Estimating Potential Increases in Travel with Autonomous Vehicles for the Non-Driving,

Elderly and People with Travel-Restrictive Medical Conditions

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ABSTRACT

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 paper 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 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.

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 paper 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 paper 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, 2013, 2003). 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., 2016; 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, 2013), 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 (Childress et al., 2015). 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 (Brown et al., 2014). 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 paper 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.

1.1 Background on the National Household Transportation Survey (NHTS)

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.

2 METHOD

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.

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.

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 (U.S. Department of Transportation, 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 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+).

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 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 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, we assumed 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.

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 1 (below). This paper 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 paper also highlights those age groups and genders within these underserved populations that could have the greatest increases in travel.

3.1 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 2 summarizes the changes in VMT due to vehicle automation that are estimated in the literature.

4 DISCUSSION

Vehicle automation can increase the mobility of currently underserved populations: non-drivers, those with travel-restrictive medical conditions, and seniors. In this paper, 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 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).

6 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. 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 paper 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.

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Tables & Figure

Between lines 22 and 23 of page 15, place Table 1 about here.

Table 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.
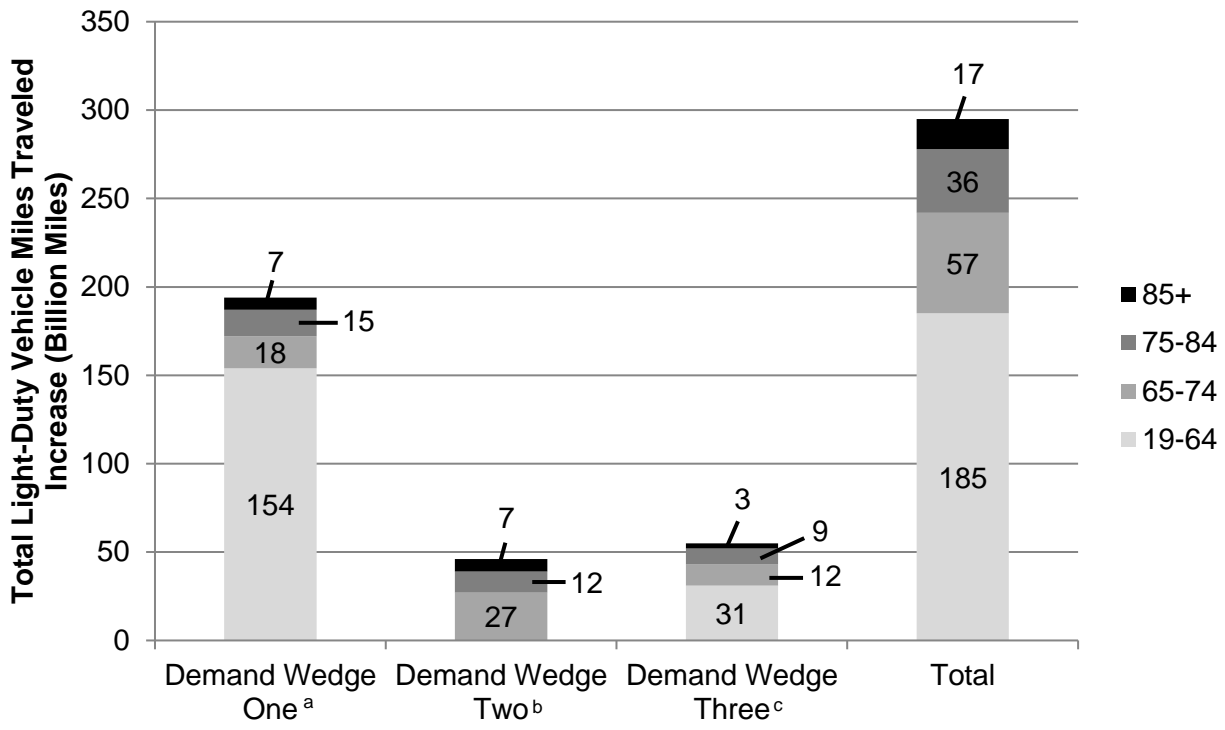
Figure 1 Annual Billion Vehicle Miles Increases for Demand Wedges One, Two, and Three With

Autonomous Vehicles

[a] Non-Drivers 19 and older

[b] Elderly Drivers Without a Medical Condition

[c] Drivers 19 and Older With a Medical Condition

Table 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%