Technologies for Safe & Efficient Transportation

THE NATIONAL USDOT UNIVERSITY TRANSPORTATION CENTER FOR SAFETY

Carnegie Mellon University | UNIVERSITY of PENNSYLVANIA

Assessment of Cost-Effectiveness of Pennsylvania's Automobile Safety Inspection Program

FINAL RESEARCH REPORT

H. Scott Matthews

Chris Hendrickson

Paul Fischbeck

Dana Peck

Contract No. DTRT12GUTG11

DISCLAIMER

Project Summary

States require inspections on vehicle safety components to be performed with varying frequencies and on various subsets of the fleet. In Pennsylvania, every passenger vehicle is inspected annually. Stakeholders have called for modifications or elimination of safety inspection programs. However, inspection data have not been available, so efforts to improve programs have been challenging.

In this work, we analyzed millions of Pennsylvania vehicle inspections from the past 8 years via comprehensive datasets pertaining to safety inspections and vehicle registrations. One of these datasets is from a collaborating partner, CompuSpections, a private PA company focused on IT solutions for inspection data management. While the conventional wisdom is that the failure rate is about 2%, our findings suggest that the actual rate is about 10 times higher. We studied this failure rate across many dimensions: time, age of vehicles, mileage driven, urban-rural, etc. We identified the major causes for inspection failure: brakes, tires, and lights, which are routine maintenance activities.

We also considered the cost-effectiveness of changes to the state inspection regime to maintain metrics of safety at socially acceptable levels. For example, the inspection cost tradeoffs in expected fatalities if the program were relaxed to exempt new or lightly driven cars from annual inspections. To accomplish this we combined our analysis of failures with a federal accident database (FARS) to estimate expected changes in annual fatalities caused by various underlying failures subject to inspection (i.e., accidents caused by brake or tire failures). The cost per life saved of the Pennsylvania program is calculated for five scenarios: the current program of inspecting all vehicles ($4.9 million per life saved); exempting vehicles 2 years old or younger ($5 million); exempting vehicles 5 years old or younger ($5.1 million); exempting vehicles in rural counties ($5 million); and inspecting only brakes, tires and lights ($2.7 million). These all show the safety inspection program to be worthwhile in comparison with the value of a statistical life of about $6 million, but that cost-effective improvements are possible.

Project Description of Work Done

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. The federal government does not, however, require inspections of personal vehicles. Without a federal mandate, it falls on the states to determine the extent and frequency of light duty vehicle[1] (LDV) safety inspections. As of January 2014, seventeen states require annual safety inspections (some of which also require emission inspections), twenty-three states require only emissions inspections, and ten states require neither. Where implemented currently, such programs call for specified safety 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 are constantly in flux, largely because of the perception, that such programs are costly to consumers and yet provide little or no benefits to society— other than revenue for auto shops that repair vehicles that fail inspection. Behind these perceptions are sentiments that cars have never been safer, yet very little data exists and thus very few analytical studies have been able to prove this. Questions as to where the benefits are, as a result of the time and effort that is spent on the inspections, have been raised. Recently, Pennsylvania legislators have been questioning the state safety inspection program, yet are not appropriately analyzing data and drawing relevant conclusions.

Previous research studies have determined the economic cost of the inspections and established a relationship between inspections and fatalities, yet mostly on a countrywide level (state by state). This general evaluation of safety inspection programs is not helpful in looking for ways to improve state programs, as the state itself must be analyzed.

In an effort expand upon these previous results, this study uses two unique datasets of the safety inspection records for the state of Pennsylvania to examine the cost-effectiveness of various data-driven inspection scenarios, while taking into account the state's vehicle distributions, such as age, mileage, or county type (urban/rural). A policy framework is established to have a reference point of whether program scenarios are better or worse and by how much. Results are identified that may help intelligently guide policy adjustments to the scope and frequency of LDV inspections.

---

[1] Light Duty Vehicle is a vehicle with gross weight less than 10,000 pounds; may include SUVs, small pick-up trucks, vans, etc.

The following policy research questions are addressed:
What is the current cost-effectiveness of the program and are there any adjustments that can be made to further improve its value? Is the current legislature valid in their attempt to modify the existing inspection program?

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 proposed. This allowed for regulations and prevention mechanisms to decrease these fatalities, including but not limited to the vehicle safety inspection program. [2] The handful of past studies performed have been high level analyses of whether states with safety inspection programs have higher crash or fatality rates which provide at best indirect measures of effectiveness. Both cross-sectional and time-series analyses were performed with varying results 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.

In 1980, Crain compared death and accident rates, through an economic analysis, in states with and without inspection programs, using 1974 cross-sectional data. [3] A benefit-cost analysis concluded that random safety inspections were as effective as the periodic inspections; and, the program should be either reevaluated or terminated, as these were not the intended results. In 1984, Loeb et al. published a time-series analysis of the efficacy of the inspection program in reducing fatalities, injuries, and accidents 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. [4] 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.

Unfortunately, the limited, more recent papers are not always driven by inspection data, and are econometric analyses based on metrics such as number of inspections performed or inspection fees, yet there is no reference scenario or base case used in these analyses to make appropriate comparisons. For example, these metrics are compared to vehicle fatality rates in states with and without inspection programs. Additionally, the papers' metrics are not explicit and methods are described with little detail. This makes new results extremely challenging to compare and reproduce. Inspection fees are also used as a comparison metric; however, fees are not standardized and may range from inspection location to inspection location. It is important to be aware of the complexity of the inspection, for example why the vehicle is failing or passing and what the measurements were, that were taken during the inspection.

Additional past studies were not found to support safety inspections, yet the methods used in these studies were vague and high-level analyses which do not represent the actual effectiveness of the state-specific programs. Finally costs of the programs were found in these studies; however benefits were never clearly defined. Additional literature review can be found in Appendix A.

Ages of vehicles are not widely considered in doing any of the noted previous literature, yet may have some importance in choosing an appropriate policy or tax for inspection programs. Previous studies show older vehicles being driven less and the general vehicle mile traveled trend generally decreasing since 2007 after its plateau in 2004, which possibly affects inspection results. [9]

III. DATA

In Pennsylvania, safety inspections of LDVs are administered annually in every county and for all vehicles. The inspection procedure is followed uniformly across the state. Some (25 of 67) Pennsylvania counties also require emissions inspections[2], generally around urbanized areas. This paper will focus solely on LDV safety inspections in Pennsylvania.

Vehicle safety inspections in Pennsylvania generally include checking vehicle components such as: steering/suspension, exhaust, fuel, body/doors/latches, glazing/mirrors, brake system, other, lighting, and tires. The result of each required component tests is coded as a pass, or one of four “fail” categories: fail, new, repair, or adjust. In order to pass the safety inspection, the checks must be within the allowable threshold. For example, the minimum threshold for tire tread depth is 2/32 inch. If a vehicle’s tire tread is measured as less than this threshold the tire would need a replacement (aka "new") for a fee, to pass the safety inspection. On the other hand, if headlights are misaimed, for a small fee, the headlights are re-aimed and the vehicle passes the safety inspection (aka "adjust").

The fail, new, repair, and adjust categories all represent ways in which a vehicle *would*

[2] Vehicle emission inspections are required in metropolitan areas, whose air quality does not meet federal standards as stated in the Clean Air Act (1990).

have failed an inspection, even if a vehicle passes when leaving the inspection station. This is important to consider especially when analyzing safety results without the inspection program, as these adjustments or replacements would have never otherwise happened.[3] If all of these components receive a "pass" and nothing on the vehicle was repaired or replaced, then the overall inspection is considered as a "pass". While inspections are systematic within a given state, inspection procedures vary state to state (see Appendix B).

In Pennsylvania, robust inspection data is recorded and held in databases owned by the PA Department of Transportation (PennDOT) as well as 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 electronic safety, "e-SAFETY", data archive ("state data"), where safety inspection stations could voluntarily report results of vehicle inspections (at a 74 cent fee per sticker issued and reduced to 18 cents in 2012). The impetus of this program was to ensure collection of data in order to distinguish "trends for future safety improvements by identifying potential vehicle safety hazards and safety patterns" [10]. For further information regarding the incentive for electronic inspection records, see Appendix B. Over time, several prominent state legislators have called for changing or repealing the program given a perceived failure rate of 2-3% [11]. Likely lost amongst the data from where these low fail rates are drawn are those various intermediate repairs or adjustments, which should have been classified as failures under the current inspection regime. Such perception does not help inform the policy debate given its weaknesses. In addition to the state data, a private vehicle inspection company has provided data on inspections ("private data").

Supplementary detailed reporting explanations can be found in Appendix B. It is generally assumed the private data is of higher quality compared with the state data, as it is not a voluntary system, is completely computerized, and is monitored by the private company for high level quality control from user inputs.

IV. METHODOLOGY

A. Raw Data

Raw data provided for this study includes Pennsylvania vehicle safety inspections ranging from 2007–2012 from two different data sources, in addition to Pennsylvania vehicle

[3] Assumes a consumer is not proactive about vehicle inspections. This topic will be addressed in a future paper with an additional dataset

registration records as of March 2012 and November 2013. The two datasets are composed of different numbers of records and summarized in Table 1.

Table 1: Initial Pennsylvania State Data Provided

Data Source	State Inspection	Private Inspection	Registration
Record Count	1.6 million	5.4 million	10.4 million

In addition to varying volume of records, there were both similarities and differences between the information provided from each dataset. Table 2 compares the datasets with items most relevant to this study.

Table 2: Datasets and Relevant Data Availability

Data	VIN	Odometer	Date	Location	Vehicle Make and/or Model	Inspection Type (e.g., annual)	Pass/Fail Component
Registration	X	X*	X*	X			
State Data	X	X	X	X	X	X	X
Private Data	X	X	X	X	X	X	X

*At time of registration for current owner in PA

With this information, various analyses can be performed, including, but not limited to, vehicle inspection failure rates or number of vehicles that "would have failed" with respect to age and/or county and/or odometer readings. Custom code written in the Python programming language was used to filter, analyze and compare each dataset (examples in Appendix C). Not all vehicles on the road are registered; however, one of the mandatory steps in the inspection process is to verify registration. Thus the registration data is a valid baseline of vehicle representation for the analysis.

B. DATA VERIFICATION AND PROCESSING

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. Various considerations and methods were carefully thought out in order to follow up on potential data imperfections. The following issues were filtered out:

- Invalid VIN (length, digits, verified)
- Duplicate entries
- Invalid date (format issue – not a date, no entry)
- Invalid odometer entry (alpha-numeric entry, no entry)
- Heavy-duty trucks

All entries containing the previously listed issues were discarded, as the entries could not be adjusted. About 10% of the registration data was filtered out, and about 2% of the private data, and about 8% of the state data was filtered. The private 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 (see Appendix C for filtering details and methodology). A post-filtering breakdown of available data is presented in Table 3. These data counts vary from the total counts of registered LDVs in the state, which was on the order of about nine million vehicles as of March 2012.

Table 3: Data Record Count by Year, After Filtering

Data Source	2007	2008	2009	2010	2011	2012	Total
State Inspection	23k	180k	240k	240k	300k	310k	790k
Private Inspection	790k	1.0M	970k	890k	680k	330k	2.7M

C. 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 or by age), 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 state data appearing to be similar to the registration data, while the private 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 Figure 1.

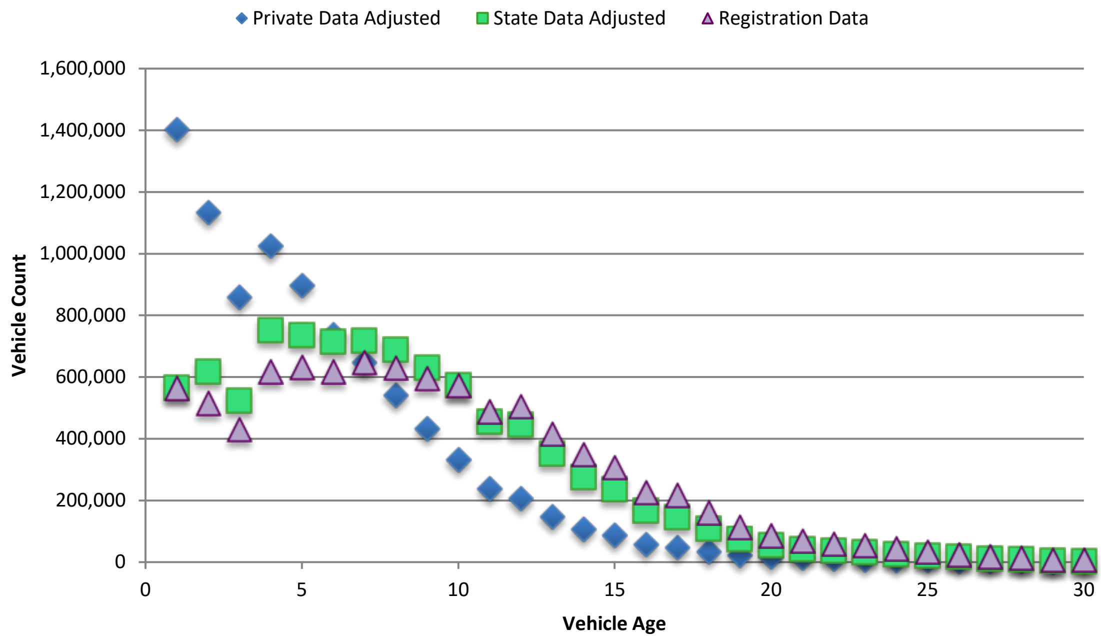

Figure 1: Dataset Representation Comparisons, 2012

These data similarities may be due to the state inspection and vehicle registration records coming from the same source. While the private data may not seem representative as a whole, the data itself must not be disregarded, especially when looking at the data by category. Further conclusions and assumptions will be made throughout the analysis as to whether some data should be discarded.

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 state and private inspection data files (at least for the registration file year of 2012), are representative of all vehicles.

In order to quantitatively compare the various dataset distributions, a series of chi-square analyses were implemented (see Appendix D). 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. This 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. Finally, it is concluded that the total number of data points is enough to be able to draw reasonable conclusions about the vehicle fleet, even if it is not statistically proven.

D. Failure Rate Metric

Once all the data was filtered, restructured, and checked for representativeness, failure rates were calculated for the different fail categories and then an overall failure rate. A failure was considered as an entry with any “fail”, “new”, “repair”, or “adjust” recorded, in both the state and private datasets. In this data model, a pass or fail was recorded as a ‘1’ or ‘0’ and only if the VIN had not already been recorded, as some VINs have multiple entries in a given year. This may occur if a vehicle gets an inspection, fails, and no work is performed immediately. Soon after, the vehicle may return to get the required work done to pass inspection. In this case, the first entry for the VIN is used as this is considered the initial safety inspection result.

The first analysis was to consider the overall LDV fail rate for the state as a whole. After filtering, the PA fleet is about nine million LDVs vehicles. Using the average overall vehicle failure rate between the state and private data of about 15% and the filtered registration total of LDVs, equates approximately 1.4 million unsafe vehicles that *would have failed* inspection. This metric clarifies the number of vehicles that would have otherwise failed inspections, without corrective action taken across the various state-mandated safety tests.

In order to setup the various scenarios to analyze, Pennsylvania was categorized based on county population density in order to distinguish between urban and rural areas. A total of six county categories were created with Type 1 denoted as most urban and Type 6 denoted as most rural using Census data. The majority of the counties are designated as being rural; however, there are more vehicles located in urban areas. See Appendix E for a more detailed breakdown of county types. Between the six types, the failure rate only ranges from 17% to 22% (see Figure 2).

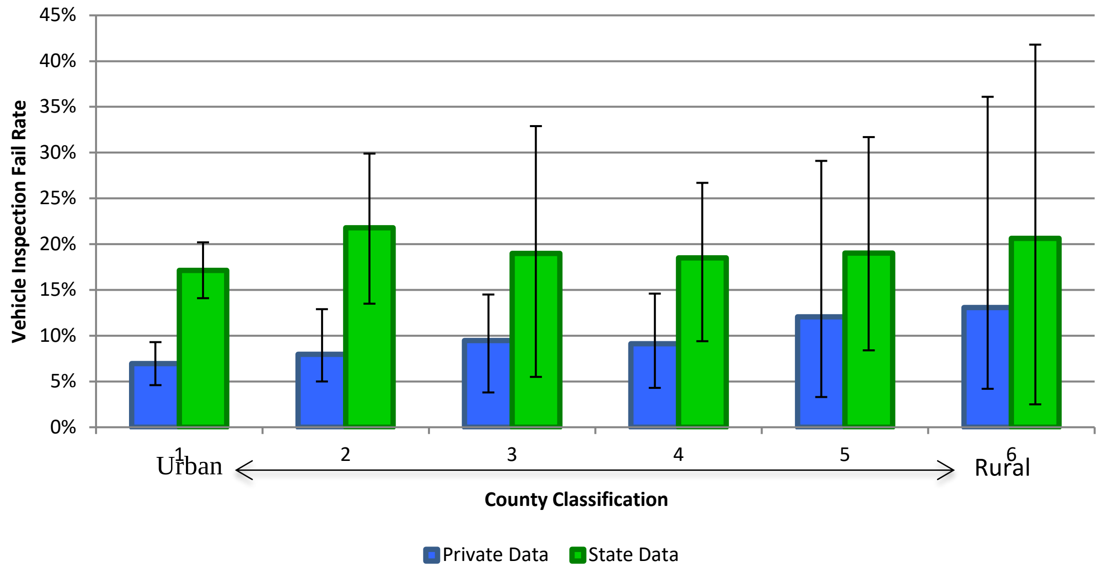

Figure 2: Failure Rates by County Classification. Error bars represent min-max range

In addition to a breakdown by county classification, vehicle age distributions were also observed in the state of Pennsylvania as a whole, using the 2012 state registration records as shown previously, in Figure 1.

Age is important to calculate because driving patterns differ as a result of vehicle age and it is also important for this analysis to see if given ages of vehicles are failing more or less than others. The age distribution may be important for policy implementation since there are much fewer older (more than ten years old) vehicles being driven. This however does not mean the old vehicles should be ignored from policy decisions. Potentially it will be easier to implement policies on the older vehicles since there are fewer. Figure 3 displays the vehicle inspection failure rate with respect to vehicle age, as well as the overall state failure rate for each dataset for comparison.

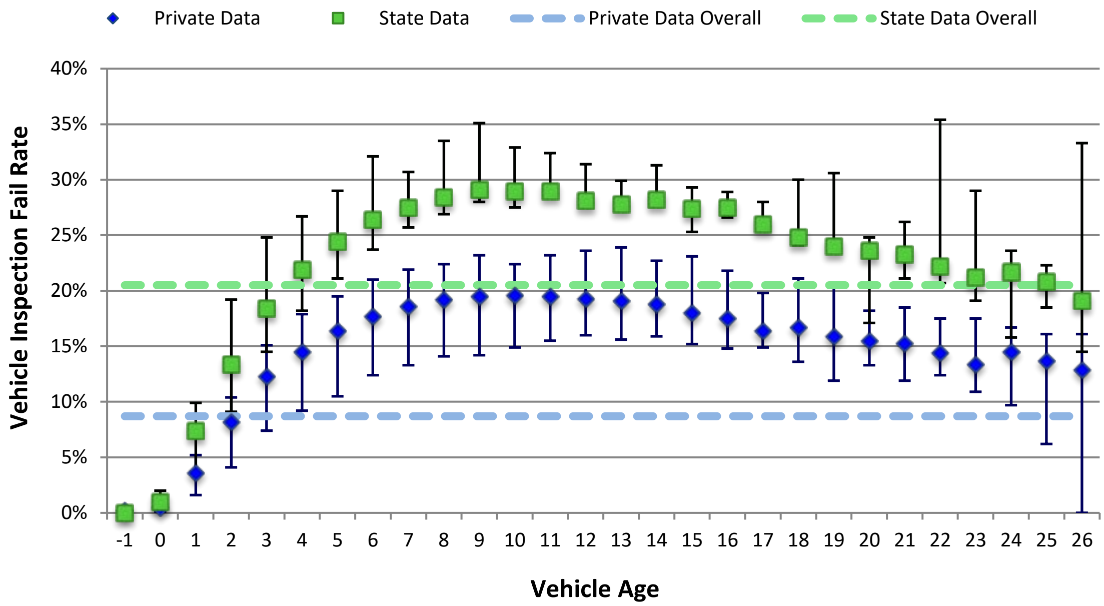

Figure 3: Failure Rates by Vehicle Age. Age notation is calculated based on the model year and the more recent inspection year of the vehicles, so that the lowest age results in '-1' (e.g., a 2008 model-year vehicle could be purchased and inspected in 2007).

Figure 3 shows a very low (but not zero) failure rate for new vehicles and around age two to three, the failure rates begin to surpass the overall state average failure rate and stay above that average for the most part. Unlike the decreasing age distribution across the registered vehicles, the failure rate across the state increases with age and remains significant with older vehicles. The maximum failure rate is at almost 30% around ages eight to nine; additionally, the failure rate distribution by age shows the majority of vehicles after age three above the state average failure rate. This means that careful consideration must be taken into account when describing the overall state failure rate since it is significantly lowered by the greater number of young vehicles (Figure 1), which fail less often. Additionally, the failure rates in the state data are consistently higher than that of the private data. This may be due to less data overall to be analyzed from the state versus the private data, or because of the hidden incentive for those participating in the state data program to participate with more failing inspection results. This may result from the need for job security for those inspectors.

A more comprehensive presentation of the data would be to calculate how many vehicles "would have failed" without the program. According to this standpoint, without the safety program, thousands would be driving failed vehicles each year. While all vehicles are important to account for, age differences are important when creating policy recommendations. While all unsafe vehicles need to be addressed, the mid-age vehicles are what these policies should focus on primarily because these vehicles generate the majority of "would have failed" vehicles, displayed in Figure 4.

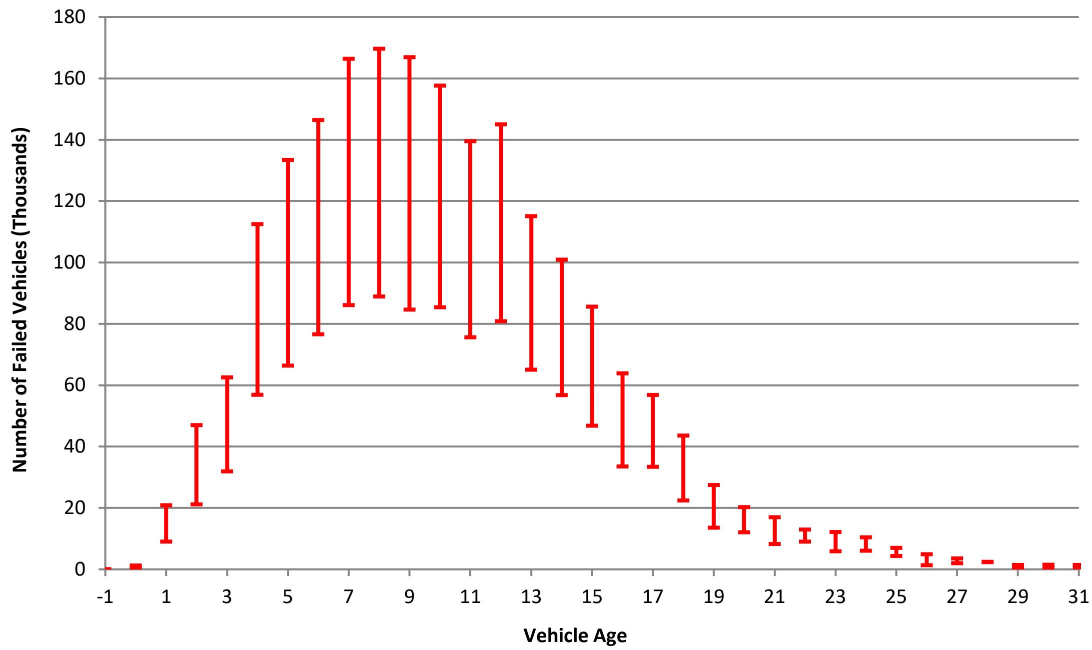

Figure 4: Number of Vehicles that Would Have Failed in 2012, by Vehicle Age (bars represent two dataset results)

In considering inspection exemption scenarios, graphs look similar to Figure 4 and are summarized in Table 4.

Table 4: Exemption Scenarios - Number of Vehicles that Would Have Failed

Number of Years Exemption	1	2	3	4	5	10	All
Number of Vehicles that Would Have Failed an Inspection (in a given year)	750	16k	50k	97k	182k	770k	1.6M

The final fail rate analysis was done by odometer. This distribution shows how the failure rate increases with mileage, so owners of vehicles with higher mileage benefit from vehicle inspections. Figure 5 displays this distribution for both the state and private company data.

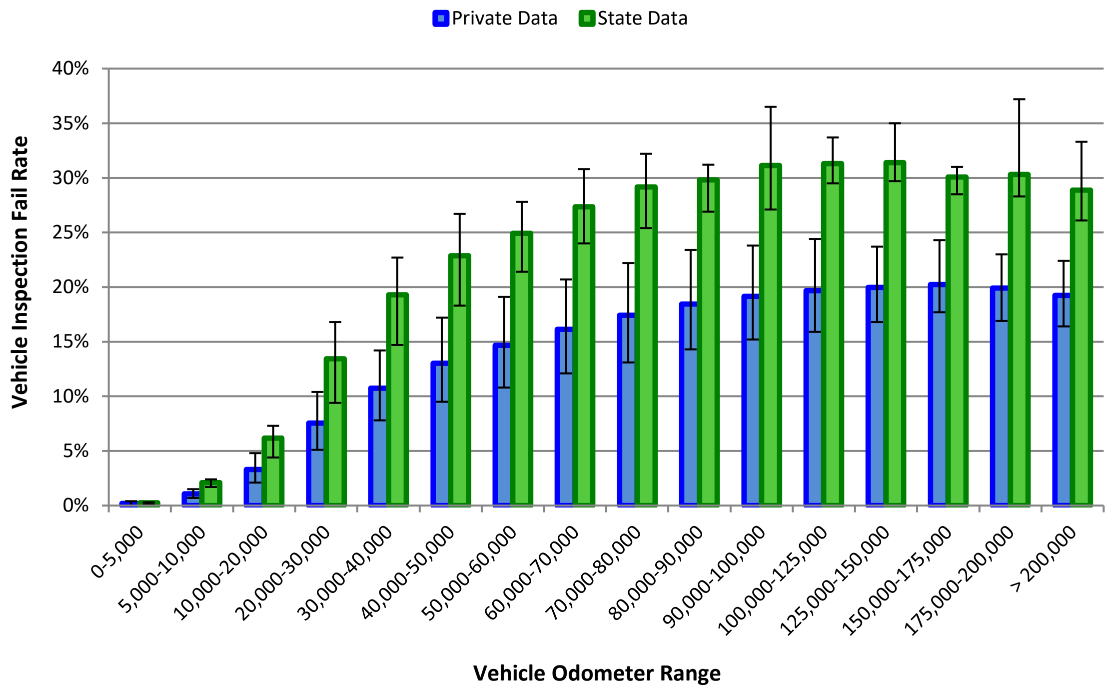

Figure 5: Failure Rates by Vehicle Odometer Value, vehicles that *would have failed* inspection

This suggests there is an increased failure rate with increased odometer values and supports the suggestion to perform safety inspections in accordance by odometer values. The categories of age and mileage can be used similarly in describing a vehicle and classifying appropriate inspection failure trends. However, these categories were shown separately in response to recent legislature proposals to exempt vehicles by specific ages or mileages. Additional analysis was executed in order to find the average ages of vehicles within these odometer bins (see Appendix F), so they can be used more interchangeably in this analysis.

E. Fatality Analysis Rating System (FARS)

The FARS database contains fatal crash information in the US. In every state, law enforcement agents are required to write crash reports at the scene for any incidents, which may result in discrepancies state-to-state depending on the first-responders, as well as the variability report-to-report. Despite these shortcomings in reporting crash information, FARS is the most comprehensive repository of information and is routinely used in transportation and safety oriented research. FARS contains data on crashes, the vehicles and drivers involved in them, and their likely causes. Crashes due to specific components (e.g., brakes) can be filtered from the totals and are used for the purpose of analyzing the safety inspection program. The safety components with the highest associated fatal crashes in FARS were brakes, tires, and lights.

In 2007, Cambridge Systematics studied Pennsylvania's safety inspection program[12]. In their analysis, four years of fatalities were examined on both the state and county-level in order to assess the effectiveness of the vehicle safety program. A key contribution of the report is a series of regression-based analyses of FARS to compare fatality rates in states with vehicle safety inspection programs to states without them. In short, the Cambridge study estimated 1-2 fewer fatalities per billion vehicle miles traveled (VMT) with a safety program.

The key summary graphic of the Cambridge report, Table 5, shows their estimates of crashes and fatalities avoided[4] as well as their estimates of overall benefits and costs of safety inspections based on a vehicle fleet size of 10.9 million.

Table 5: Analysis of Safety Benefits versus User Cost in Pennsylvania for the Vehicle Safety Inspection Program, taken from 2009 Cambridge Systematics Report

	Benefits of the Vehicle Safety Inspection Program as Calculated by Various Models			User Costs of the Vehicle Safety Inspection Program Three Scenarios		
Attribute	**State Model of Total Crashes (Table 4.3)**	**State Model of Crashes per Billion VMT (Table 4.2)**	**County Model of Total Crashes (Table 4.5)**	**High**	**Medium**	**Low**
Number of Fewer Crashes	114.30	168.91	141.37			
Number of Fewer Deaths	127	187	157			
Value of a Statistical Life	$5.8 Million	$5.8 Million	$5.8 Million			
Number of Vehicle Inspections				*10.9 Million*	*10.9 Million*	*10.9 Million*
Direct Cost of Inspection to Vehicle Owner				*$23.00*	*$19.50*	*$16.00*
Value of Vehicle Owner's Time for the Inspection				$34.00	$17.00	$8.50
Value of Action	**$736.6 Million**	**$1,084.6 Million**	**$910.6 Million**	**$621.3 Million**	**$397.9 Million**	**$267.0 Million**

In every case, the benefits outweigh the calculated program costs by at least $100M, including both cost of inspection and value of time spent for the inspection. The recommendations section of the Cambridge study specifically recommended development and use of E-Safety so as to consider modifications of the program, including refinement of the specific tests done during an inspection, so as to improve program effectiveness. The remaining section of this paper combines the results of the inspection datasets with the FARS analysis to assess such program options.

[4] On the benefits side, they assumed 1.1 occupants per vehicle, thus 1.1 fatalities per fatal crash. They also used a constant value of statistical life of $5.8 million. On the user cost side, they assumed 10.9 million passenger vehicles, and a range of direct costs of the inspection of $16-$23 as well as $8.50-$34 for the value of time spent waiting for the inspection.

V. Policy Analysis Framework

Due to recent legislature pressure, now is an opportune time to reevaluate and consider potential changes to the inspection program structure to provide the utmost effective, performance-based policy. There are various options that should be evaluated prior to any program structure change. In this analysis, five scenarios are evaluated and compared: the status quo, eliminating the safety inspection program, exempting one and two year old vehicles, exempting vehicles up to age five, exempting rurally owned vehicles, and refining inspections to only brakes, tires, and lights (see Appendix G for explanation and details). To find the most cost-effective scenario, the ratio of program cost per life saved is estimated and compared to the value of a statistical life, which is assumed to be $5.8 million, as used in the Cambridge Study (and by DOT and EPA in similar analyses).

In our framework, costs are the user cost of an inspection, excluding any cost for actual maintenance, which is assumed to be part of the responsibility of owning a vehicle. A range of costs of an inspection is taken from the state data (noting that a significant portion of inspections are performed for free in hopes of getting maintenance revenue). In addition to this direct cost, ranges of the opportunity cost of time were calculated for waiting and driving to and from the inspection. This waiting and commute time was assumed to be an hour for the average inspection[5] and a total of 30 minutes round trip drive. Additionally, a range of ±10% was added to account for uncertainty in this estimate. Fuel costs and depreciation were excluded. This indirect cost was calculated based of an average income of $30,000 [13] and calculated to be $15/hour[6]. These costs are shown in Table 6.

Table 6: Cost of Vehicle Safety Inspection Program

2012 Cost from State Data	Inspection Cost ($/inspection)	Cost of Waiting	Total Cost
Average	$32	$22	$55
5th Percentile	$2	$20	$22
50th Percentile	$27	$22	$49
95th Percentile	$61	$25	$86

Benefits are measured by calculating the delta number of fatalities between the baseline scenario of no program and the scenario being analyzed and can be thought of as the resulting

[5] As assumed in the Cambridge Study
[6] Assume work 40 hours/week and 50 weeks/year

number of lives saved as a result of a particular program. The cost- effectiveness (CE) ratio is the cost per life saved, which can be compared with the value of a statistical life.

The assumption of one to two crashes per billion VMT difference (and 1.1 fatalities per crash) from the Cambridge study is used to calculate the baseline fatalities in Pennsylvania. From the three datasets, the available information includes, but is not limited to: number of vehicles inspected, number of vehicles not inspected, number of unsafe vehicles, estimated inspection cost per year, and annual VMT of those unsafe vehicles.

Prior to any further analysis or program structure alterations, the current safety inspection program (status quo) must be compared to a hypothetical case of no safety program. In the current annual safety inspection regime, about nine million vehicles are inspected as from the Pennsylvania registration database. From the FARS data, in a given year in Pennsylvania, about 1,500 crashes occur overall, but only 65 were deemed by the crash reports to be the result of failures of vehicle safety components (e.g., tires or brakes). Using the available datasets, VMT overall and by specific targeted subsets of the PA fleet were calculated and in Table 7 (see Appendix H).

Table 7: Scenario Average VMT

Scenario	Average Miles/vehicle/year
Overall Fleet	10,000
Vehicles Age 0-2	11,500
Vehicles Age 0-5	11,000
Rural-housed Vehicles	10,600

Assuming the current system inspects all vehicles, that the "no program" option inspects no vehicles, and each scenario inspects a subset of the fleet, the VMT of uninspected vehicles can be calculated for all scenarios by multiplying the average VMT per vehicle by the total number of uninspected vehicles in the scenario. The data is presented in Table 8. This allows the number of expected fatalities to then be calculated.

Table 8: Program Scenarios (Averages only)

Option	# Vehicles Inspected (million)	# Vehicles Not Inspected (million)	# Would Have Failed (thousand)	Un-inspected VMT
No Program	0	9	1,600	90
Status Quo	9.0	0	0	0
Exempt first 2 years	8.2	0.81	16	9
Exempt first 5 years	6.6	2.4	180	26

Exempt Rural Counties	7.0	2.0	330	21
Inspect only brakes/tires/lights	9.0	0	1,300[7]	0

Under the current program where all LDVs are inspected annually, there are 65 fatalities due to safety-related issues, as previously defined and this is assumed as the number of fatalities with all vehicles participating in safety inspections. We thus assume a minimum of 65 fatalities due to safety-related crashes. Equation 1 was used to calculate the delta safety-related fatalities per year for each option:

$$\frac{\Delta\, safety\, fatalities}{Year} = 1.1 \frac{fatalities}{billion\, VMT} * X \frac{billion\, VMT}{Year} + 65\, fatalities \qquad Eq. 1$$

Once these were calculated, the "no program" option was used as a baseline with a zero cost to find the “lives saved” and cost for each scenario. Finally, the cost of the scenario inspection program was divided by the “lives saved” in order to find the cost-effectiveness of each program scenario, as presented in Table 9.

Table 9: Scenario Benefits and Costs

Option	User Cost per Year (million)	Δ Safety Fatalities per Year	Safety Fatalities per Year	Cost/Life Saved (million)
No Program	$0	160-260	Baseline	--
Status Quo	$490	65	-99 to -200	$2.5-$4.9
Exempt first 2 years	$450	75-85	-89 to -180	$2.5-$5.0
Exempt first 5 years	$360	94-120	-70 to -140	$2.6-$5.1
Exempt Rural Counties	$380	88-110	-76 to -150	$2.5-$5.0
Inspect only brakes/tires/lights	$250	74	-90 to -190	$1.3-$2.7

These results answer the initial policy question:

What is the current cost-effectiveness of the program and are there any adjustments that can be made to further improve its value? Is the current legislature valid in their attempt to modify the current inspection program?

The current cost-effectiveness of the program is estimated at about $4.9 million per life saved. Compared to the value of a statistical life of $5.8 million, the program is worthwhile from a public policy standpoint; in fact, all of these scenarios are worthwhile when compared to the

[7] Assumed to be 80% of “failed” inspections

value of a statistical life (albeit marginally so). While the current program (status quo scenario) is the second best option, in comparing the five scenarios, the most cost-effective policy would focus on inspecting only brakes/tires/lights as this shows the least cost per life saved of $2.7 million. This would mean implementing a program using the most common causes of failures, which are brakes, tires, and lights. This also directly coincides with the FARS data showing these components were the highest contributors to safety related crashes. The current legislature is valid in their attempt to modify the current program; however, their methodology and suggestions of how to improve it are not the best. The data shows the vehicle fleet's general safety improvement over time, but this trend is not fast enough (see Appendix I).

While state policymakers have the right idea that modifications may need to be made to the program, it is nowhere near ready to be eliminated. There is still significant benefit to run the program and keep unsafe vehicles off the road.

Accomplishments and Metrics

The failure rate analysis for Pennsylvania safety inspection data was published in:

> Dana Peck, H. Scott Matthews, Chris Hendrickson, and Paul Fischbeck, "An Analysis of Vehicle Safety Inspection Data in Pennsylvania: Expected Failure Rates", Transportation Research Part A, Volume 78, August 2015, Pages 252–265, 2015. **DOI**: 10.1016/j.tra.2015.05.013

We also did various policy briefings to PennDOT employees in Harrisburg as well as at the annual IM Solutions Conference (the main professional meeting for the inspection-maintenance industry).

Acknowledgements

This material was also based upon work supported by the National Science Foundation under Grant No. 0946825. The Department of Civil and Environmental Engineering at Carnegie Mellon University also supported this research. The Pennsylvania Department of Transportation provided vehicle inspection data and vehicle registration data. An anonymous safety inspection company provided a secondary inspection database.

REFERENCES

[1] F. A. Administration, “Aviation Maintenance Technician Handbook - General,” pp. 1–34, 2008.

[2] *Highway Safety Improvement Program History*. [Online]. Available: http://safety.fhwa.dot.gov/hsip/gen_info/hsip_history.cfm. [Accessed: 03-Jan-2014].

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

[4] 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.

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

[6] 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.

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

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

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

[10] P. D. O. Transportation, “Pennsylvania’s e-SAFETY Program Publication,” vol. 1, no. 1, pp. 1–4, Oct. 2007.

[11] C. Moraff, “It’s Time to End Vehicle Inspections in Pennsylvania,” *Philadelphia*, pp. 1–3, 15-Mar-2012.

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

[13] *Pennsylvania State and County QuickFacts*. [Online]. Available: http://quickfacts.census.gov/qfd/states/42000.html. [Accessed: 03-Jan-2014].

[14] 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.

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

[16] *GM VIN Check Digit Verification*. [Online]. Available: http://people.virginia.edu/~sns5r/resint/empiostf/checkdigit.htm. [Accessed: 03-Jan-2014].

[17] *VIN to Year Chart*. [Online]. Available: http://support.alldata.com/alldata-repair-online-article/vin-to-year-chart. [Accessed: 03-Jan-2014].

[18] National Highway Traffic Safety Administration and P. D. O. Transportation, *Vehicle Identification Number Requirements: Final Rule*. 2008, pp. 1–77.

[19] *Urban-Rural Classification*. [Online]. Available: http://www.cdc.gov/nchs/data/oae/NCHSUrbruralFileDocumentation.pdf. [Accessed: 03-Jan-2014].

ADDITIONAL LITERATURE REVIEW

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 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 accidents and mortalities. [14] 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. [15] Again, 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. [5] 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 off the frequency of inspections and these resulting variables were used in an econometric equation along with both fatal and non-fatal estimated models. [6] Rather than comparing fatal and non-fatal models, a more concrete analysis would be to first distinguish a base case of fatalities and how it changes due to these 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 revenue. Their results indicated that inspections had no significant impact on old cars or the repair industry. [7] This study did not identify how or if the inspection program with older vehicles was compared to the program for the entire vehicle fleet versus only for the older vehicles. Additionally, Sutter and Poitras (2002) examined political motives 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. [8] This study does not use a valid metric to quantify the benefits of an inspection program.

INSPECTION RESULTS

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.

DATA

A few years prior to the commencement of the state program, the private company released software to manage and monitor vehicle safety inspections, also in the state of Pennsylvania. These two datasets are compiled of relatively the same data; however, may be differentiated by the details for each data point they contain.

DATA REPORTING

All safety inspection stations are subject to random station audits of the detailed, typically hand-written, inspection records. This may be important in order to back-check any repairs made to a vehicle involved in an accident or to monitor reported failures to be sure they are not over-reported. Both the state and private company's software program allow for quick and detailed access to records for inspection stations during times where previous records must be accessed. 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 the same model-year vehicles.

The state data is comprised of voluntary data and therefore may be biased toward stations with very high fail rates or to report safety inspection fails more often. Higher fail rates helps justify the continuation of the inspection program, which brings in revenue for those inspection garages. On the other hand, the private data is comprised of stations that buy the software to manage the inspection data and may not be representative of the state vehicle composition. Rather than inspections being voluntarily submitted, the private company is able to collect all of the data entered into the system.

An inspection test is recorded according to if the vehicle had any work done during the safety inspection or as a result of the safety inspection. This is a necessary metric to account for the rationality of the program, since this is the direct result of implementing the program. A program would not affect a vehicle that enters and leaves a station as a fail; therefore, these are not the only "fails" that should be considered. Instead, the metric of "work performed" on the vehicle is considered a "fail", as this work may not have been performed if the program did not exist.

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.

DETAILED VIN FILTERING

Prior to 1981, there was no standard in recording VIN data and 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.

In order 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 Figure **6**.

```
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
```

Figure 6: 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 Figure **7**.

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

Figure 7: 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.[16]

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
```

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.

Another data issue, shows sequential odometer differences that are too large for an appropriate annual mileage, for example larger than 50,000 miles in a given year. 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, although they contained invalid readings, were not discarded at this time.

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. Table **10** [17] below shows the year designations.

Table 10: VIN Model Year Encoding

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. [18] 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, 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.

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.

CHI-SQUARED

Each dataset permutation, consisting of the state, private, and 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.

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 state nor private inspection programs.

COUNTY CLASSIFICATION

In order to setup the various scenarios to analyze, Pennsylvania was categorized based on county population density in order to distinguish between urban and rural areas, as shown in Figure **8**. [19] It is hypothesized that county types will reflect varying driving patterns and/or inspection results.

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
.	Missing	No code for Yellowstone Park, Montana. It no longer exists.
Total	All categories	

Figure 8: 2006 NCHS Urban-Rural Classification Scheme for Counties

Table **11** shows the 2012 Pennsylvania vehicle registration breakdown between the different urban-rural classifications as well as vehicle representation.

Table 11: 2012 Registration Data Summary by Urban-Rural County Classification

Classification	# Vehicles (1,000)	Vehicle State Representation	# Counties	Average Vehicles per County Type (1,000)
1	1,400	16%	2	700
2	2,600	29%	9	290
3	2,800	32%	16	180
4	530	6%	6	88
5	580	7%	8	73
6	920	10%	26	35

This is important to consider when designing policies since the majority of the vehicles are located in urban counties, yet the majority of counties are rural. While the vehicle distribution between county types is drastically different, the inspection fail rates for the various county types are somewhat consistent.

Additionally, failed vehicles are also categorized by county classifications and 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 is displayed in Figure **9**.

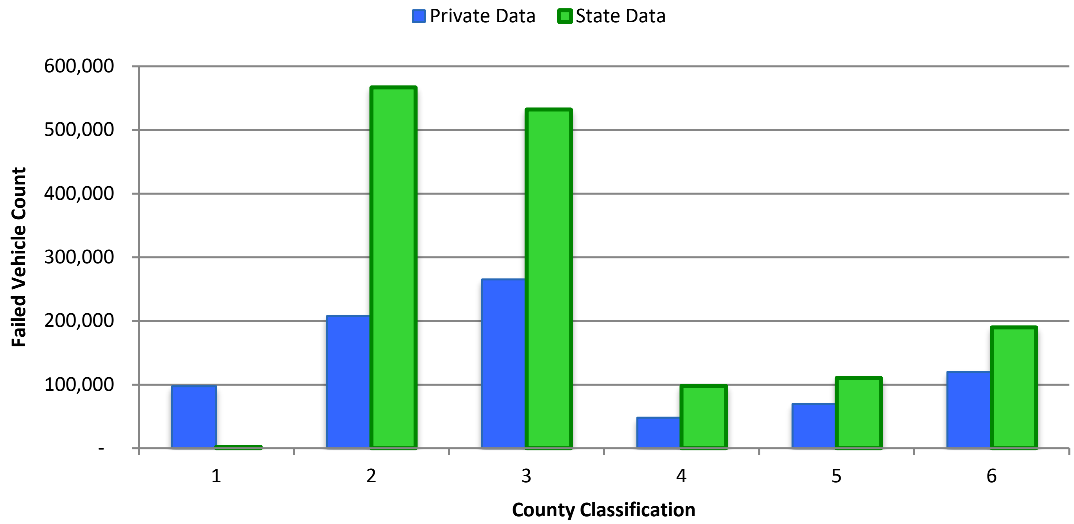

Figure 9: Number of Vehicles that Would Have Failed in 2012, by County Classification

From this graphic is seems as though a potential policy scenario would be to exclude rural counties. This is done in the analysis and while it is not the most cost-effective option, it is still not the worst option.

VEHICLE AGE-ODOMETER VALUE RELATIONSHIP

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.

Table 12: Average Vehicle Age by Mileage Bin

Mileage Range	CompuSpections	e-SAFETY
< 5,000	-0.2	-0.1
5,000-10,000	1.2	1.6
10,000-20,000	1.8	2.4
20,000-30,000	2.8	3.4
30,000-40,000	3.6	4.3
40,000-50,000	4.4	5.3
50,000-60,000	5.3	6.2
60,000-70,000	6.0	7.0
70,000-80,000	6.7	7.8
80,000-90,000	7.3	8.4
90,000-100,000	8.0	9.1
100,000-125,000	9.0	10.0
125,000-150,000	10.2	11.1
150,000-175,000	11.2	12.1
175,000-200,000	12.0	12.7
> 200,000	11.7	13.2

COMMON FAILURES IN SAFETY INSPECTION

On average, vehicles tend to fail safety inspections on the order of one or two components when an overall failure is found. In 2012, of all vehicles analyzed and in both inspection datasets, the highest component in failure rates were ordered with brakes as the most common, followed by lighting and with doors and fuel as the least common failure modes. In vehicles with 30,000 miles or less, which are the younger vehicles, the most common failure component was tires/wheels followed closely behind by brakes. Vehicles with 30,000 to 125,000 miles had brakes as the primary failure component followed closely behind by lighting. In vehicles with over 125,000 miles, the oldest vehicles in the fleet, lighting was the most common failure component in vehicles followed by brakes. Typically, for any mileage vehicle, glazing of mirrors, doors, and fuel are the least common failure components. These category failure component trends vary by the year of data analyzed, however they do follow these loose patterns. These failure trends are important to evaluate in order to conclude on whether policy changes can be made to the safety inspection program to make it more cost effective.

Over the five or six years of data, these trends generally follow the same patterns with the most and least common failure components. Looking more generally at failure rates as a whole over the six years of data, there is not an obvious trend.

ANNUAL VEHICLE MILES TRAVELED – AGE TREND

From the available data, the annual VMT can be calculated based on various categories. Here is an example of annual VMT versus age. The general trend shows a decreasing trend in VMT as vehicles become older and is seen in Figure **10**.

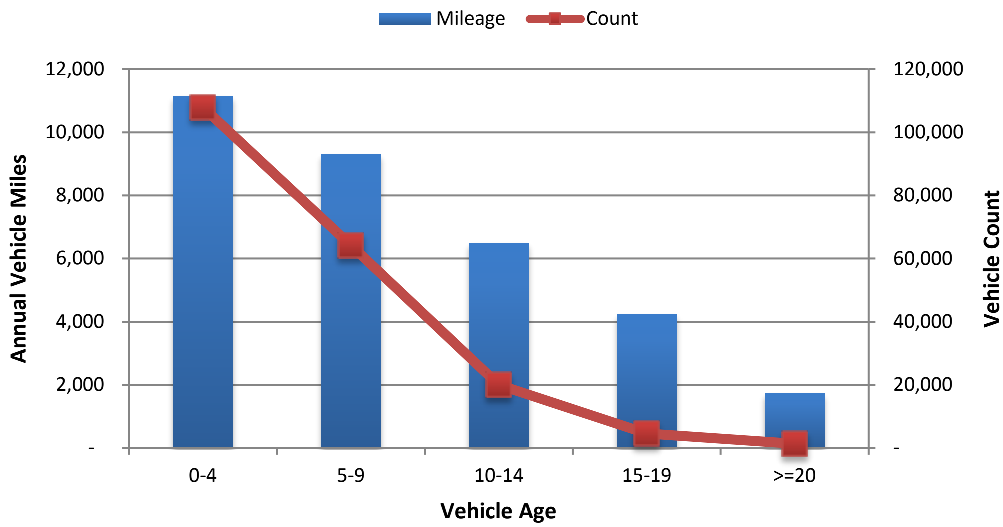

Figure 10: Annual Vehicle Miles Traveled as a Function of Age

From this underlying data, the average annual VMT was calculated in order to estimate VMT to different age groups when looking at the different exemption scenarios.

VEHICLE FLEET SAFETY IMPROVEMENT OVER TIME

It is also important to note that some vehicles generally have higher safety ratings separate from the maintenance and upkeep of the vehicles, which must be kept isolated. While technology has vastly improved over the past years, and vehicles are overall much safer to drive, yearly maintenance is still important to keep vehicles functioning as safe as the newest vehicles on the road. It is expected overtime that maintenance will be necessary.

The initial legislature sentiment that prompted the study was that vehicles "have been getting safer" and modifications to the current vehicle safety inspection program are in order. While this is true, vehicle safety has improved, the failure rate over time for recent model years follows a decreasing trend (Figure 11), and qualitatively does not appear to be reaching a failure rate of zero in the near future.

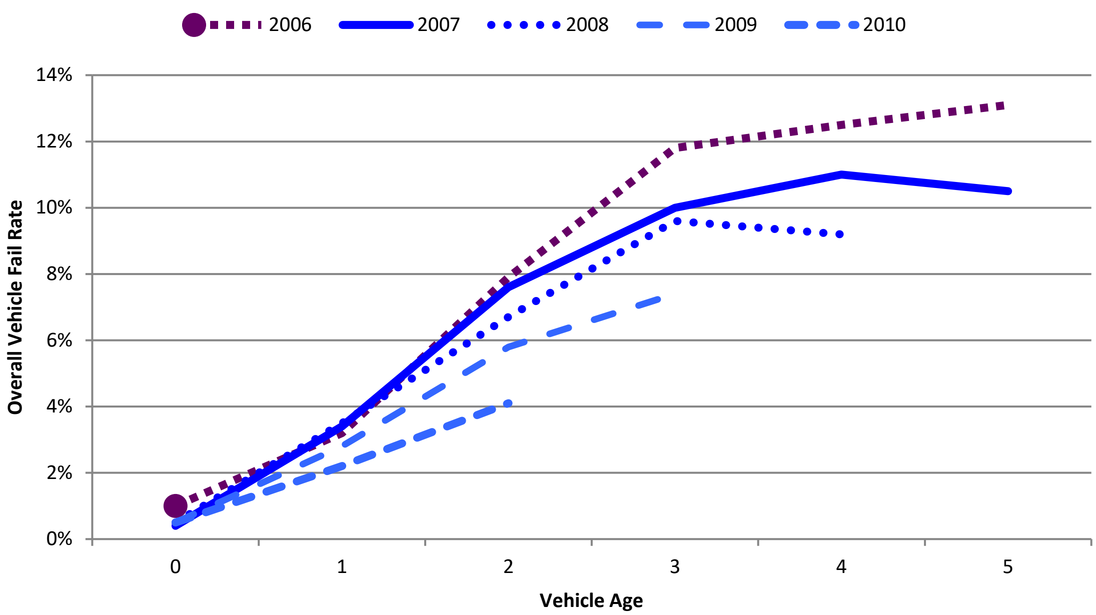

Figure 11: Private Data Vehicle Failure Rates, Time-series

However, this can also be due to factors such as the government financial recession and the overall population generally driving less.