual conditional on that individual either being an innovator, imitator or non-adopter. This component captures variation across classes with respect to choice set, tastes and sensitivities, decision protocol and covariance structure of the error term (Gopinath, 1995).

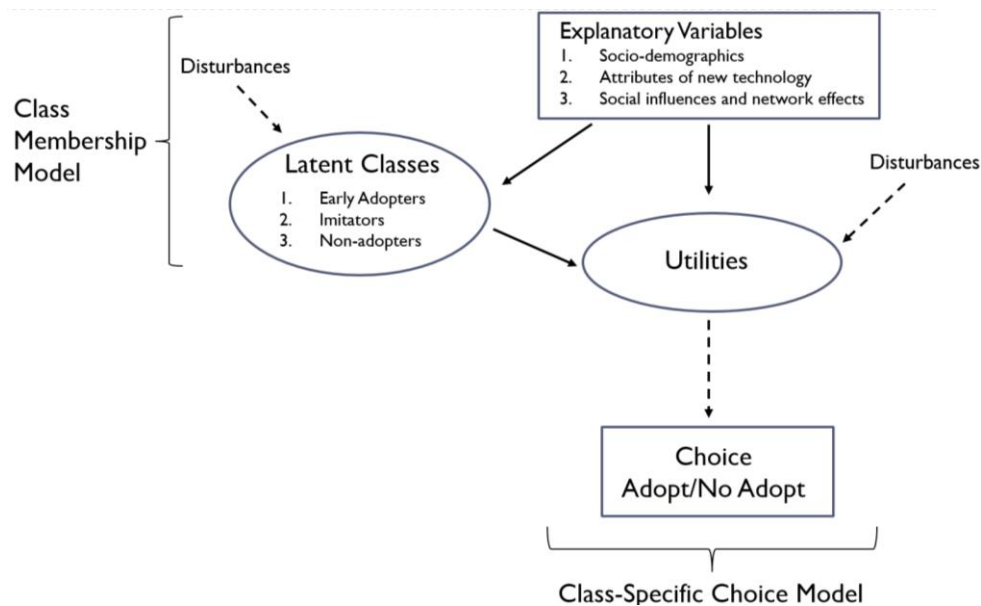


Figure 2: Latent Class Choice Model Framework

As we are interested in modeling the adoption process for each market segment, we should cater for the temporal dimension of technology diffusion as decision-makers will adopt the new technology at various time periods according to the aforementioned explanatory variables. Hence, the probability that individual n during time period t after the new technology was available in the market adopted or chose to not adopt could be written as:

$$P(y_{ntj}|Z_{nt}, X_{ntj}, q_{ns}) \forall j \in \{0,1|y_{n(t-1)j}\}$$

where y_{ntj} equals one if individual n during time period t chose to adopt the new technology (j=1) and zero otherwise, conditional on the characteristics of the decision-maker during time period t denoted as Z_{nt} and attributes of the new technology (j=1) during time period t denoted as X_{ntj} , and conditional on the decision-maker belonging to latent class s (q_{ns} equals one and zero otherwise).

Now, evaluating the probability of adoption or non-adoption will be based on a binary logit formulation that transforms the utility specification into probabilities. Let $U_{ntj|s}$ denote the utility of adoption (j=1) or not (j=0) to the new technology during time period t for individual n conditional on him/her belonging to latent class s which is expressed as follows:

$$U_{ntj|s} = V_{ntj|s} + \varepsilon_{ntj|s} = z'_{nt}\beta_s + x'_{ntj}\gamma_s + \varepsilon_{ntj|s}$$

where $V_{ntj|s}$ is the systematic utility that is observed by the analyst, z'_{nt} is a row vector of characteristics of the decision maker n during time period t, x'_{ntj} is a row vector of attributes of the new technology (j=1) during time period t for individual n, β_s and γ_s are columns vectors of parameters specific to latent class s and $\varepsilon_{ntj|s}$ is the stochastic component of the utility specification. Since we have prior assumptions about the behavior of the two various types of adopters (innovators versus imitators) based on the existing technology diffusion literature, the systematic utility of adoption for each of the three latent classes was specified according to the following rationale. The systematic utility of adoption of innovators shall include characteristics of the decision-maker and attributes of the new technology as we are interested in assessing the significance of those explanatory variables on the decision process of adopting or not. The systematic utility of adoption for imitators is also modeled as a function of the characteristics of the decision-maker and attributes of the new technology. However, this is the latent class whose adoption behavior is influenced by the extent of social influence and accumulating pressure with the increase in the previous number of adopters (Bass, 1969). That is why we are interested in determining the effect of the previous number of adopters on the utility of adoption of imitators at a certain time period. Finally, the systematic utility of adoption of the third latent class (non-adopters) consists of an alternative specific constant (ASC) only. Ideally, this ASC should attain a highly negative value via estimation to ensure that this class will most likely never adopt the new technology. The systematic utility of adoption / non-adoption for innovators, imitators and non-adopters is specified in the following manner:

$$\begin{cases} V_{adopt,n,t|s=innovator} = z'_{nt}\beta_1 + x'_{ntj}\gamma_1 \\ V_{non-adopt,n,t|s=innovator} = 0 \end{cases}$$

$$\begin{cases} V_{adopt,n,t|s=imitator} = z'_{nt}\beta_2 + x'_{ntj}\gamma_2 + \Delta_{(t-1)}\alpha_2 \\ V_{non-adopt,n,t|s=imitator} = 0 \end{cases}$$

$$\begin{cases} V_{adopt,n,t|s=non-adopter} = \lambda \\ V_{non-adopt,n,t|s=non-adopter} = 0 \end{cases}$$

where $\Delta_{(t-1)}$ depicts the cumulative number of adopters of the new technology during time period (t-1), and λ is an alternative specific constant.

Now, in order to assess the impact of the spatial/network effect of the new technology on the utility of adoption, we resided to quantifying the level of accessibility brought about by the new mode of transportation. Accessibility is defined as the “ease with which any land-use activity can be reached from a location, using a particular transport system” (Dalvi et al., 1976). There are several types of accessibility measures: cumulative opportunities measures, gravity-based measures, and utility-based measures (Handy and Niemeier, 1997). We will focus on utility-based measures for the assessment of accessibility through developing a destination choice model. Utility based measures of accessibility have desirable advantages

over other methods as they account for flexibility in travel purposes and sensitivity to travel impedance measures in terms of time and cost. Also, they capture individual-level preferences and socio-demographic influences on travel behavior. In those types of models, we assume that given a certain origin, each decision-maker associates a utility to each of the available destinations in his/her respective choice set C_n and will end up choosing the alternative i.e. destination which maximizes his/her utility. Accessibility is defined as the logsum measure of those destination choice models as it “measures the expected worth of certain travel alternatives” (Ben-Akiva and Lerman, 1985).

Let U_{nij} denote the utility of individual n conducting a trip from origin i to destination alternative j . Determining the systematic utility specification requires assessing the explanatory variables that influence an individual’s decision to conduct a trip from a certain origin to a certain destination. Travel impedance whether in terms of travel distance or cost is an important variable as travelers prefer conducting shorter trips. Second, since travel is a derived demand whereby an individual goes from a certain origin to a destination to conduct an activity, evaluating the available number of opportunities or attractions at the destination is important. In addition to that, an individual is more likely to use the new technology (mode of transport in our case) if it provides a relatively close destination spot to his home. Finally, socio-demographic variables can play a role in defining some characteristics that can drive individuals into conducting certain trips. That is why we resided to expressing U_{nij} in the following manner:

$$U_{nij} = V_{nij} + \varepsilon_{nij} = d_{ij}\beta + \ln(\text{size}_j)\alpha + Z_n\gamma + X_{nj}\theta + \text{home}_n\delta + \varepsilon_{nij}$$

where V_{nij} is the systematic utility observed by the analyst, d_{ij} denotes a friction factor of traveling from origin i to destination alternative j which is the travel distance associated with origin-destination pair (i,j) , size_j represents the attractions associated with destination j which will be governed by the employment rate at the destination (number of employees per square mile) as it is considered to be the driver behind trip attractions, Z_n represents socio-demographic characteristics of decision-maker n , X_{nj} denotes attributes of the new technology at destination alternative j for individual n , home_n is a dummy variable which will be equal to one if decision-maker n resides within a certain proximity as his/her corresponding destination alternative, β , α , γ , δ , and θ are parameters associated with the explanatory variables, and ε_{nij} is the stochastic component of the utility specification.

Assuming that all individuals are utility maximizers and that ε_{nij} follows an i.i.d. Extreme Value Type I distribution across individuals, origin and destination alternatives with mean zero and variance $\frac{\pi^2}{6}$, the accessibility measure is expressed as the following logsum measure:

$$\text{Accessibility}_{n,i,t} = \ln \left[\sum_{j=1}^{J_t} e^{V_{nij}} \right]$$

where i denotes an origin alternative and J_t is the total number of distinct destination alternatives available at time period t .

Now that we have defined the formulation of the network effect model denoted by accessibility, we return to the formulation of the class-specific choice model. Assuming that all individuals are utility maximizers and that $\varepsilon_{ntj|s}$ follows an i.i.d. Extreme Value Type I distribution across individuals, time periods, alternatives and latent classes with mean zero and variance $\frac{\pi^2}{6}$, the class-specific choice model could be formulated as such:

$$P(y_{ntj}|Z_{nt}, X_{ntj}, q_{ns}) = P(U_{ntj|s} \geq U_{ntj'|s} \forall j' \in C) = \frac{e^{V_{ntj|s}}}{\sum_{j'=1}^J e^{V_{ntj'|s}}}$$

where C denotes the choice set i.e. either adopting to the new service or not which is common to all individuals.

Assuming that the class-specific choice probabilities for individual n across all choice situations are conditionally independent given that he/she belongs to latent class s , then the conditional probability of observing a vector of choices y_n becomes:

$$P(y_n|q_{ns}) = \prod_{t=1}^{T_n} \prod_{j \in C} P(y_{ntj}|Z_{nt}, X_{ntj}, q_{ns})^{y_{ntj}}$$

where T_n is the total number of time periods available for individual n until he /she adopts.

The class membership model on the other hand predicts the probability that decision-maker n with characteristics Z_n belongs to latent class s and is defined as such:

$$P(q_{ns}|Z_n)$$

Let U_{ns} denote the utility for individual n from latent class s which is expressed as follows:

$$U_{ns} = V_{ns} + \varepsilon_{ns} = z_n' \tau_s + \varepsilon_{ns}$$

where V_{ns} is the systematic utility, z_n' is a row vector of socio-economic and demographic variables for decision-maker n , τ_s is a column vector of parameters, and ε_{ns} is the stochastic component of the utility specification. Again, assuming that all individuals are utility maximizers and that ε_{ns} follows an i.i.d. Extreme Value Type I distribution across individuals and latent classes with mean zero and variance $\frac{\pi^2}{6}$, the class membership model could be formulated as such:

$$P(q_{ns}|Z_n) = P(U_{ns} \geq U_{ns'} \forall s' = 1, 2, \dots, S) = \frac{e^{V_{ns}}}{\sum_{s'=1}^S e^{V_{ns'}}}$$

where S denotes the total number of distinct latent classes which is equal to three in our case.

Now, to put things in perspective with respect to our methodological framework, the figure below displays all three components in our analysis.

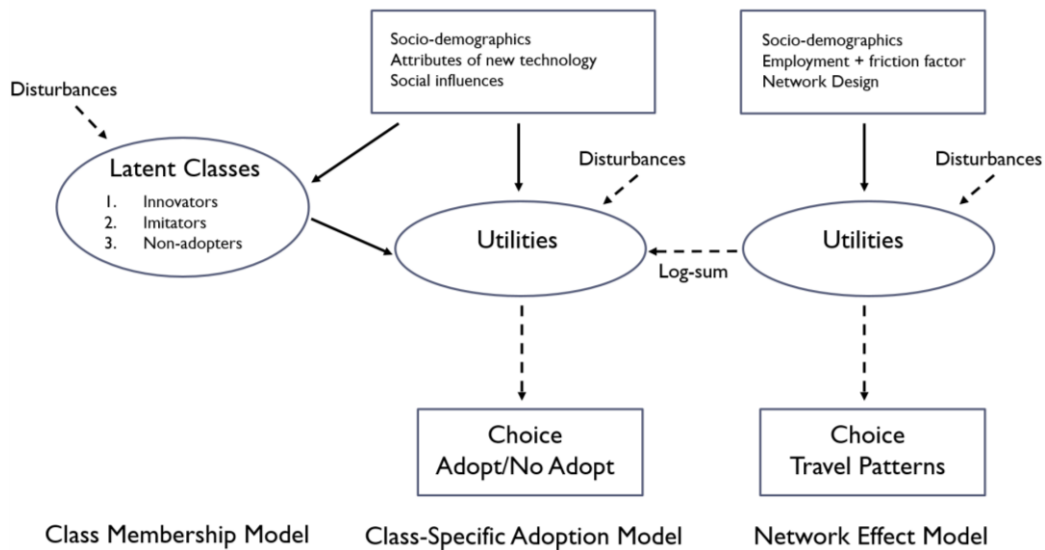


Figure 3: Generalized Technology Adoption Model

The destination choice model will dynamically feed into the class-specific adoption model in terms of evaluating the accessibility measure at different time periods. Afterwards, joint estimation of the class-specific adoption model and class membership model will take place.

The marginal probability $P(y)$ of observing a vector of choices y for all decision-makers is:

$$P(y) = \prod_{n=1}^N \sum_{s=1}^S P(y_n | q_{ns}) P(q_{ns} | Z_n) = \prod_{n=1}^N \sum_{s=1}^S P(q_{ns} | Z_n) \prod_{t=1}^{T_n} \prod_{j \in C} P(y_{ntj} | Z_{nt}, X_{ntj}, q_{ns})^{y_{ntj}}$$

Finally, the technology adoption model predicts the probability that a certain individual will adopt the new technology/service at a certain time period, and is explained by social influences, network effect, socio-demographics and level-of-service attributes. The model was estimated via the Expectation- Maximization (EM) algorithm. This optimization technique enhances the computation power of model estimation by making use of conditional properties that exist in our model.

4. DATASET

We will use revealed preference (RP) time series data to estimate the integrated discrete choice and technology adoption model from a one-way carsharing system that is currently operating in a major city in the United States. The name of the carsharing company was withheld for confidentiality reasons. Our data focuses on the adopters of the service ever since it was launched. Signing up to be a member of this carsharing system requires a membership fee but no monthly nor annual fees. Currently, there are 14 pods/stations in addition to 5 locations for on-street pick-up/drop-off locations. The dataset entails zip code information about members of the new transportation service which drove our analysis to be zip code focused. In total, there are 16 zip code based stations for the car sharing service as some of the on-street pick-up/drop-off locations exist in the same zip code as other stations.

The dataset consists of all individuals that have signed up for the service for a time period of 2.5 years after being launched in addition to their registration date, gender and zip code associated with their residential location or zip code at which the registration payment was performed. Moreover, travel patterns via the carsharing service for a period of 6 months were recorded. Information about which user conducted a trip was recorded in addition to the origin and destination carsharing stations used. Our main focus revolves around the technology adoption behavior of residents of that major city and hence we are only interested in those adopters that had a location zip code affiliated with it which summed up to 1847 adopters. Figure 4 below highlights the cumulative number of adopters over the entire time period that are active users of the service in order to project where exactly on the ‘‘S’’ diffusion curve the carsharing system’s current market share is.

Finally, in order to have a representative sample of the population, we wanted to enrich the sample with a random draw of 2724 observations from the Household Travel Survey (2013) of the same state to which the city we are working with belongs. We will also assume that the individuals from this random sample are non-adopters i.e. did not adopt to the new service for the entire data collection time period (2.5 years). The prior probability of being an adopter in the city of interest is 3×10^{-4} given the number of adopters and the population. Hence, the expected number of adopters in the random sample is approximately one.

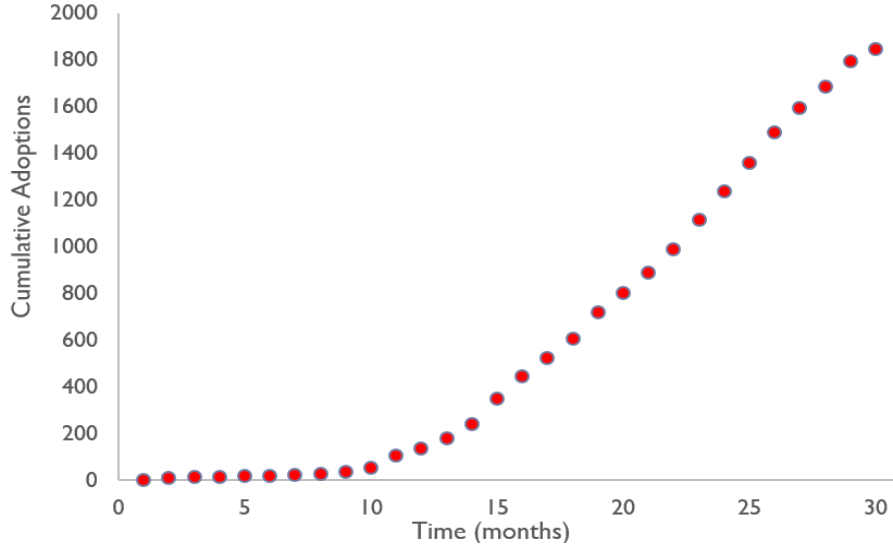


Figure 4: Cumulative Number of Adopters of Carsharing Service

Our technology adoption model shall assess the impact of socio-demographics, carsharing supply (fleet and pricing), social influences and network effect on the adoption behavior of innovators, imitators and non-adopters. Identifying network effect that is governed by the construct of accessibility shall be restricted to be zip code based for the same reason mentioned above. We would like to identify the level of accessibility associated with each zip code based station of the carsharing system depending on the spatial distribution of potential destinations i.e. stations. The origins and destinations entail the full set of the carsharing system's stations. The destination choice model will be estimated based on trips that were conducted by users over a period of 6 months. For our formulation with this dataset, the accessibility measure will be non-zero only for users that have a home zip code associated with one of the stations or on-street parking locations. To account for that, we wanted to assign an accessibility measure for zip codes which do not entail a station/pod or on-street parking. We were interested in imputing the accessibility for those zip codes from the accessibility of the nearest zip code that had either a station or on-street parking while taking a friction factor into consideration, distance in our case. The accessibility measure for individual n with home zip code i which does not have a station or on-street parking at time t could be defined as follows:

$$Accessibility_{n,i,t} = \frac{Accessibility_{n,k,t| \text{nearest active station } k \text{ at time } t}}{(distance_{i,k})^\alpha}$$

where α denotes the degree of the distance friction effect which will be estimated in the model.

Moreover, the sample population we are working is choice-based whereby each choice in the available choice set (adopt, not adopt) corresponds to a separate stratum (carsharing members versus household travel survey sample). However, the sampling fractions are not equal to the population shares especially that we have accounted for all adopters of the carsharing system and hence are highly over-represented in our sample. To cater for that and yield consistent parameter estimates, each observation needs to be weighted by $\frac{W_g}{H_g}$ where W_g is the population fraction and H_g is the sample fraction of members of stratum g (Ben-Akiva and Lerman, 1985). Accordingly, the marginal probability $P(y)$ of observing a vector of choices for all decision-makers should be expressed as follows:

$$P(y) = \prod_{n=1}^N \left(\sum_{s=1}^S P(q_{ns}|Z_n) \prod_{t=1}^{T_n} \prod_{j \in C} P(y_{ntj}|Z_{nt}, X_{ntj}, q_{ns})^{y_{ntj}} \right)^{\frac{W_g}{H_g}}$$

Figure 5 below displays the growth in the number of pods/stations and on-street pick-up/drop-off locations for the 2.5-year time period.

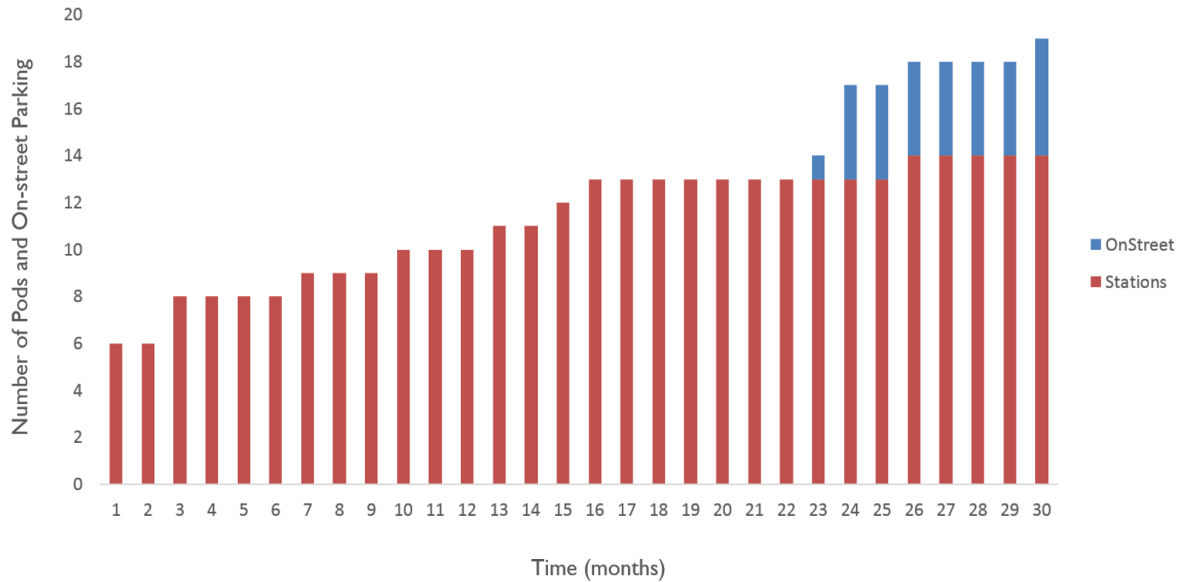


Figure 5: Growth in Number of Pods/Stations and On-Street Parking over Time

5. ESTIMATION RESULTS AND DISCUSSION

The following section entails results of the destination choice model which will be used to compute the accessibility measure that is used as an explanatory variable in the technology adoption model. Followed by that, results of the technology adoption model will be presented.

Results of the destination choice model for the 16 zip code based stations are tabulated below including parameter estimates (and t-statistics). We included 4 alternative specific constants (ASCs) for 4 stations as we considered them to be hubs for trips conducted using the carsharing service. The four exogenous variables used were distance, employment rate, home dummy, and on-street parking. The on-street parking variable was introduced in the destination choice model utility specification in order to quantify and understand the effect of having on-street parking versus stations on the projected number of adopters. The on-street parking variable used was a dummy variable which will be equal to one if the destination alternative (zip code) entails on-street parking structure for the new transportation service and zero otherwise.

We did not include ASCs in all 16 utility equations because that will be problematic when evaluating accessibility when new stations are introduced as it will be difficult to assess the ASC of the new destination i.e. station. In addition to that, a dummy variable between a major technology firm’s headquarters and a major airport in the city was introduced which takes a value of one if a trip takes place between the technology firm and the airport stations. That dummy variable was of interest as 46% of the total trips of the car sharing service had either that technology firm or airport as an origin or destination. Finally, a dummy variable between the major airport and the city’s downtown region was introduced which takes a value of one if a trip takes place between the airport and downtown.

Table 1: Destination Choice Model

Variable	Parameter Estimate
Distance in 100 Kilometers	-0.24 (-2.06)
Employment in Zip Code (employees/miles ²)	0.18 (10.06)
Home	1.55 (20.51)
On-street Parking	0.34 (5.47)
Trip between Major Technology Firm and Downtown	1.00 (14.18)
Trip between Major Technology Firm and Major Airport	2.78 (45.46)
<u>Alternative Specific Constant</u>	
Technology Firm	1.10 (13.27)
Airport 1	1.76 (23.07)
Airport 2	0.61 (5.90)
Airport 3	0.93 (10.32)

Since we had apriori hypothesis regarding the number of latent classes in our model, determining the final model specification was based on varying the utility specification for both sub-models i.e. class membership and class-specific choice models. Tables 2 below presents detailed parameter estimates (and t-statistics) for the class membership of the technology adoption model.

Table 2: Class Membership Model

Variable	Class 1 – Innovators	Class 2 - Imitators	Class 3 – Non-Adopters
Alternative Specific Constant (Adoption)	--	7.00 (37.09)	7.51 (56.78)
Monthly Income (\$1000)	--	-0.23 (-13.01)	-0.04 (-3.86)
Male	--	-0.77 (-8.70)	-1.72 (-23.56)

-- Not applicable

The rho-bar-squared ($\bar{\rho}^2$) measure for this technology adoption model is 0.993 with a total number of 4571 individuals and 120,665 observations. $\bar{\rho}^2$ has such a high value because of the weights applied to each of the observations. Currently, the market share of the carsharing adopters is very minimal compared with the rest of the population which forces the increase in model fit.

The class membership model includes parameter estimates which correspond to the influence of socio-demographic variables on class membership. The class membership model results reveal that all else equal, an individual is more likely to be a non-adopter, high-income groups and men are more likely to be early adopters (innovators). The monthly income used in our analysis was the average zip code based income since that socio-demographic variable was not provided in the data.

Tables 3 below presents detailed parameter estimates (and t-statistics) for the class-specific model corresponding to the adoption behavior of the new technology. As for the class-specific model results, the parameter estimates for the utility of adoption for the two types of adopters have the right sign and are significant at the 1% level except for the major technology firm employee variable for the innovators latent class. This agrees with the behavioral interpretation of the adoption process for each class. Early Adopters' utility of adoption increases with an individual being an employee of the major technology firm and having a station or on-street parking for the new transportation service in his/her corresponding zip code. Also, an increase in the accessibility of a certain home zip code that has neither a station nor on-street parking will in turn drive an innovator to adopt. A similar behavioral interpretation applies for home zip codes that do have stations or on-street parking. Imitators' utility of adoption increases with an individual being an employee of the major technology firm and with an increase in the cumulative number of adopters in the previous time period. This is the class which is highly influenced by previous adopters. Moreover, as the accessibility of the home zip code which has neither a station nor on-street parking increases, an imitator is more likely to adopt. The same rationale also applies for home zip codes that do have stations or on-street parking. The behavior of the non-adopters latent class is deterministic as the probability of adoption is almost equal to one for each individual that belongs to this market segment at each time period.

Table 3: Class-specific Technology Adoption Model

Variable	Class 1 – Innovators	Class 2 – Imitators	Class 3 – Non-Adopters
Alternative Specific Constant (Adoption)	-7.88 (-78.08)	-14.71 (-78.63)	-100.00 (--)
Station in Zip Code	1.38 (3.61)	--	--
On-street Parking in Zip Code	1.18 (3.99)	--	--
Major Technology Firm Employee	1.33 (1.89)*	7.10 (46.43)	--
Accessibility for Zip Codes Containing a Station or On-street Parking	0.44 (5.29)	0.68 (55.39)	--
Accessibility for Zip Codes Containing neither a Station nor On-Street parking	0.91 (22.77)	0.59 (22.64)	--
Cumulative Number of Adopters at (t-1) in 100's	--	0.14 (24.21)	--
Degree of Distance Friction Effect for Accessibility	1.00 (--)		

-- Not applicable; * Insignificant at the 5% level

Now that we have estimated a technology adoption model, we want to use it to forecast adoption into the future for various potential scenarios. More specifically, we are interested in using the model to understand the potential effectiveness of new pods and on-street parking facilities placed in different locations. In order to do so, we should calibrate our model first by adjusting the values of the alternative specific constants (ASCs) of the utility of adoption for innovators and imitators. That will minimize the difference between projected and actual demand. In order to do so, we will perform sample enumeration on the entire population of the major city using our estimated model in order to predict the number of adopters that joined

the service during the last month of the data’s time horizon. We will adjust the ASCs in order to equate the predicted number of adopters for the last month from the model with the actual number of adopters for that month from the data itself.

There were three scenarios that we were interested in assessing their impact on the adoption of the new transportation service besides the base case scenario. The base case scenario comprises not investing in any new station or on-street parking facility in any of the zip codes. The three scenarios are:

- a- Stations/pods outside a second major technology firm
- b- Stations/pods in a new zip code in the downtown region
- c- On-street parking facilities instead of stations/pods in the same zip code as in scenario b

Figure 6 below displays how the cumulative adoption “S” diffusion curve will be projected into the future under the aforementioned potential scenarios. Also, figure 7 below identifies the forecasted cumulative monthly adoptions of the new transportation service for the next year on a month to month basis. It is evident that investing in stations/pods outside another major technology firm will increase the monthly number of new adopters the most. There is no significant difference in the number of new monthly adopters for the downtown region between having a station or on-street parking. That is because, the only way we were able to incorporate the effect of each was via dummy variables. Ideally, we would have been interested in incorporating the number of cars in each station/pod or total area allocated for on-street parking but that information was not available. That said, the power of the integrated discrete choice and adoption model we developed lies in projecting adoption into the future and identifying the most effective policy that will cater for behavior change and maximize adoption.

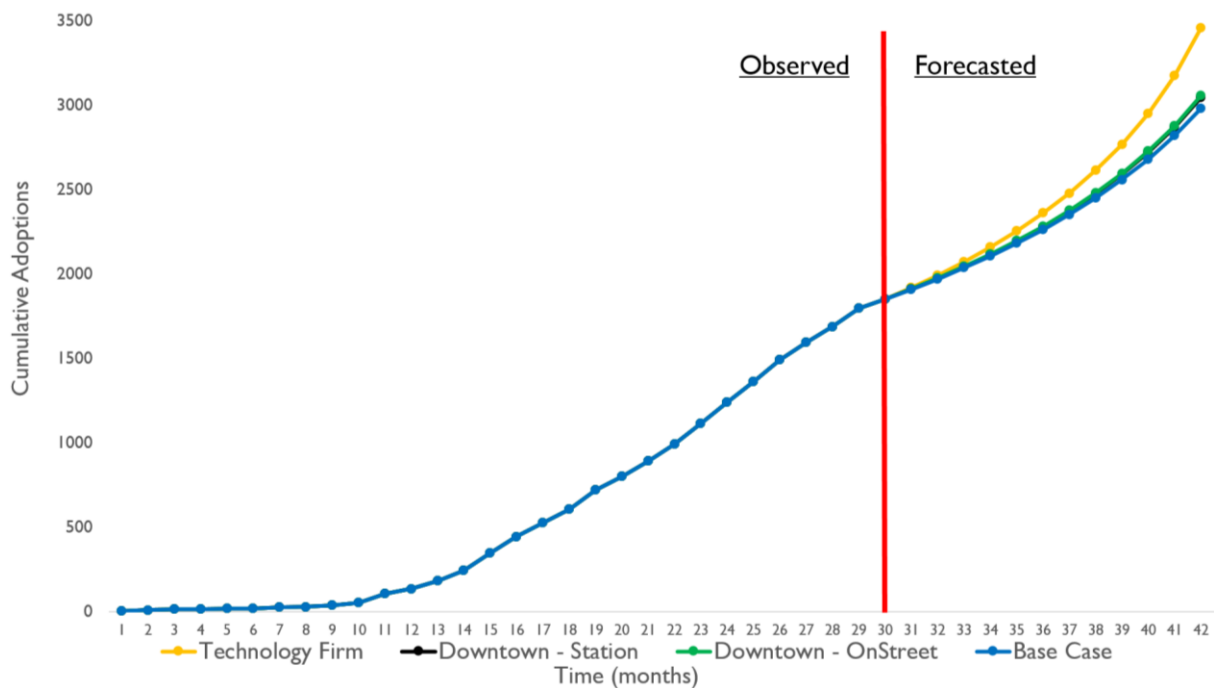


Figure 6: Cumulative Adoptions for New Transportation Service

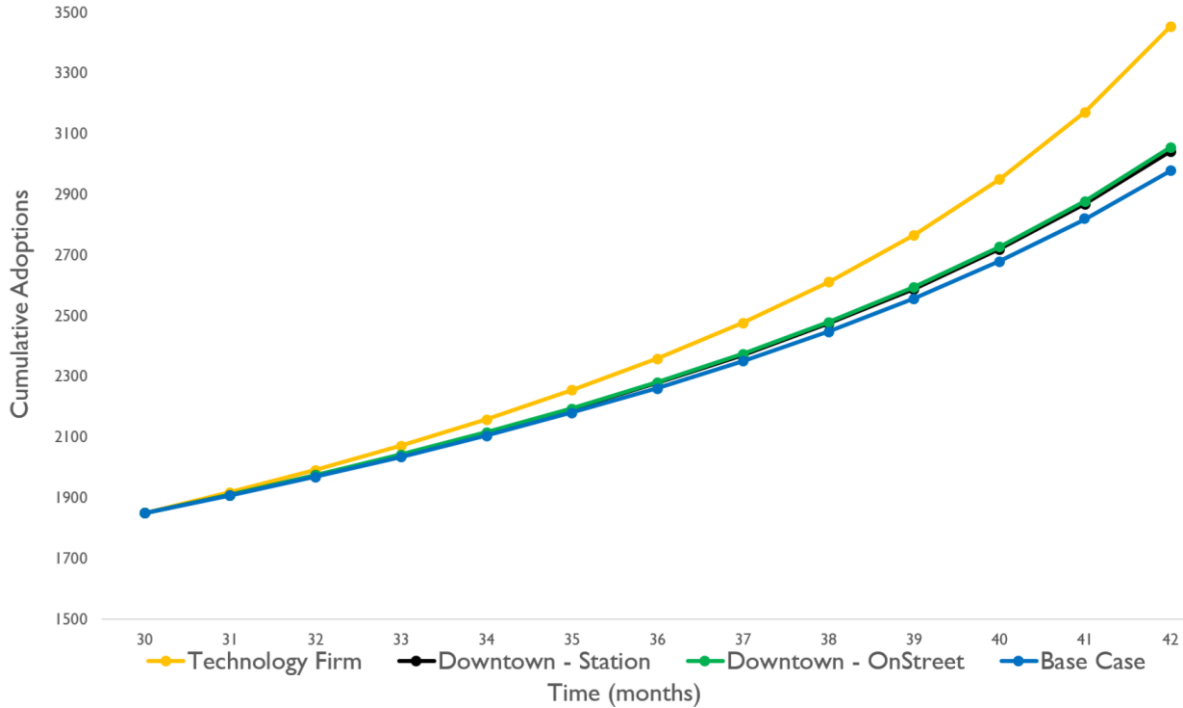


Figure 7: Forecasted Adoption for New Transportation Service

We were also interested in assessing the aggregate technology adoption process using the Bass model to highlight the advantages of our adopted methodological framework in this paper. The three variables that need to be calculated which define the “S”-shaped diffusion curve of the cumulative number of adopters of the one-way carsharing service are: the coefficient of innovation p , for coefficient of imitation q , and total potential market M . In order to compute the values for those three variables, we need to define the following formulation (Bass, 1969):

$$S(t) = pM + (q - p)Y(t) - \frac{q}{m}Y^2(t)$$

$S(t)$ depicts sales of a product over time which is the expected number of adopters of the carsharing service at time period t . The discrete time series data was used to run the required regression analysis in order to estimate p , q and M that attained the following values respectively: 0.0051, 0.2108 and 2200. The figure below displays how the number of adopters $S(t)$ and cumulative number of adopters $Y(t)$ will evolve over time. It is evident that the Bass model suffers from the following limitations: (1) lack of including important policy variables into model parametrization which hinders its forecasting power in terms of identifying effective policies and investment strategies that maximize the expected number of adopters; (2) absence of key variables that shape the adoption process of a new transportation service such as the spatial configuration of the service; and (3) absence of incorporating the effect of socio-demographic variables onto the diffusion process which should be accounted for to capture heterogeneity in the decision making process across different consumers. That is why, the Bass diffusion model forecasts displayed below, will be identical across each of the aforementioned three potential investment strategies / policies.

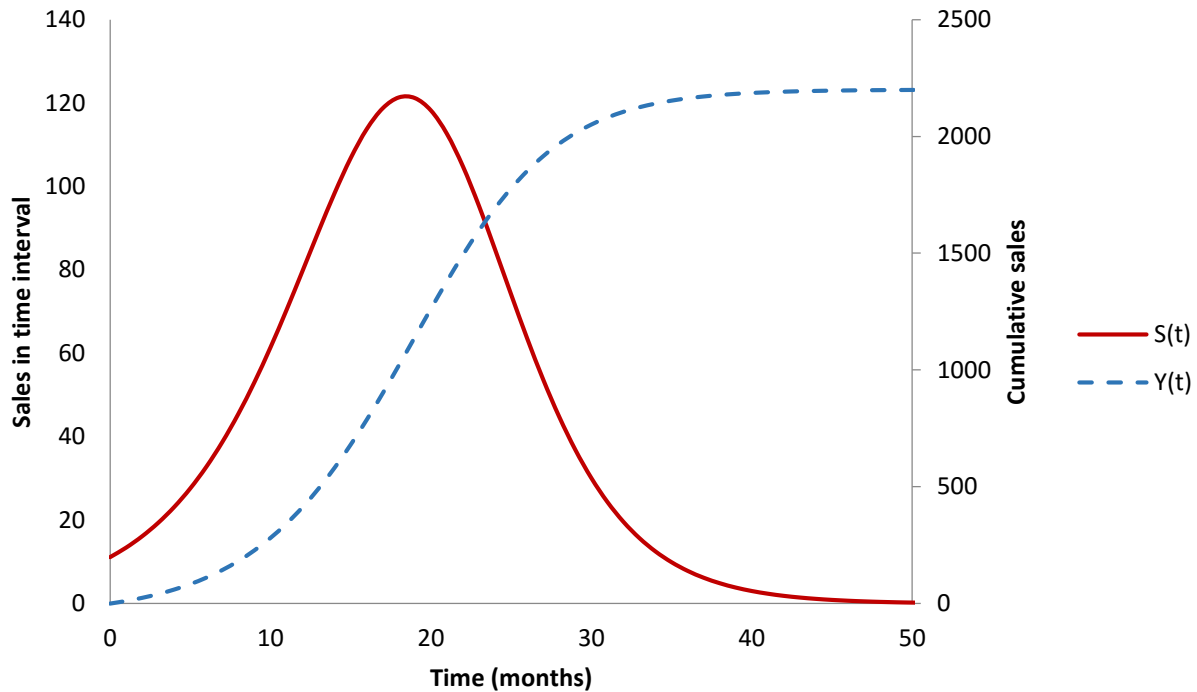


Figure 8: Adopters vs. Cumulative Adopters over Time Using Bass Model

6. CONCLUSION

Major technological and infrastructural changes over the next decades, such as the introduction of autonomous vehicles, implementation of mileage-based fees, carsharing and ridesharing are expected to have a profound impact on lifestyles and travel behavior. However, the dominating mechanism for predicting the 20-30 year forecasts across transportation networks suffers from its inability to project membership of upcoming modes of transport. The methodological framework used in our analysis to study technology adoption consisted of an integrated latent class choice model (LCCM) and network effect model that was governed by a destination choice model. The latent classes used in the analysis are supported by the technology diffusion literature across multiple disciplines and are defined as: innovators/early adopters, imitators and non-adopters. These latent classes are able to capture heterogeneity in preferences towards technology adoption. Each class entails a distinct set of sensitivities and parameter estimates pertinent to the exogenous variables used in estimation. The adopted methodological framework focused on understanding the relative impact of the following set of covariates: social influences, network/spatial effect, socio-demographics and level-of-service attributes.

One major contribution for this research project is defining a methodology to capture the impact of the network/spatial effect of the new technology. We were interested in understanding how the size of the network, governed by the new mode of transportation, would influence the adoption behavior of the different market segments as the ability of reaching out to multiple destination increased i.e. the size of the network grew bigger. This is a critical component in our analysis as it will quantify the effect of placing stations or on-street parking facilities in different locations and prioritize locations in the transportation network that will maximize the expected number of adopters. Our generalized technology adoption model has two other major advantages whereby it employs a microeconomic utility-maximizing representation of individuals and captures various sources of heterogeneity in the decision-making process.

The empirical results look very promising in terms of defining the adoption behavior of the three classes. Finally, the model was calibrated and used to project adoption into the future for various potential scenarios. Some findings from our technology adoption model are: (1) a decision-maker is more likely to be a non-adopter, high-income groups and men are more likely to be early adopters or innovators; (2) network/spatial effect, socio-demographics, social influences and level-of-service attributes of the new technology have a positive set of sensitivities in the utility of adoption across latent classes which is consistent with our a-priori hypotheses and the diffusion literature; (3) placing a new station/pod for the carsharing system outside a major technology firm will increase the expected number of monthly adopters the most; and (4) no significant difference is observed regarding the expected number of monthly adopters for the downtown region between having a station or on-street parking.

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Integrated Hidden Markov and Discrete Choice Models: Developing a Forecasting Framework for the Transition Matrix Model

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Feras El Zarwi (corresponding author)
Department of Civil and Environmental Engineering
University of California at Berkeley
116 McLaughlin Hall
Berkeley, CA 94720-1720
ferasz@berkeley.edu
+1 510 529 8357

Akshay Vij
Institute for Choice
University of South Australia
Level 13, 140 Arthur Street
North Sydney, NSW 2060
vij.akshay@gmail.com
+61 08 8302 0817

Joan L. Walker
Department of Civil and Environmental Engineering
University of California at Berkeley
111 McLaughlin Hall
Berkeley, CA 94720-1720
joanwalker@berkeley.edu
+1 510 642 6897

Abstract

Activity-based travel demand models are the dominant approach that metropolitan planning agencies use to predict 20-30 year forecasts of traffic volumes, transit ridership, bike and walk mode shares across networks brought about from large scale transportation investments. However, current travel demand models are unable to capture and predict structural shifts in trends of overall travel behavior, for example the peak auto phenomenon or the rise of carsharing. We propose integrating discrete choice and hidden markov models (HMM) to address the aforementioned issue. In doing so, we will use the construct of modality styles which are defined as lifestyles built around the use of a travel mode or set of travel modes that capture what modes people consider when making mode choice decisions. Our model identifies various market segments of the population: drivers, bus users, bus-metro users (transit), and auto-metro users (transit). The market segments differ in terms of their choice set consideration and their sensitivity to level-of-service attributes (travel time, travel cost, etc.). The transition probability model identifies how decision-makers can transition from one segment to the other as a function of socio-demographics and the derived consumer surplus from subscribing to a certain market segment. This dynamic model will help policy makers assess the influence of a certain policy/investment on the projected market shares of the various modes of transport in order to identify the most effective policy that caters for behavior change.

1. Introduction

The nonstop growth in population and urban development has impacted societies in one way or another from air pollution to greenhouse gas emission, climate change and traffic congestion. This made policy makers more inclined towards the development of smart cities that promote sustainable mobility and multimodality. As such, major technological and infrastructural changes over the next decades such as the introduction of autonomous vehicles, advances in information and communication technology, California High Speed Rail, carsharing and ridesharing are expected to traverse our societies. This shall induce potential paradigm shifts in the cost, speed, safety, convenience and reliability of travel. Together, they are expected to influence both short-term travel and activity decisions, such as where to go and what mode of travel to use, and more long-term travel and activity decisions, such as where to live and how many cars to own. Hence, those major technological and infrastructural changes shall in turn have a profound impact on modality styles i.e. lifestyles built around the use of a travel mode or set of travel modes that people consider when making mode choice decisions (Vij, 2013), and travel behavior.

Activity-based travel demand models are the dominant approach that metropolitan planning agencies use to predict 20-30 year forecasts of traffic volumes, transit ridership, bike and walk mode shares across networks brought about from large scale transportation investments and policy decisions. These models try to assess the impacts of transportation investments, land use and socio-demographic changes on travel behavior with the main objective of predicting future mode shares, auto ownership levels, etc. These forecasts are critical in assessing the viability of any infrastructure investment and policy intervention/decision (e.g., parking, HOV lanes, etc.) as they predict how decisions now will play out in the future. Furthermore, results from these models will: (1) provide insight into locations and corridors that will suffer from congestion in future years, (2) identify impacts of a certain infrastructure investment or policy in mitigating congestion along congested spines or corridors and (3) assess increase/reduction in greenhouse gas emissions (GHG). However, current travel demand models are unable to capture and predict structural shifts in trends of overall travel behavior, for example the peak auto phenomenon or the rise of carsharing.

2. Literature Review

Over the course of the next few paragraphs we will describe the three central pieces of the framework governed by taste heterogeneity in travel mode choice models, preference instability in discrete choice models, and dynamic choice models.

2.1 Taste Heterogeneity in Travel Mode Choice Models (Modality Styles)

Activity-based travel demand models comprise the primary approach metropolitan agencies use to forecast mode shares and travel behavior as a result of potential transportation investments and land use changes. They also aim at identifying potential future congested corridors in a transportation network in addition to forecasting GHG emissions. Activity-based travel demand models rely on the notion that a decision-maker engages in conducting a trip from a certain origin to a certain destination to participate in certain activities (work, shopping, recreational, etc.). These models focus on behaviorally richer and realistic approach in modeling travel mode choice as opposed to the tradition four step travel demand models. Travel demand models evaluate travel and activity behavior as a series of nested logit models that comprise several interdependent models: travel mode choice, vehicle availability, and time-of-day models, etc. In order to do so, a population synthesizer is required in the activity-based modeling system which entails the full range of characteristics of the targeted population. These models typically assume that individuals consider all available transportation modes in their respective consideration set. Some models try to address this issue in a deterministic manner, for example, restricting a maximum walking distance from a certain origin to destination. In this case, individuals with trip patterns that consist of a

longer distance than this maximum walking distance will not consider walking in their respective consideration set. Also, these models incorporate a limited representation of heterogeneity or taste variation in the choice process that are usually represented either in a systematic or random manner. The first approach entails interactions between observed level-of-service attributes and socio-demographic variables while the latter comprises having parameters follow a certain distribution (usually normal distribution) rather than using point estimates.

These assumptions overlook lifestyles built around the use of different travel modes that identify decision-maker's preferences toward mode choice and travel behavior. The construct of modality styles (Vij, 2013) addresses those two issues that exist in current travel demand models. Modality styles try to capture distinct segments of the population with different preferences i.e. modes considered in the choice set and sensitivity to level-of-service attributes and socio-demographic variables. With new modes of transport existing in the choice set not to mention investment in infrastructure, choice set consideration will be altered in one way or the other. For example, nowadays carsharing and ridesharing constitute a reasonable market share in several regions across the United States. Obviously those two new modes exist in the consideration set of certain distinct market segments in the population. Other decision-makers do not consider those two modes as they might prefer driving or are more attached to their current commuting habits. That is why the construct of modality styles is key to our analysis as it addresses those variations in preferences that we are interested in modeling. Modality styles will capture the various market segments that consider those upcoming modes of transport in addition to the various sensitivities to level-of-service attributes and socio-demographics. Moreover, the share of people in different modality styles shall change/evolve in response to societal changes and the emergence of newer ways for travel and activity engagement. Hence, analyzing what types of lifestyles have emerged or declined over time is key to understanding mode share shifts which are a manifestation of individual preferences (Vij, 2013). Finally, decision-makers that belong to a certain modality style (market segment) will react different to a new transformative policy or investment strategy that is trying to impact the transportation network and cause a behavioral change.

2.2 Preference Instability in Discrete Choice Models

One of the most common limitations in discrete choice models constitutes the fact that preferences, which constitute choice sets and taste parameters, are assumed to be “exogenous to the choice situation and stable over time” (Vij et al., 2014). This means that the alternatives in the choice set and sensitivities to socio-demographic variables and attributes of the different alternatives remain fixed over time. Vij et al. (2014), estimated latent class choice models (LCCMs) to identify various modality styles in a given population that are different in their choice set consideration and sensitivities to attributes of the alternatives. However, they focused on defining a methodological framework that could model how an individual's set of preferences could evolve as a result of changes in the transportation system which could be brought about by a transformative transportation policy that impacts the network or by introducing a new mode in the transportation system. Their formulation consisted of parametrizing the class membership model of the LCCM to comprise socio-demographic variables and the consumer surplus that is offered by each class. This parametrization allows assessing the impact of changes in the built environment on a decision-maker's set of preferences.

Why would one expect preferences to evolve and change over time due to changes in the transportation network? Let's consider the following example to motivate this notion. Introducing autonomous vehicles will definitely alter the choice set consideration of decision-makers that consider this mode when making work and non-work trips. However, being in an autonomous vehicle will allow an individual to multitask which will alter his/her preferences. Individuals are now: (1) less sensitive to driving during the peak hours and getting caught up in congestion, (2) not worried about finding a parking spot in congested cities nor paying parking fees, (3) less restrictive in terms of residential choice location that they might consider

residing outside of the city and commute via the autonomous vehicle for work and other activities as driving has become less onerous. All of these factors will play a role in influencing preferences, mainly value of time (VOT). That is why, current travel demand models that assume preference stability can be used in forecasting over short term periods whereby preferences are more or less invariant or stable. However, in terms of forecasting over long term horizons, we need to take into account that various shocks/changes in the built environment and the transportation system are bound to happen within the era of transformative mobility. Hence, disregarding the evolution of preferences as a result of these changes will result in inconsistent and unreasonable forecasts.

The methodological framework in Vij et al. (2014) is key to our approach. However, their formulation was adopted in a static framework through the development and estimation of a LCCM which is not exactly what we will be using. However, the parametrization of the LCCM provides a good structure to incorporating the influence of changes in the built environment onto the evolution of preferences.

2.3 Dynamic Choice Models

Activity-based travel demand models and the construct of modality styles were applied in a static context as we have previously discussed. However, we are interested in assessing the evolution or change in trends of overall travel behavior conditional on adoption to a new technology or infrastructure which is why we need to extend our framework to a dynamic context. Dynamic choice models try to account for the influence of past experiences on present choices. According to Kenneth Train (2009), current choices affect future choices as past choices affect current choices and this causality provides the basis for dynamic discrete choice modeling. Moreover, the choice an individual makes at a certain time period influences the attributes and availability of alternatives in the following choice situations. For example, in the context of car ownership, a car is considered a durable good that yields utility over time. An individual's choice of whether to purchase a car at a certain time period or postpone the purchase depends on how that individual expects to use the car now and in the future. Dynamic discrete choice models incorporate both static and dynamic individual characteristics and product attributes into the utility functions, and allow a consumer at each time period to either buy a car or postpone the purchase to the next time period. This is an example of the optimal stopping problem which was first proposed by Rust (1987). Those models focus on individuals maximizing their current and expected discounted utility when making a decision at a certain time period and hence the importance of the forward-looking behavior of decision-makers. Given the future's uncertainty, an individual chooses the alternative in the current time period which maximizes his/her expected utility over the current and future periods. Recently, dynamic discrete choice models that incorporated the optimal stopping problem have been applied in the transportation sector to model car ownership (see for example Cirillo and Xu, 2011 and Glerum et al., 2013). According to Rust (1987), a dynamic problem is modeled by a Markov decision process (MDP) which constitutes two variables that need to be defined for every individual at each time period. These two variables are the state variable s_t and decision variable d_t which determine the utility at time t defined as $U(s_t, d_t)$. A Markov transition probability $p(s_{t+1}|s_t, d_t)$ is defined to determine the evolution of the states across time. At each time period, the individual maximizes the expected utility to determine the optimal decision. Rust (1987) adopted this methodology to the problem of bus engine replacement whereby the optimal stopping rule reflected "replacing the bus engine at each time period or not".

Choudhury et al. (2010) estimated a dynamic discrete choice model to study the "evolution of unobserved driving decisions as drivers enter a freeway". This model focused on planning and action in a choice model which better represents the hierarchy behind a decision process using the hidden markov model (HMM). The rationale behind this model is that an individual plans ahead before he/she executes a certain action which is a manifestation of the chosen latent plan. In their work, they were more interested in the evolution of the unobserved driving decisions i.e. plans rather than discounting future expected utility. HMMs can be either homogenous or heterogeneous. Homogenous HMMs assume that the transition

probability model between states from one time period to the other is consistent/time-invariant (e.g., Choudhury et al., 2010, and Xiong et al., 2014). Heterogeneous HMMs on the other hand are formulated such that the transition probability model varies over time (e.g., Vij, 2013). As we are more interested in the dynamics underlying preferences as denoted by the construct of modality styles rather than the dynamic underlying choices, we will employ an integrated hidden markov and discrete choice model (HMM/DCA) to model the evolution of the modality styles. We are not interested in evaluating the expected utility of a certain mode as the scope of our analysis does not revolve around the replacement/ownership of a certain good.

Using the HMM, the following two assumptions are made:

- 1- The observed mode choice at a certain time t is only dependent on the corresponding modality style during that time period
- 2- An individual's modality style during a certain time t is only dependent on his/her modality style during the previous time period

The figure below depicts the HMM assumptions and illustrates how a modality style (state) at time period t affects the manifested mode choice (action) over time. It is important to note that modality style₀ seeks to determine the effects of inertia and past experiences on the probabilistic assignment of each individual to each of the available modality styles during the first time period i.e. $t=1$. That said, an issue with using HMMs is that the initialization condition must be specified appropriately, or else the model might result in inconsistent estimates.

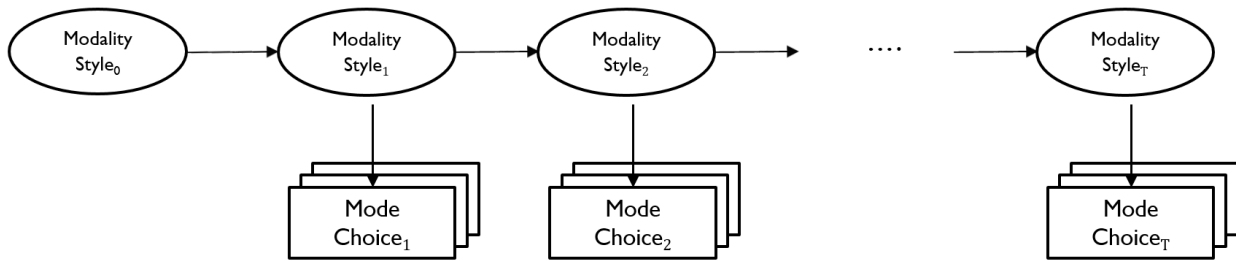


Figure 1: First-order Hidden Markov Model

3. Methodological Framework – HMM/DCA

In developing a methodological framework for dynamic travel model choice that seeks to inform policy makers and transportation specialists about the 20-30 year forecasts made from large-scale urban travel demand models, we employed an integrated hidden markov and discrete choice model (HMM/DCA). Our dynamic framework consists of hidden states which denote modality styles and transition probabilities to model the evolution of those modality styles over time which shall capture shifts in travel behavioral trends. Our dynamic framework requires a transition matrix that can capture shifts in modality styles brought about either by major changes to the transportation system (sharing, automation, transit on demand) or by shifts in attitudes (e.g. towards/away from auto-orientation). We are interested in forecasting, and thus require a structural model for the transition matrix that captures the influence of transportation and societal changes. For this we employed a homogenous HMM which assumes that the transition probability model between modality styles (states) from one time period to the other is consistent/static i.e. transition probabilities between subsequent waves is time-invariant. The figure below displays the dynamic nature of modality styles and their influence on the observed mode choice at each time period.

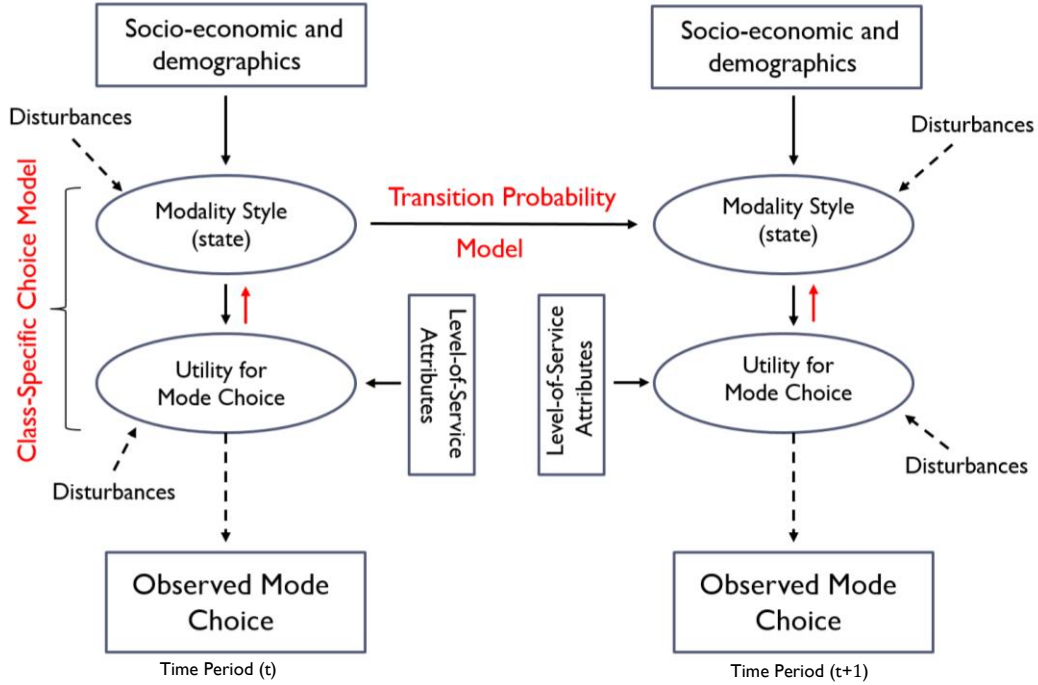


Figure 2: Hidden Markov Model Methodological Framework

There are three pieces to the HMM: class-specific travel mode choice model, initialization sub-model and the transition probability model which will be further explained below.

3.1 Class-specific Travel Mode Choice Model (Action Given State)

Let $U_{ntkj|s}$ denote the utility of alternative j during choice situation k over wave t for individual n conditional on the decision-maker belonging to modality style s which is expressed as follows:

$$U_{ntkj|s} = V_{ntkj|s} + \varepsilon_{ntkj|s} = x'_{ntkj}\beta_s + \varepsilon_{ntkj|s}$$

where $V_{ntkj|s}$ is the systematic utility that is observed by the analyst, x'_{ntkj} is a row vector of attributes of alternative j during choice situation k over wave t for individual n , β_s is a column vector of parameters specific to modality style s and $\varepsilon_{ntkj|s}$ is the stochastic component of the utility specification. Now, assuming that all individuals are utility maximizers and that $\varepsilon_{ntkj|s}$ follows an i.i.d. Extreme Value Type I distribution across individuals, waves, choice situations, alternatives and states (modality styles) with mean zero and variance $\frac{\pi^2}{6}$, the class-specific choice travel mode choice model could be formulated as such:

$$P(y_{ntkj} = 1 | q_{nts} = 1) = \frac{\exp(x'_{ntkj}\beta_s)}{\sum_{j' \in C_{ntk|s}} \exp(x'_{ntkj'}\beta_s)}$$

where $P(y_{ntkj} = 1 | q_{nts} = 1)$ denotes predicting the probability that individual n over wave t and choice situation k chose alternative j (implying y_{ntkj} equals one and zero otherwise) conditional on the same individual having modality style s during wave t (q_{nts} equals one and zero otherwise), and $C_{ntk|s}$ denotes the choice set available for individual n at wave t for modality style s .

Assuming that the choice probabilities for individual n across all choice situations for wave t are conditionally independent given that the individual has modality style s during wave t , then the conditional probability of observing a vector of choices y_{nt} for a certain wave t becomes:

$$P(y_{nt} = 1 | q_{nts_t} = 1) = \prod_{k=1}^{K_{nt}} \prod_{j \in C_{ntk|s}} P(y_{ntkj} = 1 | q_{nts_t} = 1)^{y_{ntkj}}$$

where K_{nt} is the distinct number of choice situations faced by individual n over wave t .

3.2 Initialization Sub-model

Let $P(q_{n1s} = 1 | Z_{n1})$ denote the probability that individual n has modality style s during the first wave.

$$P(q_{n1s} = 1 | Z_{n1}) = \frac{\exp(z'_{n1} \tau_s)}{\sum_{s'=1}^S \exp(z'_{n1} \tau_{s'})}$$

where z'_{n1} is a row vector of socio-economic and demographic variables for individual n during the first wave and τ_s is the associated column vector of parameter estimates for each modality style. Finally, S denotes the total number of modality styles in the sample.

3.3 Transition Probability Model (Evolution of States/ Modality Styles)

Let $U_{nts|(t-1)r}$ denote the utility derived from transitioning into modality style s during wave t conditional on individual n having modality style r during the previous wave $(t-1)$ which is expressed as follows:

$$U_{nts|(t-1)r} = V_{nts|(t-1)r} + \varepsilon_{nts|(t-1)r} = z'_{nt} \gamma_{sr} + \varepsilon_{nts|(t-1)r}$$

where $V_{nts|(t-1)r}$ is the systematic utility, z'_{nt} is a row vector of observable socioeconomic and demographic characteristics of individual n over wave t and γ_{sr} is a column vector of parameters specific to modality style s at wave t given that the individual has modality style r over wave $(t-1)$, and $\varepsilon_{nts|(t-1)r}$ is the stochastic component of the utility specification.

Assuming that all individuals are utility maximizers and that $\varepsilon_{nts|(t-1)r}$ follows an i.i.d. Extreme Value Type I distribution across individuals, waves and modality styles with mean zero and variance $\frac{\pi^2}{6}$, the transition probability model could be formulated as such:

$$P(q_{nts} = 1 | q_{n(t-1)r} = 1) = \frac{\exp(z'_{nt} \gamma_{sr})}{\sum_{s'=1}^S \exp(z'_{nt} \gamma_{s'r})}$$

where $P(q_{nts} = 1 | q_{n(t-1)r} = 1)$ denotes one entry of the transition probability matrix which involves predicting the probability that individual n has modality style s during wave t , for $t > 1$, conditional on the individual having modality style r during the previous wave $(t-1)$.

Now, the transition probability model is merely a function of socio-demographics. However, wouldn't changes in the transportation network such as reductions in travel time or travel cost, etc. influence the

transition from one modality style to the other? If a new mode of transportation is introduced in a transportation system, say a metro system, then it is important to model the impact of such a shock on the transportation system onto the transition probabilities. If the new metro system is efficient and cost effective, then we should be able to cater for those effects on the transition probabilities of modality styles that include this new mode. This way, we can quantify the attractiveness of the new mode in our transition probability model in a more representative manner. That is why we need to assess the influence of the built environment or changes that occur in the transportation network on the transition from one modality style to the other.

To develop a structural transition matrix model that is sensitive to changes in the transportation system, we propose to make the transition probabilities a function of the consumer surplus each decision-maker would derive via subscribing to different modality styles (building off the static modality style framework in Vij et al., 2014). Hence, incorporating consumer surplus will provide a method of capturing influences of changes of the built environment onto transition probabilities and allows forecasting them into future years. Assuming error terms to be i.i.d Extreme Value Type I, then the consumer surplus offered by modality style s to individual n for wave t is defined as a logsum measure:

$$CS_{nts} = \frac{1}{K_{nt}} \sum_{k=1}^{K_{nt}} \log \left[\sum_{j \in C_{ntk|s}} \exp(x'_{ntkj} \beta_s) \right]$$

Hence, the transition probability model we are proposing is given by:

$$P(q_{nts} = 1 | q_{n(t-1)r} = 1) = \frac{\exp(z'_{nt} \gamma_{sr} + CS_{nt} \alpha_{sr})}{\sum_{s'=1}^S \exp(z'_{nt} \gamma_{s'r} + CS_{nt} \alpha_{s'r})}$$

where α_{sr} is a parameter associated with the consumer surplus specific to modality style s given that the individual has modality style r over wave $(t-1)$.

Now, the marginal probability $P(y_n)$ of observing a sequence of choices y_n for decision-maker n over T waves is expressed as follows:

$$P(y_n) = \sum_{s_T=1}^S P(y_{nT} = 1 | q_{nTs_T} = 1) \sum_{s_{T-1}=1}^S P(q_{nTs_T} = 1 | q_{n(T-1)s_{T-1}} = 1) P(y_{n(T-1)} = 1 | q_{n(T-1)s_{T-1}} = 1) \dots$$

$$\sum_{s_2=1}^S P(q_{n3s_3} = 1 | q_{n2s_2} = 1) P(y_{n2} = 1 | q_{n2s_2} = 1) \sum_{s_1=1}^S P(q_{n2s_2} = 1 | q_{n1s_1} = 1) P(y_{n1} = 1 | q_{n1s_1} = 1) P(q_{n1s_1} = 1 | Z_{n1})$$

The model was estimated via the Expectation-Maximization (EM) algorithm (forward-backward algorithm) which provides a computationally robust method of optimization that takes advantage of the conditional independence properties of the model framework. The EM algorithm is particularly useful for HMMs without feedback because in the M-step, each of the class-specific choice models, the initialization model and transition probability model can be maximized independent of the other sub-models. For HMMs with feedback through consumer surplus however, the class-specific choice models and the transition probability model can no longer be separated and maximized independently because the sub-models are joined through the consumer surplus construct. Consequentially, the EM algorithm is no more useful than traditional gradient-based optimization routines.

4. Dataset – HMM/DCA

The dataset used to develop the integrated hidden markov and discrete choice model comes from Santiago, Chile (Yañez, 2010). The data entails an opportunity to assess impacts on travel behavior once a shock is introduced in a transportation network. During February 2007, the city of Santiago introduced Transantiago, a complete redesign of the public transit system in the city. Prior to that, the public transportation system in Santiago consisted of privately operated system of buses that had an inefficient fleet and was characterized by small headways and high frequencies at congested spines and corridors. However, regions that were less congested suffered from inadequate service. The public transportation system also included jitneys, shared taxis and the Metro. The Metro system only comprised 8% of the city's trips even though it is more reliable and faster than the bus system. A Chilean team of consultants tried to address these issues in 2005 by a complete redesign of the public transit system (Transantiago). The Santiago region was divided into ten zones which were to be operated by ten new companies. The bus system was divided into feeder networks to connect the zones with the Metro lines and trunk routes to supplement the Metro lines in providing more coverage for transportation mobility across the network. This way, the bus system would provide a backbone to the Metro lines and will no longer operate inefficiently. In addition to that, an integrated fare collection system (smart card) was introduced.

The redesign of the transportation system was not marketed with the community of Santiago as it was introduced without informing the public about it. The dataset is longitudinal as it entails four one-week pseudo travel diaries throughout a twenty-two month period which overlapped with the introduction of Transantiago. The introduction of Santiago happened three months after wave one. The travel diaries across the four waves were conducted on the following dates: December 2006, May 2007, December 2007 and October 2008 respectively. The longitudinal dataset entailed full-time employees working at the campuses of Pontificia Universidad Catolica de Chile all over Santiago and focused on work trips during the morning peak hours. The dataset has a good level of distribution of origin and destination pairs. After data cleaning, 220 individuals were kept in the dataset that had recorded travel diaries across the four waves which resembles the low attrition rate the survey has. Each individual has 5 choice situations recorded during each of the four waves corresponding to a total of 4400 choice situations. The survey entailed questions about the level-of-service attributes of the morning work trip, socioeconomic and demographic characteristics of the decision makers, activities during, before and after work, chosen transport mode for the corresponding work trip in addition to subjective perceptions about the performance of the new system (collected during second and third waves) and finally decision-maker's agreement with attitudinal statements about the system's performance which were collected during the fourth wave only. The available travel modes were aggregated into the following modes: auto, metro, bus, walk, bike, drive to metro and bus to metro.

The figure below denotes the chosen modes of transport across the four waves for all 220 individuals. It is evident that there was a big reduction in choosing the bus system as a mode of transport for work tours after wave one (post introduction of Transantiago). The mode share for bus was 40.6% during the first wave, 21.5% during wave two, 18.2% and 21.6% during waves three and four respectively. Moreover, the mode share for drive to metro and bus to metro drastically picked up after the introduction of Transantiago. The major shifts in the mode choices occur between waves one and two as one would expect. Shifts tend to stabilize over time as people get more adjusted with their new work trips mode choice habits.

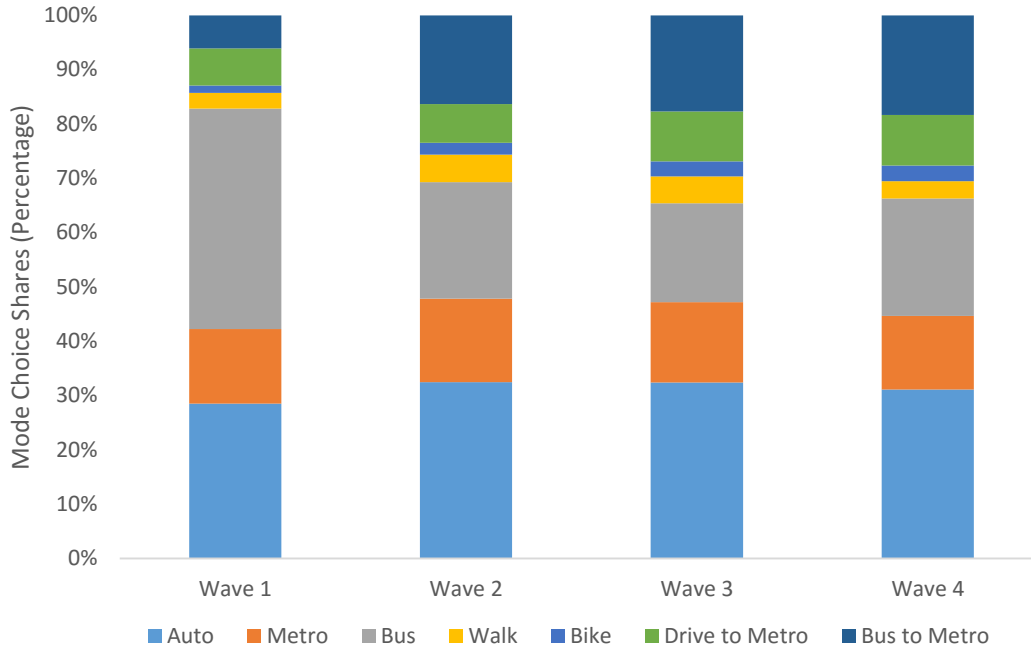


Figure 3: Mode Choice Shares across All Waves

5. Estimation Results and Discussion

The following section entails results of the HMM/DCA travel behavior model which studies the evolution of modality styles. Determining the final model specification was based on varying the utility specification for all sub-models i.e. initialization sub-model, transition probability model and class-specific choice model. The method of identifying the number of distinct modality styles that exist in the sample population is iterative. We first started estimating a model that comprised two modality styles and built on that to increase the number of modality styles. Since we only had 220 individuals in our dataset, it is quite difficult to attain a big number of classes (modality styles). Determining the number of modality styles in our sample will be based on model comparison criteria in terms of the final log-likelihood, and measures of statistical fit: rho-bar-squared ($\bar{\rho}^2$), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

We ended up selecting the four modality styles case as our optimal scenario. This entailed a behaviorally richer and interpretable scenario in addition to the best statistical measures of fit that are tabulated below for the two, three and four modality style cases. It is clear that with an increase in the number of classes, rho-bar-squared increased while the AIC and BIC decreased.

Table 1: Measures of Model Fit

Classes	Log-Likelihood	$\bar{\rho}^2$	AIC	BIC
Two	-2365	0.514	4798	5015
Three	-1599	0.636	3328	3743
Four	-1234	0.649	2680	3357

Tables 2 and 3 below present detailed parameter estimates (and t-statistics) of the class-specific travel model choice model, initialization sub-model and transition probability model.

Table 2: Class-specific Travel Mode Choice Model

Dependent Variable / Choice: Travel Model Choice				
Variable	Class 1 Drivers	Class 2 Bus Users (Transit)	Class 3 Bus-Metro Users (Transit)	Class 4 Bus-Auto Users (Transit)
<u>Alternative Specific Constant</u>				
Auto	0.00 (-)		--	0.00 (-)
Metro	-3.92 (-25.90)		0.00 (-)	2.29 (3.52)
Bus	-4.26 (-9.44)		-7.64 (-30.05)	
Walk	1.94 (9.05)	--		
Bike	-0.71 (-1.89)			
Auto-Metro	-3.44 (-31.08)			4.44 (7.94)
Bus-Metro	-3.62 (-12.68)		2.21 (24.14)	
Travel Time (mins)	-0.03 (-10.96)	--	-0.09 (-38.11)	-0.07 (-7.17)
Walk Time (mins)	-0.04 (-5.87)	--	-0.13 (-24.13)	-0.10 (-2.15)
Travel Cost (CLP)	-0.01 (-3.45)	--	-0.10 (-41.30)	-0.08 (-5.00)
Waiting Time (mins)	-0.02 (-2.25)	--	-0.29 (-41.13)	-0.05* (-0.88)
Number of Transfers	-	--	-1.14 (-14.40)	-

-- Not applicable; * Insignificant at the 5% level

Table 3: Initialization and Transition Probability Model Results

Variable	Class 1 Drivers	Class 2 Bus Users (Transit)	Class 3 Bus-Metro Users (Transit)	Class 4 Bus-Auto Users (Transit)
Initialization Model (Wave 1)				
Alternative Specific Constant	0.00 (-)	2.98 (6.46)	-0.26 (-0.55)	0.22 (0.45)
Household Income (100,000s CLP)	0.00 (-)	-0.51 (-4.18)	-0.08 (-1.29)	-0.16 (-1.99)
Male	0.00 (-)	0.24 (0.72)	0.69 (1.27)	0.60 (1.17)
Number of Vehicles	0.00 (-)	-1.00 (-4.08)	-0.50 (-1.21)	-0.49 (-1.72)
Transition Probability Model (Given Class 1, Wave > 1)				
Alternative Specific Constant	0.00 (-)	-1.96 (-1.35)	0.96 (1.97)	-1.69 (-5.20)
Household Income (100,000s CLP)	0.00 (-)	-0.12 (-0.31)	-0.61 (-3.81)	-0.09 (-1.72)
Male	0.00 (-)	0.49 (0.55)	-1.93 (-2.62)	0.30 (0.80)
Number of Vehicles	0.00 (-)	-0.67 (-0.67)	-0.96 (-1.73)	-0.18 (-0.93)
Transition Probability Model (Given Class 2, Wave > 1)				
Alternative Specific Constant	0.00 (-)	2.47 (13.89)	1.50 (4.38)	-1.04 (-3.22)
Household Income (100,000s CLP)	0.00 (-)	-0.40 (-8.93)	-0.26 (-3.48)	-0.15 (-2.78)
Male	0.00 (-)	1.37 (9.58)	1.17 (3.41)	-33.87 (-92.00)
Number of Vehicles	0.00 (-)	0.19 (1.76)	-0.40 (-1.25)	0.33 (1.73)
Transition Probability Model (Given Class 3, Wave > 1)				
Alternative Specific Constant	0.00 (-)	4.16 (3.09)	3.21 (32.31)	2.66 (8.36)
Household Income (100,000s CLP)	0.00 (-)	-0.98 (-1.89)	-0.11 (-7.41)	-0.88 (-16.83)
Male	0.00 (-)	0.11 (0.16)	1.28 (12.08)	-0.52 (-1.41)
Number of Vehicles	0.00 (-)	-1.83 (-2.19)	-1.22 (-13.20)	-0.11 (-0.52)

Transition Probability Model (Given Class 4, Wave > 1)				
Alternative Specific Constant	0.00 (-)	0.73 (0.53)	0.48 (0.82)	1.30 (11.74)
Household Income (100,000s CLP)	0.00 (-)	-0.47 (-1.11)	-0.33 (-2.69)	-0.07 (-5.79)
Male	0.00 (-)	1.55 (2.15)	1.50 (3.06)	0.23 (1.55)
Number of Vehicles	0.00 (-)	-1.38 (-1.29)	0.31 (0.85)	0.51 (5.32)

-- Not applicable; * Insignificant at the 5% level

Class 1 denotes drivers and in particular multimodal users that consider all available modes of transport in their choice set and are sensitive to travel time and travel cost. However, when we performed sample enumeration for this class, 70% of the trips were conducted via the auto alternative. Class 2 is a deterministic class i.e. it is the class that considers one and only one alternative for all trips which is the bus alternative. Class 3 was labelled bus-metro users (transit) since that group highly considered the metro, bus and bus-metro alternatives for their work trips. Class 4 was labelled auto-metro users (transit) as the choice set depicts auto, metro and auto-metro alternatives. It is evident from the class-specific travel model choice model that each market segment is different in its choice set consideration and its respective sensitivity to travel time, waiting time, number of transfers and travel cost. In addition the tabulated model results are behaviorally consistent whereby parameter estimates in the class-specific travel mode choice model have the right sign and are highly significant.

We were also interested in understanding the evolution of modality styles as a result of the introduction of Transantiago (shock to the transportation network) as individuals started adopting to it. In order to do so, we performed sample enumeration to determine the percentage share of individuals that belong to each of the four modality styles across the four waves as predicted by the model. The figure below displays the results of the sample enumeration procedure. It is evident that a shock to the transportation network along the lines of Transantiago did force people to reconsider their mode choice for travel. The share of drivers, and bus-metro (transit) users has increased after the introduction of Transantiago while the market share for bus users has drastically decreased. The market share for the auto-metro class remained almost stable throughout the four waves.

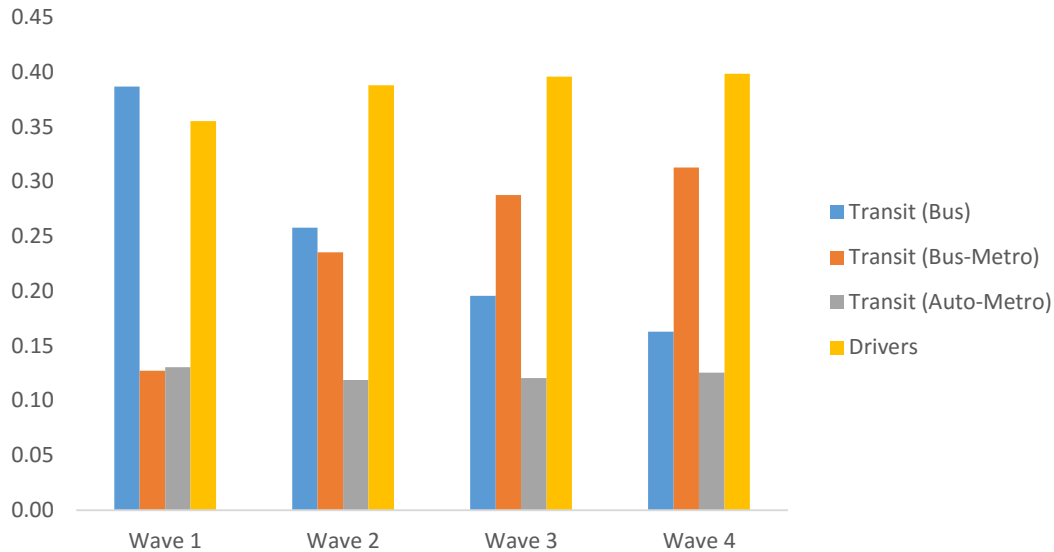


Figure 4: Percentage Share of Individuals in Each Modality Style across Waves

6. Conclusion

An integrated hidden markov and discrete choice model (HMM/DCA) was developed to capture the dynamics behind travel behavior in response to changes/shocks that occur in the transportation network via studying the evolution of modality styles. Based on behavioral interpretation and statistical fit measure, we resided to selecting the four modality style dynamic model of travel behavior. The four modality styles were drivers, bus users, bus-metro users (transit) and auto-metro users (transit). The results look promising in terms of defining the utility associated with each of the available modes in the choice set. Parameter estimates in the class-specific travel mode choice model have the right sign and are highly significant. Also, the sample enumeration of modality styles across the four waves support the intentions and major goals behind Transantiago in making people reconsider their modes of travel. The share of drivers, and bus-metro (transit) users has increased after the introduction of Transantiago while the market share for bus users has drastically decreased. The market share for the auto-metro class remained almost stable throughout the four waves. The adopted methodological framework in this paper provides a methodology that should be taken into consideration to improve the accuracy of the 20-30 year forecasts made from large-scale urban travel demand model. Also, this framework provides a quantitative tool to understand and predict structural long-range trends of travel behavior that are bound to occur in this transformative mobility era.

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WHAT CAN THE LITERATURE ON TECHNOLOGY ADOPTION TEACH US ABOUT AUTONOMOUS VEHICLES?

Thoughts in progress

by Prof David Zilberman, Feras El Zarwi, Prof Joan Walker (UC Berkeley)

Autonomous cars are on the horizon and are expected to induce societal benefits on many different levels from improving quality of life, ensuring economic vitality, encouraging multimodality, promoting connectivity, mitigating the escalating stress encountered when driving in addition to reducing congestion levels and emissions. However, this transformative mobility trend has no defined path. We should be cautious with how the future is going to play out and the role that policy may play in guiding the transformation.

There are four key research questions to be addressed:

1. Short-, medium- and long-run transportation infrastructure development, particularly concerning the transition period from conventional to autonomous and the period of mixed vehicles.
2. Synergies between transportation and energy infrastructure, including the adoption of electric vehicles and the growth of the electric power system.
3. The market share between owners of autonomous vehicles and those using a shared vehicle fleet.
4. Supply chain issues including who will develop the technology and infrastructure.

Essential within each of these questions is the potential role of government, i.e. the potential effect of policies and investment strategies. Effective policies and investment strategies whether on the public or private level will play a key role in guiding the evolution of the autonomous vehicles market.

In this paper we focus on how the literature on technology adoption can help us understand and predict the expected market penetration rates of autonomous cars and guide the diffusion of this new technology.

There are three distinct components that need to be analyzed to address the research question we have in mind. These components are: the adoption process which will constitute our main focus in this report followed by supply chain systems, and political economy considerations. Those three components, together with their interactions and functionality will yield and define how the diffusion process of autonomous vehicles is going to look like.

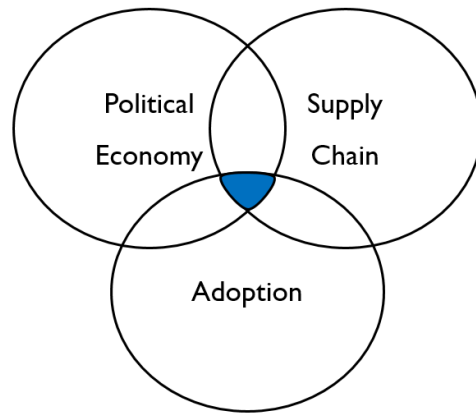


Figure 1: Three Components of the Diffusion of Autonomous Vehicles

First, we will dwell upon the adoption process of autonomous vehicles. The adoption process entails several stages: (1) awareness of the new technology i.e. autonomous vehicles which is affected by formal sources of information such as advertisement and mass media, and informal sources of information induced by the imitation process. The imitation process is rooted in the technology diffusion literature as it stresses on the importance of the role of two different two types of adopters in shaping the market penetration rate of a new technology. These distinct types of adopters are: innovators and imitators. Innovators are individuals that “decide to adopt an innovation independently of the decisions of other individuals in a social system” while imitators are adopters that “are influenced in the timing of adoption by the pressures of the social system” (Bass, 1969); (2) assessment of the new good or service which takes into account risk considerations, potential welfare gains from adoption in addition to the product’s respective fit with the consumer’s lifestyle and needs. This stage is influenced by the way the product is packaged and introduced in the market (buying, leasing, renting, etc.); (3) decision to adopt the new technology or not which is influenced by various exogenous variables such as socio-demographics, social influences, attributes of the autonomous vehicles, and most importantly safety. When we talk about safety, it is important to keep in mind that the coexistence of autonomous cars and conventional cars will be tricky. The ability to have insurance, as well as liability rules that will make the introduction of autonomous cars economically viable will be challenging; and (4) reevaluation of the adoption decision in terms of consumer satisfaction and other criteria.

A very important notion in the adoption process is heterogeneity that exists among different decision-makers which drives different consumers to adopt a new technology at different time periods. Potential adopters will vary according to socio-demographic variables such as age, education level, gender, income level, etc. The diffusion process, and in particular the steepness of the “S”-shaped diffusion curve and the time period at which it exhibits a plateau, is directly influenced by new segments of adopters entering the market and adopting the new technology. In the context of autonomous vehicles, one can consider three key variables that are trivial in identifying potential adopters. These variables are age, income level and land use density. The table below categorizes different potential consumers based on the aforementioned variables and whether they are more likely to own a car, own an

autonomous vehicle (AV) or share an AV according to a-priori hypotheses and lessons from the diffusion literature. The table highlights the effect of income, land use density and age on the willingness to own a car or autonomous vehicle versus share an autonomous vehicle.

Table 1 : Effect of Land Use Density, Income and Age on Adoption of Autonomous Vehicles

Age	Young	Land Use Density			
		Low		High	
		Low Income	High Income	Low Income	High Income
		own car	own AV own car	share AV	share AV
Senior	share AV	own AV	share AV	own AV	

Furthermore, it is essential to identify different consumer groups that will be affected by the introduction of autonomous cars as an alternative mode of transportation. Those groups comprise various companies and communities and will be discussed hereafter. Companies like Uber and Lyft and other carsharing services will be more inclined to take part in the sharing economy and adopt the new technology in order reduce the incurred cost of driving. Moreover, senior/disabled communities are more likely to adopt and be part of the sharing autonomous vehicles market as it provides a reliable and safe alternative to compensate for their inability to drive. Transit providers (like BART) will try to pursue autonomous vehicles sharing arrangements to provide riders with a better feeder network to use the transit service in addition to reaching their final destination from the transit system i.e. work or home, etc. Finally, estates or facilities that control large amounts of land and are in need of a transportation service that provides mobility and connectivity to conduct various activities such as gold courses, big industrial plants, military bases and farms will highly consider acquiring autonomous cars.

All of those types of companies and communities may be early adopters of autonomous vehicles and will in turn refine the technology and the industry itself. The early adopters are more likely to be individuals that prefer conducting a trip via a car (private transportation) but are incapable of driving nor enjoy driving. Richer busy senior people are definitely more inclined toward owning autonomous cars and be early adopters of this new technology.

Another important dimension to be tackled in the adoption process is the relationship and interaction between autonomous cars and public transportation. In regions with accessible and reliable public transportation system, the need for private transport systems such as regular cars and autonomous vehicles might be minimalistic. However, autonomous cars can be used to complement the existing transit system through providing a reliable feeder network so that individuals can easily access the transit station/stop from their respective origins and reach their final destination. On the other hand, when the public transportation system is less developed, people have to travel more frequently to conduct their respective activities which induces a higher auto ownership level. In these regions, autonomous

vehicles might have much higher market penetration rates to relieve the escalating stress of driving and ensure a higher connectivity than the existing transit service.

Now that we have identified the main aspects of the adoption process, we will briefly discuss the remaining two components that will shape the diffusion process of autonomous cars: supply chain system and political economy. The supply chain is a key element in technology diffusion of any innovation as it is involved in the development, up-scaling, commercialization, marketing, distribution and many other processes pertinent to the good or service. Frequently, the basic research that leads to products is supported by the government and may be done by research institutes and companies. The more applied research is more likely to be done by the private sector. Development and commercialization are undertaken by the private sector, but are often times subsidized by the government. We all know that once autonomous vehicles are introduced in the market, they will be expensive which will in turn drive the early adopter market segment to be constitute the entities previously mentioned. However, the supply chain system will expand and refine itself to promote higher market penetration rates by reaching out to a larger range of income levels. Ultimately, the purchase price of autonomous vehicles will decrease over time and more consumers will likely to adopt.

Finally, a brief overview of political economic considerations that should be taken into account. Every new technology is expected to face some sort of objection from individuals and organizations that will be negatively affected by it. In the case of autonomous cars, the biggest losers may be drivers. We are aware of the fights between taxi and Uber drivers. But both parties might be expected to unite against the new technology so that they can preserve their revenue streams from their current services. On the other hand, if autonomous cars can improve the fate of older people by providing them with an alternative that promotes mobility and connectivity, then one would expect the American Association of Retired Persons (AARP), as an example, to support government programs that encourage the need for having autonomous cars.

Furthermore, to cater for the temporal dimension of the diffusion of any technology, it is important to understand the role of different dynamic processes that occur once the new good or service is introduced in the market. From the supply side, "learning by doing" will reduce fixed costs through knowledge accumulation by the manufacturer. Also, continuous R&D studies and development can further enhance the new technology and make it operate more efficiently in addition to developing newer technologies. Finally, the role of distribution channels and their expansion rates could affect the dynamic process of market penetration on a larger scale. From the demand side, "learning by using" whereby a consumer becomes better equipped in using the technology, learning from other adopters of the new product and their experiences, branding and marketing effects, and network externalities (implying that as the benefits to users from the new technology become greater than that is expected to have an increase in the number of adopters) will impact the adoption rate at different time periods.

One final thought entails possible synergy with electric vehicles. So, it may be that locations that invest in infrastructure for electric cars (charging stations) may be the locations that will also invest in self-driving cars. For example, if a city or an organization, out of concern for climate change, is able to obtain affordable clean energy to support an electric car network, it may also encourage adoption of autonomous vehicles. To some extent, the dynamics and the pace of evolution of electric and autonomous cars will be highly correlated.