TRANSITIONING TO A CONNECTED AND AUTOMATED VEHICLE ENVIRONMENT:

Opportunities for Improving Transportation

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Corey David Harper

B.S., Civil & Environmental Engineering, Morgan State University

M.S., Civil & Environmental Engineering, Carnegie Mellon University

Carnegie Mellon University

Pittsburgh, Pennsylvania

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Thesis Committee Members

Chris T. Hendrickson

Hamerschlag University Professor Emeritus

Director, Traffic 21 Institute

Civil & Environmental Engineering

Engineering & Public Policy

Heinz School of Public Policy

Constantine Samaras

Assistant Professor

Director, Center for Engineering and Resilience for Climate Adaptation

Civil & Environmental Engineering

Allen Biehler

Distinguished Service Professor of Transportation Systems Emeritus

Heinz School of Public Policy

Zhen (Sean) Qian

Assistant Professor

Director, Mobility Data Analytics Center

Civil & Environmental Engineering

Heinz School of Public Policy

Scott Matthews

Professor

Civil & Environmental Engineering

Engineering & Public Policy

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Abstract

Over the past few years automotive and technology companies have made significant advances in what has been traditionally a completely human function: driving. Crash avoidance features such as lane departure warning and forward collision warning are becoming increasingly more common and cheaper to obtain, even on non-luxury vehicles. Technology companies and auto manufacturers have announced plans to have self-driving vehicles ready for public use as early as 2020. The mass adoption of automated vehicles (AVs) could significantly change surface transportation as we know it today. This thesis is intended to provide a technical analysis of the potential impacts of AVs on current light-duty vehicle miles traveled (VMT) and parking decisions, the economic desirability of widespread deployment of partially automated technologies, and methods for existing roadways to transition to connected and automated vehicle (CAV) transportation, so that policymakers can make more informed decisions during the transition to CAVs. This work takes a look at AVs from a point in time where vehicles are equipped with driver assistance systems (Level 1) to a point in time where AVs are driverless (Level 5) and can self-park.

The results of this work indicate that the fleet-wide adoption of partially automated crash avoidance technologies could provide net-benefit of about $4 billion at current system effectiveness and could provide an annual net-benefit up to $202 billion if all relevant crashes could be prevented. About 25% of all crashes could be addressed by the crash avoidance technologies examined in this dissertation. Over time, as technologies become more effective and cheaper due to economies of scale, greater benefits than the $4 billion could be realized.

As automated technologies become more advanced and widespread, existing roadways will need to be able to accommodate these vehicles. This work investigates the effects of a dedicated truck platoon lane on congestion on the Pennsylvania Turnpike and provides a method for existing roadways and highways to determine viable platoon demonstration sites. The initial results suggest that there are several sections of turnpike that could serve as commercial truck platoon demonstration site while still providing a high LOS to all other vehicles.

Once AVs can safely and legally drive unoccupied, vehicles will no longer be limited to their driver's destination and can search for cheaper parking in more distant parking locations. This work simulates a fleet of privately owned vehicles (POVs) in search of cheaper parking in Seattle, using a rectangular grid throughout the study area. Model results indicate that we are not

likely to see significant increase in vehicle miles traveled (VMT) and energy use from cars moving from downtown parking lots to cheaper parking in distance locations but at higher penetration rates, parking lot revenues could likely decline to the point where operating a lot is unsustainable economically, if no parking demand management policies are implemented.

Driverless vehicles also promise to increase mobility for those in underserved populations. This work estimates bounds on the potential increases in travel in a fully automated vehicle environment due to an increase in mobility from the non-driving and senior populations and people with travel-restrictive medical conditions. Three demand wedges were established in order to conduct a first-order bounding analysis. The combination of the results from all three demand wedges represents an upper bound of 295 billion miles or a 14% increase in annual light-duty VMT for the US population 19 and older. AV technology holds much promise in providing a more accessible and safe transportation system. This thesis can help policymakers and stakeholders maximize the benefits and minimize the challenges.

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Chapter 1: Introduction

1.1 General Motivation

Modern economies rely heavily on transportation systems. Sustainable and efficient operation of our nation's transportation system significantly contributes to the economic and social well-being of our society. Because our roadways are human developed systems and are occupied and currently utilized by human drivers, there are a number of negative impacts such as congestion and crashes. The National Highway Traffic Safety Administration (NHTSA) reported that there were about 35,000 road fatalities in 2015, the largest increase in traffic deaths in the past 50 years (NHTSA 2016b). Crashes contribute significantly to congestion, which costs Americans about $124 billion annually with about $78 billion resulting from time and fuel wasted in traffic and $45 billion from indirect costs passed onto American consumers (Guerrine 2014). In addition, many Americans have difficulty traveling freely and independently and spend large amounts of time searching for parking in dense urban areas (Anderson et al. 2014).

Automated vehicle technologies have the potential to greatly improve travel by reducing congestion, travel times, crashes, and potentially energy consumption, as well as enabling greater mobility for the disabled and elderly (Anderson et al. 2014; Harper et al. 2016b; a; Levin and Boyles 2015; Mersky and Samaras 2016; Wadud et al. 2016). Ride-sharing services could lead to a shift from personal car ownership to shared mobility (Schiller 2016), while driverless parking technologies could lead to significant changes in land use and urban form due to reduced parking demand in downtown and dense urban areas where parking costs are relatively high (Anderson et al. 2014). Some architectural companies are already preparing for for a future with self-driving cars by building parking structures that can be easily converted into an office or work space (Findling 2017). In addition, this technology could change the value of travel time for both passengers and "drivers" by shifting the burden of driving on the car so that users can now work on their laptops, eat a meal, or call family and friends, safely, on their way to work and other destinations.

Automated vehicle (AV) technologies are advancing rapidly and highly automated vehicles could be on streets and highways within the next decade. Many automakers are already marketing cars with some automated features such as adaptive cruise control and active lane keeping technologies (Newcomb and Colon 2017) and are progressively working to develop more highly automated and self-driving vehicles. Tesla motors has been equipping every new Model S sedan and Model X SUV with the necessary technology for full self-driving capability, in exchange for about $8,000 (Stewart 2017). Ride-sharing company Uber has deployed a fleet of self-driving cars in Pittsburgh, Pennsylvania and several other cities, and has offered some customers the option of riding in these vehicles, with human drivers present to take control when the AV encounters difficulties (Brian 2016; Zurschmeide 2016). In September of 2016 the United States Department of Transportation (USDOT) released a federal policy on AVs, which provides guidelines to manufacturers and other entities in the safe design, development, testing, and deployment of highly automated vehicles (HAVs) (NHTSA 2016a). The mass adoption of AVs could significantly change surface transportation as we know it today.

Although AVs possess many advantages, there are still many barriers that stand in the way of transitioning to a fully automated light-duty vehicle fleet. Cybersecurity concerns associated with highly automated vehicles still exist, as outlined in the National Highway Safety Administration's (NHTSA) Preliminary Statement of Policy Concerning Automated Vehicles (NHTSA 2013a). At both the state and federal levels there are currently no regulations established beyond testing purposes for AVs. Furthermore, how insurance company business models and liability laws will be affected by this technology are unclear at this point. To aid the development of effective policies and legislation, transportation researchers and professionals must first assess the safety, infrastructure, and environmental implications of AVs.

This thesis focuses on several analyses, assessing how connected and automated vehicles could impact parking and travel demand as well as the number of crashes that occur each year so that policymakers can plan for a smooth transition to a highly automated light-duty vehicle fleet. It also outlines recommendations for policymakers at the state and federal government levels so they can accommodate and further encourage populations with historically lower mobility to use shared mobility services. In order to conduct these analyses, we use various transportation datasets, which provide us with the best information to bound the future of vehicle automation. To date, there has not been significant sector-specific research done exploring the policy and economic implications of this revolutionary technology, which is necessary for policymakers to make effective policies. This work is meant to aid policymakers in making more informed decisions and ensuring socially optimal outcomes during the transition to CAVs. In addition, I hope that this research serves as a foundation for impactful research in the future.

1.2 Research Topics & Automated Vehicle Level Definitions

This dissertation research examines the likely implications of AVs through a four-part assessment, as follows:

- Project 1: Potential Economic and Safety Impacts of Driver Assistance Systems
- Project 2: Transitioning to Connected and Automated Vehicle Transportation
- Project 3: An Agent-Based Driverless Vehicle Parking Decision Model, and
- Project 4: Potential Travel Demand impacts from New Demand from New Users

Project 1 examines the costs (technology purchasing costs) and benefits (less severe and prevented crashes) of fleet-wide deployment of driver assistance systems or Level 1 AV technologies. This chapter explores the economic feasibility of equipping the light-duty vehicle fleet with crash avoidance technologies and discusses the potential impacts this could have on the number of crashes that occur annually. A version of this chapter (Harper et al. 2016a) has been published in the peer-reviewed journal, *Accident Analysis and Prevention,* and presented at the 96th Annual Transportation Research Board Meeting.

Project 2 characterizes near and long-term scenarios for existing roadways to begin transitioning to an automated highway system and focuses on commercial truck platooning (Level 3 and above). Specific recommendations for potential platoon demonstration sites and characteristics are identified. This set of chapters also assesses the economic and highway capacity implications of the proposed changes. We use the Pennsylvania Turnpike as a case study for this analysis but the results and recommendations found within this chapter could be applied to other existing roadways as well. A version of this section will be submitted for review for presentation in the 97th annual Transportation Research Board Meeting.

Project 3 of this work transitions from partially automated to driverless vehicles (Level 5) and offers a detailed look into the parking decisions of AVs that are no longer limited to their driver's destination. This chapter uses Seattle parking lot information to investigate the potential travel, economic, and energy implications of changes in parking decisions due to vehicle automation (focuses on personally owned vehicles). This work assumes a rectangular gridded network with perfect connectivity. This work captures market penetration rates from the point in time where AVs have only been partially adopted by those in higher income households to a point in time where AVs transition from high-income early adopters to total market penetration and varies base-parameter settings to understand how they impact performance outcomes. A version of this section is under review for publication in *Transportation Research Part C: Emerging Technologies*.

Project 4 is a bounding exercise looking at how driverless vehicles could increase mobility for those in underserved populations. This chapter presents an overview of the current travel characteristics for the elderly, non-drivers, and those with medical conditions. By creating three-demand wedges we are able to conduct a first-order bounding analysis in order to estimate the upper bound increase in vehicle miles traveled (VMT) for underserved populations. The bounding estimate is meant to identify which demographics could increase their travel the most and highlight those age groups and genders within each population that will contribute most to the increases. A version of this section (Harper et al. 2016b) has been published in the peer-reviewed journal, *Transportation Research Part C: Emerging Technologies*, and presented at the 94th Transportation Research Board Meeting.

In September 2016, the United States Department of Transportation (USDOT) announced that it now uses Society of Automotive Engineer's (SAE) six level of automation in its Federal Automated Vehicles Policy report (NHTSA 2016a; SAE International 2016). Figure 1.1 (shown below) provides a visual representation of SAE's six levels of automation definitions using emojis. The following automation levels summarize the SAE definitions:

Level 0: No Automation. The full-time performance by the human driver of all aspects of the dynamic driving task, even when enhanced by warning or intervention systems

Level 1: Driver Assistance. The driving mode-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the human driver performs all remaining aspects of the dynamic driving task.

Level 2: Partial Automation. The driving mode-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration using information about the driving environment and with the expectation that the human driver performs all remaining aspects of the dynamic driving task.

Level 3: Conditional Automation. The driving mode-specific performance by an Automated Driving System of all aspects of the dynamic driving task with the expectation that the human driver will respond appropriately to a request to intervene.

Level 4: High Automation. The driving mode-specific performance by an Automated Driving System of all aspects of the dynamic driving task, even if a human driver does not respond appropriately to a request to intervene.

Level 5: Full Automation. The full-time performance by an Automated Driving System of all aspects of the dynamic driving task under all roadway and environmental conditions that can be managed by a human driver.

Level	Name	Who is Driving?	Who is Monitoring?	Who Intervenes?
0	No Automation	😀	😀	😀
1	Driver Assist	😀🤖	😀	😀
2	Partial Automation	🤖😀	😀	😀
3	Conditional Automation	🤖	🤖	😀
4	High Automation	🤖	🤖	🤖😀
5	Full Automation	🤖	🤖	🤖

Figure 1.1 Society of Automotive Engineer International's Six Levels of Automation Depicted Using Emojis[1]

These levels of automation provide consistent terminology for use by transportation professionals, policymakers and researchers. While the National Highway Traffic Safety Administration (NHTSA) has developed an alternative 5-level (0-4) framework of driving automation for on-road vehicles (NHTSA, 2013), all discussions used in this document will refer to SAE's definitions.

1.3 Research Background

1.3.1 Safety

The number of road fatalities in the US has increased over the past two years. From 2014 to 2015 the total number of traffic deaths has increased from 32,500 to approximately 35,100, translating to a one year increase of about 7%. NHTSA along with the National Safety Council (NSC) are projecting that this trend will continue in 2016 (National Safety Council 2017; NHTSA

[1] Samaras, Constantine (@CostaSamaras). "For my talk today at Berkeley on safety & energy futures with robocars, I'm using emojis to describe the six levels of vehicle automation." February 17, 2017. Tweet.

2017). Figure 1.2 below shows the trend in traffic deaths per 100 million VMT from 1975-2015. The rate of crash deaths per 100 million miles traveled increased from an all-time low of 1.08 in 2014 to 1.12 in 2015 (IIHS 2016b).

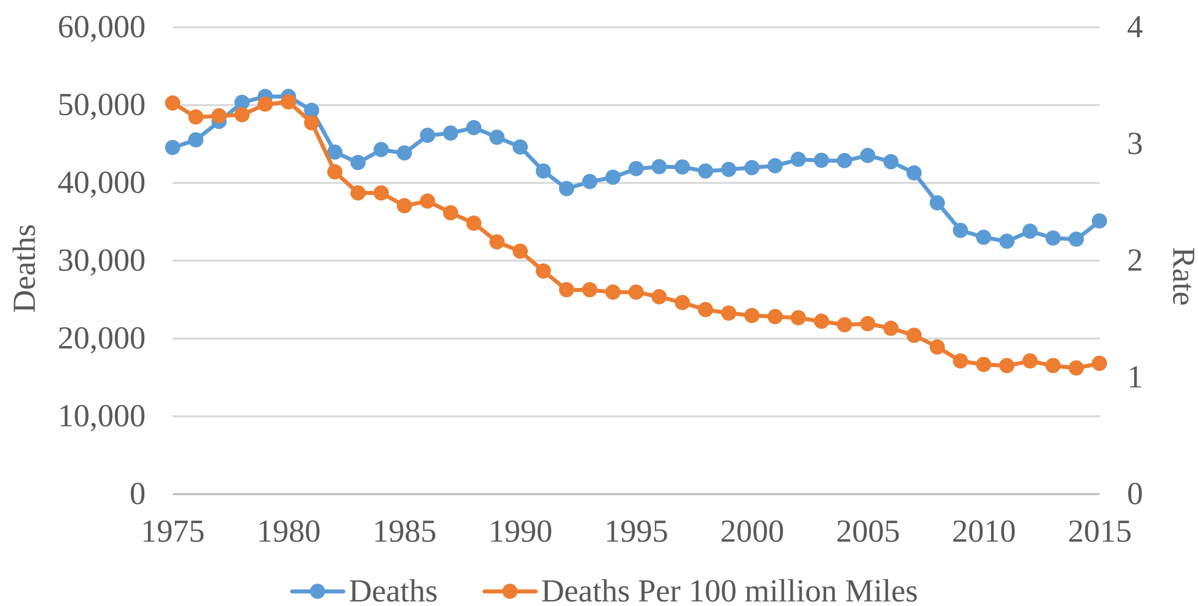


Figure 1.2 Motor Vehicle Crash Deaths and Deaths per 100 Million Miles, 1975-2015

Connected and automated vehicles could improve road safety by reducing the number crashes that result from human error (Harper et al. 2016a). Driver error is the primary cause of about 90% of all road crashes (Olarte 2011). Drunk driving, distracted driving, failure to stay in travel lane and failing to yield the right of way contribute to high number of crashes that occur each year. The Insurance Institute for Highway Safety (IIHS) estimates that if all vehicles had been equipped with forward collision warning (FCW) there would be about 700,000 fewer police reported crashes annually (IIHS 2016a). FCW is an example of a level 1 vehicle automation, since this technology assists in monitoring the roadway by providing an alert to the driver if there is an impending rear-end collision. The crash reduction potential of automation increases at each automation level, with the greatest reduction in crashes being at level 5 or driverless automation, where the car is in complete control of all driving functions. Chapter 2 explores the costs and benefits of fleet-wide partial automation and provides estimates on the number of crashes that could be made less severe or prevented if equipped on all light-duty vehicles.

1.3.2 *Platooning*

The trucking industry could greatly benefit from a more efficient commercial vehicle fleet. The average per mile cost of driving a heavy duty vehicle (HDV) is about $1.68 in $2013, with fuel accounting for about 38% of the total per mile cost followed by driver wages and benefits, which collectively account for about 33% of the total cost (Torrey and Murray 2015). Combination trucks comprise about 4% of the total number of registered highway vehicle in the US (Bureau of Transportation Statistics 2016), but account for approximately 23% of the total energy consumed by the transportation sector, in large part due to low fuel efficiency and the large amount of miles a truck travels annually to deliver goods (Energy Information Administration 2016). Looking into the future, trucking is likely to continue to have play a large role in energy use and GHG emissions for the transportation sector as truck transport is growing at more rapidly and this trend is likely to continue (Energy Information Administration 2014). According to the 2013 Pennsylvania Department of Transportation Statewide crash dataset, there were about 1,500 crashes that occurred on the Pennsylvania Turnpike in 2013. Out of these 1,500 crashes about 240 or 17% of crashes involved at least one HDV, including 3 fatal and 88 injury crashes. CAVs can potentially help reduce energy consumption and GHG emissions from the transportation sector as well as provide safety benefits in the form of prevented and less severe crashes. Platooning is a promising CAV technology that could experience widespread adoption over the next 5 to 10 years.

Platoons are groups of vehicles following closely behind one another at high speeds and communicate through connectivity. The first truck in the platoon serves as the lead vehicle with each successive vehicle in the platoon following the lead vehicle. Level 3 automation can permit platooning without driver intervention. Heavy duty vehicles traveling in a platoon can reduce fuel consumption anywhere between 4.5%-8%, depending on the time gap and travel speed, by reducing the drag force experienced by the trucks (Alam et al. 2010). This decrease in fuel consumption could reduce emissions from truck travel and save truck companies considerable amounts of money. Peloton, a CAV technology company, is currently testing its truck platooning technologies on the Ohio Turnpike (Christ 2017). In the future there could be dedicated lanes for truck platooning and special electronic passes to gain entry to these lanes. Although a dedicated platoon lane could provide fuel cost savings and crash prevention benefits, there could be adverse impacts on congestion. As a result, proper congestion impact analyses should be conducted before implementation. Chapter 3 focuses on the role of truck platooning in commercial trucks and the congestion implications of a dedicated truck platoon lane.

1.3.3 Parking

Parking in downtown urban areas can be a difficult experience for many drivers. The downtown lots and garages are usually relatively expensive and curb-parking while usually cheaper is usually overcrowded, which leads to large amounts of congestion from drivers cruising for parking to avoid paying for off-street parking. Shoup (2006) estimates that about 30% cars in our downtown urban areas are cruising for parking and argues that better management of our on-street parking could alleviate a lot of congestion that occurs from drivers looking for cheap parking (Shoup 2006). The city of San Francisco implemented a variable-rate parking program where on-street parking prices are adjusted based on demand to better ensure that there is always a space available, and also to reduce the amount of time spent searching for a parking space (San Francisco Municipal Transportation Agency 2014).

Although variable demand based parking is an important near-term step, level 5 or driverless AVs could eliminate the burdens and high costs associated with parking. We expect in an automated vehicle environment for AVs to be able to drop passengers off at his or her destination, park in a cheaper more distant cheaper parking location, and return to pick up the driver when ready. The cost of driving is inexpensive (AAA 2013) and could become cheaper as we transition to fully electric vehicles. Reducing parking demand in urban areas could change land use as garages and lots go out of business and are repurposed for other purposes, such as a store front, office space, or park (Findling 2017). Chapter 4 assesses the economic and travel demand implications of personally owned vehicles moving from the downtown parking lots and garages to cheaper more distant parking locations.

1.3.4 Mobility for Underserved Populations

Today's elderly and non-driving populations as well as those with medical conditions have trouble traveling freely and independently. The 2009 NHTS reports that out of 22 million adult non-drivers, approximately 9 million reports having a medical condition that makes it hard to travel and because of this condition about 8 out of the 9 million have reduced their day-to-day travel. In comparison, there are about 200 million adult drivers in the U.S. and out of this population about 14.7 million people report having a medical condition that makes it hard to travel and because of this medical condition 11.7 million have reduced their day-to-day travel. Figure 1.3 illustrates the percent of observed drivers 19 and older with travel-restrictive medical conditions with respect to the number of miles driven annually. In comparison to elderly drivers without any medical conditions, drivers with medical conditions travel far less. Close to 33% of the people within this population drive anywhere between 0-2,000 miles annually, while 65% of the population drives less than 8,000 miles annually. People within this population on average drive about 6,400 miles annually.

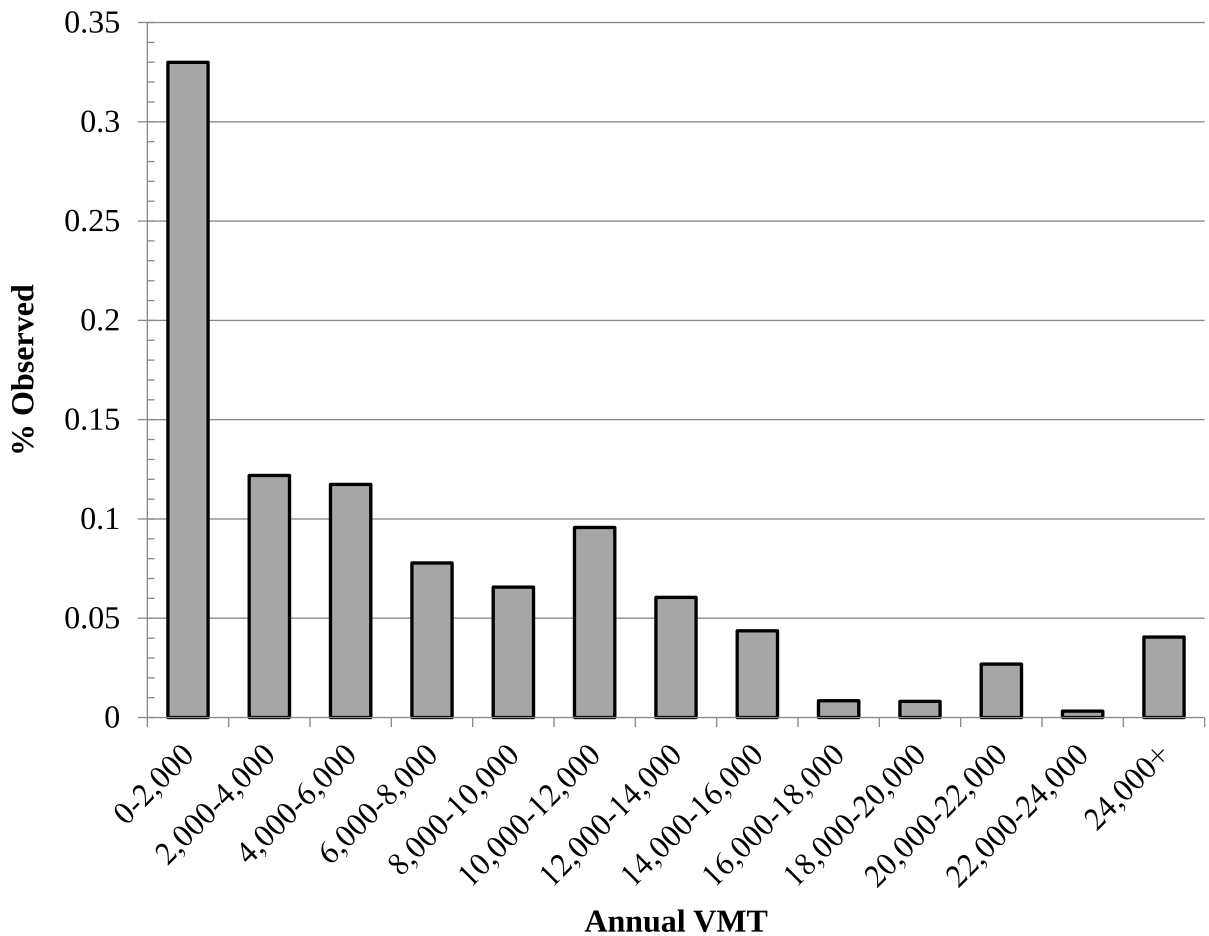


Figure 1.3 Distribution of the Percentage of Observed Elderly Drivers without Medical Condition Population Vehicle Miles Traveled

Level 5 vehicle automation could increase transportation access and mobility across a broad range of populations, including children under the age of 16. Currently the Washington

Metropolitan Area Transit Authority (WMATA) devotes about 20% or $93 million of its budget on paratransit services, which are high in cost because they require a trained and salaried driver to provide services (WMATA 2017). In an automated vehicle environment driverless shared-rides could supplement expensive paratransit services, especially for trips with medical purposes. The economic advantage of shared automated vehicles (SAVs) not only increases transportation accessibility but also social welfare as driver costs are eliminated and the cost of a trip is drastically reduced. In addition, access to more transportation options could provide access to better jobs and economic opportunities especially for those in populations with historically lower mobility (Shen 1998). SAVs could improve public transportation accessibility by providing first and last mile services to transit stops at a subsidized cost to users, but with cheaper SAV rides some users may substitute bus and rail trips with light-duty travel. Chapter 5 estimates bounds on the potential increases in travel in a fully automated vehicle environment due to an increase in mobility from populations with historically lower mobility.

Chapter 2: Cost and Benefit Estimates of Fleet-Wide Deployment of Partially Automated Crash Avoidance Technologies[2]

Many light-duty vehicle crashes occur due to human error and distracted driving. Partially-automated crash avoidance features offer the potential to reduce the frequency and severity of vehicle crashes that occur due to distracted driving and/or human error by assisting in maintaining control of the vehicle or issuing alerts if a potentially dangerous situation is detected. This chapter evaluates the benefits and costs of fleet-wide deployment of blind spot monitoring, lane departure warning, and forward collision warning crash avoidance systems within the US light-duty vehicle fleet. The three crash avoidance technologies could collectively prevent or reduce the severity of as many as 1.3 million U.S. crashes a year including 133,000 injury crashes and 10,100 fatal crashes. For this chapter we made two estimates of potential benefits in the United States: 1) the upper bound fleet-wide technology diffusion benefits by assuming all relevant crashes are avoided and 2) the lower bound fleet-wide benefits of the three technologies based on observed insurance data. This latter represents a lower bound as technology is improved over time and cost reduced with scale economies and technology improvement. All three technologies could collectively provide a lower bound annual benefit of about $18 billion if equipped on all light-duty vehicles. With 2015 pricing of safety options, the total annual costs to equip all light-duty vehicles with the three technologies would be about $13 billion, resulting in an annual net benefit of about $4 billion or a $20 per vehicle net benefit. By assuming all relevant crashes are avoided, the total upper bound annual net benefit from all three technologies combined is about $202 billion or an $861 per vehicle net benefit, at current technology costs. The technologies we are exploring in this chapter represent an early form of vehicle automation and a positive net benefit suggests the fleet-wide adoption of these technologies would be beneficial from an economic and social perspective.

[2]The results of this chapter have been published as: Harper, C. D., Hendrickson, C. T., & Samaras, C. (2016). Cost and Benefit Estimates of Partially-Automated Vehicle Collision Avoidance Technologies. *Accident Analysis & Prevention*, 95, 104-115.

2.1 Introduction

Many light-duty vehicle crashes occur due to human error and distracted driving. The National Highway Traffic Safety Administration (NHTSA) reports that ten percent of all fatal crashes and seventeen percent of injury crashes in 2011 were a result of distracted driving, while close to ninety percent of all crashes occur in part due to human error (National Highway Traffic Safety Administration 2013; Olarte 2011). Recent naturalistic driving data has confirmed the large prevalence of distracted driving and other driver-related factors in crashes (Dingus et al. 2016). Crash avoidance features offer the potential to substantially reduce the frequency and severity of vehicle crashes and deaths that occur due to distracted driving and/or human error by assisting in maintaining control of the vehicle or issuing alerts if a potentially dangerous situation is detected.

As the automobile industry transitions to partial vehicle automation, newer crash avoidance technologies are beginning to appear more frequently in non-luxury vehicles such as the Honda Accord and Mazda CX-9. The availability of Forward Collision Warning (FCW), Lane Departure Warning (LDW), and Blind Spot Monitoring (BSM) technologies could reach 95% of the registered vehicle fleet anywhere between the years 2032 and 2048 (HLDI 2014). The market penetration rate of these technologies depends on government mandates that could speed up implementation by up to 15 years (HLDI 2014). Automated vehicle technologies could have significant economic net benefits due to crash reduction (including direct cost savings and associated roadway congestion), enabling greater mobility for the disabled and elderly, and improved fuel economy due to more efficient driving (Anderson et al., 2014).

This chapter estimates the costs and benefits of fleet-wide deployment of BSM, LDW, and FCW crash avoidance systems within the U.S. light-duty vehicle fleet. Two estimates are made to provide insight on current trends and technology potential. First, an upper bound of relevant U.S. crashes that potentially could be avoided or made less severe by the three technologies is estimated, assuming 100% technology effectiveness. Next, a lower bound in U.S. crash reduction is estimated using current changes in observed insurance collision claim frequency and severity (average loss payment per claim) in motor vehicles with these technologies. After these estimates are made, an annualized cost to equip each vehicle with the technologies enables a cost benefit analysis for the lower bound and upper bound estimates of net benefits in the U.S. The technologies we are exploring in this chapter represent an early form of vehicle automation as defined by NHTSA (NHTSA, 2013b) and the estimates in this chapter can help inform near-term decisions during the transition to automation.

2.2 Literature Review

Several researchers have analyzed the effectiveness of crash avoidance technologies in reducing crashes and severity. For example, Jermakian (2011) estimates that side-view assist and FCW systems could potentially prevent or reduce the severity of as many as 395,000 and 1.2 million crashes involving passenger vehicles annually, respectively, using crash records from the 2004-2008 National Automotive Sampling System (NASS) General Estimate System (GES) and Fatality Analysis Reporting System (FARS) databases (Jermakian 2011). Kuehn et al. (2009) used insurance collision claims data along with human factors research and determined that equipping all cars with a forward collision warning and lateral guidance system that was 100% effective, could prevent up to 25% of all crashes (Kuehn et al. 2009). Sugimoto and Sauer (2005) estimated that a FCW system with autonomous braking could reduce the probability of a fatality in a rear end collision by as much 44% (Sugimoto and Sauer 2005). A 2012 study concluded that Blind Spot Monitoring (BSM) systems could potentially prevent or reduce the severity of 22,000 combination tractor-trailer crashes annually (Jermakian 2012). Kusano et al. (2014) developed a crash and injury simulation model in which each crash was simulated twice- once as it occurred and once as if the driver had a LDW system-and determined that a LDW system could potentially prevent up to 29.4 percent of all road departure crashes (Kusano et al. 2014). Blower (2013) used simulations and operational field tests to develop a range of estimates on the effectiveness of ESC, LDW, and FCW systems in reducing target crash types (Blower 2014). The American Automobile Association (AAA) along with the MIT AgeLab conducted a study in which they assessed and provided ratings for both the potential and real world benefits of LDW, FCW, ESC, and other crash avoidance technologies based on data gathered from published literature (Mehler et al. 2014). Blanco et al. (2016) estimated and compared crash risks for self-driving and national crash rates using data from Google's Self-Driving Car program and the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study. This study suggests that less-severe crashes may happen a much lower crash rate for self-driving cars (5.6 per million) when compared to the national crash rate (14.4 per million) (Blanco et al. 2016). The Insurance Institute for Highway Safety (IIHS) estimates that forward collision systems with automatic braking could reduce rear-end crashes by about 40% while standalone FCW could reduce these crashes by about 23% (IIHS

2016a).

Researchers have also attempted to estimate the economic benefit of crash avoidance technology systems. For a consistent comparison, we used the consumer price index (CPI) to convert all benefits in previous literature to $2012 (Bureau of Labor Statistics 2015). One prediction comes from Murray et al. (2009) who found that a FCW system in large trucks could provide a benefit ranging from $1.42 to $7.73 for every dollar spent on the system (Murray et al. 2009). This estimate is based on different vehicle miles traveled (VMTs), system efficacies, and technology purchase prices. Batelle (2007) reports that equipping all large trucks with a FCW system could have a negative net benefit approximately anywhere between -$66 and -27$ billion, depending on the cost of system and driver reaction time (Batelle 2007). In that study, crash reduction frequencies for a FCW system were derived from statistical modeling. Another study found that at a 90 percent market penetration rate FCW along with adaptive cruise control could provide considerable safety benefits- $52 billion in economic costs (lost productivity, travel delay, etc.) and 497,100 functional person-years (Li and Kockelman 2016). This chapter makes a contribution to the literature by estimating the economic net benefits of three crash avoidance technologies in light-duty vehicles based on changes in observed insurance collision claim frequency and severity for vehicles with BSM, LDW, and FCW crash avoidance systems. We extrapolate the observed insurance data to estimate a lower bound of fleet-wide deployment benefits. It represents a lower bound because technology cost and performance are likely to improve, and additional benefits are likely as deployment increases. To estimate an upper bound, we assume the three crash avoidance technologies examined are 100% effective in preventing relevant crashes.

2.3 Background on Datasets and Data Selection Methodology

To compute the upper bound annual net benefit of equipping all light-duty vehicles with BSM, LDW, and FCW systems, we first need to identify which types of crashes could potentially be prevented or made less severe by each technology. The primary sources of data used are the 2012 GES which provides information on crashes of all severities, the 2012 FARS which provides information on fatal crashes, and insurance data from various reports written by the Highway Loss Data Institute (HLDI). Table 2.1 (shown below) provides an overview of the primary data sources for this analysis and their use.

Table 2.1 Overview of Primary Data Sources and Their Use

Data Source	Use	Source
2012 National Automotive Sampling System (NASS) General Estimate System (GES)	Estimate Relevant Non-Fatal Crashes	NHTSA
2012 Fatality Analysis Reporting System (FARS)	Estimate Relevant Fatal Crashes	NHTSA
The 2010 Economic and Societal Impact of Motor Vehicle Crashes Report	Estimate Crash Cost	NHTSA
Basav et al. (2003) Analysis of Lane Change Crashes Report	Identify Lane Change Crashes in FARS and GES	NHTSA
Gordon et al. (2010) Safety Impact Methodology for Lane Departure Warning Report	Identify Lane Departure Crashes in FARS and GES	NHTSA
A Collection of Collision Avoidance Reports	Estimate Changes in Crash Frequency and Severity	Highway Loss Data Institute (HLDI)

2.3.1 Overview of Crash Avoidance Systems

As mentioned earlier, the crash avoidance systems we focus on for this chapter are FCW, LDW, and BSM. FCW systems are intended to detect objects ahead that are stationary or moving at a slower speed and issue a warning to the driver if his or her closing speed represents risk of an impending collision. LDW systems monitor the lane markings in the roadway and alerts the driver if they are drifting out of their own lane. BSM systems monitor the blind spots to the rear and sides of the car and issues a warning if a car enters the driver's blind spot. While these sensors serve the same purpose from vehicle to vehicle, their location on the vehicle could differ by manufacturer. For example, Honda's FCW system is located behind the windshield while Mercedes' and Acura's are located in the front bumper. Similarly, Mazda's BSM system is located in the rear bumpers, while Buick's system is located behind each rear quarter panel. Figure 2.1 illustrates how the three crash avoidance systems interact with the roadway.

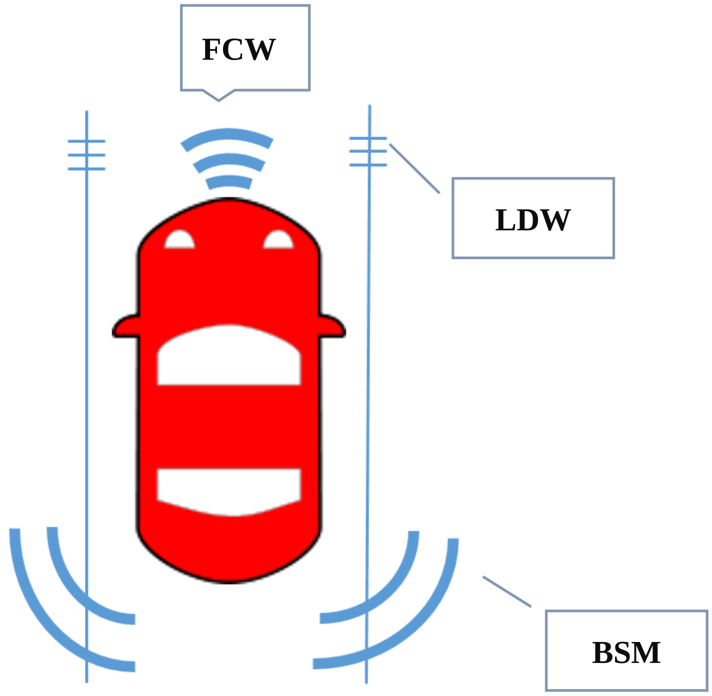


Figure 2.1 Lane Departure Warning (LDW), Forward Collision Warning (FCW), and Blind Spot Monitoring Roadway (BSM) Interaction

2.3.2 Background on the General Estimate System (GES) and Fatality Analysis Reporting System (FARS)

NHTSA annually collects information on both fatal and non-fatal motor vehicle crashes in the United States in order to aid researchers and other transportation professionals in evaluating the number of different crashes involving all types of vehicles and any relevant information regarding the crash that could be used to find and diagnose problems within traffic safety. Along with accident data, the 2012 GES and FARS datasets also include person and vehicle level data.

The 2012 GES attempts to represent the crash characteristics of the United States population on a national level and includes accidents of all severities. A weighting factor is provided for each person, vehicle, and accident included in the datasets. This weighting factor is the computed inference factor, which is intended to represent the total population from which the sample was drawn. The system has a population sample of about 62 thousand accidents that is representative of about 5.6 million crashes nationwide. All of the results presented in this report for non-fatal accidents were found using the full sample weights for the 2012 GES.

The 2012 FARS data contains information on every fatal crash occurring on a public roadway in the year 2012. In order for a crash to be included in the FARS dataset, the crash must result in the death of an occupant of a vehicle or a pedestrian within thirty days of the crash due to injuries suffered from the accident. Unlike the GES database, the FARS dataset does not include any weighted estimates since each fatal accident that meets the criteria outlined above is included in the dataset. All of the results presented in this reported related to fatal accidents were found using the 2012 FARS.

2.3.3 Data Selection Methodology

The 2012 NASS GES and FARS vehicle dataset contains information on in-transport vehicles and passengers. For all crash types, collisions that involved at least one light-duty passenger vehicles in the 2012 NASS GES and FARS files were used while all other crashes were truncated from the dataset. One and two vehicle crashes make up close to 94% of all vehicle crashes; evaluating three or more vehicle crashes adds complexity to the analysis for a small percentage of accidents, and as a result these were not considered. Crashes in the GES that were coded as fatal were excluded from the analysis since we were only interested in examining injury-related crashes from this dataset. In order to account for any missing data in the vehicle files, imputed data were used where available.

Target crash populations for each technology were established in order to sort crashes into identifiable categories, making it easier to estimate the relevant number crashes for each technology. For this analysis the three target populations are: lane-change crashes, lane-departure crashes, and rear-end collisions, which are most closely related to BSM, LDW, and FCW, respectively. These crash technologies are functional at certain speeds depending on the automaker. In order to identify vehicles that were traveling at a speed greater than or equal to the functional speed of the technologies in the vehicle file, the vehicle speed was taken into account. In cases where the vehicle speed was unknown, the roadway speed limit was considered due to the large percentage of unreported travel speeds. If the vehicle speed was unreported it is assumed that when the crash occurred, the vehicles involved were traveling at a speed greater than or equal to the reported speed limit. The functional speeds established for this analysis are 20, 40, and 20 miles per hour (MPH) for BSM, LDW, and FCW, respectively (HLDI 2011a, 2012a).

2.3.3.1 Blind Spot Monitoring

BSM systems are designed to alert the driver when a vehicle encroaches into their blind spot by using cameras or sensors to monitor areas to the side of a vehicle. BSM would be most useful in preventing or reducing the severity of lane change crashes. A lane-change crash was defined as where two vehicles were initially traveling along parallel paths in the same direction and the encroachment of one vehicle into the travel lane of another vehicle, was the primary reason for the crash occurring. The method used to identify lane-change crashes is outlined in Table 2..2, and a similar method was used for lane departure and rear-end crashes. Crashes that occurred off-road and crashes involving loss of control were not included in the target crash population, since we are only concerned with crashes that occur on a roadway that are not a result of loss of traction due to wet surface, etc. Additionally, in cases where it was not clear whether or not two vehicles were traveling in the same or opposite direction, or if it appears two vehicles were initially traveling in the same lane, these entries were eliminated from the dataset. System limitations that could affect the operation of BSM were also taken into account. BSM systems use sensors and cameras to detect nearby vehicles and could become unreliable in inclement weather (rain, sleet, snow). As a result, crashes that occurred in inclement weather were not considered. The filtering of the lane-change crashes was done by using the pre-crash movement, critical event, accident type, and vehicle speed variables. This target crash population includes only two-vehicle crashes. BSM may have avoided some of these omitted crashes, hence as a result the BSM savings estimate provided here is more conservative. More information regarding lane-change crashes can be found in NHTSA's analysis conducted by Basav et al. Analysis of Lane Change Crashes report (Basav et al. 2003).

Table 2.2 Methods Used to Identify Lane Change Crashes in GES

Filter #	SAS Code to Identify	Description
1	Identify which crashes involve at least one passenger car	Analysis concerned with crashes involving at least one passenger car.
2	if 44<= acc_typ<=49 or 70<=acc_typ<=75 and veh_invl=2	Selects accident types that a lane change crash could fall under and crashes that involved two vehicles
3	if not 1<= p_crash2 <=09	Eliminates Crashes involving loss of control.
4	if not 80<=p_crash2<= 92	Eliminates crashes involving pedestrians and pedal cyclists, animals, or other objects.
5	if not p_crash2= 54 62, 63, 67, 71, or 72	Eliminates crashes involving vehicles initially traveling or turning in the opposite direction.
6	if not p_crash2 = 59, 68, 73, or 78	Eliminates crashes where it is not clear if vehicles were initially traveling in same or opposite direction.
7	if not (acc_typ = 75 or 76 and p_crash2= 15 or 16) or (p_crash1 = 10 or 11)	Eliminates crashes that do not conform to the definition of lane change crashes.
8	if not p_crash2 = 50, 51, or 52 for one vehicle, and p_crash2 = 18 or 53 for the other vehicle	Eliminates crashes in which it appears the vehicles were initially traveling in the same lane are eliminated.
9	if 20<= speed <=151 or (speed=997) or (speed=998 or 999 and 20 <= spdlim)	Functional speed of Blind Spot Information 20+ mph.
10	if not weather ≠ 2,3,or 4	Eliminates crashes that took place in inclement weather

Source: Adopted from Basav et al.'s Analysis of Lane Change Crashes report (Basav et al. 2003).

2.3.3.2 Lane-Departure Warning

The crashes included in the lane-departure crash target population are assumed to be situations where a LDW system would be active. As a result, lane-departure crashes are defined as one where the vehicle inadvertently departs its travel lane and the driver of the vehicle is not actively maneuvering the vehicle other than the general intent of lane keeping. This target crash population includes both single and two-vehicle crashes. The crash scenarios examined for this analysis in which LDW would issue a warning are: prior lane keeping, lane departure and single-vehicle lane departure. The critical events that would correspond to a lane or road departure are: “vehicle traveling over left of lane”, "vehicle traveling over the right lane line", "vehicle off the edge of the road on the left side" and "vehicle off the edge of the road on the right side". “Going straight” and “negotiating a curve” were the pre-crash movements chosen for the lane departure scenario: prior lane-keeping, lane departure, where the vehicle was going straight or negotiating a curve (pre-crash movement) and at some point departed its lane (critical event). In addition to the pre-crash maneuvers of the vehicle, target crashes were also identified by looking at other factors such as whether the vehicle was involved in the first harmful event and its accident type, and the speed at which the vehicle was traveling. Because LDW uses cameras to monitor the vehicle’s position within the lane markers, crashes that occurred while there was snow on the roadway were filtered from the dataset. While LDW (similarly to BSM) warn of sideswipe crashes, the FARS and GES datasets do not indicate the driver’s intention (drift out of lane or active lane change), and as a result crashes with the pre-crash movement: “changing lanes” were not considered for the lane departure crash population. More information regarding LDW system crashes can be found in Gordon et al.’s Safety Impact Methodology for Lane Departure Warning report (Gordon et al. 2010).

2.3.3.3 Forward Collision Warning

FCW systems are designed to prevent or reduce the severity of rear-end collisions by using a camera or radar to detect whether a vehicle is approaching another object-vehicle, bicycle, or pedestrian- at an unsafe speed and issues alerts to the driver. In addition to FCW systems, some vehicles also include crash imminent braking (CIB) systems that apply autonomous braking to the vehicle after a warning has been issued. Rear-end collisions were identified in both the FARS and GES data sets by referring to the accident type variable. Accident type variable codes in GES 20-

29 correspond to a rear-end collision and were used to filter out accidents in which FCW systems would be active. Once the crashes that met the desired accident types listed above were identified, vehicle speed, pre-crash movement, and critical event were then taken into account. In cases where a lane change or merge occurred directly before the crash, these entries were eliminated since it is not clear whether or not a FCW system would have been effective in these scenarios. Crashes that occurred during inclement weather were filtered from the target crash population, since rain, snow, etc. could hinder the performance of the system. The pre-crash scenarios examined in this chapter that could lead to a rear-end crash are: the lead vehicle stopped, lead vehicle decelerating, and lead vehicle moving at lower constant speed. The rear-end collision target crash population only includes two-vehicle crashes.

2.3.4 Estimation of Crash Frequency and Crash Cost Reduction

To estimate the existing effectiveness of each technology, insurance data on changes in collision claim frequencies and severity (average loss payment per claim) were gathered from the HLDI (HLDI 2011b; c; a, 2012a; b, 2014). The HLDI derives its data by comparing the insurance records of vehicles with crash avoidance features against vehicles of the same model year and series assumed not to have any features.

First, it is assumed that a change (positive or negative) in collision claim frequency is the equivalent change in crash frequency for single and multiple-vehicle accidents. While not all accidents are reported to insurance companies and collision claim frequency does not mirror crash frequency, there is a relationship between the two statistics. Second, it is assumed that a change in collision claim severity is the equivalent change in crash cost for related accidents that are not prevented. Crash avoidance technologies could reduce crash severity, which should in turn reduce crash costs, as supported by the observed data.

The HLDI reports the number of insured years for each technology (blind spot monitoring, etc.) by vehicle make. To convert all reported values into a single value for each technology, a weighted average was calculated based on the total vehicle exposure. Specifically, the collision claim frequency of a technology by make with a higher exposure was weighted greater than those with a lower exposure. For example, if Hondas with FCW have a total exposure of 28,000 insured vehicle years and Volvos with FCW have a total exposure of 15,000 insured vehicle years, the change in collision insurance claim frequency for Hondas FCW system would contribute more to the final weighted average claim frequency for FCW than would that of Volvo. It should be noted that some of the insurance data reported by the HLDI for some vehicles are not statistically significant. Most crash avoidance technologies are fairly new and it is expected that they will improve with time.

2.4 Benefit Cost Analysis

The annual net benefit of crash avoidance systems is the difference between the total annual benefits and total annual costs and is expressed in Eq. (2.1):

$$NB = TB - TC \tag{2.1}$$

where NB is the annual net benefit, TB the total annual benefits, and TC is the total annual costs.

The total annual benefits are the savings that result from a reduction in crash frequency and crash costs due to the deployment of BSM, LDW, and FCW crash avoidance systems throughout the light-duty vehicle fleet. The total annual benefits of crash avoidance technologies for single and multiple-vehicle accidents are expressed in Eq. (2.2):

$$TB = CS_{CP} + CS_{LS} \tag{2.2}$$

where TB is the total annual benefit of equipping all light-duty vehicles with crash avoidance technologies, CS_{CP} the cost savings from crash prevention, CS_{LS} the cost savings from less severe crashes.

The total annual costs are the incremental annualized costs associated with equipping all light-duty vehicles in the vehicle fleet with the technologies. So the total costs can be expressed in Eq. (2.3):

$$TC = TP_C \tag{2.3}$$

where TC is the total annual costs of equipping all light-duty vehicles in vehicle fleet with BSM, LDW, and FCW crash avoidance systems, TP_C is the technology purchasing cost. Figure 2.2 (shown below) shows the processes and steps taken to estimate the technology purchasing costs, and upper and lower bound benefits and net benefits.

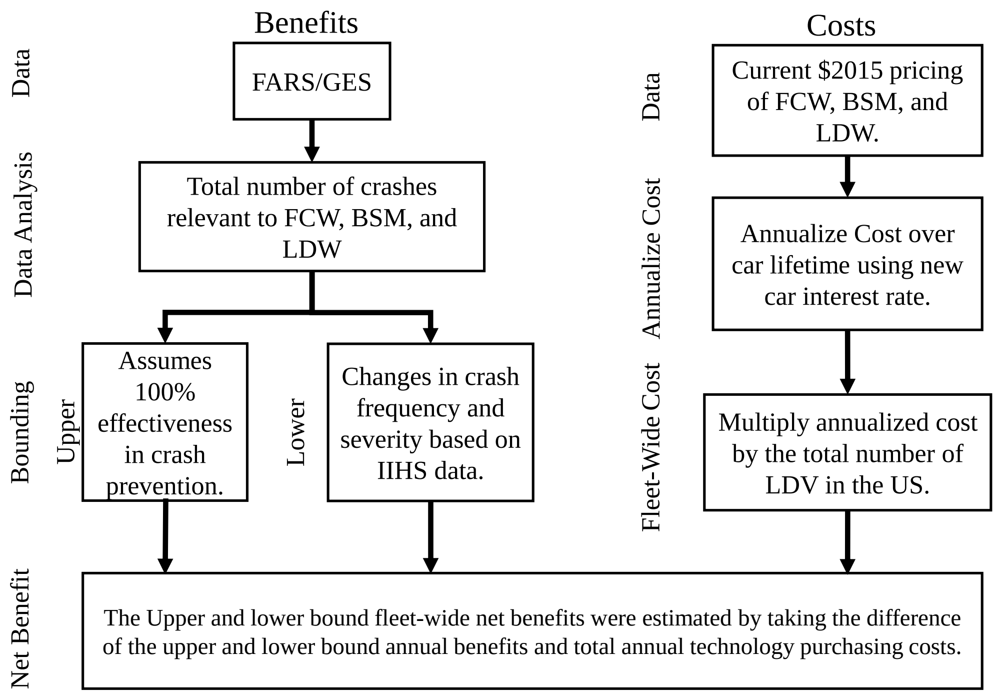


Figure 2.2 Flow Chart of Cost and Benefit Estimates Process for Costs and Benefits

2.4.1 Total Annual Benefits

The annual benefits of equipping all light-duty vehicles with the technologies come from a reduction in crash frequency and severity. Upper bound annual fleet-wide technology diffusion benefits are estimated by assuming all relevant crashes are avoided. Lower bound annual fleet-wide benefits are projected using crash frequency and severity reduction from current insurance data and estimated by applying observed changes in crash frequency to the total number of crashes that occurred in 2012 and changes in crash severity to relevant crashes not avoided.

Using the 2012 GES and FARS, we can generate estimates of relevant crashes for the technologies under consideration, and descriptive statistics about the sample sizes. We estimated that approximately 24 percent of the 5.6 million police reported crashes are relevant to at least one of the following three crash avoidance technologies: BSM, LDW, and FCW. With 100% effectiveness and deployment, the combination of all three technologies could prevent or reduce the severity of as many as 1.3 million crashes annually, including 133,000 injury crashes and 10,100 fatal crashes (See Table 2.3). Of the three technologies examined in in this chapter, FCW has the greatest potential to prevent or reduce the severity of the largest number of crashes overall. This technology could prevent or reduce the severity of close to 800,000 crashes or 14% of all crashes. The technology that could affect the largest number of fatal crashes is a LDW system, which has the potential to prevent or reduce the severity of up to 9,020 fatal crashes or 29% of all fatal crashes. BSM addresses the second most crashes of any severity out of all three technologies. There are about 267,000 crashes including 17,000 injury crashes and 280 fatal crashes, relevant to this technology. The standard errors of the estimates for non-fatal crashes are listed in Table 2.3. The dataset used to estimate fatal crashes for this analysis, FARS, contains data on each police reported fatal crash, and as a result has no standard error associated with its estimate. Standard errors for non-fatal crashes were estimated using NHTSA's 2013 Traffic Safety Facts Report (NHTSA 2014b).

Table 2.3 Relevant Crashes from the 2012 GES and FARS Data, Which Represent the Upper Bound that Potentially could be Prevented or Made Less Severe Annually by Crash Avoidance Technologies Given System Limitations

Technology	All Crashes	Injury Crashes (A or B)	Fatal Crashes	Non-Fatal Crash Standard Error
Blind Spot Monitoring	267,000	17,200	280	19,927
Lane Departure Warning	262,000	58,100	9,000	18,944
Forward Collision Warning	795,000	58,000	750	58,706
Total	1,320,000	133,000	10,100	99,678
Percent of Total Crashes	23.58%	8.16%	32.63%	N/A

Source: The 2012 National Automotive Sampling Survey General Estimate System and Fatality Analysis Reporting System Accident & Vehicle File, U.S. Department of Transportation.

Note: A or B refers to incapacitating and non-incapacitating injuries, respectively, as defined by the KABCO injury scale.

To estimate a lower bound fleet-wide reduction in crashes and severity, we use current insurance data for vehicles with these technologies and project the savings across assumed fleet-wide technology diffusion. Table 2.4 summarizes the change in crash frequency and severity for each crash avoidance technology from current insurance data. Vehicles with a FCW system show the greatest reductions in both collision claim frequency and severity. Collision claim frequency and severity for vehicles with this technology were reduced by about 4 percent and $225, respectively. BSM lowers collision claim frequency and severity by about 0.5 percent and $80, respectively. Vehicles with a BSM system have the lowest reduction in both collision claim frequency and severity. LDW has second highest reduction in both categories out of all three crash avoidance systems. This technology reduces both collision claim frequency and severity by about 1.2 percent and $155, respectively. Table 2.4 lists the exposure, measured in terms of insured years by technology for collision coverage. This statistic is intended to give the reader an idea of the total length of time the vehicles with the crash avoidance features examined in this study were insured under a given coverage type. The exposure for the control group, vehicles without any features, are not easily discernable from the data available online, and as a result are not reported in this chapter.

Table 2.4 Observed Changes in Crash Frequency and Cost and Collision Exposure By Crash Avoidance Technology ($2012)

Crash Avoidance Technology	Change in Collision Claim Frequency[a]	Change in Collision Claim Severity[a]	Collision Exposure[c]
Blind Spot Monitoring	-0.53%	-$80	439,600
Forward Collision Warning[b]	-3.97%	-$221	272,900
Lane Departure Warning	-1.21%	-$147	229,900
Average	-1.90%	-$149	N/A

Source: A collection of Collision Avoidance Reports written by the Highway Loss Data Institute (HLDI, 2014b, 2012a, 2012b, 2011a, 2011b, 2011c).

[a]Weighted Average Based on Vehicle Exposure

[b]Some of the vehicles included in this estimate had a forward collision warning system that includes autonomous emergency braking

[c]This column represents total exposure for each technology, measured in terms of insured vehicle years.

In 2010 there were approximately 5.4 million crashes that resulted in about 1.5 million injuries and 30,196 fatalities. The economic toll and societal harm of motor vehicle crashes that year totaled about $836 billion, which includes $242 billion in economic costs and $594 billion due to loss of life and decreased quality of life from injuries (Blincoe et al. 2015). This would result in each crash costing close to $154,000 in $2010. Because the crash data used for this chapter is from the year 2012, the Consumer Price Index (CPI) was used to find the total cost of a crash in 2012 dollars, which is approximately $162,400 or $47,021 in economic costs and $115,414 in quality-adjusted life years (QALYs) cost. Private Insurers cover $25,391 or about 16 percent of the total cost of a crash, while about 7 percent or $10,815 is paid by households. Third parties (uninvolved motorists in congestion, charities, etc.) pay about 5 percent or $7,523 of the total cost and public revenues pay about 2 percent or $3,291. The remaining 71% comes from costs associated with lost QALYs from injuries or fatalities.

The direct benefits of equipping all light-duty vehicles with crash avoidance technologies consist of the cost savings from crash prevention and less severe crashes. Indirect benefits include savings from increased QALYs from more people living healthier lives from avoided crashes. The economic savings from crash prevention explain that private insurers, households, third-parties, and public-revenue sources saved money since each crash avoidance technology prevents a number of crashes. If these crashes had occurred each entity would need to pay a percentage of the cost of each crash. The lower bound fleet-wide annual accident prevention cost savings is shown in Table 2.5. The values in this table were estimated by using the using the average change in collision claim frequency and severity from Table 2.3 along with the total number of crashes that occurred in the year 2012. Total crash prevention cost savings are the sum of the economic cost savings and the cost savings from increased QALYs. The calculation of the total lower bound annual crash prevention cost savings is based on the following formula:

$$
\begin{aligned}
&\textit{total current crash prevention cost savings} \\
&\quad = NC \times CF \times SC \\
&\quad = 5.6\ \textit{million crashes}\ \times 1.90\%\ \times \$162{,}400\ \textit{per crash} \\
&\quad = 106{,}872\ \textit{crashes}\ \times \$162{,}400\ \textit{per crash} \\
&\quad = \$17.4\ \textit{billion}
\end{aligned}
$$

$where,$

$NC = \textit{total number of crashes which occured in } 2012$

$CF = \textit{the average change in collision claim frequency for all three technologies}$

$(\textit{listed in column } 2 \textit{ of Table } 2.4)$

$SC = \textit{social cost of a crash}$

Less severe crash cost savings describe the savings to private insurers due to lower collision claim loss amounts. Because this chapter uses a bounding assumption on 100% effectiveness and deployment of crash avoidance technologies it is assumed that all relevant crashes not prevented will have a reduction in average severity. The calculation of the total lower bound annual cost savings from less severe crashes is based on the following formula:

$$
\begin{aligned}
&\textit{total current cost savings from less severe crashes} \\
&= NO \times CP \\
&= (1.3\ \textit{million crashes} - 106{,}478\ \textit{crashes}) \times \$149\ \textit{per crash} \\
&= 1.2\ \textit{million crashes} \times \$149\ \textit{per crash} \\
&= \$181\ \textit{million}
\end{aligned}
$$

$where,$

$NO = number\ of\ crashes\ expected\ to\ still\ occur\ from\ upper\ bound\ estimate$

$CP =\ average\ change\ change\ in\ collision\ claim\ severity\ for\ all\ three\ technologies$
$(listed\ in\ column\ 3\ of\ Table\ 2.4)$

The total annual benefits (TB) from cost savings due to less severe and prevented crashes were estimated using Eq. (2.2). As presented in Table 2.5, the total lower bound annual benefits are approximately \$18 billion. It is shown that the most important sources of benefits are cost savings from crash prevention (\$17 billion), and less severe crashes (\$180 million). In this estimation, cost savings from people living healthier lives are only based on crashes that were prevented by the crash avoidance technologies, since we are not aware of how each technology impacts injury severity if a crash does occur. Although, more crashes are assumed to have a reduction in average severity than prevented, crash prevention provides a far greater benefit since the cost savings from less severe crashes is very small compared to the cost savings from avoiding a crash.

In order to estimate an upper bound fleet-wide benefit from the three technologies we will assume that each technology is 100% effective in preventing crashes from their respective target crash population. The calculation of the total upper bound annual crash prevention cost savings is based on the following formula:

$$upper\ bound\ crash\ prevention\ cost\ savings$$
$$= M \times SC$$
$$= 1.3\ million\ crashes \times \$162{,}400\ per\ crash$$
$$= \$215\ billion$$

Where,

$M = upper\ bound\ estimate\ of\ crashes\ that\ could\ be\ prevented\ or\ made\ less\ severe\ by\ technologies\ (listed\ in\ column\ 2\ of\ Table\ 2)$

$SC = Social\ Cost\ of\ a\ Crash$

Table 2.5 shows the upper bound benefit from equipping all light duty vehicles with FCW, LDW, and BSM. If each technology could prevent all crashes from their respective target crash populations, they would collectively provide an annual benefit of $215 billion. The most significant cost saving technology is FCW, which could provide an annual benefit of up to $129 billion or 60% of the total upper bound benefit. The large potential economic benefit from this technology can be attributed to the high number of rear-end collisions that occur annually. BSM and LDW systems could provide an upper bound annual benefit of about $43 and $42 billion, respectively. The upper bound benefit is representative of what may be achievable from an economic perspective as these technologies become more effective and widespread. It should be noted that the upper bound annual benefit does not consider less severe crashes since all relevant crashes are assumed to be prevented.

Table 2.5 Estimation of Lower and Upper Bound Annual Benefits from Fleet-wide Deployment of Crash Avoidance Technologies in Light-Duty Vehicles

Item of Benefits	Monetary value of the benefits (Billion $2012)	
Crash Prevention Cost Savings	Lower Bound Benefits	Upper Bound Benefits
Private Insurers	$2.90	$35
Households	$1.40	$17
Third-Parties	$0.78	$10
Public Revenue	$0.50	$6.2
QALYs	$12	$147
Total cost savings from Crash Prevention (CS_{CP})	$17	$215
Cost savings from Less Severe Crashes (CS_{LS})	$0.18	$0
Total annual benefits of fleet-wide deployment of crash avoidance technologies in light-duty vehicles (TB)	$18	$215

Note: Figures may not sum exactly due to rounding.

By using Bureau of Transportation Statistics (BTS) data of the number of light-duty vehicles in the US in 2012, the annual upper and lower bound per vehicle benefits of fleet-wide deployment can be estimated. BTS estimates that there were approximately 234 million registered highway vehicles in the US in 2012 (Bureau of Transportation Statistics 2015). By dividing the number of light-duty vehicles by the total annual lower and upper bound benefits, we estimate a lower and upper bound per vehicle benefit of roughly $76 and $918, respectively.

2.4.2 Total Annual Costs

The total direct costs (TC) of fleet-wide crash avoidance technology deployment are the technology purchasing costs associated with purchasing a BSM, LDW, and FCW system for a bounded estimation where the entire light-duty vehicle fleet was equipped with these technologies, as shown in Eq. (3). This cost is annualized over the average lifetime of a vehicle in order to compare annual fleet-wide costs and benefits. Changes in car sales and travel lengths over time were not taken into account for this analysis. Most manufacturers offer the customer the option of adding a safety package onto higher model vehicles. When the three technologies were not a standard option, it is assumed for this analysis that the cost to add BSM, LDW, and FCW technologies to a vehicle is about $600, which is reflective of the current price drop in vehicle safety packages from Toyota (Lienert 2015). If the same technology was available in 2012 the price would have been about $582. While most other manufacturers offer the same safety package for around $2,100 we assume that they too will eventually decrease the price of their safety features in order to remain competitive. Since this chapter evaluates the annual net benefit, the total unit technology cost was converted to an equivalent uniform annual cost (EUAC) by assuming a vehicle lifetime of 14 years and an average car loan interest rate of 4.46% (Andriotis 2013; Ford 2012; Tuttle 2012). The total annual cost assumes that this equipment is placed on new vehicles and the cost to purchase the technologies is annualized over the lifetime of the vehicle. This would be the total annual cost to purchase the technologies if all of today's light-duty vehicles were replaced with new cars equipped with these three technologies. This resulted in an annualized cost of approximately $57 for each light-duty vehicle. The calculation of the total annual technology purchasing costs is based on the following formula:

$$
\begin{aligned}
&\mathit{total\ annual\ technology\ purchasing\ cost} \\
&= LDV \times VT \times [r/1-(1+r)^{-n}] \\
&= 234\ \mathit{million\ vehicles} \times \$582\ \mathit{per\ vehicle} \times 4.46\%/1-(1+4.46\%)^{-14} \\
&= 234\ \mathit{million\ vehicles} \times \$582\ \mathit{per\ vehicle} \times 0.098 \\
&= 234\ \mathit{million\ vehicles} \times \$57\ \mathit{per\ vehicle} \\
&= \$13\ \mathit{billion}\ \text{in total costs to equip LDV fleet with these technologies (TPc)}
\end{aligned}
$$

$\mathit{where,}$

$LDV = \mathit{total\ number\ of\ short\ base\ and\ long\ base\ light\ duty\ vehicles}$

$VT = \mathit{per\ vehicle\ technology\ purchasing\ cost}$

$r = \mathit{rate\ of\ return\ period}$

$n = \mathit{number\ of\ periods}$

According to the Bureau of Transportation Statistics, in 2012 there were approximately 234 million registered highway light-duty vehicles in the United States, which excludes motorcycles, buses, truck combinations, and single-unit trucks (Bureau of Transportation Statistics, 2015). The results above show that the total annual technology purchasing costs are about $13 billion.

2.4.3 Comparison of Benefits and Costs

In order to analyze the current economic feasibility, the annual net benefit (NB) was estimated from Eq. (2.1). The total annual benefits (TB) are the benefits that we would expect to accrue each year the vehicle is in operation from prevented and less severe crashes. The equivalent uniform annual costs (TC) are the total fleet-wide technology purchasing costs annualized over the lifetime of a vehicle. The annual net benefit is the difference between these two annual values.

It is shown in Figure 2.3 that the current lower bound annual net benefit of fleet-wide deployment of crash avoidance technologies in light-duty vehicles is positive, which means that the benefits currently exceed the costs. In monetary value, the lower bound annual expected net benefit of equipping all light-duty vehicles with a BSM, LDW, and FCW system is about $4 billion. When we compare annualized per vehicle cost and lower bound per vehicle benefits, the annual lower bound per vehicle net benefit is approximately $20. The positive net benefit can be largely attributed to the low cost of the technologies. The lower bound annual net benefit is assumed to be the lowest net benefit achievable by these technologies since technology cost and performance are likely to improve, and additional benefits are likely as deployment increases.

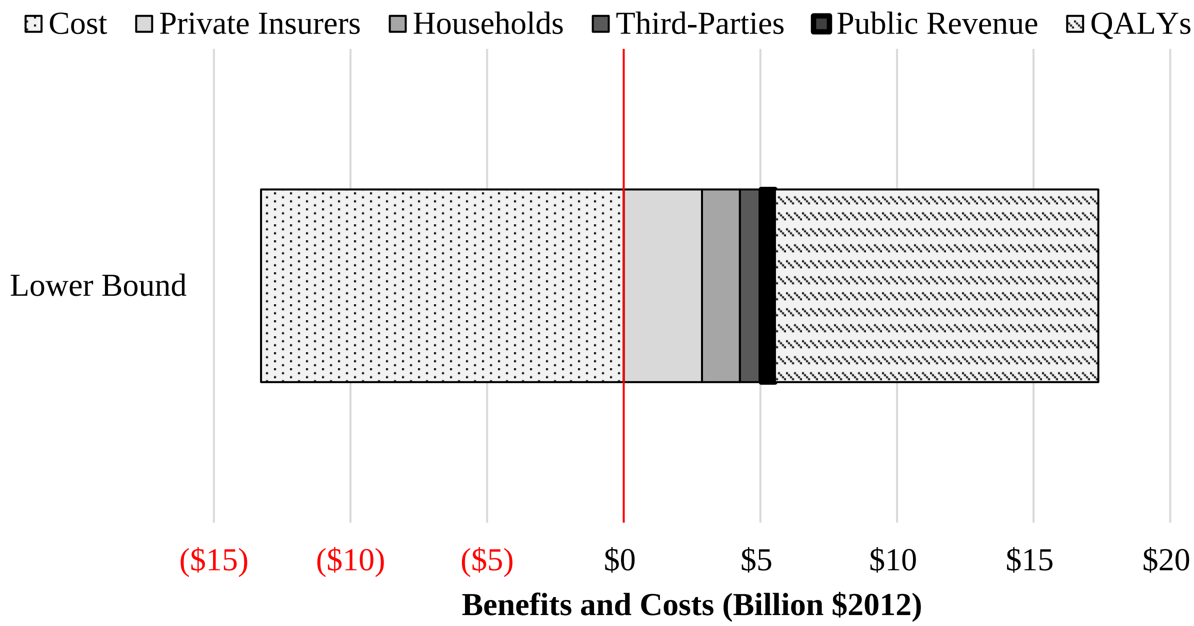
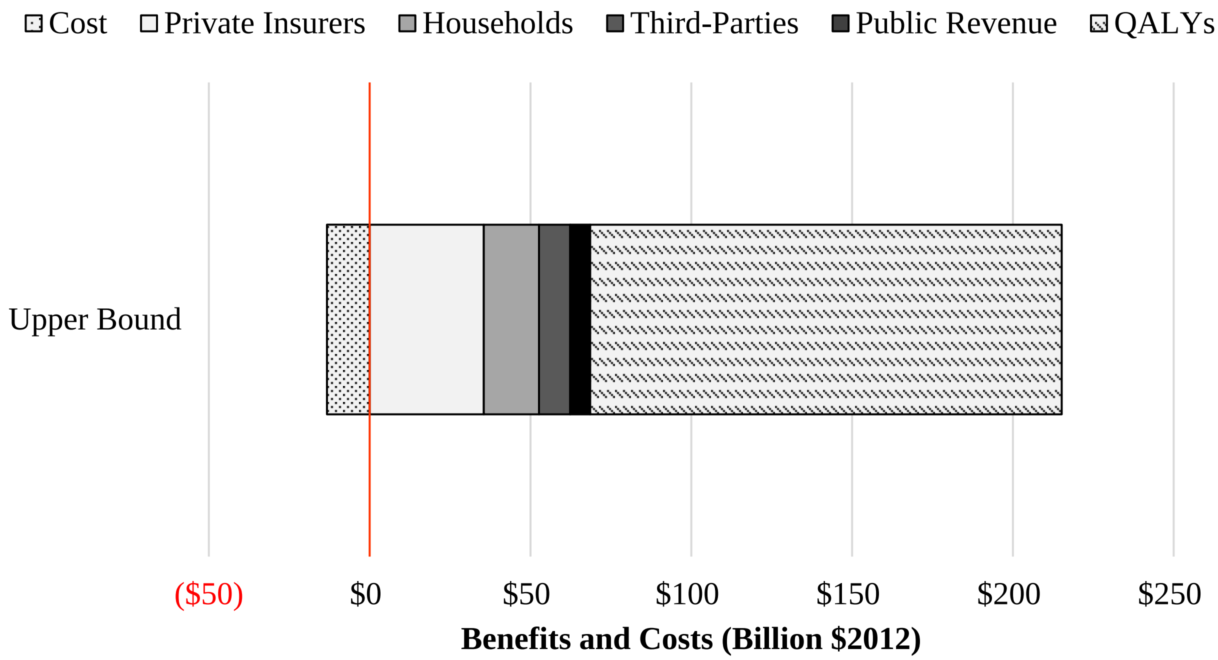


Figure 2.3 Approximately $4 Billion Annual Lower Bound Net Benefit of Fleet-wide Deployment of Crash Avoidance Technologies in Light-Duty Vehicle Fleet

Similarly to the lower bound annual net benefit, the upper bound annual net benefit is positive since the upper bound annual benefits far exceed current annualized technology costs. As shown in Figure 2.4, the upper bound annual net benefit from all three technologies collectively at current technology prices, is about $202 billion or an $861 per vehicle net benefit. The upper bound annual net benefit is assumed to be the highest net benefit achievable, depending on the current price of the crash avoidance technologies.



Note: Upper bound annual net benefit represents an upper bound that is dependent on the current price of crash avoidance technologies.

Figure 2.4 Approximately $202 Billion Annual Upper Bound Net Benefit of Fleet-wide Deployment of Crash Avoidance Technologies in Light-Duty Vehicle Fleet

2.4.4 Sensitivity Analysis

The current annual net benefit shown above are based on a variety of assumptions, the most significant being the annualized technology purchasing cost and the effectiveness of each technology in reducing crash frequency and severity. Improvements in all three categories could result in a higher annual net benefit. As shown, it is economically feasible to equip the entire light-duty vehicle fleet with the three crash avoidance technologies examined in this chapter. Higher annual net benefits can still be achieved either by lowering the cost of purchasing the technologies and/or making the technologies more effective in preventing and reducing the severity of crashes. In order to evaluate the impact other scenarios would have on the annual net benefit, two-way sensitivity analyses were conducted to examine how changes in the number of crashes prevented or a change in crash cost from less severe crashes along with the annualized technology cost per vehicle, would impact the annual net benefit.

Table 2.6 displays the sensitivity of the current annual net benefit to the annualized technology cost and the percentage of crashes prevented. A first prospective technology scenario, with conservative changes to the base case assumptions -annualized technology cost per vehicle of $40 and 10% reduction in crash frequency-would result in an annual net benefit of about $82 billion. A second prospective technology scenario with more aggressive changes to the base case assumptions-annualized technology cost per vehicle of $20 and 20% reduction in crash frequency-would result in an annual net benefit of about $178 billion.

Table 2.6 Annual Fleet-Wide Net Benefit from Changes in Crash Frequency and Technology Purchasing Costs (Billion $2012)

		Annualized Technology Cost per Vehicle ($2012)						
		$0	$20	$40	$60	$80	$100	$120
Percentage of Total 2012 Crashes Prevented	2%	$18	$13	$8	$3	-$1	-$6	-$11
	5%	$46	$41	$36	$32	$27	$22	$18
	10%	$91	$87	$82	$77	$73	$68	$63
	15%	$137	$132	$128	$123	$118	$114	$109
	20%	$182	$178	$173	$168	$164	$159	$154
	24%[a]	$215	$210	$206	$201	$196	$192	$187

Note: Areas shaded green indicate a positive annual net benefit whereas areas shaded yellow indicate a negative annual net benefit.

[a]Upper bound percentage of crashes that can be prevented, collectively by Lane Departure Warning, Forward Collision Warning, and Blind Spot Monitoring.

At low cost savings from less severe crashes, the annual net benefit is positive at most technology costs. At much higher technology costs than those assumed for the base case analysis, the net benefit remains positive at high crash prevention cost savings, but is negative at lower cost savings. While there are a much larger number of crashes assumed to be less severe than prevented, less severe crashes have a smaller impact on the net benefit. The sensitivity of the annual net benefit to the annualized technology cost and cost savings from less severe crashes is shown in Table 2.7.

Table 2.7 Annual Fleet-Wide Net Benefit from Changes in Crash and Technology Purchasing Costs (Billion $2012)

Cost Savings from Less Severe Crashes for Each Technology (Thousand $2012)	Annualized Technology Cost per Vehicle ($2012)						
	$0	$20	$40	$60	$80	$100	$120
$0	$18	$13	$8	$4	-$1	-$6	-$11
$2	$20	$15	$10	$6	$1	-$4	-$8
$4	$22	$18	$13	$8	$4	-$1	-$6
$6	$25	$20	$15	$11	$6	$1	-$3
$8	$27	$22	$18	$13	$8	$4	-$1
$10	$29	$25	$20	$16	$11	$6	$1
$12	$32	$27	$23	$18	$13	$9	$4
$14	$34	$30	$25	$20	$16	$11	$6

Note: Areas shaded green indicate a positive annual net benefit whereas areas shaded yellow indicate a negative annual net benefit.

2.5 Discussion

In this chapter a cost-benefit analysis of equipping the entire U.S. light-duty vehicle fleet with crash avoidance technologies is carried out based on the best available information about changes in collision insurance claim frequency and severity for vehicles with crash avoidance technologies. Insurance data was obtained from the HLDI and relevant crash data were from the 2012 FARS and GES datasets.

Approximately 24 percent of all crashes are relevant to one of the three crash avoidance technologies: blind spot monitoring, lane departure warning, and forward collision warning. All three technologies could collectively prevent or reduce the severity of as many as 1.3 million crashes a year including 133,000 injury crashes and 10,100 fatal crashes. FCW systems would address the greatest number of crashes overall and injury crashes, while a LDW could affect the largest number of fatal crashes.

In order to conduct a net benefit analysis to evaluate the economic feasibility of crash avoidance systems in light-duty vehicles, it was assumed crash frequency and crash cost mirrored changes in collision claim frequency and severity, respectively. If all three crash avoidance technologies were equipped on all light-duty vehicles, this would provide a lower bound annual benefit of about $18 billion with private insurers, households, and third-parties receiving annual benefits of about $2.9, $1.4, and $0.78 billion, respectively, from prevented and less severe crashes. Most of the benefit can be attributed to prevented crashes that accounts for almost 98% of the total benefit although a very small percentage of crashes are assumed to be prevented as opposed to less severe. With 2015 pricing safety options, the total annual cost to purchase all three technologies for the entire light-duty vehicle fleet would be about $13 billion-resulting in an annual lower bound net benefit of approximately $4 billion or a $20 per vehicle net benefit. The technologies we explore in this chapter represent an early form of vehicle automation and a positive net benefit suggests the fleet-wide adoption of these technologies would be beneficial from an economic and social perspective. Since the annual cost to purchase the crash avoidance technologies would come from household expenditures, all benefits to private insurers, third-parties, and public revenue sources should be realized when only considering technology purchasing costs.

If all three technologies could prevent all crashes in their respective target crash populations this would provide an upper bound annual benefit of about $215 billion. Of the three crash avoidance technologies examined in this chapter, FCW could provide the greatest annual benefit. This technology could provide an upper bound annual benefit of up to $129 billion or a per vehicle benefit of up to $551, due to the relatively large number of crashes this technology addresses. At 2015 technology costs, the upper bound annual net benefit is approximately $202 billion or an $816 per vehicle net benefit. According to the GES and FARS datasets, in 2012 collectively there were about 5,000 and 125,000 pedestrian and pedalcyclist fatalities and injuries, respectively, from crashes involving motor vehicles. While these crashes were not considered for this analysis, FCW could have considerable additional benefits by potentially reducing the frequency and severity of these crashes, resulting in higher economic benefits, which further supports the case that these technologies would provide a benefit if equipped on all vehicles.

The crash avoidance technologies examined in this chapter are fairly new and have only recently begun to appear in non-luxury cars. The HLDI estimates that in 2013 the three crash avoidance technologies examined in this chapter each came standard on about 2% of new car models. As a result, this is only a preliminary cost analysis as we expect the technologies to improve, costs decline, and diffusion increase - resulting in potentially higher changes in collision claim frequency and severity. In addition, some of the system limitations assumed for the current technologies in this analysis may not exist in the future and as result these technologies could become more effective in circumstances such as inclement weather, which would increase the number of relevant accidents, ultimately providing a larger benefit. One policy option for insurance companies would be to provide insurance premium discounts as an incentive to encourage drivers to adopt these technologies. As autonomous technology diffuses and starts to improve safety, there is the potential risk of an enhanced immunity fallacy (Will 2005; Will and Geller 2004), where occupants perceive a false sense of immunity from risk for injury in crashes. This could result in reduced use of seat belts or child restraints, which is not commensurate with the reduced risks. In the transition to partial vehicle automation, regulators take best practices from the risk perception literature should build upon previous efforts (Will 2005) to enhance risk communication.

While the results from net benefit analysis offer a new understanding of the economic benefits and costs of equipping the entire light-duty vehicle fleet with three crash avoidance technologies, there are several opportunities for improvement. Rather than calculating benefits for crash prevention solely on a per crash basis, future cost analyses should take crash severity in account. Changes to market penetration rates and VMT could also be incorporated, to reflect the influence that consumer demand and VMT could have on the net benefit. Different system efficacies could be taken into account in order to better model a real transportation system where crash avoidance technologies do not work perfectly and could be potentially disabled by the user of the vehicle.

Chapter 3: Investigating the Effects of Reserved Lanes for Commercial Truck Platooning on Congestion: Pennsylvania Turnpike Case Study

The previous chapter discussed the economic feasibility of equipping all light-duty vehicles with forward collision warning, blind spot monitoring, and lane departure warning crash avoidance technologies. This chapter explores methods to determine initial platoon testing areas on highways and investigates the effects of a dedicated truck platoon lane on congestion.

Traffic safety remains a significant issue on today's public roadways. In addition to safety concerns, traffic congestion continues to be a problem for everyday commuters who are likely to encounter high levels of traffic when going to and from work. Connected and automated vehicles (CAVs) have the potential to provide a safer and more cost-effective, and efficient transportation system. This chapter outlines a method to determine feasible platoon demonstration sites and investigates the impacts of a dedicated truck platoon lane on peak hour traffic flow on the Pennsylvania Turnpike. The Pennsylvania Turnpike contains 12 sections where there are at 3 lanes in at least one direction for greater than 2 miles, that could be used as platoon demonstration sites. We chose this as our filtering criteria because we do not think it is feasible to dedicate a lane to platooning if there are only 2 travel lanes available and a test section of greater than 2 miles would be needed for calibration and robust results. Our results suggest that the five and six lane segments in Western and Central Pennsylvania could be viable options for a platoon site demonstrations because these areas have relatively low peak hour traffic and a high proportion of vehicles traveling on these road segments are commercial trucks. As a result, high Level of Service is maintained even at low platoon penetration rates. The 5 and 6 lane road segments located in Eastern Pennsylvania, near Philadelphia, contain road segments that have relatively high peak hour traffic flows and the majority of vehicles traveling on this sections of road are passenger cars. Therefore, dedicating a lane to platooning on these sections would result in additional congestion during peak hour travel times. Our results also suggest that platoon lane based time of day and day of week restrictions should be considered.

3.1 Introduction

Traffic safety and congestion remain significant issues on today's public roadways. The National Highway Traffic Safety Administration (NHTSA) reports that in 2012 there were a total of 5.6 million crashes including, 33,000 fatal crashes and 2.3 million injury crashes, the majority of which occurred due to human error (NHTSA 2014a; Olarte 2011). In addition to safety concerns, traffic congestion continues to be a problem for everyday commuters who are likely to encounter high levels of traffic when going to and from work (Ohnsman 2017). Connected and automated vehicles (CAVs) have the potential to provide a safer, more cost-effective, and efficient transportation system (Anderson et al. 2014). In this chapter we focus on truck platooning, which could experience widespread adoption in the next 5 to 10 years (Christ 2017). Trucks are ideal applications for platooning since these vehicles could enhance fuel economy through drag reduction, as well as drive for long distances along the same route, often concentrated in few corridors. The study investigates the effects of reserved lanes for truck platooning on congestion. We use hourly traffic flow data from the Pennsylvania Turnpike to estimate how peak hour level of service (LOS) could change with a dedicated truck platoon lane. From these results, we discuss the potential safety benefits of a truck platooning and provide recommendations to the Turnpike on feasible platoon demonstration sites.

Platoons are groups of vehicles that follow closely behind one another at high speeds and communicate through connectivity. The first truck in the platoon serves as the lead vehicle with each successive vehicle in the platoon following the lead vehicle with limited driver intervention. Platoons have the opportunity to reduce energy consumption resulting from aerodynamic drag. For example, HDVs traveling in a platoon can reduce fuel consumption anywhere between 4.5%-8%, depending on the time gap and travel speed of the vehicles in the platoon (Alam et al. 2010). This decrease in fuel consumption could reduce emissions from truck travel and save truck companies considerable amounts of money, as fuel costs are about 1/3 of the total per mile cost to operate a HDV (Torrey and Murray 2015). HDVs, while only comprising about 4% of the total number of registered highway vehicle in the US (Bureau of Transportation Statistics 2016), account for about 23% of the total energy consumed by the transportation sector, in large part due to the low fuel efficiency of these trucks and the large amount of miles a truck travels annually to deliver goods (Energy Information Administration 2016). In the U.S. truck transport is growing at a rapid pace and this trend is likely to continue into the future (Energy Information Administration 2014).

This chapter characterizes near and long-term scenarios for the Pennsylvania Turnpike to begin accommodating connected and automated vehicle technologies. Specific recommendations for potential platoon demonstration sites and characteristics are identified. For this project we use hourly traffic flow data from the Pennsylvania Turnpike and estimate changes in peak hour LOS if a dedicated truck platoon lane were implemented on selected segments of this road. We use the Pennsylvania Turnpike as a case study for this analysis but the results and recommendations found within this chapter could be applied to other existing roadways as well.

3.2 Literature Review

Several researchers have proposed steps towards transitioning to connected and automated vehicle transportation. For example, Shladover (2000) suggests deployment steps by first defining a set of principles to govern platoon based highway system deployment strategies and proposing a deployment sequence-beginning with adaptive cruise control, transitioning to implementing protected lanes, and ending with the addition of a link and network layer (Shladover 2000). Bayouth and Koopman (1998) propose a set of functional evolution reference models for highways to accommodate connected and automated vehicle transportation: vehicle automation, the addition of inter-vehicle communications, and the addition of infrastructure support (Bayouth and Koopman 1998). The three-staged reference evolution model presented by the authors starts with first automating in-vehicle functions and then adding vehicle communications and infrastructure support as later additions. Tsao (1995) identifies barriers for the deployment of a platoon based highway system and proposes steps for transitioning toward CAV transportation, beginning with an automated shuttle in mixed traffic supervised by a professional driver, followed by the construction of a high-occupancy vehicle (HOV) highway-to-highway connecter ramps and equipping HOV lanes for automated driving (Tsao 1995). Chen et al. (2017) developed a formulation to examine feasible lane policies to accommodate AVs such as exclusive AV lanes or mixed-traffic lanes and found that the most capacity effective lane policy is highly dependent on the AV penetration rate (Chen et al. 2017).

Traffic flows along with long-held assumptions about maximum roadway capacity and volume-delay functions could change with automation. Equipping vehicles with automated technologies will likely reduce crashes and in turn decrease non-recurrent congestion. According to the Federal Highway Administration (FHWA) close to 60% off all road congestion is caused by crashes, construction, or emergencies, which suggests that a more coordinated vehicle fleet could substantially reduce travel times and delay (FHWA 2014). By reducing the average safe inter-vehicle distance between vehicles, highway capacity could increase by as much as 273% when using both sensors and vehicle-to-vehicle communication technologies (Tientrakool et al. 2011). Milanés et al. (2014) presents the design, development, implementation, and testing of a cooperative adaptive cruise control (CACC) systems, which were implemented into four production Infiniti M56s (Milanés et al. 2014). The authors concluded that by introducing vehicle to vehicle (V2V) to cars with adaptive cruise control (ACC) systems enables significant reductions in intervehicular gaps. VanderWerf et al. (2002) concluded that increases in highway capacity increase quadratically with CACC market penetration (Vander Werf et al. 2002). Lioris et al. (2017) estimates that platooning can increase saturation flow rates by a factor as large as two or three (Lioris et al. 2017). The authors focused on a road network near Los Angeles and utilized a discrete event simulation to estimate their results. Researchers at Carnegie Mellon University evaluated the impacts of automated vehicles on 24-hour road volumes on the Parkway East (I-376). They find that automation could increase 24-hour road volumes along this road up to 10% and that reducing lateral lane sizes could increase roadway capacity by allowing for additional lanes to be constructed (Hendrickson et al. 2014). Using simulation, Talebpour et al. (2017) examined the impacts of reserving a lane for AVs on congestion and travel time. It was found that increase throughput at AV penetration rates above 50% and 30% on two and four lane highways, respectively (Talebpour et al. 2017).

This chapter makes a contribution to the literature by using the Pennsylvania (PA) Turnpike's hourly traffic flow data, which provides information on traffic volumes by vehicle class, to identify potential platoon demonstration sites and to estimate how implementing a truck platoon lane on these portions of the roadway could impact current LOS. This chapter has a different objective than previous platooning studies. In particular, this study should enable stakeholders and other organizations to understand the impacts and feasibility of dedicating a lane on existing road networks to truck platooning and presents a method to determine initial testing areas.

3.3 Methods & Data

To assess the changes in LOS from reserving a lane for truck platooning, we first need to identify those portions of the Pennsylvania Turnpike that could be suitable to launch potential platoon demonstrations. Once these sections are identified we can then estimate peak hour LOS and how this could change if we reserve a lane for truck platooning. The primary source of data for this project are hourly Traffic Flow Reports of the Pennsylvania Turnpike from Monday, May 1, 2017 to Friday, May 5, 2017. The dataset, which was obtained through a "Right to Know" request, contains traffic flow data on both electronic toll collection (ETC) and non-ETC traffic for all 24 hours of the day arranged by vehicle classification type, direction (East/North or West/South), and turnpike interchange.

The Pennsylvania Turnpike has a number of roadway sections that could potentially be converted into platoon demonstration sites. We develop a sample set of potential platoon demonstration sites by identifying those portions on the Turnpike with at least 3 lanes in one direction for greater than 2 miles, as shown in Figure 3.1. We chose this as our filtering criteria because we do not think it is feasible to dedicate a lane to platooning if there are only 2 travel lanes available and think that a section of at least 2 miles would be required for a robust demonstration. Each entrance and exit interchange combination along the roadway has a separate hourly traffic flow rate. Because we are interested in vehicular volumes, if an identified 5 or 6 lane portion of the roadway was continuous and intersects more than one interchange combination, this larger section was divided up into smaller sections representative of the changes in traffic flow rates. For example, Sections 11, and 12, both located in eastern Pennsylvania, are collectively, a continuous 6 lane segment of the PA Turnpike that spans about 10 miles, but were divided into 2 different segments to capture the changes traffic flow rates along this section of the roadway.

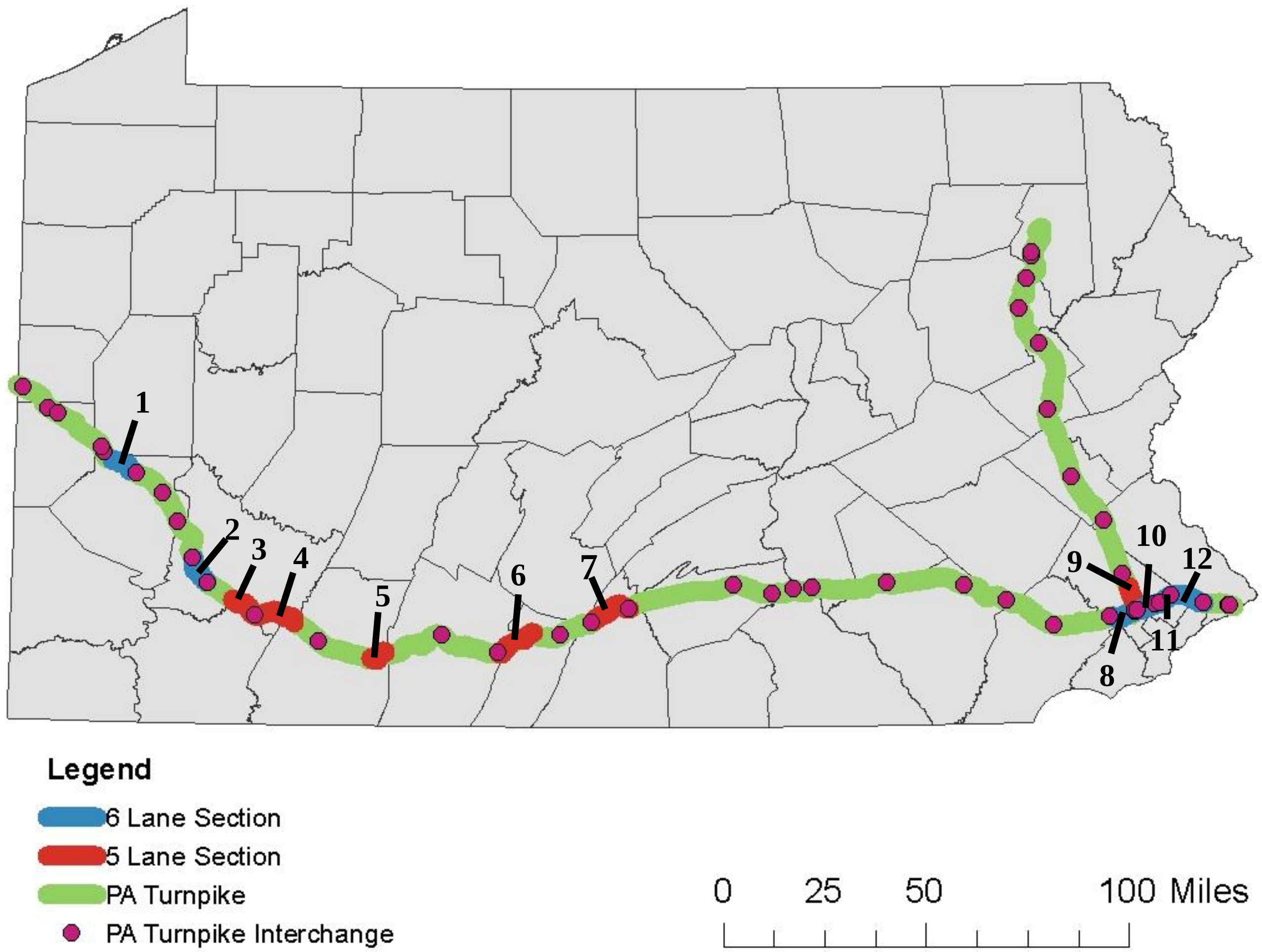


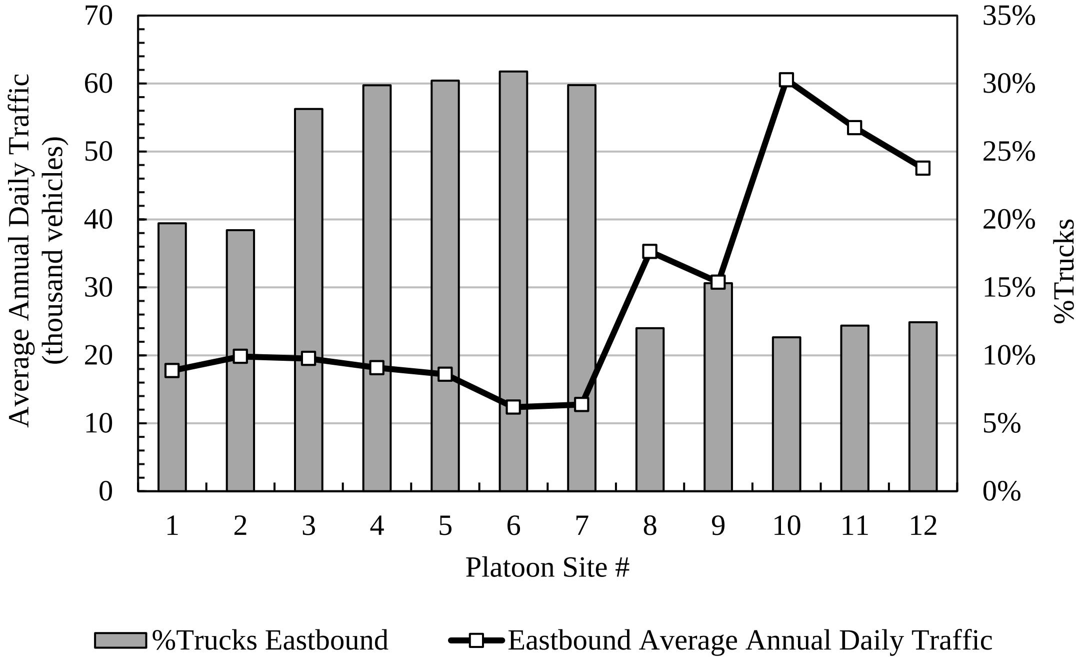
Figure 3.1 Five and Six Lane Sections of the Pennsylvania Turnpike Greater than 2 Miles in Distance

The ideal platooning site would be one that maximizes the potential fuel saving benefits of platooning, while minimizing the impacts to the current level of service provided to passenger car and light and medium-truck traffic. Out of the 12 potential platoon demonstration sites identified, half of them have 6 total lanes, 3 lanes in both the east and west directions, while the other half have a total of 5 lanes, with only 3 lines in one direction. Seven sites are located in Western and Central Pennsylvania, respectively, while the remaining 5 sites are located in Eastern Pennsylvania near Philadelphia. Platoon site 7, located in in northern Franklin County, is the longest potential platoon site on the Turnpike, followed by Platoon Site 4, located in Westmoreland County. In comparison, the overall average annual daily traffic (AADT), is about 5% higher at Platoon Site 7 than Platoon Site 4, with truck traffic being about the same at both sites. Platoon Site 12 has the highest AADT in both directions. Platoon sites 11, 12, and 13, all located in Montgomery County, have both the highest AADT and the lowest proportion of truck traffic, when compared to all of the other potential platoon sites. There are about 108,000 total vehicles that travel on platoon site 12 throughout the course of the day, while there are about 92,000 vehicles that travel on platoon site 13 each day. Platoon site 11 has the highest AADT when compared to the other sites, there are about 120,000 total traveling on this platoon site each day but only about 14,000 or 11% of these vehicles are trucks. Platoon site 7, has the highest proportion of truck traffic, with trucks making up about 30 and 33 percent of vehicles traveling in the east and westbound directions, respectively. In addition, platoon sites 3, 4, 5, and 6 all have a relatively high proportion of trucks traveling on these sections on the turnpike. Overall, eastbound traffic flow rates are slightly higher than those in the westbound direction, but there are a slightly higher proportion of trucks traveling westbound. The location and length of each potential platoon site is outlined in Table 3.1, which provides information on AADT and truck traffic for each platoon site for both east and west directions. The AADT values (shown below in Figure 3.2) provide a simple and useful measurement of how busy each platoon site is over the course of a typical day. In the next section we will discuss how we convert hourly traffic volume to a passenger car unit to assess the peak hour traffic flow and LOS at each platoon site.

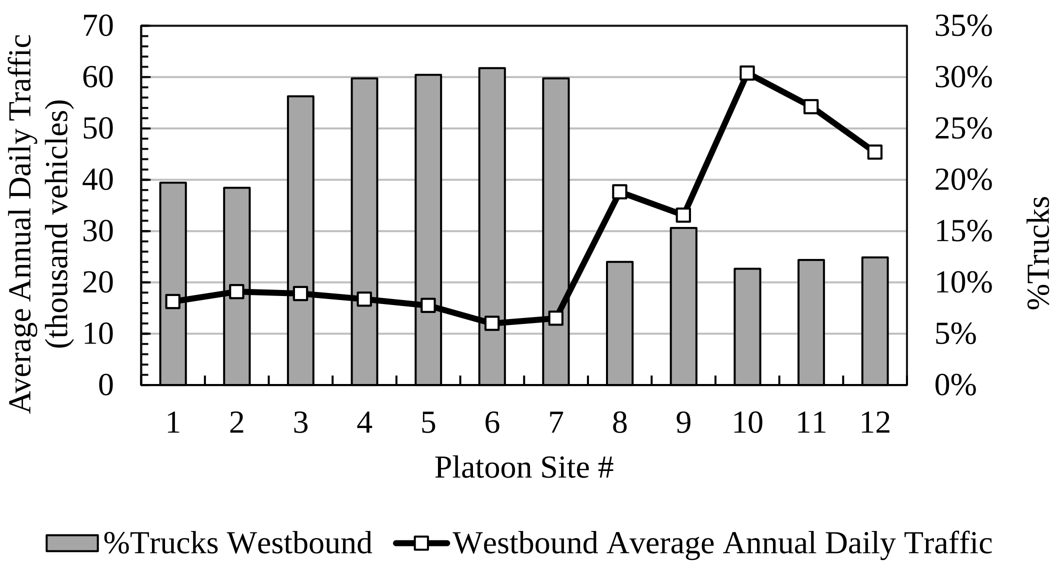
Table 3.1 Five and Six Lane Sections of Pennsylvania Turnpike Location and Length Information by Platoon Site

Platoon Site #	No. Lanes	3 Lane Direction	Interchange	Interchange	County	Length (miles)
1	6	Both	Warrendale	Butler Valley	Allegheny	6.2
2	6	Both	Irwin	New Stanton	Westmoreland	7.3
3	5	East/North	New Stanton	Donegal	Westmoreland	7.9
4	5	East/North	Donegal	Somerset	Westmoreland	9.4
5	5	West/South	Somerset	Bedford	Somerset	5.0
6	5	East/North	Breezewood	Fort Littleton	Fulton	3.4
7	5	West/South	Willow Hill	Blue Mountain	Franklin	10.5
8	6	Both	Valley Forge	Norristown	Montgomery	5.9
9	5	West/South	Mid-County	Lansdale	Montgomery	6.0
10	6	Both	Mid-County	Fort Washington	Montgomery	4.1
11	6	Both	Fort Washington	Willow Grove	Montgomery	2.6
12	6	Both	Willow Grove	Bensalem	Montgomery	7.8

Note: Each 5 and 6 lane road segment is designated a number starting from the left of the Figure 1 and increases as you move east along the Turnpike.



(a)



(b)

Source: Pennsylvania Turnpike Monthly Traffic Flow Reports from January, 2016 to December, 2016.

Note: % Trucks includes Light (>7,000 lbs.), Medium, and Heavy duty trucks; no passenger cars are included in this estimate.

Figure 3.2 (a) Pennsylvania Turnpike Average Annual Daily Traffic and Proportion of Trucks in Eastbound Direction by Platoon Site. **(b)** Pennsylvania Turnpike Average Annual Daily Traffic and Proportion of Trucks in Westbound Direction by Platoon Site

As mentioned previously, the PA Turnpike reports its traffic flow data by vehicle classification group. The Turnpike does not follow the Federal Highway Administration's (FHWA) 13 category vehicle group classification (Hallenback et al. 2014). Instead, the PA Turnpike follows a 9-category vehicle group classification system (Pennsylvania Turnpike Commission 2017), for the purposes of calculating toll rates, as shown below in Table 3.2. The turnpike arranges all passenger cars into one group, with the other 8 classes grouped in terms of vehicle weight. In the state of Pennsylvania, a commercial motor vehicle is defined as a single-vehicle with a gross vehicle weight of 26,001 or more pounds (Pennsylvania Department of Transportation 2015). Since we are interested in estimating the congestion impacts of devoting a lane for commercial truck or heavy duty vehicle platooning, we focus on those trucks in vehicle class groups 5 to 9 for the remainder of this analysis. Although class group 4 does contain some commercial trucks by definition, non-commercial trucks are also grouped into this category. Since there is no way to distinguish non-commercial and commercial trucks in class group 4 from the data given, we treat all vehicles in this group as non-commercial vehicles for the purpose of this analysis.

Table 3.2 Pennsylvania Turnpike Vehicle Class Definitions

Class Group	Class Definition
1	Passenger Car
2	7,001 to 15,000 lbs.
3	15,001 to 19,000 lbs.
4	19,001 to 30,000 lbs.
5	30,001 to 45,000 lbs.
6	45,001 to 62,000 lbs.
7	62,001 to 80,000 lbs.
8	80,001 to 100,000 lbs.
9	100,001 lbs. and over

Source: Pennsylvania Turnpike Commission. *Toll Schedule 2017*. Harrisburg, PA, 2017.

The PA Turnpike's hourly traffic flow data tells us the number of vehicles that pass between two successive interchanges in each direction during each hour of the day. The presence of heavy vehicles in the traffic stream decreases the free flow speed (FFS) as these vehicles take up more roadway space and behave differently than a passenger car would under certain conditions (weather, steep road grades, etc.). In order to assess the overall effect of each vehicle type on traffic operations, the hourly traffic volumes were converted to an equivalent flow rate expressed in terms of passenger cars units (pcu). For simplicity, we assumed that each platoon site has a rolling terrain and that there is no single grade at any platoon site that has a significant impact on traffic operations. The pcu conversion factor for trucks and buses on extended general highway segments on rolling terrains, as defined by the Highway Capacity Manual (HCM) (Transportation Research board 2010), was applied to all vehicles outside of class group 1 and summed together to estimate the passenger car equivalent traffic (pce) volume during peak hour traffic. The 2010 HCM provides pce values for trucks and recreational vehicles (RVs) as a function of terrain (grade and length of grade), but does not provide pce equivalent estimates as a function of vehicle weight. Some of the vehicles included in classes 2-4 may be RVs or U-Hauls, hence as a result the pce estimate provided here is more conservative. We choose to focus on peak hour traffic for this analysis since this is the time of day that a dedicated truck platoon lane could have the most significant impact on traffic operations. The eastbound peak hour traffic volume, expressed in passenger cars per hour (pcu/hr) is the sum of the number of passenger cars and the pce number of trucks and is expressed in Eq. (3.1):

$$Vol_{East_i} = [PC_{East_i} + (R \times Trucks_{East_i})] \tag{3.1}$$

where Vol_{East_i} is the total eastbound peak hour traffic volume (pcu/hr) at platoon site i, PC_{East_i} is the eastbound peak hour passenger car traffic volume at platoon site i, R is the passenger car equivalent conversion factor trucks and buses for extended general highway segments on rolling terrains ($R = 2.5$), $Trucks_{East_i}$ is the number of light (>7,000 lbs.), medium, and heavy duty trucks traveling on platoon site i during peak hour traffic in the eastbound direction. The traffic flow rate (pc/hr/ln) can be estimate by dividing the passenger equivalent traffic volume by the number of lanes, which in each case is 3. Once we estimate the traffic flow rate, we refer to the 2010 HCM Basic Freeway Segments Speed-Flow Curve and using a free flow speed of 70 mi/h estimate peak hour LOS. A similar method can be followed to estimate peak hour passenger car equivalent traffic flow rate in the westbound direction.

Each potential platoon site has at least 3 lanes in one direction and travel in any of these lanes is not restricted by time of day, vehicle class group or occupancy. In order to estimate changes in peak hour LOS, we repurpose one lane at each platoon site where originally any car could travel and restrict travel in this lane to commercial trucks with platoon capabilities, which we will refer to as the dedicated truck platoon lane. All passenger cars, vehicles in class groups 1 through 4, commercial trucks without platooning capabilities are now only permitted to travel in the "non-dedicated lanes" and are restricted to two lanes of travel instead of three. In this model, platoon penetration rates determine the number of connected and automated commercial trucks that will make use of the dedicated platoon lane, which we assume to be uniform across each platoon site on the turnpike. For example, a platoon penetration rate of 25% means that 25% of all commercial trucks at each platoon site are now assumed to have platooning capabilities and will choose to use the dedicated platoon lane. The estimated peak hour LOS when there is a dedicated truck platoon lane, refers to the quality of traffic service in the non-dedicated platoon lanes; the traffic operations in the dedicated truck platoon lane are assumed to be free flow at high traffic density. Peak hour traffic volumes for each vehicle class are assumed to remain constant for the purpose of this analysis. The eastbound peak hour traffic flow rate when there is a dedicated platoon lane is estimated using the following method, expressed in Eq. (3.2):

$$Vol_{Platoon-East_i} = Vol_{East_i} \times [1 - (C_{East_i} \times AV)] \tag{3.2}$$

where $Vol_{Platoon-East_i}$ is the eastbound peak hour traffic volume (pcu/hr) when there is a dedicated platoon lane at platoon site i, Vol_{East_i} is the total eastbound peak hour traffic volume (pcu/hr) at platoon site i and is expressed on Eq. (3.1), C is the proportion of commercial trucks traveling during peak hour on platoon site i, AV is the commercial truck platoon penetration rate, which is assumed to be uniform at all platoon sites. The traffic flow rate (pcu/hr/ln) when there is a dedicated platoon lane can be estimated by diving the peak hour traffic volume by the number of non-dedicate lanes, which in each case is 2. Once we estimate the traffic flow rate, we refer to the 2010 HCM Basic Freeway Segments Speed-Flow Curve and using a free flow speed of 70 mi/h estimate peak hour LOS. A similar method can be followed to estimate peak hour passenger car equivalent traffic flow rate, when there is a dedicated platoon lane in the westbound direction.

3.4 Results

An objective of this chapter is to estimate how implementing a platoon lane on existing highways could impact traffic conditions. We start by estimating the impacts from a point in time where platooning technologies have only been partially adopted and are only implemented on brand new trucks to a point in time where the truck industry transitions to total market penetration. From these results, we discuss how the Pennsylvania Turnpike and other existing roadways could begin to transition towards CAV transportation.

3.4.1 Peak Hour Level of Service on Pennsylvania Turnpike

There are several potential platoon sites on the Turnpike where there is free flow (LOS A) and reasonable free-flow (LOS B) traffic during peak hour travel times. At each potential platoon site, passenger cars make up the majority of vehicles traveling during peak hour traffic in both directions. In the eastbound direction peak hour tends to occur during the early evenings, between 4PM and 5PM, most commonly on Thursdays and Fridays. In comparison, peak hour travel in the westbound direction tends to occur in the mornings, between 6AM and 8AM, most commonly on Tuesdays and Fridays. In the eastbound direction, platoon sites 2, 3, 4, and 6 operate at LOS A during peak hour traffic, which means that vehicles are unimpeded in their ability to maneuver within the traffic stream. Platoon site 1 operates at LOS B in the eastbound direction, which indicates that vehicles traveling during peak hour are almost completely unimpeded in their ability to move within the traffic stream. In the westbound direction, platoon sites 1, 2, 5, 7, and 8 all operate at LOS A during peak hour traffic, while the remaining sites operate at LOS D or below, which indicates that maneuverability is low and traffic operations are approaching capacity. In both directions, platoon sites 9, 10, 11, 12, and 13 have the highest peak hour traffic volumes and the lowest LOS grades when compared to the other platoon sites, and have relatively low amounts of commercial truck traffic. For example, there are about 6,400 passenger car equivalent vehicles traveling from the Fort Washington to Mid-County interchange (Platoon site 10) during peak hour travel with 90 and 6 percent of these vehicles being passenger cars and commercial trucks, respectively. Platoon sites 7 has a relatively low peak hour traffic volumes, but a very high proportion of vehicles traveling through this section are commercial trucks. Tables 3.3 and 3.4

show the east and westbound peak hour traffic volumes in terms of passenger car units, as well as the peak hour flow rate, expressed in terms of passenger cars per hour per lane (pcu/ln/hr), and LOS for each potential platoon site.

Table 3.3 Peak Hour Level of Service on Pennsylvania Turnpike by Platoon Site in the Eastbound Direction

Platoon Site #	Day of Week	Eastbound Peak Hour	Eastbound Peak Hour Traffic Volume (pcu/hr)	% Commercial Trucks[a]	Peak Hour Traffic Flow Rate (pcu/ln/hr)	LOS
1	Thursday	4PM-5PM	2,500	16%	840	B
2	Friday	4PM-5PM	2,300	12%	760	A
3	Friday	11AM-12PM	2,200	26%	730	A
4	Friday	12 PM- 1PM	2,000	27%	680	A
5	na	na	na	na	na	na
6	Friday	11AM-12PM	2,000	26%	650	A
7	na	na	na	na	na	na
8	Friday	1PM-2PM	4,700	4%	1,600	C
9	Thursday	4PM-5PM	4,200	10%	1,400	C
10	Friday	3PM-4PM	6,400	6%	2,100	E
11	Friday	4PM-5PM	6,000	6%	2,000	D
12	Thursday	4PM-5PM	5,700	6%	1,900	D

Note: pcu= Passenger Car Units ; NA= Not Applicable

[a]Weighted percentage based on passenger car equivalence.

Note: Values only reported for those potential platoon sites that have 3 lanes in eastbound direction.

Note: The number of total travel lanes for each potential platoon site is 3.

Note: Posted speed limit is 70 miles per hour (MPH) at each platoon site.

Table 3.4 Peak Hour Level of Service on Pennsylvania Turnpike by Platoon Site in the Westbound Direction

Platoon Site #	Day of Week	Westbound Peak Hour	Westbound Peak Hour Traffic Volume (pcu/hr)	% Commercial Trucks[a]	Flow Rate (pcu/ln/hr)	LOS
1	Tuesday	7AM-8AM	2,100	22%	710	A
2	Friday	7AM-8AM	2,000	16%	670	A
3	na	na	na	na	na	na
4	na	na	na	na	na	na
5	Friday	1PM-2PM	2,100	27%	700	A
6	na	na	na	na	na	na
7	Friday	2PM-3PM	1,100	48%	370	A
8	Tuesday	7AM-8AM	5,300	8%	1,800	D
9	Tuesday	6AM-7AM	4,100	11%	1,400	D
10	Friday	6AM-7AM	7,100	7%	2,400	E
11	Friday	6AM-7AM	6,000	11%	2,000	D
12	Thursday	6AM-7AM	5,600	12%	1,900	D

Note: pcu= Passenger Car Units ; na= Not Applicable

[a]Weighted percentage based on passenger car equivalence.

Note: Values only reported for those potential platoon sites that have 3 lanes in eastbound direction.

Note: The number of total travel lanes for each potential platoon site is 3.

Note: Posted speed limit is 70 miles per hour (MPH) at each platoon site.

3.4.2 Level of Service on Turnpike with Dedicated Truck Platoon Lane

The Pennsylvania Turnpike has several sections where implementing a commercial truck platoon demonstration site could be a viable option. At very low penetration rates, the LOS decreases the at most platoon sites, with the exception of platoon site 7 going westbound, which never experiences a decrease in LOS at any penetration rate, even if there were no trucks platooning during peak hour traffic. This is most likely due to the relatively low peak hour traffic volume and high proportion of commercial trucks traveling on this roadway section during peak hour travel. Sections 1, 2, 3, and 4 could also be viable options for implementing a platoon lane even at low penetration rates and in both directions. While, LOS does decrease during peak hour traffic, the current LOS in these sections are already high so motorists still have a high level of physical and psychological comfort and are able to travel at the posted speed even with a dedicated platooning lane. The LOS on these sections never reach free flow, even when all commercial trucks are diverted to the dedicated platoon lane, because of the high volume of passenger cars and non-commercial trucks traveling on this road during peak hour traffic. The only way to achieve LOS A would be to construct another non-dedicated lane for travel. On the other hand, Platoon sites 8 through 13, currently have low LOS and proportionally low truck traffic during peak hour travel in both directions, so reserving a lane for platooning only decreases the LOS to the point where all passenger cars and trucks without platooning capabilities traveling on these portions of the turnpike move in lockstep with the vehicle in front of it, with frequent slowing required. Tables 3.5 and 3.6 display how LOS on the turnpike changes with a dedicated platoon lane.

Table 3.5 Eastbound Level of Service with Dedicated Platoon Lane by Platoon Penetration Rate

Platoon Site #	% Commercial Trucks[a]	Current Peak Hour Traffic Flow Rate (pcu/ln/hr)	Peak Hour LOS	Commercial Truck Platoon Penetration Rate 0%	5%	25%	50%	75%	100%
1	16%	840	B	C	C	B	B	B	B
2	12%	760	A	B	B	B	B	B	B
3	26%	730	A	B	B	B	B	B	B
4	27%	680	A	B	B	B	B	B	A
5	na	na	na	na	na	na	na	na	na
6	26%	650	A	B	B	B	B	B	A
7	na	na	na	na	na	na	na	na	na
8	4%	1,600	C	E	E	E	E	E	E
9	10%	1,400	C	D	D	D	D	D	D
10	6%	2,100	E	F	F	F	F	F	F
11	6%	2,000	D	F	F	F	F	F	F
12	6%	1,900	D	F	F	F	F	F	F

[a]Weighted percentage based on passenger car equivalence.

Note: pcu= Passenger Car Units ; na= Not Applicable

Note: Values only reported for those potential platoon sites that have 3 lanes in eastbound direction.

Note: Posted speed limit is 70 miles per hour (MPH) at each platoon site.

Table 3.6 Westbound Level of Service with Dedicated Platoon Lane by Platoon Penetration Rate

Platoon Site #	% Commercial Trucks[a]	Current Peak Hour Traffic Flow Rate (pcu/ln/hr)	Current Peak Hour LOS	Commercial Truck Platoon Penetration Rate 0%	5%	25%	50%	75%	100%
1	22%	707	A	B	B	B	B	B	B
2	16%	672	A	B	B	B	B	B	B
3	na	na	na	na	na	na	na	na	na
4	na	na	na	na	na	na	na	na	na
5	27%	696	A	B	B	B	B	B	A
6	na	na	na	na	na	na	na	na	na
7	48%	370	A	A	A	A	A	A	A
8	8%	1,769	D	F	F	F	F	F	F
9	11%	1,382	C	D	D	D	D	D	D
10	7%	2,352	E	F	F	F	F	F	F
11	11%	1,986	D	F	F	F	F	F	F
12	12%	1,877	D	F	F	F	F	F	F

[a]Weighted percentage based on passenger car equivalence.

Note: pcu=Passenger Car Units; na= Not Applicable

Note: Values only reported for those potential platoon sites with at least 3 lanes in the westbound direction.

Note: Posted speed limit is 70 miles per hour (MPH) at each platoon site.

3.5 Discussion

Connected and automated vehicles are expected to improve safety, congestion, emissions, and energy consumption and address the growing need for mobility in our transportation system. In proportion to the number of registered highway vehicles, heavy-duty vehicles consume a disproportionately high proportion of energy consumed by the transportation sector, which leads to high operating expenses for trucking companies. Platooning has the potential to provide significant fuel cost saving benefits and reduce HDV emissions by increasing the density of trucks on the road, which reduces the aerodynamic drag. This chapter presents a method to determine viable platoon demonstration sites on highways. In particular, this chapter identifies those five and six lane portions of the Pennsylvania Turnpike where a lane could be reserved for a platoon demonstration site and estimates how current LOS at these potential platoon sites could be impacted at different penetration rates, using the best available traffic information about the passenger cars and trucks traveling on this highway. The main dataset used for this chapter was the Pennsylvania Turnpike's hourly traffic flow reports from May 1, 2017 to May 5, 2017, which contains vehicle class group level data of the traffic flow between interchanges for each hour of the day over the course of 5 days. For this chapter we focus on commercial trucks since these vehicles drive for long distances along the same route, often concentrated in few corridors and could benefit greatly from platooning due to their low fuel efficiency.

In order to determine feasible testing areas on the Pennsylvania Turnpike we first identify those portions of the highway that have a total of five, 3 lanes in one directions, or six lanes, 3 lanes in both direction, for greater than 2 miles as we do not think it is reasonable to dedicate a lane to platooning if there are only 2 lanes available and do not think sections shorter than 2 miles provide are long enough in length to hold a demonstration. There are a total of 12 sections on the turnpike where a potential platoon demonstration site could take place. Out of these 12 sites, six have three lanes in both directions and six have three lanes in only one direction. Seven are located in Western and Central Pennsylvania, collectively, while the remaining five are located in Eastern Pennsylvania near Philadelphia.

Our results suggest that those five and six lane segments in Western and Central Pennsylvania could be viable options for a platoon site demonstrations because these areas have relatively low peak hour traffic and a high proportion of vehicles traveling on these road segments are commercial trucks. The longest potential platoon demonstration site, platoon site 7, is located in Northern Franklin County, PA, between the Willow Hill and Blue Mountain Interchange, but has 3 lanes only in the westbound direction. This platoon site also has the lowest peak hour traffic flow rate and has the highest proportion of commercial truck traffic when compared to the other platoon sites, and operates at LOS A during peak hour traffic. This is the only site observed in the analysis that does not experience a decline in peak hour LOS from reserving a lane for platooning, regardless of the commercial truck platoon penetration rate. In the eastbound direction, the longest platoon site, platoon site 4, is about 9.5 miles in length and is located in Westmoreland County, between the Donegal and Somerset interchanges. There is a relatively high proportion of commercial trucks traveling on this platoon site during peak hour traffic. While the LOS does decline with the implementation of a platoon demonstration site, cars should still be able to travel with spacing between vehicles adequate enough to maintain a high level of physical and psychological comfort for motorists. Platoon sites 1 and 2 have three lanes in both directions and are about 6 and 7 miles in length, respectively. Platoon site 1 is located in Allegheny County, between the Warrendale and Butler Valley interchanges, while platoon site 2 is located in Westmoreland County between Irwin and New Stanton. The LOS are likely to decline these areas if a platoon lane is reserved but similarly to platoon site 4, vehicles should still be able to travel at reasonably free flow. There is a trade-off between safety and capacity so the Turnpike may be willing to consider these section, since drivers will still be able to travel at free flow speeds and the likelihood of a crash between passenger cars and commercial trucks would decrease. The recommended platoon demonstration sites are shown in Table 3.7.

Table 3.7 Recommended Platoon Demonstration Sites on Pennsylvania Turnpike

Platoon Site #	No. Lanes	3 Lane Direction	County	Length (miles)	Eastbound Peak Hour Level of Service	%Commercial Trucks Eastbound[a]	Westboud Peak Hour Level of Service	%Commercial Trucks Westbound[a]
1	6	Both	Allegheny	6.2	B	16%	A	22%
2	6	Both	Westmoreland	7.3	A	12%	A	16%
3	5	East/North	Westmoreland	7.9	A	26%	NA	NA
4	5	East/North	Westmoreland	9.4	A	27%	NA	NA
5	5	West/South	Somerset	5	NA	NA	A	27%
6	5	East/North	Fulton	3.4	A	26%	NA	NA
7	5	West/South	Franklin	10.5	NA	NA	A	48%

[a]Weighted percentage based on passenger car equivalence.

Note: pcu= Passenger Car Units ; NA= Not Applicable

Note: Level of service only reported for those directions with 3 travel lanes

Although there are some viable options to launch a platoon demonstration site there are also areas of the turnpike where reserving a lane could have detrimental impacts on traffic flow and LOS. Platoon sites 8 through 12, all located in Montgomery County, PA, currently have a lower LOS than the other platoon sites and a very low proportion of vehicles traveling on these sections are commercial trucks. For example, if we take a look at platoon site 8, 4 and 8 percent of vehicles traveling on this road segment during peak hour in the eastbound and westbound directions, respectively, are commercial truck, out of 12,000 total vehicles. If we dedicate a lane to platooning, there are not much trucks traveling in this direction and passenger cars are now limited to travel in two lanes, which could result in a constant traffic jam where vehicles traveling on these sections move in lockstep with the vehicle in front of it, with frequent slowing required. Regardless of the commercial truck platoon penetration rate, LOS during peak hour traffic remains at an F grade at these 4 sites.

Time of day and day of week restrictions could be considered when choosing a platoon demonstration site, to better ensure that the LOS on the turnpike is minimally impacted. In the eastbound direction, the highest traffic flow rates most commonly occur on Thursday and Fridays from the early afternoon to the early evening. In comparison, peak hour traffic usually occurs in the westbound direction on Mondays and Tuesdays in the morning to the early afternoon. Setting up platoon demonstrations on off-peak days and hours would provide trucks with potential fuel savings benefits, while still allowing all other vehicles to travel at or near free flow. The Pennsylvania Turnpike would also need to consider how to control access to these platoon lanes. Trucks with platooning capabilities entering the turnpike could be required to have a special E-ZPass that would provide it with access to the platoon lane, while keeping all other vehicles in their respective lanes. Non-commercial trucks or commercial trucks without platooning capabilities that decide to enter the platoon lane could be issued a ticket or fine using the E-ZPass system. Similarly to dedicated bus lanes, a dedicated platoon lane could provide numerous social and economic benefits. Dedicated platoon lanes separate commercial trucks from mixed traffic, allowing commercial trucks to travel more quickly through the turnpike. In addition, dedicated platoon lanes reduce interaction between commercial trucks and other vehicles, minimizing the risk for traffic crashes.

The platoon demonstration could be an on-road Level 3 automated truck demonstration pilot between commercial trucks that are connected by Vehicle to Vehicle (V2V) communications.

The lead driver controls the acceleration and braking of all of the trucks in the platoon, while the drivers in the successive or trailing vehicles are present but aren't required to steer or control vehicle speed, but must respond appropriately in a request to intervene. This demonstration could be done in two phases. In phase one there could be a dedicated lane for platoon demonstrations. In phase two there will no longer be a dedicated protected lane and all platoons will travel in mixed traffic situations. The purpose of both phases would be to identify any risks or hazards, conduct a before and after analysis on truck travel times, fuel consumption, and congestion, compare results between phases, and provide a smoother transition to CAV transportation. Data should be collected on vehicle speed and acceleration, brake pressure, and spacing between vehicles at both constant and varying lead vehicle speeds. Demonstrations should be done in inclement (rain, sleet, snow, and fog) and non-inclement weather and artificial work zones (i.e. jersey barriers) could also be implemented to assess traffic operations and safety. The demonstrations would take place for a limited time frame and eventually all AVs and platoons will travel in general traffic.

According to the 2013 Pennsylvania Department of Transportation Statewide crash dataset, there were about 1,500 crashes that occurred on the Pennsylvania Turnpike in 2013. Out of these 1,500 crashes about 240 or 17% of crashes involved at least one HDV, including 3 fatal and 88 injury crashes. According to the National Highway Safety Administration (NHTSA), the cost of a crash (Blincoe et al. 2015) is close to $154,000 in $2010. Because the crash data is from the year 2013, the Consumer Price Index (CPI) was used to find the total cost of a crash in 2013 dollars, which is approximately $163,700 or $47,400 in economic costs and $116,340 in quality-adjusted life years (QALYs) cost. This would result in an annual loss of about $39 million or $11 million in economic costs and $28 million in QALYs cost, from crashes involving heavy duty vehicles on the Turnpike. Accommodating CAVs on the turnpike could aid in reducing the frequency and severity of crashes involving HDVs, which could result in economic benefits to household, public revenues, and private insurers. For example, if 25% of all HDV crashes on the turnpike were avoided, this would provide an annual benefit of about $10 million. If all HDV crashes could be avoided this would result in an upper bound annual benefit of about $39 million. Greater benefits could be realized as more roadways transition to CAV transportation. Automobile manufacturers and automated and connected vehicle technology companies are investing millions of dollars to make CAVs vehicles a reality. Policymakers, engineers, as well as turnpike commissions should begin to consider ways how mixed-traffic could impact congestion, safety, energy use, and traffic operations so that we may have a smooth transition and minimize any negative consequences on our way to a fully automated light and heavy-duty vehicle fleet.

Chapter 4: Exploring the Economic, Environmental, and Travel Implications of Changes in Parking Choices due to Driverless Vehicles

The previous chapter investigated the effects of a dedicated platoon lane on congestion and outlined a method that could be used to determine viable platoon demonstration sites, using the Pennsylvania Turnpike as a case study. This chapter explores the economic, environmental, and travel implications of AVs moving away from downtown parking lots to more distant, cheaper parking locations.

Automobile commuters in urban areas often use downtown parking garages and are charged relatively high daily parking prices. Fully driverless automated vehicles (AV) could significantly alter the proximity value of parking, due to an AV's ability to drop passengers off at their destination, search for cheaper parking, and return to pick up their occupants when needed. This study estimates the potential impact of driverless vehicles on vehicle miles traveled (VMT), energy use, emissions, parking revenue, and daily parking cost savings in the city of Seattle, Washington from changes in parking decisions using an agent-based simulation model. Each AV considers the operational cost to drive to each parking spot, the associated daily parking cost, the parking availability at each location, and ranks each choice in terms of economic cost. The simulation results indicate that VMT and energy use could increase by as much as 2.5 and 2.1 percent, respectively, with each AV willing to travel a relatively far distance to obtain free parking. Annual parking cost savings are estimated to be about $4,500 for each driverless vehicle, which represents about $18 per work day. The results also suggest that as AV penetration rates increase, parking lot revenues decrease significantly and could likely decline to the point where operating a lot is unsustainable economically, if no parking demand management policies are implemented. This could lead to changes in land use as amount of parking needed in urban areas is reduced and cars move away from the downtown area for cheaper parking in more satellite locations. The initial results suggest driverless valet vehicles will considerably alter the economics of parking, which will affect energy, emissions, VMT, and urban form in cities.

4.1 Introduction

Automated vehicle (AV) technologies are advancing rapidly and highly automated vehicles could be on streets and highways within the next decade. Many automakers are already marketing cars with some automated features such as adaptive cruise control and active lane keeping technologies (Newcomb and Colon 2017) and are progressively working to develop more highly automated and self-driving vehicles. Tesla motors has been equipping every new Model S sedan and Model X SUV with the necessary technology for full self-driving capability, in exchange for about $8,000 (Stewart 2017). Ride-sharing company Uber has deployed a fleet of self-driving cars in Pittsburgh, Pennsylvania and several other cities, and has offered some customers the option of riding in these vehicles (Brian 2016; Zurschmeide 2016). In September of 2016 the United States Department of Transportation (USDOT) released a federal policy on AVs, which provides guidelines to manufacturers and other entities in the safe design, development, testing, and deployment of highly AVs (NHTSA 2016a). This technology has the potential to greatly improve travel by reducing congestion, travel times, crashes, and potentially energy consumption, as well as enabling greater mobility for the disabled and elderly (Anderson et al. 2014; Brown et al. 2014; Harper et al. 2016b; a; Levin and Boyles 2015; Mersky and Samaras 2016; Wadud et al. 2016). There are six levels of automation, from "no automation" (level 0) to "full automation" (level 5), as defined by the Society of Automotive Engineers (SAE) (SAE 2016). Level 5 AVs or fully driverless cars could change parking patterns and decrease the need for proximity parking, which could lead to AVs parking further away in more satellite locations (Anderson et al. 2014). The purpose of this study is to assess how changes in parking choices due to driverless vehicles could impact vehicle miles traveled (VMT), parking revenues, daily parking cost savings, energy, and emissions. We construct an agent-based model to simulate AVs and parking choices in a case study using data from Seattle, Washington. From these results, we discuss the safety and land use implications of driverless vehicles in an urban environment.

Automobile commuters in urban areas often use downtown parking garages and are charged relatively high daily parking prices. Street parking, while cheaper, is usually scarce in dense urban areas and requires drivers to spend time cruising in search of an available curb space, which tends to create large amounts of congestion (Liu and Geroliminis 2016; Shoup 2006). In many cities, parking facilities tend to occupy considerable amounts of land that if not occupied for parking could be used for other purposes such as parks, office space, or dedicated bike lanes. Shoup

(2005) estimates that about 5 to 8 percent of urban land is devoted to curb parking. Manville & Shoup (2005) estimated that the parking coverage -the ratio of parking area to land area- in Downtown LA and Houston are about 81 and 57 percent, respectively, if each parking space- curb parking, surface lots, and parking structures- were spread horizontally over a surface lot (Manville and Shoup 2005). Driverless cars could enable avoiding the garage charges, since these vehicles could self-park in cheaper, more distant parking locations (Anderson et al. 2014).

Fully automated (Level 5) vehicles could significantly alter the proximity value of parking, due to the ability of an AV to drop its passengers off at their destination, search for cheaper parking, and return to pick up their passengers when needed (referred to as driverless valet parking throughout this chapter). As the automobile industry begins to transition towards partial vehicle automation, "limited" self-parking technologies are beginning to appear on the market in vehicles such as the Tesla X and BMW 7-series (D'Orazio 2016; Gorzelany 2016). In light of continued advancements in AV technologies, driverless valet parking systems could be on the market as soon as 2020 (Tilley 2016), although there remains uncertainty on when Level 5 technology will be ready for commercial implementation. Due to the large amount of land used by both curb parking and parking garages in dense urban areas, it is important for urban planners and transportation professionals to begin exploring the implications of driverless vehicles on travel patterns, parking revenues, as well as impacts from driverless trips (Stephens et al. 2016).

This chapter investigates the economic, energy, environmental, and travel implications of driverless vehicles by estimating changes in parking revenues and daily parking cost savings, greenhouse gas (GHG) emissions, and VMT from changes in parking choices in Seattle, Washington. These estimates are based on an agent-based model of driverless vehicles in Seattle with constructed grid network of .07 mile street segments. The model uses parking data from the 2013 Puget Sound Regional Council (PSRC) Parking Inventory and simulates changes in parking decisions. Each AV selects a parking spot based on economic cost, which includes the operational cost of driving (maintenance, tires, fuel) to the parking spot, increased depreciation from the extra travel, as well as the associated daily parking cost. In addition, the AV also considers parking availability at each location. Within the models we vary influential parameters such as the cost of driving and AV penetration rates. The results indicate that paid public parking lot and garage revenues and occupancy rates are likely to be impacted and travel patterns could change from driverless and empty vehicle travel. The estimates in this chapter are meant to provide discussion on the potential impact of AVs on the built environment and can help inform near- and long-term decisions during the transition to automation.

4.2 Existing Literature

There have been many studies that discuss parking economics and choice. Hess (2001) investigated the impacts of free parking on mode choice using a multinomial logit model. This study concluded that approximately 78% of commuters would commute to work by light-duty vehicle if parking was free; this number dropped significantly, to 50% if there was a $6 daily parking charge (Hess 2001). Waraich and Axhausen (2012) constructed an agent-based model traffic simulation model that focused on parking choice and reducing traffic volumes by reducing parking supply in a central location in Zurich (Waraich and Axhausen 2012). The authors focused on four different parking scenarios (public, reserved, private, and preferred parking) and set static prices for both garage and on-street paid parking. Bonsall and Palmer (2004) developed models based on data from a parking simulator to determine how factors such as parking price, walk, queuing and drive time influence parking choice (Bonsall and Palmer 2004). Willson and Shoup (1990) reviewed previous studies of how employer-paid parking influences travel choice and conclude that somewhere between 19 to 81 percent fewer employees drive to work when they do not receive any parking subsidies (Willson and Shoup 1990). Pierce and Shoup (2013) evaluate the impacts of demand-based on-street parking prices on demand. This study estimates that a -$0.50 and $0.25 change in parking price have price demand elasticities of -0.82 and -0.71, respectively (Pierce and Shoup 2013). Ottosson eat al. (2013) used the 2010 Seattle parking inventory dataset to estimate the elasticity of on-street parking demand in response to a change in pricing, modified by time of day and neighborhood characteristics (Ottosson et al. 2013). Qian and Rajagopal (2014) investigate how parking demand could be managed by dynamic parking pricing and conclude that parking price and provision of parking information serve as effective ways of managing traffic (Qian and Rajagopal 2014).

In comparison, the available literature that addresses the implications of AVs on parking demand is limited. Fagnant and Kockelman (2015) estimate approximately $250 in parking savings per new AV could be realized through reallocating parking from Central Business Districts (CBD) to less dense areas and car-sharing (Fagnant and Kockelman 2015). Fagnant and Kockleman assume that AVs could save $1 in daily parking cost per work day. Zhang et al. (2015)

investigated the impact of shared autonomous vehicles (SAV) on urban parking demand using an agent-based model simulation, conducted on a 10 x 10 mile grid-based hypothetical city. The main source of data for that study was the 2009 National Household Transportation Survey, which is used to assign departure and trip length for each trip generated in this model. Their study results indicate that SAVs could eliminate up to 90% of daily parking demand for clients who choose to adopt the system, at low penetration rates (Zhang et al. 2015). However, Zhang et al.'s study suggests that a reduction in parking demand comes at a cost, with significant increases in VMT due to empty vehicle cruising. Zakharenko (2016) developed a model to estimate the impacts of AVs on urban land use. Their study suggests that vehicle automation could cause cities to shrink by reducing the demand for parking land (Zakharenko 2016). Zakharenko assumes that there is a fixed amount of space for each resident and AVs return home for parking. Fagnant and Kockleman (2014) explore the travel and environmental implications of SAVs using agent-based model scenarios and estimate that daily VMT could increase by about 11% from vehicles relocating to new zones when unoccupied (Fagnant and Kockelman 2014).

This chapter makes a contribution to the literature by using Seattle parking lot price and daily occupancy data to develop an agent-based model that simulates changes in parking choices in the Seattle region due to vehicle automation. This chapter evaluates different scenarios than previous agent-based AV studies. In particular, this is the first study we are aware of that quantifies the changes in travel demand, energy use, and parking revenues, when privately owned vehicles (POV) that currently park in downtown garages and lots become driverless and could self-park in cheaper more distant parking locations. There are already several studies that estimate the travel, parking, and environmental implications of shared AV use at different penetration rates, so we chose to focus on POVs for this study. This analysis provides a discussion on how urban form as well as the expected number of crashes could change as we advance towards a fully automated light-duty vehicle fleet based on the results from this simulation. It is still unclear how much parking occupancy and revenue is likely to be impacted due to this technology as well as the impacts of certain policies on AV parking decisions. This chapter fills this gap through a simulation model, which is developed to estimate the potential impact of driverless valet systems on parking demand in Seattle's downtown area.

4.3 Data

The data for this project were obtained from the Puget Sound Regional Council (PSRC) 2013 Parking Inventory, which includes off- street parking data or public garages and surface lots located in the King, Kitsap, Pierce, and Snohomish Counties of Washington State. Each lot was surveyed during one morning (between the hours of 9:30 a.m. and 11:30 a.m.) and one afternoon period (between the hours of 1:30 p.m. and 3:30 p.m.). Each parking lot was coded to the 2010 census block-level in which it was located. The information collected includes the total number of parking lots and stalls and average daily occupancy rates, as well as average hourly and daily parking price. The entire Puget Sound Region consists of 2,443 parking lots including 569 lots that are located in downtown Seattle. Of these 569 lots, approximately 365 have daily parking costs recorded in the dataset, while other lots may be free short-term parking reserved for customers of restaurants or convenience stores, are reserved for employee parking, or do not have recorded daily parking cost information.

Since we are interested in exploring the changes in parking choice and urban form in dense urban areas due to driverless vehicles, we only consider parking lots located in downtown Seattle, while all other paid parking lots located outside of these areas were not considered. Seattle has about 270 paid parking garages and lots, with about 70% of these lots located in the downtown area. Entries with morning, afternoon, or average daily occupancy rates greater than 100% were disregarded from the dataset. Similarly, entries that report daily occupancy rates of 0%, were not considered. Entries with missing occupancy, daily parking rate, and/or total stalls data were truncated from the dataset. Some of the daily lot revenues and occupancy rates were unrealistically low for the purpose of our analysis. For example, there are several census blocks that have average daily parking occupancy rates below 5% and/or total daily parking revenues below $100. Entries with estimated total daily lot revenues[3] below $250 or per lot occupancy rates below 10% were removed from the dataset. A report done by the city of Seattle estimates that it costs about $190 a day in $2002 to operate a staffed surface lot facility with 100 stalls in the city of Seattle when considering operating costs such as labor, accounting, and utility costs (City of Seattle 2002). Because the parking inventory data used for this chapter is from the year 2013, the Consumer Price Index (CPI) was used to convert all daily operating costs to 2013 dollars, which is approximately

[3] $Esimated\ Daily\ Revenue = Avg.Daily\ Occupancy\ Rate \times Total\ Number\ of\ Stalls\ per\ lot\ \times Daily\ Parking\ Price$

$250, which is why this value was chosen as our truncation point (Bureau of Labor Statistics 2017).

Table 4.1 lists descriptive statistics for surveyed off-street parking in downtown Seattle at the census block-level. There are about 47,000 total daily parking stalls in our sample. The average daily rate to park in an off-street parking facility in downtown Seattle is about $19. On average each census block in the downtown area that has a daily parking lot, generates about $3,500 in total daily parking revenue and the garages in these census blocks have an average occupancy rate of about 68% throughout the day. Each census block generates about $12.70 in daily revenue per stall and in most cases contains about 1 or 2 lots with each lot having about 250 total parking spaces.

Table 4.1 Summary Statistics of Puget Sound Regional Council Parking Inventory Census Block-Level Attributes

Statistic	Mean	SD	Min	Max
Census Block Records (n=192)				
Daily Occupancy Rate	68%	16%	13%	100%
Total Daily Revenue ($2013)	$3,500	$4,121	$260	$21,000
Daily Price	$19	$7	$7	$42.00
Daily Revenue Per Stall	$13	$6	$1.5	$35
Total Stalls	250	260	20	1,500
No. of Lots[1]	1.50	0.80	1	5

Note: SD=standard deviation; min=minimum; max=maximum

[1]Descriptive Statistics for paid surface lots and parking garages with daily parking at the census block-level.

Although, some employers currently subsidize employee parking downtown, it is possible in a fully automated vehicle environment for employers to instead reimburse travel cost for parking. The data does not specify what percentage of cars in each individual garage are there for shopping, entertainment, leisure, or are commuters. In addition, the level of subsidy varies from employer to employer and it is not certain as to how employers will handle parking subsidies in a fully AV environment where distant parking is now possible. As a result, we assume that all drivers parked in the downtown garages and lots currently pay the total daily parking cost and that each AV will make a decision based on this cost.

4.4 Methods

To simulate how driverless valet parking could change parking choices we first identify those areas in Seattle with free or unpaid parking. We model unrestricted parking in ArcGIS by creating sample zones throughout Seattle where AVs can park during the day with no parking restrictions. We then develop our agent-based model, assuming a gridded network, where agent AVs search for cheaper parking and make decisions based on parking availability as well as cost. The simulation ignores the actual roadway geometry and assumes a rectangular grid throughout the entire study area.

4.4.1 Estimation of Unrestricted Parking Spaces in Seattle

Seattle has free, available parking spaces that outnumber paid garage spaces. According to the 2013 PSRC Parking Inventory, there are about 30,000 cars parked in downtown Seattle throughout a typical day. Seattle is estimated to have about 500,000 curb parking spots with about 470,000 and 12,000 total unrestricted and paid street parking spots, respectively, while the remaining parking spots are restricted parking spots (e.g. residential parking zones) that require a permit to park. We developed a sample set of unrestricted street parking zones close to downtown by identifying those portions of Seattle with abundant amounts of unrestricted parking available, using data from the Seattle Department of Transportation (SDOT), as shown in Figure 4.1. SDOT has street block face data available that contains parking information for each block face in the city of Seattle. This dataset contains estimates on the number of unrestricted, paid, and residential parking spots as well as their locations. Seattle defines unrestricted parking as a type of on-street parking where there are no signs restricting the time or type of vehicle that can park there (Seattle Department of Transportation 2016a). The City of Seattle estimates the total number of parking spots on each block face by assuming that 30% of the road segment is occupied by driveways and alleys and that the size of a standard parking spot along curb is 17.5ft (Seattle Department of Transportation 2016b) (Seattle Department of Transportation, 2016b), and we used these assumptions in estimating the number of unrestricted parking spaces in the sample zones. Our sample unrestricted parking zones consist of about 67,000 total parking spaces, and we assumed about 33,000 of these parking spaces to be available on a typical day. These zones represent about 14% of the total unrestricted curb parking in the city.

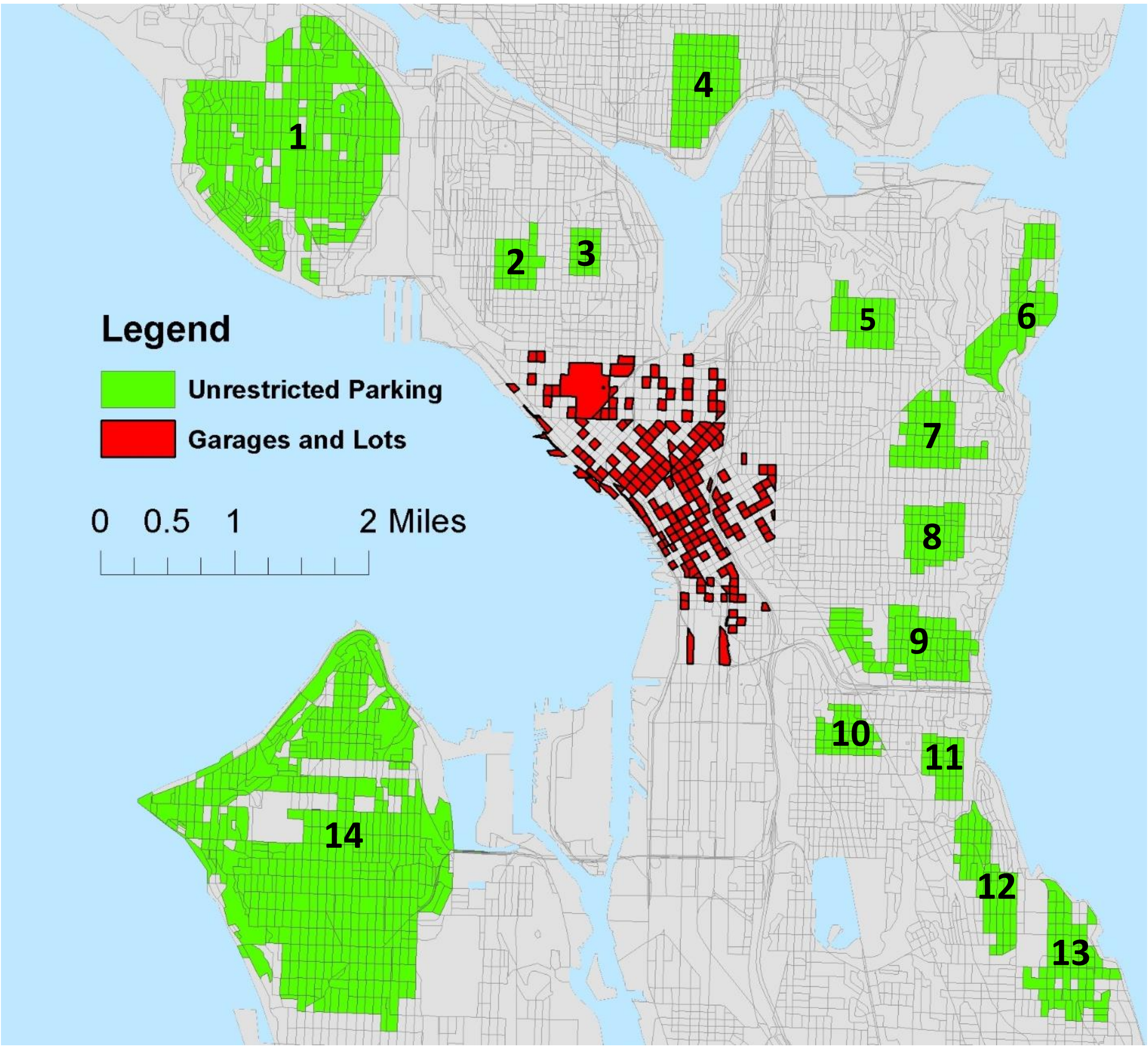


Figure 4.1 Seattle's Sample Unrestricted Parking Zones (numbered 1-14) and Downtown Daily Parking Lots and Garages

Note: Each unrestricted parking zone is designated a number that starts from the top left corner of the figure and increases clockwise.

The total number of unrestricted spots on each block are estimated in the dataset by subtracting the number of time limit, residential parking, and no parking spaces from the total number of spaces. Although, the city of Seattle estimates the total number of unrestricted parking spots on each block, most of these parking spots are located in residential areas and could be occupied by cars during course of the day. The number of available parking spaces (Table 4.2 column 7) is the product of the total number of unrestricted parking spaces in zone and the percentage of occupied parking and is expressed in Eq. (4.1):

$$AS = US \times P_{OS} \tag{4.1}$$

Where AS is the total number of available unrestricted parking spaces in each zone, US is the total number of unrestricted parking spaces and P_{OS} is the percentage of parking spots assumed to be already occupied by cars; for each zone we assume 50%.

The number of parking spots in each sample unrestricted parking zone (UPZ) is shown in Table 4.2. UPZ 14, located in west Seattle, has the largest number of available parking spaces, followed by UPZ 1, located in the northwest Seattle neighborhood, Magnolia. In comparison, the parking density, number of unrestricted parking spots per acre of land, is about 30 percent higher in UPZ 1 than UPZ 14. UPZ's 2 and 3, both located in Queen Anne, a neighborhood just north of downtown Seattle, have the least amount of parking when compared to the other zones. UPZ 2 has about 1,000 total unrestricted parking spots, while UPZ 3 has about 900 total unrestricted parking spots. Although, UPZ 3 has the least amount of total unrestricted parking spots when compared to the other zones, the parking density in this zone is the highest at 17 parking spots for each acre of land.

Table 4.2 Unrestricted Parking Information by Sample Zone

Sample Unrestricted Parking Zone # (UPZ)	Neighborhood	Area (acres)	Total Unrestricted Parking Curb Miles	Total No. of Unrestricted Parking Spots	No. of Available Parking Spots[a]	Parking Density[b]
1	Magnolia	1,200	88	16,000	8,000	14
2	Queen Anne	80	6	1,100	500	13
3	Queen Anne	50	5	900	400	17
4	Wallingford	230	18	2,900	1,500	13
5	Capitol Hill	100	9	1,600	800	14
6	Central Area, Capitol Hill	210	14	2,600	1,300	13
7	Central Area	150	13	2,400	1,200	15
8	Central Area	130	11	1,900	1,000	15
9	Central Area	260	21	3,800	1,900	15
10	Beacon Hill	90	8	1,500	700	16
11	Rainer Valley	80	7	1,300	700	16
12	Rainer Valley	170	14	2,700	1,400	16
13	Seward Park	200	17	3,200	1,600	14
14	West Seattle	2,100	130	24,000	12,000	11
Total	na	5,100	360	66,000	33,000	na

Note: numbers may not sum exactly due to rounding.

[a]50% of Total Unrestricted Parking spots assumed to be occupied by cars in each zone.

[b] Total No. of unrestricted parking spots/acres of land.

4.4.2 Model Parameters and Specifications

This simulation is conducted on a 6.5 × 6.5 mile grid based on the city of Seattle. The resolution of the grids is 0.07 miles, representative of the average city block length in Seattle's downtown area, which was estimated using ArcGIS. The agents in this model are empty AVs starting in downtown Seattle in search of cheaper parking. AV penetration rates vary between each scenario, from a single driverless vehicle making parking choices in the initial scenario to all cars being fully automated in the highest AV penetration scenario. AVs are deployed randomly from each downtown parking lot and the simulation continues to run until all AVs have selected a parking spot. The model assumes that each driver's final destination is within comfortable walking distance (1/4 mile) of their parking location. As a result, we use the parking lot where the driver is initially parked as a proxy for the AVs starting location. We believe that starting the AVs at the downtown parking location is within the bounds of existing uncertainty for this model. Each AV selects a parking spot based on economic cost, which includes the roundtrip operational cost of driving to the parking spot, increased depreciation from extra travel, as well as the associated daily parking cost; in addition, the AV must also consider parking availability at each location. Before an AV makes a parking decision it first considers all of its parking choices and ranks them in terms of economic cost. If parking is not available at the parking spot with the lowest cost, the AV then considers the parking option with the second lowest associated cost and so forth until an available parking spot is found. Once the AV determines the most economical parking location with an available space, the AV reserves this parking space and the model estimates the increases in travel, energy use, and emissions from this parking decision. The model does not allow for more than one AV to compete for the same parking spot. Instead, once one AV decides to travel to and reserves a parking space, this space is no longer available to the other AVs. The model does not allow for the number of AVs traveling to a parking location to be greater than the parking availability at this location. AVs estimate the distance from their starting location to each available parking spot using the sum of the absolute value of the difference between the x and y coordinates or the Manhattan distance.

This analysis assumes that the existing Seattle light-duty vehicle fleet, comprised of passenger cars, pickup trucks, and SUVs and minivans, will be replaced with conventionally fueled fully automated mid-sized sedans. This model assumes that vehicle ownership remains constant and drivers do not shift to shared mobility. This analysis is only focused on simulating changes in parking decisions for AVs, and as a result all non-AVs in this model are assumed to start and end the day at its original parking location and have no changes in parking decisions. The operational per mile cost of driving a medium-sized sedan, which includes maintenance, tires, depreciation, and fuel, as well as increased depreciation costs from extra travel are assumed to be about 25 cents per mile and obtained from the 2013 AAA Your Cost of Driving report (AAA 2013). To formulate our optimization problem, we first define a set of decision variables:

$Dist_{ij}$
$= Manhattan\ Distance\ from\ node\ i\ (starting\ location\ )\ to\ node\ j\ (parking\ destination)$
$Drive =$ per $-$ mile operational cost of driving a medium sized sedan
$Daily_j =$ is the cost to park at node j

The objective function and constraints for the agents in this model are expressed in Eq. (4.2) and Eq. (4.3), respectively:

$$\min \qquad TC_{ij} = \min[2 \times (Dist_{ij} \times Drive) + Daily_j], \quad \forall\, i, \forall j \tag{4.2}$$

$$subject\ to \qquad Avail_j \geq 1 \quad for\ j = 1, \ldots, m \tag{4.3}$$

where, $\min TC_{ij}$, the minimum total cost from your starting point (denoted as i) to your parking destination (denoted as j), is the sum of the round-trip operational cost of driving from your starting point to your parking destination and the daily cost to park at your parking destination. Your decision variables are as follows: $Dist_{ij}$ is the Manhattan distance from node i to node j, $Drive$ is the per-mile operational cost of driving a medium sized sedan in 2013, $Daily_j$ is the cost to park at node j for the duration of the day, and $Avail_j$ is the parking availability at node j, which is meant to ensure that there is at least one parking spot available at the desired parking spot.

The chapter assumes a connected, automated environment where vehicles can communicate with each other, as well as with infrastructure and city networks, which is one proposed system architecture for driverless vehicles. In this system, the location and status of all current parking spaces is known, and demand can be assigned by a parking system operator for all vehicles communicating with the system once the vehicle begins a journey. Even non-autonomous but connected vehicles could participate in this system, and any deviations where a non-connected car occupied a reserved space, the next closest space would automatically be found and the driverless car routed to it by the system operator. Each AV in this model is hence assumed to be fully autonomous and connected and have perfect information of the locations and parking occupancy of each parking garage and UPZ in Seattle, and do not spend time cruising or searching for available parking. The implications of this assumption are discussed in the Sensitivity Section.

Whenever an AV chooses to move to a parking spot, we estimate the roundtrip distance traveled by the empty AV, the loss in downtown parking revenue, energy used, GHGs emissions emitted, and the change in parking occupancy. These increases are summed and used to determine how changes in parking choices could change light-duty VMT and emissions and parking revenue in the city of Seattle. By the end of the simulation, parking occupancy will be estimated for each census block that contains a daily parking garage in downtown Seattle. The total GHG emissions generated from extra travel for parking is expressed in Eq. (4.4):

$$E = \sum_{i}^{n} [(CO_2/gal) \times (gal/mile) \times VMT_i] \tag{4.4}$$

where E is the total GHG emissions emitted from empty AVs traveling longer distances for more economical parking, CO_2/gal is the amount of direct CO_2 in a gallon of gasoline (8,890 g), $gal/mile$ is the average fuel consumption for passenger cars in the city of Seattle for the year 2014 ($\frac{1\,gal}{23\,miles}$), and VMT_i is the additional roundtrip travel miles from empty vehicle i, and (Seattle Office of Sustainability and Environment 2016). As the fleet of driverless vehicles are likely to have higher fuel economy and/or increasingly be electrified vehicles in the future, our per mile results represent an upper bound. Using 127.109 MJ/gallon (Energy Information Administration 2016; NHSTA 2010), we also estimate energy use from the additional travel.

The simulation model is programmed in Python with the data visualization done in ArcGIS. In this model, AV penetration rates determine the amount of AVs in search of cheaper parking, which we assume to be uniform across the parking lots and garages in downtown Seattle. For example, an AV penetration rate of 10% means that 10% of the cars in each downtown parking lot are now assumed to be driverless and can now search for parking elsewhere in the city. This model simulates AV parking decisions based on cost and parking availability and estimates the increases in VMT, emissions, and energy use from this extra travel. The extra VMT from AVs in this model would be traveling in the opposite direction of most traffic, as well as benefit from the congestion reducing features of AVs and a connected, vehicle to infrastructure environment. Therefore, any additional congestion impacts from AVs are assumed to be negligible. The AV considers and ranks all available parking choices in our parking sample, both free and paid, and chooses the parking spot that minimizes cost to the user and has at least one available parking spot. The reference point from which we estimate distance, travel cost, and emissions for AV parking decisions, is the centroid coordinates of the census blocks that contain a daily parking lot. For the unrestricted parking zones we use the centroid coordinate of the most centrally located census block as a reference point from which we calculate distance, emissions, and associated travel costs for the entire zone. The centroid of each census block included in this analysis is assigned to the node on the grid closest in proximity.

4.5 Results

To model potential travel, economic, and environmental impacts due from changes in parking choices due to AVs, we placed a single driverless vehicle in downtown Seattle and increased the AV penetration rate until all parked cars became fully driverless. The following sections describe the results from which we estimate changes in the impacts mentioned above, discuss the results, and provide guidance for other regions interested in planning for automated vehicle futures. The model simulates individual parking choices based on economic feasibility and parking availability. Inputs to the model include the operational cost of driving, AV market penetration rates, the amount of unoccupied parking in each unrestricted zone, and vehicle fuel efficiency. These scenarios explore how driverless cars can influence parking choices, parking revenues, and travel demand impacts from empty vehicle trips.

4.5.1 Single Driverless Vehicle in Downtown Seattle

We start by placing a single driverless vehicle in downtown Seattle and ranking the potential parking choices in the city, which allows for an understanding of the decision process that an AV agent uses when selecting a parking location as well as the potential cost savings from driverless valet parking systems. In this scenario, one non-autonomous vehicle in a downtown Seattle area parking lot is replaced by a driverless vehicle that is now in search of cheaper parking. The AV considers the cost to travel and park at each UPZ and downtown parking lot in Seattle, ranks these choices in terms of cost, and calculates the cost savings as well as the emissions and VMT generated from this one trip.

Given the relatively high cost of parking in and around downtown Seattle and the low cost of driving, a single driverless vehicle can minimize daily parking costs by traveling to free parking. In order to visually demonstrate the parking decisions made by AVs in this model, we position a single driverless vehicle in the largest census block (in terms of area) in downtown Seattle with at least one public daily parking garage. This census tract and block is located in north downtown Seattle and contains 3 daily parking lots with approximately 100 stalls each and average daily parking prices and occupancies of $12.70 and 36%, respectively. The most economical parking spot from this starting location is a free parking space located about 1 mile away and if parking is available could save each driver about $12 in daily parking costs, when only considering the round trip operational cost of driving. If parking is not available at the parking spot with the lowest cost, the AV then considers the parking option with the second lowest associated cost and so forth until an available parking spot is found. The second and third most economical parking spots are 1.5 and 2.5 miles away, respectively, from this starting point and parking at one of these parking zones could reduce daily parking costs by about $11. Figure 4.2 (shown below) displays the top three most economical parking locations in Seattle respective to the AV's starting location in this example.

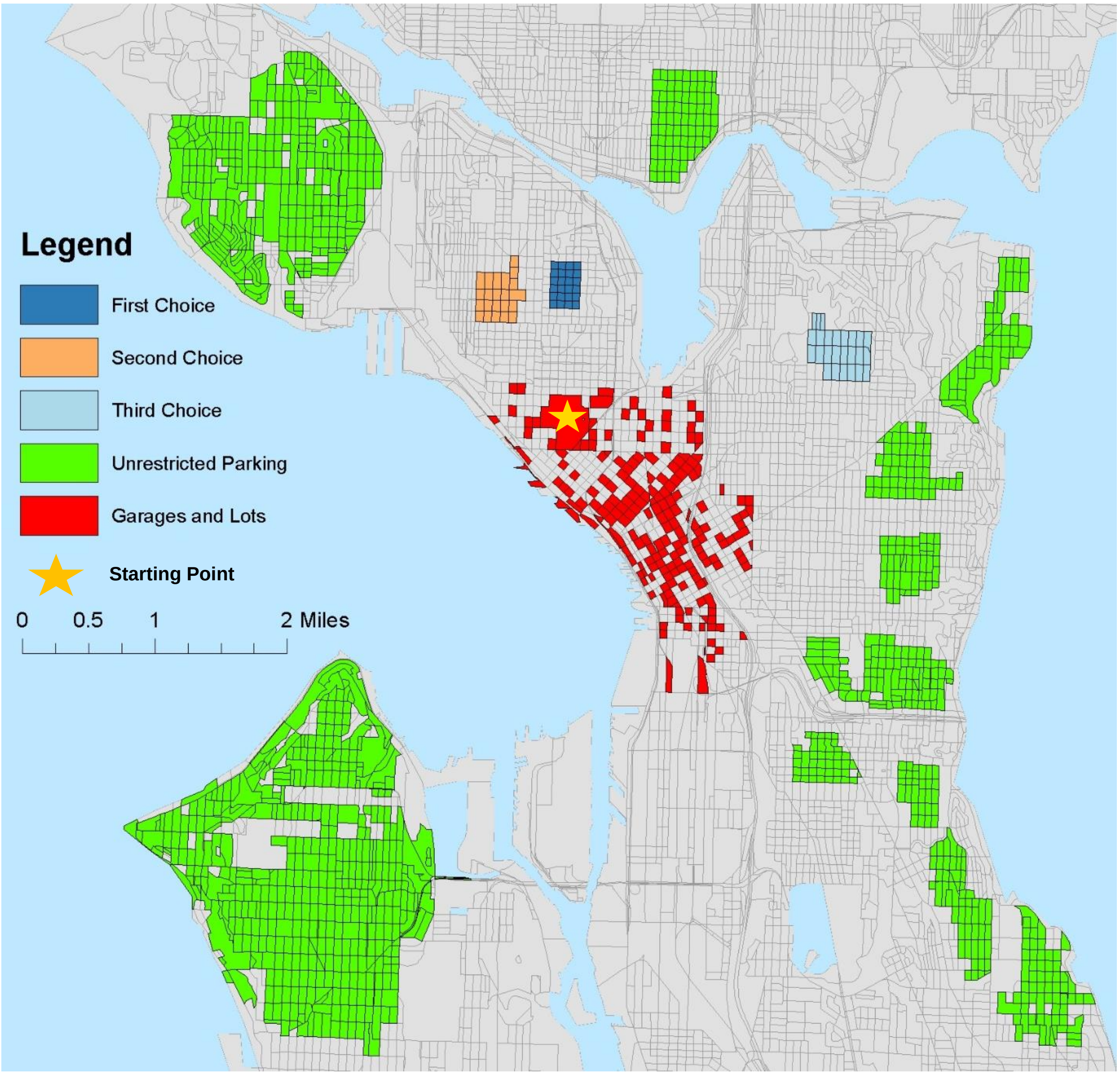


Figure 4.2 Top Three Parking Choices to Minimize Daily Costs for a Single Driverless Vehicle Starting in Downtown Seattle

AV parking choices are shown below in Table 4.3 and ranked in ascending order in terms of economic cost. Free parking could range anywhere between 1 and 7 miles away from the starting location and could save the vehicle owner considerable amounts of money. As expected, the farther away from the AV moves from downtown area, the more free parking becomes available. There are about 1,100 more parking spots in the fifth ranked parking choice, which is about 3 miles away when compared to top ranked parking choice, which is only about a mile away. While the fifth most economical parking is not close to the AV's starting location, parking here would only cost the vehicle about $1.60 in daily parking costs. Even if the AV decided to travel to the farthest UPZ for an available parking space, which is located about 7.5 miles away from the starting location, this round-trip would only cost the vehicle about $4.00 in daily parking costs. Although, AVs have the ability to park in cheaper, more distant parking locations, this added VMT could generate emissions and energy use that would otherwise not occur. For example, if this AV traveling to its first or third ranked parking choice, would generate about 0.80 kg or 1.90 kg of CO_2, respectively. While, this added emissions to the Seattle region may have insignificant impacts on total GHG at low AV penetration rates, this could begin to cause environmental concerns at higher penetration rates, which will be explored further in the next section. We do not explore the impacts of conventional air pollutants from tailpipes in this study, which requires a higher resolution localized analysis in future work.

Table 4.3 Ranked Parking Choices for a Single Driverless Vehicle Starting in Downtown Seattle[a]

Parking Choice Rank[b]	No. of Available Parking Spots	Round-Trip Distance (miles)	Round-Trip Travel and Parking Cost	Round-Trip Emissions (kg CO_2)	Round-Trip Energy Use (MJ)	Daily Cost Savings
1	400	2.1	$0.55	0.80	12	$12
2	500	3.1	$0.80	1.20	17	$12
3	800	5.0	$1.30	1.90	28	$11
4	1,200	5.7	$1.50	2.20	32	$11
5	1,500	6.0	$1.60	2.30	33	$11
n	…	…	…	…		…
206	200	1.4	$42	0.60	15	-$30

Note: Results will vary by starting location of driverless vehicle.

Note: It is assumed that driverless vehicle will drop-of and pick passenger up at starting location.

[a]Driverless vehicle was positioned to start at Tract 7001 and Block 2001.

[b]Parking choices are ranked in ascending order based on economic costs.

4.5.2 Market Penetration Rate of Fully Automated Vehicles in Downtown Seattle Increases

In order to assess the travel, environmental, and economic implications of driverless vehicles we increase the market penetration rate of AVs in the downtown Seattle area in search of parking. This captures market penetration rates from the point in time where AVs have only been partially adopted by those in higher income households to a point in time where AVs transition from high-income early adopters to total market penetration. The model will continue to replace human-driven cars parked in daily parking lots in the downtown Seattle area with driverless vehicles that now have the ability to search for more economical parking elsewhere. The number of AVs from each parking lot in search of parking is dependent on the market penetration rate. For example, a 5% market penetration rate means that 5% of the cars that were originally parked in each respective parking lot are driverless and will now choose parking based on cost and occupancy instead of proximity to destination. It is assumed that each AV will start and end in the same position of the parking lot where it was originally parked. AVs are deployed randomly from each parking lot to search for parking and will continue until each AV has chosen a parking spot.

Seattle has about 47,000 total paid garage parking spaces in its downtown area. According to the 2013 Seattle Parking Inventory, on average about 65% or 30,000 of these parking spaces are occupied by cars at any time during the day. Total daily parking garage revenue for the downtown Seattle region is about $666,000; this would equal about $170 million in total annual parking revenue from drivers parking in downtown Seattle on weekdays. On-road GHG comprise about 66% of Seattle's emissions. Total emissions in the transportation sector have been decreasing as recent advances in technology have increased the average fuel economy for cars in Seattle from 21 miles per gallon of fuel in 2008 to about 23 miles per gallon in 2014. Currently, the annual emissions from the transportation sector total about 2.34 million metric tons CO_2e with passenger cars comprising about 75% or 1.77 million metric tons CO_2e of all transportation emissions in the city (Seattle Office of Sustainability and Environment 2016). In order to estimate the total annual average weekday VMT for the city of Seattle we use the trip dataset from the 2014 PSRC Household Activity Travel Survey. From this survey we estimate that light-duty vehicles travel about 10.3 million miles daily in the city of Seattle (see Table 4.4). This is the total VMT from all light-duty vehicles traveling starting in and/or ending in Seattle in 2014 and was estimated by counting 100% of trips contained within Seattle, 50% of trips with an origin or destination in Seattle, and 0% of trips that both start and end outside Seattle, towards the daily VMT total. This process is very similar to that used in the 2014 Seattle Community Greenhouse Gas Emissions Inventory report to calculate 2011 VMT. In this scenario we vary the penetration rates to estimate how the number of AVs searching for parking could impact VMT, emissions, and parking occupancy and revenue in the Seattle region.

Table 4.4 Total Daily Light-Duty Vehicle Miles Traveled in City of Seattle by Destination and Origin (million miles)

		Destination	
		Seattle	Outside Seattle
Origin	Seattle	4.1	3.2
	Outside Seattle	3.1	na

Source: The 2014 Puget Sound Regional Council Household Travel Survey, Daily Trip and Vehicle File, Puget Sound Regional Council.

VMT and energy use increase as the AV penetration rate goes up, but we do not see significant increases due to the relatively low number of cars parking in the daily parking lots and garages, when compared to the total number cars making trips in and out of Seattle during the day. Parking lot revenues decline to the point where owning a parking lot or garage would no longer be feasible from an economic perspective. At low penetration rates AVs are usually able to obtain their top ranked parking choice, which in most cases is the free parking zone closest to their starting location and as a result the increase in VMT and emissions per AV at a 5% penetration rate is the lowest. At this penetration rate each vehicle would increase their daily travel by about 3.6 miles and due to the low penetration rate would have negligible impacts on light-duty VMT and emissions in the Seattle region. At a 75% penetration rate each AV travels about twice as much on average as they did at the 5% penetration rate. This indicates that AVs would rather travel longer distances for free parking than to park close by in a paid parking garage or lot due to savings in cost. If 75% of all cars parked in the downtown Seattle region had the ability to park in cheaper, more distant parking locations, this would only increase daily light-duty VMT and emissions in Seattle by 1.4% and 1.3%, respectively. Even at a 100% penetration rate daily light-duty VMT and emissions would only increase by about 2.5% and 2.1%, respectively, with each AV traveling about 8 additional miles each day. In this simulation parking lot revenue loss is equivalent to the AV penetration rate since it is currently cheaper to travel to park in an unrestricted parking zone than to park in a garage downtown for the day. The least expensive daily parking spot in downtown Seattle cost about $7, which is still more expensive than a car traveling the length of the grid (6.5 miles) to obtain a free parking spot. On average, each AV saves users about $18 in daily parking costs from choosing more distant, cheaper parking. Estimates of changes in VMT and emissions in the city of Seattle is shown below in Table 4.5.

The low increases in VMT and emissions at high penetration rates can be attributed to the fact that there are much more cars making trips in, out, and around Seattle than there are cars parked in the paid lots and garages in downtown Seattle during the day. There are a total of about 30,000 passenger cars and trucks parked in the paid parking garages within downtown Seattle during the day, while there are about 456,000 non-commercial passenger cars and trucks registered in Seattle ZIP codes (Balk 2014). If we assume that all of the cars parked in Seattle's downtown parking lots are registered in Seattle ZIP codes, only about 7% of these cars are now in search of parking, resulting in relatively low increases in VMT and emissions. In addition, this model only considers cars parked in lots and garages in downtown Seattle that have paid daily parking, so cars parked in employee or customer parking lots, cars occupying paid on-street parking spaces, or cars parked in paid garages and lots outside of downtown Seattle are not accounted for in this model. As fuel economy increases and/or cars become electrified, the relative emissions and energy impacts would decrease further.

Table 4.5 Changes in Vehicle Miles Traveled, Emissions, and Energy Use from Changes in Parking Choices in the City of Seattle

AV Penetration Rate	Number of AVs[a]	Total Increase in Daily VMT	% Increase in Total Daily Seattle VMT	Total Increase in Daily Emissions (metric tons CO_2)	Total Increase in Daily Energy Use (GJ)	% Increase in Total Daily Seattle Emissions and Energy Use[b]
5%	1,600	5,500	0.05%	2	30	0.05%
25%	8,000	32,000	0.30%	10	180	0.25%
50%	16,000	90,000	0.90%	30	500	0.80%
75%	23,000	170,000	1.70%	60	940	1.40%
100%	31,000	260,000	2.50%	90	1,400	2.10%

Note: AV is automated vehicle

[a]Column represents the number of automated vehicles now in search of cheaper parking at each penetration rate.

[b]Percent increase in total daily emissions and energy use are identical.

An objective of this chapter is to estimate the changes in parking occupancy as the market penetration rate of AVs increases. Table 4.6 displays the changes in the parking occupancy rates of the census blocks located within the downtown Seattle area with daily parking garages or lots as AV penetration rates increases. When there are no AVs in the downtown Seattle area, approximately 50% and 35% of the census blocks contain paid parking lots and garages with parking occupancy rates between 51%-75% and 76%-100%, respectively. At the 5% penetration rate, the number of census blocks with greater than 75% occupancy rates drops by about 30% while the number of census blocks with occuppancy rates between 51%-75% increases by about 16%. As the penetration rate increases to 75% just about all the occupancy rates drop below 25% and at 100% AV market penetration all cars would have shifted from paid parking to more distant, cheaper parking. The changes in parking occupancy for both paid and urestricted parking are illustrated below in Figures 4.3, 4.4, 4.5, 4.6, and 4.7. It should be noted thast this analysis assumes that all cars are willing to travel for cheaper parking and that the only determinants for a parking decision are economic costs and availability. At 50% AV penetration we begin to see noticeable increases the number of parking garages and lots with very low occupancy rates, between 1% and 25%. There is a direct relationship between the daily parking occupancy rate and daily parking revenue, and at 50% AV penetration and higher we could begin to see an increasing number of paid parking lots become unprofitable.

Table 4.6 Downtown Seattle Daily Paid Parking Lot and Garage Parking Occupancy Rates from Increased AV Penetration Rates

		AV Penetration Rates					
		0%	5%	25%	50%	75%	100%
Parking Occupancy Rate	0%	0%	0%	0%	0%	0%	100%
	1%-25%	2%	3%	4%	13%	100%	0%
	26%-50%	11%	12%	38%	87%	0%	0%
	51%-75%	51%	59%	58%	0%	0%	0%
	76%-100%	36%	26%	0%	0%	0%	0%

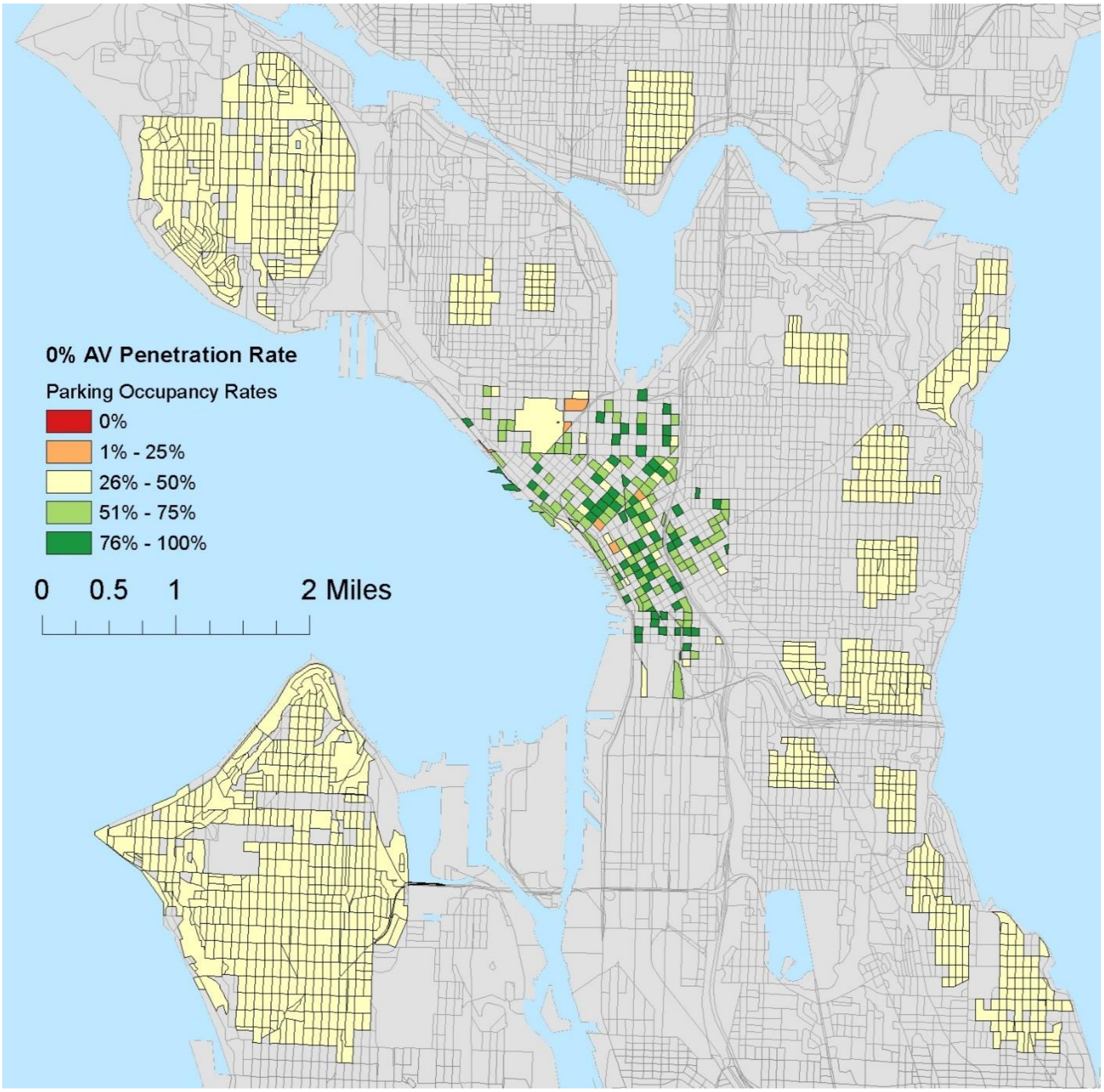


Figure 4.3 Parking Occupancy Rates in Seattle at 0% Driverless Vehicle Penetration

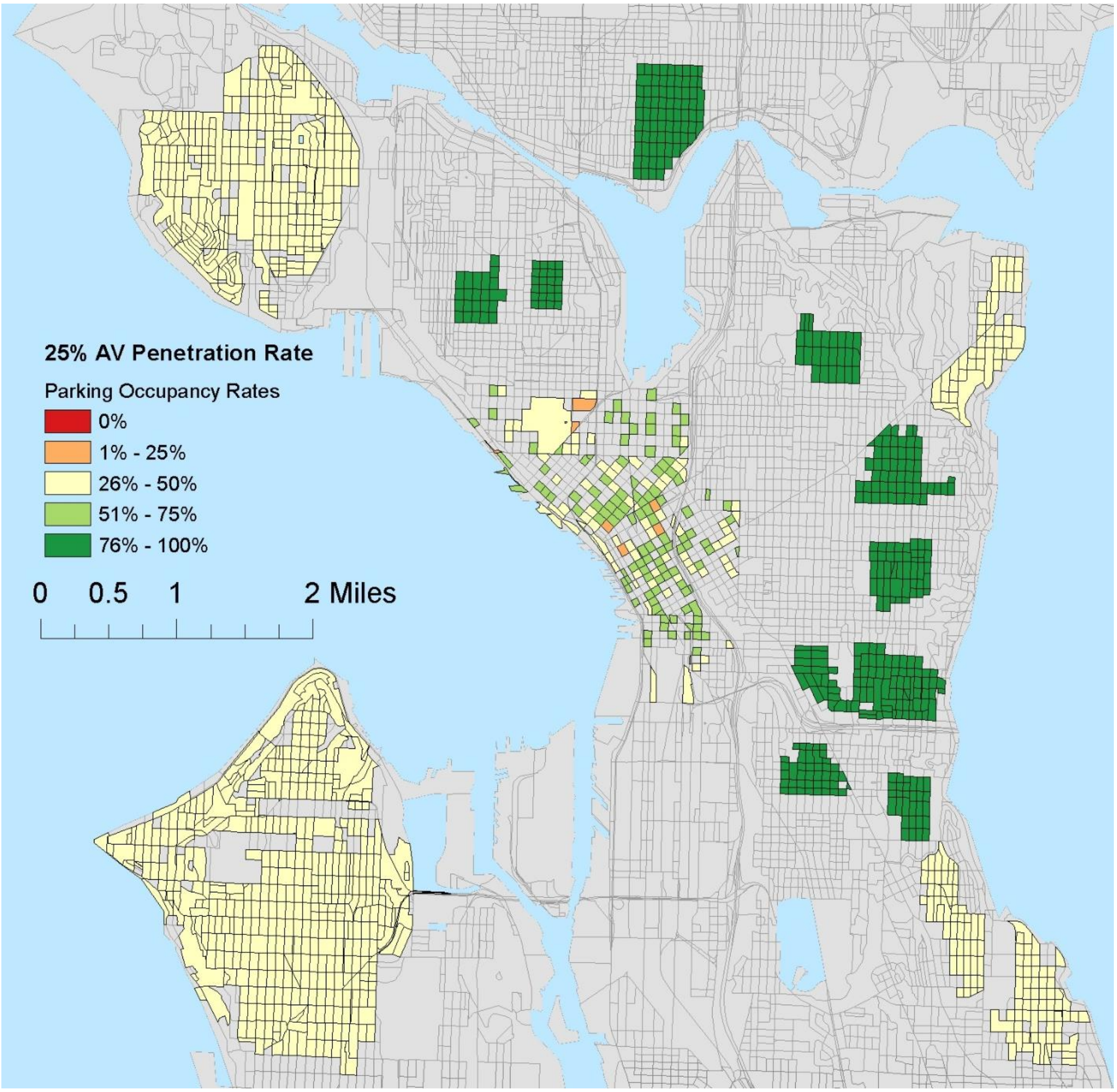


Figure 4.4 Parking Occupancy Rates in Seattle at 25% Driverless Vehicle Penetration

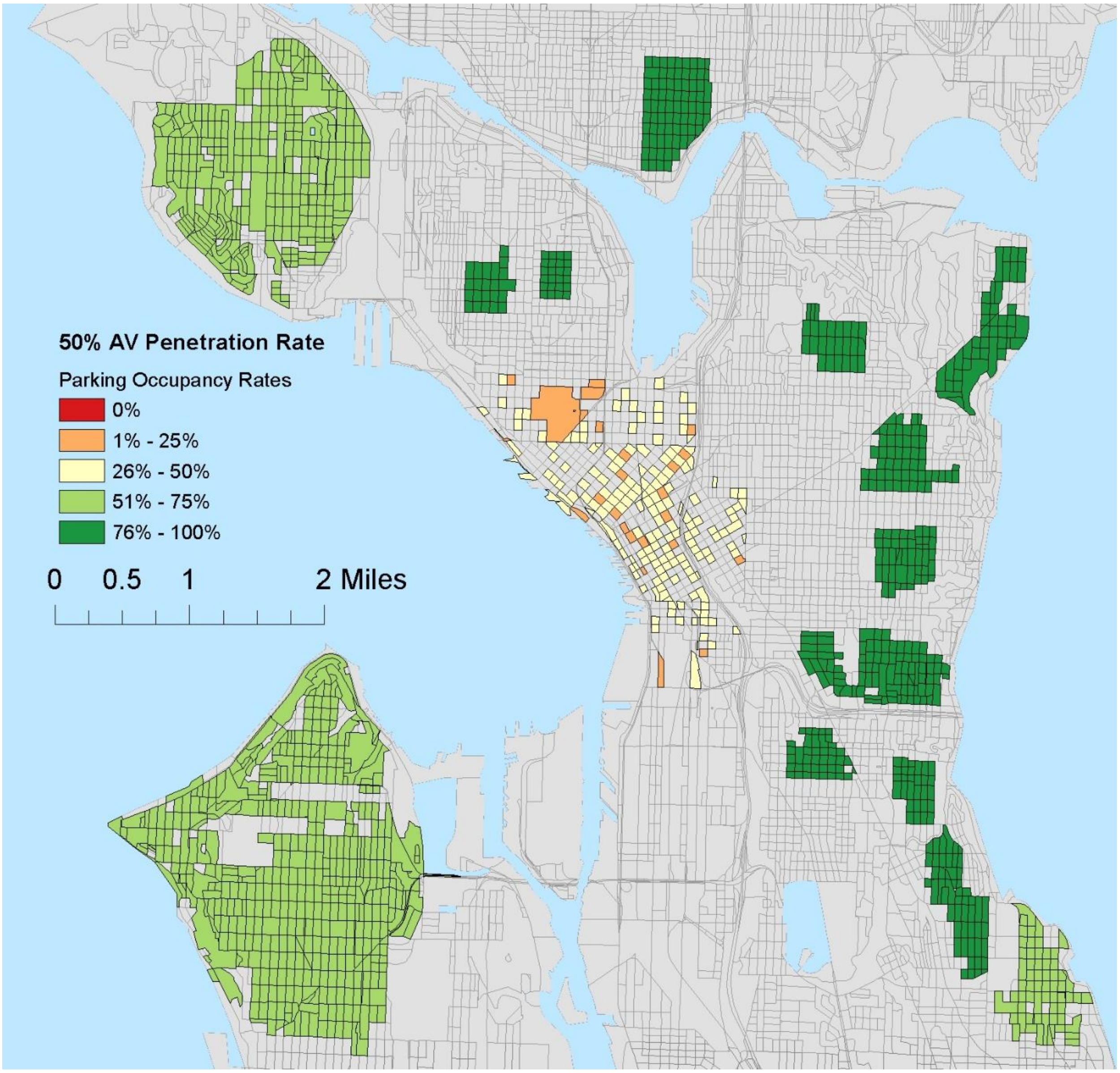


Figure 4.5 Parking Occupancy Rates in Seattle at 50% Driverless Vehicle Penetration

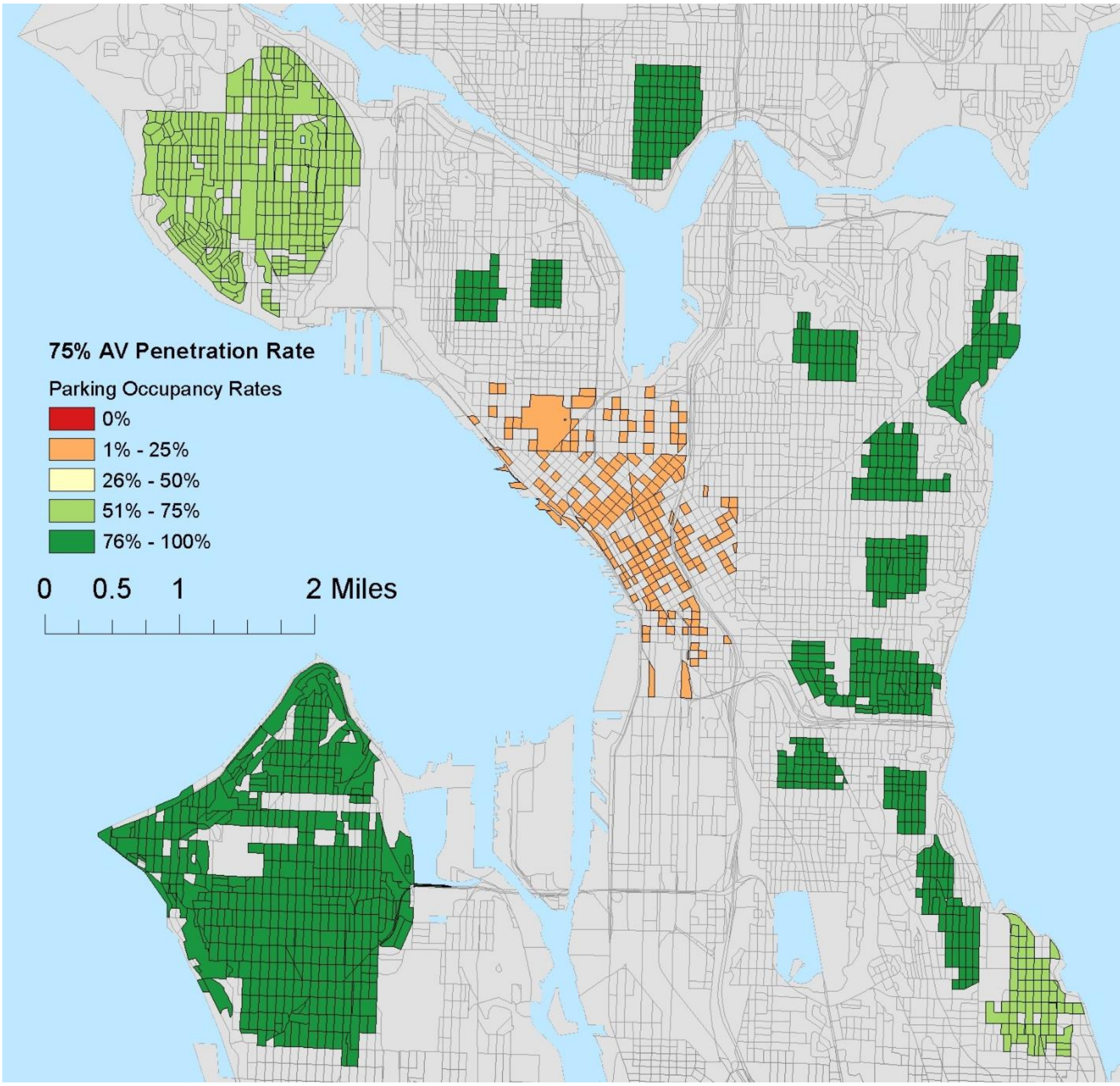


Figure 4.6 Parking Occupancy Rates in Seattle at 75% Driverless Vehicle Penetration

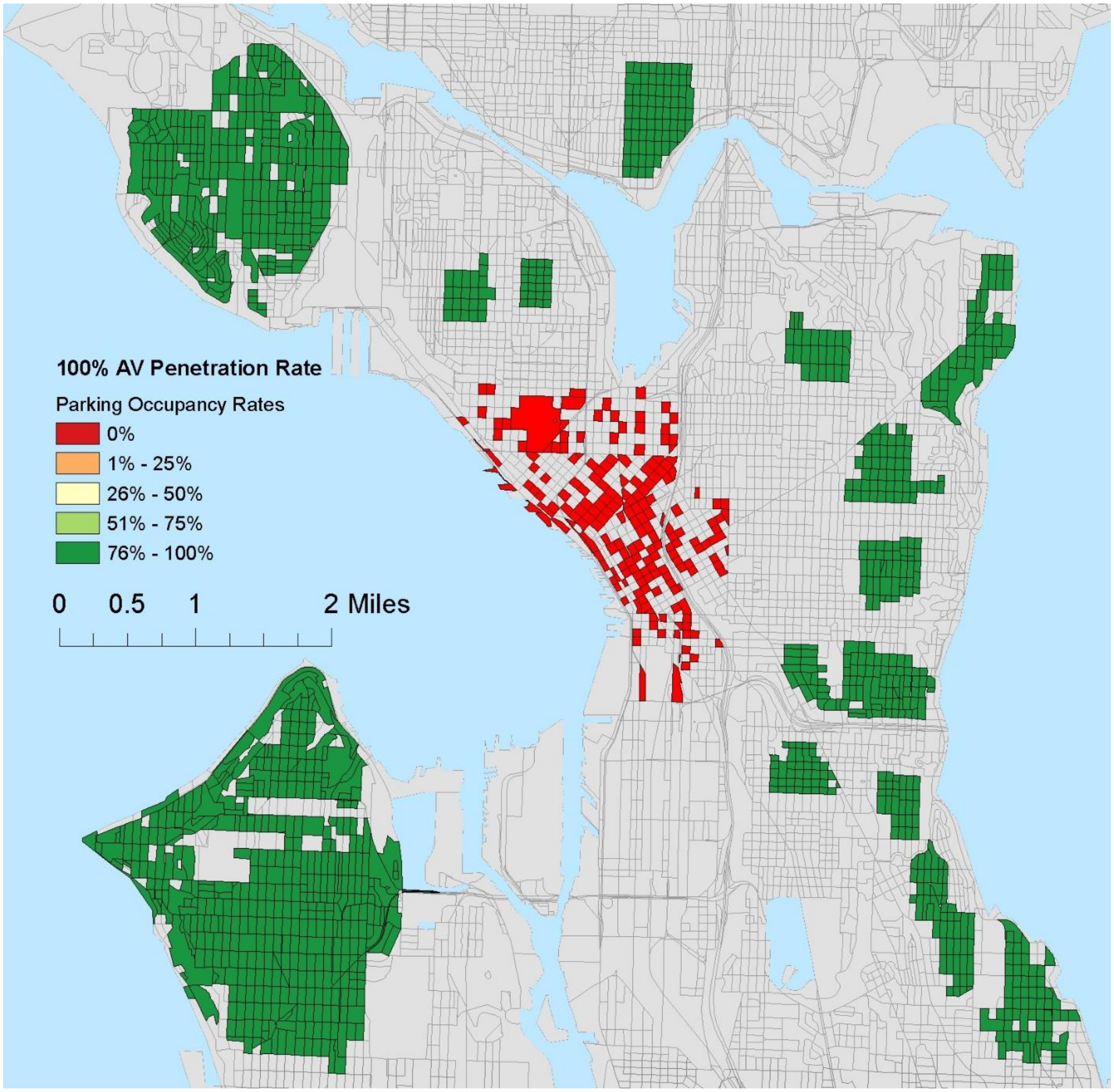


Figure 4.7 Parking Occupancy Rates in Seattle at 100% Driverless Vehicle Penetration

4.5.3 Sensitivity Analysis

The increases in VMT and emissions as well as the changes in parking occupancy rates are based on a variety of assumptions, the most significant being the AV penetration rate and the cost of driving. Changes in both categories could result changes in the parking decisions made by AVs. As shown, it is currently more economical for AVs to travel longer distances to obtain free parking than to park downtown in a paid parking lot. Different parking decisions could be made with a higher cost of driving and/or by enforcing parking restrictions in the UPZ. Our base case assumption for the cost of driving is about 25 cents per mile. In order to evaluate the impact other scenarios would have on the VMT as well as the parking occupancy rates in the downtown Seattle area, two-way sensitivity analyses were conducted to examine how changes in the cost of driving could impact AV parking decisions and travel patterns in Seattle. The range in the cost of driving represents the uncertainty associated with driverless vehicle technology costs, changes in fuel economy, changes in fuel prices, congestion/parking fees, emissions fees, or other internalized social costs.

Table 4.7 displays the sensitivity of Seattle's daily light-duty VMT to the AV penetration rate and per-mile cost of driving. At the 5 and 25 percent AV penetration rates, the increases in daily VMT are similar at most price points, which indicates unless there are significant increases in the cost of driving (either because of technology or policy), most AVs will choose to leave the downtown area and search for cheaper parking elsewhere at low penetration rates. This is due to the fact that at low AV penetration rates AVs are able to obtain their first ranked parking choice, which are usually relatively close to the downtown area. At the 50 and 75 percent penetration rates, the AV's decision to park away from the downtown area does not change until the per-mile cost of driving reaches \$1.50 and \$1.00, respectively. Similarly, at the 100% AV penetration rate AVs are less willing to travel far distances for free parking as the per-mile cost of driving increases. Although the per-mile operational cost of driving itself is not likely to reach above \$1 even in a fully AV environment, if Seattle chooses to implement a parking tax for AVs choosing to leave the downtown area for parking this would have an impact on parking decisions.

Table 4.7 Percent Increases in Seattle Daily Light-Duty VMT from changes in AV Penetration Rates and the Per-Mile Cost of Driving

		AV Penetration Rate				
		5%	25%	50%	75%	100%
Cost of Driving ($/mile)	$0.25[a]	0.05%	0.30%	0.90%	1.70%	2.50%
	$0.50	0.05%	0.30%	0.90%	1.70%	2.50%
	$1.00	0.05%	0.30%	0.91%	1.60%	2.33%
	$1.50	0.05%	0.30%	0.68%	1.19%	1.73%
	$2.00	0.05%	0.28%	0.56%	0.63%	0.80%
	$2.50	0.05%	0.25%	0.42%	0.48%	0.57%

Note: Areas shaded green indicate the price point at which AVs begin to make parking decisions different to those in the base case.

[a] Current per mile operational cost of driving a mid-sized sedan.

In addition, there is uncertainty associated with the model's assumption of perfect information of parking space status. The additional VMT associated with cruising for parking is known (e.g Shoup et al. 2006), has a spatial and temporal component (Van Ommeren et al., 2012), and even moderate information or pricing provisions can reduce search time (e.g. Qian and Rajagopal, 2014; Wang and He, 2011) (Qian and Rajagopal 2014; Wang and He 2011). Hence the likely upper bound of the uncertainty would be additional VMT from existing cruising for parking estimates, while in actuality the system would perform much closer to how we described in the chapter due to parking system operator model. It is important to note that incorporating parking decision uncertainty in our model will not likely change the conclusions of this chapter. If every single car parked in the downtown parking lots and garages became driverless and could self-park then we will see relatively small impacts to travel demand and energy use, in large part due to the relatively small number of cars parked in the downtown parking garages lots compared to the total number of cars making trips in, out, and around Seattle each day. Any additional cruising because of parking space uncertainty in the model is unlikely to affect the magnitude of the estimate, in a connected, automated vehicle environment.

4.6 Conclusions

This study developed a simulation to evaluate the potential impact of driverless vehicles on VMT, emissions, parking revenues, and daily parking cost savings due to changes in parking decisions, based on the best available information about the paid parking lots and garages in Seattle. The main dataset used for this chapter was the 2013 PSRC Parking Inventory, which contains census block-level data of off-street parking lots and garages in King, Kitsap, Pierce, and Snohomish Counties of Washington State. For this chapter we focus on the downtown area of Seattle as this is a dense area where people must often pay for garage parking due to lack of curb or customer parking close to shops, restaurants, etc.

This model first simulates the decision process that an AV could go through when deciding where to park by placing a single driverless vehicle in downtown Seattle, ranking all of its parking choices based on economic cost, and calculating VMT, energy, emissions, and cost savings for each possible choice. The results indicate that AVs could substantially reduce daily parking costs by choosing to travel, sometimes far distances, to obtain cheaper parking instead of remaining in the downtown area and parking in a paid garage or lot. On average, each AV saves drivers approximately $4,500 in annual parking costs, which represents about $18 per work day. In comparison, as AV penetration rates increase and cars begin to leave the downtown parking lots for cheaper parking outside of the CBD, parking revenues decrease significantly, which means that operating and owning a parking garage or lot would likely become unsustainable from an economic perspective.

As the AV penetration rate increases, VMT and energy use in the city of Seattle increases slightly. At low penetration rates AVs are usually able to obtain a higher ranked parking choice and as a result we see relatively small increases in VMT and GHG emissions. Even if all cars were driverless, the increase in VMT from cars leaving the downtown area to park in more distant parking locations is relatively small when compared to Seattle's total daily light-duty VMT. Our simulation estimates that at 100% AV penetration, Seattle's daily light-duty VMT and GHG emissions would increase by approximately 2.5 and 2.1 percent, respectively. However, cars are willing to travel far distances to obtain cheaper parking - with each AV traveling about 7.5 extra miles per day. The congestion that is generated from this extra travel is dependent on the time of day these trips are taking place and the corridors used to travel to parking destinations. Instead of congestion occurring from drivers cruising in search of an available parking spot in dense urban areas with scarce amount of parking, congestion could occur during peak hours in the opposite direction of traditional traffic flow, from increased AVs on roadways traveling to distant parking locations. While the technology features of automated vehicles and connected infrastructure should alleviate some of this congestion, policy makers should plan for alleviating additional congestion from AVs.

Over the course of a year driverless vehicles could increase Seattle light-duty VMT by as much as 95 million miles. According to the National Highway Traffic Safety Administration (NHTSA) the crash rate per 100 million VMT is about 200, with about 77 of these crashes resulting in injury (NHTSA 2015). If AVs perform as safe as human-driven cars, this could result in as much as 190 or 1.6 percent more crashes including 75 more injury crashes in the city of Seattle (Seattle Department of Transportation 2015). Less than one percent of these crashes would involve a non-occupant (pedestrian or pedalcyclist). However, we expect driverless cars to be much safer (Blanco et al. 2016; Harper et al. 2016a) and as a result would consider this an upper bound increase in crashes that could occur due to this added VMT.

According to the 2013 PSRC Parking Inventory, there are about 47,000 off-street parking stalls within the paid daily parking garages and lots in Downtown Seattle. Many of the parking spaces in CBDs are in vertical or underground structures, but as an illustration we estimate how much land Seattle's parking garage and lot spaces would occupy if they were spread horizontally over a surface lot. Curb parking typicaly takes up about 160 feet per curb space while a parking off-street parking space in a lot or garage reqiuires about twice that area (Durning 2013). Curb parking usually requires less land than off-street parking spaces since the traffic lanes serve as driveway and manuevering room. The 47,000 garage spaces in the downtown Seattle region would cover 400 acres of land, or 28% of the total downtown area, if we assume that these parking spots are spread out at ground level. This ratio, of parking area to land area, can be called the "parking coverage" rate, and to some extent speaks to the amount of space devoted to the car in downtown Seattle. At level 5 vehicle automation, an AV could drop its passenger off and park in a satellite parking location, significantly cutting parking costs and reducing the amount of parking needed in dense urban areas. At 50% vehicle automation we begin to see relatively significant increases parking lots with very low occupancy rates, which could lead to space that was once devoted to parking storage used for another purpose. In addition, AV technology could lead to drivers switching from personal vehicle ownership to shared mobility services, further reducing the demand for parking (Fagnant and Kockelman 2014; Greenblatt and Saxena 2015; Zhang et al. 2015). Shared automated vehicles (SAVs) could reduce the number of cars on the road and after completing a trip would proceed to pick up the next passenger, instead of parking.

Although our simulation model adds understanding of how driverless cars may influence future urban parking and travel demand, the proposed AV parking model can be further improved from several perspectives. This study assumes that all AVs are aware of the amount of available parking in each UPZ and garage and lot, but this may not always be the case. Future modeling efforts should consider this and incorporate how AVs searching for cheaper parking without perfect information could impact VMT and emissions. Rather than using a gridded network to generate results, a more realistic road network could be incorporated to better capture the travel demand effects of these changes in parking decisions. While, this study assumes that all cars that traditionally park in downtown Seattle will search for cheaper parking if available, this may not always be the case. For example, users could deploy their cars for ridesharing during the day- picking people up and dropping them off- instead of searching for parking and vehicle ownership rates may change as drivers switch from personal to shared mobility. This study assumes that each AV adds 2 extra trips a day (traveling to and from a satellite parking location), but cars that act as shared mobility providers are likely to take more trips and travel more during the course of a day. Shared AVs could reduce energy use and emissions when compared to current light-duty vehicles by having the ability to right-size and reducing the number of vehicles on the road, but could likely increase VMT from the additional trips generated (Fagnant and Kockelman 2014; Greenblatt and Saxena 2015). Some users may also decide to continue to pay the higher parking price of parking in downtown garages due to the fact that curb parking does not provide shelter your car from inclement weather (rain, sleet, or snow) and extreme temperatures and sunlight. This analysis assumes that all cars are conventionally fueled, but in a fully AV environment many cars are likely to be electric vehicles (EVs), which means that the energy, emissions, and operational cost of driving (fuel and maintenance) could be further reduced. Downtown garages are likely to adjust their daily parking prices as customers begin to leave lots for cheaper parking, which is not accounted for in this analysis, but should be considered in future modeling efforts. If parking lots adjust their prices to compete with unrestricted parking this could lead to induced travel demand as some users who usually bike or use public transportation to commute to and from work, may begin to drive. Future analyses should also consider how increases in travel demand could impact travel time and congestion, especially at higher AV penetration rates where there is a mixed traffic flow. Regardless, our initial results suggest driverless valet vehicles will considerably alter the economics of parking, which will affect energy, emissions, VMT, and urban form in cities. Stakeholders could institute dynamic parking or roadway pricing policies to minimize extra VMT from AVs travelling outside of downtown to outer zones (and potentially back to the owner's home) for cheaper parking. Automobile manufacturers and ridesharing companies are investing millions of dollars to make self-driving vehicles a reality. Policymakers, engineers, as well as urban planners should begin to consider the impacts of this technology on land and energy use, parking decisions, as well as public revenues so that we may have a smooth transition and minimize any negative consequences.

Chapter 5: Estimating Potential Increases in Travel with Autonomous Vehicles for the Non-Driving, Elderly and People with Travel-Restrictive Medical Conditions[4]

The previous chapter explored the economic, environmental, and travel Implications of changes in parking choices due to driverless vehicles. This chapter presents a bounding exercise that estimates the upper bound increase in potential travel from populations with historically lower mobility in a fully automated vehicle environment.

Automated vehicles represent a technology that promises to increase mobility for many groups, including the senior population (those over age 65) but also for non-drivers and people with medical conditions. This chapter estimates bounds on the potential increases in travel in a fully automated vehicle environment due to an increase in mobility from the non-driving and senior populations and people with travel-restrictive medical conditions. In addition, these bounding estimates indicate which of these demographics could have the greatest increases in annual vehicle miles traveled (VMT) and highlight those age groups and genders within these populations that could contribute the most to the VMT increases. The data source is the 2009 National Household Transportation Survey (NHTS), which provides information on travel characteristics of the U.S. population. The changes to light-duty VMT are estimated by creating and examining three possible travel demand wedges. In demand wedge one, non-drivers are assumed to travel as much as the drivers within each age group and gender. Demand wedge two assumes that the driving elderly (those over age 65) without medical conditions will travel as much as a younger population within each gender. Demand wedge three makes the assumption that working age adult drivers (19-64) with medical conditions will travel as much as working age adults without medical conditions within each gender, while the driving elderly with medical any travel-restrictive conditions will travel as much as a younger demographic within each gender in a fully automated vehicle environment. The combination of the results from all three demand wedges represents an upper bound of 295 billion miles or a 14% increase in annual light-duty

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[4] The results of this chapter have been published as: Harper, C. D., Hendrickson, C. T., Mangones, S., & Samaras, C. (2016). Estimating Potential Increases in Travel with Autonomous Vehicles for the Non-driving, Elderly and People with Travel-restrictive Medical Conditions. Transportation Research Part C: Emerging Technologies, 72, 1-9.

VMT for the US population 19 and older. Since traveling has other costs besides driving effort, these estimates serve to bound the potential increase from these populations to inform the scope of the challenges, rather than forecast specific VMT scenarios.

5.1 Introduction

Many seniors (those over age 65) and people with medical conditions often face challenges traveling freely and independently and must rely on family, friends, government, or other providers to meet their basic mobility needs. Automated vehicles represent a pathway that could increase the mobility, and hence the vehicle miles traveled (VMT), of the senior and disabled populations by decreasing human involvement during driving (Anderson et al. 2014). The objective of this chapter is to estimate bounds on the impact of a fully automated vehicle environment based on VMT by the current U.S. population 19 and older due to new demand from currently underserved populations. The results from this analysis are intended to provide insight on the magnitude of potential future increases in total travel demand from these underserved populations under vehicle automation. In addition, this bounding analysis presents the current basic travel characteristics of: adult non-drivers, the elderly (those over age 65) without medical conditions, and adults with a travel restrictive medical condition, and determines which of these three demographics could increase there VMT the most in magnitude due to vehicle automation. Within each of these underserved populations, we also highlight the age group and gender combinations that could contribute the most to these increases in total light-duty VMT. We also highlight the data, results, and assumptions of previous studies that have estimated how VMT could change due to vehicle automation. Although travel from working age drivers (ages 19-64) without medical conditions could either increase due to easier travel from automated vehicles or decrease due to various effects from car-sharing, urban density, and VMT rebound (Anderson et al. 2014), this chapter is only concerned with changes in the travel patterns of the elderly, non-driving populations, and those with a travel restrictive medical condition relative to current conditions. This provides a bound to help understand the magnitude of the benefits and challenges of a transition to vehicle automation. The primary source of data for this project is the 2009 National Household Transportation Survey (NHTS), which provides information on current travel characteristics of the U.S. population (USDOT 2011).

According to the Current Population Survey (CPS), there were about 34.2 million people in the U.S. age 65 and older in 2003 (U.S. Census Bureau 2003). From 2003 to 2013 the senior population has increased by about 27% to almost 43.3 million people (U.S. Census Bureau 2003, 2013)In the U.S. and other industrialized nations, the senior population is expected to continue to grow in both absolute terms and relative to the rest of the population. By 2030 it is projected that there will be roughly 74 million seniors living in the United States that will represent close to 26% of the total US population (Rosenbloom and Winsten-Bartlett 2002).

A large increase in the travel of seniors would result in many current transportation systems facing challenges in providing efficient and reliable service to users. Among today's senior population, driving by car is still the most common mode of transportation. About 89% of all trips made by seniors are by automobile, and 80% of all trips made by those with a medical condition are by automobile. Very few older Americans rely on walking, biking, or transit to make trips and this trend is likely to continue (Santos et al. 2011). For example, working adults who used public transit for non-work trips before retirement, tend to rely on an automobile for these same trips once they enter retirement. Although older adults depend heavily on light-duty vehicles (LDV) for the large majority of trips, the percentage of trips made as drivers declines with age and this trend is especially evident within the older female population who often stop driving at an earlier age than their male counterparts (Reimer 2014). With autonomous vehicles, these groups could continue to use LDVs, either as self-driving taxis or private vehicles.

While issues related to mobility exist within the senior population due to reduced cognitive abilities and increased medical issues or disabilities, there are indications that today's senior population is healthier and possesses more disposable income than their previous senior cohort (Currie and Delbosc 2010; Cutler 2001). Due to the increasing size, overall wealth, and life expectancy of the senior population, advancements in personal mobility will inevitably become more important. Páez et al. (2012) found that people with disabilities who have used a car within the past 12 months are about 28% more likely to desire more leisure activities compared to those who have not (Páez and Farber 2012).

Many companies have announced plans to develop self-driving vehicles, and twelve companies have applied to test self-driving cars in California as of 2016 (Chew 2016). Vehicle automation has the potential to greatly improve travel by reducing congestion, travel times, crashes, and potentially energy consumption (Anderson et al. 2014; Brown et al. 2014; Harper et al. 2016a; Levin and Boyles 2015; Mersky and Samaras 2016; Wadud et al. 2016). The ability for smart vehicles to interact with smartphones and act as a taxi service to transport people to their destinations also serves as an advantage, reducing travel costs by almost 75 percent (Litman 2013). This technology could also potentially have large environmental benefits by reducing energy consumption and greenhouse gas emissions (GHGs) from the ability to deploy vehicles according to each trip's occupancy (right-sizing) (Greenblatt and Saxena, 2015). Fully self-driving Level 4 automated vehicle technologies, as defined by the National Highway Traffic Safety Administration (NHTSA) (NHTSA 2013b), will likely promote an increase in per capita VMT within the elderly, disabled, and non-driving populations due to their potential latent demand and since they would rely less on walking, public transit, or family members and friends for daily travel. At high market penetration rates, automated vehicles could increase accessibility to jobs, leisure, and resources for both low and high-income groups (Childress et al. 2015). Higher accessibility to jobs for low-income groups would likely increase employment, provide better job opportunities, and increase disposable income along with travel (Ihlanfeldt and Sjoquist 1990; Shen 1998).

There have been several researchers who have estimated how VMT could change in the future due to automated vehicles, and each result depends on the data and assumptions used. Wadud et al. (2016) estimates that vehicle automation could increase VMT anywhere between 2%-10% from increased travel due to new user groups. As an upper bound, the authors assumed that everyone aged 62 and above will travel as much as a person 62 years of age. Fagnant and Kockelman (2015) assumes that vehicle miles traveled (VMT) per automated vehicle is 20% higher than a non-automated vehicle at a 10% market penetration rate and 10% higher at a 90% market penetration rate, resulting in an increase in total VMT of 2% and 9%, respectively (Fagnant and Kockelman 2015). A recent agent-based analysis of shared autonomous vehicles estimated overall emissions benefits through vehicle replacement, but individual trips were longer (Fagnant and Kockelman 2014). Another bounding study assumed autonomous cars are directed to pick up other household members for trips, resulting in a 75% increase in annual mileage per vehicle and a reduction in vehicle ownership of 43% (Schoettle and Sivak 2015). Childress et al. (2015) used Seattle region's activity model to estimate how changes in the value of travel time, road capacity, parking costs, and per mile driving costs could change VMT. One of the scenarios examined in this analysis assumed road capacity will increase by 30% while the value of travel times and parking costs will decrease by 65% and 50%, respectively, resulting in a 20% increase in VMT. Brown et al. (2014) estimated that new demand from underserved populations could increase VMT by as much as 40%, using the 2009 NHTS and the 2003 “Freedom of Travel” study. This upper bound is estimated by assuming that each population segment from age 16 to 85 begins to travel as much as the top decile or travelers. This chapter takes a different first-order analysis approach by bounding future VMT based on three possible demand wedges, which could cause an increase in VMT due to vehicle automation.

5.2 Data and Methods

The U.S. Department of Transportation (USDOT) periodically releases information on the travel and transportation characteristics of the United States by conducting a representative nationwide survey, in order to assist policymakers and transportation planners in quantifying travel behavior and analyzing changes in travel characteristics over time. The 2009 National Household Travel Survey is the most recent national survey and contains significantly more data than any previous survey in the NHTS series, which allows for an expanded assessment of the travel behaviors in the United States. Specifically, the 2009 NHTS dataset contains a large sample size of 150,147 households for the U.S. Along with any household information, the 2009 NHTS dataset also includes person, vehicle and daily (travel day) trip level data.

The 2009 NHTS attempts to represent the travel characteristics of the United States population on a national level. A weighting factor is provided for each person, household, trip, and vehicle included in the datasets. This weighting factor is the computed inference factor, which is intended to represent the total population from which the sample was drawn. The survey’s sample population only includes people from ages 5 to 88 inclusively and up to age 92. As a result, the total weighted person estimate from survey comprises approximately 94% of the total U.S. population in 2009. Collectively, more than 99% of all adult respondents 19 and older who participated in the survey provided a response to driver status or whether or not they have a medical condition. All of the mean estimates presented in this report were found using the full sample weights, while the standard error estimates were found using the replicate weights for the 2009 NHTS. More information regarding the datasets or survey methodology and procedures for the 2009 NHTS can be found in the 2009 NHTS User guide (USDOT 2011).

According to the NHTS, there were about 201 million drivers and 20.1 million non-drivers 19 and older in the U.S in 2009. Non-drivers are defined in the NHTS as those who cannot drive for physical, legal, or financial reasons or because they do not possess a driver’s license. Within the senior population in the NHTS there were approximately 30 million drivers and 7.8 million non-drivers who make up about 15% of the adult (ages 19+) driving population and 35% of the adult non-driving population, respectively. There were close to 14.7 million adult drivers, who have a medical condition that makes it difficult to travel (7.3% of the total driving population), and almost 9.6 million (69%) within this population are between the ages of 19 and 64. The NHTS reports that approximately 11% of all senior drivers have a medical condition that affects their ability to travel and out of this population, about 82% have reduced their day-to-day travel and about 11% have given up driving altogether because of this medical condition. On the other hand, there were approximately 186.2 million adult drivers without a medical condition and out of this population there were about 25.7 million seniors.

In order to estimate an upper bound of the increase in annual light-duty VMT due to greater mobility from vehicle automation from these underserved populations, we first created several demand wedges that assumes that each person within the elderly and non-driving populations and those with medical conditions, will increase their VMT to a certain threshold. Once the demand wedges are established, we then decided which data to include and exclude in order to complete our analysis using the 2009 NHTS data.

5.2.1 Estimating Demand Wedges from the Elderly Population and People with Travel-Restrictive Medical Conditions

Loss in one's ability to drive due to old age or a disability results in both restrictions of personal mobility and the reliance on others to help meet basic daily needs (Marottoli et al., 1997). The 2009 NHTS reports that about 25% of the elderly population and about 35% of people with travel-restrictive medical conditions spend their day in the same place. Fully autonomous (self-driving) vehicles can have profound impacts on daily travel by reducing driver stress and providing independent mobility for non-drivers (Anderson et al. 2014). As a result of these potential benefits, populations that have legal or personal restrictions on travel could have increased independent mobility and accessibility. This increased demand would result in more travel than would otherwise occur. In order to set a range of the possible increase in VMT, the following demand wedges (demand wedge one, two, and three) were developed:

- Demand Wedge 1: Non-drivers 19 and older will begin to travel as much as the drivers within each age group and gender.

- Demand Wedge 2: Elderly Drivers without any travel-restrictive medical condition in the youngest elderly cohort (65-74) will begin to travel as much as working age adults (19-64) within each gender. While, elderly drivers without any medical condition in the middle (75-84) and oldest elderly (85+) cohort will travel as much as a person 65 years of age within each gender.
- Demand Wedge 3: Working age adult drivers (19-64) with a medical condition that makes it hard to travel will begin to travel as much as working age adults without medical conditions in each gender. Elderly drivers with travel restrictive medical conditions in the youngest elderly cohort (65-74) will begin to travel as much as working age adults (19-64) within each gender. Elderly drivers with a medical condition in the middle (75-84) and oldest elderly (85+) cohort will travel as much as a person 65 years of age within each gender.

To form an upper bound for VMT from underserved groups due to vehicle automation, we made assumptions regarding the travel characteristics of the populations in demand wedges 1, 2, and 3. With the advent of autonomous vehicles, we assumed that each person within these populations will increase their annual VMT to a threshold similar to that of a younger or comparable population that currently drives more. As automobile travel becomes more efficient and travel times are reduced, people are likely to take more trips and travel longer distances, as opposed to reducing the time they spend traveling, (van Wee et al. 2006; Zahavi and James 1980). Of course, demand wedges two and three are unlikely to occur even in a fully automated vehicle environment due to differences in age and employment, but this represents an upper bound increase in VMT from the driving senior population to help policymakers understand the potential magnitude.

Annual vehicle miles driven (VMD) per person or per capita VMT were calculated for each of the three demand wedges defined above using the person and daily trip files from the 2009 NHTS. VMT for each trip was computed by processing the TRPMILE and DRVR_FLG variables in the daily trip dataset. The daily trip file is a person trip file, which means that if two household members went somewhere together by LDV, that trip is reflected by two separate entries in the daily trip dataset. In order to ensure that each trip is counted as a vehicle trip, the driver's record was used.

The populations included in each wedge were made exclusive in order to develop an upper bound estimate of VMT increase by combining results from all three wedges. Wedge one only includes all non-driving adults 19 and older. Wedge two includes only elderly drivers without travel-restrictive medical conditions but does not include any of the non-driving population regardless of age or medical condition, drivers with medical conditions, or the non-senior population. Wedge three includes only drivers with a travel-restrictive medical condition. The non-elderly who are drivers and have no travel-restrictive medical condition were excluded from all three wedges.

5.2.2 Data Selection Methodology

The 2009 NHTS daily trip dataset contains information for every trip taken by each household member during their randomly assigned "travel day." Respondents were assigned travel days for all seven days of the weeks over the course of a 10-month period including holidays, in an attempt to accurately represent the daily travel patterns of the United States. This resulted in a final sample size of approximately 1.1 million daily trips. In addition to trip data, households also provided information regarding the persons living in the households. Detailed information regarding trip or person level data can be found in (USDOT 2011).

For our analysis we considered all trips made by a household LDV (car, van, SUV, pickup truck) while all other modes of transportation defined in the NHTS day trip file were excluded in this study. The NHTS does not report VMT for non-personally owned LDVs and as a result VMT from taxis are not included in this analysis. Less than 1% of all LDV trips made by adults 19 and older in the US are by taxi. We included the U.S. population 19 years of age and older, while trip and person data from respondents 18 and younger are omitted. For demand wedge one, if a respondent did not provide a yes or no answer regarding his or her driver status the entry was disregarded in both the person and daily trip file. Similarly, for demand wedges two and three if a respondent did not provide a yes or no answer regarding whether or not he or she has a medical condition that makes it difficult to travel, the entry was not considered. Some of the trip distances reported by respondents were unrealistically long for the purpose of our analysis, so trip distances greater than 500 miles were truncated from the dataset. In cases where there is more than one person riding in a vehicle during a trip, the trip distance would only count towards the total VMT of the driver's population, in order to ensure that a trip is only counted once. For example, if a younger driver was driving an older passenger (e.g. a parent or other elderly relative) to the older passenger's destination, the VMT from this trip would be attributed to the driver. The filtering of the dataset and attribution of VMT from the 2009 NHTS is solely to calculate current per capita

VMT, while estimations of increases in future VMT come from the demand wedges outlined in section 5.2.1.

We also grouped the population by age: working age adults are defined to be those individuals between the ages of 19 and 64 inclusively while older adults are individuals 65 and older. In order to better analyze the travel characteristics of the elderly, the senior population was broken down into three separate groups: the youngest senior cohort (65-74), middle senior cohort (75-84), and the oldest senior cohort (85+).

5.3 Demand Wedge Results

Once the annual per capita VMT were computed and analyzed for drivers, non-drivers, the elderly and those with and without a travel-restrictive medical condition, the estimated changes in total light-duty VMT due to changes in travel patterns from the demand wedges defined in section 2.1 can be quantified. Table 5.1 (shown below) shows the total increase in annual light-duty VMT from each demand wedge and age group for this bounding analysis. The standard errors reported in Table 5.1 come from the NHTS and can be used to construct a 95 percent confidence interval around the mean for uncertainty due to sampling. For example, the interval 6,866 miles to 10,367 miles is the 95% confidence interval of estimated annual per capita VMT for drivers with medical conditions ages 19-64 that would have been obtained if a complete census of households were conducted using the same procedures outlined in the 2009 NHTS.

In demand wedge one, the assumption is made that non-drivers would travel as much as drivers within each age group and gender in a fully automated vehicle environment. If this occurred, the total annual light-duty VMT for the U.S. population 19 and older would increase by 194 billion miles, which is equivalent to about a 9% increase in total light-duty VMT. The biggest increase in VMT would come from both males and females 19-64, which can be attributed to their relatively large non-driving populations and the substantial difference in VMT between drivers and non-drivers within this age group. Working age adults would contribute about 80% of the VMT increase by increasing their current VMT by 154 billion miles or by about 8%. The young, middle, and oldest senior cohort populations would increase their VMT by about 12%, 25%, and 85%, respectively, but make up a much smaller portion of the projected total increase in VMT for this demand wedge. Females would contribute the most between the two sexes overall, making up almost 53% of the VMT increase for demand wedge one.

Demand wedge two assumes that the young elderly cohort without medical conditions will travel as much as working age adults within each gender, while those in the middle and elderly cohorts will travel as much as a person 65 years of age in a fully automated vehicle environment. The total increase in VMT for the U.S. population 19 and older for demand wedge two would be about 46 billion miles or a 2% increase in total annual light-duty VMT. The oldest senior cohort would increase their VMT by 83% or 7 billion miles and make up 15% of the increase in VMT for this demand wedge. The middle senior cohort would travel about 21% more miles annually, contributing to 27% of the VMT increase. The youngest senior cohort would drive 17% more miles annually, making up about 58% of the VMT increase for demand wedge two.

Demand wedge three follows the assumption that working age adult drivers with a medical condition will travel as much as working age adults without medical conditions within each gender in a fully automated vehicle environment Similarly to demand wedge two, demand wedge three assumes that young elderly drivers with a medical condition will began to travel as much as working age adults within each gender, while drivers with a medical condition in the middle and elderly cohorts will travel as much as a person 65 years of age in a fully automated vehicle environment. This would result in the U.S. population 19 and older traveling about 55 billion miles more annually, which would be equivalent to about a 2.6% increase in light-duty VMT. Males would contribute slightly more overall to the VMT increase than females in this demand wedge. Working age adult males and females would contribute most individually to the VMT increase for both sexes. The large increase in VMT by working age adult males and females is greater than that of their respective elderly cohorts, mainly because the number of male drivers with a travel-restrictive medical condition in the working age adult population far exceeds those in the other age groups and within this age group exists the largest difference in VMT between drivers with medical conditions and those without. Working age adults would make up about 56% of the VMT increase for demand wedge three and increase the total VMT for this age group by 1.6% overall. Males and females in the oldest senior cohort have a minimal impact on increasing the annual VMT, mainly because of the relatively small population size of drivers with medical conditions over age 85. The youngest and middle senior cohort populations would increase their VMT by about 8% and 15%, respectively.

Table 5.1 Annual Vehicle Miles Currently Driven and Possible Increases in Vehicle Miles Automatically Driven for Demand Wedges One, Two, and Three

Demand Wedge	Age Group	Male	Standard Error	Female	Standard Error	Total Increase in VMT (Billion Miles)	% Increase in Total VMT[c]
Demand Wedge 1: Adult Non-Drivers[a]	19-64	0	0	0	0	154	7.20%
	65-74	0	0	0	0	18	0.80%
	75-84	0	0	0	0	15	0.70%
	85+	0	0	0	0	7	0.30%
Demand Wedge 2: Elderly Drivers Without a Medical Condition	65-74	11,259	455	6,076	241	27	1.30%
	75-84	8,879	524	3,944	259	12	0.60%
	85+	4,561	509	3,752	549	7	0.30%
Demand Wedge 3: Adult Drivers With a Medical Condition[b]	19-64	8,970	706	6,184	700	31	1.40%
	65-74	6,818	945	4,306	654	12	0.60%
	75-84	5,224	1,125	1,804	198	9	0.40%
	85+	4,073	1,262	1,528	393	3	0.10%

Source: The 2009 National Household Transportation Survey, Daily Trip & Person File, U.S. Department of Transportation.

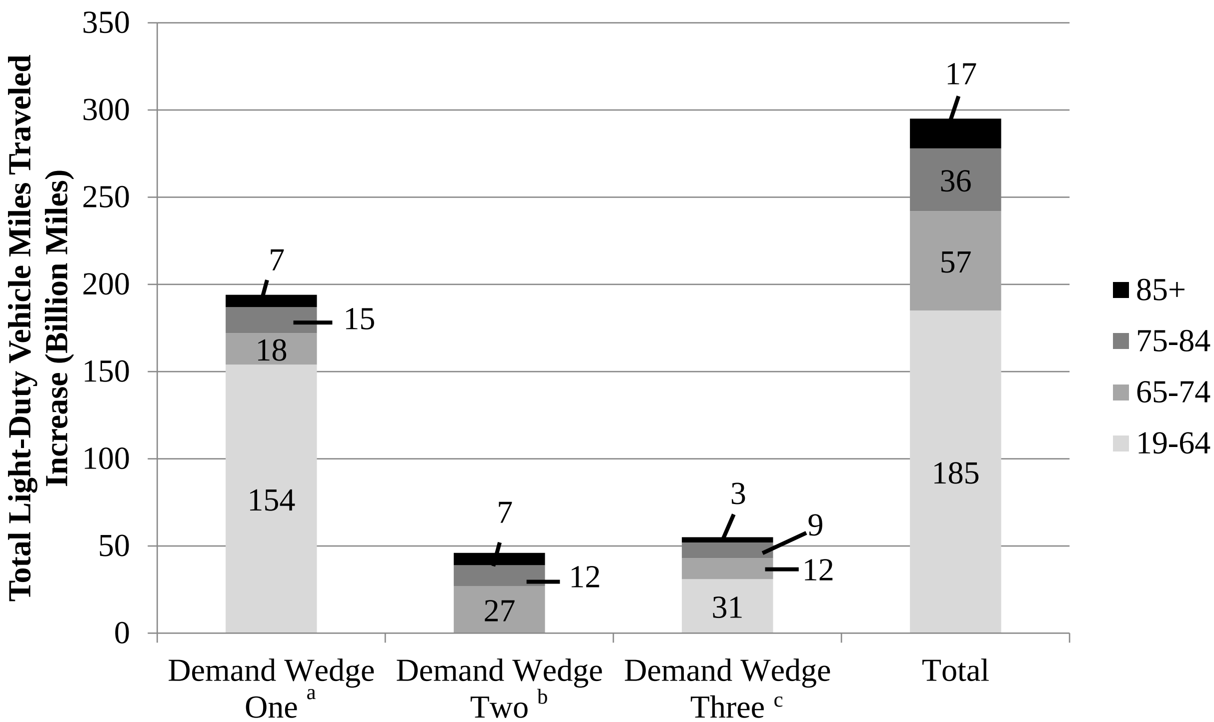
Note: Vehicle Miles Traveled (VMT) and Vehicle Miles Driven (VMD) are equivalent for this analysis

[a] According to the 2009 National Household Transportation Survey non-drivers do not drive and as a result have an annual per capita vehicle miles traveled of zero.

[b] Survey Respondents were asked if they had a medical condition that made it hard to travel outside the home. It is important to note that this is a self-reported medical condition, and does not correspond to the Americans with Disabilities Act of 1990 or any other formalized definitions of a person with a disability.

[c] Total annual light-duty vehicle miles traveled for adults 19 and older is about 2,138 billion miles.

If all three demand wedges were combined and assumed to take place simultaneously, total annual light-duty VMT by the U.S population 19 and older would increase by about 14% or 295 billion miles. Our study, estimated that non-drivers could increase total light-duty VMT by as much as 194 billion miles (9%) while elderly drivers and those with medical conditions could increase light-duty VMT by as much as 46 billion miles (2.2%), and 55 billion miles (2.6%), respectively, as shown in Figure 5.1 (below). This chapter makes a contribution to the literature by presenting the current travel characteristics of the non-driving and elderly populations and those with medical conditions by gender and age groups, and assessing how new demand from these populations due to easier driving and increased accessibility from vehicle automation could increase VMT. In addition, this chapter also highlights those age groups and genders within these underserved populations that could have the greatest increases in travel.



[a] Non-Drivers 19 and older

[b] Elderly Drivers Without a Medical Condition

[c] Drivers 19 and Older With a Medical Condition

Figure 5.1 Annual Billion Vehicle Miles Automatically Driven Increases for Demand Wedges One, Two, and Three

5.4 Summary of Previous Studies

While each of the estimates in previous studies depend on the data and assumptions used, our estimate is close to Wadud et al.'s (2016), who estimated an upper bound increase in travel due to new demand from user groups by assuming that everyone above age 62 will travel as much as a person 62 years of age. Their estimate is based on the assumption that automation could address the natural rate of decline of travel needs that typically occurs starting at age 44, then declines steadily through age 62 and more steeply after. Wadud et al. (2016) concluded that annual VMT could rise as much as 10% from increased travel due to new users. Brown et al. (2014) estimated that underserved populations traveling more due to vehicle automation could increase VMT by as much as 40% using the 2009 NHTS along with the 2003 "Freedom of Travel" study. The authors estimated this upper bound by assuming that the population segments from 16 to 85 would begin to travel as much as the top decile.

Other studies have estimated how VMT per vehicle and daily VMT could change as a result of automation. Schoettle and Sivak (2015) estimated that VMT per automated vehicle could increase by as much as 75% due to a reduction in vehicle ownership rates, while Fagnant and Kockelman. (2015) estimates that VMT per automated vehicle could increase 20% and 10% at a 10% and 90% market penetration rate, respectively. Table 5.2 summarizes the changes in VMT due to vehicle automation that are estimated in the literature.

Table 5.2 Literature Estimates of Changes in Vehicles Miles Traveled (VMT) Due to Vehicle Automation

Study	Data	Method	Estimate	Source(s) of Increase or Decrease in VMT
Brown et al. (2014)	2009 NHTS and 2003 Freedom of Travel study	Additional miles if all people over 16 had VMT of highest demographic	Upper bound annual VMT: +40%	New demand from underserved populations (youth, disabled, and elderly)
Childress et al. (2015)		Activity-Based Model	Daily VMT: -35% to 20%	Changes in value of travel time, road capacity, parking costs and per mile driving costs.
Faganant and Kockleman (2014)	2009 NHTS	Agent-Based Model	Daily VMT: +11%	Relocation of unoccupied autonomous taxis.
Faganant and Kockleman (2015)		Assumptions based on published literature	VMT per AV: +10% to +20%[a]	Induced Demand
Schoettle and Sivak (2015)	2009 NHTS	Developed trip overlap and household requirements in an AV environment	Upper Bound VMT per AV: +75%	Reductions in household vehicle ownership
Wadud et al. (2016)	2009 NHTS	Assumptions based on natural declines in travel due to age	Upper Bound Annual VMT: +10%	New demand from new user groups
This study	2009 NHTS	Demand Wedges	Upper Bound Annual VMT: +14%	New demand from underserved populations

Note: AV is automated vehicle

[a]This estimate assumes that at a 10% market penetration rate VMT per AV increases 20% and at a 90% market penetration rate VMT per AV increases 10%.

5.5 Discussion

Vehicle automation can increase the mobility of currently underserved populations: non-drivers, those with travel-restrictive medical conditions, and seniors. In this chapter, we characterize each of these populations as a demand wedge and used U.S. travel survey data from the NHTS to estimate bounds on how VMT from these demand wedges could change with autonomous vehicles. The travel behavior between younger and older adults in the U.S. are quite different, although both populations rely heavily on automobiles to meet their daily transportation needs. Older adults tend to drive less than their younger cohorts and in proportion to their each cohorts population size, the percentage of overall VMT decreases with age. Elderly women in particular show a substantial reduction in VMT and at a much earlier age than men. This is very evident in the young senior cohort age group where women begin to drive about 6,000 miles annually while males in the same age group drive close to 11,000 miles annually. The United States Census Bureau projects that the senior population in the U.S. will increase by about 71% by the year 2030 (U.S. Census Bureau 2014). In 2013 there were about 43 million seniors in the U.S. (U.S. Census Bureau 2013); if this increase occurred the senior population would increase to about 74 million by 2030. If we assume that senior drivers in 2030 continue to travel as much as senior drivers today, the population increase alone would result in a 201 billion miles or a 9.4% increase in light-duty VMT relative to 2013.

The largest difference in travel behavior exists between drivers and non-drivers who, due to their inability to drive, travel far less than their counterparts within all age groups. The 2009 NHTS reports that out of 22 million adult non-drivers, approximately 9 million reports having a medical condition that makes it hard to travel and because of this condition about 8 million have reduced their day-to-day travel. In comparison, there are about 200 million adult drivers in the U.S. and out of this population about 14.7 million people report having a medical condition that makes it hard to travel and because of this medical condition 11.7 million have reduced their day-to-day travel. In proportion to their total populations only about 6% of drivers have reduced their day-to-day travel because of a medical condition compared to 37% of non-drivers who have. If all three of the demand wedges we analyzed were combined and assumed to occur simultaneously, total annual light-duty VMT by the U.S population 19 and older would increase by about 14% or 295 billion miles. Females would make up most of this increase and the oldest senior cohort would have the largest percent increase in VMT. Working age (19-64) adults would have the lowest percent increase in VMT of all age groups but would increase their VMT the most overall in magnitude by almost 185 billion miles annually, while non-drivers could increase total VMT more than any other demand wedge. The combination of the of the three demand wedges represents an upper bound for underserved populations since it assumes 100% autonomous vehicle adoption by the elderly and people with a travel-restrictive medical condition and that each person within these populations would increase their VMT to a certain threshold. The effects of VMT on the broader population are highly uncertain, and an important subject for continued research as automated vehicles enter the market. Vehicle automation could either result in a net increase or decrease in VMT depending on policy, technology, adoption, and consumer preferences about time and price (Anderson et al., 2014). As mentioned above, it is unlikely that the elderly begin to travel as much as young adults even in a fully automated vehicle environment due to differences in age and employment, but this does represent an upper bound increase in VMT from the driving senior population relative to current patterns. This provides policymakers insight into the scale of some of the benefits and challenges associated with automated vehicles.

In this estimate we account for driver condition, age, gender, and driver status when analyzing mobility patterns. Other variables such as work status or income can be accounted for in future research. Only VMT from household-based LDVs are reported in the 2009 NHTS and as a result VMT from taxis were not included in the analysis. Trips from other forms of public transportation such as bus or rail are also not included in this analysis but the people who usually use these forms of transportation were included in the bounding of the increase in VMT. This bounding exercise is intended to inform policymakers and transportation professionals of how autonomous vehicles could affect VMT from populations currently underserved due to age and medical conditions, as well as highlight those age groups and genders within these populations that could have the greatest increases in light-duty VMT. Although, fully automated vehicles could also increase the VMT for those ages below the age of 19, we believe the changes in travel patterns for teenagers are highly uncertain at this time and deserve separate, lengthier treatment.

It is also important to note the effect of vehicle automation on the travel characteristics of the elderly and those with a travel-restrictive medical condition will highly depend on the cost of an automated vehicle and their willingness to adopt the new technology (Bansal et al., 2016) It will also depend on the time of day and location that new demand from these populations is generated. In addition, in a fully automated environment comprising mostly of taxis, there would be additional VMT when the vehicles have no occupants. Although, the elderly and people with a travel-restrictive medical condition would greatly benefit from autonomous vehicles by being able to independently travel, an increase in VMT would likely result in higher roadway repair and maintenance costs, higher energy use and emissions, and potentially other impacts of transportation than would otherwise occur. Also, the increase in VMT could conceivably result in transportation expenses comprising a higher percentage of household expenditures for these populations. During the transition to automated vehicles, it is important for policymakers to encourage the potential benefits while minimizing the potential challenges.

5.6 Recommendations for Policymakers

This study focuses on how new travel demand from populations currently underserved could impact current light-duty VMT due to vehicle automation, and finds that the estimated 14 percent increase in VMT is non-trivial, but also can be managed with focused planning. Today's underserved population currently relies on relatives, public transportation, and/or some form of government assistance to meet their daily travel needs. Vehicle automation has the potential to increase mobility and access for currently underserved populations, thereby also increasing their VMT.

This study provides insight for state and local government agencies to begin assessing the potential scale of the challenges of automation, and to plan for ways to effectively accommodate the new demand for more LDV travel. This could include determining services and accommodations that could make automated travel more appealing for the elderly and those with medical conditions to account for the absence of human interaction that once existed. Local and state governments along with private companies that offer shared services could study how automated vehicles could become more accessible and used more frequently than existing on-demand mobility services for underserved populations that have difficulties traveling due to medical conditions and/or age. The need for and value of any financial incentives to encourage automation for these populations could also be evaluated. Further research is needed on understanding the unique transportation needs of different disability categories (blindness, deafness, autistic, etc.) since these populations along with the elderly could become more frequent users of shared and personally-owned automated vehicles.

Federal agencies such the Federal Highway Administration (FHWA) could use the results and discussion provided in this study when considering bounds on future highway costs, benefits, and capacity needs. The USDOT could consider the results of this study for future initiatives that are intended to promote economic growth and job creation in local communities (e.g. Strong Cities, Strong Communities initiative).

5.7 Bounding model limitations and future work

While the results from this bounding analysis offer a new understanding of the impact automated vehicles could have on VMT, there are several opportunities for future research. Rather than only looking at changes in the travel characteristics of the elderly, non-drivers, and those with medical conditions, future estimates should also consider the implications of vehicle automation on the travel patterns of drivers outside of the three demand wedges. Total demand from underserved populations in a fully AV environment could be greater than the upper bound estimated in this paper. Right now we assume that each person's travel is bounded by a healthier or younger population, which may not be the case in some instances. Cheaper SAV rides could impact transit demand and could encourage individuals to switch to light-duty travel as the cost to operate a taxi becomes more comparable to the actual cost of driving, due to the elimination of the driver. Changes to population size over time, automated vehicle price, and market penetration rates could also be incorporated, to better model transportation demand variations from population change and to reflect the influence that consumer demand could have on future VMT. As noted by Childress et al. (2015), regions could conduct stated preference surveys to gain some additional understanding on how consumers might travel differently with automated vehicles. These types of surveys will be important to help understand the potential for disruptive changes in vehicle use, but their results will only be validated through the revealed preferences of actual users of automated vehicles.

Although this chapter produces estimates based on the assumption that vehicle automation will increase the VMT of those populations who usually find it hard to travel, there are also factors that could decrease VMT that are not accounted for. For example, improvements in public transportation, increases in urban density and car sharing, as well as increases in the cost of vehicle ownership could cause people to rely less on personal vehicles for travel especially in urban areas. In addition, there could be other aspects of travel besides actual car time itself that even with automation could still make it difficult for those in underserved populations to travel freely that could be accounted for in future research. There is also some portion of the population who may not want to travel more or cannot travel independently even with the existence of driverless cars.

Chapter 6: Conclusions and Future Work

Over the next decade, automated vehicle technologies will likely become more widespread and prominent daily life. While we are not fully certain of how AVs will influence mode choice and vehicle ownership rates, AVs should provide new benefits to drivers in terms of safety, parking, and accessibility, but are likely to increase VMT and generate new demand from new users, which could lead to greater congestion costs. With the proper planning and research any negative externalities that could arise from the adoption these technologies could be minimized. An objective of this dissertation is to aid policymakers in making more informed decision so that we can have a smooth transition to a fully connected and automated light-duty vehicle fleet.

6.1 Summary

This dissertation spans several topic areas: from cost benefit analyses and travel demand estimations to parking demand modeling and level of service estimations. We began by exploring economic feasibility of equipping all light-duty vehicles with crash avoidance technologies. We then develop a method for existing roadways to determine viable platoon demonstration sites and estimate the impacts this could have on congestion and level of service. After that, we develop an agent-based model to quantify the changes in VMT and energy use from driverless vehicles moving from downtown garages and lots to more distant cheaper parking and discuss the impacts this could have on safety and urban form in our cities. Finally, we assessed the impact of AVs on the mobility of the elderly and those with medical conditions and determined those age groups, genders, and populations that could have the greatest increases in travel demand in a driverless vehicle environment.

Chapter 2 used observed insurance data from the IIHS to develop estimates on the changes in collision claim frequency and severity for vehicles equipped with FCW, LDW, and BSM. In addition, publically available data from 2012 GES and FARS were used to form estimates on the number crashes relevant to each technology. These estimates allowed for an estimation of the annual economic benefits these technologies could provide collectively and independently. The result of this work shows that the fleet-wide adoption of commercially available crash avoidance technologies, blind spot monitoring, lane departure warning, and forward collision, is currently feasible from an economic perspective and could provide an upper bound annual net benefit of approximately \$202 billion or \$816 per vehicle if all relevant crashes could be prevented. The technology with the greatest cost save potential is FCW, which could provide up to \$129 billion in annual benefits. Considerable benefits from prevented and less severe crashes can be derived from levels 1 and 2 AVs.

Having concluded that the fleet-wide adoption of crash avoidance technologies provides a positive annual net benefit, Chapter 3 focuses on highways and roadways transitioning to accommodating CAVs. Chapter 3 provides a methodology for roadways to determine potential platoon demonstration sites and the impacts this could have on current LOS by using the Pennsylvania Turnpike as a case study. In this chapter we identified those portions of the turnpike with at least three lanes in one direction, for greater than 2 miles, and estimate how dedicating a platoon lane for commercial truck platooning on these highway sections could impact current LOS. The results indicate that there are several sections of the Pennsylvania Turnpike where implementing a commercial truck platoon demonstration site could be a viable option. However, setting time of day and day of week lane-based restrictions during peak hours and peak travel days would minimize disruptions to traffic flow. In addition, there are potential cost saving benefits from heavy duty vehicle platooning. For example, if all HDV crashes on the turnpike could be avoided this would result in an upper bound annual benefit of about \$39 million. Greater benefits could be realized as more roadways transition to accommodating CAVs. Turnpike commissions as well as state and local governments should begin to plan for a highway system that accommodates CAV transportation.

Chapters 4 and 5 take a step forward to a point in time where all light-duty vehicles are driverless (Level 5). Chapter 4 uses Seattle parking lot occupancy and price data to estimate the potential impact of driverless vehicles on VMT, energy use, emissions, parking revenue, and daily parking cost savings in the city of Seattle, Washington from changes in parking decisions using an agent-based simulation model. Generally speaking, we found that if the POVs parked in the downtown parking lots and garages moved to more distant, cheaper parking locations, we are not expected to see substantial increases in overall VMT and energy use. The results also suggest that as AV penetration rates increase, parking lot revenues decrease significantly and could likely decline to the point where operating a lot is unsustainable economically, if no parking demand management policies are implemented. This could lead to changes in land use as amount of parking needed in urban areas is reduced and cars move away from the downtown area for cheaper parking in more satellite locations. Driverless valet vehicles could considerably alter the economics of parking, which will affect energy, emissions, VMT, and urban form in cities.

Finally, Chapter 5 uses national household travel data to assess the increases in light-duty VMT from new demand from populations with historically lower mobility in a fully AV environment. The changes to light-duty VMT are estimated by creating and examining three possible travel demand wedges. The combination of the results from all three demand wedges represents an upper bound of 295 billion miles or a 14% increase in annual light-duty VMT for the US population 19 and older. Since traveling has other costs besides driving effort, these estimates serve to bound the potential increase from these populations to inform the scope of the challenges, rather than forecast specific VMT scenarios. Increased mobility could result in underserved populations to travel more for leisure, work, and medical purposes and government as well as private companies should look to encourage those types of trips.

6.2 Research Contributions

This thesis answers important questions regarding how AVs could impact safety, parking, decisions, mobility, and congestion and is meant to aid policymakers in making more informed decisions during the transition to connected and automated vehicles. While there has been research done in the past that have discussed the safety and parking implications of CAVs, this thesis takes a different approach and experimentally studies different scenarios. To my knowledge, it is the first to use observed insurance data to estimate the economic feasibility of fleet-wide partial automation. It is the first work that quantifies the changes in travel demand, energy use, and parking revenues, if privately owned vehicles (POV) currently parked in downtown garages and lots became driverless and could self-park in cheaper more distant parking locations. It is also the first work to make use of hourly traffic flow data to estimate the congestion impacts of dedicating a lane to commercial truck platooning. To my knowledge, this is the first work to estimate the changes in light-duty VMT from new demand from new users by creating and examining three possible travel demand wedges.

The key deliverables of this work are peer-reviewed journal publications. Chapter 2 has been published in *Accident Analysis and Prevention* and had media coverage in several outlets, including Forbes and Congressional Quarterly Researcher. In addition, this work was presented at various conferences including the Traffic 21 Seminar Series, Intelligent Transportation Systems

Pennsylvania Annual Meeting (2016), Transportation Research Board Conference (2016), ITS America Next Generation of Mobility Transportation Technology Fair on Capitol Hill (2017), Lifesavers National Conference (2017), and the Society of Collision Repair Specialists Roundtable Discussion (2017). Chapter 5 has been published in *Transportation Research Part C: Emerging Technologies* and selected among papers in all of Elsevier's 2,600 academic journals for the Elsevier Atlas Award in December 2016. In addition, this work was presented at various conferences including the Traffic Transportation Research Board Conference (2015), Intelligent Transportation Systems World Congress (2015), and the Eisenhower Fellowship Research Showcase (2016). Chapter 4 has been submitted for publication in *Transportation Research Part C: Emerging Technologies* and has received favorable reviews. Chapter 3 will be submitted for publication in the near future. The results of Chapters 1 and 5 have also been disseminated through CMU press releases. I will seek out similar outlets to disseminate the results of chapters 3 and 4 once that work is published.

6.3 Policy Implications

The methods and results outlined in Chapters 2 and 3 help to illustrate some of the congestion and economic implications of transitioning to partial vehicle automation. The cost benefit approach employed in Chapter 2 allows for a comparison between the social costs and benefits of fleet-wide partial automation in the United States. The approach highlights the lower and upper bound annual benefits to private insurers, households, and third-parties from equipping the light-duty vehicle fleet with three different crash avoidance technologies. The cost benefit approach could serve as a resource for insurers exploring the implications that AVs could have on their business models and future incentives (i.e. discounts on insurance premiums) and for federal agencies in future vehicle safety rulemaking discussions and decisions. The methods and recommendations outlined in Chapter 3 could serve as a resource for turnpike commissions and infrastructure managers interested in transitioning towards CAV transportation. Instead if acting in isolation, collaboration between turnpike commissions could allow for a smoother transition to accommodating CAVs on private roads.

The methods and results in Chapters 4 and 5 help to illustrate some of the mobility and parking implications of fully AVs or driverless cars. GHG emissions forecasts for the transportation sector should begin including the increase in energy use from new demand from new users and zero occupancy vehicle trips. Cities could prepare for themselves for the underutilization of parking lots and garages in dense urban areas by adapting parking requirements for a future of self-driving cars. By building garages with horizontal floors, and exterior ramps, rather than interior ramps, parking deck structures could be more easily converted to traditional office spaces. Much of the land devoted to parking in today's cities could be converted into parks, bike lanes, or sidewalks could be widened making it easier for pedestrians to move around the city, as driverless cars can drop passengers off and park in cheaper, more distant parking locations, reducing the need for exorbitant amounts of parking in urban areas. The National Association of City Transportation Officials (NACTO) has created guides on sustainable urban and transit street design and could provide valuable insight for cities interested in sustainable and equitable transportation development (National Association of City Transportation Officials 2017). Cities would need to look for other sources of revenues to supplement the money lost from parking taxes, paid parking, and parking tickets. Some cities may implement a parking tax for AVs choosing to exit the downtown area to obtain cheaper parking. Ridesharing could change attitudes towards car ownership and in dense urban areas we could see many trips made by driverless taxis instead of a POV. Shared vehicles could create new demand from new users (i.e. children/teenagers, those with medical conditions, non-drivers, and the elderly) and could change attitudes towards car ownership. In order to increase transportation accessibility in a fully AV environment, PPPs will play an essential in making shared travel more accessible to those in underserved populations. Although AVs could be a step towards a more equitable transportation system demand and congestion must be managed properly. We could see significant increase in travel from not only underserved populations but from those who users who are currently able to drive and from zero occupancy trips. Cities will need to determine how to best meet these demands at reasonable costs, while still being able to provide efficient service to users. Automated vehicles should make driving easier and more efficient but should not replace existing forms of public transportation, which are essential components of our transportation system, but are a step in the right direction towards zero deaths. Ultimately, by gaining a better understanding of the challenges we face on the transition to driverless cars, decision-makers can start to better plan for a future where the burden of driving is placed on the car instead of a human operator.

6.4 Future Work

While this dissertation work assesses possible AV implications in great detail, much future work remains during the transition to CAVs. First, this work assumes that the elderly and those with medical conditions will begin to travel as much as those in healthier or younger populations in a fully automated vehicle environment, an assumption that will likely not hold. Although most underserved populations will begin to travel more, it is not likely that the people within these populations will increase their travel to match that of a younger or healthier population as taking more trips would comprise a higher percentage of household expenditures, which may not be feasible for some individuals who do not have the disposable income. Young children (16 and under) are likely to travel more in a fully AV environment and could even take trips as "drivers" one day. This work assumes that VMT will increase but there are factors that could decrease VMT that are not accounted for. For example, decreases in vehicle ownership rates, greater subsidies and improvements in public transportation, and increases to urban density. Many experts predict that SAVs will replace many of today's POV as a primary mode of transportation. A drawback of SAVs are empty or zero-occupancy trips to relocate and pick up passengers, which could increase VMT, congestion, and energy use. Estimating the energy implications of this extra travel, taking into account future fuel economy standards, as well as strategies to better utilize existing capacity can provide feasible and practical solutions to better plan for an automated vehicle future.

The cost and benefits estimates of partial automation could be expanded beyond a national analysis to a regional analysis. It is possible to recreate net benefit estimates for all regions of the country, showing where the highest net benefits could be achieved. In addition, the scope of this analysis could be expanded to include HDVs, bicycles, and pedestrian. For example, a future cost benefit analysis could assess the economic feasibility of equipping HDVs with forward collision warning or platooning technologies. Rather than estimating benefits solely on a per crash basis, future cost analyses should take into account crash severity.

Other work could seek to develop a parking model with a transportation network using Seattle's actual transportation network and travel demand flows; develop a better AV parking choice methodology (e.g. one where agents make parking decisions that are not only economical but also minimizes transportation system congestion and energy use vs. solely making decisions on based on parking price and occupancy); incorporate dynamic pricing in the parking lots and garages as AVs leave the downtown for cheaper parking in more distant parking locations (currently downtown parking lot and garage pricing static), evaluate the impacts of travel demand on congestion and the social cost this could have on the public at large, explore the impacts SAVs could have on vehicle ownership as it is likely for vehicle ownership rates to change as we transition to automation.

While the future remains uncertain, the results of this thesis indicate that vehicle automation are likely to bring substantial economic, mobility, and safety benefits to the traveling public. Vehicle automation has the potential to reduce a substantial amount of crashes that occur annually and provide substantial economic benefits to private insurers, household, and in terms of QALYs. Driverless vehicles have to ability to self-park in more distant, cheaper parking locations, saving drivers money and freeing up space in downtown areas for shops, parks, or office space where parking lots once existed. While new demand from new user groups and empty vehicle travel from cars looking for parking are likely to increase travel demand, AVs will likely have more efficient operating characteristics than current vehicles and in a connected environment with vehicle to infrastructure communication, congestion impacts would be lower than in a non-connected environment. With the appropriate policymaking and planning people around the world should be able to travel in a safer, more cost effective, and sustainable transportation system that is equitable and meets everyone's travel needs at a lower overall cost.

Chapter 7: References

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