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DATA-DRIVEN ANALYSES & POLICY IMPLICATIONS IN THE TRANSPORTATION WORLD:

A Focus on Pennsylvania Inspection & Registration Data and Nationwide Crash Data

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Abstract

Vehicles are an integral part of today's society and there is a large dependence on them for both business and pleasure. With the increasing concerns in vehicle congestion, air pollution, costly crashes, and highway funding sources, technological advances in data collection and analysis are now necessary in the transportation sector and must be taken to the next level.

This thesis focuses on various analyses that can be performed pertaining to light-duty vehicles by primarily using one, low-cost data source from the annual vehicle safety inspection records in Pennsylvania. It also exemplifies how adding additional, low-cost, data sources can add even more depth and breadth to data-driven transportation analyses. By using these combined data resources, various research and policy questions can be answered through data-driven analyses. Data analyses in transportation studies do not always take into account factors such as urbanity and vehicle age, yet as shown in this thesis, these factors are necessary to make effective policy recommendations.

Chapter II of this dissertation assesses various vehicle safety inspection failure rates using the VSIR data by using the data fields resulting from the safety inspections. This information provides both technical measurements and general pass/fail metrics in order to determine if any maintenance was necessary during the inspection. The data show clearly that vehicles require more maintenance for each of the following: the higher the odometer reading, the older the vehicle, and the more rural the registration zip code. Additionally, the claimed 2% failure rate only applied to vehicles within their first year. Failure rates were found to be much higher for all other vehicles with the average found to be around 12%-18%.

Chapter III examines whether the vehicles safety inspection program saves lives. It can be concluded safety inspections are statistically effective in reducing fatality rates by approximately 1-2 fatal crashes per billion VMT in a given year. Additionally, urbanity was always found to be significant, which confirms the need for robust VMT estimates. Results show there are approximately 1,540 fatalities avoided in current safety states. On the other hand, in states with no safety program about 2,600 fatalities could be avoided if a program similar to PA were implemented.

Chapter IV increases the breadth of analysis with this inspection data by using it to analyze travel patterns for individual vehicles and households with multiple vehicles. The

primary contribution of this chapter is to provide data-driven insight to annual travel patterns based on age, urbanity, and time, in order to eventually be able to make informed policy decisions in order to distribute funding most efficiently. While average VMT data is publically available as averages for each urban and rural area by state, it is not available on a zip code level nor does it contain ranges or other characteristics of vehicles, such as age. Results from this thesis show that while VMT is generally decreasing in recent years, when observing average VMT by vehicle age, VMT is increasing in recent years. This leads to the conclusion that owners are keeping their older vehicles longer and driving them more than the average. Differences in travel and vehicle ownership at a home zip code level are observed and therefore variations within counties and overall urbanity in the state are also seen. Additionally, we observe that while average annual VMT over time is relatively consistent over many of the years observed and much higher in rural areas, vehicle ages consistently increase each year and are approximately the same in comparing urban versus rural areas. Finally, calculations are made in order to assign vehicles to households. This limited the analyses largely due to low sample sizes and the inability to check for representativeness, but loose conclusions could be drawn between households based on vehicle counts and align with a similar study using NHTS data.

Chapter V provides the summary, policy implications of the research, and final conclusions. The vehicle safety inspection program has long been debated within states over the past ten years. This state-driven policy must be analyzed, using a data-driven approach, on a zip code or county level, for the entire U.S. There are questions as to whether this program is effective in keeping roads safe and worth the money being spent. It is calculated that for states without a current safety program, the cost effectiveness (defined in terms of $/life saved) of implementing a safety inspection program similar to PA is about $6.8M ($1.9M - $180M), which falls entirely around the U.S. DOT's value of a statistical life of $5.2 million to $13 million. It is noted that this calculated cost per life saved is likely an upper bound since the estimate does not include benefits of non-fatal crashes avoided and assumes that every vehicle has some repair performed (versus paying only the inspection cost or a zero repair cost). A bigger question is if these state-mandated vehicle policies make sense, especially in areas where there is a lot of cross-border traveling. The cost-effectiveness in this sense may not be accurate.

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Chapter I: Introduction

I. Research Motivation

Vehicles are an integral part of today's society and there is a large dependence on them for both business and pleasure. Today, in 2015, there are 250 million vehicles registered in the U.S. and a total of 3 trillion miles are driven annually. [1] If we were to consider vehicles an investment, assuming an average vehicle costs about $15,000, the U.S. society invests in $3.75 trillion worth of vehicles on the road. In addition to the dependence and investment, vehicle travel impacts health, energy, and the environment. We see health effects due to air pollution, such as smog, and transportation accounts for about one-third of energy use in the U.S. Another motivator and one key aspect of this thesis is safety. In 2013, 45,000 vehicles were involved in 30,000 vehicle crashes, which were the cause of 32,000 deaths. [2] Finally, research on vehicle use among households has little literature and this understanding may be important for setting policy standards in the future based on vehicle travel by considering multi-vehicle households differently. With the increasing concerns in vehicle congestion, air pollution, costly crashes, and highway funding sources, technological advances in data collection and analysis are now necessary in the transportation sector and must be taken to the next level.

Robust databases are vital for analyzing current systems and suggesting effective changes for the future. To date, available transportation data has largely been collected via survey collection systems or self-reported by users. Unfortunately, there are many limitations to using these types of databases, mainly the reporting of inaccurate information and the use of representative population samples. Data from sensors and GPS are becoming more prevalent in transportation applications; however, there are common concerns of privacy, which limits the analyses using this data. As listed as one of critical issues in transportation in the Transportation Research Board's 2013 publication [3], funding has been a top concern for policy makers as the Highway Trust Fund runs out of funds, with only temporary funding extensions being applied. A long-term solution is a priority, which could be primarily solved with data-driven solutions.

In the state of Pennsylvania, efforts have been made to digitize the required, statewide, annual, vehicle safety inspection records (VSIR) in order to examine performance standards and increase the safety of vehicles, specifically pertaining to vehicle maintenance. These inspections are specifically required for light-duty vehicles. A broad range of analyses can be performed with this one database and, more importantly, without interfering with privacy concerns and costs that sensor and GPS data produce. First and foremost, this data can be used to identify safety concerns in vehicles and can identify problems prior to deaths and crashes occurring by monitoring trends more closely. Furthermore, this data can help identify who uses the roads most in a given year, by utilizing odometer readings from each year, allowing for the monitoring of vehicle miles traveled (VMT). VMT can accurately be expressed as a function of vehicle age, vehicle make, vehicle location (e.g., county or zip code), owner age, owner income, etc. These results can all be used in order to strategically create policies that reward drivers for maintaining their vehicle or limiting their VMT. Those who travel more (e.g., use the road commodity more) or who do not maintain their vehicles properly (e.g., endangering themselves and other drivers around them) could provide a funding source to the quickly deteriorating Highway Trust Fund.

This thesis focuses on various analyses that can be performed pertaining to light-duty vehicles with this one, low-cost data source from the annual VSIR in Pennsylvania. It also exemplifies how adding further available, low-cost, data sources can add even more depth and breadth to data-driven transportation analyses. By using this low-cost, easily accessible data, various research and policy questions can be answered through data-driven analyses. Data analyses in transportation studies do not always take into account factors such as urbanity and vehicle age, yet as shown in following sections, these factors are necessary to make effective policy recommendations.

II. Research Topics

The aforementioned concerns in the transportation sector can be mitigated through data-driven analyses and informed policy recommendations, which is addressed in this dissertation. Each section provides a different analysis that can be performed with the available data, including any data verification and manipulation that may be necessary.

Pennsylvania VSIR provides anonymized, vehicle-specific information (e.g., make, model, year, odometer, etc.) each year for any vehicles inspected in inspection stations participating in electronic record keeping (this is optional currently). The vehicle safety inspection system, initially implemented in all states sometimes multiple times per year, is now implemented in only 13 states annually and another 10 states infrequently. The remaining states have no vehicle safety inspection requirements. The initial argument in many states and the current argument in Pennsylvania, that the vehicle safety inspection program is expensive and ineffective, must be thoroughly clarified. A more important question must be addressed prior to the elimination of the safety inspection system—where is the available data to support this statement of program ineffectiveness?

Chapter II of this dissertation assesses various vehicle safety inspection failure rates using the VSIR data by using the data fields resulting from the safety inspections. This information provides both technical measurements and general pass/fail metrics in order to determine if any maintenance was necessary during the inspection. Failure rates are calculated based on the definition of vehicles that passed as a result of some maintenance that was performed during the inspection. Because this data is typically paper-based and is not electronically recorded in all stations throughout the state, results must be scaled in order to represent the actual Pennsylvania vehicle fleet. In order to do this, VSIR is supplemented with the Pennsylvania vehicle registration database. Statistical methods are used to test the representativeness of the inspection sample databases to the registration database to ensure representative results. This analysis, if implemented more frequently, can help clearly present strengths and weaknesses of the program in an effort to minimize cost and maximize safety.

Chapter III examines whether the vehicles safety inspection program saves lives. As of 2013, accidents were in the top five for the leading cause of death over all age groups and motor vehicle crashes were the leading cause of death for those between the ages 1 to 44 [4]. This statistic is alongside deaths resulting from heart disease, cancer, and chronic lower respiratory disease. The safety inspection failure rate analysis is taken one step further by incorporating fatal crash records, publically provided by the National Highway Traffic Safety Administration (NHTSA) in order to analyze the nationwide effectiveness of the safety inspection program. This data is used to compare states based on the intensity and frequency of vehicle safety inspections using the metric of fatal crashes per vehicle mile traveled. Statistical significance is determined by implementing ordinary least squares regressions and two-proportion hypothesis tests. These tests are repeated on a number of different models and parameters to guarantee a robust analysis.

Limitations to these NHTSA databases include the accuracy of the reported information. Most commonly, an officer on site reports the information and these officers are not necessarily trained to define how a crash occurred. For example, there may have been obviously bad weather, but perhaps the brake pads were below the threshold measurement, which added to the bad weather environment, but were the main reason for the crash. Looking at the situation, an officer may just report the crash as a result of the bad weather, not able to measure the brake pad at the crash site. While this information may not always be as accurate as necessary, it is the most robust database available with vehicle crash information.

Chapter IV increases the breadth of analysis with this inspection data by using it to analyze travel patterns for individual vehicles and households with multiple vehicles. The primary contribution of this chapter is to provide data-driven insight to annual travel patterns based on age, urbanity, and time, in order to eventually be able to make informed policy decisions in order to distribute funding most efficiently. In addition, this analysis may help in determining how households drive each of their vehicles in comparison to their other vehicles, other similar households, and households with a different number of vehicles per household. VMT can accurately be expressed as a function of vehicle age, vehicle make, vehicle location (e.g., county or zip code), urbanity, etc. In order to do this, a unique, anonymized, insurance policy value is also provided in order to approximate vehicles within a household and each of their travel patterns as well as for the household as a whole. The Pennsylvania vehicle inspection records contain odometer readings for specific, anonymized vehicles over about a 6-year timeframe that can be used to calculate the associated VMT values, which would be the first step in this analysis. In addition to odometer readings, vehicle-specific data and user-specific data are provided for each vehicle entry. With the detailed, current data provided for Pennsylvania vehicles, models can be created and combined to offer a unique tool for data-driven policies and decision-making.

Chapter V provides the summary, policy implications of the research, and final conclusions. With constant changes in technology and travel patterns, there is a need for a more analytical decision-making model in the transportation sector. The vehicle safety inspection program has long been debated within states over the past ten years. This state-driven policy must be analyzed, using a data-driven approach, on a zip code or county level, for the entire U.S. There are questions as to whether this program is effective in keeping roads safe and worth the money being spent. A bigger question is if state vehicle policies make sense, especially in areas where there is a lot of cross-border traveling.

Often there are incentives presented to invest in some alternative transportation options the question of when or where these transportation options are used is not commonly answered with support from data, yet it would be useful and beneficial to create VMT models and apply data analytics to make informed policy decisions. This would efficiently help decision-makers and policy analysts plan where funding should be spent, rebates offered, or where new projects should be pushed (e.g., updating public transportation or offering rebates for buying a hybrid vehicle). Gasoline, electric, and hybrid passenger vehicles, car-share programs, and public transportation are all prominent options for transportation means currently in the U.S, but they are not all the best option, depending on location and driving habits. Finally, robust databases and active data collection systems of transportation data, real-time monitoring of driving patterns can be analyzed and tracked, creating a safer, more effective transportation network.

III. Research Background

Due to an unfortunately high rate of traffic fatalities in the mid-1900s, the Highway Safety Act of 1966 was enacted [5]. Until 1973, the states were federally required to have safety inspection programs in order to qualify for federal highway funds with the notion that these inspections, along with a roadway revamp (hence the federal highway fund), would reduce traffic fatalities. The handful of previous studies have been high level analyses of whether states without safety inspection programs have higher crash or fatality rates which provides at best indirect measures of effectiveness. In recent publications, there have been numerous approaches to improve vehicle safety on the road.

Several recent publications model safety-related driving behavior, the effectiveness of safety-based incentives, crash analysis, and road safety forecasting. In 2005, Bonsall, et al. identified key parameters of traffic simulation models to project real, unsafe behavior of drivers instead of ideal, safe behavior of drivers to help improve the safety of driving conditions. [6] Noland and Quddus examined whether time periods with congestion versus without congestion influenced factors affecting number of the fatalities resulting from vehicle crashes. [7] Abdel-Aty et al., in 2013, investigated whether it is informative and worthwhile to use macro-level modeling of vehicle crashes, by using Geographic

Information System (GIS), to help inform policy and decision makers of safety investments. [8] In 2013, Weijermars and Wesemann used road safety forecasting and ex-ante evaluation in policy making in the Netherlands to achieve road safety targets and reduce fatalities and serious road injuries. [9] However, vehicle safety inspections haven't been studied as a tool extensively and may help in reducing fatal crashes and keeping roads safe by requiring vehicle owners to maintain the condition of vehicle components effectively.

In 1980, Crain compared death and accident rates, through an economic analysis, in states with and without inspection programs, using 1974 cross-sectional data [10]. In states with inspection programs, a benefit-cost analysis concluded that random safety inspections were as effective as the periodic inspections in preventing crashes and deaths; and, the periodic inspection program thus should be either reevaluated or terminated, as they are more costly than periodic inspections, yet have the same effect as the periodic inspections. In 1984, Loeb et al. published a time-series analysis of the efficacy of the inspection program in reducing fatalities, injuries, and crashes using data from the state of New Jersey. A benefit cost-analysis proved the inspection program to be cost-effective and significantly reduced the number of highway fatalities [11]. Even just looking at these two studies, it can be seen that a state-specific analysis yields different results from the high-level countrywide analysis comparing states with and without inspection programs. The safety inspection program is in need of a state-focused analysis rather than a general nation-wide analysis.

Around 1985, Loeb created an econometric model for efficacy of inspection in reducing fatalities and injuries using cross-sectional data from 1979. He used his previous work from New Jersey as a reference state to compare to the other states across the country. Loeb concluded that there was significant evidence of the efficacy of motor vehicle safety inspections in reducing motor vehicle related crashes and mortalities [12]. Garbacz and Kelly (1987) implemented a national time-series analysis to analyze mandated vehicle safety inspections impact on fatalities. An ordinary least squares regression was presented, using fatalities from the National Safety Council (1952-1982) and then adjusted for traffic fatalities. The results showed no evidence that safety inspection reduced fatalities. A benefit-cost analysis was performed and found that the vehicle safety inspections had no benefits, and were not cost-effective [13], [14]. In light of these conflicting results, the safety inspection program is in need of a state-focused analysis rather than a general nation-wide analysis.

In 1994, Leigh found that vehicle safety inspection laws were not found to significantly reduce fatalities per capita. Leigh compared the quantity of inspections required and the effects of those inspections on fatalities per capita [15], [16]. Merrell et al. (1999) also found no evidence that inspections significantly reduce fatality or injury rates. The state-level model in this analysis was based on the frequency of inspections; the resulting variables were used in an econometric equation along with both fatal and non-fatal estimated models [5], [17]. Rather than comparing fatal and non-fatal models, a more concrete analysis would be to first distinguish a base case of fatalities and how these fatality counts change due to the inspection frequency changes. In 2002, Poitras and Sutter analyzed inspection effectiveness by observing the presence of older vehicles on the road and the impact on the repair industry. Their results indicated that inspections had no significant impact on old cars or the repair industry [10], [18]. This study did not identify how or if the inspection program with older vehicles was compared to the program for the entire vehicle fleet. Additionally, Sutter and Poitras (2002) examined political motives for inspections and produced a model between the incidence of inspection across states and inspection fees. They concluded the inspection program existed primarily due to political transaction costs [11], [19].

Ages of vehicles and urbanity of where the vehicle is driven are not widely considered in any of the noted previous literature, yet likely have importance in designing an appropriate policy or tax for inspection programs. Previous studies show older vehicles being driven less and the U.S. vehicle miles traveled trend decreasing since 2007 after its plateau in 2004, which possibly affects inspection results [5], [12], [20]. While this trend of decreasing VMT with increasing age is clear, age is not widely included in VMT analyses or reported along with VMT in the commonly used NHTS datasets. Due to the distribution of vehicle ages within a given location, a resulting distribution of VMT would be most appropriate rather than single average estimates that are currently published. In addition to VMT distributions according to age, VMT should also account for the urbanity of the area where the vehicle is driven.

Figure 1 shows that urban and rural VMT trends differ, with a bigger gap in 2008 than in 1991. [20] Results in a report published by NHTSA show fatal vehicle crashes are higher in rural areas than in suburban areas as displayed in Figure 2. [21]

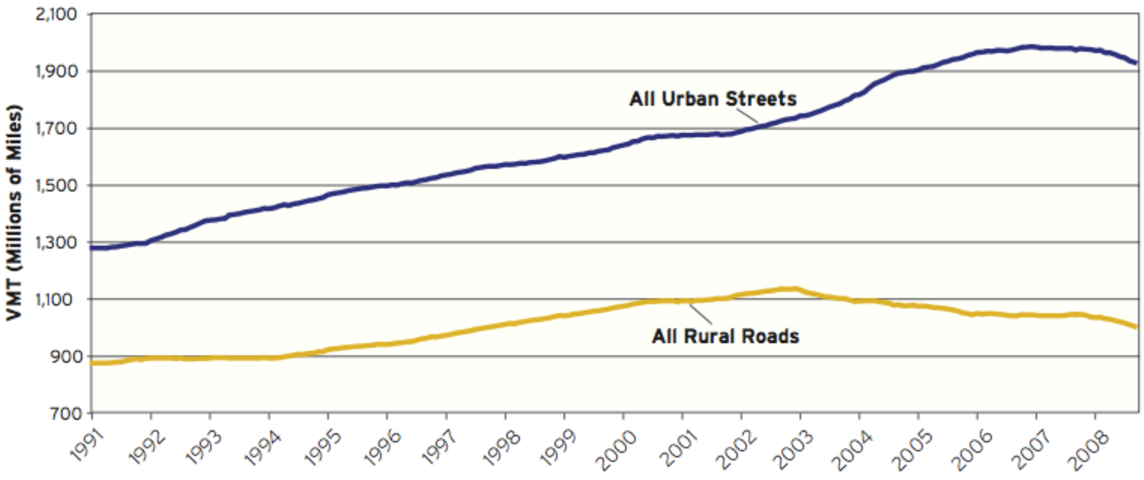

Figure 1. Urban versus Rural VMT [20]

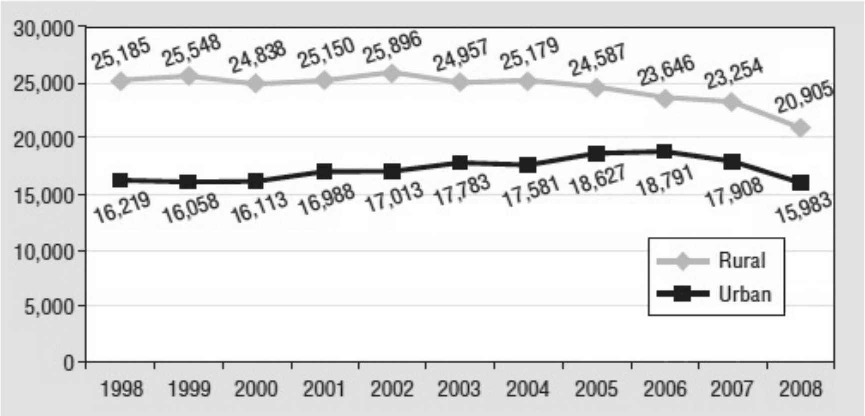

Figure 2. Motor Vehicle Traffic Fatalities by Year and Location, 1998-2008 [21]

These results are important when analyzing safety fatalities as well as VMT patterns since there is lower rural total VMT (an artifact of fewer vehicles) than that of urban yet more rural fatal crashes than that of urban. This results in higher rural fatality rates; thus, NHTSA highly recommends that urban and rural fatality rates be calculated separately, rather than calculating an overall state average fatality rate. Calculating an overall state fatality rate may lead to a state with a higher percentage of urban VMT (urban state) appearing to have a lower fatality rate than a state with a higher percentage of rural VMT (rural state), even if each urban and rural fatality rates are each separately greater when comparing them between the urban state than the rural state.

Two state-level studies exist for the states of Pennsylvania and North Carolina. In 2007, the Pennsylvania DOT hired Cambridge Systematics to study it's safety inspection program [10], [22]. Pennsylvania is considered to be one of the most rigorous safety inspection programs implemented in the country. In their analysis, four years of data on fatalities were examined at both the state and county-level to assess the effectiveness of the vehicle safety program. They used various national databases (e.g., NHTSA's Fatality Analysis Reporting System, U.S. Census, National Oceanic and Atmospheric Administration, etc.) to account for weather, demographics, and socioeconomic variables. The Cambridge Systematics study estimated 1-2 fewer fatalities per billion vehicle miles traveled (VMT) for any state with a safety program and concluded that the vehicle safety inspection program was effective. The Cambridge Systematics study specifically recommended development and use of the electronic state safety inspection ("e-SAFETY") program. A contradicting 2008 study, sponsored by North Carolina legislators, found that "no evidence exists showing the safety program is effective" and "program oversight by DMV is inadequate". The study used crash data from *Nebraska's* Division of Motor Vehicles comparing the three-year crash average before and after the discontinuation of their safety inspection program. While they do not find the inspection to effectively reduce vehicle component fatal crashes, they state a limitation to the analysis is that "because law enforcement personnel are not mechanics and receive a minimal amount of training in compiling and reporting accident data, it is unlikely a true assessment of how many accidents result from mechanical defects is possible" [11], [23]. Additionally, they use a safety inspection dataset consisting of about six million records over only one year (2007) and the study is not in-depth enough to be extrapolated to the entire country. Furthermore, those certified by the DMV to oversee the inspection stations and audit them yearly were reported to have spent less than three percent of their time on this activity. The report admitted that the quality and uniformity of inspections is difficult to enforce, especially in a decentralized inspection program such as North Carolina's.

Historically, both cross-sectional and time-series analyses of vehicle safety inspections were performed over a 10-year period. It is important to note that vehicle technologies have rapidly changed, and analyses from 30 years ago are not comparable to today's vehicle travel and inspection analyses. However, methods can be observed and applied on the present vehicle data, with current travel patterns and vehicle inspection results. Overall, these past studies have varying conclusions as to whether or not the vehicle safety inspection program is effective.

This overview of previous literature shows that the majority of vehicle safety inspection publications are relatively old and showed mixed conclusions on whether or not safety inspection programs were effective. Furthermore, these analyses were mostly high-level, comparing overall state inspection program effectiveness and generally not using detailed, county-level, inspection record datasets. It is important to do a more detailed analysis due to the varying implementation of the safety inspections from state to state and varying driving patterns from vehicle to vehicle. This may show that a state with stronger oversight and rigorousness may prove to be a more effective program overall. As shown in the following discussion, within the state of Pennsylvania, vehicle ages, locations, and total miles traveled vary and the need for state-specific analyses is necessary. Additionally, no paper was found to explicitly analyze actual safety inspection pass or fail rates, which may greatly aid an effectiveness study on the inspection level rather than fatal crash level. The remainder of this paper assesses the vehicle safety inspection program in the state of Pennsylvania on a detailed level addressing failure rates by urban/rural county types, vehicle age, and overall vehicle odometer reading.

A much larger selection of papers examines the effects of driving by using different tools. Small and Van Dender estimated the rebound effect for passenger-vehicle use across the U.S. states and over time. [24] They showed that higher income drivers are less sensitive to fuel costs as it consists of a smaller percentage of their income. So, over time the rebound effect diminishes with income as a result of rising incomes and falling real fuel costs. In 2010, Gillingham used vehicle registration data and vehicle smog check data from 2001 to 2008 in California. He found that gasoline demand is relatively inelastic and there is some heterogeneity in driving behavior, which he shows from the high variance calculated in the VMT estimation. "Results suggest that consumers are responsive to gasoline prices in both vehicle choice and driving decisions…these responses vary by income, geographic, and demographic groups." [25], [26] Unfortunately, there is no extrapolation of his conclusions in his papers that generalizes to the rest of the country. This may be difficult to do since California has different standards, such as smog control, and are more sensitive to environmental regulations. Clark et al. evaluated the effect of population density on the rates of motor vehicle mortality in rural and urban areas, while controlling for VMT. [27] This analysis uses data from both FARS and FHWA and finds that mortality rates are much higher in rural areas than urban areas. This is important to note when analyzing fatalities in an entire state as they should be weighted according to the states' urban-rural compositions. This is similar to the report referenced previously, published by NHTSA summarizing urban and rural fatality trends.

Many papers present analyses relating VMT to other variables, such as variations in gasoline prices, spatial economics, or the built environment and land use patterns. For example, in general studies have found that gasoline price changes have a relatively inelastic effect on high-income household and a more elastic effect on low-income households, as fuel makes up a larger portion of their percentage of income. External factors may include higher income households owning a second, more fuel-efficient vehicle, which they switch to using as gas prices fluctuate. [26] Prior to these analyses, it is important that a baseline understanding of driving patterns is understood. It is true that external factors such as gasoline prices and economics play a role in driving patterns, but it is first import to see how VMT changes based on geography or driver characteristics, for example. Rural, suburban, and urban counties or zip codes may change due to a change in gasoline prices; however, these counties may exhibit internal relationships primarily, aside from any external factors changing. Factors such as availability and convenience play a role in locations where public transportation is unavailable or sparse. Regulations may be more beneficial if applied on smaller levels such as the zip code or county level instead of state or country levels.

A robust dataset is also necessary in performing the above baseline analyses. Current VMT estimates stem from survey results and traffic counts and are reported as two average values in each state – one for urban locations and one for rural locations. However, the accuracy and reliability of this data is questioned. For example, the National Household Transportation Survey records vehicle information based on phone surveying, which depends on the accuracy of the respondent reported results and asks the respondent to report the number of miles traveled on every vehicle in the household over the past year. This survey also only accounts for 0.1% of the total households in the U.S. More detail about this database can be found in Chapter IV. The same question is asked regarding the reliability of the vehicle count data reported and maintained by the Federal Highway Administration's Office of Highway Policy Information. The VMT estimates reported here are based on hourly traffic count data reported by the States from approximately 4,000 continuous traffic counting locations nationwide. [28] If data is unavailable for a given state, average values from surrounding states are used and if that is unavailable, the national average is used. Chapter IV investigates if a new method of estimating VMT can be used and compares it to these estimates.

Chapter II: Vehicle Safety Inspection Failure Rates[1]

I. INTRODUCTION

In the United States, mass transportation vehicles such as public transit, commercial flight, and passenger rail are federally mandated to undergo safety and maintenance inspections. However, the federal government does not require inspections of personal vehicles even though it is the most pervasive travel mode according to passenger-miles traveled [30]. Without a federal mandate, states determine the extent and frequency of light duty vehicle (LDV) safety inspections. As of January 2014, thirteen states require annual safety inspections (some of which also require emission inspections), a handful of states require safety inspections at change of vehicle ownership, about half of states require only emissions inspections, and ten states require neither [13].

Safety programs call for specified inspections to be performed on automobiles and light trucks with varying frequencies (e.g., annually) and on various subsets of the fleet (e.g., exempting new cars). These state safety inspection requirements change over time, largely due to the general perception that such programs are costly to consumers and provide little or no benefits to society. Behind these perceptions are perceptions that cars have never been safer. States are also considering eliminating safety inspections entirely as government reports indicate the vast majority of vehicles successfully pass the inspection requirements. Pennsylvania is one of those states.

Legislators in Pennsylvania have claimed (without literature attribution) that 98% of inspected vehicles pass inspection [15], implying a 2% failure rate. Stakeholders in other states have made similar statements, thus implying that the failure rate is so low that it presents an unnecessary burden on drivers or that there is no evidence it is an effective program.[2, 3] With lack of substantial evidence, these other states have recently discontinued their safety inspection programs. However, during the inspection process, vehicles may

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[1] D. Peck, H. S. Matthews, P. Fischbeck, and C. T. Hendrickson, "Failure rates and data driven policies for vehicle safety inspections in Pennsylvania ," Transportation Research Part A, vol. 78, no.

[2] According to a Washington Post article, "D.C. officials said that only about 20 states have inspection programs and that there is no evidence that routine inspections make District vehicles less accident-prone." [31]

[3] According to New Jersey news, "the [safety] inspections resulted in a rejection rate of less than 6 percent for "serious" defects — such as those related to brakes, steering or suspension, state officials said." [32]

provisionally fail, receive repairs, and then be classified as "pass." The intermediate repairs or adjustments, which are likely lost amongst the data from where the low failure rates are drawn, should have been classified as failures under the current inspection regime. Determining failure rates before and after maintenance is essential to assessing and improving safety inspection programs. To account for this, in this study vehicles recorded as "work performed to pass" are considered to have failed. This modification will yield an improved failure rate estimate. More importantly, this updated failure rate assesses the direct effect of the program by identifying vehicle owners who rely on vehicle safety inspections to identify safety problems and maintain their vehicle. For instance, drivers who proactively maintain their vehicle(s) are assumed to fix problems as they occur and therefore would not be represented in this improved failure rate estimate methodology. Using this assumption, it is possible this fail rate estimate may be an underestimate of actual vehicle fail rates. However, conclusions cannot be drawn here because these analyses can only be performed by observing multi-point data inspections or by comparing the condition of vehicles in non-inspection states; however, there is no available data to reflect this.

This study uses two unique datasets containing anonymized vehicle safety inspection records for the state of Pennsylvania to examine the actual failure rate of inspected vehicles, and projected failure rates of various data-driven inspection scenarios. In addition to overall failure rates, we examine failure rates by vehicle mileage, vehicle age, urbanity, and failure rate trends over time. In addition, the question of whether accurate inspection data is available and correctly analyzed is addressed. Finally, conclusions are drawn on the changes in vehicle safety, the importance of continued vehicle maintenance, various policy perspectives on the implementation of the current program, and whether the current safety inspection program seems to be worthwhile to continue in the future at this point.

II. VEHICLE SAFETY HISTORY AND LITERATURE REVIEW

Due to an unfortunately high rate of traffic fatalities in the mid-1900s, the Highway Safety Act of 1966 was enacted [5]. Until 1973, the states were federally required to have safety inspection programs in order to qualify for federal highway funds with the notion that these inspections, along with roadway improvements (hence the federal highway fund), would reduce traffic fatalities. Previous studies of safety inspection programs have been high-level analyses of whether states without safety inspection programs have higher crash or fatality rates, which provides at best, indirect measures of effectiveness. In recent publications, there have been numerous approaches to improve vehicle safety on the road.

These recent publications include, but are not limited to modeling safety-related driving behavior, the effectiveness of safety-based incentives, crash analysis, and road safety forecasting. In 2005, Bonsall, et al. identified key parameters of traffic simulation models to project real, unsafe behavior of drivers instead of ideal, safe behavior of drivers to help improve the safety of driving conditions. [6] Noland and Quddus examined whether time periods with congestion versus without congestion influenced factors affecting number of fatalities resulting from vehicle crashes. [7] Abdel-Aty et al., in 2013, investigated whether it is informative and worthwhile to use macro-level modeling of vehicle crashes, by using Geographic Information System (GIS), to help inform policy and decision makers of safety investments. [8] In 2013, Weijermars and Wesemann used road safety forecasting and ex-ante evaluation in policy making in the Netherlands to achieve road safety targets and reduce fatalities and serious road injuries. [9] Vehicle safety inspections, however, haven't been studied extensively as a tool even though they may help in both reducing fatal crashes and keeping roads safe, by requiring vehicle owners to actively maintain the condition of vehicle components.

Historically, both cross-sectional and time-series analyses of vehicle safety inspections have been performed; yet, the majority are now outdated. Vehicle technologies have rapidly changed, and analyses from 30 years ago are not comparable to today's vehicle travel and inspection analyses. However, methods can be observed and applied on the present vehicle data, with current travel patterns and vehicle inspection results. Overall, these past studies have varying conclusions as to whether or not vehicle safety inspection programs are effective.

In 1980, Crain compared death and crash rates, through an economic analysis, in states with and without inspection programs, using 1974 cross-sectional data [10]. In states with inspection programs, a benefit-cost analysis concluded that random safety inspections were as effective as the periodic inspections in preventing crashes and deaths; and, the periodic inspection program thus should be either reevaluated or terminated, as they are more costly than periodic inspections, yet have the same effect as the periodic inspections. In 1984, Loeb et al. published a time-series analysis of the efficacy of the inspection program in reducing fatalities, injuries, and crashes using data from the state of New Jersey. A benefit cost-analysis proved the inspection program to be cost-effective and significantly reduced the number of highway fatalities [11]. Even just looking at these two studies, it can be seen that a state-specific analysis yields different results from the high-level countrywide analysis comparing states with and without inspection programs. The safety inspection program is in need of a state-focused analysis rather than a general nation-wide analysis.

Loeb created an econometric model for efficacy of inspection in reducing fatalities and injuries using cross-sectional data from 1979. He used his previous work from New Jersey as a reference state to compare to the other states across the country. Loeb concluded that there was significant evidence of the efficacy of motor vehicle safety inspections in reducing motor vehicle related crashes and mortalities [12]. Garbacz and Kelly (1987) implemented a national time-series analysis to analyze mandated vehicle safety inspections impact on fatalities. An ordinary least squares regression was presented, using fatalities from the National Safety Council (1952-1982) and then adjusted for traffic fatalities. The results showed no evidence that safety inspection reduced fatalities. A benefit-cost analysis was performed and found that the vehicle safety inspections had no benefits, and were not cost-effective. [14] In light of these conflicting results, the safety inspection program is in need of a state-focused analysis rather than a general nation-wide analysis.

In 1994, Leigh found that vehicle safety inspection laws were not found to significantly reduce fatalities per capita. Leigh compared the quantity of inspections required and the effects of those inspections on fatalities per capita. [16] Merrell et al. (1999) also found no evidence that inspections significantly reduce fatality or injury rates. The state-level model in this analysis was based on the frequency of inspections; the resulting variables were used in an econometric equation along with both fatal and non-fatal estimated models. [17] Rather than comparing fatal and non-fatal models, a more concrete analysis would be to first distinguish a base case of fatalities and how these fatality counts change due to the inspection frequency changes. In 2002, Poitras and Sutter analyzed inspection effectiveness by observing the presence of older vehicles on the road and the impact on the repair industry. Their results indicated that inspections had no significant impact on old cars or the repair industry. [18] This study did not identify how or if the inspection program with older vehicles was compared to the program for the entire vehicle fleet. Additionally, Sutter and Poitras (2002) examined political motives for inspections and produced a model between the incidence of inspection across states and inspection fees. They concluded the inspection program existed primarily due to political transaction costs. [19]

Ages of vehicles are not widely considered in any of the noted previous literature, yet likely have importance in designing an appropriate policy or tax for inspection programs. Two travel trends may have effects on safety inspection results. First, previous studies show older vehicles being driven less and second, the total vehicle miles traveled has been flat or decreasing since 2004 according to the Federal Highway Administration [33].

Two state-level studies exist for the states of Pennsylvania and North Carolina. In 2007, the Pennsylvania Department of Transportation (PennDOT) hired Cambridge Systematics to study its safety inspection program [22]. Pennsylvania is considered to be one of the most rigorous safety inspection programs implemented in the country. In their analysis, four years of data on fatalities were examined at both the state and county-level to assess the effectiveness of the vehicle safety program. They used various national databases (e.g., NHTSA's Fatality Analysis Reporting System, U.S. Census, National Oceanic and Atmospheric Administration, etc.) to account for weather, demographics, and socioeconomic variables. The Cambridge study estimated 1 to 2 fewer fatalities per billion vehicle miles traveled (VMT) for any state with a safety program and concluded that the vehicle safety inspection program was effective. The Cambridge study specifically recommended development and use of the electronic state safety inspection ("e-SAFETY") program. A contradicting 2008 study, sponsored by North Carolina legislators, found that "no evidence exists showing the safety program is effective" and "program oversight by DMV is inadequate". The study referenced the use of crash data from Nebraska's Division of Motor Vehicles comparing the three-year crash average before and after the discontinuation of Nebraska's vehicle safety inspection program. While they do not find the inspection to effectively reduce vehicle component fatal crashes, they state a limitation to the analysis is that "because law enforcement personnel are not mechanics and receive a minimal amount of training in compiling and reporting accident data, it is unlikely a true assessment of how many accidents result from mechanical defects is possible". [23] Additionally, they use a safety inspection dataset consisting of about six million records over only one year (2007) and claim the study is not in-depth enough to be extrapolated to the entire country. Furthermore, those certified by the DMV to oversee the inspection stations and audit them yearly were reported to have spent less than three percent of their time on this activity. The report admitted that the quality and uniformity of inspections is difficult to enforce, especially in a decentralized inspection program such as North Carolina's.

This overview of previous literature shows that the majority of vehicle safety inspection publications are relatively old and showed mixed conclusions on whether or not safety inspection programs were effective. Furthermore, these analyses were mostly high-level, comparing overall state inspection program effectiveness and generally not using detailed, county-level, inspection record datasets. It is valuable to do a more detailed analysis due to the varying implementation of the safety inspections from state to state and varying driving patterns from vehicle to vehicle. This may show that a state with stronger oversight and rigorousness may prove to be a more effective program overall. As shown in the following discussion, within the state of Pennsylvania, vehicle ages, locations, and total miles traveled vary and the need for state-specific analyses is necessary. Additionally, no paper was found to explicitly analyze actual safety inspection pass or fail rates, which may greatly aid an effectiveness study on the inspection level rather than fatal crash level. The remainder of this paper assesses the vehicle safety inspection program in the state of Pennsylvania on a detailed level addressing failure rates by urban/rural county types, vehicle age, and overall vehicle odometer reading.

III. THE PA STATE VEHICLE INSPECTION PROGRAM, PROCESS, AND DATA RECORDS

In Pennsylvania, safety inspections of LDVs are administered annually in every county and for all vehicles. Inspection stations in Pennsylvania are an open market; if an individual or business decides to perform inspections in Pennsylvania, they apply to PennDOT. Upon verification that they meet the requirements and have cleared screening at PennDOT they are appointed as a certified safety inspection station. The number of safety inspection stations depends on the number of stations that have been certified. In order for individuals to perform safety inspections, they must be trained and certified by PennDOT. Inspectors are compensated by the business for which they work, as per the business' individual practices. Both the inspection stations and inspectors receive periodic oversight audits and are monitored by the State Police Vehicle Fraud Unit. Any violations, such as lost stickers, improper use of license, or affixing stickers incorrectly, are subject to possible suspension and fines. The cost of a vehicle inspection is market-set, where each inspection station chooses how much it will charge. In most cases, vehicle owners are charged an inspection fee in addition to any maintenance performed; however, some businesses may choose to offer annual inspections free of charge. PennDOT charges inspection stations or inspectors approximately two dollars per inspection sticker (which is used to distinguish a vehicle has been inspected). A vehicle with an expired inspection sticker in the state of Pennsylvania is subject to various fines. Additional detailed information on the Pennsylvania vehicle inspection program can be found in The Pennsylvania Code 67 Pa. Code § 175. [34]

Vehicle safety inspection regulations and processes are uniform across Pennsylvania yet vary between states. For example, one state may check brakes via a "skid" test, measuring the distance to stop from a given speed and pressing the brakes. Another state may physically measure the thickness of the brake pads. This could create an inconsistency in inspection results state to state since the different inspection methods are not correlated against each other, and thus are likely to give different safety outcomes. Some Pennsylvania counties (25 of 67) also require emissions inspections, generally around urbanized areas whose air quality does not meet federal standards as stated in the Clean Air Act (1990). This paper focuses solely on safety inspections as pertaining to LDV's in Pennsylvania.

Initially, certified inspection stations in Pennsylvania were required by the state to document all inspection results using a paper MV-431 form (refer to the Supplemental Material). Historically, these detailed but typically hand-written inspection records were subject to periodic station audits to assure proper recordkeeping. This form of decentralized record keeping prevents data analytics from being performed and is most likely why there have been so few studies on this topic.

Vehicle safety inspections in Pennsylvania include checking vehicle components such as: steering/suspension, exhaust, fuel, body/doors/latches, glazing/mirrors, brake system, lighting, tires, and other. The "other" category includes all or some of the following categories: wipers, bumper, defrosters, battery hold-down, brake warning lights, odometer, speedometer, etc. To pass the safety inspection, the state of the vehicle after inspection, with or without maintenance, must be within the applicable, allowable thresholds. For example, the minimum threshold for tire tread depth is 2/32 inch. The result of each required component check is coded as a pass, fail, new, repair, or adjust. Figure 3 explains the various paths that can be taken during the safety inspection process, starting with the initial inspection that identifies potential component problems.

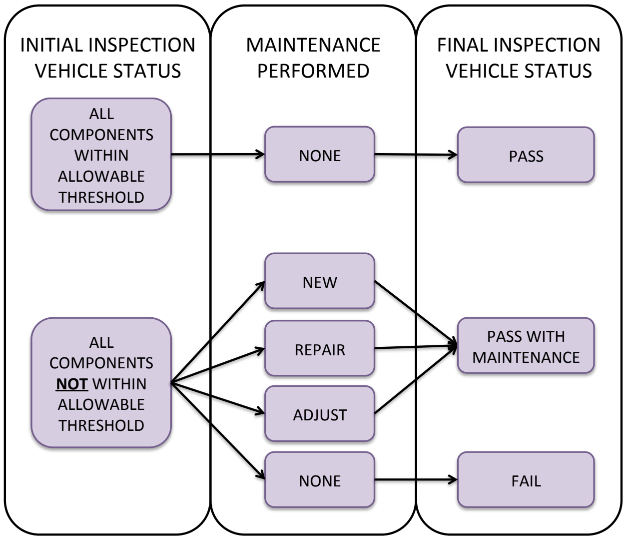


Figure 3. Representation of Inspection Process

Table 1 presents examples of component inspection problems identified with a corresponding maintenance solution, along with the reason for the type of failure, or the "work performed" at the inspection station.

Table 1. Definition of Action Categories with Example Solutions

Action	Scenario	"Work Performed"
New	A vehicle's tire tread is measured as less than threshold tired depth	Tire is replaced, a new tire is installed
Repair	The hood latch is broken or is not keeping the hood locked down	The latch is repaired so it functions properly
Adjust	Headlights are mis-aimed	Headlights are re-aimed, or adjusted

If all tested components are initially within the allowable threshold, then the final inspection status is considered a *pass*; and no maintenance was required to receive the inspection sticker. The *pass with maintenance* designation represents a vehicle with one or more components identified during the initial inspection as requiring maintenance because they were not within the allowable threshold. Once all suggested maintenance is performed and all components are within the allowable threshold, the vehicle passes and receives an inspection sticker. The *fail* designation represents a vehicle with one or more components identified during the initial inspection as requiring maintenance because they are outside of the allowable threshold, yet not all required repairs were performed. This vehicle will not leave the inspection with a new safety inspection sticker. For example, the vehicle owner may be told work is necessary for the vehicle to pass; however, the suggested work may not always be performed at that time and the owner may return at a later date. Identifying failure rates based only on results of final inspection status ignores the fact that maintenance is often required, and may lead to false perceptions of failure.

The fail, new, repair, and adjust categories, combined, all represent ways in which a vehicle *would have failed* an inspection if maintenance was not performed and reflect a vehicle's initial state when entering the inspection station, regardless of the final status. This is important to consider when estimating the safety effects in a regime without an inspection program, as these adjustments or replacements may have never otherwise happened without the required safety inspection program. Since vehicles must have valid safety inspection permits to be driven, owners request the inspection facility to make the necessary repairs and adjustments to the vehicle so that all components eventually receive a new safety inspection sticker. Thus, the majority of vehicles are considered to have successfully passed inspection. Examining the underlying information about maintenance during an inspection is thus necessary.

In Pennsylvania, inspection data is recorded and held in databases owned by PennDOT as well as by privately owned IT contractors and inspection companies. Full inspection data records are considered proprietary, and are not generally used for program performance assessment.

Five years ago, PennDOT launched the "e-SAFETY" program, an electronic data archive of safety inspection results, where safety inspection stations voluntarily report results of vehicle inspections. The impetus of this program was to ensure collection of data to distinguish "trends for future safety improvements by identifying potential vehicle safety hazards and safety patterns". [35] When the e-SAFETY program was introduced, part of the incentive to participate was that the MV-431 paper forms were no longer necessary for record documentation. Some stations still may choose to keep them as the primary inspection record.

Prior to the commencement of the e-SAFETY program, a private company, CompuSpections, LLC (CompuSpections), released commercial software to manage and monitor vehicle safety inspections on behalf of stations, such as those required by states like Pennsylvania. Rather than inspections being voluntarily submitted, the private company is able to collect all of the data entered into the software system. The initial incentive for this private electronic system was to be used for a managerial device and was not necessarily intended to use to report these safety inspection results. The CompuSpections database offers the option to print MV-431 forms from the entered information.

Both the CompuSpections and e-SAFETY datasets have comparable data, but differ by the details for variables they contain (see Methodology section). Both the e-SAFETY and CompuSpections databases allow inspection stations to have quick and detailed access to previous records when necessary. This may be important in order to back-check any repairs made to a vehicle involved in a crash or to monitor reported failures to be sure they are not over-reported. Additionally, this program allowed vehicles to be tracked according to any type of changes made for a "failing" vehicle in order to prevent or look for similar failures in same model-year vehicles. The key difference between the two datasets lies in composition of types of inspection stations. The majority of the e-SAFETY data records are comprised from independent inspection stations, while records in the CompuSpections database are mainly from dealership inspection locations. Additionally, e-SAFETY records have higher odometer readings, on average, given a specific vehicle age. By combining these inspection datasets, these data samples are assumed to be representative of safety inspection failure rates in the entire state.

By combining inspection details from both datasets and comparing various distributions with state registration data distributions, we can examine how many vehicles have safety issues and are repaired as a result of the current annual safety inspection program. With this information, various analyses can be performed based on vehicle inspection failure rates or number of vehicles that "would have failed" with respect to the characteristics such as urban/rural county types, vehicle age, and overall vehicle odometer reading.

IV. METHODOLOGY FOR FILTERING, VALIDATING, AND ANALYZING STATE VEHICLE RECORDS TO CALCULATE INSPECTION FAILURE RATES

In calculating vehicle safety inspection failure rates, this study focuses on three main parameters by which failure rate is analyzed. These parameters consist of vehicle failure rate by urban/rural county classification, age, and odometer reading. Age is an essential variable by which to calculate failure rates because driving patterns differ as a result of vehicle age, with VMT decreasing about three percent per year, on average. Furthermore, there are fewer older (more than ten years old) vehicles being driven [36]. This however does not mean the old vehicles should be ignored from analyses since they still contribute to fatal crashes. An additional reason to consider fail rate by age is because PA state legislators have proposed to exempt safety inspections based on a vehicle's age (e.g., exempt first two years of safety inspections). A county-scheme distribution allows for conclusions to be drawn based on the population density of a given location, allowing for assertions to be made depending on varying driving patterns due to driving location (e.g., rural county vehicles are driven more yet represent less of the state). Finally, failure rates are examined based on odometer readings, which perhaps reflect both vehicle age and driving location, as younger vehicles tend to be driven more than older vehicles and vehicles in rural counties tend to be driven more than those in urban counties. The following sections present the data available for this analysis, validation and regression of the data, as well as each of the previously stated failure rate distribution scenarios.

V. Raw Data

Raw data provided for this study includes anonymized Pennsylvania vehicle safety inspections ranging from 2008–2012 from two different data sources, in addition to anonymized Pennsylvania vehicle registration records as of March 2012 and November 2013. The two datasets are composed of varying volumes of records, vehicle characteristics, and inspection information. No information pertaining to the vehicle owner or drivers of the vehicle was identified or released. Table 2 summarizes the main similarities and differences pertinent to the study.

Table 2. Pennsylvania Data Used

	e-SAFETY	CompuSpections	Registration
Record Count	980k (total)	3.3 million (total)	10.4 million (each)
Frequency	5 years (2008-2012)	5 years (2008-2012)	2 snapshots (March '12 & November '13)
Percent of Registered Vehicles per Year	~3%	~10%	
VIN	X	X	X
Odometer	X	X	X*
Date	X	X	X*
Location (zip code)	X	X	X*
Vehicle make and/or model	X	X	
Inspection Type (e.g. annual)	X	X	
Inspection Action (e.g. pass, new, etc.)	X	X	

*At time of registration for current owner in PA

Custom code written in the Python programming language was used to filter, analyze and compare each initial, raw dataset to remove entries with invalid or incomplete information. Filters used on each dataset included, but were not limited to, the following primary issues:

1) Invalid VIN (length, digits, verified)
2) Duplicate Entries
3) Invalid Date (format issue – not a date, no entry)
4) Invalid Odometer Entry (alpha-numeric entry, no entry)
5) Heavy-duty trucks (>10,000 lbs and ≥ Ford F-350)
6) Permanently registered vehicles (police cars and ambulances)
7) Low category counts (<1,000 vehicles in a given category i.e., age 25 vehicles)

The Supplemental Material (Section 2.2 Raw Data Filtering Results) contains detailed filtering and methodology information. About 10% of the registration data, about 2% of the

CompuSpections data, and about 8% of the e-SAFETY data were removed from the initial datasets leaving sufficient, complete, and valid entries to complete the analyses.

Registration data reported in the data sets was used to assess the representativeness of the vehicles in each data set since one of the mandatory steps in the inspection process is to verify registration. Thus the registration data is considered to be a valid baseline of vehicle representation for the analysis. Representativeness was examined between each registration dataset as well as between registration and inspection datasets. While chi-squared analyses suggest that the distributions compared are statistically different (see Section 3 in the Supplemental Material), the distributions do appear to follow the same trends and overall distribution appearance. However, there are specific reasons as to why only certain years were included in the data analysis, specifically pertaining to the quantity of records in each inspection dataset contributing to the overall, combined inspection dataset.

A limitation to the two inspection databases is that they are not randomly selected records of vehicles overall in the state or of types of stations (e.g. independent or dealership). And, while the inspection datasets provide an ample amount of inspection data points, it is concluded the statistical difference merely indicates the vehicle fleet is rapidly changing with many new cars moving onto the market, old cars off of the market, and cars moving into and out of the state. Another problem in checking for statistically similar data distributions may stem from vehicles being registered in Pennsylvania and getting inspected in a station that does not partake in the electronic state inspection program, but rather in a station that still uses the paper MV-431. Finally, it is concluded that the total number of data points (refer to Table 2) is enough to be able to draw reasonable conclusions about the vehicle fleet, even if it is not statistically proven.

VI. Data Validation and Regression Analysis

In order to determine if any independent variables of vehicle characteristics are statistically significant in predicting the dependent variable of vehicle safety inspection outcome (whether a vehicle will pass or fail inspection), a logistic regression is performed using the statistical software package R. The outcome in this equation is treated as a Bernoulli trial and the following logistic function is used:

$$p(x) = \frac{1}{1 + e^{-\eta(x)}}$$

- where p(x) is the probability of the outcome x (i.e., p(failing inspection));
- and $\eta(x)$ is a linear combination of explanatory variables:

$$\eta(x) = \beta_o + \beta_1 * age + \beta_2 * currentOdometer + \beta_3 * weight + \beta_4 * fuelEconomy + \beta_5 * InspectDate + \beta_6 * urbanity + \beta_7 * body + \beta_8 * make + \beta_9 * fuelType$$

- where age, currentOdometer, weight, fuelEconomy, InspectDate, urbanity (of registration location), are continuous variables;
- and body, make, fuel are binary variables;

To test for multicollinearity, we have calculated and provided a correlation matrix showing variable relationships. Note that the regression model incorporates urbanity index as a categorical variable, but for the sake of looking at the correlation between variables, the urbanity level was assumed to be continuous based on the urbanity scale explained in the following section of the paper. The correlation matrix of the independent, continuous variables are shown in Table 3.

Table 3. Correlation Matrix of Independent, Continuous Variables Included in the Logistic Regression

	Vehicle Age	Current Odometer	Vehicle Weight	Fuel Economy	Urbanity Level	Inspection Date
Vehicle Age	1	0.79	-0.13	-0.05	0.08	0.19
Current Odometer		1	-0.06	-0.05	0.11	0.16
Vehicle Weight			1	-0.78	0.03	0.04
Fuel Economy				1	-0.04	-0.03
Urbanity Level					1	0
Inspection Date						1

These correlation results show that, as would be expected, odometer and age are correlated at about 0.8, as well as fuel economy and weight, which are correlated at about -0.8.

After observing two pairs of variables in the logistic regression with high correlation values, we are careful to observe the standard error values of the coefficients in the logistic regression results. These results are summarized in Table 4.

Table 4. Summary of Continuous Variable Estimates from Logistic Regression

Variables	Coefficient	Standard Error	z value	Pr(>|z|)
(Intercept)	-31	1.9	-1.7E+01	< 2e-16 ***
Vehicle Age	5.7 E-02	4.9 E-04	1.2E+02	< 2e-16 ***
Current Odometer	1.2 E-05	4.4 E-08	2.6E+02	< 2e-16 ***
Vehicle Weight	9.4 E-05	4.1 E-06	2.3E+01	< 2e-16 ***
Fuel Economy	2.1 E-02	6.5 E-04	3.2E+01	< 2e-16 ***
Inspection Date	1.3 E-06	9.2 E-08	1.4E+01	< 2e-16 ***

*** *highly significant*

According to Menard (2001), high multicollinearity increases standard errors, yet coefficients remain unbiased. As observed in Table 4, standard errors are small enough that we can conclude multicollinearity is not a concern and that it does not affect our coefficient estimates, since they are significant even when including all variables [37]. All coefficients in the regression were found to be highly significant, as shown by the very small probabilities in Table 4. In effect, the dataset is sufficiently large and varied to allow good estimation of effects such as age versus odometer reading. In order to further prove that multicollinearity should not be a concern, model checking and fit measures of models excluding the various combinations of correlated variables, in addition to the base case including all variables shown above, is presented in the Supplemental Material (Section 3.1 Logistic Regression).

After noting that all variables in the regression are significant, any of them can be used to make policy decisions for the vehicle safety inspection program. As a result, in following section, various failure rate scenarios are considered based on those that would be easiest to implement policy-wise.

VII. Vehicle Failure Rate Definition and Analysis

We calculate failure rates for the different fail categories and then an overall failure rate for the state. As described in Section 3, the possible results of an initial inspection include: pass, fail, new, repair, and adjust. The final failure rate, considering only *fail* final inspection status, is calculated to be less than 0.1 percent. This rate is an order of magnitude lower than the implied 2% fail rate as stated by opponents of safety inspections. It must be noted that while this < 0.1% failure rate is very low, it may be an underestimate of the actual “fail” designation. This underestimate may result from lack of thorough recordkeeping. Vehicles that fail inspection may leave and return for maintenance at a later date, but because recordkeeping is only done once results are final (typically when a sticker is issued), this initial failed inspection may not be recorded. As previously explained, the vehicle owner may be told work is necessary for the vehicle to pass; however, the work may not always be performed at the time of the inspection. It is possible, since no sticker was issued, that there was no concern to record and/or report this inspection, solely for recordkeeping. This final failure rate alone, however, would not be indicative of the percent of unsafe cars on the road if the safety inspection program did not exist nor is it representative of the lack of compliance to the inspection law. A failure in this context should include the *pass with maintenance* final inspection status, which considers entries with any fail, new, repair, or adjust designations recorded in both the e-SAFETY and CompuSpections datasets. In this data model, a pass or fail (including *pass with maintenance*) was recorded as a ‘0’ or ‘1’, respectively. Multiple entries in a year may occur if a vehicle gets an inspection, fails, and no work is performed immediately. This inspection is recorded as a fail. Soon after, the vehicle may return to get re-inspected and pass inspection and thus a pass is recorded for the same vehicle. In this case, the first entry for the VIN is used as this is considered the initial safety inspection result. On the other hand, if this initial failed inspection is not recorded, as it would only be for record-keeping, and there is only record of the vehicle passing after it returns, this may result in an overestimate (underestimate) of the pass rate (failure rate). While this is important to note as an observation in the data, it was concluded that these entries were minimal compared to the quantity of data in total (see Supplemental Material Table 2), and therefore was not assumed to have an effect on the overall failure rate estimates.

The first analysis was to consider the "overall" LDV fail rate for the state as a whole by including pass with maintenance results. After filtering the registration database for the Pennsylvania state fleet, we are able to analyze about nine million LDVs of the 10.4 million registered vehicles. There were two methods used for calculating the overall state failure rate. First, the registration and inspection data was disaggregated by age, since this was the most detailed, common variable between datasets. Due to varying composition breakdowns by age between the inspection and registration data sets, we evaluate overall state failure rate by two different methods (see Supplemental Material Figure 4). Initially, using the failure rate by age combined with the vehicle distribution in the registration dataset, the overall state failure rate range was calculated to be about 18%. Then similarly using the failure rate by age, but instead using the inspection vehicle distribution, the overall state failure rate was calculated to be about 12%. These two values are both used in describing the failure rate for the state as being a range from 12% to 18%. Using the average overall vehicle failure rate range and the registration total of about 10.4 million LDVs, equates approximately 1.3 to 1.9 million vehicles that *would have failed* inspection, in a given year. This metric clarifies the number of vehicles that would have otherwise failed inspections, without corrective action taken across the various state-mandated safety tests, which are currently implemented. Comparing this 12% to 18% failure rate back to the initial statement of the failure rate being only 2%, equates to a difference in vehicles that would have failed inspection in a given year totaling between one and two million. This calculated failure rate range is one to two orders of magnitude higher than the failure rate claimed by state legislators. This large difference must not be ignored and creates a concern since there is suggestion to modify or eliminate the vehicle safety inspection program in the near future. These overall state failure rates of 12 - 18% can be defined on a finer level by examining the vehicle failure rates by age, odometer reading, and county classification. In addition to these three listed characteristics, safety inspection failure rates by vehicle body can be found in the Supplemental Material (see Supplemental Material Figure 7).

Figure 4 displays the average vehicle inspection failure rate with respect to vehicle age, as well as the overall state failure rate for comparison.

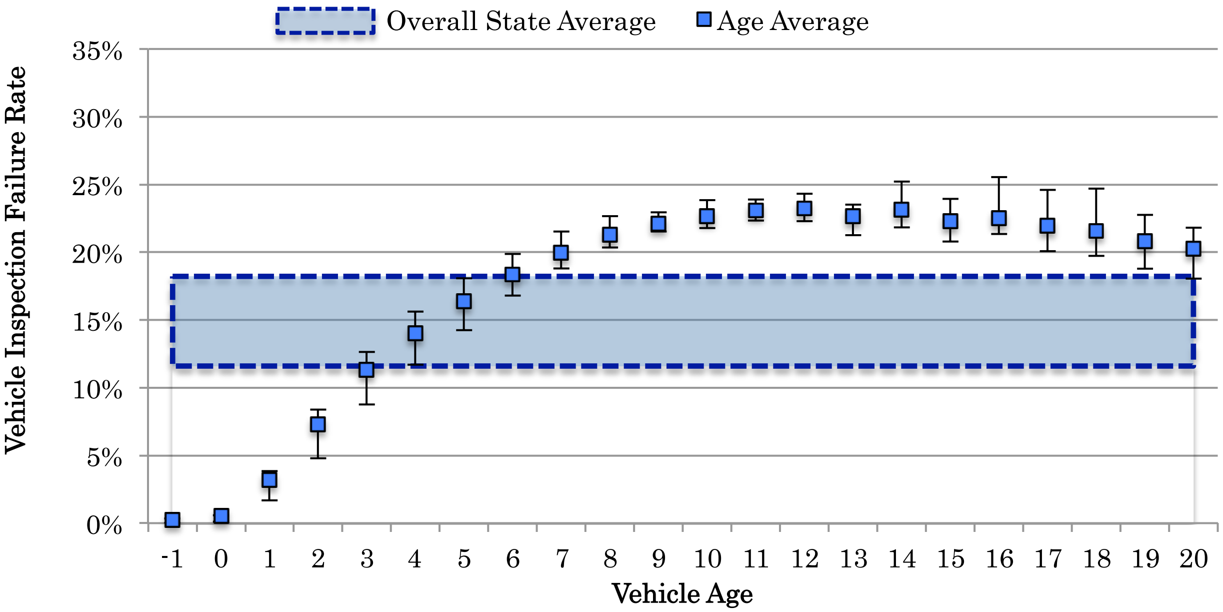


Figure 4. Failure Rates by Vehicle Age (error bars represent min-max failure rate range from 2008-2012). Age notation is calculated based on the model year and the more recent inspection year of the vehicles, so that the lowest age results in '-1' (e.g., a 2008 model-year vehicle could be purchased and inspected in 2007). Shaded range is the overall average failure rate for all vehicles during this time period.

Figure 4 shows a very low (but not zero) failure rate for new vehicles; vehicles aged -1 and 0 have average failure rates of 0.2% and 0.5%, respectively and a failure rate of 3.2% beginning at age one. Even with one year of driving, the failure rate is already above the promoted 2% failure rate. Unlike the decreasing age distribution across the registered vehicles, the failure rate across the state increases with age and remains significant with older vehicles. Vehicles over eight years old consistently show a failure rate at or above 20%, with the maximum failure rate of about 23% for vehicles around age 16. Careful consideration must be taken into account when describing the overall state vehicle fleet since there is a large frequency of young vehicles with lower failure rates, compared to the older vehicles with much higher failure rates (see Supplemental Material Figure 4). It is also interesting to note that older cars fail less often than mid-range cars, perhaps due to less frequent driving trends in older vehicles, as mentioned previously. Furthermore, it is assumed people driving older cars are generally better at maintaining them or proactively making repairs themselves and therefore cause this decreased failure rate.

A more comprehensive presentation of the data would be to calculate how many vehicles "would have failed" without the current program. According to this standpoint, by eliminating the safety program, in 2012 on the order of 1.4 to 1.7 million failed vehicles would have been on the road in that year. Figure 5 combines the calculated failure rates from each inspection database with the number of vehicles from the registration database in order to represent the estimated number of vehicles that "would have failed" in the state in a given year.

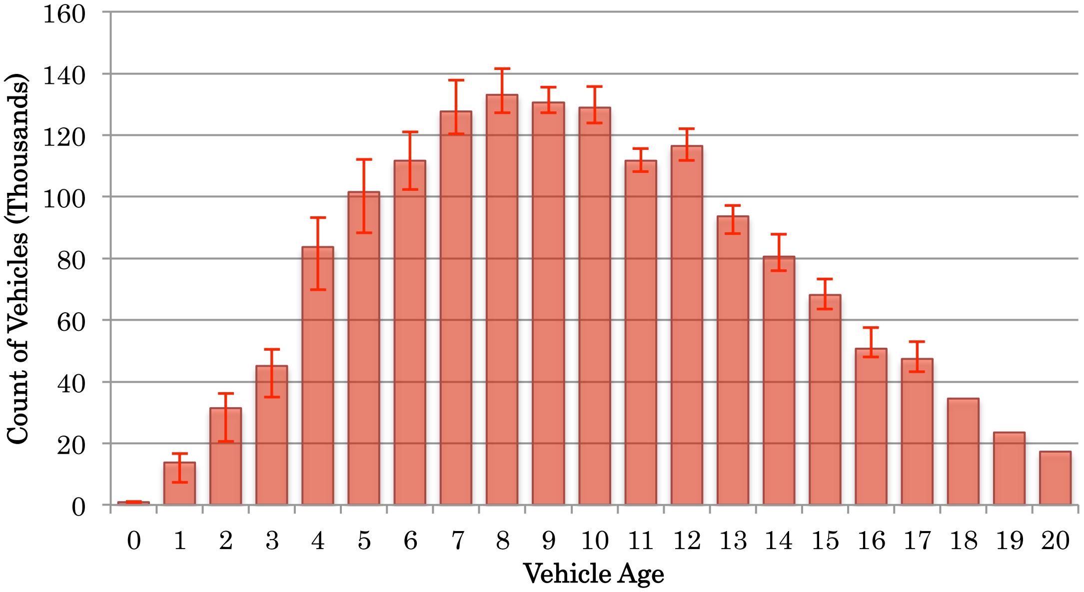


Figure 5. Estimated number of vehicles that would have failed in 2012, by vehicle age (bars represent range between 2008-2012

The mid-aged vehicles generate the majority of "would have failed" vehicles. Estimates of the number of vehicles that would have failed by county can be found in the Supplemental Material Figure 5.

Next, the fail rate was examined by odometer reading and is displayed in Figure 6.

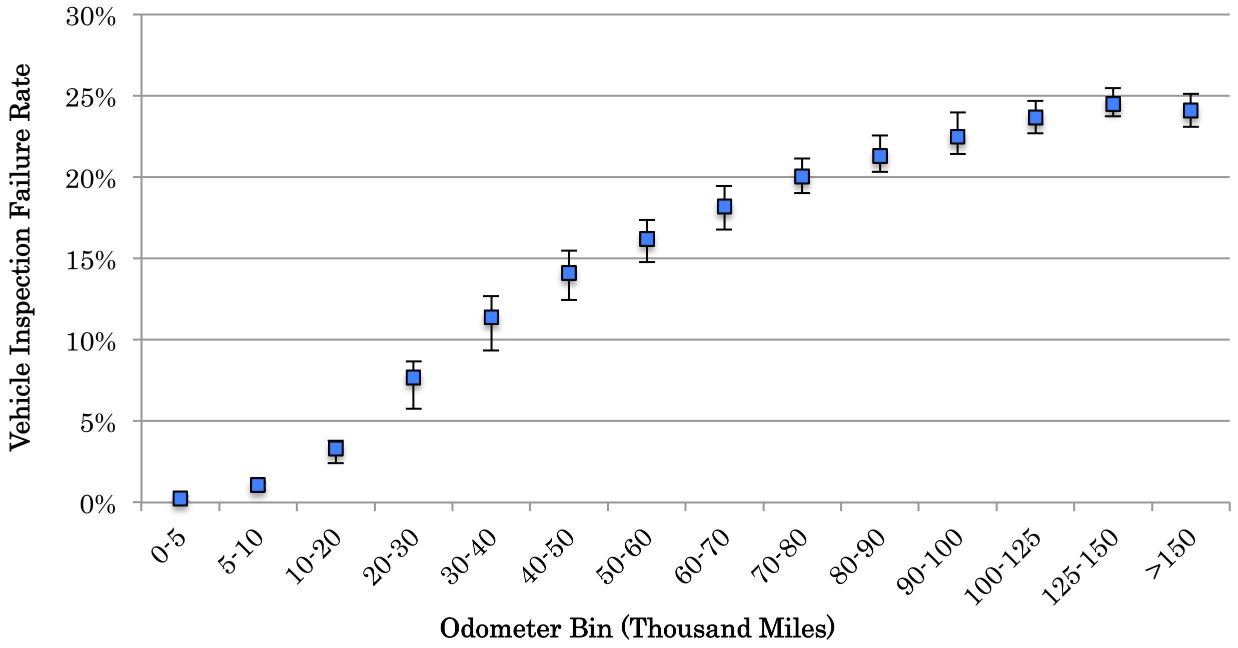
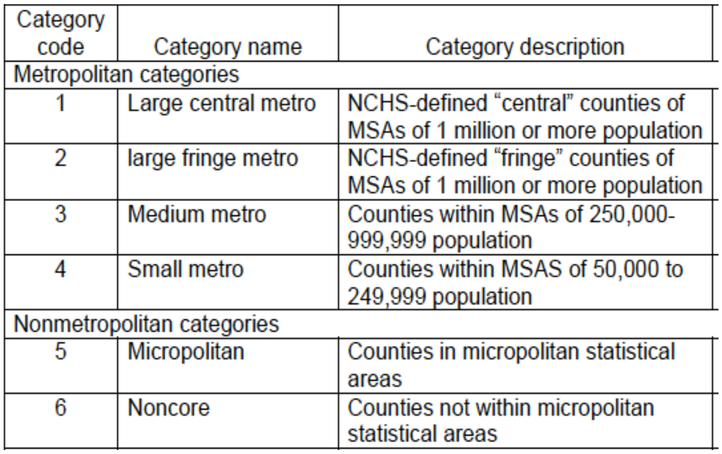


Figure 6. Average failure Rates by Vehicle Odometer Value (error bars represent min-max failure rate range from 2008-2012)

This trend suggests that there is an increased failure rate with increased odometer values. The failure rate peaks in the 125,000 – 150,000 mileage bin, reflecting a failure rate of 24.5%. The age and mileage characteristics are not mutually exclusive – older vehicles tend to have higher odometer readings. For example, in the combined inspection database, a three-year-old vehicle has about a 25,000 to 35,000 mile odometer reading and a ten-year-old vehicle has about a 120,000 to 130,000 mile odometer reading. For a more detailed comparison refer to the Supplemental Material – Vehicle Miles Traveled. It is additionally noted that the failure rates are not zero for new vehicles, which are found in the two lowest odometer bins. Vehicles in odometer bins 0-5,000 miles and 5,000-10,000 miles have failure rates of 0.2% and 1.1%, respectively and the bin for 10,000-20,000 miles driven, which equates to about a one-year-old vehicle, on average, has a failure rate of 3.3%, which is above the stated 2% fleet average.

Finally, we examine failure rates by county types, which may reflect varying driving patterns and/or inspection results. The Center for Disease Control's National Center for Health Statistics (NCHS) Urban-Rural classification scheme is used to distinguish between urban and rural areas (see Figure 7). A total of six county categories were used with Type 1 denoted as most urban, Type 2 – Type 4 as less urban, Type 5 as rural and Type 6 as the most rural. We then used 2010 Census data [38] to assign the NCHS classification to Pennsylvania's 67 counties.



Category code	Category name	Category description
Metropolitan categories		
1	Large central metro	NCHS-defined "central" counties of MSAs of 1 million or more population
2	large fringe metro	NCHS-defined "fringe" counties of MSAs of 1 million or more population
3	Medium metro	Counties within MSAs of 250,000-999,999 population
4	Small metro	Counties within MSAS of 50,000 to 249,999 population
Nonmetropolitan categories		
5	Micropolitan	Counties in micropolitan statistical areas
6	Noncore	Counties not within micropolitan statistical areas

Figure 7. 2006 NCHS Urban-Rural Classification Scheme for Counties [39]

Table 5 shows the 2012 Pennsylvania county breakdown and vehicle registration representation within the urban-rural classification scheme in the state.

Table 5. 2012 Registration Data Summary of Light-Duty Passenger Vehicles by Urban-Rural County Classification

County Classification	# Counties	Total Vehicles in Classification (1,000)	% of Vehicles in State	Average Age
1	2	1,400	16%	8.7
2	11	2,700	31%	8.5
3	14	2,700	31%	9.4
4	5	490	6%	9.4
5	22	1200	14%	9.7
6	13	310	4%	9.7

The number of counties that are designated as being rural (35) is about equal to those designated as urban (32); however, there are far more vehicles located in urban areas. While the vehicle distribution between county types is different, the inspection fail rates between the urban and rural county types are relatively consistent, ranging from 11% to 15% (see Figure 8). The calculated failure rates in each urban-rural classification are underestimates of the actual failure rates in the overall state and by urbanity classification. This underestimate is due to the difference in composition of vehicles in the inspection databases in comparison to the registration database, which represent a larger, overall percentage of younger vehicles with lower failure rates. Refer to the Supplemental Material (Data Representation, Supplemental Material Table 4) for a detailed disaggregation of each database by urbanity classification with averages and ranges of vehicle ages within each and further explanation of this data discrepancy.

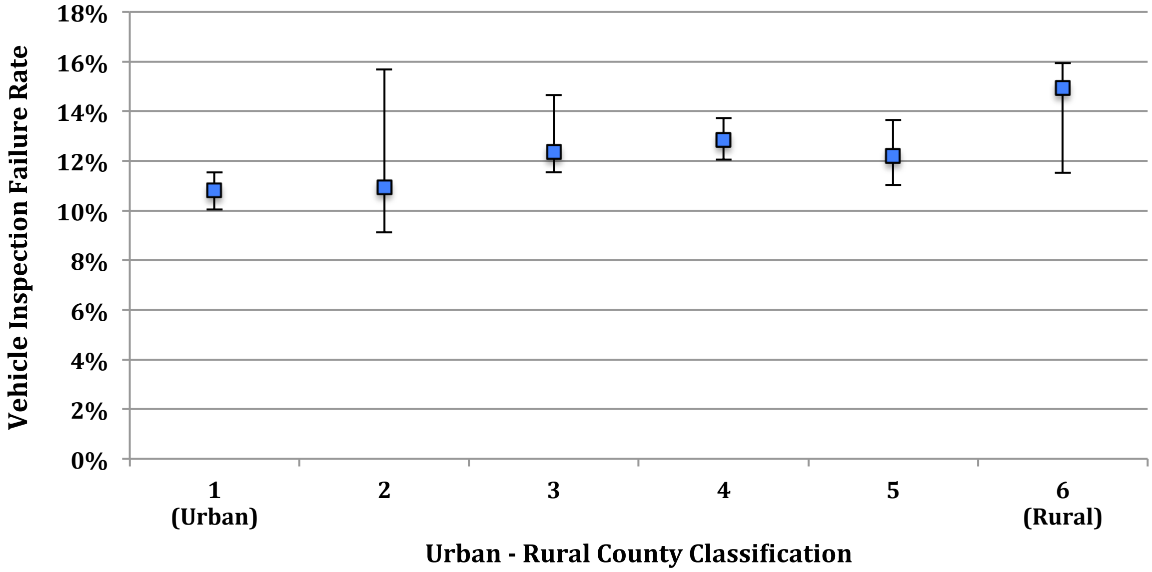


Figure 8. Average failure Rates by County Classification with error bars that represent min-max failure rate range from 2008-2012.

While these failure rate estimates are lower overall, general conclusions can still be made on the differences between urban and rural counties. The vehicle safety inspection failure rate across the state is calculated to be about 11.6%, according to the metric described previously, which analyzes vehicles that need maintenance in order to pass inspection by urbanity. Using the county classification designation, the failure rate is seen to be consistent across the state, yet slightly higher in the more rural areas. Urban counties, classified as Type 1 – Type 4 according to NCHS, have a failure rate of about 11.5%, similar to the calculated overall state failure rate, as these are where just over 80% of vehicles in PA are represented. The rural failure rate, counties classified as Type 5 and Type 6, was about 12.4% and represents just under 20% of the vehicle fleet in the state (Type 5 counties represent about 80% of the vehicles registered in the rural category and Type 6 only 20% of the rural vehicles registered). As noted previously, since the inspection database has a much higher percentage of younger vehicles than registered in the state, the urban and rural failure rates, in addition to the overall state failure rate, is likely underestimated. This conclusion is proven further by referring to the failure rate distribution by age (Figure 4) alongside the age distribution by county classification (Supplemental Material Table 4).

On a more detailed level, the difference in failure rate between the most urban and most rural county classification ranged from 11% in the most urban category to 15% in the most rural category (equating a four percentage point difference). Looking more in depth at the vehicle fleet between the most urban and most rural county classifications, a calculated one year difference in vehicle age as well as a 20,000 mile difference in odometer reading is observed (refer to Table 5). From these results, it can be concluded that on average, vehicle odometer readings and ages are higher in more rural settings than in urban settings, resulting in higher failure rates in rural categories.

Using the failure rate by age distribution along with the average vehicle age in the most urban (8.7 years) versus the most rural (9.7 years) counties that was calculated previously, it is observed that this age difference is associated with a failure rate difference of about 1.5 percentage points (refer to Figure 4). This observed rate is less than the 2 percentage point average difference between most urban and most rural counties and higher than the 1 percentage point difference when comparing the average urban (11.5%) and average rural failure rates (12.4%). As a result, this high rural failure rate can partially be attributed to rural counties having slightly older vehicles on average.

Using this failure rate by odometer distribution along with the average vehicle mileage in the most urban (40,000 miles) versus the most rural (59,000) counties that was calculated previously, it is observed that this 20,000 mile odometer difference, in this odometer bin range, is associated with a failure rate difference of about 4 percentage points (see Figure 6), more than the failure rate difference calculated in the vehicle age urban-rural difference. This observed rate is equal to the four percentage point difference between the most urban and most rural counties, calculated previously, and higher than the 1 percentage point difference when comparing the average urban (11.5%) and average rural failure rates (12.4%). As a result, this high rural failure rate is concluded to be a result of the larger observed odometer readings in rural counties with even stronger evidence than seen when analyzing the differences in ages. Observing that vehicle safety inspection failure rates are consistent across counties and failure rate differences are primarily due to age and odometer differences, a safety inspection program implemented by county classification, similar to the current emission inspection program, is not ideal from a policy perspective.

Vehicle age and mileage can be used similarly in describing a vehicle and classifying appropriate inspection failure trends; however, these characteristics were shown separately in response to the recent legislature proposals to exempt vehicles by specific ages or mileages. The noticeable difference between these two distributions in Figure 4 and Figure 6 is the size of the range bars on the average estimates; they are much smaller when looking at the odometer distribution graph. This means mileage may be a better predictor of failure rates rather than age of vehicles. Additional analysis was executed in order to find the average ages of vehicles within these odometer bins (see the Supplemental Material Table 11). The findings align with the average vehicle driving about 10,000-12,000 miles per year.

VIII. LONG-TERM FAILURE RATE TRENDS

One of the initial sentiments that prompted the study was that vehicles have “never been safer” according to recent studies by the National Highway Traffic Safety Administration (NHTSA) and state legislators’ beliefs that modifications to the current vehicle safety inspection program are in order. Typically this phrase that vehicles have “never been safer” corresponds to protecting users from crashes and loss of life, by improving the anti-lock brake systems or vehicle frame technology to resist crashes (or at least mitigate harmful crashes); the focus here is improved personal safety technology. In this respect, vehicle safety has improved each year (as vehicle technology also improves each year); in fact, NHTSA found that “fatal crashes decreased by 2.2 percent from 2009 to 2010, and the fatality rate dropped to 1.11 fatalities per 100 million vehicle miles of travel in 2010” compared to 1.73 fatalities per 100 million vehicle miles traveled in 1994. [40] In the case of this study, we focus specifically on observing the safety of vehicle components because, as with any item that incurs stress or wear, maintenance is necessary for proper functioning. We identify vehicle safety in terms of vehicle maintenance by analyzing failure rate trends over time. This is reflected in Figure 9, where failure rates are followed for a given model year vehicle as it ages.

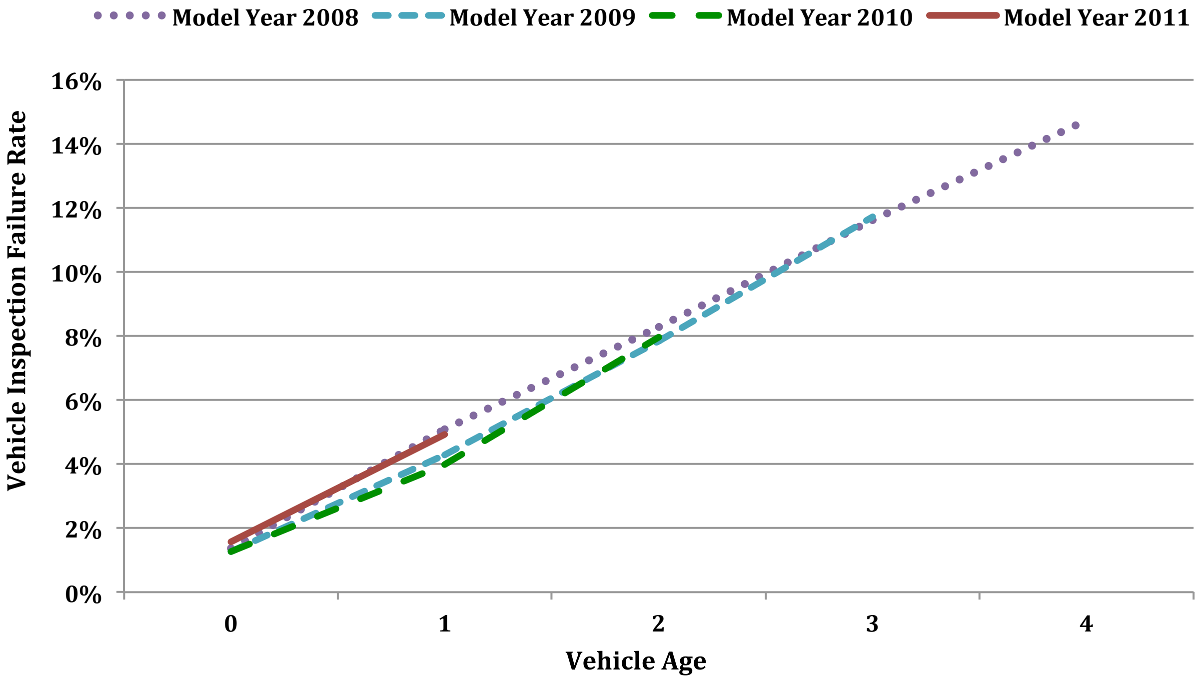


Figure 9. Time-series analysis comparing vehicle model year failure rates as the vehicle ages.

Looking at each newer model year, the same failure rate trend is still observed in an increasing trend as vehicles age. Additionally, comparing each model year by its age, a consistent failure rate is observed, resulting in the conclusion that even as technology improves, therefore improving vehicle safety ratings, failure rate trends do not appear to decrease with newer model years (Figure 9). Finally, as stated previously, brand new vehicles are not averaging a zero fail rate and any vehicle greater than one year old has a higher failure rate than the 2% failure rate referred to by policymakers.

Over four model year vehicle fleets, a consistent failure rate trend is observed as a vehicle ages. There is not enough data for model year 2011 vehicles to draw any conclusions other than that the failure rates are non-zero and mostly above the 2% promoted failure rate at age 0 and age 1, respectively. Comparing model years 2008 through 2010 from oldest to newest, a slight decrease in failure rates is observed. This is illustrated more clearly in Figure 10.

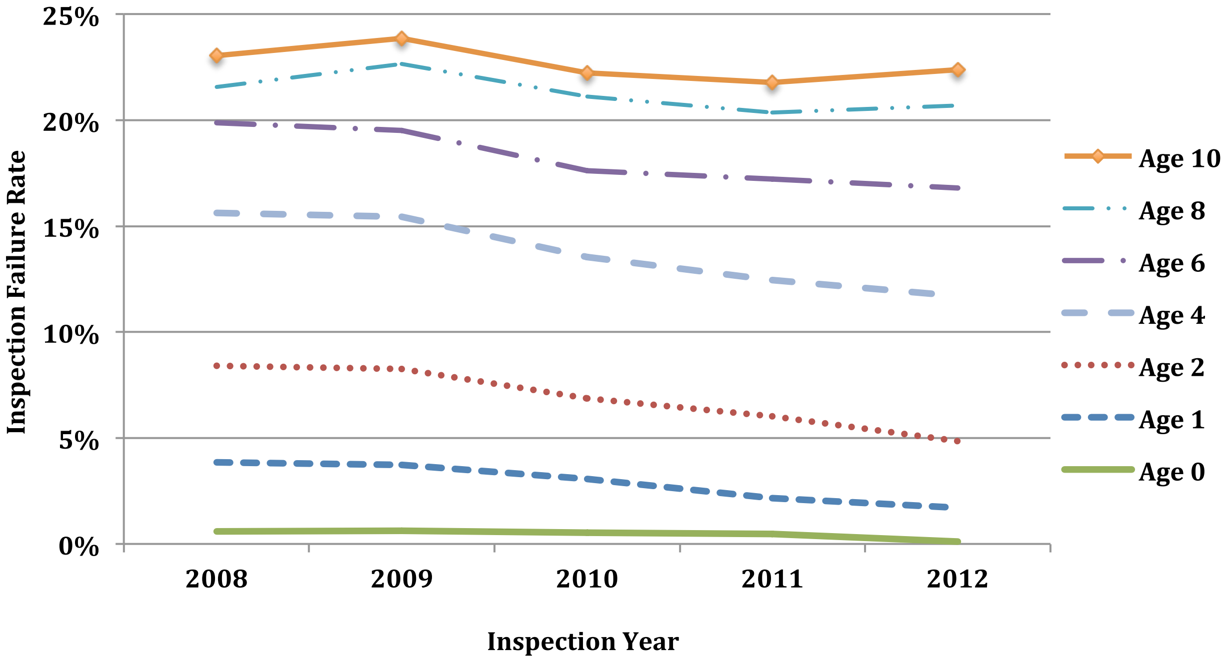


Figure 10. Inspection Failure Rate Time Series, Comparing Vehicle Age

Some vehicles generally do have higher safety ratings in newer car models; however, this must be kept isolated from the maintenance and upkeep of the vehicles. While technology has vastly improved over the past 10-20 years, and newer vehicles have higher safety ratings, yearly maintenance is still crucial to keep vehicles functioning as safe as the newest vehicles on the road; thus the importance of vehicle safety inspections.

The decreasing failure rate trend seen above in the same-aged vehicle failure rate over time, could be due to improvements in vehicle safety, but also due to factors such as the overall decrease in per capita VMT (e.g., less wear on vehicle). [41] Since people are driving less in recent years, there is less wear on the vehicle, and as a result there is a slight decrease in the observed failure rates.

IX. CONCLUSIONS

State policymakers periodically question the effectiveness of the passenger vehicle safety inspection programs. By considering how the inspection process works and analyzing the state of the vehicle upon entering the inspection rather than leaving, a more comprehensive examination of the current inspection program and its effectiveness can be provided. These compelling findings put into question why safety inspections are not federally mandated along with emission inspections, as safety inspection failure rates remain high.

The average initial vehicle inspection failure rate range between all databases is about 12% to 18%, at least an order of magnitude higher than the assumed rate of 2%. After inspection and repairs, the failure rate of vehicles with *fail* as the final inspection status is much lower, with only 0.1% of vehicles ultimately failing. Additionally, this estimated 12% to 18% rate, combined with the Pennsylvania vehicle fleet size of about 10.4 million, equates to on the order of 1.2 to 1.9 million vehicles that would have failed the safety inspection in a given year—the number of vehicles that would have failed without the current program. Furthermore, when analyzing the data in more detail, many groups of vehicles are well above this average fail rate, especially vehicles more than three years old or with more than about 30,000 cumulative miles. Vehicles less than one year of age still do not average a zero failure rate and most one-year-old vehicles are at or above the believed 2% failure rate. Policy makers must use this information as the basis for policy change, rather than the pass or fail rate with the current inspection program in place (i.e., as a vehicle leaves the inspection station).

While estimates of the safety inspection program's effect on highway crashes or fatalities in Pennsylvania are outside the scope of this paper, Cambridge Systematics, Inc. (2009), previously summarized in the literature review of this paper, estimated 1 to 2 fewer safety related fatalities per billion VMT in a state with versus without a safety inspection program. Based on this paper's model results, they find Pennsylvania benefits from between 127 and 187 fewer fatalities each year, as a result of the vehicle safety inspection program. Applying the value of a statistical life to these fatality avoidances, this benefit of lives saved is then compared to user costs of the inspection program. The authors of the Cambridge paper conclude that in every case, the benefits outweigh the calculated program costs by at least $100M, making the program worthwhile to continue to implement. Future work should include an in depth analysis of current inspection program costs, including costs to both the user and the state, versus the program's benefits in reducing fatalities.

Broader collection of accurate inspection data is needed as well as a more randomly selected fleet of vehicles. If electronic inspection databases were the norm, real-time data analysis would be invaluable in showing the most realistic failure rates. While the e-SAFETY and CompuSpections databases provide varying samples of the population, they are the only databases available with this information. Both are similar in information that is collected; however, the CompuSpections database seemed to have a larger sample size and more accurate information (e.g., fewer data entries needed to be filtered out). Eventually, fully electronic record collection would be ideal in order to monitor failure rates of specific stations and even specific inspectors, so as to eliminate any incorrect assessments as they happen or soon after.

A larger and more comprehensive data collection system is key to a more effective inspection program and will allow for stronger oversight and improved management. Initially the vehicle safety inspection program was periodically audited by state police officers two times per year per station. These audits have decreased significantly and now vary between attainment and non-attainment emission counties. The paper-based inspection program requires significant program oversight, traveling, and training. A system similar to the CompuSpections and e-SAFETY programs, with electronic data collection as well as error checking, would provide more efficient recording of data, as well as data analysis in order to provide on-demand reports of how the program is performing. This study is limited to the available data. Currently, there are few states with vehicle safety inspection programs and even fewer with electronic safety inspection records. Without this information, these results are limited to the state of Pennsylvania. Data from other states would allow this study to be extrapolated to the national level and in return, this would validate the results in Pennsylvania.

Chapter III: Vehicle Safety Inspection Effectiveness[4]

I. INTRODUCTION

Today, technology plays a large role in society and is becoming extremely prominent in the transportation sector. Unfortunately, even with great improvements in technology, fatal vehicle crashes still occur. It is possible that vehicles safety inspections could help reduce these fatal crashes further; however, there are many limitations with the currently available data. Researchers in the health sector are currently able to access electronic records to do analyses that may lead to life-saving results. It is likely if better attention to data technology in transportation, similar to the health sector, fatal crashes can be further reduced. This chapter focuses on analyses related to fatal crashes in light-duty vehicle transportation, and more specifically, the effectiveness of personal vehicle maintenance.

I.1. *Motivation*

In recent years, states have been questioning the effectiveness of vehicle safety inspections. Common perceptions include that such programs are a waste of time and money, and inspectors identify false problems in hope to make more money. In 2009, Washington D.C. eliminated their safety inspection program due to claiming there was no evidence that the program resulted in fewer accidents. [42], [43] Similarly, in 2010, New Jersey no longer required safety inspections due to "lack of conclusive data" and the inability to justify the expense. [32] For the same reasons, Oklahoma discontinued their program back in 2001. [44] The common sentiment of many states that there is lack of data providing evidence that vehicle safety inspections aren't worth the time and money; yet, it cannot be inferred safety inspections do not reduce fatalities. More analyses are necessary before this statement can be confirmed and conclusions drawn. These questions may help lead toward a helpful conclusion on this topic of vehicle safety inspection programs.

These analyses are necessary especially with the increasing prominence of "big data". In order for performance of programs, such as vehicle safety inspection programs, to be assessed, the data must be reliable. In the near future, as more automation is introduced in vehicles, collection of quality vehicle data will be a likely benefit. Personal vehicle safety

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[4] Peck et. al., "The Effect Of Vehicle Safety Inspections On Urban/Rural Fatality Rates". *Transportation Research Record*. Submitted August 1, 2015

inspection programs today vary widely across their execution and oversight, making the program challenging to analyze and identify any benefits or disadvantages. This paper aims to classify current safety inspection programs in various models by their frequencies and rigorousness to find if there is any advantage in supporting these programs. In parallel, the quality of data used in this study is evaluated.

II. LITERATURE REVIEW

According to the Center for Disease Control (CDC), motor vehicle crashes remain a major source of morbidity and mortality in the US for many years now. As of 2013, accidents were in the top five for the leading cause of death over all age groups and motor vehicle crashes were the leading cause of death for those between the ages 1 to 44. [4] This statistic is alongside deaths resulting from heart disease, cancer, and chronic lower respiratory disease. "The National Highway Traffic Safety Administration estimates that highway crashes alone have an annual price tag of around $871 billion in economic loss and social harm." [45], [46] Motor vehicle crashes are rightfully a large concern for the US population, yet there are few immediate solutions that will help reduce these high fatality rates.

Prior to data analysis and policy recommendations, it is important to understand how fatalities vary by region. Puentes and Tomer (2008) showed that urban and rural VMT trends differ, with a bigger gap in recent years. [20] Since vehicle fatalities are higher in rural areas than in urban areas [21], [27], [47]-[50], NHTSA suggests that motor vehicle fatalities be reported in terms of fatalities per VMT and separated by urban and rural regions. This results in higher rural fatality rates than urban fatality rates. [51]

There are multiple reasons attributed to higher rural fatality rates, some of which include higher speeds and VMT. [47] NHTSA reported that 2010 fatality rates were 2.5 times higher in rural areas than in urban areas; as a result, "states are encouraged to present both rural and urban VMT rates along with their overall VMT rate." [50] Furthermore, Kmet and Macarthur (2006) concluded that rural regions, both hospitality and death rates, among youth, were significantly higher. [52]

One goal of this paper is to compare safety caused crashes in states with versus states without a safety inspection program; however, this may be limited by the quality of data in FARS. Castle et. al. (2014) compared death certificates from motor vehicle crashes to FARS data and found FARS data to show "considerable variation in the magnitude of underreporting". Furthermore, they suspect similar underreporting in other types of injury deaths. This phenomenon is suggestively similar for underreporting vehicle component caused crashes and may hurt the understanding of the safety inspection policy issue. [53] A similar study showed that reported crashes from where police were absent had much higher percentages of missing data for the contributing factors of the crash. As a result, without knowing the source of data from which crashes were obtained, conclusions on crash causes may not be as strong. [54]

Previous studies on vehicle safety inspections were not always supportive of the programs, yet the methods used in those studies were vague, high-level analyses, which do not represent the actual effectiveness of the state-specific programs. A commonly referred to study by Cambridge Systematics, evaluated the effectiveness of Pennsylvania's vehicle safety inspection program. While conclusions aligned with findings in this paper, Cambridge Systematics did not account for urbanity differences in their model, the review of the state safety inspection programs was vague, and only one average time period was used. Since safety inspection states have a more urban composure than non-safety inspection states, it is possible results could be confounded. [22] Another paper evaluated the Pennsylvania safety inspection program vehicle failure rates. The authors show that without the current vehicles safety inspection program in Pennsylvania, about 1-2 million vehicles would be in unsafe conditions to drive. Furthermore, older vehicles have a consistently higher failure rate along with high mileage vehicles. [29]

III. DATA

This analysis combines multiple data sources, including vehicle travel data from the U.S. Department of Transportation (USDOT), population data from the Census Bureau, and vehicle crash data from the National Highway Traffic Safety Administration (NHTSA).

III.1. *Office of Highway Policy Information: Highway Statistics Series*

The USDOT Federal Highway Administration's Office of Highway Policy Information (OHPI) Highway Statistics Series reports urban and rural vehicle miles traveled (VMT) for each U.S. state and the District of Columbia. This specific VMT breakdown is available from 1997 through 2011. Prior to 1997 overall U.S. urban and rural statistics are reported as country averages and are not state-by-state specific averages. As a result, this limits the analysis to beginning in 1997. [55]

III.2. *United States Census Bureau: Population*

The Census Bureau's Population Estimates Program releases data annually that estimates population based on current data containing births, deaths and migration. Both national estimates as well as more aggregate levels of population estimates, such as by state and county, are estimated. As a result, population estimates are used by state and by urbanity level. [38]

III.3. *Fatality Analysis Reporting System*

NHTSA publishes a national database "detailing factors behind traffic fatalities on the road", known as the Fatality Analysis Reporting System (FARS). [40] This database contains fatal crash statistics, beginning in 1975, resulting from numerous variables, including the vehicle related factors that are inspected in states requiring vehicle safety inspections; for example, brake, tire, or steering failures. The FARS database includes records of all crashes involving at least a motorized vehicle traveling on a public road and a resulting death within 30 days of the crash. Entries are recorded by police officers on duty and at the crash site location. Depending on state officer training and the available crash evidence, the cause of crash may not be determined correctly and may lead to inaccurate or unrepresentative results. While the database contains certain limitations that should be kept in mind, it is the best available national data and widely used to analyze fatal crashes.

III.4. *National Automotive Sampling System - General Estimates System (NASS GES)*

This sampled data, provided by NHTSA, is from various police jurisdictions around the U.S. This data system, which collects police-reported crashes ranging from minor to fatal, began in 1988 to identify traffic safety problem areas. According to NHTSA, "in order for a crash to be eligible for the GES sample a police accident report (PAR) must be completed, it must involve at least one motor vehicle traveling on a traffic way, and the result must be property damage, injury, or death". [56] While this data is the best available for analyzing non-fatal vehicle crashes, there remain numerous challenges and concerns by including this dataset.

First, the data does not contain a "state" definition field; therefore, the driver zip code attribute was decoded and matched to a state. For consistency, the same method was used on the FARS data. Next, a representative test was performed to compare fatal crashes in GES with those in FARS. The two-sided t-test resulted in a p-value of 0.028; therefore the null hypothesis that the GES fatalities are equivalent to the FARS fatalities must be rejected. Since GES data is a sample, it may not be sampled from all 50 states and this was evident when comparing the fatal crashes between the two databases. As a result of these large variations in fatality samples, GES crash data was not able to be used in this analysis.

III.5. *Vehicle Safety Inspection Programs*

The National Traffic and Motor Vehicle Safety Act of 1966 was initiated due to the increasing concern over the rising number of motor vehicle traffic fatalities. Safety inspection programs were federally mandated until 1973 for states to qualify for federal highway funds. [5] In addition to this Act, the automobile industry was pressed to focus on safety rather than aesthetics when designing new vehicles, which has had an impact on decreasing death rates. [57] After 1973, the vehicle safety inspection program became state mandated. Today, states may either require a strict safety inspection program, no program, or something in between. Since the federal government does not regulate vehicle safety inspections, each state manages the rigorousness of its own program (e.g., removing brake pads and measuring the thickness, measuring tire tread depth, testing aim of headlights and functionality of blinkers), and may decide to modify and/or discontinue its own state program at any time.

For the purpose of this analysis, states are separated into two categories: annual inspections (annual) and no safety inspections (none). This information can be found on the AAA website which contains a digest of motor laws, specifying safety inspections in each state, if they exist at all. [13] Additionally, each state's website information is then compared to the AAA website information. For this analysis, as of July 2015, a total of 14 states are classified as annual, 30 states are classified as none, and 7 states are classified as periodic. This information is presented in Table 6.

Table 6. Vehicle Safety Inspection Classification by State, as of June 2015

Annual (14*)	None (30)		Periodic (7)
District of Columbia*	Alabama	Maryland[+]	Delaware
Hawaii	Alaska	Michigan	Missouri
Louisiana*	Arizona	Minnesota	New Jersey*
Maine	Arkansas	Montana	Nevada
Massachusetts	California[+]	Nebraska	Oklahoma
Mississippi	Colorado	New Mexico	Rhode Island
New Hampshire	Connecticut[+]	North Dakota	Utah
New York	Florida	Ohio	
North Carolina	Georgia	Oregon	
Pennsylvania	Idaho	South Carolina	
Texas	Illinois	South Dakota	
Vermont	Indiana	Tennessee	
Virginia	Iowa	Washington	
West Virginia	Kansas	Wisconsin	
	Kentucky	Wyoming	

* Program has recently been modified

[+] Safety inspection required only at first registration of vehicle into the state

Note here that a state requiring vehicle safety inspections only at first registration is listed here under the “None” category and denoted with a “+”. In the least stringent model analyzed, these states are modeled as safety states, but as soon as the models become more stringent in defining safety programs, they are modeled as non-safety. A limitation to any such classification in a historical analysis is that states can modify their program over time. Washington, D.C. and New Jersey have discontinued their safety programs within the past few years and Louisiana just made annual inspections an alternative to the now required biennial inspections. To simplify this complexity, fatality rates are analyzed until 2009, prior to program modifications, except Oklahoma is defined as periodic since its regulations changed in 2001, over the analysis period. In addition to states modifying their programs at any time, states also vary in the depth and breadth of the inspection.

A typical vehicle safety inspection in the U.S. (though they do vary slightly state to state) includes checking components such as brakes, tires, lighting, etc. These safety components are checked either against an allowable minimum threshold or if the component is functioning appropriately. For example, tire tread depth must be greater than the legally defined minimum depth. Furthermore, each station within each state may vary in the intensity of the inspection and this is assessed based on rough estimates of how long an inspection takes in a given state.

In order to make a comparison of whether vehicle safety inspections reduce fatality rates, the analysis compares fatality rates in states denoted as annual to fatality rates in states denoted as none, The hypothesis for this analysis is that both urban and rural fatality rates are lower in states with an annual safety inspection program than in those with no safety inspection program. It is even more important to separate urban and rural rates since safety states seem to have much more urban composition than non-safety states, with much more rural composition, as shown in Figure 11.

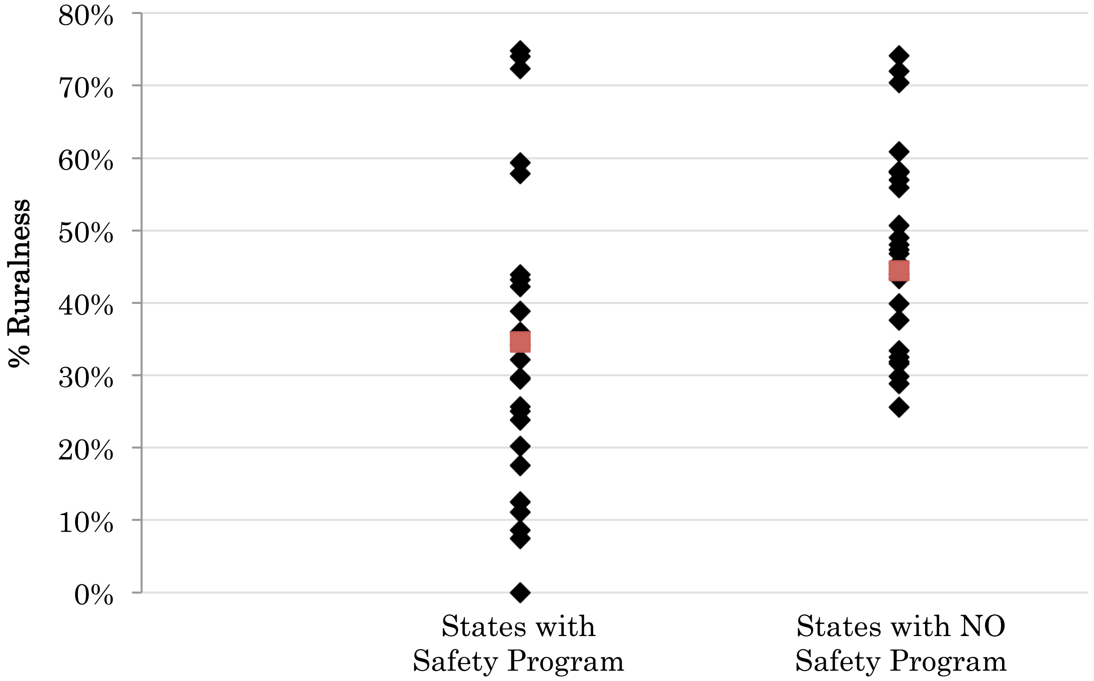


Figure 11. Percentage of rural VMT comparison between defined safety states and non-safety states with each state plotted and average values shown in red

Figure 11 shows the comparison of rural composition between types of states. A t-test was performed to test the null hypothesis whether the percentage of rural VMT is equal between types of safety states. This test results in a p-value of 0.02, below the significance level (0.05). Therefore, we reject the null hypothesis that the rural composition is equal between the two types of states; we cannot accept that these percentages are the same.

III.6. *Metrics Used*

In order to compare crashes between states (and years), the crash statistics must be normalized because locations and years vary in driving patterns. NHTSA has developed performance measures to be used in performing research analyses. They define the fatality rate per mile of travel (fatalities/VMT) to be used to track safety trends. According to their report on performance measures, reporting fatalities alone will not accurately represent smaller states with fewer possible fatalities and that traffic fatalities are "most obviously affected by the amount of travel" [50]; therefore, the metric of fatalities (or fatal crashes) per VMT is used in this analysis. From here forward, both fatality rates and fatal crash rates are calculated yet will only be referred to as fatality rates; both rates are reported in the results.

Fatalities in FARS are organized by state and separated into categories of urban and rural within each state for each year of analysis, from 2000 through 2009. Using the VMT data provided by OHPI, fatality rates are then calculated, along with each state's urban-rural VMT values, as this varies within each state. All of these estimates are necessary because each state's overall fatality rate will vary depending on the type of area analyzed; this is where accounting for Simpson's Paradox is critical. Table 7 shows an example of this (values are taken from NHTSA's report as an example).

Table 7. Simpson's Paradox of State Fatality Rates [50]

	Urban fatality rate	%Urban VMT	Rural fatality rate	%Rural VMT	State Average	Urban/Rural Weighted State Average
State A	0.92	80%	2.68	20%	1.8	1.27
State B	0.87	23%	2.49	77%	1.68	2.12

State B has lower fatality rates for each of the urban and rural locations when compared to State A's equivalent. However, State B's rural composition is greater than State A, so as a result State B's weighted average rate will appear much higher overall than that of State A's. Using this information, overall state average fatality rates can be equivalently calculated both by weighted VMT (Equation 1a) and as an overall average (Equation 1b).

$$weighted\ average\ fatality\ rate_i = \left[\%\ urban * \left(\frac{Fatalities_i}{VMT_{i,}}\right)_{urban}\right] + \left[\%\ rural * \left(\frac{Fatalities_i}{100\ million\ VMT_{i,}}\right)_{rural}\right];$$

$$where \qquad i = state \qquad \text{Eq. 1a}$$

$$overall\ average\ fatality\ rate_i = \frac{\sum Fatalities_i}{\sum 100\ million\ VMT_{i,}};$$

$$where \qquad i = state \qquad \text{Eq. 1b}$$

Equation 1a and Equation 1b are equivalent when percent urbanity is calculated using VMT proportions. This shows that fatality rates must be analyzed by urbanity since these percentages have an impact in calculating overall fatality rates. To observe the true effectiveness of a program based on VMT, urban and rural rates must be analyzed separately due to Simpson's Paradox, or urbanity of a state must be accounted for in any statistical tests on fatality rates.

Equation 2 denotes the formula, as specified in NHTSA's performance measures, for calculating fatality rates in a given state for a given area (urban or rural), which is calculated for each year and averages across years, between 2000 through 2009.

$$fatality\ rate_{i,j} = \frac{Fatalities_{i,j}}{Vehicle\ Miles\ Traveled_{i,j}}; \qquad \text{Eq. 2}$$

$$where, \qquad i = state$$

$$j = urban\ or\ rural$$

Due to Simpson's Paradox, and as specified by NHTSA, state fatality rates must be analyzed separately for urban and rural areas. As a result, states are broken down into the following four categories for the purpose of this analysis: urban-safety, urban-non-safety, rural-safety, and rural-non-safety. This accounts for fatalities and driving patterns differing between urban and rural areas, in addition to differences in rural composition between states.

IV. METHODS

It is hypothesized that safety inspection states have lower fatality rates than those without safety inspections. To test this hypothesis, states are first defined either as a safety state or not (refer to Table 6) then separated into urban and rural categories, where fatality rates are calculated.

IV.1. *Definition of Safety States*

States are defined by two methods: binary (safety or not) and continuous (based on percentage of vehicles inspected and intensity of inspection). Various binary combinations were created depending on how stringent states are defined. For example, the least stringent model assigns the safety designation to states with any partial inspection program. Another more stringent model, would assign the most minimal inspection programs as not safety and the rest as safety. The most stringent model, the continuous model, uses the percentage of vehicles inspected as a proxy for estimating the fraction of the safety program implemented from 0 to 1. Binary inspections are assigned a safety value of 0.5 in this case, since vehicles are inspected every 2 years (approximately half of the fleet every year). Additionally, after researching the state programs, it was found that each program may be implemented in varying intensities, defined based on approximated times of an inspection in that state versus another similarly defined state. These assumptions must be made since the safety programs are only state mandated rather than nationally mandated.

IV.2. *Defining the Crash Data*

Fatalities from FARS are used to analyze whether safety inspections are statistically significant in reducing fatality rates. Limitations to the data recorded in FARS include but are not limited to the reason attributed with the crash (safety cause or otherwise), the vehicle that caused the crash in multivehicle crashes, and crashes occurring in different states from where the vehicle is registered. Inconsistency in the reason attributed with the crash cause may be due to either laziness in recording the crash, misclassification of the crash cause, or another contributing reason being more apparent or obvious than the recorded reason. For example, a vehicle may have been speeding, yet had underlying bare tires or worn brake pads. Additionally, in states where safety inspections are not executed, unsafe vehicle components may not be an obvious reason for a crash, whereas the opposite may occur in a state that requires safety inspections – these safety states are more aware of safety issues.

In a multivehicle crash there is no variable to distinguish which vehicle caused the crash; thus, it may be difficult to assign a registration state or reason to the crash. Furthermore, wrong designations to a crash may occur if one vehicle is from a safety state and the other from a non-safety state. Because this analysis is based on a policy that originates in a vehicle's registration state, it is important to either test to see how often the crash state and registration state matches or filter crashes to only those that occur in the same state where the car was registered. A two-sided t-test for the null hypothesis that crashes assigned to the registration state were equal to crashes assigned to the crash state resulted in a p-value of 0.246. This led to the conclusion that the null hypothesis cannot be rejected; therefore, filtering of the unmatched registration and crash locations in crashes was not implemented.

The registration state is assigned to a crash since this is where the vehicle would have been inspected. Aside from checking the vehicle's registration state against the crash state, checks were also made between vehicles in multivehicle crashes. Crashes were only included if all vehicles' registration states matched since the fault in the crash is unknown and may lead to inconsistency in choosing one vehicle's (varying) attributes over another. This filter still allowed for 92% of the total crashes to be included in the analysis.
Finally, the crashes are identified as either urban or rural based on the location of the crash, as crashes are more prominent in rural areas than urban areas and are less affected by the registration urbanity. The following sections go into detail on the analyses performed to calculate whether safety inspections are effective in reducing fatality rates. Additionally, it is examined whether safety-component caused fatalities are lower than other crash causes in states with safety inspection programs. However, the crash cause variable is a known weakness in the data and must be cautiously analyzed due to inconsistent reporting between states.

IV.3. *Ordinary Least Squares (OLS) Regression*

In order to identify program effectiveness, OLS regressions are implemented, for each model accounting for the varying state definitions. Fatality rates in the US are compared in safety states vs. non-safety states. The dependent variable used in these regressions is the fatalities per 100 million VMT, as defined in Eq. 1a and Eq. 1b. The independent variables initially chosen for the regression included: safety (binary, continuous); state census region (categorical); state census division (categorical); and rural or urban (categorical). Years included in the analysis ranged from 2000 through 2009. The general regression equations used are displayed in Equation 3(a-c).

$$Fatality\ rate \sim \beta_0 + \beta_1 * Safety + \beta_2 * Urbanity \qquad \text{Eq. 3a}$$

$$Fatality\ rate \sim \beta_0 + \beta_1 * Safety + \beta_2 * Urbanity + \beta_3 * Division \qquad \text{Eq. 3b}$$

$$Fatality\ rate \sim \beta_0 + \beta_1 * Safety + \beta_2 * Urbanity + \beta_3 * Region \qquad \text{Eq. 3c}$$

Various regressions were evaluated, with all combinations of independent variables, years of analysis, and safety state designations to observe the safety variable coefficient and significance. Significance of the regression formula in determining the effectiveness of the safety program in reducing fatality rates was determined by whether the safety variable's p-value was less than the critical p-value of 0.05 and whether the coefficient was negative, indicating a lower rate for safety states when compared to non-safety states. Regression analyses were repeated and adjusted various times. In the first few adjustments, the years analyzed were varied between 2000-2009 as well as how the years were averaged (1-10 years) in calculating fatality rates. In the following adjustments, DC was excluded in the regressions due to its unique composition and minimal fatalities in comparison to other states.

IV.4. *Hypothesis Test*

A two-proportion z-test is used to test whether the proportions of fatalities associated with a safety cause differs between safety states and non-safety states. First, the null hypothesis (H_0) is defined: the percentage of safety-attributed fatalities in safety states is equal to the percentage of safety-attributed fatalities in non-safety states (Equation 4), repeated for both urban and rural locations. Additionally, this same hypothesis is checked for non-safety-attributed fatalities. Significance of this hypothesis is compared with an alpha value of 0.05.

$$H_0: p_{safety\ states,i} = p_{non-safety\ states,i}\ and\ H_a: p_{safety\ states,i} \neq p_{non-safety\ states,i} \qquad \text{Eq. 4}$$

where,

$p = proportion\ of\ fatalities,$

$i = safety - attributed\ or\ non - safety\ attributed$

It is hypothesized that the percentage of safety-attributed fatalities will be lower in safety states than non-safety states and that there will be no difference in percentage of non-safety attributed fatalities in either defined state. And these results will be similar in both urban and rural regions.

V. RESULTS

While numerous iterations were performed for all of these statistical tests for the various model combinations that were produced, only an example selection are presented, though all models are summarized. Other results are available upon request from the author.

V.1. *OLS Regression*

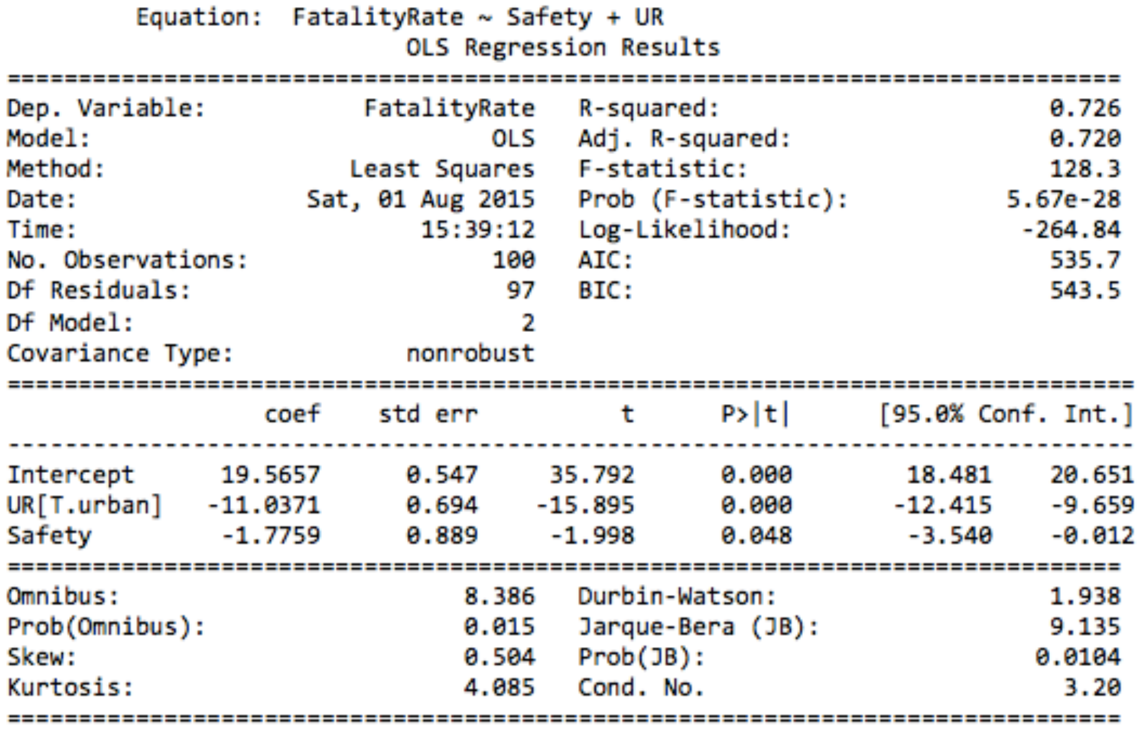
In all the regression models, urbanity was always included due to the NHTSA specifications previously explained in the Data Section. Regression results never led to the conclusion that safety states had statistically significant more fatalities. About 95% of the regression models were in support of the safety inspection program, showing a negative safety coefficient. The 5% of the regression models that did not support the safety inspection programs resulted from the models where one-year averages were used. These models inherently use of less data in the analysis. More compellingly, statistically significant results in support of safety programs were found in about 7%-8% of the models. In these models, of the statistically significant regressions, it can be concluded safety inspections are statistically effective in reducing fatality rates by approximately 1 fatal crash per billion VMT in a given year.

The sample results found in Table 8 correspond to the regressions using average rates from 2000 through 2009. Results did vary depending on the years analyzed in the regression due to larger averages over years incorporating more data than a single year average. For each rate, model, and formula analyzed, the results shown include the Bayesian Information Criterion (BIC), the coefficient and p-value on the safety variable, as well as the number of observations in the regression.

Table 8. OLS Regression Results, 2000-2009 Average

Rate	Model	Formula (Eq. 3)	BIC	Safety Coefficient (per billion VMT)	Safety p-value	No. Obs.
Fatal crash	Binary Safety Variable	a	519	-0.70	0.26	100
		b	512	-0.30	0.65	100
		c	497	-0.34	0.59	100
	Continuous Safety Variable	a	518	-1.36	0.08	100
		b	512	-0.42	0.63	100
		c	497	-0.53	0.54	100
Fatality	Binary Safety Variable	a	543	-0.81	0.25	100
		b	535	-0.25	0.73	100
		c	520	-0.27	0.71	100
	Continuous Safety Variable	a	541	-1.65	0.06	100
		b	535	-0.42	0.67	100
		c	520	-0.57	0.56	100

In comparing fatality rate regression results to fatal crash rate regression results, there are large similarities; however, using fatal crash rates results in a model with slightly better predicting capabilities by comparing the BIC values. Furthermore, the model with the continuous versus binary safety variable has an almost unnoticeable difference, yet the continuous variable is slightly better when comparing Equation 3a. Finally, Equation 3c has the best predictive ability over Equation 3a and Equation 3b when comparing BIC values. Equation 3c includes the safety variable, urbanity variable and region variable. By incorporating region in addition to urbanity, weather and road conditions can be accounted for since rural roads in the north are different from rural roads in the south. Figure 12 shows the regression results for Eq. 3a (accounting only for safety and urbanity) and average rates between 2000-2008. This example also shows a case when the safety variable is statistically significant.



```
        Equation:  FatalityRate ~ Safety + UR
                            OLS Regression Results
==============================================================================
Dep. Variable:           FatalityRate   R-squared:                       0.726
Model:                            OLS   Adj. R-squared:                  0.720
Method:                 Least Squares   F-statistic:                     128.3
Date:                Sat, 01 Aug 2015   Prob (F-statistic):           5.67e-28
Time:                        15:39:12   Log-Likelihood:                -264.84
No. Observations:                 100   AIC:                             535.7
Df Residuals:                      97   BIC:                             543.5
Df Model:                           2
Covariance Type:            nonrobust
================================================================================
                  coef    std err          t      P>|t|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------
Intercept      19.5657      0.547     35.792      0.000        18.481    20.651
UR[T.urban]   -11.0371      0.694    -15.895      0.000       -12.415    -9.659
Safety         -1.7759      0.889     -1.998      0.048        -3.540    -0.012
==============================================================================
Omnibus:                        8.386   Durbin-Watson:                   1.938
Prob(Omnibus):                  0.015   Jarque-Bera (JB):                9.135
Skew:                           0.504   Prob(JB):                       0.0104
Kurtosis:                       4.085   Cond. No.                         3.20
==============================================================================
```

Figure 12. Regression results for Equation 3a using years 2000-2008

Figure 12 includes a continuous safety variable and categorical urbanity variable to predict fatalities per billion VMT. While this BIC is not quite as good as the results from Equation 3c, the adjusted R-squared value of 0.72 reflects that this model is sufficient in its predictive capabilities. Finally, all independent variables are significant below an alpha value of 0.05. These results show that urban fatality rates are significantly lower than rural fatality rates and the more rigorous a vehicle safety inspection program is the more it can reduce fatalities rates (up to about 1.8 fatalities per billion VMT). Using the national average of about 3 trillion VMT, the safety program can avoid about 1,800 deaths in the US in a given year by implementing a well-enforced safety inspection program. Furthermore, the urbanity coefficient is highly significant and has a much larger coefficient of about 11 fatalities per billion VMT between urban and rural areas (higher rural fatality rate). This leads to the conclusion that urbanity must be accounted for in this analysis and similar analyses in the future.

V.2. *Hypothesis Test*

In addition to checking for differences in fatality rates between the defined safety and non-safety states, a two-proportion z-test was performed. The null hypothesis (H_0) is defined, as the percentage of safety-attributed fatalities in safety states is equal to the percentage of safety-attributed fatalities in non-safety states, for both urban and rural locations. A hypothesis was also tested to see if the percentage of non-safety-attributed fatalities in safety states is equal to the percentage of non-safety-attributed fatalities in non-safety states.

Both of the tests led to the opposite conclusion of what was initially hypothesized. First, both rural and urban areas led to the same conclusions, and these were that in all cases, the results were statistically significant and therefore the null hypothesis was rejected. However, it was found that the percentage of safety-caused crashes was different between safety states and non-safety states (resulting in safety states with a higher percentage). Furthermore, the percentage of non-safety-caused crashes was different between safety states and non-safety states (resulting in safety states with a lower percentage). These results appeared to be consistent across the ten years evaluated.

This test proved to be more challenging as a vehicle registered in a safety state may be involved in a crash in either type of state, and same scenario for a non-safety state registered vehicle. Some literature had discussed the large underreporting of various attributes in crashes, which can lead to a very thin data sample. Furthermore, there is common belief that safety states are more aware of safety features in a crash, whereas in non-safety states, they are less aware. Moreover, challenges also occur in deciding whether to assign the registration state or the crash state to the fatality count because if they differ in states, they differ in safety inspection quality and perhaps even having a program versus not having a program. This leads to discrepancies in how crashes are recorded in each state and how detail-oriented those crashes are recorded.

It is therefore concluded that these hypothesis tests contradict one-another and no insightful conclusions can be drawn on specific coded fatalities. The lack of consistency here is evident and more strongly suggests the need for data consistency, management, and oversight. Robust data is necessary for the advancement and improvements in vehicle safety.

VI. FUTURE WORK

Limited access to quality data in transportation is a problem currently and will become even more evident with the current push for “big data” and resulting analyses. The transportation sector is changing fast with the introduction of more automated features in vehicles and this will require a stronger need for high quality transportation data to monitor resulting changes. This implies that stronger policies are needed for data gathering and improved data collection. Any crash that costs money, likely caused damage and would be recorded in an insurance claim. If there is proper oversight this data could provide valuable information on crashes of all costs, from property damage to vehicles that are totaled. This allows for the inclusion of non-fatal crashes into the analysis, in addition to the ability to identify which vehicle, if more than one is involved, is at fault, allowing for reliable multivehicle crash analyses.

Maintaining vehicles is a necessary step in keeping driving conditions safe. With higher quality vehicle inspection data, stronger predictions will be made on the exact time of when certain vehicle maintenance work is necessary. With increased automation in vehicles, it is predicted there will be a decrease in crashes due to driver error. As a result, it is likely other crash causes will become even more visible, such as maintenance issues, which are largely under- and un-reported currently. For example, a stopping algorithm in an automated vehicle is based on the tested stopping distance of the brakes. However, worn brake pads result in greater variation of this stopping distance, which will likely be larger. An added benefit with higher quality inspection data leads to the ability to track a vehicle in a crash back to the last inspection to identify any possible reason, outside driver error, for the crash, including the possibility that the inspector should not have passed the vehicle. This leads to the further need for high quality inspection data, which allows for monitoring of the performance of both inspectors and inspection stations to be sure honest and accurate evaluations of vehicles are made.

Vehicle safety inspections provide numerous advantages outside of safety. More analyses are necessary to identify the effect on local economies as a result of these required inspections in certain states. Inspections provide jobs and likely have a positive effect on local economies. Additionally, recording vehicle conditions allows for the ability to calculate annual mileage driven, leading to the opportunity to implement mileage fees to support the on-going issue of highway funding. Vehicles that use the roads more must invest in them more.

VII. CONCLUSION

While this analysis was limited to fatal crashes and limited knowledge on the intensity of each state's inspection program, some models were found to strongly support the vehicle safety inspection program. The results showed that safety inspections were statistically significant in reducing the fatality rate in states by about 1.8 fatalities per billion VMT and also resulted in a highly significant urbanity coefficient of about 11 fatalities per billion VMT difference in urban versus rural locations (higher rural fatality rate). This led to the conclusion that urbanity must be accounted for in these analyses.

There is no national standard for safety inspections; therefore, even states that do have programs may not execute them the same way. This led to limitations in accurately analyzing the program and resulted in numerous regression models to check any possible scenario. Lack of consistency of the crash attributions across crash data reported by each state and the difficulty in identifying the best way to assign a vehicle to a state (either registration or crash state) was a downfall to this section of the analysis. Improvements in data reporting, collection, and program oversight for both data collection and safety inspection programs are integral in further reducing vehicle crashes and therefore assessments of differences in fatality rates.

Chapter IV: Vehicle Travel Variations and Comparisons Across Vehicle Age, Zip Code Urbanity, and Time by All Vehicles and Households

I. Introduction

VMT estimation aids in observing patterns in vehicle maintenance, vehicle crashes, vehicle congestion, pollution, and various other travel-related questions in current research. In the previous two chapters, VMT was largely used as a descriptor variable used for comparing vehicle safety inspection failure rates and vehicle fatality rates. Currently, there are two common ways of estimating VMT: multiplying average daily traffic counts by length of road and surveys. The count method results in only a single average VMT value that is reported for each urban and rural type of road for each state. The survey method depends on accurate and truthful reporting of travel by household members. While these estimates are better than one overall average for the entire state, it still does not provide the distribution of vehicle travel within the state, which is especially important since each vehicle is driven differently.

The results of the previous two chapters found that vehicles that travel more miles annually, require more maintenance and have a higher probability of being involved in a fatal accident in a given year, due to more travel exposure. For example, the question of what is the distribution of VMT estimates for one-year-old vehicles is raised and if this distribution varies between urban and rural areas. Thus, the need for a more detailed analysis of vehicle miles traveled was the driving motivation for this chapter. Furthermore, VMT analyses aid in decision-making for policies to help reduce congestion, improve air quality, and distribute funding throughout the country. Any of these policy decisions require that VMT be measured with high certainty and at a detailed level, which leads to is the question posed here: Are the current methods of estimating VMT good enough?

The availability of the VSIR database for a sample of the Pennsylvania vehicle fleet allowed for detailed analyses of VMT distributions within the state of Pennsylvania. Using comprehensive Pennsylvania VSIR data, such as the one million vehicle safety inspection records (10% of the PA vehicle fleet and 100 times more than the NHTS sample which represents the entire county), VMT can be thoroughly analyzed, as this data is recorded by vehicle mechanics—professionals in the field. However, there is still potential for error, as VMT is entered by hand into such databases. With this data, VMT can accurately be expressed as a function of vehicle-specific data and user-specific data, such as vehicle age, vehicle make, vehicle location (e.g., county or zip code), owner age, owner income, etc. The Pennsylvania vehicle inspection records contain odometer readings and associated dates at the time of inspection for specific vehicles over about a 6-year timeframe (2008-2014) that can be used to calculate the associated VMT values, which would be the first step in this analysis. Furthermore, knowing the expected VMT range for an entered car with certain characteristics will allow for more detailed error-checking and verification when new data is entered into the system. As a result, simple mistakes will be instantly caught allowing for improved confidence in the database entries.

An additional step is taken to approximate household travel patterns. Households are matched based on anonymized insurance NAIC and policy numbers for each vehicle, and is explained in more depth further in this chapter.

II. Background and Current Literature

Until now, one of the most comprehensive and widely used database to do VMT analyses was the National Household Travel Survey (NHTS) collected by the Department of Transportation Federal Highway Administration (FHWA) [58]. While this survey contains the necessary information to do a VMT analysis, there are limitations to the accuracy of the information. The NHTS sampling system is based on a phone call made to a randomly selected household in the U.S. with a land-line telephone (randomized via a list assisted, random digit dialing, computer-assisted telephone interviewing system), asking any household member older than 16, yet not necessarily the primary driver of the vehicle, about each household vehicle. Data collected primarily focuses on details pertaining to daily trips taken in 24-hour periods, yet one question does ask for an estimate of the total mileage over the previous year. This database contains approximately 300,000 vehicle records from about 150,000 households, for the entire U.S. population (0.1% of all U.S. households [59]).

NHTS data reports two estimated VMT values: self-reported and best-estimate. The self-reported is a result of the survey answers from respondents. NHTS reported that about two-thirds of the collected data was deemed useable by their quality check of the data and it is used to form a regression equation using the self-reported annual mileage and vehicle age in order to predict the remaining one-third of the collected data. NHTS implements six different approaches to estimate the 'BESTMILE' and can be found in detail in their report prepared for FHWA summarizing their methods. [60] Their estimations are largely based on the self-reported annual mileage values whereas the method used in this chapter calculates the actual difference between two odometer readings and adjusts for the 365 day/year value, which is explained in detail in the next section.

Finally, and most striking is that, this data is only collected every five to eight years (the annual publication uses the most recently collected sample); as a result, any analyses done today in 2015, must use data from 2009. Historically, U.S. estimates of VMT steadily increased; however, in 2004 VMT plateaued and then started a decreasing trend in 2007. These annual changes were found using the traffic count method for estimating VMT, but if only NHTS data were available, these trends would not be as noticeable since NHTS is only implemented every five to eight years. NHTS still serves as a unique inventory source of the nation's daily travel and specific purposes of travel, yet more robust data is essential in order to make informed policy recommendations and this is possible with the large improvements in technology.

Also provided by FHWA is traffic count data, which is recorded at 4,000 permanent locations across the country (a minimum of 6 per state for each grouping of functional classified roadway) and multiplied by the length of length of each road segment and summed for all similar road segments for each day in the year. [20], [28] This process is performed each month and the VMT estimates are then updated accordingly. The data is adjusted to eliminate effects of weekday, weekend, and holiday differences.

Detailed databases of state vehicle safety inspection, emission inspection, and registration, for the state of Pennsylvania have since been acquired, which provide more specific information on vehicles driving since it uses mandatory registration information as well as information recorded by mechanics, rather than either the vehicle owner or a relevant household member as in the NHTS data. Vehicle specialists record details about the vehicle, such as mileage, during the vehicle inspection and report these records to the inspection databases. On the contrary, NHTS is a phone survey and does not have an in depth quality check, nor do the users necessarily have the vehicle in front of them when reporting the information. With state specific data, such as the Pennsylvania safety vehicle databases, more detailed conclusions can be drawn on vehicle travel patterns. This will then allow for generalizations to be made about the overall vehicle fleet in travel habits.

Chapters 2 and 3 discuss the importance of separating vehicle-based analyses according to urban and rural locations. While high-level studies have shown the results of higher VMT in rural areas than urban areas in a given state, the PA safety inspection data is unique and allows for the use of easily attainable data in the state of PA to help provide insight to detailed VMT patterns on the county, zip code, vehicle, and household level.

The majority of literature in transportation uses VMT data. As some specific examples, Green (2010) finds that data show a statistically significant effect of gasoline price on vehicle travel, yet these conclusions are based on total U.S. highway vehicle miles of travel by passenger cars and light trucks estimated by FHWA. The author notes that the FHWA's compilation of state DOTs are the source of vehicle travel statistics; however, each state varies in their definition of passenger cars and light trucks. [61] Su (2009) examines the relationship between travel demand in terms of per-capita VMT and urban spatial characteristics. Annual VMT per capita used in this study is calculated by combining daily traffic of a roadway section and the length of section of that road for freeways and principal arterial streets, yet the author notes that estimates for collector/distributor roads is likely to be consistently underestimated. [62] Woldeamanuel and Kent (2014) uses NHTS data as a source of per capita VMT in California in order to separate determinants of per capita VMT. [63]

The California Smog Check Program records allow researches to calculate annual VMT estimates using similar methods to those suggested in this chapter, resulting in the ability to make confident comparisons between vehicles of similar characteristics. Sandler (2012) uses this data in order to evaluate the cost-effectiveness of the California Smog Check Program by having specific details and characteristics of vehicle driving patterns. [64] Cook et. al. uses this same data in VMT calculations for their study of elasticity of VMT and note the benefits of using this unique, vehicle-specific data. [65] To date, no Pennsylvania specific analyses on the variation of travel across the state have been published, aside from annual state reports that briefly overview the state's trend over time compared to the country. In fact, a report submitted to PennDOT regarding the statistical evaluation of projected traffic growth in order to help direct transportation funding specifically states the need for a more robust estimation of state VMT in order to improve the model's funding forecasts and budgets. [66]

This chapter goes into detailed analyses that are possible with the unique, electronic, PA VSIR, which provide more precise calculations of VMT by using multiple odometer readings. This method of calculating VMT allows researchers to follow one specific vehicle across its lifetime to track very specific travel patterns, without the privacy concerns of sharing GPS coordinates. Furthermore, the data allow for the calculation of household VMT along the same lines as the single vehicle calculations. This approach of calculating household VMT allows researchers to investigate, more precisely than NHTS, how households drive according to various characteristics of each of their vehicles. The next few sections use the PA VSIR to investigate a subset of potential variables that may influence VMT and there relationship to each other, across different portions of the state ranging from the zip-code level to the overall state level. Additionally, the available inspection data allows for the estimated grouping of household travel within the state and compares these results with the national household results using NHTS, published by the U.S. Energy Information Administration (EIA), finding that households with more vehicles put more miles on their most-used vehicle compared to households with fewer vehicles. [67] Primarily, this chapter focuses on answering the following questions: How are vehicles used in the state? And, does this differ depending on the number of vehicles in a household?

III. Data Filtering, Initial Methods, and Data Verification

The Pennsylvania VSIR data provided initially included a sample of vehicles that underwent a vehicle safety inspection at a location using the e-SAFETY system discussed in Chapter 2. As a result, VSIR vehicle data may include non-light-duty vehicles such as heavy-duty trucks, buses, taxis, and other permanently registered vehicles. It may also include multiple records for the same vehicle in a given year. Table 9 shows a breakdown of the raw inspection data by inspection year and its comparison to the approximately 11 million registered vehicles in the state as of the end of 2014.[5]

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[5] Registration data was not available every year, but both 2013 and 2014 were available and there was only an increase of 5% more vehicles in 2014 from the year before. If the rate is assumed to be constant each year, it is calculated that the sample percentage of inspected vehicles registered is the same even with the overall total registered being less.

Table 9. Raw Data Counts by Inspection Year

Inspection Year	Unique Counts	% of Unique VIN Total in Year	% of Registered
2008	206,000	14%	3%
2009	274,000	18%	3%
2010	299,000	20%	3%
2011	337,000	22%	4%
2012	356,000	23%	4%
2013	548,000	36%	5%
2014	579,000	38%	5%
Total (2008 - 2014)	1,526,000		14%

There are about 1.5 million unique VINs recorded in the data over all years of data. Similar to Chapter 2, the following methods were used for filtering the data of invalid, non-light-duty personal vehicles by using Python (a programming language):

1. Invalid VINs
2. Duplicate entries
3. Invalid date (format issue – not a date, no entry)
4. Invalid odometer entry (alpha-numeric entry, no entry)
5. Heavy-duty trucks (> 10,000 lbs and ≥ Ford-350)
6. Permanently registered vehicles and fleet vehicles (police cars and ambulances)

Records are then sorted by VINs in order to find unique VINs with more than one entry so the annual mileage can be calculated. About 647,000 VINs have only one record making these VINs immediately unusable because two entries are necessary to calculate the annual 365-day adjusted VMT value; therefore, these VINs are filtered because there is not enough data for the analysis. Initially, the assumption was made that if a VIN cannot be decoded using its 10th digit to find the model year, it cannot be considered a light-duty vehicle (because it does not follow the VIN format for light-duty vehicles); however, this filter resulted in too much data being filtered. It was reasoned that due to some of the data being manually entered, there is higher probability of data-entry error in the VIN, thus it is necessary to apply three checks to decode VIN based on its model year, the model year check, a VIN decode database check, and if the entries matched from year to year in the inspection record for each VIN (refer to the Supplemental Material for more details). This results in fewer data records being filtered for the analysis. After filtering for validity of entries and VINs with more than one entry, total data available for the analysis is about 855,000 unique VINs over the 7 years of available data.

Once the initial filtering is completed, entry pairs (every two entries per VIN) are used to calculate annual mileage traveled for that vehicle. Main issues include odometer readings that have little or a lot of time in between readings (e.g., 1 month or 3 years), as they will not be accurate representations of annual driving patterns. The VMT is calculated and assigned to the more recent date entry. Dates that are a lot more than one year apart are still included in these results in order to have more data points for the analysis. With more available data in the future, this filter will be added to remove VMT estimates with dates more than 18 months apart (1 year and 6 months). Dates that are very close together are removed if they are less than nine months apart. This threshold is created to capture vehicles that are brought in early for inspection, which is allowed as early as three months prior to their actual inspection month. This allows filtering of very close dates, which may have created large over- or under-estimates of VMT, yet still captures vehicles that may be earlier than one year. In order to normalize annual VMT values, differences are calculated between odometer readings and dates and then scaled to a standard 365-day VMT calculated value, which as stated previously, is not done in the NHTS annual VMT calculation. (Equation IV-1).

$$\text{adjusted annual VMT} = \frac{\text{OdometerReading}_{\text{f}} - \text{OdometerReading}_{\text{i}}}{\text{Date}_{\text{f,days}} - \text{Date}_{\text{i,days}}} * 365 \text{ days} \qquad \text{Eq. IV-1}$$

Another filtering requirement includes matching zip code and county urbanity when calculating annual VMT. A VMT estimate is only kept and considered valid if both zip code values are equivalent, but the single odometer readings are all kept in case there are additional data points that do match. Without this filter, two odometer readings may be a year apart yet may have “lived” in two very different locations in terms of the level of urbanity. This leads to issues of with which zip code or county to associate the VMT and if travel patterns changed due to the urbanity change. As seen in previous literature review, urban and rural travel patterns are very different. Unfortunately, it is unknown when the urbanity change took place thus entries for a specific vehicle do not have matching zip code or county urbanity levels, then those entries will not be used.

Final filters are applied as follows:

1) Date differences that are equal to zero (9,000 filtered entry pairs)
2) Negative or zero calculated VMT values (10,500 filtered entry pairs)
3) Odometer Reading is more than 6 digits (730)
4) Vehicle age is invalid, refer to the Supplemental Material for details (500 filtered entry pairs)
5) Entry pairs less than 9 months apart, with the assumption these vehicles would not be coming in for the annual inspection and any 365 day adjustment may cause an under- or over-estimate of the annual VMT calculation (23,000 filtered entry pairs)

Most of these filtered values are considered as an incorrectly typed entry in the data due to the inconsistencies involved in manual data entry whereas others are chosen not included, such as the filter for days between inspection records. Table 10 presents an overview of the data count progression as filters are applied, starting from the total unique VIN count presented in Table 9.

Table 10. High-level Summary of Data Counts

	Total Unique VIN Records	% Unique Valid
Total, pre-filtering	1,526,000	--
Total, >1 entry per VIN	855,000	56%
Total Valid, post-filtering	752,000	50%

The majority of unusable entries stemmed from data with only one inspection entry per VIN, rather than the applied filters, and accounted for filtering roughly half of the unique VIN data. In other words, about half of vehicles only appeared once in the VSIR dataset and therefore an annual VMT value could not be calculated.[6] This is again an artifact of PA's voluntary e-safety program. These counts can be compared to those in the most recent NHTS data from 2009, which consists of a sample of 1,600 vehicles (800 households) in PA and 300,000 vehicles (150,000 households) in the entire U.S. For a closer comparison, PA data is broken down by year and displayed in Table 11.

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[6] By incorporating data from additional data sources such as those used in Chapter II, the percentage of single VIN entries will likely decrease

Table 11. Unique VIN records by inspection year

Year	Unique VIN Count
2008	50,000
2009	83,000
2010	101,000
2011	112,000
2012	120,000
2013	154,000
2014	132,000
Total	752,000

In 2009, the PA safety inspection data consists of 50 times the number of records as there are in the NHTS data. Additionally, there are even more records each year after 2009 which aren't even available from NHTS data.

IV. Overall State Distributions

After all filtering scenarios, a total of about 750,000 valid, unique VINs with more than one entry remain for this analysis. In order to clearly understand the range of VMT, the 95.5 percentile value of the data is found to be about 40,000 miles (both overall and for each inspection year) and the maximum overall was about 1,065,000 miles. Because the top 0.5% of the data (about 3,750 VINs) was found to have such a large range (1,025,000 miles), it was necessary to identify whether the high VMT estimates should be considered as either outliers or incorrectly entered. There is no documented maximum VMT value to use in this type of analysis published by the DOT or any similar studies, thus a maximum VMT heuristic was estimated. In 2006, Midas, Inc. (an automotive service company) awarded "America's Longest Commute" to a person who drove about 370 miles round-trip to work each day, which equates to just under 100,000 miles per year of driving for just commuting purposes. As a result, 100,000 miles is taken as a maximum threshold for annual VMT. This resulted in the assumption that any VMT value greater than 100,000 miles would be considered an incorrectly entered odometer reading. Additionally, due to the manual entry of odometer readings, there may be some uncertainty around the accuracy of all the remaining calculated VMT values.

Thus, the upper 0.1% of the data (965 entry pairs) with calculated annual VMT values greater than 100,000 miles are filtered out for this overall state analysis, resulting in a tighter distribution of VMT. This leads to the calculated mean (μ) VMT decreasing by about 340 miles from 9,770 to 9,430 and significantly reduces the calculated standard deviation (σ) from 14,000 to 6,860 miles. This progression is shown in Figure 13.

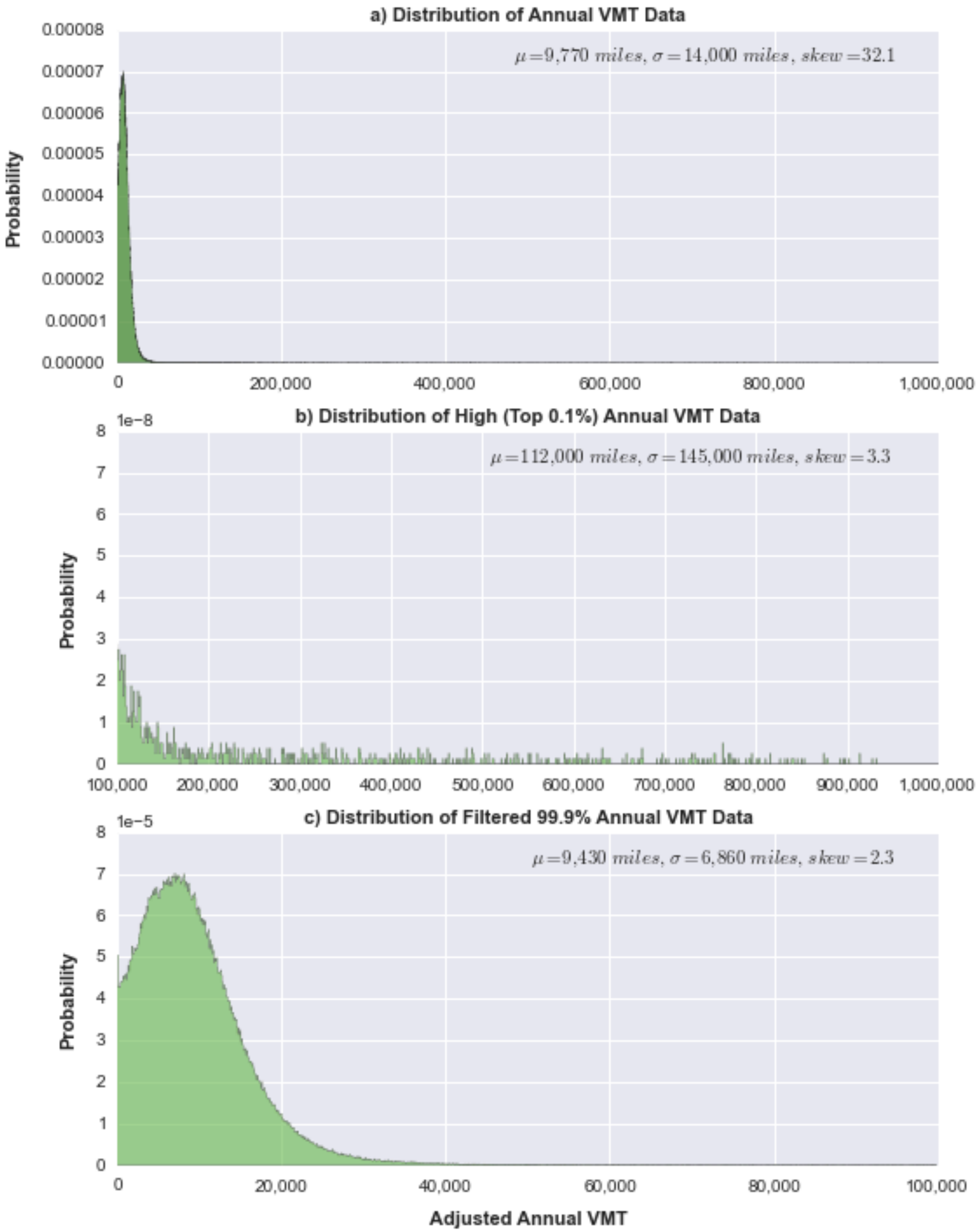


Figure 13. Distribution of Adjusted Annual VMT, 2008-2014 (a) overall, (b) the top 0.1%, and (c) the remaining 99.9% after filtering the top 0.1%

Due to the small effect on the mean annual VMT and much tighter distribution (smaller standard deviation), the filtering out of VMT estimates greater than 100,000 annual miles was assumed to be appropriate. The change in average mean and standard deviation of VMT over time is also observed (Figure 14).

Figure 14. VMT Standard Deviation versus Mean by Inspection Year

The mean VMT from 2008 through 2009 increased, and then from 2009 through 2014 the mean VMT decreased, similar to recent trends published by FHWA on the current decreasing VMT pattern for the overall U.S. vehicle fleet. [33] The standard deviation (or range of VMT over the vehicle fleet) stayed between 6,600 miles to 7,000 miles. In addition, we can visualize how the VMT distribution changes over these inspection years (Figure 15).

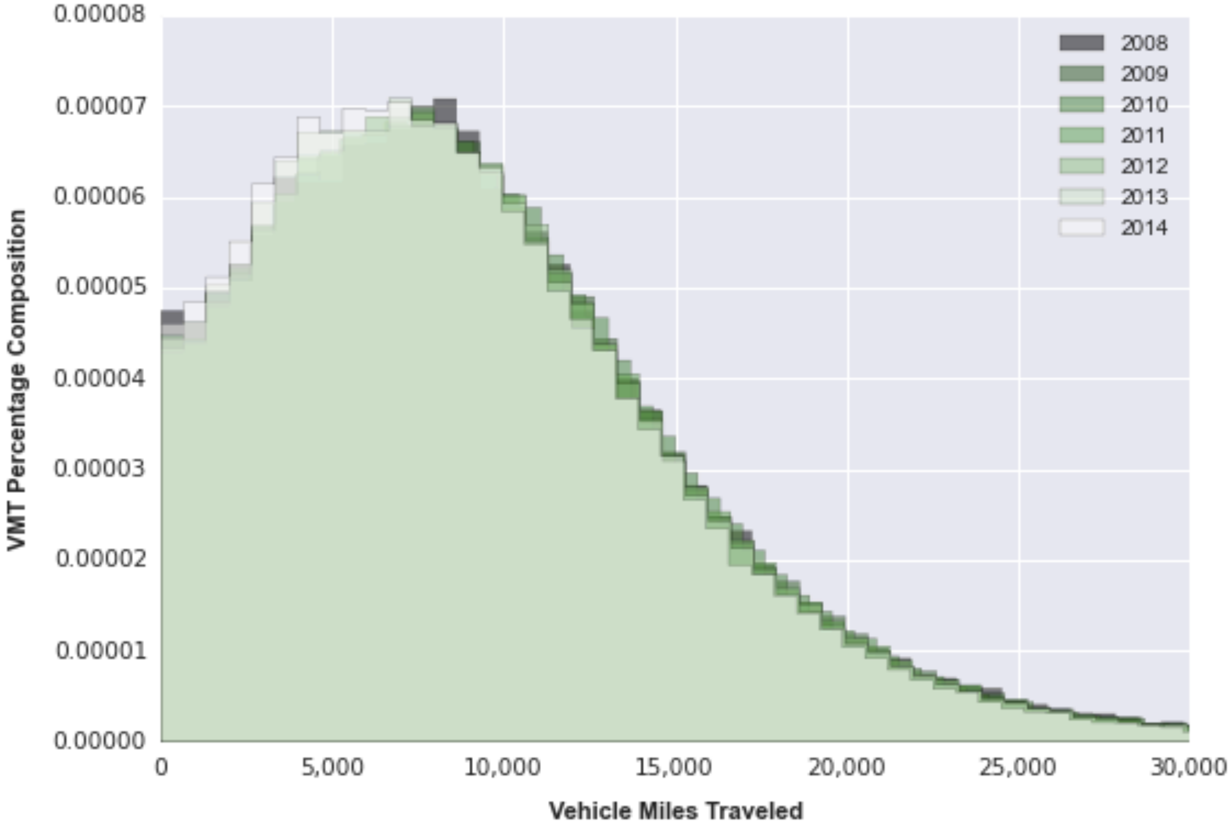


Figure 15. VMT Distribution of the PA Sample Fleet by Inspection Year

Figure 15 displays a slight shift to the left (lower VMT values) as the inspection year increases from 2008 to 2014; however there are no stark differences between inspection years as was shown in Figure 14. In order to understand this decreasing trend more closely, other fleet trends are identified later in the chapter, such as changes in average vehicle age and any urbanity trends.

The final step prior to further data analysis was the verification of the sample data in relationship to the population fleet. In order to do this, the vehicle registration data for 2013 was obtained and registration zip codes were used to approximate number of VINs registered per urbanity location. Due to limited availability to years of previous registration data, the assumption was made that the proportions of vehicles registered in each urbanity type remained constant. This breakdown was also calculated for the inspection databases, by inspection year and then the average over the inspection years was compared to the registration breakdown to check for representativeness. This is presented in Table 12.

Table 12. Inspection Data Summary by Inspection Year

Urbanity	Inspection Year	Counts	% Breakdown	Average Vehicle Age	Average VMT
Rural	2008	28,000	8%	7.0	10,000
	2009	45,000	12%	7.4	10,200
	2010	51,000	14%	8.0	10,200
	2011	53,000	15%	8.2	10,200
	2012	56,000	16%	8.6	10,100
	2013	71,000	20%	9.0	9,900
	2014	60,000	16%	9.9	9,700
Suburban	2008	13,000	6%	6.8	9,000
	2009	23,000	10%	7.1	9,100
	2010	30,000	13%	7.5	9,200
	2011	35,000	15%	7.8	9,200
	2012	38,000	17%	8.2	9,200
	2013	47,000	21%	8.6	9,100
	2014	41,000	18%	9.4	8,900
Urban	2008	6,000	6%	7.1	8,200
	2009	11,000	11%	7.5	8,200
	2010	16,000	15%	7.8	8,100
	2011	20,000	19%	8.1	8,200
	2012	22,000	20%	8.5	8,200
	2013	29,000	27%	8.9	8,100
	2014	3,000	2%	9.8	8,000

Only one year of registration data was available to test inspection data representation; therefore, the inspection data was averaged over the six years of inspection data to compare against the registration data. This comparison can be found in Table 13.

Table 13. Average Inspection Data Representation in Comparison with 2013 Registration Data

Dataset	Urbanity	Counts	% Breakdown	Average Vehicle Age
Registration Data 2013	Rural	5,050,000	55%	8.7
	Suburban	2,430,000	26%	8.5
	Urban	1,650,000	18%	9.0
Inspection Data (2008-2014)	Rural	364,000	52%	8.5
	Suburban	226,000	32%	8.1
	Urban	109,000	16%	8.3

It is concluded that the composition of e-SAFETY inspection data by urbanity is fairly representative of the registration data and therefore can be used as a sample of the PA vehicle fleet; however, adjustments are made for the small differences in composition when average VMT is calculated. There is a difference seen is the calculated average vehicle age in each urban location when comparing the two datasets. In the registration data, urban vehicles are oldest on average, whereas rural vehicles are the oldest on average in the inspection data. Overall, however, they are all very close in comparison. Additionally, the sample data count is very small for 2014 urban locations, yet the averages still follow general trends of the data for average ages and VMT in the different urbanity groups.

After filtering the VMT values greater than 100,000, no changes in the mean or standard deviation of vehicle model year (or age) were observed, contrary from the large decrease in standard deviation there was for VMT. Since multiple inspection years are included in the overall distribution and in order to easily compare the vehicle age fleet over time, the vehicle age distribution is presented rather than the model year distribution, which normalizes the model year by the inspection year from which the data comes (Figure 16).

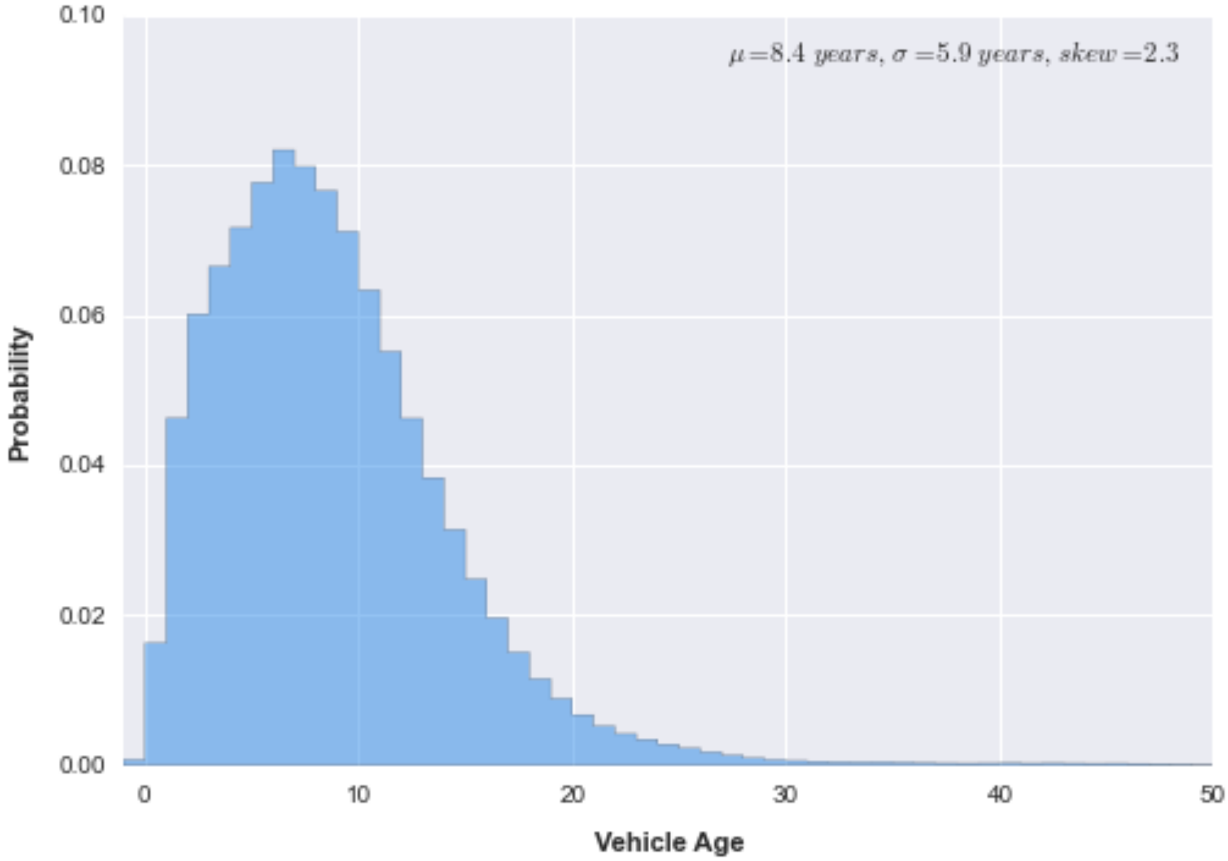


Figure 16. Distribution of Vehicle Age in PA Inspection Data, 2008-2014

Figure 16 shows that the average age of vehicles in the state sample over the 2008-2014 inspection years was about 8 years with a standard deviation of about 6 years. This distribution shows that the majority of vehicles (over the six inspection years) are less than ten years old, which aligns with literature findings. Figure 17 breaks down the mean age and standard deviation estimates by inspection year in order to observe any time series trends.

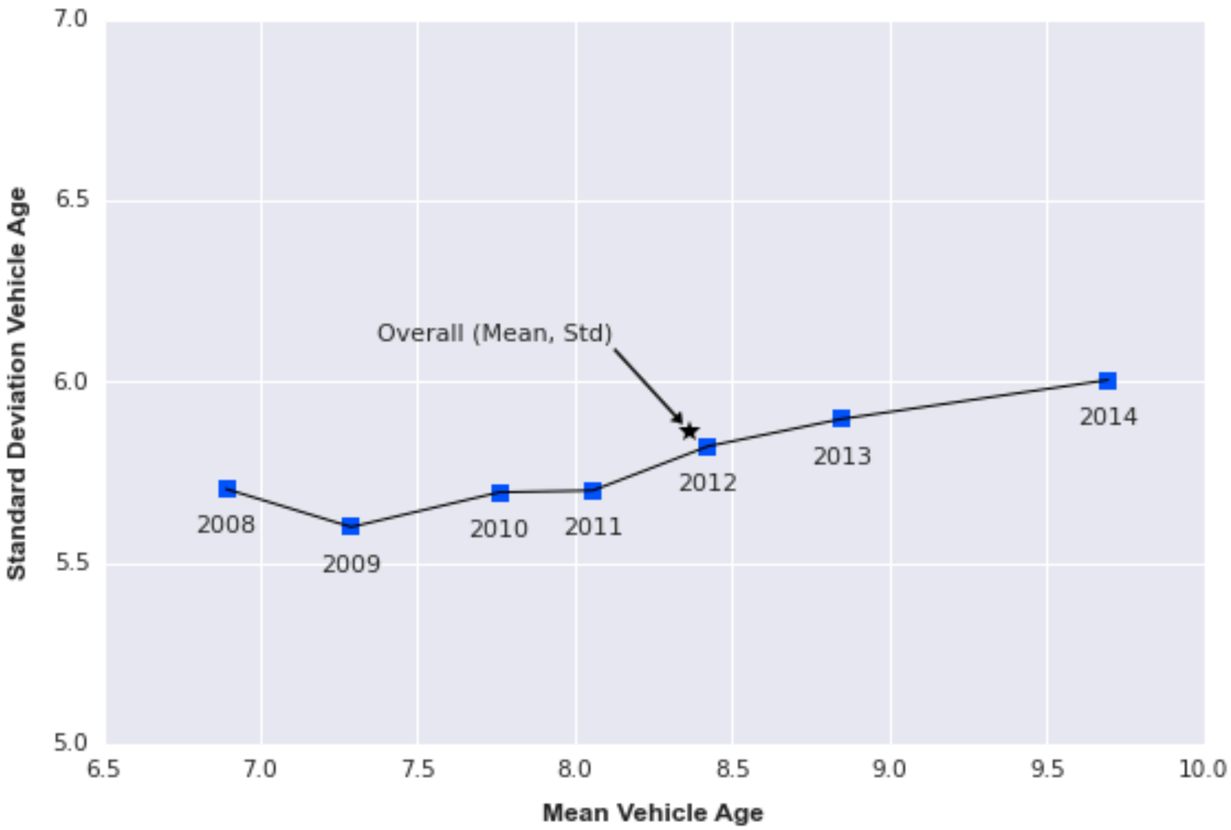


Figure 17. Vehicle Age Standard Deviation versus Mean by Inspection Year

The trend seen in Figure 17 shows that the average age of vehicles has become older each year from 2008 to 2014 and the standard deviation of the ages has remained relatively the same between 5.6 to 6.0 years. We can also visualize the change in the distribution of vehicle age over this time period (Figure 18).

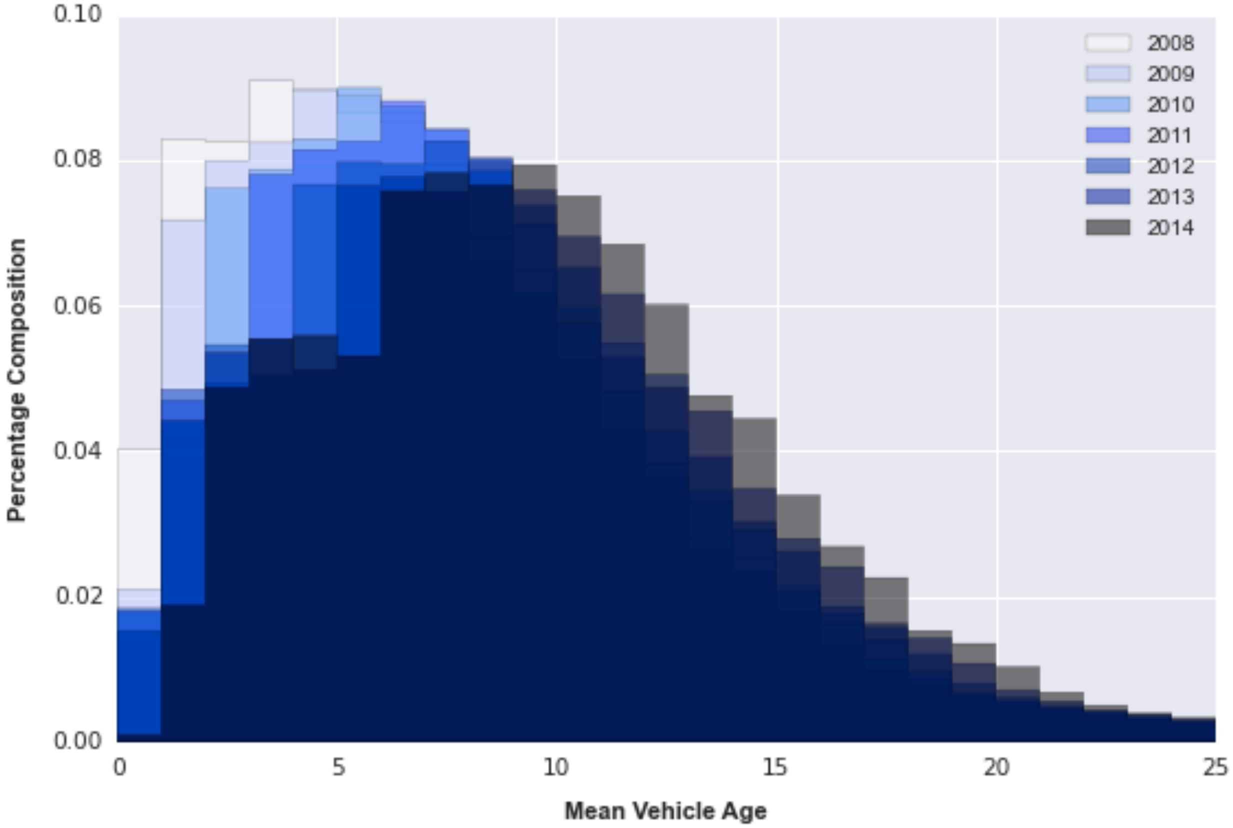


Figure 18. Age Distribution of the PA Sample Fleet by Inspection Year

From Figure 18 we can observe that the vehicle fleet has been aging together over the past five years, or fewer vehicles are being retired and/or replaced with newer ones. It is likely this trend is linked to the recent recession; however, no definite conclusion can be drawn due to limited data prior to the start of the recession.

Once the high mileage filter was verified to have little effect on the mean and tighter distribution of VMT and had no effect on vehicle age, with only 0.1% of the data removed, more in depth relationships were calculated, such as the relationship between annual VMT and age. This result is shown in Figure 19.

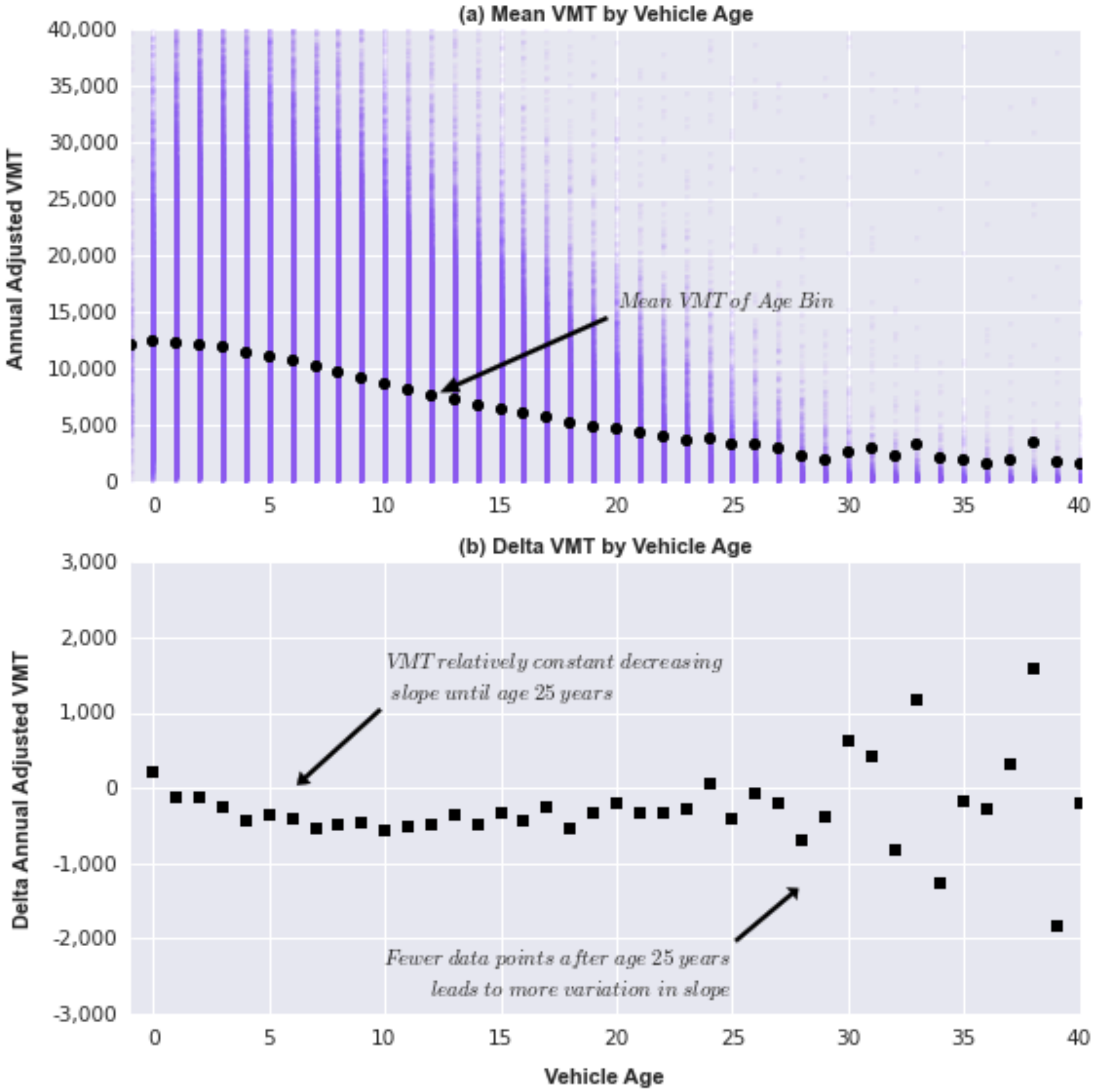


Figure 19. (a) Mean Annual Adjusted VMT versus Vehicle Age overall from 2008-2014; (b) Calculated delta VMT by Vehicle Age overall from 2008 – 2014

The trend of mean VMT per age of vehicle is monotonically decreasing until age 25 and then fluctuates from year to year, since the sample sizes become so small for the very old vehicles, as seen in the data counts listed. The estimation confirms that as a vehicle ages, it is driven fewer miles, as is the trend seen in literature [68]. This trend is of importance in vehicle emission and congestion calculations, safety investigations of vehicles, and looking at the effect of vehicle age on travel in different locations (e.g., urban versus rural zip codes or counties). Using the inspection data it is estimated that a brand new vehicle (age -1 to 0) is driven about 12,500 miles annually and as it ages each year, the vehicle is driven about 300 fewer miles, until age 25, where there is then no clear trend. This lack of trend after age 25 is attributed to the low sample sizes in the older vehicle data. In 2014, Oak Ridge National Laboratory (ORNL) published the Transportation Data Book using the most recent NHTS data, which was from 2009. Their data showed a similar decreasing trend, on average -400 miles per year [1], but not as consistent as shown in the data from the PA sample.

More interestingly, it appeared according to the ORNL trends that vehicles follow the overall decreasing VMT trend over time; however, older vehicles were driven more in the more recent years. This trend was investigated and similar results were found in the PA sample data (Figure 20).

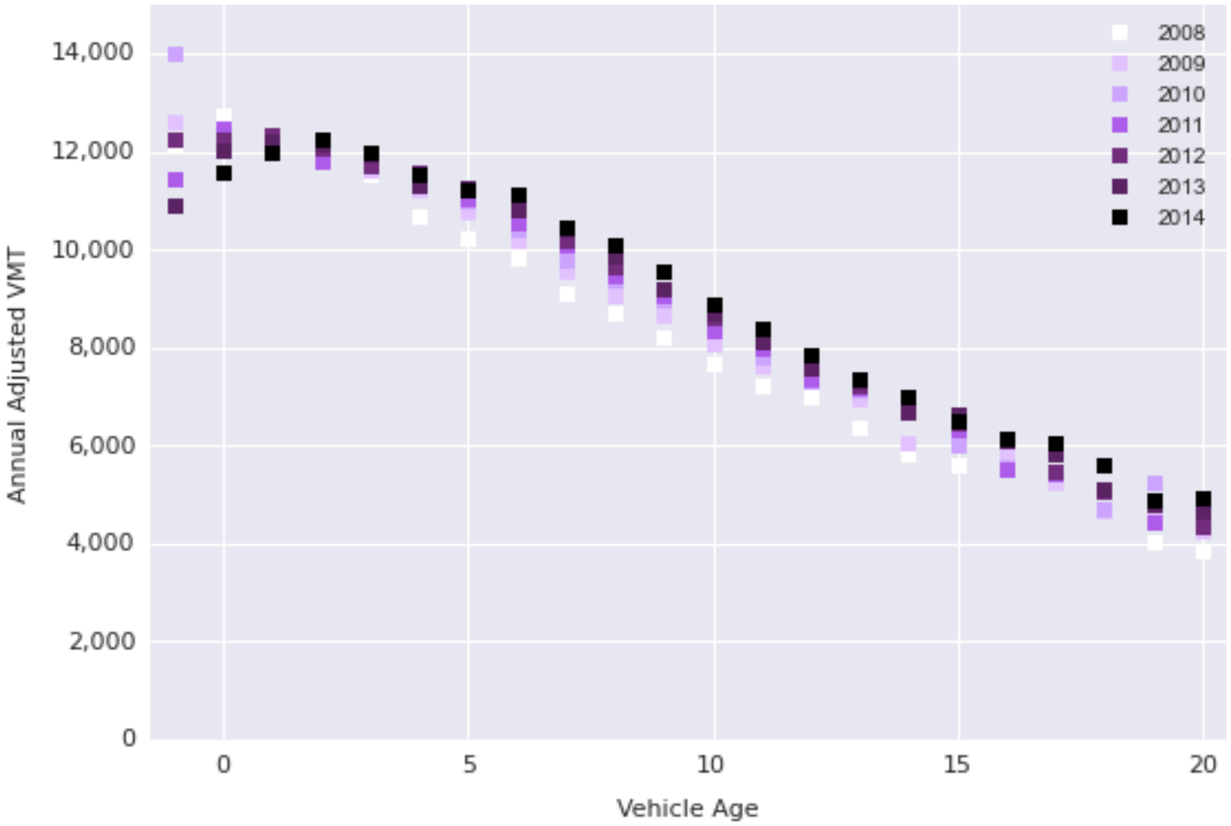


Figure 20. Average Annual Adjusted VMT versus Vehicle Age by Inspection Year

Figure 20 shows that over time, younger vehicles are driven approximately the same, on average, yet the older vehicles are driven more than in previous years. The overall decreasing VMT trend over time results primarily from the aging vehicle fleet as seen in Figure 18, which consistently follows the decreasing VMT trend as a vehicle ages. So, this decrease in overall VMT is not solely due to all vehicles driving less than the previous year's average at a given age. This leads to the conclusion that even though we see a decreasing trend of VMT as a vehicle ages, according to our sample of PA data, vehicle owners are either not purchasing new vehicles as frequently, or they are retaining their old vehicles longer as seen in the previous distributions of VMT and vehicle age over time. These trends over time are much clearer than the results seen from the NHTS data due to the increased frequency of sampling and larger data sample.

The data is investigated further by looking at these relationships by urbanity characteristics for each urbanity classification and it is hypothesized that VMT patterns and vehicle ages, vary additionally by urbanity of the vehicle's registration location.

IV.1. *Overall State Distributions by Urbanity*

In Chapter 2 and Chapter 3, analyses are done separately for urban and rural areas, as suggested by NHTSA. As a result, in this section, the data is observed by level of urbanity. In Chapter 2 the county classification scale published by NCHS is used, defining urbanity on a county basis, ranging from 1-most urban to 6-most rural. In this chapter, home zip code is used to find the associated population density and is assigned an urban, suburban, or rural value, as defined by the US Department of Defense TRICARE definition (Table 14). The county urbanity classification does not exactly match the zip code urbanity classification because the county classification takes into consideration if there is an urban center. In the case of Allegheny County, on the county classification scale, it is considered urban; however, when looking at the population density of the entire county, it would be considered Suburban, although this is the overall population density across very different zip codes.

Table 14. Zip code urbanity classification

Population Density (population per square mile)	Urbanity
≥ 3,000	Urban
≥ 1,000 & < 3,000	Suburban
< 1,000	Rural

It is important to compare the urbanity definitions on the county level versus zip code level. The range of urbanity within each county can be seen in Figure 21.

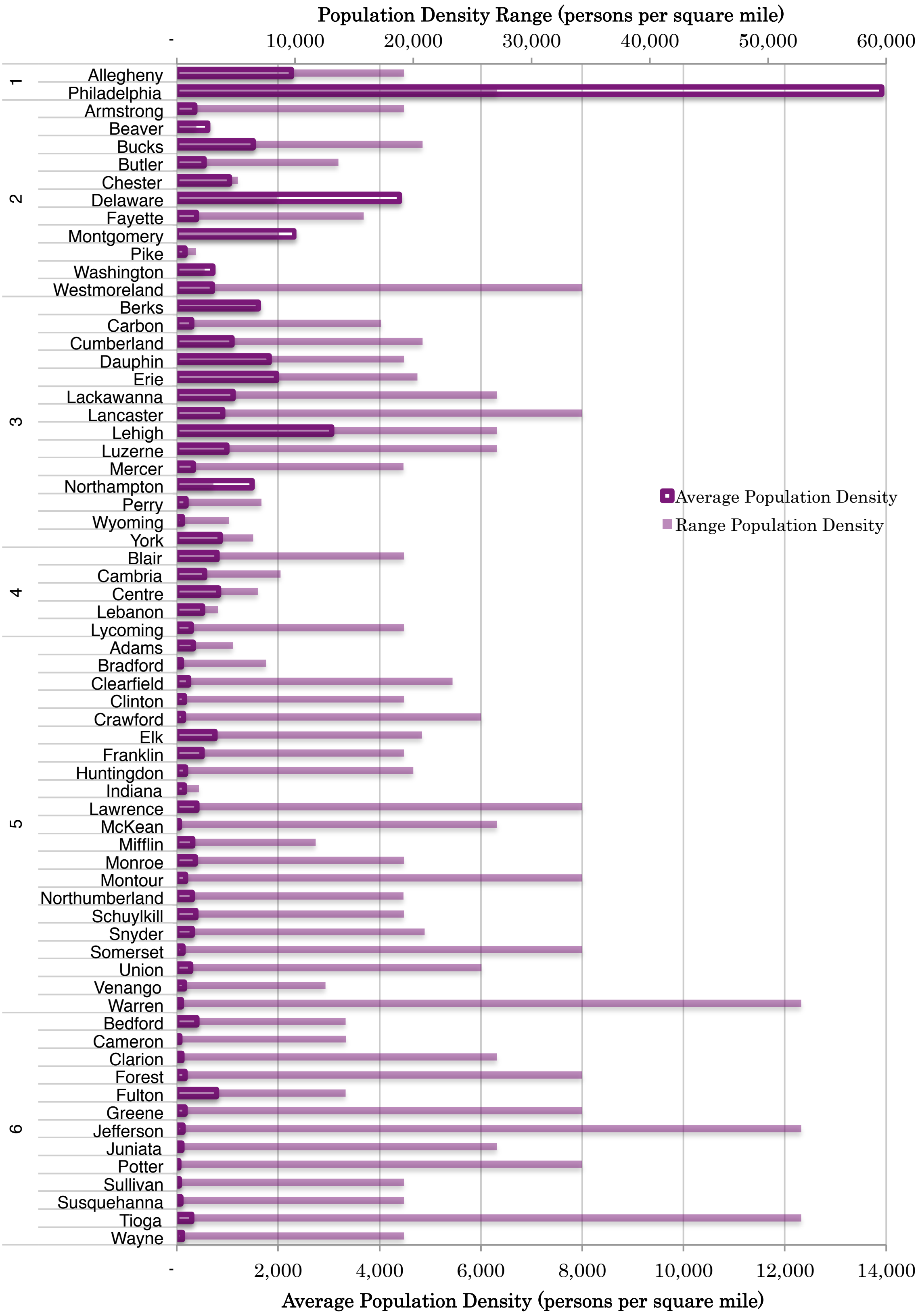


Figure 21. Population Density by County, grouped by county urbanity with min-max range values

While many counties are considered strictly rural, donated by the average bolder bars in Figure 21, they have a very wide range of population densities by zip code as seen with the lighter bar. For example, Allegheny County contains Pittsburgh with only accounts for less than 10% of the land area in Allegheny County, yet results in the county being classified as urban. However, when observing the population density of zip codes within the county, only zip codes around Pittsburgh are considered urban. Figure 22 displays this breakdown of urban, suburban, and rural zip codes within Allegheny County.

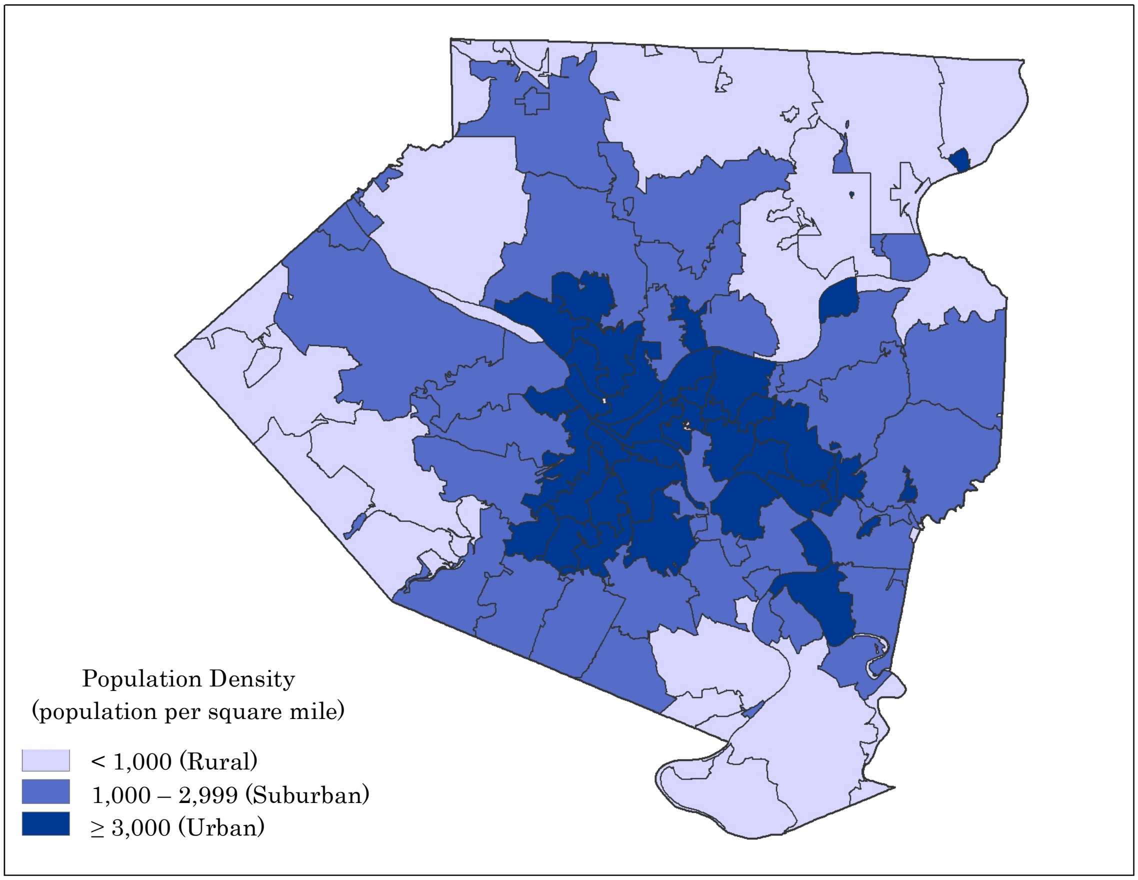


Figure 22. Zip code urbanity using population density in Allegheny County

As seen in these results, population density varies greatly even within one county, such as Allegheny where within the city limits of Pittsburgh is considered urban and as you move farther away it is more suburban and rural, yet this range is all within Allegheny County which is classified overall as urban. The VMT distribution is also examined for Allegheny County (Figure 23).

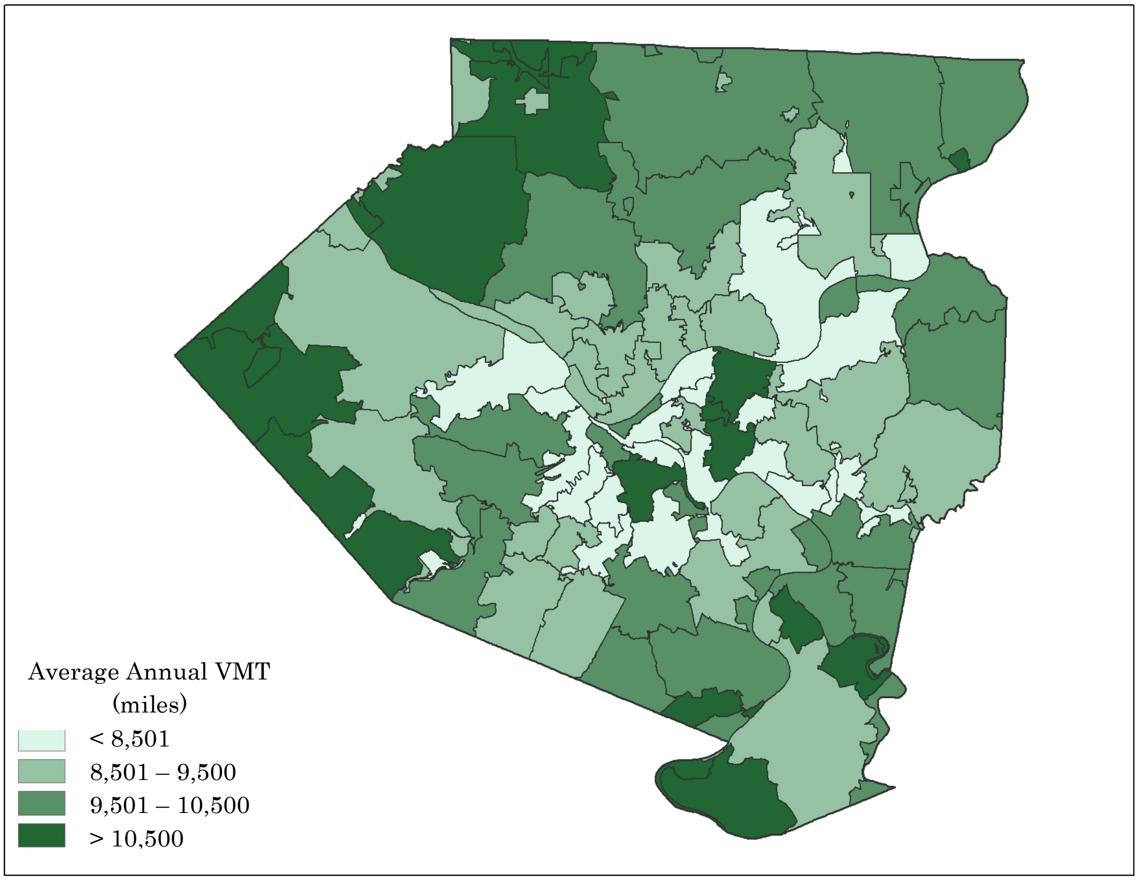


Figure 23. Average Annual Vehicle Miles Traveled by zip code in Allegheny County

Figure 23 shows that driving patterns vary even within one county and does not necessarily match the population density breakdown as displayed in Figure 22. As a result, this chapter uses the zip code urbanity classification rather than the county urbanity classification. This analysis is not possible with currently published VMT data by state, which only provides averages (without ranges) for each urban and rural area within that state.

Similar to the previous section, the data is broken down by inspection year to observe any differences between the inspection years of available data. Figure 24 compares urban averages against rural averages for both VMT and vehicle age, using the zip code urbanity classifications.

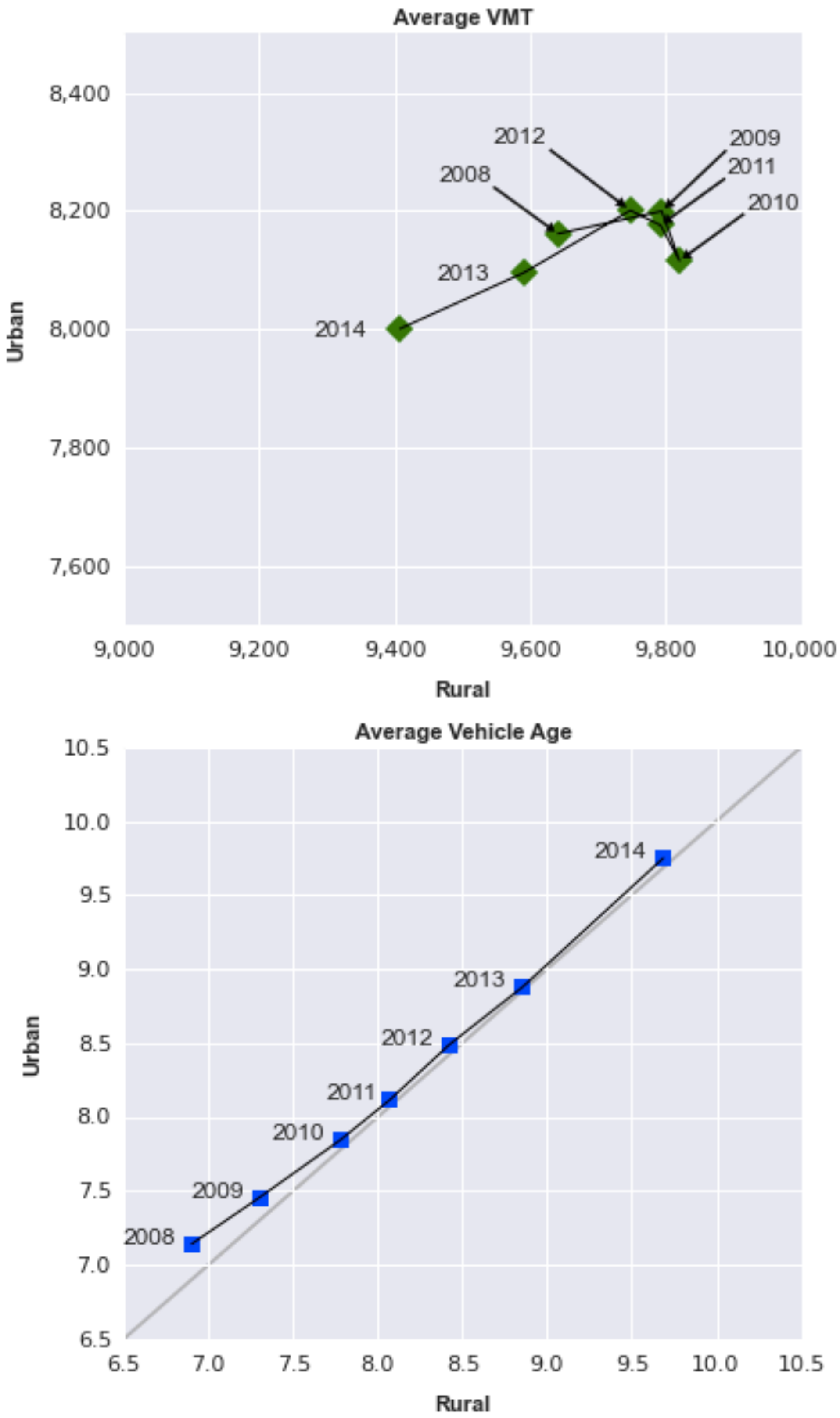


Figure 24. Urbanity Comparison of Average (a) Average VMT and (b) Average Vehicle Age, by inspection year

Figure 24 shows a consistent increasing trend in vehicle age, while there is no clear trend for change in VMT from 2008 through 2012, and then a clearer decreasing trend for both urban and rural locations from 2012 through 2014. It must be noted here that VMT is always greater in rural areas and falls below the y=x line which is not visible in the graph. While, it is clearly evident that there is always greater VMT in rural areas than in urban areas over the timespan observed, average vehicle age between the two is approximately equivalent over this same timespan. In Chapter 2, it was observed that both vehicle travel and age were similar predictors of inspection failure rate, yet here it is clear the trends over time are very different. As a result, VMT may in fact be a more appropriate variable to define potential maintenance issues because while vehicle ages are approximately equal between urban and rural, VMT is quite different. The relationship between VMT and age is compared separately for each urbanity classification over time in Figure 25.

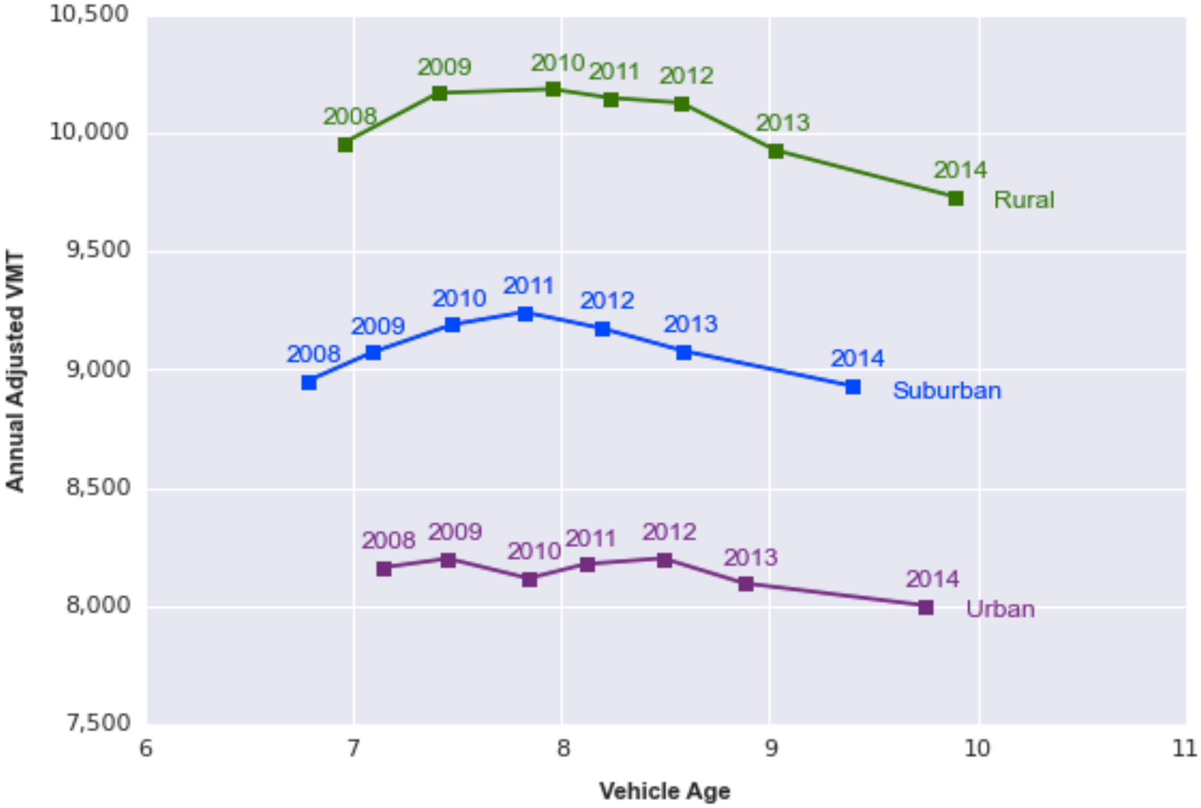


Figure 25. Average Annual Adjusted VMT versus Average Vehicle Age observed over time and separately for each urbanity location

As seen previously, vehicles are driven more in rural counties compared to those in urban counties, as they age. Additionally, variation in each mean estimate is shown in Figure 26.

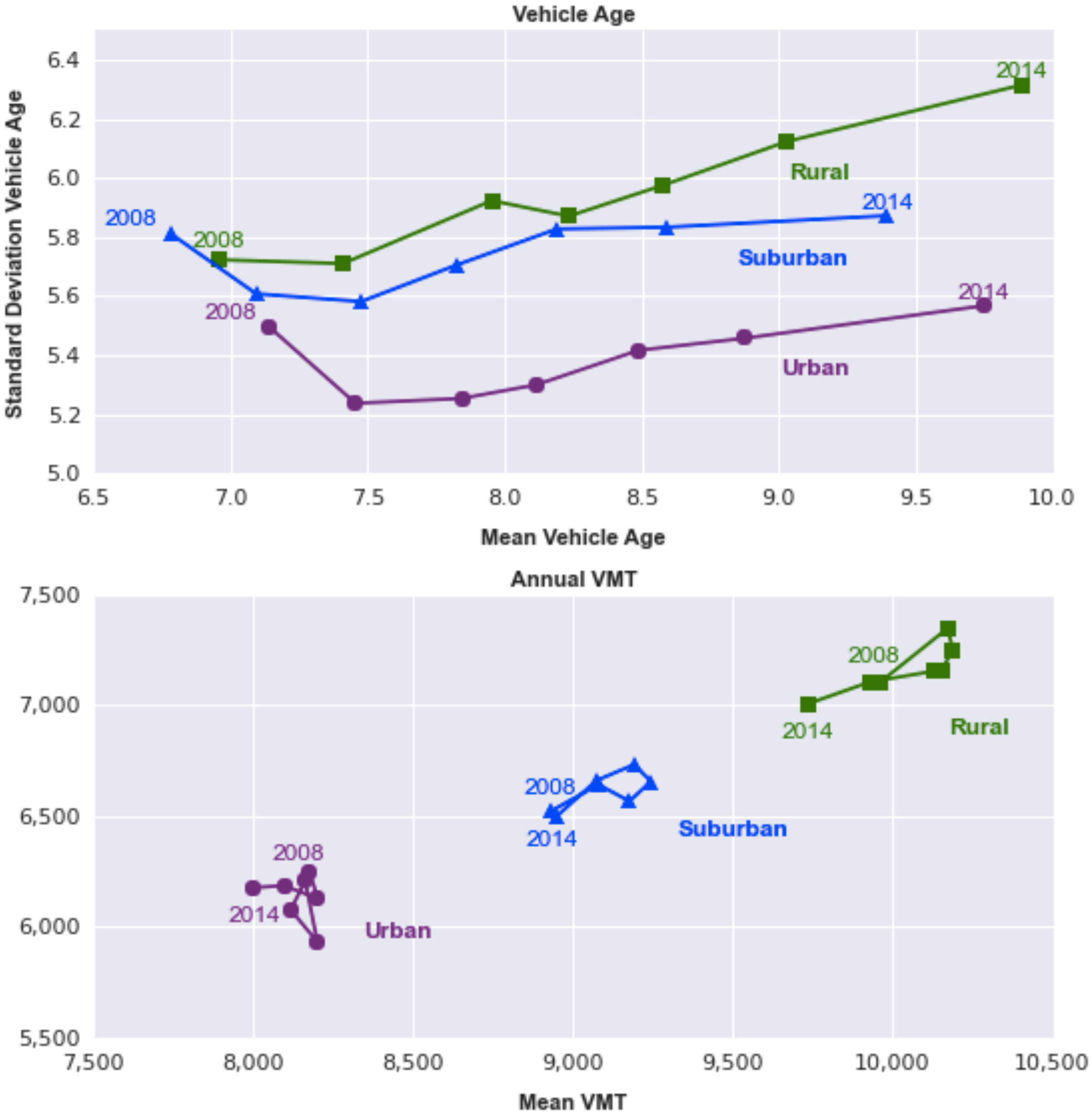


Figure 26. Standard Deviation versus Mean by Inspection Year for (a) Average Vehicle Age and (b) Annual VMT

When comparing the distribution of each mean by observing the associated standard deviation, rural always has the largest standard deviation and urban the smallest, this is especially noticeable for the VMT averages. Looking at mean vehicle age, suburban vehicles are youngest on average in any given year and rural oldest except in 2008. However, this could be an artifact of not having as much data in 2008. There is no overlap in mean VMT between urbanity locations, though the ranges are very large, leading to the conclusion that there are some vehicles that travel in urban areas similar to those in rural areas and vice versa, but looking only at the means, these VMT patterns differ by about 1,000 miles between urbanity locations.

While we see very different driving patterns in each urbanity location, we still observe that as the fleet ages, vehicles are driven less, which is consistent with the trend seen in previously in Figure 19 and is shown separately for each urbanity classification in Figure 27.

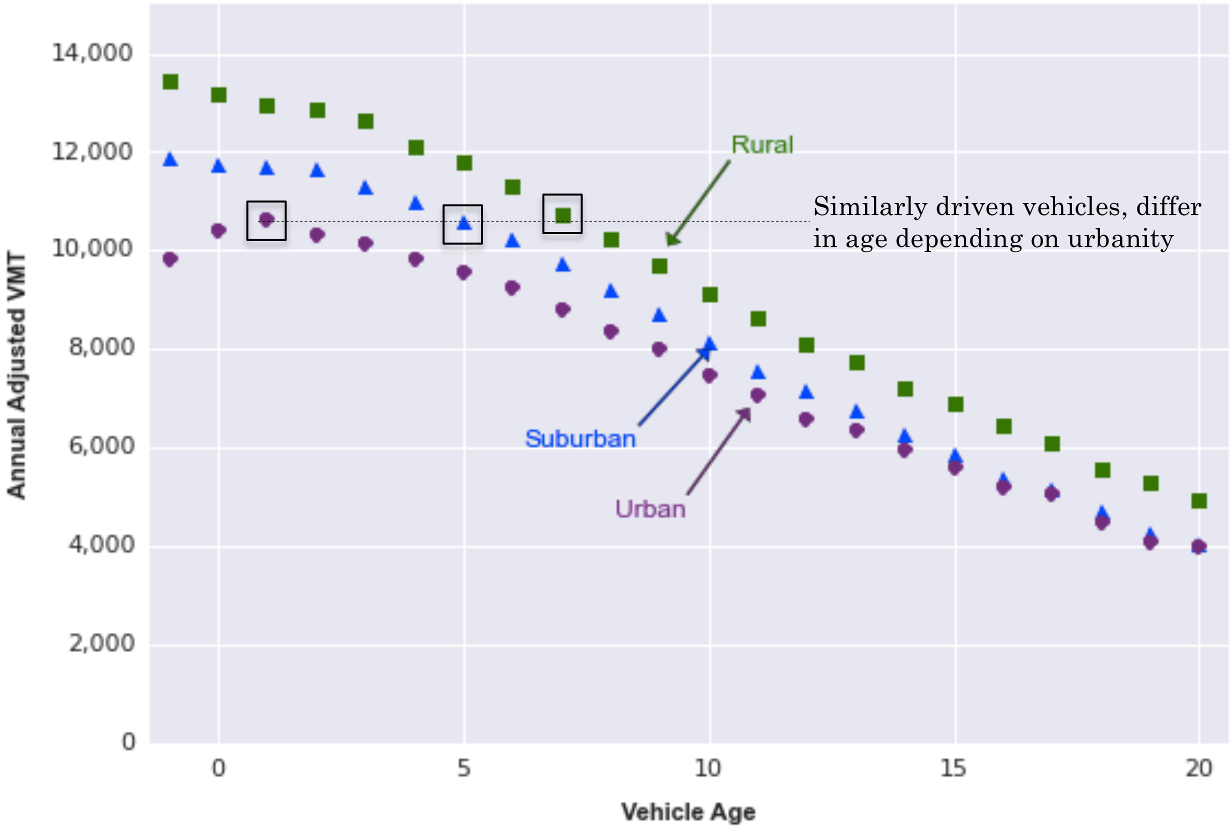


Figure 27. VMT Distribution as vehicles age by zip code urbanity

While the trends are very similar between zip code urbanity classifications for annual VMT by vehicle age, there is still a noticeable difference between urban and rural driving. It is seen in Figure 27 that a one-year-old vehicle in an urban area is driven, on average, similarly to a five-year-old vehicle in a suburban area and a seven-year-old vehicle in rural areas. These distinctions between urbanity locations become less noticeable as average vehicle age surpasses ten years old. These clear differences in how vehicles driven as they age in different urbanity locations could help guide policy makers in the future when designing policies based on vehicle age, the simplest to implement without requiring the collection of odometer readings or vehicle owners to report odometer readings.

While a zip code level of urbanity classification distinctly classifies home zip codes accordingly, it is argued here that in doing travel analyses, in many cases, a vehicle will not only be driven in the home zip code and possibly even outside of the home county. As a result, it is not necessarily preferred to analyze travel using zip code urbanity designations, but instead would depend on the type of analysis being performed.

The following section proposes a method to assign these vehicles to households based on insurance policy values and observes any differences in travel based on households rather than single vehicles.

V. Household Data

Currently, available household travel data primarily comes from surveys conducted under the supervision of the U.S. DOT FHWA. These surveys take a lot of time as they are conducted over an entire year and require phone calls to be made and vehicle owners to be willing to participate. The NHTS data is comprised of about 150,000 households across the U.S., which accounts for approximately 0.1% of all households, as noted previously. In comparison, the PA safety inspection data allows the same calculations for the sample size of about 580,000 households (8% [59]) over 6 years (about 100,000 per year in the more recent years), after filtering, for only the state of PA, which provides more data with less time, effort, and cooperation. Additionally, this data is available yearly, whereas NHTS data is only published every five to eight years. This section uses the same PA VSIR data to define households in order to compare travel patterns by household similar to the vehicle travel patterns in the previous sections of this chapter. Finally, a study published by NHTSA using NHTS data is replicated using the PA data.

Households in PA are approximated by grouping vehicles together based on their associated insurance policy values, with the assumption that vehicles in a given household are all insured under the same insurance policy. This required combining the insurance

NAIC value, which identifies the company, with the insurance policy number, which identifies the policy under which vehicles are listed. This method allowed for the formation of households to be made, and by sorting vehicles into unique households, household size values based on the number of vehicles under a given insurance value were assigned to each vehicle. The resulting household data is summarized by inspection year and household size and presented in Table 15.

Table 15. Summary of Household Travel by Inspection Year and Household Size

Inspection Year	Vehicles per Household	Number of Households	Number of Vehicles	Annual VMT Total (million miles)	Annual VMT per Household (miles)	Annual VMT per Household Vehicle (miles)
2008	1	35,000	34,000	327	9,480	9,480
	2	3,700	7,400	69.3	18,700	9,370
	3	410	1,200	10.7	26,100	8,690
	4	56	220	2.06	36,800	9,210
2009	1	56,000	55,000	535	9,610	9,610
	2	6,900	14,000	128	18,800	9,380
	3	970	2,900	26.8	27,700	9,220
	4	140	550	4.79	34,700	8,680
2010	1	68,000	68,000	651	9,580	9,580
	2	8,800	18,000	166	18,700	9,370
	3	1,300	3,800	35.3	27,600	9,210
	4	170	700	6.19	35,600	8,900
2011	1	76,000	76,000	725	9,540	9,540
	2	9,800	20,000	182	18,600	9,300
	3	1,400	4,100	37.1	27,200	9,050
	4	230	930	8.54	36,500	9,120
2012	1	83,000	83,000	792	9,490	9,490
	2	10,000	20,000	188	18,600	9,310
	3	1,400	4,300	38.9	27,100	9,040
	4	210	860	8.00	37,400	9,350
2013	1	100,000	100,000	964	9,340	9,340
	2	12,000	25,000	226	18,300	9,130
	3	1,800	5,400	47.5	26,400	8,810
	4	290	1,200	11.4	39,400	9,850
2014	1	88,000	87,000	806	9,200	9,200
	2	10,000	20,000	180	17,700	8,860
	3	1,300	4,000	34.6	26,000	8,680
	4	180	720	6.03	33,500	8,370
Average (2008-2014)	1	73,000	72,000	741	9,440	9,440
	2	8,800	18,000	176	18,400	9,220
	3	1,200	3,700	36.5	26,900	8,970
	4	180	730	7.75	36,600	9,140

The majority of household data were classified as single-vehicle households (88%), followed by two-vehicle households (10%). It is noted that this data is a sample and because reporting of data is under the discretion of the inspection stations, it may not contain every vehicle in a given household. Additionally, the method of assigning households depends on a household insuring all of their vehicles under the same policy in addition to all of the vehicles actually being housed at the registration zip code location. It is possible a household has separate vehicle insurance policies. Also, it is possible vehicles are registered at a given zip code, yet the majority of the time are housed and driven elsewhere. Finally, due to manual entry of inspection data, there may be incorrectly recorded policy values and as a result, vehicles cannot be assigned to the appropriate household. For example, in the sample data, a 3-vehicle household may be classified as a 1-vehicle household if only one of these vehicles is recorded in the sample data. Due to these limitations, we expect greater uncertainty and standard deviations in these household estimates than the previous analysis when observing each vehicle equally.

As a result of small sample sizes for each defined household, analyses are performed as an average over the available inspection years and no urbanity analysis is performed. With more data, these analyses would be possible. The most data is calculated for 2013, likely due to the most inspection matches being able to be made between years prior to and after 2013, capturing the most pairs. Over the six years of data and the average of the six years, single-vehicle households have the highest annual VMT per household vehicle (Figure 28).

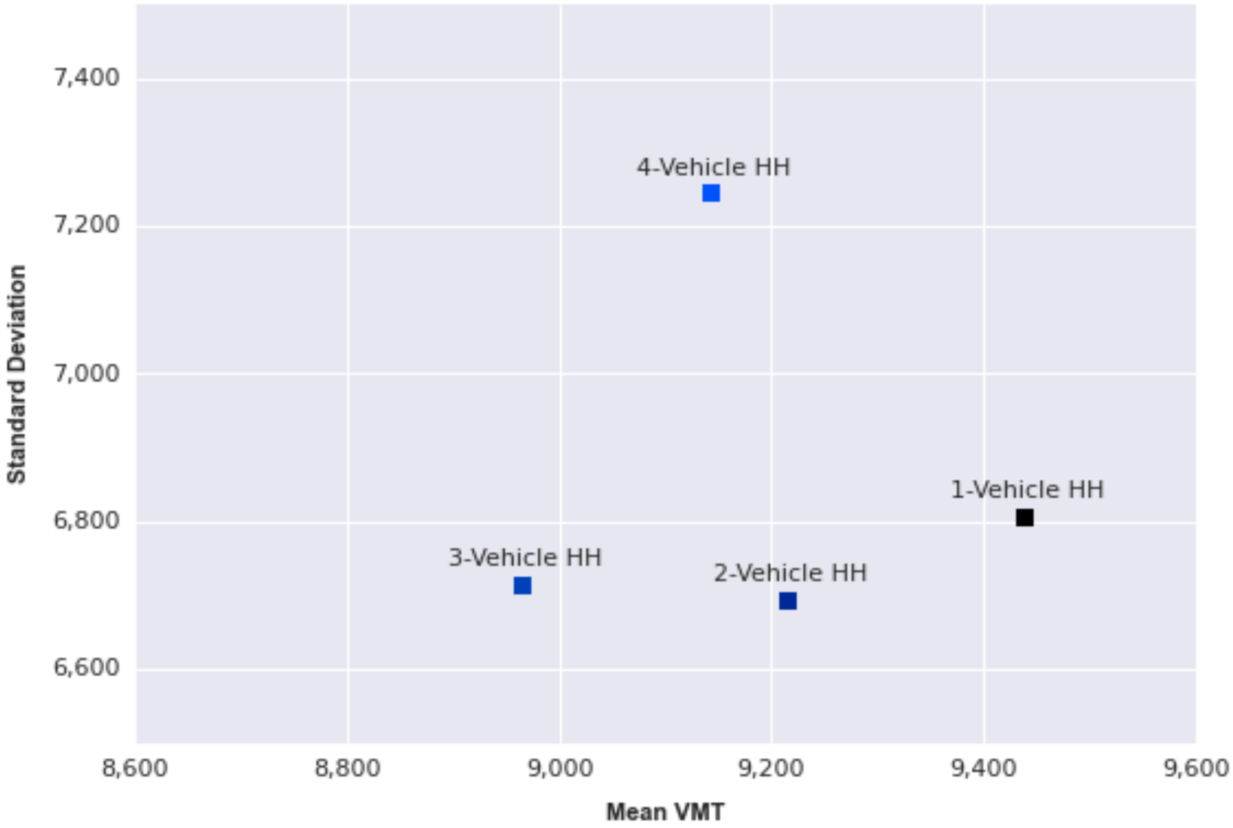


Figure 28. Average annual VMT and standard deviation by household vehicle count, average 2008-2014

The average household per-vehicle annual VMT over all the data was found to be approximately 9,000 miles and the mean VMT between each type of household only varied by 500 miles. On the other hand, large standard deviations are observed for all households (between 6,600 to 7,300 miles). It is possible these very high standard deviations are due to not accounting for urbanity in the household analysis. As we saw previously, urbanity is an important predictor in VMT.

These results do not match results from NHTS data, which shows that 2-vehicle households on average drive more per vehicle. Additionally, since the number of registered vehicles in each household is not available for the state on this detail, the representativeness of this sample data cannot be checked. As a result, while this shows an estimated result, it is still possible some households are classified incorrectly due to lack of data or misclassified households.

Vehicle age is observed by household vehicle size and it is found that households with more vehicles tend to have an older average overall age (Figure 29).

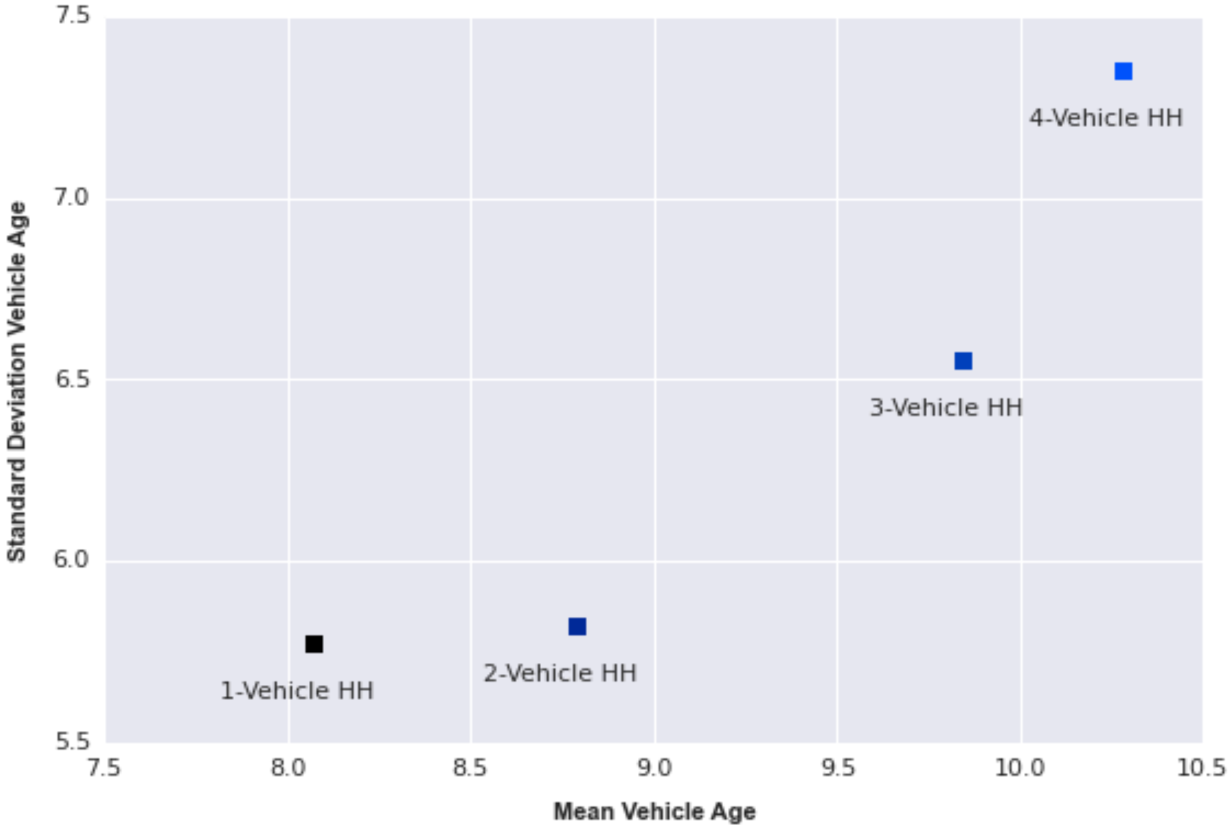


Figure 29. Average household vehicle age versus standard deviation by household vehicle count, average 2008-2014

Based on the previous VMT results by household vehicle count, this is opposite what is expected; in the previous section it was observed that younger vehicles drive more and VMT decreases with age. Here, it is observed that while 1-vehicle households drive most on average per vehicle, 4-vehicle households have the youngest average vehicle age (though they drive least). Due to this phenomenon, average annual VMT by vehicle age is observed for each household. The summary result over the six inspection years is presented in Figure 30.

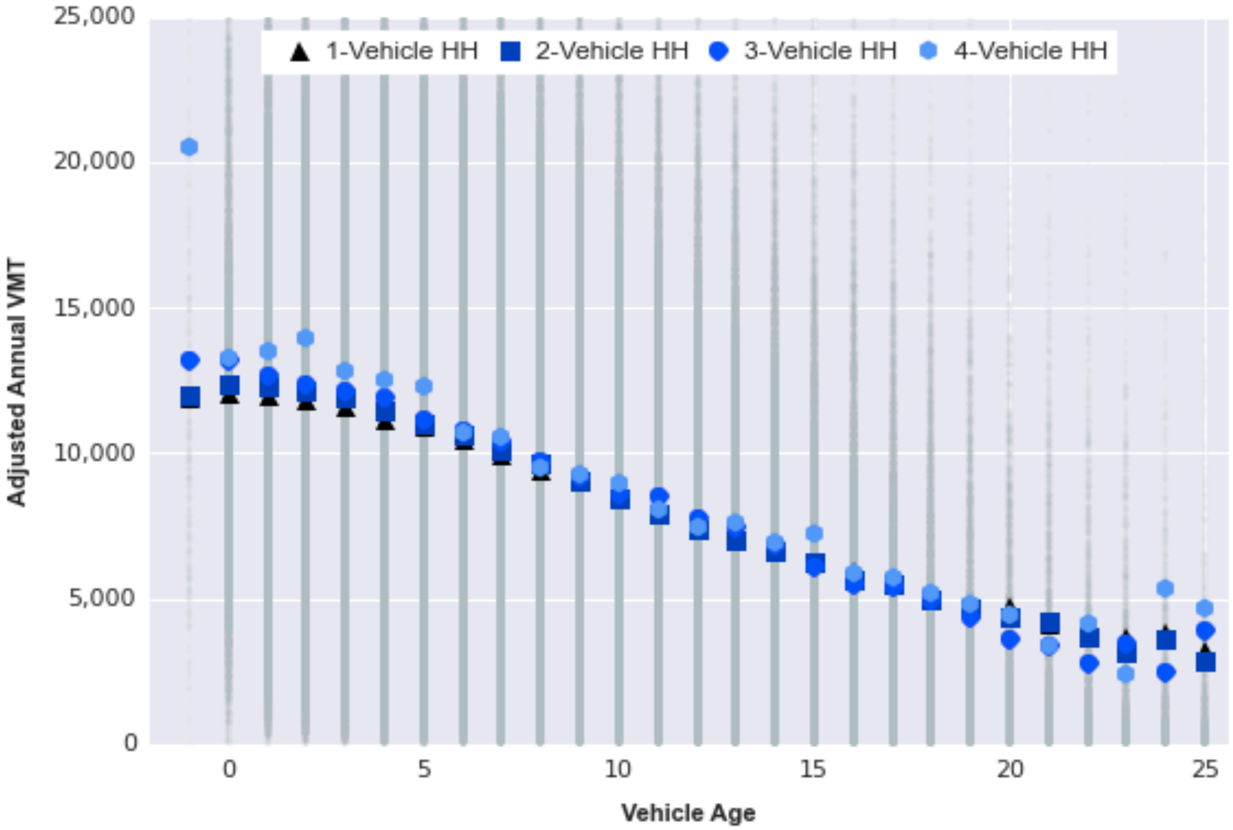


Figure 30. Average Household Adjusted Annual VMT versus Vehicle Age by Household Vehicle Count, average 2008-2014

Each household, no matter the number of vehicles, follows approximately the same relationship trend between the household adjusted annual VMT and the average vehicle age in the household. These results are also consistent with the analysis on a single vehicle basis, prior to assigning the vehicles to households. Since there are no obvious differences in VMT between households for vehicles of the same age, further analysis is necessary to determine any reasoning behind the larger households having the youngest average age yet driving the least and vice versa. Additionally, it is investigated why NHTS results show 2-vehicle households having the highest average per-vehicle VMT while the PA sample results show 1-vehicle households having the highest. Again, it would be best to know the distribution of number of registered vehicles per household in the state in order to find the representativeness of the sample data.

V.1. *Vehicle rankings: Most-driven vehicles in households*

In April of 2015, the US Energy and Information Administration released an article on household vehicle travel, using data from NHTS, concluding that households with more vehicles put more miles on their most-used vehicles compared to households with fewer vehicles. Their findings are summarized in Figure 31.

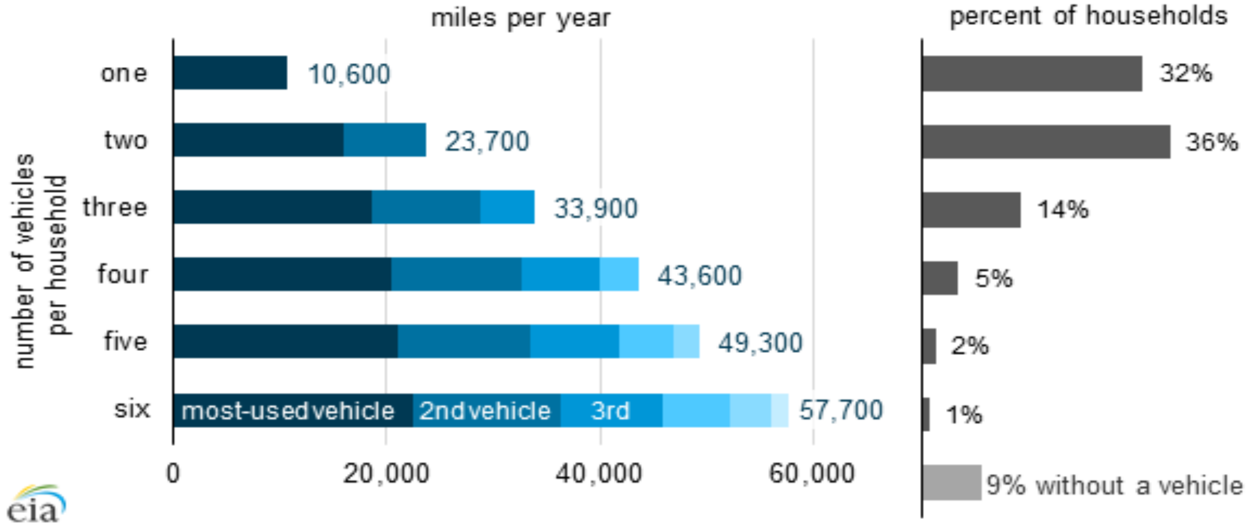
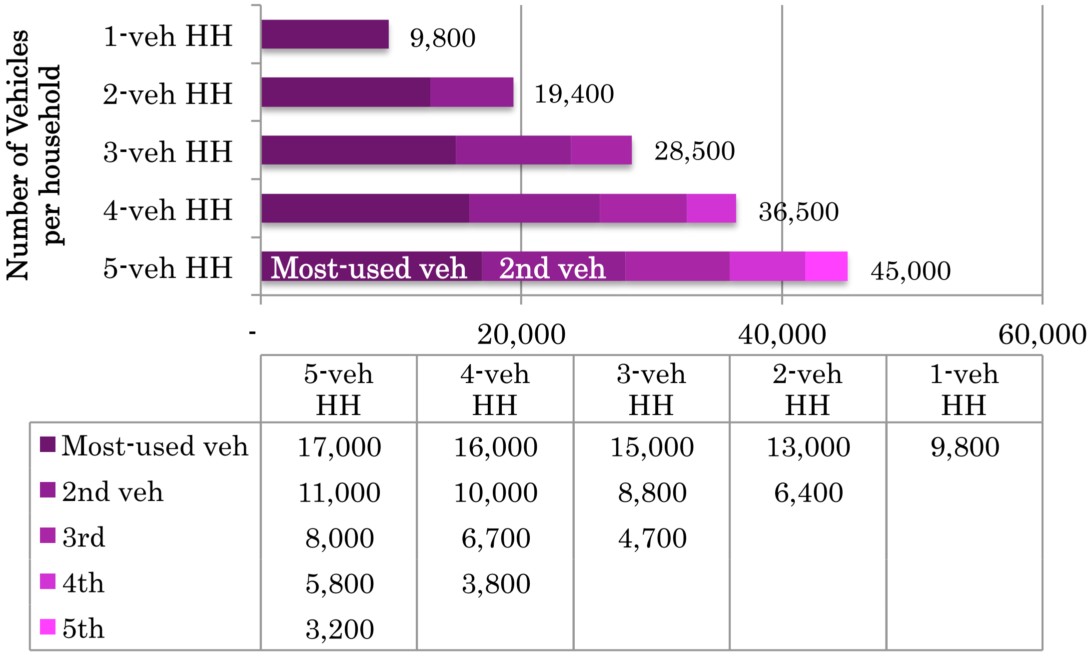


Figure 31. Average annual vehicle miles of travel per household using NHTS data [69]

The data used in this analysis comes from the NHTS latest 2009 household survey data (refer to the background section of this chapter). With the PA data, Figure 32 was created in order to compare findings.



	5-veh HH	4-veh HH	3-veh HH	2-veh HH	1-veh HH
■ Most-used veh	17,000	16,000	15,000	13,000	9,800
■ 2nd veh	11,000	10,000	8,800	6,400	
■ 3rd	8,000	6,700	4,700		
■ 4th	5,800	3,800			
■ 5th	3,200				

Figure 32. Average annual vehicle miles of travel per household using PA safety inspection data, average 2008-2014

While the total miles per year is slightly higher using the NHTS data compared to the results using the PA data, the overall findings of VMT per vehicle rank are very similar. First, this may be due to the difference in the annual VMT between PA, of 99 billion miles, and the overall U.S. state VMT weighted average of 124 billion miles. [28] So, the PA data should in fact have smaller VMT values. Households with more vehicles drive their most-driven vehicle more and this trend continues for each additional vehicle in multivehicle households. Likely, the reason behind these results is that households invest in more vehicles because their main vehicle is unavailable (due to high usage) and there are multiple drivers. Even though households with more vehicles put more miles, annually, on their most-driven vehicle, the annual VMT averages of each sized household were all still approximately the same, calculated previously (refer to Table 15 and Figure 28). These findings based on the most-used vehicle in a household are presented graphically in Figure 33.

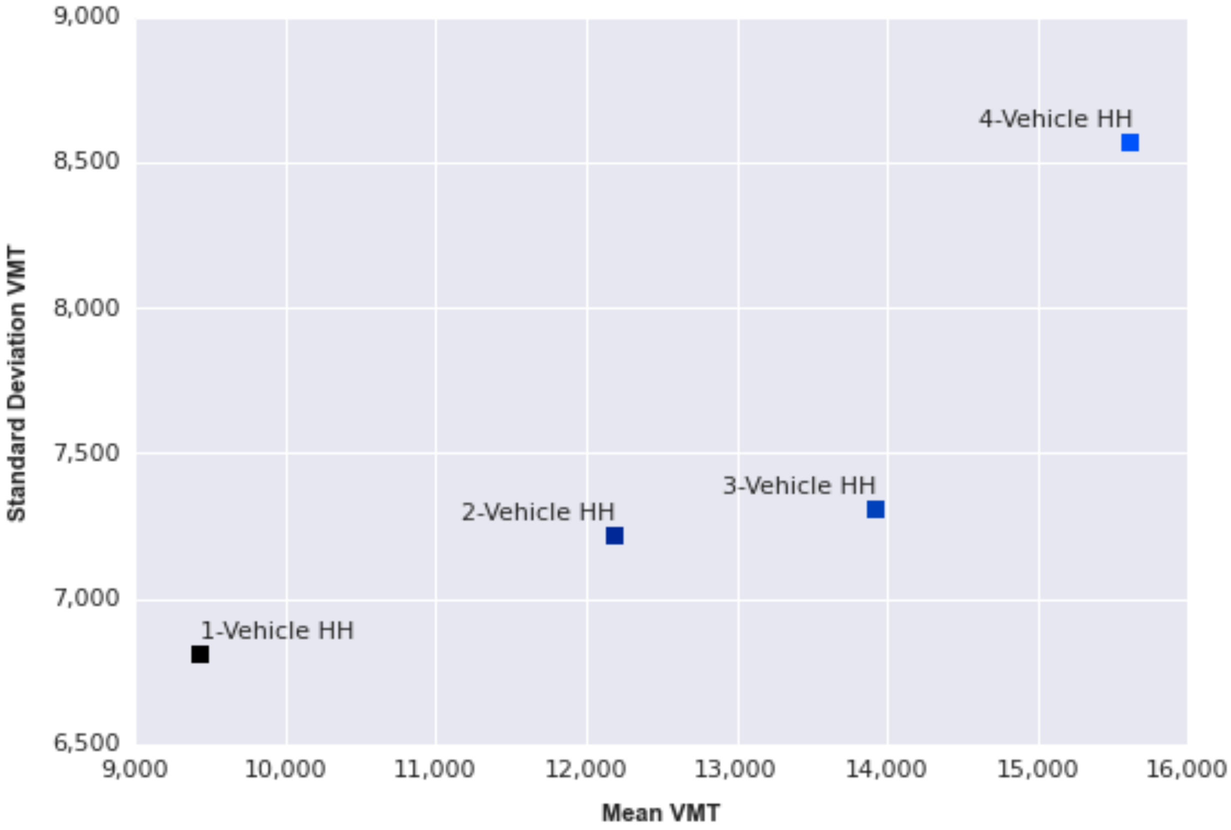


Figure 33. Mean and standard deviation of annual VMT for the most-driven vehicle by household vehicle count, 2008-2014

These results are opposite of the overall household averages. Here, 4-vehicle households drive most and decrease according to the number of vehicles. In comparing standard deviations, 4-vehicle households consistently result in the highest standard deviation, likely due to the smaller sample sizes than the other households. The age distribution for the most-driven vehicles by household vehicle count was also calculated and is presented in Figure 34.

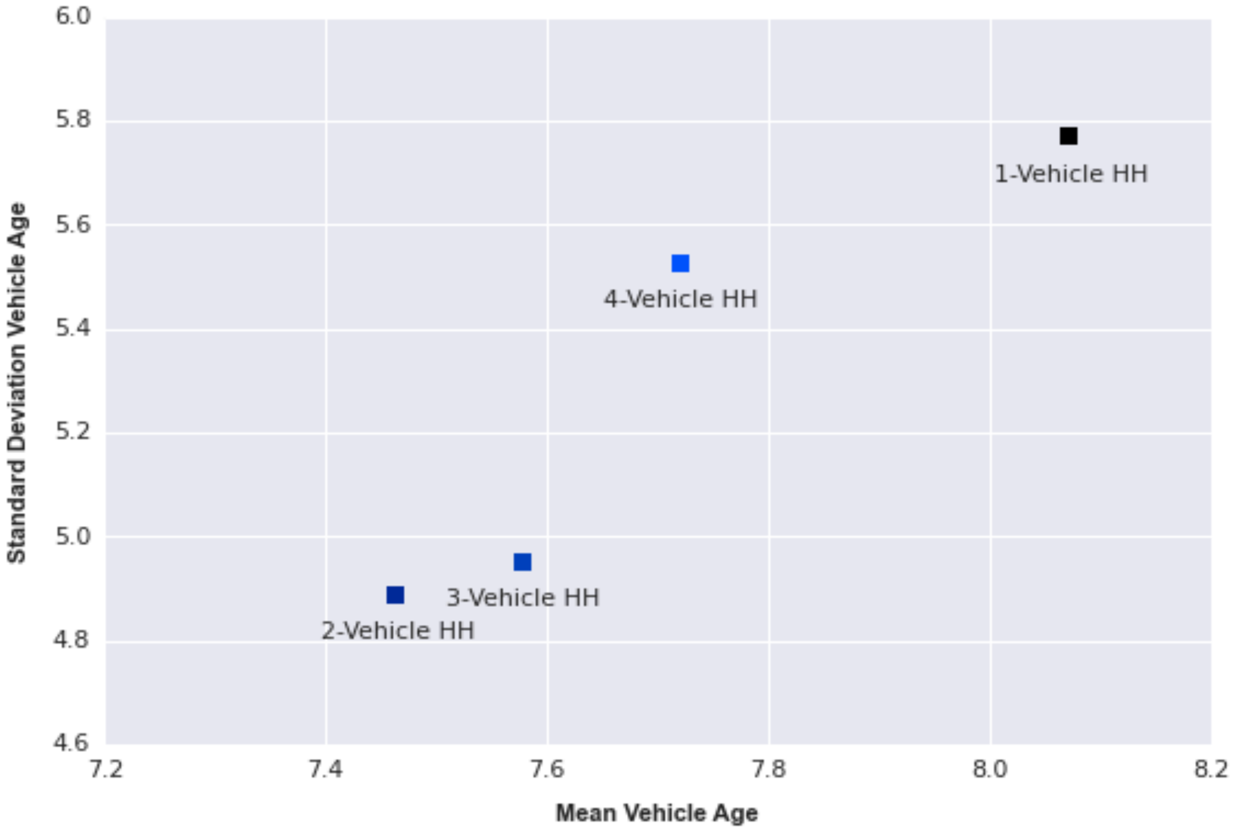


Figure 34. Mean and standard deviation of vehicle age for the most-driven vehicles by household vehicle count, 2008-2014

The results here show that on average, the most driven vehicle in 1-vehicle households are the oldest, followed by the most-driven vehicle in 4-vehicle households, and the most driven vehicles in 2-vehicle and 3-vehicles households on average are approximately the same age and also the youngest. However, they are all very close in age resulting in only a one year difference between the youngest and oldest most-driven average household vehicle. Furthermore, these same pairs of households have very similar standard deviations. Looking back to the averages for the overall households, 1-vehicle households had the youngest vehicles, yet had the highest annual VMT.

Finally, the relationship between average annual VMT and vehicle age is calculated for the most-driven vehicle in each household (Figure 35).

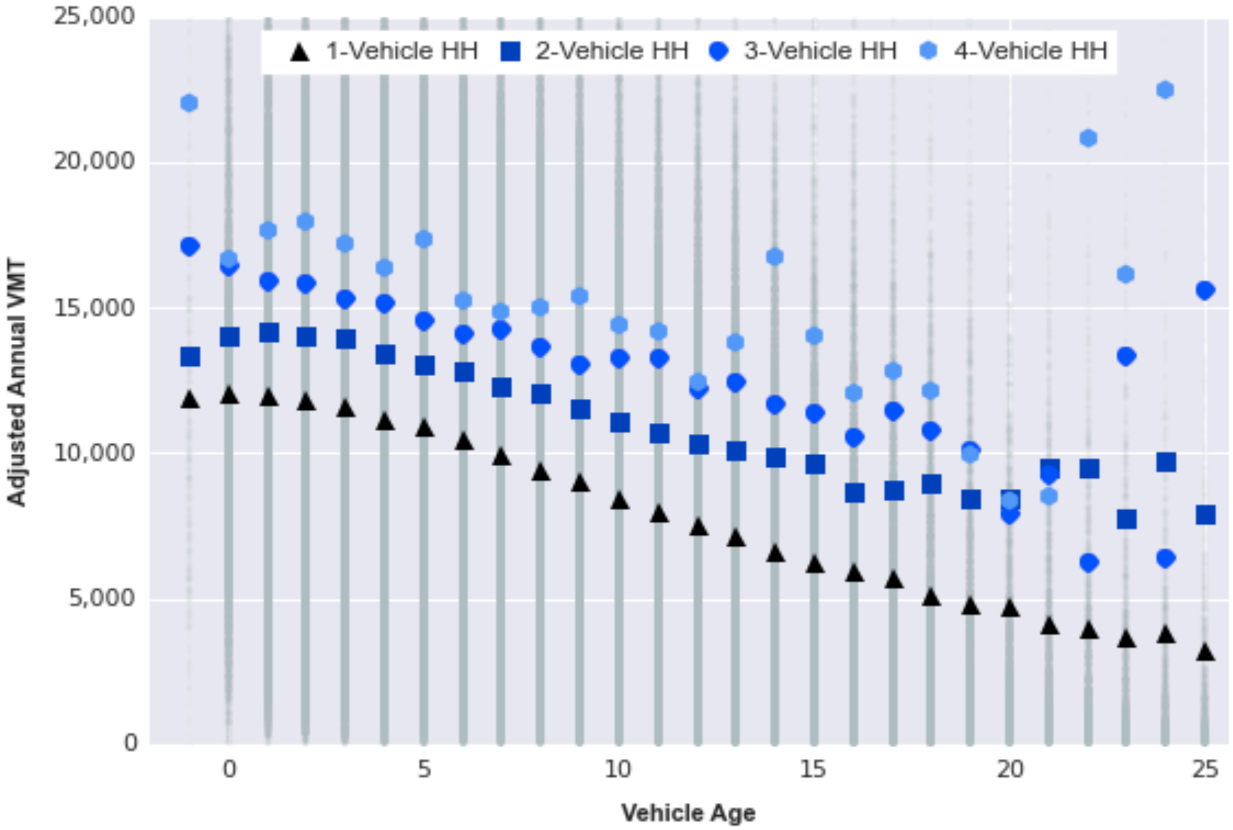


Figure 35. Household Annual VMT versus Vehicle Age for the most-driven vehicle by vehicle-sized households, 2008-2014

All households follow the same trend of decreasing annual VMT as the vehicle ages and all have approximately the same slope of decreasing annual VMT by vehicle age. As seen in the annual VMT distributions for the different households, the most driven vehicle in the larger vehicle-sized households have larger intercepts, again showing that in larger vehicle-sized households, the most-driven vehicle is driven more. This is consistent at any vehicle age. To further understand these comparisons of households, the same calculations were performed for the youngest vehicle in each household type.

V.2. *Vehicle rankings: youngest vehicles in households*

When observing the most-used vehicle in a household, the EIA did not try to distinguish the age distribution of those vehicles using the NHTSA data, nor did they rank households by the youngest or oldest vehicle. The following analyses are similar to the previous section, yet vehicles ranked by age rather than VMT and the youngest vehicles in each household are now considered (Figure 36 and Figure 37).

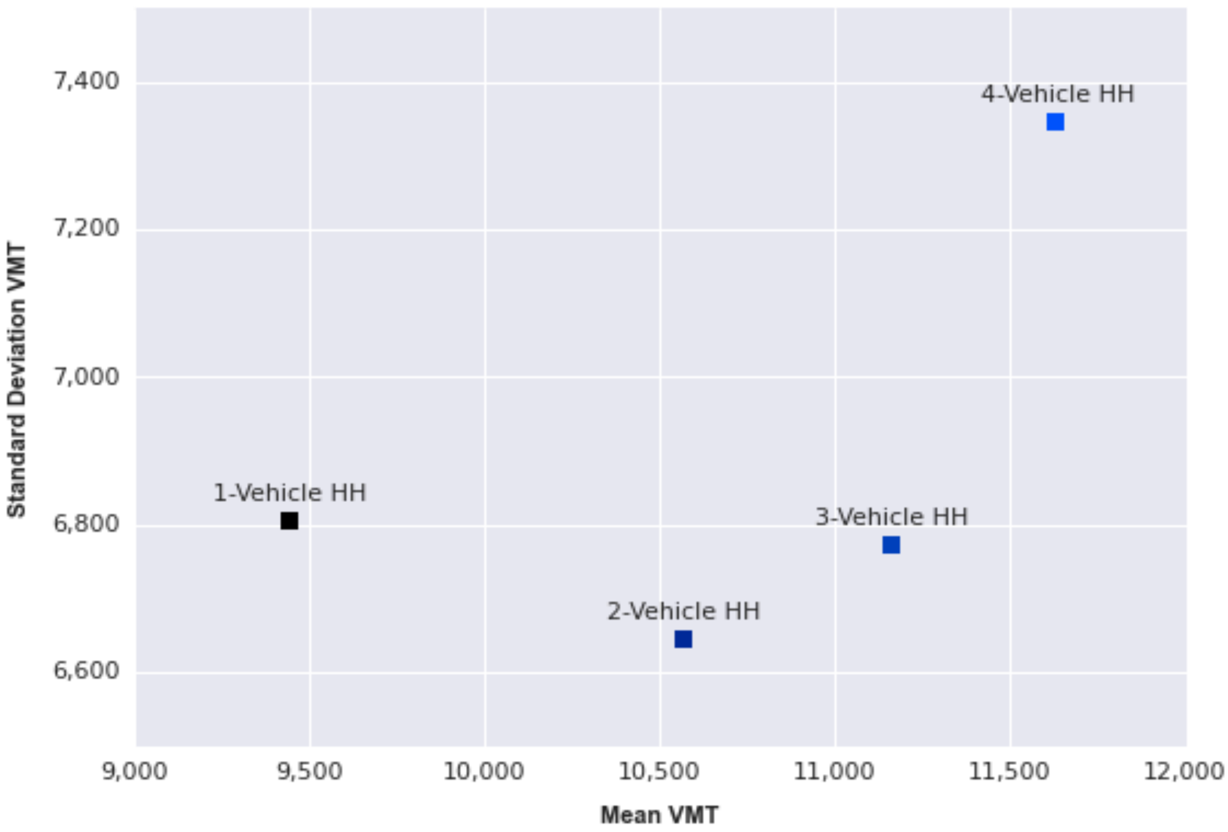


Figure 36. Mean and standard deviation of annual VMT for the youngest vehicle in each vehicle-sized household, 2008-2014

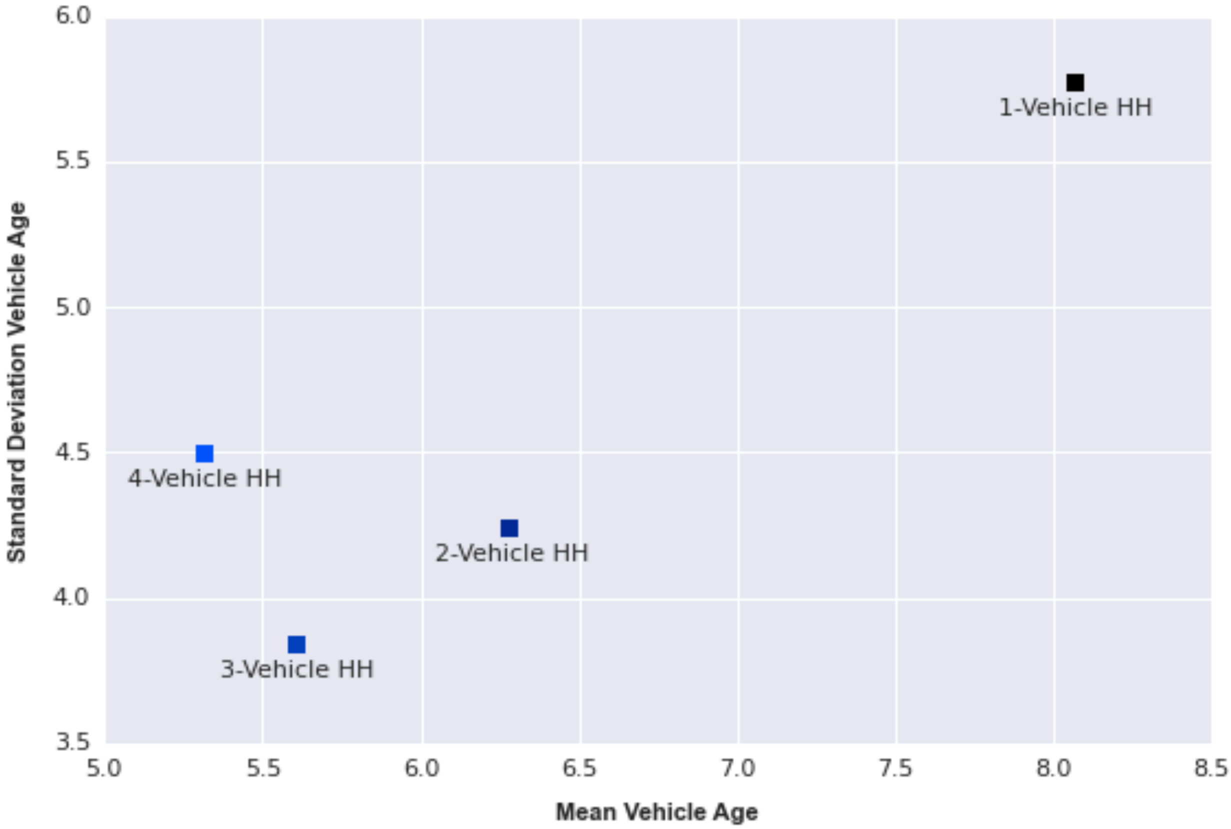


Figure 37. Mean and standard deviation of average vehicle age for the youngest vehicle in each vehicle-sized households, 2008-2014

Observing VMT and average ages of the youngest vehicles in the different households based on vehicle count, on average, the youngest vehicle in the households with more vehicles are driven more than those in households with fewer vehicles, as seen in Figure 36, which aligns with findings from the most-driven vehicles. However, this is opposite the VMT results seen in the overall average for the entire household (Figure 28). Figure 37 shows that 1-vehicle households are oldest in comparing the youngest vehicles per household and have the largest standard deviation. The youngest vehicles in 2-, 3-, and 4-vehicle households are all similar in mean and standard deviation of vehicle age. In comparing annual VMT to average age for the youngest vehicles in households, those with more vehicles drive the newest vehicle more than those with fewer vehicles. In addition, these vehicles are also younger, on average, compared to single-vehicle households. This result aligns with the phenomenon that younger vehicles are driven more than older vehicles.

Finally, comparisons of annual VMT as vehicles age are made between households in Figure 38.

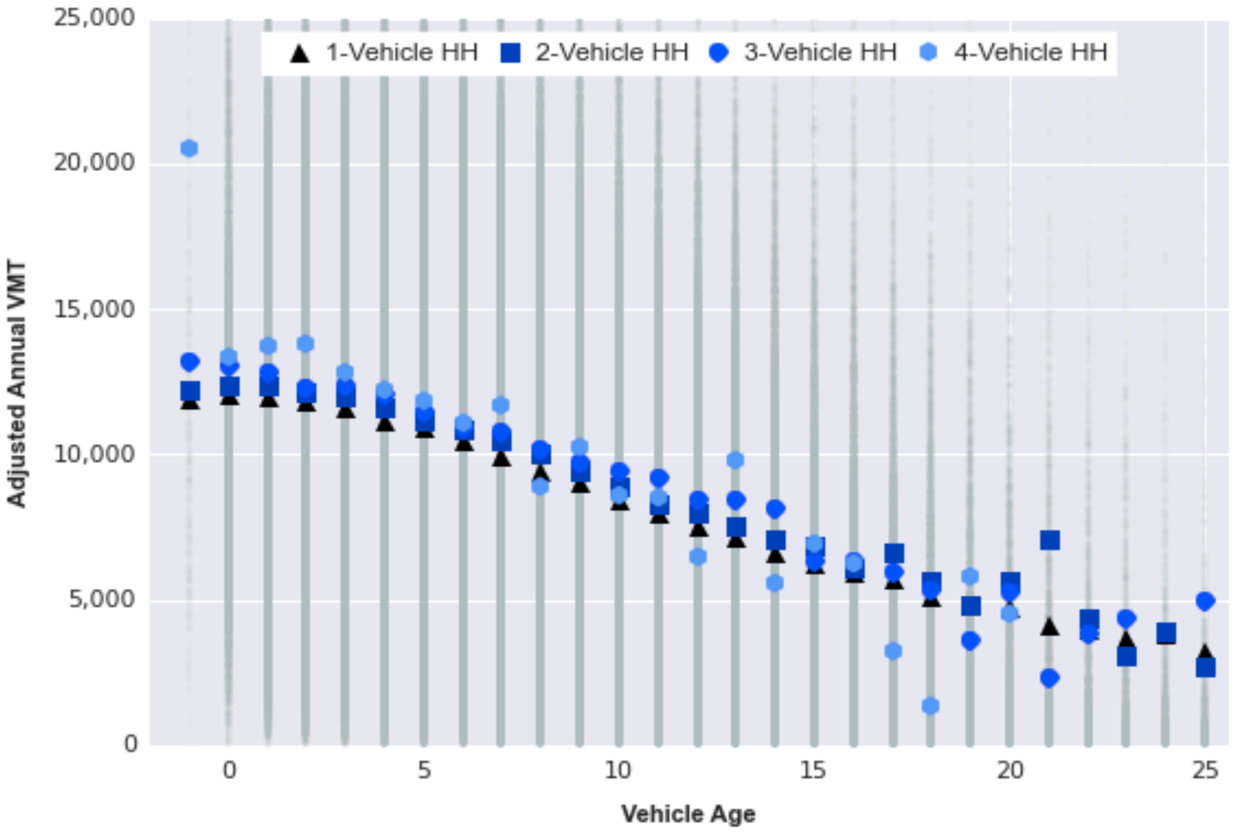


Figure 38. Household Annual VMT versus Vehicle Age for the youngest vehicle by vehicle-sized households, 2008-2014

The same trend of decreasing VMT as vehicles age is observed for the youngest vehicle in households. These results, for the youngest vehicle, show much more similar driving patterns for overall households than in the results seen for the most-driven vehicle in households, where there was more distinction between average VMT as vehicles aged. The averages are more scattered in the oldest vehicle ages due to low sample size.

Chapter V: Conclusions, Policy Implications, and Future Work

In the next decade, changes in transportation will become immense and prominent in daily life. Furthermore, with exponential advances in technology, specifically the increase in autonomy in vehicles, there will be strong, uncertain influences on modes, choices, and trade-offs in transportation, especially when it comes to vehicle safety and travel patterns. This thesis delves into the vehicle-specific data, provided at large by the state of Pennsylvania in order to perform various data-driven recommendations to policy questions pertaining to vehicle safety and vehicle travel both at the vehicle and household levels. Finally, funding sources for the transportation sector is nearly depleted with no clear long-term solution of how to supplement the current mode of monetary contributions by the gas tax and while there are a myriad of options that have been discussed, no moves have been made aside from short-term extensions. [70]

I. Summary and Recommendations

As discussed in Chapter II, legislators in Pennsylvania have been currently discussing and debating the necessity of the annual vehicle safety inspection program. Since there are no recent studies providing the necessary analysis proving the effectiveness of the safety inspection program, many states have recently discontinued their programs, prompting Pennsylvania to ask the same question. At large, Chapter 2 answers the question of whether safety inspections in Pennsylvania keep vehicles safe, strictly from a maintenance perspective. Pennsylvania is unique in the sense that it records a sample of these inspections electronically, allowing for initial data-driven analyses of the program's performance. The data show clearly that vehicles require more maintenance for each of the following: the higher the odometer reading, the older the vehicle, and the more rural the registration zip code. Additionally, the claimed 2% failure rate only applied to vehicles within their first year. Failure rates were found to be much higher for all other vehicles with the average found to be around 12%-18%.

In order to make this program more effective, it is recommended that oversight of the safety inspection program be increased drastically. With new technologies, data can be recorded and analyzed instantly for both inspection stations and each inspector to be sure they perform similarly to other inspection stations and inspectors evaluating similar vehicles.

Chapter III incorporates fatal crash data for the entire U.S. in order to observe whether states with more stringent vehicles safety inspections have lower fatality and fatal crash rates. This analysis accounted for the urbanity of each state as well as the geographical location of the state and any changes over time. Due to the difficulty in defining the stringency of each state's program, a number of models were created in order to account for the variability in defining states. Ordinary least squares regressions were implemented for each model. The findings showed that in 95% of the models implemented, the more stringent programs had lower vehicle fatality rates. The remaining 5% of the regression models that did not support safety programs resulted from only using one-year averages of fatalities. More compellingly, statistically significant results (at an alpha level of 0.05), in support of safety programs, were found in about 7%-8% of the models. In these models it can be concluded safety inspections are statistically effective in reducing fatality rates by approximately 1-2 fatal crashes per billion VMT in a given year. Additionally, urbanity was always found to be significant, which confirms the need for robust VMT estimates. Hypothesis tests were also performed in order to evaluate whether safety attributed fatalities were different between safety states and non-safety states. This test proved to be more challenging as a vehicle registered in a safety state may be involved in a crash in either type of state, and same scenario for a non-safety state registered vehicle. Also, due to potential underreporting of crash reasons, the sample size was extremely small for this analysis. It is therefore concluded that these hypothesis tests contradict one-another and no insightful conclusions can be drawn on specific coded fatalities. The lack of consistency here is evident and more strongly suggests the need for data consistency, management, and oversight. Robust data is necessary for the advancement and improvements in vehicle safety.

Chapter IV used the same PA vehicle safety inspection data from Chapter II in order to analyze travel patterns both from a vehicle and household perspective. While average VMT data is publically available as averages for each urban and rural area by state, it is not available on a zip code level nor does it contain ranges or other characteristics of vehicles, such as age. With the sample of vehicle data from the state of PA, we are able to observe differences between travel and vehicle ownership in general at a home zip code level and therefore variations within counties and overall urbanity in the state.

Additionally, we are able to see these specific comparisons and how they vary over time. We observe that while average annual VMT over time is relatively consistent over many of the years observed and much higher in rural areas, vehicle ages consistently increase each year and are approximately the same in comparing urban versus rural areas. Finally, calculations are made in order to assign vehicles to households. This limited the analyses largely due to low sample sizes and the inability to check for representativeness, but loose conclusions could be drawn between households based on vehicle counts and align with a similar study using NHTS data.

II. Policy Implications

The data-driven analyses in this thesis investigate the role of safety inspections and their relationship to vehicle maintenance in the state of Pennsylvania, the role of safety inspections across the U.S. and their effect on fatal vehicle crash rates. The question of whether Pennsylvania should continue their highly stringent vehicle safety inspection program is of great interest to legislators in the state. In addition, it may help distinguish where implementation of this program would be most beneficial, in other states.

It is estimated that the economic costs of motor vehicle crashes in 2010 was about $242 billion. [46] Fewer fatal vehicle crashes will lead to lower associated costs when considering vehicle repairs, hospital bills, and lost time. As a result, this section calculates the estimated dollar per life saved in a given year due to the vehicle safety inspection program, largely using the results from Chapter III. This is performed for two different scenarios. Scenario 1 assumes all states with no safety inspection program now implement an inspection program similar to PA, resulting in the cost per life saved due to implementing the program in those states. Scenario 2 assumes that all states with an annual inspection program eliminate them, resulting in the additional costs that are now incurred in those states. It was concluded from the regression results in Chapter III that a safety inspection program may reduce fatalities by 0.1-3.5 per billion VMT. In a small state without an inspection program, such as Connecticut, 2.0 million vehicles registered traveled approximately 31.2 billion miles in 2013. A larger state such as Florida that also does not have a safety inspection program totaled about 192 billion miles over the 7.2 million vehicles registered. [55] Additionally, we can examine the most stringent program currently implemented, in PA, which charges approximately $40 ± $10 per inspected registered vehicle and an average cost for a safety repair of $255 ± $128, calculated from the sample data.

This results in a total reduction in fatalities of about 56 (3-109) in Connecticut, which had a total of 276 deaths in 2013 [2], at a cost of $582 million ($310 million to $855 million). If Connecticut were to implement a safety inspection program similar to Pennsylvania's, they would see costs around $10.4 million per life saved ($2.8 - $274 million per life saved). In comparison, a similar calculation is performed for Florida, which resulted in an approximate cost of about $6.1 million per life saved ($1.7 - $162 million per life saved). The Department of Transportation recommends that a minimum and maximum value of a statistical life (VSL) be used, rather than an average, in analyses ranging from $5.2 million to $13 million. [71] It is concluded from these results that the value of the safety inspection program, one similar to that of Pennsylvania's is worthwhile depending on where the cost per life saved falls within the calculated range. Additional calculations are made for all states under these same scenarios, cost assumptions, and fatality reductions, and the results are presented in Table 16.

Table 16. Overall U.S. Estimated Cost per Life Saved by Scenario

	Vehicle Miles Traveled (billions)	Vehicles Registered (millions)	Delta Fatalities	Average Cost per Life Saved (5th-95th Percentiles)
States with No Inspection Program, **now implemented**	1,430	60	2,600 (140 – 5,000)	$6.8M ($1.9M - $180M)
States with Annual Inspection Program, **now eliminated**	860	40	1,500 (86 – 3,000)	$7.1M ($1.9M -$190M)

These costs assume that any vehicle inspected will incur some sort of repair cost, which results in an upper bound cost range. Additionally, the benefits from the safety inspection program only consider the reduction of fatalities, excluding any benefits due to decreased non-fatal crashes. This creates a lower bound for the estimated benefit from the program. As a result, the average and range values shown in Table 16 are likely higher bounds of actual results, leading to the conclusion that states highly consider and carefully calculate the resulting benefits from the vehicle safety inspection program.

It is therefore recommended that Pennsylvania continue to implement their program and furthermore, other states should look into also implementing the program if they do not currently have one.

Another policy implication that stems from this thesis research, involves using the estimated VMT values from Chapter IV. Over the past year, numerous discussions have been held by Congress, discussing the current state of the Highway Trust Fund, the main source of funding for roads and transit in the U.S. The current source of money for this account is from gasoline tax, which first, has not been increased since 1993 (20 cents per gallon), but second and more importantly, does not provide as large of a source of monetary value as it used to as vehicles have been come more fuel efficient. In fact, electric vehicles are completely excluded from this tax. In 2009, Zhang et al. proposed a vehicle mileage fee be placed based on income and spatial equity, based on households. This is accomplished by employing vehicle ownership and type-choice models and regression-based vehicle-use models. More specifically, distributional effects of the VMT fee (based on residential urbanity and income levels) are not found to be significant; they need not be a factor in a future implementation of a VMT fee. [72] In December of 2012, GAO similarly recommended that Congress further explore mileage fees and consider implementing a pilot program. [73] In order to tax on VMT, a robust source of VMT data is necessary in order to find the most effective policy to implement. An additional benefit to a finer level availability of VMT data may help lead to more precise analyses in a variety of situations where transportation investments should be made.

In the near future, with the introduction of increased autonomy in vehicles, vehicle owners who had less desire or ability to drive may now be more willing to drive with the autonomous capabilities vehicles will have to offer. It is possible this advantage of increased safety (by reduction of distracted driving) due to autonomous feature in vehicles, may also lead to a disadvantage of increased travel that a VMT fee would mitigate. However, there is also the potential effect of fully autonomous vehicle ride-share, which may help with congestion, but a fully automatic vehicle may not be allowed on the roads for quite a while.

III. Future Work

After completing the work in this thesis, additional questions have become evident and are detailed in this section. First, we saw in chapters II and III depended greatly on VMT estimates and at a more detailed level than just estimating state averages. In chapter IV when VMT was analyzed by urbanity, it was evident that vehicle age and vehicle miles traveled did not follow the similar trends over time. Rural VMT is much higher than urban, yet vehicle age was observed to be equivalent between urban and rural zip codes. The question arises if this is the same trend that would be found in all states? Moreover, circling back to the initial safety inspection program motivation, the question of how VMT and vehicle age in safety versus non-safety rural areas vary. Data for the entire U.S., similar to that of PA is necessary for this analysis.

Similarly, future work and more data would include household analyses separated by urbanity, as this is an important variable in determining VMT patterns as seen earlier in the chapter. Unfortunately, the analysis and data presented in this thesis did not consist of a large enough sample size to breakdown household travel by urbanity. It would also be beneficial to obtain counts of number of licensed drivers per household in order to note differences in travel patterns based on more than the number of vehicles per household. Additionally, comparisons between households with the same number of vehicles could be made.

Along these same lines of needing additional data to increase sample sizes, future work will include adding in all the CompuSpections inspection data from Chapter II to the analyses in Chapter IV, which uses only e-SAFETY data, for the VMT analysis for vehicles in the state of PA in addition to the households. These two datasets are composed of different VINs of vehicles in the state and therefore would only add to the sample size.

Additionally, another analysis would compare the differently ranked vehicles between households to see if there are any similarities. For example, based on the results found previously, it may be concluded that the 2nd or 3rd ranked vehicles in the households with more vehicles are driven similarly to the vehicle driven in the single-vehicle household. This means households with one-vehicle may still drive less annually than the lower ranked vehicles in the households with more vehicles. At this point, it is necessary to look at number of licensed drivers per household as households with more licensed drivers may require more vehicles as each driver is similar to a single-vehicle household and therefore no confident conclusions can be drawn on households by vehicle count from this household-level analysis, though they can still be compared to one another. In addition to number of licensed drivers per vehicle, income distributions would be a helpful variable in classifying how households vary from one another.

This thesis work was based solely on the safety and travel patterns of light-duty vehicles, yet the data is comprised of fleet and heavy-duty vehicles as well. This leads to the recommendation that heavy-duty vehicles be analyzed. Class 8 (heavy-duty/combination) trucks, which are least fuel-efficient and also contribute to 30% of annual VMT on average in the U.S. Furthermore, when comparing travel between urban and rural areas, there is less of a difference than for that of light-duty vehicles seen in the previous chapter. [74]

Last, obtaining registration data for the U.S. would allow us to compare fleets in different states based on whether there is a currently implemented safety inspection program. It is hypothesized that states with more stringent safety programs are younger on average than those with less stringent programs, as the program assists in removing the older, more dangerous cars from the road. This may lead to substantial benefits separate from safety-related effects, such as improved fuel economy resulting in lower emissions, increased new vehicle purchasing resulting in increased spending and economic benefits, and finally increased job opportunities such as increased work opportunities for mechanics.

Bibliography

[1] S. C. Davis, S. W. Diegel, and R. G. Boundy, *Transportation Energy Data Book*, 33rd ed. Oak Ridge National Laboratory, 2014.

[2] Insurance Institute for Highway Safety, Ed., *Fatality Facts: General Statistics*. [Online]. Available: http://www.iihs.org/iihs/topics/t/general-statistics/fatalityfacts/state-by-state-overview. [Accessed: 30-Jul-2015].

[3] Transportation Research Board of the National Academies, "Critical Issues in Transportation 2013," pp. 1–16, Nov. 2013.

[4] National Center for Injury Prevention & Control, "10 Leading Causes of Death by Age Group, United States - 2013."

[5] U. S. D. O. Transportation, Ed., *Highway Safety Improvement Program History*. [Online]. Available: http://safety.fhwa.dot.gov/hsip/gen_info/hsip_history.cfm. [Accessed: 03-Jan-2014].

[6] P. Bonsall, R. Liu, and W. Young, "Modelling safety-related driving behaviour—impact of parameter values," *Transportation Research Part A: Policy and Practice*, vol. 39, no. 5, pp. 425–444, Jun. 2005.

[7] R. B. Noland and M. A. Quddus, "Congestion and safety: A spatial analysis of London," *Transportation Research Part A: Policy and Practice*, vol. 39, no. 7, pp. 737–754, Aug. 2005.

[8] M. Abdel-Aty, J. Lee, C. Siddiqui, and K. Choi, "Geographic unit based analysis in the context of transportation safety planning," *Transportation Research Part A*, vol. 49, no. C, pp. 62–75, Mar. 2013.

[9] W. Weijermars and P. Wesemann, "Road safety forecasting and ex-ante evaluation of policy in the Netherlands," *Transportation Research Part A*, vol. 52, no. C, pp. 64–72, Jun. 2013.

[10] W. M. Crain, "Vehicle safety inspection systems: How effective?," American Enterprise Institute, Washington, D.C., P-25 Series, 1980.

[11] P. D. Loeb and B. Gilad, "The Efficacy and Cost-Effectiveness of Vehicle Inspection," *Journal of Transport Economics and Policy*, vol. 18, no. 2, pp. 145–164, May 1984.

[12] P. D. Loeb, "The Efficacy and Cost Effectiveness of Motor Vehicle Inspection Using Cross-Sectional Data," *Southern Economic Journal*, vol. 52, no. 2, pp. 500–509, Oct. 1985.

[13] *Digest of Motor Laws*. [Online]. Available: http://drivinglaws.aaa.com/laws/safety-inspection/#. [Accessed: Mar-2014].

[14] C. Garbacz and G. Kelly, "Automobile Safety Inspection: New Econometric and benefit/cost estimates," *Applied Economics*, vol. 19, no. 6, pp. 763–771, 1987.

[15] T. Barnes, "Pennsylvania measure would end inspections for new vehicles," *Post-Gazette*, 15-Oct-2012.

[16] J. P. Leigh, "Nonrandom Assignment vehicle safety inspection laws and highway fatalities," *Public Choice*, no. 78, pp. 373–387, 1994.

[17] D. Merrell, M. Poitras, and D. Sutter, "The Effectiveness of Vehicle Safety Inspections: An Analysis Using Panel Data," *Southern Economic Journal*, vol. 65, no. 3, pp. 571–583, Jan. 1999.

[18] M. Poitras and D. Sutter, "Policy Ineffectiveness or Offsetting Behavior?," *Southern Economic Journal*, vol. 68, no. 4, pp. 922–934, Apr. 2002.

[19] D. Sutter and M. Poitras, "The Political Economy of Automobile Safety Inspections - Springer," *Public Choice*, vol. 113, no. 3, pp. 367–387, 2002.

[20] R. Puentes and A. Tomer, "The Road…Less Traveled: An Analysis of Vehicle Miles Traveled Trends in the U.S," 2008.

[21] U S Department of Transportation National Highway Traffic Safety Administration, "Traffic Safety Facts 2008 Data: Rural/Urban Comparison," pp. 1–6, Aug. 2010.

[22] Cambridge Systematics Inc., "Pennsylvania's Vehicle Safety Inspection Program Effectiveness Study," pp. 1–79, Mar. 2009.

[23] *Doubtful Return on the Public's $141 Million Investment in Poorly Managed Vehicle Inspection Programs*. [Online]. Available: http://www.ncleg.net/PED/Reports/documents/VSI/VSI_Report.pdf. [Accessed: 03-Mar-2014].

[24] K. A. Small and K. Van Dender, "Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect," *The Energy Journal*, vol. 28, no. 1, pp. 25–51, 2007.

[25] K. Gillingham, "How do consumers respond to gasoline price shocks? heterogeneity in vehicle choice and driving behavior," 2010.

[26] K. Gillingham, "Identifying the Elasticity of Driving: Evidence from a Gasoline Price Shock in California," *September) http://trid trb org/view aspx*, 2010.

[27] D. E. Clark and B. M. Cushing, "Rural and urban traffic fatalities, vehicle miles, and population density," *Accident Analysis & Prevention*, vol. 36, no. 6, pp. 967–972, Nov. 2004.

[28] Office of Highway Policy Information, "Traffic Volume Trends." U.S. Department of Transportation Federal Highway Administration, 2015.

[29] D. Peck, H. S. Matthews, P. Fischbeck, and C. T. Hendrickson, "Failure rates and data driven policies for vehicle safety inspections in Pennsylvania ," *Transportation Research Part A*, vol. 78, no. C, pp. 252–265, Aug. 2015.

[30] R. I. T. Administration, Ed., *National Transportation Statistics*. [Online]. Available: http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_statistics/html/table_01_40.html. [Accessed: 13-Feb-2014].

[31] T. Craig, "D.C. Ending Required Safety Inspections on Private Cars," *The Washington Post*, Sep-2009.

[32] M. Frassinelli, Ed., *N.J. will drop requirements for mechanical inspections of cars to save $11M yearly*, 2010. [Online]. Available: http://www.nj.com/news/index.ssf/2010/07/nj_to_drop_requirements_mechan.html. [Accessed: Jul-2014].

[33] C. McCahill, "Per capita VMT drops for ninth straight year; DOTs taking notice," State Smart Transportation Initiative, Feb. 2014.

[34] *The Pennsylvania Code*, Fry Communications, Inc., Jan. 2014.

[35] P. D. O. Transportation, "Pennsylvania's e-SAFETY Program Publication," vol. 1, no. 1, pp. 1–4, Oct. 2007.

[36] Oak Ridge National Laboratory, "Transportation Energy Databook," Jul. 2013.

[37] S. Menard, *Applied Logistic Regression Analysis*, 2nd ed. Sage Publications, Inc., 2001.

[38] U. S. C. Bureau, Ed., *Population Estimates*. [Online]. Available: http://www.census.gov/popest/data/index.html. [Accessed: 06-Mar-2014].

[39] Center for Disease Control, Ed., *Urban-Rural Classification*. [Online]. Available:

http://www.cdc.gov/nchs/data/oae/NCHSUrbruralFileDocumentation.pdf. [Accessed: 03-Jan-2014].

[40] *Fatality Analysis Reporting System Encyclopedia*. [Online]. Available: http://www-fars.nhtsa.dot.gov/Main/index.aspx. [Accessed: 21-Apr-2014].

[41] B. O. T. Statistics, Ed., *U.S. Light-Duty Fuel Consumption and Vehicle Miles Traveled*. [Online]. Available: http://www.afdc.energy.gov/data/search?q=U.S.+Light-Duty+Fuel+Consumption+and+Vehicle+Miles+Traveled. [Accessed: 06-Mar-2014].

[42] T. Craig, "D.C. Ending Required Safety Inspections on Private Cars," *washingtonpost.com*, 15-Sep-2009. [Online]. Available: http://www.washingtonpost.com/wp-dyn/content/article/2009/09/14/AR2009091402794.html. [Accessed: 30-Jul-2015].

[43] S. S. Carty, "D.C. junks car safety inspections: Will others, too?," *usatoday30.usatoday.com*, 09-Dec-2009. [Online]. Available: http://usatoday30.usatoday.com/money/autos/2009-12-10-inspections10_CV_N.htm. [Accessed: 30-Jul-2015].

[44] *Mandatory Vehicle Inspections Abolished; Repeal will Save Oklahomans $12 Million*. [Online]. Available: http://www.oksenate.gov/news/press_releases/press_releases_2001/pr050101.html. [Accessed: Jun-2014].

[45] Centers for Disease Control and Prevention, "Ten Significant Public Health Achievements -- United States, 2001-2010: Motor Vehicle Safety," *cdc.gov*. [Online]. Available: http://www.cdc.gov/Motorvehiclesafety/mmwr_achievements.html. [Accessed: 27-Jul-2015].

[46] L. Blincoe, T. R. Miller, E. Zaloshnja, and B. A. Lawrence, "The Economic and Societal Impact Of Motor Vehicle Crashes, 2010," U.S. Department of Transportation, National Highway Traffic Safety Administration, Washington, DC, DOT HS 812 013, May 2014.

[47] M. Burgess, "Contrasting Rural and Urban Fatal Crashes 1994 - 2003," U.S. Department of Transportation, National Highway Traffic Safety Administration, Washington, D.C., DOT HS 809 896, Dec. 2005.

[48] C. Zwerling, C. Peek-Asa, and P. S. Whitten, "Fatal motor vehicle crashes in rural and urban areas: decomposing rates into contributing factors," *Injury …*, 2005.

[49] J. H. Hedlund and P. R. Group, "Traffic safety performance measures for states and federal agencies," 2008.

[50] J. Hedlund, "Traffic Safety Performance Measures for States and Federal Agencies," U.S. Department of Transportation, National Highway Traffic Safety Administration, Washington, D.C., DOT HS 811 025, Aug. 2008.

[51] Natiional Center for Statistics & Analysis, Ed., "Traffic Safety Facts 2010 Data," National Highway Traffic Safety Administration, DOT HS 811 637, Jul. 2012.

[52] L. Kmet and C. Macarthur, "Urban–rural differences in motor vehicle crash fatality and hospitalization rates among children and youth," *Accident Analysis & Prevention*, vol. 38, no. 1, pp. 122–127, Jan. 2006.

[53] I.-J. P. Castle, H.-Y. Yi, R. W. Hingson, and A. M. White, "State Variation in Underreporting of Alcohol Involvement on Death Certificates: Motor Vehicle

Traffic Crash Fatalities as an Example," *Journal of Studies on Alcohol and Drugs*, vol. 75, no. 2, pp. 299–312, Mar. 2014.

[54] R. Tay, L. Kattan, and Y. Bai, "Factors Contributing to Police Attendance at Motor Vehicle Crash Scenes," *Journal of the Transportation Research Forum*, vol. 53, no. 3, pp. 101–115, 2014.

[55] *Highway Statistics Series*. [Online]. Available: https://www.fhwa.dot.gov/policyinformation/quickfinddata/qftravel.cfm. [Accessed: Jul-2014].

[56] U S Department of Transportation, National Highway Traffic Safety Administration, Natiional Center for Statistics & Analysis, "National Automotive Sampling System (NASS) General Estimates System (GES) Analytical User's Manual 1988-2012," pp. 1–418, Jan. 2014.

[57] Insurance Institute for Highway Safety, Ed., "Saving lives: Improved vehicle designs bring down death rates," *iihs.org*, 29-Jan-2015. [Online]. Available: http://www.iihs.org/iihs/sr/statusreport/article/50/1/1. [Accessed: 21-Jul-2015].

[58] Federal Highway Administration, "2009 National Household Travel Survey," vol. 81, no. 2. U.S. Department of Transportation, 2011.

[59] United States Census Bureau, "USA QuickFacts." U.S. Department of Commerce.

[60] Oak Ridge National Laboratory, "Developing a Best Estimate of Annual Vehicle Mileage for 2009 NHTS Vehicles," Federal Highway Administration, Jun. 2011.

[61] D. L. Greene, "Rebound 2007: Analysis of U.S. light-duty vehicle travel statistics," *Energy Policy*, vol. 41, pp. 14–28, Apr. 2010.

[62] Q. Su, "Travel demand in the US urban areas: A system dynamic panel data approach," *Transportation Research Part A: Policy and Practice*, vol. 44, no. 2, pp. 110–117, Feb. 2010.

[63] M. Woldeamanuel and A. Kent, "Determinants of Per Capita Vehicle Miles Traveled (VMT): The Case of California," *Journal of the Transportation Research …*, 2014.

[64] R. Sandler, "Clunkers or Junkers? Adverse Selection in a Vehicle Retirement Program," *American Economic Journal: Economic Policy*, vol. 4, no. 4, pp. 253–281, Nov. 2012.

[65] J. Cook, D. Salon, J. Sanchirico, and J. Williams, "Driving Intensity in California: Exploring Spatial Variation in VMT and its Relationship to Fuel Prices, Fuel Economy the Built Environment."

[66] Michael Baker Jr. Inc., "Statistical Evaluation of Projected Traffic Growth."

[67] T. Hutchins, "Households with more vehicles travel more," *eia.gov*, Apr-2015. [Online]. Available: http://www.eia.gov/todayinenergy/detail.cfm?id=20832. [Accessed: Aug-2015].

[68] S. Lu, "Vehicle Survivability and Travel Mileage Schedules," Washington, DC, DOT HS 809 952, 2007.

[69] Energy Information Administration, *Average Annual Vehicle Miles of Travel per Household*. Energy Information Administration, 2015.

[70] M. Totty, "The Gas Tax Is Running Low. But What Should Replace It?," *The Wall Street Journal*, Sep-2012.

[71] P. Rogoff and K. Thomson, "Guidance on Treatment of the Economic Value ofa Statistical Life (VSL) in U.S. Department of Transportation Analyses - 2014 Adjustment," U.S. Department of Transportation.

[72] L. Zhang, B. S. McMullen, and D. Valluri, "Vehicle mileage fee on income and

spatial equity," *… Record: Journal of the …*, 2009.
[73] United States Government Accountability Office, "Pilot Program Could Help Determine the Viability of Mileage Fees for Certain Vehicles," Dec. 2012.
[74] Office of Highway Policy Information, "Annual Vehicle Distance Traveled in Miles and Related Data - 2013 by Highway Category and Vehicle Type." U.S. Department of Transportation Federal Highway Administration.
[75] *GM VIN Check Digit Verification*. [Online]. Available: http://people.virginia.edu/~sns5r/resint/empiostf/checkdigit.htm. [Accessed: 03-Jan-2014].
[76] ALLDATA LLC., Ed., *VIN to Year Chart*. [Online]. Available: http://support.alldata.com/alldata-repair-online-article/vin-to-year-chart. [Accessed: 03-Jan-2014].
[77] National Highway Traffic Safety Administration and P. D. O. Transportation, *Vehicle Identification Number Requirements: Final Rule*. 2008, pp. 1–77.

Supplemental Material

I. Vehicle Safety Inspection Recording System

Previously, vehicle safety inspections were recorded with this MV-431 form in paper form (Supplemental Material Figure 1). Now, stations may use the electronic version of this via the e-SAFETY program or through a private IT company such as CompuSpections.

MV-431 (12-03)

Check One for Each Type of Inspection
Year 2004
X Annual
Semi-Annual

SMITH'S AUTOMOTIVE
SEE INSTRUCTIONS ON REVERSE SIDE
AI4
1
121

COMMONWEALTH OF PENNSYLVANIA
DEPARTMENT OF TRANSPORTATION
INSPECTION RECORD
RECORD ALL PASSENGER CARS, TRUCKS AND BUSES

Station Number 0000
County BUTLER
CHARGE FOR INSP. $27.50
STICKER COST $2.00

INSP # 1 | DATE 07/06/2004 | REGISTRANT'S NAME DOE JOHN | VEHICLE IDENTIFICATION # 1C765FH4367K89996 | YR / MAKE / BODY 92 CHEV SW | REGISTRATION # AB456
WORK ORDER # OR SIGNATURE 101 | CITY BUTLER | COUNTY BUTLER | INSURANCE COMPANY NAME MECHANICS AUTO INS. | EXP DATE 07/31/2004 | POLICY # QW34657B87-38
OLD ODOMETER 55569 | CURRENT ODOM 65903 | STICKER # AI4-0000101 | STICKER EXP MO/YR 06/05 | TOTAL COST + TAX $335.47

INSP # 2 | DATE 07/06/2004 | REGISTRANT'S NAME DOE WILLIAM | VEHICLE IDENTIFICATION # B1234567890C32101 | YR / MAKE / BODY 90 JEEP SW | REGISTRATION # B11321
WORK ORDER # OR SIGNATURE 102 | CITY BROWNSVILLE | COUNTY BUTLER | INSURANCE COMPANY NAME ALLCOUNTRY INS. | EXP DATE 07/30/2004 | POLICY # A321123456
OLD ODOMETER 75320 | CURRENT ODOM 85123 | STICKER # AI4-0000102 | STICKER EXP MO/YR 06/05 | TOTAL COST + TAX $305.97

INSP # 3 | DATE 07/06/2004 | REGISTRANT'S NAME DOE JANE | VEHICLE IDENTIFICATION # C1234567890D45678 | YR / MAKE / BODY 89 PONTIAC CP | REGISTRATION # C12345
WORK ORDER # OR SIGNATURE 103 | CITY CONNELLSVILLE | COUNTY FAYETTE | INSURANCE COMPANY NAME REGRESSIVE INS. | EXP DATE 07/30/2004 | POLICY # 654321123B
OLD ODOMETER AI01234567 | CURRENT ODOM 98867 | STICKER # AI4-0000103 | STICKER EXP MO/YR 06/05 | TOTAL COST + TAX $4.24

INSP # 4 | DATE 07/06/2004 | REGISTRANT'S NAME SMITH JOHN | VEHICLE IDENTIFICATION # DIESEL D987654321B123456 | YR / MAKE / BODY 96 FORD TK | REGISTRATION # D12505
WORK ORDER # OR SIGNATURE | CITY | COUNTY | INSURANCE COMPANY NAME | EXP DATE | POLICY #
OLD ODOMETER | CURRENT ODOM | STICKER # AI4-0000104 | TOTAL COST + TAX

										FRACTION OF REMAINING BRAKE LINING OF WHEELS PULLED							VISUAL ANTI-TAMPERING					
REGISTRATION VERIFIED	TIRES, WHEELS	STEERING SUSPENSION	EXHAUST SYSTEM	FUEL SYSTEM	GLAZING & MIRRORS	LIGHTS, WIRING & SWITCHE	BODY DOORS & LATCHES	BRAKE SYSTEM	L FRONT	L REAR	R FRONT	R REAR	OTHER	ROAD TEST		CATALYTIC CONVERTER	FUEL INLET RESTRICTOR	PCV VALVE	EGR VALVE	AIR PUMP	EVAPORATIVE CONTROL S'
√	6	R	R	√	√	√	√	A	5 B	6 R	5 B	6 R	√	√		N	√	√	√	-	√
√	7	√	R	√	√	R	√	N	11 R			4 R	√	√		- ALT-FUEL	-	-	-	-	-
	0 AI01234567 Windshield Replaced															-	-	-	-	-	-
√	5	√	√	√	√	√	√	√	4 B	5 R	4 B	5 R	√	√		- IM40000001	-	-	-	-	-

Supplemental Material Figure 1: Example MV-431 paper form, PA state vehicle safety inspection recording system.

II. Data Complications

Data validation is an important step prior to analysis. In this specific case, technicians in the inspection stations record data entries during or after they finish a vehicle inspection. Mistakes are inevitable when Vehicle Identification Numbers (VINs), dates, and odometers are entered by hand as they contain multiple numeric or combination alphanumeric sequences. As a result, data filtering on all three datasets was vital prior to analyzing any data.

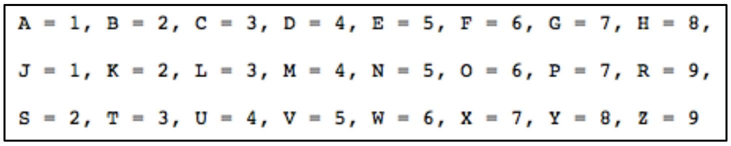
A simple finger-slip can result in an invalid entry by entering an extra digit or typing the wrong key. If VINs are entered incorrectly, they cannot be decoded to correctly identify that vehicle's characteristics, and may not match other records. It is also important that other data, such as dates and odometers, are entered correctly because an extra digit in an odometer means it is an order of magnitude more than what it should read.

II.1. *Detailed VIN Filtering*

Prior to 1981, there was no standard in recording VIN data. Depending on the manufacturer, a VIN could be a variable length and contain any digit/character combination. As of 1981, a standard was put in place for VINs to be:

1. 17 digits in length,
2. Contain no 'I's, 'O's, or 'Q's (as these letters get confused with '1's [ones] and '0's [zeros] in hand written and human read forms, and
3. The 9th digit is used as the "check" digit and should match the result of an algorithm on the remaining digits.

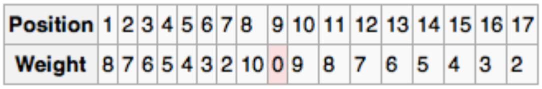
To decode a VIN, these standards must be checked and met. Without this check, characteristics such as model year, vehicle make/model, etc. cannot be verified, as these are built into the VIN composition. Initially, the VIN was checked to see if it meets those three requirements of length, composition, and check-digit value. The digit check value is calculated by the first translating any letters in the VIN to numbers according to the designation in Supplemental Material Figure 2.



```
A = 1, B = 2, C = 3, D = 4, E = 5, F = 6, G = 7, H = 8,
J = 1, K = 2, L = 3, M = 4, N = 5, O = 6, P = 7, R = 9,
S = 2, T = 3, U = 4, V = 5, W = 6, X = 7, Y = 8, Z = 9
```

Supplemental Material Figure 2: Alphanumeric Encoding Table

Once the VIN forms a 17-digit number, each of the digits is multiplied by an associated weight, which is presented in Supplemental Material Figure 3.



Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Weight	8	7	6	5	4	3	2	10	0	9	8	7	6	5	4	3	2

Supplemental Material Figure 3: Position Multiplier

Then, these weighted digit values are summed and divided by 11. The remainder of this division is the check digit result and the value that should be in the 9th position of the VIN. [75]

II.1.a Python Code To Validate Check Digit

```
def vinCheckDigit(vin): #check that vin is valid
product = []
checkDigit = vin[8]
value = {'A':1, 'B':2, 'C':3,'D':4, 'E':5, 'F':6, 'G':7, 'H':8,
        'J':1, 'K':2, 'L':3, 'M':4, 'N':5, 'P':7, 'R':9,
        'S':2, 'T':3, 'U':4, 'V':5, 'W':6, 'X':7, 'Y':8, 'Z':9}
weight = [8, 7, 6, 5, 4, 3, 2, 10, 0, 9, 8, 7, 6, 5, 4, 3, 2]
for i in xrange(len(vin)):
        if vin[i].isdigit():
        vinValue = int(vin[i])
        else:
        vinValue = int(value.get(vin[i], 100))
        product.append(vinValue*weight[i])
check = str(sum(product) % 11)
if check == "10":
        check = "X"
if check == checkDigit:
        return True
else:
        return False
```

II.2. *Raw Data Filtering Results*

While CompuSpections provided data from 2005 and 2006, similar years of data were not supplied from e-SAFETY. In order for inspection failure rate estimates from those years not to be biased toward one particular dataset, inspection data from 2005 and 2006 was omitted from the analysis. Finally, after comparing the two inspection dataset quantities, only inspection years 2008 through 2012 were used since there was significantly more data from one dataset versus the other in years prior to 2008.

The CompuSpections data in general had fewer errors as expected. After filtering, a database was compiled for VINs by year of inspection. Additional data filtering considerations were made; however, records were not discarded at this time. A post-filtering breakdown of available data, by inspection year, is presented in Supplemental Material Table 1. These data counts vary from the total counts of registered LDVs in the state, which was on the order of about nine million vehicles (post-filtering) as of March 2012.

Supplemental Material Table 1: Data record count by year, after filtering

Data Source	2008	2009	2010	2011	2012	Total
e-SAFETY Inspection	150k	200k	220k	240k	240k	980k
CompuSpections Inspection	900k	850k	840k	550k	230k	3.3M
Combined Inspection	1.1k	1.1k	1.1k	790k	470k	4.3M

II.3. *Detailed Data Filtering*

Some data contain invalid consecutive odometer values; for example, a VIN may contain two years of data, which show the odometer decreasing. Not all VINs have records every year and some have no consecutive year entries. As a result, annual mileage calculations cannot always be made for these VIN entries. And, as a result, odometer readings were not filtered according to this method of comparing odometer readings year to year. Supplemental Material Table 2 shows the number of vehicles in the inspection database with multiple records, how far apart they are, and what percentage they are out of the total number of inspection records (5.3 million) and total unique VIN entries (2.8 million).

Supplemental Material Table 2: Inspection dates X days apart for a given VIN with multiple entries

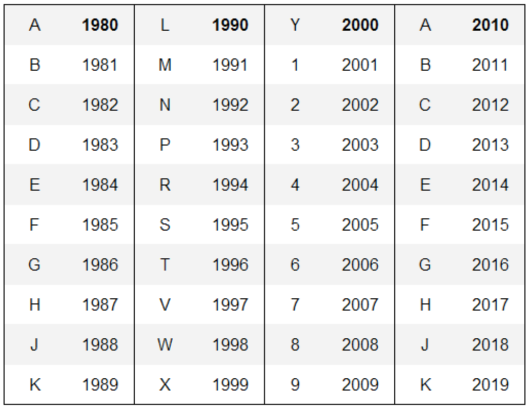
X Days Difference (Months)	Vehicle Count	% of Total Inspection	% of Total VIN
< 30 (< 1 month)	19,000	0.4%	0.7%
> 30 & < 120 (1 - 3 months)	32,000	0.6%	1.2%
> 120 & < 270 (3 - 9 months)	72,000	1.4%	2.6%
> 270 & < 365 (9 - 12 months)	620,000	12%	23%
> 365 & < 450 (12 - 15 months)	660,000	12%	24%
> 450 (> 15 months)	1,100,000	21%	40%

The category of vehicles with consecutive inspections less than 9 months apart represented about 2% of the inspection entries and just less than 5% of the total VIN entries. Of the vehicles with entries approximately one year apart, approximately 1% have records within the same inspection year entry because they are a little early (i.e., January 2009 and December 2009) and about 1% have records two years apart because they are a little late (i.e., December 2008 and January 2010). Due to the small amount of data containing VINs with consecutive entries that are not appropriately spaced, these data entries are still included in this analysis and assumed to have no effect on the results.

Another data issue shows odometer values that are too large for an appropriately aged vehicle, for example, vehicle records were filtered if odometer readings were larger than 500,000 miles (which would equate to about a 50 year old vehicle driving 10,000 miles in a given year), which is an unrealistic situation. This may be the result of an odometer being entered incorrectly with an extra digit due to a “finger slip” or simply entering the number incorrectly. All of these entries, with significantly large odometer values were considered invalid, and discarded from this analysis.

Another possible discrepancy in the data may be that the entries for a given VIN do not align. For example, two entries for a VIN’s model and year should match. Some entries have two different model years for the same VIN, which is not possible. If the vehicle model years do not match, they can be corrected by using the 10th digit in the VIN, which corresponds to the model year of the vehicle. Supplemental Material Table 3 below shows the year designations.

Supplemental Material Table 3: VIN model year encoding [76]



A	**1980**	L	**1990**	Y	**2000**	A	**2010**
B	1981	M	1991	1	2001	B	2011
C	1982	N	1992	2	2002	C	2012
D	1983	P	1993	3	2003	D	2013
E	1984	R	1994	4	2004	E	2014
F	1985	S	1995	5	2005	F	2015
G	1986	T	1996	6	2006	G	2016
H	1987	V	1997	7	2007	H	2017
J	1988	W	1998	8	2008	J	2018
K	1989	X	1999	9	2009	K	2019

In 2008, the National Highway Traffic Safety Administration (NHTSA) wrote an amendment to 49 CFR Part 565, Vehicle Identification Number Requirements to address a concern that the supply of unique VINs may run out. The document states the new rule ensures a sufficient number of unique VINs for the following 30 years. [77] This VIN rule applies to passenger vehicles, multipurpose vehicles, and trucks with gross vehicle weight rating less than or equal to 10,000 pounds. This creates a crude filter for larger trucks and other vehicles as this rule is not applied to them and will result in an invalid VIN. According to this rule, the 7th digit, in addition to the 10th digit was used to distinguish between vehicle model years 1980 – 2009 and 2010 – 2019, due to the repeating digit designation. Prior to 2010, the 7th digit was a number and it is a letter for model years after and including 2010. For consistency, VIN decoding was always applied to find a vehicle model year, rather than using the information from the original data entry.

Another filter was applied to remove permanently registered vehicles, such as police cars and ambulances. The registration file contained a column entry with this designation, which was used to keep track of those VINs. Those VINs were then used to check against the other data files and were filtered out, as these permanently registered vehicles are assumed to have uncharacteristic driving patterns.

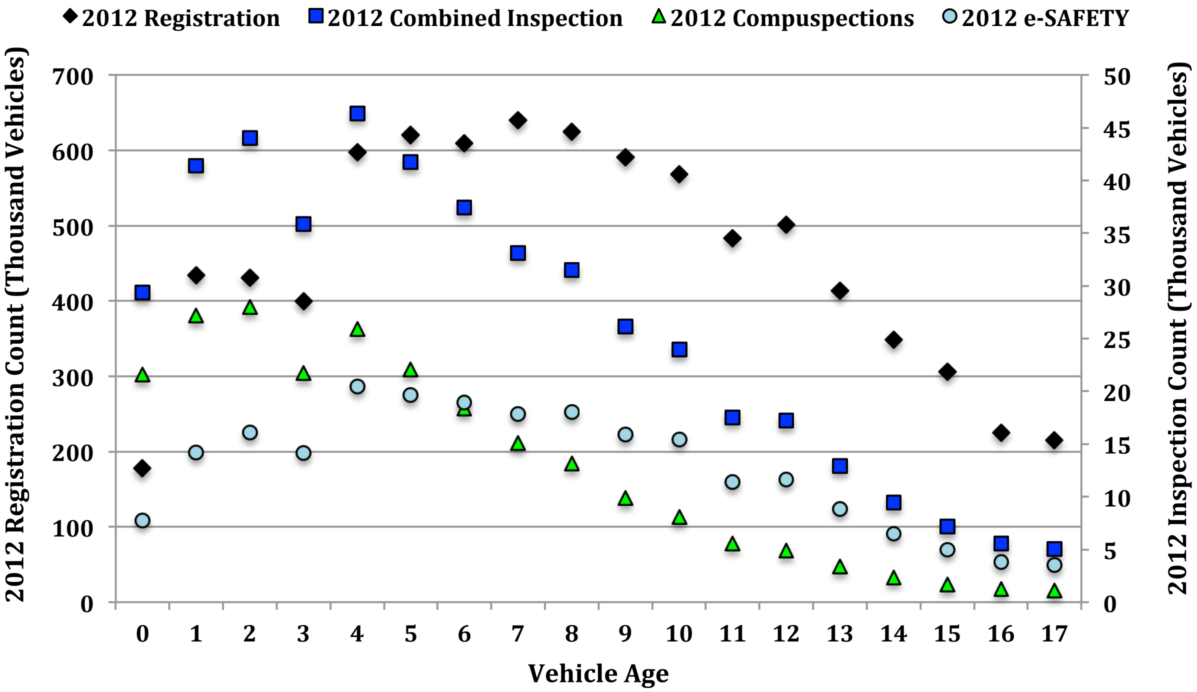
In addition to the minimal truck filter by doing the VIN check (which cannot be applied to most heavy-duty trucks), a second truck filter was applied for Ford trucks. Ford uses a specific designation for different truck models, as a result, the larger trucks (Ford F-350 and larger) typically used as construction vehicles were removed from the database.

If counties do not align entry to entry, it is assumed the vehicle moved and was correctly recorded. For this study, these scenarios are ignored even though these vehicles that have moved to a different county may have changed their driving habits within that year; however, further analysis is necessary in this case.

The March 2012 PA registration data lists 10.4 million vehicles of which 98,000 were permanently registered (i.e., police fleets), 85,000 large Ford trucks, and about 76,000 had invalid VINs. Prior to this filtering, only "passenger" and "truck" designated entries were filtered in order to primarily filter trailers, motorcycles and buses.

III. Data Representation

Preliminary representativeness tests were performed in order to justify whether the inspection data used in the analysis represented the state as a whole. The registration data consists of significantly more vehicles than the two inspection files; therefore, in order to calculate an appropriate number of vehicles in each category (i.e., by county-type, age, and odometer reading), the percentage of each category was calculated from the inspection files and multiplied by the registration total. Since the year 2012 was the only common year between all three datasets, the year 2012 is compared. This resulted in the e-SAFETY data appearing to be similar to the registration data, while the CompuSpections data contained a different vehicle composition with many more new and younger vehicles and many less older vehicles (after about age 8). Ages 6-7 have relatively the same number of vehicles in all datasets. These distributions are shown in Supplemental Material Figure 4.



Supplemental Material Figure 4: Dataset representation comparisons, 2012

These data similarities may be due to the state inspection and vehicle registration records coming from the same source. While the CompuSpections data may not seem representative as a whole, the data itself must not be disregarded, especially when looking at the data by category.

In order to quantitatively compare the various dataset distributions, a series of chi-square analyses were implemented. Each dataset permutation, consisting of the e-SAFETY inspection, CompuSpections inspection, and state registration data, was observed based on age, county, and odometer category designations. Odometer values in the registration data were recorded at the time of registration, whereas the inspection odometer values were recorded at the time of inspection. As a result, an odometer representation is not used to compare representativeness between the inspection and registration datasets. The following chi-squared formula is used, and evaluated by using observed (O_i) and expected (E_i) values.

$$\chi^2 = \sum_{i=1}^{N} \frac{(O_i - E_i)^2}{E_i}$$

The observed values were simply taken as the values from the actual datasets. The expected values were calculated based on the calculated joint value distribution between the two datasets being compared by: (1) adding the values of each dataset in each category; (2) calculating the percentage of that category of the total joint sum; and (3) finally multiplying the joint percentage of each category by the total of each initial dataset to get the expected values. These values were used in the formula and summed to get the total chi-square value.

The hypothesis here is the registration data over time (between the two available registration files) are representative of each other and that these distributions are not significantly different. Additionally, it is hypothesized that the distributions of data in each the e-SAFETY and CompuSpections inspection data files (at least for the registration file year of 2012), are representative of all vehicles.

The results of the chi-squared analyses revealed, with any data comparison, the data distributions were all significantly different. This means it cannot be stated that these datasets are representative of one another. This includes the representative test between the two registration files, which are a snapshot of the Pennsylvania state vehicle composition about 1.5 years apart. Aside from a rapidly changing vehicle fleet, another problem may stem from vehicles being registered in Pennsylvania and getting inspected in a station that partakes in neither the e-SAFETY nor CompuSpections inspection programs.

Further breakdown of these datasets can be observed by the differences in ages. Supplemental Material Table 4 displays the dataset breakdowns in the overall state in addition to a primary breakdown by the urbanity.

Supplemental Material Table 4: Comparison of age distributions between datasets, by the overall state and urbanity breakdown

Urbanity Index	Dataset Comparison	5th Percentile	50th Percentile	Average	95th Percentile
Overall	Registration	5	8	9.0	12
	Inspection (Combined)	1	3	4.3	7
	Inspection (CompuSpections)	1	3	3.7	6
	Inspection (e-SAFETY)	3	6	6.5	9
1	Registration	1	8	8.7	18
	Inspection (Combined)	-1	3	3.9	12
	Inspection (CompuSpections)	-1	3	3.5	11
	Inspection (e-SAFETY)	0	5	5.7	15
2	Registration	1	8	8.5	18
	Inspection (Combined)	-1	3	4.1	12
	Inspection (CompuSpections)	-1	3	3.4	10
	Inspection (e-SAFETY)	1	6	7.0	15
3	Registration	1	9	9.4	20
	Inspection (Combined)	-1	4	4.5	13
	Inspection (CompuSpections)	-1	3	3.9	12
	Inspection (e-SAFETY)	0	6	6.6	15
4	Registration	1	9	9.4	20
	Inspection (Combined)	0	4	5.2	14
	Inspection (CompuSpections)	0	4	4.3	12
	Inspection (e-SAFETY)	1	7	7.5	16
5	Registration	1	9	9.7	21
	Inspection (Combined)	0	4	4.9	14
	Inspection (CompuSpections)	0	3	4.4	12
	Inspection (e-SAFETY)	0	5	5.9	15
6	Registration	1	9	9.7	21
	Inspection (Combined)	0	4	5.0	13
	Inspection (CompuSpections)	0	3	3.9	11
	Inspection (e-SAFETY)	0	5	5.7	14

The Supplemental Material Table 4 breakdown shows that there are many more young vehicles than old vehicles in the inspection dataset, resulting in a smaller overall average state failure rate when calculating failure rates by urbanity. Due to this higher representation of younger vehicles in each county type, it is noted that the failure rates by county classification are likely underestimates of the actual failure rate of the fleet in that county type. A more accurate estimate of failure rates would be to use the age distribution from the registration database (rather than from the inspection databases) along with the failure rates by age in order to calculate a more representative failure rate in each county type. However, the calculated failure rates by county classification are still well above the stated 2% failure rate reported by state legislators.

IV. Logistic Regression

This regression analysis is executed using the R Project for Statistical Computing Software by performing a stepwise regression, using the following code:

```
# From the stats package, glm is used to fit generalized linear models
null <- glm(overallInspectResult ~ 1, data = df, family = binomial(link = "logit"))

# Omitted dummy variables: fuelGas, makeHonda, body=Sedan)
full <- glm(overallInspectResult ~ age + currentOdom + weightVal + mpgVal +
            factor(body) + factor(make) + factor(fuel) + factor(INSPECTDATE),
          data = df, family = binomial(link = "logit"))

#stepwise regression
step(null, scope = list(upper = full), direction = "both")
```

The results from this stepwise regression led to the inclusion of all variables in the regression model. Since two pairs of variables are correlated and show multicollinearity is not a concern, we produce eight models, in addition to the base case Model 0 including all variables, with each variable combination variation. The combinations are shown in Supplemental Material Table 5, providing which variables are excluded in the regression, and the variable coefficient estimates and standard errors are shown in Supplemental Material Table 6.

Supplemental Material Table 5: Model Definitions

Model	**Excluded Variables**
0	None
1	Age
2	Odometer
3	Weight
4	Fuel Economy
5	Age, Fuel Economy
6	Odometer, Fuel Economy
7	Age, Weight
8	Odometer, Weight

Supplemental Material Table 6: Variable Coefficient Estimates and Standard Errors for All Models

		Model 0		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
		Coefficients	Standard Error	Coefficients	Standard Error	Coefficients	Standard Error	Coefficients	Standard Error	Coefficients	Standard Error	Coefficients	Standard Error	Coefficients	Standard Error	Coefficients	Standard Error	Coefficients	Standard Error
CONTINUOUS VARIABLES	(Intercept)	-31	1.9	-63	1.8	-37	1.8	-36	1.8	-36	1.8	-63	1.8	-43	1.8	-61	1.8	-45	1.8
	age	5.7E-02	4.9E-04			1.5E-01	3.4E-04	5.3E-02	4.7E-04	5.3E-02	4.8E-04			1.4E-01	3.2E-04			1.4E-01	3.1E-04
	currentOdom	1.2E-05	4.4E-08	1.5E-05	3.1E-08			1.2E-05	4.4E-08	1.2E-05	4.4E-08	1.5E-05	3.0E-08			1.5E-05	3.0E-08		
	weightVal	9.4E-05	4.1E-06	-4.8E-05	4.0E-06	1.4E-04	4.1E-06			2.7E-06	3.0E-06	-6.6E-05	2.9E-06	3.4E-05	3.0E-06				
	mpgVal	2.1E-02	6.5E-04	4.3E-03	6.4E-04	2.4E-02	6.4E-04	1.1E-02	4.7E-04							9.5E-03	4.7E-04	9.2E-03	4.7E-04
	INSPECTDATE	1.3E-06	9.2E-08	3.0E-06	9.1E-08	1.7E-06	9.2E-08	1.6E-06	9.2E-08	1.6E-06	9.2E-08	3.0E-06	9.1E-08	2.0E-06	9.1E-08	2.9E-06	9.1E-08	2.1E-06	9.1E-08
CATEGORICALVARIABLES	factor(body)Convertible	-1.8E-01	1.2E-02	-8.9E-02	1.2E-02	-4.4E-01	1.2E-02	-1.9E-01	1.2E-02	-2.1E-01	1.2E-02	-9.7E-02	1.2E-02	-4.8E-01	1.2E-02	-8.0E-02	1.2E-02	-4.6E-01	1.2E-02
	factor(body)Pickup	2.5E-02	6.8E-03	8.0E-02	6.8E-03	2.1E-03	6.8E-03	5.8E-02	6.7E-03	-3.9E-02	6.5E-03	6.5E-02	6.5E-03	-7.2E-02	6.5E-03	6.3E-02	6.7E-03	5.2E-02	6.6E-03
	factor(body)SUV	6.4E-02	5.0E-03	2.7E-02	4.9E-03	1.3E-01	4.9E-03	8.4E-02	4.9E-03	9.2E-03	4.6E-03	1.6E-02	4.6E-03	6.3E-02	4.6E-03	1.5E-02	4.8E-03	1.6E-01	4.8E-03
	factor(body)Van	2.0E-01	6.4E-03	2.1E-01	6.4E-03	3.0E-01	6.3E-03	2.4E-01	6.1E-03	1.7E-01	6.4E-03	2.0E-01	6.4E-03	2.8E-01	6.3E-03	1.8E-01	6.1E-03	3.7E-01	6.1E-03
	factor(body)Wagon	7.2E-02	9.2E-03	9.8E-02	9.2E-03	8.0E-02	9.1E-03	7.9E-02	9.2E-03	6.1E-02	9.2E-03	9.5E-02	9.2E-03	6.7E-02	9.1E-03	9.6E-02	9.2E-03	9.1E-02	9.1E-03
	factor(make)Acura	4.5E-01	1.1E-02	4.3E-01	1.1E-02	4.8E-01	1.1E-02	4.5E-01	1.1E-02	4.0E-01	1.1E-02	4.2E-01	1.1E-02	4.3E-01	1.1E-02	4.3E-01	1.1E-02	4.8E-01	1.1E-02
	factor(make)Audi	2.1E-01	1.9E-02	1.9E-01	1.9E-02	2.2E-01	1.9E-02	2.1E-01	1.9E-02	1.5E-01	1.9E-02	1.8E-01	1.9E-02	1.6E-01	1.9E-02	1.8E-01	1.9E-02	2.3E-01	1.9E-02
	factor(make)BMW	9.1E-01	1.0E-02	8.9E-01	1.0E-02	8.6E-01	1.0E-02	9.0E-01	1.0E-02	8.4E-01	9.9E-03	8.7E-01	9.9E-03	7.9E-01	9.8E-03	8.9E-01	1.0E-02	8.6E-01	1.0E-02
	factor(make)Buick	8.1E-01	9.5E-03	9.3E-01	9.5E-03	6.1E-01	9.5E-03	8.2E-01	9.5E-03	7.7E-01	9.5E-03	9.2E-01	9.4E-03	5.7E-01	9.4E-03	9.2E-01	9.5E-03	6.3E-01	9.5E-03
	factor(make)Cadillac	6.2E-01	1.3E-02	7.1E-01	1.3E-02	4.2E-01	1.3E-02	6.4E-01	1.3E-02	5.6E-01	1.2E-02	7.0E-01	1.2E-02	3.5E-01	1.2E-02	7.0E-01	1.2E-02	4.5E-01	1.3E-02
	factor(make)Chevrolet	7.4E-01	6.1E-03	7.7E-01	6.1E-03	6.6E-01	6.1E-03	7.3E-01	6.1E-03	7.0E-01	6.0E-03	7.6E-01	6.0E-03	6.2E-01	6.0E-03	7.7E-01	6.1E-03	6.6E-01	6.1E-03
	factor(make)Chrysler	9.8E-01	9.2E-03	9.9E-01	9.2E-03	9.1E-01	9.1E-03	9.7E-01	9.2E-03	9.3E-01	9.1E-03	9.8E-01	9.1E-03	8.6E-01	9.0E-03	1.0E+00	9.2E-03	9.0E-01	9.1E-03
	factor(make)Dodge	9.1E-01	7.9E-03	9.3E-01	7.9E-03	8.8E-01	7.8E-03	9.0E-01	7.9E-03	8.6E-01	7.8E-03	9.2E-01	7.7E-03	8.2E-01	7.7E-03	9.4E-01	7.9E-03	8.7E-01	7.8E-03
	factor(make)Ford	7.9E-01	6.3E-03	8.2E-01	6.3E-03	7.2E-01	6.3E-03	7.7E-01	6.3E-03	7.4E-01	6.1E-03	8.0E-01	6.1E-03	6.6E-01	6.1E-03	8.3E-01	6.3E-03	6.9E-01	6.2E-03
	factor(make)Geo	1.8E-01	3.7E-02	4.3E-01	3.7E-02	-5.4E-02	3.7E-02	1.5E-01	3.7E-02	1.9E-01	3.7E-02	4.3E-01	3.7E-02	-4.2E-02	3.7E-02	4.6E-01	3.7E-02	-9.1E-02	3.7E-02
	factor(make)GMC	6.3E-01	1.1E-02	6.9E-01	1.1E-02	5.7E-01	1.1E-02	6.5E-01	1.1E-02	6.0E-01	1.1E-02	6.8E-01	1.1E-02	5.4E-01	1.1E-02	6.8E-01	1.1E-02	6.0E-01	1.1E-02
	factor(make)Hummer	4.5E-01	4.5E-02	4.6E-01	4.5E-02	3.1E-01	4.5E-02	4.6E-01	4.5E-02	4.0E-01	4.5E-02	4.5E-01	4.5E-02	2.6E-01	4.5E-02	4.5E-01	4.5E-02	3.3E-01	4.5E-02
	factor(make)Hyundai	6.6E-01	8.9E-03	6.0E-01	8.9E-03	5.9E-01	8.8E-03	6.4E-01	8.8E-03	6.2E-01	8.8E-03	6.0E-01	8.8E-03	5.4E-01	8.7E-03	6.2E-01	8.9E-03	5.6E-01	8.8E-03
	factor(make)Infiniti	2.7E-01	2.4E-02	2.3E-01	2.4E-02	2.2E-01	2.4E-02	2.6E-01	2.4E-02	1.9E-01	2.4E-02	2.2E-01	2.4E-02	1.3E-01	2.4E-02	2.4E-01	2.4E-02	2.1E-01	2.4E-02
	factor(make)Isuzu	6.6E-01	3.8E-02	7.7E-01	3.8E-02	6.5E-01	3.8E-02	6.5E-01	3.8E-02	6.0E-01	3.8E-02	7.5E-01	3.8E-02	5.8E-01	3.8E-02	7.8E-01	3.8E-02	6.3E-01	3.8E-02
	factor(make)Jaguar	1.0E+00	2.7E-02	1.1E+00	2.7E-02	8.2E-01	2.7E-02	1.0E+00	2.7E-02	9.2E-01	2.7E-02	1.0E+00	2.7E-02	7.3E-01	2.7E-02	1.1E+00	2.7E-02	8.2E-01	2.7E-02
	factor(make)Jeep	8.0E-01	9.4E-03	7.9E-01	9.4E-03	7.7E-01	9.3E-03	7.6E-01	9.3E-03	7.2E-01	9.1E-03	7.8E-01	9.1E-03	6.7E-01	8.9E-03	8.2E-01	9.3E-03	7.1E-01	9.1E-03
	factor(make)Kia	6.9E-01	1.3E-02	6.3E-01	1.3E-02	5.8E-01	1.2E-02	6.6E-01	1.2E-02	6.4E-01	1.2E-02	6.2E-01	1.2E-02	5.2E-01	1.2E-02	6.4E-01	1.2E-02	5.3E-01	1.2E-02
	factor(make)LandRover	1.1E+00	2.6E-02	1.2E+00	2.6E-02	9.9E-01	2.5E-02	1.2E+00	2.6E-02	1.1E+00	2.6E-02	1.2E+00	2.6E-02	9.6E-01	2.5E-02	1.2E+00	2.6E-02	1.1E+00	2.5E-02
	factor(make)Lexus	3.5E-01	1.1E-02	3.5E-01	1.1E-02	3.0E-01	1.1E-02	3.5E-01	1.1E-02	2.9E-01	1.1E-02	3.4E-01	1.1E-02	2.4E-01	1.1E-02	3.5E-01	1.1E-02	3.0E-01	1.1E-02
	factor(make)Lincoln	3.6E-01	1.9E-02	4.8E-01	1.8E-02	1.8E-01	1.9E-02	3.9E-01	1.8E-02	3.1E-01	1.8E-02	4.7E-01	1.8E-02	1.2E-01	1.8E-02	4.7E-01	1.8E-02	2.2E-01	1.8E-02
	factor(make)Mazda	4.4E-01	1.2E-02	3.9E-01	1.2E-02	4.0E-01	1.2E-02	4.1E-01	1.2E-02	3.8E-01	1.2E-02	3.8E-01	1.2E-02	3.3E-01	1.2E-02	4.1E-01	1.2E-02	3.4E-01	1.2E-02
	factor(make)Mercedes-Benz	8.5E-02	1.6E-02	1.1E-01	1.6E-02	-1.0E-02	1.6E-02	8.9E-02	1.6E-02	1.5E-02	1.6E-02	9.4E-02	1.6E-02	-9.1E-02	1.6E-02	1.1E-01	1.6E-02	-3.1E-03	1.6E-02
	factor(make)Mercury	6.6E-01	1.2E-02	7.3E-01	1.2E-02	5.2E-01	1.2E-02	6.5E-01	1.2E-02	5.9E-01	1.2E-02	7.1E-01	1.2E-02	4.5E-01	1.2E-02	7.4E-01	1.2E-02	5.1E-01	1.2E-02
	factor(make)Mini	1.4E+00	2.3E-02	1.4E+00	2.3E-02	1.3E+00	2.3E-02	1.4E+00	2.3E-02	1.4E+00	2.3E-02	1.4E+00	2.3E-02	1.3E+00	2.3E-02	1.4E+00	2.3E-02	1.3E+00	2.3E-02
	factor(make)Mitsubishi	9.0E-01	1.4E-02	8.6E-01	1.4E-02	9.4E-01	1.4E-02	8.8E-01	1.4E-02	8.4E-01	1.4E-02	8.5E-01	1.4E-02	8.7E-01	1.4E-02	8.7E-01	1.4E-02	9.1E-01	1.4E-02
	factor(make)Nissan	3.8E-01	8.9E-03	3.4E-01	8.9E-03	3.4E-01	8.8E-03	3.6E-01	8.8E-03	3.3E-01	8.8E-03	3.3E-01	8.8E-03	3.0E-01	8.7E-03	3.5E-01	8.8E-03	3.2E-01	8.8E-03
	factor(make)Oldsmobile	7.7E-01	1.4E-02	9.5E-01	1.4E-02	6.0E-01	1.4E-02	7.8E-01	1.4E-02	7.3E-01	1.4E-02	9.4E-01	1.4E-02	5.5E-01	1.4E-02	9.6E-01	1.4E-02	6.0E-01	1.4E-02
	factor(make)Plymouth	4.5E-01	2.2E-02	6.3E-01	2.2E-02	3.1E-01	2.1E-02	4.3E-01	2.2E-02	4.2E-01	2.2E-02	6.2E-01	2.2E-02	2.7E-01	2.1E-02	6.5E-01	2.2E-02	2.7E-01	2.1E-02
	factor(make)Pontiac	8.2E-01	9.4E-03	8.3E-01	9.3E-03	8.1E-01	9.3E-03	8.2E-01	9.3E-03	7.8E-01	9.3E-03	8.2E-01	9.2E-03	7.7E-01	9.2E-03	8.4E-01	9.3E-03	8.0E-01	9.3E-03
	factor(make)Porsche	-2.6E-01	5.6E-02	-1.9E-01	5.6E-02	-6.5E-01	5.6E-02	-2.9E-01	5.6E-02	-3.7E-01	5.6E-02	-2.1E-01	5.5E-02	-7.8E-01	5.6E-02	-1.7E-01	5.5E-02	-7.0E-01	5.6E-02
	factor(make)Saab	5.4E-01	2.1E-02	5.1E-01	2.1E-02	6.0E-01	2.1E-02	5.3E-01	2.1E-02	4.8E-01	2.1E-02	5.0E-01	2.1E-02	5.3E-01	2.0E-02	5.1E-01	2.1E-02	5.9E-01	2.1E-02
	factor(make)Saturn	6.1E-01	1.1E-02	6.1E-01	1.1E-02	6.2E-01	1.1E-02	5.9E-01	1.1E-02	5.9E-01	1.1E-02	6.1E-01	1.1E-02	6.0E-01	1.1E-02	6.2E-01	1.1E-02	5.9E-01	1.1E-02
	factor(make)Scion	3.4E-01	2.1E-02	2.2E-01	2.1E-02	3.0E-01	2.1E-02	2.9E-01	2.1E-02	3.1E-01	2.1E-02	2.2E-01	2.1E-02	2.7E-01	2.1E-02	2.4E-01	2.1E-02	2.4E-01	2.1E-02
	factor(make)Subaru	5.4E-01	1.0E-02	4.9E-01	1.0E-02	5.5E-01	1.0E-02	5.1E-01	1.0E-02	4.9E-01	1.0E-02	4.7E-01	1.0E-02	4.9E-01	1.0E-02	5.0E-01	1.0E-02	5.1E-01	1.0E-02
	factor(make)Suzuki	8.7E-01	2.3E-02	7.8E-01	2.3E-02	8.2E-01	2.3E-02	8.2E-01	2.3E-02	7.9E-01	2.3E-02	7.7E-01	2.3E-02	7.3E-01	2.3E-02	8.1E-01	2.3E-02	7.4E-01	2.3E-02
	factor(make)Toyota	3.8E-02	6.4E-03	3.0E-02	6.4E-03	4.1E-03	6.4E-03	3.1E-02	6.4E-03	2.9E-02	6.4E-03	2.8E-02	6.4E-03	-5.3E-03	6.4E-03	3.3E-02	6.4E-03	-5.9E-03	6.4E-03
	factor(make)Volkswagen	5.1E-01	1.2E-02	4.7E-01	1.2E-02	5.4E-01	1.1E-02	5.0E-01	1.2E-02	4.6E-01	1.2E-02	4.6E-01	1.2E-02	4.9E-01	1.1E-02	4.8E-01	1.2E-02	5.2E-01	1.1E-02
	factor(make)Volvo	4.0E-01	1.5E-02	3.8E-01	1.5E-02	4.6E-01	1.5E-02	4.0E-01	1.5E-02	3.4E-01	1.5E-02	3.7E-01	1.5E-02	3.9E-01	1.5E-02	3.9E-01	1.5E-02	4.5E-01	1.5E-02
	factor(fuel)DIESEL	-4.3E-01	3.3E-02	-3.1E-01	3.3E-02	-2.8E-01	3.2E-02	-3.3E-01	3.3E-02	-2.5E-01	3.2E-02	-2.7E-01	3.2E-02	-7.8E-02	3.2E-02	-3.6E-01	3.3E-02	-1.3E-01	3.2E-02
	factor(fuel)FFV	-4.1E-02	8.2E-03	-7.3E-02	8.2E-03	-1.2E-02	8.1E-03	-1.4E-02	8.2E-03	-2.7E-02	8.2E-03	-7.0E-02	8.2E-03	5.6E-03	8.1E-03	-8.9E-02	8.1E-03	3.0E-02	8.0E-03
	factor(fuel)HYBRID	-6.5E-01	2.1E-02	-4.3E-01	2.0E-02	-6.6E-01	2.0E-02	-4.7E-01	1.9E-02	-2.8E-01	1.7E-02	-3.6E-01	1.7E-02	-2.4E-01	1.7E-02	-5.3E-01	1.9E-02	-3.9E-01	1.9E-02
	factor(UrbRur)urban	-6.1E-02	4.9E-03	-5.0E-02	4.9E-03	-1.3E-01	4.8E-03	-6.1E-02	4.9E-03	-6.2E-02	4.9E-03	-5.0E-02	4.9E-03	-1.3E-01	4.8E-03	-5.0E-02	4.9E-03	-1.3E-01	4.8E-03

After executing all regression model variations, we find standard error values of the continuous variables to be between 10^{-4} and 10^{-6}. In our case, since our standard error values are so small, we can still confidently say that our model is accurate and does not have unstable variable estimates; thus, multicollinearity is not a concern. We also see this by comparing the variable estimate coefficients, which do not change much from model to model.

The regression results, from the base model and the models excluding one of each of the correlated variables (Model 5 to Model 8), were tested for goodness of fit and validated using a few different metrics in order to provide the most accurate model. McFadden's r-squared value is similar to the r-squared value obtained from a linear regression model, yet falls within a smaller range. For instance, 0.2 is considered strong, so our value of 0.1 is considered to be a reasonably good fit. The log likelihood and r-squared values are better when larger. The largest values are found for Model 0, the full model including all variables. The Bayesian Information Criterion (BIC) measures the efficiency of the parameterized model in terms of predicting data, penalizes a model for including more independent variables and takes into account the size of the dataset. These previously stated goodness-of-fit metrics are calculated and shown below in Supplemental Material Table 7.

Supplemental Material Table 7: Additional Goodness-of-Fit Measures

Model	Log-likelihood from the Fitted Model	Max likelihood pseudo r-squared	McFadden's pseudo r-squared	Cragg and Uhler's pseudo r-squared	Bayesian Information Criterion
0	-1784547	0.07424	0.09991	0.1380	3569929
5	-1791043	0.07190	0.09663	0.1336	3582890
6	-1820197	0.06130	0.08193	0.1139	3641197
7	-1791094	0.07188	0.09661	0.1336	3582992
8	-1820068	0.06135	0.08200	0.1140	3640939

All goodness-of-fit metrics result in the same conclusion of choosing Model 0. While Model 0 is shown to be the best overall model, after observing the various goodness-of-fit measures in the other models excluding variables, estimates, standard errors, and fit metrics are not very different.

We also used 5-fold cross validation to look at the error in model predictability. This relies on splitting the data five ways, using 80% of the dataset as "training" data to create the initial model, and then the remaining 20% of the dataset as the "testing" data to check the model. This process is repeated with the five random samples and averaged error rates are calculated. When comparing the different models, again we see the most predictive model is that which includes all variables, Model 0, as it results in the smallest prediction error (Supplemental Material Table 8).

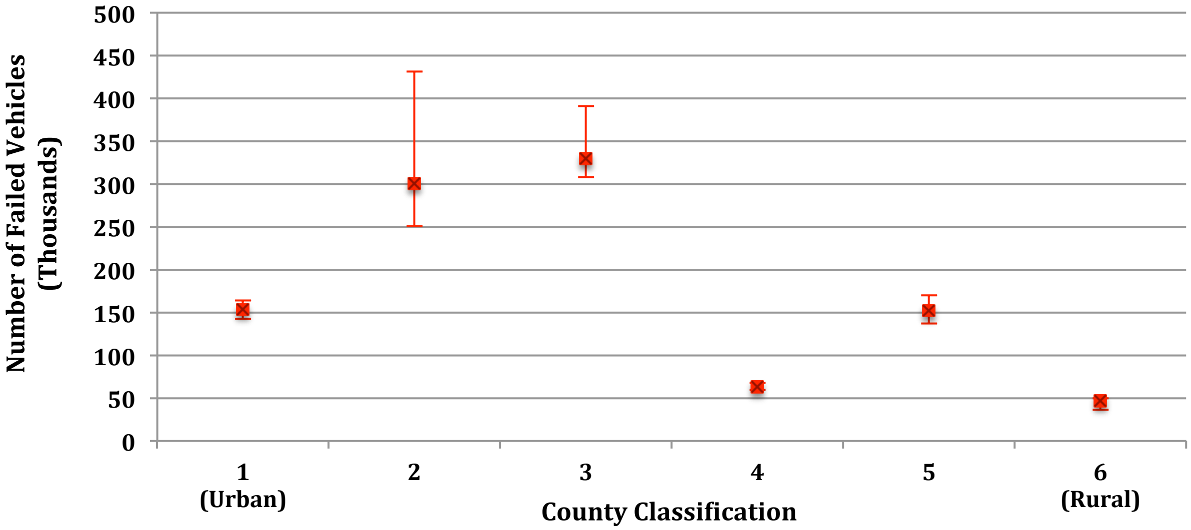
Supplemental Material Table 8: Model comparison by prediction error, resulting from cross-validation

Model	Variables Excluded	Raw cross-validation estimate of prediction error	Adjusted cross-validation estimate
0	None	0.1052	0.1052
5	Age, Fuel Economy	0.1054	0.1054
6	Odometer, Fuel Economy	0.1068	0.1068
7	Age, Weight	0.1054	0.1054
8	Odometer, Weight	0.1067	0.1067

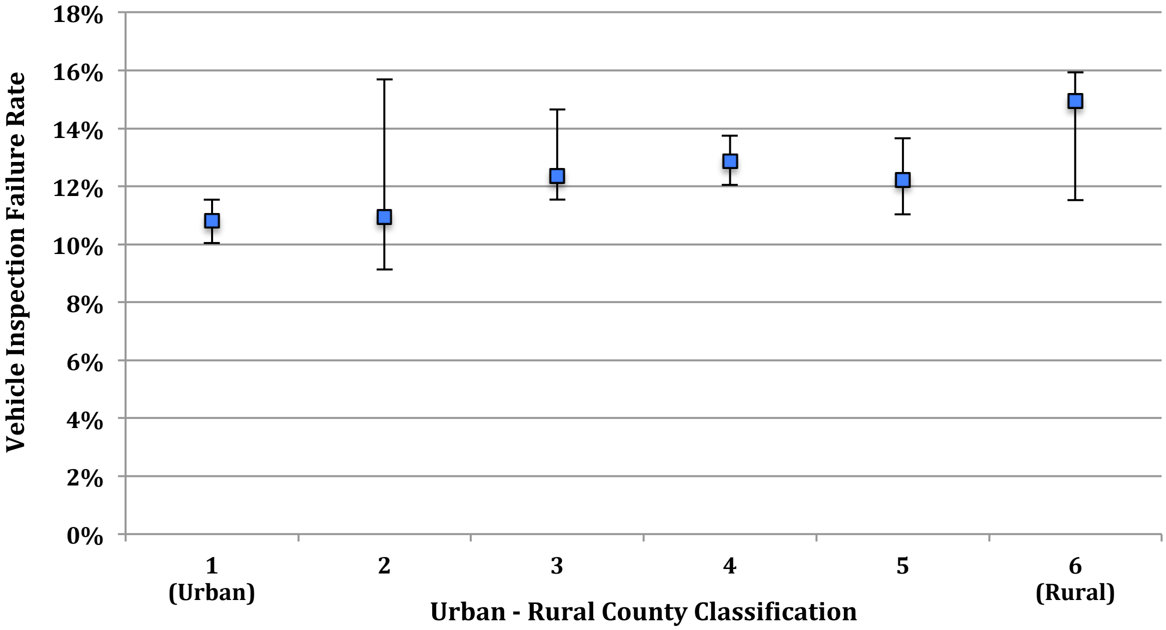
If a policy maker considered which of these highly correlated variables were better predictors than the others they could compare the prediction errors above the various goodness-of-fit measures. Therefore, with only certain information available about a vehicle, predicting safety inspection failure rates will still result in sufficient conclusions compared to the Model 0 scenario results. Thus, for a more accurate prediction of safety inspection failure rates, using age would be more direct and reliable than using odometer reading. And, looking that these same results, there is not an obvious advantage to using fuel economy versus weight.

V. Number of vehicles that would have failed estimates, by NCHS County Classification

Here, comparisons are made between failure rates and counts for both county classification and age. Failure counts are shown beside the failure rate graph in order to make easy comparison and look at both trends together. While the overall fail rate is constant across the counties, there are significantly more vehicles in the urban counties causing there to be many more failed vehicles. This can be compared between Supplemental Material Figure 5 and Supplemental Material Figure 6.



Supplemental Material Figure 5: Number of vehicles that would have failed in 2012, by county classification



Supplemental Material Figure 6: Average failure rates by county classification with error bars that represent min-max failure rate range from 2008-2012

Supplemental Material Table 9 provides a breakdown of specific characteristics of each county class. These characteristics include the average failure rate, the 2012 registered vehicle count, average vehicle age, and average vehicle odometer reading.

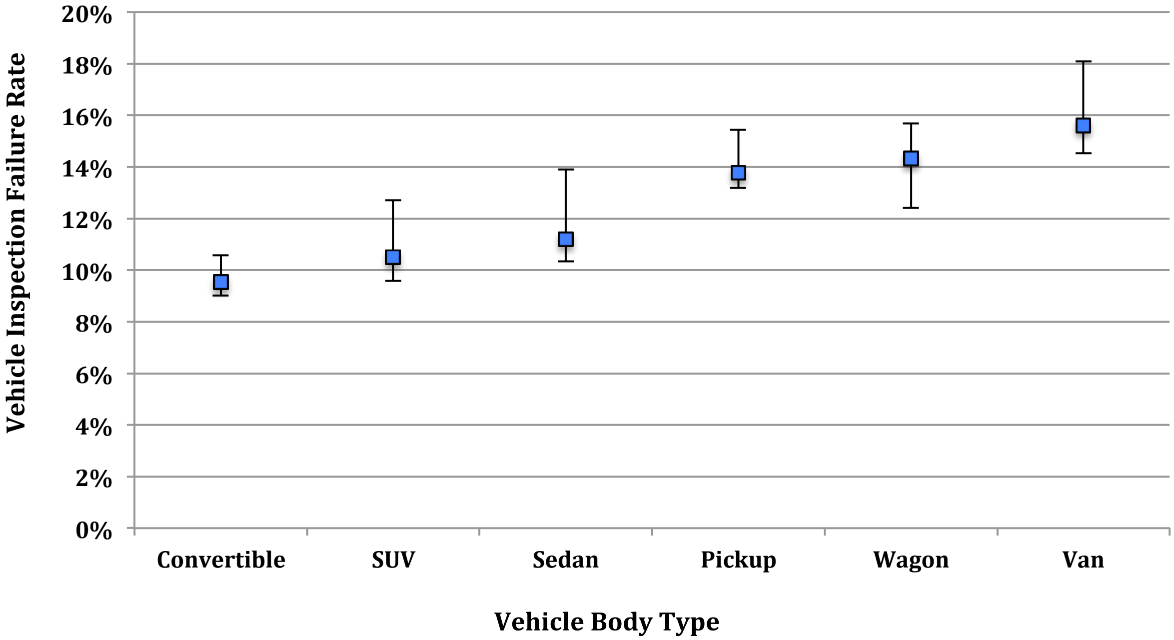
Supplemental Material Table 9: Detailed information by county class, inspection database

County Classification	Vehicle Inspection Failure Rate	2012 Inspection Database Vehicle Count	Average Age	Average Odometer Reading
1 - Urban	10.8%	850,000	3.9	40,000
2	10.9%	1,500,000	4.1	46,000
3	12.4%	1,500,000	4.5	50,000
4	12.9%	140,000	5.2	56,000
5	12.2%	290,000	4.9	56,000
6 - Rural	14.9%	26,000	5.0	59,000

As stated in the main body of the paper as well as the previous supplemental material section, it was found that the ages of inspected vehicles by county are much lower than those calculated in the registration database. As a result, it is likely these failure rate estimates by county classification are underestimates. More adjustments must be made to these failure rate estimates by county classification by applying failure rates associated with the average ages using the registration database, in those counties, which are on the order of 8 to 10 years old, corresponding with failure rates on the order of 20%.

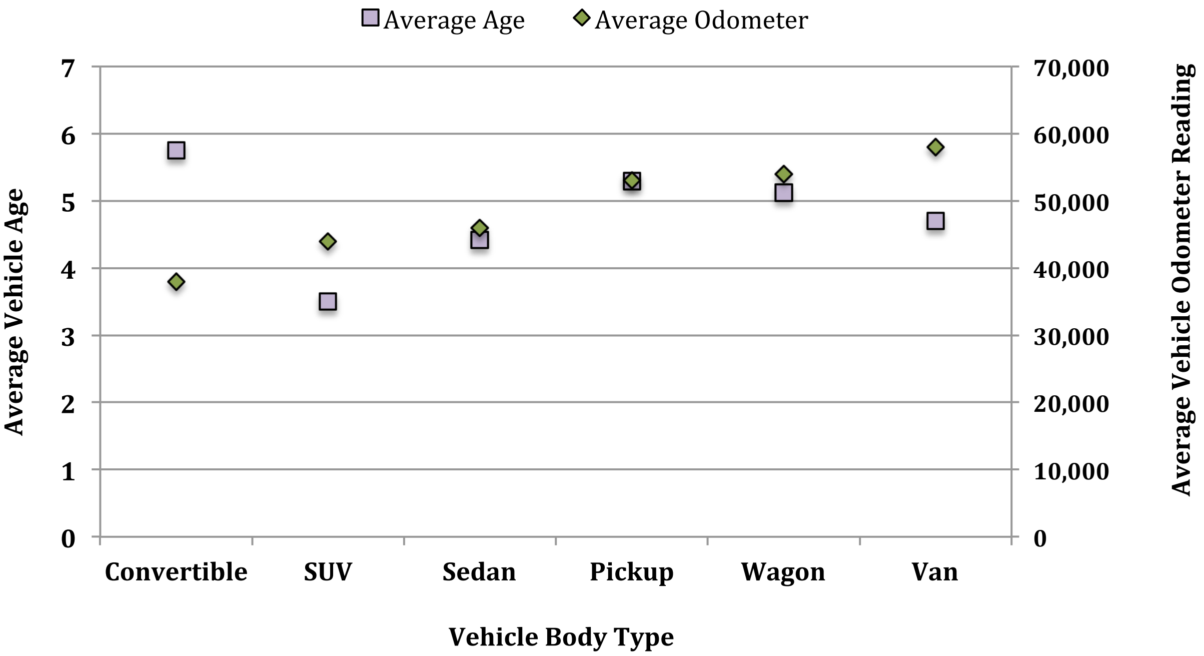
VI. Vehicle Safety Inspection Failure Rate by Vehicle Body Type

Failure rates by vehicle body type show that, on average, there are not large differences between failure rates by the body type (Supplemental Material Figure 7). While this is a noteworthy breakdown of failure rate, it is not considered when evaluating the vehicle safety inspection program. This is due to the policy aspect of this research, where creating varying safety inspection schedules for the different body types will not be easy to implement or necessarily effective.



Supplemental Material Figure 7: Average failure rate by vehicle body type and failure rates ranging from lowest to highest (error bars represent min-max failure rate range from 2008-2012

A closer look at the vehicle driving patterns and ages of these vehicle body types is displayed in Supplemental Material Figure 8. These figures are both arranged in order from lowest to highest failure rates. While odometer appears to be correlated with failure rate by vehicle body breakdown (increasing from convertible to van), age does not.



Supplemental Material Figure 8: Average vehicle age and odometer reading by vehicle body type, from lowest to highest failure rates

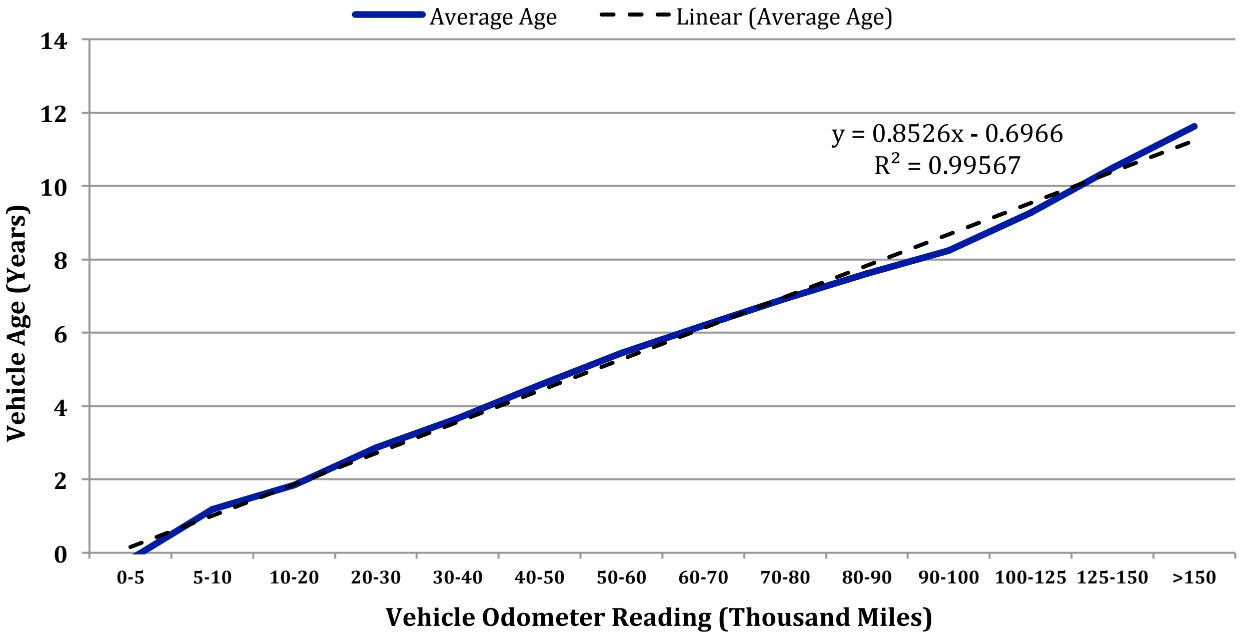
While this breakdown presents valuable information by vehicle type, it is not appropriate to create a policy to perform safety inspections based on vehicle body types. If executed, this type of policy would have many subsequent effects on types of vehicles being purchased and driven. As a result, these current conclusions would likely change. This data is broken down in Supplemental Material Table 10, and is then ordered by inspection year and increasing failure rate. It can be observed that convertibles consistently have the lowest failure rate, followed by SUVs, likely due to the associated travel patterns (presented here as odometer reading). Vans, wagons, and pickups consistently have the highest failure rates.

Supplemental Material Table 10: Vehicle characteristics by body type and inspection year

Vehicle Body Type	Inspection Year	Average Age	Average Odometer Reading	Failure Rate	Count
Convertible	overall	5.8	38,000	10%	78,000
SUV	overall	3.5	44,000	11%	1,200,000
Sedan	overall	4.4	46,000	11%	2,200,000
Pickup	overall	5.3	53,000	14%	390,000
Wagon	overall	5.1	54,000	14%	100,000
Van	overall	4.7	58,000	16%	300,000
Convertible	2008	4.4	31,000	9%	18,000
SUV	2008	2.8	37,000	10%	280,000
Sedan	2008	3.6	40,000	10%	540,000
Pickup	2008	4.5	47,000	13%	92,000
Van	2008	3.8	49,000	15%	74,000
Wagon	2008	4.8	54,000	15%	24,000
Convertible	2009	5.2	35,000	10%	19,000
SUV	2009	3.3	42,000	11%	290,000
Sedan	2009	4.0	43,000	11%	540,000
Pickup	2009	5.1	52,000	14%	92,000
Wagon	2009	4.9	52,000	15%	24,000
Van	2009	4.4	56,000	16%	71,000
Convertible	2010	5.7	38,000	9%	19,000
SUV	2010	3.3	43,000	10%	300,000
Sedan	2010	4.3	45,000	10%	530,000
Wagon	2010	4.7	51,000	13%	26,000
Pickup	2010	5.2	53,000	13%	91,000
Van	2010	4.7	59,000	15%	68,000
Convertible	2011	6.8	43,000	9%	14,000
SUV	2011	3.9	48,000	11%	240,000
Sedan	2011	5.1	52,000	12%	380,000
Wagon	2011	5.2	54,000	12%	21,000
Pickup	2011	5.7	56,000	14%	72,000
Van	2011	5.3	64,000	16%	51,000
Convertible	2012	8.2	52,000	11%	8,000
SUV	2012	5.1	59,000	13%	130,000
Sedan	2012	6.4	62,000	14%	220,000
Pickup	2012	6.9	66,000	15%	47,000
Wagon	2012	6.8	68,000	16%	13,000
Van	2012	6.5	75,000	18%	31,000

VII. Age versus Vehicle Miles Traveled Trend

Mileage bins and associated average age for each database. It can generally be concluded from the following table that the age of the vehicle increases as the odometer mileage increases. These values can be used to equate age exemption scenarios with mileage bins. The relationship between average ages from each database and general mileage ranges is presented in Supplemental Material Figure 9 and corresponding data in Supplemental Material Table 11.



Supplemental Material Figure 9: Average vehicle age versus odometer reading bin

This linear estimation results in an r-squared value very close to one, which means it is a good approximation of the relationship between the two variables.

Supplemental Material Table 11: Average vehicle age by mileage bin

Mileage Range	Overall Inspection Database
< 5,000	-0.2
5,000-10,000	1.2
10,000-20,000	1.9
20,000-30,000	2.9
30,000-40,000	3.7
40,000-50,000	4.6
50,000-60,000	5.5
60,000-70,000	6.2
70,000-80,000	6.9
80,000-90,000	7.6
90,000-100,000	8.2
100,000-125,000	9.3
125,000-150,000	10.5
> 150,000	11.6