

Will Millennials Save the Planet?
Generational Trends in Vehicle Ownership & Use

by

Elizabeth Anne Murphy

S.B. Materials Science and Engineering
Massachusetts Institute of Technology, 2015

Submitted to the Institute for Data, Systems, and Society
in partial fulfillment of the requirements for the degree of

Master of Science in Technology and Policy

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2018

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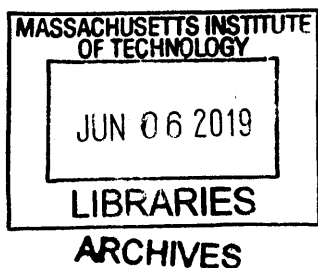
Author
v U Institute for Data, Systems, and Society
July 31, 2018

Signature redacted

Certified by
- Christopher Knittel
George P. Shultz Professor of Applied Economics
Director, Center for Energy and Environmental Policy Research
Thesis Supervisor

Signature redacted

Accepted by
Munther Dahleh
W.A.Coolidge Professor, Electrical Engineering and Computer Science
Director, Institute for Data Systems and Society



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Abstract

Anecdotes that Millennials are fundamentally different from prior generations are prevalent in the American media. One claim often repeated is that Millennials, happy to rely on public transit or ride-hailing, will not purchase personal vehicles. This claim has the potential to both upset the economy and to reduce greenhouse gas emissions (GHGs) from transportation. This work explores Millennials' preferences for personal vehicles from a quantitative approach utilizing data from the US National Household Travel Survey, Census, and American Community Survey to determine whether observed decreases in vehicle ownership and use by Millennials are due to shifts in preferences, or if demographic changes have altered Millennials' consumer behaviors. I employ econometric techniques to explicitly compare Millennials' vehicle ownership and use to prior generations without the confounding effect of demographic variables using linear regressions, Oaxaca decomposition, and nearest neighbor matching estimators. Additionally, the underlying demographic differences between generations are explored with econometric approaches. The findings from these analyses indicate no significant difference in preferences for vehicle ownership between Millennials and prior generations when confounding variables are controlled, and a preference for higher use in terms of vehicle miles traveled (VMT) by Millennials. The difference in observed vehicle ownership and use arises from both age effects and different underlying demographics. Millennials may be saving the planet with their changing demographics, not because they are fundamentally rejecting personal vehicle ownership and use.

Thesis Supervisor: Christopher Knittel

Title: George P. Shultz Professor of Applied Economics

Director, Center for Energy and Environmental Policy Research

Acknowledgments

I am deeply indebted to the community at MIT for the guidance, mentoring, and motivation to complete this work. A special thanks to my advisor, Prof. Chris Knittel, for his patient and detailed explanation of econometrics and Stata. Additionally, I would like to thank Randall Field and the entire Mobility of the Future research team for their feedback and thought provoking questions, which helped me shape the direction and scope of work.

The TPP Administration has made this program a family and has fostered a community that I have valued immensely during my time here. Dr. Frank Field has pushed me to question the assumptions I did not even realize I had. Ed Ballo has made every TPP event enjoyable and meaningful. Barbara DeLaBarre has been there to answer all my questions and to provide advice on how to handle problems. And most importantly, she has never failed to have candy to get me over the afternoon slump.

Lastly, I would like to thank my friends and family, who have supported me through busy semesters, interviews, and the pains of thesis writing. I am grateful for my parents, who supported me when I left my job and returned to school, and my sisters, Sarah and Kate, who have been my role models since day one. I have learned so much from my fellow TPP classmates, and I have enjoyed every debate and discussion we have had. I have grown from being in such a diverse, talented group. I am thankful for the time I have spent at MIT, and I look forward to seeing all the ways my fellow TPP classmates change the world.

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Chapter 1

Introduction

In the past twenty years, the American automotive industry has been through a dramatic series of ups and downs, and these experiences have shown that the economy as a whole is inextricably linked to the success of the automotive industry. At the same time, both political and environmental pressures to reduce greenhouse gas emissions have highlighted the large contribution that personal transportation makes to carbon footprints. An emphasis on a new approach to low or zero-carbon transportation has gained momentum. These competing interests complicate the future of personal vehicle ownership, as there are clear economic benefits to increased sales, but also environmental downsides to more vehicles on the road.

Compounding these challenges in predicting the future of personal mobility and its effect on the economy and environment is the uncertainty of future demand for personal vehicles based on personal preferences and changes in consumer demographics. While consumer preferences can vary due to a wide variety of factors, a common refrain is that the Millennial generation no longer wants to own personal vehicles, and instead they will rely on ride-hailing and public transportation. However, Millennials' true preferences and behaviors have not been extensively studied quantitatively. Understanding the preferences members of the Millennial Generation have, as well as the demographic makeup of the generation, can provide insight into the future landscape of mobility and provide both the automotive industry and policy makers with more information about what business practices and policies to implement with

consideration of both economic and environmental outcomes.

1.1 Effects of Personal Vehicles on the Economy and Environment

According to the Auto Alliance, the US automotive industry employs over 7 Million Americans, including automakers, auto dealers, and auto suppliers [1]. Automotive sales constitute 3-3.5% of the GDP of the US, and in 2017 17.5 million light duty vehicles were sold [2]. To fuel these vehicles, US drivers consumed on average 391 million gallons of motor gasoline per day [3]. Personal vehicles play a huge role in the economy, but also contribute a great deal to greenhouse gas emissions. Therefore, while increasing vehicle sales contribute to a strong economy, continuing to utilize personal vehicles powered by fossil fuels will have detrimental environmental effects.

The interconnected nature of America's financial well-being and the auto industry became painfully clear during and after the 2008 Financial Crisis. Among other factors, the lack of available credit and financing for leasing and purchasing cars contributed to a significant drop in vehicle sales [4] and industry profits to the point that GM and Chrysler required a government bailout in order to avoid Chapter 11 bankruptcy [5]. Unlike many private companies that would simply be allowed to fail and go bankrupt, there was significant motivation to bail out the auto industry due to the role these companies play in the economy. Automotive companies do not simply employ a large number of workers directly. They also support a number of other industries indirectly, including an entire supply chain and hundreds of suppliers who primarily served the US automotive companies. These suppliers would have been dramatically affected by the bankruptcy of a major automotive company [6]. Therefore, while there was significant pushback to the bailouts, President Obama signed legislation to provide federal funds to the companies to avoid bankruptcy and restructure the companies [7].

This decision exemplifies the importance of the automotive industry to the US

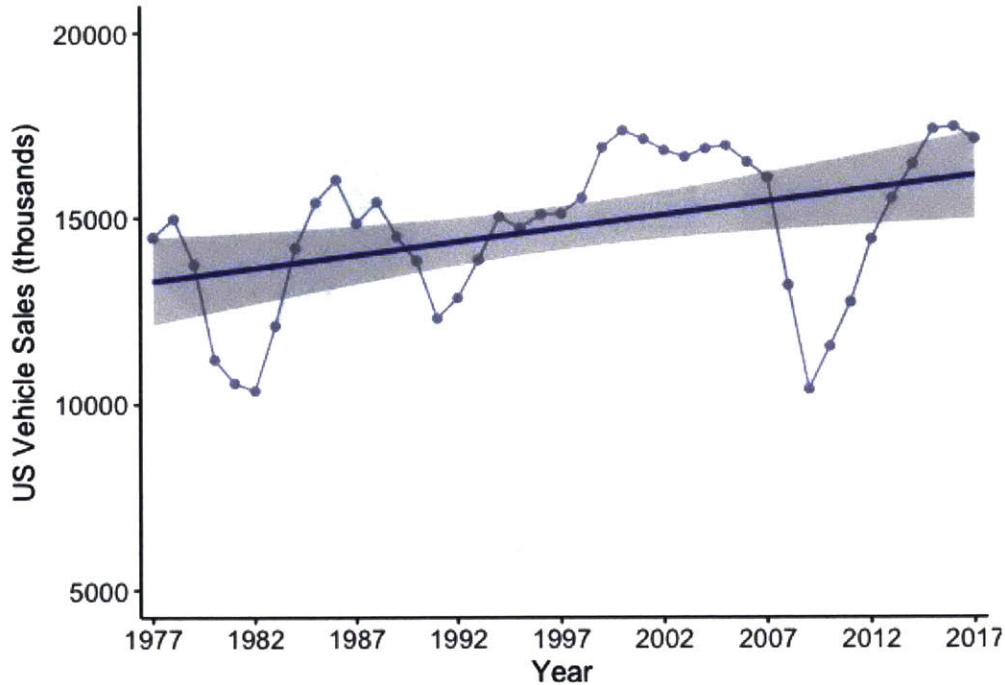
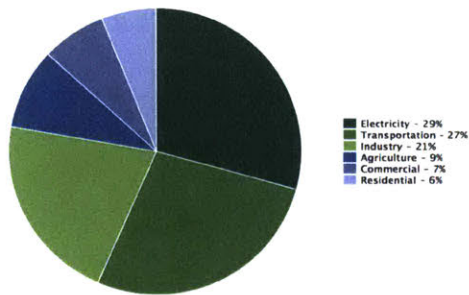


Figure 1-1: US automotive sales and trends, 1977-2017 [8]

economy. Future disruptions to demand and sales continue to be important to both the industry itself and the economy as a whole. While the financial crisis had dramatic effects on both the industry and demand, recent data show that personal vehicle sales have been increasing from the 2009 low and have recovered to pre-recession levels [8]. Figure 1-1 depicts US vehicle sales since 1977 and while there has been volatility year to year, there is a slight upward trend over time. Many factors may affect whether this trend continues. Technological developments, policies, and consumer behaviors will all play significant roles in the future outlook of the automotive industry.

While there is economic pressure to continue growing this industry, there is also pressure to decarbonize the transport sector and reduce greenhouse gas emissions. As depicted in Figure 1-2 from the US Environmental Protection Agency, transportation contributes 27% of the United States' total greenhouse gas emissions, and 60% of transportation emissions are from light duty vehicles, such as vehicles that households use for personal transportation. Given the goals outlined in the Paris Climate Accord, "deep decarbonization" is needed, and changing the transportation sector is

2015 U.S. GHG Emissions by Sector



2015 U.S. Transportation Sector GHG Emissions by Source

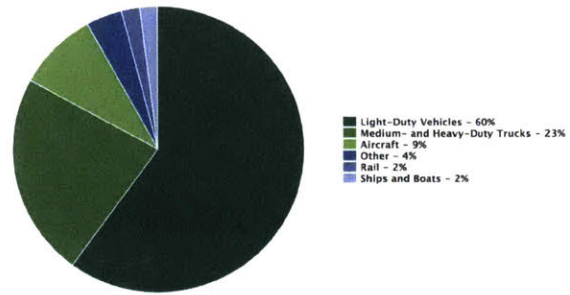


Figure 1-2: US GHG emissions by industry and within the transportation sector [9]

critical [10]. In the EU, transportation contributes to approximately 25% of greenhouse gas emissions, and 90% of personal vehicles are powered by petroleum [11]. To achieve decarbonization, the transport sector could shift towards more sustainable options, such as electric vehicles powered by renewable energy sources, bicycles, or public transit.

Public policy to reduce greenhouse gas emissions may shape the future of personal mobility. However, in the absence of such regulations, consumer preferences and behaviors will shape future mobility trends. This work seeks to understand what the current consumer behaviors are, specifically for Millennials as compared to previous generations, as these behaviors will greatly impact both the automotive industry and the environment.

1.2 Understanding Millennial Vehicle Demand

Current and future demand will be largely driven by the purchasing habits of Millennials, a generation defined here as individuals born between 1980 and 1994 [12]. In 2015, the Millennial generation surpassed Baby Boomers as the largest generation by population in the United States, and as Baby Boomers and other generations age this dominance will grow [13]. As shown in Figure 1-3, the portion of total vehicle sales attributed to Millennials has been rising from 2011-2016, though ownership rates still lag behind Baby Boomers. Understanding current demand and forecasting

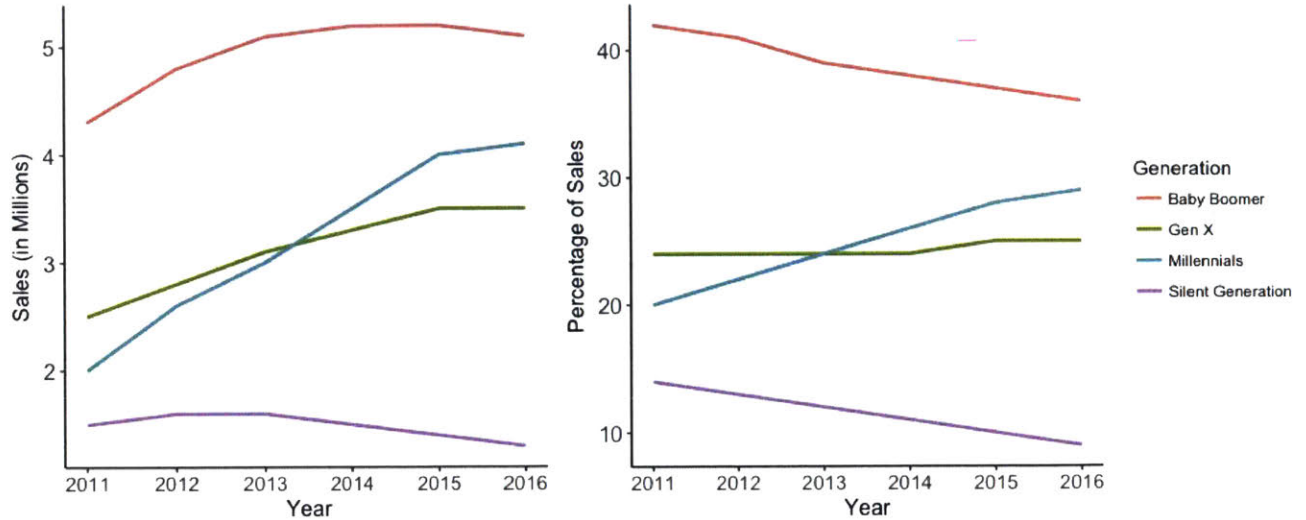


Figure 1-3: US vehicle sales by generation [16]

future vehicle sales and usage is heavily dependent on understanding how Millennials demand for vehicles may differ from previous generations.

Because of Millennials large and ever-increasing role in the economy, there is significant focus on their purchasing habits in nearly every area of the economy. From differences in preferences for eating at chain restaurants [14] to changes in the investments they make [15], the common consensus is that Millennials are disrupting a wide variety of industries due to their fundamental differences in purchasing preferences. This claim has been invoked for a wide variety of industries without significant evidence. Both the veracity and the longevity of such trends has not been investigated.

There has been significant speculation that Millennials display transport preferences different from previous generations, with claims that Millennials are the “go nowhere generation” meaning they are more risk averse and less mobile [17], or the “cheapest generation,” who are not interested in making large investments in cars or houses [15]. In addition to these potential changes in transportation preferences, the demographics of the Millennial generation differ from previous generations. At the same time, the automotive industry is undergoing dramatic technological changes. These changes range from the advent of ride-hailing, with companies like Uber and Lyft, to the development of autonomous vehicles



Figure 1-4: Media depiction of “cheap” Millennials
[15]

This work aims to address vehicle purchasing and use by Millennials to understand whether the observed decreases in vehicle sales and vehicle miles traveled by Millennials [18] is a manifestation of a fundamental shift in preferences away from personal vehicles, or due more to the changing demographic makeup of Millennials as compared to prior generations. Several hypotheses could describe the observed differences in vehicle ownership and usage habits by Millennials, which can be grouped into two general categories, Millennials’ endowments and preferences. These terms are inspired by the work of Ronald Oaxaca [19]. “Endowments” here captures the factors inherent to the Millennial generation that differ from previous generations. These differences include both endogenous contributions from the changing demographic makeup of Millennials, as well as exogenous factors, primarily those related to the macroeconomic situation in which Millennials are growing up and entering the workforce. Generally, these factors are easily measured and often reported in survey data, such as the US Census. The term “preferences” here captures changes in transport habits motivated by cultural and technological changes. These contributions are described in Figure 1-5.

Several key demographic variables have shown shifts over time, with the Millennial generation generally marrying later [20], having fewer kids [21], and preferring to live in urban locations [22]. All of these factors could be contributing to lower car sales, as Millennials are putting off the traditional “American Dream” of having 2.5 children, a house in the suburbs, and a commute to work in a personal vehicle.

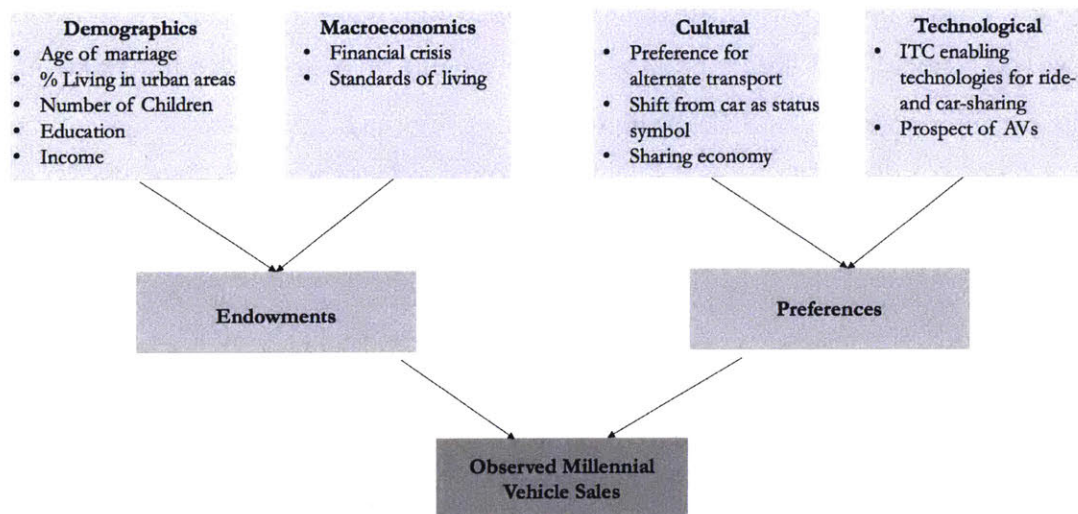


Figure 1-5: Potential factors contributing to decreased vehicle sales

In addition to the demographic makeup of Millennials, the economic conditions in which Millennials have entered the workforce could also be affecting vehicle ownership. Many Millennials entered the workforce during or after the financial crisis, which has affected both their wealth and spending habits [23]. On average Millennials are not earning the same income, in inflation adjusted dollars, that their parents had been at the same age [24]. All of these factors, the “endowments” of the Millennial generation, could be depressing vehicle ownership and usage rates. However, many of these factors are likely to be temporary or change over time, as Millennials eventually regain wealth lost in the financial crisis, settle down, and have children.

In contrast, the “preferences” that could be the cause of depressed vehicle ownership and usage statistics would indicate potentially more permanent trends in transport for Millennials. Millennials have grown up in a different cultural and technological world than previous generations. Therefore, it is plausible to think that Millennials’ decrease in vehicle ownership and usage truly is from a distinct change in behavior from previous generations. Millennials may prefer other forms of transport, want to avoid large financial investments, or place less value on owning a car as a status symbol [25]. In addition to these cultural changes, Millennials are also the first

generation to grow up with the information and communication technologies (ICT), such as the internet and smart phones. These technologies are now ubiquitous and disrupting many industries. ICT technologies have enabled ride-hailing services, such as Uber and Lyft, and carsharing services, like Zipcar. Additionally, technological advances have made partially automated vehicles a reality, and fully automated vehicles are now seen as technologically feasible. While autonomous vehicles are not a significant factor in personal transport now, and may not be for years, ride-hailing and carsharing may be encouraging Millennials to put off or eliminate vehicle purchases.

Teasing apart endowment and preferences, two broad categories of potential contributors to lower vehicle sales and usage among Millennials, can provide significant insight into the nature and endurance of the observed trends in vehicle ownership and usage. If the factors are primarily demographic, it is likely that Millennials will eventually purchase vehicles as they progress through life stages. If the preferences of Millennials are actually different, Millennials may never want to own or drive their own vehicles. Econometric methods are applied to separate these two contributing factors and better understand the Millennial generation.

1.3 Scope of Work

This work focuses on two key dependent variables to understand Millennials' relationships with personal vehicles. First, I investigate the number of personal vehicles in a household. This analysis provides insight into the fundamental question of whether households belonging to the Millennial Generation are purchasing their own vehicles. This variable relates most closely to the economic question surrounding vehicle sales. The second variable, meant to capture more information about the vehicle use patterns by Millennials is vehicle miles traveled. Vehicle miles traveled describes the total number of miles an individual drove himself or herself each year.

In addition to narrowing the scope to focus on these two variables, the geographic scope of this work is limited to the United States. This decision was made for multiple reasons. First, as will be discussed in more detail in later sections, the definition

of generations is not constant in different countries, as generations are defined by relevant geopolitical events and significant cultural factors affecting different cohorts, which are not consistent world-wide. Additionally, the United States is a heavily car-dependent society, so the question of Millennial ownership is especially interesting for the US, where car saturation has already begun [26]. Lastly, the US has robust data available on transportation trends, so meaningful conclusions can be gleaned from the analysis.

To supplement the in-depth analysis of vehicle ownership and VMT, several other variables are investigated to gain a fuller understanding of both the Millennial generation and transport trends. Given the focus on demographics inherent to this work, I analyze current demographics as they relate to vehicle ownership, investigating how demographic variables affect each other as well as how they affect vehicle ownership and usage. The data available for vehicle ownership and VMT analysis also includes information on ride-hailing and carsharing, which can provide more insight about how generations behave in comparison to each other. This work does not include as rigorous of an analysis of these transport services as that which is employed to understand vehicle ownership and VMT, but it is meant to provide some preliminary findings on trends for which less data is currently available.

In order to answer the motivating questions about vehicle demand, this work relies on a quantitative comparison between generations to understand the observed differences between generations' vehicle ownership and use habits. This work uses simple econometric approaches to rigorously investigate the uncertainties in generational behavior and provide resolution to the debate about whether Millennials differ in their demand for personal vehicles due to the "endowments" of the generation or the "preferences" of the generation. Regressions relate variables to each other to understand how one variable may influence or be correlated with another variable. In the simplest application, a regression essentially calculates the resulting slope when two variables are plotted against each other.

This simple concept can be applied to understand more complex relationships. Regressions can relate one independent variable to a dependent variable, referred to

as a simple regression, or many independent variables to a dependent variable, a multiple regression. Many softwares exist to calculate complex multiple regressions with many variables, allowing for much more power for data analysis and expanding the possible relationships that can be examined. This approach is applied to this work to understand how a variety of demographic variables are related to the number of personal vehicles a household owns and how many miles members of the household travel. The power that regressions provide to this work is the ability to strip away the “endowments” of each generation and obtain an apples-to-apples comparison of generations that can then reveal the differences inherent to each generation arising from preferences. The assumption here is that when the endowments, which are fairly easy to measure, are stripped away from the generations, the remaining observed differences are from preferences, which are more difficult to measure in surveys. Additionally, the more complex technique, Oaxaca decomposition, is used to explicitly separate groups differences due to endowments versus behaviors. A final check on the robustness of findings is done with nearest neighbor matching estimators, which compare individual survey respondents from each generation to the most similar respondent in the comparison generations.

While regression analysis can be very powerful, the results from regression models must be interpreted thoughtfully, as the results do not necessarily provide causal relationships, but rather correlative relationships. Therefore, it is crucial that the interpretation of linear regressions consider the findings as relationships rather than causes. This will be expanded upon in the Results chapter, and the precise interpretations of the model outputs will be explained in detail.

The question of the future trends of mobility is immense and will be affected by a wide range of variables that this work does not attempt to quantify or predict, as it would be both unreasonable and impractical to attempt to guess exactly what the future looks like. Because this work assumes a paradigm of personal vehicle ownership, it is important to highlight the potential shift from this model to one defined by fleets or sharing, which this econometric analysis cannot capture.

Lastly, to tie these components together and provide more useful information for

business and policy decisions, estimates of Millennials' future vehicle ownership and use are done based on econometric models and projections of their demographics. These projections are meant to provide rough estimates of what the future *may* look like, ignoring the wide range of uncertainties from the many outside variables, given what this work finds for Millennials' preferences and demographics. No matter how detailed a forecast is, the forecast is "always wrong" [27]. That does not mean that forecasts are useless, but rather attempts to create a perfectly predictive forecast are futile, and rather efforts should be made to try to estimate a reasonable range of future scenarios.

Chapter 2

Literature Review

This work utilizes and builds upon many excellent studies on the theory of generations, Millennial behaviors, transport trends, and technology adoption. Each of these general topics of research has provided useful background in outlining the scope of work as well as insight to identify useful parameters to explore in this work. Additionally, the prior work has provided further clarity on current gaps in the research-space regarding generational transport preferences. The existing literature summarized in this section has been roughly grouped into four subsections pertaining to the topics studied. First, the history of the theory of generations and their sociological construction is provided. Because this work is using generational assignment as a key variable, it is important to understand precisely what generations are, how they are defined, and why they are important social constructs. Second, an overview of primarily descriptive and anecdotal work regarding Millennials perceived general preferences and behaviors is summarized. Third, descriptions and analyses about Millennial travel habits and licensing are discussed. Fourth, the relationships between generations, transport, and technology adoption are investigated to provide perspectives about how variables outside the direct scope of this study may influence results and change Millennials' behaviors.

2.1 The Theory of Generations

The notion of subdividing society into age cohorts has roots back to ancient Greece [28], but the contemporary sociological definition of generations was articulated by Karl Mannheim in 1923 [29]. Mannheim described generations as a cohort of similar-aged members of society who had experienced the same events as youths and young adults. Since then, significant research has been done on what delineates generations, how people within a generation perceive each other, and how they perceive other generations. The sociological field focused on generation theory is widely studied. Understanding what generations are and how they come to be provides more depth to understanding this work, and explains the current convictions that Millennials are fundamentally different without rigorous analysis to back up these claims.

First, and critically relevant to the scope of this work, is the notion that generation classifications are not a static and universal concept. Groupings like Baby Boomers and Millennials, which are commonly used in the US, are used to subdivide the population into cohorts of individuals with common characteristics. Factors that go into the generation delineations are demographics, major events, and attitudes towards contentious topics. As such, generations are not a fixed concept internationally, because local events, ruling governments, and cultures vary widely. For example, the US and Western Europe's definitions of current generations hinges greatly on World War II, with the Greatest Generation generally being used to describe those who were young adults during World War II. However, other nations have different geopolitical events that have dramatically affected the population and thus the resulting generations. In China, while World War II was a hugely consequential event, the Cultural Revolution [30] also dramatically changed the fabric of society, and thus the US definition of generation would not be appropriate.

Although different countries and cultures may define their generations based on different key events, the fields of sociology and psychoanalysis have identified common factors affecting how generations come to be, and how individuals within generations recognize their cohorts as distinct from others. Work in sociology has hypothesized

that individuals are most susceptible to influence from exogenous events in their adolescence, and many core beliefs are developed in teenage years [29],[31]. Therefore, while the generations themselves may not be delineated the same in different countries or between different cultures, generations arise from the same key factors. There are several common threads that explain how generations are formed and how an individual views his or her generation, as well as other generations. [32].

While the traditional delineations and definitions of generations have followed the patterns outlined above, in recent years there have been calls for changing how generations are defined. The driving force for this reorientation of how generations are viewed is the transformative effect the information and communication technology revolution has had on society. Because of the speed that technology is changing, some claim that generations should simply be defined by the types of technology they use, as that can clearly define the era in which individuals grew up [33]. This proposal has merit, as the technology paradigms are rapidly changing, as depicted in Figure 2-1. While this alternative approach is not investigated significantly in this work, the influence and impact of technology on generations' behaviors will be discussed, with particular focus on its effects on whether an individual from a certain generation will

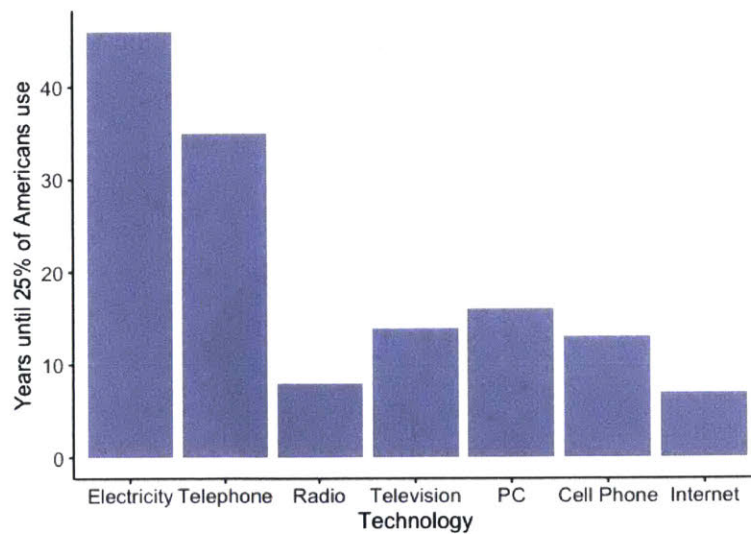


Figure 2-1: Years from commercialization before 25% of Americans utilize new technology

[33]

utilize a new technology.

In addition to understanding how generations are defined and come to be, there has also been work done to understand how generations perceive both themselves and other generations. The field of psychoanalysis focuses on how individuals become aware of their generation, with members of the field claiming individuals become aware of how their generation is truly different from previous generations sometime in early adulthood [35]. It is at this point that some in the field claim people appreciate the temporal separation between others rather than primarily spatial separation. As members of a generation age, it is common for feelings of “juvonia,” or the perception that the younger generation is “worse behaved” than previous generations [36], to arise. For decades, people have noted this trend for older generations to continually question the behavior of younger generations. Figure 2-2 is a cartoon published in 1950 which notes this trend, which continues today [34]. This trend is of note for this work as it may explain the overly critical focus on Millennials, accusing them of being industry disrupters and fundamentally different from prior generations. Additionally, the concept of juvonia motivates investigating the true trends of Millennials which are likely to be exaggerated by commentary from older generations.

Another generational concepts crucial to understanding and interpreting this work is the distinction between age and cohort effects. Here, cohort effects are the differ-



Figure 2-2: A satirical take on the negative perceptions of younger generations
From [34], By Bill Maudlin, Originally Published in *Life Magazine* in 1950

ences between two observed groups due to the generation an individual belongs to, rather than the age that person is. For example, a cohort effect could explain why Millennials learn to use technologies more quickly and utilize these high-tech approaches more often than older generations. The cohort, Millennials, are adopting the technology more quickly because they grew up with the technology. In contrast, an age effect would be an attribute that is making those aged as Millennials especially adept at using that specific technology. Age effects captures observed changes that occur as individuals age and progress to middle-age. Based on claims of age effects, perhaps younger people are simply more interested in learning new technologies, and as they age they will not want to use these technologies anymore. It can be difficult to separate age and cohort effects, and this challenge will be revisited in the later section discussing technology adoption.

Lastly, it is important to note how the generations used in this analysis are defined. Rather than attempt to independently define generations, this work utilizes the definitions from Pew Research Center’s “The Hows and Whys of Generational Research” [30]. This report clearly outlines defining events and their thought process for picking the year delineations for each generation. These divisions are restated in Table 2.1. There is not a single correct answer on what the cutoff should be for any generation. Therefore, other work may use slightly different delineations, and those born on the cusps of different generations may have features that most closely match a mix of the two generations. Generations are not homogeneous entities, and significant differences in behaviors and preferences will exist within a generation, just as the generations themselves are distinct from each other.

Generation	Birth Years
Generation Z	1995- ?
Millennials	1980-1994
Generation X	1965-1979
Baby Boomers	1946-1964
Silent Generation	1928-1945
Greatest Generation	1901-1927

Table 2.1: Generation assignments for households in the United States

2.2 The Millennial Worldview

There is significant speculation about how Millennials may be fundamentally different from previous generations. Many of these studies have little grounding in data or rigorous analysis, but they still provide insight into what areas of study may be interesting and what cultural factors may be influencing Millennials' behaviors. First, many articles have highlighted differences in how the Millennials view both the world and their place in the world, which may have an effect on number of personal vehicles and VMT. These articles cover a wide range of topics. In Mark Guays article in the *Huffington Post*, he claims Millennials no longer define the American Dream in the same way that previous generations did. He claims Millennials are interested in a purpose driven life in which they have positive effects on the world [37]. Elaborating on this point, Amanda Machado highlights in her article in *The Atlantic* that Millennials are choosing to spend money on long, self-discovery international trips, and are willing to take risks now given the uncertainty in the future [38]. Rather than focus on obtaining physical goods, Millennials seem to be prioritizing experiences. In contrast to these assertions, Todd and Victoria Buchholz penned an op-ed in The New York Times describing Millennials as the "Go-Nowhere Generation," sedentary and shaken by the great recession [17].

Millennials may also have different preferences for private ownership beyond vehicles than previous generations had. A *Forbes* article notes that Millennials are much more comfortable with sharing, as evidenced with the rise of businesses like Rent the Runway, Uber, and Air BnB [39]. While the concept of getting in a stranger's car, allowing strangers to share your house, or borrowing clothes for special events may have seemed foreign just a few years ago, such business models have become normal and may be changing how Millennials view the importance of ownership. Additionally, several articles highlight the increasing preferences Millennials have to live in cities rather than the suburbs, and rent apartments rather than purchase houses [22],[40]. As with speculation on vehicle ownership, the root of these changes as well as the duration of such choices has not been investigated significantly.

In contrast to these assertions, some works propose that perhaps Millennials are not really so different from previous generations. A study done by the carsharing company Zipcar found that rather than generations differentiating travel patterns, the real distinction comes from whether one lives in a city or not. City-dwellers align with the typical rhetoric of Millennials when it comes to traveling habits [41]. Along the lines of the “juvenioia” perceptions, a *Forbes* article suggests that Millennials on the whole are not significantly different, and older generations should accept and embrace the differences Millennials bring [42]. These conflicting reports provide useful background to frame the work, as well as motivation to answer whether Millennials are as different as many authors claim. Moving into the next subsection, works more specifically related to vehicle ownership and use are summarized.

2.3 Millennial Transport Habits

The literature uses three general approaches to assess Millennial travel habits: descriptive analysis, surveys, and statistical analysis. The descriptive analyses and surveys provide interesting qualitative information, while the statistical analysis provides a useful framework and example for work similar to the methodology for this work. The majority of the work summarized below is from the US, though select articles from international perspectives, primarily Western Europe and Canada, are included as well. These provide a comparison for the US-centric data, and provide insight about how the trends in the US may mirror or differ from other countries.

First, the descriptive articles regarding Millennials’ travel habits are detailed. Researchers at the University of California found that economic factors most significantly affect personal vehicle miles traveled. Technology, whether the respondent lives with his or her parents, and whether the respondent has a drivers license are also significant factors [43]. The results were suggestive rather than definitive, but provide motivation for investigating the relationships between economic prosperity, macroeconomic conditions, and car ownership. Another study by the US Public Interest Research Group also studied why Millennials appear to be driving less. The report notes the

current dip in vehicle miles traveled by younger people, and speculates that ICT may be a factor. Importantly, the report goes so far as to propose that policies for future transportation planning and investments should no longer assume that car use will increase for perpetuity, as had been the assumption previously [44].

Work done in the Netherlands by the Ministry of Infrastructure and Environment gathered data from focus groups and surveys, and its findings support the hypothesis that Millennials have not abandoned car ownership. The results imply Millennials intend to purchase cars later in life. This work assumes that the macroeconomic effects such as the recession, which reduced car ownership, are likely to be temporary [45]. Another survey focused on the reasons young people haven't gotten drivers licenses found that the time it takes to get a license was the number one reason an individual reported not have a drivers license. Additionally, the work found that nearly 70% of respondents without drivers licenses do intend to get a license at some point in the future [46]. A different study on the same topic found alternative reasons for not being licensed: not having a car, being able to get around without a car, and the costs associated with driving. The study also points out large negative disparities in licensing rates in black and Hispanic households compared to white households, as well as low-income households compared to those with higher incomes [47]. These works further highlight the need to understand how the Millennial generation has been affected by the financial meltdown and slow recovery, and the critical role that financial stability plays in vehicle preferences. Additionally, the findings from this work emphasize the temporary nature of many of the trends observed. Millennials are achieving many of the same life milestones, though they are delaying them.

The more rigorous studies involving statistical and econometric analysis focus mainly on VMT, with licensing as a secondary concern and little focus on vehicle ownership. Two of the works discussed are based on the National Household Transportation Survey, one of the data sets used in this work. An article out of the University of South Florida investigated how demographic factors for Millennials may be affecting their VMT based on data from NHTS. Variables investigated include urban versus rural location, race, labor force participation, income, car ownership, as well

as others. The work concluded that little evidence exists that Millennials with similar socio-demographic and economic conditions as prior generations have any different behavior. The work highlights economic conditions as the key indicator as to whether Millennials will catch up with previous generations [48]. In a separate study responding to the Buchholz article in *The New York Times* which called Millennials the go nowhere generation [17], the NHTS data was again analyzed with similar conclusions. The paper attributes the decreased VMTs for Millennials as compared to Generation X to demographic shifts, differing attitudes to mobility and residential location, and a general dampening of travel demand in the 2000s [49]. These works provide further weight to the hypothesis that Millennials are not so different. Additionally, the similar methodologies used in the prior works provides some framework for this work.

In an alternate approach, researchers from Georgia Tech studied Millennial mobility and automobility using the American Time Use Survey to compare how Millennials are spending their time compared to Generation X [50]. The results from this work echo the analysis from the two prior articles, noting that there do not seem to be generation-specific effects when demographic and period specific effects are considered. The differences seen now are expected to dampen as Millennials progress through life stages. Lastly, a study out of Canada using the General Social Survey “Time Use” cycle finds that though Millennials had been lagging in licensure and vehicle usage, the generation is catching up to the rates of previous generations. Millennials do not seem to rely less on vehicles than prior generations had [51].

While the data analysis does not utilize data from international sets, it is meaningful to understand how the US compares to other countries. In one such paper, the authors compare the US, UK, Japan, France, Germany, and Norway. The study concludes that the US is observing larger reductions in car sales compared to the other countries. Older generations are offsetting reductions from younger generations in other countries, but the older generations in the US have already reached car saturation and are not increasing sales [52].

Another study of fifteen primarily developed countries, found two general trends. In Sweden, Norway, Great Britain, Canada, Japan, South Korea, Germany, and the

US, a decrease in young drivers was seen along with an increase in older drivers [53]. In contrast, Israel, Finland, Latvia, Poland, Spain, Switzerland, and the Netherlands had increased drivers in both younger and older generations. This work highlights the need to consider how generations are not identical across countries and can be heavily influenced by societal and cultural factors. Therefore, work heavily focused on the US does not translate to what is occurring elsewhere, but it can be used as a comparison for what is happening elsewhere to gain a more complete understanding of the future of personal transit globally.

All of these analyses provide useful preliminary conclusions that the differences in travel habits are likely to be temporary rather than permanent. However, they are missing several components that this work is interested in. First, previous work has not focused on vehicle ownership. Second, few of these papers have gone further to provide insight on what the results mean in terms of the economy, the environment, or needed policies. There is room for more work on this subject to gather a better understanding about current behaviors and future demand.

2.4 Technology Adoption and Transport Applications

How technology will develop and how it will alter transportation habits are critical questions for forecasting the future of mobility. One can think of many ways in which technology has already affected travel habits. For example, telecommuting may be reducing travel miles to and from work. Other technological factors to consider are ride-hailing, like Uber, and the potential future for autonomous vehicles. The extent to which all these technologies may disrupt the current transportation paradigm are unknown, but this is an important component to study to understand how current demand may be affected and what future demand may be. These technologies are critical factors which may be affecting Millennials' preferences, and as such should be investigated.

Researchers at Imperial College London performed a study with travel diaries and online pseudodiaries to better understand how online activity may affect car use [54]. While the data is somewhat outdated from 2005, the results do show that all else equal, internet usage was associated with higher level of car use (though large amounts of time online were associated with less driving). Bert van Wee provides interesting discussion on how ICT may be replacing travel. While this piece is mainly speculative, it points out a major flaw in efforts to predict future travel [55]. Van Wee notes how assessments do not build in technological development as a component in econometric analyses. He asserts that we may be in a long-wave transition from car-based travel to ICT-based interactions. He speculates that these effects may in fact be larger than any supposed generational effects. This work motivates the discussion of paradigm-shifts in conjunction with the results of this work, as a potential future where the personal vehicle ownership model no longer exists should be considered.

While these works discuss ICT advances and their effects on travel abstractly, work has also been done to better understand how carsharing and autonomous vehicles may affect travel habits more concretely. One study examined how carsharing was affecting vehicle ownership. The work elicited survey responses from members of a variety of carsharing services, and asked questions about how being a member of the carsharing service affected their decisions about car ownership [56]. The report found that before joining carsharing, the respondents had an average of .47 cars per household, but after joining the respondents had .24 cars per household, a statistically significant decrease in vehicle ownership. Additionally, the work found that the cars eliminated by carsharing had 10 miles/gallon on average worse fuel economy than the carsharing vehicles. The work then estimates that carsharing had eliminated 90,000-130,000 personal vehicles, though it does not attempt to estimate changes in VMT as there could be both positive and negative effects of carsharing on total VMT.

In addition to efforts to understand carsharing's effects on VMT and vehicle ownership, some work has also been done to estimate how autonomous vehicles may influence travel decisions. Given the nascent stages of this technology, as well as the unknowns about the future development, this work is mainly descriptive and specula-

tive, but it raises some important points about how travel may change in the future. MacKenzie et al. explore multiple scenarios for AV development and adoption to estimate effects of AVs on energy intensity [57]. Given the potential positive and negative effects on energy intensity, the results find a broad range of possible outcomes, with the primary conclusion being that while AVs have the potential to reduce energy consumption and emissions, reductions are not guaranteed. Regardless, the work concludes that AVs can dramatically change mobility patterns.

Another study goes further to understand how shared AVs may change vehicle demand by modeling a shared ride AV system in a medium sized city modeled on Austin, Texas to see how many cars each shared AV could replace [58]. Using a modest adoption of just 3% shared AVs in the fleet, the results found that for rides 15 miles or less, each shared AV replaced about 11 conventional vehicles, though more miles were traveled so net emissions are positive. The question of whether these vehicles would supplement or replace personal vehicles was not answered.

In sum, estimating the effects of technological advances on travel behavior is difficult, but technology changes are likely to have dramatic effects of future vehicle demand. In addition to the new technologies available, it is important to also consider who adopts these technologies and how long it takes for widespread adoption to occur. These questions are likely to be affected by generation cohort effects. While the focus of this work is not to delve deeply into the theories and models of technology adoption, it is useful and pertinent to discuss how technology diffusion may be different between Millennials and older generations and how these differences may be affecting current and future behaviors of Millennials.

The remaining part of this section will summarize the research on adoption and use of two key technologies likely to affect both current and future transport decisions made by Millennials: ride-hailing and autonomous vehicles. Considering first the recent development of ICT-enabled shared mobility, such as Uber and Lyft, Pew Research has published information regarding the breakdown of users, as well as how often the users utilize the service [59]. Interestingly, while Uber and Lyft and greatly disrupted the taxi industry, only approximately 15% of Pew's respondents

had used a ride-hailing service. The users tended to be younger, college educated, wealthier, and living in urban areas [60]. These trends are not shocking, as these demographics are also less likely to own vehicles but still have the disposable income to use ride-hailing rather than public transportation. While this report provides several pieces of useful information for understanding the adoption of ride-hailing technology, several questions about the trends remain. First, it is unclear whether the prevalence of younger users (ages 18-29) is actually due to a permanent trend in younger users preferring this technology and as they age they will use it less (age effects), or whether adoption is higher for younger people and they will continue to use it as they age (cohort effects).

There are possible explanations for the trend of greater ride sharing for Millennials that fall along both the cohort and age effect theories. If use of ride-hailing is a cohort effect, the only reason Millennials are using more ride-hailing as compared to previous generations is that the technology became available when Millennials were young, so they adopted it early and are comfortable using it. However, if there are age effects as well, it would be unclear whether the Millennial use will continue to increase, or drop off as is seen in older generations. Perhaps there is an age effect in that as the cohort ages and has children or moves into the suburbs, they no longer utilize the service as much. Again, it is important to understand and emphasize that the current trends are not necessarily indicative of future trends.

The other primary technology investigated in this work is vehicle automation. While in depth studies on perception and adoption of autonomous vehicles are not frequent, there is some existing work on generational differences in both views of driving and opinions of automated vehicles. Several news outlets have published stories about the aversion of older generations to autonomous vehicles due to their feelings about driving and the connotations of freedom that driving has [61], [62]. However, these same articles do highlight the huge benefits autonomous vehicles could have on older people who are no longer physically able to drive.

Somewhat surprisingly, a study from Pew Research has found there is actually little difference in acceptance of autonomous vehicles between younger and older

generations [63]. Using data from 2013 that likely does need to be updated given the rapid advances in technology, the study found that across age groups, the interest to ride in a driverless car hovers around 50%. The differences in interest and acceptance of autonomous vehicles falls along the lines of education and urbanity rather than age. Those with college education were found to be more accepting of autonomous vehicles, as were respondents from urban areas. These results imply that while the common school of thought is that older respondents may be opposed to giving up driving, the real differences in future adoption may come down to demographic factors rather than age or cohort effects. These preferences should be considered in future work, rather than simply assuming that the younger generation as a whole will choose to adopt autonomous vehicles.

This existing work provides useful information about how technology may be affecting preferences, and how it is likely to continue changing the transport sector. The existing literature motivates further investigating into adoption of transport technologies. These factors will be considerations when coming to conclusions about what the future of mobility for Millennials may be.

Chapter 3

Methodology

The first chapter briefly discussed the econometric approaches used in this work to understand what factors explain the observed differences in Millennial vehicle ownership and usage. This section goes into detail about the data sources, the assumptions and processes used to clean the raw data, the models constructed, and the reasoning behind these choices.

3.1 Data Sources and Assumptions

The data sources for this work are the Department of Transportation’s National Household Travel Survey (NHTS) and the US Census and American Community Survey (ACS) The NHTS survey is conducted every 5-7 years and elicits information from a nationally representative set of households regarding personal travel, demographics, and vehicle ownership. This data set is rich in information related to the motivating questions of this work, and it provides detailed information from respondents at the household, person, and vehicle level. The data include weights for representativeness. I utilize surveys from 1990, 1995, 2001, 2009, and 2017.¹

Data from the US Census and the American Community Survey were also analyzed to provide a robustness check on the results observed from the NHTS analysis as well

¹The 2016 survey spans April 2016 through April 2017. It will be referred to as the 2017 survey throughout this work.

as to provide a more complete picture of the changing demographics within the US. Both the Census and American Community Survey data used in this analysis are provided by the Integrated Public Use Microdata Series compiled by the University of Minnesota. These data have detailed information on demographics, as well as information on vehicle ownership. In contrast to the NHTS, the data set does not have information on VMT. Data from Census years 1990, 2000, and 2010 are included in the vehicle analysis, as well as the American Community Survey from 2015, an off-cycle year for the US Census. These years were selected as they were the only years in the data set in which the number of household vehicles was reported.

Both data sets contained responses at both the person- and household-level. The vehicle analysis is done at a household-level, since vehicles are often attributed to households rather than individuals, households typically share the expenses of a vehicle, and the data sets recorded household identification for the vehicles rather than personal designation. VMT is analyzed at the person level. Each response had unique year- and person- identification numbers, so in any instances where only person-level data were available, it could be combined to gain a household-level value.

Several steps to clean and organize the data were necessary to analyze households based on the generation to which they belonged. To assign the appropriate generation to each household, the head of household was identified from the person-level responses by selecting the eldest member of each family. Their birth year was used to assign a generation to the household based on the delineations in Table 2.1. The attributes of the identified head of household for each family provide the data for vehicle analysis as well as the demographic data.

For the baseline regression models, detailed in the following section, the only households included in the analysis were those for which the head of household age fell in the range of ages available for Millennials. This decision was made deliberately to reduce any effects observed from data of older heads of households for which there is no corresponding data for Millennials. For the NHTS data the most recent data set was from 2017, so ages 18-37 are included in the analysis. For the Census and ACS data, with the most recent data from 2015, ages 18-35 were included. Additionally,

the data used in the model incorporates the applicable household or person-level weights from the data sources to ensure a nationally representative sample.

In addition to these steps for data cleaning, several translations were needed between the different iterations of the surveys. For example, the encoding for urban versus rural locations were not consistent year to year in the NHTS data set. Careful note of the definitions and differences year to year were made.

The 2017 NHTS data include new variables which were not present in prior data sets because gathering such data was not particularly relevant in earlier survey years. The variables of interest for this work pertain to ride-hailing and carsharing. In the past 8 years since the 2009 survey, advances in technology have made ride-hailing and carsharing a reality. The ride-hailing and carsharing variables record the number of times the respondent utilized the respective service in the past year. Both variables will likely affect vehicle sales and use, so an investigation of the generational trends is included.

3.2 Descriptive Statistics

This section provides detailed summaries of both the NHTS and Census/ACS data sets. Relevant data pertaining to vehicle ownership, vehicle miles traveled, and demographics are provided.

3.2.1 National Household Travel Survey Data

To understand the data used in the regression analysis, a detailed summary of key variables is provided. The two primary variables of interest, household vehicles and personal VMT, are plotted in Figure 3-1. This depiction represents the raw data from the NHTS data set, and does not include the survey weights, which are used in the later analysis. This visualization can provide an initial insight into what general trends are observed for each variable and can motivate further analysis.

Figure 3-1 depicts the average values for household vehicles on the left plot and personal VMT on the right for each of the five survey years used in this work. Con-

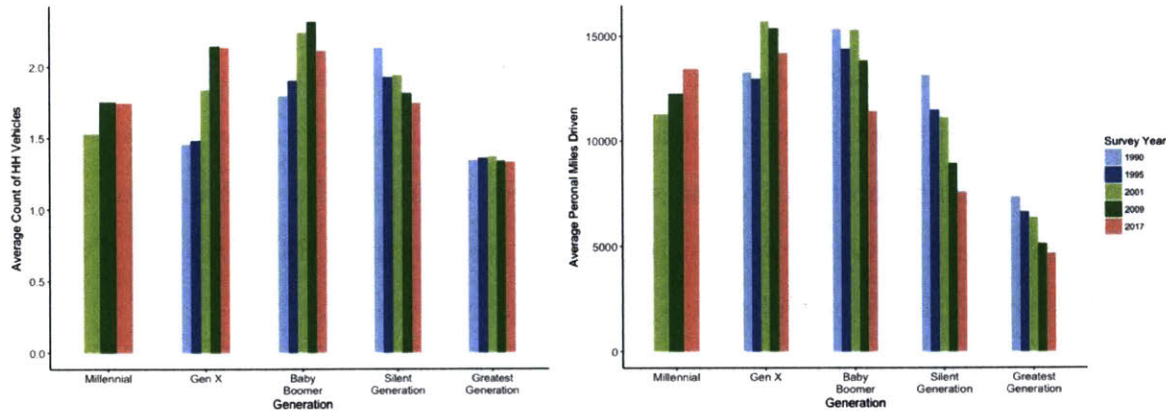


Figure 3-1: NHTS HH vehicle count and personal VMT for each survey year

sidering first vehicle ownership, the average number of household vehicles follows a trend in which younger generations own fewer vehicles, then vehicle ownership peaks with generations of middle age and decreases again for older generations. This can be observed for a single generation as well when looking at the average ownership rates for Baby Boomers. From 1990-2009, their vehicle ownership was increasing. In the most recent data from 2017, ownership rates have dropped, suggesting that Baby Boomers are transitioning into the latter section of vehicle ownership trends and will continue to own fewer vehicles. This observed pattern provides important insight for answering the question whether Millennials are different from prior generations. Because there is a clear age effect, Millennials have likely not reached their point of maximum vehicle ownership. Comparing sales from Millennials now to Baby Boomers now would not account for the different points in their life cycle that each generation currently occupies.

The plot of average VMT tells a similar story. The shape of the plot supports the conclusion that age plays a role in how much someone drives. Younger and older generations are driving less than Generation X and Baby Boomers. Interestingly, the peak age for VMT is earlier than the peak ages for vehicle ownership, and drops off more significantly for older generations. These findings are logical, as one can imagine that drivers may be more willing to commute long distances in their 30s and 40s. At older ages, they still own cars, but they do not use them as often. These results provide interesting explanations of differences between vehicle ownership and usage

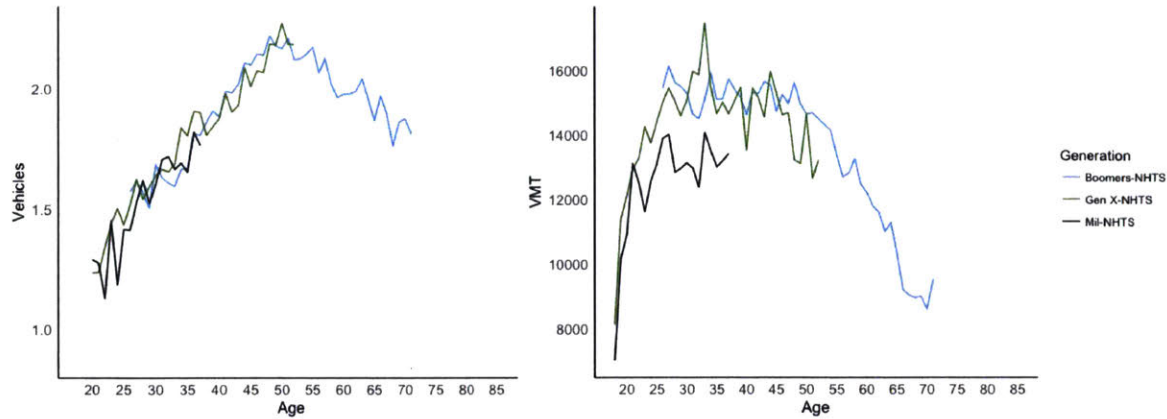


Figure 3-2: NHTS HH vehicle count and personal VMT as generations age

rates, and together provide further motivation for quantitative analysis of comparisons between generations, as the underlying trends in the data are affecting the observed differences in generational behaviors.

An alternative way of visualizing this data is to examine how average vehicle ownership and VMT changes as members of each generation age. Figure 3-2 shows average vehicle ownership and VMT by generation for each age, including the survey weights. The vehicle ownership rates appear very similar for all three generations. Again, strong age effects are observed, and vehicle ownership appears to peak at approximately age 50. In contrast, the average VMT for the three generations differs dramatically between Millennials and prior generations. While Generation X and Baby Boomers have fairly similar rates, with peaks in mid- to late-thirties followed by plateaus, Millennial VMT is much lower for the years which are currently available. However, this plot still does not paint a full picture of what is at the root of differences in VMT, or how enduring these differences may be. Understanding how both the age effects and demographics are affecting vehicle ownership and VMT will allow a more complete understanding of what motivates these differences and what the future may look like.

To gain a fuller understanding of the raw data, Table 3.1 lists the summary statistics for household vehicle count and personal VMT. The table includes summary values for each generation both when all ages available in the data set are included,

		(1)	(2)	(3)	(4)
	<i>Statistic</i>	All Ages HH Vehicles	Ages 18-37 HH Vehicles	All Ages Personal VMT	Ages 18-37 Personal VMT
Gen Z	Mean	1.53	1.53	8646.76	8646.76
	St. Dev.	1.08	1.08	11151.04	11151.04
	N	540	540	4764	4764
Millennials	Mean	1.75	1.75	12937.85	12937.85
	St. Dev.	0.925	0.925	13557.99	13557.99
	N	19465	19465	39996	39996
Gen X	Mean	2.03	1.82	14674.39	14692.61
	St. Dev.	1.10	0.945	14173.17	14513.46
	N	55941	20507	92776	43107
Baby Boomers	Mean	2.17	1.74	13408.75	15072.17
	St. Dev.	1.22	0.897	13406.14	16107.85
	N	153259	9220	213258	16234
Silent Gen	Mean	1.84		9553.63	
	St. Dev.	1.06		10218.64	
	N	104683		114242	
Greatest Gen	Mean	1.35		6194.60	
	St. Dev.	0.947		7038.71	
	N	36146		24695	
Total	N	369602	49732	489731	104101

Table 3.1: NHTS raw data for HH vehicle count and personal VMT

as well as when only ages 18-37 are included. Several important notes are needed to interpret this table, as well as later results from regression analyses. First, as mentioned in the previous chapter, vehicle count is examined at the household level while VMT is at the person level. Therefore, there are many more observations for VMT than vehicle ownership. Secondly, the data reported here represents the responses in the data set which have complete information for the variables summarized here. In later analysis, where additional variables are considered, the number of complete responses decreases as some respondents did not provide all the information needed in the analysis. The number of respondents in this table may not match the number listed in later analyses tables. Additionally, these data do not include weights. Instead, this table is meant to provide a view into the data set, which will be explored more fully in the regression analysis. Lastly, data for Generation Z is included in this table, but is dropped in later analysis. The number of data points available is small, so no meaningful conclusions can be made.

The unweighted data in Table 3.1 show that Millennials own on average 1.75 vehicles, while Baby Boomers own on average 2.17 vehicles. When the data set is restricted to only include ages for which data on Millennials is available, the difference between the two is greatly reduced, as the Baby Boomer average ownership becomes 1.74 vehicles. This provides motivation for examining the vehicle data more closely for other underlying variables affecting observed vehicle ownership, namely the endowments. Looking at the VMT data, the age effect does not seem as pronounced. Millennials have even larger difference from Baby Boomers when the ages are restricted. These findings require further investigation, but can provide some initial insights.

In addition to examining the dependent variables of interest, an investigation into several key demographic variables was also done. Four key variables are discussed: urban status, family life cycle,² household size, and household income. These variables were selected based on literature claims that changes in economic conditions, geographic locations, and timing of the beginning of families may be affecting vehicle ownership. Figure 3-3 shows a summary of household urban status by generation. Urban status is divided into three primary categories: urban areas, urban clusters,

² Family life cycle is available in only the NHTS data set. The ACS/Census data contains variables on marital status and number of children. These variables are summarized in place of life cycle.

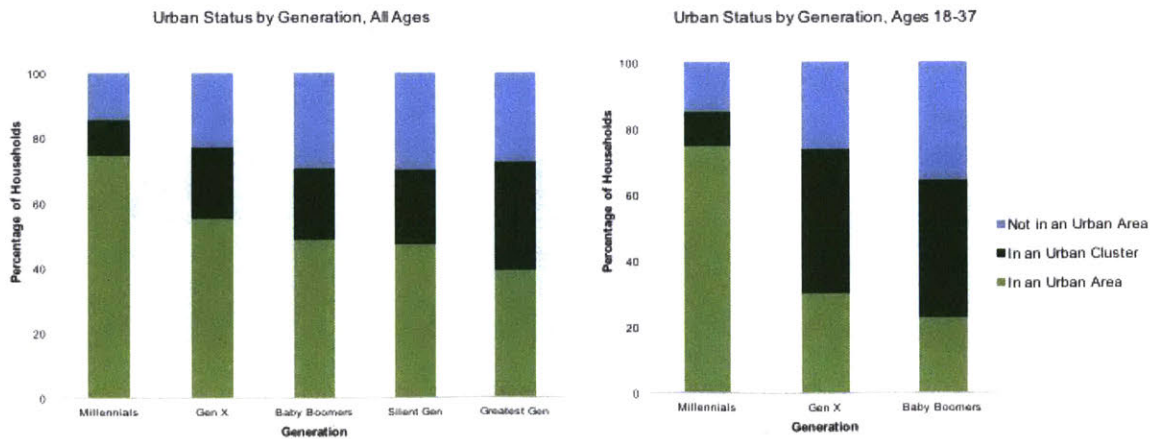


Figure 3-3: NHTS urban status of households by generation

and not urban areas. These definitions are based on those used in the US Census. Urbanized areas represent geographical areas of 50,000 or more people, while urban clusters contain at least 2,500 people and fewer than 50,000 people. This classification does not include the granularity to distinguish between high density cities, like New York City, where public transit is available, and lower density cities or large suburbs.

The plot shows both the breakdown when all ages are included as well as when only ages 18-37 are included. It is immediately apparent that the share of Millennials living in urban areas, indicated in light green, is much larger than for prior generations. This trend is even more apparent when only Millennial ages are included in the plot. There are different underlying distributions of urban versus not urban households in Millennials as compared to other generations.

Figure 3-4 examines the family life cycle for each household in the data set. The data are limited to households aged 18-37 because many of the categories in the life cycles are not yet applicable to Millennials, such as households consisting of retired adults. These comparisons of the family life cycles provides additional perspective into differences between the generations. The majority of Millennial households have no children, indicated in dark blue for households of one person and light blue for households of two. The light blue color, indicating a household comprised of only one adult, is largest for Millennials. A small portion of Millennials have children aged 6 or older, indicated in the two shades of green. In contrast, both Generation X and Baby Boomers have a minority of households with no children. Baby Boomers have a

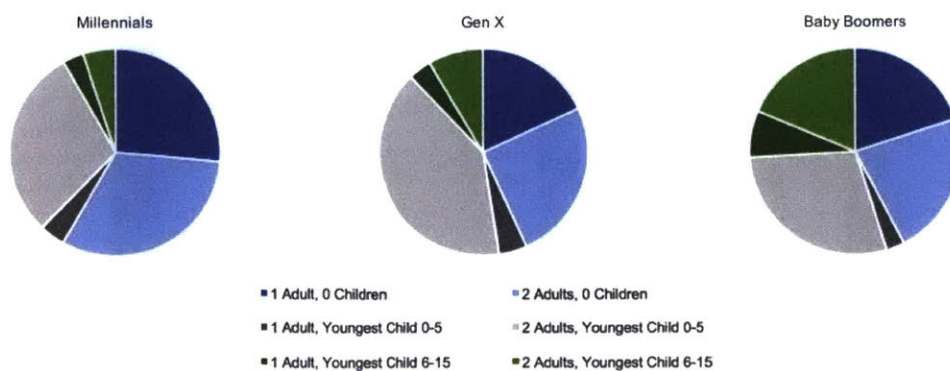


Figure 3-4: NHTS family lifecycles of households by generation

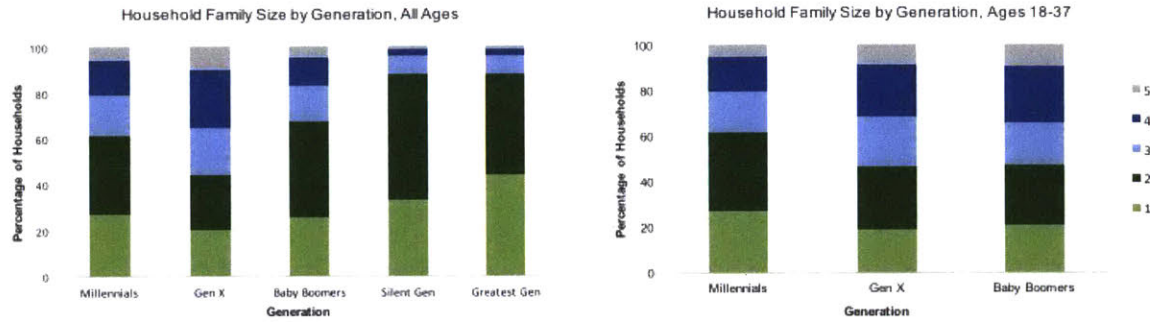


Figure 3-5: NHTS household size by generation

large number of households with children aged 6 or older. These findings support two conclusions. First, Millennials are getting married later than previous generations. Additionally, they are choosing to have children later. It is unclear from this data if Millennials marriage and child-bearing rates will reach the levels of Baby Boomers.

Figure 3-5 provides more detail on Millennials' family choices by comparing household sizes. While household size does not translate directly to marital status or number of children, in conjunction with Figure 3-4, a more full understanding of the choices Millennials are making can be made. The left plot with household size for all ages shows the trend that young and older generations consist of smaller households, while middle-aged generations have larger households. Therefore, looking at Millennial household sizes now compared to other generations now is not very instructive. Subsetting the data to look only at ages 18-37 reveals that Millennial household size is somewhat different from prior generations. A larger percentage of Millennials are in one person households, while fewer are in households of three or more. This confirms the findings from Figure 3-4 that Millennials aged 18-37 both seem to be marrying at lower rates and having fewer children compared to Baby Boomers or Generation X.

The final demographic variable of interest is household income in 2015 US dollars, plotted in Figure 3-6. The left plot describes income for households of all ages and shows a trend similar to trends in vehicle ownership and usage, where a peak occurs in midlife. There are clear age effects at play here. Limiting the ages of inclusion to 18-37 accounts for these age effects, but a difference is still observed in Millennials' income distributions compared to prior generations. There are several potential explanations

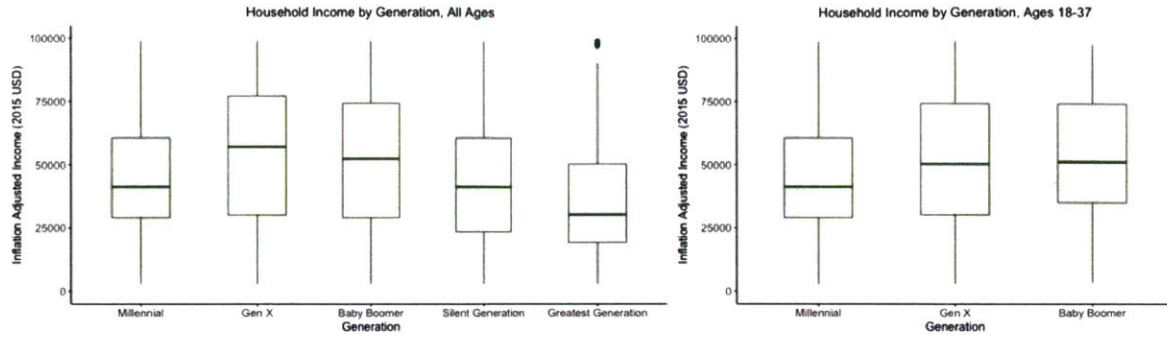


Figure 3-6: NHTS household income (in 2015 USD) by generation

for these findings, including fallout from the financial crisis, increasing costs of higher education, and the hollowing out of the middle class. Regardless of the cause of this difference, income is likely an influence on vehicle ownership, and as such knowing there are different underlying distributions is important to the analysis.

Ride-hailing and carsharing are not a primary focus of this work. However, the 2017 NHTS data set includes variables to capture use, so a cursory analysis is included. The primary motivation for this analysis is to understand how adoption rates differ by generation, as well as how usage differs among adopters. These findings can be used to inform policies in the future. The survey asks respondents to report how many times they have used ride-hailing or carsharing services in the past year. Figure 3-7 depicts the raw data from the NHTS survey. The first row looks at the data from all respondents, separated first by generation and then by age. Two takeaways are especially striking. First, total usage of ride-hailing is fairly low. Even for Millennials, who have by far the greatest usage, the average annual usage is 0.8 rides. Therefore, many people are not using the service at all. Second, the usage peaks in the late twenties and early thirties, and the distribution is heavily skewed left.

The second row of graphs looks only at respondents who have used the service before. In other words, all respondents who reported 0 usage were dropped from the data set. This was done to understand how usage varies across those who have adopted the technology. In this comparison, the generation and age trends are much less pronounced. On average, Millennials are still using ride-hailing more, with 4 uses per year compared to approximately 3 uses per year for Baby Boomers. However,

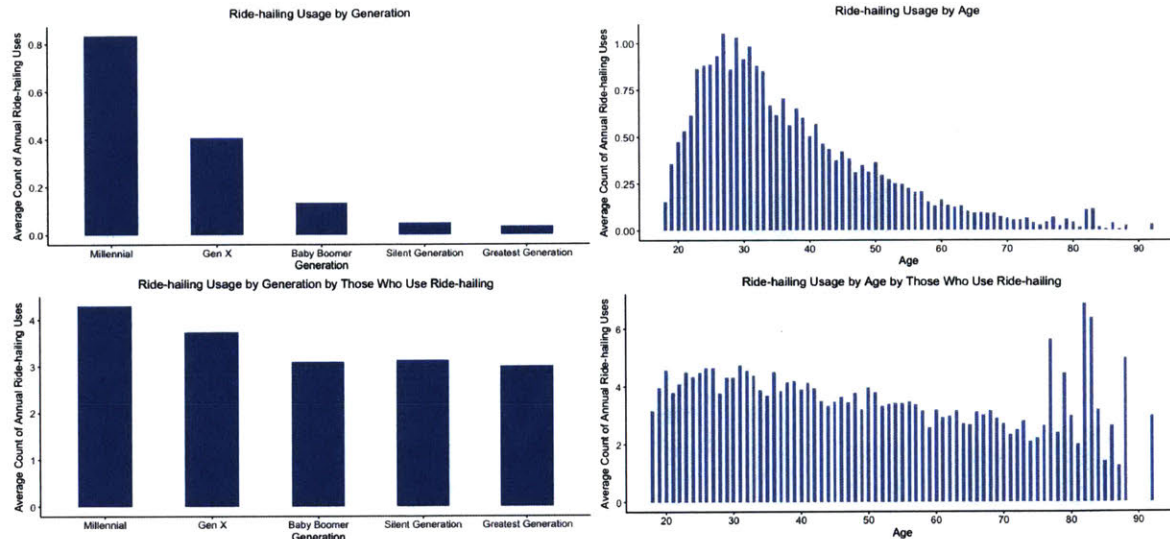


Figure 3-7: Average annual ride-hailing usage by generation and age

the age distribution shows interesting features in that the distribution is no longer as heavily skewed to the left. There are some outlying usages at very old ages. This finding supports the hypothesis that once people have adopted the technology, the use rates are not so different. In fact, the oldest users make use of the service more than many younger adopters. The difference in usage by generations and ages seems to be from difference in adoption rates. The implications of these findings will be discussed in conjunction with the analysis results.

Figure 3-8 displays comparable information to Figure 3-7 but for carsharing programs. These programs like ZipCar allow users to pay hourly rates to borrow cars for specified amount of time. Comparing the magnitude of usage of carsharing to ride-hailing, many fewer individuals are using carsharing. Also of note is the somewhat higher usage among the oldest respondents, the Greatest Generation. Their rate of usage matches Generation X. The age distribution does not have as clear of a trend as ride-hailing, but in general not many people are using carsharing.

When considering only respondents who have used the service, the group with highest usage is the Greatest Generation. Once a generation or age-group has adopted carsharing, the older respondents seem to use it more. Given the small number of respondents who have used this technology, this data visualization may not be fully

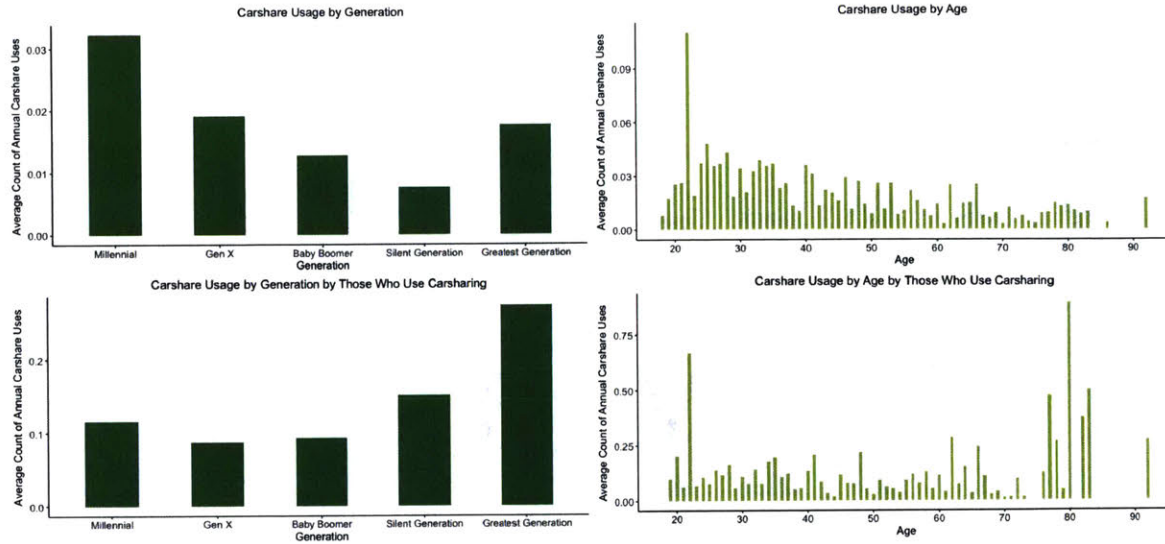


Figure 3-8: Average annual carsharing usage by generation and age

representative of the underlying trends. However, the findings support the conclusion that carsharing is not a widely utilized service, especially compared to ride-hailing.

The NHTS data provides further motivation for doing a deeper, quantitative dive into the data underlying the observations that Millennials own fewer cars. Age effects are clearly affecting vehicle ownership and usage. Additionally, there are distinct differences between Millennials and other generations in terms of their demographic makeups. The regression analysis aims to separate these factors from preferences to gain a full understanding of Millennials' behaviors.

3.2.2 Census and American Community Survey Data

The Census and American Community Survey contains many of the same variables as NHTS. This section discusses the data in the survey in a similar manner to the prior section. Some differences in how demographic variables are described are discussed in this section. The Census/ACS data set also contains many more data points for each variable as compared to the NHTS due to the scale of the surveys. Additionally, as mentioned in earlier sections, vehicle ownership is reported in the survey but vehicle miles traveled is not.

The data for vehicle ownership shown in Figure 3-9 displays similar trends as the

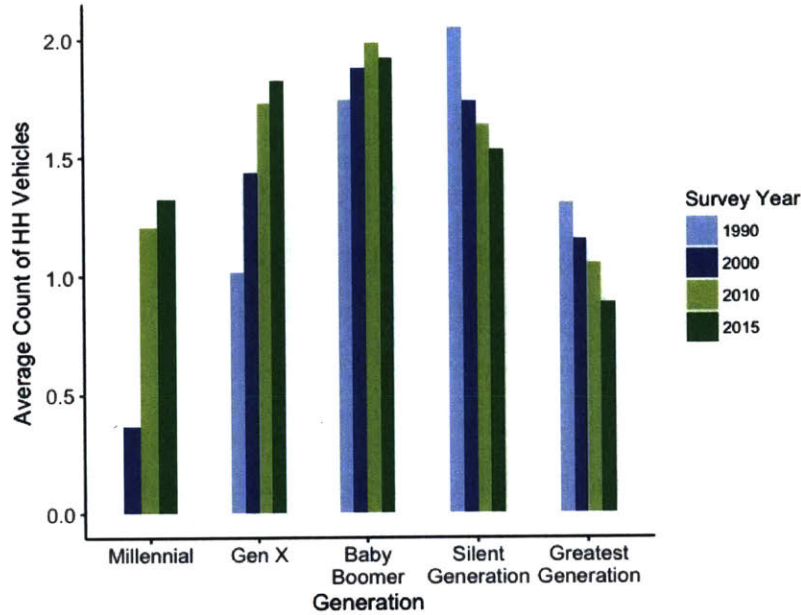


Figure 3-9: ACS/Census HH vehicle count for each survey year

NHTS data set. There are clear age effects in play, and ownership appears to peak in middle age. The magnitude of the average vehicles owned differs. As this is the unweighted data, it is not meaningful to compare the raw values but these differences should be noted in the further analysis.

When the data is plotted looking at average vehicle ownership as members of a generation ages in Figure 3-10, the behavior of Millennials looks fairly similar to prior

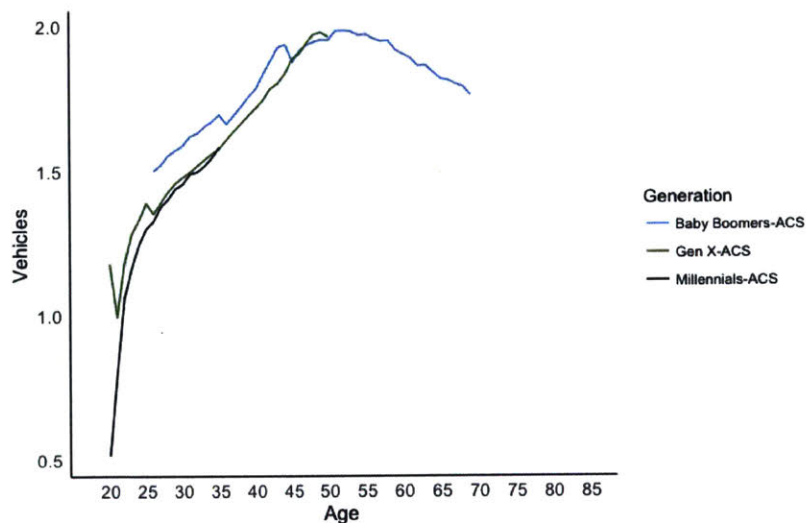


Figure 3-10: ACS/Census HH vehicle count and personal VMT as generations age

generations. This behavior is especially true for ages 25 to 35. The data for Millennials at lower ages shows lower vehicle ownership rate. Baby Boomers show higher vehicle ownership at younger ages, but Generation X reaches comparable average ownership rates near age 50. Again, this data does not tell the entire story, as all the confounding demographic variables of interest are not considered. However, this visualization again provides some initial insights on how age affects vehicle ownership, and how the generations compare to each other when the members of the generation were certain ages.

Table 3.2 displays the quantitative results for vehicle ownership underlying these figures. As with Table 3.1, both the statistics for the full data set as well as the subset of data for which data on Millennials is available is included. There is significant difference in ownership rates between Millennials and prior generations when examining the full data set. When the age effects are accounted for by subsetting the data, a large reduction in difference between the generations occurs once again.

		(1)	(2)
		All Ages	Ages 18-35
	<i>Statistic</i>	HH Vehicles	HH Vehicles
Gen Z	Mean	0.135	0.135
	St. Dev.	0.514	0.514
	N	26469	26469
Millennials	Mean	1.12	1.12
	St. Dev.	1.04	1.04
	N	422909	422909
Gen X	Mean	1.47	1.36
	St. Dev.	1.03	0.980
	N	2028895	20507
Baby Boomers	Mean	1.84	1.60
	St. Dev.	1.07	0.899
	N	5052759	9220
Silent Gen	Mean	1.84	
	St. Dev.	1.00	
	N	3093705	
Greatest Gen	Mean	1.23	
	St. Dev.	1.00	
	N	2352961	
Total	N	12977689	2934397

Table 3.2: ACS raw data for HH vehicle count

There are still large gaps between Millennials and other groups. Examining the underlying demographics is again an important factor in understanding the root of the differences.

Even more so than the NHTS data, the ACS/Census data set has a huge amount of demographic information with a many respondents. The demographic information from the ACS/Census data set will be used in the latter half of the regression analysis to understand the connections between different demographic variables and between demographic variables and vehicle ownership. Several of the key variables likely to affect vehicle ownership are summarized below. They capture the same facets of Millennial households that the NHTS work above did: urban status, family life cycle, household size, and household income. However, this information is provided in the ACS/Census survey in a slightly different manner, primarily in terms of family life cycle. The ACS/Census data set has explicit variables for whether the head of household has been married, as well as how many children are in the household.

Examining first the urban status of households, Figure 3-11 shows the breakdown of households by urban versus rural. Unlike the NHTS data set, the distinction between “Urban Areas” of higher density and “Urban Clusters” of lower density is not included. The ACS/Census variable does not provide quite as much granularity. As such, less information can be gleaned from this summary. In contrast to the data from NHTS, these results show little apparent difference in urban status. This can be explored more fully in the demographic regression analysis.

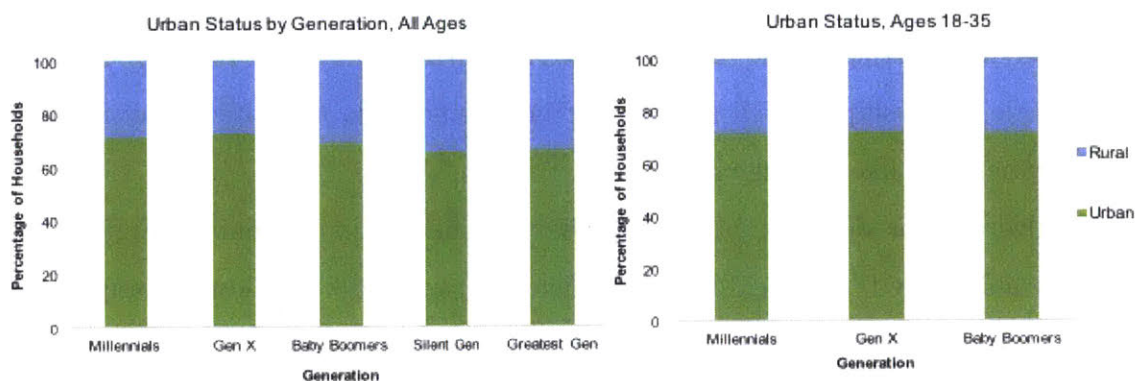


Figure 3-11: ACS/Census urban status of households by generation

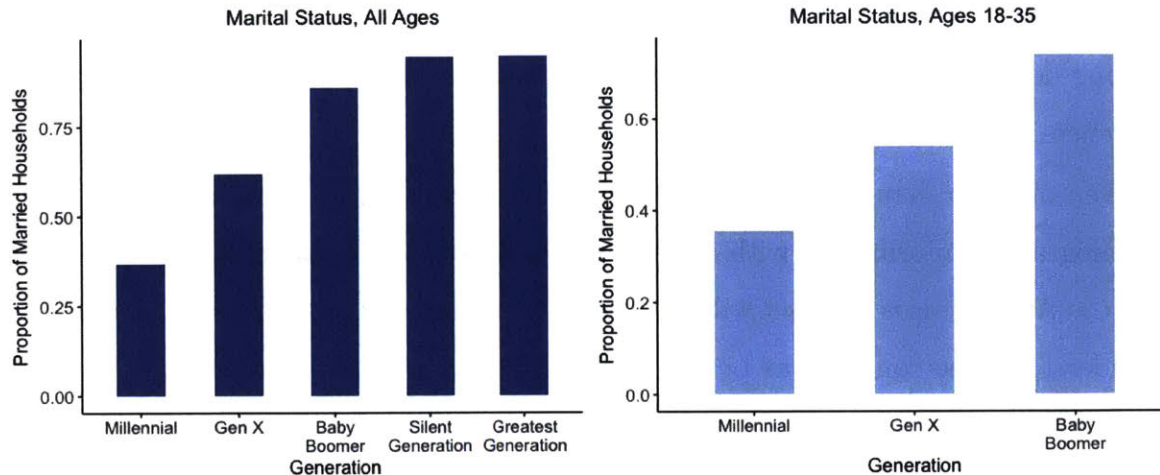


Figure 3-12: ACS/Census household marital status by generation

Unlike urban status, marital status does appear very different for Millennials as compared to other generations. Figure 3-12 shows both the fraction of married households in the full data set, as well as that same fraction for ages 18-35. The marital status variable captures whether the head of household has been married at some point in the past. The head of household may be divorced, separated, or widowed now. This variable is meant to capture the fraction of households who have made the life transition to be married at some point.

It is not surprising to see a positive trend over time, as more people marry as they age. A difference between generations becomes apparent when only Millennial ages are evaluated. Fewer than 40% of Millennial households aged 18-35 are headed by someone who has been married, while Gen X approaches 60% and Baby Boomers are over 70%. This provides significant weight to the hypothesis that Millennials are either delaying marriage or not getting married. Either decision could have effects on both vehicle ownership as well as other demographic variables which may influence vehicle ownership, like having children.

The decrease or delay in Millennials having children is evident in Figure 3-13. For households aged 18-35, Millennials have on average 0.5 children compared to Baby Boomers' nearly 1. Not surprisingly, the household sizes follow this same trend, confirming Millennials are lagging behind or changing their behaviors when starting families. Having children may be an important influence on vehicle ownership, as

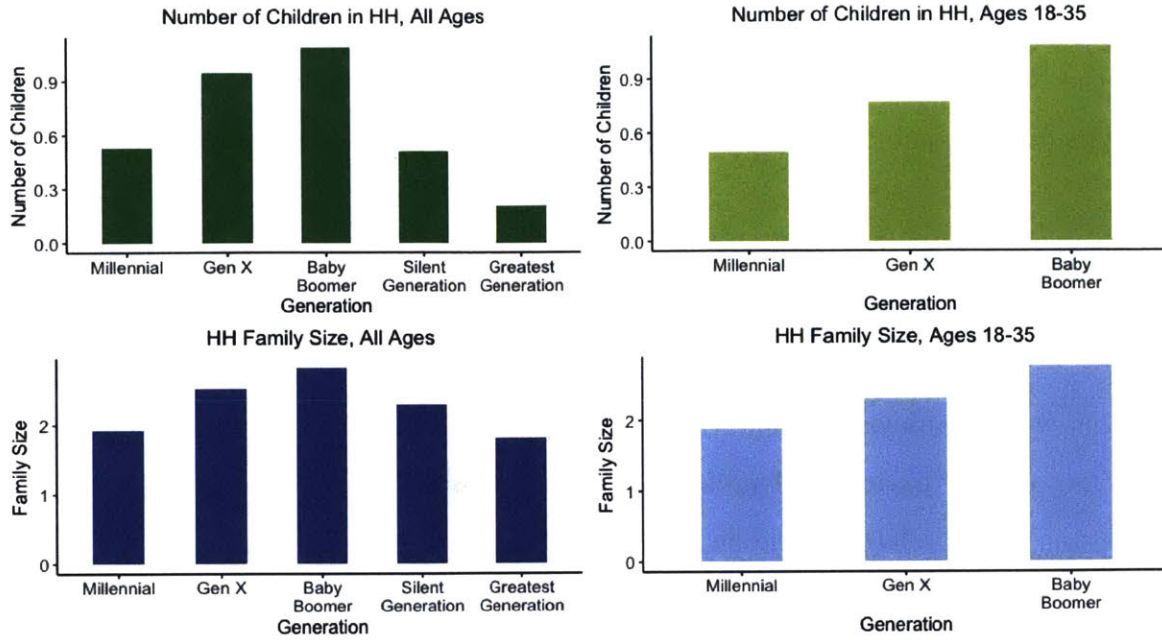


Figure 3-13: ACS/Census number of children and household size by generation

alternative forms of transport such as public transportation become much more difficult when traveling with infants or small children. The findings from the ACS/Census data set align with those from the NHTS life cycle and household size data and further motivate continued investigation into the underlying endowments of Millennials compared to other generations.

Lastly, as with the NHTS data set, the inflation adjusted income in 2015 US dollars is compared between generations, both for the full data set and the subset of the data set aged 18-35. Figure 3-14 shows similar trends as the NHTS data set did,

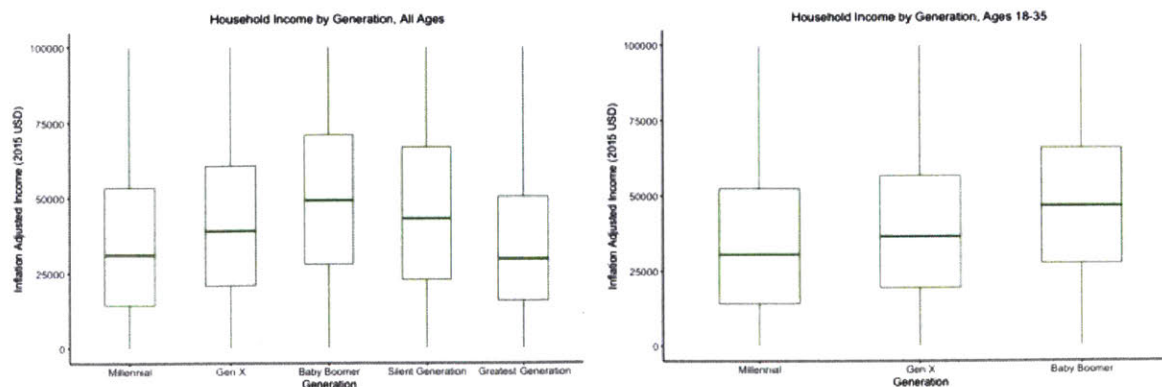


Figure 3-14: ACS/Census household income by generation

where income peaks around middle-age, which corresponds to Baby Boomers. As with the NHTS, when only ages 18-35 are included, the Millennial generation has a lower median income compared to the other generations when they were those ages.

3.3 Linear Regression Models

This work employs econometric techniques to provide further understanding of what factors are driving Millennials' observed behaviors. A linear regression model is constructed to relate vehicle ownership and usage to each generation, and control variables are included in order to create an apples-to-apples comparison between generations. By including demographic variables as controls in the model, influence of factors differing between generations such as age of marriage and household size can be stripped away in order to compare households that differ only by what generation the head of household belongs. Several key demographic variables which may influence vehicle ownership and usage were identified. These variables are listed in Table 3.3. Ideally, all these variables are included in every model, but certain information was not available in both data sets, as noted in the table.

Control Variables
Income
Household Size
Location: Urban v. Rural
Location: State
Education
Survey Year
Age
Sex
Race
Family Life Cycle†
Marital Status*
Number of Children*

Table 3.3: Demographic variables included in models

†-Variable available in NHTS data set only

*-Variable available in Census/ACS data sets only

3.3.1 Vehicle Ownership and VMT

For each modeled dependent variable, one model without any control variables and one including the variables of interest from Table 3.3 were constructed. The model without control variables represents what is observed typically, as it captures the differences in the average vehicle ownership or VMT for each generation. The model which includes control variables is the apples-to-apples generation comparison, which provides the insight as to whether Millennials are different more due to their endowments or their preferences.

The following description of the model focuses on vehicle ownership, but the models and interpretation of the regression coefficients can be applied to VMT as well. The general regression equations without any control variables are identical for both the NHTS and ACS data sets. However, the regression equations differ when including control variables, as different variables were available for the two data sets.

First, a simple model relating household generation to the dependent variable of interest was constructed without any demographic control variables. This model relates the variables of interest to the generation as noted in Equation 3.1, where the variable $x_{i,Gen}$ is a categorical variable that describes which generation a household belongs to (Millennial, Gen X, Baby Boomer, Silent Generation, or Greatest Generation.)

$$y_{Vehicles} = \beta_0 + \beta_1 x_{Generation} \quad (3.1)$$

More explicitly, this model assigns a binary value to each household indicating to which generation the household belongs. A value of 1 indicates the household belongs to that generation while a 0 indicates the household does not belong to that generation. Additionally, to avoid collinearity, the model excludes one generation to be a baseline to which the remaining generations are compared. As shown below in Equation 3.2, the omitted generation in these models is Baby Boomers.

$$y_{Vehicles} = \beta_0 + \beta_1 x_{Mil} + \beta_2 x_{GenX} + \beta_3 x_{SilentGen} + \beta_4 x_{GreatestGen} \quad (3.2)$$

This model outputs coefficients for each of the independent variables that can be interpreted to understand how that independent variable relates to the dependent variable. Considering first vehicles owned, each coefficient for the respective generations indicates on average how many vehicles a household of that generation owns in comparison to the baseline omitted generation, Baby Boomers. For example, a positive coefficient of 0.1 would indicate that the average member of the generation owns on average .1 more vehicles than the average member of the baseline generation, Baby Boomers. When investigating VMT rather than vehicles owned, the coefficients indicate the average number of miles traveled in comparison to the baseline group, so a coefficient of -4,000 would indicate that the average household in the comparison group drives 4,000 fewer miles than the baseline group.

Equation 3.3 below displays the model with all the control variables included. Both numerical variables and categorical variables, indicated with an i in the subscript, are included in this regression. The variables marked with an asterisk were only available in the Census/ACS data set, and those marked with a dagger are only in the NHTS data.

$$\begin{aligned}
y_{Vehicles} = & \beta_0 + \beta_{1i}x_{Gen} + \beta_2\ln(x_{Income}) + \beta_3\ln(x_{Income})^2 + \beta_{4i}x_{HighIncome} \\
& + \beta_5\ln(x_{HHSize}) + \beta_6\ln(x_{HHSize})^2 + \beta_{7i}x_{UrbIndicator} + \beta_{8i}x_{State} \\
& + \beta_{9i}x_{Educ} + \beta_{10i}x_{Year} + \beta_{11}\ln(x_{Age}) + \beta_{12}\ln(x_{Age})^2 + \beta_{13i}x_{Sex} \\
& + \beta_{14i}x_{Race} + \beta_{15}x_{Married} * + \beta_{16}x_{HasChild} * + \beta_{17i}x_{FamLifeCycle}
\end{aligned} \tag{3.3}$$

The goal of this model is to capture the influence of many demographic variables on vehicle ownership. By including these control variables, the effects that different demographic compositions have on the total vehicle ownership can be separated so that the coefficient for each generation represents the true preference of members of that generation without the confounding effect of different demographics.

Several of the variables are included with transformations in order to capture the likely relationships we could see between the independent and dependent variables.

For example, inflation adjusted income is included with both the log and log-squared. This relationship was chosen rather than a linear relationship because it is unlikely that the number of vehicles a household owns continues to increase linearly as wealth increases. While the initial relationship may follow a linear trend, as incomes reach higher values the relationship is likely less linear as households do not continue buying many more vehicles than they need simply because they make more money. Another benefit of this approach is that these transformations give the model flexibility to capture the relationships. The variable “High Income” indicates any household that was in the highest income bracket, typically \$100,000 or more in the NHTS data sets. Because there is no upper bound to this bracket, the variable capturing the potentially very high income households was included.

3.3.2 Demographics

Analogous to the work described above for vehicle ownership and usage, linear regression analyses of several key demographic variables were also done to better understand how the control variables differ between generations. This understanding may explain some of the observed differences in vehicle and transportation demands. While one can easily look at differences between demographics without using the linear regression approach by simply looking at differences in distributions between the different generations, using the linear regression approach can help shed light on whether the demographic differences are influenced by other demographic differences.

The Census and American Community Survey Data from 1990-2015 is utilized for the demographic data analysis. Models both with and without control variables are constructed. In these models the dependent variables correspond to demographic variables of interest, illustrated below in Equation 3.4. The main distinction for the demographic work compared to the vehicle ownership and usage work is that for each demographic variable analyzed as a dependent variable, that variable is excluded from the control variables, as using the same variable on both sides of the equations would be illogical.

$$y_{DemVariables} = \beta_0 + \beta_{1i}x_{Gen} + \beta_{2i}x_{Controls} \quad (3.4)$$

The exact regressions, as well as discussion of variable interactions and how to interpret these models fully, is discussed in detail in the Results chapter. This technique provides a deeper understanding about demographics in the same way that the prior regressions revealed more about vehicle ownership. By including these control variables, this method can distinguish between whether Millennials are making completely different life choices, or whether their decisions are influenced by a variety of other, interconnected demographic variables.

In addition to this discussion of the interconnections of demographic variables, an analysis of how the demographic variables affect vehicle ownership for each generation is also done. This provides finer details about how the underlying demographics are affecting the vehicle ownership for each generation. An interaction term can capture this difference in behavior. A simplified version of this concept is noted below in Equation 3.5.

$$y_{Vehicles} = \beta_0 + \beta_{1i}x_{Gen} + \beta_{2i}x_{Controls} + \beta_3x_{Gen*Control} \quad (3.5)$$

The Results chapter goes into more detail on the specific interactions of interest, as well as how to interpret the findings and how they are instructive.

3.4 Oaxaca Decomposition Model

The linear regression approaches above allow the two categories of factors contributing to vehicle ownership, endowments and preferences, to be separated to some extent. To add further robustness to these results, I use Oaxaca Decomposition. This method developed by Ronald Oaxaca provides an approach to understand the source of differences between two groups [19]. Originally used to understand differences in wages between males and females, this approach can also be used to compare the two groups of interest in this analysis, Millennials and previous generations. For this

application, the value of interest is number of vehicles owned and VMT, rather than wages. This approach quantifies how much of the difference in vehicle ownership between Millennials and prior generations is due to differences between two groups based on the endowments, and how much is due to members of a generation behaving differently from the other generation due to differences in preferences. This approach builds upon and provides a robustness check for the linear regression approaches.

Equations 3.6 and 3.7 detail the models used to describe vehicle ownership for Millennials, denoted with the subscript M, and the comparison generation, denoted with the subscript C, which will be Generation X in the first iteration and Baby Boomers in the second. The two equations are identical and duplicate the form used in Equation 3.3. The only difference is that for each of these equations, only the data for the generation indicated is included, and thus a generation variable is not necessary.

$$\begin{aligned}
y_{M,Vehicles} = & \beta_{M,0} + \beta_{M,1}\ln(x_{M,Income}) + \beta_{M,2}\ln(x_{M,Income})^2 + \beta_{M,3i}x_{M,HighIncome}^\dagger \\
& + \beta_{M,4}\ln(x_{M,HHSize}) + \beta_{M,5}\ln(x_{M,HHSize})^2 + \beta_{M,6i}x_{M,UrbIndicator} \\
& + \beta_{M,7i}x_{M,State} + \beta_{M,8i}x_{M,Educ} + \beta_{M,9i}x_{M,Year} + \beta_{M,10}\ln(x_{M,Age}) \\
& + \beta_{M,11}\ln(x_{M,Age})^2 + \beta_{M,12i}x_{M,Sex} + \beta_{M,13i}x_{M,Race} \\
& + \beta_{M,14}x_{M,Married} * + \beta_{M,15}x_{M,HasChild} * + \beta_{M,16i}x_{M,FamLifeCycle}^\dagger
\end{aligned} \tag{3.6}$$

$$\begin{aligned}
y_{C,Vehicles} = & \beta_{C,0} + \beta_{C,1}\ln(x_{C,Income}) + \beta_{C,2}\ln(x_{C,Income})^2 + \beta_{C,3i}x_{C,HighIncome}^\dagger \\
& + \beta_{C,4}\ln(x_{C,HHSize}) + \beta_{C,5}\ln(x_{C,HHSize})^2 + \beta_{C,6i}x_{C,UrbIndicator} \\
& + \beta_{C,7i}x_{C,State} + \beta_{C,8i}x_{C,Educ} + \beta_{C,9i}x_{C,Year} + \beta_{C,10}\ln(x_{C,Age}) \\
& + \beta_{C,11}\ln(x_{C,Age})^2 + \beta_{C,12i}x_{C,Sex} + \beta_{C,13i}x_{C,Race} \\
& + \beta_{C,14}x_{C,Married} * + \beta_{C,15}x_{C,HasChild} * + \beta_{C,16i}x_{C,FamLifeCycle}^\dagger
\end{aligned} \tag{3.7}$$

The Oaxaca Decomposition aims to gain understanding about the underlying effects that result in different mean vehicle counts between the two groups by separating

the difference in mean into two elements: the explained and unexplained. The explained portion captures the difference in means due to differences in the underlying distribution between the two groups. For this example, this difference captures the difference in endowments, the demographics and economic conditions between the two groups. The unexplained portion is the difference in means due to factors not explained by the difference in the underlying distributions of the group. For this application, those differences represent consumer behavior separate from behavior attributed to demographics, such as preferences to own a vehicle.

To separate the difference in means into these components, first a counterfactual of Millennials' behavior must be constructed, as shown in Equation 3.8. This counterfactual uses the coefficients calculated for the model of the generation being compared to Millennials, which captures that generation's behavior given its demographic characteristics. Those coefficients are applied to Millennials' data to understand what the average number of vehicles owned by a Millennial would be if they had the same preferences (coefficients) as Generation X, and differed only due to their underlying endowments. Equation 3.8 shows the resulting regression model applying the comparison generation's coefficients, denoted with the subscript C, to Millennials data, denoted with the subscript M.

$$\begin{aligned}
y_{M,Vehicles}^* = & \beta_{C,0} + \beta_{C,1}\ln(x_{M,Income}) + \beta_{C,2}\ln(x_{M,Income})^2 + \beta_{C,3i}x_{M,HighIncome} \\
& + \beta_{C,4}\ln(x_{M,HHSize}) + \beta_{C,5}\ln(x_{M,HHSize})^2 + \beta_{C,6i}x_{M,UrbIndicator} \\
& + \beta_{C,7i}x_{M,State} + \beta_{C,8i}x_{M,Educ} + \beta_{C,9i}x_{M,Year} + \beta_{C,10}\ln(x_{M,Age}) \\
& + \beta_{C,11}\ln(x_{M,Age})^2 + \beta_{C,12i}x_{M,Sex} + \beta_{C,13i}x_{M,Race} \\
& + \beta_{C,14}x_{M,Married} * + \beta_{C,15}x_{M,HasChild} * + \beta_{C,16i}x_{M,FamLifeCycle}
\end{aligned} \tag{3.8}$$

Using Equation 3.9, the difference in the two groups' means can be separated into two components. The first component, $y_{C,Vehicles} - y_{M,Vehicles}^*$, captures the difference in endowments between the two groups. The second, $y_{M,Vehicles}^* - y_{M,Vehicles}$ captures the difference not explained by the endowments. This represents the difference in

preferences for vehicles.

$$y_{C,Vehicles} - y_{M,Vehicles} = y_{C,Vehicles} - y_{M,Vehicles}^* + y_{M,Vehicles}^* - y_{M,Vehicles} \quad (3.9)$$

Ultimately, the Oaxaca regression succinctly addresses why two groups differ by separating underlying differences between two groups and the differences in their behaviors. These results can be used to bolster the findings from the linear regressions.

3.5 Nearest Neighbor Matching Estimator

A third econometric approach, a nearest neighbor matching model, serves as a final check on the robustness of the results from linear and Oaxaca regressions. Matching models have the benefit of comparing individuals in generations rather than aggregate generations. The matching model here aims to compare the vehicle ownership and usage between pairs of individual Millennials and individuals belonging to other generations who have similar endowments. Rather than looking at generational averages, the model takes an individual in the group of interest, here Millennials, and attempts to find an individual in the comparison group, Baby Boomers, who has very similar demographic endowments. This closest match is referred to as the nearest neighbor. The model then compares their vehicle ownership or usage. This is done repeatedly for a sample of the data in order to get an average treatment effect of being a Millennial compared to being a member of a different generation.

In this work, several key demographic variables are used to find matches between the different generations. The selected variables are education, inflation adjusted income, household size, urban status, age, and life cycle/marital status. A script searches for households that are most similar based on those variables and compares the dependent variables of interest, which are vehicle ownership and VMT. One problem that can arise in nearest neighbor matching estimators is existing bias between groups, as there may be inherent differences that do not allow all the data to be matched. To address this to the best extent possible, bias adjustment terms are in-

cluded in the script for income, household size, urban status, and age. The resulting equation for the average difference for between generations is

$$\Delta y_{Vehicles} = y_{Vehicles}(w_{Gen} = Mill) - y_{Vehicles}(w_{Gen} = Comparison) \quad (3.10)$$

The difference in the dependent variables, $\Delta y_{vehicles}$ or Δy_{VMT} can be estimated by finding the sample average treatment effect for N matches, which is

$$\overline{\Delta y_{Vehicles}} = \frac{1}{N} \sum y_{Vehicles}(w_{Gen} = Mill) - y_{Vehicles}(w_{Gen} = Comparison) \quad (3.11)$$

A major motivation for including this third econometric approach is to address any concerns that the data available for Baby Boomers and Millennials does not provide the same ages of households for comparison, and thus an average comparison between the two groups may be less robust. In both data sets, the youngest Baby Boomers are 26 due to survey year limitations, compared to Millennials and Generation X which have respondents as young as 18 included in the data set. This concern was not identified as critical since the inclusion of young Baby Boomers would only lower the average number of vehicles owned by Baby Boomers given the importance of age effects. Therefore, using slightly older Baby Boomer households provides a conservative approach. To quantitatively confirm this assertion, the matching model allows for a simple comparison of as like as possible members of each generation, removing this potential issue of different ages in the data.

3.6 Preferences for Ride-hailing and Carsharing

Because the ride-hailing and carsharing variables have only one survey year of usable data, the approach used above to investigate only households with the head of household in the Millennial age range is not possible. However, other demographic variables can be controlled for to get as close comparison between the generations as possible. In a similar approach, linear regressions with each of the two different

dependent variables are done with the remaining demographic variables, shown for ride-hailing below in Equation 3.12.

$$\begin{aligned}
y_{Ride-hailing} = & \beta_0 + \beta_{1i}x_{Gen} + \beta_2\ln(x_{Income}) + \beta_3\ln(x_{Income})^2 + \beta_{4i}x_{HighIncome} \\
& + \beta_5\ln(x_{HHSize}) + \beta_6\ln(x_{HHSize})^2 + \beta_{7i}x_{UrbIndicator} + \beta_{8i}x_{State} \\
& + \beta_{9i}x_{Educ} + \beta_{10i}x_{Year} + \beta_{11}\ln(x_{Age}) + \beta_{12}\ln(x_{Age})^2 + \beta_{13i}x_{Sex} \\
& + \beta_{14i}x_{Race} + \beta_{15i}x_{FamLifeCycle}
\end{aligned} \tag{3.12}$$

Results from these regressions are useful for multiple reasons. The ride-hailing and carsharing results can indicate how significant the generational trends are in the use of these technologies, as well as provide more detail on what demographic factors affect adoption. Additionally, by investigating both overall use and use by those who have adopted the technology, the analyses can attempt to tease apart the age and cohort effects.

3.7 Projections of Future Transport Trends

The regression analyses investigate past and current trends of Millennials. This work can be used to gain a clearer idea of the future. Ultimately, the actual behavior of Millennials in terms of vehicle ownership and usage is the most critical factor for economic and environmental planning. Therefore, rather than simply understanding if Millennials are behaving differently based on their demographic endowments, it is crucial to estimate what the eventual behavior is given these endowments. There are many exogenous factors that may influence future vehicle ownership, such as technology advancements in autonomous vehicles. This work does not attempt to predict what the future technologies will be, or when they would be adopted. Rather, this work exists in the current paradigm of personal vehicle ownership driven by a human driver. The goal of this work is to forecast key demographic variables and use those forecasts to estimate future vehicle ownership and usage for Millennials as they

age.

The above regressions on demographic variables and vehicle ownership and VMT can be combined together to create projections to the future. The approach for these forecasts is to project key demographic variables for each generation at different ages, and plug these findings in vehicle ownership and VMT regression models to understand what future ownership and VMT may be for Millennials as they age. The same key demographic variables are used in these projections as were discussed in the descriptive statistics demographic analysis. These variables are urbanity, household size, marital status, and household income.

These demographic variables are inherently interdependent in the sense that each demographic variable may both affect other variables as well as be affected by other variables. For example, urbanity may influence marital status, as those in cities may be less likely to be married, but at the same time marital status may affect urbanity, as married couples may be less likely to live in cities. To address this interdependence of variables, regressions of demographic variables have been done in a successive manner in multiple different orders of iterations. This idea is illustrated in detail.

The concept behind these projections is to see how different demographic variables change as Millennials age. Therefore, each of the four demographic variables are investigated in a specific order, in which the findings for the first variable are fed into the regression models for the successive variable to account for the influence of each variable on each other. For example, an iteration of this work would first investigate urbanity with the following regression equation:

$$y_{Urban} = \beta_0 + \beta_1 \ln(x_{Age}) + \beta_2 \ln(x_{Age})^2 \quad (3.13)$$

This estimates the percent of respondents living in an urban area for each generation as at different ages. With the results for urbanity at different ages from Equation 3.13, another demographic variable can be investigated. Equation 3.14 shows a potential second equation

	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5
Iteration 1	Urban	Marital Status	ln(HH Size)	ln(Income)	Vehicles/VMT
Iteration 2	ln(Income)	Marital Status	ln(HH Size)	Urban	Vehicles/VMT
Iteration 3	Marital Status	ln(HH Size)	Urban	ln(Income)	Vehicles/VMT
Iteration 4	Urban	Marital Status	ln(Income)	ln(HH Size)	Vehicles/VMT
Iteration 5*	Urban	ln(Income)	Marital Status	ln(HH Size)	Vehicles/VMT

Table 3.4: Order of variables in iterations of projections.
Marital status only included in ACS/Census projections.
*-Iteration for ACS/Census only

$$y_{Married} = \beta_0 + \beta_1 \ln(x_{Age}) + \beta_2 \ln(x_{Age})^2 + \beta_3 x_{Urban} \quad (3.14)$$

The results from equation 3.14 estimates marriage rates given urbanity. The values for urbanity at different ages from 3.13 are used to calculate $y_{married}$, thus capturing some of the dependence between the demographic variables. This successive methodology is continued for the remaining demographic variables, until estimates for each demographic variable of interest are available at a range of ages. These values can then be plugged into equation 3.15 for vehicle ownership or VMT to estimate what vehicle ownership and VMT are at different ages.

$$y_{Vehicles} = \beta_0 + \beta_1 \ln(x_{Age}) + \beta_2 \ln(x_{Age})^2 + \beta_3 x_{Urban} + \beta_4 \ln(x_{HHSize}) + \beta_5 \ln(x_{Income}) \quad (3.15)$$

This model has the advantage of accounting for some of the dependencies between demographic variables. However, by using this successive approach, the model assumes a certain path of causation. Equation 3.14 assumes that marital status is dependent on urbanity, but urbanity is not dependent on marital status. Because the actual arrow of causation is unclear, a variety of different iterations is done to capture the uncertainty in how the variables relate to each other. Five different iterations of the projections were done. The iterations are summarized in Table 3.4

These iterations were chosen because they represent some reasonable conjectures about the primary direction of influence between variables. This approach is applied to both the NHTS and ACS/Census data sets, with the primary difference being that the NHTS data set does not have a variable for Marital Status. Therefore, only

three demographic variables are included, and as a result only four of the above five iterations are relevant, as the fourth and fifth iteration are identical when marital status is excluded.

Forecasting the future is difficult because it can be challenging to capture trends for the older ages which are distinctly different from trends for younger ages. For example, vehicle ownership has a clear bell shape. However, for Millennials the only data available is for younger ages when vehicle ownership is steadily increasing. The challenge that this presents, as well as attempts to address it, will be discussed more fully in the Results chapter.

Chapter 4

Results

This chapter details the results from the econometric analyses of the NHTS and Census/ACS data sets. Summary graphs of key results are provided in the main text, and the full tables of regression results can be referenced in Appendix A. First, the vehicle ownership results are presented from both the NHTS and Census/ACS data sets. Following the discussion of those results, the NHTS VMT results are presented. Then an in-depth look at the underlying demographics of each generation is provided based on the Census/ACS data, as well as an analysis of how demographics influence vehicle ownership by quantifying generation interaction terms with key demographic variables. Results from the Oaxaca Decomposition of vehicle count for both data sets and VMT for the NHTS data set are summarized to explicitly separate the contributions to observed differences between Millennials and other generations which arise from differing endowments, and those which arise from different preferences. The findings from the matching estimators are discussed. Summary of the ride-hailing and carsharing results is provided. Lastly, the projections of Millennial future vehicle ownership and VMT are provided.

4.1 Vehicle Ownership and Usage Linear Regression Results

The data available on vehicle ownership is especially robust, as comparisons can be made between the NHTS and ACS data sets. The same methodologies were applied to both the NHTS and Census/ACS data sets, and the precise regression models used for each are detailed below. As the results will show in detail, under a variety of models meant testing the robustness of the results, both the NHTS and Census/ACS data sets reveal little difference in preferences for vehicle ownership by Millennials as compared to other generations. Rather, the differences in observed vehicle ownership rates arises from a combination of age effects and underlying differences in endowments.

4.1.1 National Household Travel Survey Vehicle Ownership Results

Under a variety of models, the NHTS data reveals little difference in vehicle ownership preferences between Millennials and other generations when age effects and endowments are controlled. Figure 4-1 summarizes the coefficient results for each generation as compared to the baseline, Baby Boomers. Seven different models were constructed to understand the preferences of Millennials and evaluate the robustness of the findings. The lines from each point represent a 95% confidence interval. The table of results can be referenced in the Appendix in Table A.1.

The first model, indicated in the light blue color, includes data from households of all ages 18 and older. The regression does not include any demographic controls (Equation 3.2). The resulting coefficients for each generation are similar to the plots of the descriptive statistics. The primary difference between the results from this model and the descriptive statistics from the prior section is that these regressions include the survey weights, and thus are more representative of the national population. The coefficient for Millennials is strongly negative, indicating that that average Millennial owns approximately .4 fewer vehicles than the average Baby Boomer. The coefficients

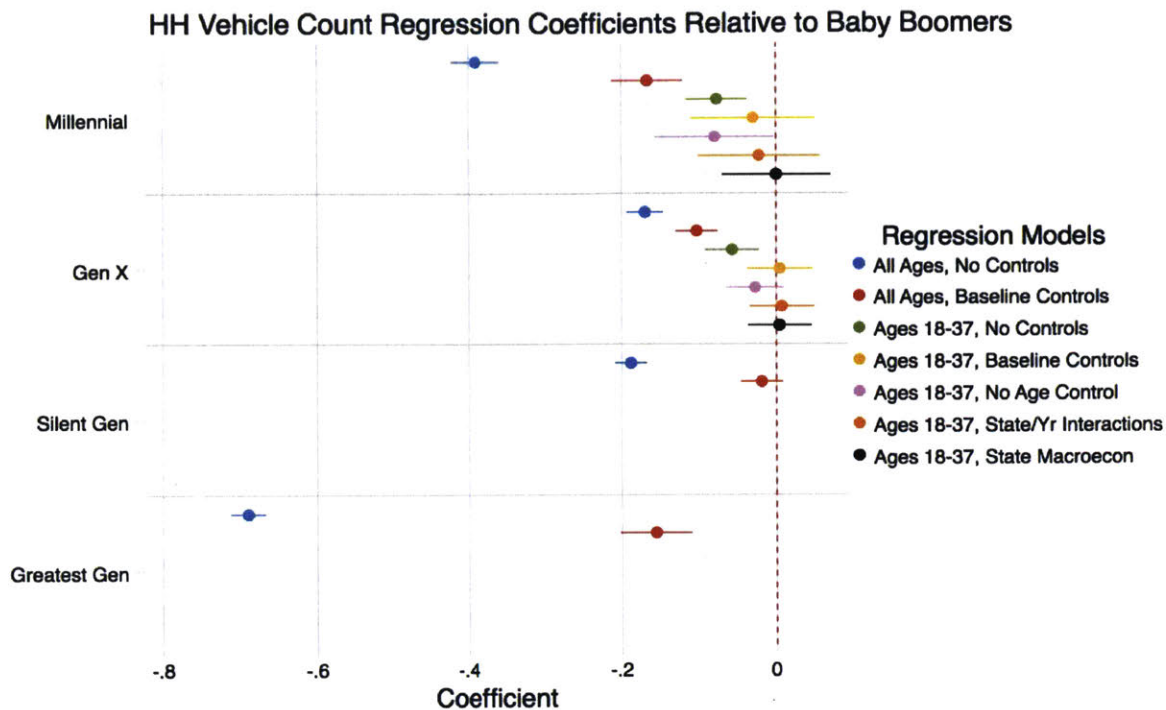


Figure 4-1: NHTS vehicle count regression coefficients by generation

for each generation show the same trend as seen in the descriptive plots, where vehicle ownership increases with age to a certain point then begins to drop as one ages past a certain point. This model represents the most easily observed trends in vehicle ownership among Millennials, as vehicle ownership is quantified based solely on what generation a household belongs to. However, this model does not address the root question of this work: what is contributing to these differences?

The second model differs from the first only in that the baseline controls for demographics and economic factors are included (Equation 3.3). The inclusion of these control variables dramatically reduces the magnitude of the coefficients for each generation. This indicates that the underlying endowments of the generations are not consistent across the generations, as is to be expected from the discussion of the data in the previous chapter. These endowments are affecting vehicle ownership. The coefficient for Millennials is still significant and without further analysis the interpretation of the coefficient is that the average Millennial owns approximately .2 fewer vehicles than the average Baby Boomer. However, this model is still incomplete

as there are weaknesses in how it controls for age.

Though age variable controls are included in the regressions, these variables cannot truly capture the age effects inherent to trends in vehicle ownership because there is no way to compare a 50 year-old Baby Boomer to a 50 year-old Millennial because a 50 year-old Millennial does not exist as of 2017. To address this limitation in the age control variables, the remaining regression models only include heads of household aged 18-37. With this added level of control, the models can more appropriately compare Millennials to other generations when the members of those generations were the same ages for which data on Millennials is available.

The third plot, indicated in green, shows the regression coefficients for the model where only ages 18-37 are included, and does not include any of the demographic control variables. Essentially, this model is comparing the mean vehicle ownership rates for each generation when they were aged 18-37 using Equation 3.2. The results of this model show an even smaller magnitude coefficient for Millennials, emphasizing the importance of age effects in vehicle ownership. This model does not ultimately answer the question of whether the endowments of the generation are driving the observed differences, or if there are still underlying differences in preferences. To address this, the yellow plot depicts the results for households aged 18-37 and includes the full set of demographic variables.

This model constitutes the baseline used in this work to make conclusions. The model uses the same regression equation noted in Equation 3.3, and examines the subset of the data for households aged 18-37. The resulting coefficients for both Millennials and Generation X approach 0, and neither are statistically significant from 0. These results support the conclusion that Millennials do not have different preferences from previous generations when both age effects and endowments are accounted for in vehicle ownership rates.

To further explore the robustness of the findings, three additional models were constructed to understand if the conclusion from the baseline model is appropriate. The fourth plot in pink shows the results from a model in which the age control

variables are no longer included in the regression equation. The resulting equation is

$$\begin{aligned}
y_{Vehicles} = & \beta_0 + \beta_{1i}x_{Gen} + \beta_2\ln(x_{Income}) + \beta_3\ln(x_{Income})^2 + \beta_{4i}x_{HighIncome} \\
& + \beta_5\ln(x_{HHSize}) + \beta_6\ln(x_{HHSize})^2 + \beta_{7i}x_{UrbIndicator} + \beta_{8i}x_{State} \\
& + \beta_{9i}x_{Educ} + \beta_{10i}x_{Year} + \beta_{11i}x_{Sex} + \beta_{12i}x_{Race} + \beta_{13i}x_{FamLifeCycle}
\end{aligned} \tag{4.1}$$

The goal of this model is to understand if a control variable for age is necessary in addition to the subsetting of the data set to include only ages 18-37. The result from this regression model shows a larger in magnitude coefficient, indicating a difference in preferences for vehicles by Millennials. Upon consideration of this model as well as the baseline, the baseline model is a more accurate way of representing the data. The age variables are clearly affecting the model outcomes. The determination on which model is more appropriate depends on whether the underlying age distribution between generations is a relevant variable to consider in the endowments. I argue that such a control variable is necessary, for two primary reasons. First, there is a clear age effect in the data, and as a result the distribution of ages for each generation is not identical and should be controlled for. Additionally, the sub-setting of data to only include households aged 18-37 does not result in the same ages available for all generations. For example, the range of ages for Baby Boomers, which have been defined as those born 1946-1965, does not range from 18-37, but rather only from ages 26-37 since the oldest data set used is 1990. Therefore, it is important to use the age control variable since the distribution of Baby Boomers will be different than for that from Generation X and Millennials.

The following two models investigate whether the macroeconomic factors affecting vehicle ownership are adequately captured in the baseline model. The baseline model using Equation 3.3 includes a variable for the survey year, which is meant to capture macroeconomic effects such as recessions or economic booms. However, this variable captures fixed effects at the national level. Because this assumption may not be appropriate, two additional models were run to examine macroeconomic effects at a more granular level. The sixth model (in orange) includes a term in the regression

model for state/year interactions. This term gives the model the flexibility to capture different macroeconomic conditions in different states. The interaction term represents the conditions in each state for each year. The following equation describes the model

$$\begin{aligned}
y_{Vehicles} = & \beta_0 + \beta_{1i}x_{Gen} + \beta_2\ln(x_{Income}) + \beta_3\ln(x_{Income})^2 + \beta_{4i}x_{HighIncome} \\
& + \beta_5\ln(x_{HHSize}) + \beta_6\ln(x_{HHSize})^2 + \beta_{7i}x_{UrbIndicator} + \beta_{8i}x_{State} \\
& + \beta_{9i}x_{Educ} + \beta_{10i}x_{Year} + \beta_{11}\ln(x_{Age}) + \beta_{12}\ln(x_{Age})^2 + \beta_{13i}x_{Sex} \\
& + \beta_{14i}x_{Race} + \beta_{15i}x_{FamLifeCycle} + \beta_{16i}x_{State*Year}
\end{aligned} \tag{4.2}$$

The resulting coefficients do not differ considerably from the results from in the baseline model. This supports the baseline model's more simple approach of using only the year variable rather than an additional interaction term which does not change the coefficients of the generation in a significant way.

The last model, noted in the black plot, explores the macroeconomic effects more quantitatively. In this model, actual state macroeconomic data on gross state product and state unemployment rates are included in the regression, rather than the year term. The resulting regression equation is

$$\begin{aligned}
y_{Vehicles} = & \beta_0 + \beta_{1i}x_{Gen} + \beta_2\ln(x_{Income}) + \beta_3\ln(x_{Income})^2 + \beta_{4i}x_{HighIncome} \\
& + \beta_5\ln(x_{HHSize}) + \beta_6\ln(x_{HHSize})^2 + \beta_{7i}x_{UrbIndicator} + \beta_{8i}x_{State} \\
& + \beta_{9i}x_{Educ} + \beta_{10}\ln(x_{Age}) + \beta_{11}\ln(x_{Age})^2 + \beta_{12i}x_{Sex} + \beta_{13i}x_{Race} \\
& + \beta_{14i}x_{FamLifeCycle} + \beta_{15}\ln_{GSP} + \beta_{16}\ln x_{GSP}^2 + \beta_{17}\ln_{StUnemp} \\
& + \beta_{18}\ln x_{StUnemp}^2
\end{aligned} \tag{4.3}$$

After including these quantitative values to capture state level macroeconomic conditions, the results from the model in the final plot in black again show very little difference in the coefficients as compared to the baseline model in yellow. Therefore, the simpler use of the year variable is sufficient for capturing macroeconomic effects, as the coefficients hardly change when a more detailed model is constructed.

In sum, these seven models together provide a clear picture of what is contribut-

ing to the difference in vehicle ownership rates between Millennials and other generations. There are both significant age effects and differences in underlying endowments. When these two factors are accounted for, nearly all the differences between Millennials' and Baby Boomers' vehicle ownership rates are eliminated. Therefore, these results together provide significant evidence that Millennials' preferences for vehicle ownership are not so different from prior generations. To provide a further check on this conclusion, this data can also be compared to the results from the Census/ ACS data set, discussed in the following section.

4.1.2 Census and American Community Survey Vehicle Ownership Results

The models constructed for the Census/ACS data set are based on the same assumptions and areas of interest as the NHTS data set. The primary differences in the models arise from the different survey years available, as well as differences in terms of how the demographic information is presented. The difference in study years alters the maximum age of Millennials, limiting it to 35 rather than 37 given that the most recent study year included in the analysis is 2015. The other primary difference is that the Census/ACS data set includes explicit variables on whether the respondent is married and has children. Therefore, rather than using the family life cycle variable as included in the NHTS regressions, the models include explicit binary variables for whether the head of household has been married, and whether the household has children. The baseline equation that is used to capture demographics is Equation 3.3, with the relevant note that the variables marked with the dagger are only used in the NHTS model. The summary results are available in Table A.2.

The models in Figure 4-2 mirror those from the NHTS results, and thus serve as an effective comparison to the NHTS results to provide a further check on the robustness of the results. Looking at these findings, very similar results are shown in the trends as compared to the NHTS. Large negative coefficients are found in the models where all ages are included, as well as when the demographic variables are

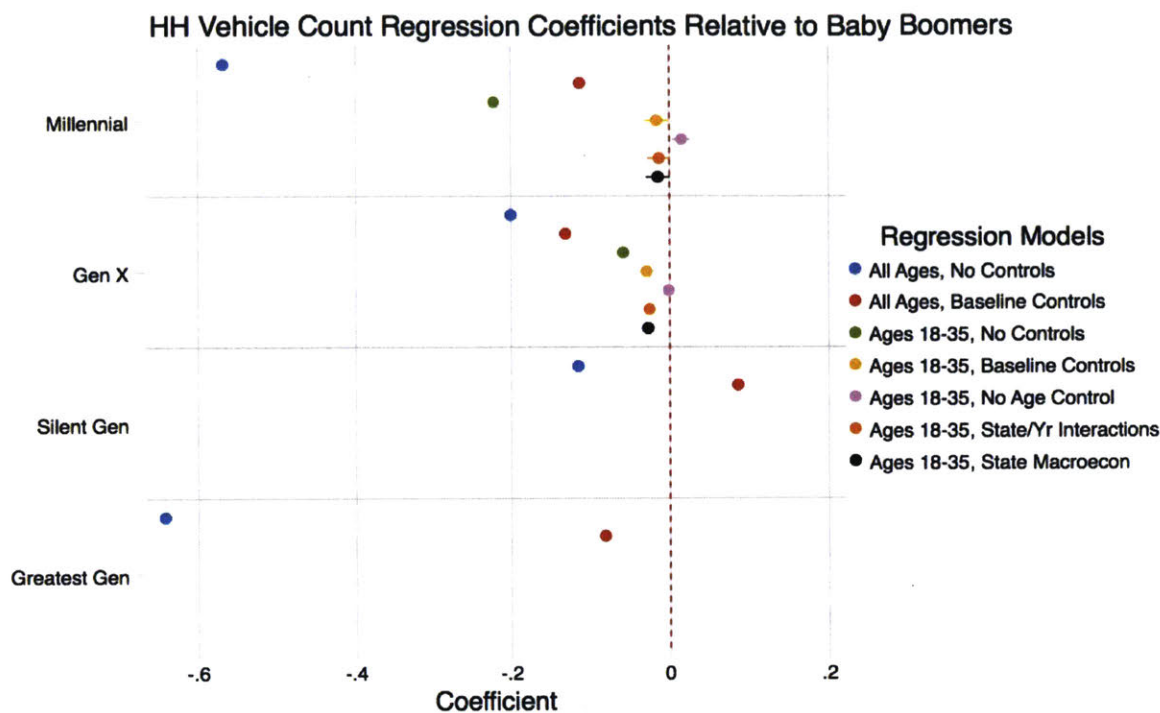


Figure 4-2: Census/ACS vehicle count regression coefficients by generation

not controlled.

The baseline model, the fourth plot indicated in yellow again, shows a similar result to the NHTS results with a small negative coefficient, approaching 0. However, unlike in the NHTS data set where the 95% confidence interval is fairly wide and includes 0, the results for Millennials in ACS is statistically significant from 0. The magnitude of the coefficient is very small. These results provide a confirmation on the conclusions from NHTS that the difference in preferences between Millennials and prior generations is not actually large, but rather plays a negligible part in the observed differences in vehicle ownership rates for Millennials compared to other generations.

In sum, the results from the ACS and Census data set align well with those found in the NHTS results. Both data sets support the conclusion that the observed differences in Millennials' sales are primarily from their different endowments, as well as age effects. The environmental and economic implications of these findings is in the following chapter, as are policy recommendations based on these findings.

4.1.3 National Household Travel Survey VMT Results

The same methodology was applied to the NHTS data set for vehicle miles traveled. Vehicle miles traveled here is measured at the person level rather than household, as each adult respondent was asked to report the number of miles they had driven in the past year. This measure does not include all miles driven in a vehicle, but rather specifically quantifies the miles the respondent reported driving himself or herself.

The results from the regressions are depicted in Figure 4-3, and the table of data is in the Appendix in Table A.3. The same seven regression models as constructed for the vehicle ownership regressions were done, with the only difference being the dependent variable. Examining the results, Millennials again appear to be very different from Baby Boomers when neither age effects nor demographics are included. These results correspond to the model in blue labeled “All Ages, No Controls.” These results show nearly 2,000 fewer miles driven by Millennials as compared to Baby Boomers. When the control variables are included in the “All Ages, Baseline Controls” model,

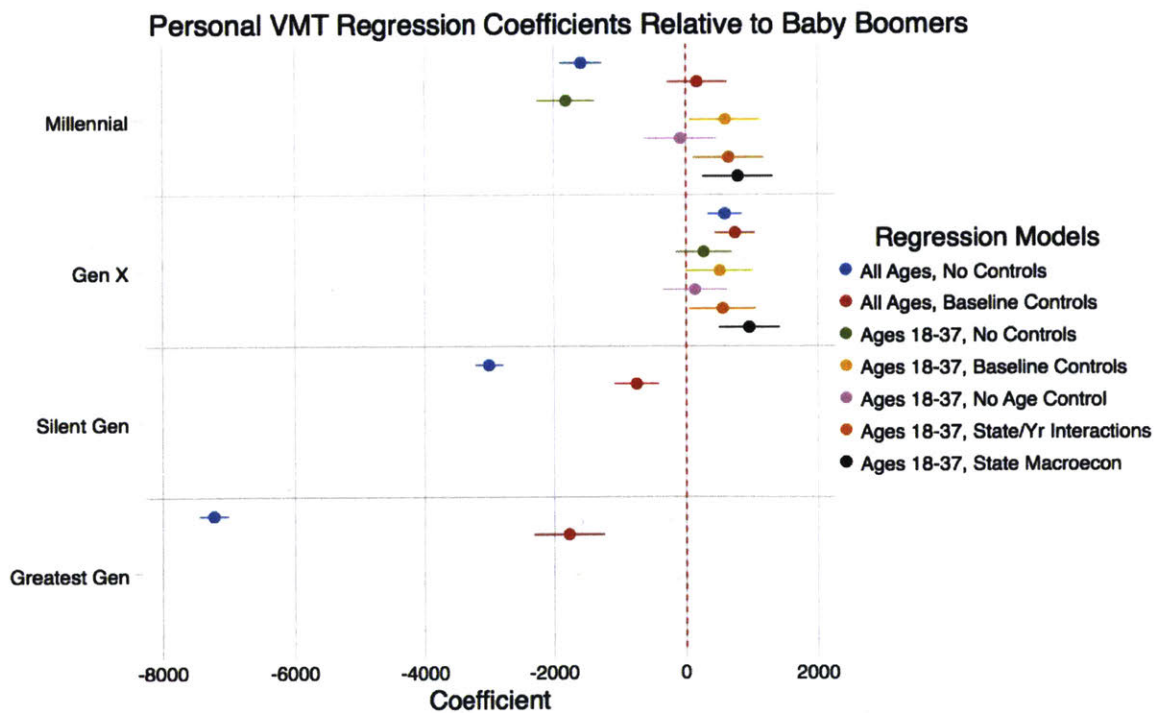


Figure 4-3: NHTS VMT regression coefficients by generation

the negative coefficient between Millennials and prior generations disappears, and the result is no statistically significant difference between Millennials and Baby Boomers.

Interestingly, in the model that subsets the data to only include households aged 18-37 without any variable controls, the difference between Millennials and Baby Boomers is actually more pronounced. This large difference dissipates again when the control variables are included. This result is interesting as it appears the age effects between Millennials and Baby Boomers are not a considerable contribution to observed differences between the two generations. Rather, the bulk of the difference arises from the differences in endowments. When these endowments are accounted for via the control variables, the coefficient flips to being positive, indicating that in reality Millennials are driving slightly more than Baby Boomers were when both age effects and endowments are considered. This result is significant from 0 with 95% confidence.

The additional models evaluating the exclusion of the age variable and the additional methods for including macroeconomic variables mirror the results found in the vehicle analysis. The exclusion of the age variable shifts the coefficient to the left, while both the models which alter the methods for capturing macroeconomic variables do little to change the coefficient found in the baseline model in yellow (Ages 18-37, Baseline Controls). These results support the robustness of the findings from the baseline model.

This work, in conjunction with the results from vehicle ownership rates, allow preliminary conclusions to be drawn on which further comments of economic and environmental implications can be made. The results show Millennials own on average just as many vehicles as Baby Boomers when ages and endowments are controlled, and they drive more miles. The significance of these findings will be more fully explored in the following chapter.

4.2 Demographic Analysis Linear Regression Results

4.2.1 Comparison of Generation Endowments

Given the significantly larger number of respondents in the ACS/Census compared to the NHTS, as well as the finer detail information on demographic variables such as marital status and children in the household, the ACS/Census data set was used for the deeper dive into the demographic data. Here, rather than simply looking at the raw data, a more rigorous analytic approach is used similar to that employed for understanding vehicle ownership and usage. Linear regression techniques are employed to gain information on how demographic variables are influencing each other and how demographics differ between generations.

Four key demographic variables are investigated in this section: whether the household is in an urban or rural area, whether the head of household has been married, household size, and inflation adjusted income. Given the importance of age on demographic variables as made evident by the data from the descriptive statistics in the Methodology Chapter, this work includes only households aged 18-35, the ages corresponding to Millennial ages in the ACS/Census data set. An example regression equation, showing the regression of urban status of the household, is noted below in Equation 4.4. Note that urbanity is not included as a control variable since it is the dependent variable of interest.

$$\begin{aligned} y_{UrbIndicator} = & \beta_0 + \beta_{1i}x_{Gen} + \beta_2\ln(x_{Income}) + \beta_3\ln(x_{Income})^2 + \beta_4\ln(x_{HHSize}) \\ & + \beta_5\ln(x_{HHSize})^2 + \beta_{6i}x_{State} + \beta_{7i}x_{Educ} + \beta_{8i}x_{Year} \\ & + \beta_9\ln(x_{Age}) + \beta_{10}\ln(x_{Age})^2 + \beta_{11i}x_{Sex} + \beta_{12i}x_{Race} \\ & + \beta_{13}x_{Married} + \beta_{14}x_{HasChild} \end{aligned} \tag{4.4}$$

For each of the four demographic variables of interest, regressions were run with generations and the other demographic variables as independent variables. Variables that may capture the same phenomenon, such as household size and whether the

household has a child, were excluded when household size was the dependent variable. The results include coefficients for both when the control variables are not included and when they are. The table of results is in Table A.4 in the Appendix.

The urban status does not indicate a large difference in Millennial behavior compared to other generations. The results show that about 1% fewer Millennials live in cities than other generations had at Millennial ages. When controls are included, this coefficient flips to a positive value, indicating that given Millennials' other endowments a greater proportion of them live in cities than prior generations had. However, the urban concentration does not seem to be a significant factor in Millennial endowments. This finding comes with a caveat, though, as the sensitivity of the urban variable in the ACS/Census data set is fairly low. The variable differentiates between "urban" and "not urban." There is no distinction in the data set between true urban settings with high population density and potential public transport networks, and lower density suburban areas. Therefore, while it is interesting to look at this variable, outside analyses that investigate urbanity with finer detail may be able to provide greater insight on how geographic concentrations differ between generations.

The results from the regressions on marriage show a stark difference between Millennials and prior generations. The "Previously Married" variable is a binary variable, so the coefficient observed indicates what portion of the population is married in comparison to the baseline generation. Without any other variable controls, the coefficient on Millennials is nearly -0.3 and statistically significant, indicating that a Millennial household is 30% less likely to be married than a household in the Baby Boomer generation. The magnitude of this difference is much less when other demographic variables are included as controls, but the coefficient is still negative and statistically significant. This finding is important for two reasons. First, this result further highlights the finding that the underlying endowments for Millennials are very different from Baby Boomers. Additionally, the finding that the coefficient is negative and significant even with the other demographic controls supports the hypothesis that Millennials may have different preferences for marriage. Part of the difference can likely be explained by the other demographics, but even with those differences ac-

counted for a negative coefficient persists. Therefore, as Millennials age, low marriage rates may persist, and they may never reach the levels of prior generations.

Household size is likely to be related to marriage rates, both because Millennials may not yet be living with a partner and they may not have started families yet. Therefore, it is not surprising that the coefficient on Millennials for household size when other variable controls are not included is significantly negative. The coefficient of -0.561 indicates that the average Millennial household consists of -0.561 fewer people than the average Baby Boomer household had when Baby Boomers were aged 18-35. Much of this difference disappears when other variables are included, and the coefficient is no longer statistically significant. This finding highlights that Millennials may have smaller families, but given their marriage rates and other variables of interest, these differences are not surprising.

The last variable of interest, household income normalized to 2015 USD, is useful both because it describes underlying endowments but also indicates more broadly what macroeconomic trends may be influencing generations. The results for household income without controls show Millennials are making significantly less money than prior generations had, with a statistically significant coefficient of -\$11,934. This value alone may not be as useful, as the prior results show many more households are headed by individuals rather than couples. However, when these additional factors are controlled for, the difference is still nearly -\$1000. Therefore, Millennials have lower incomes compared to prior generations, which may affect how they choose to make investments in large expenses like vehicles.

This work exemplifies how the underlying differences between generations is significant for many variables. From these results, there is some evidence suggesting Millennials have different preferences for family composition. They appear to have differences in preferences for marriage, and such choices may continue to cause observed changes in other demographic variables and in the primary variables of interest in this work, vehicle ownership and usage. While it is impossible to say whether Millennials will eventually reach the same marriage rates as prior generations, this is an important statistic to continue to track in the future as it may have far-reaching

consequences.

While it is important to understand the difference in underlying demographics, for this work it is especially relevant to know how the different generations' vehicle ownership and usage change based on their evolving endowments. The following subsection discusses how generations react to these four variables in particular, and what such differences in responses may mean for understanding future demand for vehicles by Millennials.

4.2.2 Generational Response to Demographic Variables

The previous section makes clear that the underlying demographics of Millennials are different from Baby Boomers in many respects. These demographics are influencing vehicle ownership as shown in the earlier regression analysis of vehicle ownership with demographic control variables. However, that analysis does not show how demographic variables may affect generations differently. The work to this point does not allow one to make claims about how Millennials' vehicle ownership changes when their income changes. This section examines the same four demographic variables as before: whether the household is in an urban area, whether the head of household is or has been married, household size, and income. The ACS/Census data set is utilized once again, and only respondents aged 18-35 are included in the analysis.

Figure 4-4 plots the interaction coefficients for each generation and the demo-

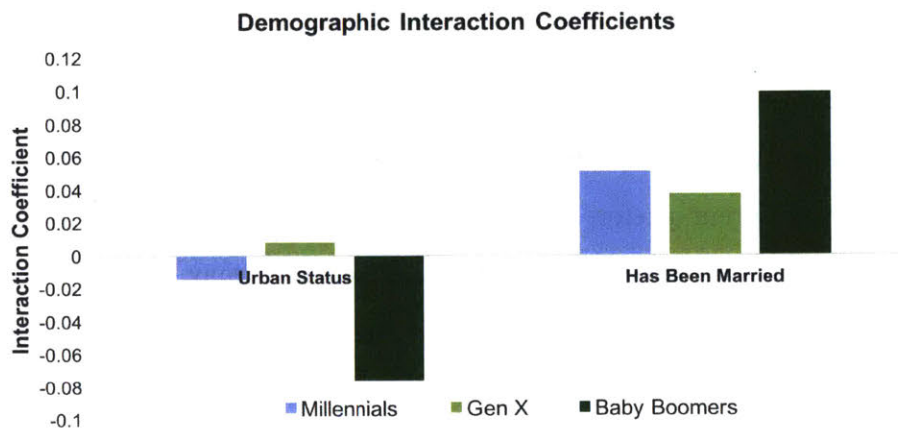


Figure 4-4: Generation interaction coefficients for urban and marital statuses

graphic variable of interest. The full equation for urban status interaction is

$$\begin{aligned}
y_{Vehicles} = & \beta_0 + \beta_{1i}x_{Gen} + \beta_2\ln(x_{Income}) + \beta_3\ln(x_{Income})^2 + \beta_4\ln(x_{HHSize}) \\
& + \beta_5\ln(x_{HHSize})^2 + \beta_6i x_{UrbIndicator} + \beta_7i x_{State} + \beta_8i x_{Educ} \\
& + \beta_9i x_{Year} + \beta_{10}\ln(x_{Age}) + \beta_{11}\ln(x_{Age})^2 + \beta_{12i}x_{Sex} + \beta_{13i}x_{Race} \quad (4.5) \\
& + \beta_{14i}x_{Married} + \beta_{15i}x_{HasChild} + \beta_{16}x_{Mil*UrbanIndicator} \\
& + \beta_{17}x_{GenX*UrbanIndicator}
\end{aligned}$$

These interaction coefficients provide information to differentiate how different generations react to changing demographic endowments. In the above equation, the coefficient β_6 is the effect of living in an urban area for the omitted group, here Baby Boomers. This coefficient is found to be -0.076 and is plotted in Figure 4-4 for Baby Boomers. The coefficient β_{16} captures the specific effect of living in an urban area for Millennials. The total effect of living in an urban area for Millennials is then $\beta_6 + \beta_{16}$, which results in a total effect of -0.015. The total effect for Generation X is $\beta_6 + \beta_{17}$, which results in a total effect of .008. β_6, β_{16} , and β_{17} are all significant with 99.9% confidence.

These coefficients are instructive because they distinguish how different generations' vehicle ownership changes depending whether they live in urban or rural areas. For Baby Boomers, the effect of living in an urban area is strongly negative. However, for Millennials the magnitude is a fraction of that. Therefore, even if Millennials are living in urban areas in greater percentages and for a longer portion of their lives, the effect on vehicle ownership is not as significant as it would be for Baby Boomers.

The coefficient for marriage was estimated in the same manner. The regression model was identical to Equation 4.5 except the interaction terms β_{16} and β_{17} are for generation variables interacted with the marriage variable rather than the urban variable. The coefficient β_{14} variable represents the effect of marriage for the baseline group, Baby Boomers. This coefficient equals 0.099. The sum β_{14} and the interaction terms for Millennials and Generation X, respectively, are 0.051 and 0.037. These results support the conclusion that being married has a larger effect on Baby Boomers'

vehicle ownership than it does on Millennials' vehicle ownership. On average, being married increases Baby Boomers' vehicle count by nearly twice as much as it does for Millennials. While Millennials are marrying later or perhaps less than Baby Boomers, such demographic change will not affect vehicle ownership as much as it would have for prior generations.

To understand the effects of both household size and income, a more complex approach is necessary given the natural log transformations of the variables in the regression models. One way to depict how each of these variables influence vehicle ownership is to plot the derivative of vehicle ownership with respect to the variable of interest. The model including the interaction term is

$$\begin{aligned}
y_{Vehicles} = & \beta_0 + \beta_{1i}x_{Gen} + \beta_2\ln(x_{Income}) + \beta_3\ln(x_{Income})^2 + \beta_4\ln(x_{HHSize}) \\
& + \beta_5\ln(x_{HHSize})^2 + \beta_{6i}x_{UrbIndicator} + \beta_{7i}x_{State} + \beta_{8i}x_{Educ} \\
& + \beta_{9i}x_{Year} + \beta_{10}\ln(x_{Age}) + \beta_{11}\ln(x_{Age})^2 + \beta_{12i}x_{Sex} + \beta_{13i}x_{Race} \quad (4.6) \\
& + \beta_{14i}x_{Married} + \beta_{15i}x_{HasChild} + \beta_{16}x_{Mil*\ln(HHSize)} \\
& + \beta_{17}x_{Mil*\ln(HHSize)^2}
\end{aligned}$$

and the resulting derivative for vehicles with respect to household size for Millennials is

$$\frac{dV}{dH} = \beta_4 + 2\beta_5\ln(x_{HHSize}) + \beta_{16} + 2\beta_{17}\ln(x_{HHSize}) \quad (4.7)$$

while the derivative for non-Millennials is

$$\frac{dV}{dH} = \beta_4 + 2\beta_5\ln(x_{HHSize}) \quad (4.8)$$

These two equations for the derivatives are plotted in Figure 4-5. The y-axis captures how the coefficient would change if household size increases by 100%. A Millennial whose current household size is 1 would have a coefficient increase of approximately 0.7 should the household size double. A 1% increase in household size

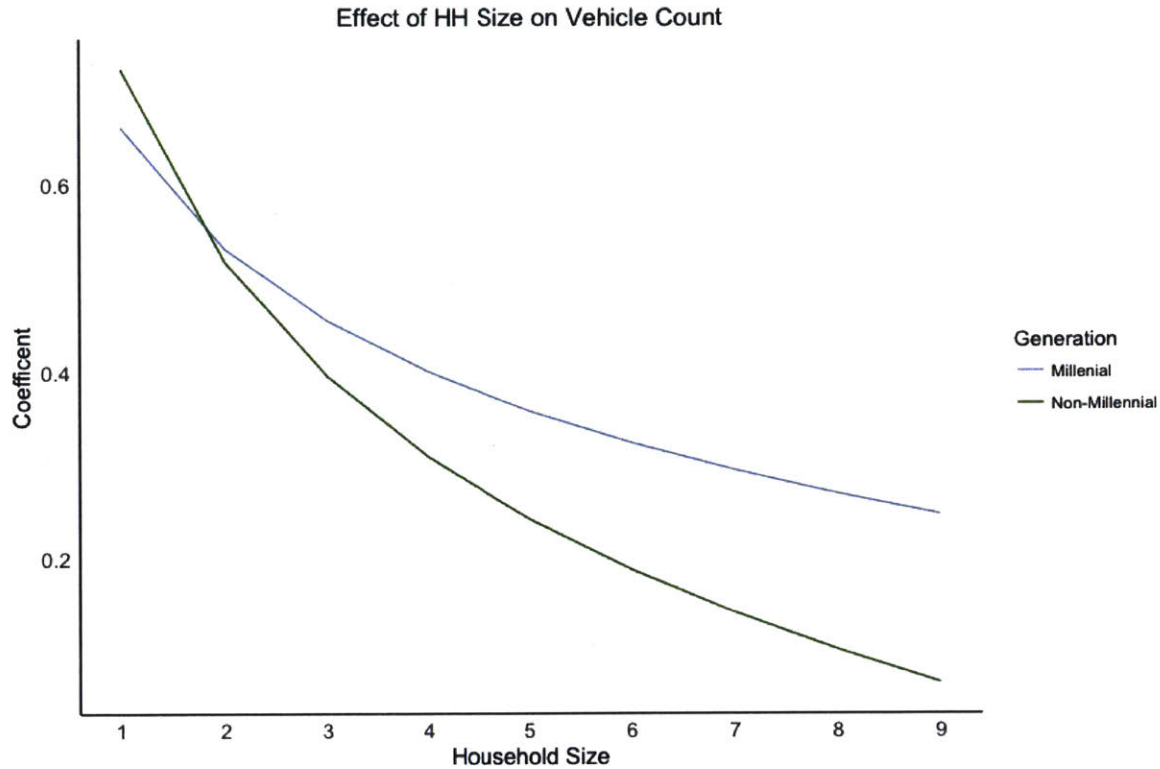


Figure 4-5: Derivative of vehicle ownership with respect to household size

would increase the coefficient by 0.07. So if a family is growing from 2 to 3, perhaps after having a child, the resulting coefficient increase would be the value for Millennials at 2, approximately 0.55, times the percent increase, .33, which results in a total coefficient increase of 0.19.

Millennials with small household sizes (1-2) do not increase their vehicle ownership as much when their household size increase, but the plots cross over at approximately 2 and Millennials increase their vehicle ownership at a higher rate than non-Millennials. Therefore, the change in Millennial behavior moving from a one person family to a two person family is less significant compared to other generations than the change from a two person family to a three person family. It is not surprising that the rate of change of the coefficient decreases as household size increases, as an ever increasingly large family does not necessitate more vehicles beyond a certain point.

The last demographic variable of interest is household income. The regression model for income is analogous to household size. The resulting derivative equations

when income is interacted with the Millennial coefficient is

$$\frac{dV}{dI} = \beta_2 + 2\beta_3 \ln(x_{Income}) + \beta_{16} + 2\beta_{17} \ln(x_{Income}) \quad (4.9)$$

and the derivative for non-Millennials is

$$\frac{dV}{dI} = \beta_2 + 2\beta_3 \ln(x_{Income}) \quad (4.10)$$

Figure 4-6 plots these derivatives. The coefficients can be interpreted in the same way as for household size. At each x-axis value of income, the corresponding y-value coefficient is the change in vehicle ownership due to a 100% increase in income. A 1% increase in income results in a change in vehicle ownership equal to the coefficient divided by 100. The shape of the curves for Millennials and non-Millennials is similar, but the Millennial curve is flatter. This indicates that Millennials' vehicle ownership is less sensitive to income than prior generations. A 100% increase in income for a Millennial making \$25,000 results in approximately .15 increase in vehicle ownership.

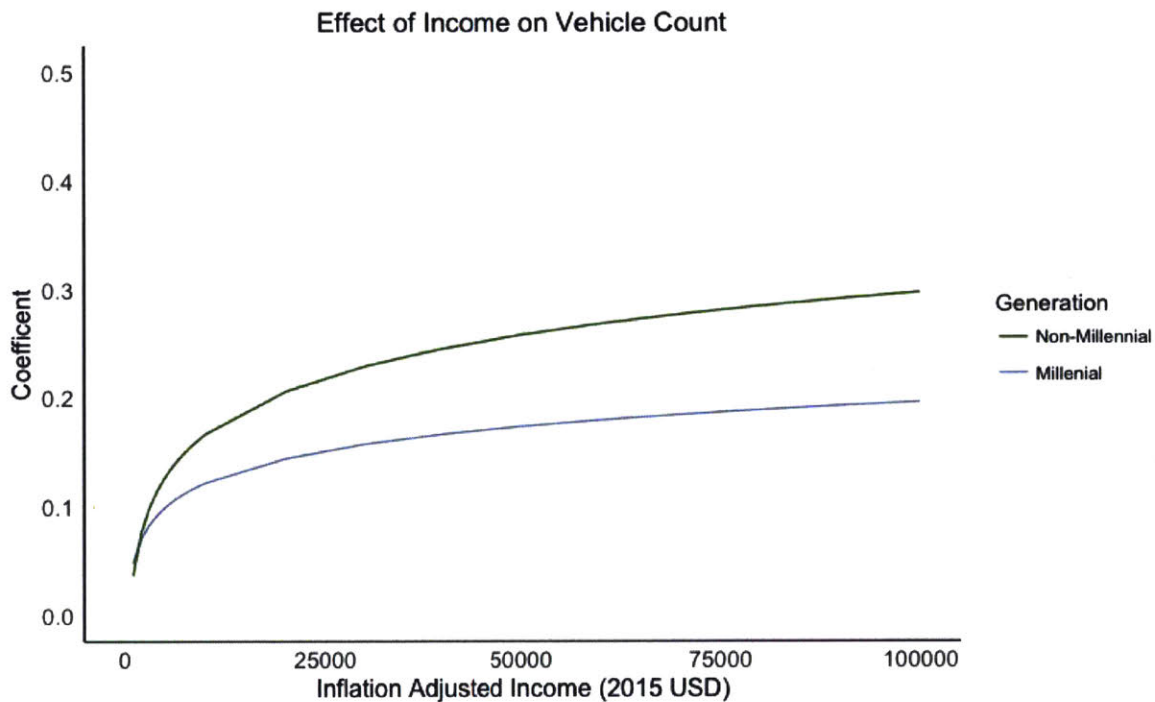


Figure 4-6: Derivative of vehicle ownership with respect to income

For non-Millennials making \$25,000, a doubling of their income increases vehicle ownership by approximately 0.22.

These results together show that the effect of demographics on different generations is not homogeneous. For urban status, marital status, and income, Millennials' vehicle ownership sensitivity to changing demographics is less than prior generations. For household size, the response is different as well, with the increase in family from two to three being more consequential for Millennials than other generations. On average, the results of the earlier regressions find that these differences cancel out. Looking forward, it is important to continue tracking these relationships.

4.3 Oaxaca Decomposition Results

First, a comparison between the Oaxaca Decomposition results for vehicle ownership is provided. The results from the Oaxaca Decomposition analysis using the equations from Chapter 3 are in Table A.5 for the NHTS data set and Table A.6 for the ACS/Census data set. For each data set, Millennials are compared to one generation at a time to understand from where the observed differences in vehicle ownership arise. The first column of results compares Generation X to Millennials. The coefficient for Generation X is found to be 1.626, compared to the Millennials' 1.595. The difference between these two groups' coefficients is 0.0313, indicating that the average Generation X member owns 0.0313 more vehicles than the average Millennial. The lower portion of the graph disaggregates the observed differences into what contribution comes from endowments and preferences as well as the interaction between the two.

Based on endowments alone, Generation X would be expected to own 0.114 more vehicles than Millennials. The preference coefficient of 0.0604 indicates that Generation X has a slight preference for vehicles compared to Millennials, though this coefficient is not significant. Therefore, there is not a statistically significant difference between the preferences of Millennials and Generation X, and most of the observed differences arise from the endowments.

The same interpretation can be applied to the decomposition of differences between Millennials and Baby Boomers, who are listed in the second column. This analysis estimates that the average Baby Boomer owns 1.687 vehicles, compared to the Millennials' 1.595 vehicles, a difference of .0920 vehicles. This difference can be decomposed into a contribution of .147 from the endowments of Baby Boomers, which have the effect of Baby Boomers owning a greater number of vehicles. The difference in preferences between the two groups is negative, indicating that Baby Boomers have a negative preference for vehicles as compared to Millennials. All else being equal, Millennials prefer to own 0.113 more vehicles than Baby Boomers.

The ACS results show similar results to the NHTS for this analysis. When comparing Millennials and Generation X, the difference between the two is 0.0659 vehicles, though these results show a slight preference of 0.0243 vehicles by Millennials as compared to Generation X. This difference is significant with 99.9% confidence. Again, when the difference between Millennials and Baby Boomers is decomposed, the difference arising from endowments favors Baby Boomers having a larger number of vehicles, and the preference term is negative. This again supports the conclusion that Millennials actually have a preference for vehicles greater than Baby Boomers had when Baby Boomers were the age that Millennials are now. The observed decrease in ownership is due primarily to different underlying endowments, which the previous section showed are significant. These results provide further evidence for the conclusion that Millennials preferences are not the primary motivation for differences in vehicle ownership.

Table A.7 contains the results from the Oaxaca decomposition on VMT. Millennial VMT is approximated to be 12,417.8 mile compared to Generation X's 14,279.3 miles and Baby Boomer's 15,313.4 miles. For both generations compared to Millennials, the endowments contribute to a large portion of the observed differences between the two groups, and these differences are significant at the 0.001 level. However, in contrast to the earlier linear regressions, the preferences in this analysis support the conclusion that Millennials have a negative preference for VMT compared to prior generations. For Generation X, the results show Generation X has a preference to

drive approximately 900.6 more miles a year than Millennials. Baby Boomers have a preference to drive 3,200.5 miles more than Millennials. These findings are initially surprising given that the linear regressions found Millennials had a preference for a larger number of VMT compared to Baby Boomers. However, when the interaction term plays a large role in the total difference according to the decomposition. The large negative interaction terms indicate that Millennials' preferences for VMT is heavily influenced by endowments.

4.4 Nearest Neighbor Matching Estimator Results

The results of the matching models for both vehicle ownership and VMT support the conclusions from the linear regression and Oaxaca decomposition results. Summarized in Table A.8, the results from the matching estimator on the complete NHTS data set find even stronger evidence that Millennials own more vehicles and drive more miles than members of prior generations when demographics are accounted for. When comparable Millennials and Baby Boomers are examined in the matching estimator, a Millennial owns 0.11 more vehicles than a Baby Boomer, and drives 2,234 more miles per year.

These results find even larger coefficients for Millennials' preferences for vehicles and VMT than the linear regressions, as this approach compares pairs of Baby Boomers and Millennials with as many similarities as possible. Additionally, this estimator finds a larger coefficient than the linear regression results because the differences in age distributions between the two generations is not affecting the coefficient. The linear regression results capture a conservative estimate of differences between Millennials and Baby Boomers since young Baby Boomers are not included, but even those results find no significant difference between Millennials and Baby Boomers. The matching estimator further confirms the hypothesis that the linear regression results are a conservative estimate, and that the true differences in preferences are likely even larger than the linear regression results find. These results further confirm that Millennials' observed decrease in vehicle ownership and VMT arises from differences

in demographics, and when Millennials and Baby Boomers with similar demographics are compared to each, Millennials have higher ownership rates and VMT.

4.5 Forecasting Future Trends

The prior sections have focused in detail on how demographics and preferences together affect the observed vehicle ownership and usage rates. This section summarizes forecasted results for vehicle ownership and usage. The iterations are shown, and the order for each iteration can be referenced in Table 3.4. This section details considerations made in attempts to obtain realistic models, and reasons the approaches may differ. Much of the decision on methodology relies on how the models and projections fit the existing data, and whether the projections seem realistic based on the reported data and trends from other generations.

The three demographic variables included in all the forecasts are urbanity, income, and household size. Marital status is included in the ACS/Census forecasts. The results from the four iterations relevant for NHTS are plotted below in Figure 4-7. The ages that are available for the projections show an increasing trend in vehicle ownership, as is expected since the oldest Millennial in the NHTS data set is 37.

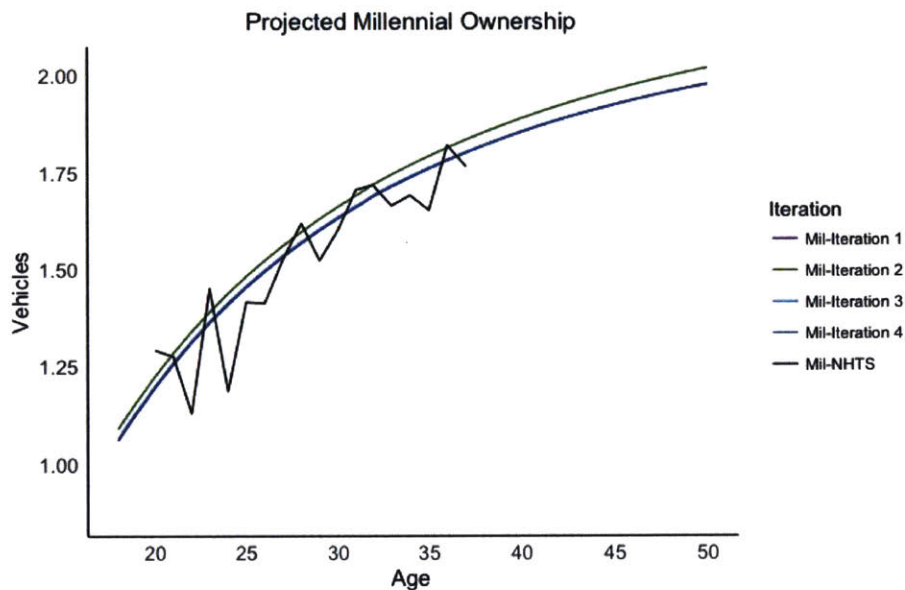


Figure 4-7: Vehicle ownership forecasts for Millennials using NHTS

Therefore, it is difficult for the approach used in these projections to capture the downward trends when there is no data from the older ages. Therefore, the projections are limited to age 50, as after that point it is likely vehicle ownership will begin declining.

The four iterations show little difference in the resulting projections, and each of the four seem to capture the trends observed in the reported survey data. The range in predicted vehicle ownership at age 50 is small, from 1.98 to 2.02. In comparison to the actual data from prior generations at age 50, plotted earlier in Chapter 3 in Figure 3-2, Millennial vehicle ownership will be lower than prior generations. At age 50, the average Generation X household had 2.27 and Baby Boomers had 2.17. Millennials may have 11-13% fewer vehicles at age 50 than Generation X, and they may own 7-9% fewer vehicles than Baby Boomers. Again, these forecasts are simplified and can not account for many potential changes in behavior. However, there is indication that Millennials may own fewer cars than older generations due to the differences highlighted in earlier sections. These reflect changes in life choices and demographics, not a distinct change in preference for vehicles.

Similar forecasting approaches were applied to the ACS/Census data set as plotted

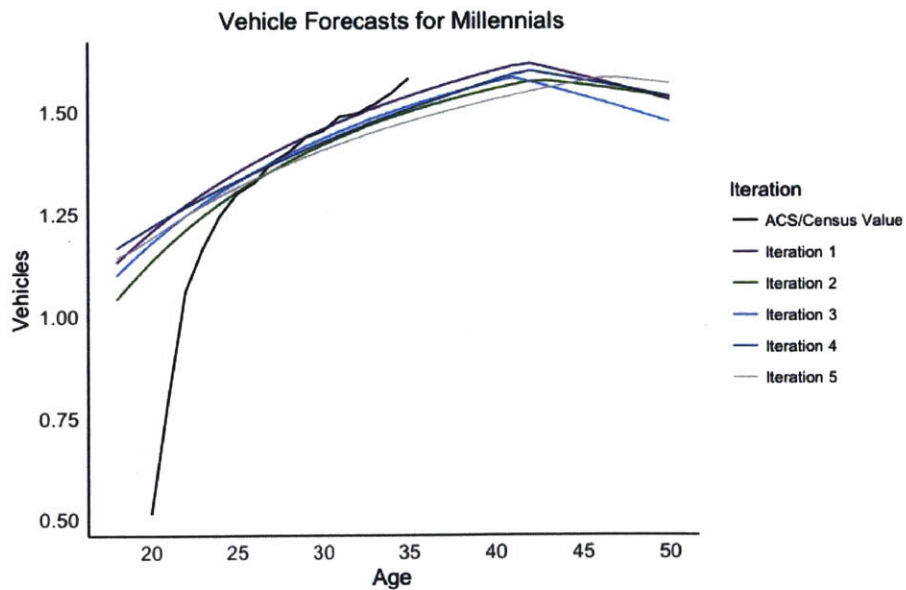


Figure 4-8: Vehicle ownership forecasts for Millennials using ACS/Census

in Figure 4-8. These forecasts predict peak vehicle ownership in early 40s, with peak ownership under 1.6 vehicles per household on average. However, given the trends in both Baby Boomers and Generation X where peak vehicle ownership is in late 40s and early 50s, there is reason to think that these forecasts are not capturing the true peak values of vehicle ownership. Data from Generation X and Baby Boomers at later ages can inform more realistic forecasts of Millennial behaviors.

Forecasts for Millennials based on both generations' behaviors was done to try to give a range of potential outcomes depending on whether Millennial ownership looks more similar to Generation X or Baby Boomers. Because the work from the regression analysis supports the conclusion that Millennials differ from Baby Boomers and Generation X primarily from endowments, the theory behind these forecasts is to apply the coefficients found for Baby Boomers and Generation X in each iteration to the endowments found in the forecasts for Millennials.

In addition to applying the coefficients from Baby Boomers and Generation X directly to the endowments of the Millennials, a third approach to forecasting was also implemented in which only the age coefficients from Baby Boomers and Generation X are applied to Millennials. This approach uses the Millennials' coefficients and endowments for all the demographic variables except for age. The coefficients found for Baby Boomers' and Generation Xs' age were applied to Millennials and used in the final calculation of Millennial vehicle ownership.

Fifteen different forecasts were modeled using Millennial endowments from each of the iterations and Baby Boomer or Generation X coefficients from the corresponding iteration. Figure 4-9 displays the results up to age 50 for these fifteen different combinations. Only data to age 50 are included since the Generation X forecast does not capture the future ages of Generation X well. However, it does capture some of the trends in the data up to age 50, which can be useful in looking at the future for Millennials. Despite the wide differences in vehicle ownership at young ages and the shapes of the curves, the forecasts for peak vehicle ownership at age 50 show less variation between the different models. At age 50, the models converge into a range of vehicle ownership rates. The maximum value for vehicle ownership at age 50 is 2.08,

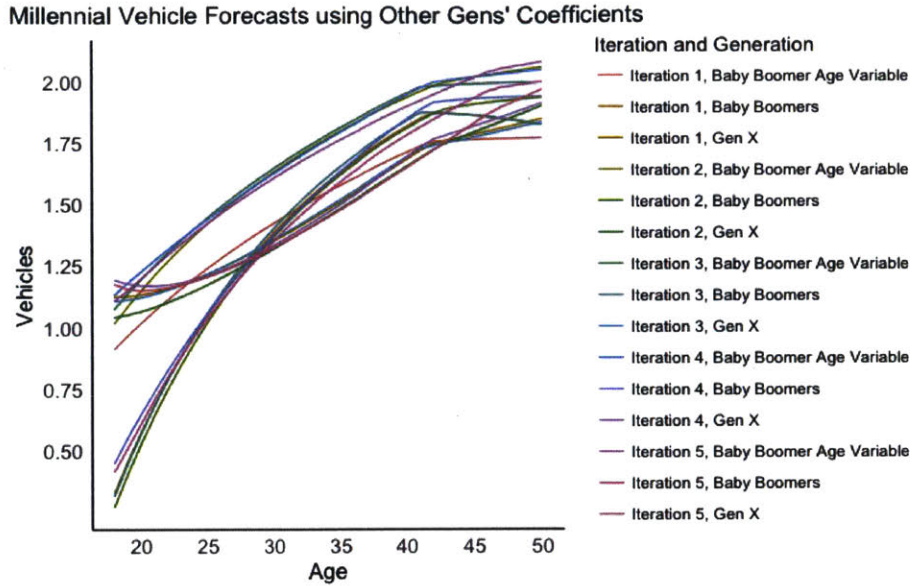


Figure 4-9: Vehicle ownership forecasts for Millennials with Gen X, Boomer coefficients using ACS/Census

while the minimum value is 1.77. These forecasts provide a range of possible outcomes that we may see from Millennials based on their demographic endowments. These forecasts provide a reasonable range of possible outcomes that may be observed, but there is still uncertainty in terms of what the observed vehicle ownership rates will be for a Millennial aged 50.

Compared to the values for Generation X and Baby Boomers noted in Figure 3-10, the range of forecasted outcomes for Millennial vehicle ownership either slightly exceeds or falls short of ownership rates for prior generations at age 50. Both Generation X and Baby Boomers have vehicle ownership rates of approximately 1.95 at age 50. Given the forecast results, Millennials may own between 6.7% more vehicles to 9.2% fewer vehicles at age 50 than Baby Boomers or Generation X.

Together, these forecasts support the conclusion that due to the differing endowments, Millennial vehicle ownership rates in the future are likely to differ from those of prior generations. These forecasts are rough estimates of the expected behavior of Millennials based on their endowments, but they provide a plausible range of future vehicle ownership rates. The NHTS forecasts support the hypothesis that a 7-13% dip in vehicle ownership may occur, while ACS/Census forecasts are not conclusive

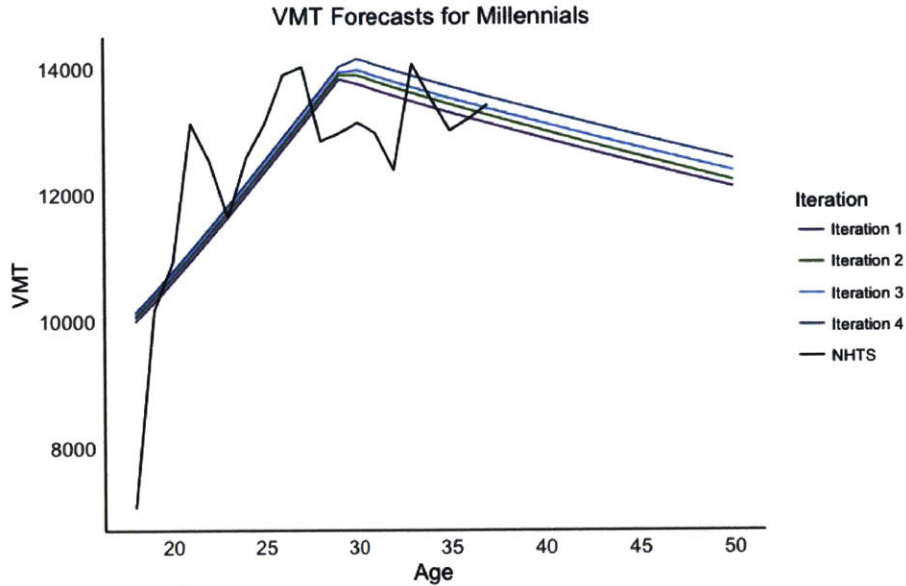


Figure 4-10: VMT ownership forecasts for Millennials using NHTS

as to whether vehicle ownership rates for Millennials will exceed or lag behind prior generations.

In addition to forecasting vehicle ownership rates, it is also of interest to better understand future VMT rates for Millennials. As noted in Figure 3-2, Millennial VMT is lagging behind prior generations. However, the findings from the regression analyses indicate this drop in VMT is motivated by endowments, not preferences. The challenge with forecasting VMT is that the relationship between age and VMT is less quadratic than was seen in vehicle ownership. To better capture the true relationship, spline regressions were used for VMT. This allows the regression to be calculated in multiple segments rather than across all ages. Figure 3-2 shows steep slope when members of the generation are in their 20s. From approximately age 30 to 50, the VMT rates plateau and decrease slightly, then drop significantly again at higher ages. This shape makes a quadratic forecast less appropriate.

Figure 4-10 shows the results of the spline regression, which used age 30 as the break point. The different iterations show fairly similar results, differing slightly in predictions for maximum VMT and how VMT will decrease as one ages. Because data for ages 38 and higher are not available, the approach for this forecast treated years 18-29 and 30-50 differently. For years 18-29, the Millennials' data and resulting

coefficients were used. For the years 30-50, rather than using Millennials' coefficient on age, Generation X's age coefficient for that range was applied. This allows for a more confident forecast for what future VMT may look like given the age trends in this cohort. The primary difference between Generation X's coefficients and those of Millennials is that Millennials data predicts a sharper decrease in VMT which may overestimate the rate at which VMT decreases from an approximate peak near age 30.

This approach has some weaknesses, but the forecasts provide a general idea of what the future of VMT may be for Millennials. One difficulty in this approach is identifying where the knot or discontinuity should be placed. Age 30 was chosen based on historical data, but it is possible that Millennials will show a later peak in VMT than earlier generations had due to demographic changes. Therefore, this forecast may underestimate VMT. However, this spline approach provides more realistic projections than the quadratic approach given the observed trends in VMT usage as one ages.

Comparing the expected Millennial VMT rates to prior generations, there currently is and continues to be a significant decrease in VMT for Millennials as compared to prior generations. If Millennials follow trends similar to prior generations, their VMT may have already peaked at approximately 14,000 miles, compared to Generation X and Baby Boomers, who peaked at approximately 17,000 and 16,000 miles respectively. It is worth following the ongoing Millennial behavior, as the earlier work showed they have a preference for VMT. There may be future increases as Millennials' demographics change and the positive preference remains.

4.6 Ride-hailing and Carsharing Linear Regression Results

The tables for ride-hailing and carsharing are listed in the Appendix in Tables A.9 and A.10, respectively. Considering first the results from ride-hailing analysis, when

all respondents are considered Millennials show significant preference for using ride-hailing services compared to previous generations. The preference is diminished when controls are included, but a positive coefficient remains. Interestingly, the other generations also have positive coefficients when the control variables are included. When only respondents who have used the service are included, the Millennial coefficient is even larger, with a value of 1.072 that is statistically significant at a 0.001 confidence level. However, when the controls are included in this analysis, the coefficient is reduced to 0.364 and is no longer statistically significant. Surprisingly, the Greatest Generation has a coefficient of 1.879 in this model, though the results are not significant. None of the generation variables' coefficients are statistically significant in this model. This finding supports the conclusion that for those who have adopted the technology, the generation to which the person belongs is not a significant influence. Rather, it appears the adoption rates between the generations are different, with a greater proportion of Millennials and Generation X utilizing the service compared to the other generations.

The carsharing results in Table A.10 mirror the findings from the descriptive statistics of the data in Chapter 3. Generally, the difference in usage rates between the generations when all respondents are included is fairly minimal, regardless of whether the model includes the control variables or not. This is likely due to the overall low usage rates of carsharing regardless of generation. More illuminating results are available when only those who have reported using carsharing are used. However, none of the results are statistically significant, likely because so few respondents from each generation have actually used the service so the uncertainty of the results is high. Generally, carsharing does not seem to be a major factor in meeting transportation needs, and that trend does not vary widely by generation.

4.7 Discussion

These results paint an interesting picture of both the makeup of Millennials, their preferences, and the future of transport in the US. Millennials' observed difference in

vehicle ownership from prior generations arises primarily from the age effects inherent to vehicle ownership and usage, as well as differing demographics, as explained in section 4.1. The results from Section 4.2 further highlight that Millennials are different in many ways from prior generations in terms of their demographic endowments, but when looking how the generations respond to those demographics the resulting difference in vehicle ownership is dampened. The Oaxaca Decomposition provides an alternate approach to understand where the observed differences in vehicle ownership are coming from, and the results provide further evidence that preferences are not a major contributing factor to difference in vehicle ownership and usage. The nearest neighbor matching estimator provides further confirmation that Millennials' have a higher preference for vehicles and VMT when comparable Millennials and Baby Boomers are examined.

Using the relationships between demographic variables and vehicle ownership from linear regressions, the forecasts provide a preliminary look at what the future for vehicle ownership may be for Millennials as they age. The results of the forecasts support the findings from the earlier work. The last component of the results provides an initial analysis of ride-hailing and carsharing. These results highlight that Millennials are adopting the technology at rates much higher than older generations. However, when only households who have adopted the technology are considered, the difference between generations is significantly reduced. The difference in generation comes more from adoption than from frequency of use. Therefore, once someone has adopted the technology, their use is less age sensitive. This finding is interesting because it provides evidence that ride-hailing and carsharing may continue to be an important transport option for Millennials as they age. The reason older generations are not using the services is they seem more reluctant to adopt the technology. However, if Millennials and younger generations have already adopted it in their youth, they may continue using it as they age, and ride-hailing and carsharing may be more influential on older drivers in the future than it is now. The final chapter will devote time to understanding the economy-wide consequences of these findings, as well as how Millennials' behaviors will affect the environment more generally.

Chapter 5

Conclusions

As of April 2018, Millennials are the largest generation in the workforce, exceeding Generation X by 3 million workers and Baby Boomers by 15 million [64]. While Millennials are often still thought of as young adults just entering adulthood, a large portion of Millennials are now over age 30. Millennials are becoming the dominant generation in society, so their behaviors and preferences will have far-reaching effects. This chapter discusses the social implications of the changing demographics in the US, the economic effects of the findings from the analysis in this work, and how Millennial transport preferences will affect the environment. Lastly, I recommend transport-oriented policies to balance the economic and environmental interests of society going forward based on the findings of Millennials' demographics and preferences.

5.1 Social, Economic, and Environmental Implications

As noted in earlier chapters, the underlying demographics of Millennials differ greatly for many important characteristics. Millennials are marrying later, potentially at lower rates, having fewer children, and making less money. These findings are well supported by other studies [65]. Such changes are likely to have broader implications. While this work finds that many of these demographic factors do not

affect vehicle ownership as strongly as they did for prior generations, the differences in demographics should still be considered when trying to understand current Millennial preferences and predict future behaviors. Additionally, the changing demographics of American generations is likely to continue, and future generations may be even more different from Baby Boomers. I do not attempt to hypothesize what the broad societal outcomes will be, but I wish to highlight that the existing assumptions about marriage rates, birth rates, and income distribution is unlikely to hold in the future, and these changes are important to continue to explore.

The results regarding Millennials' preferences and the forecast for their future vehicle ownership dispels the myth that Millennials have fundamentally different transport preferences from prior generations. The doom-and-gloom scenario that Millennials would destroy the automotive industry is likely not true. Rather, Millennials are behaving similarly to both Generation X and Baby Boomers, who both owned on average nearly 2 vehicles per household at age 50. Therefore, in the next 15-20 years it is unlikely that the automotive industry will see a large dip in vehicle sales due to Millennial preferences.

Although Millennials display preferences for more VMT, the observed and projected VMT rates lag behind prior generations significantly. This may be a concern for the oil industry. However, this work does not capture miles driven by ride-hailing, so the total VMT for vehicles on the road may not necessarily be much lower than reported by prior generations. Future VMT for Millennials has many uncertainties. Though Millennials' underlying preferences for VMT is positive, the eventual effect on oil demand may still be net negative.

Public transit entities may also be less optimistic about these findings. There is no evidence that Millennials are shifting away from personal vehicle ownership. In fact, the work relating demographic variables to vehicle ownership showed that Millennials living in urban environments were more likely to own vehicles than Baby Boomers in urban environments. It is possible that urban Millennials will rely on vehicles more than prior generations had. This choice could come at the expense of transit companies. Further work on these trends is needed, but the general reliance

on vehicles does not appear to be changing.

The future of personal vehicle ownership and usage does not seem to hinge on Millennial preferences given the current transit options available. However, this work does not attempt to predict what the future of mobility looks like, or what new policies may take effect that would force changes. Therefore, there is still significant uncertainty about the future of transport, and what the economic effects will be. This work allows one uncertainty to be reduced, as the results provide evidence that Millennial behaviors and preferences to date are not actually very different from prior generations.

The optimism that Millennials may be key to “saving the planet” due to their eco-consciousness and preference for environmentally friendly products is not likely to heavily influence transit. The American dependence on personal vehicles has been ingrained in much of US society, and it does not appear that Millennials will behave any differently. Many Millennials report they prioritize environmentally friendly products, but the so-called “Green Generation” [66] does not exhibit significantly different preferences when it comes to transport.

These findings do not inherently mean Millennials do not consider the environment in their transport decisions, but for many Millennials having a vehicle may not be a choice. The US can not rely on Millennials’ preferences alone to save the planet. They operate under many of the same constraints as prior generations, so they still need vehicles. Vehicle ownership in the US is still a necessity for a large portion of the population due to many historical policy choices [67], so regardless of Millennials’ preferences for using less environmentally damaging products, they may have little choice.

These findings are not meant to be seen as hopeless for the future of GHG reductions in the US. Rather, the work shows that environmental improvements are not inevitable based on Millennials’ preferences alone. Millennials’ demographics are influencing lower VMT, but the decreased environmental impact is more of an inadvertent result of their other life choices rather than a purposeful effort to reduce environmental footprints. Millennials have some underlying tendencies to drive less

based on their endowments, but intervention with government policies will be necessary to continue nudging Millennials towards cleaner transport options. A balance between promoting economic growth and environmental protection is necessary. The following section discusses potential policies that can balance these interests.

5.2 Recommended Policies

The results from this work highlight Millennials' continued reliance on vehicles. While this is good news for the automotive industry, the societal implications are not solely positive. Continued use of fossil fuel-powered vehicles will have adverse effects on the environment. The future is not bleak, though, as many qualities of Millennials make them a more promising group to reduce GHG emissions with the implementation of well-crafted policies which consider the economic implications as well.

As previously emphasized, the demographic makeup of Millennials is different from prior generations. These differences can be leveraged in policies and investments that would encourage less fossil fuel intensive modes of transport. First, the NHTS data finds that Millennials are living in urban areas at higher rates than prior generations. Therefore, investments in alternative transit options in urban areas could affect a larger number of people than they would have for prior generations. Installation of new public transit services and expansion of current networks could affect Millennials more significantly than such investments would have affected prior generations. Given this larger percentage of Millennials living in urban areas, the existing public transit networks may experience increased strain and congestion. The Metropolitan Transportation Authority in New York City has experienced increased delays due to congestion [68], which may dissuade current users to continue riding the subway. To maintain current ridership and increase use in the future, significant investment in maintaining and improving these networks is necessary.

While investments in urban public transportation are crucial to promoting use and reducing GHG emissions from private vehicles in cities, a large portion of Americans

still live outside of central city areas where limited or no public transit is available. While recommending implementation of public transit is an easy answer, such a solution does not suit low density areas well. Therefore, it is likely that a large portion of the country will continue to rely on private vehicles to some extent. Therefore, policies for these areas must focus on making the best use of private vehicles and encouraging the cleanest vehicles to be on the road.

The claims are largely anecdotal, but the notion that Millennials may have preferences for environmentally friendly products may provide a mechanism to increase the sales of less environmentally-damaging vehicles. However, Millennials' inflation-adjusted income is lower than prior generations' incomes at comparable ages. Therefore, while Millennials may wish to own cleaner or more environmentally-friendly vehicles, these vehicles can be more expensive so they may not be able to afford them. Government subsidies for cleaner vehicles may nudge Millennials to purchase cleaner vehicles. Since the interest in clean vehicles may already be there, giving Millennials better access to the less environmentally-damaging vehicles may be enough to push them to cleaner technologies. Since much of the focus on vehicle ownership is encouraging Millennials to purchase more fuel-efficient vehicles, the resulting economic effects would not be dramatic for the automotive industry. However, the oil industry will have to cope with reduced gasoline usage. This is inevitable if reductions in GHGs are to be made, and there will be both winners and losers in this future scenario.

In addition to a focus on improving the average efficiency of vehicles in the personal vehicle fleet, the results from this work also emphasize the need to consider methods to reduce VMT, as Millennials have a preference for driving a larger number of miles than prior generations. There are multiple methods for reducing VMT: using public transit, carpooling, and ride sharing. As mentioned earlier, public transit may not be a realistic option for a wide swath of America for which little existing infrastructure is available. However, the other options have potential for reducing both the number of vehicles on the road at a given time as well as the total number of miles that vehicles are driven in the US.

There are many existing policy mechanisms for encouraging carpooling, such as high occupancy vehicle (HOV) lanes and reduced tolls for vehicles with multiple passengers. However, in 2013 fewer than 10% of commuters carpooled to work [69]. The existing incentives are not sufficient to overcome the inconvenience of coordinating carpools. Ride-hailing combined with ride-sharing may overcome some of the obstacles that carpooling has not been able to. The technology to match riders efficiently takes much of the effort out of coordination, and riders are more flexible to come and go with different riders. Millennials display a higher rate of ride-hailing adoption, as discussed in Chapter 4, so there may be appetite for this alternative. Policy makers should provide incentives for ride-hailing facilitated ride-sharing, such as Uber Pool or Lyft Line, in areas where public transit is not a feasible alternative to driving. This would encourage higher occupancy vehicles and reduce per-capita VMT.

These recommended policies mainly focus on incremental changes that could reduce GHG emissions. To reduce GHGs to the extent necessary to meet international treaties and goals, more radical changes are likely necessary. These changes would involve revolutions in both the energy production and the transport sector, as the clearest way to dramatically reduce GHGs in personal transport is to decarbonize the transportation system entirely by transitioning to low-carbon or carbon-free electricity powered vehicles. Such a transformation will take significant political will, which is not currently available to make the change. Therefore, meaningful steps that can be implemented feasibly in the present are described here, though comprehensive climate change policies such as carbon taxes would be more effective and efficient to fundamentally change the transport sector.

5.3 Looking to the Future

Just because Millennials' preferences do not provide evidence that they will save the planet does not mean that Millennials can not save the planet. As Millennials continue to progress through live events and fill elected positions, take leadership roles in Fortune 500 companies, and make decisions for their families, the future will be in

their hands to shape. Therefore, while these results show Millennials are behaving in similar manners to Baby Boomers in terms of their transport preferences, Millennials are not necessarily destined to follow in Baby Boomers footsteps. The future has the potential to shape Millennials behavior as new technologies or policies come into effect, but at the same time Millennials have the power to shape the future. The resulting outcomes for both transport and society as a whole are dependent on how Millennials choose to respond.

Appendix A

Tables of Regression Results

Tables of results from the regression analyses are listed below. Select variables are included, as the full set of variables is cumbersome. Discussion of the results is in Chapter 4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All Ages No Controls	All Ages Controls	Age ≤37 No Controls	Age ≤37 Controls	Age ≤37 Exclude Age Var.	Age ≤37 St./Yr Int	Age ≤37 St. Macro Inc.
Millennials	-0.391*** (-23.69)	-0.167*** (-7.08)	-0.0771*** (-3.79)	-0.0300 (-0.72)	-0.0799* (-2.02)	-0.0224 (-0.55)	0.000268 (0.01)
Gen X	-0.170*** (-14.11)	-0.103*** (-7.39)	-0.0574** (-3.17)	0.00464 (0.21)	-0.0276 (-1.43)	0.00692 (0.32)	0.00415 (0.20)
Silent Gen	-0.188*** (-17.83)	-0.0191 (-1.35)					
Greatest Gen	-0.691*** (-59.99)	-0.156*** (-6.59)					
ln(Income)		-0.438*** (-6.01)		-0.0157 (-0.10)	-0.0432 (-0.28)	-0.0352 (-0.23)	-0.0220 (-0.14)
ln(Income) ²		0.0385*** (10.74)		0.0139 (1.83)	0.0157* (2.07)	0.0149* (2.01)	-0.0142 (1.88)
ln(HH Size)		1.777*** (17.52)		1.468*** (5.73)	1.452*** (5.64)	1.465*** (5.82)	1.463*** (5.73)
ln(HH Size) ²		-0.303*** (-7.18)		-0.442*** (-4.61)	-0.431*** (-4.47)	-0.442*** (-4.70)	-0.440*** (-4.60)
Urban Cluster		0.114*** (11.70)		0.105*** (5.68)	0.104*** (5.60)	0.110*** (5.87)	0.0841*** (4.84)
Not Urban		0.414*** (38.91)		0.294*** (14.28)	0.294*** (14.24)	0.302*** (14.59)	0.281*** (14.01)
ln(HH Max Age)		1.731*** (6.17)		-0.126 (-0.06)		-0.069 (-0.03)	-0.269 (-0.13)
ln(GSP)							0.845*** (3.73)
ln(GSP) ²							-0.0300*** (-3.46)
ln(St Unemp)							0.485 (1.62)
ln(St Unemp) ²							-0.130 (-1.63)
Constant	1.987*** (297.21)	-2.156** (-3.22)	1.673*** (122.75)	-0.592 (-0.17)	-0.405 (-0.51)	-0.961 (-0.28)	-6.359 (-1.69)
<i>N</i>	369602	334292	49732	46121	46121	46121	46121

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.1: NHTS vehicle ownership regression results, select variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All Ages	All Ages	Age ≤35	Age ≤35	Age ≤35	Age ≤35	Age ≤35
	No Controls	Controls	No Controls	Controls	Exclude Age Var.	St./Yr Int	St. Macro Inc.
Millennials	-0.568*** (-266.06)	-0.113*** (-30.04)	-0.222*** (-94.25)	-0.0163* (-2.14)	0.0149* (2.49)	-0.0133 (-1.74)	-0.0148 (-1.93)
Gen X	-0.200*** (-139.64)	-0.131*** (-64.07)	-0.0585*** (-34.22)	-0.0291*** (-7.41)	-0.00126 (-0.50)	-0.0255*** (-6.48)	-0.0273*** (-6.96)
Silent Gen	-0.115*** (-94.18)	0.0854*** (51.49)					
Greatest Gen	-0.641*** (-527.91)	-0.0815*** (-29.72)					
ln(Income)		-0.482*** (-82.68)		-0.310*** (-26.48)	-0.320*** (-27.14)	-0.311*** (-26.58)	-0.309*** (-26.44)
ln(Income) ²		0.0370*** (130.31)		0.0251*** (42.51)	0.0255*** (42.86)	0.0252*** (42.67)	0.0251*** (42.48)
ln(HH Size)		0.786*** (279.99)		0.708*** (112.84)	0.706*** (113.81)	0.707*** (113.08)	0.708*** (112.88)
ln(HH Size) ²		-0.109*** (-62.72)		-0.137*** (-40.15)	-0.137*** (-40.68)	-0.137*** (-40.23)	-0.137*** (-40.18)
Not Urban		0.207*** (180.15)		0.172*** (71.80)	0.173*** (72.20)	0.172*** (71.38)	0.168*** (70.17)
ln(HH Max Age)		2.363*** (73.96)		-5.021*** (-17.45)		-4.96*** (-17.24)	-4.996*** (-17.35)
Has Been Married		0.00892*** (5.66)		0.0580*** (21.94)	0.0556*** (21.20)	0.058*** (22.06)	0.0581*** (21.99)
Has a Child		-0.0829*** (-51.04)		-0.337*** (-100.68)	-0.337*** (-101.17)	-0.337*** (-100.79)	-0.337*** (-100.61)
ln(GSP)							0.437*** (13.08)
ln(GSP) ²							-0.0140*** (-11.29)
ln(St Unemp)							-0.0484 (-1.74)
ln(St Unemp) ²							0.0161 (1.84)
Constant	1.837*** (2287.24)	-2.353*** (-34.30)	1.491*** (1166.45)	10.13*** (21.00)	1.752*** (28.62)	10.04*** (20.82)	6.936*** (12.70)
N	12805865	9106362	2818509	1961523	1961523	1961523	1961523

t statistics in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001

Table A.2: ACS vehicle ownership regression results, select variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All Ages No Controls	All Ages Controls	Age ≤37 No Controls	Age ≤37 Controls	Age ≤37 Exclude Age Var.	Age ≤37 St./Yr Int	Age ≤37 St. Macro Inc.
Millennials	-1583.1*** (-9.52)	172.1 (0.74)	-1812.5*** (-7.98)	601.4* (2.17)	-83.08 (-0.29)	650.4* (2.35)	793.9** (2.89)
Gen X	592.3*** (4.44)	743.5*** (4.70)	269.5 (1.22)	512.3 (1.95)	135.5 (0.53)	556.7* (2.13)	964.3*** (4.09)
Silent Gen	-2986.6*** (-26.88)	-751.3*** (-4.34)					
Greatest Gen	-7235.7*** (-64.08)	-1775.4*** (-6.43)					
ln(Income)		6291.8*** (5.76)		5574.9** (2.73)	8118.6*** (3.98)	4991.0* (2.48)	6030.3** (2.93)
ln(Income) ²		-187.7*** (-3.55)		-171.4 (-1.74)	-287.0** (-2.92)	-143.7 (-1.48)	-193.6 (-1.96)
ln(HH Size)		-521.1 (-0.51)		-3934.4* (-2.13)	-4842.1** (-2.60)	-3986.7* (2.15)	-4348.2* (-2.34)
ln(HH Size) ²		-2.436 (-0.01)		846.1 (1.18)	907.1 (1.26)	830.6 (1.16)	999.0 (1.39)
Urban Cluster		833.5*** (6.27)		852.5*** (3.44)	837.5*** (3.37)	897.2*** (3.48)	1073.5*** (4.88)
Not Urban		3517.0*** (25.39)		4045.7*** (14.12)	4086.0*** (14.16)	4166.8*** (14.14)	4084.0*** (14.70)
ln(Age)		68107.6*** (22.27)		133512.1*** (8.67)		132900.9*** (8.65)	128292.1*** (8.34)
ln(Age) ²		-9310.8*** (-21.57)		-19329.3*** (-8.24)		-19240.59*** (-8.22)	-18510.6*** (-7.90)
ln(GSP)							9075.5** (2.93)
ln(GSP) ²							-388.9** (-3.27)
ln(St Unemp)							-3236.9 (-0.75)
ln(St Unemp) ²							876.1 (0.78)
Constant	13890.3*** (199.19)	-157518.3*** (-19.28)	14119.7*** (83.30)	-255804.5*** (-9.41)	-41081.4*** (-3.80)	-259085.9*** (-9.64)	-301081.5*** (-8.77)
N	489731	448058	104101	95654	95654	95654	95654

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: NHTS VMT regression results, select variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Urban	Urban	Previously	Previously	HH	HH	Income	Income
	Status	Status	Married	Married	Size	Size	2015 USD	2015 USD
	No Controls	Controls	No Controls	Controls	No Controls	Controls	No Controls	Controls
Millennials	-0.0164*** (-12.72)	0.0618*** (18.06)	-0.297*** (-248.08)	-0.0138*** (-3.70)	-0.561*** (-164.48)	-0.0137 (-1.32)	-11934.8*** (-97.29)	-937.6** (-2.65)
Gen X	-0.0175*** (-22.87)	0.0736*** (43.31)	-0.0973*** (-109.35)	0.0128*** (7.57)	-0.184*** (-68.34)	0.00157 (0.38)	-3890.1*** (-43.22)	-233.6 (-1.84)
ln(Income)		-0.0952*** (-20.69)		-0.344*** (-40.02)		-0.389*** (-21.90)		
ln(Income) ²		0.00594*** (25.75)		0.0242*** (56.32)		0.0217*** (24.40)		
ln(HH Size)		-0.0173*** (-6.68)						36775.6*** (113.05)
ln(HH Size) ²		-0.00626*** (-4.30)						-12711.9*** (-75.21)
ln(HH Max Age)		1.711*** (12.97)		2.276*** (17.45)		-4.142*** (-11.32)		-317433.8*** (-24.93)
ln(HH Max Age) ²		-0.246*** (-12.54)		-0.274*** (-14.06)		0.856*** (15.55)		56825.9*** (29.37)
Has Been Married		-0.0536*** (-45.38)				1.255*** (365.49)		19373.6*** (148.80)
Has a Child		-0.0282*** (-19.01)		0.361*** (335.22)				-14699.1*** (-77.09)
Urban				-0.0665*** (-55.85)		-0.173*** (-47.12)		5878.8*** (55.58)
Constant	0.785*** (1690.10)	-1.693*** (-7.67)	0.678*** (1040.64)	-3.047*** (-14.22)	2.647*** (1406.41)	8.339*** (13.89)	59077.3*** (1058.04)	441213.1*** (21.11)
N	2134476	1961523	2818509	1961523	2818509	1961523	2575106	2002776

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: ACS demographics regression results, select variables

	(1)	(2)
	Generation X	Baby Boomers
Differential		
Vehicle Count	1.626***	1.687***
For Comparison Gen	(127.32)	(110.51)
Vehicle Count for Millennials	1.595***	1.595***
	(106.92)	(106.92)
Difference	0.0313	0.0920***
	(1.59)	(4.31)
Decomposition		
Endowments	0.114*	0.147***
	(2.25)	(5.00)
Preferences	0.0604	-0.113**
	(1.53)	(-2.70)
Interaction	-0.143*	0.0583
	(-2.33)	(1.25)
<i>N</i>	37911	26792

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: NHTS vehicle ownership Oaxaca decomposition results

	(1)	(2)
	Generation X	Baby Boomers
Differential		
Vehicle Count	1.503***	1.615***
For Comparison Generation	(1102.71)	(1596.38)
Vehicle Count	1.437***	1.437***
For Millennials	(480.33)	(480.33)
Difference	0.0659***	0.178***
	(20.03)	(56.23)
Decomposition		
Endowments	-0.00412	0.192***
	(-0.45)	(52.17)
Preferences	-0.0243***	-0.0258***
	(-7.03)	(-6.87)
Interaction	0.0943***	0.0116**
	(10.37)	(2.78)
<i>N</i>	1050717	1058674

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: ACS vehicle ownership Oaxaca decomposition results

	(1)	(2)
	Generation X	Baby Boomers
Differential		
VMT for	14279.3***	15313.4***
Comparison Gen	(99.26)	(72.18)
VMT For	12417.8***	12417.8***
Millennials	(85.70)	(85.70)
Difference	1861.5***	2895.7***
	(9.12)	(11.27)
Decomposition		
Endowments	3357.4***	5282.4***
	(6.52)	(7.22)
Preferences	900.6**	3200.5*
	(2.70)	(2.02)
Interaction	-2396.4***	-5587.2**
	(-4.01)	(-3.22)
<i>N</i>	77589	52309

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: NHTS VMT Oaxaca decomposition results

	(1)	(2)
	NHTS	NHTS
	Vehicle Count	VMT
Millennials v. Baby Boomers	0.114*	2234.67***
	(0.045)	(506.68)
<i>N</i>	163159	239559

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.8: Nearest neighbor matching estimator results

	(1)	(2)	(3)	(4)
	Ride-Hailing All Respondents No Controls	Ride-Hailing All Respondents Controls	Ride-Hailing Have Used Service No Controls	Ride-Hailing Have Used Service Controls
Millennials	0.679*** (57.49)	0.389*** (5.49)	1.072*** (10.64)	0.364 (0.74)
Gen X	0.253*** (23.26)	0.123* (2.17)	0.505*** (4.62)	0.603 (1.29)
Silent Gen	-0.105*** (-8.78)	0.201*** (5.09)	-0.0934 (-0.38)	0.00350 (0.01)
Greatest Gen	-0.120* (-2.27)	0.405*** (3.48)	-0.223 (-0.16)	1.879 (1.33)
ln(Income)		-1.178*** (-3.50)		0.213 (0.08)
ln(Income) ²		0.0604*** (3.85)		-0.00282 (-0.02)
ln(HH Size)		-1.147*** (-4.68)		-2.679 (-1.23)
ln(HH Size) ²		0.293** (3.21)		0.524 (0.58)
Urban Cluster		-0.227*** (-9.00)		-0.243 (-0.47)
Not Urban		-0.214*** (-11.17)		-0.738*** (-3.33)
ln(Age)		1.273 (1.12)		-9.235 (-0.91)
ln(Age) ²		-0.268 (-1.69)		1.022 (0.72)
Constant	0.154*** (25.80)	5.184* (2.27)	3.223*** (41.91)	20.47 (0.99)
<i>N</i>	156599	152213	12337	12134

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: NHTS ride-hailing regression results

	(1)	(2)	(3)	(4)
	Carsharing	Carsharing	Carsharing	Carsharing
	All Respondents	All Respondents	Have Used Service	Have Used Service
	No Controls	Controls	No Controls	Controls
Millennials	0.0178*** (5.54)	0.0387 (1.66)	-0.0313 (-0.08)	1.321 (0.73)
Gen X	0.00472 (1.59)	0.00984 (0.76)	-0.579 (-1.37)	-0.355 (-0.28)
Silent Gen	-0.00677* (-2.07)	0.00189 (0.12)	-0.675 (-1.06)	1.613 (1.27)
Greatest Gen	0.00321 (0.22)	0.000506 (0.02)	-0.308 (-0.15)	2.194 (0.82)
ln(Income)		0.0262 (0.36)		3.345 (0.67)
ln(Income) ²		-0.00132 (-0.37)		-0.167 (-0.70)
ln(HH Size)		-0.167 (-1.31)		-2.840 (-0.51)
ln(HH Size) ²		0.0611 (1.71)		1.203 (0.65)
Urban Cluster		-0.0162* (-1.99)		0.264 (0.27)
Not Urban		-0.0124*** (-3.45)		-0.497 (-0.64)
ln(Age)		-0.0478 (-0.12)		34.19 (1.44)
ln(Age) ²		0.00556 (0.10)		-4.757 (-1.41)
Constant	0.0144*** (8.86)	-0.0196 (-0.03)	3.142*** (11.62)	-74.81 (-1.42)
<i>N</i>	156601	152212	921	897

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: NHTS carsharing regression results

Bibliography

- [1] “America’s automobile industry is one of the most powerful engines driving the US economy.” <https://autoalliance.org/economy/>.
- [2] “Automotive Industry Spotlight.” <https://www.selectusa.gov/automotive-industry-united-states>.
- [3] “How much gasoline does the United States consume? - FAQ.” <https://www.eia.gov/tools/faqs/faq.php?id=23&t=10>.
- [4] E. Benmelech, R. R. Meisenzahl, and R. Ramcharan, “Why Did Car Sales Drop So Dramatically During the Financial Crisis?.” <https://insight.kellogg.northwestern.edu/article/was-the-government-bailout-of-car-financers-necessary>, 2016-04-04 CDT09:04:03-18000.
- [5] “Bailout List: Banks, Auto Companies, and More.” <https://projects.propublica.org/bailout/list>, Jan. 2018.
- [6] D. Gross, “Why Ford, GM and Chrysler Need A Bailout.” <http://www.newsweek.com/why-ford-gm-and-chrysler-need-bailout-84665>, Nov. 2008.
- [7] J. Greenberg, “Did President Obama save the auto industry?.” <http://www.politifact.com/truth-o-meter/article/2012/sep/06/did-obama-save-us-automobile-industry/>, June 2012.
- [8] “U.S. vehicle sales 1977-2017 — Statistic.” <https://www.statista.com/statistics/199983/us-vehicle-sales-since-1951/>.
- [9] O. US EPA, “Carbon Pollution from Transportation.” <https://www.epa.gov/air-pollution-transportation/carbon-pollution-transportation>, Sept. 2015.
- [10] J. Greenwald, “The Transportation Sector: Why it Should be a Priority for Decarbonization.” <https://www.aspeninstitute.org/blog-posts/the-transportation-sector-why-it-should-be-a-priority-for-decarbonization/>, May 2017.
- [11] A. Eisenkopf and A. Knorr, “Decarbonizing Europe-Will the Transport Sector Undermine This Policy?,” 2017.
- [12] P. R. Center, “The Generations Defined,” May 2015.

- [13] R. Fry, “Millennials overtake Baby Boomers as America’s largest generation.” <http://www.pewresearch.org/fact-tank/2016/04/25/millennials-overtake-baby-boomers/>, Apr. 2016.
- [14] K. Taylor, “Millennials are killing chains like Buffalo Wild Wings and Applebee’s.” <http://www.businessinsider.com/millennials-endanger-casual-dining-restaurants-2017-5>.
- [15] D. Thompson and J. Weissman, “The Cheapest Generation,” *The Atlantic*, September 2012 Issue.
- [16] D. Kurylko, “The millennials are coming: Slow to recover from recession, but fast becoming a major buyer segment.” <http://www.autonews.com/article/20170227000100/RETAIL/302279963?template=print>, Feb. 2017.
- [17] T. Buchholz and V. Buchholz, “The Go-Nowhere Generation,” *The New York Times*, Oct. 2012.
- [18] T. Dutzik, J. Inglis, and P. Baxandall, “Millennials in Motion: Changing Travel Habits of Young Americans and the Implications for Public Policy,” tech. rep., U.S. PIRG, Frontier Group, Oct. 2014.
- [19] R. L. Oaxaca and M. R. Ransom, “On discrimination and the decomposition of wage differentials,” *Journal of Econometrics*, vol. 61, pp. 5–21, Mar. 1994.
- [20] S. Martin, N. M. Astone, and H. E. Peters, “Fewer Marriages, More Divergence: Marriage Projections for Millennials to Age 40.” <http://www.urban.org/research/publication/fewer-marriages-more-divergence-marriage-projections-millennials-age-40>, June 2016.
- [21] N. M. Astone, S. Martin, and H. E. Peters, “Millennial Childbearing and the Recession.” <https://www.urban.org/research/publication/millennial-childbearing-and-recession>, June 2016.
- [22] “Millennials Prefer Cities to Suburbs, Subways to Driveways.” <http://www.nielsen.com/us/en/insights/news/2014/millennials-prefer-cities-to-suburbs-subways-to-driveways.html>, Apr. 2014.
- [23] A. Bahney, “How the financial crisis affected Millennials, 10 years later.” <http://money.cnn.com/2017/12/04/pf/impact-recession-millennials/index.html>, Dec. 2017.
- [24] A. Atkinson, “Millennials Are Worse Off Than Gen Xers Were at Their Age.” <http://time.com/money/5165475/millennials-poorer-generation-x/>.
- [25] D. Ross, D. Ross, and D. Ross, “Millennials Don’t Care About Owning Cars, And Car Makers Can’t Figure Out Why.” <https://www.fastcompany.com/3027876/millennials-dont-care-about-owning-cars-and-car-makers-cant-figure-out-why>, Mar. 2014.

- [26] P. Mourdoukoutas, “The Coming Collapse In U.S. Auto Sales.” <https://www.forbes.com/sites/panosmourdoukoutas/2017/05/03/the-coming-collapse-in-us-auto-sales/#1d2b2e7c1660>.
- [27] R. de Neufville and S. Scholtes, *Flexibility in Engineering Design*. MIT Press.
- [28] J. Pilcher, “Mannheim’s Sociology of Generations: An Undervalued Legacy,” *The British Journal of Sociology*, vol. 45, no. 3, pp. 481–495, 1994.
- [29] K. Mannheim, *The Problem of Generations*. Routledge, 1927.
- [30] C. Doherty, Kiley, Jocelyn, A. Tyson, and B. Jameson, “The Whys and Hows of Generations Research,” Sept. 2015.
- [31] T. Erickson, “Generations Around the Globe.” <https://hbr.org/2011/04/generations-around-the-globe-1>, Apr. 2011.
- [32] S. J. Czaja, N. Charness, A. D. Fisk, C. Hertzog, S. N. Nair, W. A. Rogers, and J. Sharit, “Factors Predicting the Use of Technology: Findings From the Center for Research and Education on Aging and Technology Enhancement (CREATE),” *Psychology and aging*, vol. 21, pp. 333–352, June 2006.
- [33] K. McKinney, “Ignore age-define generations by the tech they use.” <https://www.vox.com/2014/4/20/5624018/should-technology-define-generations>, Apr. 2014.
- [34] A. Thierer, “Why Do We Always Sell the Next Generation Short?.” <https://www.forbes.com/sites/adamthierer/2012/01/08/why-do-we-always-sell-the-next-generation-short/#5809ab282d75>.
- [35] D. Goldman, *A Beholder’s Share: Essays on Winnicott and the Psychoanalytic Imagination*. Taylor & Francis, May 2017.
- [36] C. Ferguson, “What’s Really Wrong With Young People Today: Juvenonia.” <http://time.com/19818/whats-really-wrong-with-young-people-today-juvenonia/>, Dec. 2014.
- [37] M. W. Guay, “How Millennials Are Redefining the American Dream,” Apr. 2015.
- [38] A. Machado, “How Millennials Are Changing Travel,” *The Atlantic*, June 2014.
- [39] J. Fromm, “Affluent Millennial Travelers Embrace The Sharing Economy.” <http://www.forbes.com/sites/jefffromm/2015/12/17/affluent-millennial-travelers-embrace-the-sharing-economy/>.
- [40] C. Coletta and J. Cortright, “Young at Heart: Finding The Key Demographic Needed To Revitalize America’s Inner Cities.” <https://www.planetizen.com/node/18472>, Oct. 2006.

- [41] L. Wester, “Zipcar Annual Millennial Survey Suggests Being a ‘Millennial’ is Related to Where You Live, Not When You Were Born — Zipcar Press Center.” <http://www.zipcar.com/press/releases/2015millennials>, Apr. 2015.
- [42] M. M. Biro, “Reconsidering Millennials: They’re Not That Different From You.” <https://www.forbes.com/sites/meghanbiro/2014/09/05/reconsidering-millennials-theyre-not-that-different-from-you/>.
- [43] E. Blumenberg, B. D. Taylor, M. Smart, K. Ralph, M. Wander, and S. Brumbagh, “What’s Youth Got to Do with It? Exploring the Travel Behavior of Teens and Young Adults,” *eScholarship*, Sept. 2012.
- [44] B. Davis, T. Dutzik, and P. Baxandall, “Transportation and the New Generation: Why Young People are Driving Less and What it Means for Transportation Policy,” tech. rep., U.S. PIRG, Frontier Group, Apr. 2012.
- [45] P. Jorritsma and J. Berveling, “Not-carless-but-car-later: For young adults the car is still an attractive proposition,” tech. rep., Ministry of Infrastructure and Environment, Netherlands, May 2014.
- [46] B. Schoettle and M. Sivak, “The Reasons for the Recent Decline in Young Driver Licensing in the United States,” *Traffic Injury Prevention*, vol. 15, Aug. 2013.
- [47] B. Tefft, A. F. Williams, and J. Grabowksi, “Timing of Driver’s License Acquisition and Reasons for Delay among Young People in the United States, 2012,” tech. rep., AAA Foundation for Traffic Safety, Aug. 2013.
- [48] S. E. Polzin, X. Chu, and J. Godfrey, “The impact of millennials’ travel behavior on future personal vehicle travel,” *Energy Strategy Reviews*, vol. 5, pp. 59–65, Dec. 2014.
- [49] N. McDonald, “Are Millennials Really the ”Go-Nowhere” Generation?,” *Journal of the American Planning Association*, vol. 81, pp. 90–103, Sept. 2015.
- [50] V. Garikapati, R. Pendyala, E. Morris, P. Mokhtarian, and N. McDonald, “Activity patterns, time use, and travel of millennials: A generation in transition?,” *Transport Reviews*, vol. 36, pp. 558–584, June 2016.
- [51] B. Newbold and D. Scott, “Driving over the life course: The automobility of Canada’s Millennial, Generation X, Baby Boomer, and Greatest Generations,” *Travel Behavior and Society*, vol. 6, pp. 57–63, Jan. 2017.
- [52] T. Kuhnimhof, D. Zumkeller, and B. Chlond, “Who Are the Drivers of Peak Car Use? — A Decomposition of Recent Car Travel Trends for Six Industrialized Countries,” *Journal of the Transportation Research Board*, vol. 2383, pp. 53–61, 2013.
- [53] M. Sivak and B. Schoettle, “Recent Changes in the Age Composition of Drivers in 15 Countries,” *Traffic Injury Prevention*, vol. 13, pp. 126–132, Mar. 2012.

- [54] S. Vine, C. Latinopoulos, and J. Polak, “Establishing the Links Between Online Activity and Car Use,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2405, pp. 68–77, July 2014.
- [55] B. van Wee, “Peak car: The first signs of a shift towards ICT-based activities replacing travel? A discussion paper,” *Transport Policy*, vol. 42, pp. 1–3, Aug. 2015.
- [56] E. Martin, S. Shaheen, and J. Lidicker, “Impact of Carsharing on Household Vehicle Holdings: Results from North American Shared-Use Vehicle Survey,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2143, pp. 150–158, 2010.
- [57] D. MacKenzie, Z. Wadud, and P. Leiby, “A First Order Estimate of Energy Impacts of Automated Vehicles in the United States,” in *Energy Impacts of Vehicle Automation*, 2016.
- [58] D. Fagnant and K. Kockelman, “The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios,” *Transportation Research Part C: Emerging Technologies*, vol. 40, pp. 1–13, Mar. 2014.
- [59] A. Smith, “2. On-demand: Ride-hailing apps,” May 2016.
- [60] R. Clewlow and G. S. Mishra, “Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States,” Research Report UCS-ITS-RR-17-07, University of California, Davis, 2017.
- [61] B. Allenby, “The Self-Driving Car Generation Gap,” *Slate*, June 2016.
- [62] K. Lunau, “For today’s youth, cars no longer represent freedom.” <http://www.macleans.ca/society/technology/for-todays-youth-cars-no-longer-represent-freedom/>.
- [63] A. LaFrance, “One Thing Baby Boomers and Millennials Agree On: Self-Driving Cars,” *The Atlantic*, Oct. 2015.
- [64] R. Fry, “Millennials are the largest generation in the U.S. labor force,” Apr. 2018.
- [65] D. Schneider, K. Harknett, and M. Stimpson, “What Explains the Decline in First Marriage in the United States? Evidence from the Panel Study of Income Dynamics, 1969 to 2013,” *Journal of Marriage and Family*, vol. 0, no. 0.
- [66] “Green Generation: Millennials Say Sustainability Is a Shopping Priority.” <http://www.nielsen.com/us/en/insights/news/2015/green-generation-millennials-say-sustainability-is-a-shopping-priority>, May 2015.
- [67] R. Buehler, “9 Reasons the U.S. Ended Up So Much More Car-Dependent Than Europe.” <http://www.theatlanticcities.com/commute/2014/02/9-reasons-us-ended-so-much-more-car-dependent-europe/8226/>, Feb. 2014.

- [68] E. G. Fitzsimmons, F. Fessenden, and K. K. R. Lai, “Every New York City Subway Line Is Getting Worse. Here’s Why.,” *The New York Times*, June 2017.
- [69] B. McKenzie, “Who Drives to Work? Commuting by Automobile in the United States: 2013,” *US Census Bureau*, vol. American Community Survey Reports, Aug. 2015.