Impact of ride-sharing on mobility trends and vehicle stock

by

Suhrid Deshmukh

B.S.,University of Minnesota (2012)
S.M., Massachusetts Institute of Technology (2014)

Submitted to the Department of Mechanical Engineering
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2018

© Massachusetts Institute of Technology 2018. All rights reserved.

Author . . . . . .
Department of Mechanical Engineering
May 18, 2018

Certified by . . . . . .
Dr. Richard Roth
Research associate, MSL MIT
Thesis Supervisor

Certified by . . . . . .
Prof. Warren Seering
Professor of Mechanical Engineering, MIT
Thesis Supervisor

Accepted by . . . . . .
Prof. Rohan Abeyaratne
Chairman, Department Committee on Graduate Theses

Impact of ride-sharing on mobility trends and vehicle stock

by

Suhrid Deshmukh

Submitted to the Department of Mechanical Engineering
on May 18, 2018, in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Abstract

North American transportation industry is on the verge of a revolutionary change. With the advent of car-sharing services and ride-sharing companies, the transportation industry is experiencing a fundamental way in which people choose to travel. This particular thesis looks at the impact of these disruptive changes in transportation on the way people choose to travel, the car based vehicle miles travelled (VMT) and the national vehicle stock. In particular, this work tries to look at how people choose to make a travel decision when embarking on a particular trip and how that translates to an effect on the national level vehicle stock. When presented with a particular mode of travel, the most relevant aspects associated with that particular mode of travel were explored and evaluated. Each mode was evaluated based on cost, time and comfort associated with the mode. Multi-attribute utility theory was used to study and evaluate how people make decisions about mode choice when choosing a particular mode for a trip. This work tries to look at the impact of ride-sharing on modal changes and shits that result in a less or more use of personal car travel.

Apart from the travel behavior associated with modes, this work also estimates impact of ride-sharing on the total vehicle usage in urban areas. Once the modal share of different modes was estimated, an overall passenger trip demand was generated at the national level. This trip demand was broken down into car-based trips and non-car based trips from the modal share result. Combined with occupancy assumptions, this passenger trip demand was converted into a car based VMT estimate. Finally, combining the car based vehicle miles travelled with the average vehicle utilization, the national vehicle stock was calculated.

In order to measure the impact of these futuristic technologies on modal share, VMT and the national vehicle stock, scenario analysis was the method chosen. In order to have a reference case, a base case scenario was designed assuming the world remains as it is today and nothing changes. A series of progressive scenarios related to ride-sharing were then tested to gauge the impact of ride-sharing. It was found that ride sharing has the most significant impact in the urban areas for short trips. The national level vehicle stock in the year 2050 declined by approximately 1.0% in the improved ride-sharing scenario. Higher-electrification of vehicles along with

improvements in ride-sharing did not decrease the stock further by much, as compared to just the improved ride-sharing scenario. In an aggressive scenario, with improved ride-sharing, improved transit and anti-car policies, the national level stock value in year 2050 declined by approximately 6% compared to the base case scenario. Finally, in the scenario with improved ride-sharing and higher autonomy, the national level VMT increased by 1.3%, but the vehicle stock declined by 9.9%. The results from this work can be further used to inform certain decisions regarding changing travel behaviors or explore questions related to higher level policy analysis.

Thesis Supervisor: Dr. Richard Roth
Title: Research associate, MSL MIT

Thesis Supervisor: Prof. Warren Seering
Title: Professor of Mechanical Engineering, MIT

Acknowledgments

This thesis would not have been possible without the contributions of from a number of people. First and foremost, I would like to thank my advisor Dr. Richard Roth for for his guidance and invaluable support throughout the PhD journey. I was humbled by the opportunity he gave me to work at the Material Systems Lab (MSL) after my masters when I was trying to find a new advisor. His lively conversations during the meetings and his sense of humor have lightened the mood during many stressful times. I am also greatly thankful to my industry sponsor, Rio Tinto, for funding this project during my PhD at MIT.

I would also like to thank my committee members, Dr. Randolph Kirchain, Prof. John Heywood and Prof. Warren Seering. Randy has always been a source of inspiration with his attention to detail and his patience and perseverance. I would like to thank Prof. Seering for agreeing to be the committee chair and giving valuable insights throughout the committee meetings. I would also like to thank Prof. Heywood, an expert in the field of transportation, for providing a rigorous academic direction to this work. I was amazed and humbled by his kindness and humility, and I want to thank him for providing encouraging words throughout the committee meetings. I am grateful to Prof. Tim Gutowski for giving me the opportunity to TA his course during the last semester of my PhD. I was able to appreciate how he makes time to enjoy life and maintains excellent health, in spite of being an extremely busy Professor, and I hope to take a leaf from his book. I am also grateful to Dr. Frank Field, who has been instrumental on helping me get started with R and I would like to thank him for guiding the project in the earlier stages.

Its hard to overstate the importance of admins in a graduate student's career. Know-how about the professors, last minute signatures, guiding through the advisor search process, providing free candy and words of encouragement when the going gets tough, they are arguably the people who keep the institute running smoothly. I am grateful to the MechE graduate office - Leslie Regan and Una Sheehan and Terra Cholfin at MSL, for their assistance in all the department related matters.

I am extremely thankful to the members of the MSL group, both past and present. They have been a constant source of support and an excellent source for discussing research ideas and more importantly, life ideas. I am also thankful to the amazing people I have met at MIT over the years. Being at MIT has been a very awarding and a humbling experience. Roaming through the hallowed hallways at MIT, I was constantly reminded the value and power of knowledge. At MIT, people are always willing to share and learn from each other, build things, work hard and play harder - there has never been a dull day on campus. The willingness of people at MIT to help each other out selflessly is truly inspirational and humbling. In spite of all the ups and downs through out the PhD journey, I can definitively say that my days as a graduate student at MIT have been the best days of my life so far.

This acknowledgement cannot be complete without profusely thanking my parents and my grandmother who taught me the value of perseverance, compassion, patience and hard work and showered upon me their constant blessings and support for all these years. I would also like to thank my sister for providing the much needed dose of humor when it was necessary. I would also like to thank my in-laws who have been there for me whenever I needed them. I am also grateful to my extended family here in the US and India who have always given me their love and support. I am thankful to my wife, Madhura, for the constant support and patience throughout this PhD journey, I hope to return the favor during your PhD. Last but certainly not the least, I thank God, the supreme cosmic energy which drives us all to persevere through adversity.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Today, the transportation industry stands at what could be a revolutionary change, the one that drives people away from driver-driven personally owned vehicles to shared autonomous vehicles. These revolutionary changes could come in many different forms. Given that we are living in the age of Internet of Things(IoT), a lot of blending between the Internet applications and transportation services has happened. This blending could lead to changes such as greater availability of transportation options to those who did not have any before and improved availability of transportation in general. Improved technology will change the way people get around and the way people choose to travel. IoT has already had a significant impact in the transportation industry and it is responsible for changing the dynamics of travel behavior. Because of IoT and mobility on demand, futuristic technologies like autonomous vehicles seem within reach. This might have an impact on the way vehicles are designed and the way they look. A push towards automation might require the sizes of the car to be smaller because smaller cars are easier to automate and hence decrease the size of an average sedan. All these changes affect automotive market differently. For example, a higher push towards, "greener" and "cleaner" cars might give a boost to electric vehicle sales. This can have major environmental implications as well. Because people might choose to travel in these vehicles operated by a mobility fleet, this might lead to a change in the total number of vehicles on the road needed to transport people. Therefore, these disruptive technologies might have an effect on the car fleet size as

well.

Automakers care about fleet sizes because it helps them plan their production accordingly. Policy-makers, government and private transportation service providers also care about fleet size as it impacts their future planning. The changes taking place in the transportation sector today might change the way people get around dramatically. People changing the way they get around might affect the above stake holders differently. As of today, car sharing services like Uber and Zip Car are becoming increasingly popular and the trend in transportation is moving towards this concept of "Fleet on demand". A lot of ride-hailing services are available as of today at a very competitive price that is moving people away from public transit for certain trips. As a result people are changing their priorities when it comes to choosing between public transit and a transport on demand service.

Due to the advent of ride-sharing and car-sharing, cars themselves have experienced change. With some of the ride-sharing companies exploring concepts like mobility on demand and maintaining a mobility fleet of autonomous vehicles, this might lead to a change in the shape and sizes of cars in the future. Cars might become pods, requiring less materials for manufacturing. Operating a mobility fleet might also impact congestion in dense areas, either in a positive or a negative way. This will have environmental implications as well.

People choose how to travel based on numerous factors. Some of them are cost, length of trip, reliability of options to travel and various other factors. The importance of these travel decision factors are different for different types of trips. For example, one might not care about the cost if the trip was very important, whereas if it was not important one might look for a cheaper option. Many times, the type of trips taken in a particular mode also depend on the area that the people are living in and their economic background. Transportation demand models exist at the inter-city level to study the impacts of these aspects on transportation, but not at the national level. Methods are needed to formulate a transportation demand model that can capture these disruptive changes in the technology and show its impact on the transportation demand and therefore the fleet size.

Apart from the travel demand models, models developed for estimating the car fleet sizes are also beneficial to the above stakeholders. Knowing the car fleet size is essential in planning and supply chain management. A lot of work has been done in modeling the car fleet size. What is needed is to incorporate these disruptive changes into the travel demand models and only then study the impact on the car fleet. The travel demand models that predict how people will change their travel behavior and the models that predict the size of the car fleet need to be linked so that the effect of these disruptive changes in transportation are directly translated to an effect on car fleet size.

1.1 Research Questions

Given all the changes in the transportation industry resulting from these disruptive technologies, there has been a lot of talk on how the travel demand affects the car fleet size. In the recent years, the private vehicle use in the US has stagnated. The average per-capita vehicle miles traveled(VMT) have declined, after a long steady growth in the previous decades[58]. Changes in occupancy and utilization could change the fleet size in either direction and it is not entirely obvious how these parameters are going to change overtime.

This work tries to explore some of the key questions around these disruptive technologies like the following. What aspects of disruptive technologies in the transportation sector are going to influence transportation choice, and the resulting car fleet size? Disruptive technologies by their nature are rapidly changing and there is quite a bit of uncertainty about their future. This thesis will explore how the different future assumptions about the disruptive technologies will affect the resulting transport choice, vehicle miles travelled and car fleet size. The goal of the work will be to create a framework for understanding the impact of different future trends on the transportation sector.

In particular, the future cost, time, availability and comfort of these technologies will be critical in determining future transportation choices. Furthermore, changes

in the way vehicles are used and owned, in particular the occupancy and average utilization will affect the translation of those transportation choices into the need for vehicles and a vehicle fleet. Context will also play a critical role as transport options are highly dependent on the purpose of the trip, trip distance and location among others. Changes resulting from ride-sharing services have been evolving rapidly and this has had an impact on the way people get around and way the society interacts with transport. While there are lots of questions surrounding the impact of ride-sharing on the transportation industry, this work focuses on three key questions:

- How will ride-sharing change the ways people get around?
- What will be the impact of ride-sharing on the total car based vehicle miles travelled (VMT)?
- What will be the impact on the national level vehicle stock?

Disruptive technologies like ride-sharing are already implemented. Autonomous vehicle technology is showing great promise. Both of these technologies can have an impact on the vehicle fleet through changing the way people get around. Both of these technologies have the potential to change the VMT through higher occupancy. These technologies can also affect the car fleet size through changing utilization. This could also result in a higher vehicle turnover.

Apart from the emergence of different technologies, people behavior also plays a critical role on the size of the car fleet. National level changes come from individual players and these individual players are different in different demographics. For example, people who are retired have very different traveling habits than people who are working. Also, people in urban areas have different options than people in the suburbs. Therefore, the disruptive technological changes and the availability mentioned earlier impact these demographies differently.

This work tries to study the impact on the national level stock by studying how people choose their mode of travel and how that changes with ride-sharing services becoming more available. Ride-sharing might lead to an increase in the total VMT

because ride-shared vehicles need to travel in between trips to pick up passengers. But due to higher occupancy and utilization of these vehicles, they might offset this increase in the VMT by requiring fewer vehicles. Apart from changes in the vehicle stock, these technologies have the potential to impact many other things including congestion, environment, travel policies etc. This particular work focuses on the three things mentioned above.

To address these issues, this work explores how disruptive technologies affect the vehicle stock in a variety of different contexts. We will explore how (1) changes in cost and (2) changes in time and availability of the disruptive technologies affect the system. We will also explore how implementation of these disruptive technologies potentially affect (1) occupancy of the vehicles and (2) their utilization.

1.1.1 Impacts of costs of disruptive technologies

This work explores the impacts of different future cost structures for the disruptive technologies on transportation choice and the resulting vehicle fleet. Cost is a complicated subject as there are many aspects to a detailed cost modeling. Many types of costs are associated with these technologies. Operating cost, insurance, context specific costs like parking, charging, etc. all play different role in the total expense of the vehicle. Each of these different costs will affect the choices to use and own these technologies in a different way.Different aspects of the cost structure related to these technologies need to be considered. Whether cost corresponds to just a niche sector or does it play a role in large scale universal access needs to be determined. Different assumptions about the future cost of these technologies, will change the fleet differently. We will explore the different cost structures that affect the fleet differently. Future will affect different aspects of the cost differently. The user decision of the mode and the ownership will also get affected differently due to a different cost structures. The ownership decision will be different for an upfront cost than for an operating cost. These aspects of the cost structure warrant a more detailed study on how these costs impact the overall transportation system when these disruptive technologies are introduced.

1. As the disruptive technologies advance resulting in them getting cheaper and more available, how does this impact the overall car fleet?

1.1.2 Impacts of changing availability and travel times associated with different disruptive technologies

Travel is often associated with time taken to travel in a particular mode and the availability of that mode in general. People actively think about how quickly can they get to their destination, what is the average speed of their commute, what would be the effect of congestion on their trip etc. Another aspect of time comes in the form of availability. There are certain technologies and services which are not available in certain areas. For example, the time required to hail a ride-sharing service in an urban neighborhood might be very little due to high availability. Whereas in a rural neighborhood, there are no ride hailing services and therefore the time taken to hail a ride is essentially infinite. Therefore considering the time aspect of trips is important when it comes to talking about a mode choice.

The concept of time when calculating the total time taken for a trip is made up of different kinds of "time". The total time taken for a trip can be thought of as time taken to get to the mode from the origin, time taken to wait for the mode, time spent traveling in the mode, time taken to park and finally time taken to go from parking to the final destination. When technologies become more available, they are bound to have an impact on the total trip time. The total number of cars, either rising or falling, will also affect congestion levels and as a result affect the total trip time. These aspects related to time will be studied in more detail in this work.

1.1.3 Impact on occupancy and utilization due to disruptive changes technologies

While ride-sharing does not necessarily mean increased occupancy, there is an increasing trend towards the higher occupancy pooled trips. If people start using ride-sharing as a primary mode of transportation, one might see the average occupancy of ride-

sharing vehicles go up. As a result, this trend due to penetration of ride-sharing has the potential to affect the VMT as well as the vehicle stock. Also, with ride-shared vehicles becoming more popular and more available, this might mean increased ride-shared trips. This in turn will require ride-shared vehicles to travel between different trips to pick up passengers at various location, leading to an increase in the utilization of ride-shared cars. If these services penetrate in the sub-urban and rural areas, one might expect the utilization of these ride-sharing vehicles to go up and private vehicles to go down.

Along with the ride sharing vehicles, autonomous vehicles also have a huge potential to impact the occupancy and utilization rates. Imagine an autonomous car dropping one person off to his or her workplace and then coming back to pick up the second person to drop him or her again. This will tremendously impact the utilization of autonomous vehicles, either private or ride-shared. This will lead to a tremendous increase in the occupancy and utilization of these vehicles leading to a heavy impact on the vehicle stock. This work tries to explore some questions around these ideas.

1. What is the impact on occupancy and utilization due to disruptive technologies getting cheaper and more available for everyone?

1.1.4 Impacts of existing competing transportation options

While the disruptive technologies are certainly looked upon as newer and more modern, their traditional counter parts like private cars and public transit might experience some changes themselves. Traditional technologies might also benefit by borrowing some of the technologies from the futuristic autonomous vehicles. Transit options might also improve due to government investments. Local and national government might impose policies that favor one transportation option over another. This work will look into how is the vehicle stock affected by the conditions of the existing competing transportation options.

1. How do different assumptions about the rates of improvements of the existing technologies (both car and non-car options) affect transportation choice and the

resulting fleet?

2. How do policy decision including investments in the other transportation options like, mass transit, will affect the situation?

3. How will policies around gasoline usage, congestion, etc. might change the situation?

Chapter 2

Literature review

Given the research questions discussed earlier, a model for the overall travel demand, modal shares and what that means for the vehicle stock is needed. Much work has been done when it comes to travel demand modeling and modal choice modeling. But most of the work mainly centers around new methods and case studies at the city level. Given the national level scope of this work, there are still some existing gaps that need to be addressed in this area. This chapter reviews some of the prior work in the field and elaborates on the gaps in the field that need to be addressed.

2.1 Literature review and gap analysis

Transportation demand has been studied using a variety of modeling techniques. Some of the popular techniques used in transportation demand modeling are system dynamics models by Shephard et al.[46] and time series regressions by Schafer[44]. Many models are also based on the idea of formulating how trips are generated and how they are assigned to a mode. One of the widely- used model is the popular four-step model[56][53] that considers trip generation and trip assignment to forecast the overall traffic and revenues generated due to transportation. With the advent of computational power becoming accessible to everyone, people have combined probabilistic modeling with agent based models as shown in work done by Adler[3], Azevedo et al.[5], and Shiftan and Ben-Akiva[47]. Apart from these traditional modeling tech-

niques, there are other resource intensive techniques like survey sampling and utility based models that require conducting survey amongst a statistically significant population as shown by Oppenheim[40]. Some of the models use scenario testing to generate scenarios by tweaking some of the key variables as shown in Kobos et al.[30] and Zmud et al.[59]. The next section describes the above works in more detail. While many of these models are widely used in modeling transportation demand, they are mostly used to model inter-city transport demand at the macro level and not intra-city demand at the national level. A variety of work has been done on car fleet models where the size of the car fleet is predicted using various traditional methods like time series modeling and econometric models. Dargay and Gately[14] used the Gompertz function to predict the motorization rate (the number of cars per 1000 persons) on the basis of GDP/capita for a large number of countries. Some other models take a survey based approach where a lot of resources are put into measuring the travel patterns on a per household basis. One such work is the work done by NHTS for the Federal Highway Administration[15]. Another popular method to model car stocks is the stock and flow method which takes into consideration vehicle stock and a retirement and scrappage rate. One such stock and flow model is described in the work done by Fridstrom et al.[21].Finally a lot of work has also been done using utility theory to explain car adoption and exploring its effects on the car stock. A lot of work using discrete choice analysis has been done to explain both, the over all travel demand as well as the overall rate of adoption of cars. Work done by Rich and Nielson[41] on car ownership via Discrete Choice modeling explores the idea of owning zero, one, two or more cars based on random utility theory.

2.2 Literature review: Models of transportation demand

2.2.1 Literature review: Four-step model and survey sampling models

Norbert Oppenheim [40] conducted a critical survey of the methods that were developed for urban and regional modeling. In this book, he points out that there is a strong bias towards a top-down methodology for urban modeling. These models are typically built upon the prior assumptions that show up in the formulation than what is observed in the future. Therefore models that rely on the top-down approach tend to not explain the causal relationships very well. Oppenheim also suggests that because urban systems are comprised of a lot of social interactions, both qualitative and quantitative factors need to be taken into account. Traditional models that assume market equilibrium based on a demand and supply might not represent the true behavioral economics that guides human decisions when it come to modeling travel demand. Transportation models need to incorporate macro-level interactions as well as micro-level of analysis which could help in developing models' sensitivity to scenario changes.

Travel demand modeling has focused mostly on Metropolitan area level to estimate the intra-metropolitan travel demand [56]. Transportation research board found that the four-step model remained the most used approach to model transportation demand. This is a trip based travel demand model and is called as such due to four main steps involved; trip generation, trip distribution, mode choice and trip assignment. This trip based model estimates the travel demand at the aggregate level. An alternative to the trip based model is the activity based model which takes into account the micro-level information and estimates the travel demand at the individual level. This is then added back up to produce an aggregate demand. The four-step model performs well when its forecasting the aggregate demand but yields less satisfactory results when trying to model problems at the individual level. Due to the

aggregate nature of the model it cannot capture the individual level changes that affect travel demand like the preference towards technological progress, congestion pricing etc.

The four-step travel demand model mentioned above was basically used exclusively for intra-city travel demand. This model has been extensively used to model the intra-city demand due to its existence for many decades and its usability. When trying to move away from intra-city travel demand to inter-city travel demand, the four-step model still provides a basic structure to model the travel demand. While intra-city model receive a lot more attention from scholars and researchers, the inter-city travel demand models lack such attention[56]. Some of the reasons for lack of this attention could be that intercity travel modeling does not lie under the ownership of a single planning agency within a city. Also, intercity models tend to be more complicated and require more resources to be maintained and studying inter-city models requires more intricate area definitions, behavioral representation, and more intensive data collection.

Yao and Morikawa [53] did a study on intercity modeling to model a major corridor in Japan. This model was done to study the proposed travel demand for the high speed rail project. Yao and Morikawa made improvements to the initial four-step model for their work. In order to improve the four-step model Yao and Morikawa combined the aggregate trip data and the disaggregate data which were obtained by using a revealed preference and stated preference questionnaire respectively, in modeling mode and route choice. They improved the model by considering the underlying behavioral aspects of travel and incorporating them as well in the original four-step model.

2.2.2 Literature review: Agent based and probabilistic models

A study done by Adler et al.[3] takes a probabilistic approach. In this work, key inputs and assumptions that determine travel demand are represented by a probability

distribution. Using these as priors, the posterior distributions of these inputs are calculated after running the model. The output is also a probability distribution of the "most likely" scenarios that occur. These output probability distributions are either be determined analytically or through a Monte-Caro simulation. The model structure is roughly as follows. First, the important model parameters are decided. Then, the future conditions that can affect travel demand are estimated. These act as inputs to the forecasting model. The output of the forecasting model is then put through a response surface analysis to get a synthesized model. After getting the synthesized model, the probability distributions of the input model parameters and the future conditions are then put through a Monte Carlo simulation to get the traffic and revenue probability distributions[3].

The development of activity-based models as a tool to analyze travel behavior and forecast transport demand has been motivated by the growing complexity in activity patterns resulting from socio-economic changes, growing congestion, and negative externalities, as well as the need to estimate changes in travel behavior in response to innovative policies designed to achieve sustainability. This approach is used in the work done by Ben-Akiva and Shiftan[47] to forecast transportation demand while taking into consideration changes in travel behavior. Along with activity based models, agent based models have also gained popularity in modeling transport.

Agent-based models have gained wide acceptance in transportation planning, as with increasing computational power it is now possible to run large-scale people-centric mobility simulations. Several modeling efforts have been reported in the literature both on the demand side (with sophisticated activity based models in the works mentioned above that monitor individuals daily travel pattern) and the supply side (simulation of dynamic traffic assignment). The work done by Azevedo, Ben-Akiva et al. [5] explores and evaluates various autonomous vehicle systems using agent based models.

2.2.3 Literature review: Scenario based and Time-series based models

Some studies have taken a scenario based approach where the experts-based knowledge on transportation is converted into a PKT and the distribution across the modes, such as in the Future of Mobility study[59]. Another scenario based approach is implemented in Kobos et al.[30]. A logistic growth model is used to estimate provincial demand for travel in China and then various scenarios are explored by tweaking key variables in the model.

Apart from scenario analysis, some of the more traditional models are time series based models as shown in Schafer[44]. They use time series methods and multinomial logit models to project the travel demand and then assign the PKT to the competing modes. Work done by [44] is responsive to the changes in income, mode speeds, and prices, but does not take into account the behavioral aspects associated with travel demand.

2.2.4 Literature review:System Dynamic models

Some works[54] study the impact of urban growth on transportation demand and try to relate the city growth to it s transportation need. This is done through system dynamics model by taking into consideration the interplay between different components like population, economy, housing, transport, and urban/land development. System dynamic models have been widely used in transportation demand modeling to model macro level phenomenon and gauge the effect of external factors like congestion, fuel price, road network etc.

2.2.5 Literature review: Utility theory based models

Some authors have used utility theory to explain travel activity patterns. Work done by Fujiji et al. [22] explores how people used the subway before and after the opening of a new subway line in Kyoto, Japan. Support is obtained for several predictions about why behavioral intentions are, or are not, implemented. This was mainly done

using a stated preferences technique and combining some microeconomic principles. The work done by Joh et al.[25] predicts activity patterns as a result of a set of decision heuristics and activity utility functions. Abou-Zeid and Ben-Akiva [2] have studied the subjective topic of well-being and connected it to travel demand using random utility theory. They present empirical and theoretical analyses to investigate the relationship between happiness (or subjective well-being) and activity participation and develop a framework for using well-being data to enhance activity-based travel demand models. These models combine activity based modeling with utility theory and agent based modeling with utility theory to predict how travel choices are made.

2.3 Literature review: Models of vehicle fleet

The models above discuss how the fundamental drivers of passenger travel demand change. The above models do not discuss how the total travel demand is converted to a vehicle stock. A variety of work exists on forecasting Vehicle stock. Some of the more popular vehicle stock forecasting models are the stock and flow models, econometric and time series models, survey and sampling based models, and utility based discrete choice models. The next few subsections describe each of these models briefly with examples of works that use them to predict vehicle stock. An exhaustive survey of vehicle stock models and vehicle ownership models is given in Jong et al.[27].

2.3.1 Literature review: Stock and flow models

Various works in the literature use stock and flow models to predict the vehicle stock at the aggregate level. The stock of vehicles, be it at the global, national, local or company level, is the result of several flows operating over time: new registrations, scrapping, and second hand import and export. To keep track of how fast technological developments and other changes in the attributes of new vehicles penetrate into the vehicle fleet, a stock-flow cohort model is usually the model of choice because of its relative ease to implement. One such stock and flow model is described in the work done by Fridstrom et al.[21]. This work takes into consideration the vehicle stock as a

result of several flows occurring from second hand imports, scrapping, de-registration etc. Combining the stock and flows, the model predicts the vehicle stock and also the emissions resulting from the stock.

2.3.2 Literature review:Econometric and time series models

Some of the more traditional techniques use the econometric and time series models to forecast the vehicle stock.One such model is the work done by Whelan[52]. This model takes into consideration the information on household income and household type, car-type, and area time to derive a probability that a household owns a car, two cars or more than two cars. Ingram and Liu[24] use a double logarithmic function to explain car and vehicle ownership across many countries in the world. Dargay and Gately[14] used the more flexible Gompertz function to predict the motorization rate (the number of cars per 1000 persons) on the basis of GDP/capita for a large number of countries, including developed and developing countries. This function gave the long?run equilibrium prediction. Besides GDP/capita, aggregate time series models can use fuel prices, population density, road network density and rail network density to explain vehicle ownership trends.

2.3.3 Literature review: Survey and sampling based models

Some of the methods rely on surveys and data collection to estimate the overall car ownership and vehicle stock. For example, the work done by Energy Information administration for the Federal Highway administration[15] uses the NHTS survey to calibrate their model for car fleet. These methods rely on surveying thousands of households, with and without cars, to gauge their driving patterns. These methods then quantify a PMT and VMT per household and then forecast this demand forward based on a population estimate and some other macroeconomic factors like GDP/capita, income etc.

2.3.4 Literature review: Utility based discrete choice models

This category deals with the discrete choice models that deal with the number of cars owned by a household. One application of discrete choice models for vehicle fleet estimation and car ownership modeling is done by Rich and Nielsen[41].These models define a choice for every household to have a car or not based on the amounts of people with driving license present in the house. These choices are modeled as binary logit models, estimated on disaggregated data from surveys. These models are based on random utility theory and can be interpreted within this behavioral framework. Rich and Nielson[41] present the long-term travel demand model for households where the maximum number of active workers is two. While car ownership was not the main focus of their paper, it was still explicitly treated. The model was specified as a nested logit model with two main components, a work modeling choice of the work location and car ownership, and a residential location model modeling the zone and the type of residence. The car ownership is then modeled as a function of the number of working people in the household and the location where they live.

Many researchers have combined utility models and agent based methods to model transport demand in the past. An activity based travel demand model by Ben-Akiva et al.[9] combines decision theory and utility models to decide how people make trip choices. To model behavioral aspects related to how a trip is chosen, a combined travel demand model (CTDM) is adopted to estimate the long-term equilibrium network condition due to network disruptions in the work done by Chen et al.[12]. Specifically, this work adopts the mathematical programming formulation provided by Oppenheim[40], which is based on the concept that a traveler is a consumer of urban trips, reflecting the traveler's utility maximization and budget constraint choices.

2.4 Gap analysis in travel demand and vehicle fleet models

Many of the travel demand models and car fleet models that exist cannot accurately simulate the competing characteristics of the different transportation choices. These models also lack the ability to capture difference at the micro-level of aggregation. The next few sections describe the strengths and gaps in the travel demand and the car fleet models.

2.4.1 Gaps in travel demand models

The system dynamic models enable us to understand the dynamic behavior of the system under consideration from a macro point of view. They do not try to model the micro-level changes at the individual level that impact the transportation behavior at the aggregate level. Using system dynamics models, one cannot capture the effect of changing human behavior towards transportation at the individual level.

More traditional models such as time-series regressions assume that the way people have exercised their travel habits in the past will remain the same. These models have a solid foundation on a statistical basis. But these models assume that the historical behavior remains intact going forward and therefore cannot capture disruptive changes in the economy. Also, statistical regressions are used to model group behavior and not individual behavior. This is true for both, the travel demand models and the vehicle fleet models.

Survey based methods and the four step model provide a reasonably realistic description of what are the current trends that people are thinking of in terms of transportation and the way they travel. But in order to get an accurate estimate, a statistically significant sample is needed and this becomes extremely resource intensive. This becomes almost impractical if one wants to model transportation demand at the national level in a limited amount of time.

Agent based models and probabilistic models are useful in terms of modeling

the interactions at the individual level in terms of utility maximization, but in order to determine the utility functions, significant surveys are needed to accurately capture the preference functions of the individuals. Agent- based models combined with utility theory and multinomial logit models have found wide varie ty of applications in transportation literature[6][55]. Utility models are well suited for certain transportation modeling problems because they can capture individual interactions at the micro-level. Utility models are usually easily interpretable. Combined with agent-based modeling, utility models are extremely robust in trying to capture the micro-level interactions and aggregate the results to gain insight for a macro level demand. The challenges associated with a utility based approach is the derivation of the preference functions and monitoring the preferences of individuals. This requires a lot of surveys and data collection to get a statistically significant sample. Much of the preference function estimation can be subjective and there might be more than one way to get to the same solution using different preference functions. Therefore the solution that one models might not be unique.

2.4.2 Gaps in car fleet estimation models

Similar issues exist when modeling car fleets. The car fleet models that use time series regressions while being good at having a statistical basis cannot capture the disruptive changes. Stock and flow models themselves assume a certain set of parameters that they use as inputs in their models. These parameters themselves are subject to change due to these disruptive changes, and hence stock and flow models alone cannot quite predict the impact of disruptive changes on the car fleet. Survey based techniques based on stated preferences method can be good at estimating the impact of hypothetical scenarios but are very resource intensive. Car fleet models themselves can offer little insight if they do not take into account the resulting changes in the fundamental travel behavior. The travel behavior changing as a result of disruptive changes like car-sharing and autonomy need to be taken into consideration when estimating vehicle stock in the future. Work done by Martin and Shaheen[38] tries to quantify this impact through a survey based method. Schoettle et al. [45] tries to

quantify the impact of autonomous vehicles on the number of vehicles per household. Again these models use survey based techniques and do not link the fundamental travel behavior to its impact on car fleet.

2.4.3 Linkage of travel demand and car fleet models

A linkage between the travel behavior and travel demand and car fleet size is necessary to better understand the overall future transportation characteristics. This work aims to address this gap.

As can be seen from the literature above, many models either model the microlevel travel demand at the inter-city level or the macro-level travel demand without really capturing the interactions between the individuals. Various car-fleet models exist that model the stock and flow behavior of the vehicle stock to estimate the number of cars on the road. These car-fleet models also do not take into consideration the changing dynamics of the travel behavior that results in people making different choices when it comes to traveling. Therefore, a model that links the effects of travel behavior on the vehicle stock is warranted. This work tries to quantify the impact of individual decisions of choice of a particular mode chosen for travel on car fleet. The interactions at the individual level are modeled and their impact on the total vehicle stock is estimated. The link between the travel demand models and the car fleet models is critical when trying to estimate the impact of disruptive changes in travel behavior on vehicle stock.

Chapter 3

Methodology: Travel demand using decision theory and car-fleet model

This chapter describes the model structure and the theory behind it. The method developed in this work takes an approach of using a multi-attribute utility model at the individual level, and then running a stochastic simulation for a group of individuals repeatedly to determine how each of those groups make choices. Given the models that were mentioned above, a modified multi-attribute utility based approach was chosen for this particular work of modeling transport demand at the national level. Multi-attribute utility captures the individual level interactions and can propagate the effects of individuals' decisions on the aggregate transport demand. This work combines the agent-based modeling approach and the trip based travel demand modeling to combine the individual level interactions into a aggregate transport demand.

The method mentioned above to estimate the travel demand is essentially a combination of various aspects of the four step model[54], the agent-based models[5], and a few aspects from system dynamics models. The method used in this work combines utility theory along with agent based modeling to model the activity based trip generation. Once different trips are simulated, the mode choice is determined using multi-attribute utility theory. This then further lead to an estimation of the total transport demand in terms of passenger miles traveled.

Once the aggregate transport demand was determined, this travel demand was

converted from passenger miles traveled to a vehicle miles traveled by all the vehicles through an assumption about occupancy per vehicle. This vehicle miles traveled is further converted into a vehicle stock by assuming a certain mileage for each vehicle.

As can be seen from the literature above, few models exist to quantify the impact of disruptive changes on transportation on car fleet. Most of the methods rely on survey methodologies. This link between travel demand and the vehicle stock has been explored in more detail in the work done in this thesis. The overall multi-attribute utility theory (MAUT) procedure is described in the next section followed by revealed and stated preferences method. The description of a stochastic MAUT approach used in this work is described next, with its associated benefits and challenges. Once the travel demand was estimated using MAUT, this demand was converted into a vehicle stock. The MAUT model output are taken as inputs in the fleet model to calculate the overall fleet.

3.1 MAUT Theory

Multi-attribute utility theory (MAUT) is a multi-criteria analysis technique that is rooted in von Nuemann and Morgenstern's Expected utility theory which originated in 1940s[50]. While this work laid solid theoretical foundation, it found practical breakthrough when Keeney and Raiffa published their work on using utility theory to assist in making decisions regarding multiple alternatives[28]. MAUT theory concerns mainly with individuals making decisions about the alternatives available to them. This work modifies the MAUT method applied at the individual level to include decisions made at a group level. These two aspects are described in the next sections.

3.1.1 MAUT Theory: Individual level

Multi-attribute Utility Theory is an analytical method rooted in decision theory and expected utility theory that helps an individual decision maker to appropriately rate a set of multiple competing objectives. MAUT uses utility functions and preferences to model the selected attribute levels for the different alternatives under considera-

tion. The multi-attribute utility for each alternative is a score between 0 and 1, zero indicating no satisfaction, and one indicating highest satisfaction.

The MAUT technique developed by Keeney and Raiffa is based on a six step process as outlined below:

1. Identify the alternatives available. These alternatives are the choices that are available to the decision maker.

2. List the objectives that must be satisfied by making the decision.

3. Formulate the attributes associated with each objective to measure the degree to which each objective is satisfied. Each objective will have its own attribute measurement scale.

4. Clarify the preferences of each stakeholder with reference to the decision objectives and attributes. Survey the stakeholders to asses their relative importance of each objective and attribute. Determine the weights for each attribute that reflect the preference of stakeholders.

5. Develop a utility function to characterize stakeholders preference towards the alternatives and the utility function for particular attributes associated with the alternatives. A single attribute utility function is derived for each attribute, which takes the physical measures of the attributes and transforms them into a dimensionless scale of zero to one. Then, using the weights determined previously to reflect the stakeholders' preference amongst different attributes, the individual utilities are combined to get a multi attribute utility function.

6. Formulate the multi attribute utility for all the alternative under consideration. The best alternative is the one that has the highest multi-attribute utility.

The model equations describing the above points are shown below.

$$1 + \kappa u(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} 1 + \kappa k_i u_i(x_i) \tag{3.1}$$

In the above equation $u_i(x_i)$ is the single attribute utility function of the attribute i at the level x_i and $u(x_1, x_2, \ldots, x_n)$ is the multi attribute utility. Both of these are normalized to the range [0,1]. The $k_i's$ are the weights that were described in the earlier procedure that are used to take into consideration of the relative importance of different attributes to reflect stakeholders' preferences.

In assessing the $u_i(x_i)$, the single attribute utilities can take any form; however, MAUT requires monotonic functions. This means that the higher attribute levels are always better in terms of utility than the lower attribute levels. If the decision maker values each unit of attribute the same, then we get what is called risk neutral utility preference. If the decision maker's utility increases more than a unit for each unit improvement in the attribute, then we get a nonlinear utility preference for example risk averse or risk seeking single attribute utilities. Properly assessing single attribute utilities means understanding decision makers preference for all the attributes across their range.

One of the largest challenges with MAUT is the determination of proper weights, $k_i's$, for each of the attribute in the equation for multi attribute utility. At the individual level, the weights can be assessed a using a variety of methods. One such method involves conducting systematic surveys and interviews. These surveys should evaluate the individual's trade-offs between the attributes through a systematic evaluation of where the indifference points for the attributes lie. Other methods involve simply having a range of experts comment on how the weights are and what the relative importance is amongst the attribute. Another approach, and the one used in this study is the use of revealed preferences which is described later.

3.2 MAUT Theory: Group level

When it comes to the individual level for a single decision maker, MAUT provides a methodology to select the best alternative from a choice set. It however does not mention anything about the overall market share of the alternative across a group of decision makers. This section describes how this work took the MAUT applied to

an individual level and modified that to be able to apply it to a group to gain some insights on the market share.

Theoretically, the single attribute utility functions, $u_i(x_i)$, vary across each decision maker i. However, the general shape of the curve and the general trend in the curve stays the same. For this reason, the single attribute utility curve for each attribute is asserted to be the same for each decision maker. It is the value of the physical attribute that is different across different decision makers. This simplification is appropriate given the objective to roughly asses the high level shape of the single attribute utility functions.

Many MAUT studies rely on the opinions of experts to provide the weights for the multi attribute utility function[37][39]. However, it is inevitable that different individuals will have different attribute weights that will lead to different alternatives having the highest utility. Therefore, relying on experts who give different attribute weights for different products might lead to the decision maker choosing different alternative.

This thought provides the basis for a little modification of the traditional MAUT procedure that allows MAUT to capture the market share of the alternatives. If the weights that are used in the MAUT procedure have a distribution associated with them, then these weights would represent the range of preferences across various decision makers. It could also represent this idea that even if all the decision makers were the same, different situations lead them to change their preferences. In the traditional approach, each of these would be modeled individually, but that would be impractical. The application of a distribution around the preferences allows one to lump circumstances and consider multiple decision makers.

Applying a distribution around the weights of each attribute allows one to run a Monte-Carlo simulation that simulates the concept of multiple decision makers trying to choose amongst different alternatives depending on the specific set of attribute weights used by each decision maker. Once the Monte-Carlo simulation is complete the market share of each alternative can be calculated by taking the number of times the multi-attribute utility of each alternative was the highest and dividing it by the

total number of runs in the Monte-Carlo simulation.

Applying the above concept to the current work under consideration meant deciding what constituted different groups when it came to travel demand modeling. Different people have different characteristics and they take trips that are variable in nature. Therefore, simulating everyone using one representative distribution is not feasible. If such a universal distribution existed, one could model travel behavior using such a distribution. But due to lack of existence of such a distribution, there is a need to divide the population under consideration into different groups, where within each group, entities behave in a more or less similar manner with some variation. For this particular work, the population was divided into six groups. Three groups based on geography; urban, suburban and rural, and two groups based on income, low/middle income and high income.

3.3 Simulating different travel conditions for groups

When it comes to travel, people travel differently for different purposes. For example, people choose the mode of travel differently when going to work as opposed to going for a leisure trip. A work trip might be thought of as a more important trip where the mode of travel needs to be very reliable and reasonably quick. A leisure trip on the other hand need not be very timely and therefore time is not as important of a factor as it is in the work trip. This attitude of choosing the mode based on a particular trip purpose warrants a different model for different types of trips. A study done by NHTS takes into consideration various different types of trips like work, work related business, social and recreational trips, church/school trips and so on. While doing a large number of trips leads to a more accurate model, it also makes the model more complex. Keeping this in mind, this work divides the trips taken by people into four main categories; work, leisure errands and other. These four trips were modeled by making them have different trip characteristics. Once the grouping for trips was decided, a similar thing was done for grouping people belonging to different categories.

People who belong to a higher socio-economic class travel differently than people who belong to a lower socio-economic class. People who have great access to the public transit might use it more than people who do not. This results in different people making different choices for modes not only when it comes to trips, but also depending on what demographics they belong to. For example, people in urban areas who are rich might still take the public transit just to avoid the hassle of parking a car. On the other hand, a person from a high income bracket living in the suburbs might not even have access to transit leaving car as the only option. To take these factors into consideration, people were divided into three different categories based on residence; urban, sub-urban and rural, and two different categories on income; low/middle income and high income.

This results in six different people categories and four different trip types. This made the modeling tractable from the point of view that people belonging to the same group behaved similarly. For example, all urban middle income people had similar preferences for urban work trips, sub-urban high income people had similar preferences towards leisure trips and so on. This model is discussed in greater detail in the implementation section later.

3.4 Assessing preference function for each group: Revealed preference vs. stated preference

The population was divided into six groups as was mentioned earlier and assessing the preferences of each group meant constructing a preference function for each group. When evaluating the preference functions, it was decided to evaluate each mode chosen for a particular trip based on cost, time and comfort of the mode for that chosen trip. Past data as was reported in the NHTS surveys was used to decide the preference functions for each group.

There are broadly two methods to state the preference functions; reveled preference and stated preference method. When experts explicitly indicate their preference

structure, thats usually constituted as a stated preference method. Stated preferences are learned through survey responses by constructing a hypothetical scenario. Another approach is the revealed preferences method. In a reveled preferences method, the choices and actions made in the past dictate the preference functions of the individual. For example, if we think about travel mode choice for a work trip, it is the mode that the individual actually took to work while making the trip. Stated preference example in this case would be the mode that they indicated for a work trip in a hypothetical scenario on a survey.

Revealed preference data is usually preferred as reveled preference data is more reliable and accurate. It eliminates the uncertainty associated with the decision maker's choice. While the uncertainty associated is less with the revealed preferences method, it can provide insight only about the past. Stated preference models on the other hand can provide some insight on the future by asking respondents about hypothetical future scenarios. In order to calibrate the model so that the preference functions assumed in the model reflect the current preferences of the people towards the travel modes available today, a reveled preference method was used. We need to understand the preference functions of people when they choose how to travel. One method would be to ask and interview a statistically significant sample and try to infer their behavior from the past and the results of the survey. This turns out to be too burdensome and therefore revealed preferences method was chosen as the method to implement.

3.5 Applying preference and utility functions to transportation choices

Once the method of formulating the preference functions was determined, the next step was to actually formulate the preference functions for the different attributes. In this work, cost, time and comfort were chosen as the three attributes to evaluate the modes for a given trip. In order to formulate a preference function, a detailed model was constructed for cost of a mode for a particular trip. Models for time and comfort

were also constructed. These models are explained in the next chapter. Once an estimate for the cost, time and comfort was determined, it was converted into a single attribute utility score. Depending on which factor amongst cost, time and comfort was the most important for a given trip, an importance weighting was assigned to each of the attribute. This importance weighting took the form of a number between zero and one. With these importance weightings, the attributes were converted into a multi-attribute utility according to Equation 3.1. The implementation of the model and calibration through revealed preferences is discussed in the next two chapters.

3.6 Macro level fleet demand: Model description

Once the market shares for the different types of trips in different modes are obtained, the next task was to convert these market shares into a vehicle stock. The market shares are essentially reported as a percentage of trips taken in a certain mode, namely, private car, transit, ride-share or walk. These market shares were reported for each type of trip; like work leisure, errands and other. These market shares were also reported for the above four trips taken in different geographies and people from two different income levels; urban, suburban and rural and high or low/middle income. Along with the mode shares, the average passenger trip distances were also calculated by the model. Total work, leisure, errands and other trips taken nationally were estimated from the NHTS data by assuming that trips per capita stay constant in the US. Combining the total number of trips taken from these various geographies and the average trip distance for each of these trips, a total passenger miles traveled (PMT) was calculated. Applying the modal share result to these trips, a car-based PMT and non-car-based PMT was calculated. A certain occupancy was assumed for private and ride-shared cars. Using occupancy, the respective PMTs (private car PMT and ride-shared PMT) were converted to the vehicle miles traveled(VMT). The last step was to go from vehicle miles traveled to a vehicle stock value, which was done by assuming a utilization rate for vehicles.

Vehicle miles traveled(VMT) was converted to a vehicle stock value by asserting a

utilization rate, miles traveled per year, for each type of car; private and ride-shared. A different utilization rate was also asserted for conventional power-trains, electric power-trains and autonomous vehicles. Assuming a certain mix of power-trains for different scenarios, an average utilization rate was calculated for all the car modes. This utilization rate was then used to calculate the vehicle stock for each type of car; private and ride-shared. This then gave the total vehicle stock.

3.7 Stochastic Travel demand and car fleet model: Benefits and challenges

For forecasting purposes, the stochastic MAUT method can be applied by taking into consideration the changing attribute levels of the alternatives in the future in order to obtain market share of the alternatives in the future. On top of this, the attribute weights themselves can change, portraying this idea of changing preferences amongst individuals due to exogenous factors affecting their decisions. Expert inputs are also taken into consideration in order to comment on how the weights and the attributes will change over time.

In order to apply this model for estimating travel demand, the group based approach for MAUT was used as was described earlier. For example, the different trips considered were work, leisure, errands and other trips. Trips taken by people were also divided into categories like trips from urban, suburban and rural areas and trips from people in middle and high income bracket. Each trip was modeled individually for a particular group of people, for example, urban work trips taken by people who belong to a high income bracket is a type of group. All the trips in this group were assumed to behave more or less the same. Each trip belonging to a group was modeled with three attributes; cost, time and comfort associated with the trip. Each trip within a particular group was modeled with a cost, time and comfort that had a mean and a standard deviation associated with it to account for the fact that even within a group not all trips are exactly the same. This aspect of stochasticity meant

that even within a group, if a number of trips are simulated, each will have different cost, time and comfort. Preference functions were decided for each attribute, cost, time and comfort. As a result, each trip within a group will have a different utility associated with it when the trip is made with a personal car, transit, walking or a car-share service. The market share for the different modes for a particular group was calculated as the number of times the utility of a particular mode was the highest amongst all the simulated trips.

The approach of using MAUT to describe choices that groups of people make is unusual in the sense that most of the times MAUT is used only for modeling individual choices. This approach requires us to apply MAUT at a group level. Group based modeling was done for the prototypical trips and assumptions were made about how much would the quantities within the group would vary. Some of the strong points of this method are that considering different groups we can model at the level of nuance that gives good insights into the trends that the transportation demand faces while keeping the problem tractable. The method could also translate the impact of decisions made at the individual level into an aggregate demand.

Some of the short-comings of this method are that the qualitative aspects of total trip demand, like time taken to complete a typical trip, comfort of a trip, etc. need to be defined. Along with that, the preference functions for these qualitative factors need to be assessed. Ideally to get an accurate estimate of what these preference functions should be, a combination of stated preferences and a revealed preference method should be used by monitoring a survey for a statistically significant sample. But due to the constraints, a Monte-Carlo simulation was done to make sure that we capture the necessary variation that exists amongst different individuals. Running a Monte-Carlo simulation with different agents that select trips based on different preferences can account for the theoretical representation of variance, but ideally, one would model this variance in people behavior more accurately.

Chapter 4

Model implementation: Travel behavior module and vehicle stock module

This chapter mentions the details and the model structures of the different parts of this work. The method explored to answer the research questions proposed earlier in this work was divided into two different modules. The overall model consists of two modules; the travel behavior module and the vehicle stock module as shown in Figure 4-1. The first section in this chapter describes the working of the travel behavior module in detail. The second section of this chapter describes the vehicle stock module. The first two sections in this chapter do not describe the assumptions and the numbers used in the models. The explanation about the specific assumptions about the inputs comes in the next chapter.

4.1 Travel Behavior Module

Many people take many different trips and travel to many different places. Each of those trips could have a different purpose. Some of the trips could be for work purposes while others could be a random errand to the grocery store. Each of these trips satisfy a different purpose and a different set of criteria. In this model, the

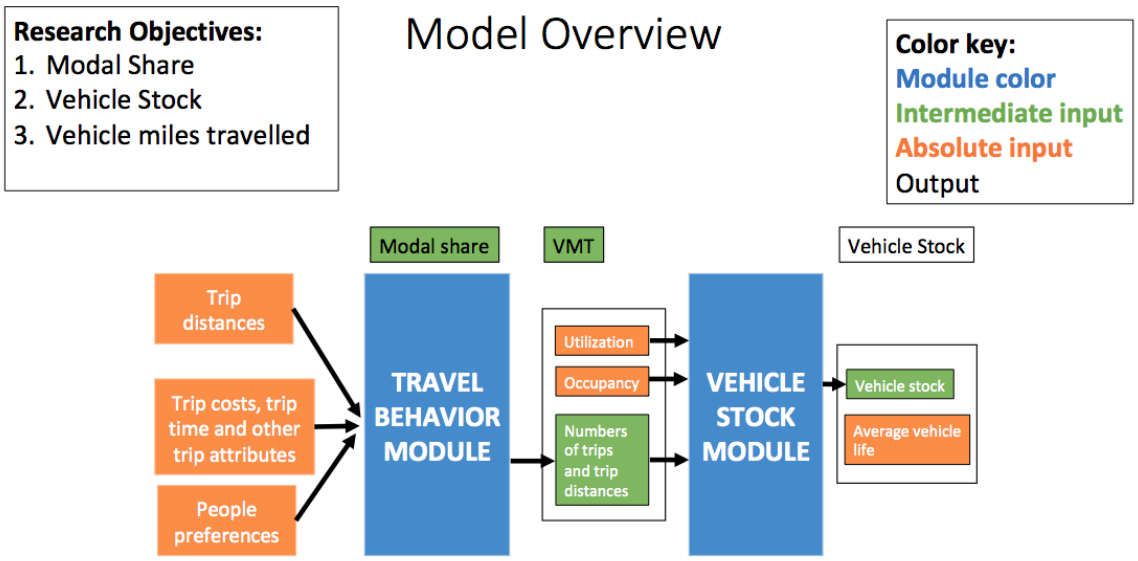

Figure 4-1: Model Overview

trips taken for various purposes are simulated. NHTS considers various types of trips including work trips, work related business trips, social/church trips, errands, leisure/recreational and other trips. The level of disaggregation given in NHTS was beyond the scope of this work and therefore the trips considered in NHTS survey were lumped into four main categories.

In accordance with the work done by NHTS, there were four different types of trips considered in this work; work trips, leisure trips, errand trips, and other trips. A work trip was defined as a trip that was related to an individuals work or work related business. A leisure trip was a trip that was done for recreational purposes and non-work related activities which happen on a somewhat regular basis. For example, going to the movies or going to a park. Errand trips on the other hand were the infrequent trips such as the trip to a doctor, or a one-off trip to a store etc. Finally, all the trips that did not fall into the work, leisure or errands category were grouped into the "Other" category. Apart from the trips, different modes were explored that were used to fulfill each of these trips.

4.1.1 Choice of modes considered in this work

In this work, four different kinds of modes were chosen for exploration. The first mode was a personal car. A personal car was defined as a car which was privately owned by an individual for personal use. The second mode that was considered was public transit. Public transit in this work consisted of all forms of public transit such as trains, light-rails, buses and other government funded transit options. A third mode that was considered was walking. And finally, the fourth mode that was considered, which was the central piece if this work was ride-sharing. Ride-shared car was defined as a car which was used by multiple people without necessarily owning it. Ride-sharing services for example included services provided by companies such as Uber, Lyft, Car2Go etc. Ride-sharing also included the Taxi and Cab services. This rather broad definition of ride-sharing was chosen so that the effect of ride-sharing services could be captured at a broad level without the need to model the micro level differences between different types of ride-sharing. These were the modes that were used in the simulation to study the shits in mobility between different people in different locations.

4.1.2 Choice of demographics of people considered in this work

Different people make different trips for different purposes. The way people make those trips and choose the modes for fulfilling those trips is also dependent on where those people are located. There does not exist an analytical formulation for the total travel demand. Treating every person belonging to the same group and assuming the same travel behavior for each person also does not capture the variability in travel trends amongst different people. One can imagine that people with good access to public transit or walking paths might make fewer use of personal car. On the other hand, if there is no public transit readily available, and the trip distances are long, then a car based mode remains an only option for that particular trip. The availability of other transport options than car based modes is particularly more in

the urban clusters than the sub-urban areas. There are some transit options in the densely populated suburban areas, but for long trips, a personal car is still the most dominant mode as of today. In the rural areas, almost all of the travel happens in personal cars. NHTS considers travel patterns based on age, gender, household income, personal income, MSA size and various other factors. While surveying a vast majority of individuals was beyond the scope of this project, this work considered formulating different groups for studying different kinds of trips taken by people in different geographical locations and different income brackets. Taking this difference of location affecting trips into consideration, three different geographies in which the trips take place were chosen to study; urban clusters, sub-urban areas and rural areas. People living in these areas also travel differently depending on their income level.

Two different income levels were considered for this study, low/middle income (under 55k/year household income) and high income(above 55k/year household income). Once can imagine, that people with different income levels choose to travel differently. People in the higher income bracket are less prone to give up their personal car travel while people in the low/middle income bracket might be more likely to switch to public transit use if the cost of travel becomes high.

As a result, in total, we considered three different geographies, urban, suburban and rural, and two different income brackets. This gave 6 different groups for types of people that were considered in the simulation. Along with these 6 people types, four trips were considered; work, leisure, errands and other trips. This gave a total of 24 different people-trip type combinations. Each of these combinations were treated as a group, and people in the same group were assumed to behave in a largely similar manner. For each type of people-trip combinations out of the 24 possible combinations, an agent based simulation was performed, where the agents were the trips taken by various individuals.

4.1.3 Simulation of a single trip

The travel behavior module in particular takes the trip specific information as inputs. Some of these inputs are the trip distances, trip speeds, time taken to do those trips in

a particular mode and so on. Each of these trips could have a different trip purpose. For each single trip, the individuals were presented four different options for the modes; personal car (PC), Public transit, Ride-shared car, and Walking. Each of these four modes were evaluated on three different attributes. The first attribute was the cost associated with making that trip in all the four modes. Second, the time associated with making that trip in all the modes. And finally, the comfort associated with the mode. Each of these attributes were converted using into a single attribute utility value using the following relation shown in Equation 4.1, where x is the value at which current attribute that is being evaluated, X_{best} and X_{worst} are the best possible and the worst possible values associated with the attribute. Therefore, $u(x)$ basically normalizes the absolute value of the attribute to give a score between 0 and 1, with 0 being the least favorable and 1 being the most favorable. The simulation for a single trip is shown in Figure 4-2.

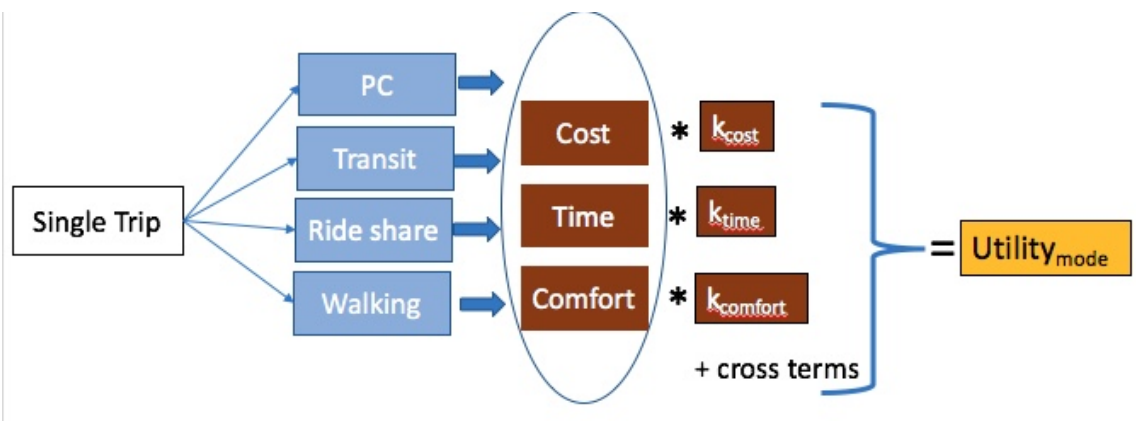

Figure 4-2: Simulation of a single trip

$$u(x) = \frac{x - X_{worst}}{X_{best} - X_{worst}} \tag{4.1}$$

These single attribute utility functions were developed for all the three attributes, cost, time and comfort. Single attribute utilities were then combined into a single multi-attribute utility score according Equation 4.2.

$$1+U(x) = [1+\kappa * k_{cost} * u_{cost}] * [1+\kappa * k_{time} * u_{time}] * [1+\kappa * k_{comfort} * u_{comfort}] \quad (4.2)$$

This multi-attribute utility score was calculated for each mode when considering a single trip. For example, for an urban work trip taken by people belonging to the high income bracket, a multi-attribute utility was calculated for each of personal car, transit, ride-shared car, and walking associated with that trip.

4.1.4 Stochastic simulation for different groups and trips

There are billions of trips taken in the US every year[42]. And as mentioned before, each trip has different characteristic and purpose. Therefore the cost, time and comfort associated with each trip is different. Different people also travel differently. As mentioned before, in this work, three geographic regions, and two different income categories are considered. People also travel differently based on the trip purpose and for this reason, there were four different types of trips considered. This gave a total of 24 different groups for simulation.

Once the people-trip combination were formed, stochasticity was assumed within each group as well to reflect the fact that the trips in one group are not necessarily all the same. There might be some variability even within the trips that belong to the same people-trip type. For example, when we consider trips taken in an urban area by people belonging to low/middle income bracket, not all the trips have the same trip distances, not all trips take the same amount of time and so on. Also, not all people in the same people-trip category have the same preferences towards cost, time and comfort either. Largely, one can assume that people in the low/middle income category might be more sensitive to cost, rather than time and comfort. That is, people in this group might take a longer, less comfortable trip just for a little cheaper cost. While this might represent most of the people in this category, there might be a small percentage of people in this category who might still take a costlier trip as opposed to a longer, less comfortable and a cheaper trip. To represent this fact,

a stochasticity was assumed on every input parameter even within each group. For example, for urban low income work trip, there were various inputs related to the cost, time and comfort associated with the trip and the modes for that trip. Each of these input had a distribution around it. For example, the time to wait for a ride shared car was assumed to be distributed normally with a mean of 5 minutes and a standard deviation of 2. Similarly, the speeds associated with cars in urban areas was assumed to be normally distributed with a mean of 25mph with a standard deviation of 4. For each people-trip type, 10,000 samples were sampled from various distributions for each input parameter. These 10,000 samples referred to the 10,000 trips that were simulated for each of the 24 groups.

The above simulation was done for each of the 24 people-trip type combinations. For each group, 10,000 trips were simulated, and for each of those 10,000 trips, the cost, time and comfort associated with each of the mode was calculated. Calculation of the cost, time and comfort associated with each trip made the calculation of single utility for each of the attributes possible using Equation 4.1. With the single attribute utilities calculated for each mode associated with each trip, the multi-attribute utilities were calculated for each mode according to Equation 4.2 for each of the 10,000 simulated trips. Therefore, each of the 10,000 trips had a set of four multi-attribute utility values associated with it, the four values corresponding to the four modes. The mode which had the highest multi-attribute utility was chosen as the "winner" for that particular trip. This simulation was done 10,000 times and that gave a market share in terms of the total number of trips taken in a private car versus transit and so on. Figure 4-3 shows the process repeated over 24 groups.

Once the total modal share was calculated for each of the 24 different groups, the modal share was converted to a passenger miles travelled value. In order to go from the modal share to the passenger miles travelled, a total number of passenger trips taken at the national level is required. This estimate for the total number of trips taken was obtained from NHTS. NHTS gives the total number of work, leisure, errand and other trips per person. Assuming that the total number of trips taken per person remain the same in the future, the national level trip demand was forecasted

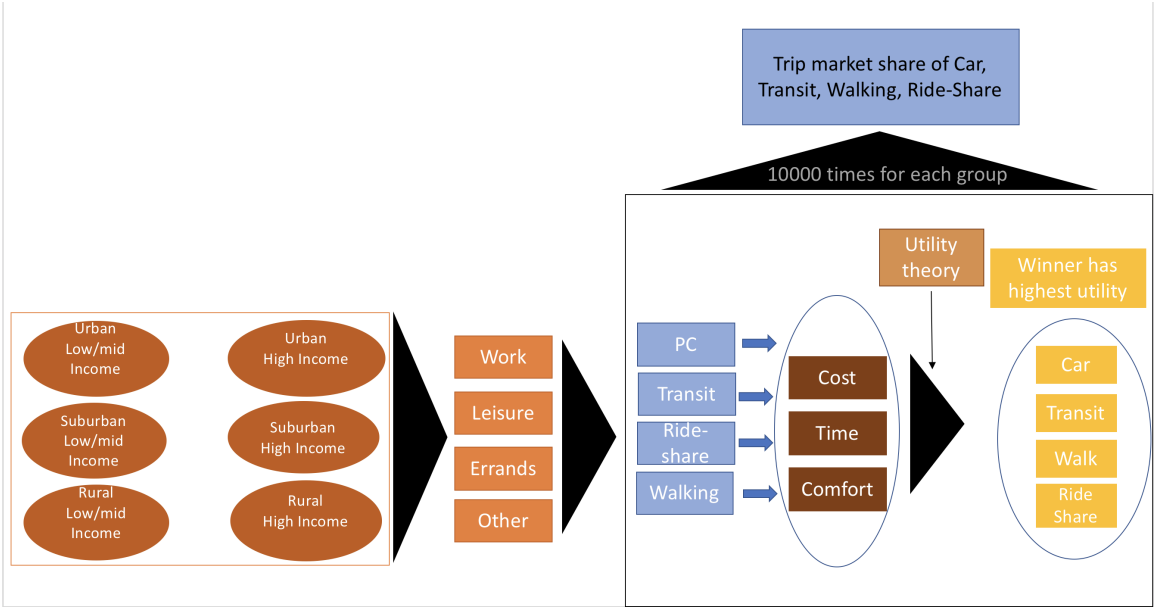

Figure 4-3: Stochastic simulation for 6 X 4 groups to get market share in terms of modal share

using a population estimate. This gave the total number of trips taken at the national level and combining these with the modal shares from the results of the simulation for each of the 24 groups, a total car-based trips and non-car based trips estimate was formulated. Once the total number of passenger trips was forecasted, the total passenger miles travelled (PMT) was estimated by multiplying the total trips taken at the national level with the average passenger trip distances corresponding to the various types of trips. This PMT was then converted to a vehicle miles travelled (VMT) using an occupancy corresponding to each trip. Once the VMT was calculated, it was converted to a vehicle stock in the second module, the vehicle stock module described later.

4.1.5 Cost, time and comfort sub-models

Each mode for a trip under consideration was evaluated based on cost, time and comfort. This section describes each of those sub-models in detail. The cost sub-model had four main components; \$/mile, \$/min, average parking cost and base cost. \$/mile was further derived by taking the information from the AAA to get an estimate of

the associated costs [1]. The different components considered in the $/mile value were the following. An average annual mileage value for cars was asserted. When EVs were considered, a kWh/mile efficiency was also factored into the cost. Electricity price in $/kWh, Insurance, miles/gallon, upfront cost, discount,, accounting life, maintenance fee/year, registration fee/year, margins to the driver and margins to the company were the factors that were used to inform the $/mile number for private cars, electric-vehicles (EVs) and autonomous gasoline vehicles and autonomous EV vehicles. The cost per mile for private car and ride-shared cars was determined using the above parameters. Cost associated with walking was considered zero. The $/mile cost associated with transit was also considered negligible as most transit systems operate with a certain base cost that is paid when purchasing the transit ticket. Apart from the $/mile, the next three components were the $/minute, parking cost and a base cost.

The $/minute was used to calculate the cost associated with ride-sharing cars for the amount of time spent during each trip. The parking cost was used to calculate the cost associated with parking a personal car for different trips. And finally the base cost was used to estimate the minimum price that one has to pay to make a ride-shared trip or a transit trip. Using these four main components of the cost, a cost model was created for each of the four modes under consideration.

- Cost of a personal car trip = Average Parking Cost($) + $/mile * trip distance (miles)
- Cost of a ride-shared car trip = $/mile * trip distance (miles) + $/minute * trip time (minutes) + Base cost
- Cost of Transit = Base cost
- Cost of walking = free

Apart from the cost model, a similar model for time was developed. The time model had five different components. Time to get to the mode, time to wait for the mode, time spent traveling in the mode, time to find parking and time to get to the

final destination from the parking spot. Therefore the, time model for different modes was as follows.

- Time taken to do a personal car trip = Time taken to get to personal car + Time taken to
- Time taken to do a ride-shared car trip = Time to get to the ride-shared car + Time spent waiting + Time spent traveling + Time to go from parking(drop off point) to final destination
- Time taken to do a transit trip = Time to get to the transit station + Time spent in transit + Time to go from transit station to the final destination.
- Time taken to do a walking trip = Time taken to walk from starting point to the final destination

The cost and time models were implemented the way in which they are described above. Figure 4-4 shows the different elements of the cost and time model subcomponents associated with each mode for each trip. The comfort model on the other hand was more of a qualitative model where it was asserted that personal car travel is by far the most comfortable mode of travel and transit was the least comfortable mode of travel. Comfort for each mode was assigned a value between 0 and 1 with 0 being the least comfortable and 1 being the most comfortable. Apart from this assumption, more nuances were added in the comfort model for the walking and ride-shared modes. It was assumed that a non-leisure walking trip of more than 20 minutes would start becoming more and more uncomfortable and decrease its comfort value. On a scale of 0 to 1, walking was considered "0.9" in comfort for the first 20 minutes. After the initial 20 minutes, walking comfort was reduced to a value of 0.1 for a 60 minute trip. A similar thing was assumed for ride-shared trips. Ride-shared trips beyond 10 minutes were assumed to lose their comfort value exponentially. Until the first, 10 minutes, the ride-shared vehicles were associated with a comfort of 0.8 on a scale of 0 to 1. Beyond the first 10 minutes of a trip, the value of comfort started to decline until it reached a value of 0.1 for a trip longer than an hour. These were the cost,

time and comfort models associated with predicting the three attribute levels for each mode considered for each trip. Once the cost, time and comfort for each of the modes were calculated for every trip, a single attribute utility could be calculated using the Equation 4.1. Once the single attribute utility of cost, single attribute utility of time and single attribute utility of comfort associated with all modes for a given trip were calculated, these utilities were then converted into a multi-attribute utility score for each mode, using Equation 4.2. The weighting constants, k's, in Equation 4.2 were derived using the revealed preferences methodology described in section 3.4. The next section describes the method used for the evaluation of the weighting constants.

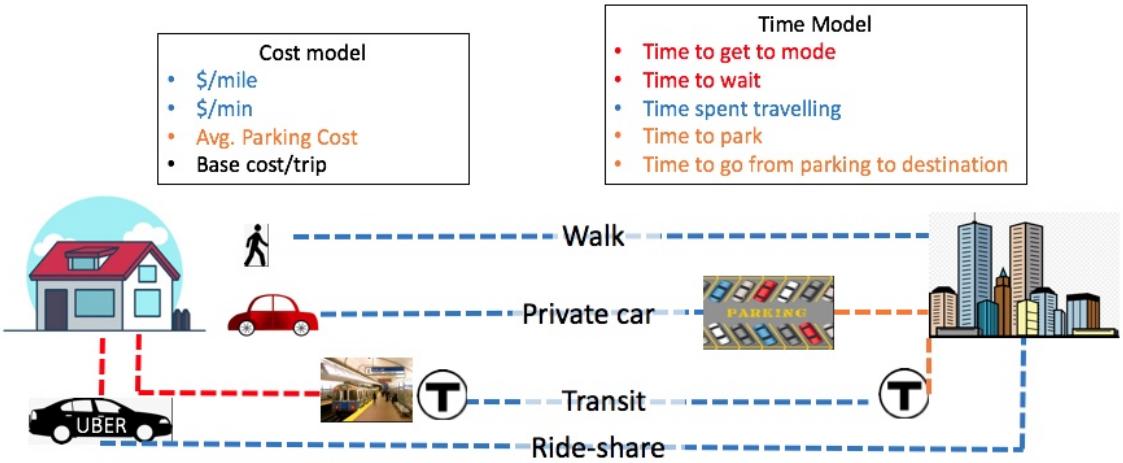

Figure 4-4: Cost and time sub-model components for various modes

4.2 Estimating the preference functions

One of the critical steps in model implementation was deciding the preference weights in Equation 4.2. The k's were calculated by taking help from NHTS data at the national aggregate level. Ideally, the k's in Equation 4.2 should be calculated by conducting an extensive survey and then taking a statistically significant sample from that survey to assess how people prefer the different attributes. In this particular study, that meant looking at how people value cost, time and comfort on a relative basis when choosing a particular mode for a particular trip. For example, one can

intuitively guess that people belonging to lower income bracket might be more sensitive to cost, therefore their k_{cost} will be higher than the k_{cost} for high income bracket people. Similarly, one can intuit that the k_{time} for work trips for most people will be higher than k_{time} for leisure trips, as people tend to be more concerned about time duration of a work trip as opposed to the time duration of a leisure trip. Taking into consideration these logical relationships, a hybrid of revealed preferences and stated preferences methodology was adopted to derive the k's in Equation 4.2.

NHTS provides modal shares by trip purpose at the national aggregate level. These modal shares are shown in Figure 4-5. As can be seen from Figure 4-5, most of the travel is car dominated in the USA for all four types of trips considered, work leisure, errands and other. Work trips and errands are particularly car dominated. Looking at these current driving patterns, the k's in Equation 4.2 were calibrated such that the preferences for each of the 24 groups considered in this work (6 people types X 4 trips) reflected by the k's matched the market shares reported by NHTS at the national aggregate level. While NHTS provided this information at the national aggregate level, there was no data available at the level of granularity that was considered in this work. Therefore, certain assumptions were made which were logically consistent to break down the NHTS data at the national level, and develop a corresponding set of data for each of the 24 different groups that were considered in this work.

NHTS 2009 data gives the following four modes; Private Cars, Public transit, Walking and Other. NHTS also contains data on trips in the modes mentioned earlier by type. The modes that were considered in this study on the other hand, were private cars, transit, walking and ride-share. The initial ride-share modal share percentage was therefore not directly available from NHTS 2009 data and had to be calculated based on assuming a starting point for ride-shared modal share. Also, NHTS data was at the national aggregate level and the level of granularity that was required for this work was at the level of three different geographies, urban suburban and rural and also at the level of two different income brackets, low/middle income(below median) and high income(above median). In order to get to this granularity, a simplifying

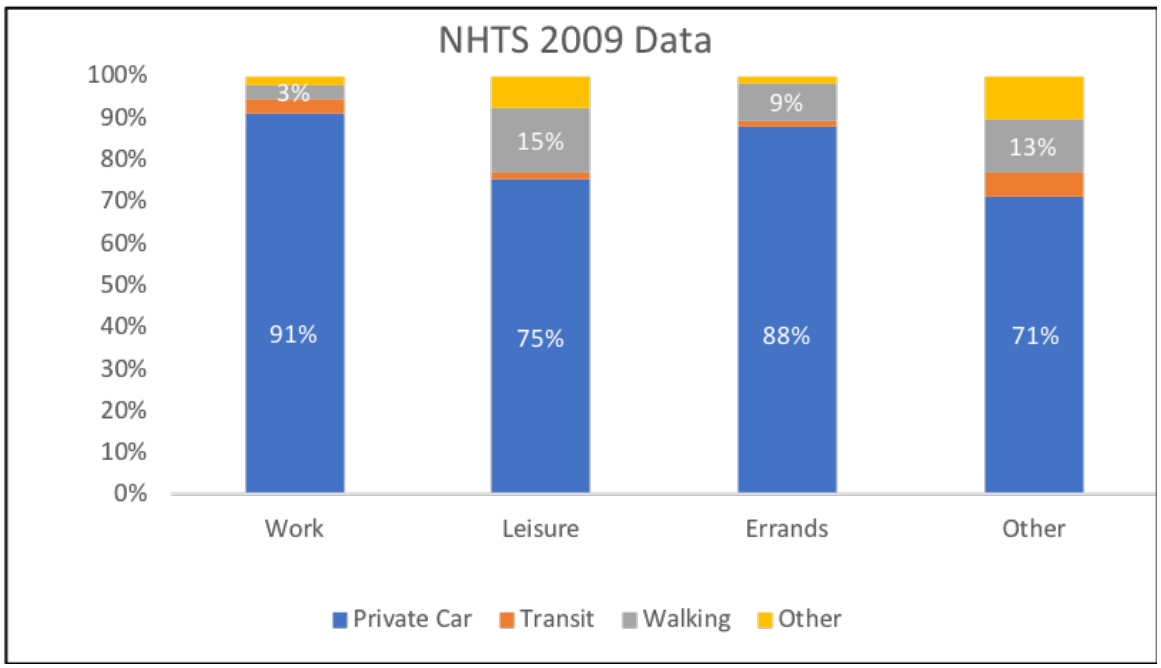

Figure 4-5: National level modal shares by trip purpose, NHTS

assumption was made that 93% of suburban trips and 98% of rural trips were made in personal cars. Using this assumption, combined with the fact that 26% of people live in urban clusters, 53% live in the suburbs and 21% live in the rural areas, a modal share for different types of trips at the level of people-trip type was estimated for each of the 24 different people-trip categories mentioned earlier. Because it was assumed that 93% and 98% of sub-urban and rural trips were in private cars, it really came down to estimating the modal shares at the urban level for the low and high income groups for the four trips that were considered. A conservative estimate for the number of ride-shared trips in urban areas was also assumed for the starting year. These assumptions helped the breakdown of NHTS numbers at the national aggregate level into the 24 people-trip type categories that were looked at in this work.

Given these assumptions, the numbers from the model were calibrated to these numbers that were backed out from NHTS data for the 24 people-trip type categories (again, mainly the data was calibrated for urban work, leisure, errand trips, with the assumption that 93% and 98% of sub-urban and rural trips were in private cars). Looking at these current driving patterns, the k's in Equation 4.2 were back-calculated

such that the k's used in the model give the modal share results that are similar to the numbers backed out from NHTS data. The detailed calibration calculations are mentioned later in the thesis. There is certainly more than one way to get to the same answer, but knowing NHTS data and trying to keep the other inputs as same to NHTS data as possible, the model was calibrated to the representation of the current state within 3% error. While it was possible to get to the same numbers to calibrate to NHTS data with a different set of assumptions, we chose a set of assumptions and the input parameters that were consistent with each other. For example, in order to estimate the waiting times for ride-sharing services in the urban, suburban and rural areas, it was assumed that waiting times in urban areas were significantly lesser than those in the suburban and rural areas. Similarly when estimating the preferences for people belonging to different categories, in was assumed that low income people would be more sensitive to cost than the high income people. This was reflected in the fact that the k_{cost} for people in the higher income bracket was lower than the k_{cost} for people in the lower income bracket. Similar other consistent approximations were taken into consideration when the model was calibrated with NHTS data.

4.3 Vehicle stock module

Once the travel behavior module was implemented, the next step was to convert the output from the travel behavior module into a vehicle stock. The output from travel behavior module were the total number of passenger trips along with average passenger trip distances for all the 24 different people-trip combinations. These passenger trips and passenger trip distances were multiplied to get an estimate of the passenger miles travelled. Once an estimate of the passenger miles travelled was derived, it was converted to a vehicle miles travelled by taking into consideration the occupancy for various trips. Using the average annual mileage of a representative vehicle in the fleet, the vehicle miles travelled were converted to a stock value. Equation 4.3 shows the calculation of passenger miles travelled(PMT) from the number of trips and trip distances. In equation 4.3, $t \in (Work,\ Leisure,\ Errands,\ Other)$,

$i \in (low/middle\ income, High\ Income)$ and $p \in (Urban,\ Suburban,\ Rural)$.

$$PMT = \sum_{persons(p), trips(t), income(i)} Trips_{p,t,i} * Passenger\ trip\ distance_{p,t,i} \tag{4.3}$$

$$VMT = \sum_{persons(p), trips(t), income(i)} \frac{Trips_{p,t,i} * Passenger\ trip\ distance_{p,t,i}}{Occupancy_t} \tag{4.4}$$

While the PMT and the VMT are calculated for each trip and for each type of person category, the national stock was calculated only at the aggregate level. For example, there was PMT and VMT associated with urban low income work trips, but there was no vehicle stock associated with urban low income work trips. Vehicle stock was only calculated at the national level using Equation 4.5

$$Stock = \frac{VMT}{Average\ Annual\ Mileage} \tag{4.5}$$

This was the output of the vehicle stock module and one of the main results that was used for sensitivity analysis.

Chapter 5

Base case analysis and intermediate results

This chapter describes the base case scenario assumptions and some of the intermediate base case results. The implementation of the model and some of the intermediate results are mentioned in this chapter. Calibration to NHTS data and validity check for the model is mentioned as well.

5.1 Base case assumptions and simulations

In order to measure the impact of ride-sharing, a reference case was needed. This reference case was the base case scenario, where it was assumed that nothing changes and the world remains mostly as it is today. The only major change assumed to occur is the fact that population of the US grows. This population growth results in more cumulative trips generated. It was assumed that trips per capita stay constant in the US. The base case scenario was basically defined as a business as usual scenario. Ride-sharing services remain just as expensive as they are today and just as available as they are today. Utilization of vehicles and the occupancy associated with different vehicles do not change with time. With these assumptions, the effect on urban car VMT, modal shares and the vehicle stock was estimated.

Once the total travel demand forecast was generated by combining trips per capita

and the national population forecast, the next step was to convert this into car-based trips and non-car-based trips. This was done by using the results from the travel behavior module, which gave the market share in terms of trips taken in car vs. non-car modes. The inputs related to different aspects of cost, time and comfort were considered constant over time as this was the reference scenario. The inputs are mentioned in detail in Section 5.2. The input parameters are mentioned in Tables 5.1 through 5.5. Some of the inputs in these tables are constants that do not change with time and some others are distributions that have a mean and a standard deviation, where the mean can change with time. For the base case, it was assumed that this mean for different distributions, does not change with time. Therefore, for example, in the base case scenario, the mean for the distribution associated with average parking cost was held constant over time, for the simulation time period of 2016 through year 2050. This meant that the average parking cost was sampled from the same distribution over time. For each of the 24 groups of people-trip combinations mentioned earlier, 10,000 "trips" were sampled from each of the input parameters belonging to a particular distribution. This gave a total of 10,000 X 24, so 240,000 trips for the people-trip groups. Amongst these 240,000 trips, the MAUT model was used to calculate the multi-attribute utility associated with each mode for each of these 240,000 simulated trips. The mode that was chosen was the mode that had the highest multi-attribute utility associated with it. This meant that the 240,000 simulated trips could be divided into groups of trips taken in car, transit, by walk or in a ride-shared vehicle. This then gave a market share in terms of trips taken in terms of car based modes and non-car based modes for each of the 24 people-trip combinations.

Once the market share in terms of the total number of trips taken in different modes was determined, this market share was applied to the actual forecast of the total number of trips taken in the US. This gave an actual number of trips taken in car based modes as a time series from 2016 through 2050. Using the average passenger trip distances reported in NHTS, a national level car based PMT was calculated. Assuming that the occupancy of different modes and trips does not change over time, the calculated PMT was converted to VMT, which was converted into a national

level vehicle stock assuming a constant vehicle utilization. This gave the national level vehicle stock for the base case scenario. These were the results that were used as a reference when comparing different scenarios.

5.2 Input parameters

As mentioned earlier, the travel behavior module had inputs specific to the trips that were taken in different modes and also the preferences associated with mode choice. This section describes the input parameters and their modeling. The inputs related to time, cost and comfort for each of the modes are described in Table 5.1, Table 5.2 and Table 5.3 respectively. The first column in each table describes the variable name, the second column describes the type of distribution the variable was sampled from, and the last column, describes the input parameters required for the distribution.

Table 5.1 shows the inputs required for modeling the time aspects of trips. In the Table 5.1 below, the variable "Time to get to (mode)" is the variable that represents the time to reach a particular mode from the origin of a trip. "Time to find parking, mode" represents the time to find a parking spot for a particular mode. For transit and walking, this variable is obviously zero. It was also assumed that ride-shared vehicles don't require parking sports and therefore time spent in finding parking for ride-share vehicles was also assumed to be zero. The variable "Time go go from parking to destination, mode" represented the time that one takes to go from the parking spot/ transit stop to the final destination.

Table 5.2 shows the variables and the costs associated with different modes. For private car, $\$/minute$ and the base cost were assumed to be zero. The cost of walking was also assumed to be zero. Similarly, for transit systems, only a base cost was assumed that you pay at the start of the trip. The rest of the cost components for transit systems were assumed to be zero. For ride-share services, only the parking cost was assumed to be zero and all the other cost components were assumed to be normally distributed with a mean and a standard deviation. The cost model parameters like $\$/mile$ were derived from a sub-model which took inputs shown in

Input parameters and their description	
Variable name	**Distribution**
Trip Distance	Lognormal
PC speed	Normal
Time to get to PC	Normal
Time to find parking, PC	Normal
Time to go from parking to destination, PC	Normal
Transit Speed	Normal
Time to get to Transit	Normal
Time spent waiting for Transit	Normal
Time to find parking, Transit	None
Time to go from parking to destination, Transit	Normal
Walking Speed	Constant (3.0 mph)
Time to mode, Walk	None
Time spent waiting, Walk	None
Time to find parking, Walk	None
Time to go from parking to destination, Walk	None
Time to mode, Ride-share	Normal
Time spent waiting, Ride-share	Normal
Time to find parking, Ride-share	Normal
Time to go from parking to destination, Ride-share	Normal

Table 5.1: Table for all the variables related to time for various modes

Input parameters and their description	
Variable name	**Distribution**
$/mile, PC	Constant, $0.63
$/min, PC	None
Average parking cost, PC	Normal
Base Cost, PC	None
$/mile, Transit	None
$/min, Transit	None
Average parking cost, Transit	None
Base Cost, Transit	Normal
$/mile, Walk	None
$/min,Walk	None
Average parking cost, Walk	None
Base Cost, Walk	None
$/mile, Ride-Share	Constant,$1.25
$/min, Ride-Share	Constant, $0.20
Average parking cost, Ride-Share	None
Base Cost, Ride-Share	Constant, $2.25

Table 5.2: Table for all the variables related to cost for various modes

Table 5.4.

The values associated with the input parameters of the comfort model, which was qualitatively assessed, are shown in Table 5.3. A comfort of 0 was assumed as the least comfortable and that of 1 indicated the most comfortable. Private cars were assumed to be the most comfortable with a mean comfort score of 0.9 and a standard deviation of 0.05. Similarly, transit was assumed to be at a comfort level much lower than car based modes at a mean comfort score of 0.45 with a standard deviation of 0.05 in urban areas. The variable "Comfort walking maximum" and "Comfort Walking, Minimum" were used to incorporate the fact that for trips longer than "Constant maximum comfort time" 20 min, the mean comfort of walking decreased exponentially from the value corresponding to "Comfort Walking, Maximum" to a value corresponding to "Comfort Walking, Minimum" across a time period of "Time-steps for decreasing comfort". Similar concept was included in the comfort associated with ride-shared vehicles. This "mean comfort" was the variable that was decaying over time as shown in Figure 5-1. This decaying mean still had a normal distribution around it, and a coefficient of variation of 0.1 was assumed for all the modes. This

Input parameters and their description	
Variable name	**Distribution**
Comfort PC	Normal
Comfort Transit	Normal
Comfort Walking, Maximum	Normal
Comfort Walking, Minimum	Normal
Time-steps for decreasing comfort, Walk	Constant (100 min)
Constant maximum comfort time, Walk	Constant (20 minutes)
Covariance coefficient, Walk	Constant (0.1)
Comfort Ride-Share, Maximum	Normal
Comfort Ride-Share, Minimum	Normal
Time-steps for decreasing comfort, Ride-Share	Constant (60 min)
Constant maximum comfort time, Ride-Share	Constant (10 min)
Covariance coefficient, Ride-Share	Constant (0.1)

Table 5.3: Table for all the variables related to comfort for various modes

Input parameters for $/mile cost sub-model for gasoline private car	
Variable name	Value
kWh/mile	$0.34
Electricity price $/kWh	$0.00
Insurance/year	$1200
miles/gallon	25
Gas Price/gallon	$2.5
Annual Mileage	13140 miles
Upfront cost	$25000
Discount	5%
Accounting Life	10 years
Maintenance/year	$700.00
Liscense registraion/yr	$1,850.00
Margin Driver	$0.00
Margin Company	$0.00
Gas price/mile	$0.1
Electricity cost/mile	$0
Ammortization	$3,237.61
Liscense regitraion/mile	$0.14
Ammortization/mile	$0.25
Total Fuel Cost/mile	$0.10
Maintenance cost/mile	$0.05
Insurance/mile	$0.09

Table 5.4: Table for all the variables related to cost of gasoline PC

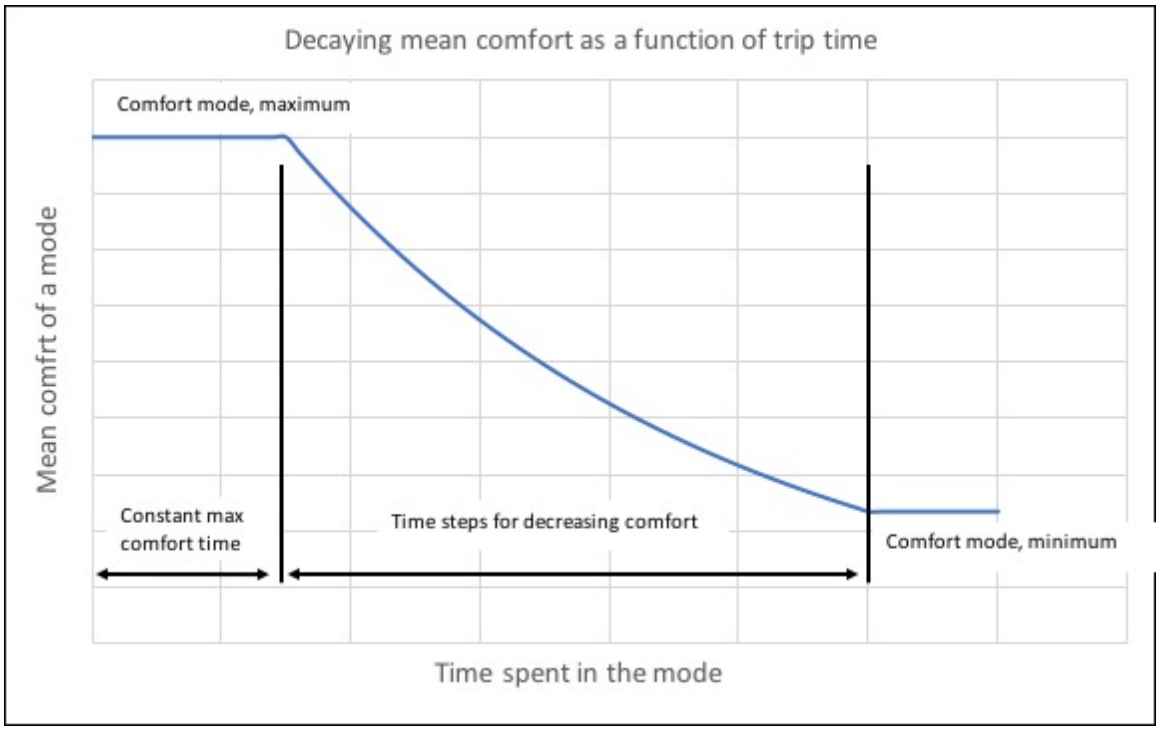

Figure 5-1: Qualitative graph of the decaying comfort concept

concept is qualitatively shown in the Figure 5-1. It was assumed that the mean comfort of ride-shared vehicles was close to that of a private car, around 0.7. But for trips longer than 10 minutes in a ride-shared car, the mean comfort score associated with ride-shared vehicles began decreasing with time spent in the vehicle.

The next Table 5.5 gives all the variables that were related to the utility theory model and modeling preferences. These are the variables that were used along with Equation 4.1 and Equation 4.2 to calculate the single attribute utilities and the multi-attribute utilities for various modes for each trip that was simulated.

All the variables mentioned in the tables above were used as inputs for all the 24 people-trip combinations. Appendix A gives the input values for all the variables shown in the tables above for urban, suburban and rural trips (Work, leisure, errands, other), and for both income groups (Low/middle income and high income). Specifically, Tables A-1, A-2, A-3, A-4 give the inputs for urban trips. Tables A-5, A-6, A-7 give the inputs for suburban trips and Tables A-8, A-9, A-10 give the inputs for rural trips. All these tables refer to the inputs used in the base case. When the scenarios

Input parameters and their description	
Variable name	**Distribution**
Best cost	\$0
Worst Cost	\$30
Best time	0 minutes
Worst time	60 minutes
Best comfort	1
Worst comfort	0
k_{cost}	Normal
k_{time}	Normal
$k_{comfort}$	Normal

Table 5.5: Table for all the variables related to preference modeling

were tested, only a small subset of these inputs were changed to reflect the changes in the scenario. These modified variables are presented in the next chapter. When testing the futuristic scenarios, all other variables were kept constant apart from these few key variables that were modified that pertain to the scenarios.

5.3 Base case scenario intermediate results

As mentioned before, 240,000 trips in total were simulated that correspond to the 24 people-trip combinations. Some of the intermediate results are shown here just for the urban low income work trips. Trips in other groups follow similar trends with different magnitudes. The results from this section are essentially presented to communicate the better understanding of the model. The first thing that was simulated for each of these groups was the trip distances. The trip distances associated with urban work trips is shown in Figure 5-2.

Once the trip distances were simulated for 10,000 trips, for a particular type of trip, the cost, time and comfort associated with different modes for those trip distances could be calculated using the equations from Chapter 4. The costs associated with different modes is shown in Figure 5-3. The cost associated with walking was assumed to be \$0. As can be seen from Figure 5-3, transit seems trips are the cheapest. Between ride-shared trips and private car trips, there are some trips which are cheaper in ride-shared car and there are some which are cheaper in a private car.

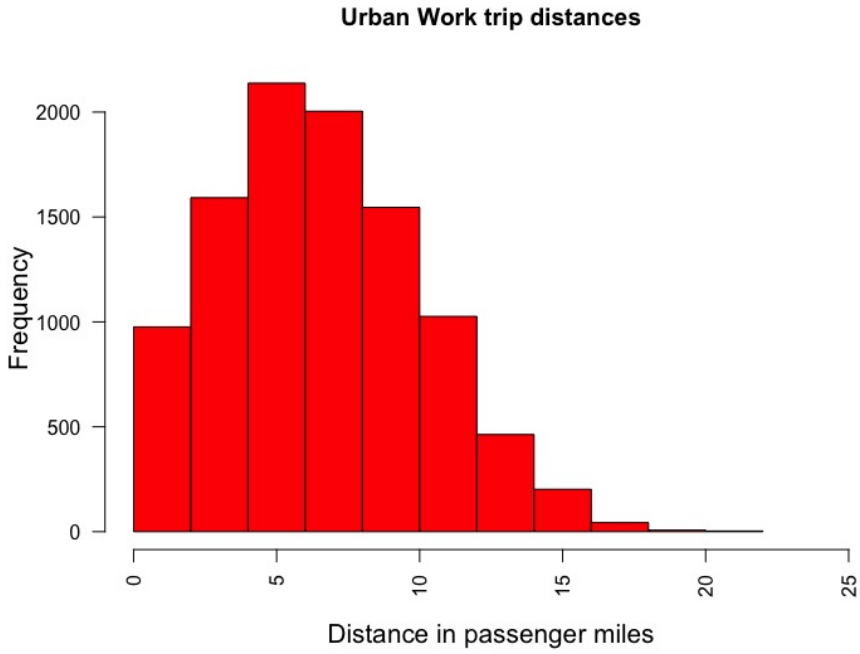

Figure 5-2: Urban Low income Work trip distances

The Figure 5-4 shows the time associated with making trips in different modes. As can be seen from this figure, the time associated with private car, transit and ride-share is clearly desirable for urban work trips. Most of the trips are less than half an hour in these modes. The time associated with work trips done by walking ranges from less than 10 minutes to five hours. This is because some of the 15 mile trips done at the speed of walking, 3mph, require around 5 hours to get completed. Therefore the time associated with walking trips covers a wider range as compared to the trips done in other modes. The thing to note here specifically is that the private car, ride-share and transit times are almost identically distributed for urban trips. Transit and ride-share are therefore competitive options for urban work trips and also other urban trips in general.

The Figure 5-5 shows the distributions for comfort associated with different modes for the simulated urban work trips. As can be seen from Figure 5-5, the comfort associated with private car trips is clearly the highest and the comfort associated with walking trips is clearly the lowest. Walking trips cover pretty much the whole range of comfort because there are some walking trips which are less than 20 minutes that

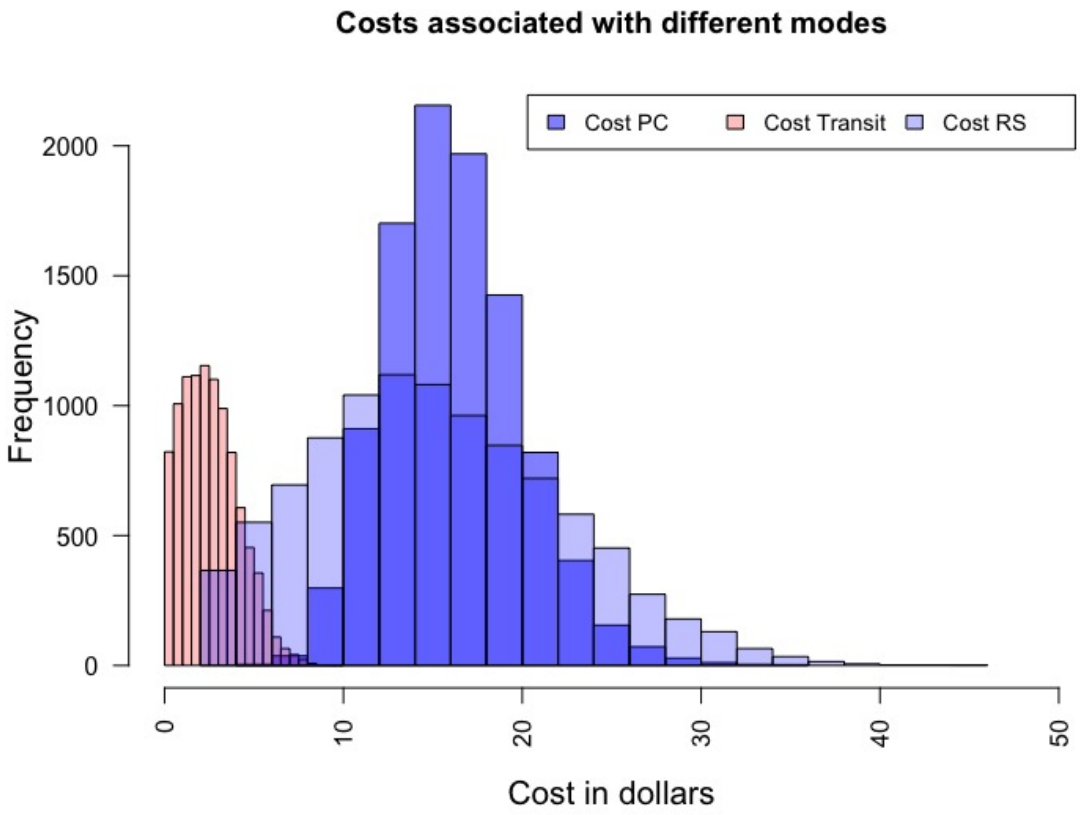

Figure 5-3: Costs associated with urban low income work trips

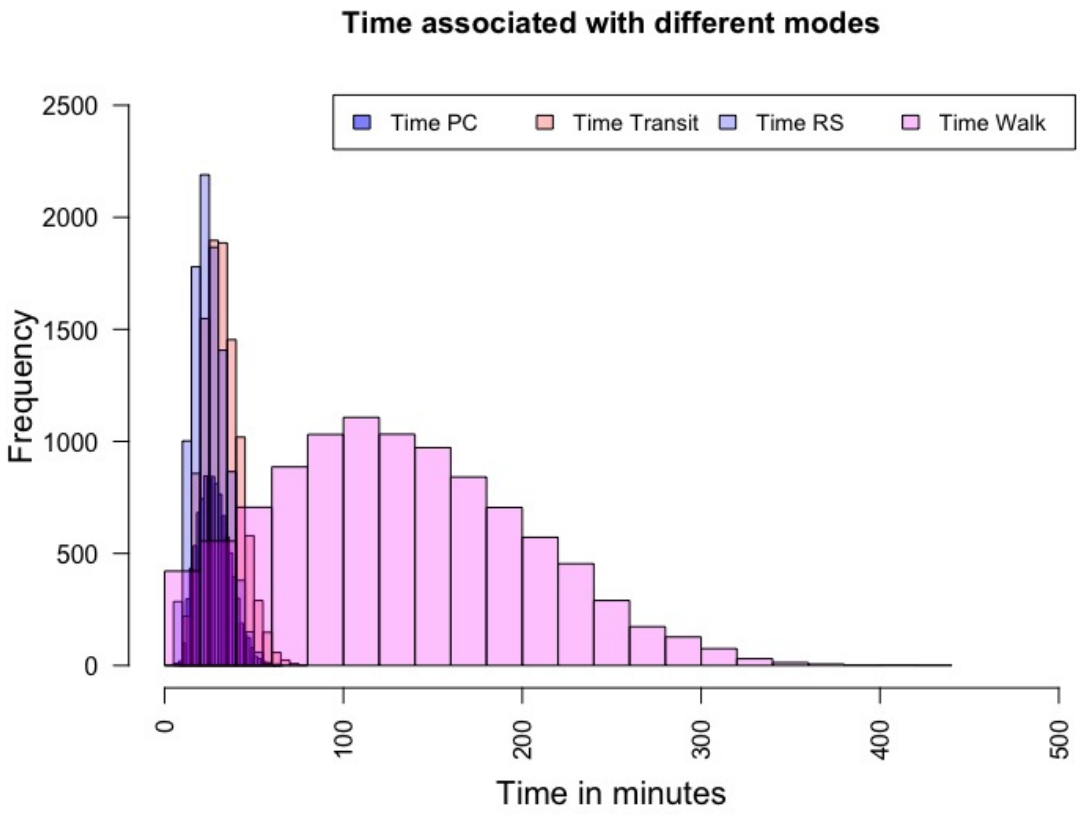

Figure 5-4: Time associated with urban low income work trips

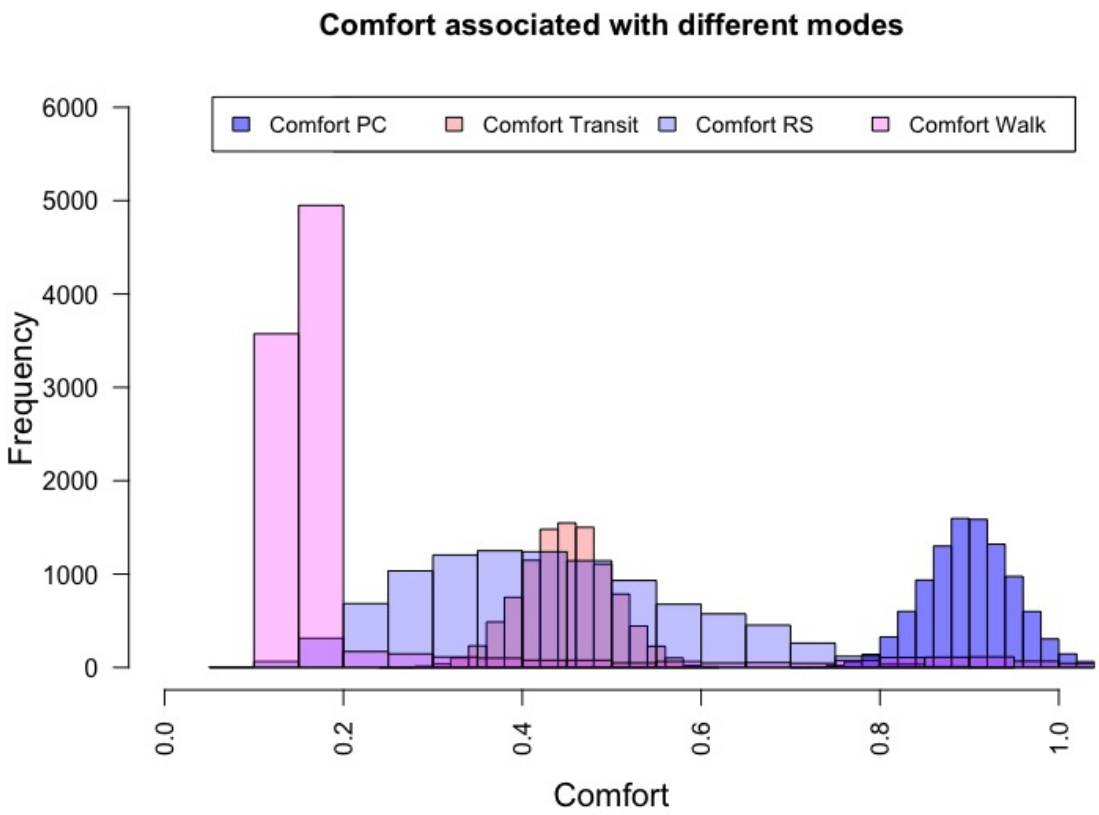

Figure 5-5: Comfort associated with urban low income work trips

have a very high value of comfort associated with them. Comfort values associated with transit lie somewhere in between walking and private car. Ride-share comfort value on the other hand are mostly better than walking trips, but not significantly better than private car trips. This is due to the fact that longer ride-shared trips have a decaying comfort value.

Once the cost, time and comfort associated with different modes were calculated for urban low income work trips, the next step was to convert each of these values associated with the simulated 10,000 trips into a utility value. This was done using Equation 4.1. The importance weights associated with cost, time and comfort attributes were simulated for each of these 10,000 trips. These are shown in Figure 5-6. As can be seen from Figure 5-6, there are some people who assign the highest importance to time, as for work trips time is a crucial factor. Also, there is a significant overlap in terms of what different people are sensitive to when it comes to cost,

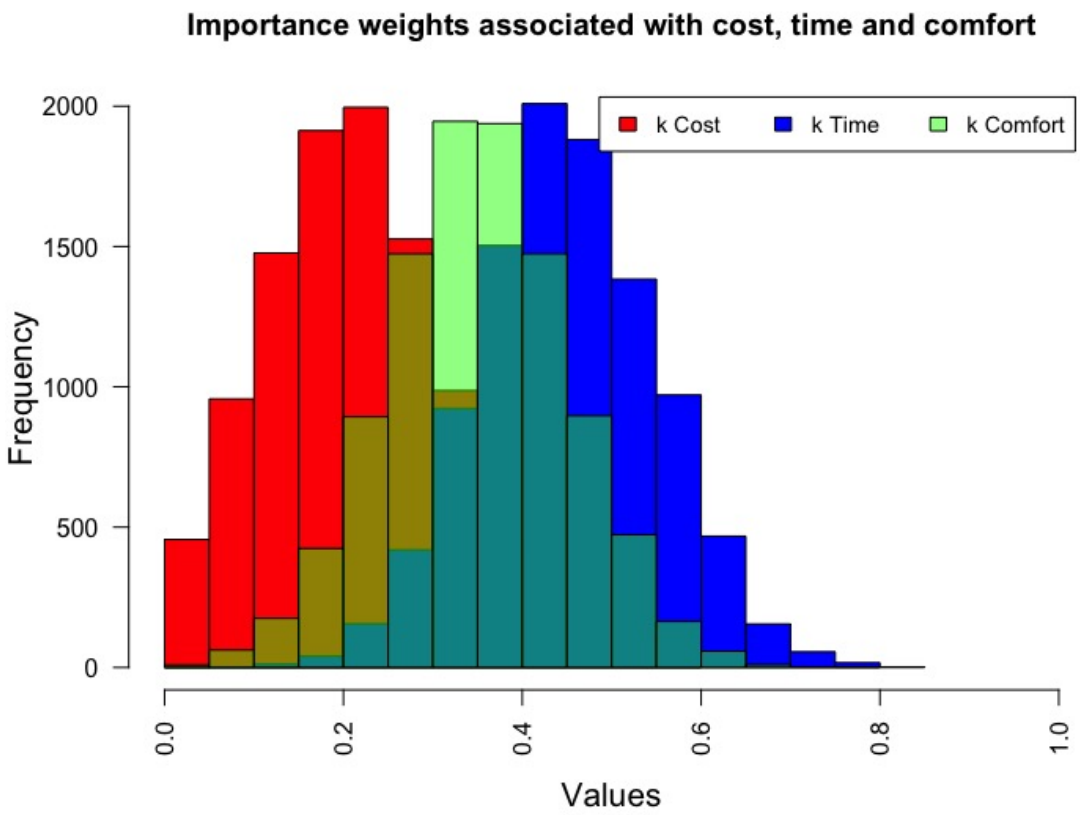

Figure 5-6: Importance weights for cost, time and comfort: Urban low income work trips

time and comfort. Once the distribution of these weights was obtained and the single attribute utilities were obtained from Equation 4.1, the two were combined together into a multi-attribute utility score for each of the modes using Equation 4.2. The multi-attribute utilities are shown in the Figure 5-7.

As can be seen from the Figure 5-7, the multi-attribute utility values for private car are to the very right of the figure suggesting that private car was the most comfortable mode. Walking had a significantly low utility. Ride-share trips on the other hand had a multi-attribute utility that covered almost the entire range, suggesting that some trips were highly desirable in a ride-shared vehicle while others were not. This process of obtaining the relative multi-attribute utility values for different modes meant that the most desirable mode could be chosen for a particular trip. After deciding the most desirable mode for each of the 10,000 simulated urban low income work trips,

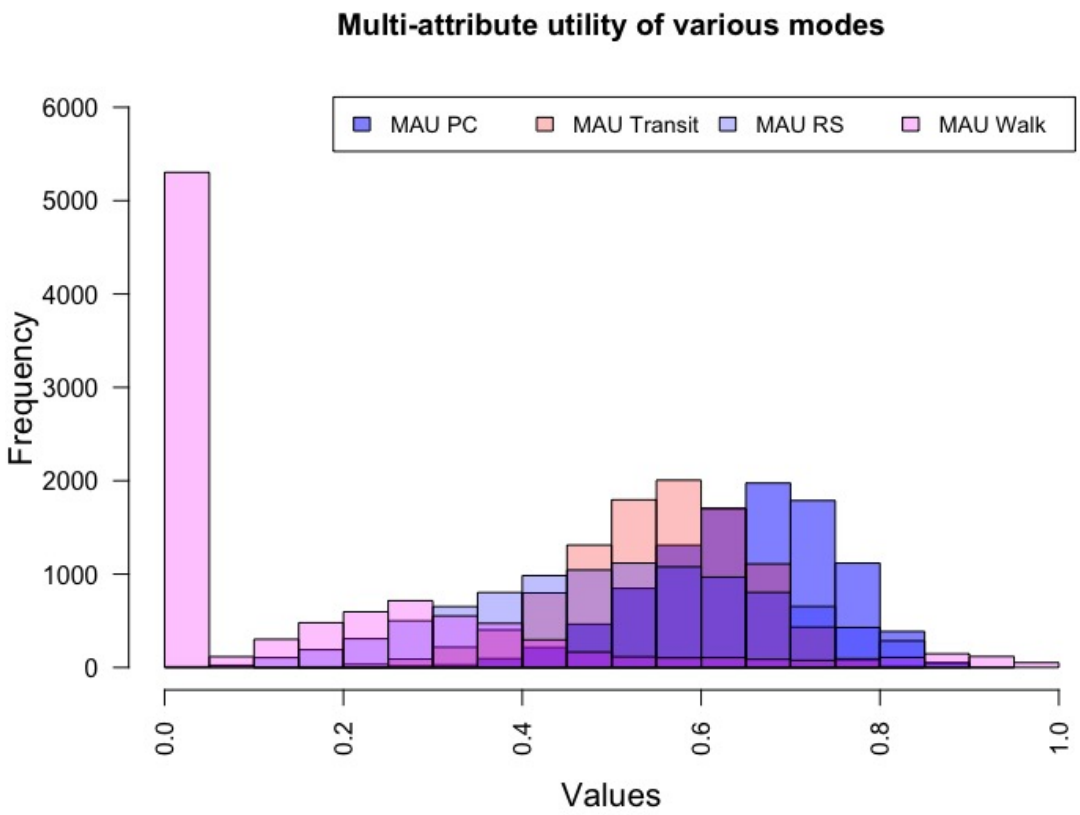

Figure 5-7: Multi-attribute utilities for different modes for urban low income work trips

a market share in terms of the total number of trips taken in different modes was determined. This is shown in Figure 7-1.

This process for the determination of market shares of trips taken in different modes was repeated for all other 23 people-trip combinations. After considering all the other 23 people-trip combinations, the total national level trip demand could be converted to car-based trips and non-car-based trips. Combining these trips with the passenger trip distances, a car based PMT was calculated. Assuming an occupancy and utilization, VMT and national level vehicle stock was calculated. These results are shown in the results chapter.

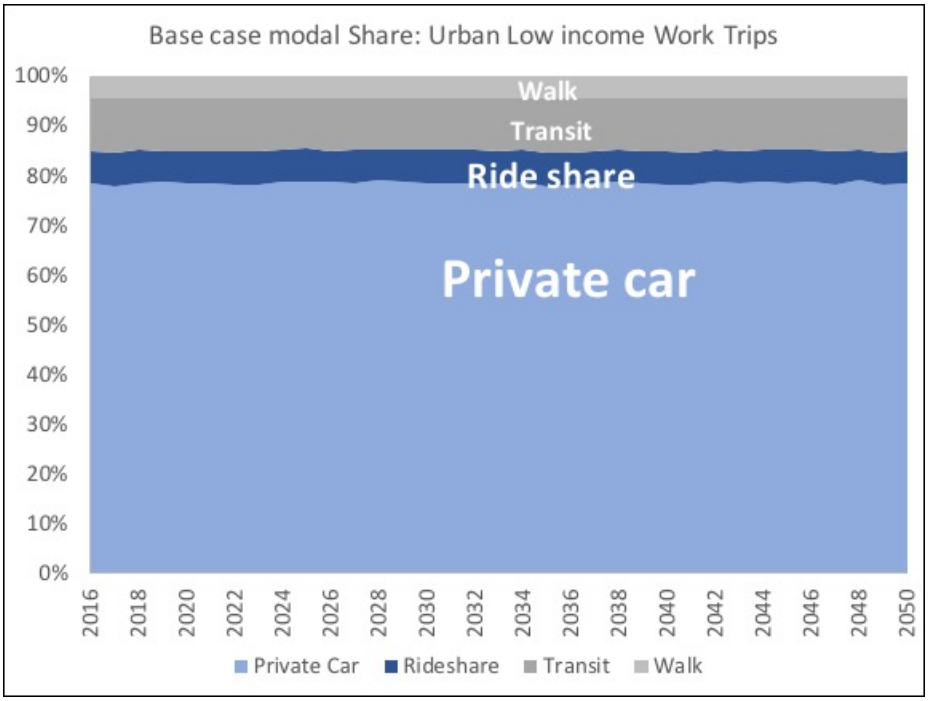

Figure 5-8: Modal shares for urban low income work trips

5.4 Model validity check with NHTS data

One of the steps that was done during the model building was model calibration with the data that was available from NHTS. NHTS gave the modal share data at the national aggregate level as can be seen from Figure 4-5. NHTS gave the modal shares at the national aggregate level and the modal shares needed for this work were at the urban, suburban and rural level. In order to break down the national level data into the level of aggregation that was required, the data was weighted according to the population composition in urban, suburban and rural areas. Specifically, According to census data, approximately 26%, 53% and 21% of the population belongs to urban, suburban and rural areas respectively[10]. On top of this it was assumed that 93% of suburban work trips and 98% of rural work trips happen in private cars. Similarly, assumptions were made about the percentage of work trips happening in modes other than private cars in non-urban areas. This information is shown in Table 5.6. This information was then used to calculate the modal shares at the urban, suburban and rural level nationally.

Breakdown of National level modal shares				
Mode	**National level NHTS data**	**Calculated Urban**	**Assumed Suburban**	**Assumed Rural**
Car	91.4%	82.8%	93.0%	98.0%
Transit	3.7%	10.2%	2.0%	0.0%
Walking	3.0%	6.7%	2.0%	1.0%
Other	1.9%	0.4%	3.0%	1.0%

Table 5.6: Calculated Urban modal shares for work trips from national NHTS data

Assumed ratios of High income/Low income			
Mode	**Urban**	**Suburban**	**Rural**
Car	1.09	1.02	1.0
Transit	0.50	0.50	1.0
Walking	0.95	0.95	0.95
Other	1.0	1.0	1.0

Table 5.7: Ratio of High income work trips/Low income work trips

It was also assumed that the low/middle income and high income population split is 50%-50%. Another assumption that was made was that the ratio of trips of high income level group vs. low/middle income level group. For example, it was assumed that the ratio of work trips taken in private cars for high income people vs. low/middle income people was 1.09. This basically reflected the fact that affluent people were more likely to take private cars to work than less affluent people. Similar assumptions were made about work trips in other modes. These ratios are shown in Table 5.7.

NHTS did not report the data on ride-sharing modal share. Therefore it was assumed that 5% of urban high income work trips happen in ride-shared vehicles, and 4% of low/middle income urban work trips happen in ride-shared vehicles, 1% suburban work trips and zero percent rural work trips happen in ride-shared vehicles. NHTS had an "other" trips category but did not have a ride-sharing category. Therefore, the "Other modes" modal share of work trips was added back to cars, transit and walking proportionally to the existing modal share of private cars, transit and walking. It was also assumed that ride-sharing "steals" equally from cars, transit and walking modes to get to its assumed modal share in terms of trips taken. Therefore,

Assumed ratios of High income/Low income			
Mode	**Urban**	**Suburban**	**Rural**
Car	1.06	1.02	1.01
Transit	0.50	0.50	1.00
Walking	0.95	0.95	0.95
Other	1.0	1.0	1.0

Table 5.8: Ratio of High income Leisure trips/Low income leisure trips

Assumed ratios of High income/Low income			
Mode	**Urban**	**Suburban**	**Rural**
Car	1.03	1.01	1.00
Transit	0.50	0.50	1.00
Walking	0.95	0.95	0.95
Other	1.0	1.0	1.0

Table 5.9: Ratio of High income errands/Low income errands

1/3 of the assumed modal share of ride-shared work trips was subtracted from the modal share of private cars, transit and walking as well. These manipulations finally gave a final set of calibration results for work trips at the level of aggregation that was needed. A similar exercise was done for leisure and errand trips as well. The ratios of high income vs low/middle income leisure trips are shown in Table 5.8. A few ratios related to the personal car trips are different from the work trips.

Finally, Table 5.9 give the ratios used for errand trips. After going through the calibration exercise, the modal shares at the level of aggregation that was required for this model were obtained. Tables 5.10, 5.11, 5.12 show the final calibration values that the model was supposed to be calibrated to. These are the values that were derived from the national level NHTS data.

Breakdown of National level modal shares						
Mode	**Urban High Income**	**Urban High Income**	**Suburban High Income**	**Suburban Low Income**	**Rural High Income**	**Rural Low Income**
Private Car	85.07%	78.27%	96.15%	94.77%	98.93%	98.93%
Transit	5.12%	12.22%	1.11%	2.45%	0.04%	0.04%
Walking	4.83%	5.50%	1.71%	1.81%	1.00%	1.06%
Ride-share	5.00%	4.00%	1.00%	1.00%	0.0%	0.0%

Table 5.10: Calculated modal shares for work trips from national NHTS data

Breakdown of National level modal shares						
Mode	**Urban High Income**	**Urban High Income**	**Suburban High Income**	**Suburban Low Income**	**Rural High Income**	**Rural Low Income**
Private Car	73.03%	68.89%	83.95%	94.77%	88.93%	88.11%
Transit	3.28%	6.71%	0.51%	1.17%	0.17%	0.17%
Walking	21.17%	21.92%	14.61%	15.33%	11.05%	11.56%
Ride-share	2.00%	3.00%	1.00%	1.00%	0.0%	0.0%

Table 5.11: Calculated modal shares for Leisure trips from national NHTS data

Breakdown of National level modal shares						
Mode	**Urban High Income**	**Urban High Income**	**Suburban High Income**	**Suburban Low Income**	**Rural High Income**	**Rural Low Income**
Private Car	66.56%	64.96%	97.38%	96.44%	98.90%	98.90%
Transit	0.24%	2.45%	0.03%	0.36%	0.01%	0.01%
Walking	27.47%	29.32%	1.84%	1.95%	1.07%	1.12%
Ride-share	5.00%	4.00%	1.00%	1.00%	0.0%	0.0%

Table 5.12: Calculated modal shares for errands from national NHTS data

Chapter 6

Scenario set up and changing model parameters

This chapter describes the specific inputs, apart from the inputs used in the base case scenario, that were changed when simulating these futuristic scenarios. The first section gives a broad overview of what scenarios were tested. The next section mentions the specific inputs that change with scenarios. All other input parameters were held the same as in the base case scenario.

6.1 Exploring the ways the world can change using different scenarios

Once the model, specifically the travel behavior module, was calibrated with the NHTS data and the base case was defined, the next step was to use the model to assess the effect of ride-sharing on the research objectives. The main research objective was to understand the effect of ride-sharing on the way people are getting around, and its impact on urban vehicle miles travelled and the national vehicle stock. As ride-sharing becomes more and more popular, it may not necessarily mean having more cars on the road or having more vehicle miles travelled. Changing utilization and occupancy means that just because ride-sharing improves does not necessarily mean

Scenarios considered	
Scenario name	Description
Scenario 0	Base case
Scenario 1.0	Improved Ride-sharing
Scenario 1.1	Improved Ride-sharing+Improved Transit
Scenario 1.2	Improved Ride-sharing+Improved Transit + Anti-car policies
Scenario 1.0EV	Improved Ride-sharing+ Higher EV penetration
Scenario 1.0EV+AV	Improved Ride-sharing + Higher Autonomous penetration

Table 6.1: Table for all the variables related to cost for various modes

that the number for cars will go up or the vehicle miles travelled will go up. This work studied the impacts of ride-sharing on three important metrics, urban personal car VMT, urban modal shares and the national level vehicle stock. In order to gauge the impact on the research metrics discussed earlier, a reference scenario had to be constructed, which was the base case.

This work will consider the impact of improvements in ride-sharing on the research metrics described earlier. The first scenario that was considered was just improved ride-sharing. The next scenario combined improved ride-sharing with transit improvements. A third scenario combined ride-sharing and transit improvements with discouraging private car policies (e.g. congestion pricing). A variant on the first scenario was also considered with higher EV penetration and higher autonomous vehicle penetration. These five scenarios give a variety of results that will be explored and discuss later. Table 6.1 gives a summary of all the scenarios that were tested.

The first scenario that was considered was the improved ride-sharing scenario. The concept of ride-sharing or similar other concepts to ride-sharing, like car-sharing, are not new in the USA. Car-pooling has existed since the World War Two[20]. Many people have also studied the possible co-existence of ride-sharing with private car usage [29]. Many researchers have also studied the increase of ride-sharing through empirical studies, its effect on congestion and the effect of ride-sharing on different socio-economic groups[23][51][33]. This scenario was defined as the scenario where the number of ride-sharing services increase. This was a scenario where ride-sharing becomes ubiquitous and there are many more ride-sharing drivers than there are

today. Cost of ride-sharing become cheaper due to competition and the utilization of ride-shared vehicles increases. This translates to some of the key inputs associated with ride-sharing in the model to change, like decreased waiting times for ride-shared vehicles, decreased costs and increased comfort.

What if along with improved ride sharing, government also decides to improve transit systems? Researcher have studied the effect of improving transit options on travel behavior[34][35][26]. Many studies have also looked at the improvements in transit and the effect on land use and transit improving algorithms [49][8].In this scenario it was assumed that along with the improved ride-sharing services, government invests in transit infrastructure so that the transit efficiency/speed increases and the waiting times for transit go down. This was the second scenario that was tested.

Along with these changes, what if the government also decides to discourage personal car use? The previous scenario was augmented with an added element of discouraging personal car policies. In this scenario, it was assumed that along with improvements in ride-share and transit systems, the government also imposes anti-private car policies. A number of studies have been published on modeling road pricing, congestion, and the effect of these pricing policies on car use [13][11][31]. Some empirical studies also exist that attempt to study the effect of congestion pricing on car use[43][32]. In order to model a similar effect in this work, a parking fee increase associated with personal car trips was associated with this scenario. Along with these scenarios, the effect of electrification and autonomy was also gauged in the next scenarios.

The effect of electrification of vehicles was estimated by taking into consideration a scenario related to higher penetration of electric vehicles in the fleet. In this scenario a higher level of EV penetration was assumed along with the improved ride-sharing services. The market penetration of electric vehicles was informed in this work by taking inspiration from other studies[4][16][57] [7]. Researchers have also looked at the effect of financial incentives and other socio-economic factors on EV adoption[48]. In order to estimate the effect of EVs on the fleet, an exogenous penetration value for EVs was assumed. A separate $/mile value was calculated for a gasoline private

car and an EV private car. Similarly, a separate $/mile value was calculated for a gasoline ride-shared car and an EV ride-shared car. Using this exogenous EV penetration and EV utilization rate, a $/mile value associated with the EV vehicles was also calculated.

Finally, a scenario was created to gauge the impact of autonomous vehicles on the national vehicle stock and on the urban modal shares and vehicle miles travelled. In this scenario, it was assumed that "Level 5" Autonomous vehicles become prominent by 2050. This leads to a higher average utilization of the fleet and also a decreased cost for mobility on demand services. This results in the costs of mobility on demand services becoming very competitive with private car costs. Autonomous vehicle market penetration and the general implementation of autonomous vehicles in society has been studied by multiple researchers [36][19][17][18]. This scenario and the parameter values of this scenario have been informed by the work done by others in this area.

6.2 Description of inputs that change with scenarios

Section 5.2 gave a list of various different variables that were used in the model for various modes. These were the variables that were tested and modified when futuristic scenarios were defined. Variables like $\$/mile$,$Time\ to\ wait\ for\ ride-share$, etc. were modified to show improvements in ride-sharing. Other variables were modified accordingly to reflect the scenario that was being studied. This section describes the variables that were changed when a particular scenario was being considered.

In the base case scenario, nothing changes apart from the fact that the total population grows. In Scenario 1.0: Improved ride-sharing, it was assumed that ride-sharing becomes more popular and the availability and cost of ride-sharing improves. In terms of the specific model inputs mentioned in Tables mentioned above, it meant decreased waiting times for ride-hailing, decreased cost of the ride-shared vehicles and increased comfort of ride-shared vehicles. Specifically the inputs changed over time

Input parameters that change with Scenario 1.0		
Variable name	**Year 2016 value**	**Year 2050 value**
Waiting time for ride-share	5 min	3 min
Base cost	$2.25	$1.50
Ride-share comfort	0.7	0.8
Utilization/Annual mileage	17,500 miles	22,776 miles

Table 6.2: Inputs that changed from the base case

Input parameters that change with Scenario 1.1		
Variable name	**Year 2016 value**	**Year 2050 value**
Waiting time for ride-share	5 min	3 min
Base cost	$2.25	$1.50
Ride-share comfort	0.7	0.8
Utilization/Annual mileage	17,500 miles	22,528 miles
Mean speed transit	24 mph	26 mph
Mean waiting time	10 min	5 min
Base Cost	$2.00	$1.80

Table 6.3: Inputs that changed from the base case

from year zero, which in this case was 2016, to year 2050 linearly. Table 6.2 shows the inputs that are different from the base case. Other input parameters were the same as that in the base case scenario.

The implication of change of these variables on the modal shares, VMT and the national vehicle stock will be explored in the results section.

The next scenario that was tested was the improved ride-sharing and improved transit scenario. In this scenario it was assumed that along with improved ride-sharing, government also invests in improving transit systems. As a result, the transit efficiency increases and there are more transit stops at major locations. In terms of the model parameters mentioned earlier, this translated to an increase in the mean transit speed, decrease in the waiting times associated with transit systems and decrease in the base cost associated with transit systems. The input parameters for this scenario that are different from the base case are shown in Table 6.3. Apart from the inputs shown in Table 6.3, all other inputs were the same as those used in the base case scenario.

The next scenario that was tested was Scenario 1.2 where it was assumed that

Input parameters that change with Scenario 1.2		
Variable name	**Year 2016 value**	**Year 2050 value**
Waiting time for ride-share	5 min	3 min
Base cost	\$2.25	\$1.50
Ride-share comfort	0.7	0.8
Utilization/Annual mileage	17,500 miles	25,000 miles
Mean speed transit	24 mph	26 mph
Mean waiting time	10 min	5 min
Base Cost	\$2.00	\$1.80
Parking cost PC	\$8.00	\$10
Time to find Parking	5 min	7 min

Table 6.4: Inputs that changed from the base case

along with improvements in ride-share and transit systems, government also discourages personal car use and therefore mandates certain policies which are anti-car. In terms of the model variables, this was reflected by increasing the parking cost associated with the trips taken in personal cars (PCs) and increase in the time taken to find parking for PCs. Table 6.4 shows the inputs that are different than the base case inputs for this scenario. Apart from the inputs shown in Table 6.4, all other inputs were the same as those used in the base case scenario.

Scenario 1.0EV assumed that along with improved ride-sharing, there is also a higher penetration of electric vehicles in the fleet. In order to incorporate the electrification component into the model, the key variable that was used was the $\$/mile$ value for PCs and ride-shared cars. An exogenous EV penetration was assumed. EV penetration was not modeled from scratch, but rather taken from existing sources that have studied the penetration of EVs in the fleet. In order to incorporate the electric vehicles, private or ride-shared, into the fleet, a $\$/mile$ value for an EV ride-shared car and an EV personal car was calculated by using the information about the input parameters shown in Table 6.5, specifically for a typical average electric vehicle. These numbers were derived from the AAA[1] model for gasoline personal cars, and then assuming conservative values for the electric efficiency and upfront cost of EVs.

Once the $\$/mile$ for personal car with an EV powertrain was calculated, the same was done for ride-shared EV cars. Table 6.6 shows the assumptions for calculating a

Input parameters for $/mile cost sub-model for an EV private car	
Variable name	Value
kWh/mile	0.25
Electricity price $/kWh	$0.15
Insurance/year	$1200
miles/gallon	NA
Gas Price/gallon	$0.0
Annual Mileage	13,140 miles
Upfront cost	$40,000
Discount	5%
Accounting Life	10 years
Maintenance/year	$700.00
Liscense registraion/yr	$1,850.00
Margin Driver	$0.00
Margin Company	$0.00
Gas price/mile	$0.1
Electricity cost/mile	$0
Ammortization	$3,237.61
Liscense regitraion/mile	$0.14
Ammortization/mile	$0.25
Total Fuel Cost/mile	$0.10
Maintenance cost/mile	$0.05
Insurance/mile	$0.09

Table 6.5: Table for calculating $/*mile* for EV private cars

Input parameters for $/mile cost sub-model for an EV ride-shared car	
Variable name	Value
kWh/mile	0.25
Electricity price $/kWh	$0.15
Insurance/year	$1000
miles/gallon	NA
Gas Price/gallon	$0.0
Annual Mileage	24,528miles
Upfront cost	$40,000
Discount	5%
Accounting Life	10 years
Maintenance/year	$700.00
Liscense registraion/yr	$1,850.00
Margin Driver	$0.35
Margin Company	$0.15
Gas price/mile	$0.1
Electricity cost/mile	$0
Ammortization	$3,237.61
Liscense regitraion/mile	$0.14
Ammortization/mile	$0.25
Total Fuel Cost/mile	$0.10
Maintenance cost/mile	$0.05
Insurance/mile	$0.09

Table 6.6: Table for calculating $/*mile* for EV private cars

$/*mile* for ride-shared EVs.

Using the values in Table 6.5 and Table 6.6, a $0.80/*mile* for EV private cars and $0.91 for EV ride-shared cars was calculated. The breakdown of these costs is shown in Figure 6-1 and Figure 6-2 for private cars and ride-shared cars respectively (for gasoline and EV powertrain).

Along with this value derived for the dollar per mile for both, ride-shared and private cars for the two powertrains, an exogenous penetration was assumed for EVs in the fleet. It was assumed that amongst the private cars, gasoline cars would comprise of 70% of the market and EVs would have a penetration of 30% in the year 2050. Amongst ride-shared cars, it was assumed that EVs would have a more aggressive penetration of 50% in the year 2050. Assuming these penetrations, a weighted average $/*mile* was calculated for PCs and ride-shared vehicles in the electrification scenario.

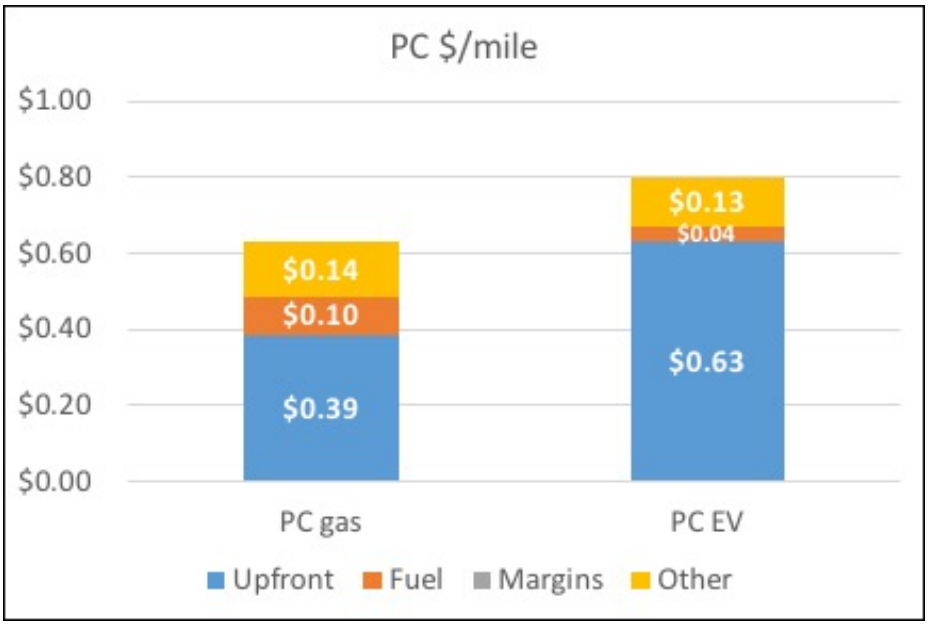

Figure 6-1: Dollars per mile private cars

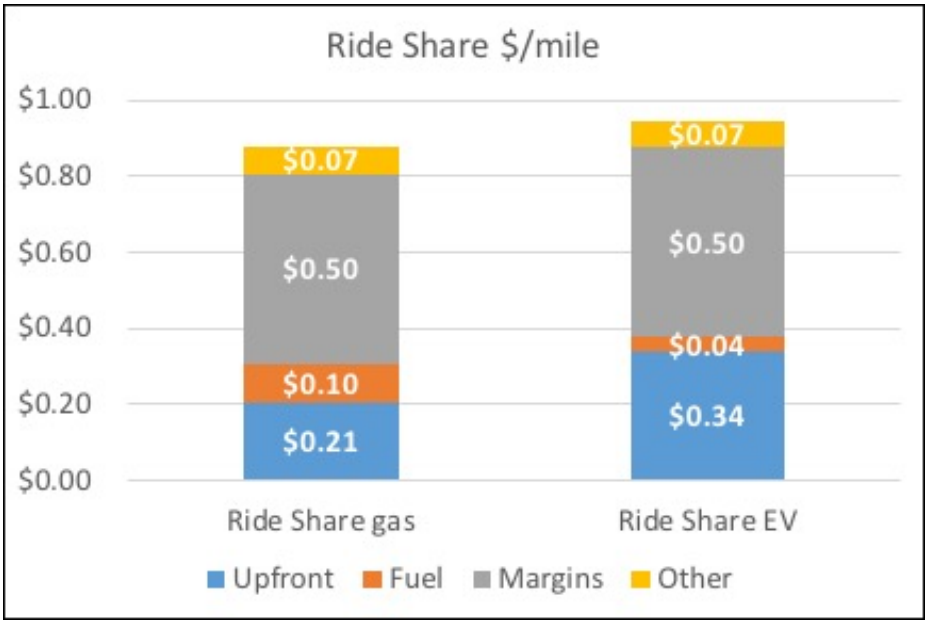

Figure 6-2: Dollars per mile Ride-shared cars

This is how electrification was incorporated into the scenario.

After incorporating the effect of electrification in the scenario, the variables that change from the base case are shown in Table 6.7.

Scenario 1.4EV+AV assumed that along with improved ride-sharing, there is also a higher penetration of autonomous vehicles in the fleet. In order to incorporate

Input parameters that change with Scenario 1.0EV		
Variable name	**Year 2016 value**	**Year 2050 value**
Waiting time for ride-share	5 min	3 min
Base cost	$2.25	$1.50
Ride-share comfort	0.7	0.8
Gasoline private car penetration	98%	70%
EV private car penetration	2%	30%
Gasoline ride-share car penetration	98%	50%
EV ride-share car penetration	2%	50%
Utilization/Annual mileage	17,500 miles	26,000 miles
$/mile ride-share	$0.89	$0.91

Table 6.7: Inputs that changed from the base case

the autonomous component into the model, the key variable that was used was the $\$/mile$ value for PCs and ride-shared cars, in a similar way to the previous scenario where higher EV penetration was modeled. In the autonomous scenario, along with an exogenous penetration of autonomous vehicles, an exogenous penetration of EV vehicles was also assumed. Autonomous and EV penetration values were not modeled from scratch, but rather taken from existing sources that have studied the penetration of different powertrains in the fleet. In order to incorporate the autonomous vehicles, private or ride-shared, into the fleet, a $\$/mile$ value for an EV ride-shared car and an EV personal car was calculated by using the information about the input parameters shown in Table 6.8, specifically for a typical average electric autonomous vehicle.The Table 6.9 shows the numbers assumed in the calculation of $\$/mile$ for autonomous ride-shared vehicles. These numbers were again derived from the AAA[1] model for gasoline personal cars, and then assuming conservative values for the electric efficiency and upfront cost of autonomous vehicles, just as was done in the previous scenario with EV penetration modeling. Finally assuming that 80% of the personal cars are still gasoline powered, 10% are electric and 10% are autonomous, a weighted average $\$/mile$ value was calculated for the private cars in the fleet. Similarly to calculate a weighted average $\$/mile$ for ride-shared vehicles, it was assumed that 50% of the ride-shared vehicles in the mobility fleet will be gasoline powered and electric and autonomous vehicles will comprise of 25% penetration each. The $\$/mile$ values used

Input parameters for $/mile cost sub-model for an Electric Autonomous private car	
Variable name	Value
kWh/mile	0.25
Electricity price $/kWh	$0.15
Insurance/year	$1200
miles/gallon	25
Gas Price/gallon	$0.0
Annual Mileage	26,280 miles
Upfront cost	$120,000
Discount	5%
Accounting Life	10 years
Maintenance/year	$700.00
Liscense registraion/yr	$1,850.00
Margin Driver	$0.00
Margin Company	$0.00
Gas price/mile	$0.0
Electricity cost/mile	$0.038
Ammortization	$19,425.69
Liscense regitraion/mile	$0.04
Ammortization/mile	$0.37
Total Fuel Cost/mile	$0.04
Maintenance cost/mile	$0.01
Insurance/mile	$0.02

Table 6.8: Table for calculating $/*mile* for autonomous private cars

in these weighted averaging are shown in Figure 6-3 and Figure 6-4.

Once the $/*mile* averaged value was determined for autonomous vehicles and non-autonomous vehicles, the scenario was ready to be tested in the usual manner. Table 6.10 shows the variables that change from the base case.

This section described all the input parameters that were assumed when testing different scenarios. The base case inputs are described in Appendix A. Only some of these inputs are tweaked depending on the specific scenario being tested. The inputs that change with a specific scenario are shown in tables throughout this chapter. The changes in these specific inputs that are different than those in the base case bring about the changes in the resulting scenario conclusions. The results form these scenarios are presented in the next chapter.

Input parameters for $/mile cost sub-model for an Electric Autonomous ride-share car	
Variable name	Value
kWh/mile	0.25
Electricity price $/kWh	$0.15
Insurance/year	$1200
miles/gallon	25
Gas Price/gallon	$0.0
Annual Mileage	52,560 miles
Upfront cost	$100,000
Discount	5%
Accounting Life	10 years
Maintenance/year	$700.00
Liscense registraion/yr	$1,850.00
Margin Driver	$0.00
Margin Company	$0.20
Gas price/mile	$0.0
Electricity cost/mile	$0.038
Ammortization	$10,360.37
Liscense regitraion/mile	$0.04
Ammortization/mile	$0.37
Total Fuel Cost/mile	$0.04
Maintenance cost/mile	$0.01
Insurance/mile	$0.02

Table 6.9: Table for calculating $/*mile* for autonomous RS cars

Input parameters that change with Scenario 1.4EV+AV		
Variable name	**Year 2016 value**	**Year 2050 value**
Waiting time for ride-share	5 min	3 min
Base cost	$2.25	$1.50
Ride-share comfort	0.7	0.8
Gasoline private car penetration	98%	80%
EV private car penetration	2%	10%
Autonomous car penetration	2%	10%
Gasoline ride-share car penetration	98%	50%
EV ride-share car penetration	2%	25%
Autonomous ride-share car penetration	0%	25%
Average car utilization	13,140 miles	14,454 miles
Average ride-share car utilization	17,500 miles	32,850 miles
$/mile ride-share	$0.89	$0.76
$/mile PC	$0.63	$0.60

Table 6.10: Inputs that changed from the base case

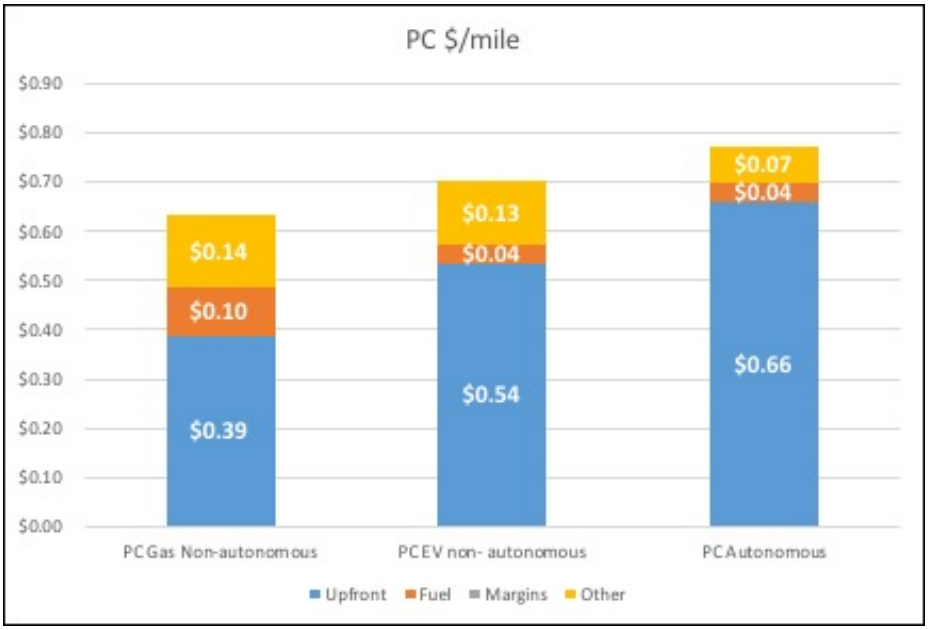

Figure 6-3: Dollars per mile private cars

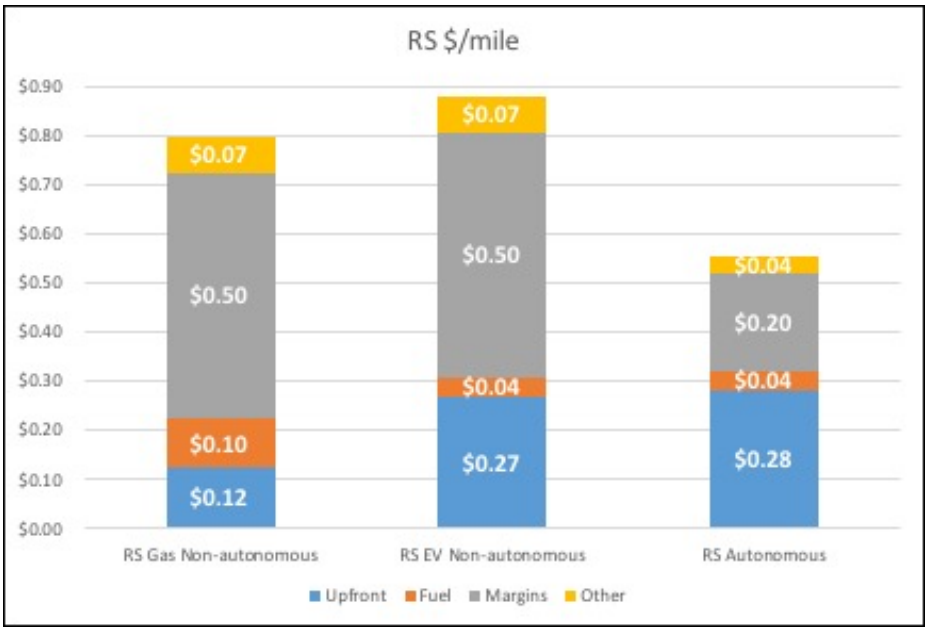

Figure 6-4: Dollars per mile Ride-shared cars

Chapter 7

Results and discussion

This chapter describes the scenario results that occur due to the deviation of select input parameters from their base case scenario values. The values that were changed from the base case values are shown in the tables in Chapter 6. The sections in this chapter show the results for the various scenarios that were developed. Each section describes the result of a scenario.

7.1 Scenario 0: Base case scenario results

In the base case scenario, as was mentioned earlier, nothing changes apart from the fact that the population grows. This results in an increase in the passenger miles travelled. Because it was assumed that the occupancy of a particular mode also remains constant over time, the vehicle miles travelled (VMT) also increased over time along with the PMT. Because the VMT increases over time and it was assumed that utilization of private cars and ride-shared cars also stays constant over time, this results in an increase in the overall national vehicle stock. Results were generated for all the 24-people trip combinations but only the results for urban low income work trips are shown for the modal shares and the vehicle miles travelled. Other people trips combinations followed similar trends. Stock was calculated only at the national level and therefore the vehicle stock results are shown at the aggregated level only.

In the base case scenario, it was assumed that ride-sharing remains just as popular

and just as expensive as it is today. Utilization and occupancy of vehicles do not change. As a result, the modal shares for for different trips also do not change with time. Modal shares for urban low income work trips are shown in Figure 7-1. As can be seen from Figure 7-1, the work trips are mostly car dominated with around 79% of people choosing personal car for work trips and 85% people choosing an overall car based mode for work travel. Apart from the cars being the dominant mode, the modal shares do not change over time. This trend was largely true in the base case scenario for all other people-trip combinations.

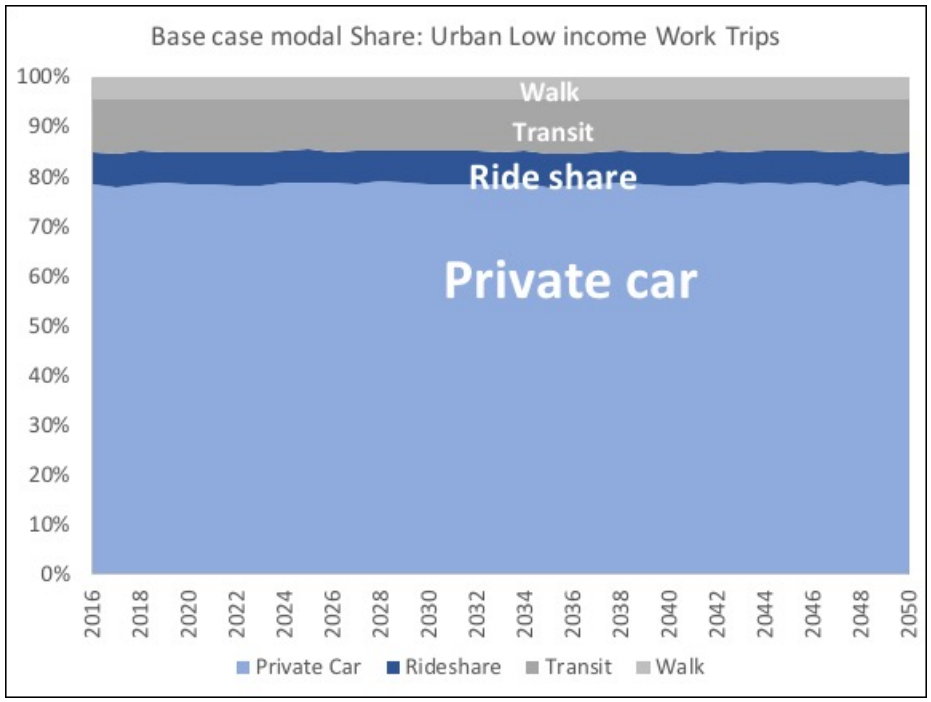

Figure 7-1: Modal shares for urban low income work trips

Even though the modal share stayed constant, but because the population increased over time, the total number of trips taken increased over time. This results in an increase in the total passenger miles travelled at the national level. Occupancy was assumed constant over time for different modes and different trips. Occupancy for work trips for personal cars and ride-shared cars is shown in Figure 7-4. The average fleet occupancy and utilization are shown in black lines. This lead to an increase in the total vehicle miles travelled as well as just the urban vehicle miles travelled. The increase in the vehicle miles travelled for urban low income work trips is shown in

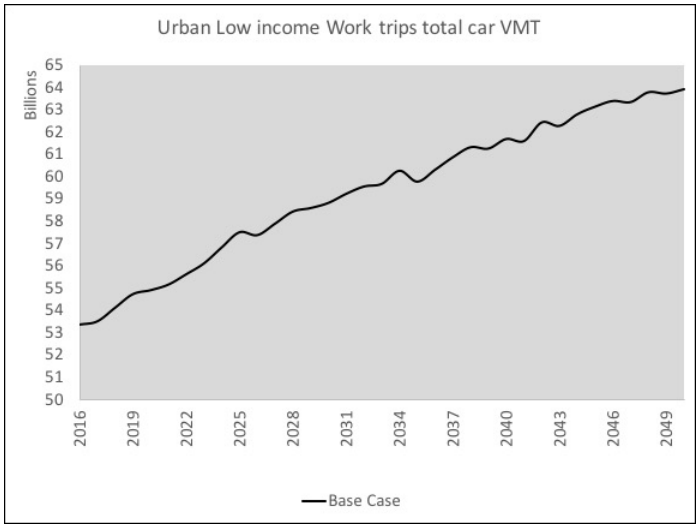

Figure 7-2: Urban Low income Work trips VMT

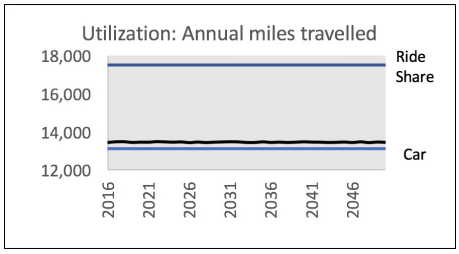

Figure 7-3: Average annual mileage, national level

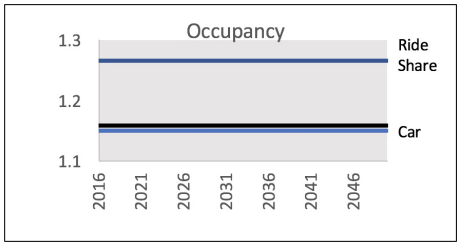

Figure 7-4: Occupancy, urban low-income work trips

Figure 7-2. This VMT includes the VMT associated with private cars and ride-shared cars.

The occupancies shown in Figure 7-4 are the private car occupancy for work trips, ride-shared car occupancy for work trips (assumed 10% higher than PC occupancy) and the average fleet occupancy for work trips. A similar thing was done with utilization, except that utilization was for the overall fleet and not for a specific type of trip. Because the utilization was assumed to be constant, the national vehicle stock, which is the ratio of the VMT to utilization, also increased over time. The utilization and the national vehicle stock are shown in Figure 7-3 and Figure 7-5 respectively.

As can be seen from Figure 7-5, the national vehicle stock increases with time. This is due to the fact that the overall VMT increases with time, while the occupancy for different trips and utilization stay constant. This was the reference scenario and

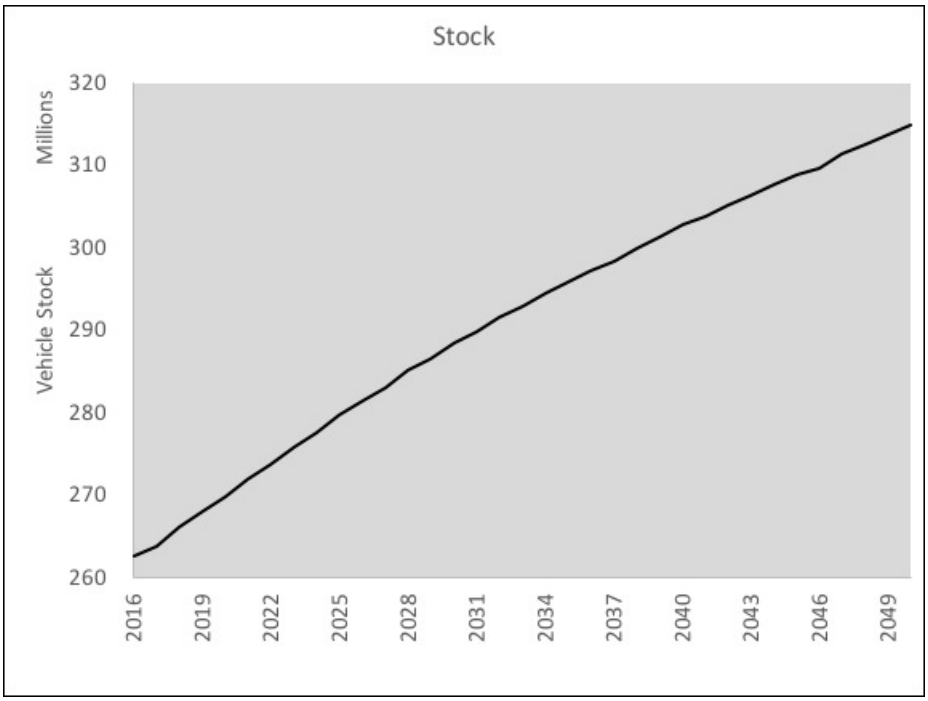

Figure 7-5: National vehicle stock, Base case

all other scenario results were compared to this particular set of scenario results.

7.2 Scenario 1.0: Improved ride-sharing scenario results

The next scenario that was tested, apart from the base case scenario, was the improved ride-sharing scenario. In this scenario, it was assumed that ride-sharing becomes more popular and therefore the availability and costs of ride-sharing services improve. This meant that the costs of ride-sharing services decreased, the waiting times for ride-sharing services decreased and the comfort associated with ride-sharing increased. This change of values in the input parameters is explained in Table 6.2. As can be seen from Table 6.2, the values in the starting year and the ending year are different for the parameters of the travel behavior module as well as the vehicle stock module. This leads to a change over time in the modal shares of trips taken in urban, suburban and rural areas. Again, as before, the result here is shown only for urban low income

work trips. Other trips in urban areas follow similar trend. Suburban and rural trips also follow similar trends but the magnitude of the shifts away from personal car in the suburban and rural areas is diminished due to the heavy inertia towards personal car travel in suburban and rural regions.

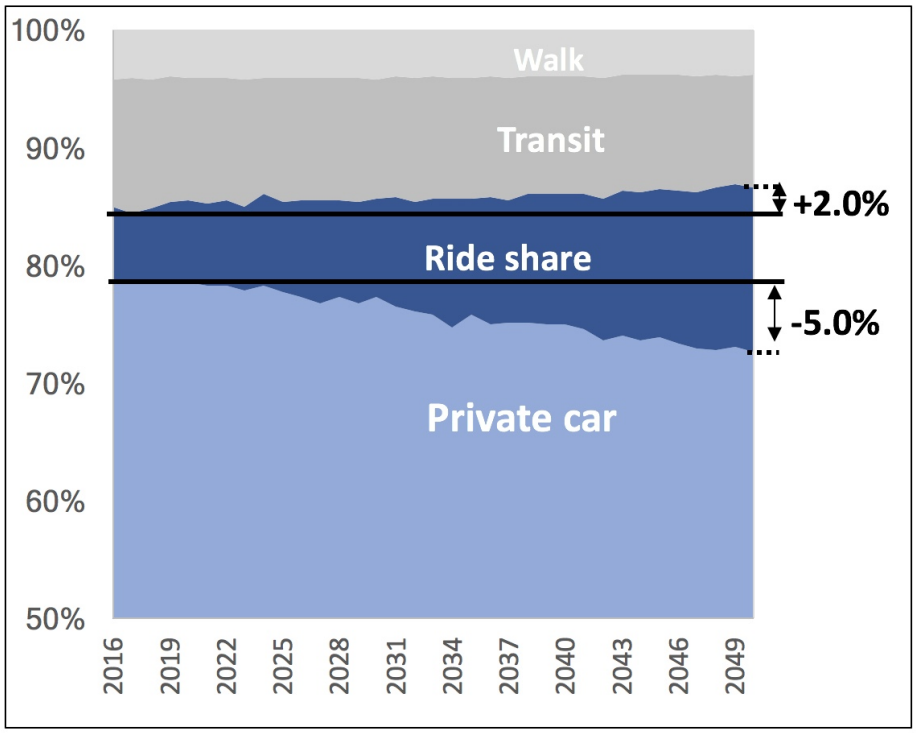

Figure 7-6: Urban low income work trips modal shares

The first results that was looked at in the improved ride-sharing scenario was the effect of improvements in ride-sharing on the modal shares of urban low income work trips. This is shown in Figure 7-6. As can be seen from the Figure 7-6, compared to the base case, people use ride-shared cars in the year 2050 as compared to using ride-shared cars in year 2016. The urban low income work trips that are substituted for the ride-share trips include work trips done by personal car and those done by transit, although a majority are substituted from the personal car trips. Another aspect that can be seen from Figure 7-6 is that even though the modal share of personal car travel fell from 79% to 72%, the total car based travel actually went from 85% to 87%, an increase of two percent. This increase in the overall car based travel also contributes to the slight overall increase in the total car VMT for urban low income work trips.

This can be seen in the Figure 7-7.

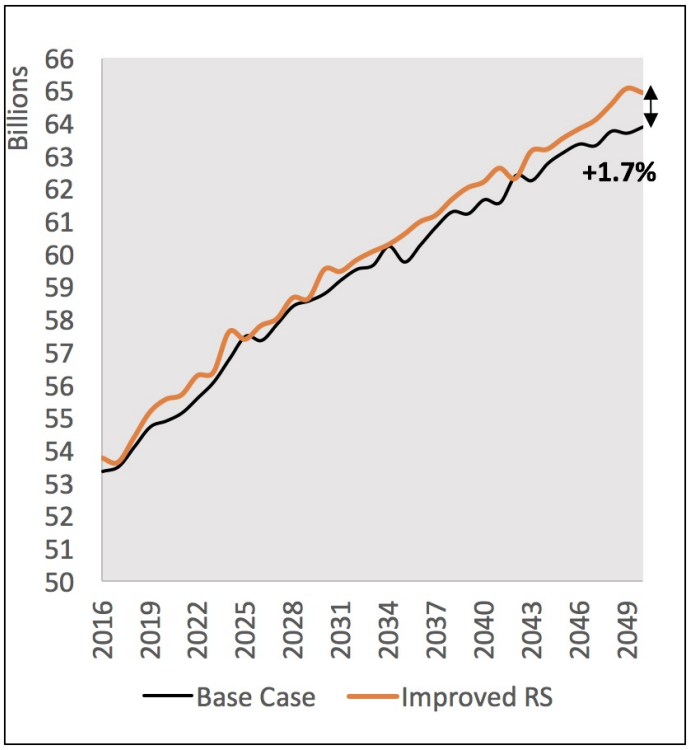

Figure 7-7: Urban low income work trips total car VMT

As can be seen from Figure 7-7, the total car based VMT for urban low income work trips increased slightly in the improved ride-sharing scenario. This is because of the overall car based travel associated with urban low income work trips increased by two percent due to improvements in ride-sharing. Occupancy for work trips was assumed to be the same as that of the base case occupancy, but the weighted average occupancy of the fleet increased slightly because of the shift in higher occupancy vehicles. This increase in the average fleet occupancy is shown in Figure 7-9. Apart from the occupancy, the average utilization or the average annual mileage of the fleet also increased slightly. The average fleet occupancy and utilization are shown in orange lines. This was because the average annual mileage of the fleet was calculated as the weighted average of the VMT associated with private cars and the VMT associated with ride-shared cars. As in the improved ride-share scenario, the VMT associated with ride-shared cars increased, this lead to an increase in the average utilization of the fleet. This increase in average utilization leads to a slight decrease

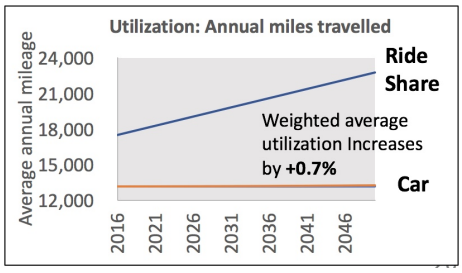

Figure 7-8: Average annual mileage, national level

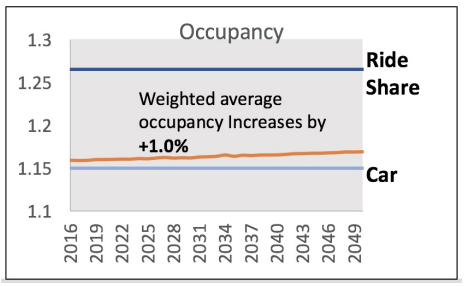

Figure 7-9: Occupancy, urban low-income work trips

in the stock relative to the base case.

The decrease in the stock at the national level, as can be seen in Figure 7-10, is due to the fact that people are moving around in higher efficiency vehicles. Particularly, more and more trips are being taken in higher occupancy vehicles and higher utilized vehicles in this scenario. This leads to a slight reduction in the total number of cars required to meet the transportation demand. This is shown in Figure 7-10.

As can be seen from Figure 7-10, the decrease in the vehicle stock at the national level is modest. This is in spite of significant changes in the modal shifts for urban work, leisure, errands and other trips. This is due to the fact that even though the shifts were prominent in the urban regions, the suburban and rural regions, which comprise of the 74% of USA population, do not experience the same kind of modal shifts in the improved ride-sharing scenario as the urban population. This is the reason for a modest decrease in the stock at the national level, in spite of significant changes in intermediate factors like VMT, utilization and occupancy.

7.3 Scenario 1.1: Improved ride-sharing scenario + Improved transit results

What if along with improved ride-sharing, government tries to invest more in transit options to improve the existing competing transport options? In this scenario, along with improved ride-sharing, it was assumed that the government will invest more in transit systems infrastructure thereby improving the efficiency and the speed of

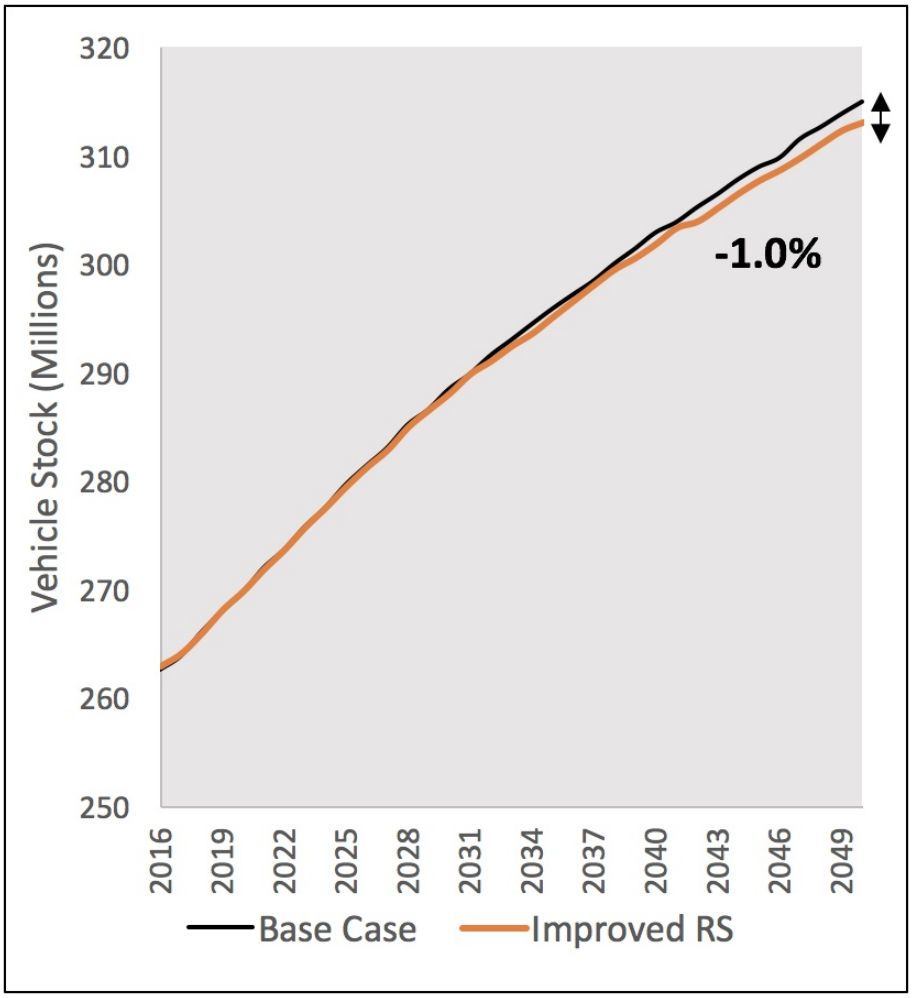

Figure 7-10: National vehicle stock,Improved Ride-sharing

transit systems. It was assumed that the waiting times for transit systems decreases and the cost associated with transit system also decreases. The speed associated with transit systems was also assumed to improve over time. The particular variables that change from the base case values are shown in Table 6.3. This scenario assumes all the improvements in the ride-sharing systems and also further improvements in the transit systems. This leads to a more aggressive scenario when it comes to modal share shifting away from personal car travel. Figure 7-11 shows the shifting trends in modal shares for urban low income work trips. As can be seen, this scenario results in more aggressive shifts away from personal car travel. In this scenario, the total personal car based travel for urban low income work trips, goes from 79% in the base

case to 68% by 2050. This scenario also leads to a decrease in the overall car based travel, personal car or ride-share, by approximately 5% for urban low income work trips. In the base case, the total car based travel was 87% and in this scenario, the total car based travel is 82%. Other trips and other income category trips, followed similar trends, with different magnitudes.

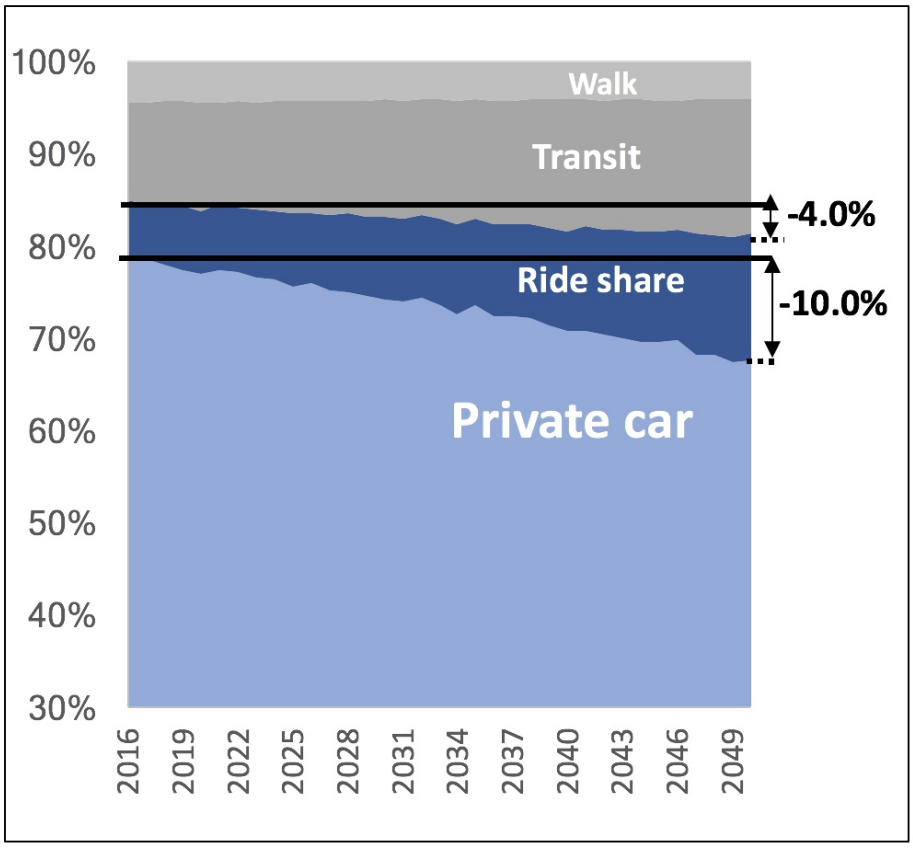

Figure 7-11: Urban low income work trips modal shares

Once the modal share shifts were determined, the modal shares were converted to absolute numbers of trips in different modes. This then leads to a measure for the PMT of trips in different modes. Assuming the occupancy values for different kinds of trips, and assuming that occupancy stays constant over time, the PMT was converted to a VMT for different modes. The occupancy for urban low income work trips for this particular scenario is shown in Figure 7-13. As can be seen from Figure 7-13, in this particular scenario, the average fleet occupancy increases as more and more people are taking trips in ride-shared cars. Figure 7-12 shows the utilization of

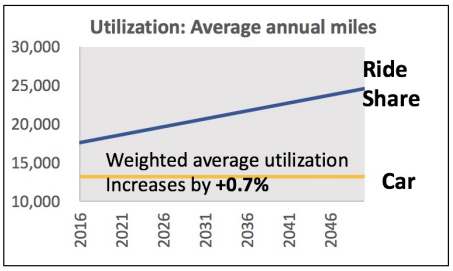

Figure 7-12: Average annual mileage, national level

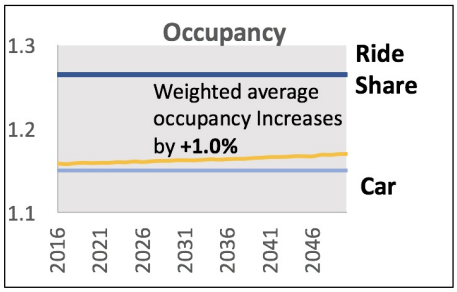

Figure 7-13: Occupancy, work trips

private cars, ride-shared cars and an average car in the fleet. The average utilization was calculated as a weighted average of VMT associated with personal cars and ride-shared cars. As can be seen from Figure 7-12, the utilization is still dominated by the share of personal cars in the fleet. Hence, the utilization of personal car and the average utilization of the fleet are represented by lines that are very close to each other.

Once again, the urban work trips VMT was calculated for this scenario. As expected, the VMT increases with time due to increase in the population. Because the population increases, the total number of trips taken increases. This leads to an increase in the PMT and assuming that average occupancy increased only a little, this also leads to an increase in the VMT. But compared to the base case scenario, in this case there was a decrease in the total car based travel for urban low income work trips as can be seen from Figure 7-11. This decrease in car based travel also leads to a decrease in the total car VMT associated with urban low income work trips. This is shown in Figure 7-14.

As can be seen from Figure 7-14, the total VMT car based VMT does go down due to the shift away from car based travel to non-car based modes, like transit. This leads to a decrease in the total VMT. This trend was true across most of the 24 people-trip type combinations. Either the VMT did not change for other non-urban trips or changed by only a little, most of the difference in the VMT change was seen in urban trips. The trend in Figure 7-14 was consistent across different urban trips, although the magnitude was slightly different. Given that the VMT decreases

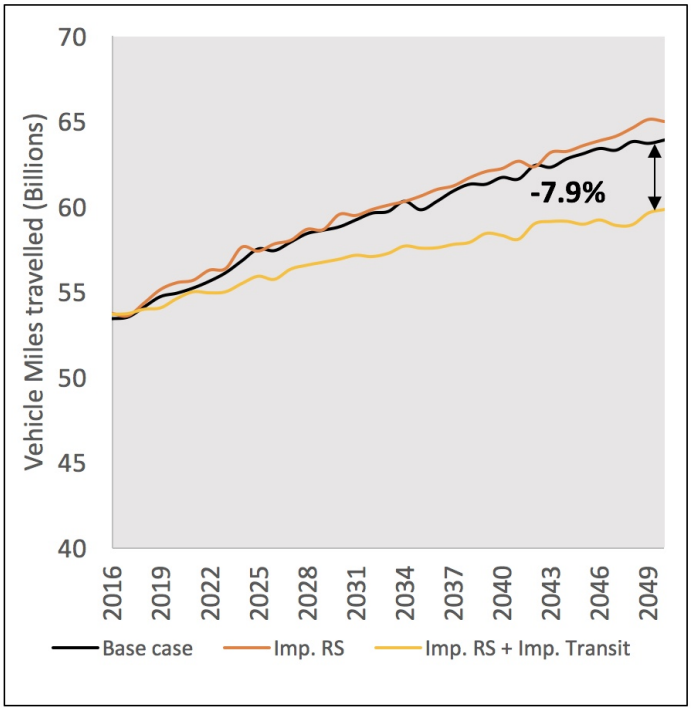

Figure 7-14: Urban low income work trips total car VMT

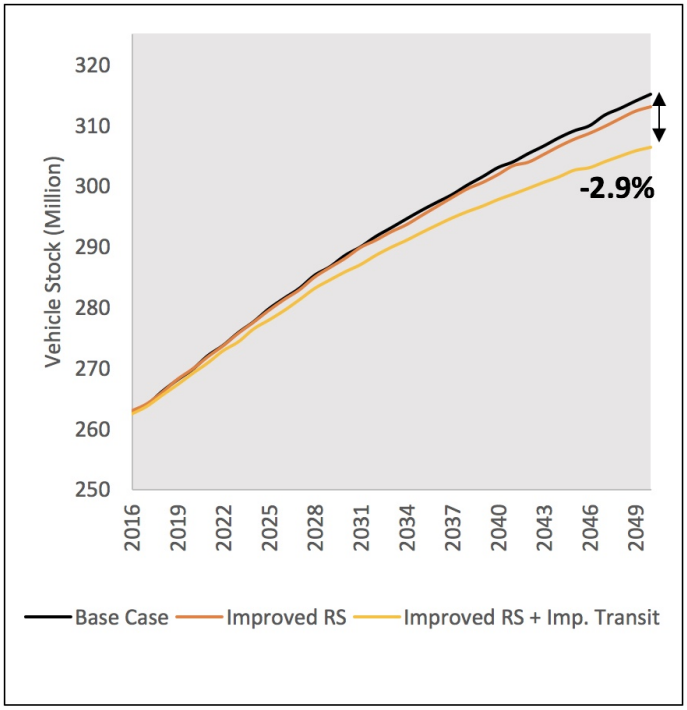

Figure 7-15: National vehicle stock,Improved Ride-sharing + Improved Transit

compared to the base case, but increases overall over time, and due to the fact that the average utilization does not change much, the overall stock at the national level also increases. The average fleet utilization, shown in yellow, increases as can be seen in Figure 7-12, due to the fact that the weighted average VMT of personal car and ride-share car is shifting very slightly towards ride-shared cars. Therefore the utilization increases slightly but is still mostly the same as that of personal cars. This leads to an increase in the stock as compared to the value in the year 2016, but due to the decrease in VM, the stock decreases in the year 2050 as compared to the stock in the base case scenario by 3.5% in the year 2050. This can be seen in Figure 7-15. As can be seen in Figure 7-15, the national stock still grows from its current value in the year 2016. But instead of reaching approximately 315 million in the year 2050, it reaches a a value of approximately 2.9% lower as compared to the base case value of 315 million.

7.4 Scenario 1.2: Improved ride-sharing scenario + Improved transit + Anti-car policies scenario results

The next scenario that was tested was the improved ride-sharing with improved transit and discouraging car policies. This scenario was fairly aggressive as can be seen from the assumptions in Table 6.4. This scenario assumed that along with improvements in ride-sharing and transit, the government also discourages personal car use. This could mean either a congestion charge, extra parking fees and other anti-car policies in general. Specifically, this scenario assumes that the time to find parking for personal cars goes up and also the parking cost associated with personal cars goes up. These are fairly aggressive assumptions considering the fact that small changes in these parameters have a big influence on people travel behavior, especially in terms of the modal shifts in urban area trips.

As can be seen from Figure 7-16, there is a significant shift of people moving away

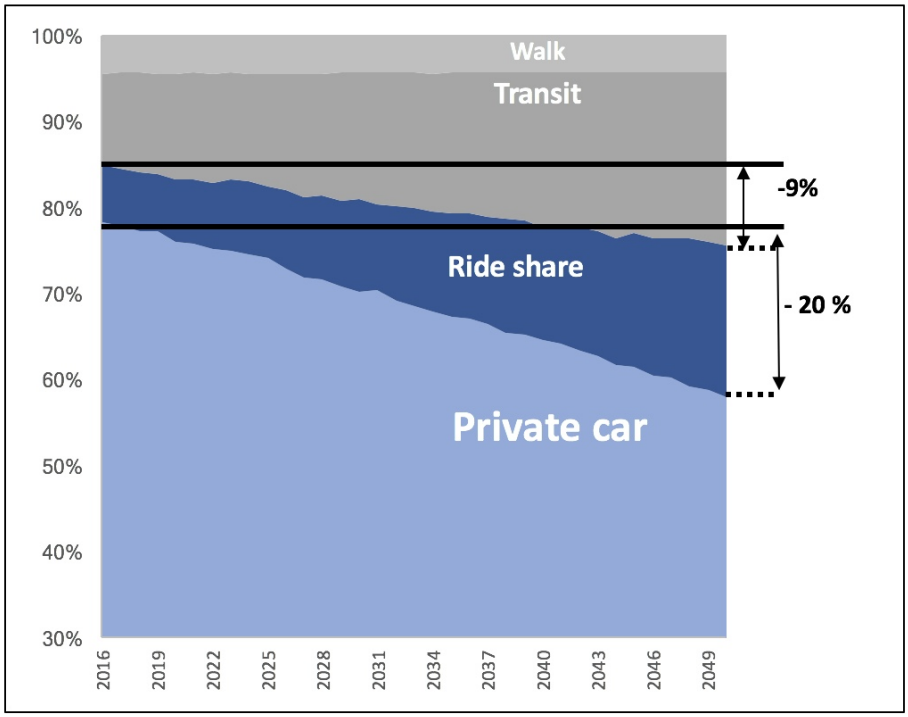

Figure 7-16: Urban low income work trips modal shares

from private car for urban low income work trips. There is almost a 20% decrease in personal car trips as compared to the base case for the urban low income group when it comes to work trips, and a 11% decrease in total car based travel for urban work trips. This aggressive shift away from personal car is largely due to the fact that along with improvements in ride-sharing, the transit systems were also improving and personal car travel was deteriorating. This results in this heavy shift towards non-personal-car based travel. In spite of these aggressive assumptions about anti-car policies, the result at the national level in terms of vehicle stock reduction is modest, but fairly significant at the urban level of disaggregation, especially on VMT.

As can be seen from Figure 7-17, because the total car based travel decreases by 11%, this results in a decrease in the total VMT in the year 2050 relative to the base case scenario. The absolute VMT increases still, compared to the VMT value in the year 2016 and this is because of the same reasons mentioned earlier. The total population increases and as a results the total number of passenger trips increases, leading to an increase in the PMT. As can be seen from Figure 7-19, the occupancy

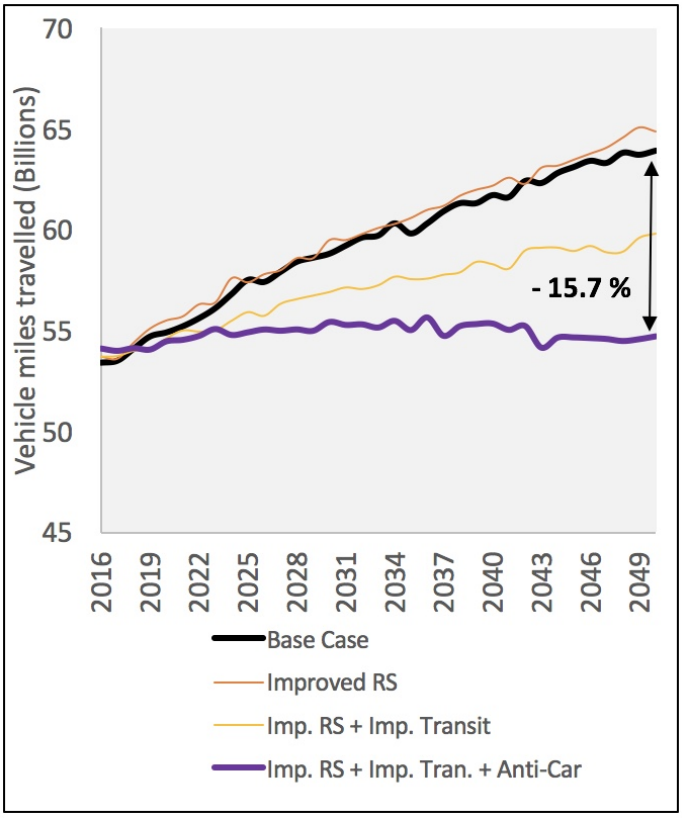

Figure 7-17: Urban low income work trips total car VMT

of the average fleet does not change much. Therefore, as the passenger trips taken increase, along with it, the VMT also increases. As can be seen from Figure 7-18, the utilization of the fleet does not change much and therefore, the vehicle stock also grows over time compared to the starting year value of 262 million in year 2016. The average fleet occupancy and utilization are shown in purple lines. This can be seen in Figure 7-20.

As can be seen from Figure 7-20, the national vehicle stock still grows in this scenario which assumed fairly aggressive anti-car effects. This is mainly due to the fact that the population grows and that creates a demand for transportation that needs to be met. The final stock value does not grow to a value as high as the base case value and is 5% lower than the base case value in the year 2050. This is mainly due to the decrease in the VMT and also due to slight increase in the utilization as can be seen from Figure 7-18, shown in purple line.

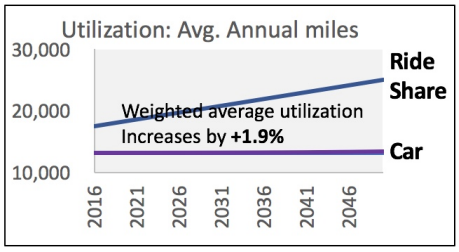

Figure 7-18: Average annual mileage, national level

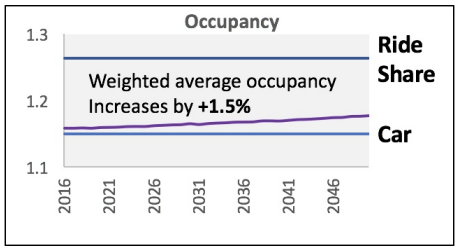

Figure 7-19: Occupancy, work trips

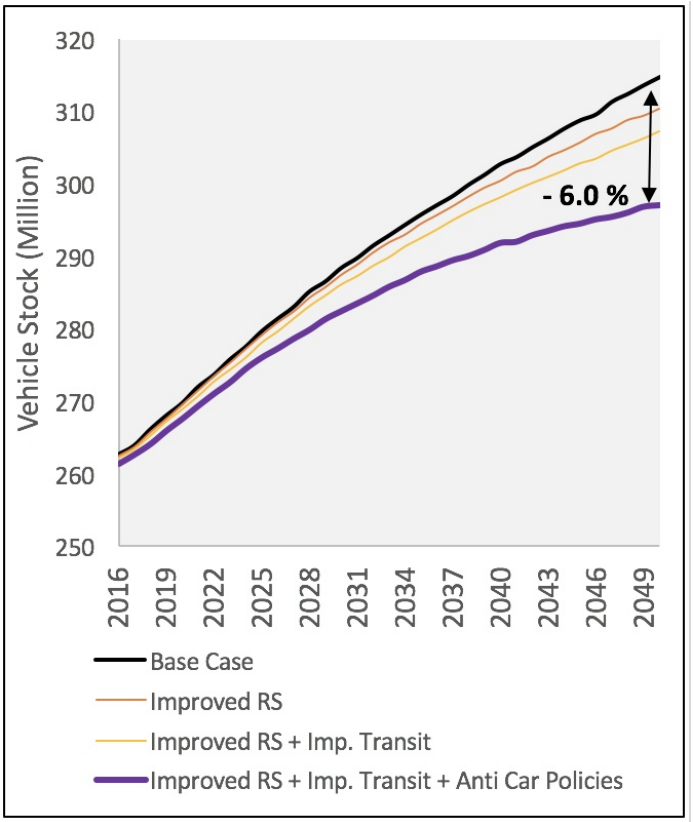

Figure 7-20: National vehicle stock,Improved Ride-sharing + Imp. Transit + Anti-car policies

7.5 Scenario 1.0EV: Improved ride-sharing scenario + Higher EV penetration scenario results

The next scenario that was tested was the higher electrification scenario, in which it was assumed that electric cars formulate a higher percentage of the fleet than as of today. Higher electrification mainly meant slightly lower cost of the $\$/mile$

value for driving. The exact inputs that change with the electrification scenario are shown in Table **??**. This scenario was very similar to the improved ride-sharing scenario in design, except that it assumed higher penetration of electric vehicles on top of improvements in ride-sharing. The way electrification was incorporated into the scenario was through modeling the $/mile for EV private cars and EV ride-shares cars along with gasoline private and ride-shared cars. As can be seen from Figure 7-21, similar to the improved ride-sharing scenario, there is a shift from private cars and transit to ride-shared vehicles for urban low income work trips.

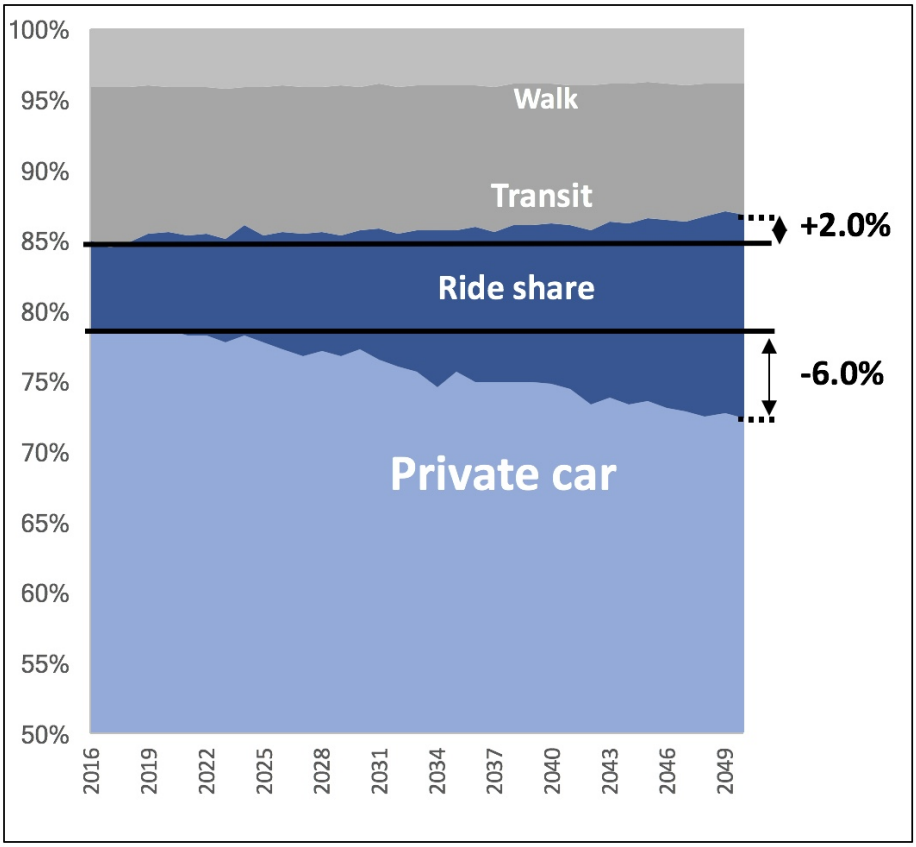

Figure 7-21: Urban low income work trips modal shares

The shift from private cars to ride-shared vehicles that can be seen in Figure 7-21 is very similar to the shift shown in Figure 7-6 in the improved ride-sharing scenario. This is basically saying that just changing the power-train will not drive the shift away from personal cars and more towards different modes. The different powertrain assumed here, in this case EV, does not change the preference functions

significantly. It changes the preference functions only through the parameter $/mile, and EV cars intrinsically do not change people behavior in a way such that the mode choice changes significantly from just the improved ride-sharing case. Apart from the modal shares, the urban work trip VMT was also investigated.

As can be seen from Figure 7-22, the total car VMT for urban work trips in this scenario are basically identical to the total car VMT in the improved ride-sharing scenario. This is not surprising as the urban low income work trip modal shares were also identical to the improved ride-sharing scenario, and therefore that translated directly into an identical effect on the VMT.

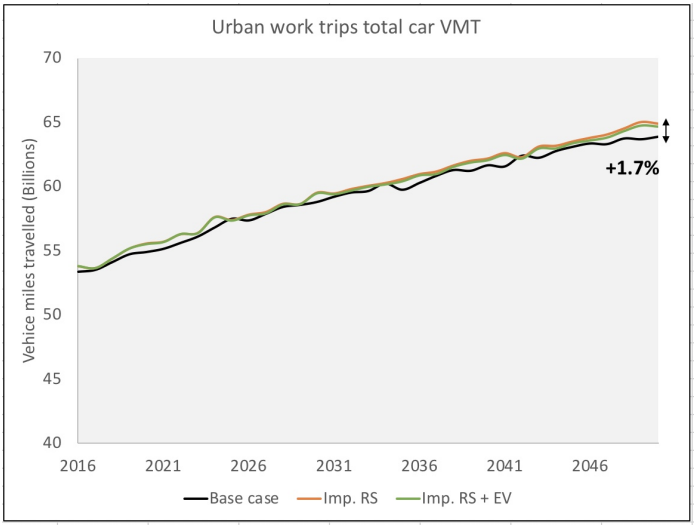

Figure 7-22: Urban low income work trips total car VMT

Apart from the VMT, the occupancy of an average car in the fleet increased, again mainly due to the improvements and shits towards higher occupancy ride-shared vehicles. This can be seen in Figure 7-24. Similarly , the utilization of the average fleet also increased, similar to the improved ride-sharing scenario. Again, this was mainly due to the fact that more people shifted towards higher utilized vehicles. This can be seen in Figure 7-23. The average fleet occupancy and utilization are shown in orange lines.

Due to the increase in occupancy and utilization of the average fleet, the vehicle stock decreases as compared to the base case scenario. This decrease in the stock in year 2050 is comparable to the decrease in the stock in the improved ride-sharing

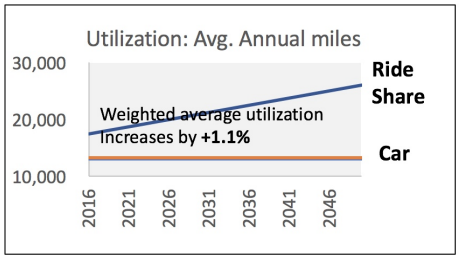

Figure 7-23: Average annual mileage, national level

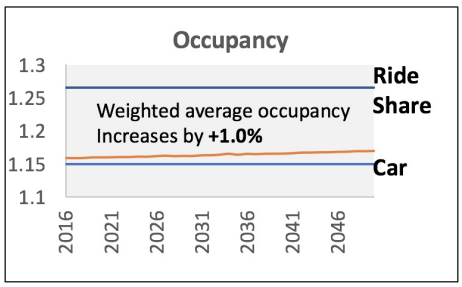

Figure 7-24: Occupancy, urban low income work trips

scenario in the year 2050. This is shown in Figure 7-25. As can be seen, the change of powertrain alone has a modest effect on the modal shares, vehicle miles travelled or the national vehicle stock. Most of the change seen in this scenario comes from the improved ride-sharing aspect of the scenario.

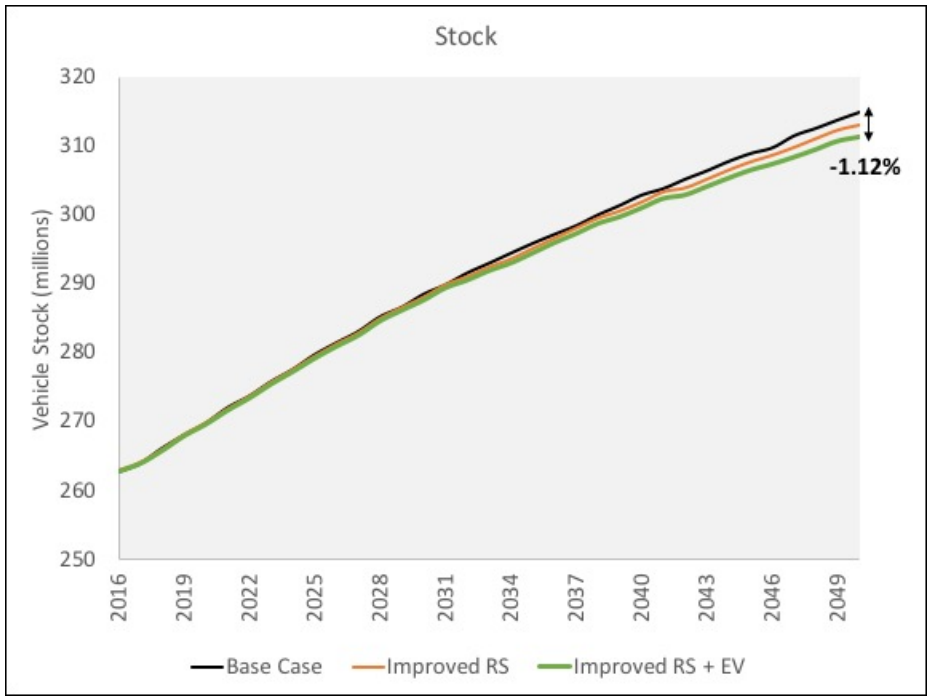

Figure 7-25: National vehicle stock,Improved Ride-sharing + Higher EV

7.6 Scenario 1.0EV+AV: Improved ride-sharing scenario + Higher autonomous penetration results

The final scenario that was considered was the improved ride-sharing with higher autonomous vehicle penetration. This scenario was different than the other scenarios tested so far, because of a strong assumption about the availability of autonomous ride-shared vehicle mobility fleet. This assumption about the availability of "Level 5" autonomy, which assumes that autonomous cars are driverless, lead to a scenario assumption that mobility fleets could be maintained and the margins that ride-sharing companies pay to the driver might go away. This assumption made the $/mile value for ride-shared very competitive with that of personal cars. It also assumed a higher utilization for vehicles due to the assumption about "empty" cars traveling back and forth between trips. The exact assumptions about the parameters that are different from the base case values are shown in Table 6.10. Another important aspect of this scenario was that the $/mile cost associated with the ride-shared vehicles became very competitive with that of private cars, due to the margins to the driver going away. This results in overall car based travel becoming very competitive in nature compared to the other non-car based modes. This results in more and more trips being taken in cars as opposed to other modes.

As can be seen from Figure 7-26, the total car based market share actually increases for urban low income work trips. The private car based travel and ride-shared car based travel, both go up by the year 2050 as compared to the starting value in year 2016. Therefore the overall car based trips for urban low income work group also go up. This results in an increase in the VMT associated with urban low income work trips as well.

As can be seen from Figure 7-27, the total VMT associated with urban work trips for the low income group also increases significantly than the base case and the improved ride-sharing scenario. This is because, the number of car based trips goes

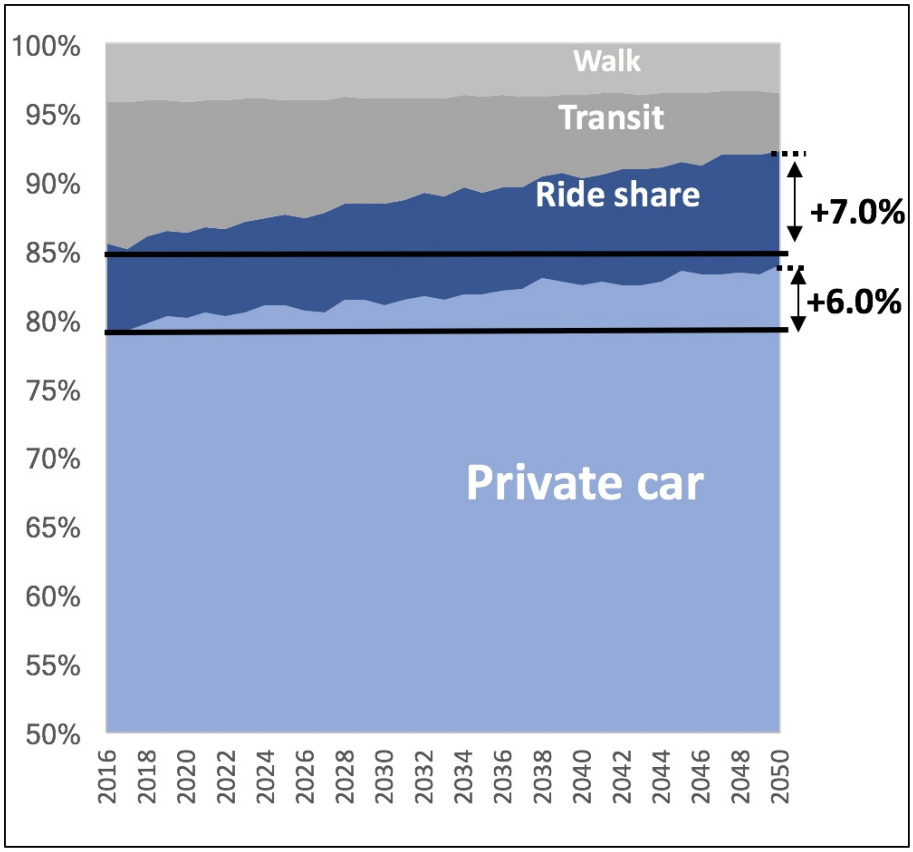

Figure 7-26: Urban low income work trips modal shares

up significantly in this scenario. In the earlier scenarios, as people were moving more towards higher occupancy and higher utilization vehicles, the average utilization of the fleet increased. This was mainly due to the movement towards higher occupancy and higher utilized cars. In this particular scenario the utilization of the average fleet increases and that is mainly because more people are taking autonomous private cars, as well as autonomous ride-shared cars. This is shown in Figure 7-28, in red. The average occupancy of the fleet on the other hand decreases, because people taking autonomous personal cars drive the occupancy of the average fleet down. This is shown in Figure 7-29, in red.

As there is more car based travel, the VMT increases. This is shown in Figure 7-27. Even if the VMT increases, the average fleet utilization increases as well in this scenario due to the assumption that there are empty autonomous vehicles driving around. This increase in the utilization is shown in Figure 7-28. Due to this increase

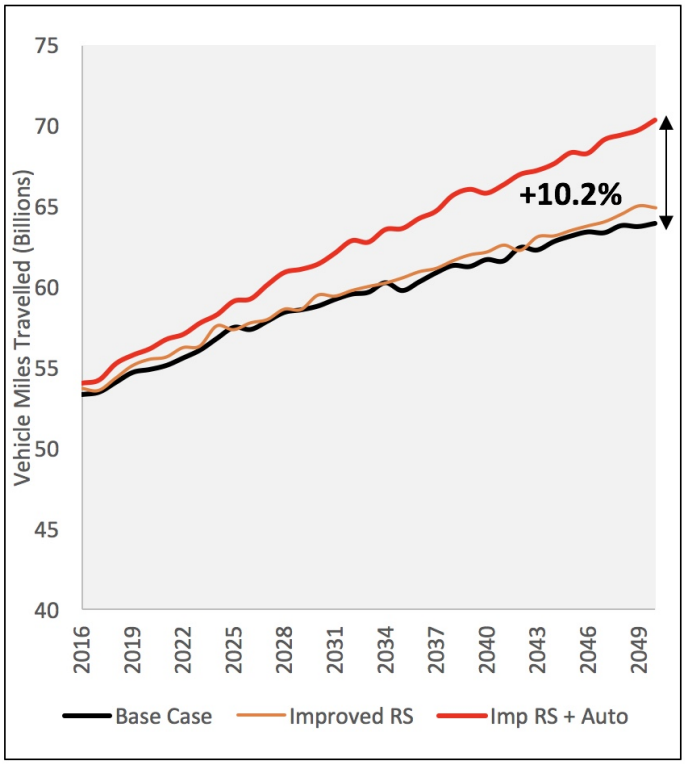

Figure 7-27: Urban low income work trips total car VMT

in the utilization, the national vehicle stock decreases significantly as shown in Figure 7-30.

To summarize this scenario, the total modal shares shift more towards car based travel in urban areas. This leads to a significant increase in the vehicle miles travelled in the urban areas. Because people choose to travel in higher utilized vehicles, the average fleet utilization increases. People also choose more private autonomous cars, moving the average occupancy of the fleet closer to the occupancy of private cars.

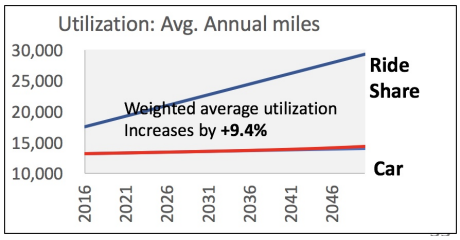

Figure 7-28: Average annual mileage, national level

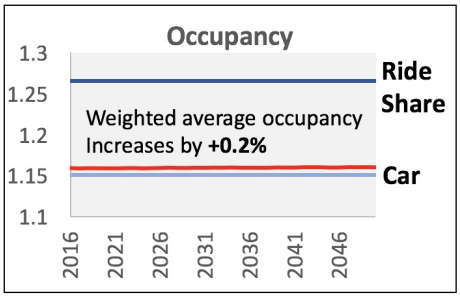

Figure 7-29: Occupancy, Urban low income work trips

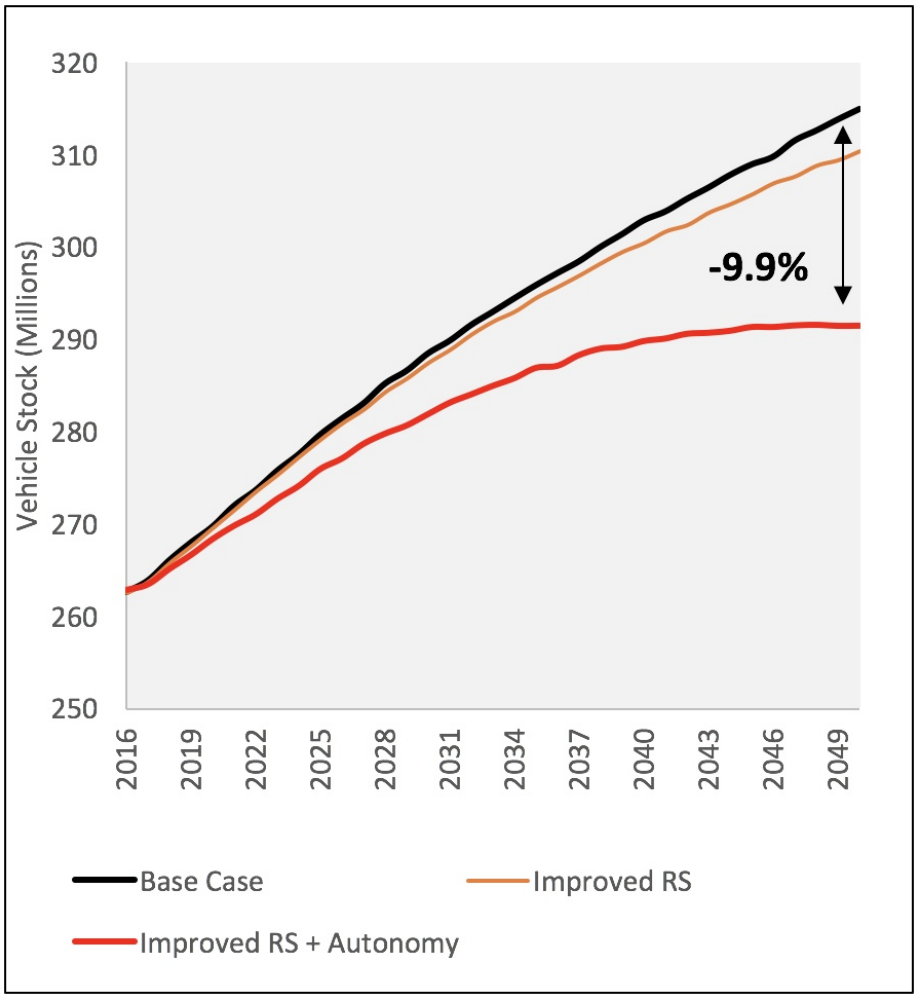

Figure 7-30: National vehicle stock,Improved Ride-sharing + Higher Autonomous vehicles

These changes lead to a decrease in the national vehicle stock in the year 2050 as compared to the base case.

7.7 Sensitivity analysis

Sensitivity analysis of the model was performed on a set of variables that were either not backed by data or that were calibrated using revealed preferences. The variables that were chosen for sensitivity analysis were chosen such that they represented the key conceptual assumptions about the model. For example, one of the key assumption in the model was that people choose a particular mode for a particular trip based on

three attributes; cost, time and comfort. Therefore, the sensitivity analysis variables that were chosen were the ones that incorporated the aspects of attributes associated with choosing a mode for a trip. Therefore, for example, the variables that were associated with cost that were chosen for sensitivity analysis were the k_{cost} in Equation 4.2, \$/mile PC, \$/mile RS, \$/min RS, Base cost RS and parking cost PC (Private Car). Similarly, for the time attribute, the sensitivity was done on k_{time} in Equation 4.2, parking time PC, transit speed and PC/RS speed. Finally for comfort, the sensitivity was tested on $k_{comfort}$ in Equation 4.2, PC comfort and RS comfort. Each of these inputs were perturbed by +/- 10% of their original value. The effect of this perturbation was then measured on the four key metrics. The four key metrics were urban low/middle income work trip modal shares for private cars and ride-shared vehicles, the vehicle miles travelled associated with urban low/middle income work trips, and the national level vehicle stock. The sensitivity analysis was done specifically on urban low income work trip results because these trips were particularly sensitive to the changes in cost time and comfort. The sensitivity was also done for the national level stock as that was a major output of the model.

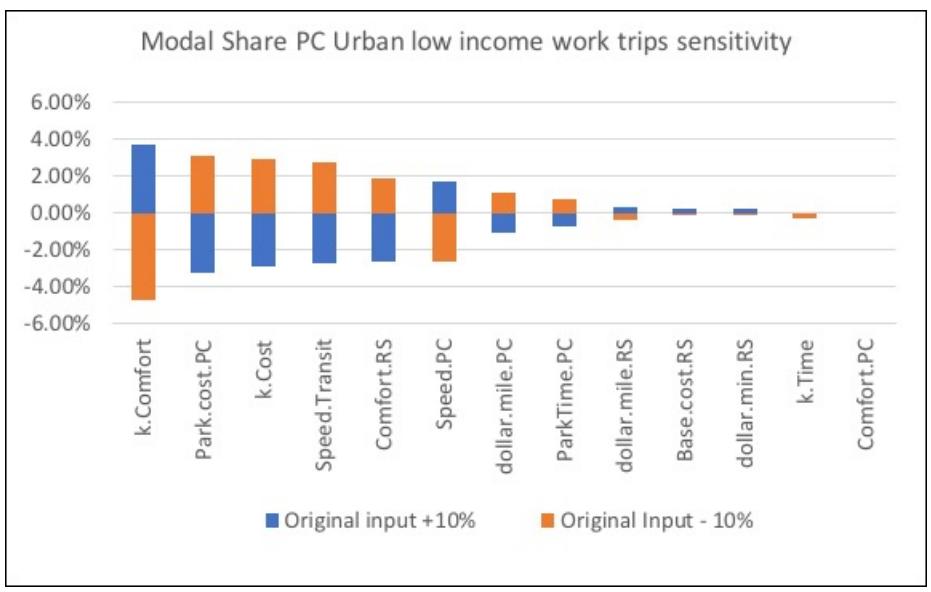

Figure 7-31: Sensitivity analysis on PC modal shares

The sensitivity analysis for urban low/middle income work trips modal shares for private cars is shown in Figure 7-31. As can be seen from Figure 7-31, the most

sensitive variables to the modal share of private cars for urban low income work trips are k_{cost}, $k_{comfort}$ and parking cost. A 10% change in causes a less than 4% change in the modal shares for all of them. The remaining variables show a less than 3% change to a perturbation of +/- 10%. One thing to note here is that while the k_{cost} shows a symmetric change for a +/-10% change in the input, the rest of the variables are almost all asymmetric. Also, the resultant change in the output is more when the input is perturbed in the positive direction. For example, an increase in the parking cost of personal cars in urban areas is causing the modal share to change a lot more than the decrease in the parking cost of personal cars. This is because, the modal share of private cars is already dominant even in urban areas. Therefore, there is not much scope for the modal share of private cars to grow further. On the other hand, if some of the aspects that make private car travel so preferable start to degrade, that creates an opportunity for a sharp dip in the modal shares associated with personal car trips. This explains why the modal share of private car trips is affected more when parking cost increases by 10%. Similar trends can be observed for other variables as well.

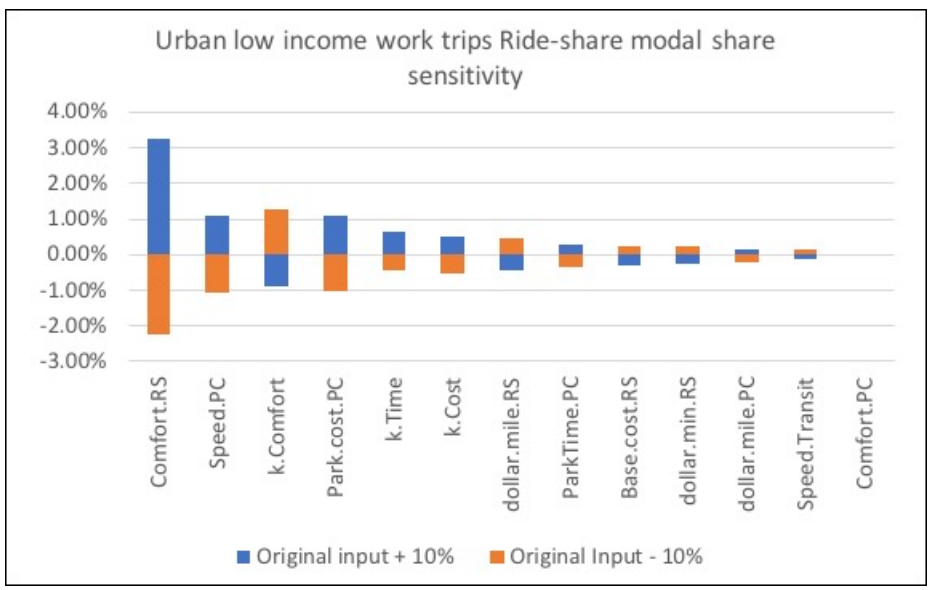

Figure 7-32: Sensitivity analysis on RS modal shares

Similarly, Figure 7-32 shows the sensitivity analysis results for the modal shares of ride-shared vehicles for urban low income work trips. The modal shares of ride-shared

vehicles were affected by less than +/-2% for a +/-10% change in the input variables. The only parameter that caused a 3% change was the comfort value associated with ride-sharing vehicles. But overall, the modal share sensitivities for private car and ride-shared vehicles showed that the model was robust against perturbations in the input parameters.

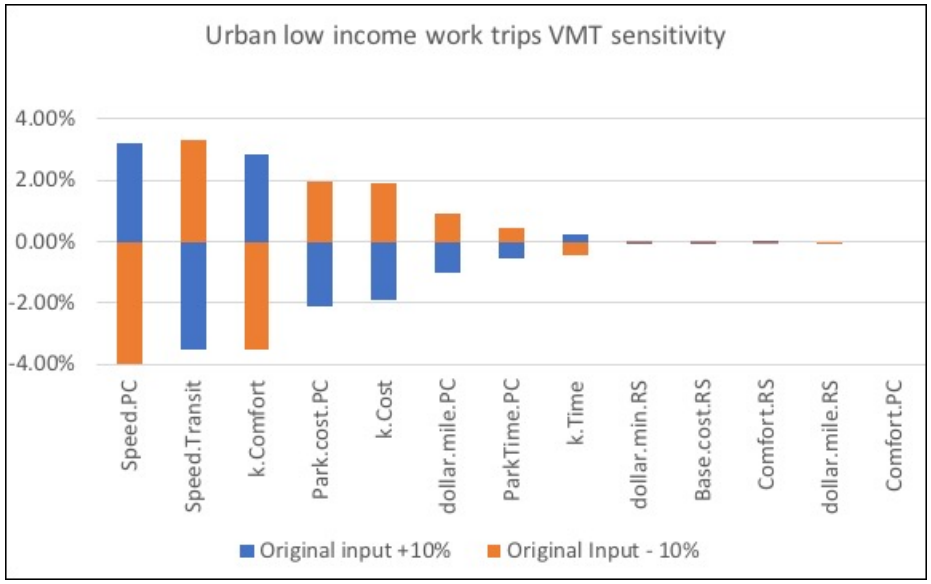

Figure 7-33: Sensitivity analysis on VMT

The sensitivity results for total car VMT associated with urban low income work trips is shown in Figure 7-33. Transit speed is the one that affects the VMT the most amongst the variables selected. This is not surprising as improvements in transit are driving people away from car based travel altogether leading to the car VMT being being avoided completely. This leads to a sharp decline in the car based VMT when transit is improved. The variables that contribute to a significant change in the total car VMT are transit speed, k_{cost}, the speed of a private car and the comfort associated with a private car. The other variables contributed to a less than 2% change to the total urban work trip car VMT when they were perturbed by +/-10%.

Finally, Figure 7-34 shows the effect of these perturbations on the national vehicle stock. As the national level vehicle stock included the effects of suburban and rural populations as well, and because the suburban and rural population did not see a significant penetration of ride-sharing vehicles, the national level vehicle stock does

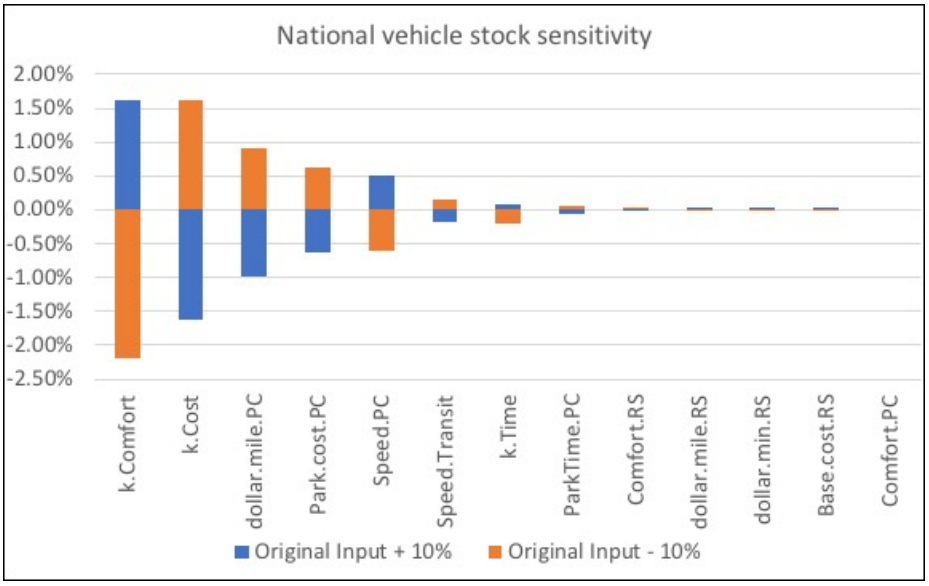

Figure 7-34: Sensitivity analysis on national vehicle stock

not change much due to these perturbations. All the variables that were tested for sensitivity changed the national level vehicle stock by less than 2% when they were perturbed by 10%. These sensitivity results show that the intermediate results in the model are affected more than the results that are aggregated at the national level. This is not surprising as urban trips are the ones that are more sensitive to these disruptive changes. This has also been documented in several studies mentioned in the literature review as well as in scenario definitions. The moment results from suburban and rural populations are included, the effect of these disruptive changes become diminished. Therefore the national level stock sensitivities turn out to be lower than the intermediate results, like urban modal shares or urban VMT.

Chapter 8

Conclusion and future work

In the last few years, new mobility services have started to capture the attention of people working in the transportation industry, the media, government and transportation enthusiasts in general. More and more people are becoming aware of alternative means of transportation and the idea of car ownership is not exactly the same as it was a few decades ago. The growth of new mobility services have already had significant implications for the automotive industry and more will become noticeable in the next few years. As can be seen from this study, increased use of these new mobility services might reduce the total number of vehicles on the road slightly, and if complemented with improvements in transit systems and biking/ walking lanes, might lead to a significant decrease in vehicle miles travelled as well. The shit towards these new mobility services will be responsible for a decrease in the national vehicle stock, but this decrease as can be seen from the results in this work will be modest, compared to the overall number of transactions involving vehicles every year. Also, with the increase in the number of vehicles used for ride-sharing, the annual mileage of the fleet is expected to increase slightly. This might lead to a higher turnover of vehicles and as a result bump up the sales, in spite of decrease in private ownership. The most important impact of ride-sharing, as can be seen from the earlier results, will not be on the volume of the total number of vehicles, but rather it will be on how people choose to travel when these new modes become available, their expectations for vehicles and their uses of these mobility services.

New mobility services are changing the way people use, value and relate to personal cars. They are changing the way people view the utility of a personal car, and that is more important in the long term than the net decrease in the total vehicle stock. New mobility services will likely contribute to changing preferences, away from vehicle ownership towards a "vehicle usership", forcing companies to explore new business models that do not necessarily involve owning a personal vehicle.

This chapter summarizes the results from the four scenarios and discusses the potential future work. This chapter also addresses assumptions of the model and what needs to be taken into account when interpreting the results. The summary of the results is presented in the same order as the scenario results shown in the earlier chapter.

8.1 Findings and summary of results

This section summarizes the high level findings from each of the scenarios, specifically the change in the VMT at the national level and also the national level vehicle stock. Every scenario result was compared to the base case scenario, which was considered as a reference. In the improved ride-sharing scenario, it was assumed that ride-sharing becomes more available and more cost-effective. This lead to an increase in the modal share of ride-shared vehicles in terms of the total number of trips taken. This effect was dominant in urban areas where other modes of transportation are readily available. In this scenario, the VMT at the national level increased by 0.44% and the national level vehicle stock decreased by 1.0% as compared to the base case scenario in the year 2050. This decrease in the stock is mainly due to the fact that people are moving in higher utilized vehicles and also in higher occupancy vehicles. This leads to a decrease in the stock. This decrease is not as drastic as the changes seen in just urban areas, because, the inertia associated with suburban and rural population diminishes the impact of these changes at the national level.

The next scenario that was tested was the improved ride-sharing along with transit improvements. In this scenario it was assumed the transit infrastructure improves

making it more efficient and more cost effective on top pf ride-sharing improvements. This scenario saw a decline in the national VMT by 2.0% and a decline in the national level vehicle stock by 2.9% as compared to the base case scenario in the year 2050. The next scenario that was tested was the improved ride-sharing scenario with transit improvements as well as anti-car policies. This was a fairly aggressive scenario against personal car travel. Due to assumptions about an extra parking cost associated with personal car travel, this lead to a decrease in the modal share associated with personal car trips in lieu of transit or ride-share trips, especially in urban areas. This lead to a decrease of 4.6% in VMT at the national level and a decrease of 6.0% for the national level vehicle stock as compared to the 2050 value in the base case scenario.

The next set of scenarios that were tested were the improved ride-sharing with higher EV penetration and improved ride-sharing with higher autonomous vehicle penetration. In the improved ride-sharing with higher EV penetration scenario, almost everything was similar to just the improved ride-sharing scenario. This suggested that just changing the powertrain of the vehicle did not cause significant shifts in travel behavior. In this scenario, the national level VMT increased by 0.47% and the vehicle stock decreased by 1.2% compared to the 2050 value in the base case.

Finally in the improved ride-sharing with autonomous vehicle penetration scenario, the national level VMT increased by 1.3% compared to the base case scenario value in the year 2050. This increase was attributed to the fact that autonomous vehicles can travel without a driver which leads to a higher VMT. In spite of a higher VMT, autonomous vehicles are also utilized more, which lead to an increase in the average annual mileage and this lead to a decrease in the vehicle stock by 9.9% compared to the base case value in year 2050. This information is summarized in Table 8.1.

Finally, as can be seen from Figure 8-1, the results from this study can be used to make certain high level conclusions. For example, if the government is trying to design policies around reducing congestion in urban areas, one metric that one might look at is the urban VMT (circled in blue in Figure 8-1). As can be seen in Figure 8-1, the improved ride-sharing with improved transit and anti-car policies might be an

Summary of all scnearios		
Scenario	**VMT change**	**Vehicle stock change**
Scenario 1.0	+0.44%	-1.0%
Scenario 1.1	-2.0%	-2.9%
Scenario 1.2	-4.6%	-6.0%
Scenario 1.1EV	+0.47%	-1.12%
Scenario 1.1EV+AV	+1.30%	-9.9%

Table 8.1: Table for all the variables related to preference modeling

effective method to reduce the urban VMT. If one is trying to reduce the GHG emissions, improved ride-sharing alone or higher autonomous vehicle penetration might not necessarily solve the problem. As can be seen from Figure 8-1, the national VMT actually increases in these two scenarios (circled in red). If the government is trying to design policies around decreasing car based trips, again the improved ride-sharing with improved transit and anti-car policies scenario suggests that this might be the way to go, as can be seen in Figure 8-1 (circled in green). These conclusions can be further used to study higher level policy analysis.

	Improved RS	+ Improved transit	+ Anti-Car	Improved RS + EV	Improved RS + Autonomy
	Scenario 1.0	Scenario 1.1	Scenario 1.2	Scenario 1.0EV	Scenario 1.0EV+AV
National Car based trips	+0.45%	-2.0%	-4.4%	+0.50%	+1.64%
Natl. Vehicle miles travelled	+0.44%	-2.0%	-4.6%	+0.47%	+1.30%
National vehicle stock	**-1.0%**	**-2.9%**	**-6.0%**	**-1.2%**	**-7.6%**
Urban VMT	+0.9%	-13.2%	-23.4%	+0.9%	+3.9%

Figure 8-1: Results summary

To summarize the results, the modal share changes and the VMT changes were largest in urban areas. Improved ride-sharing alone increased VMT, but combined with improving transit options helped reducing the VMT, especially in urban areas. VMT and vehicle stock see a diminished impact at the national level, in spite of a significant impact in the urban areas. This is due to the inertia associated with private car dominance in the suburban and rural areas, and approximately 75% of the population lives in non-urban areas.

8.2 Future work

One of the aspects of the current work that can be extended readily is better understanding of the parameters that change over time. Currently parameters like costs, time and other attributes are assume to change linearly with time. These rates of change of different parameters could be informed with more granularity. Also, additional analysis can be done with the current model by taking into consideration more granularity in terms of people-types. This work could be expanded to consider age/gender based categories on people. The model can also be used to study emissions analysis and other higher level policy questions by considering the impact on VMT.

Model extension is required to capture the impact on vehicle sales. From the vehicle sales, the model can be further extended to include commodity demand in the transportation sector. The work currently does not explicitly model vehicle ownership. This assumption works for the USA where the travel is dominated by personal cars anyway, but in developing countries the assumptions might not be valid.

The mainstreaming of ride-sharing will have broader implications for not only the automotive industry, but also for the economy, personal mobility and public policy. New mobility services have a potential to be a driver of economic development, not only through direct contributions, but also through indirect effects. For example, higher density of ride-sharing services near certain transit stations might foster multimodal trips as well as higher transit use. This can further create new opportunities for research in optimizing ride-sharing and transit networks. This can create increased access by creating opportunities for new trips previously not accessible by just using public transit which now become available by combining public transit with ride-sharing. Even if the use of new mobility services will be limited to urban areas, the wide-spread use of these services in urban areas will inspire similar modal shifts in suburban and rural areas as well.

New mobility services also present agencies with the opportunity to bring innovation to their transportation services in terms of traffic management, public transit

improvements and parking policies. Public authorities may need to, in the medium term, establish coherent regulatory environment that helps foster a productive and safe implementation of these new mobility services in conjunction with public transit use. In the long terms, public authorities may want to rethink their model and consider public-private partnerships and contracting with mobility providers. These aspects are all very recent and warrant further study. Increasing number of municipalities and transportation companies are partnering up with new mobility services providers. Some of the partnerships are with bike-sharing and car-sharing companies. These partnerships result in an opportunity to provide more transport options to their clients and also improve the public transit experience by bridging the gaps in the service, for example, in low density areas where there is no public transit or during evening or night time. Therefore, there are many models emerging where ride-hailing and public transit complement each other.

As can be seen from the results of this work, the near term growth of these disruptive technologies will be concentrated in urban areas with higher density that offer a variety of transportation options. These services will also cater to a particular type of users, mainly urban dwellers with higher levels of education and income. Even if these new disruptive technologies will not represent a substantial share of trips in the medium term, these technologies will have a significant long term impact on the way people think about transportation, the way transportation systems are organized, the expectations about transportation systems and the way the transportation systems are paid for. In the next two decades, the adoption of autonomous vehicles and especially shared autonomous vehicles have a potential to drastically change the transportation landscape. Although, these new disruptive services will not be adopted by a majority of travelers, as can be seen from this work, their operating concepts will significantly impact the use of private cars and public transit.

New disruptive technologies provide a catalyst for innovation in the automotive industry. While, in the medium term, the vehicle stock might decline a little due to the adoption of these technologies, these new technologies are prompting automakers to test new business models and innovate the way they manage their fleet. Due to

the gradual nature of the change, the traditional transportation operators, specifically the automakers, will have time to adapt to these changes as the preferences of people change. Still, they will have to come up with innovative ways to maintain their market position due to the diversification of the transportation sector. The mainstreaming of new mobility services will have broader implications, not just for the automakers, but also for economic development. These disruptive technologies will contribute to the labor market creating new positions, and play a role in renewed regional competitiveness. These services represent an opportunity for public agencies and the government to rethink the transportation systems provided by them and to make them more efficient, affordable and relevant for the needs of their citizens. Public authorities need to adopt the key concepts and modes of functioning that make these services so appealing to the users. This aspect of mutual collaboration between the mobility service providing companies and the government needs to be studied further to bring innovation into transportation policy.

Many studies have been done on the competition between the mobility service providing companies and the existing private car market, but few have examined the interactions and the relationships between these varying service and business models and the larger transportation system. These mobility services are inherently dependent on passenger vehicles and this will continue into the near future. Furthermore, automakers are experimenting with their own mobility service offerings. Therefore, rather than the common perception that ride-sharing is a threat to the automotive industry, these services provide an incentive for the development of a more resilient automotive industry, the one that can evolve quickly with the changing technology, travel behavior and people preferences. These developments might precisely prove to be the competitive advantage that the industry needs to survive the challenges of the future. Globally, the challenges might be more formidable and more immediate than in the USA and the industry must respond soon to these challenges if it wants to remain relevant and profitable.

Appendix A

Input parameter tables

Variable	Variable Description	Urban Low income Work Trips	Urban Highincome Work Trips	Urban Low income Leisure Trips	Urban High income Leisure Trips	Urban Low income Errands Trips	Urban High income Errands Trips	Urban Low income Other Trips	Urban High income Other Trips
mean.trip.dist	Mean Trip Distance	6	6	8	8	7	7	20	20
sd.trip.dist	Std. Dev. Trip Distance	4	4	4	4	4	4	4	4
mean.speed.PC.start	Mean speed PC, Year 0	25	25	30	30	25	25	21	21
mean.speed.PC.end	Mean speed PC, Year 2050	25	25	30	30	25	25	21	21
sd.speed.PC.start	Std. Dev. Speed PC, Year 0	2	2	2	2	2	2	2	2
sd.speed.PC.end	Std. Dev. Speed PC, Year 2050	2	2	2	2	2	2	2	2
mean.time.to.PC.start	Time to get to PC, Year 0	4	4	4	4	4	4	4	4
mean.time.to.PC.end	Time to get to PC, Year 2050	4	4	4	4	4	4	4	4
sd.time.to.PC.start	Std. Dev. Time to get to PC, Year 0	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
sd.time.to.PC.end	Std. Dev. Time to get to PC, Year 2050	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
mean.time.to.park.PC.start	Mean time to find parking, PC, Year 0	3	3	3	3	3	3	3	3
mean.time.to.park.PC.end	Mean time to find parking, PC, Year 2050	3	3	3	3	3	3	3	3
sd.time.to.park.PC.start	St. Dev,time to find parking, PC, Year 0	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
sd.time.to.park.PC.end	St. Dev,time to find parking, PC, Year 2050	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
mean.time.park.dest.PC.start	Mean time to go from parking to destination, PC, Year 0	5	5	5	5	5	5	5	5
mean.time.park.dest.PC.end	Mean time to go from parking to destination, PC, Year 2050	5	5	5	5	5	5	5	5
sd.time.park.dest.PC.start	St. Dev. PC, Time to go from parking to destination, Year 0	2	2	2	2	2	2	2	2
sd.time.park.dest.PC.end	St. Dev. PC, Time to go from parking to destination, Year 2050	2	2	2	2	2	2	2	2
mean.time.to.trans.start	Time to get to Transit, Year 0	5	5	5	5	5	5	4	4
mean.time.to.trans.end	Time to get to Transit, Year 2050	5	5	5	5	5	5	4	4
sd.time.to.trans.start	Std. Dev. Time to get to Transit, Year 0	1	1	1	1	1	1	1	1
sd.time.to.trans.end	Std. Dev. Time to get to Transit, Year 2050	1	1	1	1	1	1	1	1
mean.wait.trans.start	Mean time to wait,Transit, Year 0	5	5	10	10	10	10	5	5
mean.wait.trans.end	Mean time to wait,Transit, Year 2050	5	5	10	10	10	10	5	5
sd.wait.trans.start	St. Dev,time to wait, Transit, Year 0	2	2	2	2	2	2	2	2
sd.wait.trans.end	St. Dev,time to wait, Transit, Year 2050	2	2	2	2	2	2	2	2
mean.speed.trans.start	Mean time to go from parking to destination, PC, Year 0	24	24	24	24	22	22	24	24
mean.speed.trans.end	Mean time to go from parking to destination, PC, Year 2050	24	24	24	24	22	22	24	24
sd.speed.trans.start	St. Dev. PC, Time to go from parking to destination, Year 0	4	4	4	4	4	4	4	4
sd.speed.trans.end	St. Dev. PC, Time to go from parking to destination, Year 2050	4	4	4	4	4	4	4	4
time.parking.trans	Parking time, Transit	0	0	0	0	0	0	0	0

Figure A-1: Inputs for urban trips, Base case, part 1

mean.parking.dest.trans.start	Mean time to go from parking to destination, Transit, Year 0	5	5	5	5	5	5	5	5
mean.parking.dest.trans.end	Mean time to go from parking to destination, Transit, Year 2050	5	5	5	5	5	5	5	5
sd.parking.dest.trans.start	St. Dev. Transit, Time to go from parking to destination, Year 0	3	3	3	3	3	3	3	3
sd.parking.dest.trans.end	St. Dev. Transit, Time to go from parking to destination, Year 2050	3	3	3	3	3	3	3	3
walk.speed	Speed of walking	3	3	3	3	3	3	3	3
time.to.mode.Walk	Time to get to walk	0	0	0	0	0	0	0	0
time.wait.Walk	Tine to wait for walking	0	0	0	0	0	0	0	0
time.parking.Walk	Time to park walking	0	0	0	0	0	0	0	0
time.parking.to.dest.Walk	Time to go from parking spot to destination,walking	0	0	0	0	0	0	0	0
time.to.mode.Uber	Time to get to ride-share	2	2	2	2	2	2	2	2
mean.wait.Uber.start	Waiting time, ride-share, Year 0	5	5	2	2	2	2	5	5
mean.wait.Uber.end	Waiting time, ride-share, Year 2050	5	5	2	2	2	2	5	5
sd.wait.Uber.start	St. Dev,time to wait, Ride-share, Year 0	3	3	1	1	1	1	3	3
sd.wait.Uber.end	St. Dev,time to wait, Ride-Share, Year 2050	3	3	1	1	1	1	3	3
time.parking.Uber	Time to find parking, ride-share	0	0	0	0	0	0	0	0
time.parking.to.dest.Uber	Time to go from parking to final destination, Ride-share	2	2	2	2	2	2	2	2
dollar.mile.PC.start	$/mile PC Year 0	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63
dollar.mile.PC.end	$/mile PC Year 2050	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63
mean.park.cost.PC.start	Parking cost PC, Year 0	12	12	8	8	8	8	5	5
mean.park.cost.PC.end	Parking cost PC, Year 2050	12	12	8	8	8	8	5	5
sd.park.cost.PC.start	St. Dev, Parking cost PC, Year 0	3	3	3	3	3	3	3	3
sd.park.cost.PC.end	St. Dev, Parking cost PC, Year 2050	3	3	3	3	3	3	3	3
dollars.min.PC.start	$/min PC year 0	0	0	0	0	0	0	0	0
dollars.min.PC.end	$/min PC Year 2050	0	0	0	0	0	0	0	0
base.cost.PC.start	Base cost PC Year 0	0	0	0	0	0	0	0	0
base.cost.PC.end	Base cost PC Year 2050	0	0	0	0	0	0	0	0
dollar.mile.Trans	$/mile, Transit	0	0	0	0	0	0	0	0
avg.park.cost.Trans	Parking cost, Transit	0	0	0	0	0	0	0	0
dollars.min.Trans	$/minutes, Transit	0	0	0	0	0	0	0	0
mean.base.cost.trans.start	Base cost Transit Year 0	2	2	6	6	10	10	10	10
mean.base.cost.trans.end	Base cost Transit Year 2050	2	2	6	6	10	10	10	10
sd.base.cost.trans.start	St. Dev, Base cost Transit Year 0	2	2	2	2	2	2	2	2
sd.base.cost.trans.end	St. Dev, Base cost Transit Year 2050	2	2	2	2	2	2	2	2

Figure A-2: Inputs for urban trips, Base case, part 2

66	dollar.mile.Walk	$/mile, Walking	0	0	0	0	0	0	0	0
67	avg.park.cost.Walk	Parking cost, Walk	0	0	0	0	0	0	0	0
68	dollars.min.Walk	$/min, Walk	0	0	0	0	0	0	0	0
69	base.cost.Walk	Base,cost, Walk	0	0	0	0	0	0	0	0
70	dollar.mile.Uber.start	$/mile Ride-Share Year 0	1.25	1.25	1.25	1.25	1.25	1.25	1.25	1.25
71	dollar.mile.Uber.end	$/mile Ride-Share Year 2050	1.25	1.25	1.25	1.25	1.25	1.25	1.25	1.25
72	dollars.min.Uber.start	$/min Ride-Share year 0	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
73	dollars.min.Uber.end	$/min Ride-Share Year 2050	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
74	base.cost.Uber.start	Base cost Ride-Share Year 0	2.25	2.25	2.25	2.25	2.25	2.25	2.25	2.25
75	base.cost.Uber.end	Base cost Ride-Share Year 2050	2.25	2.25	2.25	2.25	2.25	2.25	2.25	2.25
76	mean.comfort.PC.start	Mean comfort, PC Year 0	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
77	mean.comfort.PC.end	Mean comfort PC year 2050	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
78	sd.comfort.PC.start	St. Dev, Comfort PC, Year 0	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
79	sd.comfort.PC.end	St. Dev, Comfort PC, Year 2050	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
80	mean.comfort.Trans.start	Mean comfort, Transit Year 0	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
81	mean.comfort.Trans.end	Mean comfort, Transit, year 2050	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
82	sd.comfort.Trans.start	St. Dev, Comfort Transit, Year 0	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
83	sd.comfort.Trans.end	St. Dev, Comfort Transit, Year 2050	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
84	mean.Walk.max	Comfort walking, maximum	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
85	mean.Walk.min	comfort walking, minimum	0.01	0.01	0.85	0.85	0.7	0.7	0.01	0.01
86	mean.walk.time.steps	Time over which comfort of walking decreases	100	100	100	100	100	100	100	100
87	mean.walk.time.flat	Time for which walking stays at maximum comfort level	20	20	35	35	35	35	20	20
88	cov.mean.walk	Mean/st. dev	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
89	mean.comfort.initial.start	Maximum Comfort of ride-share vehicles, year 0	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8
90	mean.comfort.final.start	Maximum Comfort of ride-share vehicles, year 2050	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8
91	mean.comfort.initial.end	Minimum Comfort of ride-share vehicles, year 0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
92	mean.comfort.final.end	Minimum Comfort of ride-share vehicles, year 2050	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
93	comfort.const.time.uber	Time for which ride-share stays at maximum comfort	10	10	15	15	15	15	15	15
94	total.decay.time.uber	Time over which comfort of Ride-share decreases	60	60	60	60	60	60	60	60

Figure A-3: Inputs for urban trips, Base case, part 3

best.comfort	Highest possible comfort	1	1	1	1	1	1	1	1
worst.comfort	Lowest possible comfort	0	0	0	0	0	0	0	0
best.time	Best possible trip time	0	0	0	0	0	0	0	0
worst.time	Worst possible trip time	60	60	60	60	60	60	60	60
best.cost	Best possible cost	0	0	0	0	0	0	0	0
worst.cost	Worst possible cost	30	30	30	30	30	30	30	30
k.cost.mean	Importance of cost	0.2	0.1	0.45	0.4	0.45	0.45	0.4	0.3
k.cost.sd	standard deviation on k.cost	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
k.time.mean	Importance of time	0.45	0.55	0.1	0.1	0.1	0.1	0.3	0.4
k.time.sd	standard deviation on k.time	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
k.comfort.mean	Importance of comfort	0.35	0.35	0.45	0.5	0.45	0.45	0.3	0.3
k.comfort.sd	standard deviation on k.comfort	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Figure A-4: Inputs for urban trips, Base case, part 4

Variable	Variable Description	Suburban Low income Work Trips	Suburban Highincome Work Trips	Suburban Low income Leisure Trips	Suburban High income Leisure	Suburban Low income Errands Trips	Suburban High income Errands	Suburban Low income Other Trips	Suburban High income Other Trips
mean.trip.dist	Mean Trip Distance	16	16	14	14	10	10	28	28
sd.trip.dist	Std. Dev. Trip Distance	15	15	12	12	10	10	10	10
mean.speed.PC.start	Mean speed PC, Year 0	40	40	35	35	50	50	45	45
mean.speed.PC.end	Mean speed PC, Year 2050	40	40	35	35	50	50	45	45
sd.speed.PC.start	Std. Dev. Speed PC, Year 0	2	2	2	2	2	2	2	2
sd.speed.PC.end	Std. Dev. Speed PC, Year 2050	2	2	2	2	2	2	2	2
mean.time.to.PC.start	Time to get to PC, Year 0	1	1	1	1	1	1	1	1
mean.time.to.PC.end	Time to get to PC, Year 2050	1	1	1	1	1	1	1	1
sd.time.to.PC.start	Std. Dev. Time to get to PC, Year 0	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
sd.time.to.PC.end	Std. Dev. Time to get to PC, Year 2050	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
mean.time.to.park.PC.start	Mean time to find parking, PC, Year 0	3	3	3	3	3	3	3	3
mean.time.to.park.PC.end	Mean time to find parking, PC, Year 2050	3	3	3	3	3	3	3	3
sd.time.to.park.PC.start	St. Dev,time to find parking, PC, Year 0	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
sd.time.to.park.PC.end	St. Dev,time to find parking, PC, Year 2050	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
mean.time.park.dest.PC.start	Mean time to go from parking to destination, PC, Year 0	5	5	5	5	5	5	5	5
mean.time.park.dest.PC.end	Mean time to go from parking to destination, PC, Year 2050	5	5	5	5	5	5	5	5
sd.time.park.dest.PC.start	St. Dev. PC, Time to go from parking to destination, Year 0	2	2	2	2	2	2	2	2
sd.time.park.dest.PC.end	St. Dev. PC, Time to go from parking to destination, Year 2050	2	2	2	2	2	2	2	2
mean.time.to.trans.start	Time to get to Transit, Year 0	25	25	30	20	25	25	30	30
mean.time.to.trans.end	Time to get to Transit, Year 2050	25	25	30	20	25	25	30	30
sd.time.to.trans.start	Std. Dev. Time to get to Transit, Year 0	2	2	2	2	2	2	1	1
sd.time.to.trans.end	Std. Dev. Time to get to Transit, Year 2050	2	2	2	2	2	2	1	1
mean.wait.trans.start	Mean time to wait,Transit, Year 0	15	15	20	20	20	20	8	8
mean.wait.trans.end	Mean time to wait,Transit, Year 2050	15	15	20	20	20	20	8	8
sd.wait.trans.start	St. Dev,time to wait, Transit, Year 0	2	2	2	2	2	2	2	2
sd.wait.trans.end	St. Dev,time to wait, Transit, Year 2050	2	2	2	2	2	2	2	2
mean.speed.trans.start	Mean time to go from parking to destination, PC, Year 0	22	22	22	22	22	22	22	22
mean.speed.trans.end	Mean time to go from parking to destination, PC, Year 2050	22	22	22	22	22	22	22	22
sd.speed.trans.start	St. Dev. PC, Time to go from parking to destination, Year 0	4	4	4	4	4	4	4	4
sd.speed.trans.end	St. Dev. PC, Time to go from parking to destination, Year 2050	4	4	4	4	4	4	4	4
time.parking.trans	Parking time, Transit	0	0	0	0	0	0	0	0
mean.parking.dest.trans.start	Mean time to go from parking to destination, Transit, Year 0	5	5	5	5	5	5	5	5
mean.parking.dest.trans.end	Mean time to go from parking to destination, Transit, Year 2050	5	5	5	5	5	5	5	5
sd.parking.dest.trans.start	St. Dev. Transit, Time to go from parking to destination, Year 0	3	3	3	3	3	3	3	3
sd.parking.dest.trans.end	St. Dev. Transit, Time to go from parking to destination, Year 2050	3	3	3	3	3	3	3	3
walk.speed	Speed of walking	3	3	3	3	3	3	3	3
time.to.mode.Walk	Time to get to walk	0	0	0	0	0	0	0	0
time.wait.Walk	Tine to wait for walking	0	0	0	0	0	0	0	0
time.parking.Walk	Time to park walking	0	0	0	0	0	0	0	0
time.parking.to.dest.Walk	Time to go from parking spot to destination,walking	0	0	0	0	0	0	0	0
time.to.mode.Uber	Time to get to ride-share	2	2	2	2	2	2	2	2
mean.wait.Uber.start	Waiting time, ride-share, Year 0	10	10	15	15	10	10	10	10
mean.wait.Uber.end	Waiting time, ride-share, Year 2050	10	10	15	15	10	10	10	10
sd.wait.Uber.start	St. Dev,time to wait, Ride-share, Year 0	3	3	3	3	3	3	3	3
sd.wait.Uber.end	St. Dev,time to wait, Ride-Share, Year 2050	3	3	3	3	3	3	3	3
time.parking.Uber	Time to find parking, ride-share	0	0	0	0	0	0	0	0

Figure A-5: Inputs for Suburban trips, Base case, part 1

Variable	Variable Description	Suburban Low income Work Trips	Suburban Highincome Work Trips	Suburban Low income Leisure Trips	Suburban High income Leisure	Suburban Low income Errands Trips	Suburban High income Errands	Suburban Low income Other Trips	Suburban High income Other Trips
time.parking.to.dest.Uber	Time to go from parking to final destination, Ride-share	2	2	2	2	2	2	2	2
dollar.mile.PC.start	$/mile PC Year 0	$ 0.54	$ 0.54	$ 0.54	$ 0.54	$ 0.54	$ 0.54	$ 0.54	$ 0.54
dollar.mile.PC.end	$/mile PC Year 2050	$ 0.54	$ 0.54	$ 0.54	$ 0.54	$ 0.54	$ 0.54	$ 0.54	$ 0.54
mean.park.cost.PC.start	Parking cost PC, Year 0	12	12	8	8	5	5	5	5
mean.park.cost.PC.end	Parking cost PC, Year 2050	12	12	8	8	5	5	5	5
sd.park.cost.PC.start	St. Dev, Parking cost PC, Year 0	3	3	3	3	3	3	3	3
sd.park.cost.PC.end	St. Dev, Parking cost PC, Year 2050	3	3	3	3	3	3	3	3
dollars.min.PC.start	$/min PC year 0	0	0	0	0	0	0	0	0
dollars.min.PC.end	$/min PC Year 2050	0	0	0	0	0	0	0	0
base.cost.PC.start	Base cost PC Year 0	0	0	0	0	0	0	0	0
base.cost.PC.end	Base cost PC Year 2050	0	0	0	0	0	0	0	0
dollar.mile.Trans	$/mile, Transit	0	0	0	0	0	0	0	0
avg.park.cost.Trans	Parking cost, Transit	0	0	0	0	0	0	0	0
dollars.min.Trans	$/minutes, Transit	0	0	0	0	0	0	0	0
mean.base.cost.trans.start	Base cost Transit Year 0	8	8	10	10	2	2	5	5
mean.base.cost.trans.end	Base cost Transit Year 2050	8	8	10	10	2	2	5	5
sd.base.cost.trans.start	St. Dev, Base cost Transit Year 0	2	2	2	2	2	2	2	2
sd.base.cost.trans.end	St. Dev, Base cost Transit Year 2050	2	2	2	2	2	2	2	2
dollar.mile.Walk	$/mile, Walking	0	0	0	0	0	0	0	0
avg.park.cost.Walk	Parking cost, Walk	0	0	0	0	0	0	0	0
dollars.min.Walk	$/min, Walk	0	0	0	0	0	0	0	0
base.cost.Walk	Base,cost, Walk	0	0	0	0	0	0	0	0
dollar.mile.Uber.start	$/mile Ride-Share Year 0	$ 1.18	$ 1.18	$ 1.18	$ 1.18	$ 1.18	$ 1.18	$ 1.18	$ 1.18
dollar.mile.Uber.end	$/mile Ride-Share Year 2050	$ 1.18	$ 1.18	$ 1.18	$ 1.18	$ 1.18	$ 1.18	$ 1.18	$ 1.18
dollars.min.Uber.start	$/min Ride-Share year 0	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
dollars.min.Uber.end	$/min Ride-Share Year 2050	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
base.cost.Uber.start	Base cost Ride-Share Year 0	2.25	2.25	2.25	2.25	2.25	2.25	2.25	2.25
base.cost.Uber.end	Base cost Ride-Share Year 2050	2.25	2.25	2.25	2.25	2.25	2.25	2.25	2.25
mean.comfort.PC.start	Mean comfort, PC Year 0	0.9	0.9	0.8	0.8	0.9	0.9	0.9	0.9
mean.comfort.PC.end	Mean comfort PC year 2050	0.9	0.9	0.8	0.8	0.9	0.9	0.9	0.9
sd.comfort.PC.start	St. Dev, Comfort PC, Year 0	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
sd.comfort.PC.end	St. Dev, Comfort PC, Year 2050	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
mean.comfort.Trans.start	Mean comfort, Transit Year 0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
mean.comfort.Trans.end	Mean comfort, Transit, year 2050	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
sd.comfort.Trans.start	St. Dev, Comfort Transit, Year 0	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
sd.comfort.Trans.end	St. Dev, Comfort Transit, Year 2050	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
mean.Walk.max	Comfort walking, maximum	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
mean.Walk.min	comfort walking, minimum	0.1	0.1	0.85	0.85	0.1	0.1	0.01	0.01
mean.walk.time.steps	Time over which comfort of walking decreases	100	100	100	100	100	100	100	100
mean.walk.time.flat	Time for which walking stays at maximum comfort level	30	30	40	40	15	15	20	20
cov.mean.walk	Mean/st. dev	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
mean.comfort.initial.start	Maximum Comfort of ride-share vehicles, year 0	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
mean.comfort.final.start	Maximum Comfort of ride-share vehicles, year 2050	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
mean.comfort.initial.end	Minimum Comfort of ride-share vehicles, year 0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
mean.comfort.final.end	Minimum Comfort of ride-share vehicles, year 2050	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
comfort.const.time.uber	Time for which ride-share stays at maximum comfort	15	15	25	25	20	20	20	20

Figure A-6: Inputs for Suburban trips, Base case, part 2

total.decay.time.uber	Time over which comfort of Ride-share decreases	60	60	60	60	60	60	60	60
best.comfort	Highest possible comfort	1	1	1	1	1	1	1	1
worst.comfort	Lowest possible comfort	0	0	0	0	0	0	0	0
best.time	Best possible trip time	0	0	0	0	0	0	0	0
worst.time	Worst possible trip time	60	60	60	60	60	60	60	60
best.cost	Best possible cost	0	0	0	0	0	0	0	0
worst.cost	Worst possible cost	30	30	30	30	30	30	30	30
k.cost.mean	Importance of cost	0.2	0.15	0.4	0.4	0.4	0.4	0.3	0.3
k.cost.sd	standard deviation on k.cost	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
k.time.mean	Importance of time	0.45	0.5	0.1	0.1	0.1	0.1	0.3	0.3
k.time.sd	standard deviation on k.time	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
k.comfort.mean	Importance of comfort	0.35	0.35	0.5	0.5	0.5	0.5	0.4	0.4
k.comfort.sd	standard deviation on k.comfort	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Figure A-7: Inputs for Suburban trips, Base case, part 3

Variable	Variable Description	Rural Low income Work Trips	Rural Highincome Work Trips	Rural Low income Leisure Trips	Rural High income Leisure Trips	Rural Low income Errands Trips	Rural High income Errands Trips	Rural Low income Other Trips	Rural High income Other Trips
mean.trip.dist	Mean Trip Distance	20	20	20	20	10	10	30	30
sd.trip.dist	Std. Dev. Trip Distance	4	4	12	12	4	4	2	2
mean.speed.PC.start	Mean speed PC, Year 0	50	50	55	55	50	50	55	55
mean.speed.PC.end	Mean speed PC, Year 2050	50	50	55	55	50	50	55	55
sd.speed.PC.start	Std. Dev. Speed PC, Year 0	2	2	2	2	2	2	2	2
sd.speed.PC.end	Std. Dev. Speed PC, Year 2050	2	2	2	2	2	2	2	2
mean.time.to.PC.start	Time to get to PC, Year 0	1	1	1	1	1	1	1	1
mean.time.to.PC.end	Time to get to PC, Year 2050	1	1	1	1	1	1	1	1
sd.time.to.PC.start	Std. Dev. Time to get to PC, Year 0	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
sd.time.to.PC.end	Std. Dev. Time to get to PC, Year 2050	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
mean.time.to.park.PC.start	Mean time to find parking, PC, Year 0	3	3	3	3	3	3	3	3
mean.time.to.park.PC.end	Mean time to find parking, PC, Year 2050	3	3	3	3	3	3	3	3
sd.time.to.park.PC.start	St. Dev,time to find parking, PC, Year 0	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
sd.time.to.park.PC.end	St. Dev,time to find parking, PC, Year 2050	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
mean.time.park.dest.PC.start	Mean time to go from parking to destination, PC, Year 0	5	5	5	5	5	5	5	5
mean.time.park.dest.PC.end	Mean time to go from parking to destination, PC, Year 2050	5	5	5	5	5	5	5	5
sd.time.park.dest.PC.start	St. Dev. PC, Time to go from parking to destination, Year 0	2	2	2	2	2	2	2	2
sd.time.park.dest.PC.end	St. Dev. PC, Time to go from parking to destination, Year 2050	2	2	2	2	2	2	2	2
mean.time.to.trans.start	Time to get to Transit, Year 0	30	30	30	30	30	30	30	30
mean.time.to.trans.end	Time to get to Transit, Year 2050	30	30	30	30	30	30	30	30
sd.time.to.trans.start	Std. Dev. Time to get to Transit, Year 0	2	2	2	2	2	2	2	2
sd.time.to.trans.end	Std. Dev. Time to get to Transit, Year 2050	2	2	2	2	2	2	2	2
mean.wait.trans.start	Mean time to wait,Transit, Year 0	8	8	10	10	8	8	10	10
mean.wait.trans.end	Mean time to wait,Transit, Year 2050	8	8	10	10	8	8	10	10
sd.wait.trans.start	St. Dev,time to wait, Transit, Year 0	2	2	2	2	2	2	2	2
sd.wait.trans.end	St. Dev,time to wait, Transit, Year 2050	2	2	2	2	2	2	2	2
mean.speed.trans.start	Mean time to go from parking to destination, PC, Year 0	22	22	22	22	22	22	22	22
mean.speed.trans.end	Mean time to go from parking to destination, PC, Year 2050	22	22	22	22	22	22	22	22
sd.speed.trans.start	St. Dev. PC, Time to go from parking to destination, Year 0	4	4	4	4	4	4	4	4
sd.speed.trans.end	St. Dev. PC, Time to go from parking to destination, Year 2050	4	4	4	4	4	4	4	4
time.parking.trans	Parking time, Transit	0	0	0	0	0	0	0	0
mean.parking.dest.trans.start	Mean time to go from parking to destination, Transit, Year 0	5	5	5	5	5	5	5	5
mean.parking.dest.trans.end	Mean time to go from parking to destination, Transit, Year 2050	5	5	5	5	5	5	5	5
sd.parking.dest.trans.start	St. Dev. Transit, Time to go from parking to destination, Year 0	3	3	3	3	3	3	3	3
sd.parking.dest.trans.end	St. Dev. Transit, Time to go from parking to destination, Year 2050	3	3	3	3	3	3	3	3
walk.speed	Speed of walking	3	3	3	3	3	3	3	3
time.to.mode.Walk	Time to get to walk	0	0	0	0	0	0	0	0
time.wait.Walk	Tine to wait for walking	0	0	0	0	0	0	0	0
time.parking.Walk	Time to park walking	0	0	0	0	0	0	0	0
time.parking.to.dest.Walk	Time to go from parking spot to destination,walking	0	0	0	0	0	0	0	0
time.to.mode.Uber	Time to get to ride-share	2	2	2	2	2	2	2	2
mean.wait.Uber.start	Waiting time, ride-share, Year 0	20	20	30	30	30	30	30	30
mean.wait.Uber.end	Waiting time, ride-share, Year 2050	20	20	30	30	30	30	30	30
sd.wait.Uber.start	St. Dev,time to wait, Ride-share, Year 0	3	3	3	3	3	3	3	3
sd.wait.Uber.end	St. Dev,time to wait, Ride-Share, Year 2050	3	3	3	3	3	3	3	3

Figure A-8: Inputs for Rural trips, Base case, part 1

Variable	Variable Description	Rural Low income Work Trips	Rural Highincome Work Trips	Rural Low income Leisure Trips	Rural High income Leisure Trips	Rural Low income Errands Trips	Rural High income Errands Trips	Rural Low income Other Trips	Rural High income Other Trips
time.parking.Uber	Time to find parking, ride-share	0	0	0	0	0	0	0	0
time.parking.to.dest.Uber	Time to go from parking to final destination, Ride-share	2	2	2	2	2	2	2	2
dollar.mile.PC.start	$/mile PC Year 0	0.5431156	0.5431156	0.5431156	0.5431156	0.5431156	0.5431156	0.5431156	0.5431156
dollar.mile.PC.end	$/mile PC Year 2050	0.5431156	0.5431156	0.5431156	0.5431156	0.5431156	0.5431156	0.5431156	0.5431156
mean.park.cost.PC.start	Parking cost PC, Year 0	5	5	5	5	5	5	5	5
mean.park.cost.PC.end	Parking cost PC, Year 2050	5	5	5	5	5	5	5	5
sd.park.cost.PC.start	St. Dev, Parking cost PC, Year 0	3	3	3	3	3	3	3	3
sd.park.cost.PC.end	St. Dev, Parking cost PC, Year 2050	3	3	3	3	3	3	3	3
dollars.min.PC.start	$/min PC year 0	0	0	0	0	0	0	0	0
dollars.min.PC.end	$/min PC Year 2050	0	0	0	0	0	0	0	0
base.cost.PC.start	Base cost PC Year 0	0	0	0	0	0	0	0	0
base.cost.PC.end	Base cost PC Year 2050	0	0	0	0	0	0	0	0
dollar.mile.Trans	$/mile, Transit	0	0	0	0	0	0	0	0
avg.park.cost.Trans	Parking cost, Transit	0	0	0	0	0	0	0	0
dollars.min.Trans	$/minutes, Transit	0	0	0	0	0	0	0	0
mean.base.cost.trans.start	Base cost Transit Year 0	2	2	3	3	2	2	2	2
mean.base.cost.trans.end	Base cost Transit Year 2050	2	2	3	3	2	2	2	2
sd.base.cost.trans.start	St. Dev, Base cost Transit Year 0	2	2	2	2	2	2	2	2
sd.base.cost.trans.end	St. Dev, Base cost Transit Year 2050	2	2	2	2	2	2	2	2
dollar.mile.Walk	$/mile, Walking	0	0	0	0	0	0	0	0
avg.park.cost.Walk	Parking cost, Walk	0	0	0	0	0	0	0	0
dollars.min.Walk	$/min, Walk	0	0	0	0	0	0	0	0
base.cost.Walk	Base,cost, Walk	0	0	0	0	0	0	0	0
dollar.mile.Uber.start	$/mile Ride-Share Year 0	1.1820917	1.1820917	1.1820917	1.1820917	1.1820917	1.1820917	1.1820917	1.1820917
dollar.mile.Uber.end	$/mile Ride-Share Year 2050	1.1820917	1.1820917	1.1820917	1.1820917	1.1820917	1.1820917	1.1820917	1.1820917
dollars.min.Uber.start	$/min Ride-Share year 0	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
dollars.min.Uber.end	$/min Ride-Share Year 2050	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
base.cost.Uber.start	Base cost Ride-Share Year 0	2.25	2.25	2.25	2.25	2.25	2.25	2.25	2.25
base.cost.Uber.end	Base cost Ride-Share Year 2050	2.25	2.25	2.25	2.25	2.25	2.25	2.25	2.25
mean.comfort.PC.start	Mean comfort, PC Year 0	0.9	0.9	0.65	0.65	0.9	0.9	0.9	0.9
mean.comfort.PC.end	Mean comfort PC year 2050	0.9	0.9	0.65	0.65	0.9	0.9	0.9	0.9
sd.comfort.PC.start	St. Dev, Comfort PC, Year 0	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
sd.comfort.PC.end	St. Dev, Comfort PC, Year 2050	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
mean.comfort.Trans.start	Mean comfort, Transit Year 0	0.5	0.5	0.1	0.1	0.3	0.3	0.1	0.1
mean.comfort.Trans.end	Mean comfort, Transit, year 2050	0.5	0.5	0.1	0.1	0.3	0.3	0.1	0.1
sd.comfort.Trans.start	St. Dev, Comfort Transit, Year 0	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
sd.comfort.Trans.end	St. Dev, Comfort Transit, Year 2050	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
mean.Walk.max	Comfort walking, maximum	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
mean.Walk.min	comfort walking, minimum	0.01	0.01	0.85	0.85	0.01	0.01	0.01	0.01
mean.walk.time.steps	Time over which comfort of walking decreases	100	100	100	100	100	100	100	100
mean.walk.time.flat	Time for which walking stays at maximum comfort level	20	20	35	35	30	30	20	20
cov.mean.walk	Mean/st. dev	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
mean.comfort.initial.start	Maximum Comfort of ride-share vehicles, year 0	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
mean.comfort.final.start	Maximum Comfort of ride-share vehicles, year 2050	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
mean.comfort.initial.end	Minimum Comfort of ride-share vehicles, year 0	0.01	0.01	0.1	0.1	0.01	0.01	0.01	0.01

Figure A-9: Inputs for Rural trips, Base case, part 2

mean.comfort.final.end	Minimum Comfort of ride-share vehicles, year 2050	0.01	0.01	0.1	0.1	0.01	0.01	0.01	0.01
comfort.const.time.uber	Time for which ride-share stays at maximum comfort	15	15	10	15	10	10	15	15
total.decay.time.uber	Time over which comfort of Ride-share decreases	60	60	60	60	60	60	60	60
best.comfort	Highest possible comfort	1	1	1	1	1	1	1	1
worst.comfort	Lowest possible comfort	0	0	0	0	0	0	0	0
best.time	Best possible trip time	0	0	0	0	0	0	0	0
worst.time	Worst possible trip time	60	60	60	60	60	60	60	60
best.cost	Best possible cost	0	0	0	0	0	0	0	0
worst.cost	Worst possible cost	30	30	30	30	30	30	30	30
k.cost.mean	Importance of cost	0.2	0.2	0.3	0.3	0.4	0.4	0.2	0.2
k.cost.sd	standard deviation on k.cost	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
k.time.mean	Importance of time	0.45	0.45	0.1	0.1	0.1	0.1	0.45	0.45
k.time.sd	standard deviation on k.time	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
k.comfort.mean	Importance of comfort	0.35	0.35	0.6	0.6	0.5	0.5	0.35	0.35
k.comfort.sd	standard deviation on k.comfort	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Figure A-10: Inputs for Rural trips, Base case, part 3

Bibliography

[1] AAA. Aaa shos the true cost of vehicle ownership. *http://newsroom.aaa.com/auto/your-driving-costs/*, 2016.

[2] Maya Abou-Zeid and Moshe Ben-Akiva. Well-being and activity-based models. *Transportation*, 39(6):1189–1207, 2012.

[3] Thomas Adler, Michael Doherty, Jack Klodzinski, and Raymond Tillman. Methods for quantitative risk analysis for travel demand model forecasts. *Transportation Research Record: Journal of the Transportation Research Board*, (2429):1–7, 2014.

[4] Baha M Al-Alawi and Thomas H Bradley. Review of hybrid, plug-in hybrid, and electric vehicle market modeling studies. *Renewable and Sustainable Energy Reviews*, 21:190–203, 2013.

[5] Carlos Lima Azevedo, Katarzyna Marczuk, Sebastián Raveau, Harold Soh, Muhammad Adnan, Kakali Basak, Harish Loganathan, Neeraj Deshmunkh, Der-Horng Lee, Emilio Frazzoli, et al. Microsimulation of demand and supply of autonomous mobility on demand. *Transportation Research Record: Journal of the Transportation Research Board*, (2564):21–30, 2016.

[6] Michael Balmer, K Meister, and K Nagel. *Agent-based simulation of travel demand: Structure and computational performance of MATSim-T*. ETH, Eidgenössische Technische Hochschule Zürich, IVT Institut für Verkehrsplanung und Transportsysteme, 2008.

[7] Patricia Baptista, Mário Tomás, and Carla Silva. Plug-in hybrid fuel cell vehicles market penetration scenarios. *International Journal of Hydrogen Energy*, 35(18):10024–10030, 2010.

[8] Nathaniel Baum-Snow and Matthew E Kahn. The effects of new public projects to expand urban rail transit. *Journal of Public Economics*, 77(2):241–263, 2000.

[9] John L Bowman and Moshe E Ben-Akiva. Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research Part A: Policy and Practice*, 35(1):1–28, 2001.

[10] U.S. Census Bureau. 2010 census. U.S. Department of Commerce, February 2011.

[11] Kenneth Button and Erik Verhoef. *Road pricing, traffic congestion and the environment*. Edward Elgar Publishing, 1998.

[12] Anthony Chen, Chao Yang, Sirisak Kongsomsaksakul, and Ming Lee. Network-based accessibility measures for vulnerability analysis of degradable transportation networks. *Networks and Spatial Economics*, 7(3):241–256, 2007.

[13] Sharon Cullinane. Attitudes towards the car in the uk: some implications for policies on congestion and the environment. *Transportation Research Part A: Policy and Practice*, 26(4):291–301, 1992.

[14] Joyce Dargay and Dermot Gately. Income's effect on car and vehicle ownership, worldwide: 1960–2015. *Transportation Research Part A: Policy and Practice*, 33(2):101–138, 1999.

[15] EIA. Methodologies for estimating fuel consumption using the 2009 national household travel survey. Technical report, Federal Highway Administration, 2011.

[16] Margaret J Eppstein, David K Grover, Jeffrey S Marshall, and Donna M Rizzo. An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy Policy*, 39(6):3789–3802, 2011.

[17] Daniel J Fagnant and Kara Kockelman. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, 77:167–181, 2015.

[18] Daniel J Fagnant and Kara M Kockelman. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in austin, texas. *Transportation*, 45(1):143–158, 2018.

[19] Daniel J Fagnant, Kara M Kockelman, and Prateek Bansal. Operations of shared autonomous vehicle fleet for austin, texas, market. *Transportation Research Record: Journal of the Transportation Research Board*, (2536):98–106, 2015.

[20] Erik Ferguson. The rise and fall of the american carpool: 1970–1990. *Transportation*, 24(4):349–376, 1997.

[21] Lasse Fridstrøm, Vegard Østli, and Kjell Werner Johansen. A stock-flow cohort model of the national car fleet. *European Transport Research Review*, 8(3):22, 2016.

[22] Satoshi Fujii and Tommy Gärling. Application of attitude theory for improved predictive accuracy of stated preference methods in travel demand analysis. *Transportation Research Part A: Policy and Practice*, 37(4):389–402, 2003.

[23] Robert Hahn and Robert Metcalfe. The ridesharing revolution: Economic survey and synthesis. Technical report, mimeo, 2017.

[24] Gregory K Ingram and Zhi Liu. *Motorization and the Provision of Roads in Countries and Cities*, volume 1842. World Bank Publications, 1997.

[25] Chang-Hyeon Joh, HJP Timmermans, and TA Arentze. Measuring and predicting adaptation behavior in multidimensional activity-travel patterns. *Transportmetrica*, 2(2):153–173, 2006.

[26] Jeffrey A Joireman, Paul AM Lange, Mark Vugt, Amanda Wood, Tricia Vander Leest, and Chris Lambert. Structural solutions to social dilemmas: A field study on commuters? willingness to fund improvements in public transit. *Journal of Applied Social Psychology*, 31(3):504–526, 2001.

[27] Gerard de Jong, James Fox, Andrew Daly, Marits Pieters, and Remko Smit. Comparison of car ownership models. *Transport Reviews*, 24(4):379–408, 2004.

[28] Ralph L Keeney and Howard Raiffa. *Decisions with multiple objectives: preferences and value trade-offs*. Cambridge university press, 1993.

[29] René Kemp et al. Sustainable technologies do not exist. *Ekonomiaz*, 3:2–17, 2010.

[30] Peter H Kobos, Jon D Erickson, and Thomas E Drennen. Scenario analysis of chinese passenger vehicle growth. *Contemporary Economic Policy*, 21(2):200–217, 2003.

[31] Zheng Li and David A Hensher. Congestion charging and car use: A review of stated preference and opinion studies and market monitoring evidence. *Transport Policy*, 20:47–61, 2012.

[32] Ziru Li, Yili Hong, and Zhongju Zhang. Do ride-sharing services a ffect traffic congestion? an empirical study of uber entry. 2016.

[33] Ziru Li, Yili Hong, and Zhongju Zhang. An empirical analysis of on-demand ride sharing and traffic congestion. 2016.

[34] Todd Litman. Integrating public health objectives in transportation decision-making. *American Journal of Health Promotion*, 18(1):103–108, 2003.

[35] Todd Litman. Valuing transit service quality improvements. *Journal of Public transportation*, 11(2):3, 2008.

[36] Todd Litman. *Autonomous vehicle implementation predictions*. Victoria Transport Policy Institute, 2017.

[37] Tucker J Marion, Henri J Thevenot, and Timothy W Simpson. A cost-based methodology for evaluating product platform commonality sourcing decisions with two examples. *International Journal of Production Research*, 45(22):5285–5308, 2007.

[38] Elliot Martin, Susan Shaheen, and Jeffrey Lidicker. Impact of carsharing on household vehicle holdings: Results from north american shared-use vehicle survey. *Transportation Research Record: Journal of the Transportation Research Board*, (2143):150–158, 2010.

[39] Tina Nikou and Leidy Klotz. Application of multi-attribute utility theory for sustainable energy decisions in commercial buildings: A case study. *Smart and Sustainable Built Environment*, 3(3):207–222, 2014.

[40] Norbert Oppenheim et al. *Urban travel demand modeling: From individual choices to general equilibrium.* John Wiley and Sons, 1995.

[41] Jeppe Husted Rich and Otto Anker Nielsen. A microeconomic model for car ownership, residence and work location. In *Proceedings of the AET European Transport conference, held 10-12 September, 2001, Homerton College, CAMBRIDGE, UK-CD-ROM*, 2001.

[42] Adella Santos, Nancy McGuckin, Hikari Yukiko Nakamoto, Danielle Gray, and Susan Liss. Summary of travel trends: 2009 national household travel survey. Technical report, 2011.

[43] Georgina Santos and Jasvinder Bhakar. The impact of the london congestion charging scheme on the generalised cost of car commuters to the city of london from a value of travel time savings perspective. *Transport Policy*, 13(1):22–33, 2006.

[44] Andreas W. Schäfer. Long-term trends in domestic us passenger travel: The past 110 years and the next 90. *Transportation*, 44(2):293–310, 2017.

[45] Brandon Schoettle and Michael Sivak. Potential impact of self-driving vehicles on household vehicle demand and usage. 2015.

[46] SP Shepherd. A review of system dynamics models applied in transportation. *Transportmetrica B: Transport Dynamics*, 2(2):83–105, 2014.

[47] Yoram Shiftan and Moshe Ben-Akiva. A practical policy-sensitive, activity-based, travel-demand model. *The Annals of Regional Science*, 47(3):517–541, 2011.

[48] William Sierzchula, Sjoerd Bakker, Kees Maat, and Bert van Wee. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, 68:183–194, 2014.

[49] Brandon Tingley. Improvements to existing transit detection algorithms and their comparison. *Astronomy & Astrophysics*, 408(1):L5–L7, 2003.

[50] John Von Neumann and Oskar Morgenstern. *Theory of games and economic behavior*. Princeton university press, 2007.

[51] Zia Wadud, Daniel J Graham, and Robert B Noland. Modelling fuel demand for different socio-economic groups. *Applied Energy*, 86(12):2740–2749, 2009.

[52] Gerard Whelan. Methodological advances in modelling and forecasting car ownership in great britain. In *Proceedings of the AET European Transport conference, held 10-12 September, 2001, Homerton College, CAMBRIDGE, UK-CD-ROM*, 2001.

[53] Enjian Yao and Takayuki Morikawa. A study of on integrated intercity travel demand model. *Transportation Research Part A: Policy and Practice*, 39(4):367–381, 2005.

[54] Hong Yao and Dongmei Chen. A system dynamics model for urban sustainable transportation planning. In *Geoinformatics, 2015 23rd International Conference on*, pages 1–5. IEEE, 2015.

[55] Junyi Zhang, Harry Timmermans, Aloys Borgers, and Donggen Wang. Modeling traveler choice behavior using the concepts of relative utility and relative interest. *Transportation Research Part B: Methodological*, 38(3):215–234, 2004.

[56] Ming Zhang and Binbin Chen. Future travel demand and its implications for transportation infrastructure investments in the texas triangle. Technical report, University of Texas at Austin, March 2009.

[57] Yan Zhou, Michael Wang, Han Hao, Larry Johnson, and Hewu Wang. Plug-in electric vehicle market penetration and incentives: a global review. *Mitigation and Adaptation Strategies for Global Change*, 20(5):777–795, 2015.

[58] J Zmud, IN Sener, and J Wagner. Consumer acceptance and travel behavior impacts of automated vehicles. *Texas A&M Transportation Institute: PRC*, 2016.

[59] Johanna Zmud, Liisa Ecola, Peter Phleps, and Irene Feige. *The future of mobility.* RAND Corporation, 2013.