Factors affecting the gas price elasticity of travel demand: Implications for transportation emissions policy
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Submitted to the Department of Urban Studies and Planning and the Department of Civil and Environmental Engineering in partial fulfillment of the requirements for the degrees of

| Master in City Planning |  |
| :---: | :---: |
| andMaster of Science in Transportationat the MASSACHUSETTS INSTITUTE OF TECHNOLOGY |  |
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#### Abstract

This thesis explores the possibility of reducing transportation emissions by reducing the growth of demand for travel in the United States light-duty vehicle fleet. Many government agencies seek to reduce the environmental and social ills associated with excess travel demand (e.g. congestion, reduced safety during travel, local pollution and noise, energy consumption, and climate change). These agencies have many tools at their disposal to reduce vehicle miles traveled (VMT) per capita - including encouraging compact mixed-use development, providing alternatives to single occupancy vehicle travel such as transit and biking and walking infrastructure, and restricting/regulating driving alone for instance by providing less parking. But the fastest way to reduce travel demand is through higher pricing that accounts for the externalities that drivers impose upon each other and society more broadly. The degree to which higher pricing can reduce travel demand is a function of two interrelated factors: 1) how high of a price increase is politically feasible to implement, and 2 ) the degree to which the driving public responds to the higher cost of driving. Both these factors vary over time. Given that carbon pricing and/or higher gas taxes are likely to take years to gain broader political acceptability, the future price elasticities of travel demand are just as relevant as today's elasticities.

Therefore, this thesis focuses on the variability of price elasticity, the factors that explain this variation, and how these factors might change in the future. Using a diverse set of methods including literature review, semi-structured interviews, and odometer data, I find evidence that the magnitude of price elasticity is lower for vehicles of higher fuel economy, for vehicles further from the urban center, and for vehicles in lower income zipcodes. This is the first analysis I am aware of that evaluates the variation of the price elasticity of travel demand within a metro area, an approach that is important to the understanding the political feasibility of pricing and as a lens to the future effectiveness of pricing. It suggests that gas price increases will affect certain households in very different ways, with the most inelastic households simply paying more to maintain their lifestyle and the most elastic households pushed to make significant changes to their daily travel patterns and opportunities. These two types of impact may lead to different types of resistance to the policy. As for the future, the findings regarding fuel economy and distance to the urban center are particularly relevant, as we foresee society continues to become more metropolitan and the vehicle fleet is increasingly comprised of high fuel economy vehicles. Finally, the magnitude of price response suggested by both my interviews and my odometer data analysis suggests that price is still a significant determining factor in distance driven; therefore, policy that increases the cost of driving remains an important emissions reduction strategy.


Thesis Supervisor: John B. Heywood, Sun Jae Professor Emeritus, Department of Mechanical Engineering Thesis Supervisor: Jinhua Zhao, Assistant Professor, Department of Urban Studies and Planning

## Acknowledgements

My time at MIT has been greatly enriched by the contributions of my many classmates and instructors. Most notably, Professor John Heywood has been a constant source of wisdom, guidance and inspiration, without which this thesis would not exist in its current form. Professor Jinhua Zhao has provided a fantastic sounding board and a source of much technical knowledge on the techniques required to perform the various analytical methods in this project. Professor Joe Ferreira connected me to the data source upon which I was able to base many of my conclusions, and he gave me consistent helpful support in learning the data analysis tools and interpreting the results. Tim Reardon, at the Metropolitan Area Planning Council, enthusiastically helped me access the vehicle census data and answered my many questions about nuances of the data collection and structure. Finally, the students of Professor Heywood and Professor Zhao's research groups gave helpful and insightful feedback and ideas. I benefited tremendously from opportunities to present my progress to these groups and this thesis would not be the same without their suggestions. And finally, my family and friends provided a sounding board as I designed my analysis and provided feedback and edits on the final document.

## Table of Contents

Abstract ..... 3
Acknowledgements ..... 4
Table of Contents ..... 5
Chapter 1: Introduction
Reducing transportation emissions ..... 10
Uniqueness of the contemporary context in travel demand ..... 11
Links between VMT and economic growth ..... 12
Anticipated future trends affecting travel demand ..... 13
Transportation as a service ..... 13
Changing vehicle technologies ..... 14
Slowing population growth and aging population ..... 15
Population growth ..... 15
Age structure of the population and labor force participation ..... 15
Increasing income inequality and wealth inequality ..... 17
How malleable is travel demand? ..... 18
Chapter 2. The Role of Travel Demand in Emissions Reduction Efforts
Motivation ..... 21
Emissions reductions from travel demand ..... 22
Scope, Scale, and Timeframe ..... 23
Timing and degree of permanence ..... 25
Inertial changes in the building stock ..... 25
Lower fuel intensity and GHG intensity per mile over time ..... 26
Combining travel demand reductions and technology improvements ..... 26
VMT growth and the potential to curtail it ..... 26
Fuel consumption and fuel economy ..... 29
Combined impact ..... 29
Summary ..... 31

## Chapter 3: Can urban form interventions curtail travel demand growth?

Motivation ..... 32
How the built environment has affected travel demand in the U.S. since World War II ..... 32
Policies that have accelerated land consumption and automobile dependence. ..... 33
Interstate highway system. ..... 33
Federal financial policies encouraging sprawl ..... 34
Schools, crime, and racial tension ..... 34
Zoning and leapfrog development ..... 35
Studies that estimate impact of urban form on travel demand ..... 36
Metropolitan Planning Organization (MPO) scenario planning ..... 36
Econometric modeling ..... 37
Methodological challenges and limits to generalizability ..... 39
Scale ..... 39
Residential self-selection ..... 39
Endogeneity ..... 40
Additive effects of multiple built environment features ..... 41
The rebound effect - travel time budgets ..... 41
Limits to generalizability ..... 42
How does the built environment affect price responsiveness of VMT? ..... 43
Chapter 4: How much does gas price affect travel demand?
Motivation ..... 45
Foundations of price elasticity ..... 45
What actions are taken in response to changing gas prices? ..... 46
Theory of Planned Behavior ..... 47
Types of data sources for elasticity studies ..... 49
Meta-studies of the elasticity of gasoline consumption with respect to price ..... 50
Factors affecting price responsiveness ..... 52
Price responsiveness by trip type ..... 52
Price responsiveness by salience and by the cause of the price change ..... 53
Price responsiveness by attributes of the built environment ..... 54
Price responsiveness by vehicle attributes and demographic attributes ..... 55
Vehicle attributes ..... 55
Vehicle owner attributes ..... 57
Is price responsiveness declining over time? ..... 58
Additional behavioral economic perspectives on price elasticity ..... 60
Summary - Remaining uncertainties in price responsiveness ..... 60
Chapter 5. Behavioral interviews of a diverse set of drivers throughout the U.S.
Introduction ..... 62
Purpose ..... 63
Methods ..... 63
Pre-interview questionnaire ..... 65
Financial situation ..... 65
Living environments and household attributes ..... 66
Transportation Options and Costs ..... 67
Findings ..... 68
Paying for car travel ..... 69
Travel options ..... 70
Response to a hypothetical large gas tax increase of $\$ 6.20 /$ gallon ..... 71
Scenario description ..... 71
Interviewee response to scenario ..... 71
Self-assessment of ability to reduce overall VMT in gas tax increase scenario ..... 75
Barriers to reducing VMT ..... 76
Overall Themes ..... 76
Desire for independence ..... 76
Desire for one-size-fits-all vehicle. ..... 77
Factors other than gas price ..... 78
Thrift, socioeconomics, and personality ..... 79
Inertia in travel decisions ..... 79
Ideas for future work ..... 81
Conclusions ..... 82

## Chapter 6: The Massachusetts Vehicle Census

Motivation ..... 83
Why use the Massachusetts Vehicle Census (MAVC)? ..... 83
Exploring the dataset ..... 84
Microdata. ..... 85
Trend over time ..... 85
Frequency of vehicle inspections ..... 86
Average mileage driven per year, fuel efficiency ..... 88
Spatial variations in the microdata ..... 90
Vehicle usage by type and by fuel economy ..... 92
Distributions of VMT and MPG by MAPC community types ..... 93
Summary data ..... 96
Summary ..... 99
Chapter 7: Regression analysis to explore variability of price elasticity of travel demand in Massachusetts
Motivation ..... 100
Strategy ..... 101
Data and software needs ..... 102
Methodology ..... 102
Data exploration and adjustments ..... 103
Constructing the independent variables and joining them to the MAVC data ..... 103
Filtering and sampling the data ..... 105
Performing regressions in Gret| ..... 106
Checking for conditions for inference, spatial autocorrelation and multicollinearity ..... 106
Findings and interpretation ..... 109
A significant amount of variation cannot be explained by the predictors ..... 109
Nearly all the predictors are significant ..... 110
The impact on VMT depends on more than the coefficient. ..... 111
Price response varies significantly along the attributes explored ..... 112
VMT elasticity appears to have rebounded from the estimates from the early 2000s ..... 115
Desirable Next Steps ..... 119
Test more sophisticated types of regressions ..... 119
Find and include omitted variables ..... 119
Incorporate the effects of price volatility and memory of recent gas prices ..... 120
Run a model on total VMT for each individual household ..... 120
Conclusions from the regression model ..... 122
Chapter 8: Findings and Implications
Policies that increase gas costs to reduce VMT need the right window of opportunity ..... 123
The equity of the effects of gas pricing policy on specific populations need further attention in order to improve policy design ..... 124
My findings show that price elasticity varies substantially among populations. ..... 125
Gas price matters for travel demand reduction ..... 127
Appendices
Appendix A. Outline of semi-structured interviews ..... 129
Appendix B. Limited spatial variability of gas prices. ..... 132
Appendix C: Regression Conditions for Inference ..... 134
Appendix D. Lack of spatial autocorrelation of residuals ..... 141
Appendix E. Multicollinearity test of my regressors ..... 143
Appendix F: Hierarchical Linear Modeling (HLM) ..... 144
References. ..... 146

## Chapter 1: Introduction

## Reducing transportation emissions

This thesis explores the possibility of reducing transportation emissions by reducing the growth of demand for travel in the United States light-duty vehicle fleet - the vehicles used as passenger cars weighing less than 8,500 pounds. It is an attempt to synthesize lessons from the vast literature that has been generated on policies aimed at reducing transportation demand in order to cut emissions. How much of a role can travel demand reduction play relative to the improvement of vehicle efficiency and the transformation of vehicle energy supply? To get at this question, we must understand the likely options that will be available to individual members of society as well as the psychological underpinning of intentions, motivations, and behaviors. Furthermore, the impact of demand-reducing policies may not be linearly additive, as some policies rely on each other to achieve maximal impact.

Energy consumption and emissions from transportation have been extensively studied for decades and have escalated to the top of the national agenda during crises such as the 1973 and 1979 oil embargos and the rapid increase in prices in the mid-2000s. However, transportation emissions have continued to rise faster than any other emitting sector (Cambridge Systematics, 2009). As of 2012, transportation was responsible for $28 \%$ of United States greenhouse gas (GHG) emissions (U.S. EPA, 2012), having accounted for nearly one half of the increase in U.S. GHG emissions since 1990 (Cambridge Systematics, 2009).

An increasingly common goal for municipalities and states is to reduce GHG emissions by $80 \%$ from 1990 or 2005 levels by 2050 (for instance, Massachusetts, California, and New York City have all adopted such goals). If the transportation sector is to achieve a proportional share of these emissions reductions, technology improvements and fuel switching alone will not suffice (Bastani et al, 2012; Heywood, 2015). Two other behavioral factors can also contribute: 1) reduced mileage driven, and 2) more energy efficient driving techniques such as slower acceleration and slower top speeds on the highway. The degree to which improvements in these factors can be realized depends on the amount of motivation and behavioral control individual drivers have, as well as the feasibility of alternatives to single occupancy vehicle travel.

This thesis will explore these questions by reviewing the literature on the impact of policies aiming to reduce travel demand, by conducting behavioral interviews, and by exploring a rich dataset that documents driver behavior in Massachusetts from 2008 to 2011. While the primary focus will be on emissions, it will also touch upon the differential effects of pricing policies on different populations by their income, by their urban/suburban/rural location, and by their fuel economy, since understanding these effects will be important to designing a politically palatable program. Chapter 3 reviews literature on the impact of urban form on the amount of driving people do. Chapter 4 focuses on economic forces and incentives that can modulate travel demand by reviewing the literature on gasoline price elasticity and the impact of the total generalized cost of vehicular travel. To follow this literature synthesis,

Chapter 5 presents data collected during a series of behavioral interviews on what dictates individuals' travel demand. Finally, Chapters 6-7 add to the literature on the impact of gasoline prices on travel demand by exploring variation in driving across different communities in Massachusetts, using a new detailed vehicle odometer dataset.

A helpful simple model of greenhouse gas emissions from light-duty vehicles can be illustrated as:


The first term represents the amount of travel demand in the economy, measured as the sum of the fulfilled needs and desires for transportation of each member of the population, while the second term represents the amount of vehicle miles required in order to fulfill those needs. Vehicle miles per person mile is influenced both by the percentage of trips taken by motorized vehicle and the occupancy of those vehicles. The third term represents the impact of improvements in the combined vehicle and fuel system, and has both a behavioral and technological component. The final term reflects the well-towheels GHG intensity of the fuel or energy source used. John Heywood has outlined these categories of action with the useful shorthand of "conserve, improve, and transform" (Heywood, 2015).

Many climate scientists and advocates support a policy goal of reducing GHG emissions across the entire economy by $80 \%$ by 2050 from a recent baseline (some use 1990, others use 2005). If this is to be achieved, society must achieve significant progress in each of the three broad categories outlined above. None of the three categories alone is projected to achieve anything near an $80 \%$ reduction in transportation emissions in the next thirty-five years. Yet added together, the effects of conserving, improving fuel economy, and transforming the energy supply can have significant benefits.

## Uniqueness of the contemporary context in travel demand

The current moment in history is a particularly interesting time to be evaluating travel demand policy due to the unique trends in travel demand in the past decade. Since the invention of the automobile, annual United States vehicular travel demand, measured in vehicle miles traveled per year, or VMT, has steadily increased. There have only been a few brief pauses to this growth due to World War II and the Arab Oil Embargo. However, starting in mid-2004, per capita VMT began to decline in the U.S., reaching a low about $9 \%$ below its peak by mid-2012 (Pickrell and Pace, 2013). Total VMT began to decline in mid2007 and it has only rebounded to its peak in January 2015, seven and a half years later (FHWA, 2015), despite the fact that population grew $5.6 \%$ during this period (American FactFinder, 2015). Furthermore, VMT growth has been decoupled from GDP growth for the first time ever observed (Ecola and Wachs, 2012). Sustained reduction in VMT per capita has led to much speculation about potentially durable
changes to travel demand - the debt burden of millennials and the delaying of home and vehicle purchases in this cohort, the slowing pace of suburbanization, the increased costs of owning a vehicle, and the reduction of the percentage of the population holding jobs (Pickrell and Pace, 2013).

Similar phenomena have been observed in many other developed countries. David Metz argues that growth in distance traveled per capita in Britain was fueled by increasing travel speeds facilitated by increased saturation of automobile ownership in the population, but it has come to a stop in recent years due to what he refers to as the saturation of travel demand (Metz 2010). This has happened in a time when congestion has not been increasing, and the flattening of growth preceded the increase in gas prices of the mid-2000s and the global economic downturn of 2008, leaving few alternative explanations for the cessation of VMT growth. In a follow-up paper, he shows that despite significant population growth in London since the 1990s, the number of car trips in the city and the number of VMT have both stayed steady, representing a drop in the share of journeys completed by car from $50 \%$ in 1993 to 38\% in 2011 (Metz, 2013).

Metz explains these trends by arguing that while mobility-based access to goods and services increases with the square of the speed of travel, there is decreasing marginal utility for each additional option for a given good or service that can be reached by longer travel distances once a certain level of choice is achieved. Citing data from Britain's national travel survey, he demonstrates that shopping is the most common trip purpose cited by travelers. He argues that since $80 \%$ of the urban population has access to three or more large stores within a 15-minute drive, there is more likely to be a satisfactory option for most of the population within a given distance (Metz, 2010). Furthermore, he illustrates that $80 \%$ of new development in Britain is now on brownfield land, as a result of government policy and local opposition to the development of greenfields (Metz, 2013). This last point offers a glimmer of hope, as many of the projections that have been done on the impact of land use policy have assumed that a very high percentage of new development must be mixed-use infill development in compact, walkable, and transit-friendly neighborhoods in order to make a sizable dent in GHG emissions (Cambridge Systematics, 2009).

Cities have also demonstrated this trend towards a cessation of travel growth. My analysis of publicly available Federal Highway Administration (FHWA) data on VMT per capita shows that between the early 2000s and the period from 2008 to 2010, over twice as many of the U.S. biggest metropolitan areas experienced a decrease in VMT per capita than experienced an increase. Particularly in transit-rich settings, policies and behaviors have resulted in development without an increase in traffic volume. One notable example, Kendall Square in Cambridge, MA, experienced a $38 \%$ increase in building square footage between 2000 and 2010, while automobile traffic dropped by $14 \%$ (Ferrentino, 2013).

## Links between VMT and economic growth

Transportation can be linked to the economy in two main ways - through its impact on production and its impact on consumption (Pozdena, 2009), where the former refers to transportation as an input to production, and the latter refers to transportation as a way to fulfill individual needs. It is well known that VMT has tracked economic growth over the course of the $20^{\text {th }}$ century (see Figure 1 ), though
research has not reached a clear consensus as to whether 1) VMT increases cause GDP increases, 2) GDP increases cause VMT increases, 3) the effect is bi-directional, or 4) the measures are correlated but not causally related (Ecola and Wachs, 2012). In a study modeling VMT and GDP along with personal income from 1982 to 2009, Nathan Eckstein found each of these outcomes in different sets of cities. In nearly $80 \%$ of the cities he studied, however, he found that there was no evidence of a causal connection between VMT and GDP (ibid.). This finding has optimistic implications - he interprets these results as evidence that VMT reduction policies may not result in significant drops in GDP.

Figure 1. Total VMT (automobile plus truck) and GDP. Reproduced from: Ecola and Wachs, 2012.


## Anticipated future trends affecting travel demand

The past several years have hinted at several major shifts in the way the public travels, and the potential for significant change in the near future. These trends are too numerous to address in detail, but no exploration of travel demand would be complete without mentioning their potential impact. In the face of expected demographic and social trends, how much can policy bend the trajectory of land use patterns and travel patterns? Can public policy on land use and transportation manipulate the choice set to make low vehicular travel lifestyles more appealing? Or will culture prevail over policy and can policy only serve a reactive role?

## Transportation as a service

There has been a shift towards transportation as a service that can reduce the need for individuals to own a car or even drive at all in order to access goods and services. Membership in car sharing systems has grown about fourteen-fold between 2006 and 2014 (Shaheen, 2015), complementing more
traditional car rental options and reducing the number of cars on the road in cities with car sharing systems ${ }^{1}$. Transportation-on-demand services like Uber and Bridj are becoming increasingly costeffective, and are providing compelling alternatives to taxis and car-sharing companies alike. The ripple effects of transportation-on-demand services have not yet been well-studied but some obvious potential impacts include 1) the opening of vehicular travel to more people who do not have licenses, personal vehicles, or even the ability to drive, 2) increased feasibility for urban car owners to opt out of car ownership and save money on insurance, parking, and maintenance, 3) an incentive for more urban residents to own cars and make money by driving for services like Uber, 4) reduced parking demand, and 5) erosion of political support for public transit among the more affluent users of the transit system (Buchanan, 2015). With reduced car ownership, more of the costs of driving are shifted towards marginal cost, rather than fixed cost, increasing the likelihood that people will factor in the cost when they decide whether to take specific trips in vehicles.

Similarly, the growth of online shopping may reduce needs to go out to specialized stores to buy products. The effect may be a shift of mileage from light-duty vehicles (LDVs) to freight, and the net impact will depend on how well-optimized logistics become, as well as parameters such as how common "just-in-time" ordering becomes, and how much high-speed delivery services take off (such as Amazon's one-hour deliveries). Furthermore, the impact of reduced shopping VMT may include a rebound in other trips, as time is freed for other activities.

## Changing vehicle technologies

Two technology factors seem most likely to substantially impact travel demand - fuel economy and automation. At first glance, both factors seem likely to encourage greater VMT. Although it is small in magnitude, the rebound effect has been well-studied. Particularly for some groups within the population, an increase in fuel economy has led to a small increase in the amount of mileage a vehicle owner might drive. Automated vehicles remain a big unknown. Regardless of how quickly society progresses along the spectrum towards full automation, the impacts are likely to be similar. Many people expect the convenience of features like adaptive cruise control, lane change assistance, and automatic parking, to name just a few, will make travel time more enjoyable, either by increasing the amount of attention that can be applied to other productive activities or by reducing stress for drivers who are uneasy driving. On the other hand, automation may make driving less enjoyable for drivers who enjoy the act of driving and the feeling of being in total control. Researchers have begun to evaluate the potential impact of shared autonomous vehicles on VMT and travel behavior. For instance, Fagnant and Kockelman use an agent-based modeling approach to show that in a hypothetical gridded city roughly the size of Austin, Texas, shared autonomous vehicles could support ten times as many travelers per vehicle as personally owned vehicles do, and simply from relocation of autonomous vehicles to serve the next traveler, VMT would need to be 11\% higher (2014). However, their model does not address the much bigger question of induced demand, nor does it address the fact that this scheme would shift travel costs from the fixed cost side to the marginal cost side, incenting conservation.

[^0]
## Slowing population growth and aging population

The growth rate of the U.S. population is projected to fall by a factor of two between 2015 and 2050 (U.S. Census Bureau, 2014). Nonetheless, the integrated effect of annual growth will lead to a substantial increase in the total population by 2050, which will make efforts to reduce emissions all the more challenging. For the effect on VMT, it matters where this population growth is concentrated geographically, whether in location efficient places or highly dispersed locations that induce large amounts of travel. The demographic characteristics of the population, such as the age structure, race, incomes, and household structures may also play a role.

## Population growth

By 2050, the U.S. population will have grown by $24 \%$, from today's 321 million to 398 million in 2050 (US Census Bureau, 2014). Despite the large amount of attention placed on immigration policy, the bureau projects that over $60 \%$ of the growth of the population between now and 2050 will still be from the native-born population. By 2050, the Census projects that natural population growth will bottom out around $0.35 \%$ per year and the foreign born population growth rate will decline to under $1 \%$, resulting in a total population growth rate of $0.45 \%$. A non-trivial annual decrease in VMT per capita will need to be sustained in order to simply hold the total LDV travel demand in the U.S. constant, let along reduce total demand.

This challenge is exacerbated by the fact that as cities grow, the average distance between any given origin-destination pair is likely to grow (due to the limited rate of development of infill and limited amount of infill space available), even with aggressive smart growth policies ${ }^{2}$. A recent effort by MIT researchers to model VMT in the Boston region in the context of an expected growth of $20 \%$ in the number of households in the region. They showed that VMT per household increased by 2030 even in a scenario of aggressive smart growth policies (Ferreira et al, 2013). They found that the smart growth scenario reduced VMT per household by up to $15 \%$ relative to a scenario with a more status quo land use policy that allowed more sprawl development, but this reduction was not enough to reduce VMT per household from baseline levels, let alone reduce total VMT.

Age structure of the population and labor force participation
As shown in Figures 2 and 3 , the age structure of the population is projected to significantly shift towards the older end of the spectrum. The natural birthrate is projected to decline significantly, and as healthcare improves, the total population over age 65 is expected to nearly double (U.S. Census Bureau, 2014). The age structure of the population matters because there are remarkable differences in the average mileage traveled by people of different age groups, differences which have persisted since the National Household Transportation Survey was first administered in 2009 (Pickrell and Pace, 2013). Recent evidence has pointed to the increase in driving among older adults and the significant reduction in miles traveled per year by teenagers (ibid).

[^1]Figure 2. Projected population growth by age range. Data source: U.S. Census Bureau.

| Age <br> range | Population <br> (x1000) |  | \% <br> increase |
| :--- | ---: | ---: | ---: |
|  | $\mathbf{2 0 1 5}$ | $\mathbf{2 0 5 0}$ |  |
| $0-4$ | 19,965 | 22,147 | $11 \%$ |
| $5-13$ | 36,874 | 39,887 | $8 \%$ |
| $14-17$ | 16,796 | 17,854 | $6 \%$ |
| $18-24$ | 31,214 | 32,717 | $5 \%$ |
| $25-44$ | 84,657 | 99,653 | $18 \%$ |
| $45-64$ | 84,032 | 98,074 | $17 \%$ |
| $65-84$ | 41,526 | 69,024 | $66 \%$ |
| $85-99$ | 6,232 | 18,585 | $198 \%$ |
| $100+$ | 72 | 387 | $438 \%$ |
|  |  |  |  |
| Total | 321,369 | 398,328 | $24 \%$ |

Figure 3. Anticipated population distribution in 2050 vs current age structure. Data source: U.S. Census Bureau.

## Projected age structure of the US population



The decline in the percentage of the population that is of prime working age may be coupled with a declining rate of labor force participation, which is associated to some degree with the gradual retirement of the Baby Boom generation. This will tend to reduce the importance of the commute as a percentage of total VMT. Aaronson et al project that labor force participation will continue to decline over the next decade, due to the aging of the population as well as the increase in the percentage of adults 16-24 years old in school or college, driven by the need for more education to compete in an economy where low-wage jobs are less plentiful (Aaronson et al, 2014). They demonstrate that the percentage of 16-18 year olds in school has risen steadily from around 65\% in the mid-1980s to over $80 \%$ in 2012 (ibid.). Over the same time, they show school enrollment of 19-24 year olds rising from the low $30 \%$ range to the upper $40 \%$ range (ibid.). This may result in lower travel demand if most the new
students are at urban campuses and not commuting, but if the new students are mainly at commuter campuses, the difference in travel demand may not be significant.

Increasing income inequality and wealth inequality
It is commonly known that the travel demand of a given household in the U.S. is correlated to that family's degree of affluence. Using 2009 National Household Transportation Survey data from the U.S., Wang and Chen demonstrated that households earning over \$100,000 traveled on average 60\% more miles than households earning less than $\$ 25,000$ (2014). However, this same data shows that the increase in travel demand is not linear - and in fact those households earning between \$75,000 and $\$ 100,000$ traveled more miles per day than those earning over $\$ 100,000$. In a model of determinants of travel demand for populations in each income band, Wang and Chen found that those households earning less than $\$ 25,000$ had a significant price elasticity of VMT, and a high rebound effect of induced demand associated with increased fuel economy (ibid). Thus they suggest that for this quintile of respondents, travel demand is likely not to be saturated. Thus, if poverty is reduced and an increasing share of real income goes to households earning less than $\$ 25,000$ per year, it is likely that more demand may be induced. Todd Litman reviews a number of studies that suggest at very low levels of income, vehicle ownership, fuel consumption and VMT are very sensitive to changes in income, increasing about twice as fast as income (Litman, 2013a). He also finds that studies suggest a saturation of vehicle ownership and usage at higher incomes - above a certain threshold, further increasing household income does not increase VMT (ibid.).

Given the relationship between VMT and income, it is worth assessing trends in income and wealth inequality and projections to the future. By 2010, the share of wealth owned by the top $1 \%$ of the U.S. population had increased to over $35 \%$, after bottoming out around $24 \%$ in the late 1970 s (Berman et al, 2015). However, in a model that extrapolates the savings rate and the fraction of income from labor (versus from investments and income generated by wealth), Berman et al project that the increase in wealth inequality observed over the last three decades is unlikely to continue (ibid).

As wealth has become more unequal, there has also been evidence for a recent trend towards the "suburbanization of poverty" - there are now more poor households living in suburban settings than in urban areas (Crowder, 2014), and the rate of growth of poverty in the suburbs was five times faster than the rate in primary cities (Kneebone and Garr, 2010). This is significant for travel demand because suburban and rural areas tend to require more vehicle travel. If this trend is true, poor households will be much more exposed to future oil price shocks. As some of the most price responsive populations by necessity (Wang and Chen, 2014), the poorest quintile of households may be moving to places where gas price responsiveness comes with increased impacts on livelihoods and opportunities. However, some analysis has begun to question the finding of suburbanization of poverty on methodological grounds. For instance Tim Reardon used more nuanced definitions of predominantly urban and suburban communities to replicate the analysis for the metro Boston area, and found that the definitions used in the original study significantly overstated the trend for that city (Reardon, 2013). This is an area that will require much more work for evaluating the distributional impacts of gas taxation policy.

## How malleable is travel demand?

Given the large number of demographic and technological changes that are shaping the future of travel demand, how much impact can government and private sector action have in reducing demand for single occupancy VMT? What are the factors that affect the aggregate behavior of individuals and groups in the U.S.? A broad range of evidence suggests that drivers are mildly responsive to policies, but that this response is limited by the physical environments people find themselves in, and the rate of change of these physical environments.

Government actors from the federal level all the way down to the municipal level generally have three categories of tools at their disposal: 1) providing or encouraging services that provide alternatives to single occupancy vehicle travel, 2) implementing regulations that reduce or limit demand, and 3) providing incentives to travel differently.

Services that provide alternatives to single occupancy driving include public transit, car sharing, programs to facilitate carpooling or teleworking, and a range of other ideas. Alternatives to driving can also be made feasible by regulatory policies that dictate what sort of development pattern can be pursued (e.g. smart growth versus sprawl), and what the built environment looks like and how it accommodates pedestrians, bikes, and vehicles. These policies have been widely studied, and the literature on their effectiveness is both context-specific and mixed. Reid Ewing and Robert Cervero have published a comprehensive meta-study of the impact of the built environment on travel demand. They conceptualize the impacts of the built environment around the six "D's" - density (of population, jobs, or activities), diversity (of land use), design (of street networks and pedestrian environments), destinations (ease of access to trip attractors), distance to transit (and quality of transit), and demand management strategies (such as parking prices, road capacity, etc). In evaluating how elastic VMT is to each D variable, they find that no one attribute is a magic bullet, and that the impact of each attribute on its own is relatively weak, though the combined effect of all attributes can lead to very much lower VMT within specific communities (Ewing and Cervero, 2010). The literature regarding how VMT responds to the built environment will be discussed in more detail in Chapter 3.

Regulatory strategies are the least significant of these three policy categories for reducing VMT in the US, though they do have significant impact on fuels and fuel economy. These policies include imposing non-motorized zones in central city areas and restricting parking in certain areas to push more travelers to use more energy efficient modes. Other countries such as Mexico and China have famously implemented much more draconian regulatory policies such as the even-odd plate restrictions leading up to the Beijing Olympics and the car license lotteries in several major Chinese cities. In the U.S. the most significant regulatory policies for emissions relate more to specific pollutants and technologies, as well as the average fuel efficiency of the vehicle fleet (e.g. CAFE). Since vehicles tend to become less efficient at speeds greater than typical highway speed limits, speed limits on highways are also a regulatory policy with significant implications for transportation emissions (Cambridge Systematics, 2009).

Finally, as for incentive-based methods of encouraging reduction in travel demand, pricing travel remains the biggest tool discussed. An individual's choice to drive a vehicle imposes costs on other
people - external costs, or externalities - such as increased congestion, reduced safety, increased local pollution and noise, increased GHG emissions, and increased wear and tear on the roads. Individuals who own cars will drive more miles until the cost they perceive of driving an extra mile outweighs the benefit of driving that extra mile. Therefore, if there are externalities, most individuals will drive more mileage than is socially optimal because the total cost to them is lower than the true cost. The classic solution to this common problem is called a Pigouvian tax, which is a tax set at a level which approximates the social cost that is imposed by private consumption, "internalizing" the externality.

Such policies include congestion pricing, gas taxation, VMT fees, and carbon pricing. In the table below, I have listed the externalities that each of these policies could address. The policies are listed in order of increasingly broad scope from left to right, but as the scope broadens the impact on emissions in the transportation sector may be weaker. For instance, with the broadest mechanism of cap and trade, the total emissions reduced may be the highest, but if other sectors are able to reduce emissions at lower cost, the impact on transportation emissions may be lower. This is not a critique of the policy, but it is important to note that such a broad mechanism will likely result in different sectors in the economy contributing unequally, in the name of economic efficiency. Some policy makers have advocated using a VMT fee to replace the gas tax, due to the declining ability of the gas tax to generate revenue in the context of more fuel efficient cars, declining real purchasing power of a fixed fee per gallon, and future increases in vehicle electrification. However, if used as a replacement for the gas tax, a VMT fee does not provide an incentive for higher fuel economy, so it only reduces travel emissions through its impact on mileage driven.

Table 1. Externalities addressed by pricing strategy. $\mathrm{VV}=$ the ostensible focus, $\mathrm{V}=$ ancillary benefits

|  | Congestion <br> pricing | VMT fees | Gas taxation | Carbon pricing | Cap and trade |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Travel time | $\mathrm{V} V$ | V | V | V | V |
| Travel time <br> reliability | V V | V | V | V | V |
| Safety <br> (collision risk) | V | V | V | V | V |
| Local <br> pollution | V | V | VV | V | V |
| Local noise | V | V | V | V | V |
| Climate <br> change |  | V | V | V V | VV |
| Reduced <br> energy <br> security |  | V | V | V | V |
| Road <br> degradation |  | VV | V | V |  |

Much literature has been devoted to price elasticity of gasoline demand and price elasticity of VMT, and a general consensus exists that both are inelastic (a given percentage increase in price will reduce demand by a lower percentage). However, the interaction of policies that provide transportation
alternatives and policies that provide financial incentives not to drive is critically important. If government relies solely on policies that increase the marginal cost of driving, it is up to the private sector to come up with alternatives that reduce the population's exposure to higher driving costs. But if the government simultaneously implements policies that make alternatives to driving more appealing, the price responsiveness of driving may be significantly higher in the populations that benefit from these alternatives.

Whether implemented through increased gas taxation or carbon pricing or a VMT fee, the mechanism for impact is similar: an increase in the marginal cost of driving additional miles. Therefore, I will not discriminate between gas taxes and increases in the gas price that result from carbon taxation or cap and trade programs when I analyze the factors that contribute to higher or lower elasticities in the population. It is enough to know that such Pigouvian taxes will increase the cost of gas through a highly visible policy intervention. Whether due to carbon pricing or gas taxation, the effect on the consumer is likely similar as long as the price increase is the same magnitude.

The degree to which the demand for VMT is inelastic to price changes due to policy interventions, and in what population groups, is a central question of this thesis. The answer to this question will determine how important such Pigouvian taxes might be for reducing greenhouse gas emissions.

# Chapter 2. The Role of Travel Demand in Emissions Reduction Efforts 

## Motivation

If we expect to achieve an $80 \%$ reduction in transportation-related greenhouse gas (GHG) emissions from current levels by 2050, there is a wide consensus that travel demand growth must be reduced in addition to efforts to improve fuel economy and consumption (Cambridge Systematics, 2009; Heywood, 2015; Bastani et al, 2012; Rodier, 2009). Because the topic is so broad, many researchers approach the problem by looking mainly at the technology side, and many others mainly look at the travel demand side. Fewer studies integrate these two sides in a comprehensive way. Assumptions regarding the baseline (e.g. travel demand growth, fuel economy improvement rate, and evolution of the vehicle fleet) and the degree to which interventions will have beneficial effects (e.g. the elasticity of fuel economy and travel demand with respect to both price and policy interventions), are critical in determining the study outcome.

In order to examine how much light-duty vehicle emissions can be reduced, this chapter will evaluate and integrate the conclusions of two studies, one focused on the contribution of travel demand and pricing mechanisms, and the other focused more on the contribution of technology. These studies were selected because of their comprehensiveness in their review of other literature, and their clarity in the most important assumptions that impact their analysis.

Moving Cooler, a study conducted by Cambridge Systematics in 2009, is probably the most comprehensive in explaining by how much travel demand reduction can reduce GHG emissions. It assumes that changes in travel demand growth (and average fuel economy) will be a function of baseline trends modified by factors such as pricing policy, regulations, and policies that actively shape the built environment and travel options. Bastani et al's 2012 study on the range of possible emissions reductions by 2050 and the factors that contribute to uncertainty was the study I picked that showed what could be achieved through improved vehicle fuel economy and the evolution of powertrains and vehicle sizes in the light-duty fleet. She forecasted more ambitious achievements for fuel economy and emissions intensity than Moving Cooler did. Therefore, this chapter analyzes what emissions reductions might be achieved if the more ambitious technology scenarios are coupled with more ambitious travel reduction scenarios.

The results of this analysis showed that the combined impact could reduce emissions approximately $80 \%$, but only in the most optimistic scenarios. Furthermore, the analysis showed that pricing strategies have the potential to reduce VMT much faster than they will increase fuel economy of the whole fleet, and much faster than smart growth, transit expansion, or other policy interventions can reduce emissions. However, it quickly became clear that the contributions from reducing travel demand growth were quite sensitive to assumptions about price elasticity. This observation was the primary reason that I turned my attention to price elasticity of travel demand for the bulk of this thesis.

## Emissions reductions from travel demand

Moving Cooler presents dozens of strategies to reduce emissions, analyzed both individually and as part of policy bundles. Table 2 displays my summary of their top strategies, ranked by amount of GHG reduced annually at "maximum deployment" in the year 2050. The strategies in the table cannot be added up directly because of interactions between them, but nonetheless they do show the relative scale of the impact of each strategy. A few of them seem highly unlikely to happen together, such as carbon pricing and VMT fees, since both have similar purposes and effects and both would be highly visible new taxes. And some of the policies seem likely to provide support to each other, for instance carbon pricing and smart growth land use and other non-motorized strategies, since carbon pricing motivates drivers to find ways to reduce their exposure to gas costs. The reductions estimated here can be taken as upper bounds according to the authors' judgment, since the actions required to achieve these reductions will be controversial and will entail significant changes to livelihoods and daily activity patterns.

Table 2. Annual emissions impact of each strategy in 2050. Adapted from Moving Cooler³.

| Strategy | Reduction in GHG emissions in 2050 |  | Description |
| :---: | :---: | :---: | :---: |
|  | mmt/year | $\%$ of 2010 LDV emissions |  |
| Pricing |  |  |  |
| Carbon pricing (VMT impact + MPG impact) | $132+325$ | 8.1\% + 20.0\% | Increase fuel taxes by $\$ 2.71 /$ gallon, indexed to fuel economy to maintain a cost of $\$ 0.12 / \mathrm{mile}$ on average |
| VMT fee | 90 | 5.5\% | Impose a fee of $\$ 0.12 /$ mile |
| Pay-as-you-drive insurance | 59 | 3.6\% | Convert 75\% of insurance policies to PAYD |
| Congestion pricing | 39 | 2.4\% | $\$ 0.65 /$ mile fee during congested timeframes in CBDs and major retail or employment centers |
| Land Use, Smart Growth, \& Nonmotorized Strategies |  |  |  |
| Land Use | 73 | 4.5\% | Put $90 \%$ of new development in compact ped/bike/transitfriendly neighborhoods |
| Urban transit expansion | 26 | 1.6\% | Expand service enough to grow ridership 4.67\% per year |
| Transit frequency and quality | 18 | 1.1\% | Boost transit travel speeds by $30 \%$ and reliability by $40 \%$, implement bus rapid transit features. |
| Pedestrian | 6 | 0.4\% | Complete streets policies to make walking more appealing (traffic calming, better sidewalks) |
| Bicycle | 6 | 0.4\% | Bike lanes at $1 / 4$ mile intervals in dense regions |
| Other |  |  |  |
| Speed limit reduction | 72 | 4.4\% | 55 mph for LDV and HDV ; more enforcement |
| Eco-driving education | 65 | 4.0\% | Educate $55 \%$ of the driving population |
| Employer-based commute strategies | 31 | 1.9\% | Compressed work weeks ; tax commercial parking ; subsidize transit passes; offer more vanpools |
| Urban parking restrictions | 18 | 1.1\% | Freeze the construction of new parking facilities in cities |

Their most striking finding is that a reduction in emissions equivalent to $22.9 \%$ of total light-duty vehicle (LDV) emissions could be achieved within 5 years of the implementation of a carbon tax. Reduced VMT and higher fuel economy would be the primary mechanisms through which the carbon tax would work. It is also worth noting that no other strategy comes close to the impact of the carbon tax or gas tax,

[^2]mainly because the other pricing mechanisms only provide motivation to reduce VMT, not to also improve fuel economy. Nonetheless, taken together this list of strategies shows that non-pricing strategies also have the potential to significantly reduce emissions (by over 350 million tons per year).

## Scope, Scale, and Timeframe

Three characteristics of policy tools are particularly important for understanding their impact on long term GHG emissions - their scope, their scale, and their implementation timeframe. By scope, I refer to the types of travel and geographic settings that the policy can apply to. By scale, I refer to the total amount of GHG emissions that can be averted. And by timeframe, I refer to the relative speed with which they ramp up to their full impact. Cambridge Systematics divides the policy tools they review in the Moving Cooler report into the following categories - 1) pricing, 2) land use and smart growth, 3) non-motorized transportation, 4) public transportation, 5) HOV/carpool /vanpool/commute, 6) regulatory measures, 7) system operations, and 8) bottleneck relief. These tools vary significantly in their scale and timeframe.

Table 3. Moving Cooler strategies and their timeframe, scale (including additional policy tools not listed in Table 3), and scope.

|  | Timeframe | Scale (in 2050) | Scope |
| :--- | :--- | :--- | :--- |
| Pricing | Years | Up to 653mmt/yr <br> (million metric <br> tons/year) | All personal vehicle travel |
| Land use | Decades | $73 \mathrm{mmt} / \mathrm{yr}$ | Routine travel, not vacation travel. <br> Geographic scope uncertain. |
| Non-motorized | Years | $12 \mathrm{mmt} / \mathrm{yr}$ | Mainly in dense areas and for low <br> mileage trips. |
| Public <br> transportation | Decades | $45 \mathrm{mmt} / \mathrm{yr}$ | Does not address rural VMT or most <br> suburban VMT |
| Commute | Years | $39 \mathrm{mmt} / \mathrm{yr}$ | Ignores the 72\% of VMT that is not <br> work-related |
| Regulatory <br> measures | Mixed | $90 \mathrm{mmt} / \mathrm{yr}$ | Primarily oriented towards highway <br> travel (reducing speed limit to save <br> gas) |
| System <br> operations (and <br> eco-driving) | Mixed | $100 \mathrm{mmt} / \mathrm{yr}$ | Highway focused |
| Bottleneck relief | Short term GHG <br> savings, long term <br> GHG costs | <0mmt/yr | Travel in congested areas at <br> congested times |

To demonstrate the differing scales and timeframes of a few of the major policy tools, I have plotted the emissions reductions that Moving Cooler projected from smart growth land use, transit expansion, speed limit reductions, and carbon pricing (showing the total impact of carbon pricing - VMT, fuel economy, and shift to different fuels) in Figure 4. I interpolated between the point estimates they provided for GHG reductions in 2020, 2030, and 2050, shown as X's in the figure. It has now been six years since Moving Cooler's projections were made, and several of the strategies have not been implemented as aggressively as the report said they could have been implemented.

Figure 4. Emissions reduction estimates from selected strategies researched in Moving Cooler.
Maximum deployment of strategies to reduce travel demand: GHG emissions reduced per year


Two of the larger early impacts they suggested were pricing strategies and reduced highway speed limits. These policies have not come noticeably closer to realization since the report was published, so I have fit an envelope to the graph to show the uncertainty of the timeline under which they take effect. The authors modeled carbon pricing beginning in 2015, six years after the publication of their report, and assumed that the price would be equivalent to $\$ 2.71 /$ gallon immediately, with no phase-in ${ }^{4}$. While the authors provided no estimates of GHG reductions between 2015 and 2019, it is clear they expected the price to reduce VMT rapidly, since their projection for GHG reduction in 2020 is $80 \%$ of the highest reductions of the carbon tax, which they model in 2030. This is consistent with the literature, in which models have shown that the majority of the impact of increased gas taxes on VMT would be within the first year after the price change (Puller and Greening, 1999). Furthermore, gas prices will motivate fuelconscious driving habits including slower acceleration, lower highway speeds, and better maintenance,

[^3]and these effects need not require a long time before drivers adapt. As will be explained in Chapter 4, the literature shows that the effect of a gas price increase that is due to taxes is much more salient than an increase due to commodity price fluctuations. Therefore a carbon tax or higher gas tax can be expected to have a pronounced and immediate effect.

Another reason that the carbon price would have such a rapid effect is that its scope would encompass all miles driven by households that pay for their own gas consumption and that it would likely be implemented at a national level, not just in certain cities or regions. Similarly, a reduced highway speed limit could be implemented all at once, nationwide, and therefore its impact could be achieved quickly, if it ever gained political feasibility. In contrast, each metro area would need to implement smart growth land use strategies independently and the rate of building turnover is already quite slow. Likewise, urban transit expansion would be the responsibility of each city or metro region and would require years of planning and implementation. Undoubtedly, some metro areas will take much longer than others to create effective policies that reduce unnecessary vehicle travel.

Regarding the long term impact of carbon pricing, after the first phase of rapid behavioral response, carbon pricing would continue to influence more and more long-term decisions. Therefore, Moving Cooler shows its impact increasing for at least 15 years after the policy takes effect - due to households picking places to live, work, and take care of their needs that are closer together.

## Timing and degree of permanence

## Inertial changes in the building stock

Moving Cooler defined smart growth as efforts to get more real estate developers to create or build upon compact neighborhoods that incorporate a mix of complementary uses such as residences, jobs, and retail area, reducing the average length of trips for residents and reducing the need to use a car. (I will refer to this definition throughout this thesis.) Their maximum effort scenario suggests that $90 \%$ of new development can occur in neighborhoods that adhere to smart growth principles by 2050, through the application of policies such as growth boundaries, minimum targets for the percentage of development that is multifamily, zoning that supports increased population density and transit-oriented development, and funding for incentives and implementation of smart growth.

While it is tempting to look at a graph like Figure 4 and conclude that land use and smart growth efforts are an inconsequential part of the solution due to the long time before they achieve noticeable results, it is important to note the inertia associated with the building stock and land use patterns. Given that buildings that are built today last for decades and new construction will only add a few percent to the building stock at most in any given year, the land use decisions that we make today have an impact for many more decades. One analysis indicates that the buildings built between 2007 and 2050 will account for over two-thirds of the building square footage that is standing in 2050 (Urban Land Institute, 2007). Thus for the same reason that they take so long to have a beneficial effect on GHG emissions, their effect is not easily undone, since it would also take decades to build so many new buildings in a sprawling manner. By contrast, other strategies like carbon pricing are vulnerable to political pressure
and legal and legislative action ${ }^{5}$. Therefore, the $73 \mathrm{mmt} /$ year achieved through smart growth policy by 2050 represents a significant contribution that will continue for several decades hence.

However, as noted in Chapter 1, the incentives to develop cheaper land further from urban cores are a very strong force to be reckoned with - in order to be most effective, smart growth land use will need other supportive policies in the short term (for instance, carbon pricing and changes in zoning practices).

Lower fuel intensity and GHG intensity per mile over time
Over time, as the GHG intensity of a given VMT declines, the impact of policies that reduce VMT becomes moderately less important. Most projections show that fuel economy will improve significantly and lower emissions fuels (e.g. clean electricity) will be more commonly used in the future. This means the longer it takes to implement any given VMT reduction strategy, the lower the effect on emissions.

Moving Cooler assumes that fuel economy increases by $1.9 \%$ each year in its reference case. This effect counterbalances the higher reductions in VMT that are achieved by some of these strategies over time. By 2050, Moving Cooler projects that annual VMT-related emissions reductions from carbon price and other pricing mechanisms would be slightly lower than in 2030. If the authors had not accounted for this, the reductions from each VMT-related strategy would look quite a bit higher in 2050.

## Combining travel demand reductions and technology improvements

While Moving Cooler provides much detail on policies that reduce VMT, it includes only a cursory evaluation of the potential for technology to reduce emissions. Bastani et al (2012) provide a much more detailed study that shows a baseline scenario plus a range of scenarios on either side of the baseline. Bastani forecasts the well to wheels emissions of the U.S. vehicle fleet decreasing from 1628 mmt /year in 2010 to around 850 mmt year in 2050, a $48 \%$ reduction in emissions, with a standard deviation of 230 mmt /year in 2050 between her model runs. This highlights the tremendous uncertainty associated with unknown future trends in VMT, technology improvements, fleet turnover, vehicle types, and more. Nonetheless, it is worth noting that Bastani's mean model run projects significant VMT growth even within the scenario that yields a $48 \%$ reduction in emissions. Therefore, it would be interesting to look at the emissions reduction that could be achieved in Bastani's model with the ambitious VMT growth reductions proposed in Moving Cooler.

VMT growth and the potential to curtail it
In order to combine the travel demand GHG reductions from Moving Cooler with Bastani's GHG reductions from technology improvement, I first investigated some of the underlying assumptions in each model, starting with VMT growth. In the time since Moving Cooler and Bastani et al's paper were published, projections for VMT growth have dropped significantly (Figure 5). After years of projecting relatively rapid growth in VMT, the Federal Highway Administration (FHWA) revised their VMT growth projections significantly downward in 2015. The May 2015 FHWA report suggests that over the 30 years between 2013 and 2043, VMT will grow by $0.6 \%$ per year. Adhering to projections provided by the Annual Energy Outlook and the FHWA at the time, both Bastani et al and Moving Cooler modeled VMT

[^4]growing at 1.4\% per year for the first decade in their baseline scenarios (and the latter study used this rate all the way through 2050). Bastani et al's model separately projects growth in the number of cars (mean scenario of roughly $0.8 \%$ growth per year net of scrappage), and growth in the VMT per vehicle per year ( $0.5 \%$ per year through 2020, then $0.25 \%$ per year through 2030, then none). In Figure 5 , I used her "mean" scenario to calculate the overall growth in VMT she assumed.

Figure 5. VMT growth assumptions.

# LDV VMT growth under new FHWA assumptions versus Moving Cooler and Bastani's assumptions 

| 5000000 | - |
| :---: | :---: |
| 4500000 |  |
| 4000000 | , |
| 3500000 | $\bigcirc$ |
| กิ 3000000 |  |
| $\overline{\overline{\mathcal{E}}} 2500000$ | $\qquad$ Moving Cooler original assumption, 1.4\% Growth |
| $\sum 2000000$ | - FHWA 2015 projection, $0.60 \%$ |
| 1500000 | __Bastani's model |

1000000

500000

0


Figure 5 shows that in the Moving Cooler baseline, VMT increases by $73 \%$ by 2050. This provides a sharp reminder that when we talk about VMT reductions, in most cases we are talking about reductions from a growing baseline, rather than absolute reductions from current levels. Table 4 shows that if the projections in Moving Cooler are correct, policies would need to reduce VMT more than $40 \%$ from the 2050 baseline scenario to avoid growth in VMT.

How much could growth in VMT be reduced? Moving Cooler doesn't report the amount by which they expect each policy would reduce VMT, opting instead to present the total GHG reductions associated with each policy they analyze, which also includes the effect of improved fuel economy. However, two other reports have made some calculations on how much VMT might be reduced relative to a baseline through various policy tools: Growing Cooler and Caroline Rodier's meta-study of travel demand models.

Growing Cooler, a similar type of research report to Moving Cooler, does not weigh in on the potential for pricing strategies to reduce VMT. However, the report does estimate that smart growth policies applied extremely aggressively could reduce light-duty VMT in urban areas by $12-18 \%$ relative to what
would result without smart growth policies. If their assumptions are similar to the ones in Moving Cooler, it is likely that the impact of pricing strategies may be significantly more than the impact of smart growth. Moving Cooler's 2050 GHG reduction projections assert that the impact of carbon pricing on VMT would be $80 \%$ greater than the impact of smart growth on VMT. However, the effect of smart growth and carbon pricing is difficult to disentwine, since part of how carbon pricing would reduce VMT is by making dense development more cost-competitive when factoring in transportation costs.

Caroline Rodier reviewed 40 studies that assess the impact of various types of policies on VMT (2009). She found that, of the 9 studies that addressed implementing VMT pricing (at levels ranging from $\$ 0.02 / \mathrm{mile}$ to $\$ 0.10 / \mathrm{mile}$ ), the median result was an $11.1 \%$ reduction in VMT from pricing alone (Rodier, 2009). However, most of these studies were evaluating pricing levels significantly less than the $\$ 0.12$ /mile proposed in Moving Cooler. Therefore, a commensurately higher reduction in VMT resulting from higher pricing does not seem unreasonable. Rodier also found that among the five studies that assessed the impact of combined pricing strategies (most of which included some form of per-mile charge, increased parking costs, and congestion pricing), the median result was a $16.6 \%$ reduction in VMT. Finally, when assessing six studies that looked at the combined impact of aggressive smart growth, transit, and pricing policies, she found that the median study projected a $24.1 \%$ reduction in VMT in response to the bundle of policies.

Thus, it is clear that most studies show that reducing VMT by more than $20-30 \%$ would require dramatic efforts to realign incentives towards specific development patterns and travel choices that result in lower emissions. In the face of a slowly increasing population and average travel distances potentially increasing (recall Ferreira, 2013), it is unlikely that a reduction of 20-30\% in VMT from "business as usual" trends would result in an overall decrease in VMT in 2050. This does not negate the fact that travel demand reduction strategies can result in substantial emissions reductions, rather it illustrates the scale of the challenge of containing transportation emissions in the face of steady population growth.

Table 4. Total growth in VMT by 2050 under different VMT reduction scenarios.

|  | Moving Cooler's 1.4\% <br> VMT growth rate | New FHWA 0.6\% <br> VMT growth rate | Bastani et <br> al's model |
| :--- | :---: | :---: | :---: |
| Baseline VMT increase | $73 \%$ | $27 \%$ | $53 \%$ |
| 10\% reduction in VMT due to policies | $56 \%$ | $15 \%$ | $38 \%$ |
| 20\% reduction in VMT due to policies | $39 \%$ | $2 \%$ | $23 \%$ |
| 30\% reduction in VMT due to policies | $21 \%$ | $-11 \%$ | $7 \%$ |
| 40\% reduction in VMT due to policies | $4 \%$ | $-24 \%$ | $-8 \%$ |

As discussed in Chapter 1, some policy researchers have been proclaiming that VMT per capita has likely peaked in this country. Given the uncertainty with which future transportation alternatives and technological advancements will play out, I would tend to reserve my judgment. However, if they are right, it is worth noting that the $24 \%$ increase in population would lead to a $24 \%$ increase in VMT in the absence of strong policy intervention, and that Rodier's meta-study suggests that reducing VMT by 20$30 \%$ is commonly seen as achievable with aggressive policies. Therefore, if VMT per capita has ceased to
grow naturally, policies that reduce VMT per capita could hold total VMT at the same level as today, all the way through 2050.

Before I can synthesize the effects of highly optimistic fuel economy improvement (from Bastani et al) and the effects of highly optimistic VMT reduction (from Moving Cooler), the take-home point is that Moving Cooler has estimated a baseline VMT growth that is significantly larger than Bastani's baseline (refer back to Figure 5). Since their baseline VMT forecast is so much higher than Bastani's, their analysis of policy tools likely overstates the amount of VMT reduction possible. Therefore, in order to bring Moving Cooler's travel demand reductions into Bastani's projections, even in a qualitative way, I will need to scale them down, as will be discussed below.

## Fuel consumption and fuel economy

Another big assumption that differs between Bastani's analysis and Moving Cooler is how rapidly the GHG intensity of VMT will decrease. Moving Cooler subsumes changes in the fleet composition and emissions intensities of fuels into its overall fuel economy projections. Bastani et al explicitly model energy consumption improvements for each segment of the market by vehicle type (car, SUV, or other light truck) and by drivetrain (hybrids, electric vehicles, etc.). Bastani et al then weight each segment of the market by market share. The end result of Bastani's analysis shows a reduction in the overall fleet GHG intensity per VMT of 66\% between 2009 and 2050 in their baseline model (my own calculation). This includes the effect of a shift away from larger vehicle types and a shift towards lower emission drive train types like hybrids and electric cars.

## Combined impact

Conveniently, Moving Cooler models the VMT effect of carbon pricing separately from the fuel economy effects. This allowed me to take Bastani et al's assumptions on fuel economy and add only the VMT effect of carbon pricing (and other policies) from Moving Cooler. As noted above, the higher VMT forecasted in Moving Cooler's baseline scenario provides a higher base from which any travel reduction can be modeled. To the extent that potential reductions are proportional to total VMT, this may overstate the potential impact. Similarly, since Bastani projects a more optimistic view of the improvement of fuel economy, her GHG per VMT number in 2050 is much lower than that in Moving Cooler, providing another reason why the GHG reduction estimate from Moving Cooler should be scaled down before combining it with Bastani's work.

Thus, I scaled down the impact of each Moving Cooler policy by two ratios: first, by the ratio of Bastani's predicted VMT in 2050 to Moving Cooler's predicted VMT in 2050, and second, by the ratio of Bastani's predicted GHG per VMT in 2050 to Moving Cooler's predicted GHG per VMT in 2050. I then subtracted the emissions saved by each policy from Bastani's mean model run (shown in light blue in Figure 6). If I had not made these adjustments and if I had taken Moving Cooler's estimates at face value, I would have projected total emissions of $191 \mathrm{mmt} /$ year in 2050, which is a reduction of $88 \%$ from 2010 emissions, and likely not realistic under any assumptions. The solid orange line shows the impact of all pricing strategies except a VMT fee. This includes carbon pricing (VMT impact only) plus congestion pricing plus higher parking fees plus pay-as-you-drive insurance plus cordon pricing plus increased tolls. I
excluded the VMT fee because it seemed to overlap too much with the carbon price. Carbon pricing is responsible for over $60 \%$ of the total impact of the pricing policies.

After scaling down the impacts, my projection showed emissions as low as 589 mmt /year in 2050, nearly a $64 \%$ reduction from 2010 emissions, and $30 \%$ below Bastani's mean model projection without VMT reduction. Due to the fact that many second-order effects such as induced demand for VMT may result from the higher projected fuel economy of the fleet, I would not take this estimate as a quantitatively robust projection. However, the chart in Figure 6 leads to a few interesting observations.

1) If carbon pricing and the other pricing reforms were implemented and phased in rapidly, they would have an immediate and large impact on total emissions.
2) Several non-pricing measures could be implemented quickly, but their magnitude is not as large as the pricing strategies. These include reduced highway speed limits, education on eco-driving, and employer incentives to reduce single occupancy commute trips.
3) The impact of pricing mechanisms that are based on GHG goes down significantly as the GHG intensity of a mile traveled goes down, and other measures begin to catch up by 2050.
4) The total impact of the strategies proposed in Moving Cooler plus the mean projection of technology improvement from Bastani's analysis is not enough to reduce transportation emissions by $80 \%$ by 2050 . Bastani ran many models stochastically varying her assumptions. If I had instead taken her result that was one standard deviation below her mean simulation, and added the effect of travel demand reduction to this model instead, emissions would have been reduced by $78 \%$ relative to 2010 . Using one of Bastani's lower emissions model runs may make sense because her models do not assume a major force pushing faster technology evolution. The imposition of a significant carbon tax would provide such a force.

Figure 6. VMT reduction layered on top of Bastani et al's GHG projection from the LDV fleet.


As noted earlier in this chapter, the timing of politically challenging initiatives such as carbon pricing, other transportation pricing, and speed limit reduction is highly uncertain, and expecting any of these to occur before 2020 seems highly optimistic. Nonetheless, it is useful to show how quickly pricing strategies could produce emissions reductions, and how the combined effect of technology and travel demand management could significantly reduce emissions.

## Summary

The rapid and large effects of a hypothetical carbon price from Moving Cooler's analysis prompt further exploration of the policy. Will it actually achieve the emissions reductions that the authors suggest? How quickly can the average consumer react to a change in the cost of driving, given the relatively static set of transportation options available to her, and given the long timescale on which people make decisions about vehicle ownership and home ownership?

The report actually uses a relatively conservative assumption for elasticity - a long term VMT elasticity with respect to the total cost per mile of -0.45 and a long term elasticity of fuel economy with respect to fuel price of 0.6 . The -0.45 estimate is roughly equivalent to a gas cost elasticity of VMT in the range of -0.1 to -0.2 . However, as will be discussed in Chapter 4, literature from the early 2000s had suggested that price elasticities of fuel consumption have reached historic lows in recent years, even lower than -0.05 . There are reasons to believe that price elasticities may be rebounding from their historic lows in the early 2000s, including literature from several states from the past few years. Nonetheless, additional data points on recent price elasticities, like the estimate I provide from Massachusetts data in Chapter 7, will be useful to determine whether the analysis in Moving Cooler is conservative enough.

Given the magnitude of the GHG reduction associated with pricing, it is clear that pricing will eventually be part of the solution if we expect to reduce emissions by $80 \%$ by 2050 . The cost of routine transportation needs is already substantial relative to income for many households in the U.S. (Cambridge Systematics, 2009), so proposals that would effectively double the per mile gasoline cost of vehicle transportation could have a significant adverse effect on households at the low end of the income spectrum. This will be particularly true if these costs are not mitigated by reductions in other taxes or even mitigated by rebates. However, if low income families are relatively responsive to gas price and reduce their gas demand accordingly, the financial cost could be lower. For some households, however, cost-effective transportation may be critical for access to jobs and livelihoods. Therefore, understanding the effects of a large increase in gas prices is critically important as the policy becomes more and more urgently needed.

The remainder of this thesis will use several methods to assess the variability of price responsiveness of VMT and the reasons that certain households may be more or less price responsive. The methods will include literature review, semi-structured interviews of a diverse sample of individuals, and assessment of a large dataset to look at revealed behavioral responses to price.

# Chapter 3: Can urban form interventions curtail travel demand growth? 

## Motivation

In order to investigate the effects of price on travel demand in the long term, it is important to review what is known about how the built environment determines households' travel options and how it influences travel demand. This chapter will briefly review historical policies that have resulted in higher personal vehicle travel demand and which may also limit the ability of pricing policies to reduce emissions in the short-term. It will then review the literature on the effect of the built environment on travel demand and the methodological challenges associated with inferring causation. It will conclude with a discussion of how built environment variables may affect the ability of households to reduce their VMT in response to gas price increases.

## How the built environment has affected travel demand in the U.S. since World War II

There can be little doubt that decisions that shape the built environment and the spatial structure of cities play a strong role in determining the path on which their transportation histories unfold. The interrelationship of land development and transportation infrastructure is complex and may play out differently across different scales, in different cultural contexts, and in eras of different technologies. Transportation innovations, from the advent of the streetcar to the invention of the automobile to the paving of roads and interstates, typically fuel the suburbanization process, enabling access to cheaper land and lower rents through higher transportation speeds. The monocentric model of urban spatial structure, as developed by William Alonso in 1964, posits that rents will decline as distance from the city center rises due to rising transportation costs and reduced land scarcity. Households will maximize their utility taking into account both rent and transport costs. This chapter will explore the role of the built environment in shaping households' travel options and behaviors.

In the decades following World War II the predominant pattern of urban expansion in the U.S. has been increasingly low-density growth (Bento et al, 2004). This pattern has paralleled the rapid increase of market saturation of automobiles and increasing reliance on them for daily needs. In contrast to the growth of population in Europe, the growth of the U.S. population has primarily occurred since the automobile became more common. For instance, since 1921, the population of France increased by about $70 \%$, while the population of the U.S. nearly tripled (US Census Bureau, 2014; Institut national de la statistique et des études économiques, 2014). The largest increase in automobile ownership in the U.S. came in the decades after World War II, as vehicle ownership rates went from 222 per 1000 people in 1945, to a high of 824 per 1000 people in 2007 (Transportation Energy Data Book, 2015). Population in metropolitan areas grew significantly between 1950 and 1990 while population of central cities declined by $17 \%$ (Baum-Snow, 2007).

## Policies that have accelerated land consumption and automobile dependence

It is important to pause and consider the forces that have contributed to the dispersion of population and jobs in the U.S. if one is to evaluate the potential for individuals and households to respond to changes in the marginal cost of driving, particularly in the short term. The degree to which the automobile remains the only feasible option for most trips in large portions of our metropolitan areas can be unequivocally linked to the lack of density of people and lack of density of services those people need within close proximity. Transit is doomed to never achieve cost effectiveness without sufficient density, and lack of density makes the distances too great to be conveniently covered by walking and bicycling. Analysis by Peter Newman and Jeff Kenworthy has found that towns must achieve a critical density of at least 35 persons plus jobs per hectare ( $>9,000$ per square mile) to "have any hope of not being totally dependent on the car" (Kenworthy, 2007).

Since low density and a lack of accessibility between land uses are so fundamentally connected to higher travel demand, I will focus here on what policies accelerated land consumption faster than population growth, which is one common definition of the term "sprawl" (Fulton et al, 2001). I will also focus on the policies that have contributed to keeping housing, jobs, commercial and retail spaces, and recreational spaces so well separated, which is another component of sprawl (Ewing and Hamidi, 2014).

There have been many research efforts devoted to explaining what demographic factors, economic factors, and policies have been most important in fueling U.S. sprawl. This section cannot assign relative degrees of causation to the various forces fueling land consumption and the dispersal of population, but I will address very briefly some of the forces that are often cited by scholars in the field.

## Interstate highway system

The 1956 Interstate Highway Act aimed to provide high-speed transportation to connect regions for motorists, free of charge where possible. Justified primarily for economic development, this system added 41,000 miles of interstates over the ensuing decades (Lamer, 2003). The total cost of the system was estimated at $\$ 129$ billion (FHWA, n.d.), of which the federal government paid roughly $90 \%$. The system of funding created a use-it or lose-it mentality in state governments. Faced with the opportunity for a $90 \%$ subsidy of these major transportation assets, almost all states and regions eagerly pursued the money wherever possible unless local opposition was so stiff that they could not proceed.

The pattern of development following the alignment of radial highways is a familiar phenomenon in the US. Nathaniel Baum-Snow models the impact of the number of radial highways that a city has on the total share of the metropolitan population that it retains (Baum-Snow, 2007). He finds that for every additional radial highway that serves a central city, the central city's population share declined by an additional $10 \%$ between 1950 and 1990. Essentially, the highways enabled population migration to suburban municipalities. His estimation is that highways alone are responsible for about one-third of the gap between metropolitan population growth and central city growth. As for the impact of highways on VMT and overall GHG emissions, Mishalani et al (2014) found that the number of freeway lane-miles per
capita was the variable that had the strongest predictive impact on the amount of CO 2 emissions per capita from transportation in urbanized areas of the US.

It must be noted that the association between the interstate system and the decentralization of metropolitan areas is a bit of a "chicken and egg" question (Boarnet and Haughwout, 2000). Just as highways facilitate sprawl, growth that is already occurring may serve as an impetus for highway investment. Combined with income-induced demand for more land and residential space, and combined with "flight from blight" (the informal term for the process by which more affluent city dwellers move away from higher crime urban areas), the highway system may simply have hastened a process that was already inevitable (Mieszkowski and Mills, 1993).

## Federal financial policies encouraging sprawl

The federal government's financial policies after World War II were geared towards promoting the growth of home ownership and providing inexpensive housing options for returning soldiers and their growing families (Lamer, 2003). First, Federal Housing Administration (FHA) loan policies favored purchasing new homes over renting. Second, the home mortgage interest deduction provided an incentive for Americans to buy bigger homes. And third, accelerated depreciation policies encouraged the construction of new buildings in the commercial sector.

FHA loans were responsible for helping Americans purchase an estimated 11 million new homes after World War II, most of which were single-family detached dwelling units (Lamer, 2003). The application of assembly line techniques by Alfred and William Levitt helped more Americans afford these new homes in the famous Levittown neighborhood form. Their reliance on the economies of scale of producing many identical buildings in close proximity led to the model of single-use subdivisions (ibid.).

Although scholars have noted that the mortgage interest deduction has not had resounding success in accomplishing its goal of increasing the proportion of the population that owns its own home (Glaeser and Shapiro, 2003), there is evidence that it has led to increased land consumption for residential purposes. The primary mechanism through which the deduction works is by encouraging people who would already be buying homes to spend more on building their new homes than they would have in the absence of the tax subsidy (Emerson, 2008). Larger homes on larger lots require more space, leading to increased development at the urban fringe (ibid.). The scale of the subsidy currently exceeds $\$ 40$ billion per year (ibid.), and the subsidy reduces the cost of home ownership by about $15 \%$ (Paulsen, 2006). An analogous policy for commercial real estate, the accelerated depreciation deduction was adopted in 1954, accelerating the rate of growth of suburban commercial space at the urban fringe, by creating an incentive to build new instead of retrofit existing space (Emerson, 2008).

## Schools, crime, and racial tension

Another set of factors which may have caused more rapid suburbanization was the fiscal and social problems of central cities in the 1960 s and beyond (Mieszkowski and Mills, 1993). The list of real and perceived problems included racial tensions, crime, blight, and poor public schools, as well as the general poor fiscal health of central cities. This provided incentives for wealthier families to avoid redistributive taxes by self-segregating into communities with wealthier neighbors and stronger
municipal budgets. The more wealthy families moved out, the more the fiscal health of the central city was compromised, which created a reinforcing feedback loop (ibid.). This phenomenon was central to the famous Tiebout model of municipal service provision and competition for households. Tiebout posited that municipalities could optimize their taxation and provision of services to be tailored to the type of residents and businesses they wanted to attract. According to this model, the motivation of the most mobile families to move to places where there was less crime and better schools was a primary reason for the depopulation of central cities.

The magnitude of the influence of this phenomenon is still debated. Mieszkowski and Mills (1993) suggest that the impact of this "flight from blight" is overstated and that suburbanization is a natural process stemming from increased travel speeds. They argue that suburbanization was actually faster from 1920 to 1950 than it was after 1950, and that the former time period was not known for high crime or racial tensions. Whether or not this phenomenon was the primary factor driving suburbanization, most scholars agree that it played a significant role.

## Zoning and leapfrog development

A long history of municipal competition, as described in Tiebout's model, has led to zoning policies that encouraged more sprawling land use. Municipalities have the ultimate power over land use within their jurisdiction. In many cases, they resort to fiscally-motivated zoning in order to maximize their tax base and minimize their expenditures. Common techniques include creating minimum lot sizes so that poorer families cannot move into the town, and the rejection of applications to build multifamily or affordable housing, motivated by the fear that multi-family housing may result in more low-income families with large numbers of kids that would require resources in the schools. The famous Mt . Laurel decisions in New Jersey in 1975 and 1983 set a precedent that judges could compel municipalities to allow development at higher density than their zoning allowed, as long as the builder committed to a sufficient amount of affordable housing. Despite this ruling, most suburban municipalities around the country continue to zone at lower densities than a market equilibrium would dictate (Levine, 2006). Furthermore, exclusionary zoning practices have contributed to a "spatial mismatch" of jobs and housing for low income workers - the scarcity of affordable housing in markets where there are significant amounts of jobs for low income workers results in longer commutes (Ihlanfeldt, 2004).

Another aspect of zoning that has encouraged increased automobile dependence is the near ubiquity of minimum parking requirements. Standards range from one parking space per unit, up to 2.5 spaces per unit (Hoch et al, 1979). Not only does the extra parking take up valuable real estate and land, but it also means that tenants are already paying the cost of storing a car, whether or not they plan to own one. In behavioral economics, this would be considered a sunk cost, which should not motivate a purely rational person to change his or her behavior, but which certainly could encourage more people in transit-rich neighborhoods to still own a car.

Probably the most important way in which zoning has exacerbated travel demand has been in the creation of large single-use areas. The very purpose of zoning as it was originally conceived was to protect "higher uses" from noxious impacts - conceiving of single family residential areas as the most vulnerable and most valuable land uses. And this was the predominant pattern of zoning from the 1920s
until recent decades (Hoch et al, 1979). Of course, recent market trends and planning practice has evolved and mixed use zoning has become more popular in many urban areas, but the cumulative impact of zoning on separating land uses and increasing trip lengths is undeniable.

## Studies that estimate impact of urban form on travel demand

Following decades of federal, state, and local policies that served to accelerate land consumption and suburbanization of housing, practicing planners and academics alike have turned their attention to how to mitigate some of the unanticipated costs of these policies - such as local and global environmental degradation, longer travel times, higher exposure to traffic safety risks, and the loss of productive time from the average traveler's day.

There are two bodies of work related to the impact of urban form on VMT, the models done by Metropolitan Planning Organizations (MPOs) to assess future transportation infrastructure needs and the consequences of travel demand growth, and models done by economists using data to determine causation and correlation between land use policies and outcomes and travel demand. The former is typically highly aggregate and not focused on behavioral factors, instead using traditional 4-step models (trip generation, trip distribution, mode choice, and route assignment), or in some cases using more integrated and iterative models that incorporate feedback between land use and transportation (National Research Council, 2009). The economic literature, on the other hand focuses on establishing the degree of linkage between various built environment variables and various travel behavior metrics.

## Metropolitan Planning Organization (MPO) scenario planning

As described in the Introduction, the U.S. population is expected to increase by $24 \%$ by 2050 . Therefore, policies aiming to curtail travel demand are likely only to offset demand growth rather than reduce the total VMT of the light-duty fleet. MPOs throughout the country are tasked with understanding the implications of population growth in their region and what it will mean for infrastructure needs and overall energy consumption in their region. Therefore, there are many studies available that try to sort out different scenarios of land consumption, population growth, and travel behavior patterns in the long range. The year 2050 is now approaching the long-range planning horizon of many MPOs. Typically, MPO studies simulate scenarios over a 25- or 30-year period (Rodier, 2009), which means that most studies done in the past five years would extend out at least to the 2040s. Some MPOs like the Sacramento Council of Governments have extended their planning horizon as far as 50 years (ibid.).

MPO studies have become more and more sophisticated in recent years. Typically these are integrated land use and transportation models that allow for bi-directional effects between land use, population, and transportation infrastructure. State-level mandates have begun to require some MPOs to integrate not only land use and transportation, but also air quality into their modeling (Waddell, 2011). For instance, California's Senate Bill 375 requires the state's MPOs to develop activity based models that will allow them to assess the impact of new developments or infrastructure projects on GHG emissions (Deakin, 2012). Deakin argues that this regional approach is the best scale for coordination because this is the scale on which labor markets and housing markets operate (ibid.). While MPOs have been given
the mandate to address GHG emissions, they do not have direct control over the land use of their member municipalities, so their ability to achieve these goals may be constrained without cooperation.

## Econometric modeling

Much of the econometric literature on travel demand focuses on how planning interventions can directly reduce vehicle miles traveled, or VMT. Planners, governments, and land developers all influence the built environment in ways that shape the costs and benefits of travel by each travel mode. As explained briefly in Chapter 1, some of the more important variables are famously summarized by Reid Ewing and Robert Cervero as the 6 D's - density (of population and jobs), diversity (of land use), design (of the urban environment), distance to transit, destination accessibility (of all land uses, but particularly jobs), and demand management (policies aimed to reduce the amount of vehicle miles needed to provide access to needed goods and services). Ewing and Cervero's 2010 meta-study summarizes the elasticity of VMT with respect to several variables within each of their 6 D's. In addition to VMT, several other travel metrics have been studied in association with the built environment: trip frequency, trip lengths, and mode choice. In a different meta-study, Ewing and Cervero (2001) found that both trip frequency and mode choice were most strongly related to socioeconomics, and secondarily influenced by the built environment, whereas trip length depended more upon the built environment. Total VMT is of primary interest to this study because it is most directly related to travel emissions, and total VMT will incorporate trip frequency, mode choice, and trip lengths.

The primary finding of Ewing and Cervero's work was that total VMT is quite inelastic with respect to urban form variables. They calculated weighted averages of VMT elasticity estimates with respect to each urban form variable. The vast majority of the studies they evaluated used VMT per household as the metric. Since they did not have data on the standard errors of each study, they weighted the studies based on the sample size used to calculate the elasticity. While this is a commonly used meta-study technique, it precludes the evaluation of the statistical significance of the weighted average result. Of their six D's, they find that destination accessibility has the strongest association with VMT - a location with a higher number of destinations (jobs, etc.) within a given travel time tended to have lower VMT per household. This elasticity was -0.20 , meaning that a $5 \%$ increase in destination accessibility would be associated with a $1 \%$ drop in VMT. As one might expect, they found the effect of distance to downtown to be of a similar magnitude to the effect of destination accessibility. Surprisingly, density of population had only a very weak association with VMT, with an elasticity of only -0.04 , which was smaller in magnitude than the effect of street design and density. Their interpretation of the low elasticity with respect to density is that density is correlated with other variables, so if the studies they evaluated also controlled for centrality of the location (e.g. distance to downtown, or accessibility to destinations), diversity of land use, or short city blocks that encourage walking), these other variables may be explaining more of the variance in VMT. Their summary of elasticities for each variable is provided in Table 5.

Table 5. Weighted average elasticities of VMT with respect to built-environment variables ${ }^{6}$. Reproduced from: Ewing and Cervero, 2010.

|  |  | Total number <br> of studies | Number of studies with <br> controls for self-selection | Weighted average <br> elasticity of VMT $(\boldsymbol{e})$ |
| :--- | :--- | :---: | :---: | :---: |
| Density | Household/population density | 9 | 1 | -0.04 |
| Diversity | Job density | 6 | 1 | 0.00 |
| Design | Land use mix (entropy index) | 10 | 0 | -0.09 |
|  | Jobs-housing balance | 4 | 0 | -0.02 |
| Destination | Intersection/street density | 6 | 0 | -0.12 |
| accessibility | \% 4-way intersections | 3 | 1 | -0.12 |
| Dob accessibility by auto | 5 | 0 | -0.20 |  |
| Distance to transit | Job accessibility by transit | 3 | 0 | -0.05 |
|  | Distance to downtown | 3 | 1 | -0.22 |

In another meta-study, Salon et al (2012) discuss in more detail the role of transit in predicting VMT. They conclude that until this point, the literature has largely ignored the impact of changes in measures of transit quality on VMT and instead focused on the impact of the distance to transit on VMT. These studies suggest that for locations that are relatively close to transit, VMT per household decreases by $1.3 \%$ to $8 \%$ for every mile closer to a station. Measures of transit quality have been evaluated for their impact on transit ridership, but very little has been done to translate that into an impact on VMT. Salon et al caution that the VMT reduction associated with a rise in transit ridership is likely less than one-toone because of induced demand for driving when capacity is freed by those switching to transit, and because new transit trips may be trips that wouldn't have been made at all if transit wasn't available. Paulley et al (2006) evaluate several studies of the cross elasticity of car usage with respect to bus fares, finding very small effects ranging from 0.014 to $0.057^{7}$.

Salon et al (2012) also address the VMT effect of built environment features like sidewalks, bicycle parking, and bike lane density. Similarly to the transit literature, the bulk of the focus has been on the impact of these attributes on bicycling and walking, rather than the impact on VMT. For instance, sidewalk coverage tends to increase the number of walking trips, with an elasticity in the range of 0.09 to 0.27 . However, given the small percentage of trips currently done by bicycling and walking, a large percentage change in these modes may have little impact on overall VMT. The few estimates of this effect in the literature have provided mixed results. Most of these studies do not control for residential self-selection, so this remains a gap in our understanding of the impact of built environment on VMT.

In summary, there remains significant uncertainty as to the magnitude of the effect of the built environment on VMT. For instance, some studies may fail to find any relationship between population density and VMT, while other studies may find elasticities as great as -0.34 (this range was shown in Ewing and Cervero's meta-study, alone). Most studies have shown small effects for any given built

[^5]environment variable. Given the tremendous complexity of urban systems and the difficulty of designing experiments, this is hardly surprising. One important limitation is that finding a linkage between an attribute of the built environment and travel demand is not enough to prove causation. Robust inference of causation includes four types of evidence: correlation, non-spuriousness (the effect is not due to an extraneous variable), time precedence, and a plausible mechanism of causation (Cao et al, 2008). The most challenging aspect is the proof of non-spuriousness and the lack of confounding omitted variables. The next section will address some common challenges in establishing causation and inferring the magnitude of the effect.

## Methodological challenges and limits to generalizability

Scale
Urban phenomena can be modeled at all spatial scales, from the micro level (e.g. neighborhood land use mix, street layout, road capacity), to the meso level (e.g. looking at neighborhoods as nodes of origins and destinations), to the macro level (e.g. metropolitan attributes like the size of the urban area, population, overall infrastructure network). Randall Crane argues that much more work needs to be done to understand the scales at which certain urban form variables have influence - for instance the built environment of small neighborhood settings may be of the appropriate scale to influence walking trips in the vicinity, but it is not clear what effect this will have on longer automobile trips (Crane, 2000). The National Research Council (2009) concluded that commuting trips and trips to major shopping destinations are more likely to be influenced by transit access at the origin and destination, while local trips are more likely to be influenced by neighborhood design and walkability.

## Residential self-selection

Self-selection of household residential locations reminds us that the association between the built environment and travel behavior may not be due to a one-way causal effect. People who are more interested in driving wherever they go may naturally seek to live in less dense areas where congestion is less severe, while people who value active transportation and the ability to access destinations within a short walk may seek locations that enable this lifestyle. Furthermore, urban settings may contain more people who simply don't drive as much - whether because they are poor, young, or older people without children (National Research Council, 2009). With self-selection, researchers don't know whether people whose travel preferences are not consonant with the built environment they live in are more likely to 1) gradually change their preferences, or 2) move to an area more consonant with their preferences (ibid.).

Given that the built environment also undeniably influences the costs and benefits of different travel modes, researchers must separate out the effect of household location choice and the effect of the household environment. Salon et al (2012) outline a research ideal similar to a random control trial before and after measurements, selection of experimental and control groups, and controlling for any possible differences between the groups. The largest challenge to this approach is that in "natural experiments" in the real world, experimental and control groups are rarely randomly assigned. Furthermore, the long term nature of the effects means that during the observation period many other variables that affect VMT are likely to change. This makes it difficult to separate the effect of the
variable under consideration (ibid.). Given the spatial clustering of different types of people in different neighborhoods, there are often few comparable locations suitable for finding a control group.

More studies have begun to control for the effect of self-selection on VMT, with varying conclusions. In a review of 38 studies that used nine different research approaches to model travel demand, Cao et al (2008) showed that nearly all of the studies found "resounding" evidence of statistically significant associations between the built environment and VMT after controlling for self-selection. However, some studies have failed to find a large effect. For instance, Bagley and Mokhtarian (2002) found that attitude, lifestyle, and sociodemographic variables accounted for the majority of the variation in travel demand in an analysis of the San Francisco Bay area, with neighborhood characteristics having very little influence.

Cao et al's 2008 meta-study is the best source on the types of methods used to control for self-selection and the results. They find that studies use the following techniques to address self-selection bias: surveys and questionnaires, regression equations that control for attitudes by including them as predictors, instrumental variables approaches, adjusted sample selection techniques, propensity score matching, simultaneous equations, and longitudinal studies that assume attitudes are unchanging. Studies using each of these methods found impact of the built environment on travel demand even after controlling for self-selection.

## Endogeneity

In any study designed to prove cause and effect with time series data, endogeneity can be a challenge. In the connection between VMT and the built environment, the most obvious source of endogeneity is bi-directional effects, or loops of causality between predictors and the dependent variable. For instance, VMT will affect the supply of transportation infrastructure because as roads become more crowded there will be more political pressure to increase capacity and alleviate congestion. On the other hand, the supply of infrastructure impacts travel demand, as we saw in Baum-Snow's (2007) and Mishalani's (2014) analysis of the travel demand induced by higher amounts of interstate highway capacity.

Many other causal loops problems could be posited with the connection between the built environment and travel demand. For instance, density has been shown to be correlated with lower VMT per capita. Higher VMT, on the other hand, may inhibit more density in a specific area because homeowners may strongly oppose new development or because people will be less inclined to move to the area, knowing about its traffic congestion problems. Another example is in the connection between transit and VMT. Availability of transit within $1 / 4$ mile has been shown to correlate with lower VMT. But the correlation may also be partially caused by the possibility that higher VMT and higher car mode share may reduce the likelihood that public transportation is available within $1 / 4$ mile - people who enjoy driving their cars may not exert much pressure on local governments to improve transit availability. Transit quality (and therefore measures of transit accessibility) may also be affected by VMT because buses run much slower on congested streets.

To address such simultaneity, many studies use structural equation models (SEMs) - a tool which allows for the simultaneous solution of multiple equations for variables that impact each other, beginning with assumptions about the directions of possible causal relationships. For instance, to control for the
simultaneity of fuel economy and VMT, Wang and Chen (2014) created an SEM model with fitted equations for VMT and MPG that were interdependent. Mcintosh et al (2014) use SEM to demonstrate a causal relationship between transit provision and VMT and also between urban density and VMT. Other studies use instrumental variables to address endogeneity, such as between fuel prices and VMT (Gillingham, 2014; Jenn et al, 2015).

## Additive effects of multiple built environment features

When one attribute of the built environment changes (e.g. increase of mixed use development), other built environment attributes (such as population density, job accessibility, and the effectiveness of each transportation option) are likely to be simultaneously changing. Many of the econometric studies that find the impact of a change in density are simply cross sectional observations, not longitudinal studies of actual communities that have grown more or less dense. Longitudinal studies would be useful, but the ideal of ceteris paribus is nearly impossible to obtain when analyzing the impact of policy on VMT.

Acknowledging this challenge, the Moving Cooler report attempts to model the combined effect of multiple policies that influence the built environment. They refer to a "synergy effect" as the percent by which the effect size of a certain policy bundle exceeds the effect size of all the individual components of the bundle added together (Cambridge Systematics, 2009). While they did not try to model the synergistic effects within all policy bundles, they did account for the synergy of policies that would increase population density with policies that improve the availability of non-motorized transportation options. The authors tried to account for the synergy between increased gas taxes and travel demand management strategies such as transit improvement and smart growth, but they found that existing evidence is mixed as to whether there is synergy or overlap (ibid.). Some studies show as much as a 20\% synergy and other studies show as much as $20 \%$ overlap between these strategies (ibid.). Clearly this is an area that will need much additional research.

The rebound effect - travel time budgets
Another methodological challenge in studies of the effect of urban form on VMT is how to handle rebound effects. For instance, while land use diversity may reduce the average distance needed to run an errand, individuals may reinvest their travel time savings in additional travel. If a worker doesn't need to commute 50 miles each way every day, extra road-trips or errands on the weekend may be more palatable. A series of studies dating back to the 1960s have confirmed the phenomenon of a "travel time budget." In his meta-study of travel time budgets, Schafer (2000) found that the average travel time for the traveling public was 1.2 hours per capita per day with a standard deviation of only 0.17 hours, and this was roughly stable over the years. He demonstrates that as the average speed of travel has increased, distance traveled per capita has also increased in order to keep the total travel time budget stable (ibid.).

If travel time budgets are relatively fixed, policies that reduce travel time may induce additional travel. It is for this reason that Moving Cooler argues that congestion mitigation will increase GHG emissions in the long run, even though it reduces the emissions of idling cars (Cambridge Systematics, 2009). Most studies of VMT reduction strategies measure the total VMT traveled and therefore do not need to be adjusted to account for the rebound effect. But it is worth noting that travel time savings achieved by
travel demand reduction policy have an unintended positive side effect of enabling people to do more with their time, even though travel demand isn't reduced as much as anticipated.

As described in Chapter 1, Metz (2009) argues that the cessation of growth in distance traveled per capita he observed in the 2000s in Britain may be the effect of the diminishing marginal utility of each additional mile traveled. If most people's travel time budgets accommodate their needs, as he suggests, the magnitude of the rebound effect may be relatively small. Nonetheless, it is worth considering the rebound effect when evaluating policies that reduce VMT and reduce the time needed to fulfill needs.

## Limits to generalizability

How well can one extrapolate the findings of studies on the built environment from one metro area to another? Given differing regional economic conditions and employment patterns, different climates, and different political attitudes in different parts of the country, it would not be surprising to see significant diversity in the effect of land use and built environment policy in different regions. A few studies have addressed this question by looking at the differing effect of land use variables in places at different points on the spectrum.

Salon et al conclude from their 2012 meta-study that there is evidence that elasticity estimates of VMT with respect to built environment variables are unlikely to hold across all levels of the variables measured. For instance, greater transit availability in an environment where transit is significantly less convenient than car usage may have a small impact on VMT, but when transit quality is already at a level that makes it competitive with private vehicles, changes in transit quality may change households' decisions about how many cars to own (or whether or not to own any), which would imply a sharply non-linear effect on VMT. Furthermore, the interaction of land use variables can contribute to this nonlinearity. The combined pressures of density, accessibility of jobs, land use diversity, congestion, and other built environment variables may cause permanent shifts in households' propensity to own multiple cars or even any cars at all.

Boarnet et al (2011) conclude that land use may be a weak or a strong tool for influencing VMT, depending on the context. They show that improving job accessibility throughout metro areas is a much more important means of reducing VMT than increasing population density. And they also found that efforts to increase job accessibility for households in the $3^{\text {rd }}$ and $4^{\text {th }}$ quintiles (ranked by the amount of job accessibility available to them) would have more impact than increasing job accessibility in the places with the lowest job accessibility ( $1^{\text {st }}$ and $2^{\text {nd }}$ quintiles), or the highest job accessibility.

Another question of generalizability is whether the findings of these studies will be relevant in the future. As described in the introduction to this thesis, fundamental shifts in the way that people get around metropolitan areas may be just around the corner - ride hailing services like Uber and Lyft supplementing transit, increasing vehicle automation making driving less stressful, opportunities such as Zipcar and bike shares that reduce the need to actually own any transportation assets. These innovations are just a few of the major changes in the last few years, and only time will tell exactly how they impact the way people decide how much to drive, where to live, and how to take care of their daily needs. Trends outside the transportation realm, such as the aging of the U.S. population, will also result in changing preferences and needs which may redefine what we know about the relationship of the built environment, transportation costs, and travel demand.

## How does the built environment affect price responsiveness of

## VMT?

Up until this point, this chapter has focused on the direct impact of the built environment on VMT, an important and heavily-researched question. However when considering the effects of policy tools such as gas taxes or carbon pricing, it is also necessary to evaluate the impact of urban form on the variability of the price elasticity of VMT. How much would a suburban household with no transit options adjust its travel demand when prices change? How much would a one-car family in a dense, mixed use location adjust its behavior? While the effect of urban form on travel behavior is the most commonly studied question in planning (Ewing and Cervero, 2010), studies of the impact of urban form on price elasticity are surprisingly rare. After extensive searching, I found only a few studies that address this question (Gillingham, 2014; Guo et al, 2011). These studies will be described in Chapter 4, in the section "Price responsiveness by attributes of the built environment."

Many of the methods described in this chapter would also apply directly to the study of the impact of the built environment on gas price responsiveness. The authors who used regression models would simply need to take the derivative of their fitted equations with respect to price, presuming they included the appropriate price-related independent variables. Similarly, many of the same limitations still apply - the challenges of proving causation, the endogeneity problems, the issue of self-selection of households into neighborhoods, and the limits of generalizability. The question of self-selection in this case would relate to whether relatively more thrifty or budget-conscious people self-selected into neighborhoods with certain attributes or at certain distances from downtown.

Addressing this gap in the research is of critical importance if society is to eventually move towards increased Pigouvian taxes to reduce the externalities associated with excess personal vehicle travel demand. Strategies for making these policy measures politically palatable will rely on policymakers understanding the ways in which various people are helped and harmed by such policies. Policymakers will need to use this knowledge to find win-win solutions. There are two main ways in which a household would experience disutility from increased gas taxes - first by directly paying the extra tax, and second by foregoing opportunities and trips that they would otherwise have enjoyed or benefited from. The lack of literature on the variability of price elasticity with urban form means that we do not have a good understanding of who will pay more by the former mechanism and who will pay more by the latter mechanism. The political infeasibility of gas tax increases may relate to this very issue because higher costs impose the disutility of needing to decide if any specific trip is still worth its cost, a decision which most people rarely consciously make in daily life, as I found in my behavioral interviews which will be explained in Chapter 5. Thus, an increase in gas taxes may be seen as an attack on individual freedom for those whose travel demand is more elastic, and an attack on the wallet for those whose travel is more inelastic. Which of these two resonates more with specific classes of voters has bearing on the possibility of using a policy tool like the gas tax to address travel demand.

A common theme that arose during my behavioral interviews in Chapter 5 was that interviewees wanted to have more low-pain options available to reduce their VMT in times of high gas prices. Many of them said they wanted to have multi-modal travel options and wanted to lead a less automobile-
oriented lifestyle, but their residential location and activity locations precluded them using other travel options. Therefore they were less price responsive in their total VMT than they wanted to be. Long-term decisions such as home locations and work locations may have been made during times of lower gas prices when interviewees were less concerned about vulnerability to the cost of gas, and therefore many interviewees were locked-in to a certain minimum amount of VMT, regardless of gas price. This intuitive finding further supports the need for evaluating what types of built environments tend to facilitate price responsiveness.

The question of the relative price elasticity of populations in different residential locations with different household attributes is best addressed with large datasets, given the diversity of household types and living environments to control for. The Massachusetts odometer reading dataset therefore presents a great opportunity to expand our understanding of the impacts of urban form on price responsiveness. In addition to other findings, Chapter 7 will provide an estimate of the effect of distance from downtown on price elasticity in the Boston metro area, which contributes substantially to the literature due to the dearth of such estimates. Before showing my results, I will first summarize the literature on gas price responsiveness of VMT in Chapter 4 and then present my qualitative findings on how gas price impacts the behavior of survey respondents in Chapter 5.

## Chapter 4: How much does gas price affect travel demand?

## Motivation

The most comprehensive policy studies have suggested that even if fuel economy improves dramatically, there is no way we can reduce emissions by $80 \%$ by 2050 without reducing personal vehicle travel demand. These studies have also found that the most efficient way to achieve this goal is to set a price on carbon and/or VMT that will send economic signals to reduce the least valued miles traveled. For instance, in the analysis in Moving Cooler, over 40\% of the reduction in VMT is directly attributable to higher gas costs. However, much of the public is both highly skeptical of policies that increase the cost of gas and resistant to changing their driving behavior in the face of rising gas costs.

The price elasticity of gasoline demand and of VMT have been heavily studied, yet surprisingly little consensus exists about the magnitude of these elasticities and their variation among different members of society. Because gasoline expenses are a relatively low proportion of the total cost of driving an extra mile, there even remains some division about whether gas price elasticity has the same interpretability as the price elasticities of other commodities ${ }^{8}$. Three major uncertainties are 1) whether gas price elasticity is still decreasing, 2) what role the built environment and vehicle attributes play in modulating price elasticity, and 3 ) what will be the distributional impacts of rising gas prices.

## Foundations of price elasticity

Economists generally argue that if the true marginal costs of vehicular travel demand were factored into the cost of driving one's personal car, the amount of vehicle travel would equilibrate to a socially optimal level. From this, if one can establish the socially optimal amount of travel demand (given certain assumptions about emissions intensity of travel demand), all one needs to know is the relevant price elasticities of travel demand to propose the proper pricing level. Therefore, transport price elasticities have perennially been popular research topics among environmental economists (see Havranek et al, 2011; Hughes et al, 2008; Gillingham, 2014; Fouquet, 2012; and more). There are six gas price elasticities that are often studied (Brons et al, 2008):

1) Elasticity of total gasoline consumption
2) Elasticity of gasoline consumption per car
3) Elasticity of fuel economy
4) Elasticity of total mileage traveled
5) Elasticity of mileage traveled per car
6) Elasticity of vehicle ownership
[^6]The price elasticity of total gasoline consumption (1) is the most commonly studied, and it can be represented as the sum of (5) and (6) minus (3), which is of the opposite sign from (5) and (6). Price elasticity is measured on different timescales, and it is commonly understood that short run price effects have a more limited effect on behavior than long run price effects, which give more time for more significant decisions to be made that reduce exposure to prices. In this thesis, I primarily refer to the effects of increasing gas prices, although the decisions made by individuals and households could equally well be conceptualized around their responses to decreases in gas price ${ }^{9}$.

## What actions are taken in response to changing gas prices?

As noted above, there are three main categories of response to gas prices, changes in vehicle ownership, changes in vehicle usage, and changes in the efficiency of usage. Each behavioral change may involve a different level of sacrifice or benefit, and some actions are likely to require very significant price changes before they are even considered. Table 6 illustrates some of the more common options available that directly impact gasoline consumption.

Table 6. Possible household actions to reduce exposure to increasing gas price.

| Vehicle Ownership | Long run |
| :--- | :--- |
| Short Run | Reduce number of cars owned <br> Buy an efficient car to enable reduced mileage <br> on less efficient vehicles |
| Vehicle Usage (VMT) | Long run |
| Short Run | Change location of work/school/home/ errands |
| Forego or shorten least valuable trips (e.g. impulse <br> trips, long road trips). Substitute alternative ways <br> of satisfying your needs, such as online shopping, <br> phone calls instead of visits, etc... |  |
| Combine trips of different purposes <br> Carpool | Start telecommuting |
| Switch modes when possible | Long run |
| Efficiency of usage (effective fuel consumption per mile) |  |
| Short Run | Consider MPG in future vehicle purchases |
| Drive slower on the highway |  |

[^7]Employ eco-driving techniques (slower acceleration and deceleration, reduced cargo weight, etc)

Substitute more miles onto higher MPG car if household owns a second car

Manufacturers change available vehicles and fuels

Every one of these possible actions has been studied in numerous articles. These actions may be motivated by price or they may be motivated by other factors - the literature explores both sides. Qualitative and quantitative approaches are both effectively employed. This chapter will describe some of the more significant findings of this body of work from the price response side. But first, it is worth considering how motivations are translated into behavioral changes.

## Theory of Planned Behavior

Pricing policies rely on the assumptions that in response to the policy, individuals will 1) change their intentions, 2) perceive that they have sufficient behavioral control to act upon those intentions, and 3) have the capacity to change their behaviors in a lasting way. Ajzen (1991), in his Theory of Planned Behavior, argues not only that these three assumptions are critical to the translation of intentions to behavior, but also that intentions can be predicted from attitude, subjective norms, perception of behavioral control, and situational variables.

Policy-makers who wish to change behavioral outcomes can attempt to influence each of these steps from intention formation to behavior. Attempts to influence intentions try to change one or more of the following - attitudes, values, injunctive behavioral norms, descriptive behavioral norms, or motivation. Campaigns to reduce travel demand often try to target many of these at once - for instance employers often develop Transportation Demand Management (TDM) programs to encourage carpooling. These TDM programs attempt to impact behavior in several ways: 1) changing attitudes by pointing out the environmental harms of excessive miles driven, 2) changing descriptive norms by showing visible examples of employees carpooling, and 3) changing motivation by offering incentives such as reserved convenient parking spaces for carpooling. While TDM is much more common as a private sector initiative among employers, there have also been governmental attempts to influence attitudes and encourage people to think more broadly about the social good. One famous example was the wartime campaign encouraging Americans to carpool to conserve gas for the war effort. On the other hand, Pigouvian taxes primarily aim to make people conserve resources out of their own self-interest. To a lesser extent, such taxes can also create injunctive behavioral norms (e.g. the idea that people should conserve this resource because it is valuable).

Figure 7. "Ride with Hitler" by Weimer Pursell. Licensed under Public Domain via Commons


Regardless whether the means of persuasion is primarily normative, as described above with the example of employer TDM, or primarily financial, through pricing mechanisms, simply bolstering motivation and creating intentions to conserve is not always enough. Behavioral control also mediates the response, as illustrated in Figure 8 (Ajzen, 1991; Ajzen, 2010).

Figure 8. Ajzen's model of planned behavior. Reproduced from: Ajzen, 2006.


In the case of behavioral control over mileage driven, the line between perceived control and actual control may be blurry. Perception of one's control over one's driving behavior relates to one's identity and one's perception of the reality and constraints of his or her living environment. For instance, a suburban family that wishes to reduce its mileage driven may perceive that it cannot afford to move to a more location-efficient dwelling, and this belief may preclude investigation of alternative dwellings that would enable reduced driving mileage, whether or not the option actually exists. A family that already lives in a location-efficient setting with respect to their daily needs may lack actual behavioral control if they do not have alternatives that they are not already employing or discretionary travel to eliminate. No matter how strong their intentions to reduce their exposure to gas price increases, there is little they can do.

Thus, the theory of planned behavior can provide many possible hypotheses as to why Pigouvian taxes and other financial incentives do not work uniformly across all segments of the population. This will be addressed in more detail in Chapter 5 on my behavioral interviews and Chapter 7 on the variability of observed price elasticity in Massachusetts.

## Types of data sources for elasticity studies

There are three major sources of outcome data typically used for estimation of the fuel price elasticities of various driving behaviors - aggregate gasoline consumption in a country or region, survey data from individuals and households, and odometer reading records from vehicle inspections.

The benefit of using aggregate consumption data, which can be normalized per capita, is that the broadest possible conclusions can be drawn. Many of these studies are motivated by understanding the total emissions impact of pricing policies, Knowing the amount of fuel burned during different price regimes is the most direct way to find the impacts on the well-to-wheels impact of the price change. However, these studies cannot investigate heterogeneity of responses, or even which subcomponents of the elasticity (e.g. elasticity of miles traveled per year, elasticity of fuel economy, or elasticity of vehicle ownership) contribute the most to the overall effect.

Two commonly used sources of survey data are the Consumer Expenditure Survey (CEX), and the National Household Transportation Survey (NHTS). These datasets allow for particularly rich exploration of price elasticities because demographic and socioeconomic data is collected alongside travel behavior. This has yielded some interesting findings on the variability of elasticity by household income (see Wang and Chen, 2014; West, 2004; Wadud et al, 2009). Travel survey data is unfortunately limited to the quality of the memory, estimation, and reporting of the subjects. Furthermore, the National Household Transportation Survey (NHTS) data preceding 1995 is only statistically valid to the census region level. In the 2009 survey, the NHTS includes a sample that is big enough to allow statistical validity in state-bystate analysis, but not on a sub-state level geography ${ }^{10}$ (Oak Ridge National Lab, n.d.).

[^8]Finally, as will be described in more detail in Chapter 7 on the Massachusetts Vehicle Census, recent research has now been exploring the vast datasets made available by some state RMVs (Registries of Motor Vehicles) on odometer readings from registration and inspection records. Analysis of this type of data allows researchers to look at the price responsiveness of individual vehicles and predict price responsiveness as a function of many attributes of the vehicle and the area in which the vehicle is registered. Few of these studies are able to explore household level behavior because the datasets are anonymized and it cannot easily be inferred which vehicles are registered to the same household. Thus if a household shifts mileage from a low fuel economy vehicle to a high fuel economy vehicle when prices go up, the elasticities reported for each vehicle will be biased by the presence of the other vehicle. Similarly, if a household adds an additional vehicle, the mileage on its existing vehicles will decrease substantially, creating a spurious elasticity estimates for the existing vehicles. In one study, Knittel and Sandler (2013) were able to circumvent this problem by accessing the raw RMV data and evaluating vehicles that were registered to the same address, although this relied on the assumption that vehicles belonged to the same household as long as there were three or fewer last names on the registrations and seven or fewer vehicles at the address. If vehicles from emissions checks can be grouped by household and if the emissions checks are not systematically biased, a large amount of information can be gained from analysis of these newly available datasets.

## Meta-studies of the elasticity of gasoline consumption with respect

## to price

Meta-analysis of gas price elasticity of gas demand has become increasingly popular due to the large number of studies from which to draw and the significant spread in elasticity estimates from one study to the next. While my study will instead focus on the gas price elasticity of $V M T$, these meta-studies are still useful for exploring the broader phenomenon of behavioral adjustment to gas prices. Meta-studies show us what types of analysis are most common, what the range of findings has been, and what the gaps in the literature might be. They can also show us what types of methods are likely to produce higher or lower elasticity estimates. Two particularly useful meta-studies are Molly Espey's (1998) and Martijn Brons et al's (2008).

Espey's 1998 meta-study describes in detail the differing formulations of price elasticity models among a large set of studies conducted using data anywhere from 1929 to 1990. She found that of the 363 studies that estimated short run gasoline price elasticity, by far the most common method has been to use ordinary least squares regression ( $50 \%$ of all studies), with another $26 \%$ using general least squares, and the remaining $24 \%$ split among several other regression methods. Less than $30 \%$ of these studies used cross-sectional time-series (panel) data on the dependent variable, with the vast majority simply using time-series data, most often at the national scale. It thus appears that analysis of the large datasets from national travel surveys and vehicle emissions inspections is a relatively new body of work.

The range of elasticity estimates and median value is one of the most useful contributions of metaanalyses. Espey's analysis shows the median estimates of short run and long run gasoline price elasticity are -0.23 and -0.43 , respectively, with a range that goes from 0 (perfectly inelastic) to over -1.0 for short-run elasticity and over -2.5 for long-run elasticity. She also finds a high median value for income
elasticity of gasoline demand of 0.81 , which is not elastic, but nonetheless implies that travel demands were not saturated for much of the population when these studies were conducted. More recent income elasticity estimates have implied a lower income elasticity (e.g. Wang and Chen, 2014).

Espey's final task was to perform a regression that modeled the elasticity estimate from each study as the dependent variable, and the independent variables related to the model form, variables, and lags. She found that panel data elasticity estimates tend to imply higher elasticity estimates than simple timeseries estimates. She also found that models that only use a calendar quarter for the lag term produce lower elasticity estimates in both the short-run and the long-run, which implies that the lag is not long enough to pick up enough of the behavioral adjustment to price changes.

Brons et al similarly uses regression techniques to understand which types of models give the highest estimates of price elasticity. Their addition is that they use Seemingly Unrelated Regression methods that allow them to look at the elasticity of vehicle ownership, usage, and efficiency all in the same model, whereas previous meta-studies only looked at total gas price elasticity of gas demand. Comparing their results with three recent meta-studies, Brons et al find their estimates of the mean price elasticity to be slightly higher ( -0.34 and -0.84 , respectively, for short-run and long-run estimates). Similarly to Espey, Brons et al found that dynamic models (with temporal lags) predicted lower magnitude elasticities. Additionally, they found that the specification of log models or log-linear models did not make a difference for the elasticity estimate. One notable finding was that the distribution of estimates for short-run gas price elasticity was much tighter than for long-run elasticities, concentrated in a quite inelastic range around -0.1 to -0.2 , while estimates for long-run elasticity pretty evenly distributed from -0.1 to -1.3.

Figure 9. The frequency distribution of recent price elasticity estimates for fuel consumption. Reproduced from Brons et al (2008).


Meta-studies highlight the incredible diversity in findings and estimates of elasticity of travel demand and gasoline consumption. While some of this may be explained by different datasets capturing the behavior of different groups at different times, the reported range of estimates (for instance from 0.0 to over -1.0 in Espey's meta-study) indicate that there is a lot of uncertainty in the estimates and the best way to calculate them. Oum et al (1990) note that some common methodological shortfalls can be
contributing to this diversity, including the failure of studies to control for changing prices and qualities of intermodal competition, and failure to address multicollinearity or autoregressive errors.
Furthermore, different functional forms can result in very divergent elasticity estimates, and different definitions of cost variables (e.g. total cost per mile vs gas cost per mile and inflation adjusted vs nominal prices) inhibit comparability (ibid.).

## Factors affecting price responsiveness

Among other variables, gas price responsiveness of VMT is dependent on the relative proportion of mileage driven for specific trip types, the salience of price changes, the quality of alternatives to single occupancy automobile travel, drivers' expectations of the time period over which the price change will persist, and demographic and socioeconomic characteristics of the driver.

## Price responsiveness by trip type

It is commonly understood that people value certain trip types more than others. Shown in Figure 10 below, Litman lays out the range of values of different classes of trips qualitatively to demonstrate the fact that increasing gas prices are much less likely to cause an individual to forgo an emergency trip than to cause that individual to forgo a spontaneous joyride. Individuals whose travel is dominated by trips of necessity are likely to be less price responsive than those who have more discretion. This distinction is important in the context of declining labor force participation and the decrease of the commute as a share of VMT.

Figure 10. Types of trips arranged by increasing expected price elasticity. Reproduced from: GIZ Sustainable Urban Transport Technical Document \#11 (Litman, 2013a).


Dillon et al (2015) use 2009 National Household Travel Survey (NHTS) data to evaluate the price responsiveness of different types of trips, finding that a $1 \%$ increase in gas prices reduces non-work travel by $0.17 \%$, but that gas price shows no significant effect on work trips, consistent with Litman's framework above.

This finding is significant because work travel is a lower percentage of total travel than it used to be. Using NHTS data from 1969 to 2009, the American Association of State Highway and Transportation Officials (AASHTO) demonstrates the declining importance of work travel in overall distance traveled. As shown in Figure 11, work-related travel used to be as high as about $1 / 3$ of all vehicle miles traveled, and has declined to only $28 \%$, even as women have entered the workforce and the rise of two earner families seems to have made short commutes for all members of a household less likely in aggregate. Of course during the same time, the penetration of vehicle ownership has increased, and the number of households that have more vehicles than they have workers has gone up from $32 \%$ in 1977 to $45 \%$ in 2009 (AASHTO, 2013). The decline of the share of VMT as a percentage of total travel therefore is mainly related to the fact that other, more discretionary, types of travel have grown at a faster rate than commuting travel. The large difference between work-related travel as a percentage of vehicle miles traveled and as a percentage of person miles traveled is due to the significantly lower vehicle occupancy of work-related travel versus non-commute travel, 1.13 people per vehicle and 1.67 people per vehicle in 2009, respectively (AASHTO, 2013).

All else equal, if this trend towards a higher percentage of discretionary travel continues as the labor force becomes a smaller percentage of the population, price responsiveness would be increased.

Figure 11. Trends in work travel. From AASHTO, 2013.


Figure 2-5. Work Travel as a Percentage of Total Travel Using Key Travel Measures ${ }^{11}$ Source: NHTS Series.

## Price responsiveness by salience and by the cause of the price change

 In behavioral economics, salience is the phenomenon where if attention is disproportionally directed towards one attribute of a product, that attribute will be assigned disproportionate weighting in consumer decisions. The way in which one pays for a good or service may increase or decrease the salience of the price. For instance, one classic example of success in reducing salience is theimplementation of electronic toll collection. Drivers are less aware of how much they are paying at toll booths once they stop paying in cash, and electronic tolls have been found to be 20 to 40 percent higher than they would have been without the electronic payment (Finkelstein, 2009). These higher tolls can be explained directly by the reduced salience of the toll to the average driver, and the consequently higher optimal toll rate (ibid.).

In the case of increased gas tax as a way of reducing VMT, policy makers arguably are aiming for the opposite end of this spectrum - the more salient the tax increase is, the higher the anticipated behavioral response (but also the higher the political resistance to its implementation). By looking at panel data from time periods when states increased their gas taxes, Davis and Killian found a short run price elasticity of gas consumption with respect to gas price of -0.46 (2011). They note that this estimate is much higher than many other estimates of gas price elasticity, and conclude that their finding shows that gas tax changes cause more of a behavioral response than gas price changes. Their explanation is that tax increases are likely to be more salient because of 1) the increased media and political attention associated with gas tax increases, and 2) the higher expectation that the price increase will persist for a long time (ibid.).

Li, Linn, and Muehlegger (2012) similarly find that the overall impact of gas tax increases on gasoline consumption on a one-year timescale is three times as large as the impact of gas price increases of the same magnitude, and this effect is derived from the stronger impact of the gas tax on fuel economy (ibid.). They argue that because cars are a durable good, the higher impact of gas tax changes is rational, as most consumers likely do not expect gas tax increases to be quickly repealed. Therefore, gas tax increases are likely to impact longer term decisions like automobile selection and purchase. Furthermore, they argue that the transactional costs associated with changing one's travel mode or setting up a carpool or changing one's activity locations imply a larger response for changes that are expected to be persistent (ibid.). A study by Lin and Prince supports Li, Linn, and Muehlegger's findings about the importance of expected persistence of price. Using U.S. monthly data on gasoline prices and consumption per capita, they found that consumers were less responsive to changes in gas price during times of high gas price volatility (Lin and Prince, 2013). Another instance of the amplification of the effect of a tax relative to a general price change is the case of British Columbia's carbon tax, which Rivers and Schaufele (2013) found to have an elasticity seven times as high as an equivalent change in market prices.

## Price responsiveness by attributes of the built environment

As described in Chapter 3, features of the built environment have been shown to have a significant effect on average mileage traveled after accounting for residential self-selection and other methodological challenges. Many economists have posited that price elasticity should also be a function of the built environment due to differing availability of alternatives - in our case, the feasibility of shifting from driving alone to another mode such as public transit, walking, or biking. However, the price elasticity literature is less complete in this realm. Many studies of the impact of the built environment on VMT control for gasoline prices, but they do not consistently include interaction effects in regression models that would explain how price elasticity varies along with attributes like land use diversity, population density, access to jobs, and access to transit.

Gillingham (2014) starts to address this gap with a study of California smog check odometer records. He uses data from the entire state and performs several different regressions, one of which uses California's counties for their fixed effects. He finds that a few of the more populated counties have lower elasticities, and some wealthier counties have higher elasticities, but no obvious and compelling trend across the entire state for the more rural counties versus the more urban counties. He clusters populations into six categories of income and degree of urbanization and finds strikingly different elasticities for the "semi-rural, upper class" cluster (the most inelastic, at -0.12 ) and the "rural, wealthy" cluster (most elastic at $\mathbf{- 0 . 3 0}$ ). However, his clusters do not include any poor or middle class rural residents, or wealthy or middle class urban residents, and there's no distinction made for small towns, cities, and the largest cities. He also tests how price elasticity varies with population density, and found that in the densest zipcodes, there is statistically less price responsiveness, but this counterintuitive effect does not have real world significance due to its small magnitude. In an alternate specification of his model, he removes the county fixed effects, and inserts an interaction term between gas price and average commute time by zipcode. This allows him to find that locations with high commute times are less price sensitive, likely due to the fact that with longer travel distances, there are fewer modal alternatives to driving alone.

Guo et al (2011) exploit data from the Oregon VMT fee pilot project, which assigned vehicles to pay VMT fees instead of gas taxes. Some vehicles were charged significantly more (the equivalent of a \$2/gallon gas tax) for mileage traveled inside Portland's urban growth boundary during peak commuting periods. The authors modeled the reduction in household peak hour VMT inside Portland's urban growth boundary from a baseline. Testing a large number of possible predictor variables (including distance from downtown, proximity to light rail, housing density, and entropy of land use), they found that the only urban form variable that had a significant impact on the reduction of mileage during the peak period was the land use mix. Households in areas with more mixed land uses reduced their peak period mileage more in response to the higher cost than households in more homogenous areas.

## Price responsiveness by vehicle attributes and demographic attributes

Most studies of elasticity have not effectively separated different population groups with high resolution. However, there has been increased recent interest in the heterogeneity of price responsiveness between income groups (Wang and Chen, 2014; West, 2004; Small and Van Dender, 2007; Wadud et al, 2009), populations grouped by car age and type (Bento, 2009), populations grouped amount of driving (Ficano and Thompson, 2014), and vehicles with varying levels of criteria pollutant emissions (Knittel and Sandler, 2013).

## Vehicle attributes

Several vehicle attributes stand out as attributes that might impact the price responsiveness of their usage, including the type of vehicle (because different types of vehicles may be used on average more for different types of trips that have differing values to the drivers), the overall fuel economy (because of its effect on cost per mile), the age of the vehicle (because this may correlate with income), and the amount of criteria pollutants emitted (because this will impact the co-benefits of VMT reduction).

Bento et al address a number of these variables in their 2009 study modeling the distributional effect of potential increases in U.S. gas taxes. They use a sample of 20,429 households from the 2001 NHTS and calculate four types of elasticities, as shown in Table 7. Their study does not report error bounds on elasticity estimates, nor do they make assertions as to whether the differences found are statistically significant. They make a few assertions based on this table. 1) Newer cars have a lower magnitude of response of VMT per year to operating cost changes than cars more than 12 years old (final column), which they argue may relate to the fact that lower income families tend to own older cars and they may also be more price responsive. 2) Small trucks and large SUVs (particularly among new vehicles) have the highest price responsiveness of gasoline demand (first column). 3) Gas demand in working households with children also appears to be more price responsive than other household types. However, given the large variation in observed elasticities between different studies and given the relatively small differences shown in this table, my inclination is to conclude that the relative elasticity of different vehicle types and different aged vehicles and different household types is still an open question.

Table 7. Elasticity by different household and vehicle attributes. Reproduced from: Bento et al (2009).
Table 4-Posterior Mean Long-Run Elasifity Estimaies

|  | Elasticity of gasoline use wrt price ${ }^{\text {a }}$ | Elasticity of gasoline use wrt income ${ }^{\text {a }}$ | Car ownership elasticity wrt rental price | VMT elasticity wrt operating cost ${ }^{\text {a }}$ |
| :---: | :---: | :---: | :---: | :---: |
| All | --0.35 | 0.76 | -0.82 | -0.74 |
| By household |  |  |  |  |
| Retired | -0.32 | 0.61 | -0.93 | -0.69 |
| Not retired. no children | -0.32 | 0.68 | -0.72 | -0.69 |
| Not retired, with children | -0.39 | 0.96 | $-0.85$ | $-0.83$ |
| By auto |  |  |  |  |
| By class |  |  |  |  |
| All cars |  |  |  |  |
| Compact | -0.27 | 0.83 | -0.65 | -0.59 |
| Luxury compact | -0.30 | 0.78 | $-1.25$ | -0.64 |
| Midsize | -0.28 | 0.74 | -0.67 | $-0.60$ |
| Fullsize | -0.29 | 0.75 | -0.73 | $-0.63$ |
| Luxury midsize fullsize | -0.30 | 0.79 | --1.25 | $-0.63$ |
| Small SUV | -0.29 | 0.93 | -0.73 | -0.63 |
| Large SUV/van | $-0.32$ | 0.88 | -0.98 | -0.69 |
| Small truck | -0.34 | 0.78 | -0.62 | -0.72 |
| Large truck | $-0.31$ | 0.79 | -0.85 | -0.66 |
| Minivan | $-0.31$ | 0.85 | -0.77 | $-0.65$ |
| New cars |  |  |  |  |
| Compact | -0.28 | 1.14 | $-1.44$ | $-0.60$ |
| Luxury compact | -0.27 | 0.76 | -3.14 | -0.46 |
| Midsize | -0.29 | 0.95 | $-1.58$ | -0.60 |
| Fullsize | -0.29 | 1.04 | -1.77 | $-0.61$ |
| Luxury midsize; fullsize | -0.28 | 0.83 | -3.04 | -0.47 |
| Small SUV | $-0.26$ | 1.86 | $-1.58$ | $-0.55$ |
| Large SUVivan | -0.34 | 1.06 | $-2.30$ | -0.69 |
| Small truck | -0.37 | 0.91 | -1.32 | -0.75 |
| Large truck | -0.32 | 1.05 | $-1.69$ | -0.65 |
| Minivan | $-0.31$ | 0.98 | $-1.67$ | $-0.63$ |
| Byage |  |  |  |  |
| New cars | -0.30 | 1.10 | -1.97 | -0.63 |
| 1-2-year-old cars | -0.29 | 0.79 | $-1.01$ | $-0.63$ |
| 3-6-year-old cars | -0.27 | 0.76 | -0.73 | -0.59 |
| 7. 11-year-old cars | $-0.30$ | 0.75 | -0.28 | -0.65 |
| 12.18-year-old cars | -0.31 | 0.83 | $-0.13$ | -0.68 |

[^9]Jenn et al (2015) conduct an in depth analysis of the heterogeneity of price responsiveness of VMT using 20 million vehicle odometer records from Pennsylvania between 2000 and 2010. In contrast to Bento et al, they find that the highest elasticity of VMT is from both the youngest and the oldest vehicles in the fleet, although their study uses actual odometer readings from just one state, while Bento et al used self-reported survey answers from the entire US.

Two recent studies provide compelling evidence that price responsiveness is related to the fuel economy of the vehicle. In the same study mentioned above, Jenn et al used two different regression methods to explore the impact of fuel economy on price responsiveness of VMT. First, they used dummy variable interaction terms to interact price with whether or not a vehicle was in a certain fuel economy band. The results of this model show that vehicles with fuel economy below 20MPG have gas price elasticity of miles traveled of up to -0.21 , whereas those with fuel economy between 20 and 30MPG have elasticity up to -0.11 , and highly efficient vehicles (above 30MPG) actually have positive VMT elasticities, consistent with the idea that households switch mileage from low fuel economy vehicles when prices increase. The second method applied by Jenn et al was to partition their dataset for each of these fuel economy bins and run separate regressions for them. This method achieved very similar results. Knittel and Sandler (2013) use a California dataset of smog check records from 1998 to 2008 and group vehicles into households based on address in order to estimate the magnitude of the shift of mileage from low fuel economy vehicles to high fuel economy vehicles. Their finding is that the presence of a lower fuel economy vehicle in the same household causes the magnitude of the elasticity of the higher fuel economy vehicle to be over a third lower.

Additionally, Knittel and Sandler (2013) find that vehicle emissions of nitrous oxides (NOx) and hydrocarbons are positively correlated with their gas price elasticity of VMT. The average elasticity they found was -0.15 , but the dirtiest quartile of vehicles with respect to NOx had an elasticity of -0.29 . The substantial health benefits of the fact that dirty vehicles would respond the most to fuel price increases lead them to conclude that a gas tax increase of $\$ 1 /$ gallon would improve welfare, from the NOx and hydrocarbon reductions alone ${ }^{11}$.

## Vehicle owner attributes

Income is the primary vehicle owner attribute that has received attention in studies of the heterogeneity of price elasticity. With the exception of the Bento et al piece described above, which briefly addresses race and household type, I could not find any other studies that looked at the effect of other vehicle owner attributes on elasticity. Despite the large amount of attention on variability of elasticity by income, and the policy relevance of the result, no clear consensus has emerged. The various findings are laid out in Table 8, and several of these papers are discussed in more detail in Wadud et al, 2009.

[^10]Table 8. Findings on the effect of income on price elasticity

| Poorest households exhibit the <br> most elastic behavior | Wealthiest households exhibit <br> the most elastic behavior | U-shaped pattern of elasticity <br> plotted against income |
| :--- | :--- | :--- |
| West and Williams, 2004; <br> Wadud et al, 2010; Blow and <br> Crawford, 1997Gillingham, 2014; Hughes et al, <br> 2008; Kayser 2000 | Wang and Chen, 2014; Wadud <br> et al, 2009; West, 2004 |  |

The reasons to expect price elasticity to decrease with income are intuitive, given that a higher gas price will represent a larger loss to the least wealthy households as a percentage of income. Bento et al calculates the direct increase in cost associated with a $\$ 0.25$ cent per gallon gasoline tax without recycling of revenue at $0.51 \%$ of household income for the average household with income below $\$ 25,000$ per year, while they calculate the direct increase in cost for an average household with income above $\$ 75,000$ per year at $0.33 \%$ (Bento et al, 2009). Furthermore, the 2007 Consumer Expenditure Survey shows that households in the lowest quartile spend four times as high a percentage of their income on gasoline as those households in the highest quartile (Cambridge Systematics, 2009).

On the other hand, Hughes et al (2008) lay forth several arguments for the why price responsiveness may increase with income. First, the highest income households have significantly higher levels of discretionary travel, which is easy to cut when prices become too expensive. Second, it is possible that lower income households have already reduced their driving to a bare minimum, leaving few opportunities to respond to price increases. Third, higher income households have more vehicles and therefore have the opportunity to switch mileage from low MPG vehicles to high MPG vehicles.

West (2004) notes that while price responsiveness is highest for the lowest income decile, a very low proportion of households in this decile own cars in the first place, which may mean that gas tax increases are less regressive than they may appear.

Is price responsiveness declining over time?
Several recent studies have concluded that gas price elasticity of fuel consumption and/or VMT is very low and has been decreasing. If this trend towards lower price elasticity is real and persistent, it has significant bearing on Pigouvian taxation as a method to control the growth in travel demand and gasoline demand. The more inelastic gasoline demand ends up being, the more revenue could be collected from increasing gas taxes, but less impact on transportation emissions is likely to be achieved. Many analysts have posited that behavioral and structural changes in the U.S. economy and land use have reduced price elasticities since the 1970s.

Hughes et al (2008) documented a reduction of gas price elasticity by a factor of five between the late 1970s and the early 2000s, with short run gasoline demand price elasticity as low as -0.034 in the later period. Both periods had similarly high real gasoline prices which were rising during these time periods, so it is likely that these time periods are comparable. In the 2000s, low price elasticities have become especially apparent among individuals of moderate income (Wang and Chen, 2014). Corroborating this
trend, Small and Van Dender (2007) use state-level cross-sectional time-series data from 1966 to 2001 to estimate short run elasticities over time. They find the elasticity of VMT during the last five years of their data was less than half of the average elasticity calculated from the entire time period (values of 0.022 and -0.045 , respectively). They also find gasoline demand price elasticity has decreased during this time (from -0.089 to -0.067 ), but not nearly to the extent found by Hughes et al.

Several intuitive explanations have been suggested for these findings. Hughes et al categorize the causes as factors that reduce households' motivation to adapt to rising prices and factors that reduce households' ability to adapt. For the former, they mention the trend of falling real gas prices relative to household income, and the increase in the average fuel economy of vehicles between 1980 and 2000, which means that the cost per mile has declined for any given gas price. For the latter category, they cite the pace of suburbanization, sprawling land use, and the rise of multi-earner families - factors would make finding a residential location that has multiple transportation alternatives for multiple workers in the family increasingly challenging.

Nonetheless, there are hints that the decline in price responsiveness may not be permanent. Hymel and Small (2015) report that extending Small and Van Dender's time series data from 1966 to 2009 yields evidence that price sensitivity actually increased in the last 15 years of their sample, primarily due to the increase in fuel prices starting around 2003. Fuel price is only a component of the total cost per mile of driving, and a large additional cost is the perceived value of time. Hymel and Small argue that the higher the initial gas price as a fraction of this total cost per mile, the larger the elasticity should be. However, they conclude that the effect of increasing income has offset this effect, and that it is likely to continue to do so. Lin and Prince (2013) found that higher price volatility led to reduced VMT during the period between 2008 and 2012, and that higher volatility limits price responsiveness, so if a period of lower volatility at higher prices is sustained, price responsiveness may again trend upward. Gillingham (2014) and Knittel and Sandler (2013) have done analysis that incorporates California odometer readings as recent as 2010, and their results provide some evidence that gas price elasticity of VMT is higher than the results from the studies based on early 2000s data. None of these studies challenges the notion that price elasticity decreased from the 1970s through the early 2000s, but they do provide evidence that recent price trends have mitigated some of this decrease, and they outline conditions in which elasticity might increase in the future.

Additionally, there are several trends that are just beginning that no econometric studies can resolve with certainty at the present time. Given the large number of disruptive technologies emerging in cities that facilitate lower car ownership levels, there is reason to expect that more quality options for urban mobility will result in higher price responsiveness. Many studies have found that number of cars owned significantly predicts vehicle miles traveled, and that the elimination of a car from a household fleet leads to much lower total travel by the household. Therefore, as options like Zipcar, Bridj, Uber, and even bike-shares become more widespread, lower car ownership may lead to lower mileage traveled and higher price elasticities. The outcome is yet to be determined.

## Additional behavioral economic perspectives on price elasticity

 Behavioral economics teaches us to pay attention to salience, framing effects, mental accounting, and alternate decision-making heuristics, such as pursuing any satisfactory outcome (as opposed to optimizing), when evaluating the impact of pricing policies. Salience in price response was discussed above, but these other concepts deserve additional attention.Behavioral economists might posit that in certain economic decisions, people can act more like "satisfiers" than "optimizers" - in these cases, people may have a set of satisfactory outcomes they will accept and they will cease to invest mental energy in the decision-making process once one of these outcomes has been found. In the case of travel behavior, individuals may have a certain mental budget for travel expenses and a set of trips that they need to make. If the cost of travel shifts but does not force them to exceed this mental budget, they may be unresponsive to price changes. On the other hand, pure optimizers would calculate the marginal benefit of each additional mile of travel and decide whether it was still worthwhile under the new price structure. An example of this sort of effect is that gas prices may be elevated to a new mental prominence the first time it costs a vehicle owner more than $\$ 20$ to fill their tank, or perhaps the first time they see gas prices exceed $\$ 4.00$ per gallon.

Studies have recently probed the mental accounting of vehicle drivers in the US. Godek and Murray (2011) found that prospective vacationers were quite likely to cancel an upcoming vacation when faced with a hypothetical situation in which they were informed of an increase in the price per gallon of gasoline. However, when informed simply of the total cost increase of the trip, they were much less likely to cancel it. The authors argue that the different response to these two framings indicates that drivers use a comprehensive mental account when faced with changes in the cost of driving - seeing the price change as affecting their overall well-being, these drivers are more likely to view the increased cost of a gallon of gas as a factor in determining their overall consumption and spending patterns of all goods, and an impetus to cut back spending in other areas as well. They also found that whether the prospective vacationers viewed the price increase as temporary also significantly impacted their likelihood of canceling the trip, with those expecting temporary price changes less likely to cancel.

The finding from Lin and Prince (2013) that consumers are significantly less responsive to price changes in periods when the gas price is highly volatile lends support for Godek and Murray's suggestion that viewing price changes as temporary is likely to trigger topical mental accounting rather than comprehensive mental accounting. Godek and Murray argue that practitioners interested in using price signals to induce fuel conservation may benefit from encouraging drivers to use comprehensive accounting when thinking about gas costs. Davis and Kilian (2011) modeled the change in gasoline consumption associated with a $\$ 0.10 /$ gallon tax increase on gasoline and found its effect to be higher than an equivalent increase in the commodity cost of gasoline. Like Godek and Murray, they postulate that this could be due to different consumer expectations of the longevity of the price change.

## Summary - Remaining uncertainties in price responsiveness

This chapter presents several interesting conundrums in understanding how pricing policy may impact travel demand and gasoline demand. Several findings are generally robust across the studies that
address them. For instance, very few studies consider gasoline an elastic good, and the majority of elasticity estimates are in a range of extreme inelasticity. And there is consistency in the finding that price changes due to taxation generally cause greater changes in VMT than market price fluctuations.

On the other hand, much remains to be learned to inform our understanding of how elastic gasoline demand will be in the future, and what variability exists today in the gas price elasticities of households in different population groups. For instance, it will be important to understand the difference in elasticity between rich and poor households and the difference in elasticity between urban, suburban, and rural households. No consensus has emerged on either of these topics, which both have important equity implications when considering policy that increases the cost of gas. Furthermore, recent literature has shown divergent estimates of the magnitude of gas price elasticity. Thus there is still considerable uncertainty as to both the efficacy and the equity of efforts to control emissions through pricing policy. The next several chapters will explore how both behavioral interviews and the extensive data in the Massachusetts Vehicle Census can contribute to these important questions.

## Chapter 5. Behavioral interviews of a diverse set of drivers throughout the U.S.

## Introduction

Given the wide range of findings and the significant amount of uncertainty in the literature on the built environment, travel, and price elasticity, I decided to enrich my understanding of the elasticity of travel demand by conducting behavioral interviews. Before discussing my methods and results, I will first briefly recap some of the main findings from the literature reviews in Chapters 3 and 4.

The previous chapters only scratched the surface of the vast literature on the impact of the built environment and the impact of gas prices on the amount that people drive. These topics are some of the most widely studied topics in city planning. Despite the extremely large amount of attention paid to these issues, there is much heterogeneity in the findings. Part of this variability may be due to the methodological challenges stemming from the fact that society is a complex and dynamic system and data isn't available for all potential variables of interest - when modeling travel demand there are many multi-directional effects between predictor variables and between the predictor variables and the dependent variable. Furthermore, behavior is context specific. Local cultures vary from place to place and different age cohorts of the population have different needs and preferences. A study of price elasticity in Texas may exhibit different patterns than one in New York. And as we have seen with the travel patterns of the millennial generation, the average timing of life decisions to own vehicles and homes and have children has evolved, whether by economic necessity, different preferences, or both.

My literature review on the impact of the built environment found that there is a large degree of consensus that smart growth and mixed use development do have a beneficial role in reducing overall per capita travel demand. The main uncertainty was the magnitude of such a response and whether it was primarily related to its ability to change the behavior of people generally or it was primarily related to residential self-selection, in which the people who already preferred to walk, bike, and take transit were disproportionately attracted to neighborhoods with smart growth characteristics.

My literature review on price elasticity highlighted several uncertainties that still need to be examined. First, some recent studies showed a trend toward extremely low price elasticities that called into question the degree of impact that carbon pricing is likely to have on transportation demand and emissions. Second, there is little literature that examines the differing gas price elasticity of people in urban, suburban, or rural settings or settings of mixed land use versus subdivisions. And third, there is a significant body of work attempting to understand price elasticity as a function of income, but no clear consensus exists on which quantiles of the income distribution are most price responsive.

Most of the literature uses statistical techniques to describe the determinants of travel behavior. Therefore, it cannot explore the range of ways in which individuals and households are affected by changes in their travel options. The behavioral interviews in this chapter will shed some light on how people perceive their travel is impacted by some of the same factors reviewed in Chapters 3 and 4.

I will first present the interview methods I used to gain a grounding in the diversity of attitudes towards the built environment, the price of gasoline, and vehicle usage. Then I will describe the attributes of the interviewees. And finally, I will summarize some of their responses and distill some common themes.

## Purpose

This stage of the thesis project aimed to address the gaps inherent in the travel behavior modeling literature by constructing narratives about how automobile drivers adjust their behaviors in response to price stimuli, on a disaggregate level. While the interviews were not meant to gain statistically valid data about the prevalence and magnitude of behavioral responses, they gave a qualitative understanding of the range of motivations and barriers that may exist for certain population groups that wish to increase or reduce their travel mileage and gasoline consumption. The interviews probed what policies and environments would most increase individuals' ability and desire to be price responsive. Additional topics included the timeline over which automobile drivers adapt their behavior and whether there is a divergence between their intentions and their actions due to real and perceived barriers.

Piore (2009) argues that the role of qualitative research is building theory and critically testing standard assumptions. In order to have a more complete understanding of the system, and to develop robust theories about the causes of aggregate behavior responses, one must learn from individual decisionmakers whose behavior is being modeled. Interviews provide an opportunity to construct narratives of behavioral patterns that help future studies make inferences about means, ends, and causal models (Piore 2009). Therefore, one important purpose of the interviews was to build these narratives and causal mental models of how people adjust to gas price changes to help me avoid succumbing to availability bias when interpreting the results of the quantitative models described in Chapter 7. Having thought extensively about the attitudes and motivations of a diverse set of automobile drivers spread throughout the country, I was able to more confidently interpret the results of my regression models.

## Methods

Between May and July 2015, I conducted 15 interviews with a diverse sample of U.S. citizens, selected via snowball sampling. The interviews were semi-structured because travel demand is an area that has received extensive study in the past. Semi-structured interviews allowed me to focus the interview conversation on topics of interest, yet afforded me enough flexibility to probe areas I hadn't thought of asking all subjects (Gill et al., 2008), particularly regarding the participants' understanding of their own decision-making. In developing the framework for the interview, I was careful to avoid phrasings that came across as value-laden so that my interviewees didn't feel that there were some more desirable answers than others. Much attention has been given to pollution generated by vehicles over recent decades, so some social-desirability bias is impossible to avoid, but in my framing of the questions, I avoided mentioning pollution or other negative externalities of vehicular travel. To further set the tone for open and candid responses, I started the interview with open-ended, neutral, and simple questions such as asking the interviewee to tell me the story of their household's routine travel and what they liked and disliked about their routines. The interview template and plan received approval from the MIT Committee on the Use of Humans as Experimental Subjects (COUHES). Participants were informed of
their rights and the research purpose, and were given the option to quit the interview at any time without adverse consequences.

To seed my snowball sample, I selected my first interviewees from within my personal network. Within my network, I selected subjects who were as diverse from each other as possible. Then I asked subjects to provide the name and contact information for people within their networks who would be willing to be interviewed. I specifically asked my subjects to recommend people they thought were significantly different from them in terms of their travel behavior, region of the country, age, or employment status. As the study progressed, I began to ask my subjects to recommend other subjects who fit certain holes in the demographics not covered in previous interviews. Thus, I was able to cover a significant range of variation on key demographic variables that are likely to influence travel behavior and price elasticity. Table 9 lists the demographic characteristics of interest. My final list of interviewees included a construction contractor, a recent retiree, an artist past retirement age, a new mother, a commercial truck (18-wheeler) driver, a late career executive in higher education, a custodial foreman, a building superintendent, a maid, a government employee, a telecommunications worker, an architect, two college students, and a graduate student.

Table 9. Demographic variables of interest.

| Variable | Reason for interest |
| :--- | :--- |
| Income | Higher income may lead to higher amount of travel, but also a higher portion <br> of travel that is discretionary. |
| Perceived household <br> financial stability | Those who perceived their finances as less secure may have stronger <br> motivations to reduce gas price exposure. |
| Age | People of different age ranges may have different types of daily travel. |
| Home Ownership | Home owners may be more permanent residents, or intend to be more <br> permanent, than renters. |
| Vehicle ownership | People who already own cars may see the vehicle as a sunk cost and care less <br> about the marginal cost of gas relative to people who rent or borrow cars. |
| Marital status | Households that have two adults may not have optimized the residential <br> location for one of the adult travelers. They may have different opportunities <br> related to carpooling and combining trips. |
| Number of <br> dependents | Having children in the household may increase total travel and discretionary <br> trips. |
| Urban/rural setting | The types of travel options vary greatly between urban, suburban, and rural <br> settings. |
| Frequency of transit <br> use | People who already use transit for some trips may have a lower barrier to <br> increasing their usage of transit in response to price changes. |
| Gender | Activity patterns and attitudes may be different. |
| Citizenship | Activity patterns and attitudes may be different. Non-citizens may have been <br> living in the same place for less time than some citizens. |
| Census region | Attitudes towards travel may be different in different census regions, and <br> travel options will have different feasibility, costs, and benefits in different <br> regions. |
| Frequency of filling <br> primary car's tank | People who less frequently have to pay for gas may be less concerned with <br> the price. |


| Weekly gas purchase | People who don't purchase as much gas may be less concerned with price. |
| :--- | :--- |
| MPG rating of <br> primary car | People with low fuel economy cars may be more concerned with price. |
| Distance to <br> destinations | People who live further from most of their destinations may be more <br> concerned with the price of gas. I asked subjects how many miles their <br> commute was, as well as the typical mileage of all other types of trips they <br> performed. |

## Pre-interview questionnaire

Interviewees were asked to fill out an online form that described their demographics and financial situation. The purpose of this questionnaire was mainly to ensure that I captured substantial diversity on the variables outlined above in Table 9. The majority of respondents filled out the form online, but some did not, so I asked them those questions during the interviews. For one interviewee, language barriers prevented me from gaining as much detailed and nuanced information as for the rest.

## Financial situation

The subjects were asked several questions about their income and financial status. First, they were asked what income range their household fell into. The choices given were in $\$ 20,000$ increments, ranging from "less than $\$ 20,000$ " to greater than " $\$ 140,000$." The sample did not include any households that reported earning less than $\$ 40,000$, although some respondents skipped the question, including the college students who did not have a significant amount of income. This means that none of my (non-student) respondents were below the federal poverty level. And unless one of the households that reported $\$ 40,000-\$ 60,000$ in income was well below the middle of that range, they would not be much below the U.S. median household income of roughly $\$ 51,900$ (2013 data). The responses were divided relatively evenly between the $\$ 60-80,000$ range, the $\$ 80-100,000$ range, and the $\$ 100-120,000$ range, with only one household reporting more than $\$ 140,000$ in annual income.

Because gas expenditures and travel decisions are likely to relate not only to income and assets, but also perceived financial stability, respondents were also asked to describe how they perceived their household's financial stability on a scale of 1-10. Responses ranged from 4 to 10 , with an average of 7.2 . I was unable to get a rating from the respondent for whom English was a second language, but I expect her answer may have been lower on the scale. Nonetheless, there may be a gap in the interview pool for households who feel like they are truly struggling financially. The diversity of household incomes and financial self-perceptions is summarized in Figure 12.

Figure 12. Financial metrics on interviewees.


Respondents were also asked to describe their employment status (choosing between the options listed in Figure 13.). As shown in Figure 13, the sample included mainly full time workers, but also included a few students, a worker who was also in school, and a retiree. The self-employed interviewees typically had to make calls with their clients and/or visit construction sites, and some of these people had very long hours of driving every day, as I will describe later in this chapter. Although only one of the students owned a vehicle, they were all occasional drivers, a criteria for being included in the study.

Figure 13. Employment status of the interviewee (ignoring employment of other household members)


## Living environments and household attributes

Another set of attributes that could influence price responsiveness of travel behavior is the environment the interviewee lives in. To account for this, subjects were asked to classify their homeownership, marital status, number of children or dependents, setting of residence (from urban to rural), distance to typical destinations, and state of residence.

The sample included mainly homeowners who were still paying their mortgage, but also some who lived in homes owned by family members, and some who owned and had paid off their mortgage, and some who rented. The sample included 10 respondents who were married, 4 who were single, and one who was widowed. As for number of children, four of the fifteen respondents had one or two children living in their household. The rest either had never had children, or had grown children who had moved out.

Nine of the households were in suburban settings, two households considered themselves rural, and four were located in an urban environment. One subject was from the southwest, two from the west coast, one from the Midwest, four from the south, two from the mid-Atlantic, and five from the northeast. Finally, in terms of commute distances, some subjects were within a quarter mile of work or school (all the students and one worker), and one had a 47 mile one-way commute, with the rest of the employed interviewees falling between these two extremes. However, a few of them had very high and variable work-related mileage, including the long-haul truck driver, and the two who were selfemployed contractors who had to visit multiple sites regularly.

Figure 14. Selected details on the living situation of interviewees.


## Transportation Options and Costs

The interview study also aimed to cover a spectrum of respondents with different sets of transportation options. The questions related to car ownership, transit ridership, fuel efficiency of the primary household car, the frequency with which the household filled its primary vehicle with gas, and total gallons of gas purchased per week.

## Transit and car use

The sample included mainly households that owned at least one car per driver, but $33 \%$ of respondents were in households with less than one car per driver or no vehicle at all. The undergraduate students responded to the car ownership question and other questions with their current living situation in mind, not the household they grew up in, and these were the only two "households" not owning vehicles. Most of the respondents were to some degree multimodal travelers, since a majority reported using transit with some frequency, although most these transit users used transit less than once per week.

Figure 15. Selected details on the transportation options of interviewees.


## Fuel consumption

Questions were asked to gage the level of exposure the study participants had to gas prices. Some interviewees purchased as frequently as once every four days on average, while others typically went as long as 21 days in between filling the tank. The college students in the sample did not buy gas on a regular basis except for sporadic trips with friends in rented cars or in friends' cars. Of the car owners in the sample, some of them bought as little as 5 gallons in a typical week, while others bought as much as 25 gallons. Fuel economy of the primary car had a similarly wide range, with one vehicle around 15 MPG and some very high fuel economy vehicles. The fuel economy values were self-reported estimates, and therefore may be based on the respondent's memory of the EPA rating on her car, the respondent's estimation based on measuring actual on-road gas usage, some combination of these, or just a guess.

Figure 16. Gas purchases and fuel economy of interviewees.



## Findings

Among my behavioral interviewees, none had a shortage of things to say about the way the price of gas impacted them or people they knew, even those interviewees who drove relatively infrequently. The ubiquity of gas station signs advertising prices ensures that most drivers never really forget the recent
trends in gas prices in their area. I obtained a large amount of unstructured information from my fifteen interviews, which I then reviewed for common topics and themes. I tallied the number of times each theme arose and have reported on some of the more prevalent themes in this chapter. Since these were semi-structured interviews, not all of the topics came up in each interview, so the number of times that a phenomenon was cited during the interview cannot be calculated as a percentage of respondents who felt that way. I cannot rigorously say that any one phenomenon was more common than the next since this was not a random sample of the population, but some phenomena were cited explicitly by nearly half of my interviewees and are therefore worth reviewing.

The first topic was simply an invitation for the interviewee to tell her story of how she traveled on a daily and weekly basis and how she felt about it. I then asked each interviewee to focus on the most positive and most negative components of her experience. The themes from these stories will be summarized in the conclusion of this chapter.

## Paying for car travel

The next topic of conversation related to paying for car travel. While I didn't explicitly ask the interviewees whether they had trouble affording the travel they needed to do, five people volunteered that they did have trouble affording travel expenses. The comments of four other interviewees implied that they were not concerned at all about the cost of travel. I expect that most of the remaining 6 interviewees did not have difficulty affording car travel because they did not mention it as a factor. This high number of people having difficulty affording travel surprised me since few of the people I started my snowball sample with had difficulty affording travel. I suspect that availability bias may have caused my interviewees to suggest other interviewees that had difficulty affording travel simply because these were the first people they thought of when asked to recommend talking to an acquaintance about gas prices.

I explicitly asked each interviewee what they most disliked paying for, after prompting them with a list of common vehicle expenses. Both gasoline and maintenance came up highest on the list, as one might expect. The interviewee who listed depreciation as the cost that he disliked the most was an economics graduate student, and he said that he thought of his car as something he was "using up," and this was the biggest deterrent to driving more miles. I expect that this outlook is rare in the population.

Table 10. Affordability of vehicle travel

| What aspect of driving do you most dislike paying for? | Number of respondents |
| ---: | :---: |
| Maintenance | 5 |
| Gas | 4 |
| Insurance | 2 |
| Parking | 2 |
| Depreciation | 1 |
| Vehicle lease | 1 |

## Travel options

The next topic of conversation centered on whether interviewees were happy with their travel options as defined by their home locations and vehicle availability. I posed two scenarios, one in which the interviewees' incomes doubled and one in which their incomes were cut in half. I asked them if they would change their home location and/or change their vehicle in each scenario, and why, and what the primary factors would be in making these decisions. The goal of asking about what they would do with twice their income was to understand in what ways the respondents already felt like they were conserving on housing and travel, while the goal of the scenario when their income was cut in half was to see whether they expected travel to be one of the places they would economize. Would the respondent be living in a bigger house further from the city center if they had fewer financial constraints? Would they upgrade to a heavier vehicle? A more efficient one? The summary of their responses is shown in Table 11. Some respondents did not specify what location types they would prefer, and some specified multiple attributes of locations they would want to move to. A few respondents said they would look for a home environments with seemingly contradictory features. For instance, at least one respondent wanted to move to an environment that would afford them more space, but also wanted more walkability and convenient mixed uses.

Table 11. Satisfaction with travel options (inferred)

| Satisfaction with location | Number of respondents |
| ---: | :---: |
| Satisfied, or did not specify a more preferred living environment | 5 |
| Wants more space | 2 |
| Would like a living environment that enabled sharing vehicles informally | 2 |
| Wants more walkability or convenience | 6 |
| Satisfaction with vehicle | Number of respondents |
| Satisfied, or did not specify any desired changes | 9 |
| Would prefer a different brand of vehicle | 1 |
| Would prefer a vehicle with better fuel economy | 5 |

It was surprising that so many more people specified changes they would seek in their living environment if their income doubled and fewer people specified that they would change their vehicle type. It could be that the scenario I posed of doubled income was enough to get people to consider the biggest decisions they would make. Alternatively, it's possible the respondents' cars felt like a fundamental part of their identities. Academic literature has recently begun to explore the phenomena of car pride (Zhao and Zhao, in press; Steg, 2005) and emotional attachment and even identity formation with one's car (Sheller, 2004; Nilsson and Kuller, 2000), although automobile manufacturers' marketing teams have understood these phenomena and taken advantage of them for a long time.

Furthermore, it was surprising how many people said they would want to be able to invest in a vehicle that had better fuel economy and how few people said they wanted any other type of car. Fuel economy typically ranks below many other variables when people report what influenced their decision to buy their vehicles. One possible explanation is that since I was interviewing people about their
response to gas price, they had fuel economy more on their mind. Another is that there may have been social desirability bias - although I tried to keep my language as value neutral as possible during the interviews, they may still have felt that the more socially desirable response would be to say that they were willing to reduce their fuel consumption, since I was interviewing them about their fuel price sensitivity.

## Response to a hypothetical large gas tax increase of \$6.20/gallon

## Scenario description

In the next phase of my interviews, I presented the interviewees with a scenario that involved gas price increasing far more rapidly and significantly than any of them had likely experienced, aside from during the 1970s oil crises. The increase I chose to ask them about was a scenario in which U.S. gas taxes became some of the highest among OECD countries. My prompt was "The government has decided that it will phase in a tax increase of $\$ 4 /$ gallon. This will result in the price per gallon going up from $\$ 2.20$ to $\$ 6.20$ over the course of ten years. If you used to spend $\$ 30 /$ week on gas, now you would spend roughly $\$ 80 /$ week on average (ignoring commodity price fluctuations)."

This increase is significantly more than the gas tax increase modeled in Moving Cooler of $\$ 2.71 /$ gallon, although it would be more gradual. However, the price might end up about the same since when that report was being written, gas prices had been between $\$ 3$ and $\$ 4 /$ gallon. So the authors may have been imagining a future when the gas prices including tax were around the level that I posed in the scenario.

I then asked questions about the impact this change would have on the household's driving patterns and finances - a freeform question on how they would respond to the higher prices, and a few more specific questions. The questions are listed in Appendix A. Following these questions, I asked each interviewee to think about the six types of travel listed in the columns of Table 12.1 described each type of trip using the definitions listed in this table. The interviewee then described what effect, if any, the $\$ 4 / \mathrm{gallon}$ gas tax proposed in the scenario would have on each type of travel, specifically addressing frequency, location, carpooling behavior, trip chaining behavior, and mode choice for each trip type.

## Interviewee response to scenario

Many of the interviewees were already trying to conserve gas, particularly during times of high prices. I asked about the extent that the interviewees had recently done the actions they said they would do if the price went up to $\$ 6.20$, and if they could do any of these actions to a greater extent. Many of the participants gave qualified answers to each question, not decisively committing one way or another. It was also difficult to get each interviewee to answer each question due to their perceived redundancy. Nonetheless, I attempted to interpret the responses I received and categorize them in Table 13a. Table 13a does not include all five types of changes (changing frequency, changing location, carpooling, combining trips, and switching modes) for all six types of travel. Instead, I skipped some of the questions that seemed unlikely to provide any valuable information (such as whether people carpooled more for vacation trips), and I lumped together all travel types for some actions like combining trips for simplicity.

Table 12. Matrix of types of travel and actions that could be taken to reduce gas price exposure.

|  | Commuting | Shopping/ errands | Chauffeuring | Social and recreational | Vacation | Other |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Include trips to work and/or to school for your own education. Also include trips with a business purpose. | Include trips made to purchase goods, obtain services (haircuts, doctor appointments, etc.), and personal business you must take care of. | Dropping off and picking up family members from activities. Visiting family members to take care of specific needs if they are sick or unable to perform them. | Trips for visiting friends/ family/ acquaintances. Trips to the gym or exercise facility or outdoors recreation. Trips to cultural events and other entertainment. Trips to eat out. | Exclude single day (or shorter) recreational trips, which are listed under "Social and Recreational" | Anything not captured already. |
| Would you change the frequency you go on these trips? |  |  |  |  |  |  |
| Would you go to a closer location? |  |  |  |  |  |  |
| Would you make more efforts to carpool? |  |  |  |  |  |  |
| Would you combine other types of trips more than you already do? |  |  |  |  |  |  |
| Would you choose to [walk/bike/take the bus]? Would you drive a different car? |  |  |  |  |  |  |

The most common new thing (Table 13a, Column 1) that people said they would do if gas prices were at the high level specified in the scenario was that they would cut back on vacations. Many people also said they would try to find a carpool, reduce the frequency of social visits, find closer destinations, and reduce long-distance work trips (by telecommuting or being more selective on location when accepting client work that required travel). Regarding actions that people were already taking and would do more, by far the biggest action was combining trips of different purposes, followed by finding closer destinations. Of the people who already combine trips, the majority seemed to think they would do it more when gas prices got more expensive, but of the people who already look for close destinations to take care of their needs, the majority said there was no way to find any closer locations.

Of the things that people wouldn't do in response to the dramatically higher gas prices, the most people cited cutting back on vacations. This was the action that the most people said they would take, so it seems a relatively polarizing decision. Therefore, the ratio of people who would or would not change any specific aspect of their travel behavior could be an interesting way to evaluate the data - among people who already take actions to reduce their VMT, among people who have not taken these actions, and among all participants. This would be particularly enlightening if a future study were to conduct a focused survey on a specific population within the U.S. with a higher sample size.

Although my interview sample was not designed to produce robust conclusions on this matter, I have still summarized the data In Table 13a in this way, shown in Table 13b. I grouped the people who would increase the extent to which they performed an action to reduce emissions with the people who don't already perform that action but would. Then I grouped the people who wouldn't take the action with the people who already do it but couldn't increase the extent to which they do it. The ratio of the size of these two groups for each action is an interesting measure of how many people might be able and willing to reduce emissions, at least according to their stated preferences. This ratio could also be viewed as a proxy for how painful or disruptive each behavioral adjustment is perceived to be. It is not immediately obvious whether increasing the extent to which people perform actions they are already performing would reduce emissions by more or less than having people who haven't taken the same step to try it anew. For instance, for a person who exclusively drives her car, switching some trips to a different travel mode may have a higher or lower impact on emissions than another person who already takes transit for some trips and reduces the percentage of trips done by personal vehicle. Therefore, it makes some sense to combine the people who would take actions anew with the people who would increase the extent to which they perform the actions for summary purposes.

The table shows that economizing in other aspects of life seemed to be one of the more popular ways to deal with higher gas prices and travel budgets - five interviewees suggested they would do this, while only one interviewee would not. Surprisingly, carpooling also came out quite high by this metric, with seven people stating a willingness to try it and only two saying no. Combining trips seemed to be a lowhanging fruit because most interviewees are already doing it to a certain extent, and the main reason that interviewees would not was because they had already combined as many as seemed reasonable to them. On the other hand, more efficient cars, reduced frequency of work trips, and closer destinations did not seem popular by this metric, primarily because some interviewees felt they had already taken these actions as much as they reasonably could.

Another useful way to look at the data is to look at the people who don't already take each action. What is the ratio of the people who would consider doing it to those who would not? This could be evaluated by taking the ratio of Column 1 to Column 2 in Table 13a. My results show that by this metric, finding closer destinations is seen as a more feasible opportunity in the eyes of people who don't currently think they prioritize the proximity of their common destinations. Likewise (and surprisingly), carpooling scores quite high by this metric with five people saying they would do it, and only two saying they would not. This way of looking at the data shows that while switching travel modes was relatively popular in the whole sample (Table 13b), most of the people who would switch more trips away from the car were already multimodal travelers to some extent. Among the people who were exclusively drivers, switching mode seems to have come across as not a feasible change, perhaps especially compared with the opportunity to continue to drive and find a carpool.

Table 13a. Interviewees' statements of what they would do in response to hypothetical scenario of $\$ 6.20 /$ gallon gas.

|  | Doesn't <br> do it <br> now, but <br> would | Doesn't <br> and <br> wouldn't <br> do it | Already <br> does it, <br> but could <br> do more | Already <br> does it, <br> couldn't <br> do more | Didn't <br> specify |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Reduce frequency of work-related trips by <br> car | 4 | 2 | - | 2 | 7 |
| Reduce frequency of social visits | 4 | 2 | 3 | 1 | 5 |
| Combine more trips | 1 | - | 8 | 3 | 3 |
| Find closer destinations | 4 | - | 2 | 6 | 3 |
| Experiment with carpooling | 5 | 2 | 2 | - | 6 |
| Use a more efficient car | 2 | 1 | 1 | 2 | 9 |
| Switch from car to another mode | 1 | 2 | 4 | - | 8 |
| Cut back vacations (frequency or distance) | 6 | 4 | 2 | 1 | 2 |
| Economize on other aspects of daily life | - | - | 5 | 1 | 9 |

Table 13b. Summarized version of Table 13a.

|  | Would increase <br> this behavior | Wouldn't or <br> couldn't increase <br> this behavior | Ratio: Would <br> to Wouldn't |
| ---: | :---: | :---: | :---: |
| Reduce frequency of long work trips by car | 4 | 4 | 1 |
| Reduce frequency of social visits | 7 | 3 | 2.3 |
| Combine more trips | 9 | 3 | 3.0 |
| Find closer destinations | 6 | 6 | 1.0 |
| Experiment with carpooling | 7 | 2 | 3.5 |
| Use a more efficient car | 3 | 3 | 1.0 |
| Switch from car to another mode | 5 | 2 | 2.5 |
| Cut back vacations | 8 | 5 | 1.6 |
| Economize on other aspects of daily life | 5 | 1 | 5.0 |

It must be noted that the distinction between already having taken the action listed and not having done it was subjective. First, each of the actions is relative to a baseline, which is likely quite different from one interviewee to another. Second, the interviewee may have taken the action for reasons other than reducing gasoline costs. For me to classify an interviewee as already having taken each specific action, they needed to have stated that gas prices were a motivating factor for taking that action. It did not need to be an action the interviewee was currently taking, just something that they said they had recently done.

For reducing the frequency of long work trips by car, I considered anyone who was commuting five times per week as not having taken action, and anyone who telecommuted at all, or reported having selected client-based work consciously to avoid extra gas costs, as someone who has already taken action. For reducing the frequency of social visits (or vacations), anyone who reported that they engaged in fewer social visits (or vacations) than they would have, due to gas prices, was someone who had already taken action. For combining trips, my criteria was whether they ever did it, even occasionally, and whether gas price was a motivating factor. For finding closer destinations, there are other reasons that people would go out of their way to find closer locations, such as saving time. It didn't matter how close the destinations were, so long as they were closer than they would have been due to gas prices. For using a more efficient car, my criteria was whether they stated that they picked their car with gas costs in mind.

## Self-assessment of ability to reduce overall VMT in gas tax increase scenario

 As noted above in Table 13b, the number of interviewees who said they would be willing to take relatively significant specific actions to conserve gasoline greatly outnumbered the number who wouldn't take those actions in the event of a $\$ 4 /$ gallon increase in the gas tax. But how much does this mean these interviewees would cut their VMT overall? I waited until after going over all the actions they would take during this scenario to ask them to then try to quantify the percent by which they could reduce their VMT. I was unable to get a firm answer out of many of my interviewees, which is understandable, given the poor awareness most people have of the actual distance that certain trips require. But the rest of the interviewees either provided a specific number or made statements as to the percent of their travel that was discretionary versus essential. I tabulated the number of respondents who felt they could cut $20 \%$ and $50 \%$ of their personal vehicle travel mileage in the event of the gas tax increase, and have summarized it in Table 14. My number of uncertain responses is higher in the $50 \%$ scenario because I interpreted a statement like "I would love to be able to cut my mileage by about $50 \%$ " or " $50 \%$ of my driving is discretionary" as likely to mean that the interviewee was able to achieve the $20 \%$ reduction, but it was not as clear about the $50 \%$ reduction.Table 14. Number of interviewees who could cut their VMT by specific levels.

|  | Yes, I could | No, I could not | Unsure |
| :--- | :---: | :---: | :---: |
| Greater than $20 \%$ | 8 | 2 | 5 |
| Greater than $50 \%$ | 4 | 4 | 7 |

These sound like very substantial reductions in VMT. However, it must be noted my scenario suggested that the cost of gas would increase from $\$ 2.20 /$ gallon to $\$ 6.20 /$ gallon, an increase of $181 \%$. Therefore, a
$20 \%$ cut in VMT would represent a long-term elasticity of -0.11 and a $50 \%$ cut in VMT would represent a long-term elasticity of -0.28 , both of which are within the range that recent studies have suggested for aggregate gas price response of VMT. I must caveat these numbers because hypothetical scenarios are difficult to fully internalize for an interviewee, and because price elasticities studies normally look at much smaller increases or decreases in price.

## Barriers to reducing VMT

The final component of the interviews was to determine the strongest perceived barriers to reducing gas consumption. I asked about how much travel each respondent believed was discretionary, and what limits the respondent's ability to change their behaviors. I tallied the responses to these questions in Table 15. The finding was that the most commonly mentioned barriers to conserving gas were firm job requirements and the lack of sufficient transit. Half of the interviewees living with dependent children cited these children's needs as significant barriers to reduced VMT. Only one cited the fact that she had already done most of what she could to conserve.

Table 15. Commonly cited barriers to conserving gas by driving less.

| Barrier | Number of respondents |
| ---: | :---: |
| Already doing a lot to conserve | 1 |
| Job requirements are too firm | 6 |
| Lack of sufficient transit alternatives | 7 |
| Cannot adjust children's schedules | 2 |

## Overall Themes

My general findings from the fifteen interviews can be grouped into the near universal desire for independence, the desire for a one-size-fits-all vehicle, the importance of factors other than price in determining driving behavior, the role of both personality and finances in modulating price response, and the great amount of inertia that precludes significant changes in travel patterns in response to price shifts.

## Desire for independence

Many of my interviewees cited the car as a critical enabler of their mobility and freedom, referring to mainly instrumental factors that motivated their car usage, such as speed and flexibility. Four of my fifteen respondents specifically said their vehicles were critical to their independence and their control over their daily activities. This is not surprising, given the number of interviewees in rural and suburban locations. One interviewee cited memories of her experience as a high school student in El Paso, Texas without access to a vehicle, which resulted in the constant need to rely on friends who had vehicles or her parents. This triggered a desire to never live without a car or live outside of an area with very good transit. Three interviewees explicitly relied on their cars or trucks for their job functions. Thus for these three individuals, the vehicle literally supported their livelihoods and financial security. For the suburban commuters I interviewed, several did feel that their independence would be threatened by higher gas
prices. One said he would have been scared to move to the suburbs if he had made his decision in 2008, after gas prices had run up to $\$ 4 /$ gallon in some areas.

The issue of independence also came up from the two first-time car owners in my interview sample. One of these, a self-avowed urbanite who only uses transit and a bicycle in the city, spoke of the impossibility of going back to not owning a vehicle once he got accustomed to the freedom and latitude that having a vehicle afforded him. The primary value he derived from his new vehicle was flexibility for special occasions and spontaneous trips - for instance organizing hiking trips at the last minute, or visiting family members who lived in rural areas (without needing to depend on someone to pick him up from the train). The other first-time car owner acquired her car partially as the result of having her first baby and as a result of the social stigma she felt when traveling on the train with her baby. All in all, the flexibility afforded by a car seemed to be so universal that it's likely that it simply went unstated by some of the other interviewees.

## Desire for one-size-fits-all vehicle

Recent research has pointed to the desire for the "Swiss-army knife" car, the car that is versatile enough to accomplish just about any purpose the owner could imagine, as a reason for the prevalence of larger cars and SUVs. Without a convenient way to fulfill the $95^{\text {th }}$ percentile use case, many consumers purchase a car that fills those expected needs regardless of the impact on fuel economy. Features such as added weight, more interior room, AWD, and high clearance all may adversely impact fuel economy without ever being used by the average purchaser of the vehicle. Given the relatively high initial purchase price of a typical car, and the long-term ownership of the vehicle, many people may fear buyer's remorse if they do not make sure to buy a car that meets all the possible needs they anticipate.

One antidote to the problem of needing a bigger car for infrequent occasions is to own multiple cars within the family. Several of the households I interviewed had multiple cars and had chosen one versatile car that could achieve most things they would need, and one car that was selected more based on fuel economy. However, several interviewees cited the financial barrier to buying another car. In some of these cases, the more powerful, larger capacity car won out as the first vehicle purchase. Another antidote is the availability of rentals for specialized needs, like U-Hauls, Zipcar trucks, and other cars. However, except in the urban areas with the best access to such rentals, it is hard to beat the convenience of having more capacity in the household car.

This theme came out in a few stories. One interviewee was an electrical contractor, who had all of his tools permanently stored in the back of his pickup truck. He struggled with gas expenses, but could not justify the extra expense of buying another car due to the long payback period in gas savings. The prospect of having to shuttle his tools from the truck to a smaller car and back and forth further precluded the possibility of getting a second car to be able to save gas. Another interviewee explained that he needed his larger capacity car because of home remodeling needs, and he liked to know he could haul lumber and large items whenever needed.

## Factors other than gas price

Convenience and quality of alternative travel options was frequently cited as a critical determinant of the amount the interviewees traveled by car. My interviewee in rural New Jersey lived at the end of a long driveway in a geographic setting with few stores or services. Bicycling was not an option due to weather, distance, and the need to carry things. Transit was also non-existent. Several of the suburban interviewees described their options in very similar ways. A few suburban interviewees did have access to commuter rail. They cited the ability to read or work on the train as a strong perk, but lamented the lack of flexibility due to the infrequent service. For many interviewees the quality of the time in the car was also important, and most of them talked about the ways in which they tried to increase the quality of their vehicle travel time. Some cited the ability to catch up with friends on the phone from their car. Others mentioned mental relaxation and the ability to stop thinking about work. One particularly gregarious interviewee said that the amount of trips he takes in his car is directly related to his ability to recruit passengers to accompany him, since his car was almost exclusively used for discretionary and recreational purposes. As for quality factors mainly outside of control of the drivers' control, the most commonly cited factor was congestion and uncertainty about arrival time. Several respondents referred to the phenomenon of feeling stuck and helpless when they had to drive in congestion, and this was a strong deterrent from additional driving for them.

The concept of travel demand saturation, as proposed by Metz and others, relates to the idea that limiting factors other than price keep VMT per capita from growing. First and foremost is time. As mentioned in Chapter 3, academic researchers have documented the phenomenon of travel time budgets among U.S. drivers, where many people tend towards limiting their daily travel time to approximately one hour. Two of the respondents said that they are so tired of driving for their jobs that they therefore minimize additional discretionary driving in their personal lives. If their commute travel was reduced, it is possible there might be a rebound effect since there would be weaker motivation to reduce discretionary VMT. Furthermore, for some of the self-employed workers I interviewed, gas was a tax-deductible business expense, which reduced their concern with the cost to a certain extent.

Safety was another deterrent from additional VMT. The recent mother I interviewed was concerned about the number of other drivers on their cell phones, and the consequences of a crash with her baby in the car. Safety also played a role for the truck driver, who felt he was too old to drive the same hours as younger truckers, and who was concerned with getting drowsy behind the wheel. The Federal Motor Carrier Safety Administration has regulations on the number of consecutive hours that commercial drivers can drive, but these regulations mainly do not relate to the VMT of the light-duty vehicle fleet.

All told, eight of the thirteen interviewees who had a car in the household provided additional factors such as those described above when asked what limited their total mileage driven the most. Many of these people explicitly said that these factors were more important than price for their daily driving decisions. The responses seemed heavily focused on the "instrumental" motivations for using a car - the car's ability to afford independent and flexible mobility, and the comfort, speed, and convenience of driving. The downsides of car usage seemed to be ignored and the insufficiency of other modes was commonly cited (consistent with the literature cited in Beirão and Sarsfield Cabral, 2007). Only a few people mentioned congestion or the cost of owning a vehicle, although a few respondents hinted at a
sense of guilt associated with needing to drive more than the average person and knowing that it resulted in more emissions and higher cost.

Another set of factors that may be as important as price and the instrumental motivation to drive are the symbolic and affective motivations for car usage, such as feelings of superiority, power, and control (Steg, 2005). My interviews were not designed to discriminate between instrumental and symbolic motivation, and even if I did try to find these symbolic motivations, it is possible that the interviewees wouldn't be as aware of how much symbolic motivation affected them or willing to admit that it did at all. Nonetheless, this is also a factor to be aware of beyond price in determining how much an individual may drive.

## Thrift, socioeconomics, and personality

The attitudes espoused by my interviewees did not easily break down into expected price sensitivities based on income and demographics. Two of the interviewees who were most sensitive to gas price were also part of the households with the highest incomes. Some interviewees of modest means told stories of why it was important to them to maintain their current travel lifestyle regardless of the financial cost. Of course, there were also more affluent households that reported very low price sensitivities and less affluent households that were very price conscious as well.

It therefore seems that personality is an important modulator of the way in which people respond to price changes - some of my respondents talked extensively about the importance of thrift, while others talked more extensively about the importance of being available for their children's swim meets and their family functions. Some respondents suggested that they got their thrifty behavior from their parents, while others suggested that their desire to ignore the cost of gas stemmed from a reaction to growing up in an environment where their parents needed to save money on gas, and a feeling of pride and independence from not needing to worry about gas costs.

However, regardless of how much the interviewees portrayed themselves as thrifty, none of them mentioned that they considered the cost of individual trips when deciding whether or not to drive. Some described gas price as a contributor to their overall understanding of their financial situation, and many said they would think about what kind of trips they might cut back on in the extreme gas price scenario I posed, but at current prices, the decision whether or not to drive was not consciously made prior to each specific trip. This is consistent with the literature that shows that motoring costs are perceived as unavoidable periodic events (Bonsall et al, 2006).

## Inertia in travel decisions

Decisions about where to live and what vehicle to use are known to be infrequent decisions, often triggered by changes in life stage or professional opportunities. My interviewees clearly displayed this tendency to consider vehicle and household decisions as irreversible in the short run.

Regarding the decision to own a vehicle, research from R.L. Polk suggests that during the most recent recession, the average period that a household owned a new vehicle increased to 71 months (nearly 6 years), with the average duration of owning a used car around 50 months ( $>4$ years) (Kelly Blue Book, 2012). In addition to the soft economy, they cite several reasons for which Americans are holding on to
their vehicles longer - greater prevalence of extended warranties, better build quality that makes holding a vehicle for longer less risky, and the increased prevalence of longer term financing on auto loans (ibid.). This suggests that the decision of what car to own is not an extremely long term decision, but it is not a simple spontaneous decision either. The decision of whether to own a car, and how many to own is likely a decision that has an even longer time duration, since many times when a household sells a car, they are likely to replace it and keep their level of car ownership constant.

I heard many manifestations of the long time horizon of car ownership decisions in my interviews. One suburban respondent lamented that her car was a "gas guzzler" and she wanted a more efficient car, but she would not want to sell her current car for fear of having to take out financing for another car. Her plan is to run the current car into the ground. Another suburban respondent said the exact same thing about running her existing car until it stopped working. Two respondents who were recent first time car owners said that they couldn't conceive going back to the time before they owned a vehicle because of the flexibility and freedom they now enjoyed, regardless of whether the cost to operate the car increased significantly or whether their living environment became more similar to what it was before they owned the car. In behavioral economic terms, this can be seen as a sort of "endowment effect" - that once an individual has expanded his or her options, it is very difficult to give up the new options. Another respondent experienced an inertial shift towards reduced car ownership, which I suspect is much more uncommon. He explained that during the recent recession he and his wife decided that he would try biking to work to reduce expenses. He discovered that his new commute (which was along river bike paths for most of the way) left him more energized, and he sold his second household car as a result. Living near a commuter rail stop and in an area with plenty of Zipcars gave him enough flexibility for days of inclement weather. Now that the bike commute has been a regular feature of his life for seven years, it has become part of his routine and his identity, and even since the economy recovered he still hasn't considered buying a second household car.

Regarding the inertia in household location, more of my respondents said that they weren't fully satisfied with their residential location (refer back to Table 11). Only five respondents said they were satisfied, while six said they wanted their location to be more convenient and/or more walkable. Several factors make moving between homes less frequent - for instance, the high price relative to income, the risk of loss of value, the sunk cost phenomenon (even if you aren't satisfied with your current home, neighborhood, or commute, you do not want to move because you have invested time and energy in customization), and trepidation when faced with the effort and expense required to negotiate purchase and sale, and the effort of packing up and moving all accumulated belongings. These factors demote the idea of changing one's living environment to the status of a daydream or fantasy. Several of my interviewees explained what environment they wanted to live in, but quickly discounted it and suggested it would likely never happen.

One interviewee said that commuting was her "number one source of unhappiness," and that if her income were higher, she would move closer to where she worked. Another interviewee said that she wants to be in a location more convenient to her work and hopes she will eventually move, but her house has lost value since she purchased it and she "needs to wait for the value to come back first." Several interviewees were torn between access to natural areas and solitude on one hand and
convenience and vibrancy on the other hand, lamenting that they couldn't find good places that would fill both of these needs. Several interviewees were very happy with their current residential locations, however. One of these people said that if gas prices went up significantly, he would search for a job closer to his existing house in an exurban community, rather than search for a residential location closer to his current job.

All in all, most my interviewees were keenly aware of the long-term nature of their vehicle and residential location decisions, and knew that these decisions were likely to lock them in to specific lifestyles for significant durations of time. They mainly implied that they would pay attention to factors such as the potential for much higher gas prices when making these long-term decisions, but many other factors play a role of equal importance. There was significant evidence for a catalyst model of change - once gas prices reach a certain level, they might activate a change in behavior that would persist long after the price spike or the price drop was mitigated. Catalysts also included life events, such as in the case of the new parent.

## Ideas for future work

Future studies of gas price responsiveness should evaluate several additional behavioral phenomena.
One such phenomenon, called "reactance," refers to the possibility that policies that aim to reduce a certain behavior may fail because they trigger anger or disengagement. Rossger et al (2009) explain that when people feel their options are being unfairly restricted, they may enter a state of intense adverse motivation and they may attempt to restore their options. This could take the form of driving just as much or more when gas taxes increase in order to feel unconstrained. This adverse motivation is unlikely when the policy is perceived as reasonable and fair. Reactance would be a difficult phenomenon to measure in the absence of a gas tax increase and would be difficult to discern in the aggregate data because those people who exhibit reactance will be averaged out with the people who are more price responsive. Peter Bonsall's work has shown that consumers will also disengage and avoid certain expenditures altogether if they perceive the cost structure to be too complex (Bonsall et al, 2006). The effects of this complexity-driven disengagement would be particularly interesting to study in the context of VMT pricing and congestion pricing when there may be very different costs associated with driving during different time periods and on different roads and in different zones. Guo et al (2011) was able to study the effect of a moderately complex VMT pricing scheme in Oregon, but they did not address the behavioral motivation that caused the shifts in travel behavior that they observed.

Additional work should be done to understand what reference points and anchoring effects are prevalent for gas prices, and whether crossing certain thresholds is more likely to make gas price changes more salient. For instance, people accustomed to the gas prices in the 1990s may have had some shock the first time it cost them more than a $\$ 20$ bill to fill their tank. Or in the period around 2008, the run up to $\$ 4 /$ gallon was a level that several of my respondents said really triggered additional concern for them. To what degree people would adapt to these threshold effects and to what degree they would simply accept them as the new normal is an important question to address.

## Conclusions

Despite the limitations of analyzing self-reported behavior on a small sample of people, I uncovered some interesting and useful findings about how people retrospectively describe changes in their travel patterns, and how people think they would react to hypothetical price changes that are far outside the range of any gas price changes they have ever experienced. The interviews showed that many people thought about gas price on a regular basis and that the gas price influenced how people felt about their overall financial situation (reinforcing the findings of Godek and Murray (2011) who found that viewing the price per gallon could affect consumers' behaviors through influencing their "comprehensive mental accounting"). It appears that there were high barriers to significant change in VMT for many of the people in my interview pool and that many other factors also contributed to their daily driving decisions.

Gas price was the component of the cost of driving that the government can influence that my respondents were most concerned about. The hypothetical scenario of a $\$ 4 /$ gallon increase in the gas tax sounded like it would be a catalytic event that would trigger very significant changes for many of my interviewees. Four times as many interviewees said they could reduce their mileage by $20 \%$ as those who said they could not, and equal numbers said they could and could not reduce their mileage by $50 \%$. A $50 \%$ change would be equivalent to an elasticity of -0.28 , a bit higher than the average elasticity in most recent studies.

There was a mix of frustration and satisfaction from the travel options available to each of my respondents. Many of them suggested they desired ways to change their activity patterns that reduced their VMT, but few felt that the current gas price was a strong enough motivator to change their vehicle ownership and home locations. When presented with a hypothetical significant increase in the gas tax, many ideas came forward about how they would reduce their exposure to the tax, but few people were able to confidently quantify by how much they could reduce VMT. These findings have broad applicability when thinking about the challenging politics of how gas tax increases could be implemented. Given the resounding theme of car travel being central to the respondents' feeling of independence, VMT reducing policies must be proposed strategically, with clear and concentrated benefits to politically engaged and powerful constituents. Furthermore, given the latent demand expressed for more convenient mixed-use locations with better connectivity and walkability, policy makers should not take price elasticities of VMT as a given. Rather they should expect that as travel options change, elasticity could be quite different in the future, particularly if alternatives to single occupant vehicle travel become more convenient and appealing.

Building on my understanding of the attitudes and behaviors of a broad range of interview subjects, I will now turn to quantitative data to evaluate how price elasticities may vary between population groups in different locations. For this, I will use the revealed behavior of Massachusetts vehicle owners through the dataset of odometer readings recently made available to the public.

## Chapter 6: The Massachusetts Vehicle Census

## Motivation

The previous chapter explained my findings from a set of behavioral interviews, which provide some insights into what people in a variety of socioeconomic situations perceive guides their routine travel decisions. Since there are known challenges to stated preference methods of inquiry, I next explored a revealed preference measure, the amount that people drive in Massachusetts, using a unique dataset of odometer readings, which is available for researcher access and public access. The goals of using this dataset were 1) to explain the variability in the amount that people drive based on demographic factors, fuel price, vehicle attributes, and built environment, and 2) to uncover the range of price elasticity of VMT for individual vehicles and which factors could be shown to affect this elasticity.

Before presenting the analysis that addresses the two aforementioned goals, background on this data is necessary. Therefore, this chapter will introduce the dataset, the trends in VMT over time, and the spatial variation within the state of Massachusetts. Chapter 7 will then build a regression analysis to address the variability of VMT and price elasticity. Overall, the results add to our understanding of heterogeneity of elasticity from recent work on the California and Pennsylvania datasets.

## Why use the Massachusetts Vehicle Census (MAVC)?

At least four states have provided data to researchers from their vehicle registrations and emissions testing, including California, Colorado, Massachusetts, and Pennsylvania. This data is not collected for the expressed purpose of travel pattern research, but for administrative purposes. In order to be released, it must be anonymized so that cars cannot be tracked to specific addresses and owners. Therefore it lacks some additional features that would make it even more useful, but it nonetheless provides an incredibly comprehensive view of all the driving of private cars registered in Massachusetts with fine-grained spatial resolution.

I chose to analyze the Massachusetts dataset (the MAVC) because it has been cleaned and made available to the public by a research partnership of the Metropolitan Area Planning Council (the MAPC), the Registry of Motor Vehicles (RMV), the Central Planning Transportation Staff (CTPS), and Yale University. This group of researchers has created histories of the driving patterns of individual vehicles by each successive registered owner. They have geocoded all their data and summarized it spatially, enabling researchers to integrate census variables into their analysis. Furthermore, the MAVC dataset is the most detailed, and Massachusetts is the only one of these four states to require annual inspections of all vehicles ${ }^{12}$.

[^11]The scope of data provided in the MAVC is all the sequential pairs of records of vehicle registrations and inspections that can be matched. A match means that it has the same vehicle identification number (VIN), and that there is no intermediate inspection date between the two inspections that form the record. Mileage estimates were constructed by the MAPC as described in Reardon et al (2015), using an algorithm to eliminate invalid odometer readings whenever a reading at a later point in time had a lower odometer reading.

The databases which the MAPC used to create the vehicle mileage estimates are the Automated License and Registration System (ALARS), and the Vehicle Check database. A record is created in the ALARS system whenever a vehicle is registered, the title is transferred due to purchase or sale, a registration was cancelled, a registration was renewed, or the owner changed the address (Reardon et al, 2015). A record is created in the Vehicle Check system whenever a vehicle is brought in for a safety and emissions check, which are required prior to the expiration of the previous inspection sticker or within seven days of sale. While vehicles older than 2001 model year are exempted from the emissions component of the annual inspections, it appears based on my data exploration that these vehicles do still receive odometer readings through their safety inspections.

In addition to the fact that the MAVC contains records for vehicles of all ages and in all parts of the state, another benefit of using this dataset is that it gives two forms of useful data:

1) "Microdata" - individual inspection and registration records of anonymized vehicles, affording the analysis of how price elasticity of mileage varies along with vehicle attributes, and
2) Summary data - aggregate information on all vehicle inspections that can be mapped to specific geographies, including 250-meter grid cells, census block groups, zipcodes, and municipalities.

I have analyzed both sets of data. However, the bulk of the results presented in this thesis will focus on the "microdata."

## Exploring the dataset

The data was loaded into a PostgreSQL database, visualizations were done on random samples of data with Excel and Tableau, and regressions were performed using Excel and Gretl. I first generated some basic information about the dataset. There were 19.03 million mileage estimate records in the whole dataset, representing the amount driven by 6.95 million unique vehicles during this time (each vehicle has a unique vehicle identification number, or VIN, that does not change at any time, including when the vehicle is sold). Of these 6.95 million vehicles, 1.33 million had been owned by two different owners or had their license plate number changed for any other reason.

In order to see what sample size was available for the analysis, I filtered for mileage estimates on vehicles with specific attributes, in a stepwise manner. The number and percent of records that remained after each step is shown in Table 16. It is clear that a large number of records was still available even after the filtering process.

Table 16. Number of microdata records meeting specific filters. These filters were applied cumulatively so the result in each row is the number of mileage estimates that met the filter in that row and all rows above it.

|  | \# of records | Percent of <br> records |
| ---: | :---: | :---: |
| All registration and estimate records | $19,030,499$ | $100.0 \%$ |
| $\ldots \ldots$...with a mileage estimate | $16,145,383$ | $84.8 \%$ |
| $\ldots$ with an estimate greater than 0.1 miles per day (barely driven) | $10,893,668$ | $57.2 \%$ |
| $\ldots$ with an estimate less than 200 miles per day (likely erroneous reading) | $10,771,682$ | $56.6 \%$ |
| $\ldots$ with location information and in-state registration, and | $9,689,675$ | $50.9 \%$ |
| $\ldots$ from gas, diesel, or flexfuel vehicles, and | $9,684,970$ | $50.9 \%$ |
| $\ldots$ not from motorcycles or commercial vehicles, and | $9,277,068$ | $48.7 \%$ |
| $\ldots$ with a period between odometer readings between 10 and 14 months | $6,755,492$ | $35.5 \%$ |

Just under half of the records that remained after the filtering process in Table 16 were from within the MAPC region (the 101 municipalities that are members of the MAPC are the closest to Boston, and comprise most of the towns within Boston's outer beltway, I-495).

## Microdata

## Trend over time

I next evaluated the trend over time in the average mileage driven per day by the entire fleet of Massachusetts geolocated vehicles that had valid mileage estimates. From the dataset, I excluded any mileage records that said the vehicle had been driven more than 200 miles per day (which the MAPC has stated are likely to be due to odometer transcription mistakes), and any record that said the vehicle had not been driven during the mileage estimate period. For each mileage estimate and each calendar quarter, I determined whether the mileage estimate start date preceded the median day of the calendar quarter and its end date postdated the median date. If both conditions were met, I included the mileage estimate in my average mileage traveled for the calendar quarter.

My results, which were consistent with Reardon et al, 2015 are shown below in Figure 17. There exists a sharp $10 \%$ discontinuity in the average mileage per day reported for vehicles in Q1 2009 relative to Q4 2008. This was coincident with the October 2008 financial crisis and the subsequent plummeting of gasoline prices. I therefore compared with FHWA VMT and found that during this period, national VMT dropped by only 6\%. This raised a red flag about the 2008 data. The $6 \%$ drop in FHWA's national data was representative of typical seasonal variability, whereas the drop in the MAVC averages was not, since the typical odometer reading spans roughly 12 months, thereby almost totally eliminating seasonality.

Although the MAVC averages by quarter are not significantly seasonal, I plotted them on the same graph as the FHWA national VMT data to show that the FHWA does not show a 10\% step down from 2008 to 2009. The drop in mileage in FHWA data in Q1 2008 was no more pronounced than a typical seasonal decrease for the winter period, whereas the MAVC data showed a sharp discontinuity between 2008 and 2009 unrelated to seasonality.

Figure 17. Trend in VMT per day per vehicle in MAVC data and FHWA VMT estimates for the US.

## Travel Volume Trends by Quarter



Having found this discontinuity in the data, I replicated the chart above for weekly VMT averages and found a linear decrease in the average VMT per day, starting exactly in the first week of 2009. It is hard to argue that this could be due to the impact of the fiscal crisis suddenly sinking in with the average driver, a full two months later, and no other plausible explanations came to mind other than a data collection artifact. The owners of the dataset cannot provide an explanation for what caused this significant discontinuity ${ }^{13}$, so by necessity, I removed the 2008 data from my subsequent analyses.

## Frequency of vehicle inspections

In order to understand the average length of the records, I looked at the distribution of the number of days between inspection records for a random sample ( $n=1,000,000$ ) of private non-commercial cars with valid location information (Figure 18a and b). The most common length of inspection period was 364 days, which is exactly 52 weeks. The regular spikes in the distribution are exactly 7 days apart, which can be explained by the fact that many people who have fixed work schedules likely bring their cars in for inspections on the same day of the week each year (e.g. weekends). One cause for concern is that a full $33 \%$ of the sample had over 395 days ( 13 or more months) in between their inspections, which

[^12]means that either they did not get their vehicles inspected on time, or an intermediate mileage reading had to be thrown out because of typos or recording errors.

As shown by the cumulative distribution plot (Figure 18c), only $3.6 \%$ of the inspection records were less than 304 days ( 10 months) apart, and $75.9 \%$ of them were less than 426 days ( 14 months) long, so over $70 \%$ of my records has a timescale that would be representative of one year elasticities. However, it may also be possible to study shorter time period elasticities by selecting only the data with less than a certain number of months between inspections.

Figure 18. Distribution of inspection period lengths across entire sample

b) The range of inspection lengths with the vast majority of inspection records

c) The cumulative distribution of inspection lengths


Average mileage driven per year, fuel efficiency
Next I summarized the entire dataset for the VMT per vehicle, the average 2008 EPA combined fuel economy, and the average vehicle age.

## All vehicles

From the dataset, I excluded any mileage record that said the vehicle had been driven more than 200 miles per day (which the MAPC has stated are likely to be due to odometer transcription mistakes), and any record that said the vehicle had not been driven during the mileage estimate period. After these records were filtered out, I grouped by the 3.35 million VINs remaining in the sample in order to avoid biasing the statistics with higher weighting of VINs that had been inspected more frequently. Exploration of the data yielded the following summary statistics:

Table 17. Summary statistics on all vehicles in the MAVC

|  | Mean | Std. Dev. | Min. | Max. |
| :--- | :--- | :--- | :--- | :--- |
| Annual VMT (miles) | 11,143 | 7,668 | 0 | 72,996 |
| MPG (EPA city/highway average) | 20.8 | 4.7 | 8.0 | 62 |
| Age (years) | 6.9 | 5.3 | 0 | 31 |

## Subset of vehicles

In order to remove seasonality from the dataset, I performed the next set of analysis only on vehicles whose periods between odometer readings was between 10 and 14 months. The distribution of travel distance per vehicle was skewed right with a mode of 21 miles per day, a median of 26.9 miles per day, and a mean of 29.5 miles per day, as shown in Figure 19.

Figure 19. Count of vehicles in each 3-mile bin, from 0-3 miles per day to 198-200 miles per day.


The distribution of fuel economy was more symmetric, with a mean, median, and mode all coinciding around 20MPG, shown in Figure 20.

Figure 20. Count of vehicles at each level of MPG.


## Spatial variations in the microdata

The next exploratory data analysis I did was to map the average values of a few of the major variables in the microdata to visualize patterns across each zipcode in the state. My sample of 200,000 random observations contained a widely different number of vehicle registrations in each zipcode, as expected. The zipcode with the most observations had over 1700 observations of odometer readings, while there were a few rural zipcodes which only had a few observations in them, so I suppressed the display for the zipcode if it was based on less than 10 observations. In each plot, I arranged the color scheme so that red was indicative of ranges of variables that are associated with higher emissions and green was associated with lower emissions. A few of the smallest zipcodes were plotted as small circles based on the zipcode centroid by my mapping software.

The first variable was the calculated mileage estimate, in miles per vehicle per day, shown in Figure 21a. As expected, the towns closest to the center of the metro Boston area had some of the lowest average mileages per vehicle per day. Another striking pattern was that the Springfield metro area and the surrounding college towns in the Pioneer Valley had low mileage vehicles. Finally, the mileage traveled by vehicles in the far northwestern corner of the state and Cape Cod and the islands was quite low. These two areas are also vacation areas and areas in which the highest fraction of the population is receiving retirement income, so the low mileage may be associated with people who have fewer commuting trips.

Next, I plotted the average fuel economy of vehicles by zipcode, observing the lowest fuel economy in the rural central and western parts of the state, as well as the south coast, shown in Figure 21b.

From visual inspection of Figures 21 a and b , there seems to be a weak but noticeable correlation between areas where the mileage driven is high and areas where the average fuel economy is low (excluding Cape Cod and the islands). The urban core of Boston, and the wealthy suburbs extending to the northwest of the city have some of the highest fuel economies in the state, as well as parts of the Pioneer Valley. This relationship may be surprising at first because one would expect people who need to drive a lot to own higher fuel economy vehicles and one would expect people who own higher fuel economy vehicles to use them more because they are cheaper to drive (Wang and Chen, 2014). But the opposite effect was observed. This is consistent with the regression results in Chapter 7, as well as my analysis of NHTS data (Figure 22), which showed the cities with the lowest average fuel economy in their fleets tended to be the cities with the highest VMT per vehicle. A possible explanation for this phenomenon is that people who drive a lot of mileage may prioritize larger, more comfortable, or safer cars, and each of these factors may be inversely correlated with fuel economy.

Figure 21a. Average mileage per vehicle per day by zipcode in sample.


Figure 21b. Average vehicle fuel economy (in MPG) by zipcode in sample.


Figure 22. The inverse correlation between the average fuel economy and the average distance traveled by the fleets of vehicles in the 32 largest Commute Based Statistical Areas (CBSAs) in the U.S. Source: my analysis of National Household Transportation Survey data, 2009.


Vehicle usage by type and by fuel economy
In order to see if higher fuel economy vehicles are being driven more than low fuel economy cars, I next took my 200,000 observation sample and plotted the number of vehicle inspections by the amount the vehicles were driven per day, binned into different fuel economy bands, shown in Figure 23. Though there were many fewer observations of vehicles that get less than ten miles per gallon or greater than 30 miles per gallon, a clear pattern emerges of vehicles with higher fuel economy being driven more miles per day.

Figure 23. Frequency distribution of miles traveled per day, separated by fuel economy.


I did the same procedure for vehicle types, as given in the MAVC dataset, and found that cars and trucks were typically driven less than SUVs and vans, as shown in Figure 24.

Figure 24. Frequency distribution of VMT, separated by vehicle type.


## Distributions of VMT and MPG by MAPC community types

Another way to spatially explore the data was to break vehicles into categories representative of the type of municipality they were located in. For this, I used the MAPC community types, which are described in detail on their website (MAPC, 2008). Figure 25 shows the distribution of counts for each type of community. The right tail of the distribution is significantly longer for country suburbs, and the difference in the mode is significant, from 15 miles per vehicle per day in the streetcar suburbs to 30 miles per vehicle per day in rural areas.

Figure 25. Frequency distribution of mileage per vehicle per day in my 200,000-observation sample.


Similar frequency distributions were plotted for the fuel economy of vehicles in each MAPC community type, and the distribution was similar between all community types, as shown in Figure 26. Rural areas and country suburbs had a distribution that was shifted slightly towards lower fuel economy vehicles.

Figure 26. Frequency distribution of MPG of vehicles in my 200,000-observation sample


My analysis of the age distribution of all vehicles in the sample showed that in no MAPC community type was the fraction of vehicles older than model year 1990 greater than $1 \%$. I have not included the frequency distributions by age as a figure because I did not find any significant variation in the shape of the distributions by community type. I expected to see that rural vehicles were significantly more likely to be older, but instead the communities that had the highest percentage of vehicles older than model year 2000 were the major regional urban centers (such as Lowell, Lawrence, and Fall River) and the metro Boston core communities.

Finally, the distribution of MSRPs of the vehicles in my sample was relatively similar across the community types and it is not displayed in a figure. The mode price was between $\$ 20,000$ and $\$ 24,000$
in each community type. The cumulative fraction of vehicles under $\$ 30,000$ was slightly higher for rural communities, major regional urban centers, and metro Boston core communities, relative to the various types of suburbs, but beyond that, there was little variation.

## Summary data

The summary data provided by the MAPC provides additional opportunities to quickly scan for patterns. The most useful opportunity from the summary data that cannot be obtained using the microdata is to quantify metrics on a per household basis. The MAPC obtained American Community Survey data on the number of households in each municipality in 2010. They were able to adjust the number of households to vary in time using the number of building permits in each municipality as a proxy for the change in the number of households (Reardon et al, 2015). This could then be used against the number of vehicles registered in each town in each time period, and the mileage estimates from all the odometer readings valid during each time period. Figure 27 shows variation in vehicles per household by town, while Figure 28 shows variation in VMT per household by town, both using the previously mentioned MAPC community categories. Because there are too many municipalities in Massachusetts to conveniently display in a single figure, I only display the municipalities that had over 10,000 households within their boundaries on average between 2008 and 2012.

Figures 27 and 28 show me that the MAPC community categories are powerful predictors of the number of cars owned per household and the average mileage per day per household. The towns with the highest level of car ownership had just over 2 cars per household on average, while some of the urban core towns had only 0.8 to 0.9 cars per household on average. The towns within the MAPC that had the highest VMT per household per day were classified as "Maturing New England Towns" and "Established Suburbs" and many of these towns drove over three times the VMT per household that Cambridge, Brookline, and Boston drove. Both wealthier towns and towns further from the urban core (within the MAPC) tended to own more vehicles per household as shown in Table 18. There was surprisingly little correlation between income per household and distance to downtown.

Table 18. Correlation between vehicle ownership level, income, and distance to downtown.

| Pearson's r | Distance <br> to <br> downtown | Vehicles <br> per <br> household | Income <br> per |
| ---: | ---: | ---: | ---: |
| Distance to downtown | - |  |  |
| Vehicles per household | 0.722 | - |  |
| Income per household | 0.239 | 0.656 |  |

The context that the summary data provide on the correlation between vehicles per household, distance to downtown, and income per household is helpful in explaining the results in Chapter 7, which showed lower VMT per vehicle the further the vehicle was registered from downtown Boston and the wealthier the zipcode. This makes sense when coupled with the information that vehicle ownership per household is twice as high in some of the most suburban towns and also in the wealthier towns. Because household VMT is split among more vehicles, there is less mileage driven per vehicle.

Figure 27. Vehicles per household by town


Figure 28. VMT per household by town


## Summary

The MAVC dataset provides a wealth of information about vehicle ownership and usage throughout the Commonwealth. The comprehensiveness of this dataset is unique, as it is the only state that collects odometer readings annually on all personal vehicles registered in the state. Since the dataset includes four years of data, many vehicles have had multiple mileage estimates during times of high and low gas prices and differing macroeconomic conditions, which I consider close to the minimum amount of time required to do any meaningful analysis of how VMT varies over time, particularly given that the average mileage estimate period is a whole year. The MAPC is committed to providing additional data as it becomes available, and with the next batch of data, it is likely that researchers will have access to a continuous eight year dataset, which will be useful for longitudinal analysis of recent travel trends.

My main findings on the dataset included:

1. After eliminating records that don't have a reasonable mileage estimate, don't have a location attached to them, and are not representative of mileage estimates over a 10-14 month period, there are nearly two-thirds fewer estimates, but this still leaves over 6.5 million mileage estimates available for analysis.
2. The average VMT of vehicles decreased by $10 \%$ abruptly between Q4 2008 and Q1 2009. This is a trend that was not observed broadly in the U.S. and I suspect that it is due to some bias in the early records in the dataset.
3. Over $70 \%$ of the mileage estimates were from periods roughly representative of one year of driving, 10-14 months.
4. The average VMT per vehicle in my sample was lower than most other states and the U.S. average. Of the vehicles with mileage estimates roughly representative of one year's driving, the mean distance was 29.5 miles per day, which translates to 10,770 miles per year.
5. Mean and median fuel economy was around 20MPG. The places in the state where fuel economy was lowest tended to have the highest VMT, and these tended to be rural communities.
6. Low fuel economy and high fuel economy vehicles were both driven more than vehicles that get between 20 and 30 MPG. SUVs and vans were driven more than cars.
7. Older cars tended to be clustered in Boston's metro core and in major regional urban centers like Lowell, Lawrence, and Fall River.
8. Suburban and wealthy towns tended to own more vehicles per household and drive more per household.

Chapter 7 will dig deeper into which of these variables are predictive of VMT once I control for several other sets of data which I will join to this dataset. Incorporating information on gas price and the economy will enable me to determine which factors tend to increase or decrease price elasticity, a central goal of this project.

# Chapter 7: Regression analysis to explore variability of price elasticity of travel demand in Massachusetts 

Motivation

As discussed in previous chapters, it is desirable to better understand how gas price elasticity varies in the U.S. in order to inform policy makers to draw conclusions about 1) the likely future effectiveness of pricing strategies to reduce emissions by curtailing travel demand growth, and 2) the fairness of the effects on different populations. My review of the literature suggested there was no clear consensus on the overall magnitude of gas price elasticity of VMT and the relative price responsiveness of different income quintiles. Furthermore, little work has been done on price responsiveness as a function of vehicle fuel economy or as a function of the urban, suburban, or rural nature of the setting, so additional data points on these questions will be useful. This chapter will examine each of these questions in the context of the Boston metro region using the Massachusetts Vehicle Census (MAVC). The Boston metro area is a useful region to look at for several reasons.

1) Boston's relatively monocentric character is fairly typical of many cities in the US. While there has been a degree of suburbanization of jobs in past decades in many cities, the largest concentration of jobs in most metro areas in the U.S. remains in or near a traditional downtown with the remaining jobs being more dispersed (National Research Council, 2009). Furthermore, Boston's monocentric character allows me to use the distance to downtown as a proxy for the degree to which each community is urban, suburban, or rural and thereby explore the impact of suburban and urban community types on VMT and price responsiveness.
2) There is a significant diversity of town types within the metro region, ranging from dense urban communities to low density country suburbs on the outskirts.
3) The scale of the Boston-Cambridge-Newton MSA is relatively representative of the second tier of metro regions by population. The three largest metro regions in the U.S. (New York, Los Angeles, and Chicago) may be substantially different in their travel dynamics than this second tier of cities. The MSAs that are within plus or minus $50 \%$ of the population of the Boston MSA include the 20 largest MSAs excluding the three aforementioned cities. These MSAs are of a scale to be important in understanding travel trends in the U.S. broadly.

I chose to look at the impact of three variables on price responsiveness: income, fuel economy, and distance to downtown. I picked income because in the future, rising incomes may make fuel costs a lower percentage of household budgets, reducing motivation to adapt to changes in the gasoline price. On the other hand, higher incomes may result in more discretionary VMT. I picked fuel economy because over the next several decades I expect average fuel economy to rise. Therefore, it may be useful to evaluate the price responsiveness of the vehicles of the highest fuel economy for insights into the future. Finally, I chose distance to downtown for two reasons: 1) to understand the equity implications
of gas taxation policy for more distant suburbs, 2) because even under aggressive smart growth policies, substantial population growth may lead to increased average distance to downtown because of limited opportunities for infill development (Ferreria et al, 2013).

Better understanding the barriers that specific population groups may face in adjusting their driving behavior and gasoline consumption will improve discussion of the equity implications of such policies. People may be harmed unequally by both the increased cost of gas taxes, but also by the utility loss associated with adjusting their behavior, and the loss of option values. People may also benefit unequally depending on how gas tax revenue is allocated and whether significant tax increases on gas could reduce other taxes or increase the provision of essential government services.

## Strategy

I attempted price elasticity calculations in two different ways. First, having access to pairs of mileage estimates for specific vehicles that had not changed ownership, I calculated the actual price response of individual vehicles and attempted to find patterns of different price response for different vehicle fuel economies, distances from downtown, MSRPs, and more. However, the data was too noisy to draw any firm conclusions. Many vehicles had elasticities greater than $+/-6$, which is to be expected because any unobservable change in the household's travel patterns could dramatically change total VMT and have nothing to do with gas price - events such as changing jobs, taking children to a different school, buying another car, or selling a car could all result in apparently nonsensical elasticities. Therefore, I abandoned this method.

Instead, I used a more standard econometric approach of modeling VMT as a function of gas price and a host of other variables using Ordinary Least Squares (OLS) regression. OLS modeling was a useful tool because it gave me a way to explore the impact of a large number of variables on VMT and on price responsiveness by fitting an equation to predict VMT (Equation 1 shows the general form of the equation, but there are too many variables to list all of them.). Another useful feature of my model specification was that I was able to take the natural log of the dependent variable (VMT per day) and the natural log of most of the predictor variables in order to produce coefficients that could directly be interpreted as elasticities without any further calculation. For instance, when I got a coefficient of 1.8 on my term for Massachusetts employment, it suggested that a $1 \%$ increase in employment in the state was associated with a $1.8 \%$ increase in VMT per day per vehicle.

Based on prior work on the MAVC (Reardon et al, 2015) and the Pennsylvania Vehicle Census (Jenn et al, 2015), I expected my dependent variable, the VMT per day of each vehicle, to be a function of vehicle attributes (veh), demographic attributes of its location (demo), built environment attributes of its location (built_env), state-wide employment levels during the mileage estimate period (empl), and the average gas price during the mileage estimate period (price). The subscript v indicates an attribute of the vehicle, $z$ an attribute of the zipcode, and $t$ an attribute of the time period.

$$
\begin{equation*}
V M T_{v, t}=f\left(\text { veh }_{v, t}, \text { demo }_{z}, \text { built_env }_{z}, \text { empl }_{t}, \text { price }_{t}\right) \tag{1}
\end{equation*}
$$

Taking the derivative of Equation 1 with respect to gas price, I was able to model the variability of gas
price elasticities with respect to a number of other variables (Equation 2). My final model included three predictors that were designed to test the impact of specific factors on the price elasticity, using the technique of including an interaction effect between the gas price and the factors of interest (simply creating a new variable that was the multiplicative product of the natural log of gas price and the factor of interest). The three factors were fuel economy, distance to downtown of the vehicle's zipcode, and median household income of the vehicle's zipcode.

$$
\begin{equation*}
\frac{\delta V M T}{\delta P r i c e}=\beta_{1}+\beta_{2} * \mathrm{MPG}_{\mathrm{v}}+\beta_{3}{ }^{*} \text { Distance }_{z}+\beta_{4}{ }^{*}(\text { median income })_{z} \tag{2}
\end{equation*}
$$

I conducted this OLS regression and this analysis of price elasticity variability both on an individual vehicle level, and on a municipal average level. Because of the richness of the individual vehicle dataset and because of the variability between vehicles and households in any given municipality, I will discuss only the individual vehicle VMT and price elasticity model in this thesis.

Not all variables were available both at spatially disaggregate levels and at high temporal resolution, but they were still useful predictors of VMT. For instance, the built environment features such as population density and land use diversity do vary over time, but I only took point estimates, since these variables do not change rapidly in the short term, and my VMT data spans only 4 years. Similarly, demographics like percentage of housing that is owner occupied or percent of population retired were point estimates because they are not likely to change rapidly and data is not available at high temporal resolution.

## Data and software needs

As mentioned above, I needed demographic data, built environment data, and macroeconomic data in addition to the data provided in the MAVC. Demographic data was obtained from the American Community Survey (ACS) 2012 3-year averages, the time period most representative of the mileage estimate periods in the MAVC. I also needed fuel prices and employment levels in Massachusetts at the highest temporal resolution possible. I obtained weekly Boston area regular gasoline prices from the U.S. Energy Information Administration (EIA), and employment data from the MA Executive Office of Labor and Workforce Development. Built environment variables (such as distance to downtown Boston and the ratio of transit job accessibility to car job accessibility) were calculated using MassGIS shapefiles, in conjunction with ACS data. A list of the variables gathered and calculated is provided in Table 19.

The project required several types of software:

- PostgreSQL - for manipulating MAVC data, adding variables, and exporting results for analysis,
- Tableau - for visualizing trends in the data and performing calculations that would have crashed Microsoft Excel due to the large number of records,
- Gretl - a free econometrics package with a easy to use GUI for performing regressions,
- Geoda - for analyzing the residuals for spatial autocorrelation to verify the quality of the model.


## Methodology

The plan for the analysis was to conduct an OLS regression and analyze the results with a focus on the variables that impact price responsiveness. The overall process involved:

1. exploring the data to make sure it fit common sense understandings of the spatial variation of vehicle travel and adjusting as necessary,
2. constructing independent variables and joining them to the MAVC data,
3. filtering the MAVC data to obtain just the records that met certain criteria and then taking a random sample of these records,
4. performing regressions in Gretl, and
5. checking for problems with the model results.

## Data exploration and adjustments

My findings from the data exploration in Chapter 6 suggested that I should be careful with the very earliest mileage records in the dataset due to likely bias in the pre-2008 data. Therefore, I used a dummy variable for 2008 data to account for the fact that this data may be different.

As documented in Chapter 6, the vast majority of the mileage estimate periods were within the 10-14 month range, and VMT and fuel economy both exhibited intuitive spatial variation across Massachusetts. Therefore, I felt justified proceeding with the regression with no further adjustment.

Constructing the independent variables and joining them to the MAVC data Most of the variables were either derived from straightforward calculations from American Community Survey data or derived from straightforward ArcMap calculations, and can be explained through the description in Table 19. However, a few deserve a little more attention:

## Average Price

I did not have access to historical data on the fine-grained spatial variability of gas prices in the state, so I treated it as varying only in time, not by location. Justification for this decision comes from previous econometric studies and is detailed in Appendix B.

I downloaded weekly data on regular grade gas prices from the U.S. EIA. The average price faced by any individual vehicle during a specific vehicle inspection period was calculated by taking the start date and the duration of each vehicle inspection record and matching it to a lookup table with average prices computed for each possible combination of start date and duration. This enabled me to use a price that was truly representative of the average gas price over the entire time between the start and end dates of each vehicle observation. I applied a gas price to all mileage estimates in the dataset.

## Average Employment

Average employment in the state of Massachusetts was only available monthly. Therefore, I applied the month's employment figure to all the weeks within the month, and calculated an average that spanned the time period of the mileage estimate. If a mileage estimate period included only 2 weeks in a given month (e.g. of the first or last month of the inspection period), the employment figure for that month counted roughly half as much as most of the other months that overlapped the inspection period.

## Ratio of access to jobs by transit and car

The EPA Smart Location Database provides the number of jobs accessible by transit within 45 minutes for every census block group. It also provides the same data for 45 -minutes of traveling by car. Taking
the ratio of these two numbers gives a rough indicator of how effective transit can be at taking residents to jobs relative to commuting by private vehicle. I took these ratios for each census block group, and aggregated them up to a zipcode level using a population-weighted average of each census block group within each zipcode.

Once each variable was calculated, the data was loaded into PostgreSQL and joined to the MAVC dataset so that all the independent variables could be used in the regression.

Table 19. Variable descriptions for model to predict individual vehicle VMT.
$\left.\begin{array}{|l|l|l|l|}\hline \text { Variable Name } & \text { Detailed description } & \begin{array}{l}\text { Unit and } \\ \text { Source }\end{array} & \begin{array}{l}\text { Reason for inclusion }\end{array} \\ \hline \text { Average price } & \begin{array}{l}\text { The average regular gasoline price } \\ \text { during the time between the start } \\ \text { date and end date of the mileage } \\ \text { estimate period. }\end{array} & \begin{array}{l}\text { \$/gallon, U.S. } \\ \text { E.I.A. }\end{array} & \begin{array}{l}\text { Evaluate price sensitivity of } \\ \text { mileage traveled. }\end{array} \\ \hline \begin{array}{l}\text { Average } \\ \text { employment }\end{array} & \begin{array}{l}\text { The average level of employment in } \\ \text { Massachusetts during the time } \\ \text { between estimate period start and } \\ \text { end dates. }\end{array} & \begin{array}{l}\text { \# of total } \\ \text { employees } \\ \text { (x000), MA } \\ \text { Executive Office } \\ \text { of Labor and } \\ \text { Workforce }\end{array} & \begin{array}{l}\text { Control for local } \\ \text { macroeconomic conditions. }\end{array} \\ \hline \begin{array}{l}\text { Percent owner } \\ \text { occupied }\end{array} & \begin{array}{l}\text { Percent of housing units within the } \\ \text { zipcode that are occupied by their } \\ \text { owner. }\end{array} & \begin{array}{l}\text { Unit-less, } \\ \text { Calculated from }\end{array} & \begin{array}{l}\text { Control for attributes that may } \\ \text { correlate with owning a }\end{array} \\ \text { ACS 2012 (T93 } \\ \text { housing unit (likely longer } \\ \text { and T142) } \\ \text { different family size, etc) }\end{array}\right\}$

| Model year | The year for which the vehicle was manufactured. | Calendar year, MAVC | This field was used as a proxy for vehicle age. Newer cars are likely to be driven more. |
| :---: | :---: | :---: | :---: |
| Dist_km | The straight line distance between the centroid of the zipcode and Boston's City Hall Plaza | Kilometers, MassGIS shapefiles | Control for the possibility that VMT per vehicle is higher the further from the city center. |
| Log_Price X MPG | The multiplicative product of the log of the variable "average price" and the variable "MPG (EPA est)". | Constructed from other variables | Test how price responsiveness varies with fuel economy |
| Log_Price X inc | The multiplicative product of the log of the variable "average price" and the variable "Median hh income". | Constructed from other variables | Test how price responsiveness varies with household income |
| Log_Price X dist | The multiplicative product of the log of the variable "average price" and the variable "dist_km". | Constructed from other variables | Test how price responsiveness varies with distance from downtown. |
| Q1_2008 | Dummy variable indicating whether the mileage estimate was valid in Q1 2008 | Binary, MAVC | Control for the fact that mileage estimates preceding this date seemed biased upward, possibly due being from a different data source. |
| Maturing New England Towns | Dummy variable indicating whether the zipcode was in this type of town. Town types are defined on the MAPC website. | Binary, MAPC | Control for unobserved spatial variation. |
| Streetcar Suburbs | Dummy variable indicating whether the zipcode was in this type of town. | Binary, MAPC | Control for unobserved spatial variation. |
| Mature Suburban Towns | Dummy variable indicating whether the zipcode was in this type of town. | Binary, MAPC | Control for unobserved spatial variation. |
| Established Suburbs | Dummy variable indicating whether the zipcode was in this type of town. | Binary, MAPC | Control for unobserved spatial variation. |
| Sub-Regional Urban Centers | Dummy variable indicating whether the zipcode was in this type of town. | Binary, MAPC | Control for unobserved spatial variation. |
| Country Suburbs | Dummy variable indicating whether the zipcode was in this type of town. | Binary, MAPC | Control for unobserved spatial variation. |

## Filtering and sampling the data

Once all the demographic and macroeconomic variables were joined to the mileage estimates, I needed to select a population on which to do the analysis. I filtered the data to include only vehicles that had a valid geographic location, because otherwise I would have null values for all my demographic data by zipcode. I further filtered the data to remove records from motorcycles, electric cars, and commercial vehicles. I filtered out records with estimates of greater than 200 miles per day, using the MAPC's convention to consider greater than 200 miles per day unrealistic for a single vehicle, and vehicles driven less than 0.1 miles per day, which were likely to have such low readings due to entirely different factors such as maintenance problems.

Finally, I filtered out records that were less than 304 days ( 10 months), and records that exceeded 430 days (14 months) for the following reasons. Driving patterns are known to be seasonal, so I wanted to have odometer readings that were as close as possible to one year long, to eliminate seasonality from
my analysis. Furthermore, records that are approximately one year long represents behavioral responses that most economists consider short run elasticities (Gillingham, 2014; Knittel and Sandler, 2013; Jenn et al, 2015). Finally, if vehicles were over 2 months overdue to be inspected, they could disproportionally be vehicles that are not actively used anymore, and I did not want these vehicles to bias my analysis. It must be noted that vehicles that were inspected significantly less than a year after their most recent inspection were more likely to be vehicles that were sold secondhand at that time because selling a vehicle triggers an inspection.

This filtering process left me with approximately $3,000,000$ mileage estimates upon which to perform a regression. I took a random sample of 200,000 of these to reduce computing power required. 194,397 of these had data for all of the predictor variables, and the regression was performed on this subset.

## Performing regressions in Gretl

The final model was specified by balancing the need to avoid over-fitting the model and to include the variables that I knew tend to impact VMT based on my literature review. I selected a log-log specification so that I could directly interpret the elasticities from the coefficients ${ }^{14}$. Many variables are highly collinear with each other, and care was taken not to include too many redundant variables. For instance, even though I had calculated another transit quality variable (the percentage of the zipcode within a quarter mile of a fixed guideway transit stop), I found this variable to be redundant with the variable that showed the relative amount of jobs accessible by transit and car, and I chose to only include the latter in my model. Similarly, I had to choose between mean per capita income and median household income, and I chose the latter because the median is more resilient to skew and because I wanted to evaluate household behavior. The regression technique was OLS with robust standard errors and it was not a panel regression because the time periods for subsequent mileage estimates on different vehicles do not line up.

Checking for conditions for inference, spatial autocorrelation and multicollinearity Once I had performed the regression, I checked for any problems which might interfere with my ability to draw robust conclusions from the model. Due to the nature of the data, the traditional conditions for inference could not be perfectly met, but econometric guidelines that I reviewed suggested that the risk of Type II errors was low. Furthermore, I decided that my model did a good job of avoiding spatial autocorrelation of residuals, and that the multicollinearity was not a severe problem.

## General regression conditions for inference

In Appendix C, I present the results of my tests of the conditions for inference. I found that VMT varied linearly with all but one of my predictor variables. I found that my residuals did not exhibit constant variance at different levels of predictors, a condition called heteroscedasticity. As a result, I re-evaluated my regression using heteroscedasticity-robust standard error calculations. And finally, my model residuals were mainly negative for low values of VMT and mainly positive for high values of VMT, a

[^13]condition which implies that there are most likely omitted variables. I expected not to have all the variables that could predict VMT anyway. For instance, without knowing which cars were not driven due to maintenance problems, which cars belonged to single-car households, which cars were used by individuals whose jobs required extensive travel, and countless other attributes, there is no way that a regression model could really predict the low mileage outliers and high mileage outliers. Furthermore, personal attributes such as environmental consciousness, travel preferences, and sensitivity to prices in general vary significantly from one person to the next, and cannot be included in this dataset.

In OLS, the chances of type II errors (erroneously finding statistically significant effects) typically do not always increase when conditions for inference are not met, so it is likely that my model is conservative (i.e. the most likely error is type I, or failure to detect a real effect). Therefore, I am confident that the effects I will describe are not spurious.

Nonetheless, as a precaution, I re-ran my model on a second set of another 200,000 random mileage estimates to see how stable the coefficient estimates were. If my model provided significantly different coefficients on the predictors and different standard errors, I would know that the model results were sensitive to different source data, and I would not be able to draw any conclusions from the model. Fortunately, when I ran the model on the second set of estimates, I obtained very similar coefficients ${ }^{15}$, so I expect that the results have stability and meaning.

## Spatial autocorrelation

Given that my model is of a highly spatial phenomenon (VMT per vehicle), I checked my residuals for spatial autocorrelation. If my errors clustered in certain locations, it would be clear that my model was not observing some key spatial variable that should have been used to predict VMT. Luckily, my model incorporated several spatial variables (e.g. distance to downtown, MAPC community type, population density, transit access, owner occupied housing) and resulted in no significant spatial autocorrelation. The Moran's I of the residuals was $I=-0.02$ ( $p^{\sim 0.37}$ ), indicating that there is no significant difference from a random distribution of residuals across space. The full results are provided in Appendix $D$.

## Multicollinearity

Multicollinearity refers to the degree of correlation between multiple predictor variables in a regression model. In models that aim solely to predict values of the dependent variable, it does not matter much, but in models that aim to explain the relative importance of various predictors and the magnitude of their coefficients (such as my model), it is important to be aware of the degree of multicollinearity and assess whether it may hinder one's ability to determine the true effect of each variable. However, the biggest risk associated with high multicollinearity is that, due to higher standard errors, you may fail to find an effect that you should have found. Due to the large sample size, my regression analysis found most of the predictors to be significant, as will be explained in the next section.

Table 20 shows the degree of correlation between each variable pair in the model. Dark blue indicates the highest positive correlation, while dark red indicates the highest inverse correlation. As expected,

[^14]some of the strongest relationships included the correlation between density and transit access, the correlation of household income and owner occupied housing. The strongest inverse correlation was found between owner occupied housing and both density and transit, and between distance from downtown and both transit and density, and to a lesser extent between MPG and retail price. The retail price of the car, the model year, the average price faced by each vehicle, and the average employment during each mileage estimate period had only weak relationships with the other variables, although there was some correlation between Massachusetts employment and average gas prices, due to the slow economic recovery throughout 2009 through 2011.

Table 20. Correlation matrix of selected variables in my model.

| Pearson's r | msrp | MPG | model year | percent owner occupied | percent with retirement income | transit to car access | population density | median hh income | dist km | average price | average employment |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| msrp |  | -0.508 | 0.141 | 0.126 | 0.064 | -0.069 | -0.074 | 0.176 | 0.052 | 0.012 | 0.025 |
| MPG | -0.508 | - | 0.127 | -0.090 | -0.086 | 0.098 | 0.094 | -0.032 | -0.091 | 0.023 | -0.002 |
| model year | 0.141 | 0.127 | - | 0.061 | 0.034 | -0.041 | -0.037 | 0.075 | 0.035 | 0.062 | 0.057 |
| percent owner occupied | 0.126 | -0.090 | 0.061 |  | 0.648 | -0.795 | -0.787 | 0.763 | 0.617 | 0.002 | 0.011 |
| percent with retirement income | 0.064 | -0.086 | 0.034 | 0.648 |  | -0.664 | -0.675 | 0.307 | 0.388 | 0.000 | 0.009 |
| transit to car access | -0.069 | 0.098 | -0.041 | -0.795 | -0.664 |  | 0.873 | -0.467 | -0.795 | 0.008 | 0.007 |
| population density | -0.074 | 0.094 | -0.037 | -0.787 | -0.675 | 0.873 |  | -0.483 | -0.670 | 0.011 | 0.008 |
| median hh income | 0.176 | -0.032 | 0.075 | 0.763 | 0.307 | -0.467 | -0.483 |  | 0.336 | 0.003 | 0.014 |
| dist km | 0.052 | -0.091 | 0.035 | 0.617 | 0.388 | -0.795 | -0.670 | 0.336 | - | -0.004 | -0.007 |
| average price | 0.012 | 0.023 | 0.062 | 0.002 | 0.000 | 0.008 | 0.011 | 0.003 | -0.004 |  | 0.521 |
| average employment | 0.025 | -0.002 | 0.057 | 0.011 | 0.009 | 0.007 | 0.008 | 0.014 | -0.007 | 0.521 |  |

The results of my multicollinearity test for my preferred model are included in Appendix E. A degree of multicollinearity is expected given the correlation matrix above. The variance inflation factor (VIF) is a measure of the degree of multicollinearity among a set of variables. The square root of the VIF for each predictor variable tells you how much higher the standard error for that variable's coefficient is than it would be if the variable were perfectly uncorrelated with all the other predictors. It is common practice not to worry about high VIFs for variables that have been included as interaction terms because these variables will obviously have significant correlation with their source variables. ${ }^{16}$

If I specified my model with all of the highly correlated predictors (e.g. distance to downtown, population density, owner occupied housing, household income, and transit access), at least one of them would have a VIF slightly greater than 10, which is a typical threshold used to determine whether to worry about multicollinearity. However, removing one of these variables brought all (non-interaction term) VIFs below 10 without changing the model coefficients and standard errors substantially. Therefore, I kept all the variables in the model because they all are likely to have some degree of influence on VMT. I will cautiously interpret my regression coefficients with the caveat that there is a moderate amount of collinearity present in the data, and that this could cause me to fail to find effects in the data, but it is less likely to result in the wrong signs on my coefficients.

[^15]
## Findings and interpretation

The regression results are provided in Table 21 and interpreted below.
Table 21. Regression results.
Model 9: OLS, using observations 1-200000 ( $n=193545$ )
Missing or incomplete observations dropped: 6455
Dependent variable: log_mi_per_day
Heteroskedasticity-robust standard errors, variant HC1

|  | coefficient | std. error | t-ratio |  | p-value |
| :---: | :---: | :---: | :---: | :---: | :---: |
| const | -128.803 |  | 2.021 | -63.74 | 0 *** |
| Log_avg_employment | 1.806 |  | 0.207 | 8.74 | $2.43 \mathrm{E}-18{ }^{* * *}$ |
| Log_avg_price | -0.636 |  | 0.036 | -17.70 | 5.01E-70 *** |
| Log_MSRP | 0.074 |  | 0.008 | 9.65 | 5.01E-22 *** |
| Log_MPG (EPA est) | -0.427 |  | 0.030 | -14.19 | 1.13E-45 *** |
| model_year | 0.059 |  | 5.37E-04 | 110.60 | $0^{* * *}$ |
| Log_population_density | -0.034 |  | 0.006 | -6.10 | 1.10E-09 *** |
| Log_median_hh_income | -0.040 |  | 0.021 | -1.91 | 0.0559 * |
| Log_dist_km | -0.021 |  | 0.009 | -2.27 | 0.0233 ** |
| transit_to_car_access | -0.003 |  | 0.001 | -3.28 | 0.001 *** |
| percent_with_retirement_income | -0.006 |  | 0.001 | -10.94 | $7.31 \mathrm{E}-28$ *** |
| percent_owner_occupied | 0.001 |  | $2.64 \mathrm{E}-04$ | 5.05 | $4.50 \mathrm{E}-07$ *** |
| Maturing New England Towns | 0.029 |  | 0.012 | 2.44 | 0.0147 ** |
| Streetcar Suburbs | -0.010 |  | 0.007 | -1.35 | 0.1773 |
| Mature Suburban Towns | 0.002 |  | 0.009 | 0.26 | 0.7983 |
| Established Suburbs | 0.064 |  | 0.011 | 5.79 | $6.94 \mathrm{E}-09$ *** |
| Sub-Regional Urban Centers | -0.033 |  | 0.008 | -3.99 | $6.51 \mathrm{E}-05^{* * *}$ |
| Country Suburbs | 0.031 |  | 0.015 | 1.98 | 0.0481 ** |
| q1_2008 | 0.124 |  | 0.011 | 11.43 | 3.13E-30 *** |
| Log_price X MPG | 0.015 |  | 0.001 | 12.13 | $7.52 \mathrm{E}-34^{* * *}$ |
| Log_price X dist | 0.006 |  | 4.17E-04 | 13.26 | 4.39E-40 *** |
| Log_price X income | -8.57E-07 |  | $2.14 \mathrm{E}-07$ | -4.00 | $6.32 \mathrm{E}-05^{* * *}$ |
| Mean dependent var | 3.125 | S.D. depen | t var | 0.729 |  |
| Sum squared resid | 89,721.1 | S.E. of regr | ion | 0.681 |  |
| R-squared | 0.127 | Adjusted R | uared | 0.126 |  |
| F(21, 193523) | 1,034.6 | P-value(F) |  | 0 |  |
| Log-likelihood | -200229.3 | Akaike crit |  | 400502.7 |  |
| Schwarz criterion | 400726.5 | Hannan-Qu |  | 400568.7 |  |

A significant amount of variation cannot be explained by the predictors The model has a large and significant F statistic, indicating that the model has explanatory power for VMT per day. However, the $R^{2}$ value is quite low at 0.127 . This is to be expected, given the tremendous variety of people and activity patterns that are contained within the data, and given that average values at the zipcode level are applied to specific vehicles in the absence of knowing the actual values
associated with each vehicle owner. The low $R^{2}$ is not a problem because the purpose of the model is not to predict the VMT of other vehicles not included in the sample, but rather to show how certain factors influence the VMT of a vehicle at a specific period in time.

Nearly all the predictors are significant
The asterisks in Table 21 denote the levels of significance (one asterisk for $p<0.1$, two for $p<.05$, and three for $p<.01$ ). Because the sample size is so large ( $n=193,545$ ), I expected most of the predictors to have statistical significance. As expected, 19 of the 21 variables were significant at $p<0.1$. It is important to also evaluate the variables for their real world significance. Since the model was a log-log specification, the coefficients can be directly interpreted for their real world significance, since they represent elasticities, not changes in levels.

The variables directly associated with each individual vehicle were all significant. The higher MSRP and newer model year cars were both associated with higher VMT per day, as has been shown in the literature, though both of these effects had elasticities of less than 0.1. For instance, the coefficient on MSRP suggests that a $1 \%$ increase in MSRP increases the expected VMT per day by $0.074 \%$. Surprisingly, fuel economy had a negative coefficient, though its effect was modeled as dependent on gas price. Perhaps many people prefer to drive larger, heavier cars for their longer trips because they perceive them as more comfortable and safer. In an analysis that showed that the Cash for Clunkers program did not increase household VMT for participating households, West et al (2015) argue that VMT may not be positively correlated with fuel economy because higher fuel economy vehicles are typically lower horsepower and smaller, both of which factors may reduce the enjoyment that a person gets out of driving. Therefore, it's plausible that MPG and VMT could be negatively related in our sample. This is also supported by the evidence found in Chapter 6 of the inverse correlation between MPG and VMT, both within Massachusetts and comparing U.S. city averages.

The variables associated with attributes of the vehicle's location are not all significant, though most were. Metro core communities, streetcar suburbs, and sub-regional urban centers were all associated with some of the lowest VMT per vehicle (the base condition for the model was Metro Core Communities, and each dummy compared a different type of community with the Metro Core). Suburban zipcodes were weakly associated with lower VMT per vehicle per day, as shown by the -0.02 coefficient on "dist_km" (the number of kilometers between the zipcode centroid and downtown). However, as shown in Chapter 6, zipcodes further from downtown tend to have more cars per household. Therefore the driving needs of households in more suburban zipcodes are often split between a higher number of vehicles, which could result in lower VMT per vehicle despite the fact that their total VMT per household is much higher.

The larger number of vehicles per household in wealthy locations may also be responsible for the sign on the term for median household income. This variable was weakly inversely correlated with VMT per vehicle. In less wealthy areas, family members may share usage of the same car, leading to higher mileage per vehicle. The collinearity between transit access to jobs and distance to downtown may also explain why distance to downtown had a negative effect on VMT per vehicle - transit access to jobs was
strongly negatively related to VMT, and when this variable was removed, the effect of distance to downtown vanished. If I had instead modeled VMT per household, I expect distance to downtown and median household income would have significant positive coefficients.

Transit to car access, percentage of households receiving retirement income, and percent of housing occupied by owner are all significant with the expected signs. More transit access and more retirees are both correlated with lower mileage per vehicle, while owner occupied housing is correlated with more mileage per vehicle. The effect of owner occupied housing on VMT is the weakest of these variables.

The level of employment in the Massachusetts economy was positively related with VMT per vehicle with a sizeable elastic effect, as expected. And finally, as mentioned earlier, the dataset included a strange sudden drop in VMT per vehicle from the earliest mileage estimates to the later mileage estimates. I included a dummy variable for whether or not the mileage estimate spanned the median day of Q1 $200 \mathbf{8}^{17}$. This dummy variable has an effect size equivalent to raising the mileage per vehicle by about 3 miles per day, which is commensurate with the drop that was recorded during that time.

## The impact on VMT depends on more than the coefficient

The coefficients above should be compared should be compared with typical fluctuations in these variables, since some of the variables are much more volatile than others. For instance, the coefficient on Massachusetts employment is three times as large as the coefficient on gas prices, but while a $30 \%$ fluctuation in gas prices in one year would not be out of the ordinary, a $10 \%$ increase or drop in employment in one year would be essentially unprecedented. Many of the variables included in the model are relatively stable over the short term, such as the percent of households that have at least one retiree, the percent of housing units occupied by the owner. Other variables are entirely unchanging, such as the MSRP of the vehicle, and the rated fuel economy of the vehicle. And for some of these variables, the link with gas price may not be causal.

The following example shows the impact of the scale of reasonable one-year changes on how much leverage each variable has on overall travel. The price elasticity of VMT per vehicle is -0.29 at mean values for MPG, distance from downtown, and median household income (and -0.30 when evaluated at the median of each of these variables). This is significantly less than the elasticity of 1.8 with respect to employment, and only 6-8 times the value of the elasticities with respect to population density and median household income. However, when applying these elasticities to a reasonable one-year change, the effect of price becomes much more significant than the other variables, as illustrated in Table 22.

[^16]Table 22. Translating elasticities into VMT changes

| Large hypothetical <br> one-year change | Elasticity | Effect on |  |
| :--- | ---: | ---: | :---: |
| VMT |  |  |  |
| $50 \%$ | -0.29 | $-14.4 \%$ |  |
| $-5 \%$ | 1.81 | $-9.0 \%$ |  |
| $2 \%$ | -0.04 | $-0.1 \%$ |  |
| $2 \%$ | -0.03 | $-0.1 \%$ |  |

The values for plausible short-term changes in each variable in the table above are subjective, but for reference, the price of gas fell by $50 \%$ within 6 months and rose by $50 \%$ within $6-9$ months twice, just between late 2008 and mid-2011. From the peak of employment before the 2008 financial crisis to the low point after the crisis employment levels fell by only $6 \%$ in Massachusetts. And it is unlikely that any zipcode would see its median income or population increasing in the high single digit percentages for a sustained period of time. Therefore, it is clear that this model shows that for reasonable percentage variation in time-varying factors, price has by far the strongest influence on VMT per vehicle.

Price response varies significantly along the attributes explored Since I included price interactions with fuel economy, distance from downtown, and median income, I needed to specify certain values for each of these variables to compute an elasticity. There was a significant amount of variation between the vehicles with the highest and lowest fuel economy. And the distance from downtown and median household income of the zipcodes the vehicles were located in also varied significantly. I have displayed descriptive statistics on each of these variables in Table 23.

Table 23. Descriptive statistics on the vehicle estimates in the sample.

|  | MPG | Distance from <br> downtown $(\mathbf{k m})$ | Median Household <br> Income |  |
| :--- | :---: | :---: | :---: | :---: |
| Mean | 21.1 | 20.2 | $\$$ | 86,005 |
| 5th percentile | 14.0 | 4.0 | $\$$ | 48,329 |
| 95th percentile | 30.0 | 42.0 | $\$$ | 133,930 |
| Standard Dev. | 4.9 | 11.7 | $\$$ | 28,841 |
| Min | 8.0 | 0.5 | $\$$ | 23,432 |
| Max | 58.0 | 48.7 | $\$$ | 250,000 |

I took the average gas price elasticity of VMT to be the value that was obtained when plugging in the mean value for each of the three variables whose impact on elasticity was modeled. As shown in Table 24 , this mean value was -0.29 , a value less inelastic than recent studies had suggested. Table 24 also shows the elasticities at the $5^{\text {th }}$ percentile and $95^{\text {th }}$ percentile of each variable while holding the other two variables at their mean values. There is significant variation in the elasticity with respect to each of these three variables.

Table 24. Conditional elasticities of VMT per day with respect to gas price. Each column assumes the variables in the other two variables are at their mean values.

## MPG (city/highway combined)

Mean
5th percentile
95th percentile
Zipcode distance to downtown
Mean
5th percentile
95th percentile

## Zipcode median income

Mean
5th percentile
95th percentile
An interesting result from Table 24 is that going from the $5^{\text {th }}$ percentile fuel economy ( 14 mpg ) to the $95^{\text {th }}$ percentile $(30 \mathrm{mpg})$ more than cuts the elasticity estimate in half, whereas going from the $95^{\text {th }}$ percentile median income to the $5^{\text {th }}$ percentile ( $\$ 134,000$ and $\$ 48,000$, respectively) cuts the elasticity estimate by a much smaller proportion. The range of elasticities with respect to distance from downtown is similarly large in comparison to the range associated with the variation in fuel economy and the effects are almost identical (Figure 29).

Figure 29. The variation of price elasticity of individual vehicles.

## Elasticity variability with MPG, zipcode distance

 to downtown, and zipcode median income

The intuition behind the large role of fuel economy is that for multi-vehicle households, the effect of switching from the low fuel economy vehicle to the high fuel economy vehicle increases the elasticity of the gas guzzler and may simultaneously create a positive elasticity for the more efficient vehicle. This high range in the elasticity for low MPG vehicles versus high MPG vehicles is good news from a policy perspective. It means that if gas taxes are increased, emissions may be reduced by more than is
expected from looking only at the mean elasticity, since the vehicles that would reduce their VMT the most have the highest emissions rate. Knittel and Sandler (2013) demonstrated this effect for different elasticities for vehicles that emit the most criteria pollutants per mile versus the least. In addition, as this decade's high MPG cars become (in relative terms) the next decades' low MPG cars, they will likely become more price elastic because of within-household mileage transfers to higher fuel economy cars. On the other hand, as CAFE standards become stricter and the average fuel economy of the fleet increases, we can expect VMT to be even less responsive to gas prices (Jenn et al, 2015).

Prior to performing this analysis, I did not know whether to expect the elasticity to be higher for vehicles in the urban core or for more suburban communities. On one hand, suburban communities may tend to drive more discretionary miles because they may tend to be more affluent on average, and because congestion and other deterrents to driving are not as significant in the suburbs as downtown. On the other hand, the amount of feasible alternatives to driving diminishes dramatically as one moves further from the transit-rich metro core. These suburbs lack high quality frequent transit and have very low land use diversity, necessitating longer trips that cannot be easily accomplished by walking or biking. Gillingham (2014) finds that counties with higher commute times tend to be less price responsive in California, but commute time is also affected by congestion and mode split. He clustered his data to evaluate elasticities of populations with different combinations of income and urban/rural environment, but it is hard to tease out the separate effects of these two variables when they are combined in these clusters, therefore I didn't know what to expect. For instance, his semi-rural upper middle class cluster had the lowest price response of all his clusters, whereas his rural wealthy cluster had the highest response, with the urban and suburban elasticities falling in between the two estimates for rural areas!

My model results show that zipcodes about 40 kilometers from downtown ${ }^{18}$ (about the distance of Lowell, MA, or a little further than Framingham, MA) exhibit highly inelastic travel demand with respect to gas price ( -0.17 ). Interestingly, my estimate for elasticities of these suburban commuters was close to Knittel's estimate for the statewide average elasticity of vehicles in California, and in between Gillingham's and Jenn's estimates based on Pennsylvannia's statewide data. On the other hand, I found zipcodes at or below the $5^{\text {th }}$ percentile distance from downtown (mapped in Figure 30 below) were highly price responsive. For every percent increase in gas price, my model estimates that the one-year response would reduce VMT per day by $0.37 \%$ in these highly urban neighborhoods. There is some consistency with Gillingham's California results because he found that his low income urban cluster had significantly higher elasticity than most the other clusters (at -0.26 ), although my urban elasticity was a bit higher at ( -0.37 ). His suburban elasticities in California $(-0.17$ to -0.19 ) were all the same magnitude as the elasticity $I$ calculated for zipcodes roughly $35-45$ kilometers from downtown Boston, a surprising degree of agreement.

[^17]Figure 30. The zipcodes with centroids within 4 kilometers of Boston City Hall Plaza.


The variation of elasticity with respect to the median income in the zipcode is significantly weaker than the variation along the other two variables. While the interaction effect was statistically significant, it has less real world significance; the modeled elasticity of vehicles in the wealthiest zipcodes was -0.33 while it was -0.26 in the least wealthy zipcodes. Nonetheless, this finding is interesting because it failed to find that lower income zipcodes have more price elastic vehicles. This is evidence that even relatively affluent areas are responding significantly to the price of gas. As a way of checking the robustness of this finding, I ran an alternate specification of my model in which I included an interaction term between the MSRP of the vehicle and the gas price instead of the interaction between the zipcode median income and the gas price. This alternate specification indicated that higher MSRPs are associated with more price responsiveness, which supports my finding that higher income areas had slightly higher price responsiveness because higher MSRPs are likely to be associated with higher income households. However in this case there may be additional explanations for vehicles with higher MSRPs being more price responsive because more expensive cars are likely to be bigger and have lower fuel economy.

VMT elasticity appears to have rebounded from the estimates from the early 2000s My results indicate a gas price elasticity of VMT of -0.29 on a one-year timescale when evaluated at the mean value of zipcode distance to downtown, zipcode median income, and vehicle fuel economy ( -0.30 at the median value for each of these variables). This is on the high end of recent estimates that have used similar disaggregate odometer data. These studies using similar data have recently implied VMT elasticities higher than would be reasonable if the fuel consumption elasticities reported for the early 2000s by Hughes et al (2008) and Small and Van Dender (2007) still held. Fuel consumption elasticity should be a higher magnitude than VMT elasticity because VMT reduction is only part of what individuals can do in response to increased fuel prices - they can also increase their fuel efficiency through eco-driving and switching to more fuel efficient vehicles. However, beyond this observation, it is difficult to compare my elasticity result with the rest of the literature, since most of it is cited in terms of fuel consumption elasticity, not VMT elasticity.

However, I can compare with three recent studies of VMT elasticity with respect to gas price, using odometer readings. These studies observe price response on approximately the same timescale as my model. Gillingham (2014) estimated an average elasticity of -0.22 using odometer readings of California vehicles less than six years old (from 2005 to 2009). Jenn et al (2015) used Pennsylvania odometer data from 2000 to 2010 to estimate an average elasticity that was significantly lower at -0.05 , but this could be because their data includes the early 2000s, when elasticities appear to have been at historic lows. Knittel and Sandler (2013) provide an estimate roughly halfway in between these two, at -0.15 , using California odometer readings from smog checks that were conducted between 1996 and 2010, which also includes a long period during which elasticities were known to be very low.

Several factors could account for the higher elasticity l observed - the fact that most of my odometer readings were during the recession and the ensuing recovery, the fact that prices were increasing steadily during most of my analysis period, and the fact that my vehicle population is exclusively from the Boston metro area, which includes relatively few rural vehicles.

The first explanation, the influence of the recession, is unlikely to be a major cause for this difference because I controlled for macroeconomic conditions in my model. To do this, I included the level of employment in Massachusetts as a predictor variable and found it was highly influential in the model. However, I cannot rule it out because other factors also influence people's perception of the economy.

The second factor, the steady increase of gas prices during my study, may be more important. Lin and Prince (2013) found that elasticities of gas demand tend to be higher during times of low volatility. This is probably because the low volatility gives drivers a chance to react to the price before the price trend has switched directions. While some of my data was representative of cars driven in late 2008 with its significant gas price collapse, the bulk of it comes from 2009 to 2011, a period during which prices climbed steadily without any significant dips until late 2011 (see Figure 31). This monotonic upward price movement during the recession, at a time when the $\$ 4 /$ gallon prices from 2008 were fresh in the minds of many vehicle owners, may have led to increased price sensitivity during my analysis period. In my interviews, I found that the 2008 peak in gas prices increased the salience of gas costs for many drivers. Gillingham (2014) also documents the increased salience of gas prices following 2008 and speculates that this has driven gas price elasticities upwards.

Figure 31. Gas prices preceding my study and during my study. Data source: U.S. EIA

## Boston MA, regular grade gas prices


$\$ 0.00$

| Jan 03, Jan 03, | Jan 03, | Jan 03, | Jan 03, | Jan 03, | Jan 03, |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |

The third factor, the relative lack of truly rural vehicles in my regression population sample, seems to be a particularly important distinction between my study and the others. I confined my data to the vehicles located within the MAPC region, which did not include any zipcodes more than 48 kilometers from downtown Boston. My study is the only study I am aware of that evaluates the variability of elasticity within a single metro region, although Gillingham (2014) evaluated the spatial variability of elasticity in California. As described above, I found a clear and strong association between the distance from the urban core and the elasticity of VMT. The three other studies all use data from a broader geographic area, with the California studies using the entire state and the Pennsylvania study using the entire state except for certain sparsely populated regions for which data was not available. Therefore, these studies should be expected to report lower elasticity than my study due to their inclusion of rural and small town vehicles. ${ }^{19}$ Rural drivers simply do not have as many alternative travel modes or closer destinations to take care of their needs, which was a theme that emerged strongly when I interviewed drivers from around the U.S. Furthermore, rural areas tend not to be as affluent as suburban areas and therefore many rural citizens are less likely to engage in extensive discretionary driving, which could limit their price responsiveness even more.

[^18]My finding that the mean elasticity of driving with respect to gas price was -0.29 adds important evidence that in the era since gas prices peaked at $\$ 4 /$ gallon, it appears that drivers have been resensitized to the cost of gas, at least in certain parts of the country. This follows findings from the early 2000s that showed some of the lowest gas price elasticities ever recorded (e.g. Hughes et al, 2008; Small and Van Dender, 2007). In my interpretation, the findings from these papers based on early 2000s data began to call into question the wisdom of relying on taxation policy to reduce the amount of gas consumed and emissions generated, given that the elasticities they found were in the range of -0.05 . Two of the three recent odometer studies point to a re-sensitization of vehicle owners to the cost of gas, as Gillingham (2014) reports an elasticity of -0.22 and Knittel and Sandler (2013) report -0.15 , both based on California data.

The major assumption in the Moving Cooler report on travel demand reduction was that the long-run elasticity of VMT with respect to total cost per mile was -0.45 . Using their assumptions of $\$ 3.70 / \mathrm{gallon}$ gas, average light-duty fleet fuel economy of 20.3 MPG , and a total cost per mile of $\$ 0.62$, this can be converted into a gas price elasticity of VMT of approximately -0.13 (my calculation). This is lower than my estimate of short-run elasticity from Massachusetts by more than a factor of two, and nearly a factor of two below Gillingham's 2014 short-run estimate from California ${ }^{20}$. This is remarkable because longrun VMT elasticities tend to be higher than short-run elasticities. If gas price elasticity stays in this higher range, it suggests that Moving Cooler's analysis is actually quite conservative and that a lower gas tax increase could perhaps achieve the emissions reductions they forecasted, which would be good news for the politics of the policy.

My study is an important new approach because it only looks at a single, relatively mono-centric metropolitan region, enabling the analysis of the effect of the distance from the center of the metro region on price elasticity. The United States population is increasingly metropolitan, with over $85 \%$ of the population living in a metropolitan area as of 2013 (U.S. Census Bureau, 2014), up from $80 \%$ as of 2000 and $69 \%$ in 1970 (Sellers, 2005). Within the metropolitan regions, the share that is suburban also increased from 1970 to 2000 ( $42 \%$ to 50\%) (ibid.). Recent research also points to the depopulation of many rural areas throughout the U.S. (FDIC, 2014). Therefore, the elasticity estimates I provided in this paper are likely to be of increasing relevance if the trend towards a higher share of the population in metro areas continues. Depending on whether one believes housing preferences are shifting towards denser, mixed-use developments closer to the center city or if one believes metropolitan growth will continue to be dominated by suburbanization, one's predictions for future VMT elasticity will need to bear in mind the significant difference between urban areas and suburbs far from the center city.

[^19]
## Desirable Next Steps

## Test more sophisticated types of regressions

My VMT regression exhibited some heteroscedasticity, meaning that my regression residuals were not of the same magnitude across the entire range of some independent variables. For instance, the residuals seemed to have a wider range on average for cars of moderate fuel economy than cars of very low or high fuel economy. One possible explanation is that the effects of some of my predictor variables may be different at different levels of that variable. Jenn et al (2015) showed that gas price was significant in predicting VMT for vehicles below 20MPG, but above 20MPG the effect of gas price wasn't statistically significant. Wang and Chen found much higher elasticity for the lowest income quintile of households, as well as the two highest income quintiles (e.g. an inverted-U shape curve of price elasticity plotted against income). If fuel economy and income do not have a linear effect on elasticity, another regression method such as piecewise linear regression might help.

Furthermore, treatment of the dataset as a panel may be desirable. Unfortunately, the timing of vehicle inspections and mileage estimates is different for each vehicle in the sample. It is likely therefore that the available sample size for a panel dataset would be quite low. But perhaps enough vehicles could be found that substantially overlapped in the time period of each mileage estimate and they could be compared as a panel. Another possible approach would be to use a fixed effects model where each individual vehicle/plate combo could have a fixed effect, similar to some other recent odometer reading studies like Jenn et al (2015).

Finally, studies of odometer reading datasets are limited in their inability to apply all the predictor variables to the right level of observation. Like some other studies of odometer readings, I have taken the median value of household income from a zipcode and applied it to every vehicle mileage estimate within that zipcode. The application of the same values to different households or individuals based on some grouping (in my case, zipcode) violates the regression assumption of independent errors (Moulton, 1990). Hierarchical linear modeling (HLM) allows researchers to apply geographic average values of predictor variables to more disaggregate observations without violating the independence of errors requirement. Details on HLM and its application to travel behavior are provided in Appendix F.

## Find and include omitted variables

There are certainly omitted variables in the model. This is why the model's $\mathrm{R}^{2}$ is not very high and why the model cannot predict the extremely low or extremely high mileage vehicles well. One known omitted variable is the number of other vehicles owned by the household and the fuel economy of those vehicles. This information exists in the raw version of the MAVC dataset, but is not available to the public due to privacy concerns. However, researchers at the MAPC could perform such analysis. In addition to the presence of additional household vehicles, other useful predictors could include the size of the household, the income of the household, and the employment status of the household, to name a few. These are not available even in the original non-anonymized version of the MAVC.

Incorporate the effects of price volatility and memory of recent gas prices
Behavioral economics teaches us that impressions of the price and value of commodities is often highly biased by frames of reference. Last week's or last month's gas price might influence my current driving patterns through two channels: 1) influencing my expectation of future prices, and 2) making me feel like the current price is a "good deal" or a "bad deal." What cements a reasonable price of gas in the public's mind is still subject to much uncertainty, and the longevity of reference points is also unknown. Research conducted on the VMT response to the 1970s oil crises has pointed to the importance of habituation to gas prices over time. ${ }^{21}$

A model such as the VMT regression that I ran could account for some "frame of reference" effects by matching mileage estimates with gas prices lagged by a month or a calendar quarter or more. Puller and Greening (1999) suggest that using lagged prices to explain VMT may be useful because gas prices may cause consumers to shift travel demand across seasons or years (for instance, postponing family vacations). In theory, other price-related factors could also have substantial effects on VMT, including the price in the year before the mileage estimate, the percentage change from that period to the mileage estimate period, or the volatility of the price before or during the mileage estimate period.

## Run a model on total VMT for each individual household

My model of the price elasticity of travel demand of individual vehicles is limited by the data that I have. While the MAVC provides an incredibly rich set of observations, it is not currently set up to do the sort of analysis that would help understand the dynamics of how specific families and households adjust their overall travel behavior in response to gas prices. The primary challenge of using this data is the fact that many households have more than one vehicle and households that add or subtract from their total vehicle number at any time during the observation period will likely change the amount driven on the existing vehicles. For instance, say that in a time of falling gas prices, a family purchases another vehicle. The existing vehicle would most likely receive fewer miles than it used to, even though the price went down during that period. This type of event leaves us with an elasticity of the wrong sign that limits our ability to construct a tight model. Furthermore, rising or falling gas prices provide incentives for multivehicle families to switch mileage to or from the higher fuel economy vehicle when the price of gas changes significantly. But our model does not know which families had multiple vehicles.

The publicly-available data in the MAVC has been anonymized so that there are no street addresses and the VINs and plate IDs have been scrambled so that they cannot be traced to specific owners. However, with access to the original data, which contains the correct street addresses, the price responsiveness of individual households could be modeled. Knittel and Sandler (2013) were able to use confidential

[^20]Department of Motor Vehicle records in California in order to match vehicles by address and infer different elasticities for vehicles in households that had vehicles of higher or lower fuel economy. There are many major limitations to implementing such a model with the Massachusetts data even if a researcher had full access ${ }^{22}$, but if it can be done well it could yield significant findings that haven't been explored in the literature.

[^21]
## Conclusions from the regression model

My regression model is the first price elasticity study I am aware of that explores the variation of price elasticity in different parts of a single metro area. This effort has demonstrated that there is enormous untapped potential to understand not only the effects of the built environment, demographics, vehicle attributes, and macroeconomic variables on VMT, but also the effects of some of these same variables on how much VMT responds to price changes. As described above, there are many potential refinements including adding omitted variables, attempting to reduce the heteroscedasticity, and implementing different regression techniques such as HLM. However, the model produced some plausible and interesting results that have important policy implications.

The findings suggest that for vehicles in the Boston metro area:

1) the higher the fuel economy, the less price responsive it is,
2) the further from downtown, the less price responsive it is,
3) the higher the income of the zipcode the vehicle is registered in, the more price responsive it is, consistent with the theory that the higher fraction of discretionary travel for wealthier families enables them to be more price responsive than families with mainly mandatory travel, and
4) the average price elasticity of all vehicles in the Boston metro area is higher than the price elasticities found by recent studies of odometer readings in other states.

A number of implications arise from these findings. Future increases in fuel economy may both increase VMT and decrease the effect of gas tax as a policy tool, and if future population growth continues to cause an increase in the average distance of households from downtown, the effects of gas tax increases could be further limited. If infill development does significantly densify the metro area and reduce the average distance to downtown, the opposite effect may emerge. Finally, higher incomes in the future may increase VMT by increasing discretionary travel. However, this increased discretionary travel may simultaneously increase price responsiveness, perhaps offsetting the effect of improved fuel economy on price response.

The MAVC dataset should continue to be probed with alternate model specifications and techniques, and parallel work should be done to see if the patterns I found in Boston are similar in other cities and states, as more and more odometer information becomes available to researchers. The current analysis shows that this sort of research has enormous potential in helping us understand the variability of price response and the implications for the feasibility, fairness, and effectiveness of carbon prices or gas taxation.

## Chapter 8. Findings and implications

Recent studies of emissions from the U.S. light-duty vehicle fleet show that major shifts in policy will be required to reduce emissions by $80 \%$ from current levels by 2050. Even under the most optimistic scenarios, vehicle and fuel technology alone will not accomplish this goal if travel demand continues to grow (Bastani et al, 2012). In addition to aggressively encouraging the adoption of higher fuel economy vehicles and lower emissions fuels, significant additional effort will need to be invested in finding ways to reduce travel demand growth. Economists often favor broad taxation strategies such as carbon pricing and cap and trade as ways to allow the market to find the lowest cost emissions reductions, whether they come from the increased use of efficient technologies or the reduction of the least valued demand.

## Policies that increase gas costs to reduce VMT need the right window of opportunity

 While such pricing strategies seem improbable in the short term, concern about climate change will likely grow for a broader swath of the population, particularly as natural disasters and geopolitical strife are increasingly linked to climate. John Kingdon provides a useful general model of the necessary prerequisites for the formation of "policy windows," which are rare opportunities to implement solutions to pressing social problems. The three necessary variables that must align are 1) a "problem stream," or widespread information and concern about the problem, 2) a "policy stream/solution stream," or the development and thorough analysis of a set of ideas that can be implemented to solve the problem, and 3) a "political stream," or the presence of supportive public opinion, pressure groups, and the elevation of the issue high enough on the overall public agenda to prompt the public to clamor for action (Howlett and Ramesh, 2003). Policy entrepreneurs can take advantage of the window of opportunity created by the confluence of these three streams to implement actions to address the problem (ibid.).In the case of transportation emissions' contribution to global climate change, the first stream, understanding the problem, has been firmly established through scientific research. There is also significant public awareness about the risks and current harms of climate change today, although the issue hasn't taken on as much urgency as it warrants. The second stream, or available and wellunderstood solutions, has received extensive study, discussion, and debate. But the analysis of solutions must continue to be strengthened. The literature reviews in this thesis describe the status of the solution stream for transportation emissions - our understanding of how policy interventions could beneficially reduce travel emissions, whether through pricing, regulation, or facilitation of low emission alternatives, with a focus on the gas taxation solution stream. However the third crucial ingredient, the political stream, has not reached a level that could enable policy entrepreneurs to catalyze action on policy that would dramatically reduce travel demand. Despite public awareness, the risks of emissions and climate change have been eclipsed by other issues on the public agenda that seem more immediate to the average voter. The national mood does not yet allow for the rapid action that is necessary.

## The equity of the effects of gas pricing policy on specific populations need further attention in order to improve policy design

At the same time that advocates try to hasten the opening of a policy window by shifting the political discourse and public mood, researchers must increase the robustness of the solution stream, developing new proposals and strengthening our understanding of the potential effects of current proposals. My assessment of the literature on the solutions that involve pricing gas to reduce emissions is that the biggest gap is understanding on a finer-grained level how the solutions will affect different people. And what will these different impacts imply about political feasibility? This gap leaves proposals that would increase the gas tax vulnerable to accusations that they will disproportionally harm the poor and/or the rural population. This is an important objection, particularly given the mounting evidence that lower income groups may not always be the most price responsive groups, and thus may end up paying significantly more than they currently do in fuel taxes under new pricing policies. Furthermore, as cities and transit-rich neighborhoods become more expensive and poor families move to cheaper areas that have fewer travel options, the financial impact on poorer families may grow even more significant.

However, my literature review and data analysis showed that wealthy families generally own more cars and travel much more mileage per household than poor families. Society must not continue to subsidize the external costs of driving high mileages for wealthy people just because pricing would have adverse effects on low income people. Rather, analysis must establish how the adverse effects on the least welloff can be mitigated.

Thus, in recent years, researchers have begun to attempt to understand the fairness of pricing emissions. Many policy proposals try to diffuse opposition by proposing that the pricing scheme be revenue neutral for the government, or by figuring out which groups stand to lose from the change and compensating them. As one example, British Columbia did this with its carbon tax. A retrospective study shows that this tax resulted in a $17.4 \%$ reduction in per capita emissions over just five years (Elgie and McClay, 2013). This has enabled the province to establish some of the lowest income tax rates in Canada because the carbon tax was designed in a revenue neutral way (ibid.). However, many of the poor do not pay enough in income taxes to benefit from this arrangement. Elizabeth Irvin acknowledges this in her 2015 analysis of gas taxation policies, and investigates how rebates could be distributed to families in Massachusetts who would be disproportionally harmed by a carbon tax or gasoline tax increase, finding it to be complicated and difficult to implement. Nonetheless, this is the sort of analysis that is needed in order to start to recruit a broader constituency for more economically efficient pricing.

Much can be learned by studying the impact of existing and new pricing schemes. If the policies are designed to be directly beneficial for much of the population (like British Columbia's carbon tax), fears can be allayed through convincing analysis. One upcoming opportunity arises from the fact that California has recently placed transportation fuels under the umbrella of its cap and trade program (as of January, 2015). California's odometer record dataset will soon provide useful information about how much people of different financial means, living in different geographic settings, and with different types of cars, changed their mileage driven per year in response to the price change. Increased attention to who will win and lose from pricing mechanisms is a useful next step in the literature, particularly since analysts who forecast how much travel demand could be reduced have concluded that tax increases
would need to roughly double the cost per gallon from current levels to reduce total light-duty vehicle emissions by about a quarter (Cambridge Systematics, 2009).

One important aspect of how people win or lose from increased gas taxation is whether the increase in price causes financial loss or causes loss of opportunity. Those who are most price elastic will tend not to be exposed as much to direct financial loss from pricing policies, instead forgoing opportunities (although this could also result in financial loss in some cases). On the other hand, those who are most inelastic will pay the highest additional financial cost. This area of the literature, the variability of elasticity among different population groups, is the area that is least robust, but it is centrally important to the discussion of equity of pricing mechanisms. This is one of the reasons my study focused on the variation in price elasticity within a single metro area.

## My findings show that price elasticity varies substantially among populations

My explorations of price elasticity provide an important piece of the puzzle in understanding how pricing mechanisms may affect different segments of the population in the event of concerted efforts to reduce emissions from the light-duty vehicle fleet. By examining attitudes towards gas price changes and hypothetical policy scenarios, and by analyzing the factors that contribute to variability of price elasticity in Massachusetts, I aimed to better understand how people of different financial means and people in rural, suburban, and urban environments might respond differently to gas tax increases. Several recent studies have weighed in on the relationship between gas price elasticity and income, but few have addressed the effect of the built environment. I was able to discern the impact of three important factors in determining the gas price elasticity of annual miles traveled for individual vehicles in metro Boston - the distance from the urban core, the median household income of the zipcode, and the average fuel economy in the zipcode.

The evidence I collected on the spatial variability of elasticity seemed to indicate that many rural residents feel particularly vulnerable in the case of an increase in the price of gasoline. My regression of Boston metro area elasticities showed that the most rural zipcodes in my sample demonstrated the most inelastic behavior, with an elasticity less than -0.17 . This indicates that these individuals had the least opportunity and/or the least motivation to reduce their travel. On the other hand, urban and suburban residents that I interviewed typically listed many things they would do in the event of a $\$ 4 /$ gallon increase in the gas tax, including actions that would significantly impact their daily patterns, such as trying to carpool for their commutes, cutting back on social trips, combining more trips, and switching from their car to a different mode for some trips. It remains unknown how much these hypothetical actions would be translated into real change in travel habits, but it was apparent that a hypothetical scenario with such a significant increase in the cost of driving triggered a lot of unease, particularly among the suburban interviewees. This unease was most likely due to their limited number of convenient and realistic options for reducing their vehicle use. My regression analysis of Boston supported this idea that the further from the metro core, the lower the price response of vehicle travel. The data showed that vehicles registered close to the core were highly price sensitive, with a gas price elasticity of VMT around -0.38 for zipcodes within four kilometers of Boston's center, or twice the elasticity of the most rural areas in the sample.

The implications of this significant difference in elasticity between the urban areas and the suburbs suggest that people may object to increased gas taxes for different reasons in these two community types. In the suburbs, the objection may be more financial, due to the relatively fixed amount of mileage that they drive. In the urban areas, objections may relate more to the impact on people's daily lives and the opportunities available to them. One of my urban interviewees, who was among the least financially secure people in my sample, said that she would need to sell her car and rely only on transit if the prices went up that much. This would result in a longer commute and more logistical challenges in her daily life. The implications for policy design are not immediately obvious. Even though suburban resistance could potentially be appeased with some sort of rebate, it would be hard to distribute rebates back to the people who were most harmed by the price increase. Remedies would either need to be complex or may not be equitable or effective. For a good discussion of this topic, see Irvin's (2015) analysis.

The evidence I collected on the variability of elasticity with respect to median household income was not as strong as for distance to downtown. Existing literature has weighed in on this issue with mixed results, with some studies finding the poorest households to be the most gas price responsive, other studies finding the wealthiest to be more price responsive, and still other studies finding that both groups are relatively price responsive. In my interviews, I found that some wealthy households reported they were quite sensitive to the price of gas, while others said they were not. I had a similar range of self-reported price sensitivity among my poorer interviewees. My regression indicated that households in wealthy zipcodes tended to be more price responsive than households in poorer neighborhoods, but variation in household income within each zipcode will impede stronger conclusions. Nonetheless, the higher average elasticity in wealthier neighborhoods may be a result of the fact that wealthy families tend to do more discretionary driving than poorer families. This is a discouraging finding on some levels. It indicates that poor households that rely on their cars may end up paying more because they are less price responsive than policy-makers realize. On the other hand, perhaps wealthier families will have more options to reduce their travel demand and emissions, thereby avoiding the incidence of the increased tax. My study is just one of several pieces of evidence on the relationship between income and gas price response, but it does provide additional support to the researchers who find that higher income households are more price responsive than one might expect.

My analysis showed two interesting results related to fuel economy and VMT. First, VMT and MPG seemed to be negatively correlated in Massachusetts when looked at as averages by zipcode. ${ }^{23}$ And second, MPG was a significant determining factor in the price elasticity of miles traveled. The first finding arose from the spatial analysis I did in Chapter 6 (see Figures 21a and b). It was further supported by the surprisingly strong negative relationship between MPG and VMT that I found in my regression in Chapter 7. This could be due to the fact that people prefer to use larger cars (which may also be more comfortable and safer) when they can afford to do so. In Chapter 5, my interviewees from two-car households seemed to be split on this matter. Some interviewees specifically said they already

[^22]use the higher MPG car for any longer drives, whereas other interviewees said that it was important to use their lower MPG car as often as possible because it was safer than their higher MPG car.

My second finding on MPG suggested that very low MPG vehicles were over twice as price responsive as high MPG vehicles. It is intuitive that drivers of cars with a higher cost per mile would cut back more mileage when faced with higher prices. And households that own multiple may vehicles switch some of their mileage onto higher MPG cars during times of higher fuel prices. Similarly, Knittel and Sandler (2013) found that the dirtiest cars in their study of California odometer readings tended to be the most price responsive vehicles (dirtiest in the sense of having the most criteria pollutant emissions per mile). This means that a pricing scheme to reduce gas consumption has a higher health benefit than would be the case if dirty vehicles were no more price responsive than cleaner vehicles. Vehicle age and fuel economy are correlated with criteria pollutant emissions per mile. My finding that the lowest MPG vehicles in the Boston area are most price responsive reinforces Knittel and Sandler's finding and implies that there is a higher reduction in criteria pollutants, higher health benefit, and more GHG reduction than would be the case if the elasticity of miles traveled was constant regardless of fuel economy. It is important to take note of this finding because it means that cost benefit analyses of future carbon pricing schemes or gas tax increases should be careful not to undercount the benefit of VMT reduced by erroneously assuming the response to pricing is constant across the vehicle fleet.

## Gas price matters for travel demand reduction

Overall, my findings suggest that the change in VMT per year in response to changes in the gas price may no longer be as extremely inelastic as some studies had suggested during the early 2000s. My model of the Boston metropolitan area found a short-run price elasticity of VMT of nearly -0.30 for vehicles at the median values for distance from downtown, median household income, and fuel economy. Along with the other recent studies of California odometer readings, which also reported higher elasticities, this is good news for proponents of carbon pricing.

I was motivated to investigate the price responsiveness of driving in this thesis because 1) it is clear that reducing the growth of travel demand will be essential in order to achieve anything near an $80 \%$ reduction in light-duty vehicle transportation emissions from current levels by 2050, 2) policy papers have been optimistic about the rapid effectiveness of a carbon tax in reducing VMT growth, and 3) the level of the carbon tax that would be required to achieve large demand reductions is sufficiently high to make it politically challenging to implement.

This thesis has taken an important step by being the first work to my knowledge to evaluate the variability of VMT elasticity within a single urban region. It is likely, however, that the dynamics of travel behavior vary to some degree from one city to another, particularly in different regions of the country, and this could be the reason for the recent diversity of price responsiveness findings (Jenn et al, 2015). With the availability of big datasets of odometer readings and methods for analyzing them, we can better understand the determinants of VMT and the determinants of VMT price responsiveness in more U.S. states. These findings will need to be combined with other methods of understanding the effects of carbon pricing or increased gas taxes, such as from the observation of the results of real world carbon pricing programs like California's cap and trade or British Columbia's carbon tax.

The desire to feel treated fairly regarding transportation options and costs is a unifying factor for people around the U.S. Since transportation is so central to individuals' ability to earn a living and to their quality of life, people will be protective of the status quo and suspicious of change. Even in Massachusetts, where voters are relatively tolerant of taxes, voters supported a 2014 referendum repealing a new provision to tie their gas tax to inflation, instead leaving the tax close to the same nominal level it had been since 1991, which is now considerably lower in value due to 25 years of inflation.

Gas cost increases can feel tantamount to an infringement on one's independence if they result in the need to evaluate the cost of specific trips by car. This puts a high burden on supporters of a carbon tax. Not only do they need to understand the potential effects on different segments of the population, but they also need to come up with policy design and framing that will make the increase in gas costs more politically palatable. As evidence of the severity of the climate challenge mounts, and climate change rises on the public agenda, advocates of carbon pricing must be well-prepared with a solution that is equitable, well-analyzed, and easy to communicate, and that shows clear benefits to many diverse populations. This represents one of the best chances to reduce light-duty transportation emissions with the least disruption to society.

## Appendix A. Outline of semi-structured interviews

This appendix shows the questions that were asked of all interviewees. Although this list of questions gives the appearance of a structured interview, the flow of the interview was dictated by the way in which the interviewees told their stories and what elements I felt necessary to ask follow up questions on. However, I tried to ensure that each interviewee addressed each of these questions in some form.

Interviewees were also asked to fill out a pre-interview questionnaire, which gave me a basic understanding of their living environment, economic situation, and travel patterns. This questionnaire is not printed in this thesis.

Section 1 - Details about the interviewee's attitudes towards travel

- Tell me about your daily activities and how you travel to them? How do you feel about your experience of getting from place to place?
- What do you like about how you travel? What do you dislike?
- Would you change your home location if your income doubled? Or was cut in half? What living environment would you seek?
- Would you change your vehicle and/or way of traveling if your income doubled? Or was cut in half? Describe what changes you'd make.
- Have you considered or experimented with other ways of getting to where you go? (e.g. taking the bus, traveling at a different time to avoid traffic, etc...)
- What is the most significant cost of driving for you financially? What aspect of driving do you least enjoy paying for? (gas, insurance, parking, opportunity cost of time, vehicle purchase, etc...)
- Tell me what aspects of your car you like the most.
- If you are ever constrained by not having a car available, how does this make you feel?

Section 2 - Evaluating interviewee's awareness of recent gas price changes and memory of actions she had taken in response to price changes in the past

- What do you think about gas prices now versus a year ago? How much have they changed? How did the change make you feel?
- Did you make any changes because gasoline seemed more affordable this year?
- Do you recall attempting to reduce your gas consumption during any time of rapid price increase (e.g. 2008 or 2011)?
- Tell me about what happened when the price went up. What were your options for adjusting your travel behavior, and what did you actually do?
- If you tried to reduce consumption at some times but not other times, what motivated you when you did? What prevented you when you didn't?
- Did you initially intend to change your driving patterns more or less than you actually did?


## Section 3 - Response to hypothetical very large gas tax increase

The government has decided that it will phase in a tax increase of $\$ 4 /$ gallon (to make U.S. gas taxes to be similar to many European gas taxes). This has resulted in the price per gallon going up from $\$ 2.20$ to
$\$ 6.20$ over the course of 10 years. If you used to spend $\$ 30 /$ week on gas, now you would spend roughly $\$ 80$ (ignoring inflation and commodity price fluctuations).

- What specific actions would you take in response to a higher price?
- Would you need to forego any opportunities? Would you think twice about doing specific activities you would otherwise have done?
- Would you search around for cheaper gas stations? Would you feel ok if this was the only change you made?
- Would you behave differently if instead of being due to a tax increase, the higher prices were caused by economic factors? Assume the same magnitude of increase.
- Would you change your expenditures on other goods and services as a result?

Now, let's think one-by-one about the major types of activities in your life. Would you change patterns due to this hypothetical price increase?

If not, tell me about what would be necessary to change your patterns (e.g. knowing that the price increase will persist longer, or that the magnitude would be higher, etc)

Starting with commutes, would a \$4 increase in the gas tax influence the frequency of your commute? The distance? Your likelihood of carpooling? Your likelihood of combining your commute with other trip purposes? Your likelihood of driving as opposed to getting to work by another method?

|  | Commuting | Errands | Chauffeuring | Social and <br> recreational | Vacation | Other |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Would you change the <br> frequency you go on <br> these trips? |  |  |  |  |  |  |
| Would you go to a <br> closer location? |  |  |  |  |  |  |
| Would you make <br> more efforts to <br> carpool? |  |  |  |  |  |  |
| Would you combine <br> other types of trips <br> more than you <br> already do? |  |  |  |  |  |  |
| Would you choose to <br> [walk/bike/take the <br> bus]? Would you drive <br> a different car? |  |  |  |  |  |  |

After going through this grid of questions, I asked the interviewees a few additional questions.

- Are there other ways you would adapt that I have missed?
- Having considered all these ways you could adapt, which are the most likely you would take first? How many actions would you realistically take?
- By what percentage do you expect your average travel distance per week might change? How soon?
- If you absolutely needed to reduce your driving by $50 \%$ would you be able to do it?

Note: Before asking questions about each category of travel in the grid above, I gave my interviewees these guidelines:

- Commuting - include trips to work and/or school for your own education. Also include trips with a business purpose
- Errands - include shopping trips, trips to obtain services (haircuts, doctor appointments, etc), and personal business you must take care of
- Chauffeuring and taking care of family - dropping off and picking up family members from activities. Visiting family members to take care of specific needs if they are sick or unable to perform them.
- Social and recreational - trips for visiting friends/family/acquaintances. Trips to the gym or exercise or outdoor recreation. Trips to cultural events and other entertainment. Trips to eat out.
- Vacation - exclude single day (or shorter) recreational trips (which should have been in the previous category)
- Other - anything else that you travel for


## Section 4 - A few final opportunities for the interviewee to reflect

- When your parents and/or older relatives were your age did they have the same attitude towards gas prices? Why or why not?
- How have your driving habits evolved over time? Did you always have the same attitude towards price? If not, what changed?
- Is most of your travel due to responsibilities or discretion?
- What is an acceptable amount of time for you to spend in the car every day?
- What limits your ability to change your behavior?
- Is there anything else you'd like to tell me about your travel?
- Is there anyone significantly different from you who you think I would benefit from talking to?


## Appendix B. Limited spatial variability of gas prices

My model did not treat gas price as varying geographically within the state of Massachusetts. Following the econometric literature, the spatial variability of gas prices within a state can sometimes be ignored. For instance, Jenn et al (2015) opted not to look at sub-state level spatial variation in gas prices, in the much larger state of Pennsylvania. The assumption that spatial variation in gas price is not important to account for in Massachusetts is based on three main factors:

1. Drivers may not fill their tanks in the same place where the car is registered, and in the course of driving, they may be exposed to many different gas prices on their route.
2. Variation in gas prices within a municipality tends to greatly exceed the variation of the mean gas price between the major gas markets in Massachusetts.
3. We do not know which vehicle owners had the most convenient access to the cheapest gas stations in their general area.

To demonstrate the lack of significant variation across the state, I have displayed the three gas markets for which historical average price data exists side by side. Springfield represents Western Massachusetts, Worchester represents Central Massachusetts, and Boston represents the Boston Metro area. At the time of this writing, just within the limits of the City of Boston, reported regular grade gas prices ranged from $\$ 2.09$ to $\$ 2.99$ on $10 / 23 / 2015$, a variation of $43 \%$. Springfield, MA regular grade prices on $10 / 23 / 2015$ varied by $11 \%$, from gas station to gas station. However, when one looks at the average price in the Boston Metro area, the Worchester area, and the Springfield area, one notices that not only have they experienced nearly indistinguishable trends, but the peak average prices in 2008 were within $0.7 \%$ of each other, and the lowest average prices in the winter of 2008-2009 were within $4.5 \%$ of each other.

Figure B.1. Lack of significant difference in average prices and trends between the three major gasoline markets in Massachusetts.

120 Month Average Retail Price Chart


120 Month Average Retail Price Chart


120 Month Average Retail Price Chart


## Appendix C: Regression Conditions for Inference

Simple Random Sample

Condition met. My dataset contains odometer measurements for all vehicles registered at Massachusetts addresses. I wanted to do analysis on a specific sub-population, which was the mileage estimates representative of personal cars that had non-outlier mileage estimates, located within the MAPC area. I randomly selected 200,000 records from this population. The population was obtained by filtering for only odometer readings that...

1) Were able to be assigned to a vehicle registered in a specific geographic location that was within one of the 101 MAPC member municipalities (greater Boston)
2) Had non-null values for VMT and for my predictor variables
3) Were less than 200 miles per day (equivalent to 73,000 miles per year, a level I deemed unrealistic for a passenger vehicle and more likely to be the result of an odometer reading transcription error)
4) Were greater than 0.1 miles per day (equivalent to only 36.5 miles per year, which could mean that they were not driven because of maintenance issues, or because the household had other preferred cars. Therefore the amount these vehicles was driven probably had no consistent relationship with the price of gas.)
5) Were not from motorcycles
6) Were not from commercial vehicles
7) Were not from electric cars
8) Were representative of periods of time greater than ten months and less than fourteen months (odometer readings of shorter time periods were likely from cars that were sold secondhand during the year and longer time periods may be vehicles that were not regularly used or vehicles for which there was an invalid odometer reading that was thrown out).
9) Were from records for which the odometer reading overlapped greater than $90 \%$ of the registration record (to avoid associating a mileage reading with the wrong garaging location)

## Independence of observations

Condition not met. OLS regression assumes that each observation is independent from all the others. However, my dataset includes instances where there are multiple odometer readings from the same vehicle. This means that multiple odometer readings share some unobserved attributes and therefore their errors may be correlated with each other. The best way to handle this would be to treat the data like a panel dataset, with measurements for each vehicle at each specific time. However, the time period of the odometer readings does not line up for each vehicle, so a panel approach would also be problematic. I decided to continue with the regression without removing any vehicles that had multiple odometer readings because I did want to see the effect of gas price, and these odometer readings that were matched to the same vehicle were likely the best way to discern the effect of gas price.

## Linearity

Condition mainly met. I used scatter plots to determine whether VMT was linear in each of the variables I used in my regression. Given the sheer number of data points, the default scatterplots in the regression package were not informative, filling the screen with ink and not showing a shape to the relationship, or
a density of data points, leading the eye to be tricked by outliers (e.g. Figure C.1). Therefore instead, I used Tableau to condense the data points. This visualization was supposed to answer the question: For each level of a predictor variable, what was the average VMT per day? This gave me a sense of where the data points were clustering and showed whether there was a linear trend in VMT with respect to each predictor variable. A random sample could also have been taken to assess the linearity of the variables.

Figure C.1. Problems with displaying all 200,000 data points in a scatter plot.


My plots are provided below in Figure C.2, starting with vehicle and location variables and finishing with the price interaction variables. I concluded that all but one of my variables (many of which were logged) were linear with respect to the logged version of my dependent variable, VMT per day. However, logged MSRP was not linear with respect to logged VMT. This is the same variable as shown in Figure C. 1 above. It turns out that taking the average VMT for each MSRP uncovered a trend that was not immediately obvious from the ungrouped scatterplot. The parabolic shape of the curve of VMT with respect to MSRP in Figure C. 2 shows that it may need to be treated differently in my linear regression. Nonetheless, all other variables showed well behaved linearity, and therefore I proceeded with my regression.

Figure C.2. Linearity of the variables in my model.




Model year and VMT
Density and VMT
Percent retired and VMT


$$
\begin{aligned}
& \begin{array}{l}
\text { Distance and VMT } \\
\text { 4 } \\
000
\end{array}
\end{aligned}
$$



## Constant variance

Condition met for most variables (but likely not needed anyway). I plotted the residuals (difference between actual and predicted VMT in my model) against each of my predictor variables. Most of the predictor variables exhibited homoscedasticity, meaning that for a low value of the variable the residuals weren't consistently of a greater or lower magnitude than the residuals for a high level of the variable. However, the residuals with respect to my interaction terms were clearly not homoscedastic. The residuals plotted against each independent variable are shown in Figure C.3. For perfectly homoscedastic errors, the plots should show a band of constant height from left to right across the plot and should not be sloping from one side of the plot to the other. These plots display vertical lines with gaps because many odometer readings shared the same values for some of the predictor variables. For instance in the second plot, residuals versus logged distance from downtown, there were no zipcodes between one kilometer from downtown and 1.6 kilometers from downtown, hence the big gap in the plot. And there were many odometer readings for vehicles in each zipcode, hence the collection of vertical lines of the same distance but different residuals.

The data may look more heteroscedastic than it actually is due to the fact that there are nearly 200,000 data points on each graph. If the data is significantly less dense at one end of any given predictor variable, the range of the residuals may look smaller simply because there are fewer outliers due to the lower number of data points in this region. Therefore, I was not as worried by the shapes of some of the plots, such as the plot for residuals with respect to MPG, in which there are a few (uncommon) MPG ratings that have a low range of residuals while others had a much greater range. The final two plots clearly show heteroscedasticity, with a wider spread at the low end than at the high end.

Given that there was heteroscedasticity in my residuals with respect to a few variables, I chose to use heteroscedasticity-robust standard errors, which is recommended when residuals are not homoscedastic.

Figure C.3. Residual plots against each independent variable.



## Normality of residuals

Condition not met (but likely not needed). I also generated a QQ plot, which is a plot that shows if the distribution of your residuals is normal. The fact that the observations fall below the normal quantile line on the left side of the plot shows that my most negative residuals are more negative than they would be if the residuals were normally distributed. Since the residual is the observed value minus the fitted value, having more extreme negative residuals means that my model was much less capable of predicting VMT per day that was very low. This is to be expected because I have no way of knowing which vehicles may have been sitting idle for most of the year due to maintenance issues or the owner buying a new preferred car and leaving the old one in the garage as a backup. Of my roughly 3 million odometer readings that I randomly sampled from, roughly 206,000 were less than 5 miles per day. On the other hand, there were very few vehicles that were driven more than 195 miles per day in my set of readings.

Figure C.4. QQ Plot of regression residuals with actual quantiles on the $y$-axis.


There are several reasons that it may be okay that my residuals did not match the normal distribution. First, as described above, at least one reason for them failing to match it is clear. Second, we already know that there are missing variables in the data which may cause my model to be less able to predict the exact VMT for any given vehicle at any given time, such as the number of other cars belonging to the household. The purpose of this model is to show the magnitude and directionality of the effects of the regressors on VMT and gas price elasticity of VMT, not to predict VMT for specific vehicles. And third, recent research has shown that having normally distributed residuals is not typically necessary to trust regression results when the sample size is sufficiently large ${ }^{24}$.

[^23]
## Appendix D. Lack of spatial autocorrelation of residuals

The average residual was calculated for all mileage estimates in each zipcode. These average residuals were imported into Geoda, and the autocorrelation analysis was done on a zipcode level. High levels of spatial autocorrelation would result in a steeply sloped line in the Moran scatter plot, with tight clustering around the line.

Figure D.1. Moran's I for my regression residuals


Moran's I $=-0.022, \mathrm{P}^{\sim} 0.37$
Next, a Local Indicator of Spatial Association (LISA) plot was generated. As shown below, there are not many zipcodes where both the residual was high and the residual of the neighboring zipcodes was also high. Similarly, there were few low-low matches. This indicates that there are not many areas in our dataset where local spatial autocorrelation is a problem either. The neighbor weights matrix was created using Queen's contiguity.

Figure D.2. Local Indicator of Spatial Association.

## LISA Cluster Map: MAPCzipcodes, I_Residual

$\square$ Not Significant (149)
$\square$ High-High (3)

- Low-Low (5)
$\square$ Low-High (5)
$\square$ High-Low (4)
$\square$ Neighborless (1)



## Appendix E. Multicollinearity test of my regressors

Note that all factors that are not involved in interaction terms (except transit access to jobs vs car access to jobs) have VIFs less than 10. High VIFs are expected for variables that are included in interaction terms because the interaction term is derived directly from the source variables.

Variance Inflation Factors
Minimum possible value $=1.0$
Values > 10.0 may indicate a collinearity problem

```
        l_avg_price 9.747
            1_msrp 1.870
            1_mpg2008 18.701
            l_dens2012 15.421
            l_medhhinc 20.145
                l_emplavg 1.488
                l_dist_km 18.221
    Log_priceXMPG 23.388
    Log_priceXdist 10.464
    Log_priceXinc 18.926
        Dmapc_cat_1 5.038
        Dmapc_cat_2 2.597
        Dmapc_cat_3 5.228
        Dmapc_cat_4 7.271
        Dmapc_cat_5 4.105
        Dmapc_cat_6 3.388
            pctret 2.827
            Ownocc 9.680
            q1_2008 1.204
            model_year 1.165
transtocaraccess 13.078
\(\operatorname{VIF}(j)=1 /\left(1-R(j)^{\wedge} 2\right)\), where \(R(j)\) is the multiple correlation coefficient between variable \(j\) and the other independent variables
```


## Appendix F: Hierarchical Linear Modeling (HLM)

Because land use and demographic variables are most often measured on a broader geographical scale than that of individual households, least squares standard errors can be biased downwards, leading to spurious conclusions and unwarranted confidence in the results (Boarnet, 2011). The application of the same values for these variables to different households or individuals based on some grouping violates the regression assumption of independent errors (Moulton, 1990). Recently, more studies of land use impacts on travel behavior have begun to use address this by clustering their standard errors spatially, or applying hierarchical linear modeling (HLM). For instance, Antipova et al (2011) use HLM to examine the combined effects of land use and socio-demographics on commuting behavior in Baton Rouge. Hong et al (2014) use HLM to find that land use factors have highly significant impacts on VMT even when controlling for attitudes and spatial autocorrelation. Zhang and Zhang (2015) argue that HLM can help researchers understand how land use attributes not only modify travel behavior but also modify the impacts of travel preferences on travel behaviors. HLM is also referred to using terms such as multilevel, mixed level, mixed linear, mixed effects, random effects, and a number of other names, complicating efforts to assess how commonly it is used in the literature.

HLM would be a natural method to apply to the large dataset that I used in this thesis because the data available is primarily at three levels:

1) Mileage estimate level - includes start/end dates of odometer readings, average gas prices, and average macroeconomic conditions,
2) Vehicle level - includes MPG, MSRP, model year, vehicle type, and more
3) Community level (zipcode or town) - includes median household income, distance from downtown, population density, and more.

Without training in HLM, I have opted to try both aggregation and disaggregation, although this thesis only explains the results from the disaggregate approach. In my first effort, not described in this thesis, I aggregated the dependent variable to Level 3, predicting average VMT per household in towns. The aggregation approach is problematic because up to $80-90 \%$ of the variability associated with individual differences will be lost, and could result in misrepresentations of the relationships between variables (Woltman et al, 2012).

In the second model, described in detail in Chapter 7, I disaggregated, by taking observations of zipcodes and applying them as predictors of Level 1 outcomes (VMT per day for each vehicle during a specific mileage estimate period). In the disaggregation approach, the dependent variable, VMT per day for each vehicle during a specific time period, is at Level 1 , while many of the independent variables are at Level 2 (MPG, MSRP, model year, etc). However, many of these Level 2 variables are likely influenced by Level 3 variables. For instance, the median household income of the zipcode would likely impact the MSRP and the fuel economy of vehicles in each zipcode, thereby violating the assumption of independence of errors (Woltman et al, 2012). Although I did not formally implement HLM, my disaggregate models did control for some of this problem by clustering the errors by town type.

HLM is not a panacea for all applications. While in some ways the odometer dataset is particularly wellsuited for HLM (e.g. due to the hierarchical structure of the data, and the sheer number of records and HLM's need for larger sample sizes), there are challenges associated with implementing HLM on this data. Most importantly, using HLM requires that there is no multicollinearity in the data (Woltman et al, 2012). Land use variables within Massachusetts are highly correlated with each other, so in order to use HLM, it may be necessary to omit several important land use variables from the model and eliminate interaction effects, which by definition would have high collinearity with the variables that go into the interaction. The interaction effects in the regression models in this thesis are the results of the most interest, since these are the variables that can tell us how price elasticity varies with attributes like fuel economy, income, density, and more.

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[^0]:    ${ }^{1}$ Baptista et al. (2014) review the literature on the impact of car-sharing systems on vehicle ownership, and found several studies showing that each car-share vehicle reduces the number of privately owned vehicles by 4 to 10.

[^1]:    ${ }^{2}$ Furthermore, while some recent evidence points to the slowing of suburbanization and increased demand for transit-accessible, high-amenity urban locations, it is not clear how long that trend will persist and how soon economic forces may naturally limit the refocusing of development on infill.

[^2]:    ${ }^{3}$ The authors do not distinguish between the effect of a gas tax increase or a carbon price that increases gas prices by an equivalent amount, so I will follow their convention and use them interchangeably in this discussion.

[^3]:    ${ }^{4}$ This assumption seems relatively aggressive and politically infeasible. A more likely scenario, if the U.S. moves towards carbon pricing, would gradually phase the carbon price in, so as not to create a big instantaneous shock. However, the value in this projection is showing the maximum effect that could be realized, even if not politically realistic.

[^4]:    ${ }^{5}$ Refer to the history of Australia's carbon tax, which was implemented in 2012 and repealed in 2014.

[^5]:    ${ }^{6}$ Note that the authors reversed the signs on some of the variables (distance to downtown and distance to nearest transit stop). Lower distance to downtown and lower distance to transit stops were associated with less VMT per household, despite what the signs in the table may suggest. For their reason for doing this, refer to the paper. ${ }^{7}$ However, the elasticity of bus and rail usage with respect to car cost was quite high, ranging from 0.25 to 0.59 .

[^6]:    ${ }^{8}$ Litman (2013a) points out that when considering the long term elasticity of automobile usage with respect to the total vehicle costs (including depreciation, insurance, parking, registration fees, and vehicle purchase cost), gas cost is a relatively small percentage of the total cost. He asserts that a gas price elasticity of -0.3 is comparable to a total cost elasticity of -1.2 , which is elastic.

[^7]:    ${ }^{9}$ A small number of studies have begun to question the common assumption that the elasticity is symmetric whether gas price increases or decreases, most notably Hymel and Small, 2015. They find that price responsiveness is higher during times of rising prices and reopen the question of whether travelers respond in the same way to a change in fuel economy as to a change in fuel price.

[^8]:    ${ }^{10}$ Unless the state or MPO has purchased a larger sample of data through the add-on program.

[^9]:    ${ }^{a}$ Elasticities in the By Auto panel are conditional on car choice.

[^10]:    ${ }^{11}$ The authors argue that this is a strict lower bound for the benefit of the policy because they omit benefits from particulates, congestion, greenhouse gases, and accidents and because they use conservative estimates of NOx and HC benefits.

[^11]:    ${ }^{12}$ Colorado, Pennsylvania, and California all exempt vehicles garaged in rural areas from their annual emissions inspections, and California and Colorado exempt vehicles over 6 and 7 years old, respectively (MAPC, 2015).

[^12]:    ${ }^{13} \mathrm{As}$ far as I can tell, the earliest data in the dataset was merged with pre-existing data from vehicle inspections collected for a Pay-As-You-Drive (PAYD) study. These records were any records that would have had any overlap with the 2006 calendar year, no matter how short. If the VIN ID matched between the PAYD records and the 20082011 registrations and inspections data, a mileage was calculated. It is possible that somehow these PAYD vehicles are a biased sample, and they would have been gradually phasing out during 2008 as the last of these vehicles were inspected.

[^13]:    ${ }^{14}$ I did not log transform the variables that were percentages, since this would yield very high negative values, particularly at low percentages on the original variables. Similarly the binary dummy variables were not transformed. For the interaction terms, I log-transformed the price term, but not the term I interacted with it.

[^14]:    ${ }^{15}$ Most of the coefficients obtained were within a few percentage points of the original coefficient estimate, and only a few were above $10 \%$ different.

[^15]:    ${ }^{16}$ For instance, my model contains the fuel economy of the car in addition to the interaction term created by multiplying the fuel economy by the price of gas for that car's odometer reading time period. Furthermore, there were three interaction terms that involved gas price because the model was an attempt to understand what variables impact price elasticity.

[^16]:    ${ }^{17}$ Vehicles that had estimates that began before that day would not be present in the Q1 2009 data, which is the first quarter of data after this unexplained sudden $10 \%$ drop in VMT per vehicle.

[^17]:    ${ }^{18}$ Since I limited the analysis to the metro Boston area as defined by the MAPC, my model did not estimate elasticity for vehicles registered more than 48 km from downtown, since that is the furthest MAPC zipcode from the center of the city.

[^18]:    ${ }^{19}$ Jenn et al (2015) test for this effect by comparing their overall statewide model with the results when they include only data from the Pittsburgh and Philadelphia metropolitan areas. They failed to find a significant difference in elasticity between these metro areas and the rural parts of the state. Perhaps this could be the result of differing rural/urban dynamics between Pennsylvania and Massachusetts or the result of the different time periods that the data is from (with my data being more representative of a recessionary time).

[^19]:    ${ }^{20}$ It is possible that both Massachusetts and California have slightly higher price elasticities than other states because a higher percentage of their populations live in cities that have viable transit systems and generally higher alternative mode shares than other states. However, both states do have significant populations that do not reside in high density, transit rich, or mixed use areas so I expect this effect to be relatively small.

[^20]:    ${ }^{21}$ Kamen and Toman (1970) note that many people are quickly able to equilibrate to a new conception of a "fair" price of gasoline and mute their behavioral response to price changes. Driver behavior in the 1970s shows significant evidence that habituation to higher gas prices may have occurred. Between 1970 and 1979, a time period in which gas prices went up 144\% in nominal terms, per capita VMT increased by $24 \%$. Furthermore, in response to surveys in 1979, a substantially larger percentage of drivers reported that they would not cut back on their fuel consumption at any price than those responding to the same survey in 1973 (Pitts et al., 1981). Reizenstein and Barnaby (1976) report that at least $50 \%$ of their survey respondents reported that they would not reduce their fuel consumption at any realistic hypothetical increase in prices.

[^21]:    ${ }^{22}$ First, street addresses are likely to be entered in several different formats with different abbreviations, requiring the researcher to invest effort in standardizing the addresses.
    Second, many addresses in the dataset may represent multifamily homes, which may or may not include the apartment number in the registration address. This means that the researcher must implement rules of thumb deciding whether to consider vehicles at the same address as belonging to the same household.
    Third, due to the aforementioned problem, attempts to group vehicles into households in the denser parts of the metro area are likely to be problematic. Models could look use parcel data to look exclusively at single family areas, but this would limit the usefulness of the analysis.
    And fourth, if the dependent variable of interest is VMT per household, the selection of the appropriate timevarying variables becomes challenging. For instance, if a household has two cars, one of which is inspected each January, and the other in July, the mileage of both vehicles must be added together. However, the gas prices observed by the first vehicle will be offset by six months from the gas prices observed by the second vehicle. Therefore, the researcher must take the whole eighteen month period and average the gas prices over this timeframe. For a dataset that only spans 4 years, the researcher will have smoothed out much of the total variability of gas prices by needing to aggregate vehicle mileage estimates together.

[^22]:    ${ }^{23}$ Massachusetts does not seem to be an anomaly in this regard. As discussed in Chapter 6, NHTS data suggests that cities with lower fuel economy on average have higher distance traveled per vehicle.

[^23]:    ${ }^{24} \mathrm{Jim}$ Frost and Rob Kelly, 2014. http://blog.minitab.com/blog/adventures-in-statistics/how-important-are-normal-residuals-in-regression-analysis

