IMPROVEMENT OF THE EFFICIENCY OF VEHICLE INSPECTION AND MAINTENANCE PROGRAMS THROUGH INCORPORATION OF VEHICLE REMOTE SENSING DATA AND VEHICLE CHARACTERISTICS

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IMPROVEMENT OF THE EFFICIENCY OF VEHICLE INSPECTION AND MAINTENANCE PROGRAMS THROUGH INCORPORATION OF VEHICLE REMOTE SENSING DATA AND VEHICLE CHARACTERISTICS

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To My Family, Especially to My Mom, Who Started the Journey that I am Finishing

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LIST OF ABBREVIATIONS

Adj	Adjusted
AICc	The corrected Akaike Information Criterion
AQG	Air Aqulity Group
ASM	Acceleration Simulation Mode
BAR	Bureau of Air Resources
BIC	The Bayesian Information Criterion
CAA	Clean Air Act
CAAA	Clean Air Act Amendments
CAFÉ	Continuous Atlanta Fleet Evaluation
CDF	Cumulative distribution function
ChiSq	Lists the Wald tests for the hypotheses that each of the parameters is zero
CL	Confidence limit
CO	Carbon monoxide
CO2	Carbon dioxide
D=max|F1-F2|	Lists the maximum absolute deviation between the EDF of two class levels
DMV	Department of Motor Vehicles
ERG	Exhaust recirculation
GM	General Motors
GRD	Georgia Registration database
GTRI	Georgia Tech Research Insitute
GVWR	Gross vehicle weight
HC	Hydrocarbons
HEP	High Emitter Profile
I/M	Inspection and Maintenance
ID	Identification number
IM240	240 seconds standard exhaust emission test
IR	Infra-red
KS	A Kolmogorov-Smirnov Statistic
Ksa	An asymptotic Kolmogorov-Smirnov statistic
LDT	Light duty truck
LDT1	Light duty truck
LDV	Light duty vehicle
Lower CL Dif	Shows the lower confidence limit for the difference
Mean Abs Dev	Average of the absolute values of the differences
MIL	Malfunction indicator light
MOBILE6.2	Vehicle Emission Modeling Software
MOVES	Motor Vehicle Emission Simulator
Nox	Oxides of Nitrogen

OBD	On board diagnostics
OBD II	On board diagnostics current generation
OEM	Original Equaipment Manufacturer
PCV	positive crankcase ventilation
PPM	Parts per million
Prob>|t|	the p-value for a two-sided for the parameter.
QA	Quality assurance
RFG	Reformulated gas
RMSE	root mean square error
RSD	Remote Sensing Device
RSD3000	Remote Sensing Device 3000 manufactured by ESP, Inc
RV	Recreational vehicle
SAE	Society of Automotive Engineers
SIP	State Implementation Plan
Std Dev	Standard deviation
Std Err Dif	Shows the standard error of the difference
t Ratio	the t statistic for the parameter, computed as Estimate/Std Error
Upper CL Dif	Shows the upper confidence limit for the difference
US EPA	United State Environmental Protection Agency
UV	Ultraviolet
VID	Vehicle Information Database
VIN	Vehicle identification number
VMT	Vehicle miles traveled
VOC	Volatile organic compounds
VSP	Vehicle specific power

SUMMARY

Since the 1970s, an emission inspection test has been a requirement for major metropolitan areas that were designated non-attainment areas according to the Clean Air Act. Some of the most harmful pollutants being checked include carbon monoxide, hydrocarbons, and oxides of nitrogen. In Georgia, about ten percent of tested vehicles fail emission inspections. Even though the sheer number of failing vehicles may seem to be large (about 250,000 vehicles), all of the eligible vehicles have to be tested (about 2,500,000 vehicles). It seems to be a very inefficient way to identify failing vehicles. Reducing those inefficiencies is the focal point of this inquiry. This research creates a model that assigns a probability of failure to each individual vehicle. Based on the probability of failure, vehicles then are assigned time intervals between tests. Those time intervals are set to be shorter for vehicles with a higher probability of failure and longer for vehicles with a low probability of failure. The probability of failure model is based on several components: vehicle characteristics and vehicle use, vehicle ownership history, the results of the previous emission inspection test, and remote sensing measurements. Data used in this dissertation originates from several different sources. They include the Georgia Registration Database for 2010, Georgia Inspection and Maintenance databases for 2009 and 2010, the Vehicle Identification Number decoder, the remote sensing database (Continuous Atlanta Fleet Evaluation Project for 2010), and EPA's fuel economy database.

In addition to modeling, the emission inspection program will identify vehicles with a higher probability of failure and will introduce an analytical approach to emission inspection programs and provide a more efficient way to measure a vehicle's emissions. By using this approach, a significant emission savings can be realized even if using a similar number of emission tests.

1 INTRODUCTION

Before the Industrial Revolution, outdoor levels of harmful air toxins were relatively low. With increased fossil-fuel production and usage, air quality has dramatically decreased. In 1948, a temperature inversion prevented a dense smoke cloud of sulfur dioxide and particulate matter from escaping into the atmosphere and kept it low to the ground in Donora, Pennsylvania (Melosi 2010). Nineteen people died and almost 43 percent of the town's population became ill. In 1952 "killer smog" hit London and 4,000 people perished. In 1953 New York had a serious smog attack and 200 people died. In view of the growing dangers of air pollution, in 1955 Congress enacted the National Air Pollution Control Act to generate research on air pollution. However, pollution from automobile emissions was not considered for several more years. While pollution from vehicle emissions was a growing problem in the post-World War II era, carbon monoxide, nitrogen oxides, or particulate matter pollution was not viewed as a problem by the public. Los Angeles was the first city to raise concerns over automobile emissions as early as the mid-1950s. California was the first state to establish new car emission standards (Melosi 2010). By 1966 automobile emissions accounted for 60% of the pollutants throughout the nation. The Motor Vehicle Air Pollution Act of 1965 produced national standards comparable to California law for the 1968 model year. The rise in public environmental concern led to the Clean Air Act of 1970, which ultimately led to vehicle emission standards and periodic vehicle emission inspections.

The ultimate goal for any emission inspection is to reduce pollution from vehicle emissions by identifying and repairing vehicles with failing emission control systems. In many jurisdictions, passing an emission test is a requirement for annual vehicle registration. Vehicle emission inspections in the United States are provided for by the provision of the Clean Air Act (CAA) of 1970. The Clean Air Act called for the first tailpipe emission standard. Pollutants that were controlled are carbon monoxide (CO), volatile organic compounds (VOC), and oxides of nitrogen (NOx) (United States Environmental Protection Agency 1999). The first inspection and maintenance (I/M) program implemented under this law was in New Jersey in 1974 (United States Environmental Protection Agency 1999). In 1977, the Clean Air Act Amendments (CAAA) mandated new vehicle emissions inspection programs in the areas that were considered to be in non-attainment for major pollutant categories from mobile sources. Driven by the growth in vehicle travel and continued air pollution problems, the 1990 Clean Air Act Amendments required the US EPA to develop federal regulations for two levels of emission inspection programs: basic emission inspection programs for moderate ozone non-attainment areas and enhanced emission inspection programs for serious non-attainment areas (Corley 2003). The difference between these two programs is the testing procedures, with basic programs continuing with existing technologies (e.g., idle testing) and the more advanced programs that would require more advanced testing procedures (i.e., initially IM240 and later Acceleration Simulation Mode (ASM) testing). Both advanced tests used a loaded-mode dynamometer to quantify emissions from three types of pollutants: hydrocarbons (HC), carbon monoxide (CO), and oxides of nitrogen (NOx). The goal of the loaded-mode test is to simulate vehicle's load at various driving cycles such acceleration, deceleration, and cruise modes.

Significant reductions in ambient air pollution from carbon monoxide, ozone and other pollutants (Air Trends Air & Radiation 2011) have been achieved in recent years. Emission inspections, among other factors such as vehicle technology (Kahn and Schwartz 2007) and cleaner fuel, have been very successful in curbing air pollution from vehicle emissions. Figure 1-1 represents Continuous Atlanta Fleet Evaluation carbon monoxide emissions for measurement years 1993 through 2010. During that time carbon monoxide emissions decreased more than threefold.

In addition to inspection and maintenance requirements, the 1990 CAAA requires US EPA to establish rules requiring using reformulated gas (RFG) to reduce vehicle emissions of toxic and ozone-forming compounds. The first regulations concerning certification and enforcement of RFG were issued in 1994. This was followed in 2001 by the Mobile Source Air Toxics (MSAT) rule, which placed additional controls on air-toxic emissions in all gasoline (Reformulated Gas 2007).

To evaluate I/M program effectiveness CAAA requires that enhanced I/M programs include the use of on-road testing (0.5% of the fleet by either remote sensing or road side pullovers) and conduct a biennial program evaluation (Guidance on Use of Remote Sensing for Evaluation of I/M Program Performance 2004). While emission inspections have been very successful in reducing pollution from vehicle emissions, they often have been criticized for their cost-effectiveness (Harrington, McConnell and Ando 2000); mostly because the majority of the vehicles tested has clean emissions. According to the U.S. National Research Council, U.S. emission inspection programs state that, typically, 10% of the fleet highest polluting vehicles contribute 50% or more of emissions. Emission inspections are trying to catch an increasingly smaller pool of high emitting vehicles. Nonetheless, that small number of high emitting vehicles present the greatest potential benefit gains for emission inspection programs since they are contributing a significant portion of total vehicle emissions.

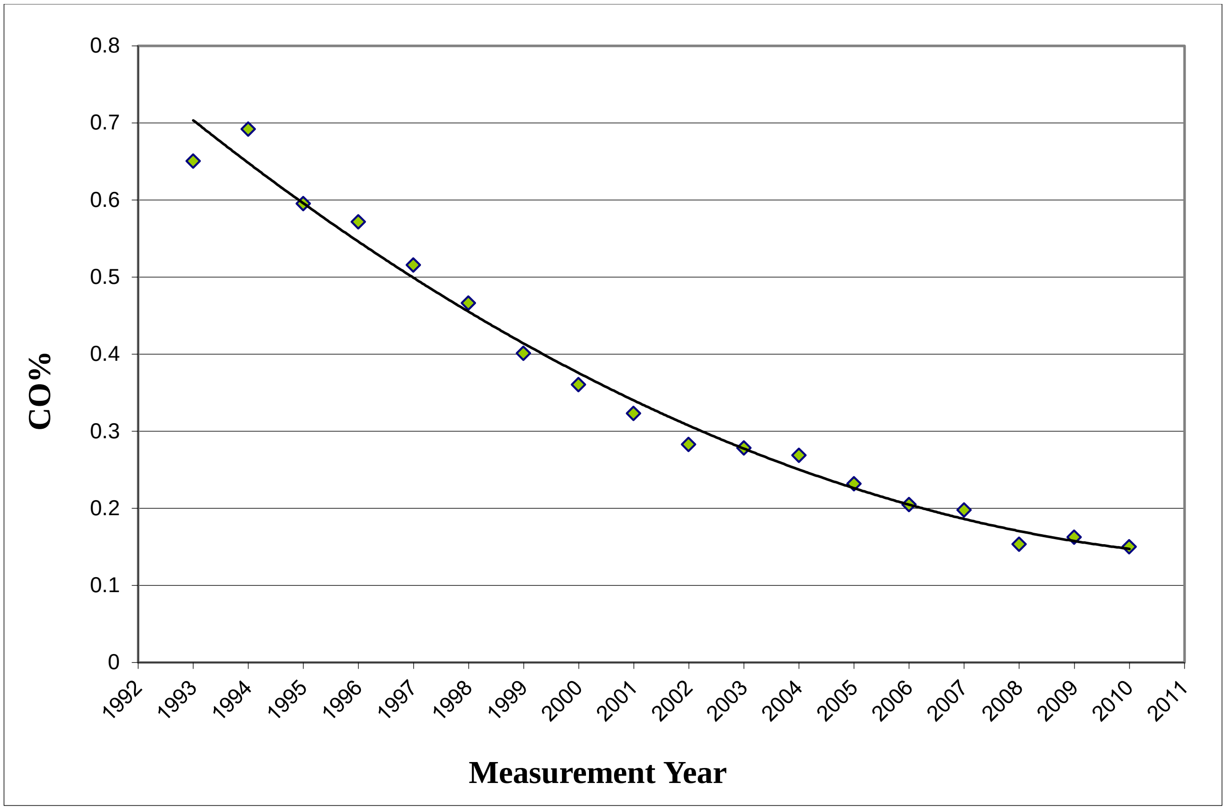

Figure 1-1 Average CO Concentration in the Atlanta CAFE 1993 - 2010

This research focuses on methods and procedures for making vehicle inspection and maintenance programs more efficient in the future by creating an algorithm for identifying vehicles that have a higher probability of failure, and testing them more frequently than vehicles with a low probability of failure. This effort is both needed and timely. While existing programs have been very successful in improving fleet-wide emissions they have, in a certain sense, become victims of their own success. As fleet-wide emissions are reduced and vehicle emission controls become more reliable, testing programs will need to test an increasingly larger number of vehicles to identify the limited number of vehicles needing repairs. In addition, this research addresses the lack of adaptability of current emission inspection programs to deal with changing vehicle fleets and emission inspection technologies as well as examining ways in which alternative testing measures such as vehicle remote sensing can be incorporated into future testing programs. It will also address the need to create a responsible ownership environment and promote good vehicle maintenance practices by incorporating vehicle usage characteristics into rules for new programs.

1.1 Research Objective

This research concentrates on creating an emission inspection program that uses variable time frequencies between vehicle emission inspections based on vehicle characteristics. The efficiency of the program in this case will be assessed by a decrease in emissions of carbon monoxide, hydrocarbons, and nitrogen oxides produced by gasoline powered vehicles. The reduction in emissions can be achieved by more frequently measuring vehicles that are likely to fail. More frequent measurements will result in repair or replacement of the polluting vehicle in a shorter time, thereby reducing pollution.

For example, in the State of Georgia vehicles are inspected on an annual basis. Therefore, even though the vehicle may fail a day after it was inspected, it will be on the road almost twelve months before its next emission inspection is due. Figure 1-2 illustrates efficiencies that can be achieved if vehicles can be tested more often. 1996-1997 Arizona remote sensing data shows a 12% reduction in CO emissions observed from its peak 3 weeks before an emission test and right before an emission test. This research suggests that vehicles are not being repaired until an emission test has to be taken.

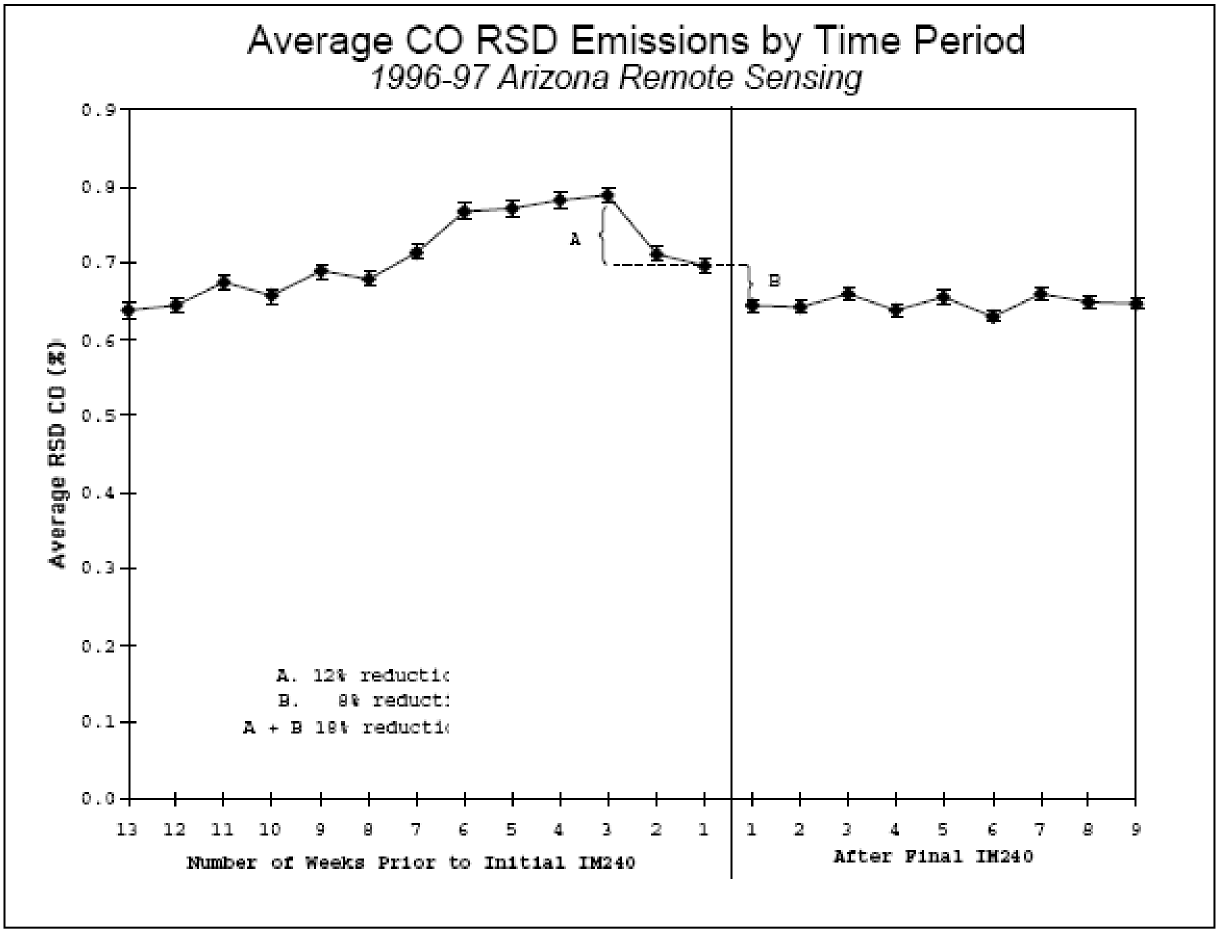

Figure 1-2 Average CO RSD emissions by time period

The proposed new program will help to incorporate other types of emission tests such as readings from wireless OBD systems, which are planned for future generations of OBD systems (Transitioning I/M Workgroup 2009) whenever a new technology comes online. Vehicle remote emission sensing measurements are also integrated into the calculations of test frequencies, including all possible alternative tests, helping more accurately estimate probabilities of the vehicle potentially being a high emitter. Vehicle remote sensing emission measurement technology allows recording vehicle's component emissions without stopping a vehicle. Furthermore, the mileage of the vehicle, annual vehicle travel, and other ownership characteristics such as length of ownership are taken into account as well.

The proposed I/M program is based on a probabilistic approach for testing vehicles. It will take into account all possible alternatives to station tests, such as a use of telemetry devices, remote sensing data, previous test results, and vehicle usage to determine the probability of the next test. For example, vehicles that barely passed previous tests and have failed a test for vehicle remote sensing will have probabilities of being tested within the next three months higher than vehicles that were very clean during the previous testing period and have passed a telemetry test and/or have clean remote sensing records. This kind of emission inspection testing will be able to adapt to changing fleet characteristics without legislatively changing emission inspection rules. If vehicle technology continues to improve, then the probability of testing newer vehicles will decrease, thereby concentrating on higher polluting vehicles.

It is the intention of this program to fully utilize existing infrastructure. Additional costs of administering new rules will occur in the administration and in alternatives to station-based tests such as remote sensing. There is no new infrastructure investment that will be necessary. By testing vehicles that have a probability of being higher polluters it will be possible to increase program effectiveness without increasing the number of tests and therefore without major capital investment for emission inspection infrastructure.

Several vehicle characteristics such as vehicle make, model year, odometer reading will be investigated and incorporated into the model that calculates the probability of failure. This program also will promote responsible ownership principles for vehicle owners that take care of their vehicles, since the probability of the vehicle being tested will be based on the individual vehicle record and on the records from the group that the vehicle belongs to. Currently, virtually all jurisdictions with emission testing programs base their subject vehicle requirements strictly on the age of the vehicle. Vehicle use is not incorporated in the rules and therefore does not have any bearing on the vehicle being tested. As part of this research, examination of the relationship between emission test failure rates and vehicle use is integrated into the model to determine emission inspection failure rates and frequency of testing.

States such as California are employing what is called a 'high emitter profile'. However, the way they use this data is vastly different than what is proposed in this research. The main difference between this proposed approach and programs such as California's is that, as opposed to looking just at high emitting vehicles and requiring them to take a smog test at a certified emission testing location. The 'high emitter profile" is based on vehicle make, model, and model year. If a vehicle falls into the category of high emitting vehicle based on the failure rates from previous emission test of vehicles with the same make, model, and model year it must be tested at a specially selected emission testing locations.

The proposed program will build on high emitter profile experience but it will go further. Not only high emitting vehicles but also clean vehicles, and based on their profile, will change the time between tests, therefore curbing vehicle emissions.

1.2 Research Hypothesis

To increase efficiency of the emission inspection program, emission tests must concentrate on the vehicles that are likely to fail, since there little or no benefit of testing vehicles that are not going to fail the test and therefore are not going to be repaired. Emphasis for testing should be placed on vehicles that are likely to fail the emission inspection and testing those vehicles more frequently. More frequent testing will reduce time between vehicle emission control systems failed and the time vehicle is fixed, thus reducing overall emission produced by the vehicle.

1.3 Research Approach

To achieve the research objectives all databases described above were merged to produce a dataset that is used hereafter. Vehicle remote sensing records, Inspection and Maintenance records, Georgia Registration database and a set of parameters such as vehicle group, OBDII codes, costs of repair, and vehicle ownership history are used to assess the probability of a vehicle failing the next scheduled emission test. Probability of failure is taken into account when calculating time intervals between emission inspection tests.

The following steps are taken to evaluate vehicle emission testing frequencies:

- Use logit model to estimate probability of failure for each vehicle.
- Based on those probabilities assign time interval coefficient for future tests.
- Use remote sensing and vehicle emission inspection data to estimate the potential benefits of testing vehicles sooner.
- Examine 2010 for failing vehicles and the time difference between test date and remote sensing measurement date.

In this research only one case study of time frequencies between emission inspection test rules is examined. However, the time interval coefficient can be changed depending on the desired emission test program effectiveness and can be adjusted without significant effort.

2 LITERATURE REVIEW

2.1 Review of Existing I/M Evaluation Methods

To evaluate inspection and maintenance program effectiveness, the U.S. EPA recommends using two separate strategies. One uses in-program data, e.g., data collected from tests administered by an emission inspection program, while the second uses out-of-program data such as data from a remote sensing device (RSD) or roadside pullovers. Combining both strategies should produce the best possible results for I/M program evaluation. (Guidance on Use of Remote Sensing for Evaluation of I/M Program Performance 2004)

In-program and out-of-program strategies will use different methods for program evaluation. In-program evaluation is based on the process and result-based analysis, whereas out-of-program evaluation can use the step change, the comprehensive, and the reference analysis methods.

The result-based analysis looks at the performance of the emission inspection and maintenance program such as pass/fail/abort/waiver rates, analysis of emission reduction and other analysis using in-program data. The process-based analysis looks at the achievement of proper fleet coverage, performance and accuracy of emission inspections, and documentation of repairs of failing vehicles. To have a comprehensive look at the I/M program, both methods should be combined. Using one without the other can't guarantee a thorough evaluation of program effectiveness.

As a part of the process-based analysis, a participation rate analysis is performed. This process is illustrated in Figure 2-1. On this chart vehicles are split into vehicles that are registered in inspection and maintenance are and vehicles that are registered outside of inspection and maintenance area. Part of vehicles that are registered in inspection and maintenance program are vehicles that are participating in inspection and maintenance program. There are also vehicles that are registered outside of inspection and maintenance program but are operating within geographical confines of inspection and maintenance program. The fleet in the inspection and maintenance area may be defined as simply vehicles registered in the area or as a set of vehicles driven in the area. (Draft Guidance on Use of In-Program Data for Evaluation of I/M Program Performance 2001)

Before evaluation of an emission inspection program can take place the participation rate of the eligible vehicles must be determined.

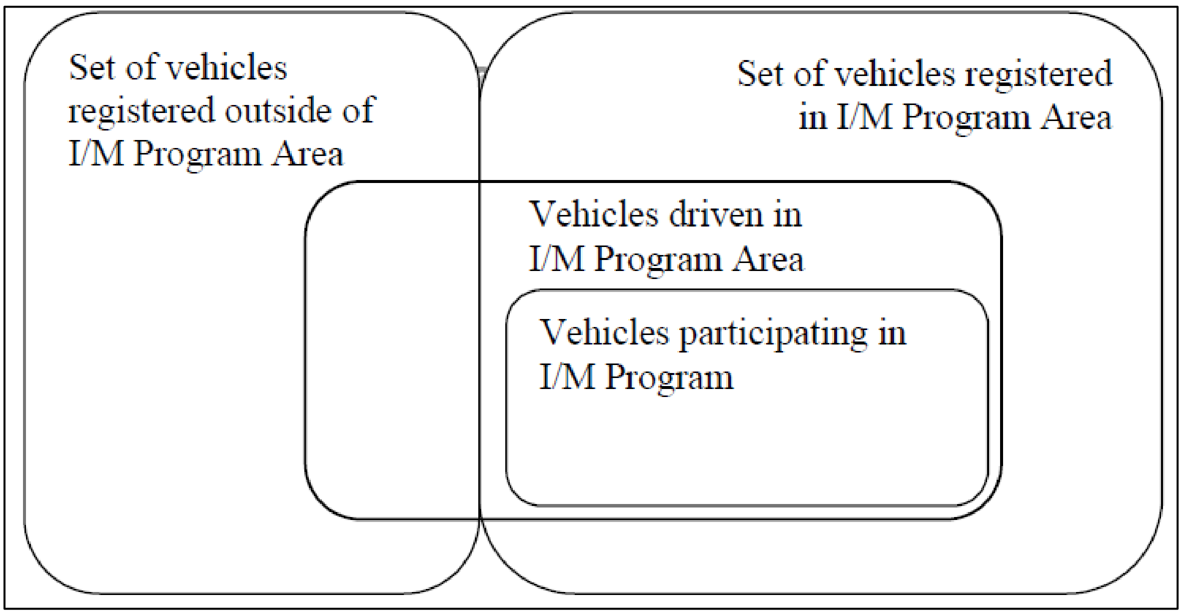

Figure 2-1 Mix of vehicles within Inspection and Maintenance program area

The goal is to compare vehicle populations that are registered in the area and undergoing emission inspection, and the population of vehicles that are driven in the area. In addition to participation rates, comparing vehicle distributions from I/M records, Registration, and matching registration records with emission inspection records, using year-to-year trends, and using multi-year trends should verify compliance rate estimates used in SIP, as well as estimate emission reductions.

Out-of-program data uses different methods for emission inspection and maintenance program evaluation. Most commonly used methods are the step change, comprehensive, and reference methods. The main difference between the step change and comprehensive method is the number of remote sensing and/or roadside pullover measurements that are needed for each method. The step method usually requires anywhere from 20,000 – 50,000 (Guidance on Use of Remote Sensing for Evaluation of I/M Program Performance 2004) measurements, but is only applicable under particular conditions (e.g., a new program), whereas the comprehensive method requires many more remote sensing measurements, usually in the range of several million, but does not have these limitations. The reference method is designed to measure the full effect of the emission inspection program by measuring subject fleets from within an I/M program area and outside of it. The success of this method depends upon locating an area containing non-I/M fleets that would be similar in vehicle distribution to the I/M fleet. This method has been pioneered at Georgia Tech and is currently employed by the Georgia Tech Research Institute when evaluating the I/M program effectiveness of Georgia’s Enhanced I/M program. The data requirements for this approach are intermediate between the step change and comprehensive methods and are usually in the range of a few hundred thousand observations.

Approaches for I/M program evaluation described above are recommended by the U.S. EPA but are not necessarily exclusive. Another approach to estimating program effectiveness is proposed by Glover and Brzezinski. The method described by Glover and Brzezinski was based on contrasting the initial test results of failing vehicles with passing results of the same vehicle. By aggregating that data they calculated the benefits of the emission inspection program. Results are based on 1995 Arizona IM240[1] test results that produced emission concentrations. The compare and contrast approach has some advantages namely volume of data required; however, one major disadvantage is the use of in-program data and lack of ability to directly determine participation rates. A similar approach was used by Wensel to analyze 1996-1997 Arizona IM240 data, which produced similar results. (Wenzel, Reducing emissions from in-use vehicles:

[1] Vehicles 1996 and newer are equipped with OBD systems and therefore, the I/M test has become optional.

an evaluation of the Phoenix inspection and maintenance program using test results and independent emissions measurements 2001)

Roadside pullover tests use remote sensing equipment used to perform Smog Check tests. The State of California employs a random roadside testing; this involves pulling a car to the side of the road and measuring its emissions. As evidenced by California roadside testing, even though vehicles were repaired in the Smog Check program their subsequent failure rate when pulled over was quite high. Even though after failing an initial test the vehicle was repaired, and passed the subsequent test, 40% of 1974-1995 model years were found to fail a roadside test within a year (California Air Research Board 2009). The high failure rate of the retested vehicles indicates that repairs that were made to a vehicle were insufficient or possibly no repairs were done to those vehicles at all.

Yet another approach to evaluate the I/M program was proposed by Eisiger based on analytical analysis to design and evaluate motor vehicle inspection programs. Eisiger's approach is based on real world data and it attempts to quantitatively calculate program effectiveness based on the capture and repair of problem vehicles as well as program avoidance by problem vehicles. Sensitivity studies suggest that identifying a greater number of problem vehicles (high emitters) and improving effective repair rates, both before and after I/M testing, will greatly improve program effectiveness (Eisinger 2005).

2.2 Cost Effectiveness

Full assessment of program effectiveness should be broader than merely an estimation of emission reductions. Costs and cost-effectiveness are very important criteria for determining whether social resources are well spent and for making decisions regarding improvements to the inspection program design. There are several costs associated with the I/M program, including the costs of finding a failing vehicle, costs to motorists, costs of program administration and oversight, and evaluation costs (Environmental Studies and Toxicology Transportation Research

Board 2001). Costs to motorists might have an adverse effect on different socioeconomic groups. These costs might include the monetary value of the I/M test and costs of repair. There are also costs of time associated with test taking.

To estimate emission benefits achieved by the Georgia emission inspection program, the reference method is employed. The reference method is often used in emission program effectiveness evaluation, as reviewed in section 2.1. The reference method compares two groups of vehicles. Vehicles subject to emission inspection were compared to vehicles not subject to emission inspection, i.e., vehicles registered outside the inspection and maintenance Atlanta area. Measurement for vehicles that were not registered in Atlanta metro were obtained by direct measurements in Macon and Augusta, GA as well as some uninspected vehicles captured in metro Atlanta locations. Macon, GA vehicles have a similar fuel composition to metro Atlanta fuel, therefore fuel differences are not examined in this research.

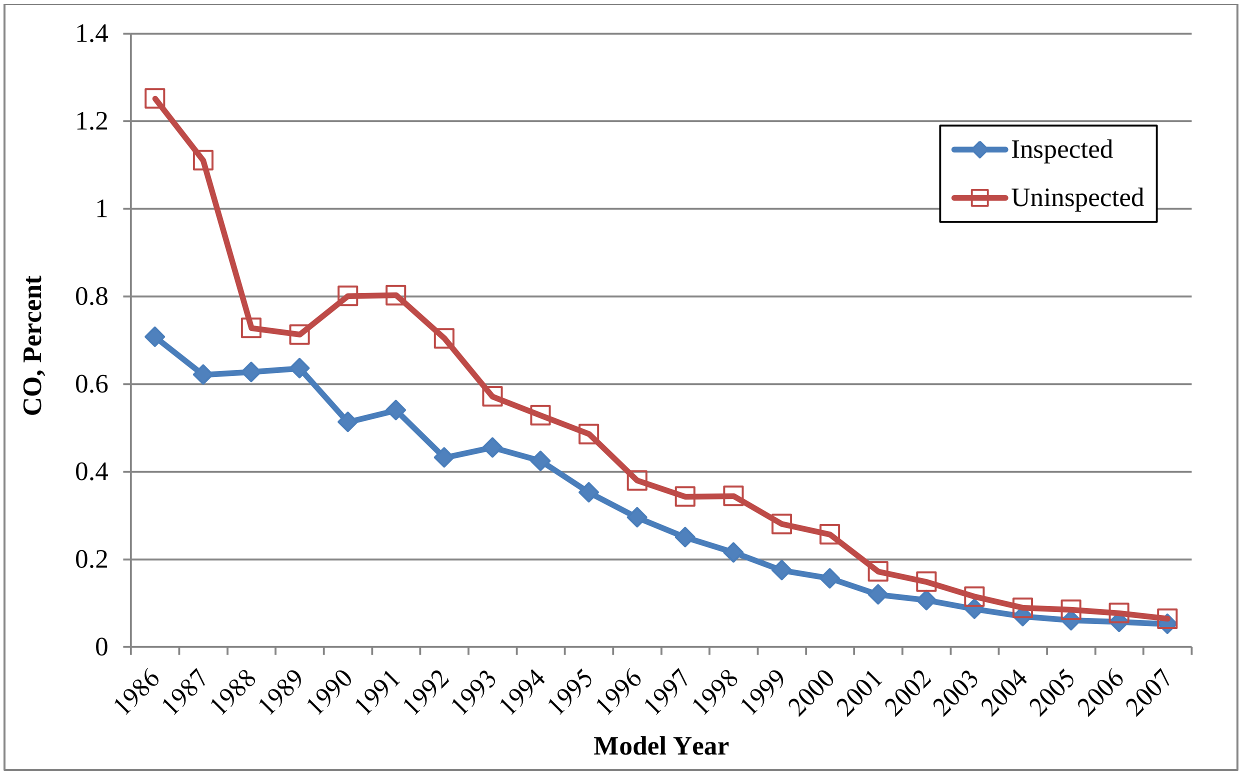

Figure 2-2 Carbon monoxide vs. model year for inspected and uninspected fleet

Figure 2-2 represents average carbon monoxide values for each model year starting at model year 1986 and ending at model year 2007 (2007 is the first year that vehicles become eligible for emission inspection in Atlanta, GA). Carbon monoxide produced 28 percent savings when inspected versus un-inspected fleets were compared. Economic benefit calculations will be presented later in the paper.

To estimate the hydrocarbon reductions from vehicle emission inspection, a technique similar to the carbon monoxide technique was applied. First, data were grouped by model year and model years for the inspected and un-inspected fleets were compared. Figure 2-3 represents average hydrocarbon emissions grouped by model year. Based on that chart vehicle emission inspection produced reduction of 18 percent for hydrocarbons. Economic benefit calculations for the hydrocarbons are discussed later in the paper.

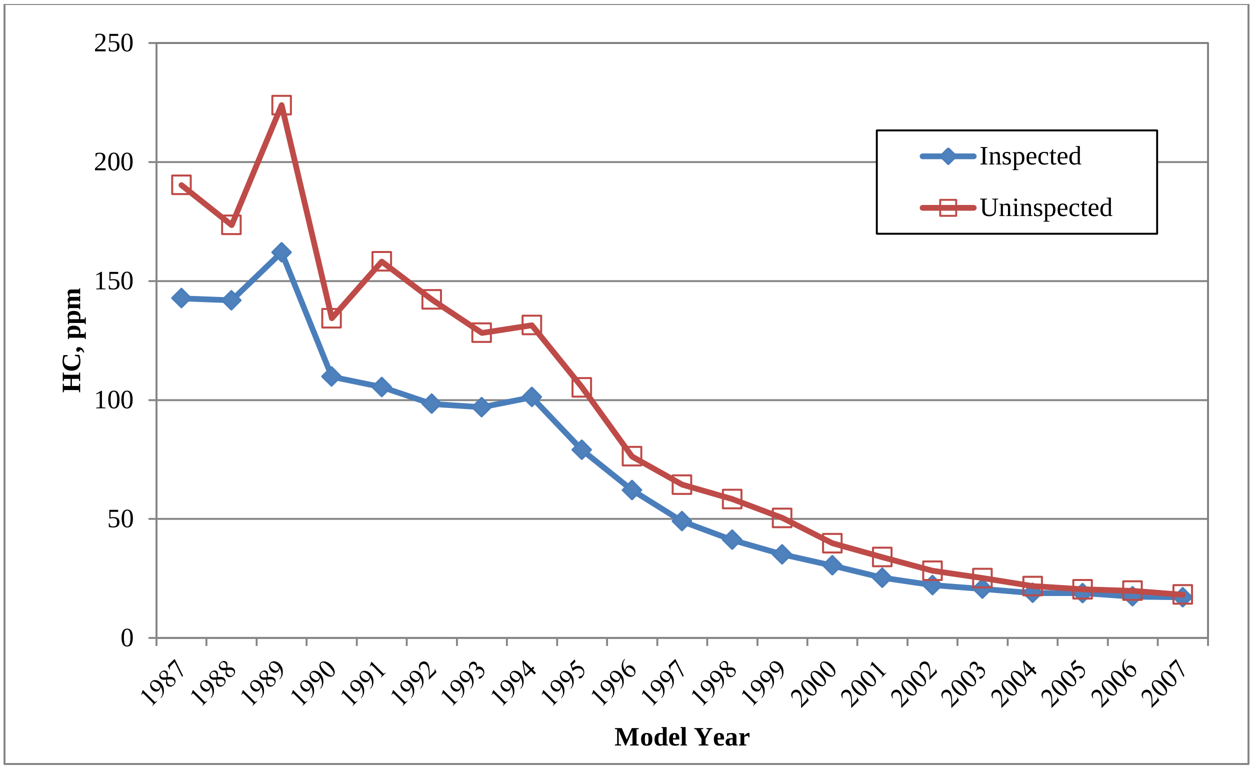

Figure 2-3 Hydrocarbons vs. model year for inspected and uninspected fleet

Calculation of emission inspection benefits for nitrogen oxides follows suit of similar calculations for carbon monoxide and hydrocarbons. It is estimated that an emission inspection program produces 25 percent cleaner vehicles than vehicles from areas without emission inspection. Figure 2-4 represents average nitrogen oxides readings for model year groups. Vehicles for every model year in areas with emission inspection are cleaner than their counterparts from the area without emission inspection.

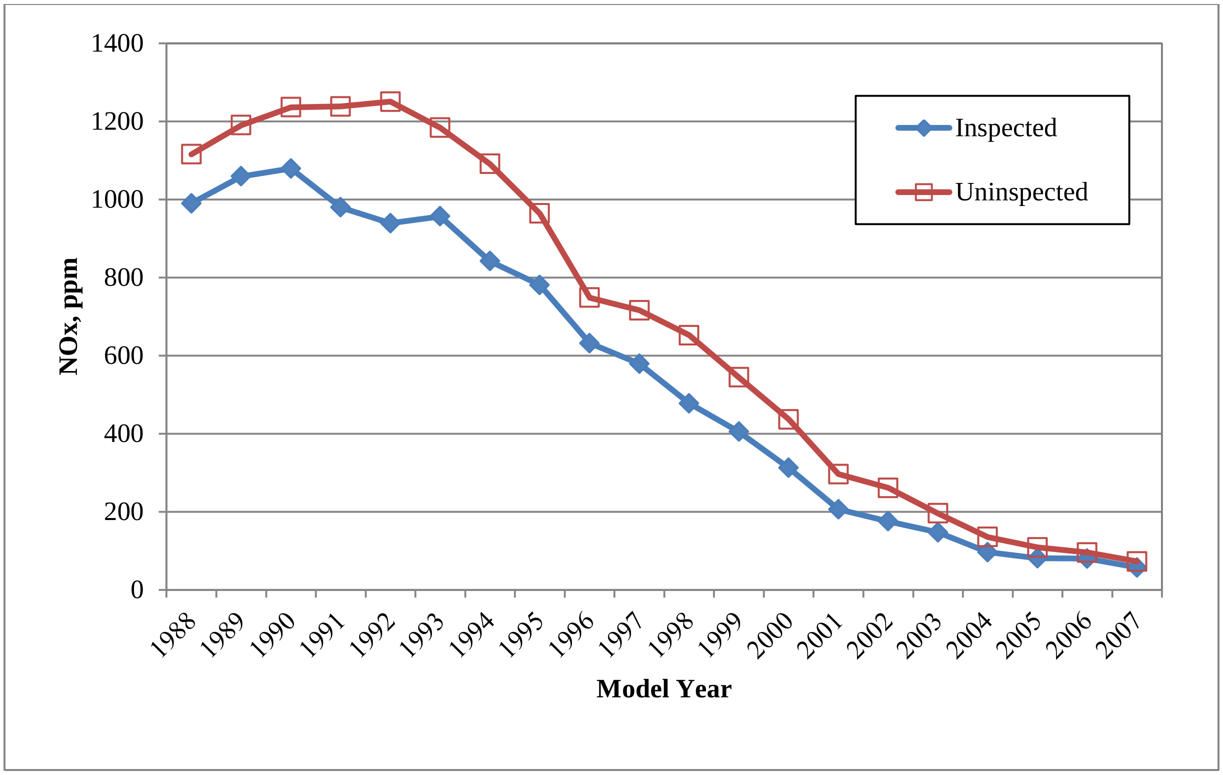

Figure 2-4 Oxides of nitrogen vs. model year for inspected and uninspected fleet

2.3 Emission Inspection Test Types

2.3.1 OBD

On Board Diagnostic (ODB) systems were first developed in 1988 by the California Air Resources Board (CARB) and the California Bureau of Automotive Repair (BAR) and was called OBD I. A second generation of OBD systems, OBD II, is used on vehicles today. The Clean Air Act Amendments of 1990 mandated that, starting with the 1996 model year, all light duty vehicles and trucks for sale in the United States must be equipped with such a system. The OBD II system can monitor all emission components and can diagnose problems of the computerized emission control. (U.S. Environmental Protection Agency n.d.)

Passing and failing vehicles can span a wide emission spectrum. The OBD II system is believed to be at least as sensitive for detecting emissions failures as any other type of testing. “A vehicle can have up to twelve monitors built into the OBD computer system. The most common monitors are:

Continuous:

- Misfire
- Fuel System
- Comprehensive Components

Non-Continuous:

- Oxygen Sensor
- Heat Oxygen Sensor
- Catalyst Efficiency
- Evaporative Emissions System
- ERG System
- Secondary Air System
- PCV System” (Agency, Illinois Environmental Protection 2013)

2.3.2 IM240 Emission Inspection Test

The IM240 test was developed by the U.S. EPA a short form of the Federal Test Procedure. It lasts 240 seconds and captures the essential elements of the Federal Test Procedure, which is a standard exhaust emission test (Enns, et al. 1999). The IM240 test is trying to simulate a real world chassis dynamometer by using a chassis dynamometer for testing of in-use light duty vehicles. It is a short, 240 second test representing a 1.96 mile (3.1 km) route with an average speed of 29.4 miles/h (47.3 km/h) and a maximum speed of 56.7 miles/h (91.2 km/h) (Emission Test Cycles: IM240 2010). Figure 2-5 below illustrates the speed and acceleration profile used in the IM240 cycle.

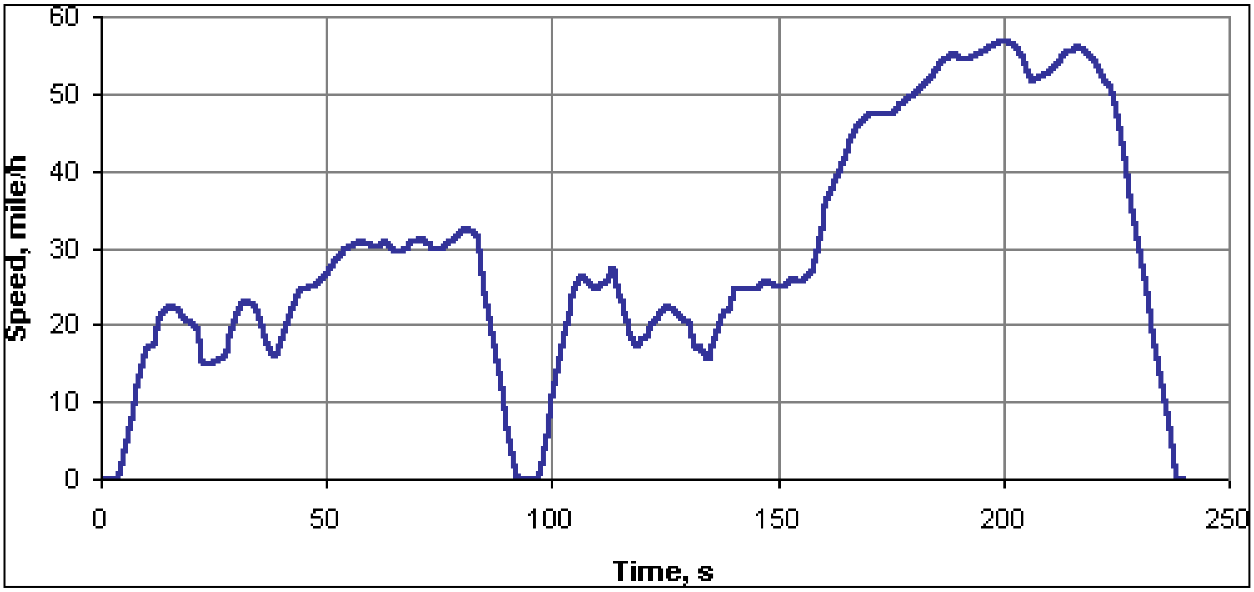

Figure 2-5 IM240 Speed Trace

2.3.3 Acceleration Simulation Mode (ASM)

The acceleration simulation mode test uses a dynamometer to simulate real world driving conditions. “In a sense it’s like a treadmill stress test for your vehicle.” (ASM/TSI Emission Testing 2011) During the test, carbon monoxide, hydrocarbons, and oxides of nitrogen are measured. Unlike the transient nature of the IM 240 test, ASM uses loaded testing at various fixed speeds in a multistage cycle (e.g. 25/25, 50/15, etc., where the numbers indicate the wheel speed in miles per hour for each test phase). ASM was developed by CARB and BAR as a cheaper alternative to the EPA IM240 test and is currently the most popular dynamometer-based testing scheme.

2.3.4 Vehicle Specific Power

One of the specificities of vehicle remote emission sensing is that driving conditions can strongly influence vehicle emissions. For example, when the car is in coasting mode, even a dirty vehicle can produce low concentration reading, and conversely, high power demand on the engine can produce enrichment for clean vehicles. Therefore, it presents the problem of identifying false clean vehicles or false high emitting vehicles. To help resolve that problem, the term Vehicle Specific Power (VSP) is introduced (Jimenez, et al. 1998). VSP is the measure that seeks to normalize vehicle power requirements by utilizing the physical characteristics of the site and driving conditions to examine instantaneous power demand. It uses the site's slope and vehicle's speed and acceleration as input parameters.

VSP can be defined as:

$$VSP = 4.39 * \sin(Slope) * V + 0.22 * V * A + 0.0954 * V + 0.0000272 * V^3$$

Where VSP is in KW/metric tonne, V is Speed in MPH, and A is Acceleration in MPH/s.

Different emission tests, including vehicle remote sensing, have different VSP profiles. Because vehicle remote sensing is a measure of real world emission and sites often are located on the up slope it has higher VSP readings than IM240 and FTP tests (see Figure 2-6). (Jimenez, et al. 1998)

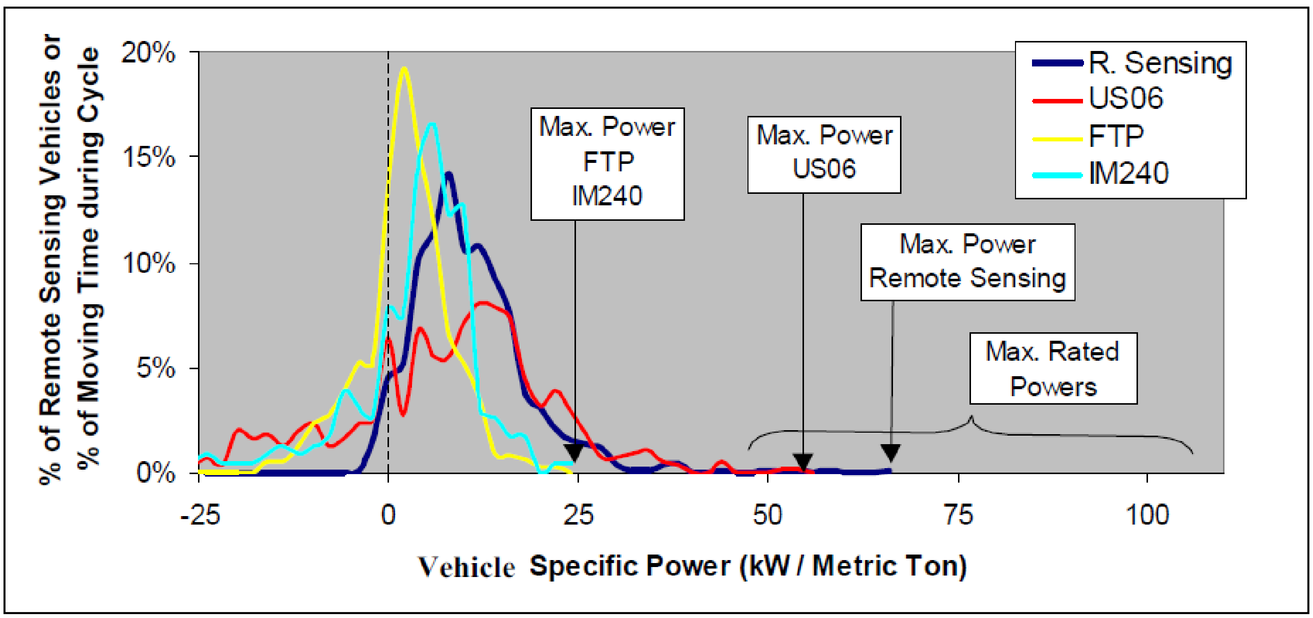

Figure 2-6 Vehicle Specific Power ranges for types of tests

To identify clean and high emitting vehicles it is recommended that a VSP range of 3 to 22 kW/Tonne should be used. (Jimenez, et al. 1998)

2.4 Existing I/M Programs

2.4.1 Georgia

Atlanta's Metro area basic I/M program started in 1981 including three counties: Fulton, Cobb, and DeKalb use a simple idle testing scheme. Gwinnett County was added to the program in 1986. Even with vehicle emission controls in place, Atlanta was still exceeding the one hour ozone concentration standard of 0.120 parts per million at the time of the 1990 CAAA and was thus subject to a requirement of enhanced testing. In 1992, the state legislature mandated that Georgia's I/M program be expanded and more advanced testing be performed. After significant debate, in 1996 the Georgia I/M program was expanded to 13 counties including Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Paulding, and Rockdale, and ASM testing was required for all vehicles. In 1999, OBD testing replaced ASM for 1996 and later model years.

A key feature of the enhanced program was the requirement that vehicles to be registered in the thirteen counties must pass an emission test if a vehicle included the following characteristics:

All gasoline-powered cars or light-duty trucks (8,500 pounds gross vehicle weight rating or less) registered in the above mentioned counties except:

- The three most recent model year vehicles are exempt from emission testing each year. For registration in 2011, this includes all 2009 and newer model year vehicles.
- Additionally, vehicles that are 25 model years or older are exempt from emission testing. This includes 1986 or older model year vehicles.
- Motorcycles, recreational vehicles (RVs) and motor homes do not require emission testing for registration.
- Diesel vehicles do not require emission testing for registration. (Division 2011)

2.4.2 California

In addition to common rules for any emission inspection program such as the type and age of the vehicle, California also employs a High Emitter Profile. The majority of vehicles directed to Test-Only stations are selected by application of the High Emitter Profile (HEP), which identifies the vehicles most likely to fail their Smog Checks. Data for High Emitter Profiling comes from several sources:

- Vehicle Information Database (VID), which consists of emission inspections performed in California
- Department of Motor Vehicles (DMV)
- BAR
- General Vehicle Information: make, model year, vehicle miles traveled and engine size (California Bureau of Automotive Repair, Department of Consumer Affairs 2011)

Above mentioned information is used to determine which vehicles are most likely to fail their Smog Checks, especially at Gross Polluter levels--at least two times the emissions level allowed for a particular vehicle. No single factor identifies a vehicle for a Smog Check to be done at a Test-Only station. The data is weighted and vehicles are selected using this computer profiling of vehicles most likely to fail their Smog Check. To create HEP and examine the probability of vehicle failure BAR uses:

- Model year, make, model, body style, engine displacement, and transmission type;
- Previous initial Smog Check inspection result for each vehicle;
- Elapsed time since each vehicle's last Smog Check certificate;
- The last Smog Check odometer reading for each vehicle. (Bureau of Automotive Repair, Directed Vehicle 2011)

However, since some of the vehicles have just a few tests and statistical significance can't be ascertained from those tests, some vehicles are clustered. For example, if there are only a few records of 2005 Ferrari models, they are combined with 2004 Ferraris. In that case they will also exclude engine and transmission types from consideration since they might be different.

Vehicle information and emission test results are compiled into HEP, that was developed by Eastern Research Group (Tom Wenzel 2003), which uses it to identify potentially high emitting vehicles.

2.4.3 States Other than Georgia and California Programs

Other jurisdictions requiring emission inspections follow similar principles with some variations. In all, 32 states and the District of Columbia have emission inspections (see Appendix Table A-1 Review of state emission inspection programs).

Approximately 30% of all emission inspections are performed biennially. New vehicle exemption ranges from two to six years. The upper age is set either by the maximum age of the vehicle (in most cases it is 25 years) or by the oldest model year that will be tested, for example 1979.

Biennial vehicle testing may lead to much higher vehicle exhaust pollution than anticipated, since if a vehicle's emission control equipment fails shortly after it was inspected it will be on the road for almost 24 months before it will have to be repaired to pass the next emission test.

Emission inspection rules have existed in the same form with minor tweaks for the majority of their existence. Vehicle technology, however, has advanced greatly in a relatively short time period of 10–15 years. For the most part emission inspection program uses single criteria to identify subject for the emission inspection fleet. Age of the vehicle is a determining factor in defining vehicle eligibility. Therefore, if technology advancements for some vehicles makes it less likely to be a high emitting vehicle it is still being tested as often as the rest of the vehicles. This research will explore a way that changes in the fleet will be accounted for, and I/M programs will make on-the-fly adjustments and will be adaptable to those changes in real time.

2.5 Wireless OBD Technologies

One upcoming innovation in vehicle emission controls will be wireless OBD systems. It is possible that the next generation of OBD technology will be wireless. While not yet official, a universal set of technical standards and protocols are currently being developed by the U.S. EPA (Transitioning I/M Workgroup 2009). It has the potential to have a great impact on reductions of vehicle emissions. By transmitting a signal that contains emission information wirelessly, it will minimize or eliminate the need for physical connection to the vehicle. Some telemetry devices such as GM's OnStar systems are already capable of transmitting a vehicle's emission readings over a wireless connection to a centrally located server.

Remote OBD Monitoring Fundamentals:

- Remote OBD gathers the same inspection data as conventional inspection, with wireless transmission replacing the cable connection used at a physical inspection facility.
- The wireless transmission of OBD data can be accomplished with Original Equipment Manufacturer (OEM) equipment, such as OnStar, or with an add-on device.
- The remote OBD link is a small unobtrusive instrument installed once in the vehicle's diagnostic link connector that can transmit at any time with the vehicles on board computer.
- Data that reflects the emissions status of the vehicle is temporarily stored in the link for transmission to remote OBD access points that convey real-time inspection records to a central database.

- Remote OBD access points consist of: 1) a ground-based network of short range radio receivers, 2) a cellular communications network or 3) satellite communications. The wireless access point then relays the vehicle inspection record to the inspection database (VID). (Transitioning I/M Workgroup 2009)

There are certain capabilities of remote OBD monitoring that may offer improvements over common periodic inspection limitations:

- Continuous Monitoring—the ability to identify OBD faults on a frequent or real-time basis can drastically reduce the period of excess vehicle emissions between inspections. This may result in a measurable and creditable emission reduction for the inspected fleet.
- Repair Factor Determination—the ability to determine the exact period after a malfunction indicator light (MIL) triggering event has occurred and the MIL is extinguished (presumably by repairs).
- Enhanced QA Capabilities—remote OBD monitoring can be used to identify inspection anomalies, defeat devices and other types of fraud.
- Continuous Repair Improvement with electronic notification—upon a change of OBD status, motorists, repair professionals and government have the means to evaluate several crucial program performance factors including repair durability, monitor readiness anomalies, deterioration rates, battery disconnects, etc. (Transitioning I/M Workgroup 2009)

Although wireless technology is currently very sparsely implemented (mostly on GM vehicles), it needs to be included in consideration for future emission inspection programs.

2.6 Vehicle Type

Differentiation among groups of vehicles is very important. Vehicles with different characteristics will produce different emissions. Figure 2-7 shows the difference between car and truck carbon monoxide emissions as identified by VIN decoder for Denver 2001 RSD data collection (Environ International Corporation March 2004). However as time goes on those differences become less noticeable. Somewhat similar results are illustrated in Figure 2-8. This figure is based on results of 2010 CAFÉ measurements. However both of those charts describe vehicle emissions based on mass emissions such as grams per mile and grams per gallon basis. Emission standards, however, look at emissions from relative emission component representation. Relative concentration differences for cars and trucks are less noticeable. For example, Figure 2-9 displays differences between automobile and truck emissions based on CAFÉ data collection for calendar year 2010. Based on Figure 2-9 there is no substantial difference in carbon monoxide emissions. Vehicle carbon monoxide emissions become somewhat different for vehicles that are older than fifteen years old, however those vehicles represent a very low percentage of the total vehicles, therefore total fleet inspection failure and emission rates may be similar.

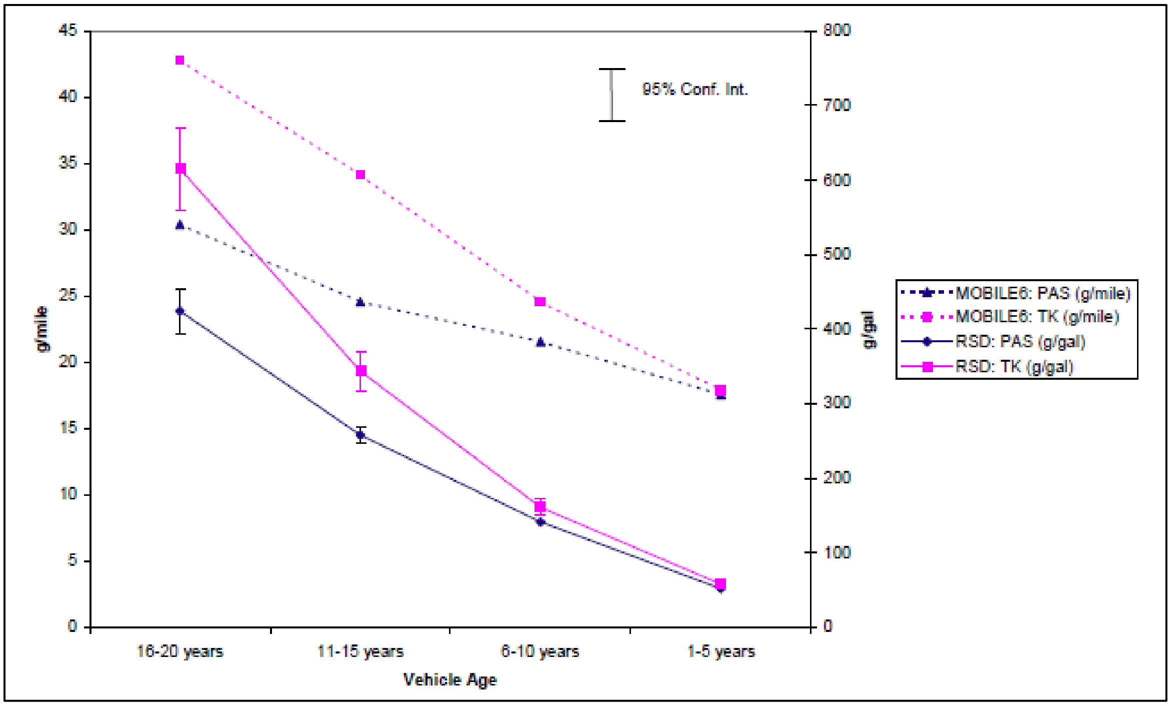

Figure 2-7 Mean CO emissions as a function of vehicle age of RSD data (g/gal) and from MOBILE6 (g/mile): Denver, 1999 – 2001

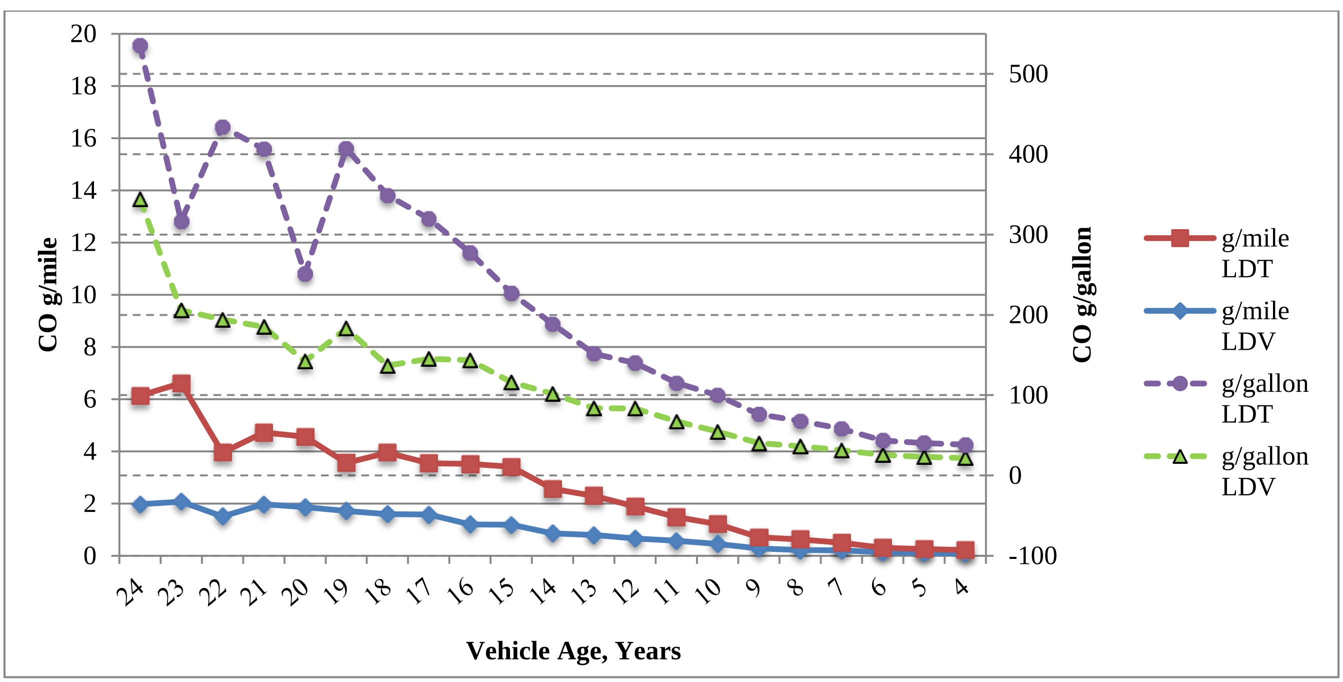

Figure 2-8 Mean CO emissions as a function of vehicle age of RSD CAFÉ 2010 data g/gallon, g/mile

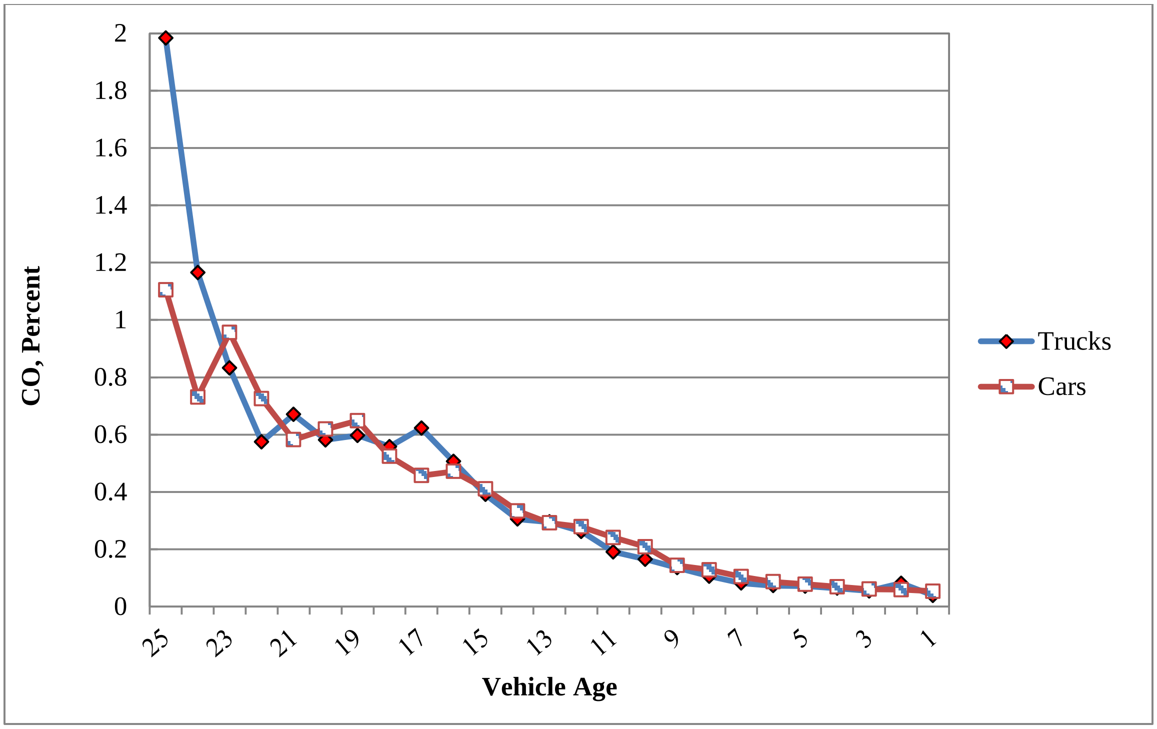

Figure 2-9 CAFÉ 2010 CO emissions vs. vehicle age for car and truck vehicle category

Even though the difference between passenger cars and trucks exists in grams per mile and grams per gallon readings, largely due to differences in fuel economy (Figure 2-7 and Figure 2-8), the difference in percent emission readings is practically non-existent (Figure 2-9).

Nevertheless, to answer the research questions posed, all vehicles are assigned to vehicle categories. Vehicle performance and durability may vary by vehicle category. This assumption will be checked in this research. In fact, several authors make predictions for future test results based only on the make, model, and model year of the vehicle (Beydoun and Guldmann 2006). However, even if that were possible one would need to collect an immense number of observations and even then not all makes and models would be covered. Results for some groups of vehicles would be greatly dependent on the vehicles that were sampled, especially if the sample size is low. To increase the sample size of each analyzed group, use of vehicle categories appropriate for a particular make and model will be utilized. This is commonly done in other contexts. For example, EPA size type and market segment categories are listed in Table A-7 in the Appendix.

Example of vehicle classification by EPA's MOBILE6.2 (Technical Guidance on the Use of Mobile6.2 for Emission Inventory Preparation 2004) or MOVES models (Draft MOVES2009 Highway Vehicle Population and Activity Data 2009) vehicle classifications seen in Appendix Table A-5 and

Table A-6 respectively. However, all passenger vehicles in those models are lumped into one category: LDV (Light Duty Vehicle). For this research that kind of classification will not provide enough in-depth information. To identify groups of passenger vehicles, EPA's vehicle size type will be more appropriate. It includes seven passenger vehicle categories. For the truck category the MOBILE6.2 vehicle classification representation seems to be more useful. For light duty trucks it includes four categories, LDT1 though LDT4. Therefore, for this research a hybrid vehicle classification composed of EPA vehicle size classes for passenger vehicles and passenger vans and MOBILE6.2 for pick-up trucks will be investigated.

To obtain MOBILE6.2 classification, CAFÉ and I/M data were decoded using a VIN decoder. The EPA's fuel economy tables will be used to coordinate makes and models to EPA size classification.

In addition to vehicle categories, vehicles are grouped based on model year and mileage records obtained from Georgia's registration database and Georgia inspection and maintenance records.

3 RESEARCH METHODOLOGY

One way to achieve more efficient vehicle emission testing with the current infrastructure is to concentrate on vehicles that have a higher potential to fail and therefore have higher emission rates. To achieve that objective several vehicle characteristics such as age, type, and engine displacement are incorporated in this research effort. Vehicle criteria related to use and ownership history are investigated as well. In addition, past emission test results as well as remote sensing measurements of a vehicle's emissions are included in the model. To compile lists of vehicle characteristics, this research draws data from several data sources: Georgia registration database for 2010, Georgia Inspection and Maintenance databases for 2009 and 2010, and VIN decoder software, developed by Eastern Research Group, as well as experimental measurements from the Continuous Atlanta Fleet Evaluation (CAFÉ) project conducted during 2009 and 2010 calendar years.

To achieve maximum effect, vehicles with higher probabilities of failure would be tested out of their schedule. Those early emission tests will reduce the total emissions produced by motor vehicles. To evaluate the potential benefits of changing the time frequency between subsequent emission tests, remote sensing data matched to inspection and maintenance data for 2010 is used. To calculate the benefit of early testing, vehicles are broken into two groups: those that did not fail an emission test during 2010 and those that failed a test in 2010 and were repaired. The next step after estimation of the potential benefits of more frequent testing are identified is to find the probability of vehicle failure for each individual vehicle. To determine the probability of individual vehicle failure based on vehicle characteristics obtained from datasets listed above, a generalized linear model with binomial distribution and logit link is used. The logit model is ideally suited for the binary nature of pass/fail outcome and therefore is employed in this research.

The general linear regression model has the form:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_m x_m + \varepsilon$$

Where y is the response, or dependent, variable

$\beta_0, \beta_1, \dots, \beta_m$ are unknown parameters

$x_1, x_2, \dots, x_m$ are the regressors, or independent, variables

ε is a random error term

The probability P of failing the test is stated as

$$P = \frac{1}{[1 + \exp(-\alpha - \beta X)]}$$

where X is a vector of independent variables

α parameter to be estimated

β parameter to be estimated

Based on the estimated probability of failure, the proposed policy will introduce a testing timetable with variable timing for each individual vehicle that directs owners of vehicles with a higher probability of failure to have more frequent tests and less frequent tests for vehicles with a low probability of failure.[2] Vehicles with a higher probability of failure will be assigned higher frequency of testing, thus reducing the amount of time they stay on the road with higher than typical emissions before repairs. Vehicles with a lower probability of failure, on the other hand, will have more time between tests. Because those vehicles are cleaner, they are unlikely to fail an emission test and therefore are not likely to be repaired. Without repair there are no changes in emissions of the vehicle. Figure 3-1 graphically represents the research methodology that is utilized in this research.

[2] Currently the majority of emission inspection programs have annual test requirements

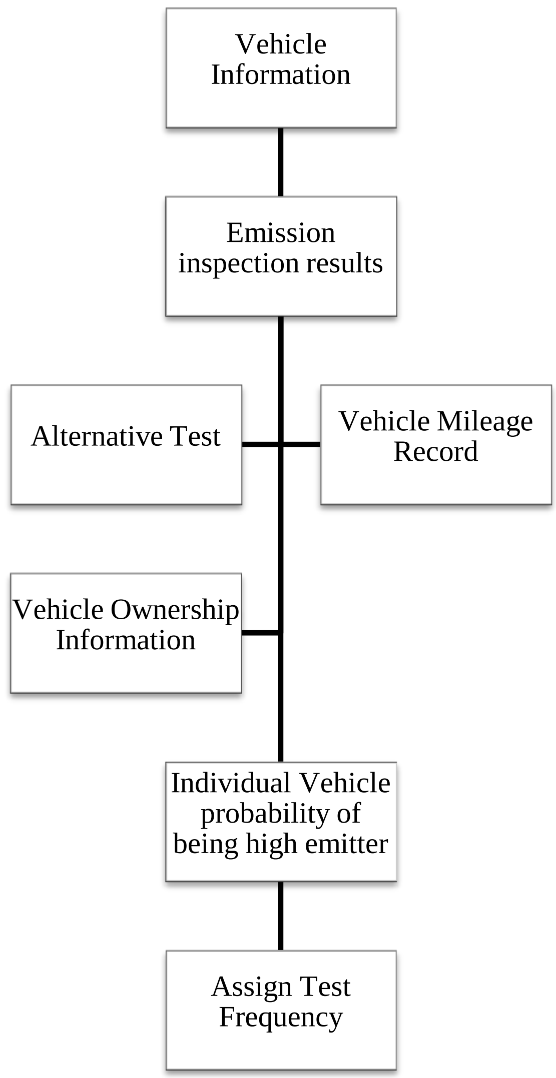

Figure 3-1 Research methodology analysis flow

3.1 Data used for this research

There are seven main data sources that will be utilized for this study. They are: Continuous Atlanta Fleet Evaluation (CAFÉ) database, Georgia Registration Database (GRD), VIN Decoder, Georgia I/M database, OBDII database, Fuel Economy database, and 2010 Census Block data.

- The CAFÉ database collected by the Air Quality Group (AQG), Georgia Tech Research Institute (GTRI) contains on-road vehicle emissions captured by a remote sensing device that examines the absorption of infrared and ultraviolet sources of lights. For the period to be examined, data were collected covering all four seasons and all twelve months. The sample was collected in 13 counties in the Atlanta non-attainment area as well as control counties located in Augusta and Macon, which are Georgia metro areas. This data set contains carbon monoxide, carbon dioxide, hydrocarbon, and nitrogen oxide measurements as well as the vehicle's speed and acceleration at the time of measurement.
- The Georgia vehicle registration database provides VIN information as well as a basic description of the vehicle such as make, model, year, and mileage reading.
- The I/M database of the State of Georgia provides Georgia's annual inspection test results. The results include but are not limited to date of the test, test results, vehicle information, and OBDII code information.
- The VIN decoder provides detailed vehicle information related to technical specifications such as vehicle engine displacement, number of cylinders, fuel aspiration and induction, emission controls, catalyst information, vehicle weight, and MOBILE6 vehicle classification.
- The EPA vehicle fuel economy database provides data compiled from individual model years from EPA's <fueleconomy.gov> web resource.
- The OBDII code database is a combination of manufacturer-specific OBDII codes as well as generic OBDII codes that are used on multiple vehicle makes and models.
- 2010 Census block data for the state of Georgia.

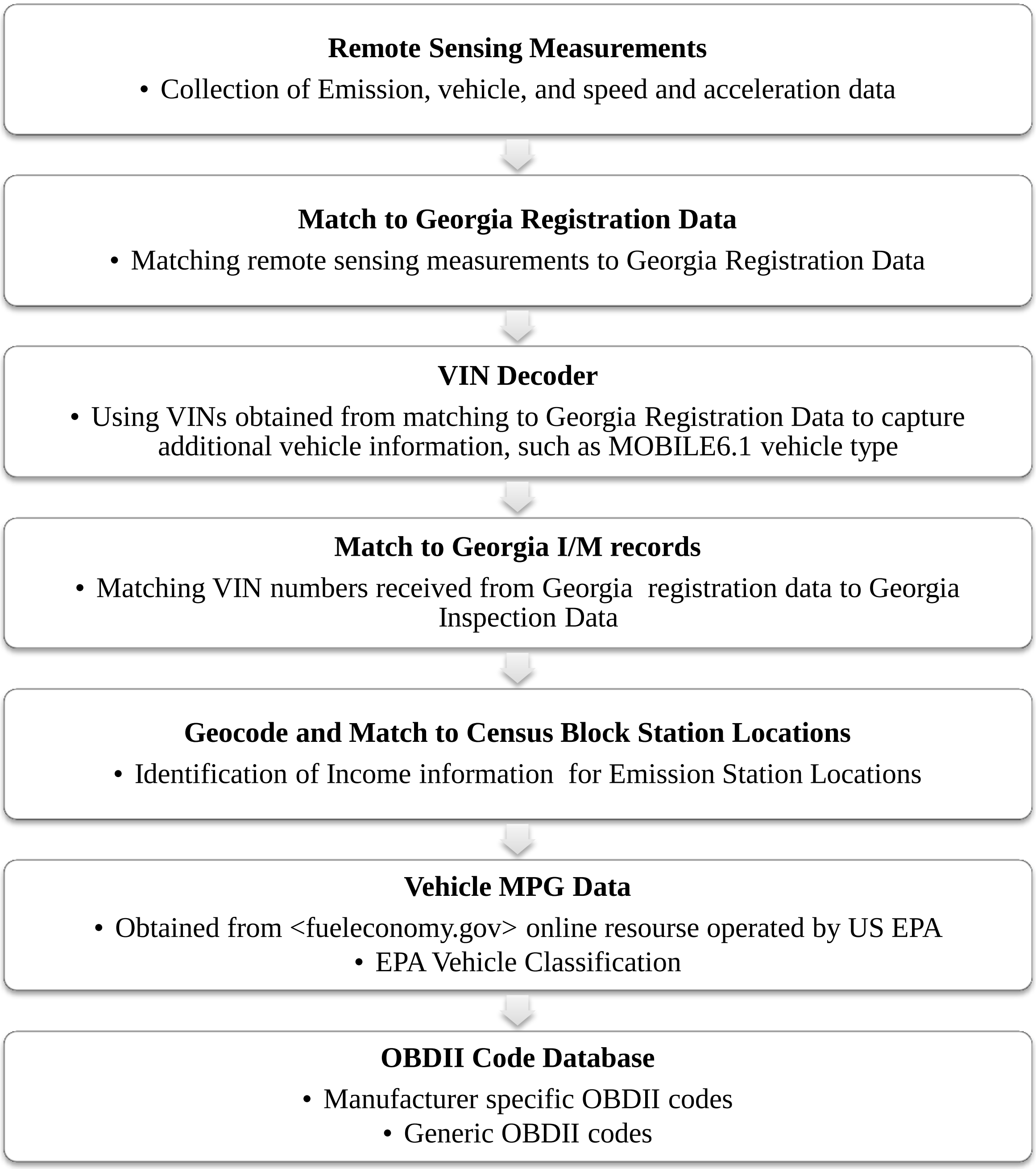

Figure 3-2 Thesis data flow

Figure 3-2 represents the generalized data flow employed in this dissertation. A more detailed survey is shown in the following figure.

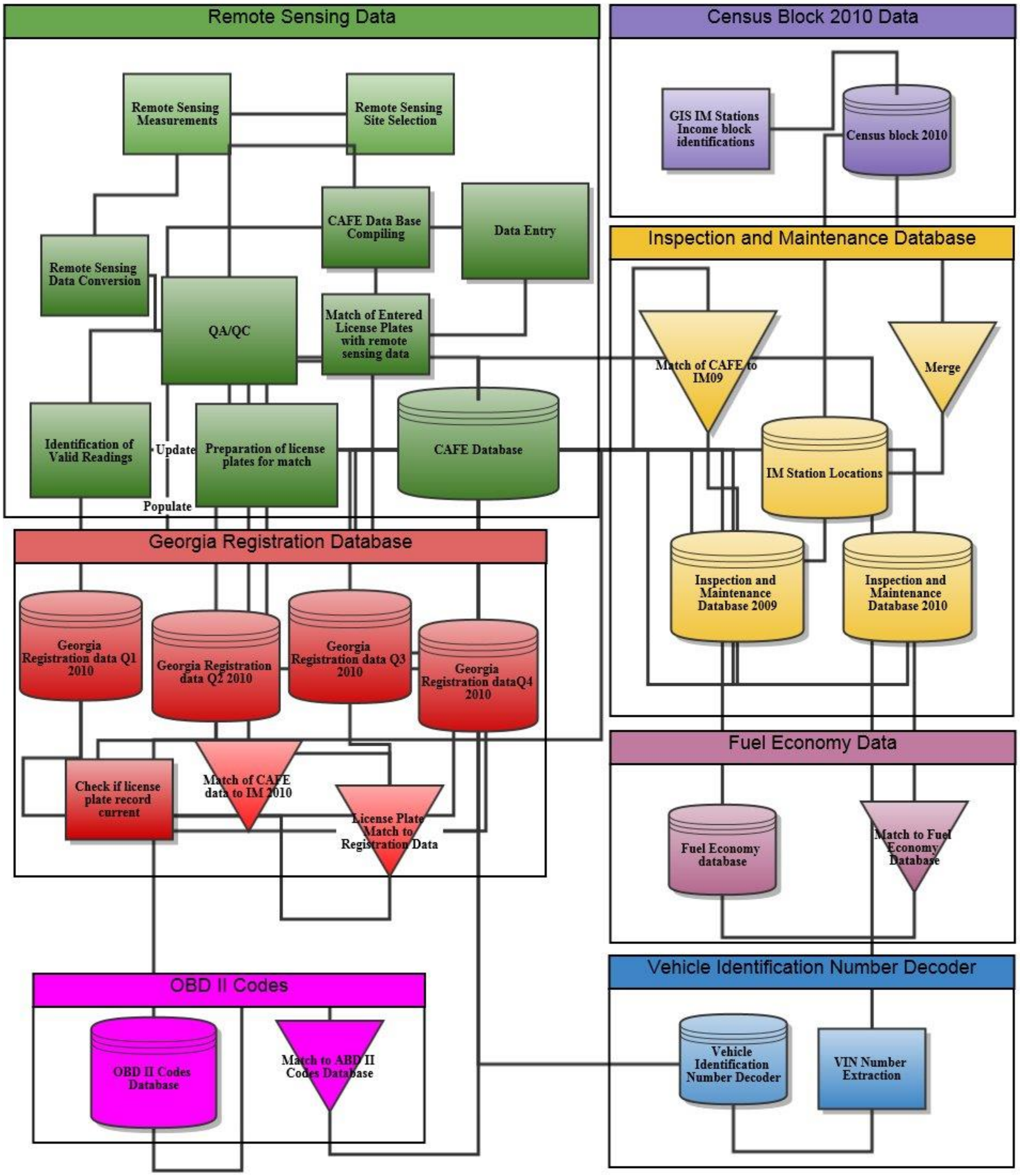

Figure 3-3 Data workflows

Figure 3-3 represents the detailed data flow used for this research.

3.1.1 CAFÉ Data

The Air Quality Group of Georgia Institute of Technology/Georgia Tech Research Institute performed pilot remote sensing studies in November of 1991. The CAFÉ project started in summer of 1993 and continues to the present time. From 1991 to 1998, CAFÉ data were collected by the School of Earth and Atmospheric Sciences, Georgia Institute of Technology. From 1998 to 2005, CAFÉ data were collected by the School of Civil and Environmental Engineering, Georgia Institute of Technology, and after 2005 by the Georgia Tech Research Institute. The Air Quality Group resided from 2005 to 2008 in the Health and Environmental Systems Laboratory and from 2008 to present in the Aerospace Transportation and Advanced Systems Laboratory. The primary objectives of the CAFÉ project are to characterize fleet emissions and observe fleet changes over time, evaluate the efficiency of Inspection/Maintenance Programs, develop recommendations regarding high emitting vehicle identification, and examine socioeconomic effects (a public policy aspect of the project). To achieve CAFÉ project objectives, collected remote sensing data with processed license plates is matched with the State of Georgia Registration database and the Georgia Inspection and Maintenance database. To obtain representative sampling, between 250,000-400,000 measurements annually were performed over the years in 40 – 50 sites selected after careful site evaluation. The Air Quality Group created guidelines for remote sensing site selection that are widely used in the industry currently. Remote Sensing measurements are performed 12 months a year. The sites represent areas with high variability of traffic mix and with various socioeconomic conditions. Initially, locations for remote sensing measurements were limited to thirteen counties in the Atlanta Metro area but were later expanded to eight additional counties adjacent to the Atlanta Metro area, and to Macon and Augusta, GA. Based on remote sensing data, the Air Quality Group performs bi-annual policy evaluations of the Georgia I/M program. Data collection results and high emitter analysis are reported annually. Evaluation of the efficiency of the Georgia I/M program was performed using the reference method by evaluating emissions in the areas with an I/M program (Metro Atlanta) and without an I/M program (Macon and Augusta, GA). Results of historical fleet evaluations can be seen in APPENDIX B, which represents excerpts from the CAFÉ report 1993–2008. Data used in this research represents a CAFÉ dataset for calendar year of 2010.

Remote sensing devices (RSD) use the principles of infrared (IR) and ultraviolet (UV) spectroscopy (Remote Sensing: A Supplemental Tool for Vehicle Emission Control n.d.). Vehicle remote emission sensing is capable of measuring CO, CO2, and HC uses non-dispersive infrared (NDIR) and NOx using ultraviolet absorption spectroscopy as well as speed and acceleration of the vehicle.

> "Remote sensing is a way to measure pollutant levels in a vehicle's exhaust while the vehicle is traveling down the road. Unlike most equipment used to measure vehicle emissions today, remote sensing devices (RSD) do not need to be physically connected to the vehicle. The concept of an efficient tool to monitor the vehicle fleet and identify excessive polluters has great appeal as a complement to traditional mobile source emission control programs. A number of instrument manufacturers are actively developing RSD systems." (Remote Sensing: A Supplemental Tool for Vehicle Emission Control n.d.)

A beam of light from the source of IR and UV radiation is directed across the road and reflected by a mirror on the other side of the road toward the receiver, which contains a series of detectors for each pollutant. When a vehicle crosses the beam, concentrations of pollutants in the exhaust plume are determined in real time based on their absorption of IR (for HC, CO, and CO2) and UV (for NOx**)** light (Bishop and Stedman 1996). At the same time, the rear view of the vehicle with license plate is captured by video camera. Total measurement takes ½ second. In real world conditions over a thousand measurements can be done during one hour.

There are several advantages and disadvantages of this technology. The main advantage of remote sensing is that it is able to measure vehicles under driving engine loads without stopping them and therefore it is measuring real world emissions. Since the vehicles are operating, collected emission data comes not from an idling engine but of an engine pulling the weight of a vehicle plus the payload. Remote sensing can make measurements very rapidly, allowing for collection of a great number of samples in a very short period of time, making data collection relatively inexpensive. The average of CAFÉ measurements in the Atlanta area is about 5,000 vehicle readings per day. Naturally, particular site vehicle counts will depend on vehicle volumes, which vary by location. One of the main disadvantages spurs from its principal advantage. Since vehicles are traveling under normal driving conditions and the measurement is being conducted with minimal influence on driving mode, each measurement depends on driving conditions. Researchers have very little control over driving conditions; therefore, depending on whether a vehicle was accelerating or slowing down when it passed the remote sensing equipment, exhaust concentrations of the vehicle can be different. There are some mitigating measures to reduce variations in driving conditions. Principally driving conditions can be controlled by proper site selection. Therefore, site selection for remote sensing measurements is a vitally important step for a successful remote sensing project.

3.1.1.1 Site Selection

Site selection is a crucial aspect of any study that employs remote sensing methods. Remote sensing sites should meet several criteria: 1) they should be safe for both drivers and operators (e.g., adequate sight distance and safe access) and have sufficient space on both sides of the roadway to safely place the equipment; 2) the sites should have road geometries and vehicle operating modes compatible with and desirable for remote sensing (e.g., single lane operation, moderate vehicle specific powers, absence of cold start emissions); and 3) sites should be geographically located in areas that are desirable for a particular study in terms of demographics and fleet composition. Figure 3-4 illustrates CAFÉ remote sensing site locations in the thirteen counties of Metro Atlanta.

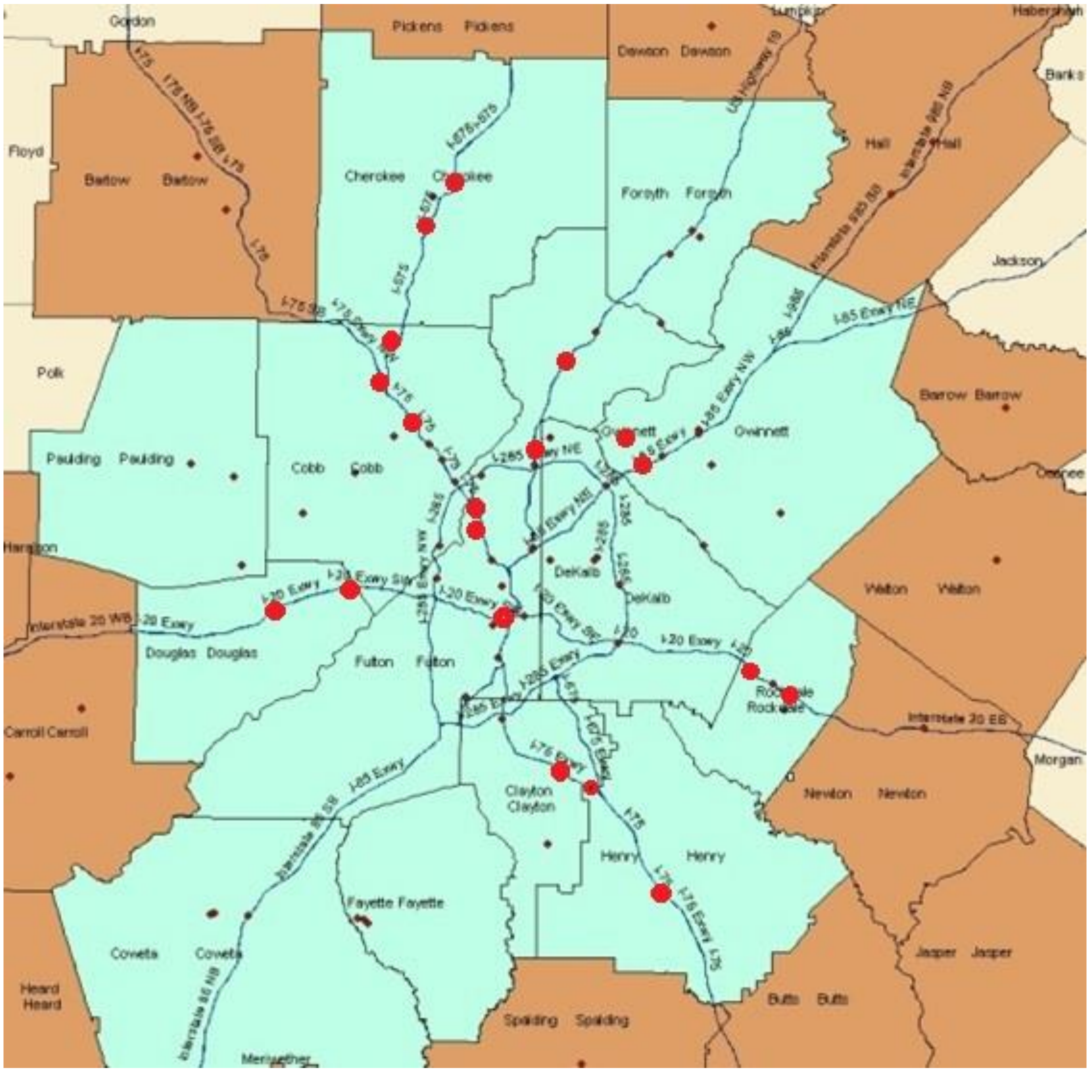

Figure 3-4 Remote sensing sites for the Continuous Atlanta Fleet Evaluation (CAFÉ) in the thirteen-county Atlanta, Georgia Metro Area

Remote sensing works best if the subject vehicles are operating in a predictable manner and the vehicles' engines are running under a moderate continuous load. This is generally easier to accomplish if the vehicles are running at moderate speeds either on a small positive grade and/or with modest positive accelerations. To achieve continuous load on the engine, small positive grades are generally more desirable.

3.1.1.2 Speed and Acceleration

In addition to exhaust components, speed and acceleration data are collected. Speed and acceleration of the vehicle is a very important parameter for estimation of vehicle emissions, since emissions greatly depend on the vehicle's engine loads. It is also significant because under real world driving conditions every driver behaves differently. Thus, by measuring speed and acceleration we are able to compare vehicles not only in the same site location but also at different remote sensing site locations.

Speed and acceleration of vehicles are measured by speed and acceleration bars (Figure 3-5) located on both sides of the roadway. One bar is equipped with two low-power lasers. The bar located on the other side of the roadway is equipped with two receivers.

Figure 3-5 Speed Acceleration Bar

3.1.1.3 Vehicle Specific Power

Because every sampling location has different geometric features, and vehicle speed and acceleration differ from vehicle to vehicle, there is a need to normalize those conditions to be able to compare vehicles at different locations and with different velocities and accelerations. To estimate engine loads, Vehicle Specific Power (VSP) is utilized.

Vehicle Specific Power is the measure that seeks to normalize vehicle power demands by using physical characteristics of the site and driving conditions. It uses the site's slope and vehicle's speed and acceleration as input parameters. VSP can be calculated as:

$$VSP = 4.39 * \sin(Slope) * V + 0.22 * V * A + 0.0954 * V + 0.0000272 * V^3$$ (J. L. Jimenez, et al. 1999)

Where V is Speed in MPH, and A is Acceleration in MPH/s, VSP is in KW/metric tonne. Example: A vehicle traveling 40 MPH with an acceleration of 1 MPH/s at the site with 2 degrees upgrade will have VSP =19.6 KW/tonne (16 HP/short tonne). It is important to note that VSP readings for CAFÉ measurements were slightly higher than those reported in the CRC E-23 Report (Slott 2002). Higher VSP readings imply that data collected for the CAFÉ project was collected from the vehicles with higher engine loads. At extremely high VSP readings it is possible for the engine to reach fuel enrichment stage and produce artificially high emission readings. However, the differences between VSP reading for CAFÉ project and are mainly due to differences in the type of site locations. E23 sites were located at the end of a cloverleaf-style ramp (A Policy on Geometric Design of Highways and Streets 2001), which produce smaller engine loads since acceleration on this kind of intersection is on the lower side of the scale. Most of the remote sensing sites in the Atlanta area are diamond-type interchange (A Policy on Geometric Design of Highways and Streets 2001), which produce slightly higher acceleration when compared to cloverleaf-style alternative.

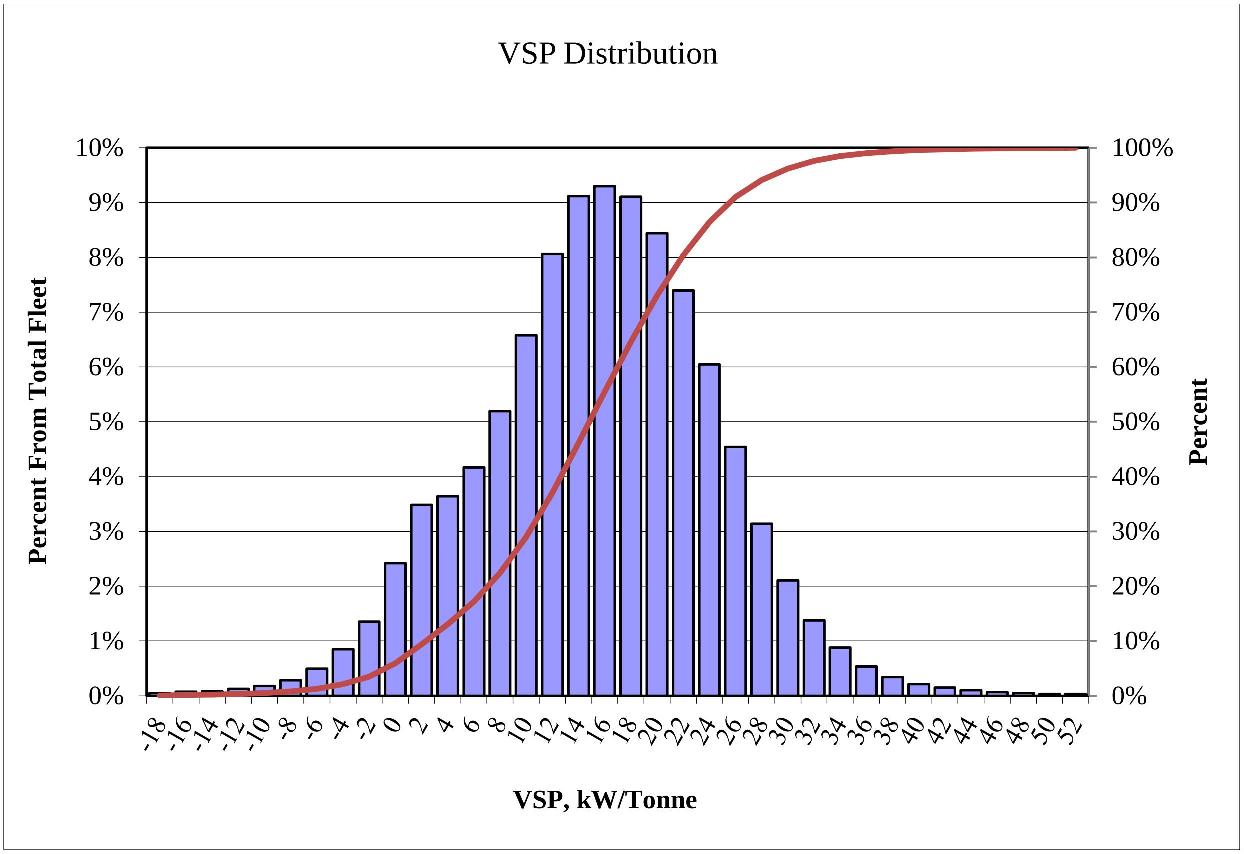

Figure 3-6 CAFÉ 2010 vehicle specific power (kW/Tonne) distribution

A desirable range of VSP for remote sensing measurements is between 0-30 kW/Tonne. Figure 3-6 shows the observed VSP distribution for the approximately 360,000 remote sensing measurements from CAFÉ 2010. The majority of remote sensing measurements are in that range.

To further understand the effects of engine load on exhaust, let's examine carbon monoxide emission (Figure 3-7) for vehicle groups based on the model year. Looking at the group of newer vehicles, in this case it is 2008 and newer vehicles, it is evident that at higher VSPs those above a VSP of 30 kW/Tonne carbon monoxide exhaust emission can be three to four times higher than those in the VSP range of 0-30 kW/Tonne. This range is consistent with recommendations from the literature (Jimenez, et al. 1998). To a slightly lesser extent negative

VSPs carbon monoxide emissions are higher than for the VSP range of 0 – 30 kW/Tonne. Therefore vehicles that are not in VSPs range of 0 to 30 are excluded from analysis.

Figure 3-7 represents VSP readings for vehicle age groups versus carbon monoxide emissions. For newer vehicles, emission control equipment can contain carbon monoxide emissions in check for a wide range from negative VSP readings to about 35 kW/Tonne. However, for older vehicles the range of acceptable VSP readings is much lower. At approximately 30 kW/Tonne, older vehicle carbon monoxide emissions start to deteriorate at a much quicker pace.

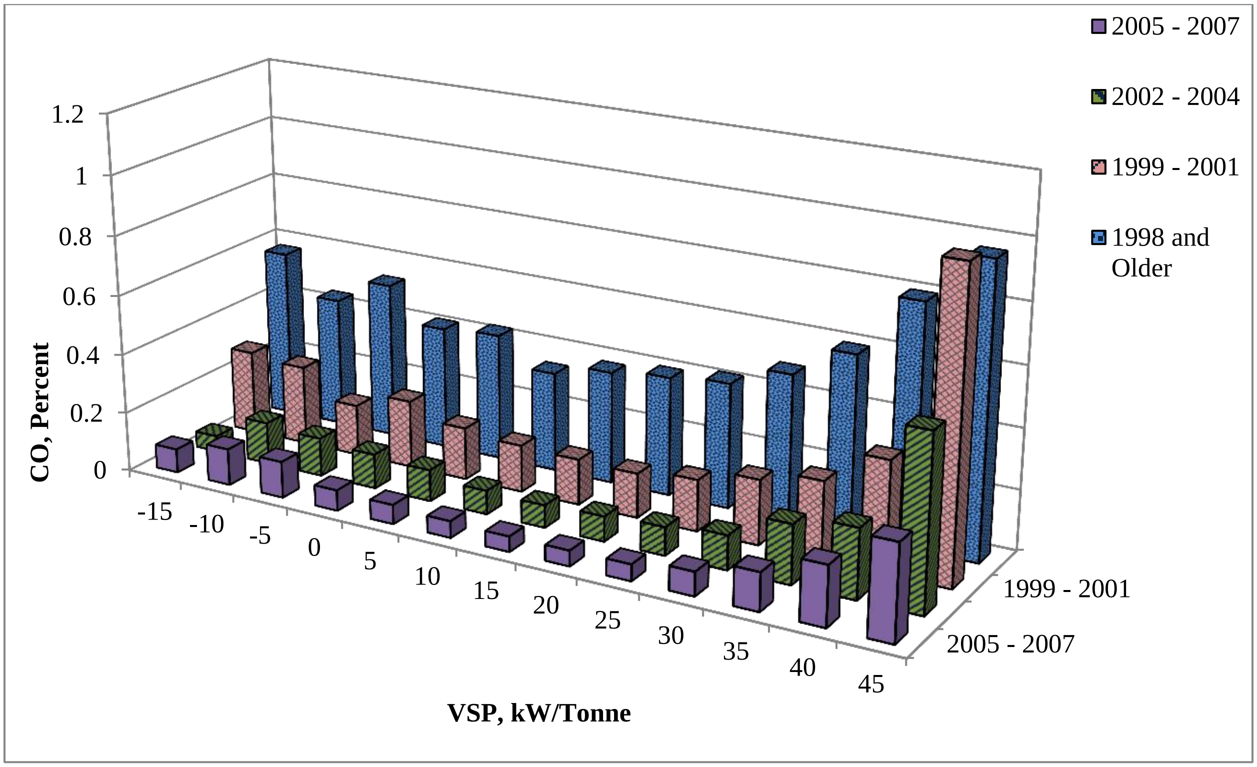

Figure 3-7 Carbon monoxide vs. VSP group by model year

Thus, analysis of vehicles that have VSP readings higher than 30 will introduce fuel enrichment and higher emission concentrations due to higher vehicle engine loads. At high VSP readings an otherwise clean vehicle can be determined to be a high emitting vehicle.

Hydrocarbon vehicle exhaust emissions behave differently than carbon monoxide emissions. For newer vehicles, hydrocarbon readings stay flat over the entire range of VSPs (Figure 3-8). Older vehicles, on the other hand, have a much higher HC reading at negative and low VSPs. Low VSPs occur mostly during deceleration. During deceleration a portion of the fuel is un-burned and coming out of the tailpipe, which increases hydrocarbon readings. Therefore vehicles with negative VSPs should be avoided when analyzing HC emissions.

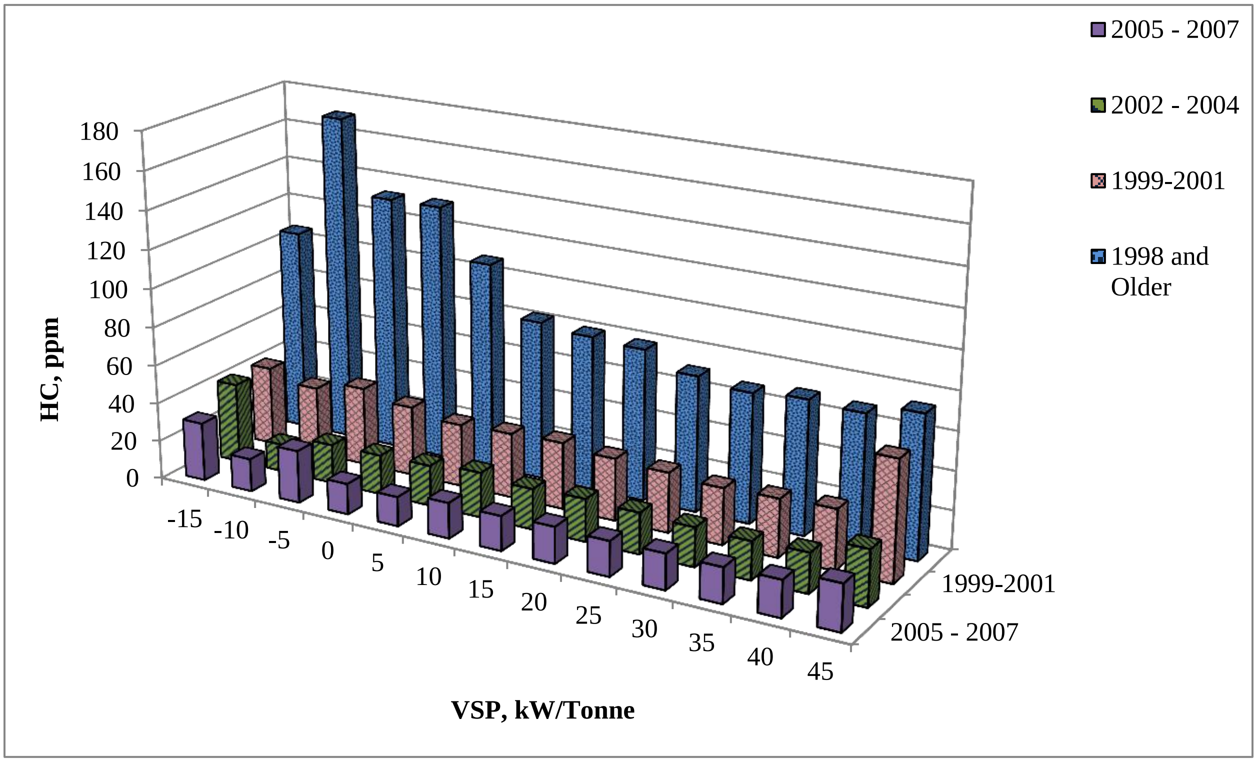

Figure 3-8 Hydrocarbon vs. VSP for model year groups

Figure 3-9 represents oxides of nitrogen readings based on vehicle age groups. On-board emission equipment of newer vehicles can control nitrogen oxide exhaust across a wide range of

VSP, spanning from the negative range to around 40 or 50 kW/Tonne. However, for older vehicles, deterioration of emission control equipment, with a few exceptions, can be seen in the whole range of VSPs.

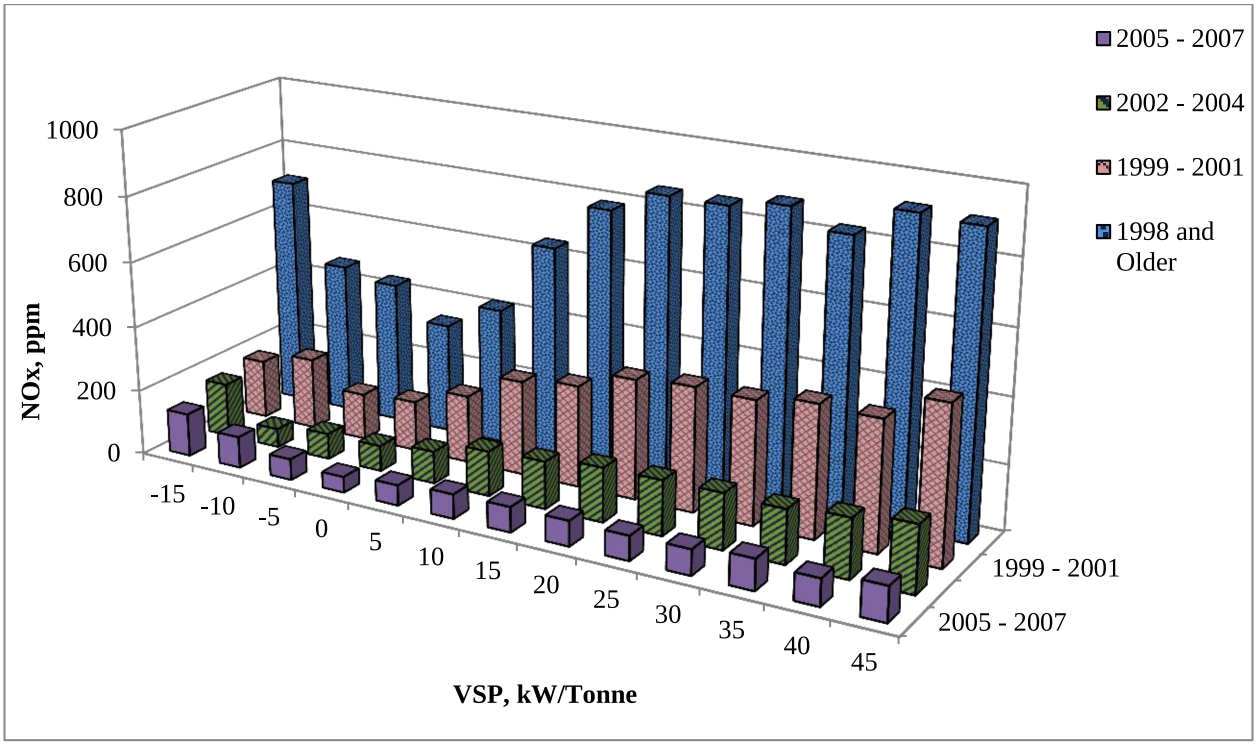

Figure 3-9 Nitrogen oxides vs. VSP for model year groups

3.1.1.4 Remote Sensing Site Evaluation

To evaluate remote sensing sites, researchers visit prospective locations and spend sufficient time to evaluate layout and traffic characteristics. Each potential remote sensing site is assigned a unique identification number (ID) for future reference and compiled into a database with site characteristics such as location, average speed (measured by laser rangefinder), average flow, road grade, latitude, and longitude, as well as photographic imagery and a site plan (Figure 3-10) that shows the equipment placement. Each location is evaluated for safety of personnel and equipment. A list of remote sensing sites can be found in the Appendix Table A-4 Remote sensing locations.

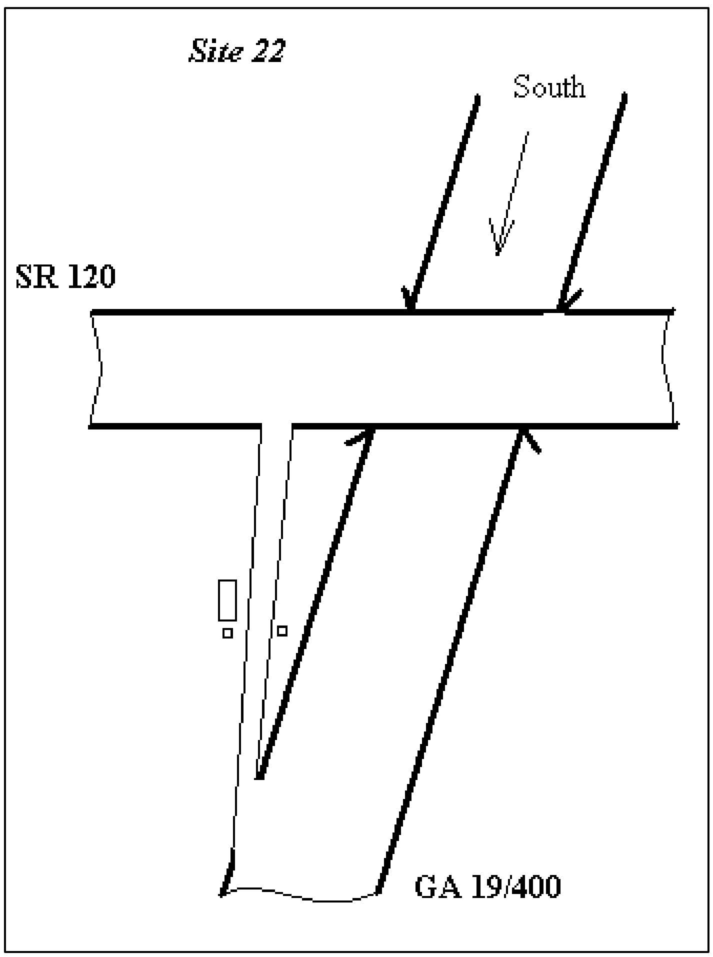

Figure 3-10 Typical remote sensing site plan

3.1.1.5 Remote Sensing Equipment

To collect vehicle remote sensing measurements, an unmarked van equipped with an RSD-3000+ system manufactured by Environmental System Products, Inc. was used. This equipment is capable of measuring carbon monoxide, carbon dioxide, and hydrocarbons using non-dispersive infrared (NDIR), and nitrogen oxides using ultraviolet absorption spectroscopy; speed and acceleration of the tested vehicles using a speed bar; and a license plate image using an automatic digital camera. The van is also equipped with a calibration system for all measured gases to ensure proper calibration of the system before and during. Figure 3-11 illustrates a typical remote sensing site equipment setup.

Figure 3-11 Typical remote sensing site setup

3.1.1.6 CAFÉ Data collection

Data collected during calendar years 2009 and 2010 consisted of data from 72 and 69 van-days of measurements utilizing 31 and 26 sites, respectively. Most of the sites were visited at least twice during different seasons to account for seasonal differences in emissions. Significance of seasonal variations is described by Wenzel (Wenzel, Seasonal Trends in Vehicle Emissions 1999). In 2010 368,180 beam blocks produced 329,722 records (89.5 percent) containing at least valid carbon monoxide readings. Detailed data collection reports for 2009--2010 data collection efforts can be seen in Appendix Table A-2 and Table A-3.

Collected in the field data is compiled into a database. The data are transformed through a series of steps before it can be presented in a format that can be easily seen and analyzed. Figure 3-12 demonstrates that path in what is called data reduction steps. Remote sensing starts with a collection of 'beam blocks'. Beam blocks are physical crossings of the remote sensing beam. Those beam blocks are later examined for validity, and valid data are selected from them. Valid data are defined as a vehicle having at least one valid gas readings such as CO, HC, or NOx. Images for valid readings are then examined for existence of license plates. If the license plate is visible plate identification is recorded in the database. Visible license plates are then divided into two categories: state of Georgia license plates and out of state license plates. Georgia license plates are matched with the Georgia Registration database. Registration data allow extraction of the vehicle identification number (VIN). Those VINs are used as an input into VIN decoder software (developed by Eastern Research Group), which provides more detailed vehicle information. As shown in Figure 3-12, valid data for different sites ranges between 66% and 99% of total beam blocks collected, with an average of about 87%. Readable license plates range from 56% to 89% with an average of 74%. Such a wide range is produced by various light conditions and geometries of road surface. State license plates on each site vary from 53% to 85% of the collected beam blocks with an average of 71%. Nearly 85% of Georgia state license plates are matched to the Georgia registration database. Between 44% and 77% of original beam blocks match to registration data. 73% of those matches are decoded by VIN decoder software. For each individual site, the range in relation to beam blocks is between 32% and 61% with an average of 45%. The reason for the low decode rate of the VIN decoder is because the version that is being used is outdated and does not decode well vehicles younger than 2006 model year. In a an absence of VIN data it is substituted by vehicle information data from other sources such as vehicle registration records or vehicle's inspection and maintenance records.

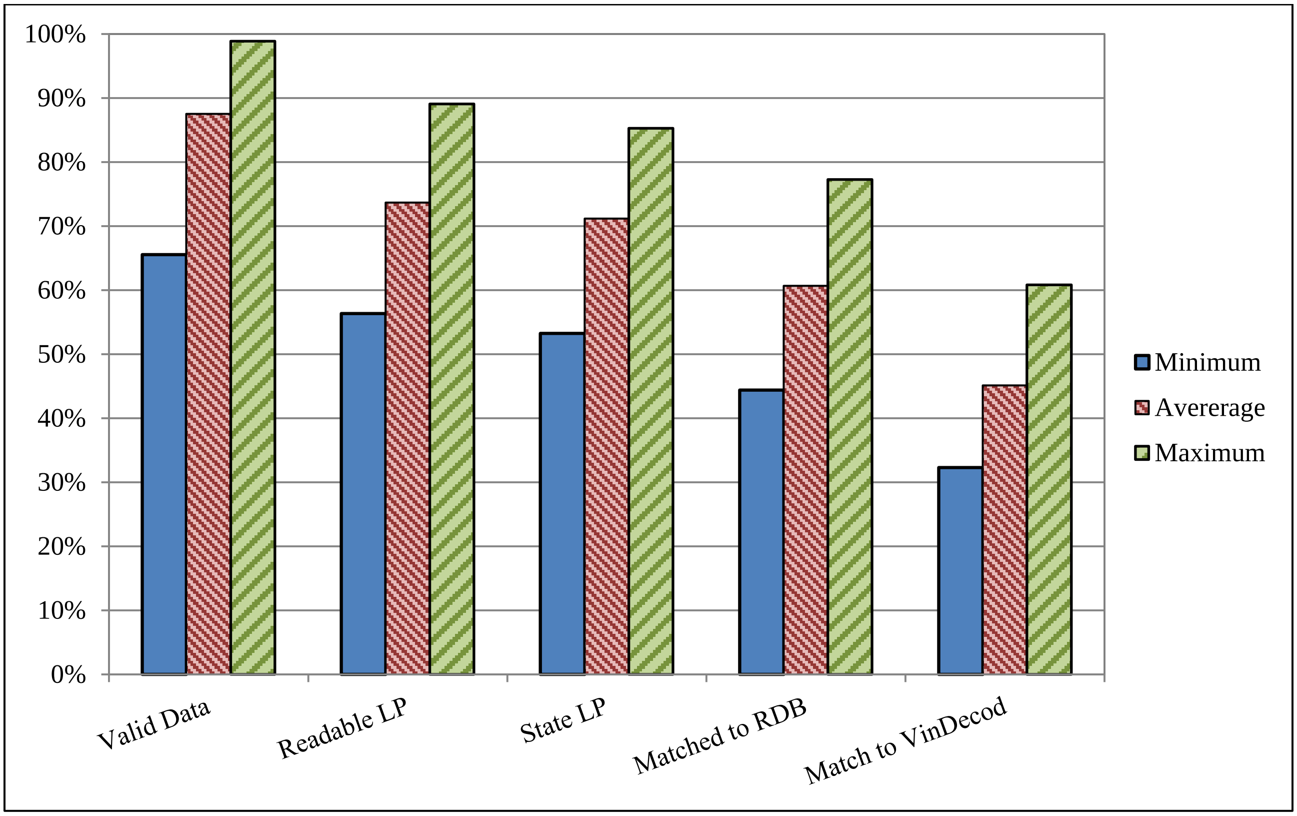

Figure 3-12 CAFÉ project data reduction flow

3.1.1.7 License Plate Entry

License plate entry was done by trained Georgia Tech Research Institute personnel familiar with the license plate type and trained with proper procedures for license plate editing to maximize matching with the Registration Database.

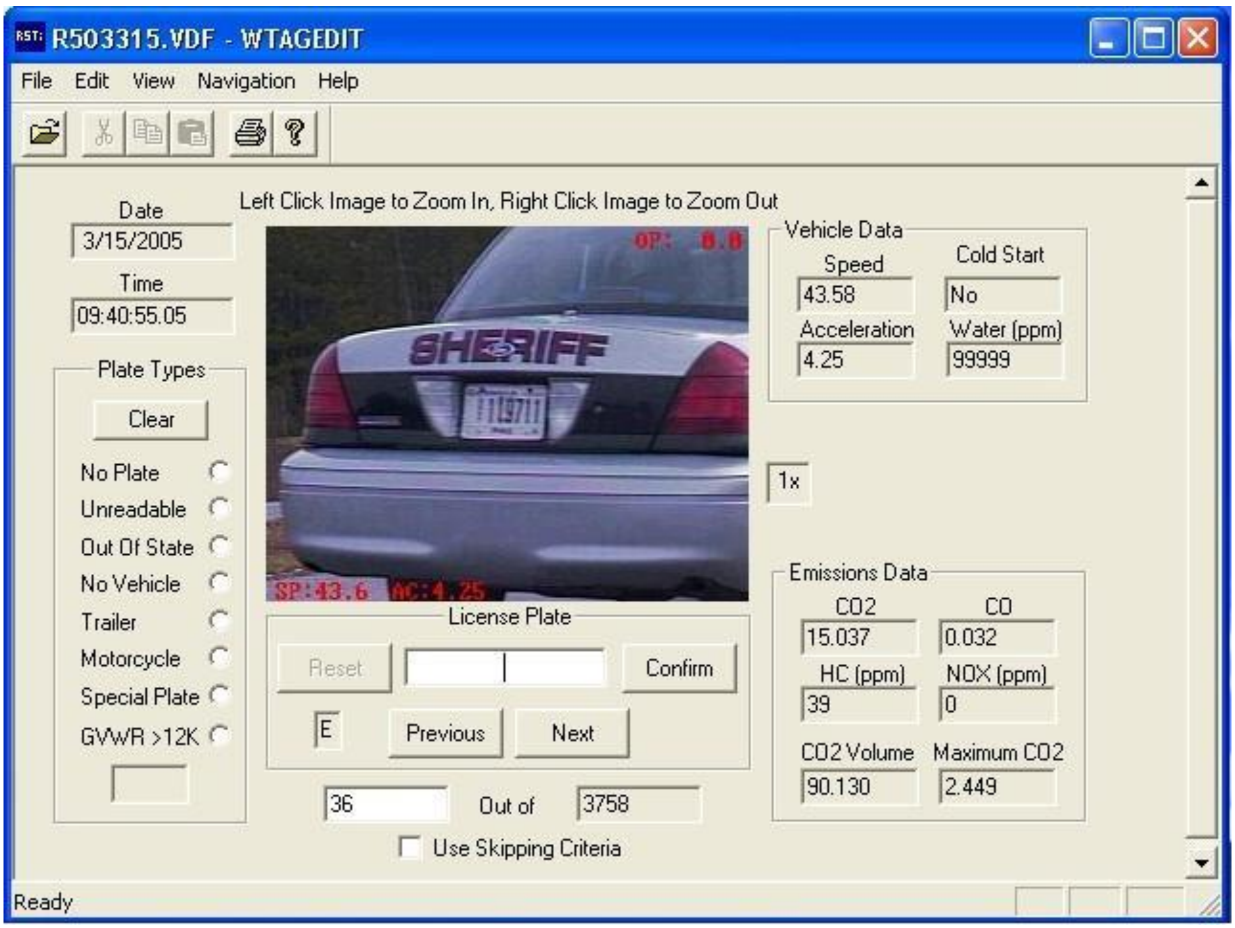

Figure 3-13 Screenshot of license plate editing software. ESP Inc. Copyright

Air Quality Group's data entry staff has extensive knowledge and experience in data entry accumulated over more than 20 years of projects performed in and outside of the State of Georgia. Correct recording of license plates has been found to significantly affect overall vehicle identification rates and the success of previous studies.

License plate entry was accomplished using digital imaging processing software (TagEdit 4.01 developed by Remote Sensing Technologies, Inc.). A screenshot of the license plate entry screen is shown in Figure 3-13.

To maximize license plate matching, types of Georgia license plates have been investigated and recorded, and images of Georgia license plate types were distributed to license plate entry staff.

3.1.1.8 Quality Control / Quality Assurance

The Quality Control and Quality Assurance plan include an array of quality control, quality assurance and maintenance procedures including, but not limited to, those procedures currently recommended by the equipment manufacturer, the U.S. EPA and the California Air Resources board.

3.1.1.9 Gas Calibration

In accordance with manufacturer specifications, calibrations using gas containing all measured compounds are performed at specified intervals before the start of measurements and every 90 minutes or less thereafter.

3.1.1.10 Camera Settings

After the initial positioning of the camera (Figure 3-14) during setup, the exposure settings are checked and fine-tuned on an as-needed basis. Alignment of the camera greatly depends on traffic speeds and light conditions. Therefore it has to be adjusted to accommodate changing conditions numerous times during data collection activities.

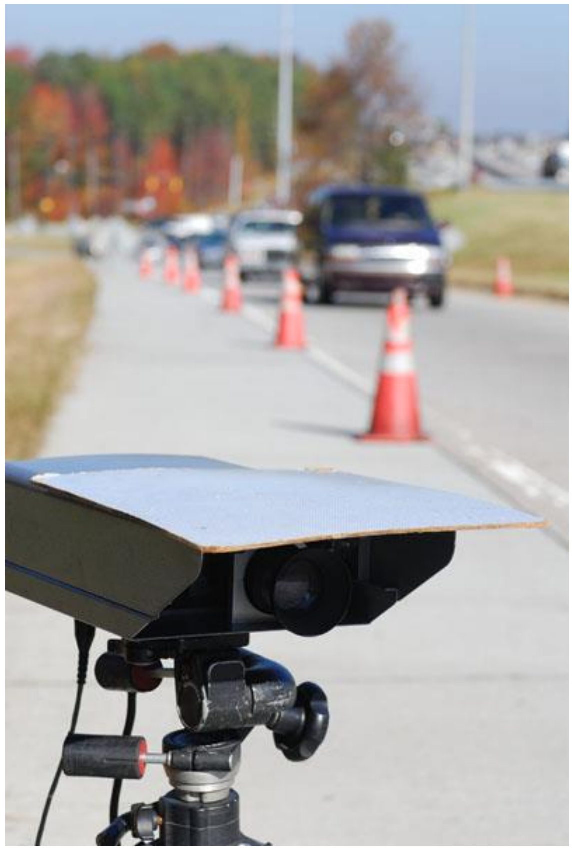

Figure 3-14 Remote sensing camera

3.1.1.11 Data Capture Rates

To verify the functioning of the system, the Hit Rate Analysis function of the RSD software is utilized. Hit Rate Analysis displays statistical parameters of the remote emission data collected after the last calibration. This function applies the operator information on a quantity of valid records that the system has captured. This data can help to determine how the system is functioning. Below is the list of parameters included in Hit Rate Analysis:

- Total Records – the number of vehicles that have passed through the system since last calibration
- Valid Records – the number of valid readings captured
- Invalid Gas – the number of records rejected because of invalid readings

- Suspect Gas – the number of records rejected because of gas readings that exceeded reasonable limits
- Small Plume – the number of records rejected because of smaller than needed CO_2 content to determine an accurate reading
- Data Capture – percent of valid emission tests
- Invalid CO_2 – the number of invalid readings
- Invalid CO – the number of invalid readings
- Invalid HC – the number of invalid readings
- Invalid NO_x – the number of invalid readings
- CO above 3.0 % – the number of readings with CO > 3.0%
- HC above 1000 ppm – the number of readings with HC > 1000 ppm
- NO_x above 2000 ppm – the number of readings with NO_x > 2000 ppm
- Number of Rejected Speed and Acceleration Readings

The Hit Rate Analysis allows for real time quality control of testing equipment. If the hit rate is extremely low it would suggest that equipment is not operating properly or the testing location does not produce a sufficient number of valid readings, which defined by measurements that have at least one valid exhaust components readings.

3.1.1.12 Remote Sensing Calibration Audits

During operation of the remote emission sensor, in addition to periodic calibration of the system, calibration audits are performed. Calibration audits are done every 90 minutes or sooner based on the time when instrument calibrations are performed. Calibration audits consist of flowing known gas mixture through the chamber inside of the remote sensing detector unit in operational vehicle measurement mode and comparing the results of those measurements of the concentrations of carbon monoxide, hydrocarbons, and nitrogen oxides, to stated gas concentration values of the calibration gas mixture. If calibration audit readings differ from readings on the gas cylinder, calibration is rejected and the system is recalibrated.

3.1.1.13 Remote Sensing Measurement Database

Upon completion of remote sensing measurements, a database containing date, time, site identification number, vehicle identification number, vehicle license plate number and state of origin, CO/ CO2/ HC/ NOx measurements, speed, acceleration, calculated vehicle specific power, and vehicle identification information is constructed. Additionally, site information calibrations are included in the database.

3.1.1.14 License Plate Matching

Remote Sensing data is matched to the Georgia Motor Vehicle Registration Database using the license plate data recorded during the sampling phase. Matched records are combined with remote sensing records to populate the database. That database is matched to the registration database of the State of Georgia and the following vehicle information is extracted: make, model, model year, fuel type; engine displacement, and gross vehicle weight rating (GVWR), county of registration, and mileage records.

The Georgia Registration database is obtained by the Georgia Tech Research Institute on a quarterly basis. Remote sensing data is coupled to the Georgia Registration database records with an appropriate date. The date of measurement is checked against the date of purchase on registration records. If the date of purchase is later than the date of measurement, the result of a match is discarded and the license plate matched to the previous quarter.

3.1.1.15 License Plate Match Rate Checks

After the remote sensing data and Georgia registration database are matched, the resulting database is checked for data consistency. To check for matching consistency, a license plate match rate check is performed. The check consists of comparing daily percentages of matched records as a proportion of readable license plates. Measurement days that have license plate match rates well below the match rate from other days are further checked for license plate entry or license plate matching errors.

3.1.1.16 Random Visual License Plate Matching Check

In addition to Match Rate Check, a random visual license plate check is utilized as well. It consists of visual validation of matched data by comparing pictures of a particular vehicle with matching records. Pictures of the identified vehicles are visually compared to registration records by comparing make, model, and color of the vehicles seen on the picture to records matched to the registration database.

3.1.2 Georgia Registration Database

The Georgia registration database includes vehicle information such as make, model, year, and VIN of the vehicle as well as the county code for county of registration.

3.1.3 VIN Decoder

VIN Decoder is software that can decode known VIN numbers. VINs provide more detailed information about the vehicle than the registration database, and includes make, model, year, emission control and fuel systems, as well as the weight of the vehicle.

3.1.4 Inspection and Maintenance Data

The inspection and maintenance database of the State of Georgia provides records of every transaction performed at emission stations. The I/M data provide detailed information generated during the test. Most notably it provides information about each test result and includes OBD fail codes, and if the vehicle failed I/M inspection.

3.1.5 OBD II Code Data

The OBD code database was compiled from codes of individual makes obtained from OBD Codes online portal (**http://www.obd-codes.com**). This portal serves as a clearing house for OBD codes for various makes and models. Close to 5,000 codes both generic and manufacturer-specific were gathered into a database.

The OBDII codes consist of five characters: a letter and four numbers. The first character is a letter and identifies a system related to the trouble code

- P - Powertrain
- B - Body
- C - Chassis
- U - Undefined

The second character is a digit identifying whether the code is generic or manufacturer-specific:

- 0 - Generic (this is the digit zero -- not the letter "O")
- 1 - Enhanced (manufacturer specific)

Third digit refers to the subsystem:

- 1 - Emission Management (Fuel or Air)
- 2 - Injector Circuit (Fuel or Air)
- 3 - Ignition or Misfire
- 4 - Emission Control
- 5 - Vehicle Speed & Idle Control
- 6 - Computer & Output Circuit
- 7 - Transmission
- 8 - Transmission
- 9 - SAE Reserved
- 0 - SAE Reserved

A fourth and fifth character refers to a particular problem.

3.1.6 Fuel Economy Data

The Fuel Economy data were compiled using www.fueleconomy.gov web resource operated by the U.S. EPA. Data from 1978 to 2010 was compiled from individual annual data files. Over 37,000 combinations of make, model, and year were assembled and formed the Fuel Economy database that is utilized in this analysis. Some useful information in this dataset includes city, highway, and combined miles per gallon fuel economy, EPA's vehicle classification, vehicle's engine displacement, number of cylinders, transmission type, and type of fuel used.

3.2 Frequency of Testing

To increase the efficiency of the emission inspection program, the frequencies of the test administered to vehicles can be manipulated based on the position of the vehicle on the scale from extra clean to gross polluting. The scale is based on the probability of failure based on the above-mentioned parameters. Data from all data sources mentioned previously formed an infrastructure for the data that is used to identify the probability of vehicle emission test failure.

A derived fit model is used for estimation of the probability of failure for each vehicle. Based on failure probability distribution, vehicles will be placed into categories that will determine vehicle-testing frequency. The envisioned emission inspection program would test potentially clean vehicles less frequently and vehicles that are more likely to be high emitters more frequently.

$$Time\ beween\ tests = Regular\ Time\ Interval * K,$$

Where, K is an adjustment coefficient:

$$K = f(Probability\ of\ Vehicle\ Failure),$$

Where,

K < 1 for high emitting vehicles

K > 1 for clean vehicles

K = 1 average vehicles

$$Probability\ of\ Vehicle\ Failure$$
$$= f(Vehicle\ Type, Model\ Year, Mileage, Alternative\ Tests, Vehicle\ Repair\ Costs)$$

When K is smaller than the one it will yield a smaller time between test. Conversely if K is greater than the one it would produce longer test frequencies.

By changing frequencies of tests, but conducting a similar number of tests per year it would be possible to increase efficiency of the program. With the same amount of capital expenditure the emission inspection program will produce lower emissions. This research will calculate the benefits and emission reductions achieved using the proposed program.

4 PROPOSED PROGRAM BENEFIT ESTIMATIONS

To estimate the potential benefits of changing the time between test frequencies for vehicles with a high probability of passing or failing emission inspection, the previously formed database was examined. In particular, two data sets including the Remote Sensing database for 2010 and the Georgia Inspection and Maintenance database for 2010 were analyzed. A 2010 emission test result and a date of emission inspection were added to emission inventory collected during the CAFÉ program. Conceptually, if the vehicle passed the emission inspection test, there should be no repairs made to the vehicle and therefore there should be no difference in emissions before and after the emission test. Passing the emission inspection test means that no repairs have been done to a vehicle due to failure of the test. Alternatively if a vehicle at any time during 2010 failed the emission test, it was deemed a failing vehicle even if the vehicle had passing results in subsequent emission tests. If vehicles failed emission inspection then the assumption is that they were repaired before they had a passing result and therefore some differences in emission should be observed. Based on those two basic premises, for this portion of analysis, vehicles were split into two groups: vehicles that passed the emission test in 2010 and vehicles that failed the test during 2010. The following sections describe the results of the analysis of those two groups.

4.1 Passing Vehicles Before and After Emission Inspection Test

The vehicle population is broken into two groups: vehicles that passed a 2010 emission test and vehicles that failed a 2010 emission test. It is important to note that based on previous discussions, to avoid fuel enrichment that occurs at low and high VSPs shown in Figure 3-7, only vehicle measurements with a VSP range between 0 and 30 are selected for this analysis. A first group of vehicles that passed the emission inspection test in 2010 and did not fail emission test at any time during the 2010 calendar year was selected from the 2010 I/M database. Those vehicles were cross-matched to the 2010 CAFÉ remote sensing database. Matching records were selected and represented in this section as vehicles that passed the 2010 I/M test. CO, HC, and NOx emissions for selected vehicles were placed in 30-day bins before and after emission inspection had taken place. In total, 90,452vehicles did not fail the I/M test and were captured by a vehicle remote emission sensor (CAFÉ Database) in 2010. Differences or similarities between groups can come from various factors: fleet composition, for example, can be a reason for differences in emissions. Newer vehicles produce fewer emissions than their older counterparts, therefore if one group has a vehicle population older than the other it can lead to differences in emission rates. As previously described, driving conditions had significant influence on vehicle emissions. Therefore, if driving conditions in one group are different from driving conditions in another group it can produce differences in emissions. Consequently, vehicles from 'before' and 'after' groups were analyzed against each other for similarities or differences in two main categories: vehicle composition and driving conditions. Driving conditions is an essential part of remote sensing since vehicle remote sensing is an open air experiment that collects data under normal driving conditions and lacks a laboratory-like controlled nature. Sample comparisons must be made to prevent analysis of vastly different samples. Vehicle composition plays a very important role since newer and older vehicles have different emission inspection failure rates. Therefore, if one sample has a vehicle age distribution that is significantly different than the other, comparing the two groups may be problematic. If the sample groups prove to be different, then the differences in emissions may not be due to vehicle's emission but due to other factors; therefore vehicles from both 'before' and 'after' samples will be compared for differences and similarities in driving conditions and vehicle age.

4.1.1 Sample description

4.1.1.1 Vehicle Specific Power

Vehicle specific power is a very important characteristic for remote sensing. One drawback of vehicle remote emission sensing is that it is difficult to control. The car can accelerate, cruise, or decelerate, and all of those conditions affect vehicle emissions, as demonstrated in Figure 3-7, Figure 3-8, and Figure 3-9. VSP is measuring load on the engine based on velocity and acceleration characteristics, and measuring the site's geometric parameters. Inclusion of grade data in VSP calculations differentiates it from simply examining speed and acceleration profiles. If VSP distributions are comparable, then any differences or similarities between emission of vehicle groups are not due to driving conditions at the time of measurement but rather some other factors.

First, analysis of the VSP distribution of the whole sample was performed. VSP distribution centers on a VSP reading of 15 kW/Tonne (Figure 4-1), which is consistent with generally expected VSP from remote sensing, shown in Figure 2-6. Therefore, the conclusion can be made that enrichment of the fuel which occurs at low or high VSP did not occur. In other words, vehicles were driven under normal driving conditions. Additionally, VSP distribution appears to be normally distributed suggesting that there was no excessive sampling from any VSP ranges. Ideally, VSP distribution should resemble a normal distribution with a majority of readings located in and around the mean. VSP readings were limited by the range between 0 and 30 arising from the discussion in section 2.3.4.

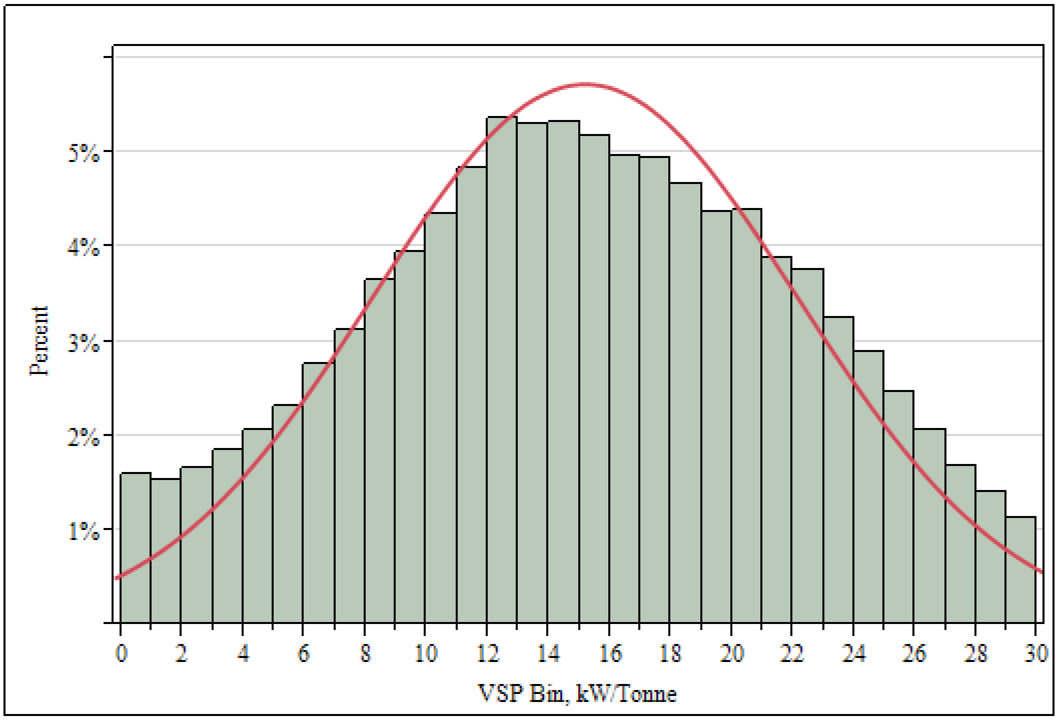

Figure 4-1 VSP Distribution of 'before' and 'after' emission test vehicle sample

Summary statistics for the sample are provided in Table 4-1 shown below. It contains summary statistics for the VSP distribution of the whole 'before' and 'after' emission inspection sample. A VSP average of 2010 CAFÉ data collection is 15.14 kW/Tonne, which is consistent with ranges for VSP readings provided in Figure 2-6.

Table 4-1 Vehicle Specific Power summary statistics of 'before' and 'after' emission test data sample

Mean	15.14
Standard Deviation	6.97
Standard Error Mean	0.02
Upper 95% Mean	15.18
Lower 95% Mean	15.09
Number of Samples	90,452

After concluding that vehicles in the sample were driven under normal driving conditions and there was no excessive sampling at low or high VSPs, the next step is to examine 'before' and 'after' emission test samples to insure validity of the comparison of the two samples. The hypothesis here is that if a difference between VSP distributions for both samples exist, that may be a reason for any differences in emission rates. Conversely, lack of statistical difference between the two samples will suggest that any difference in emissions is not due to driving conditions at the time of measurement. Figure 4-2 represents VSP distribution of 'before' emission test sample. Similar to the whole sample distribution, it is normally distributed around a VSP reading of 15 kW/Tonne.

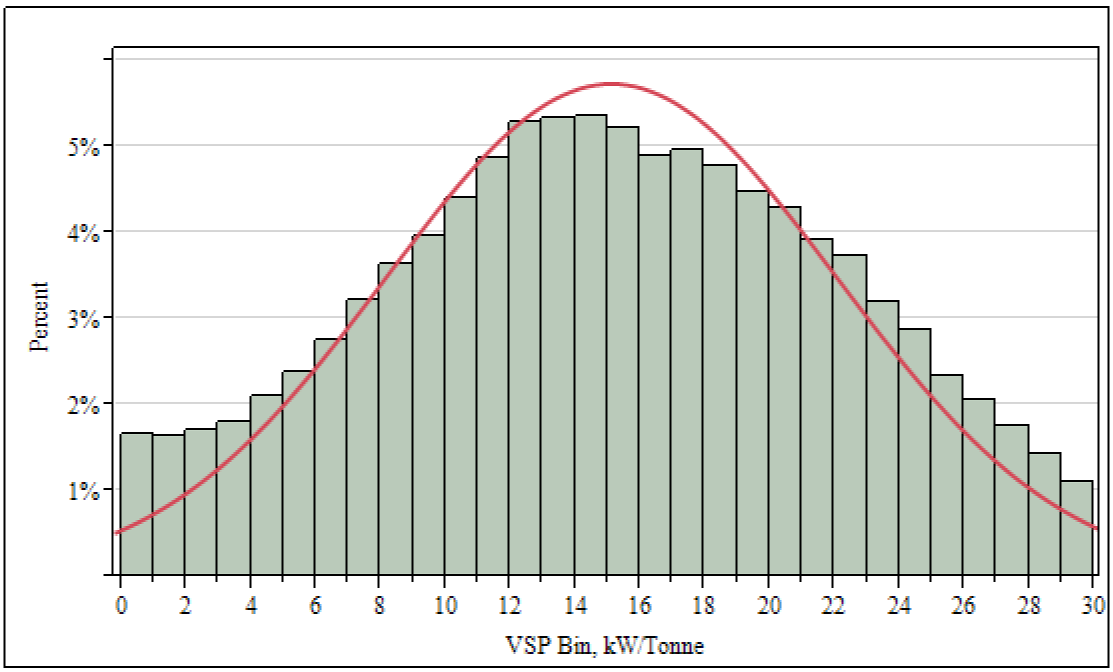

Figure 4-2 Vehicle Specific Power distribution of 'before' emission test sample

Table 4-2 shows summary statistics for the 'before' the sample. There were 41,853 samples that match both remote sensing data and the Georgia Inspection and Maintenance database of 2010. The average VSP reading is 15.09 with a standard deviation of 6.96.

Table 4-2 Vehicle Specific Power summary statistics for 'before' emission test sample

Mean	15.10
Standard Deviation	6.96
Standard Error Mean	0.03
Upper 95% Mean	15.16
Lower 95% Mean	15.03
Number of Samples	41,853

The 'after' emission test sample follows suit of the 'before' sample. The VSP distribution of the 'after' sample is also normally distributed (Figure 4-3), having an average of 15.18 kW/tonne with a standard deviation of 6.97 (Table 4-3). Both, 'before' and 'after' samples have distributions with similar shapes and the average and standard deviation readings.

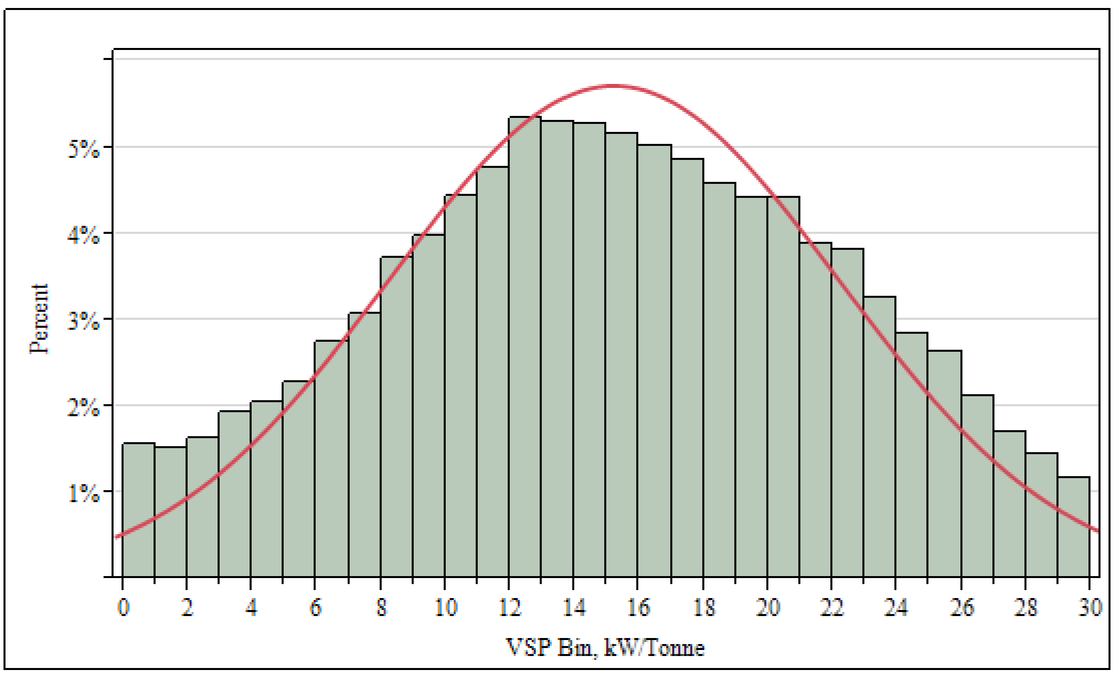

Figure 4-3 Vehicle Specific Power distribution for 'after' emission test sample

Table 4-3 Vehicle Specific Power summary statistics for 'after' emission test sample

Mean	15.18
Standard Deviation	6.97
Standard Error Mean	0.03
Upper 95% Mean	15.24
Lower 95% Mean	15.12
Number of Samples	47,809

To compare VSP distributions from the 'before' and 'after' samples a t-test for VSP distribution means was conducted. Based on the results of the t-test for VSP, the means of 'before' and 'after' emission tests are of no significant statistical difference. Therefore any differences or similarities between the two samples will not be due to the way the vehicle was driven. If there is an emission difference it is not due to driving conditions at measurement, since VSP means are similar 'before' and 'after' the emission test. Likewise, if there is no difference in emissions between the two it is not due to different driving conditions at measurement; it is due to some other factor. The results of the t-test for VSP means can be seen in Table 4-4.

Table 4-4 t-test of Vehicle Specific Power average for 'before' and 'after' emission test

Difference	-0.08652
Std Err Dif	0.04663
Upper CL Dif	0.00487
Lower CL Dif	-0.17791
Confidence	0.95
t Ratio	-1.85564
Degrees of Freedom	88123.17
Prob > |t|	0.0635
Prob > t	0.9682
Prob < t	0.0318*

4.1.1.2 Model Year Distribution of 'Before' and 'After' Emission test

The next step is to compare model year distributions for 'before' and 'after' samples. Differences between the two samples should not be statistically significant, otherwise any differences in emissions may be due to vehicle age composition and not a vehicle's emissions before and after emission tests. The first three model years are excluded from analysis since they are not subject to emission inspection tests. The distribution for the sample including vehicles from both groups is shown in Figure 4-4. Summary statistics for the sample are provided in Table 4-5.

Table 4-5 Summary statistics for sample model year distribution

Mean	2002.02
Standard Deviation	3.84
Standard Error Mean	0.01
Upper 95% Mean	2002.04
Lower 95% Mean	2001.99
Number of Samples	90,452

The average vehicle being considered for analysis is approximately eight years old and has a model year of 2002. The majority of vehicles are newer model years with more than 30% of them between three and six years old.

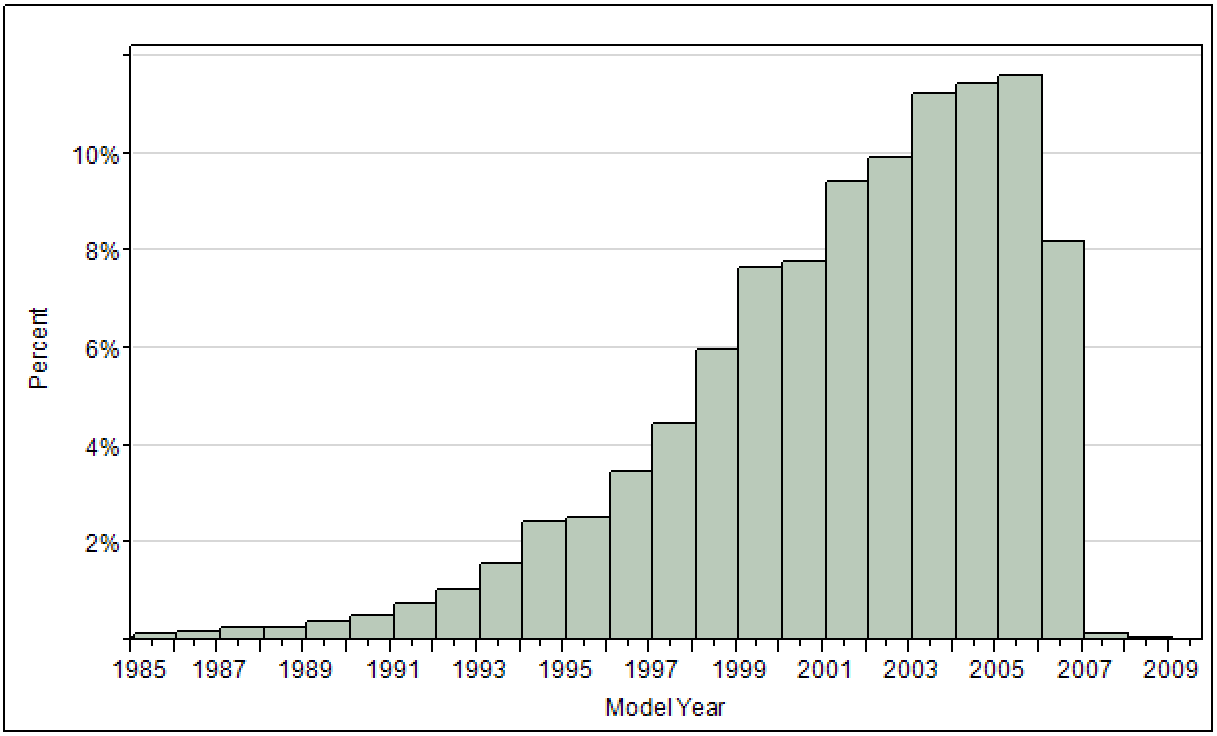

Figure 4-4 Model year distribution for combined 'before' and 'after' emission test sample

The next step is to compare 'before' and 'after' samples to examine model year distributions for both samples individually. Model year distribution for before and after the emission inspection is shown in Table 4-6.

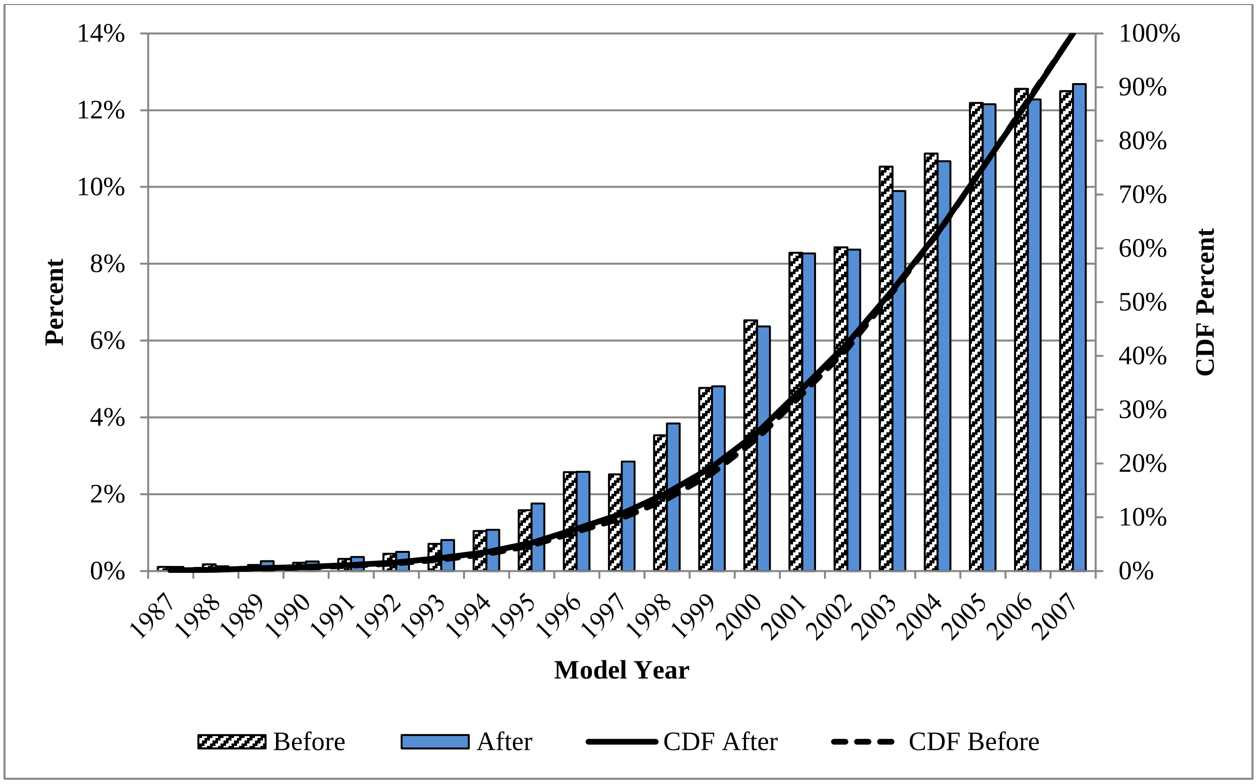

Figure 4-5 Model year distribution for 'before' and 'after' emission inspection samples

Table 4-6 Summary statistics for 'before' and 'after' samples

	Before	After
Mean	2001.81	2002.20
Standard Deviation	3.72	3.93
Standard Error Mean	0.02	0.02
Upper 95% Mean	2001.85	2002.23
Lower 95% Mean	2001.78	2002.16
Number of Samples	41,853	47,809

Model year distribution for the 'before' sample is very similar to the whole sample; vehicles are slightly older than eight years, with a standard deviation of 3.7 years. Sample composition of the 'after' group is slightly different and has an average model year at slightly higher than 2002, which is slightly younger than eight years old with a standard deviation of 3.9 years.

Vehicles are slightly older for the 'before' emission inspection sample. Even though the samples are different statistically, the difference is 0.38, which is about 5 months. It is highly unlikely that vehicle technology have changed during the 5 month period to have any impact vehicle emissions. Some vehicle technologies such as fuel injection versus carburation, or introduction of catalytic converters has an ability to significantly impact vehicle emission but none of this should have any impact on the vehicle fleet being analyzed.

Table 4-7 t-test of model year for 'Before' and 'After' emission test groups

Difference	-0.38569
Std Err Dif	0.02555
Upper CL Dif	-0.33560
Lower CL Dif	-0.43577
Confidence	0.95
t Ratio	-15.0935
Degrees of Freedom	89118.22
Prob > |t|	<.0001*
Prob > t	1.0000
Prob < t	<.0001*

Based on the t-test (Table 4-7) there is an indication of a statistical difference. Thus we can conclude that the samples are statistically different. However, as mentioned before, the difference between them is about 5 months. Looking at the other evidence such as Figure 4-5 it is evident that those differences in age composition are minimal.

4.1.1.3 Distribution of Manufacturer

There are 46 manufacturers that were identified. However, 56% of vehicles are coming from five car companies: Chevrolet, Ford, Honda, Nissan, and Toyota. Figure 4-6 presents the distribution of vehicle samples by the manufacturer.

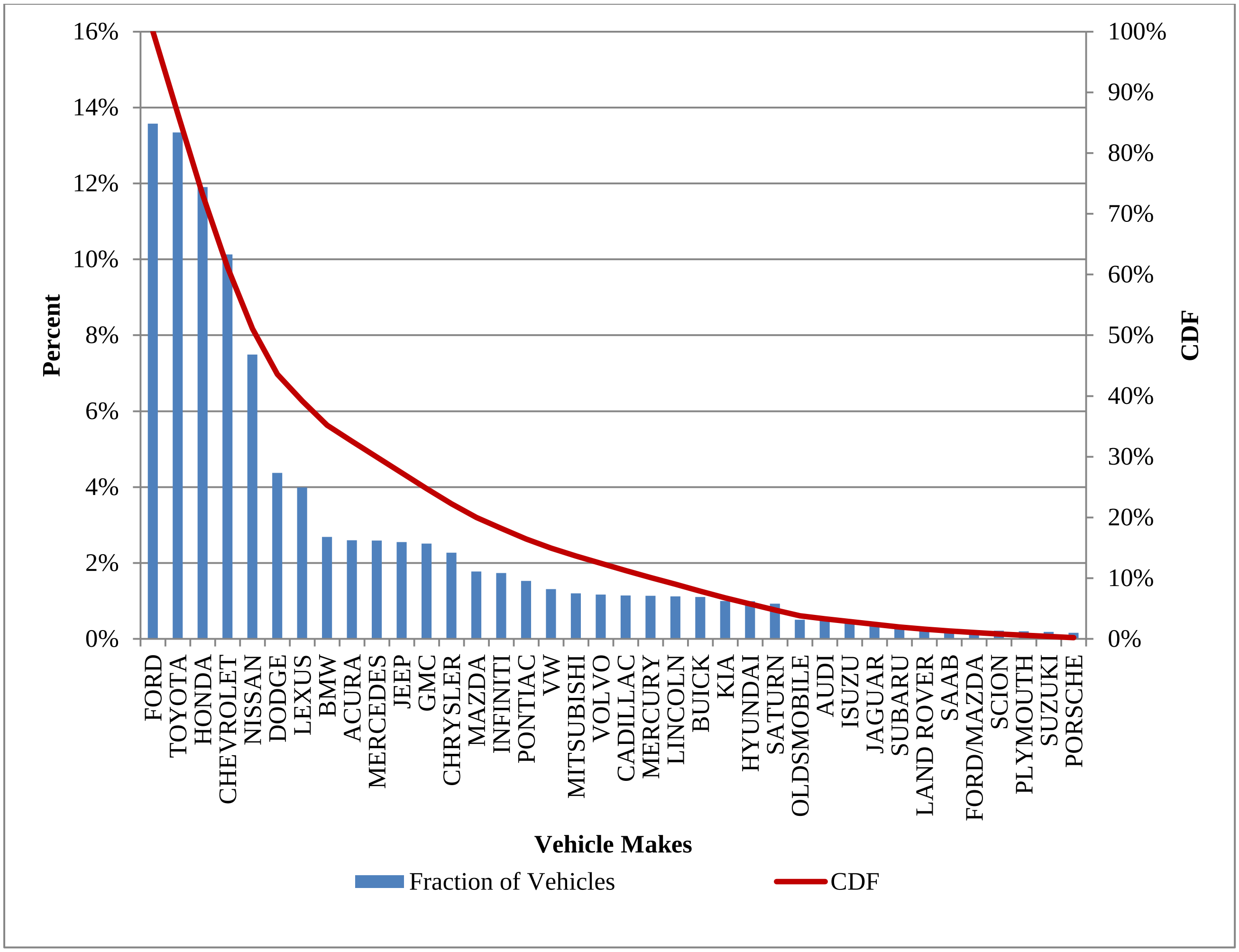

Figure 4-6 Vehicle distributions by manufacturer

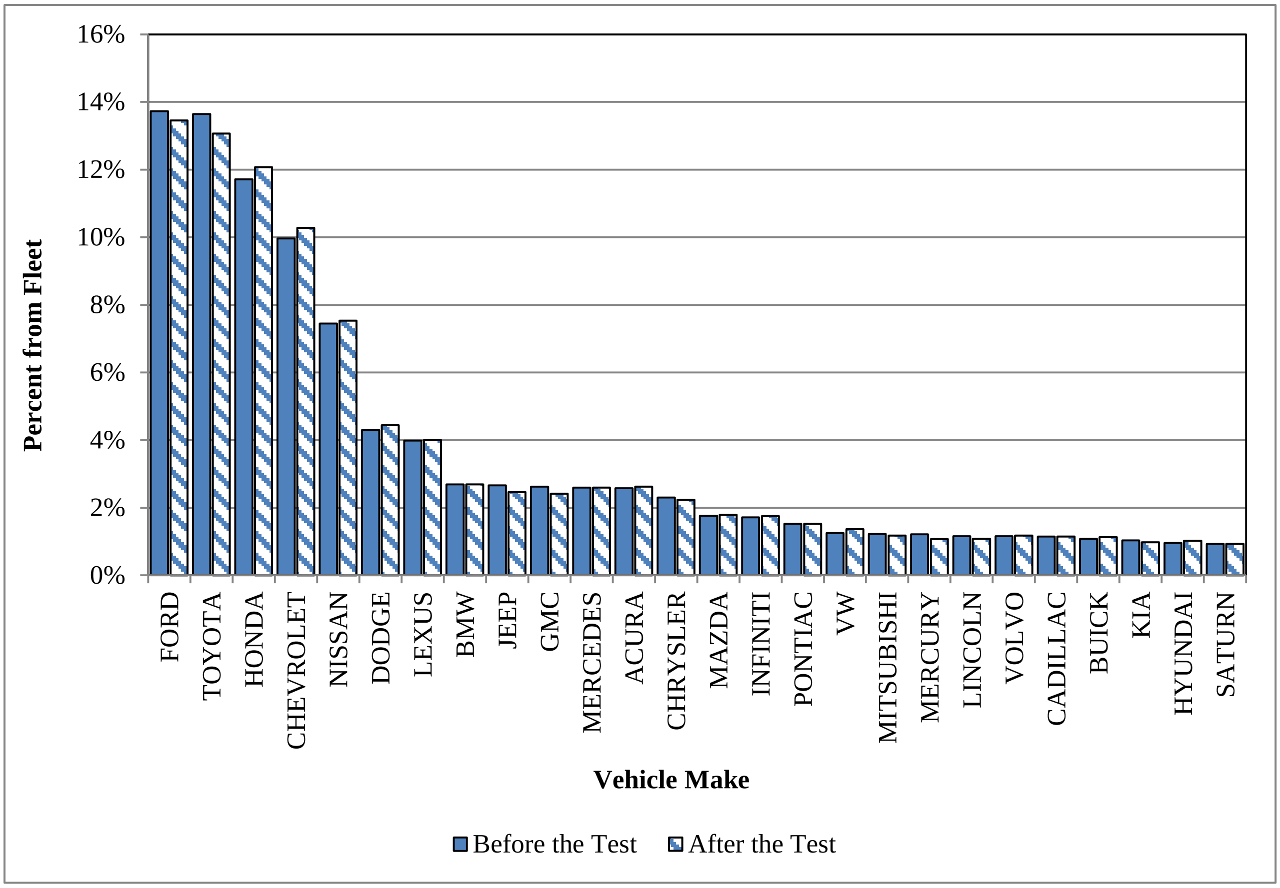

Figure 4-7 Vehicle make distribution for 'before' and 'after' the test sample

Examining the make-up of the fleet that was analyzed based on the make of the vehicle, no apparent bias is visible. Vehicle make fleet composition for ‘before’ and ‘after’ the emission test samples are very close to each other as shown in Figure 4-7. Therefore, any differences in vehicle emission for both groups will not likely be due to the vehicle make composition of those samples.

In addition to examining the distribution of vehicles by manufacturer, samples within manufacturer were investigated as well. A main emphasis of this analysis was to make sure that the distribution of ‘before’ and ‘after’ emission tests for each manufacturer was similar. If the distribution of vehicles for a particular manufacturer is different before and after the test, it can introduce bias and excessively sample some vehicles either before or after emission test.

Figure A-1 in the appendix shows vehicle makes distributions for ‘before’ and ‘after’ emission inspection samples. Those distributions appear to be normally distributed to limit sampling certain manufacturers in the ‘before’ sample and certain manufacturers in the ‘after’ sample. Manufacturers with significant vehicle sample distributions in ‘before’ and ‘after’ emission tests look to be normally distributed; therefore there are a similar number of vehicles for major makes that were sampled before and after emission inspection.

4.1.1.4 Odometer readings

Another vehicle characteristic examined is vehicle use. It is not a secret that high mileage vehicles are more prone to failures than vehicles with fewer accumulated miles; therefore, if ‘before’ and ‘after’ samples have different vehicle use profiles, then emission differences might be due to heavy vehicle use for one of the groups. To examine differences between odometer readings for ‘before’ and ‘after’ emission test groups the whole sample will be analyzed first, followed by analysis and statistical tests for each group of vehicles.

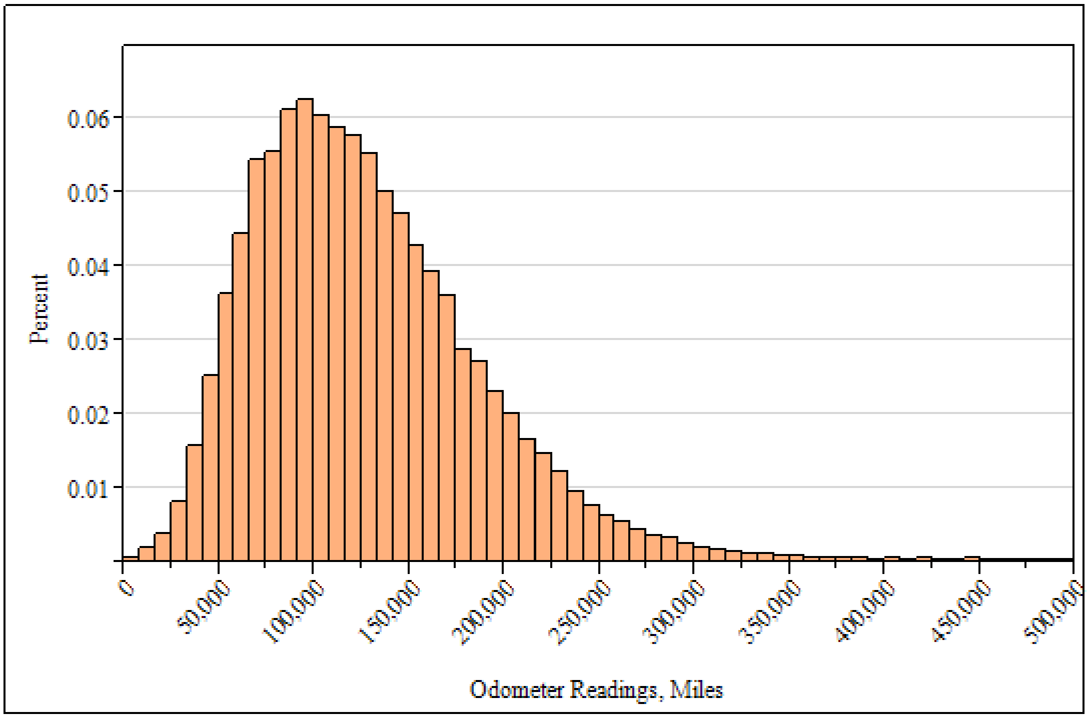

Figure 4-8 Distribution of odometer readings

Odometer readings for the whole sample are shown in Figure 4-8. The majority of vehicles have odometer readings between 50,000 and 200,000 miles.

Table 4-8 Summary statistics for odometer distribution

Mean	127,138
Standard Deviation	58,411
Standard Error Mean	216
Upper 95% Mean	127,561
Lower 95% Mean	126,715
Number of Samples	73,297

Table 4-8 represents summary statistics for combined 'before' and 'after' emission test samples. The average vehicle in the sample has close to 127,000 miles with a standard deviation of 58,000 miles.

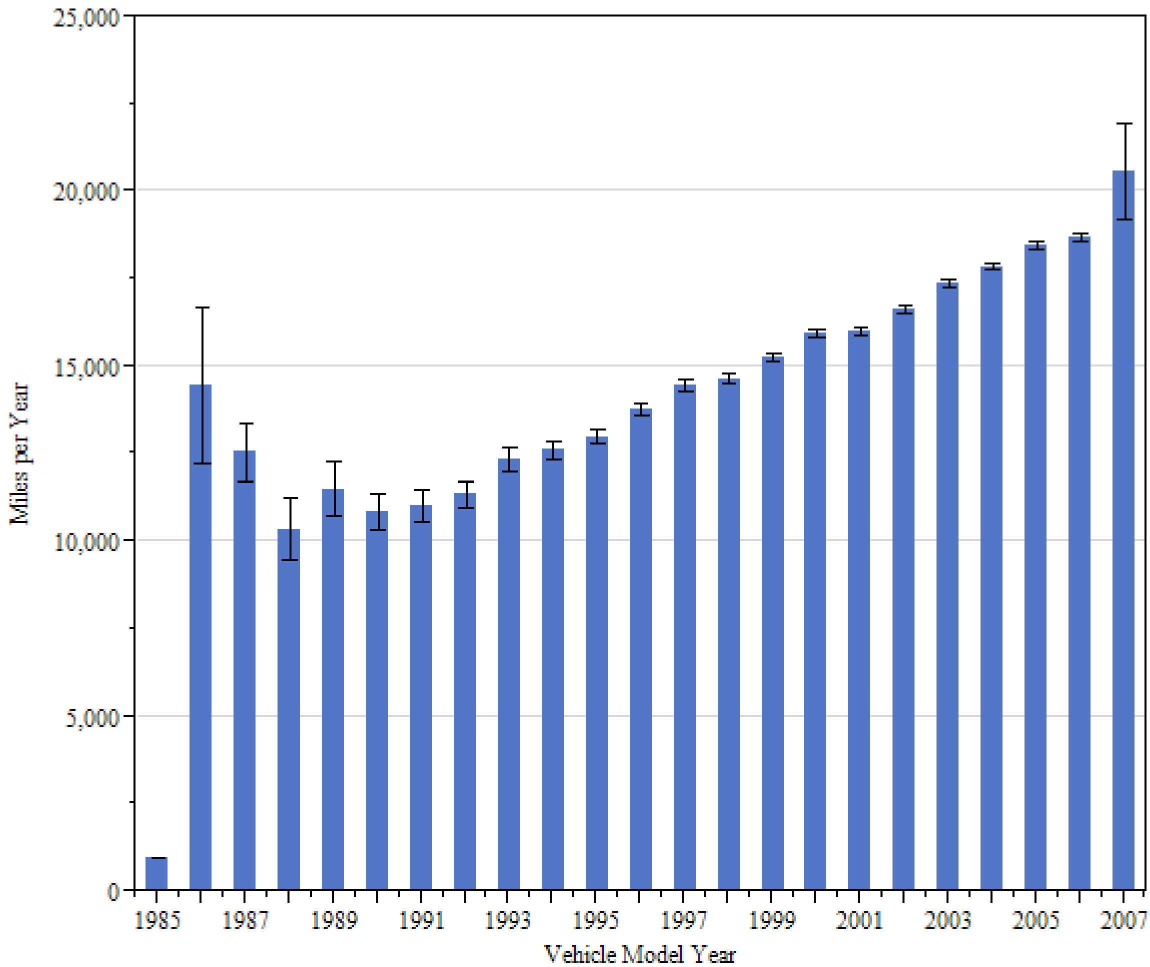

Figure 4-9 Annual mileage from 2009 to 2010 by model year

Figure 4-9 represents annual mileage based on the vehicle's model year distribution. Annual vehicle miles traveled were calculated using IM2009 and IM2010 datasets. Vehicles with extremely low or extremely high annual mileage were deemed to have errors and were excluded from analysis. Only vehicles between 0 and 60,000 miles per year were included. Figure 4-9 represents the relationship between model year and annual mileage between 2009 and 2010. Based on the data, newer vehicles are driven more than their older counterparts. As vehicles age they travel less and less. For three year old vehicles, annual travel is about 20,000 miles per year and it falls to approximately 10,000 per year for vehicles that are twenty-three years old. This represents a reduction of fifty percent over a twenty-year period. Older vehicles, 1985 – 1989, appear to have increased in annual miles traveled. This phenomenon can be due to the smaller sample size for older model years. Vehicles older than 1989 model year represent just 0.5% of the sample vehicle fleet. Increases in annual miles traveled by older vehicles can also indicate the survival effect. Older vehicles at the end of their useful life can undergo engine and transmission rebuilds and therefore with new drivetrains become more reliable and therefore driven more.

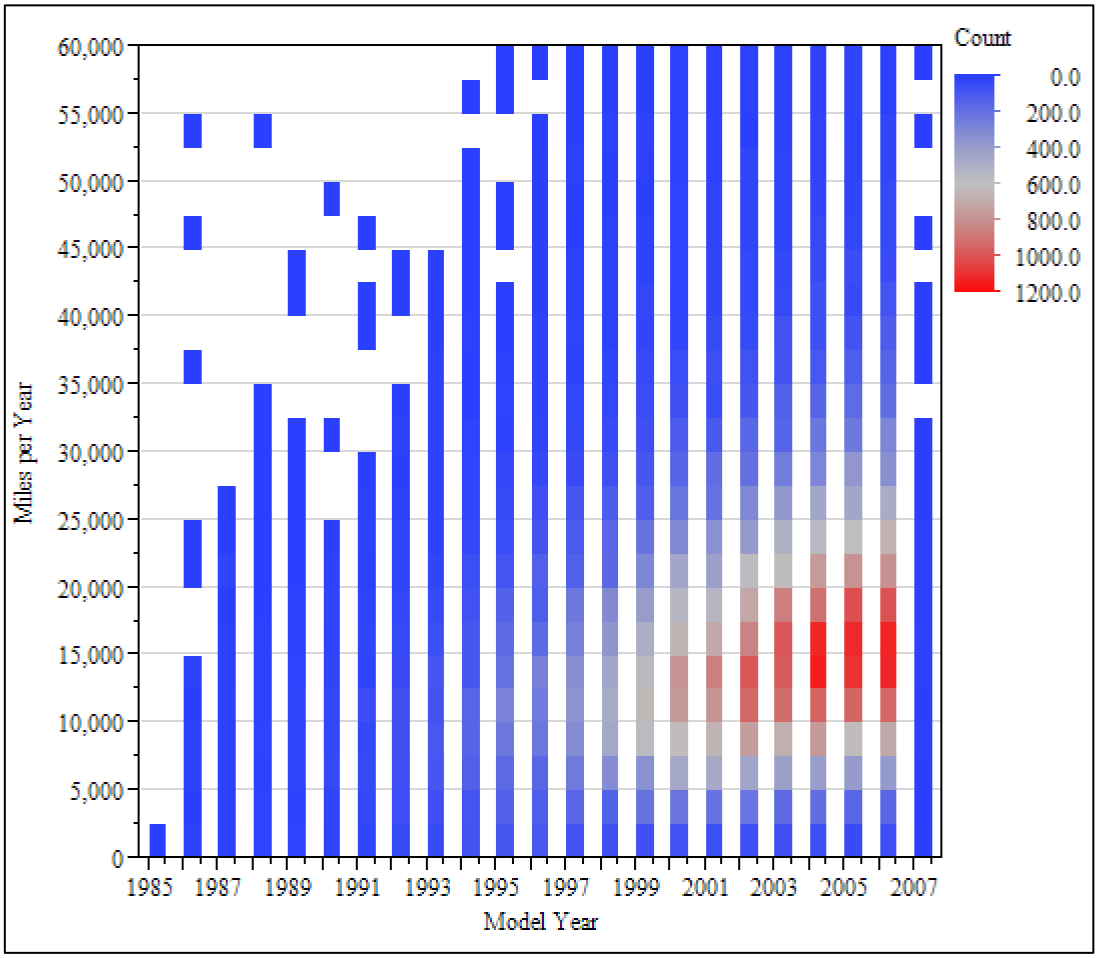

Figure 4-10 Annual vehicle miles traveled range

A slightly different representation of the data is presented in Figure 4-10. Showing the range of annual VMTs for model years, it also shows where the majority of VMTs for a particular model year reside. For newer model year vehicles, the VMT range is from 0 to 60,000;

however, the majority of vehicles accumulated between 10,000 and 20,000 miles per year. For older vehicles, distribution within the range is more uniform, In other words there is no one VMT bin group dominates the distribution. Smaller sample sizes for vehicles in 1985 – 1989 model year group also contributes to fewer miles per year bin groups being present.

When comparing odometer distributions of model year groups for ‘before’ and ‘after’ samples they appear to be similar. The new vehicle model year groups have lower odometer totals. Odometer readings for older model years tend to congregate around higher numbers.

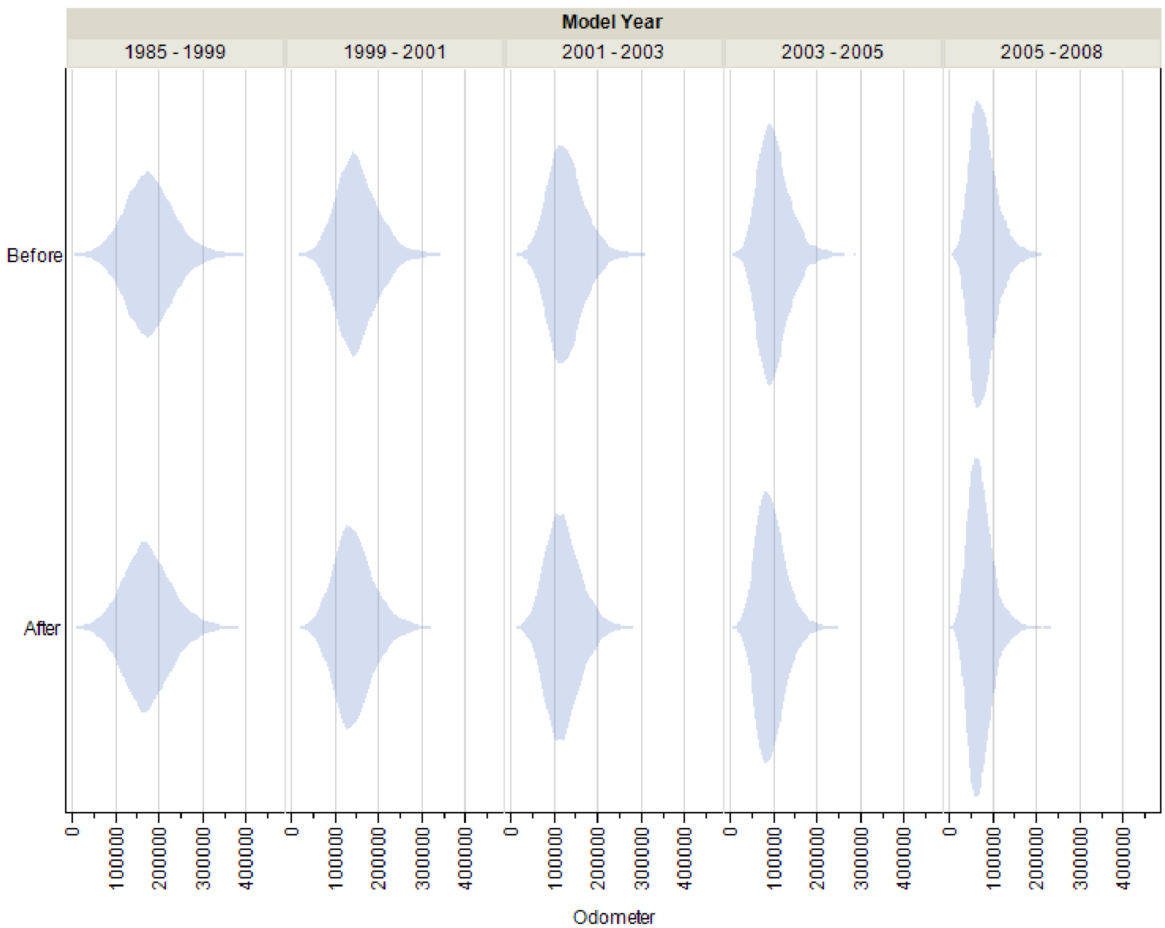

Figure 4-11 Odometer distributions for ‘before’ and ‘after’ sample by model year groups

Since the distributions are similar, there is no apparent bias in the sample associated with odometer readings.

In conclusion, after analysis of the two samples of ‘before’ and ‘after’ emission tests for vehicles that passed the emission test and did not fail in calendar year of 2010, there is no difference between VSP distributions of both samples and there is no difference between odometer readings. There is a statistical difference between ages; however, in real terms it’s only 4.5 months, which should not affect emission results. Therefore, any difference or similarities of ‘before’ and ‘after’ samples will be due to emissions of the vehicle and not because of extraneous factors such as driving conditions at the time of measurement, vehicle age, or vehicle use.

4.1.2 Before and After Emission Test Emission Differences

This section will examine variations in carbon monoxide, hydrocarbons, and nitrogen oxides emissions for ‘before’ and ‘after’ samples for vehicles that did not fail the emission inspection test in calendar year 2010. The hypothesis for those vehicles is that, looking at remote sensing measurements of carbon monoxide, hydrocarbon, and nitrogen oxides, no or minimal differences between vehicle emissions before and after I/M testing should be observed. One would expect that if the vehicles were not repaired, since they operated normally while passing an emission test, then their emissions should not change. Based on the analysis in the previous section, all the differences or similarities in vehicle emission will be due to vehicle emissions and not due to driving conditions, model year, or odometer readings. To compare ‘before’ and ‘after’ samples, emission data were placed in 30-day bins and plotted. Negative days values represent readings taken ‘before’ emission inspection samples, and positive days represent readings taken ‘after’ emission inspections samples.

In addition to comparing samples from before and after emission inspection for vehicles that passed the emission inspection test done in the previous section day bins were also compared to each other for data variability. **Error! Reference source not found.** represents chart displaying VSP readings based on day bins. To promote a valid comparison for the day bins VSP readings should remain steady throughout the range of the day bins. With the exception of a few bins VSP readings for all the bins are very consistent between 14 and 16 kW/Tonne. Minimal difference demonstrate that there was no effect of driving conditions at the time of measurement on different bins.

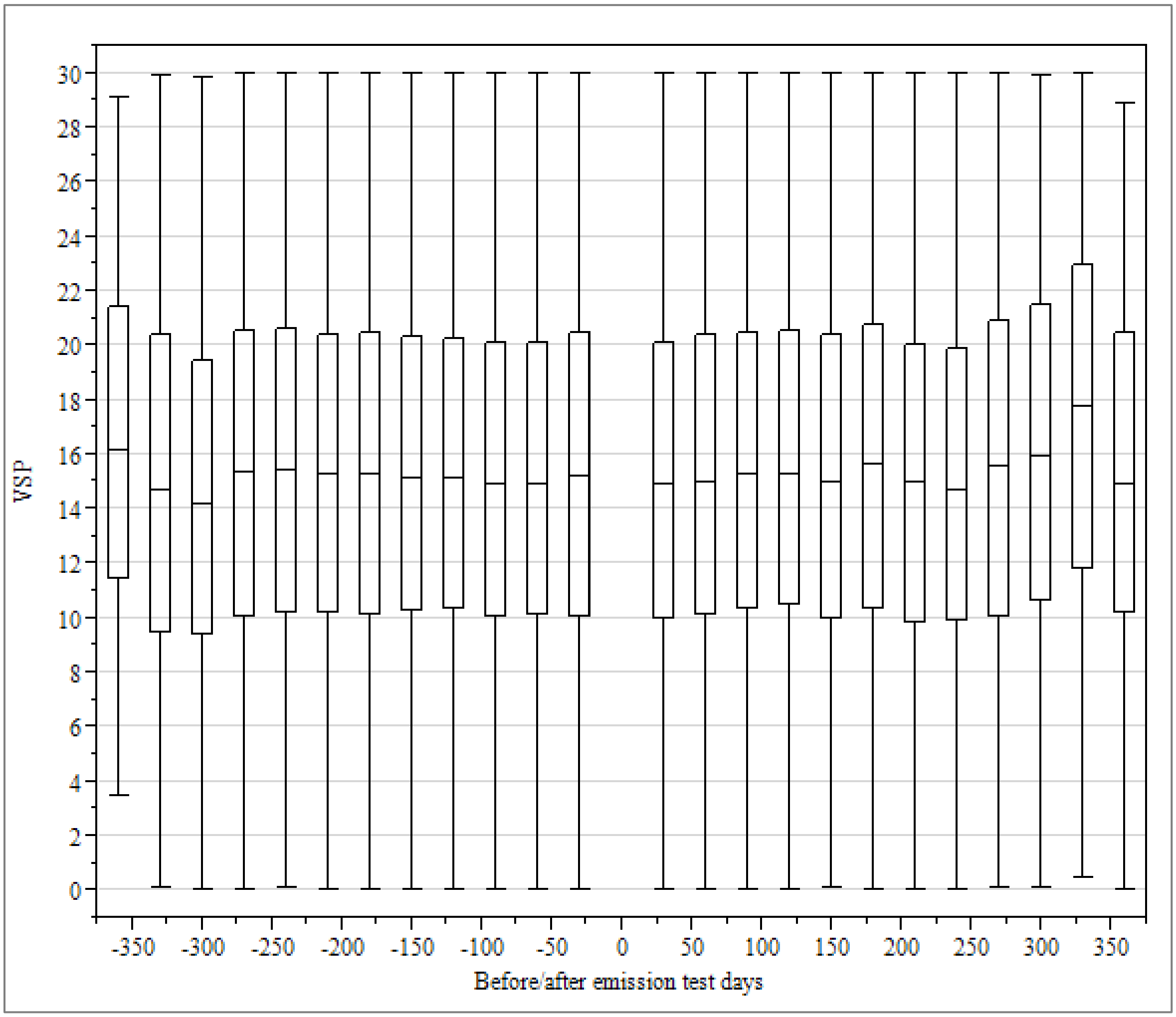

Figure 4-12 VSP vs days before and after emission inspection test for vehicles that did not fail the emission inspection test

Next model year distribution of bin range was analyzed. Hypothesis for this analysis is that vehicle model year composition should be similar for all bins. Looking at the Figure 4-13 it is indeed seems to be the case. The before emission inspection sample has model years just below year 2002 and the after emission inspection sample has model years just over 2002 model year.

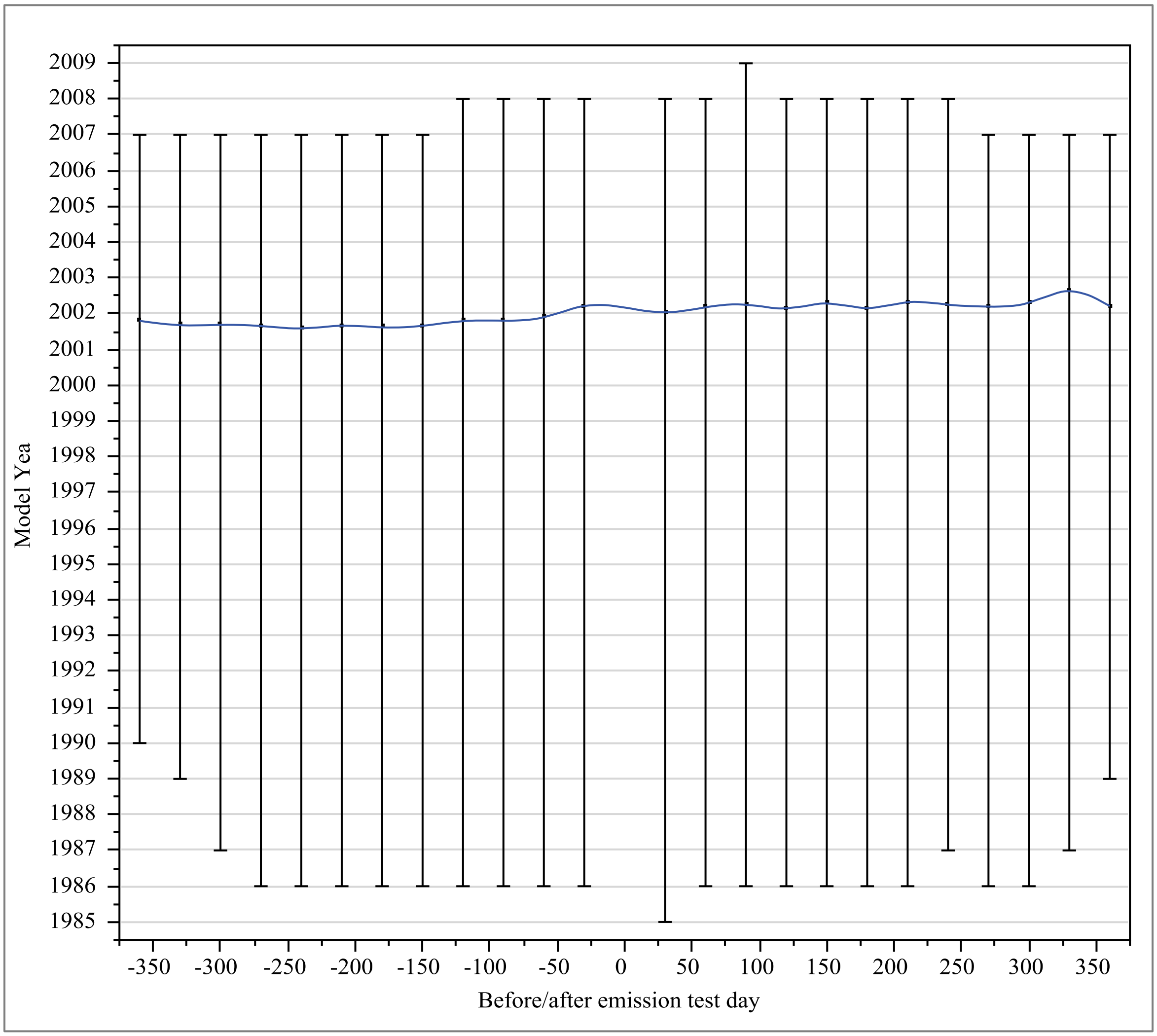

Figure 4-13 Model year vs days before and after emission inspection test for vehicles that did not fail the emission inspection test

And finally accumulated odometer reading for the bin range was compared. For the before emission inspection bins odometer readings appears to be slightly higher that for the after emission inspection sample but it is steady for bins in two samples. Differences for before and after emission inspection are not significant and should not affect emission rates of those samples. Figure 4-14 shows odometer readings based on the day bins.

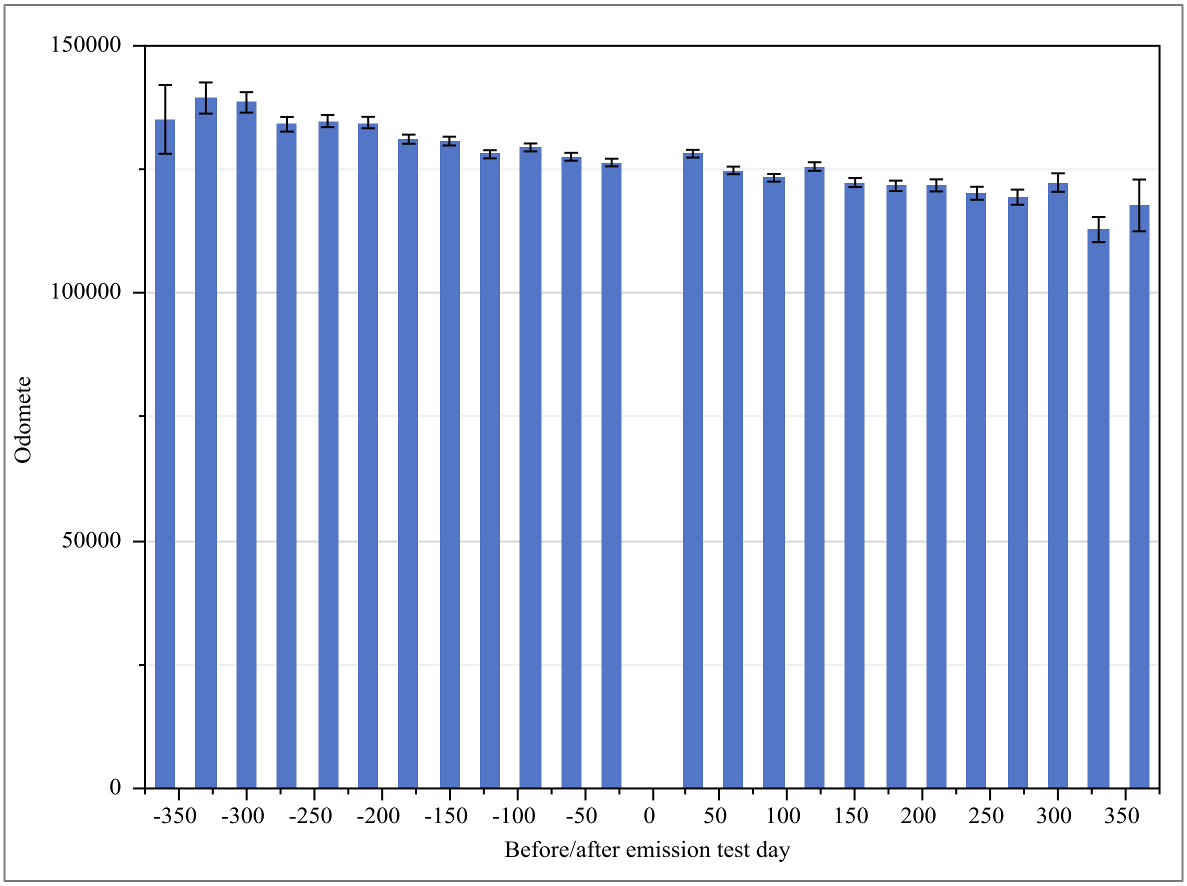

Figure 4-14 Odometer vs days before and after emission inspection test for vehicles that did not fail the emission inspection test

Figure 4-15 represents carbon monoxide CAFÉ measurements before and after emission inspection. Examination of Figure 4-15 shows no difference in the intercept values for CO concentrations before and after an I/M test and very similar trend-line slope characteristics. The trend-lines before and after emission tests is identical. These observations suggest that there is no difference between CO emissions for vehicles before and after emission tests. Vehicles that passed the emission inspection test most likely were properly operated vehicles and did not require repairs in order to pass emission inspection and therefore the CO characteristics of those vehicles did not change.

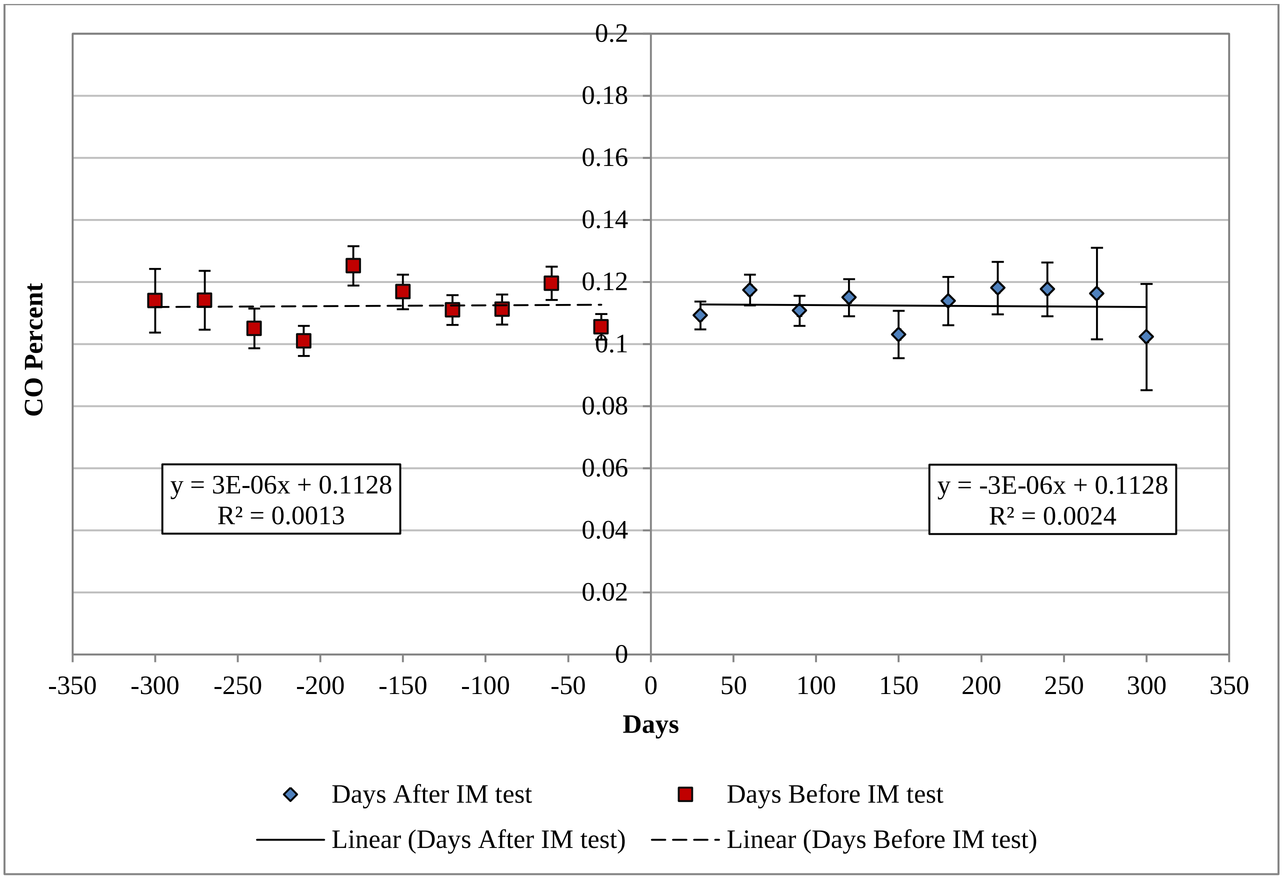

Figure 4-15 CO Measurements days before and after emission test for vehicles that did not fail the emission inspection test

Hydrocarbon measurements are similar to carbon monoxide characteristics. The intercept before the emission test is 29 ppm HC and after the emission test the intercept is 28 ppm HC. The slope of the trend-line before the emission test is slightly positive and after the emission test is slightly negative. However, differences between them are not significant; therefore, we can conclude that since significant differences cannot be observed, the two vehicle populations behave similarly before and after the emission inspection test.

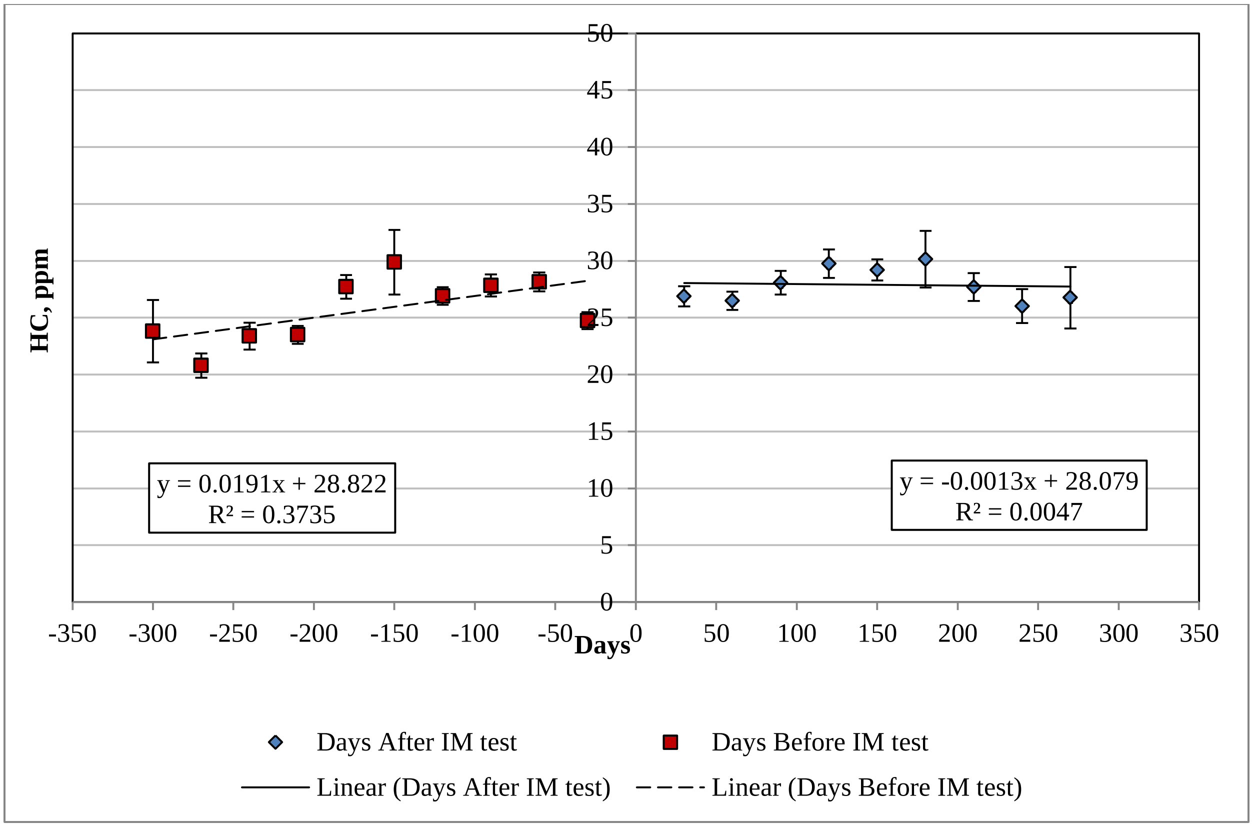

Figure 4-16 HC days before and after emission test for vehicles that did not fail the emission inspection test

Nitrogen oxides also did not display an appreciable difference before and after emission inspections. The intercept of both trend-lines were very similar. The NOx reading before the emission inspection intercept was 208.47 ppm and after the emission inspection it was 204.33 ppm. Even though the 'before' emission test trend-line slope is slightly negative and, the 'after' emission test is slightly positive, variances between them are not very significant; therefore the conclusion can be made that 'before' and 'after' emission test vehicles exhibited similar behavior, which would be an expected result if vehicles were not repaired.

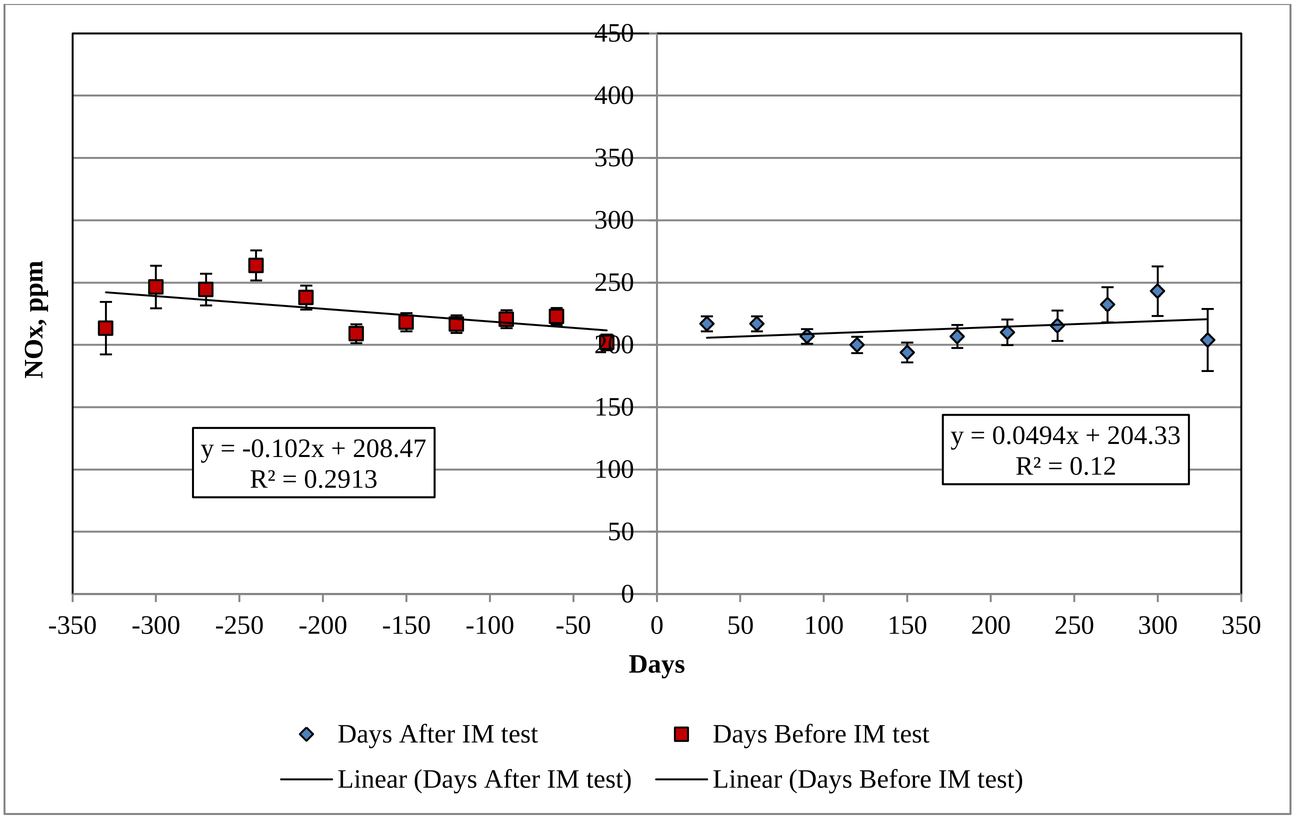

Figure 4-17 NOx days before and after emission test for vehicles that did not fail the emission inspection test

Figure 4-18 shows the histogram of the number of vehicles per bin for CO, HC, and NOx. Bins with a low number of vehicles were not included in the analysis because of significantly larger error when compared to other bins.

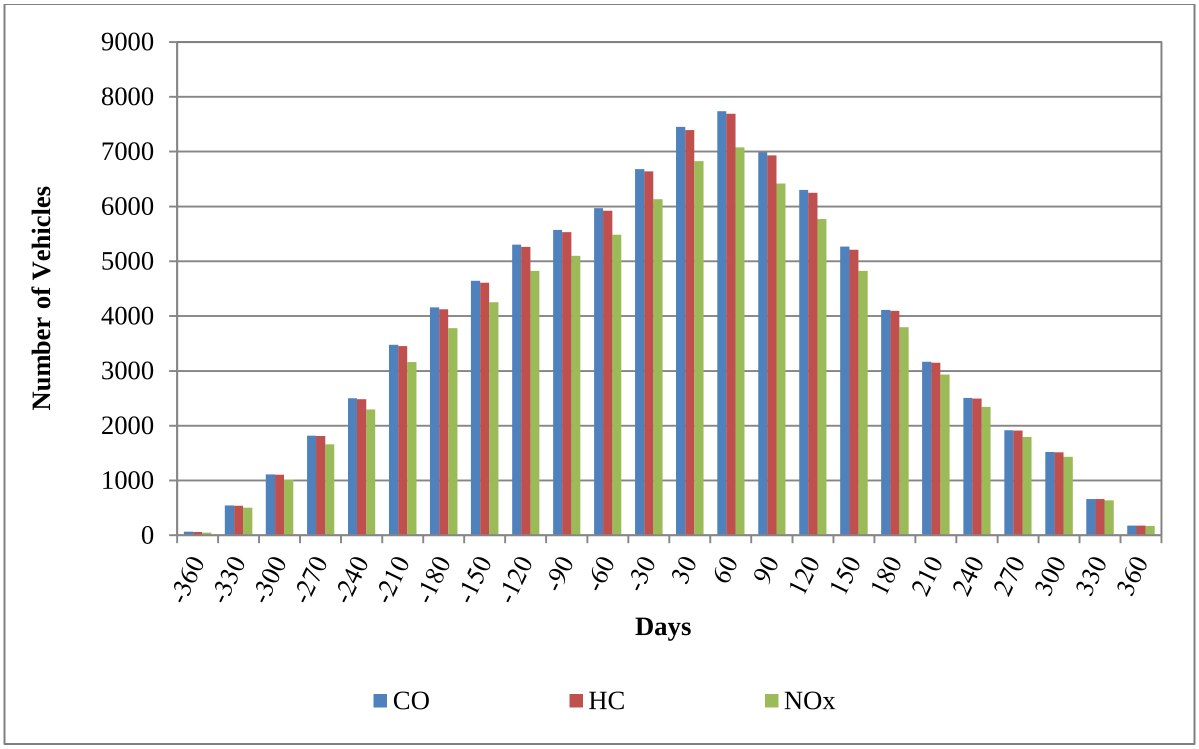

Figure 4-18 Histogram of number of vehicles per bin before and after emission test for vehicles that did not fail the emission inspection test

Figure 4-18 shows the distribution of the number of days per bin in the pyramid shape. This shape is caused by including only a single year of measurements and emission test results the analysis. The pyramid shape is due to limited opportunities to capture vehicles in high value bins either positive or negative. For example, to capture vehicles in the 330 – 360 day's bin, those vehicles would have to be measured in January. Conversely, vehicles from the (-330) – (-360) bin could have been measured only in December, whereas bins closer to 0 could have been measured at any time. Therefore there are more vehicles located in bins around 0 than in high value bins.

To check if using single-year measurements and emission test results was the cause of the pyramid shape, an additional year (2009) was added to the number of vehicles in the bin calculations. Since only a prior-to-analysis year of measurements was added, only negative bins are affected. Positive bins would only be affected if 2011 emission results were added. Figure 4-19 shows the results of that analysis. As evident by the chart, the pyramid shape goes away when an additional year was added to the analysis.

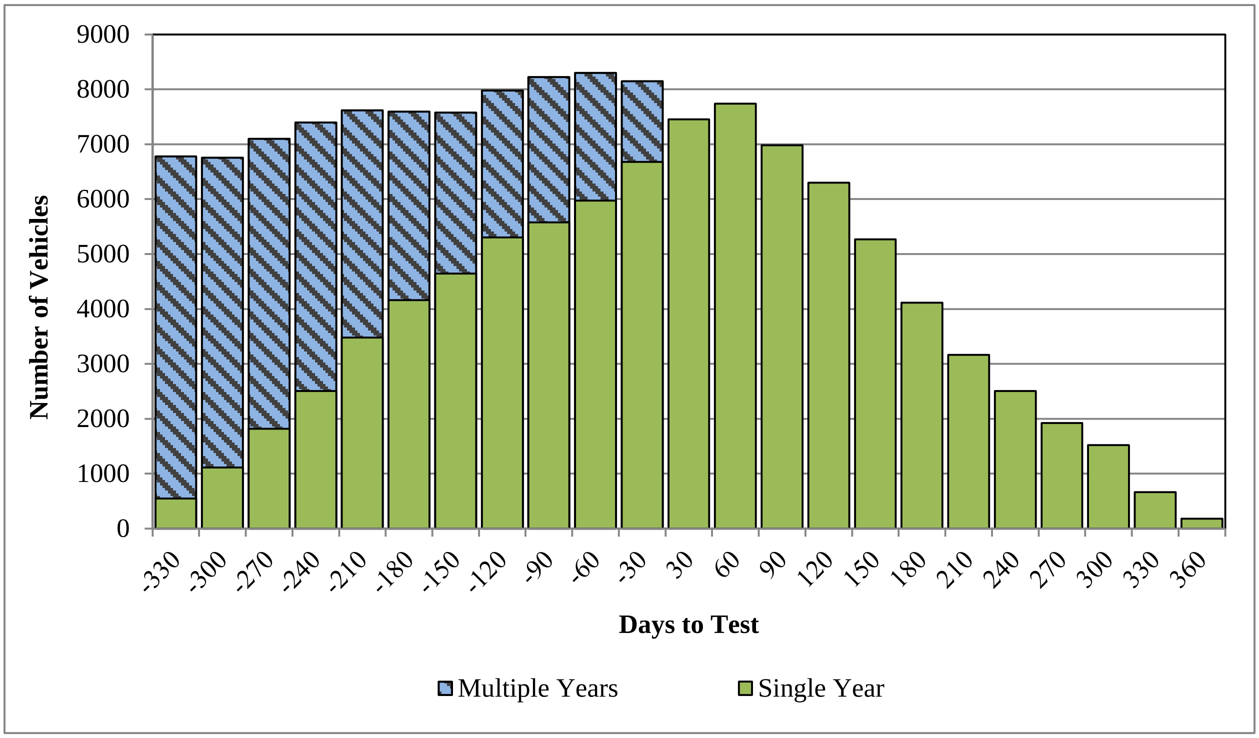

Figure 4-19 Number of vehicles in day bins: addition of multi-year emission results for the single year before and after emission test for vehicles that did not fail the emission inspection test

Therefore, the pyramid shape was caused by use of a single year of data and would be treated as normal in the following analysis.

4.1.2.1 Passing Vehicles Sample Conclusion

Passing vehicles from 'before' and 'after' samples exhibited similar sample vehicle specific power, model year, vehicle make distribution, and odometer readings. In addition, two sample groups that passed emission tests produced similar results for carbon monoxide, hydrocarbons, and nitrogen oxides concentration. As expected, since vehicles passed emission tests and were not repaired they did not produce large emission variations before and after emission test measurements.

4.2 Vehicles ‘Before’ and ‘After’ Repair

4.2.1 ‘Before’ and ‘After’ Repair Sample Evaluation

The following analysis is based on a group of vehicles that failed emission tests in 2010 and had a passing test in the same year. Those vehicles are represented in this analysis as ‘failed and repaired’ vehicles. This group of vehicles failed a test, then were repaired and passed an emission inspection test. Analysis of this group follows a similar methodology to the group of vehicles that did not fail the emission tests, with only a slight difference. Since vehicles in this group failed and were presumably repaired before they passed an emission inspection test, the date of the test signifies a repair date. Days between remote sensing measurement and the passing of the emission test is constituted as the days before and after vehicle repair. In all 9,711 vehicles failed emission tests in 2010 then passed a test and were captured by vehicle remote emission sensing. Similarly to vehicles from the ‘before’ and ‘after’ emission test groups, differences between ‘before’ and ‘after’ samples will need to be established. Those similarities or differences can manifest themselves as driving conditions and/or vehicle fleet composition or vehicle use. Therefore model year distribution for before and after repair as well as fleet composition, differences in VSP distributions, and odometer readings are studied to compare those two groups.

4.2.1.1 VSP ‘Before’ and ‘After’ Repair Sample Differences

The VSP distribution of the ‘before’ and ‘after’ repair vehicles is presented in Figure 4-20.

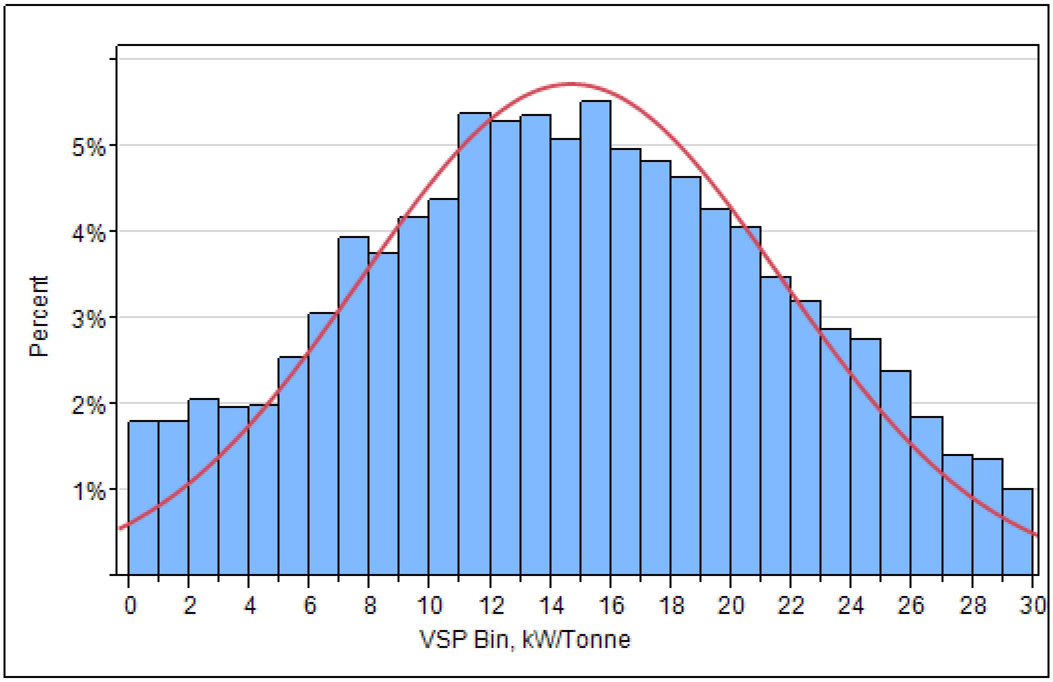

Figure 4-20 Vehicle specific power distribution of failed-and-repaired vehicles for vehicles that failed the emission inspection test

Similar to previous analyses, VSP readings were limited to the range between 0 – 30 kW/Tonne to avoid fuel enrichment.

Table 4-9 Vehicle Specific Power summary statistics for failed-and-repaired vehicles for vehicles that did not fail the emission inspection test

Mean	14.64
Standard Deviation	6.97
Standard Error Mean	0.07
Upper 95% Mean	14.78
Lower 95% Mean	14.50
Number of Samples	9,711

The VSP distribution has a mean of 14.6 kW/Tonne with a standard deviation of 6.96, which are expected values for this kind of analysis. It is important to examine the VSP distribution profile to guard against vehicles that may have clean emission readings but, due to extremely high or low VSPs, produce high emission readings. The next step is to compare VSP distribution of passing vehicles to VSP distribution of failed and repaired vehicles. The average for the passing vehicle group was 15.1 kW/Tonne with a standard deviation of 6.97. Table 4-10 contains summary statistics for VSP distribution. A VSP average of 2010 CAFÉ data collection is 15.1 kW/Tonne, which is consistent with the ranges for VSP readings provided in Figure 2-6.

The average for failed-and-repaired vehicles was 14.6 kW/Tonne with a standard deviation of 6.96. Comparing those two means and standard deviations, we can conclude that there is no statistical difference between VSP distributions of passing and failing/repaired vehicles. In other words, driving conditions that in large degree is being measured by VSP was similar in both samples.

Kolmogorov-Smirnov test between two vehicle populations, vehicle before-and-after the repair and vehicles before and after the emission test, shows statistical difference between two distributions. D-value in for this test is 0.0001 which is smaller than $\alpha = 0.05$, therefore null hypothesis of equal distributions is rejected. However, in practice the difference between means for both distributions is minimal. In addition, VSP mean is higher for vehicles that passed emission inspection; therefore, if differences in emission rates between vehicle populations of vehicles that passed the emission test and vehicles that failed the emission test exist it would not be due to driving conditions.

Now it is established that there is minimal difference in VSP distribution between ‘passing’ and ‘failed and repaired’ vehicles, the next step is to compare populations within a sample of ‘failed and repaired’ vehicles for differences in driving conditions, as well as model year distribution and odometer readings, and vehicle make distributions for ‘before’ and ‘after’ repair groups.

For the ‘before’ repair sample, the VSP distribution is centered at VSP of 14.50 kW/Tonne. It is normally distributed with a standard deviation of 6.93.

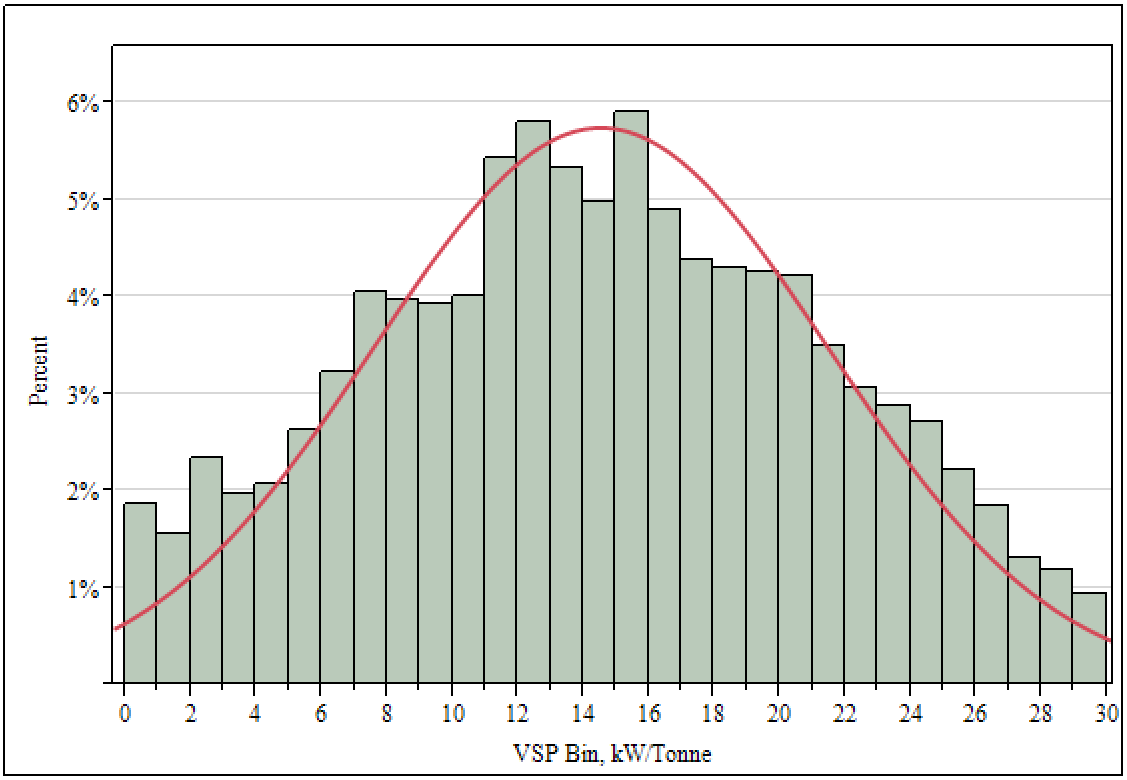

Figure 4-21 Vehicle specific power distribution for 'before' repair sample for vehicles that failed the emission inspection test

Table 4-10 Summary statistics for Vehicle Specific Power of 'before' sample for vehicles that failed the emission inspection test

Mean	14.50
Standard Deviation	6.93
Standard Error Mean	0.10
Upper 95% Mean	14.69
Lower 95% Mean	14.30
Number of Samples	4,859

For the 'after' sample for failing and repaired vehicles, the VSP distribution has a mean of 14.8 kW/Tonne with a standard deviation of 7 kW/Tonne.

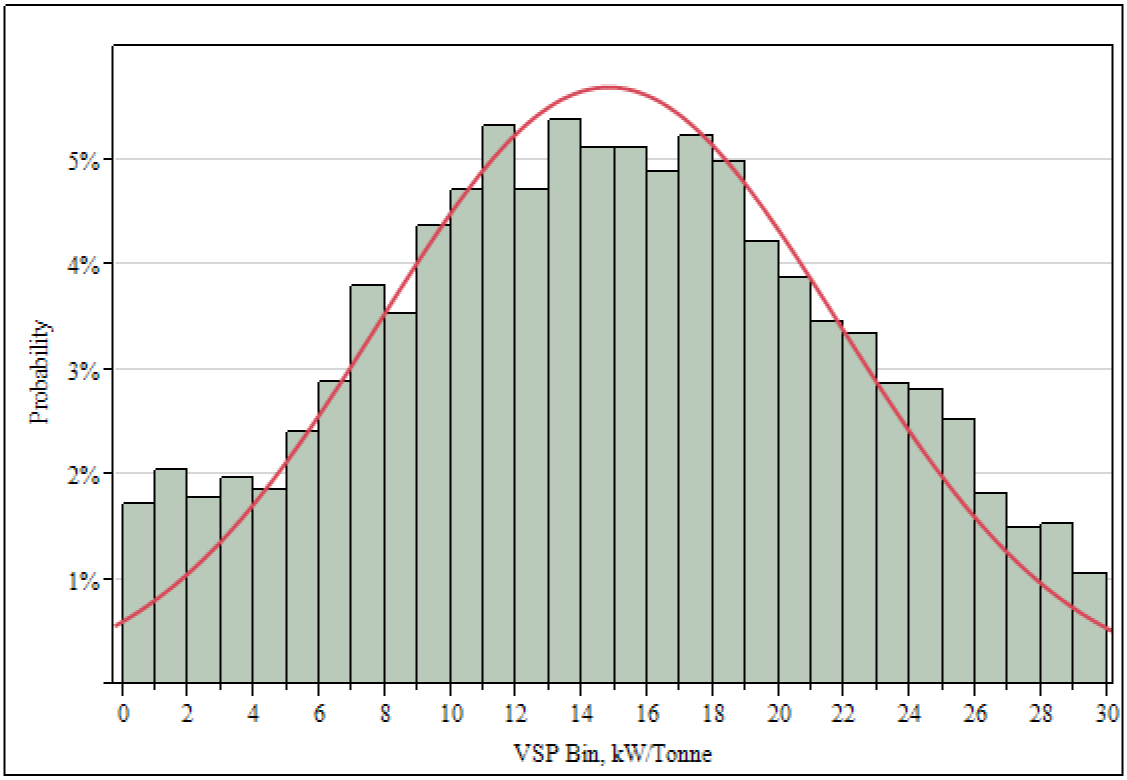

Figure 4-22 Vehicle specific power distribution for 'after' repair sample for vehicles that failed the emission inspection test

Table 4-11 Summary statistics for Vehicle Specific Power of 'after' repair sample for vehicles that failed the emission inspection test

Mean	14.79
Standard Deviation	7.00
Standard Error Mean	0.10
Upper 95% Mean	14.98
Lower 95% Mean	14.59
Number of Samples	4,852

To test if the distributions of before and after the repair VSP sample are similar non-parametric Kolmogorov-Smirnov two-sample test is used. The hypothesis Ho: that two sample populations have the same distribution. The D - value of the test is 0.1021 is greater than α =

0.05, which is a value of level of significance. The test accepts the null hypothesis therefore two sample populations have the same distribution.

Table 4-12 Kolmogorov-Smirnov test for VSP distributions of before and after emission inspection test vehicle samples

KS	KSa	D=max|F1-F2|	D-value
0.0124015	1.2195792	0.0248032	0.1021

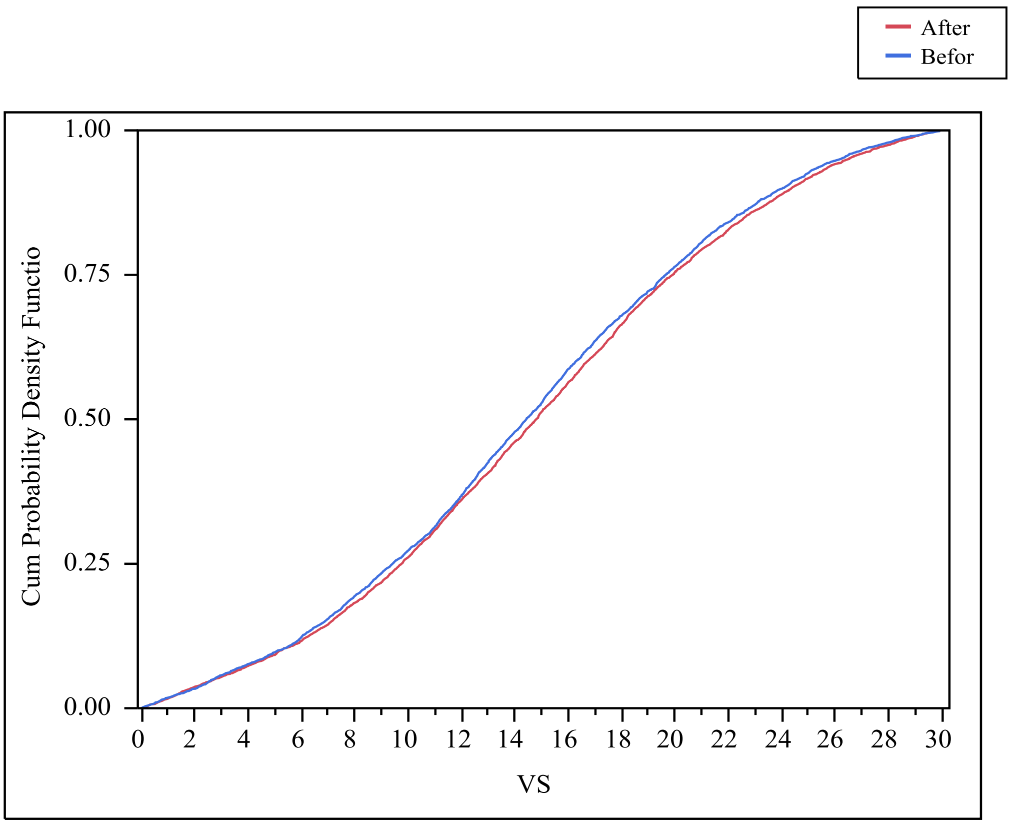

Figure 4-23 Cumulative probability density function of before and after emission test vehicle samples

4.2.1.2 'Before-and-After' Repair, Model Year Sample Differences

The next step is to compare model year distribution to ensure that samples that are being compared are similar to each other. Figure 4-24 represents the model year distribution for 'before' and 'after' repair vehicle samples. As expected, the vehicle sample is older than group f vehicles that did not fail emission test from before-and-after emission test samples (Table 4-5). The vehicle group that did not fail emission inspection was about two years younger than vehicles that failed emission tests. 'Before' and 'after' repair vehicles are on average two years older than vehicles from before and after emission tests. A detailed description of sample model year statistics is represented in for vehicles that failed the emission inspection test

Table 4-13.

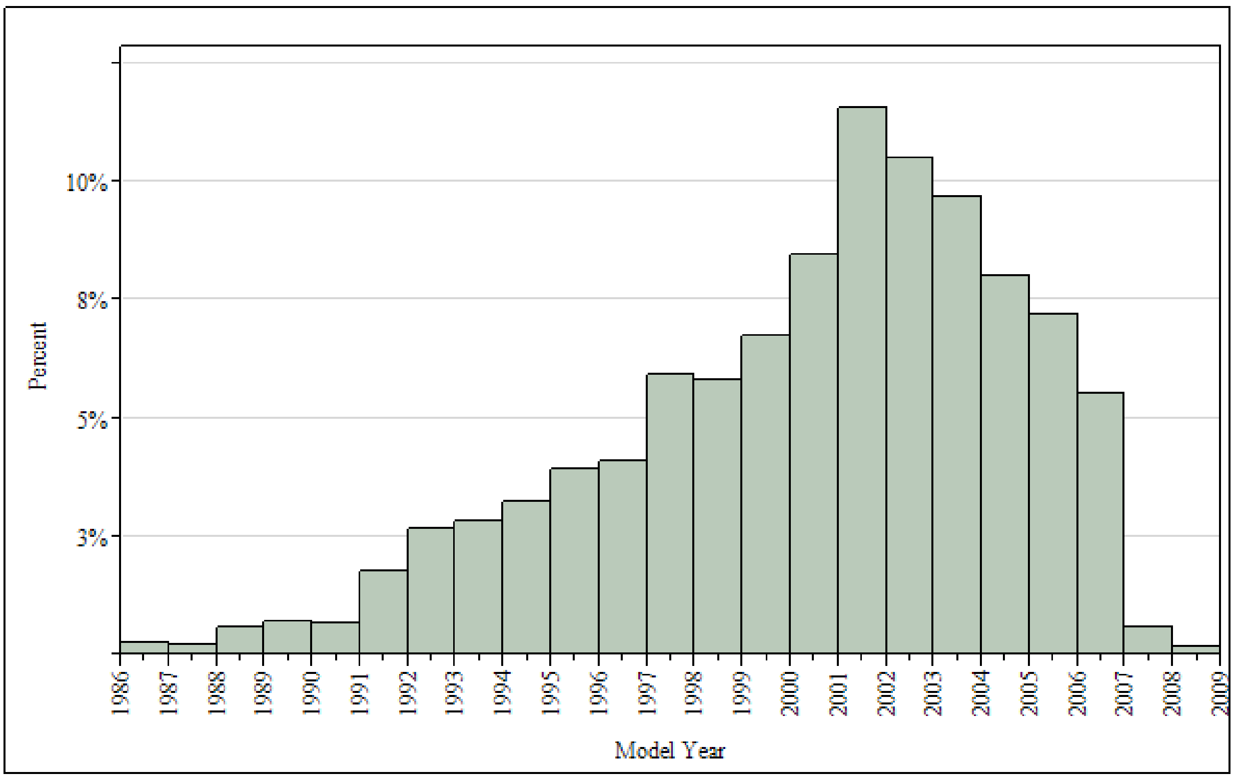

Figure 4-24 Model year distribution of 'before-and-after' repair sample for vehicles that failed the emission inspection test

Table 4-13 Summary statistics for model year distribution of 'before' and 'after' repair sample for vehicles that did not fail the emission inspection test

Mean	1999.95
Standard Deviation	4.20
Standard Error Mean	0.05
Upper 95% Mean	2000.1
Lower 95% Mean	1999.86
Number of Samples	7,698

To compare the 'before' and 'after' repair groups, their respective model year distributions were plotted and analyzed. Figure 4-25 represents model year distributions for 'before' and 'after' repair samples and their respective CDF functions.

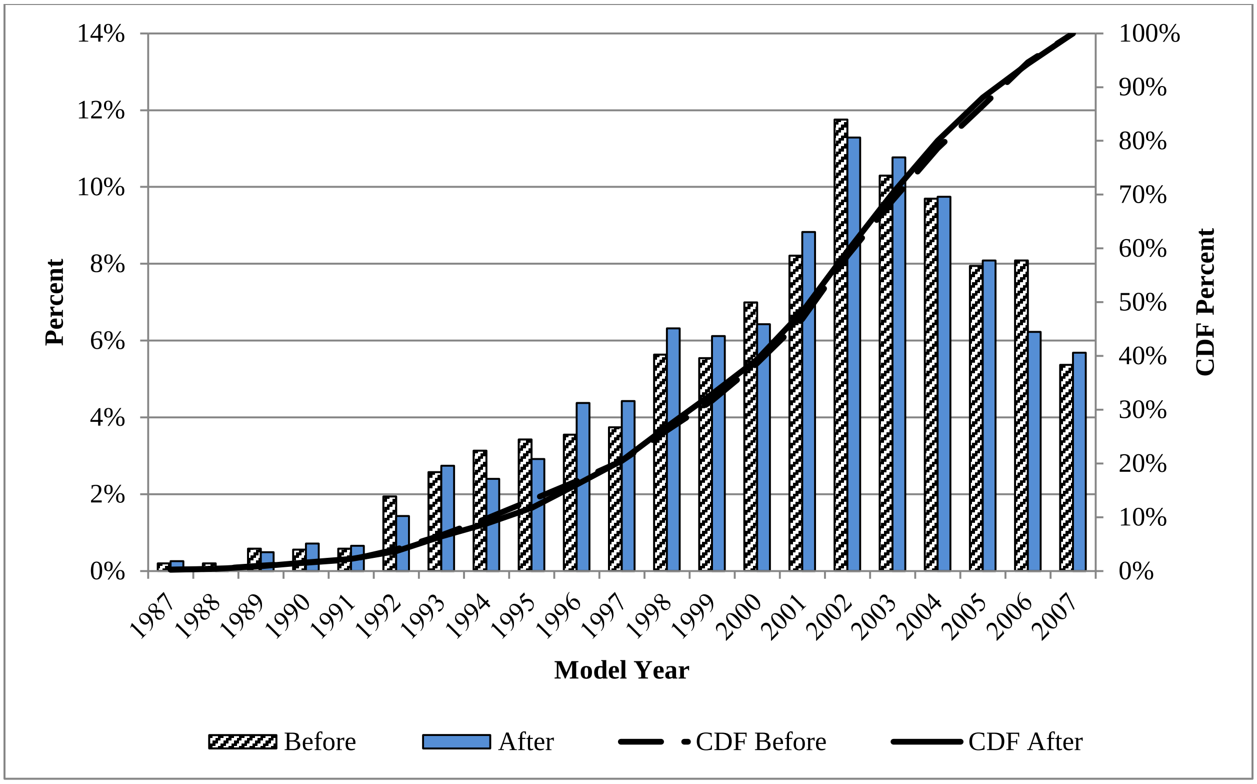

Figure 4-25 Model year distribution and CDF function of 'before-and-after' repair sample for vehicles that failed the emission inspection test

Table 4-14 Summary statistics for model year distribution of 'before-and-after' repair sample for vehicles that failed the emission inspection test

	Before	After
Mean	2000.01	1999.89
Standard Deviation	4.25	4.14
Standard Error Mean	0.07	0.07
Upper 95% Mean	2000.14	2000.03
Lower 95% Mean	1999.88	1999.76
Number of Samples	4,192	3,506

On close examination, vehicle model year distribution appears to be similar, which implies that the age distribution for both 'before' and 'after' samples are very close in nature.

To test the underlying model year distribution for before and after repair sample Kolmogorov-Smirnov test is performed. The null hypothesis for the testing is that two distributions are the same. Based on the test and resulting D-value of 0.2635 we can't reject null hypothesis therefore two distributions are the same.

Table 4-15 Kolmogorov-Smirnov test for VSP distributions of before and after repair vehicle samples

KS	KSa	D=max|F1-F2|	D-value
0.0114904	1.0061162	0.0230651	0.2635

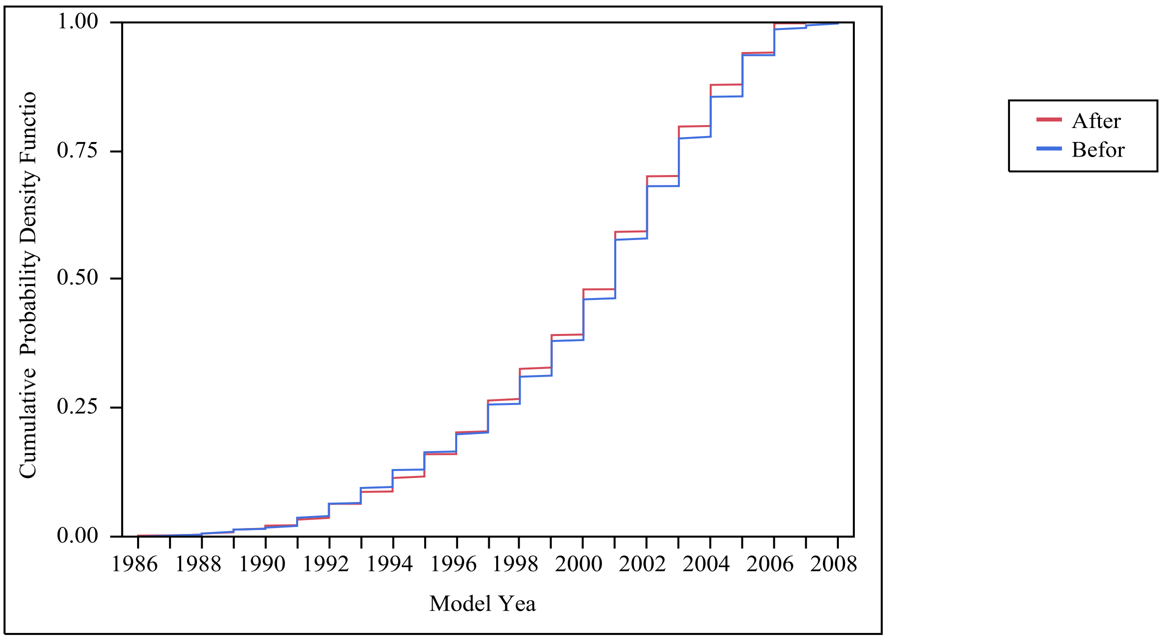

Figure 4-26 Cumulative probability density function of before and after the repair vehicle samples

4.2.1.3 'Before' and 'After' Repair Make Sample Differences

To ensure that none of the vehicle makes are over-sampled for this analysis, distribution of vehicles by make was plotted. As seen in Figure 4-27, make distribution closely follows that of the sample for 'before' and 'after' emission test vehicles. Five makes: Chevrolet, Ford, Honda, Nissan, and Toyota have major representation. Roughly they represent 56% of the sample, which is very similar to 'before' and 'after' emission test samples.

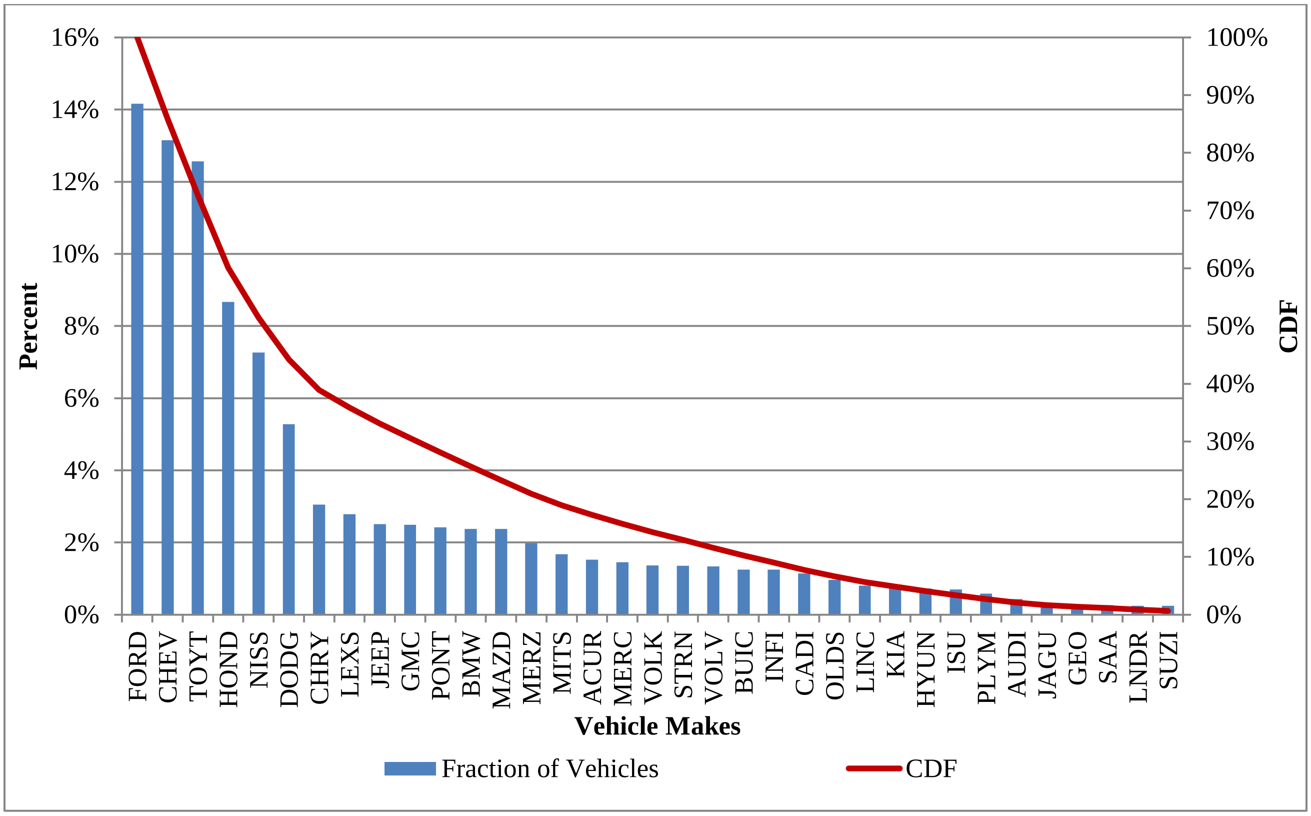

Figure 4-27 Vehicle make distribution of 'before' and 'after' repair sample for vehicles that failed the emission inspection test

After concluding that the vehicle sample is representative, the next step is to examine 'before' and 'after' repair distributions. The assumption is that equal sample distributions of vehicle makes should be shown before and after repair. Figure 4-28 represents those distributions. It appears that distributions for both vehicle groups are similar. In other words 'before' and 'after' samples have equal representation in all major manufacturer brands.

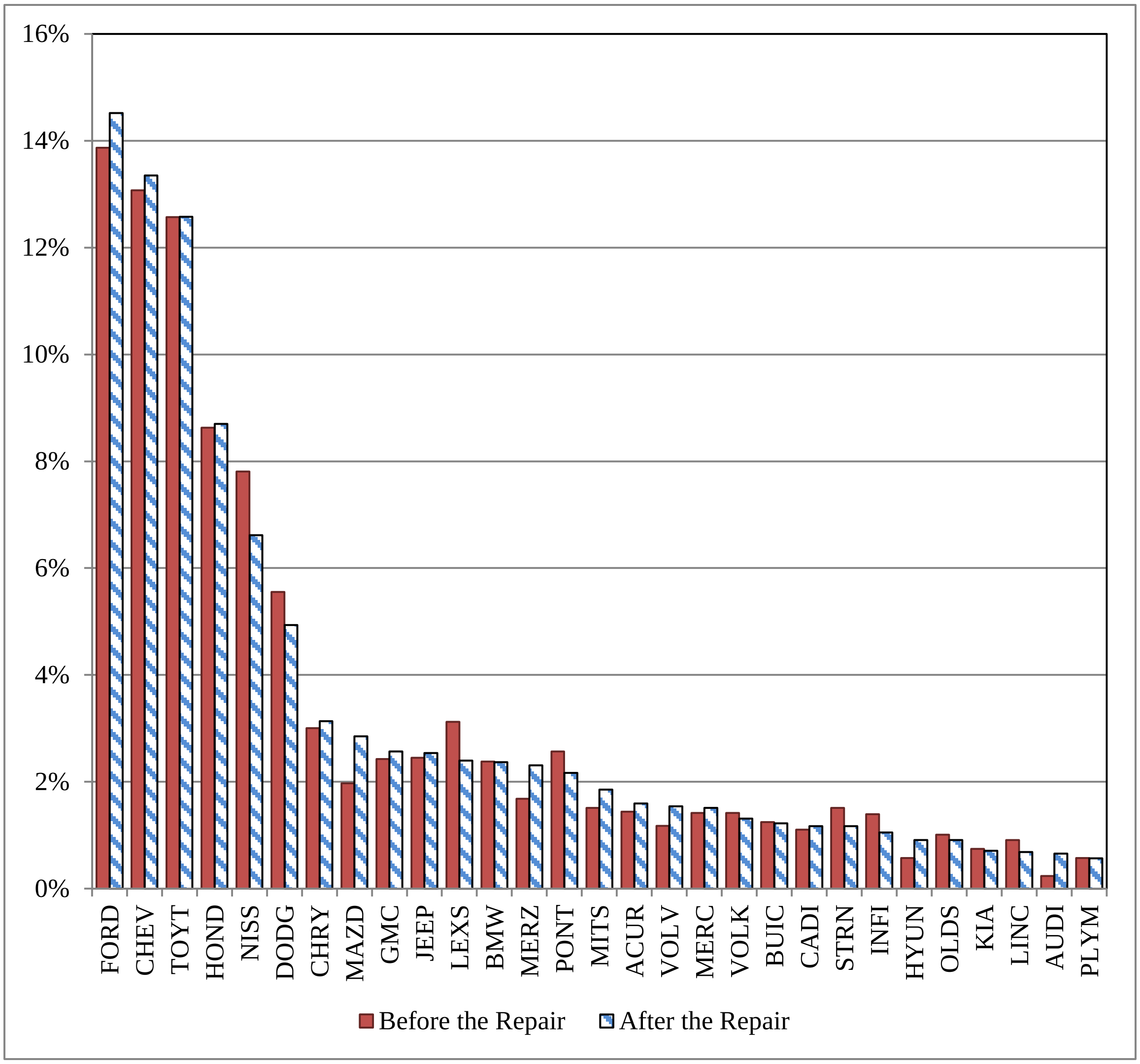

Figure 4-28 Vehicle make distribution separated by 'before' and 'after' repair groups for vehicles that failed the emission inspection test

More analysis of the data samples can be found in Appendix Figure A-4 and Figure A-5. In addition to vehicle make distribution by day, VSP profiles based on days before and after repair were plotted (Figure A-5). Those profiles indicate random distributions for days before and after repair.

Judging by the vehicle makes distributions for 'before' and 'after' repair samples, we can conclude that there is no difference in fleet vehicle make makeup. Therefore, any differences in emission could not be attributed to vehicle make.

4.2.1.4 'Before' and 'After' Repair Odometer Differences

Miles per year follows very closely what was shown in a 'before' and 'after' emission test sample. It indicates that newer vehicles are driven farther on an annual basis than older vehicles. Vehicle mileage decreases with vehicle age by about 2,000 miles.

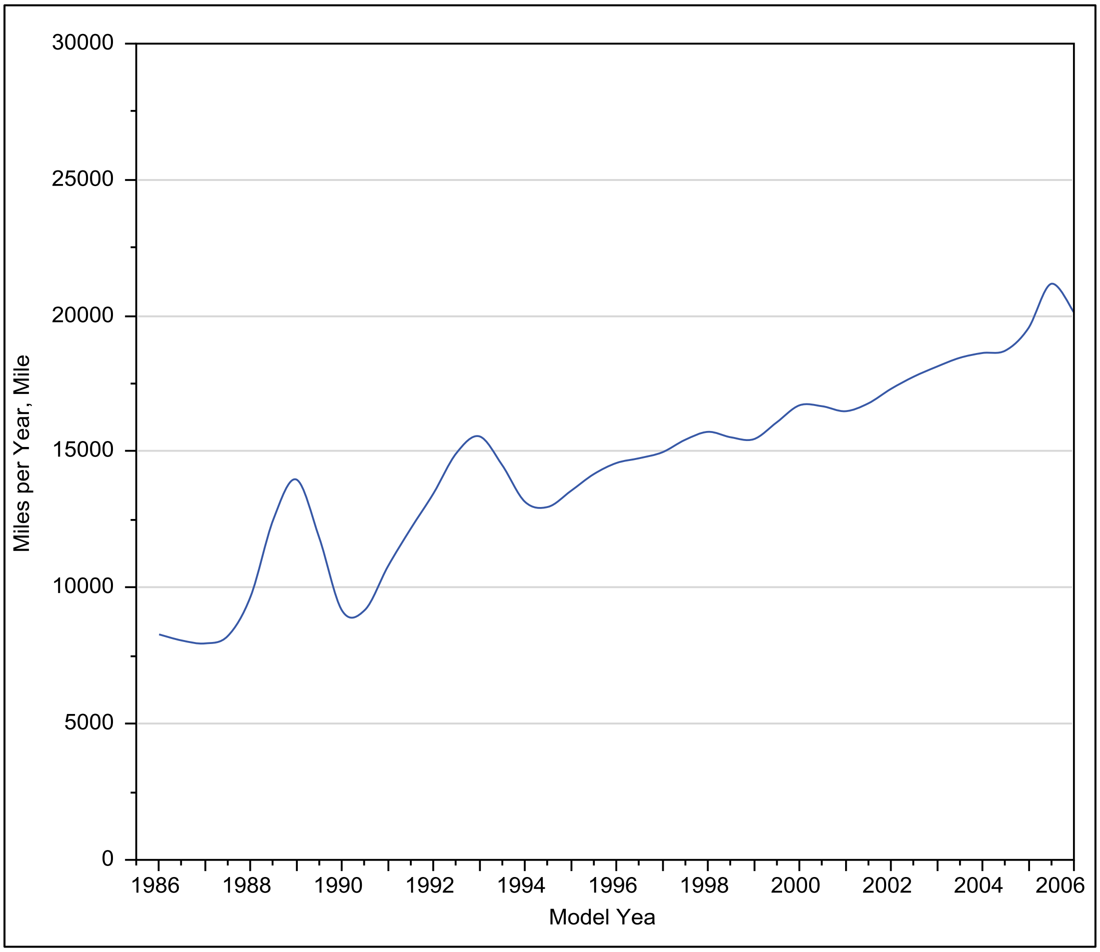

Figure 4-29 Annual miles traveled 'before-and-after' repair sample for vehicles that failed the emission inspection test

Figure 4-30 represents the odometer distribution for 'before' and 'after' repair samples divided into model year groups. Distributions for all vehicle groups look similar. Therefore there is no important difference between age groups for 'before' and 'after' samples.

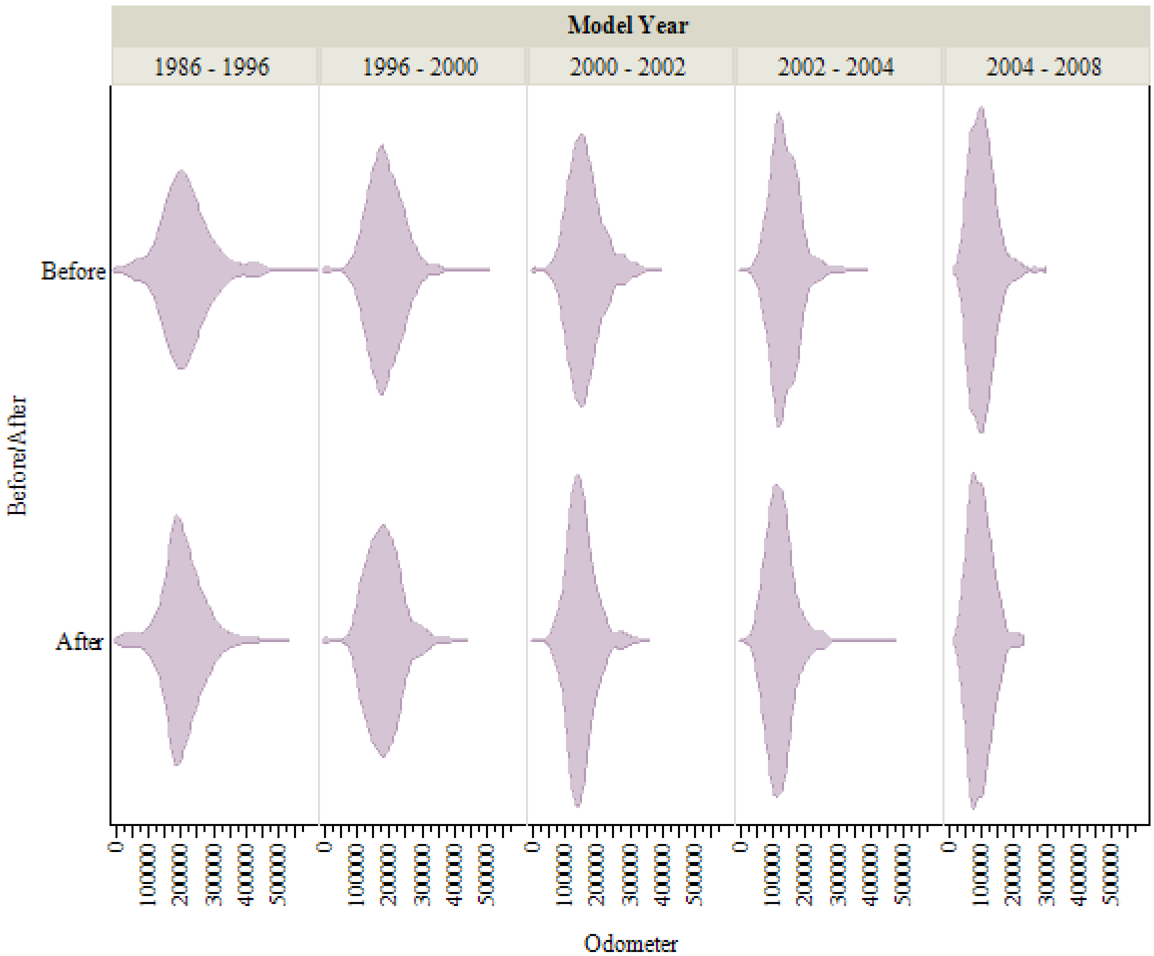

Figure 4-30 Odometer distributions for 'before' and 'after' repair by model year groups for vehicles that failed the emission inspection test

Based on analysis of odometer readings for 'before' and 'after' repairing vehicles, there is no observable difference between the 'before' and 'after' repair groups. Therefore any differences in emissions in both groups would not be due to vehicles having higher odometer readings in one group that the other.

4.2.1.5 Sample Differences Between Bins for Failed and Repaired Vehicles

To analyze differences between emission rates for vehicles before and after the repair two datasets: 1) Inspection and Maintenance database, 2) remote emission sensing formed a basis for it. Based on the date of vehicle remote emission sensing measurement and test and repair date the data was grouped in 30 day bins. The bins represent the time between remote emission sensing and time of before and after emission test failure and repair. The bins were compared to each other to make sure that they are consistent and there are no significant differences between the bins that might affect emission rates.

Bins were formed starting one year prior to the emission test failure and span to one year after the vehicle repair. Bin 1 represent vehicles that were captured by the remote emission sensing 330-360 days prior to vehicle emission inspection fail. Bin 2 had vehicles from 300 – 330 days prior to emission test failure and so on. There is a total of 24 bins: 12 bins for the time prior to emission inspection and 12 bin after vehicle repair, bin 24 representing vehicles 330 – 360 days after vehicle was repaired and passed emission inspection test. In total, 9,711 vehicles failed an emission test then passed a test and were captured by vehicle remote emission sensing.

The difference between bins can indicate/explain the change of emission rate, therefore it is important to compare bins against each other. Figure 4-31 represent odometer reading dependence on bins. It is evident that with the exception of a few low number bins and a couple of higher number bins odometer reading are very consistent across the bin range.

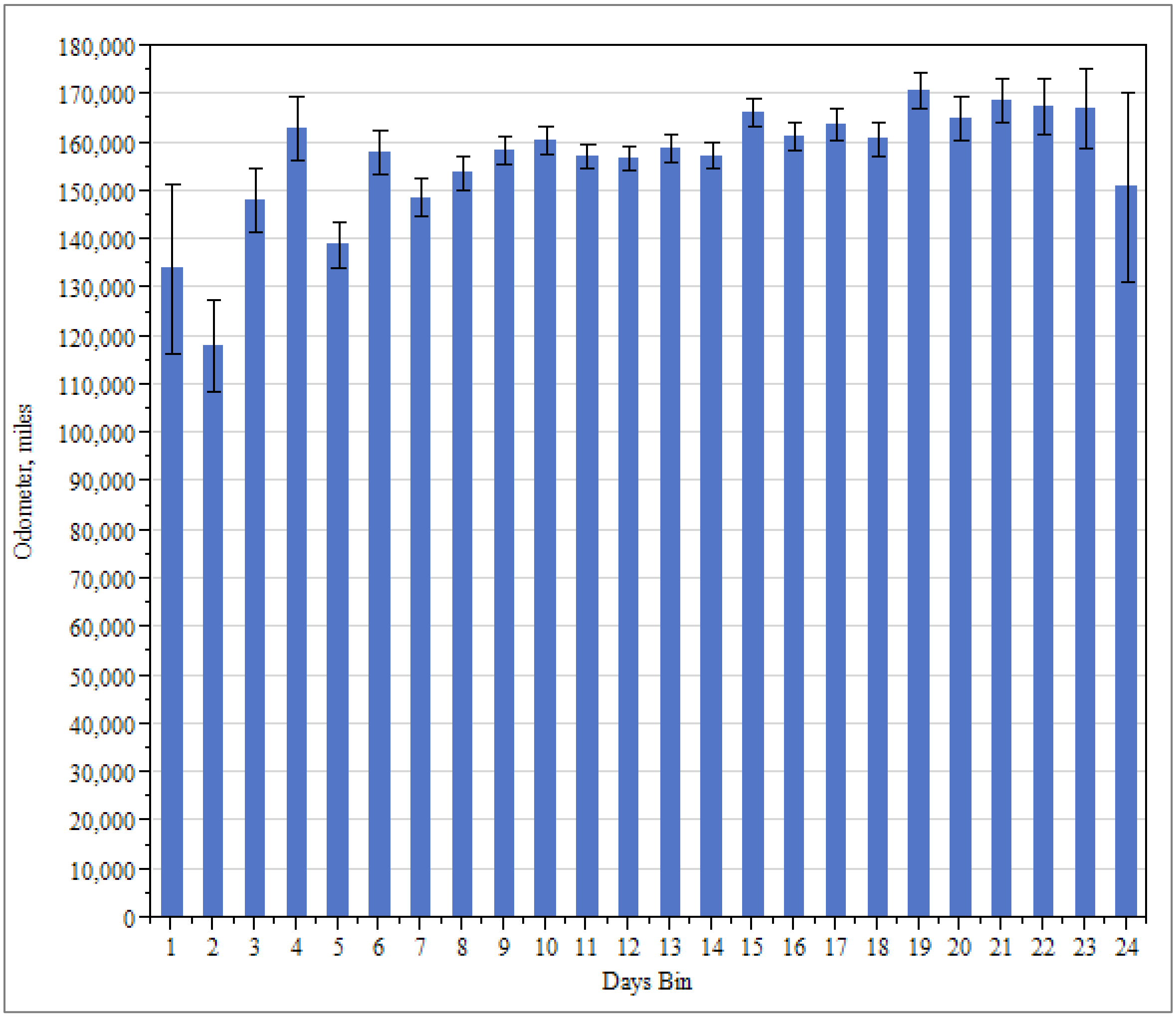

Figure 4-31 Odometer readings by day bins for failed and repaired vehicle samples

Next VSP distribution was compared across the bin range. VSP distribution is also being consistent throughout the bin range and it stays between 14 and 16 kW/Tonne. VSP versus day bins plot can be seen in Figure 4-32.

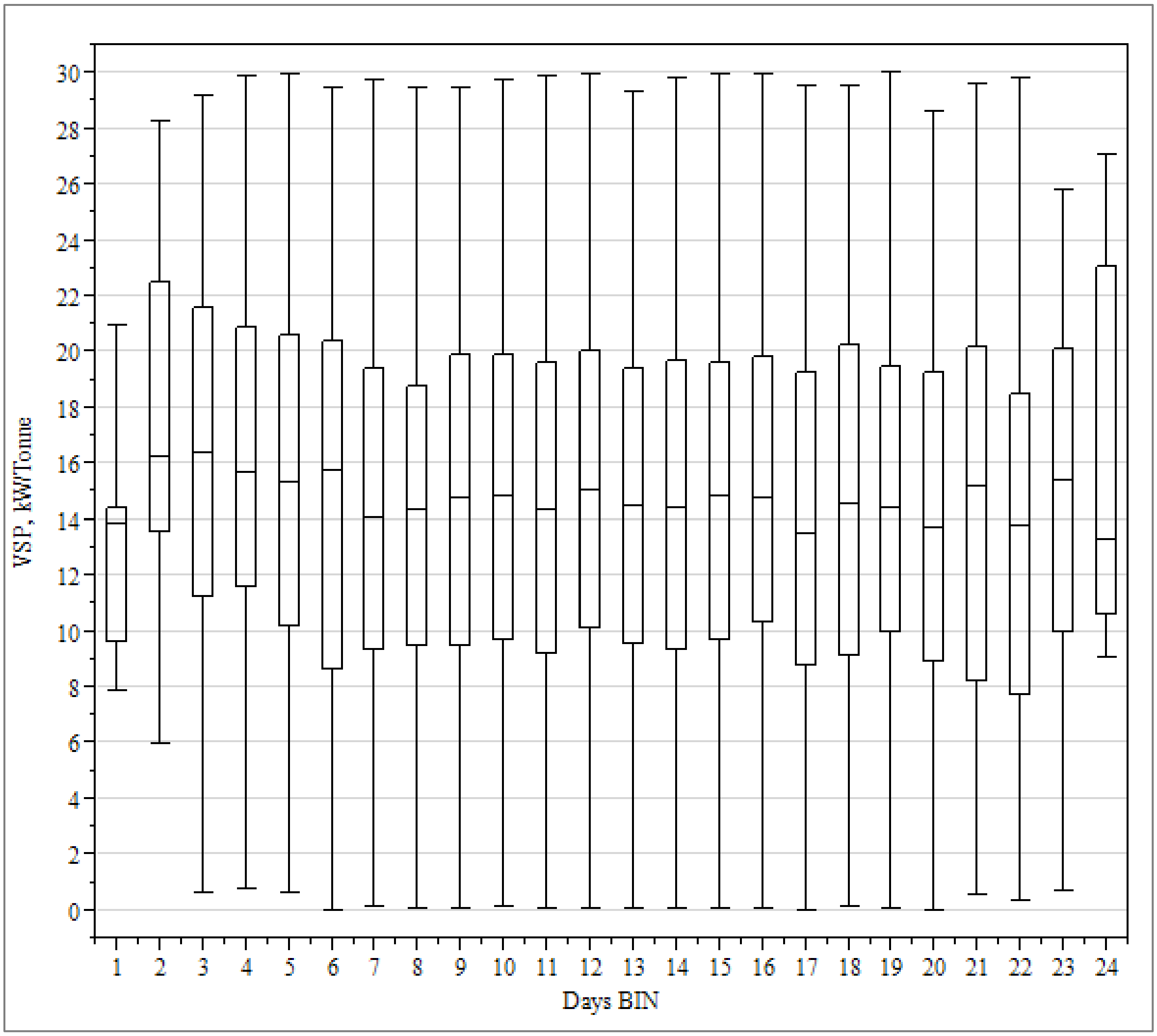

Figure 4-32 VSP readings for day bin for failed and repaired vehicle sample

And finally model year composition for the bins was examined as well. With the exception of very low and high number bins for the rest of the data model year hovers around the year 2000. Figure 4-33 represents a plot of model year based on days bin.

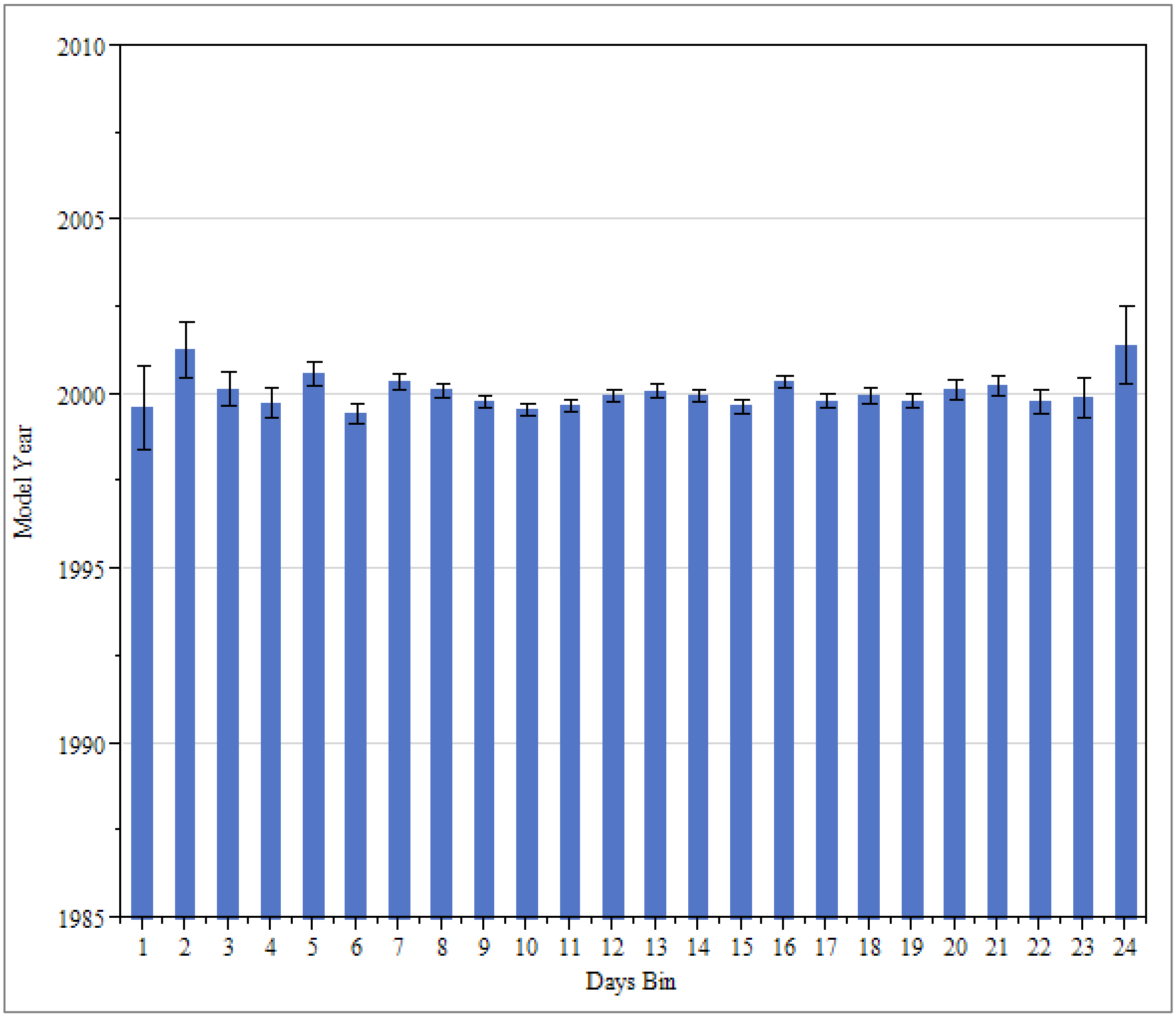

Figure 4-33 Model year for day bins for failed and repaired vehicle sample

4.2.1.6 Failing Vehicles Sample differences Conclusion

The hypothesis for this analysis was that some differences in before and after vehicle repair should be observed indicating that vehicles with high emissions were repaired and therefore reduced pollutants discharged to the atmosphere. After careful examination of several variables such as VSP distributions, model year distributions, odometer readings distribution, and miles per year distribution for before and after the repair samples as well as analysis of binned data all differences that might be observed during analysis will be due to emission controls of the vehicles and not caused by differences in vehicle fleet age, make,VSP readings, or odometer readings.

4.2.2 'Before and 'After' Repair Group Emission Differences

To calculate differences between vehicles in 'before' and 'after' repair groups, all vehicles were placed in 30-day bins. The bins represent days before and after the repair. Bins for 'before' and 'after' days were assigned to each vehicle and carbon monoxide, hydrocarbons, and nitrogen oxides were plotted against those bins.

In total, 9,711 vehicles failed an emission test then passed a test and were captured by vehicle remote emission sensing.

Vehicle selection for the following analysis consisted of vehicle remote emission data collected during the 2010 calendar year at locations around the Atlanta Metro Area. VSP for those vehicles were limited to the range between 0 and 30. Data used for the analysis is from the CAFÉ database for 2010 and the I/M database for 2010.

To repair a vehicle it took 21 days on average, with the median of almost 6 days with high standard deviation suggesting that some vehicles had an extremely high number of days between the two tests (Table 4-16). The following table shows descriptive statistics for the sample data. The distribution of days to repair is shown in Figure 4-34.

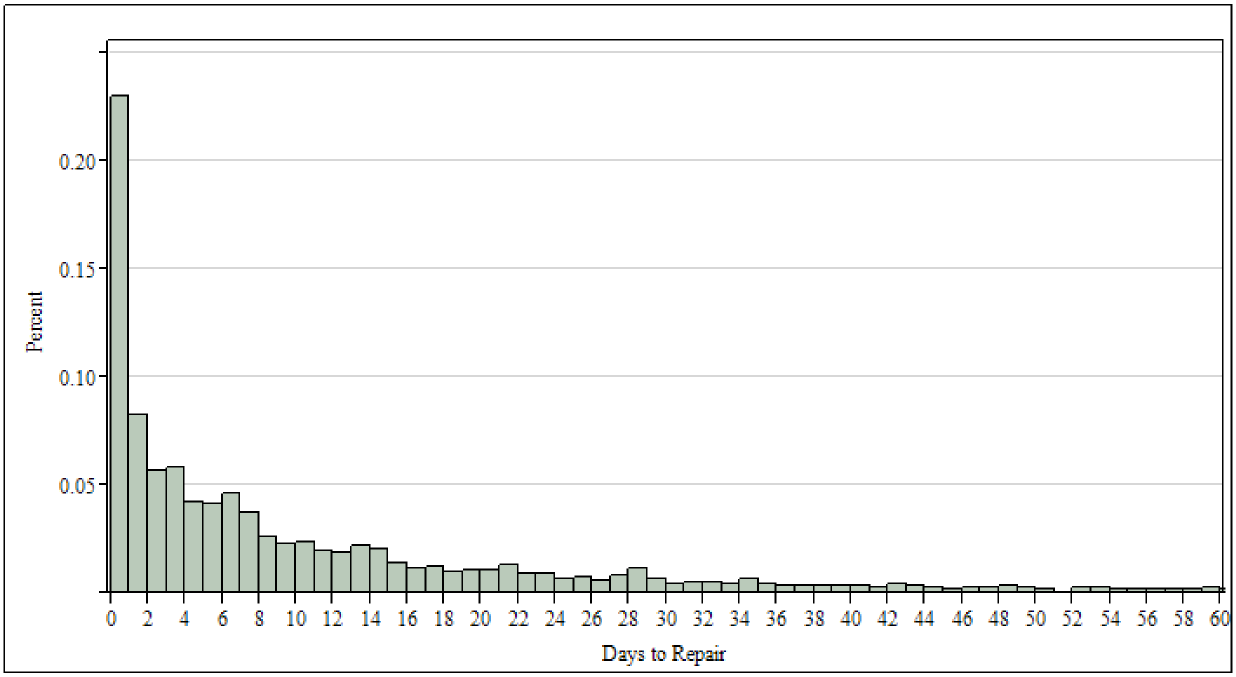

Figure 4-34 distribution of days to repair for failed vehicles

Table 4-16 Summary statistics for the repair time duration for vehicles that failed the emission inspection test

Mean	21.55
Standard Error	0.53
Median	5.97
Mode	1.14
Standard Deviation	52.52
Sample Variance	2758.13
Kurtosis	20.14
Skewness	4.38
Range	361.96
Minimum	0.00
Maximum	361.96
Sum	209312.50
Count	9,712

The following chart represents the carbon monoxide of vehicles that passed the I/M 2010 inspection and were captured by remote sensing. Carbon monoxide measurements for before and after the repair vehicle sample are shown in Figure 4-35. CO emission is steadily rising. At the time of the repair, CO concentration drops by nearly 38 percent from 0.31% to 0.19% CO and then begins to rise again, demonstrating the effect of a repair on a vehicle. What can be seen here is that vehicles are getting dirtier right before repair and getting cleaner after the repair has happened. After initial repairs, vehicles are continuing to get higher CO emissions practically at the same pace as before the repair, which may raise questions about the effectiveness of those repairs.

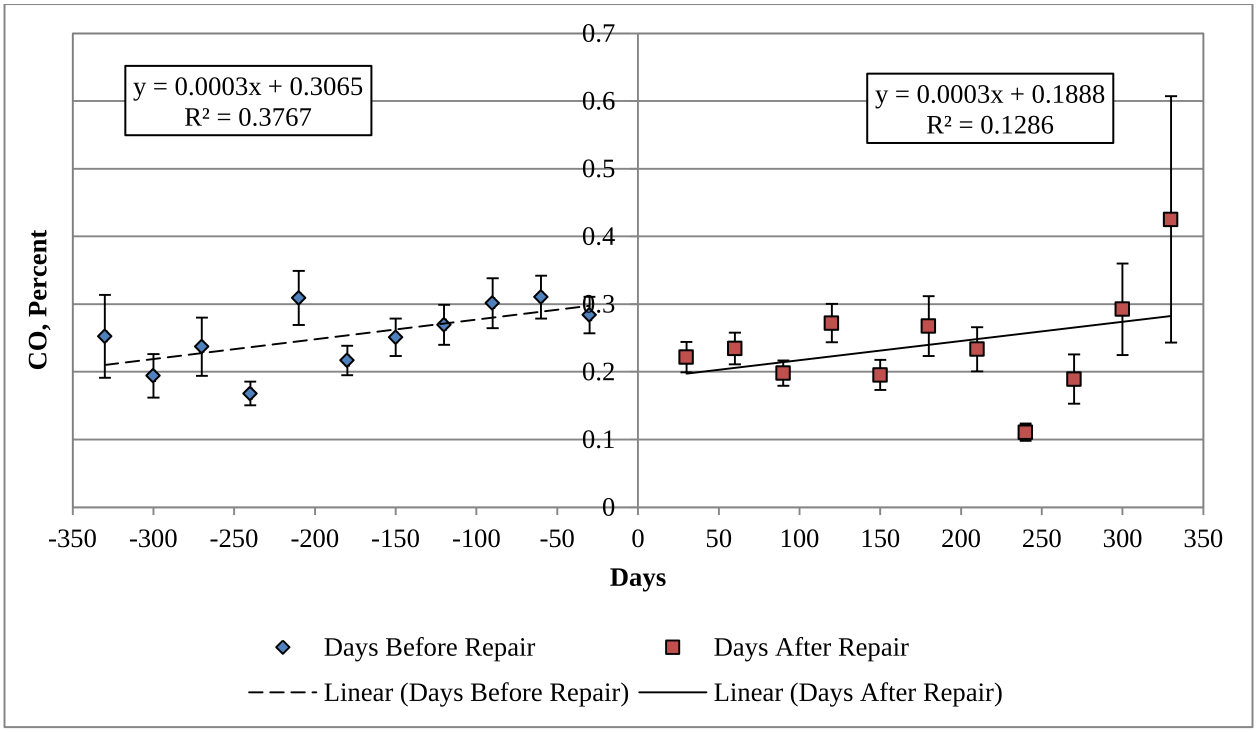

Figure 4-35 CO measurements 'before-and-after' repair for vehicles that failed the emission inspection test

If the pace of growth of CO can be slowed, then we would get benefits and a reduction in emission inventory. However, the focus of this research is on catching vehicles sooner than their scheduled emission test and thus reducing harmful emissions. If vehicles can be tested sooner, we can shorten a time that vehicle is driving with higher than normal emissions, therefore reducing those emissions.

HC measurements of vehicles before and after repair are demonstrated in Figure 4-36. Before repair has occurred, HC concentration has grown gradually. At the time of repair, the HC level drops by 13% from 54 ppm to 47 ppm and then continues to grow at a slower rate than before the repair.

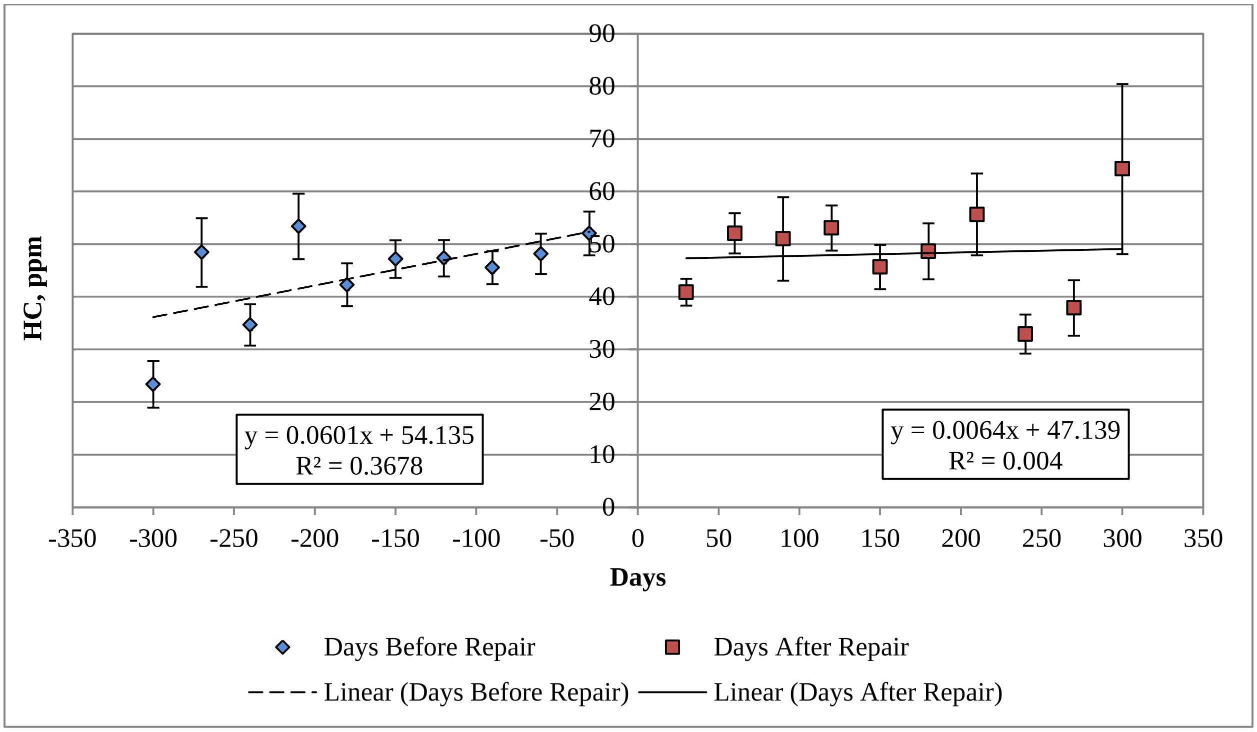

Figure 4-36 HC measurements 'before' and 'after' repair for vehicles that failed the emission inspection test

Vehicles are getting dirtier before repair and reduce their HC emissions after the repair has occurred. After repair the vehicles are continuing to get dirtier just like CO, but at a slower pace.

The NOx behaves slightly differently. Since NOx emissions depend on engine temperature (36), then reduction of NOx would indicate that the engine temperature is falling, which is consistent with CO increases. When CO emissions increase, the vehicle's engine is running rich fuel that does not burn completely, which in turn brings down the temperature of the engine. At the time of repair, however, NOx emissions drop by 5.7% and after the repair rise slightly, which once again is consistent with slower growth rates of CO.

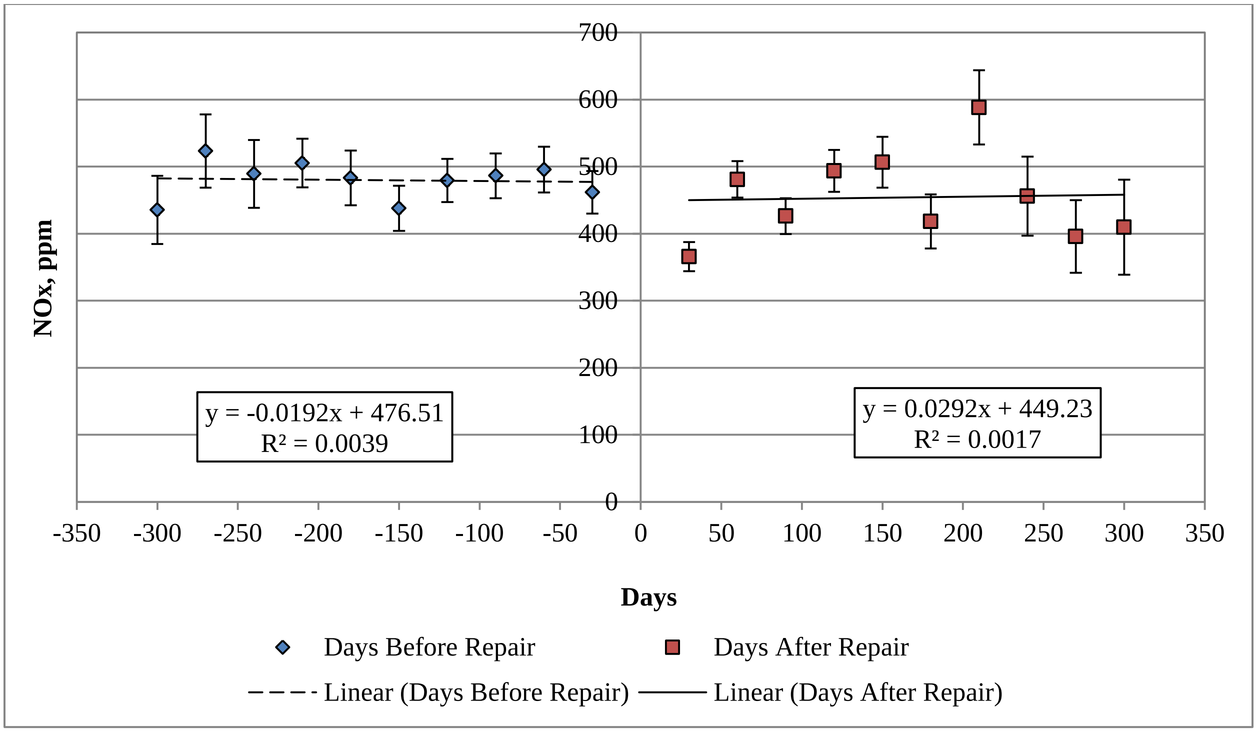

Figure 4-37 NOx measurements 'before' and 'after' repair for vehicles that failed the emission inspection test

Below is the distribution of vehicles with CO, HC, NOx emission before and after repairs. Although after the repair vehicles are slightly skewed toward the bins with a smaller number of days, there is no significant difference between these two samples. Figure 4-38 represents plot for number of vehicles in day bins for before and after vehicle repair for vehicles that failed emission inspection test.

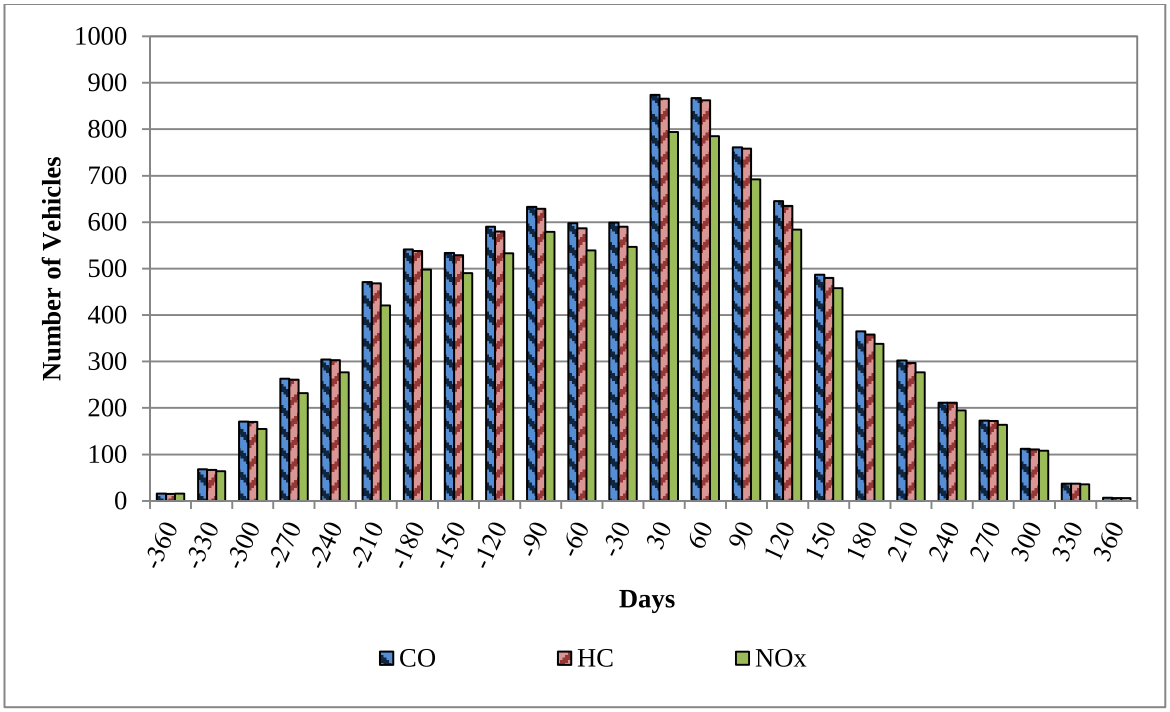

Figure 4-38 Histogram of number of vehicles per bin 'before' and 'after' repair for vehicles that failed the emission inspection test

4.2.3 Conclusion

Vehicles from the 'before' and 'after' repair groups exhibited differences in before and after repair emission rates, therefore the conclusion can be established that there is a potential benefit that can be derived by testing potentially failing vehicles before their scheduled emissions test. Doing so will reduce the amount of harmful emissions in the atmosphere. Slopes in Figure 4-35, Figure 4-36, and Figure 4-37 will be used to calculate CO, HC, and NOx emission reductions.

5 MODELING FOR PROBABILITY OF FAILURE

To estimate the probability of failure, a nominal logistic model with logit treatment was applied. Numerous variables were introduced in the model including vehicle emission reading obtained by the remote emission sensor including CO, HC, and NOx; vehicle make; vehicle model year; an odometer reading; the length of ownership; original owner; displacement recoded; emission test result from previous (2009), and annual mileage. This section examines vehicle characteristics that are used as potential variables to predict probability of failure. From 117,294 vehicles, 98,573 vehicles had VSP readings between 0 and 30 and they were selected to be entered into the model.

5.1 Model Variables

5.1.1 Carbon Monoxide Concentration

Carbon monoxide concentration readings were measured during the 2010 remote sensing measurements in the Atlanta Metro Area for CAFÉ projects. There are 98,573 valid CO measurements. Average carbon monoxide measurements during this time were 0.121% with a standard deviation of 0.431% (Table 5-1). A distribution of CO concentrations is shown in Figure 5-1.

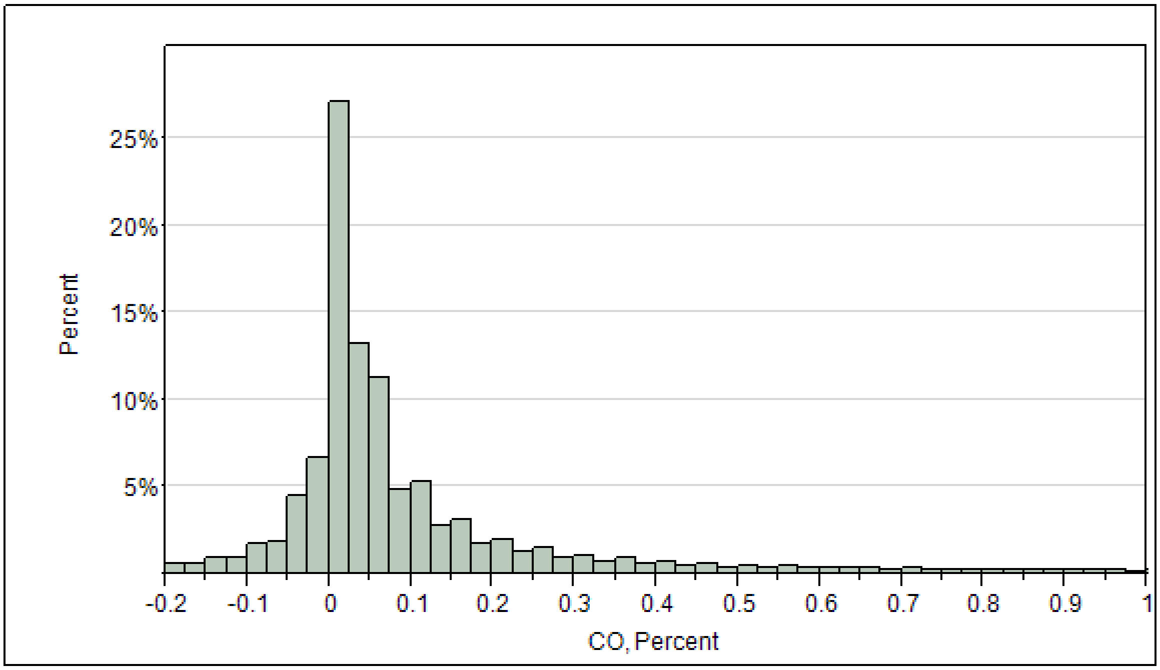

Figure 5-1 Distribution of carbon monoxide concentration

Table 5-1 represents summary statistics for distribution of carbon monoxide concentration.

Table 5-1 Summary statistics for carbon monoxide concentration

Mean	0.12
Standard Deviation	0.43
Standard Error Mean	0.00137
Upper 95% Mean	0.12
Lower 95% Mean	0.12
Number of Samples	98,573

Figure 5-2 plots carbon monoxide concentration versus model year. It is evident that as vehicles get older, carbon monoxide concentration increases. After the 1986 model year, the carbon monoxide concentration decreases. That can be a product of several factors. First there are relatively few vehicles and thus very large standard errors. Another factor that may contribute to lower readings is the "survival effect." Survival effect refers to vehicles that because of their age, become inoperable and have to be rebuilt. Those rebuilds include rebuilding of engines, transmissions, and emission control systems.

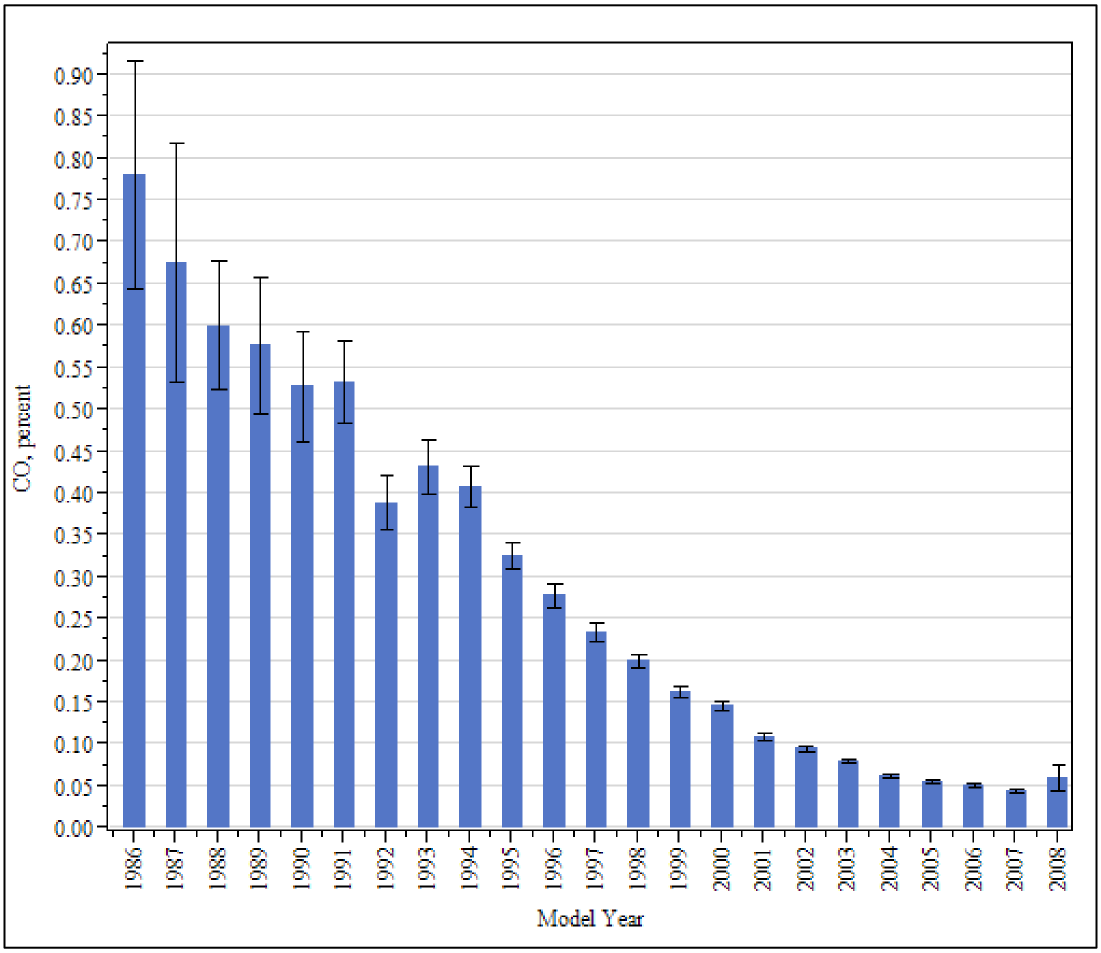

Figure 5-2 Carbon monoxide concentrations vs. model year

Since there is a clear relationship between vehicle age and CO concentration, this variable should be an explanation for vehicle emission test failure.

In addition to the relationship between carbon monoxide and the age of the vehicle there is a relationship between carbon monoxide measurements and vehicle emission inspection failure rates. That relationship is illustrated in Figure 5-3. This figure is based on carbon monoxide measurements obtained by remote emission sensing and failure rates from 2010 inspection and maintenance database. As carbon monoxide concentration increases so do the emission inspection failure rate. Since this relationship exists carbon monoxide might be a variable that partially predicts probability of failure.

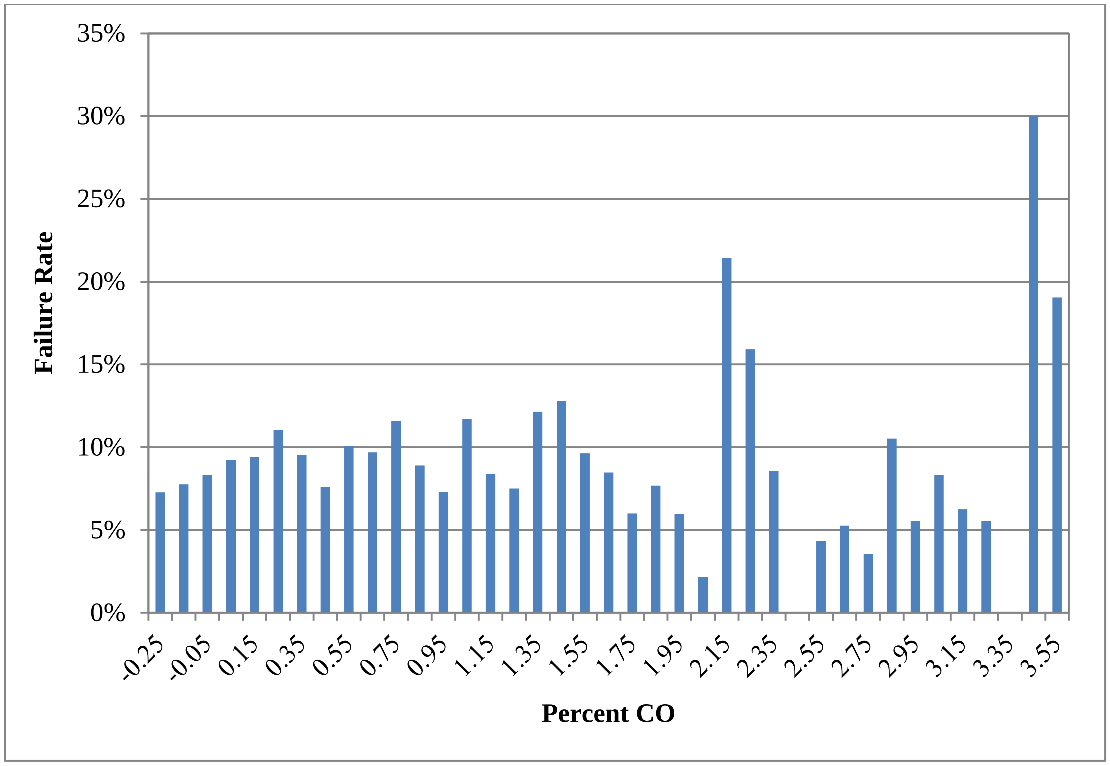

Figure 5-3 Emission test failure rate vs vehicle emission remote sensing carbon monoxide reading

5.1.2 Hydrocarbons

HC concentrations were measured by vehicle remote emission sensors during 2010 measurements in the Atlanta Metro Area for the CAFÉ project. The current dataset contains 97,855 valid HC measurements. They average 28.03 ppm with a standard deviation of 93.79 ppm. Figure 5-4 represents the distribution of HC concentrations.

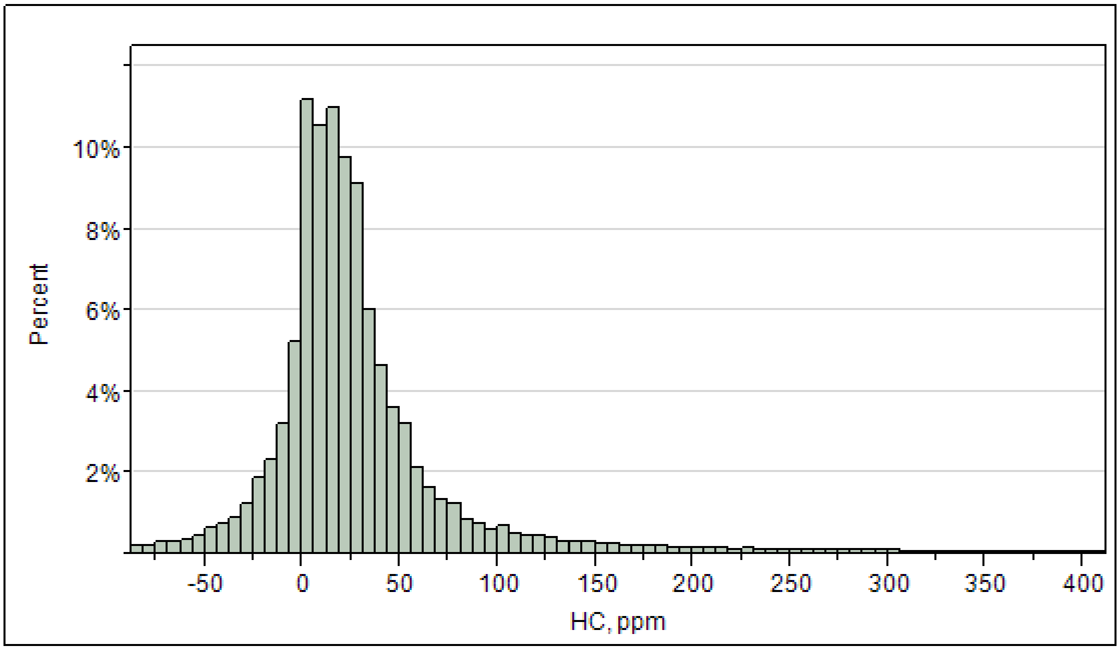

Figure 5-4 Distribution of HC concentration

Table 52 presents a summary of HC statistics. Average HC is 28.03 ppm with a standard deviation of 93.79 ppm.

Table 5-2 HC summary statistics

Mean	28.03
Standard Deviation	93.79
Standard Error Mean	0.30
Upper 95% Mean	28.62
Lower 95% Mean	27.44
Number of Samples	97,855

Similar to carbon monoxide, hydrocarbon concentration increases as vehicles age. The first several model years do not have a lot of change. However, for vehicles eight years and older, changes occur much faster. By the time vehicles reach 24-25 years old, their emissions increase 7 fold. Figure 5-5 illustrates the HC concentration distribution by model year.

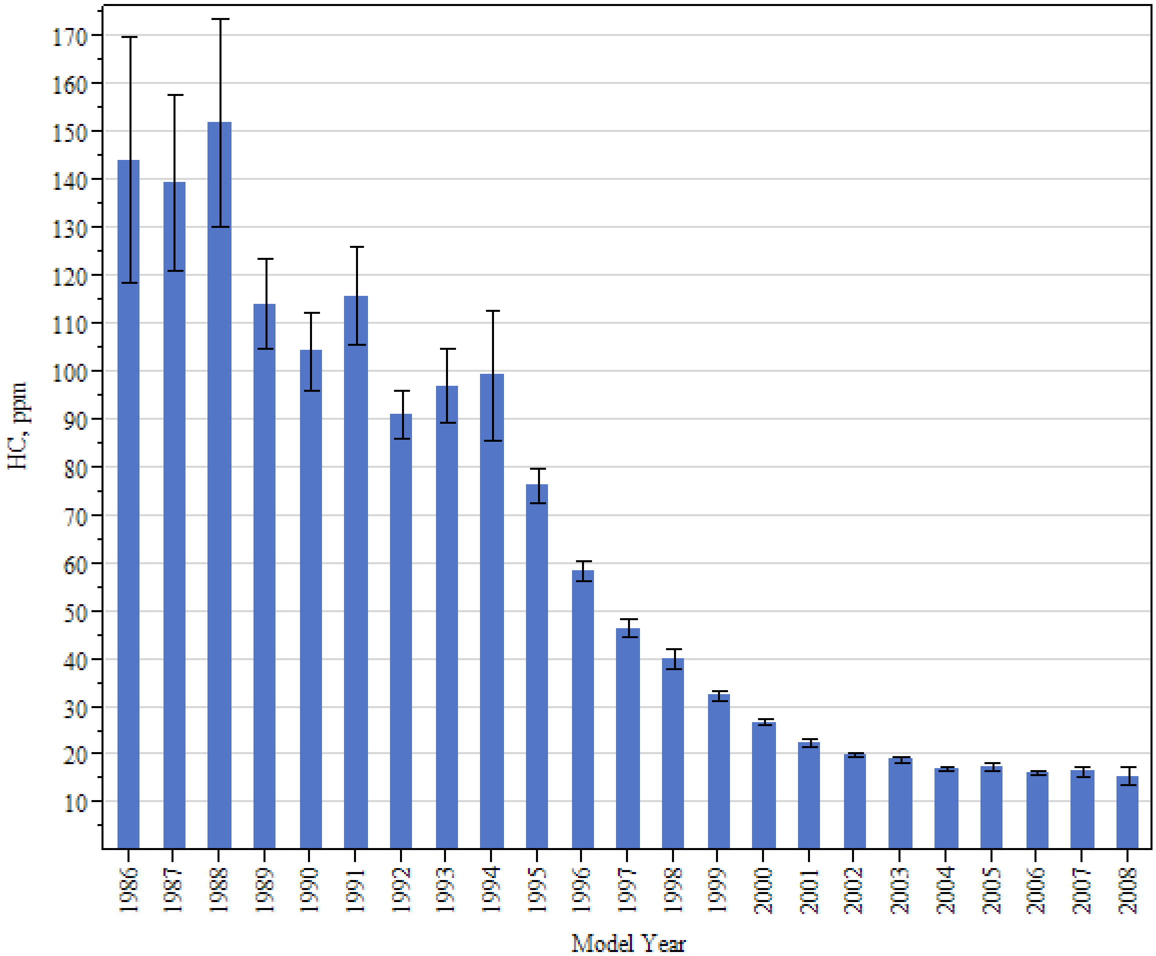

Figure 5-5 Distribution of HC concentration vs. model year

In addition to showing deterioration of vehicle's emission ass vehicles age hydrocarbons have also shown the relationship to failure rates. Figure 5-6 shows that as vehicle's hydrocarbon emissions are increasing so do the vehicle emission inspection failure rates. Hydrocarbon behaves similarly to carbon monoxide. Coliniarity of carbon monoxide and hydrocarbons will be examined in the following sections.

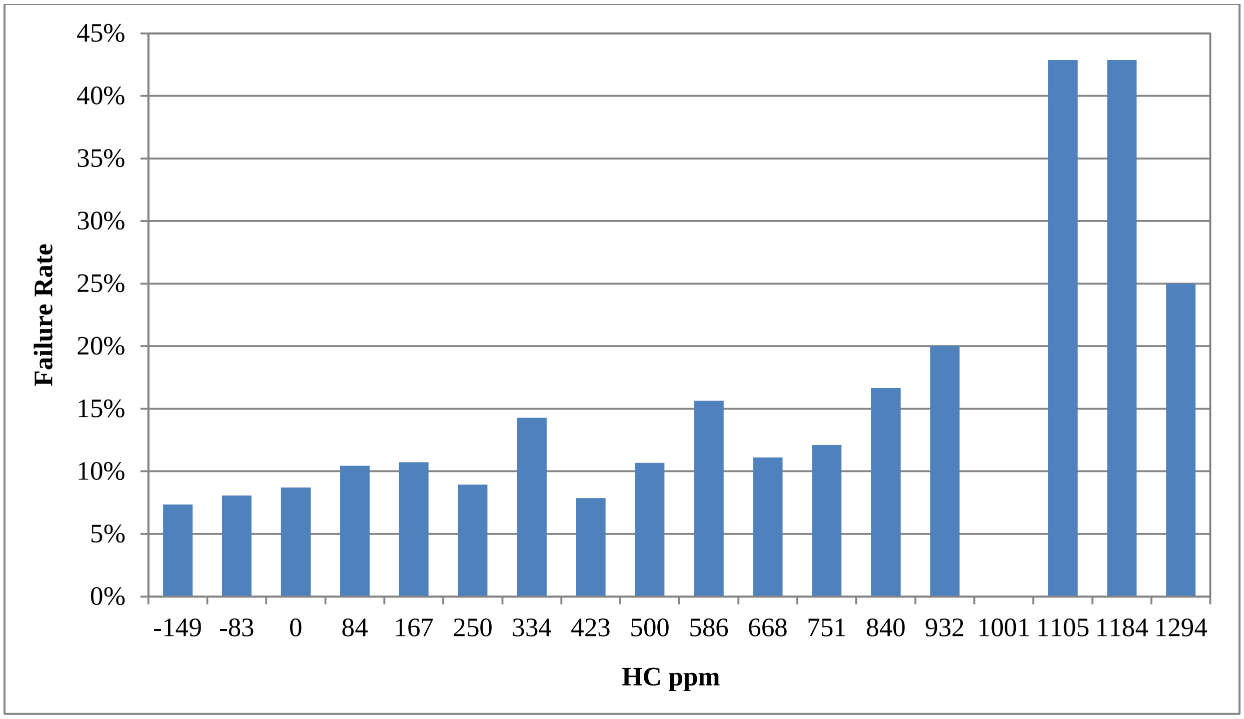

Figure 5-6 Emission test failure rate vs vehicle emission remote sensing hydrocarbon readings

5.1.3 Nitrogen Oxides

The data set used for modeling in this research contains 89,419 valid nitrogen oxide measurements. All of them were collected by remote emission sensors for the CAFÉ project in 2010. The average NOx concentration is roughly 236 ppm with a standard deviation of 519 ppm (Table 5-3). Figure 5-7 represents the NOx concentration distribution.

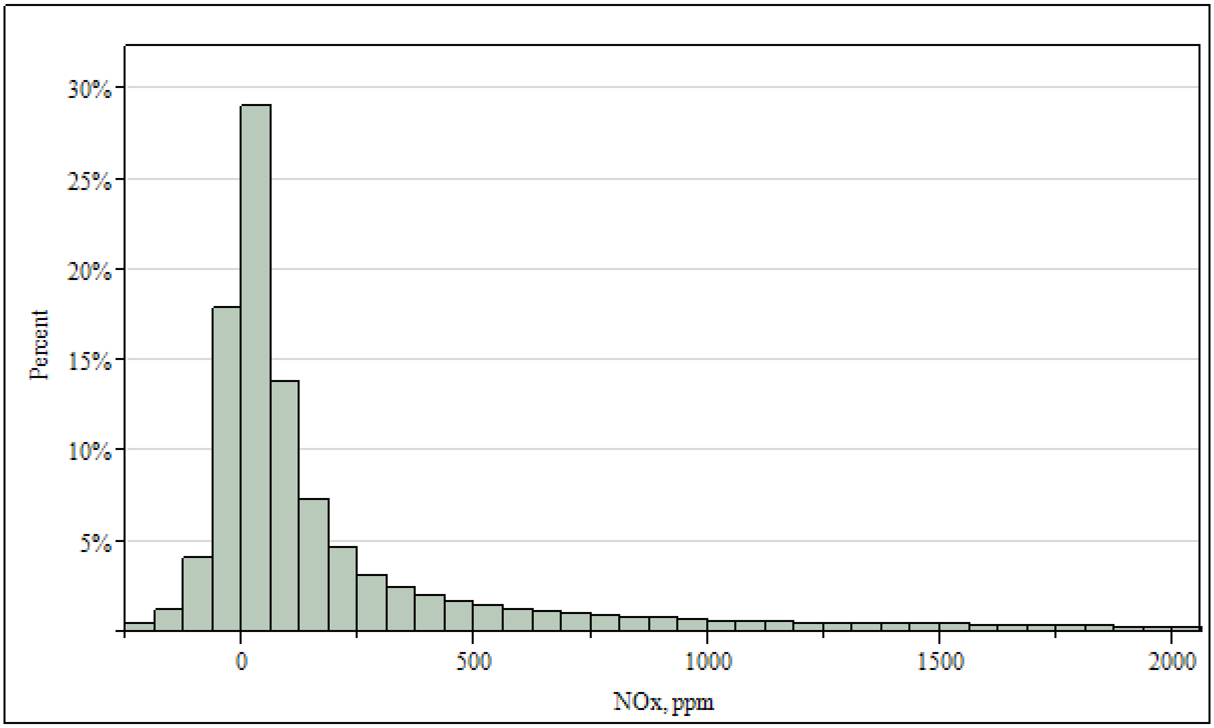

Figure 5-7 Distribution of NOx concentration

Table 5-3 NOx distribution summary statistics

Mean	235.78
Std Dev	518.74
Std Err Mean	1.73
Upper 95% Mean	239.18
Lower 95% Mean	232.38
Number of Samples	89,419

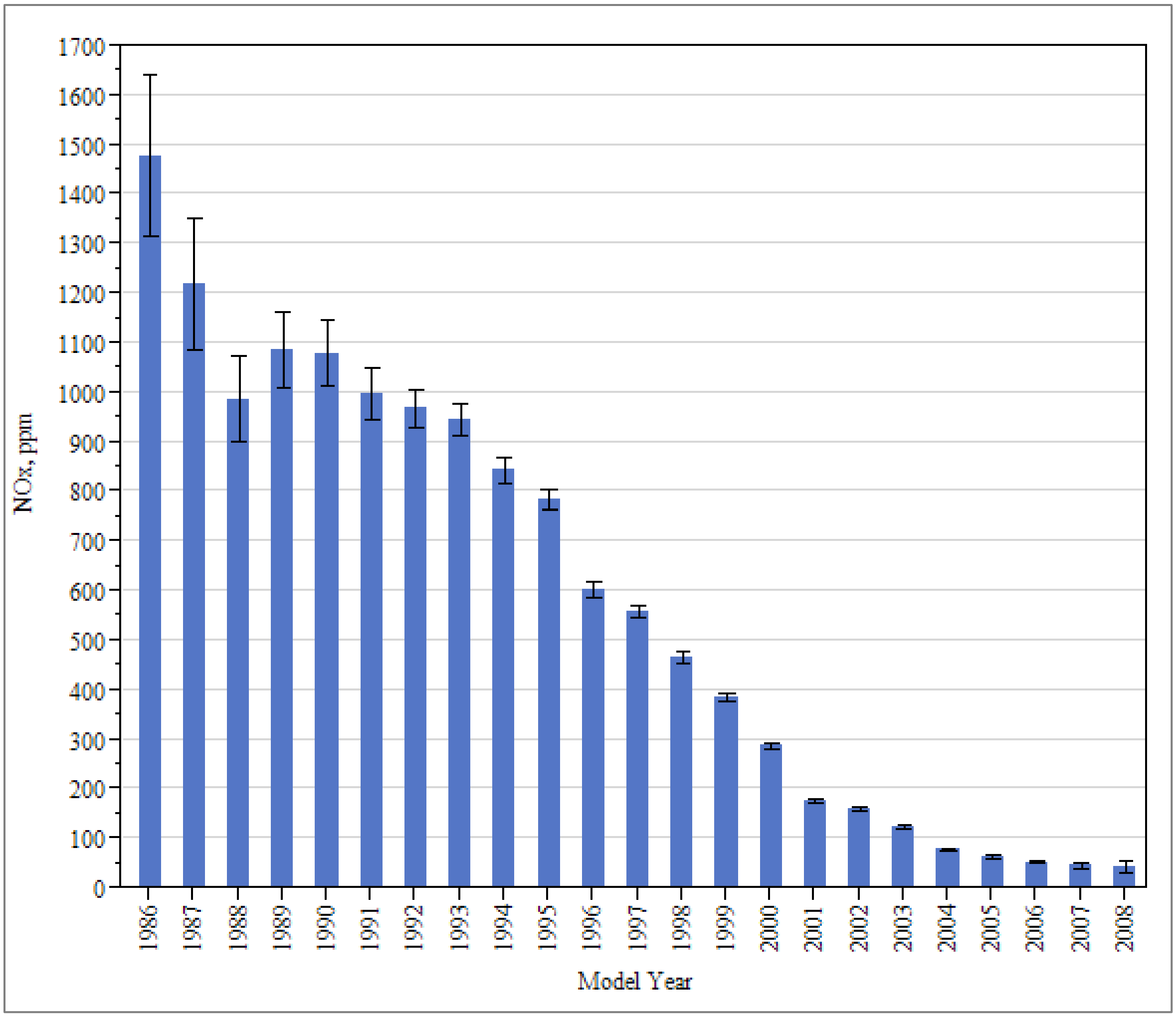

Figure 5-8 Distribution of NOx concentration by model year

Nitrogen oxide follows the trend set by carbon monoxide and hydrocarbons. As vehicles age, NOx concentration deteriorates as well. One interesting observation is that NOx starts to deteriorate faster than either CO or HC. For CO and HC, the first eight model years were very similar to each other; in the case of NOx, during the first six model years NOx does not change much; however, after that it starts to deteriorate.

Similar to carbon monoxide and hydrocarbon remote sensing measurements of nitrogen oxides also can indicate vehicle emission testing failure. As remote sensing measurements of nitrogen oxide increase the emission inspection failure rate increases as well. The relationship between remote sensing measurements of nitrogen oxides and emission test failure rate is shown in Figure 5-9.

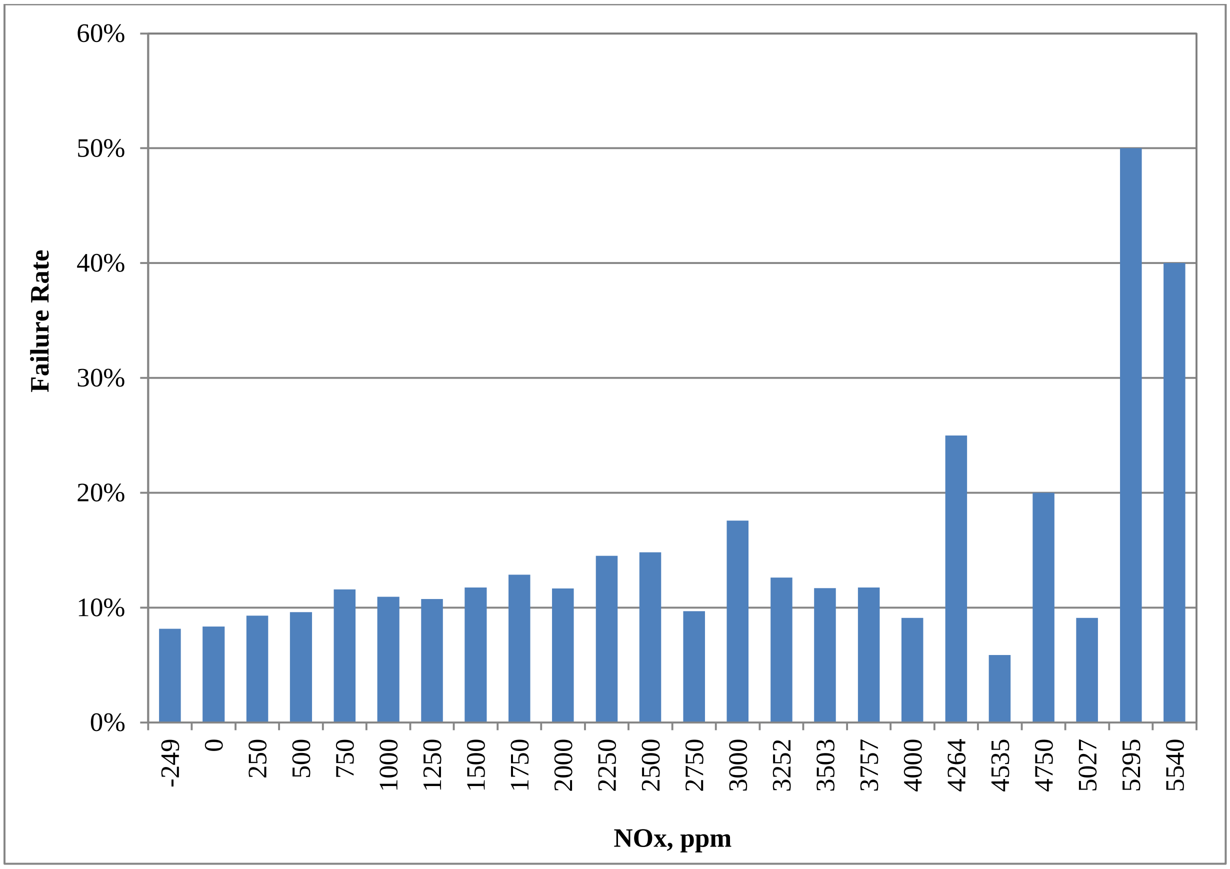

Figure 5-9 Emission test failure rate vs vehicle emission remote sensing nitrogen oxides readings

5.1.4 Make

Vehicle make information is used in this section to describe and compare vehicle samples. It is not however the variable that is being used in the modeling of probability of vehicle's emission inspection test failure. Vehicle make distribution for the data used for modeling is similar to description provided in 'before' and 'after' emission inspection and 'before' and 'after' repair sample examination since it practically combines the two samples for passing and failed vehicles.

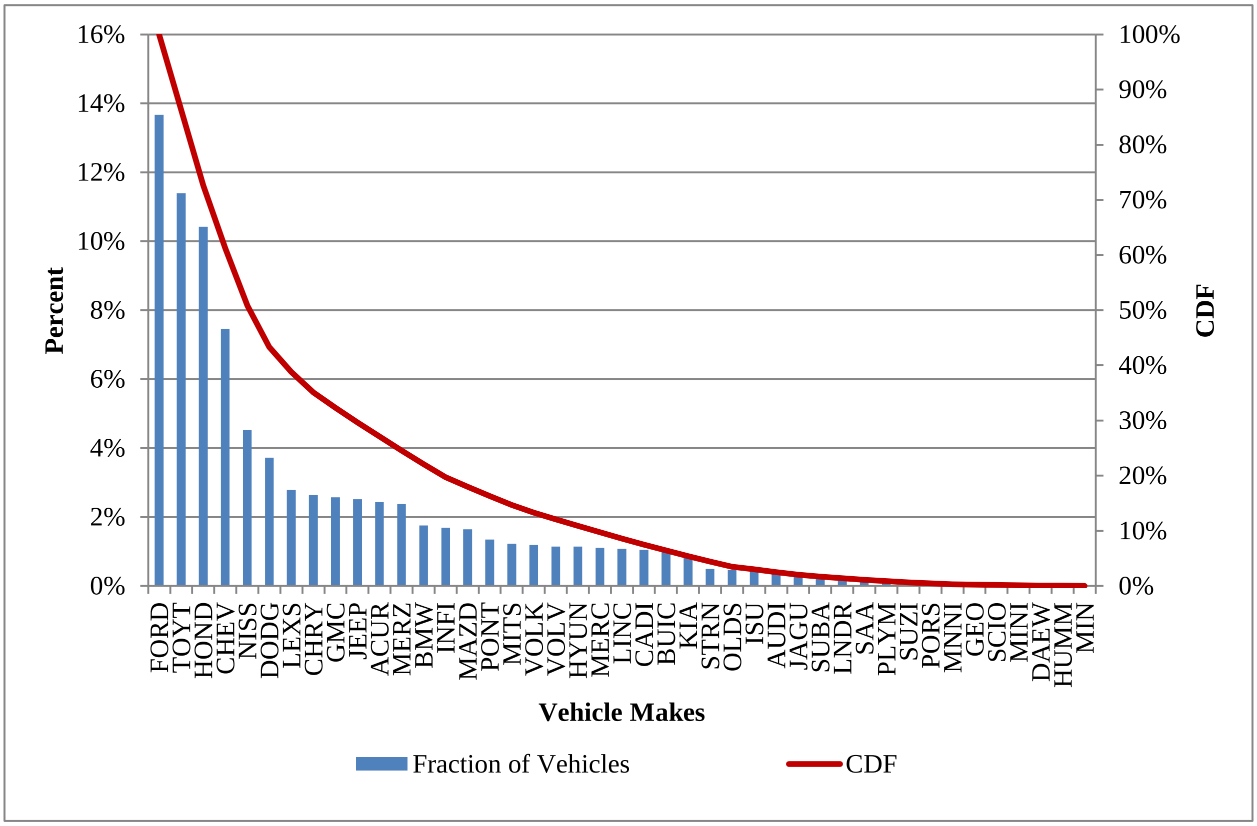

Figure 5-10 Make distribution

The majority of vehicles is produced by five manufacturers: Chevrolet, Ford, Honda, Nissan, and Toyota.

5.1.5 Model Year

Although 2010 remote sensing data is used for this research, the first three model years are not present in the data sample. As shown in Figure 5-11, a significant number of vehicles first show up as 2007 models. This is due to Georgia emission inspection law that exempts newer vehicles from emission testing. The first three model years do not have to be tested to obtain their annual registration. The model year distribution is skewed toward newer vehicles. The majority of vehicles in the sample are between three and eight years old.

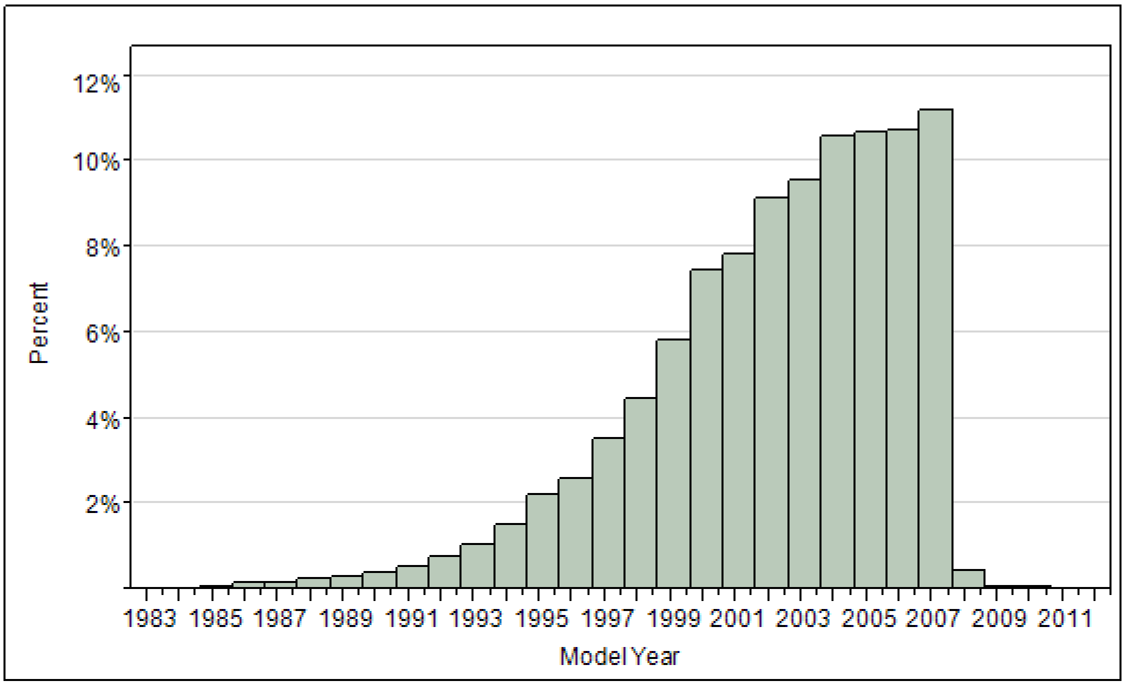

Figure 5-11 Model year distribution

The average vehicle in the sample is a 2002 model year with a standard deviation of 3.91 years.

Table 5-4 Summary Statistics for Model Year Distribution

Mean	2002.13
Standard Deviation	3.91
Standard Error Mean	0.01
Upper 95% Mean	2002.15
Lower 95% Mean	2002.10
Number of Samples	98,573

Figure 5-12 represent emission inspection failure rates based on the model year. As expected as vehicles getting older the emission inspection failure rates are increasing. Because of that fact model year of the vehicle may be a good predictor for the model.

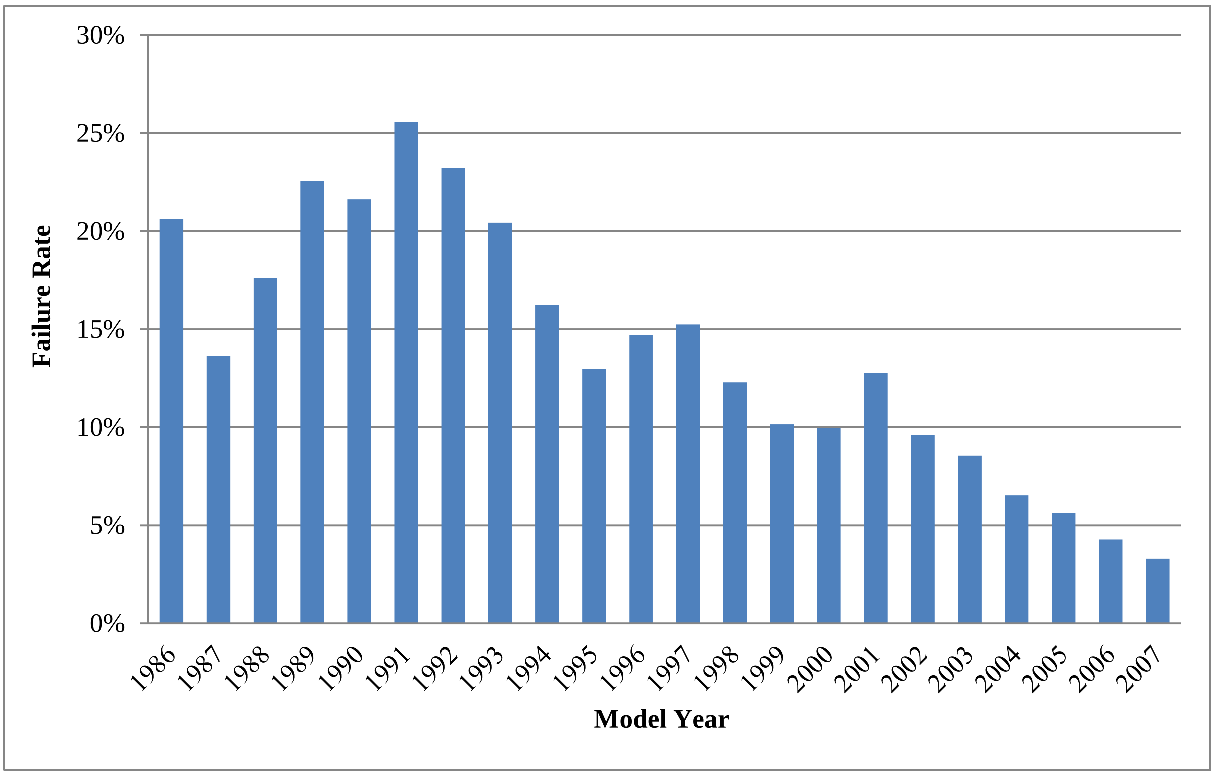

Figure 5-12 Emission test failure rate vs model year

5.1.6 VSP Distribution

VSP is also variable that is used in this research as a way to validate and compare vehicles sample in particular samples from remote sensing measurements. As described previously in this work only measurement with the certain VSP range are included in this analysis. The VSP range selected for the data used for modeling lies within 0 – 30 kW/Tonne.

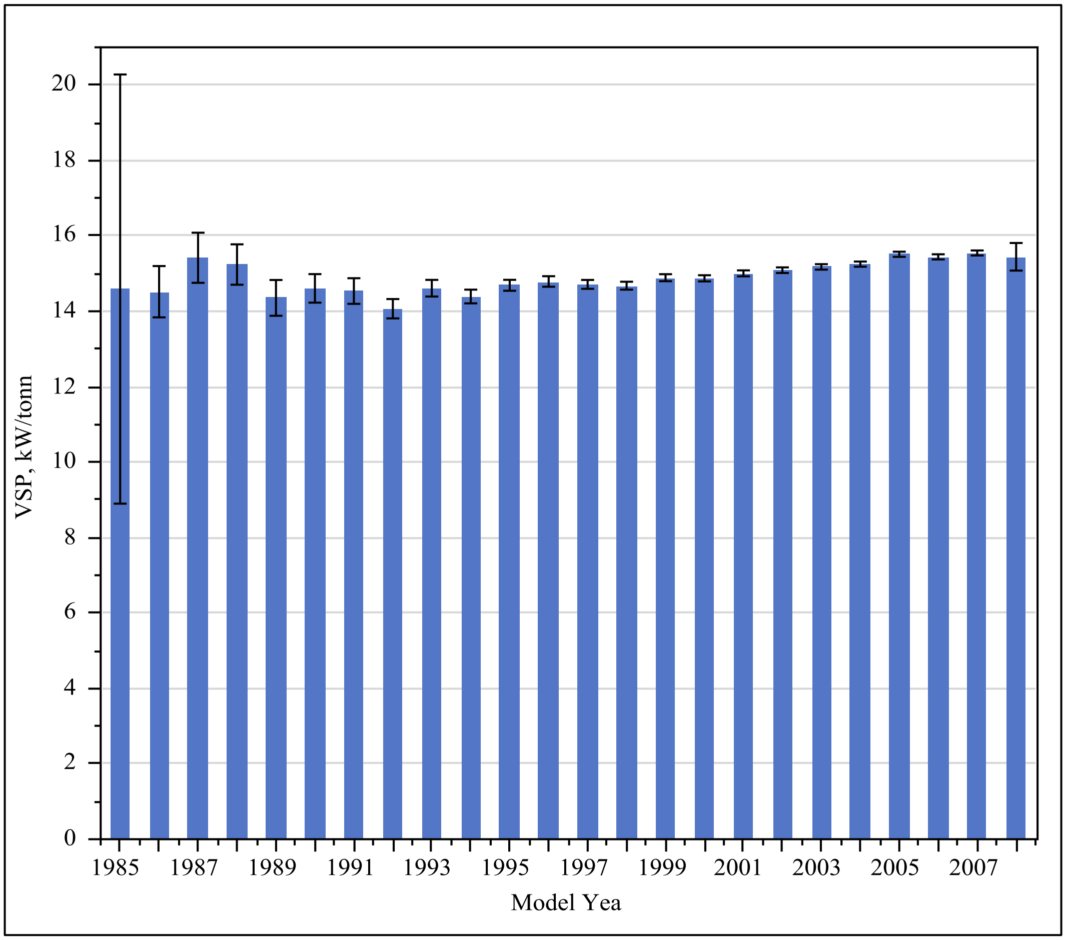

Figure 5-13 VSP distribution by model year

The VSP distribution is shown in Figure 5-13 and it floats around 15 kW/Tonne. For newer vehicles it seems to be somewhat higher than for older vehicles, but still remains within the margin of error. Due to the smaller sample size, the standard error for older vehicles is much higher. Figure 5-13 demonstrates the VSP distribution for the selected sample.

5.1.7 Accumulated VMT (Odometer)

The distribution of odometer readings was plotted (Figure 5-14). Both the Georgia Registration database and the Georgia Inspection and Maintenance database include odometer readings. The I/M database was chosen to supplement the Georgia Registration database because of missing records.

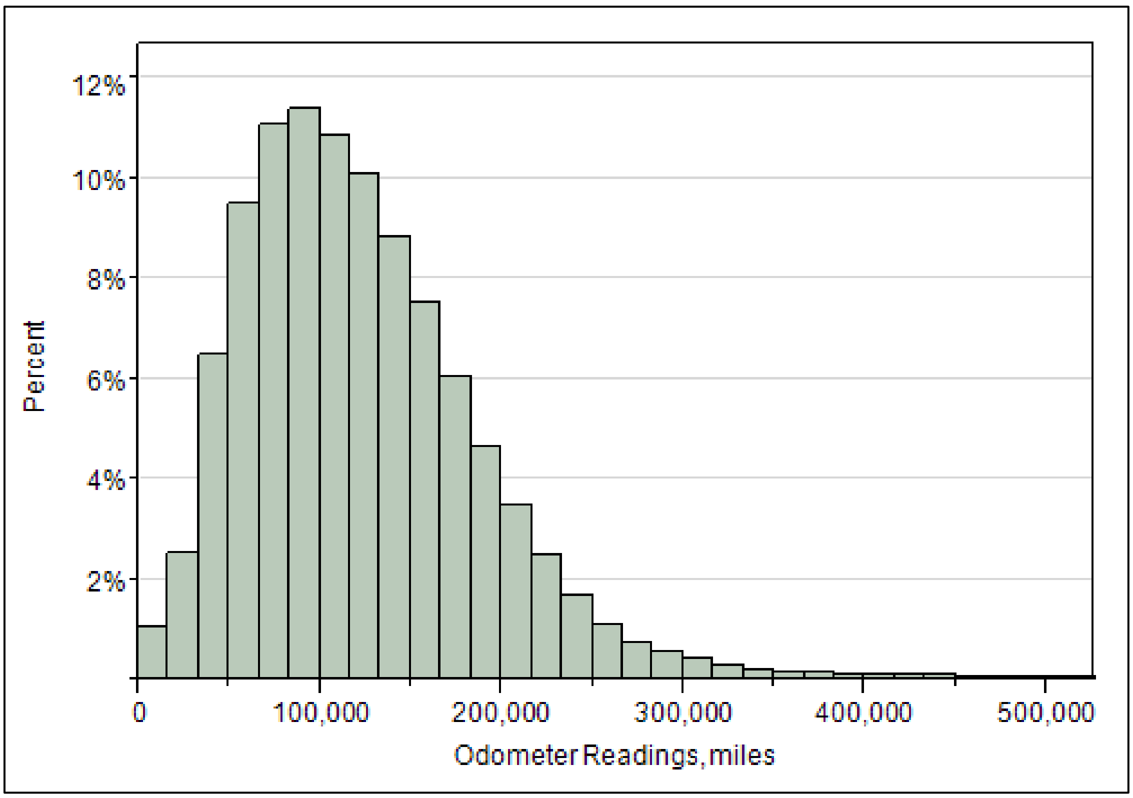

Figure 5-14 Odometer distribution

The average car that is being considered in this model has been driven approximately 121 thousand miles. Detailed statistical description of the odometer data is presented in Table 5-5.

Table 5-5 Summary statistics for odometer distribution

Mean	121,562
Standard Deviation	63,367
Standard Error Mean	202
Upper 95% Mean	121,957
Lower 95% Mean	121,166
Number of Samples	98,573

The relationship between accumulated miles and failure rate is illustrated in Figure 5-15. It is not surprising that as vehicles used more and accumulate more miles the failure rate is going up.

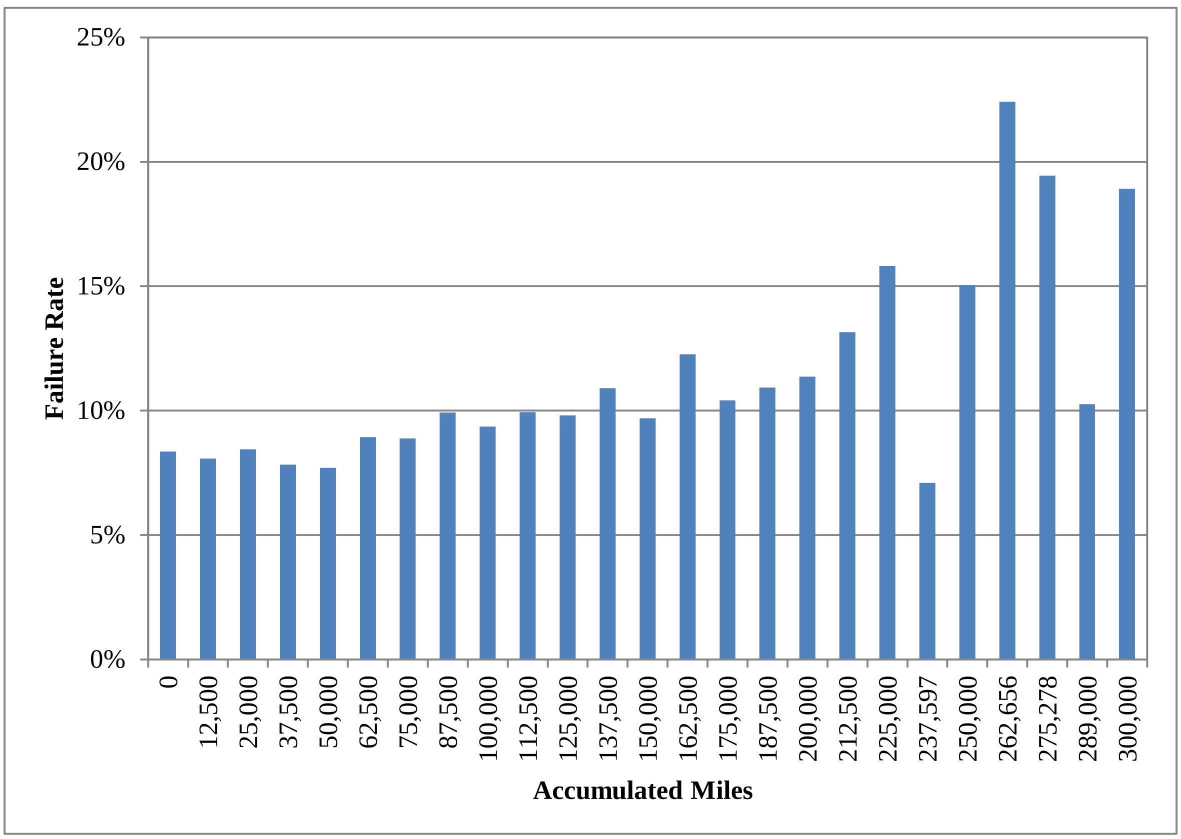

Figure 5-15 Emission test failure rate vs Accumulated Miles (Odometer readings)

5.1.8 Length of Ownership

Every owner may treat their vehicle differently. Some my pamper their cars and keep them in top mechanical condition; others may not maintain their vehicles as well. In this chapter variable that may describe the differences between owners is investigated. Resulting difference if they exist will be derived. If there is one the difference should be incorporated into considerations for frequency of emission tests. This section will examine one of the parameters that can shed some light on this question.

Length of ownership may be one of the parameters describing responsible ownership practices. Length of ownership is defined as the difference between the date of purchase and date of measurement in years. Length of vehicle ownership was examined using two techniques. One examined the full data sample including all vehicles used in the model. The second analyzed the length of ownership of two samples. Vehicles that passed the emission inspection test were separated from vehicles that failed the emission inspection test to examine if there any statistically significant differences between the two samples.

Figure 5-16 represent distribution of Length of Ownership variable. Vehicles had the range of ownership spanning from 0 to 25 year, with the majority of having the length of ownership between 1 and 6 years old.

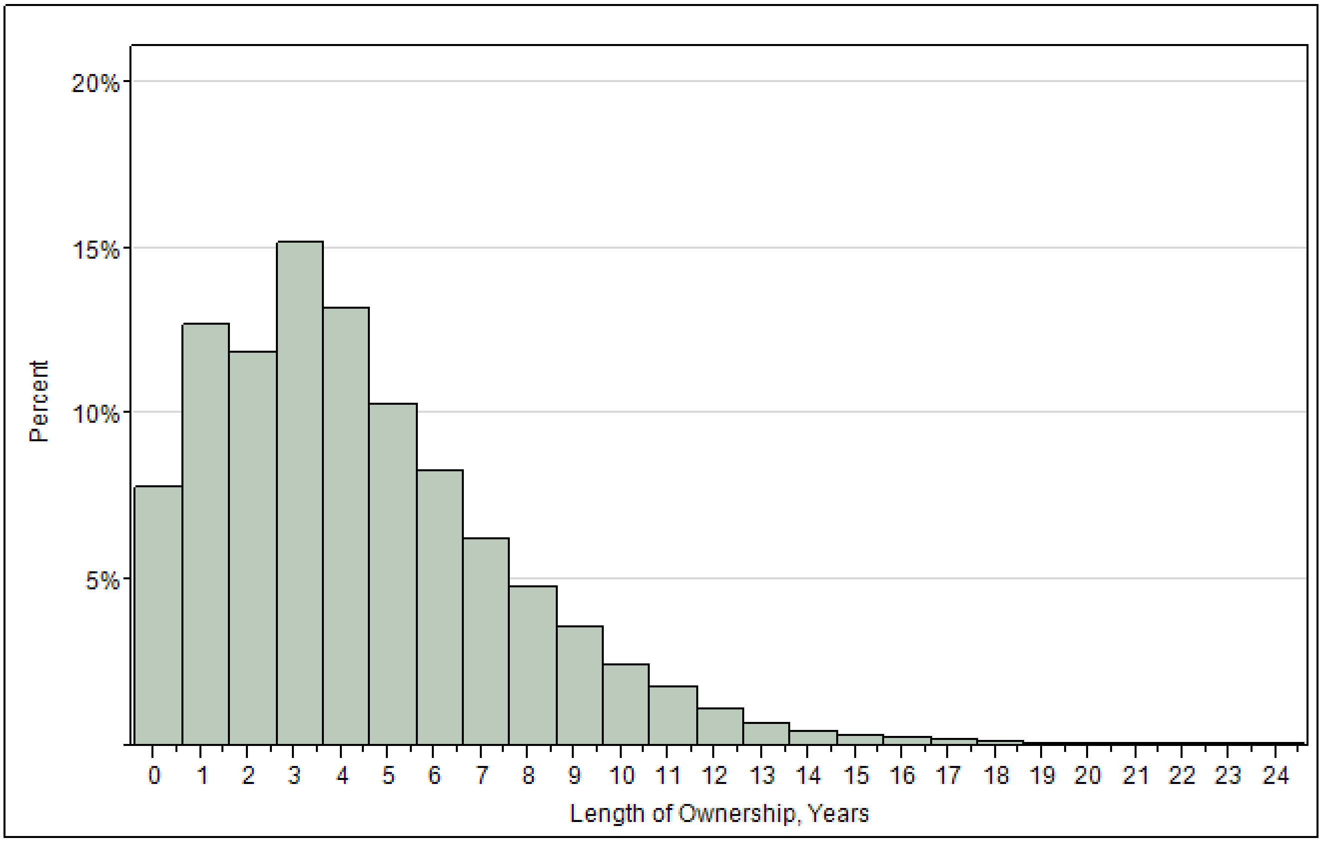

Figure 5-16 Distribution of length of ownership

Figure 5-17 represents failure rates based on length of ownership. As evidenced by the plot, failure rates fall as length of ownership increases. This may suggest that owners that keep vehicles longer take care of those vehicles well enough to pass emission tests. Data for vehicles over 15 years old were excluded because the number of samples for those groups are too low.

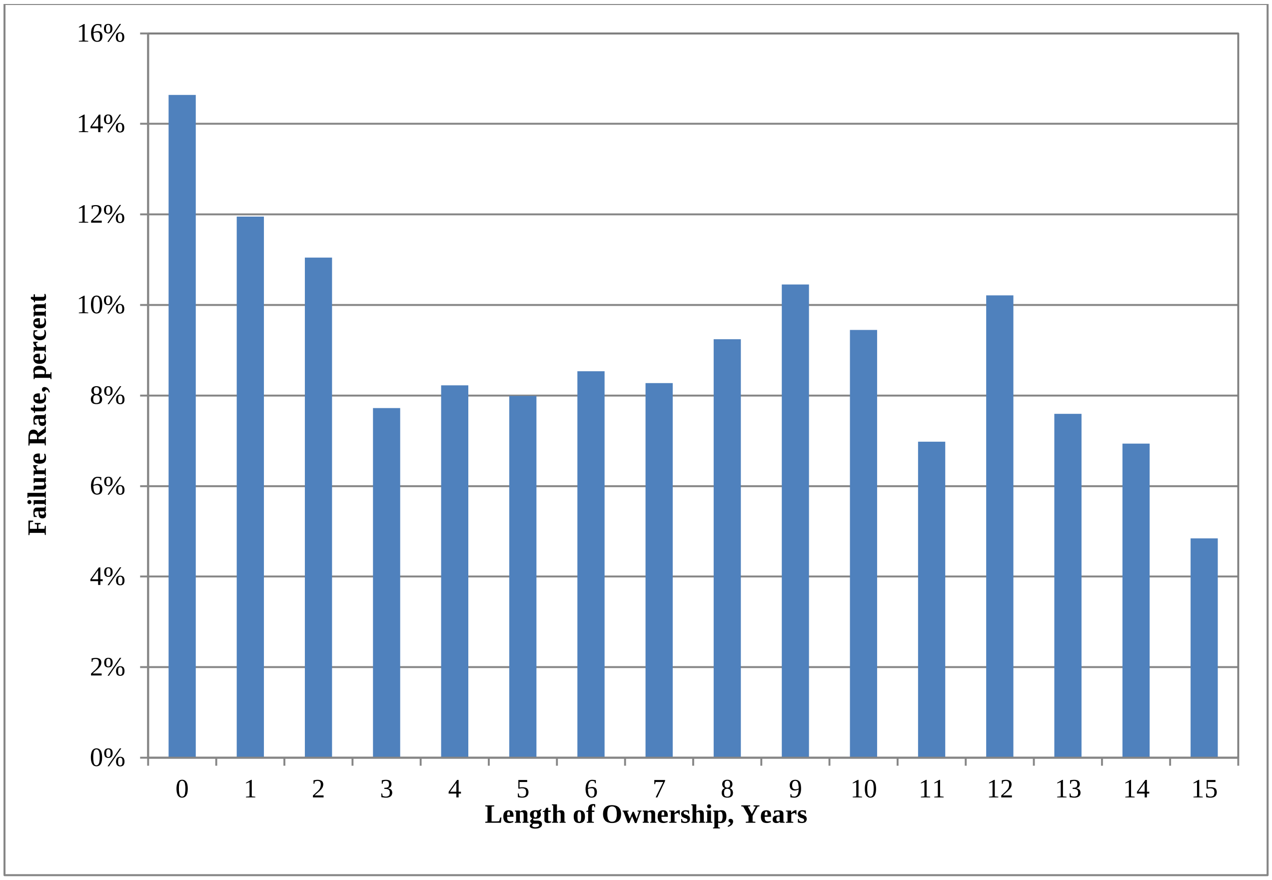

Figure 5-17 Failure rates for length of ownership

Initial analysis of length of ownership revealed that the average vehicle is owned for a little more than 4 years and the majority of vehicles are owned between one and five years. Summary statistics for the full sample can be viewed in Table 5-6.

Table 5-6 Length of ownership summary statistics full sample

Mean	4.26
Standard Deviation	3.14
Standard Error Mean	0.01
Upper 95% Mean	4.28
Lower 95% Mean	4.24
Number of Samples	98,573

Figure 5-18 represents the relationship between emission test failure rate, model year, and length of ownership. It is evident from the chart that as vehicles getting older they fail more often, however even when vehicles are getting older and length of ownership is increasing vehicle emission failure rate does not increase. For example comparing vehicles that have zero length of ownership to vehicles that have six years of ownership vehicles in the same model year have lower emission test failure rates for the vehicles with six years of ownership than vehicles with zero years of ownership.

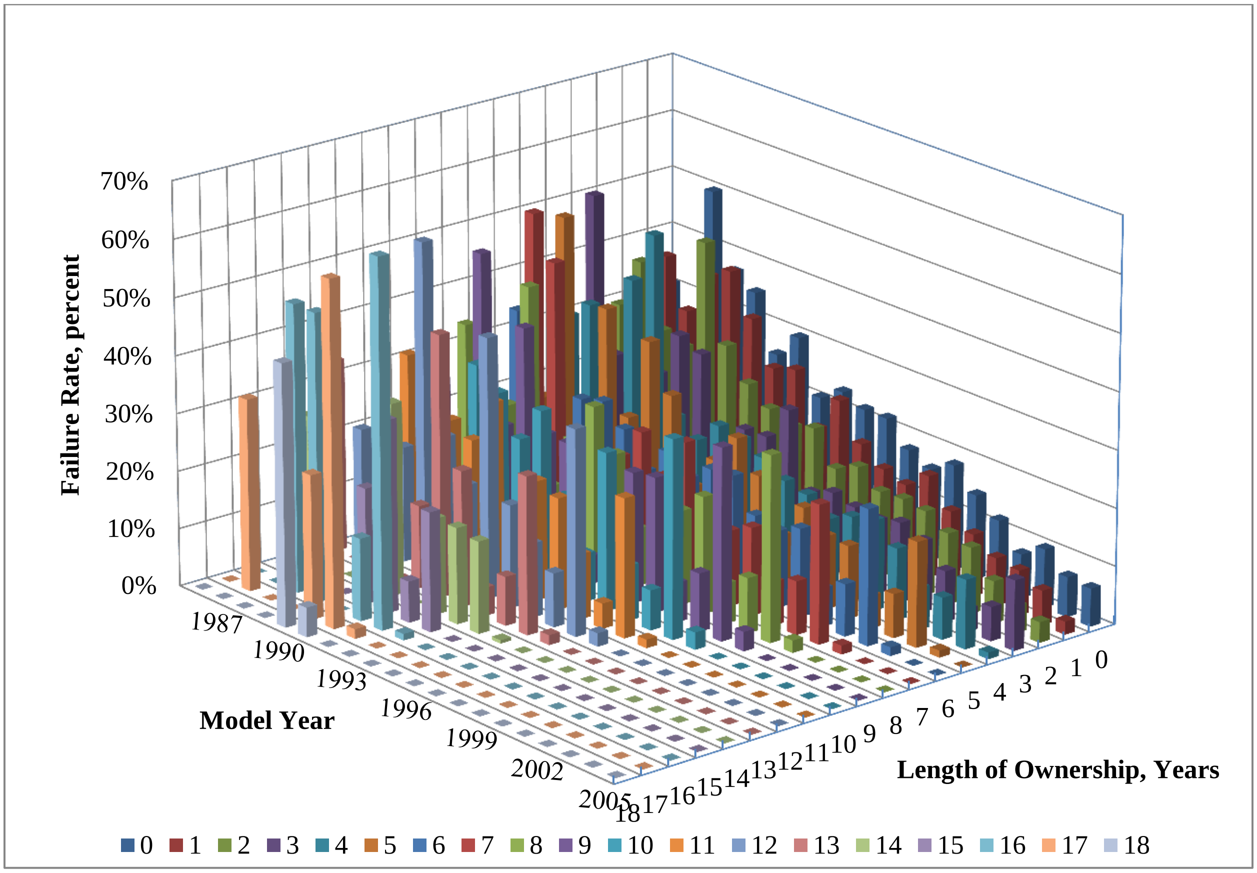

Figure 5-18 Emission inspection failure rate vs model year vs length of ownership

The next set of analysis was done separately for vehicles that passed the emission inspection test and vehicles that failed the emission inspection test. For the group of vehicles that passed the emission inspection test the average age was 4 years. Distribution for length of ownership for vehicles that passed and vehicles that failed the emission inspection is shown in

Figure 5-19. Distribution of length of vehicle ownership for vehicles that passed emission inspection peaked at about 5 years of ownership whereas vehicles that failed emission inspection peaked at about 2 years of ownership.

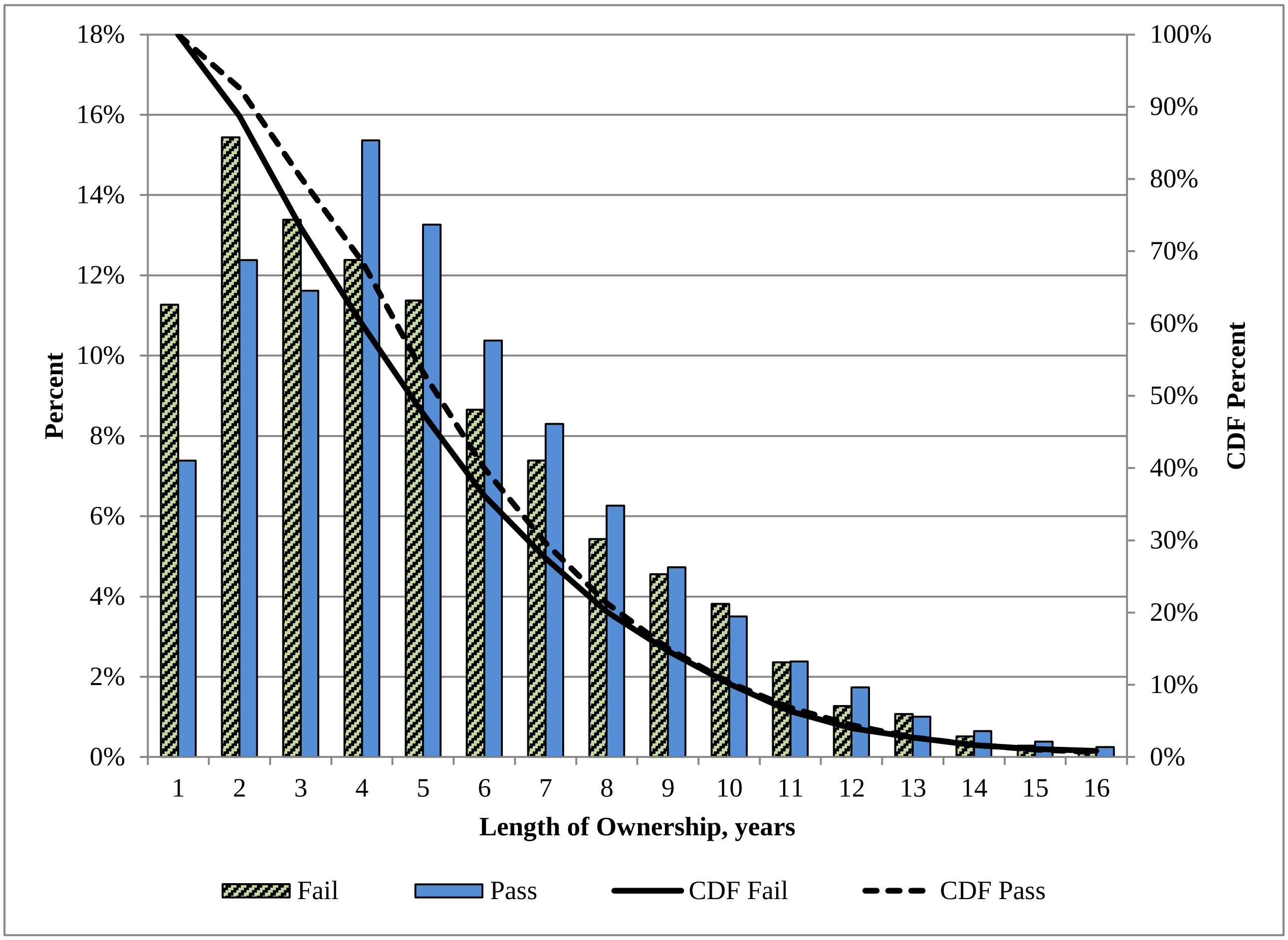

Figure 5-19 Distribution of length of ownership 'pass' and 'fail' groups

Table 5-7 shows summary statistics for length of ownership for 'pass' group.

Table 5-7 Summary statistics for length of ownership 'pass' group

Mean	4.29
Standard Deviation	3.13
Standard Error Mean	0.01
Upper 95% Mean	4.31
Lower 95% Mean	4.27
Number of Samples	89,948

Vehicles that failed emission inspection had a shorter length of ownership. The average time that the vehicle was held in this group was 3.97 years.

Table 5-8 Summary statistics for length of ownership 'fail' group

Mean	3.97
Standard Deviation	3.29
Standard Error Mean	0.04
Upper 95% Mean	4.04
Lower 95% Mean	3.90
Number of Samples	8,625

To test two populations of vehicles: one that passed the emission inspection test and one that failed emission inspection test Kolmogorov-Smirnov non-parametric test is utilized. The null hypothesis in this case it that two populations have the same distribution. The alternative hypothesis is that the distributions of two populations are different. The test reveals that two underlying distributions are different. The null hypothesis have been rejected since D-value is smaller than α=0.05.

Table 5-9 Kolmogorov-Smirnov test for the length of ownership distribution of passed and failed vehicles

KS	KSa	D=max|F1-F2|	D-value
0.0245728	7.7149621	0.0869636	<.0001*

CDF for length of ownership distributions for vehicles that passed and failed emission inspection is presented in Figure 5-20.

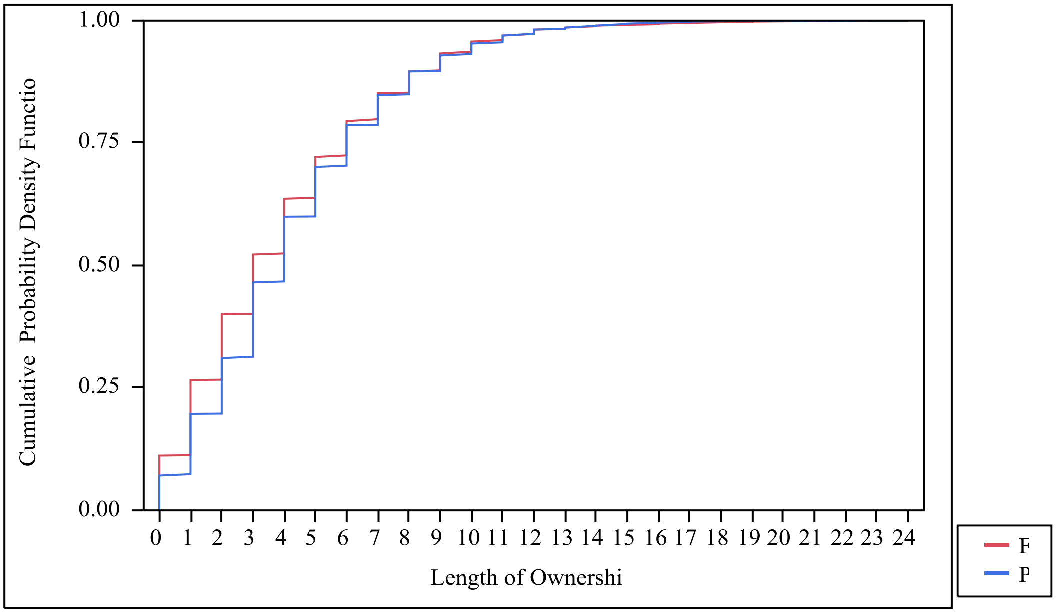

Figure 5-20 CDF of length of ownership for passed and failed vehicles.

5.1.9 Original Owner

The other parameter that can help to differentiate between responsible and less so owners can be an original owner flag. Differences for two conditions were examined: 1) if the car is owned by the original owner or 2) it was bought and sold shortly thereafter. Original owner is a categorical variable that was derived from two variables: purchase date extracted from Georgia Registration data and the vehicle's model year. If the vehicle model year and purchase date year are the same, then the original owner variable takes the value of '1', representing the original owner. If the purchase date and the model year are different then this variable was given a value of '0', representing a non-original owner.

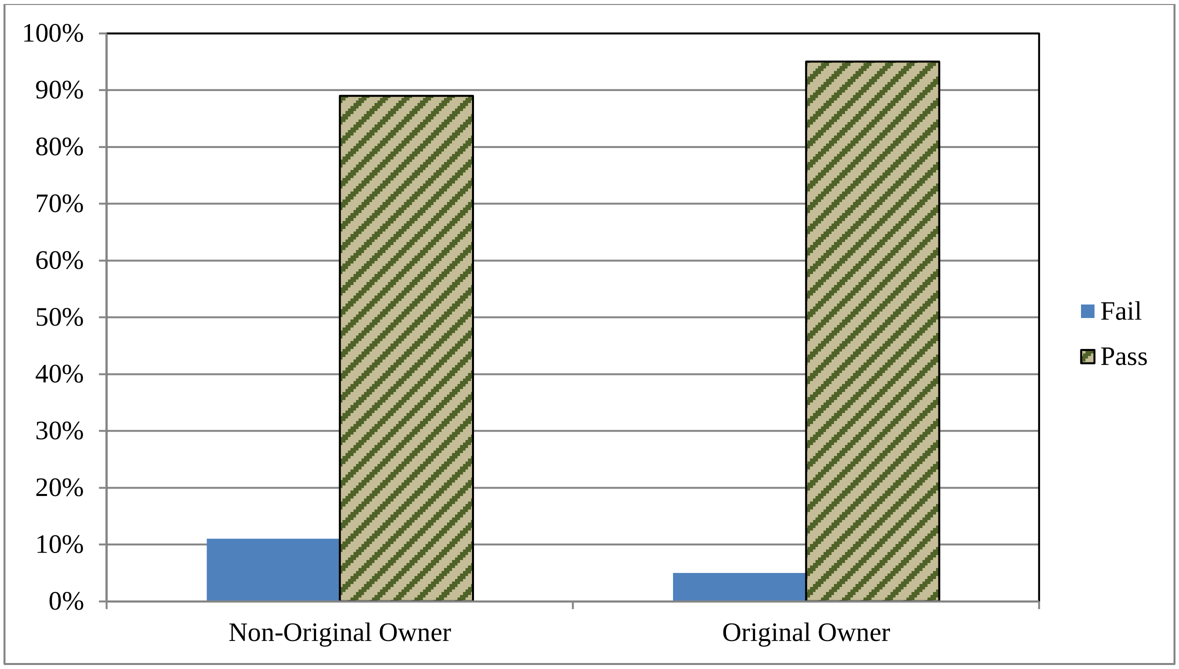

Figure 5-21 Failure rates for 'original' vs. 'non-original' owner

Figure 5-21 shows clear differences between original owner vehicles and non-original owner vehicles. However, non-original owner vehicles are older than the original owner vehicles; therefore, to truly estimate if there is a difference between the two populations, vehicles from each group were analyzed.

Table 5-10 t-test results for Pass/Fail Original Owner Populations

Difference	2.78
Std Err Dif	0.02
Upper CL Dif	2.82
Lower CL Dif	2.74
Confidence	0.95
t Ratio	135.23
Degrees of Freedom	102886.3
Prob > |t|	<.0001*
Prob > t	<.0001*
Prob < t	1.0000

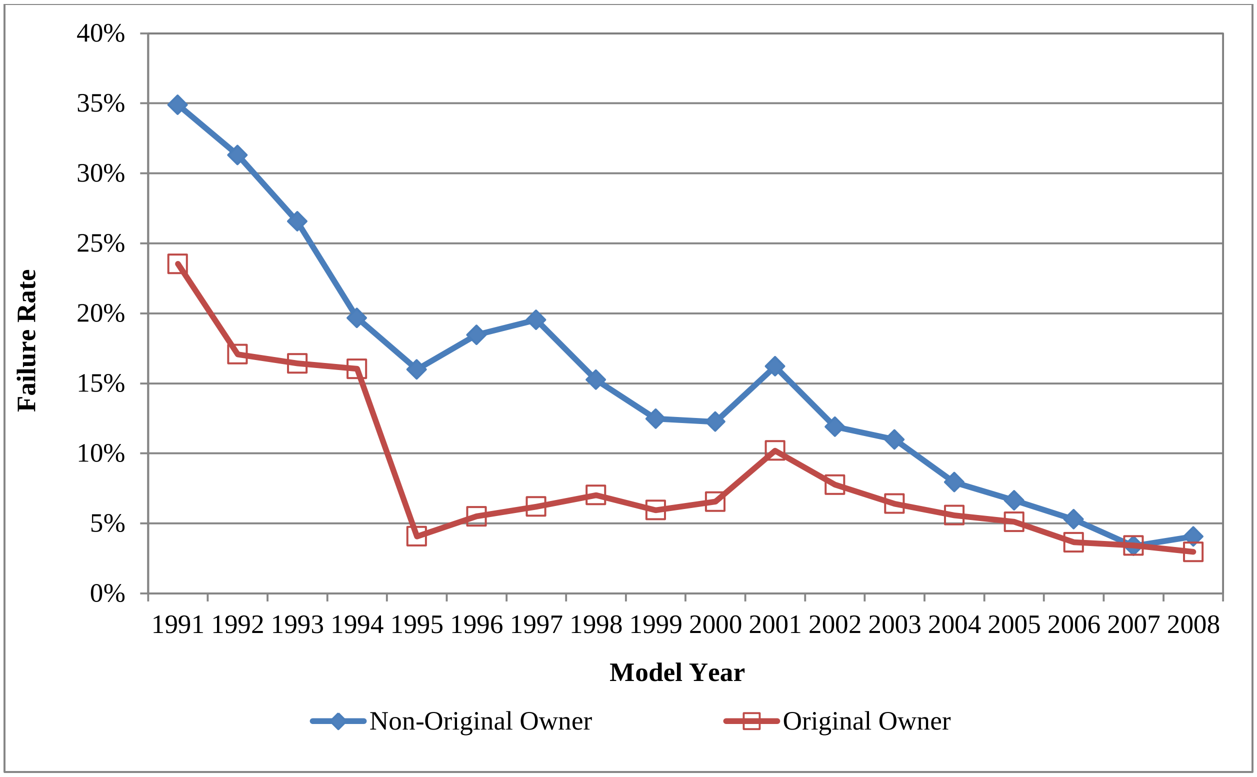

Figure 5-22 Failure rates of 'original' vs.'non-original' owner by model year

Comparing two populations of vehicles by model year showed that for nearly all model years, except for a couple of newer model years, failure rates of non-original owner vehicles were higher. Data was plotted starting from 1991, since for the model years 1986 to 1991 had a small sample size. The conclusion suggests that the original owner variable can be predictive of vehicle failure.

Table 5-11 'Original' vs. 'non-original' Owner fail / pass statistics

Count Col %	Non-Original Owner	Original Owner
Fail	6,919 10.58%	1,706 5.14%
Pass	58,448 89.42%	31,500 94.86%
	65,367 66.31%	33,206 33.69%

Table 5-11 presents a summary of the data for the original owner and non-original variable analysis.

5.1.10 Engine Displacement Category

Displacement recoded is a variable derived from vehicles displacement values obtained from the VIN decoder. Although displacement values are present in Georgia registration and Georgia inspection and maintenance databases, the VIN decoder provides more accurate results since it is decoding each vehicle's VIN identification number individually.

The displacement variable has a multitude of values. To make it more manageable, raw displacement figures were recoded into eight categories. Vehicles with displacement of one liter or less were placed into category "1." Vehicles with displacement between one and two liters were placed into category "2" and so on through category "8." The distribution of the displacement-recoded variable is shown in Figure 5-23.

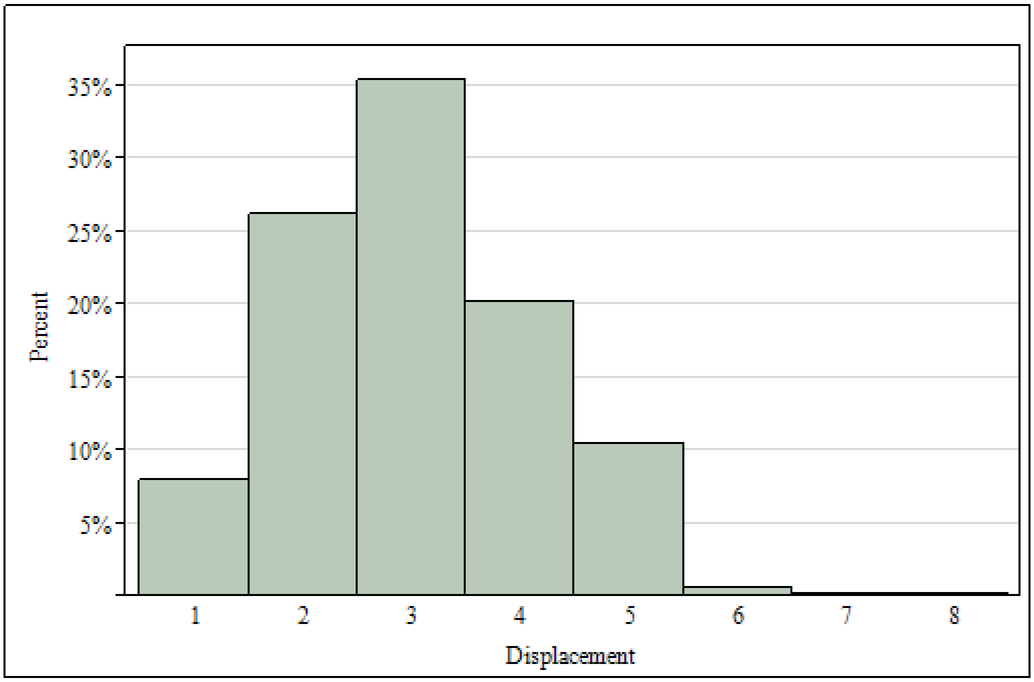

Figure 5-23 Distribution of displacement recoded categories

Table 5-12 represents summary statistics for the displacement-recoded category. The average vehicle has a three liter engine with a standard deviation of 1.1 liters.

Table 5-12 Displacement recoded categories summary statistics

Mean	3.00
Standard Deviation	1.11
Standard Error Mean	0.00
Upper 95% Mean	3.01
Lower 95% Mean	2.99
Number of Samples	99,998

The vehicle's engine displacement appears to have inverse relations to vehicle emission test failure rates. As vehicle's engine displacement increases emission testing failure rates seem to slightly decrease (Figure 5-24). This can happen for several different reason such as vehicles with larger engine, especially passenger cars, are more expensive with more sophisticated engine controls. Since they are more expensive they are most likely better maintained and therefore have lower emission failure rates. At the same time the failure rates are only significantly lower for only one vehicle displacement category (vehicles with engine displacement between 5 and 6 liters) for the rest of the vehicles failure rate is holding steady (Table 5-13).

Table 5-13 Number of vehicles and failure rates for displacement category

Displacement	Pass	Fail	Total	Percent Failed
1	650	5937	6587	10%
2	2247	19686	21933	10%
3	2683	26961	29644	9%
4	1743	15120	16863	10%
5	739	7930	8669	9%
6	25	364	389	6%

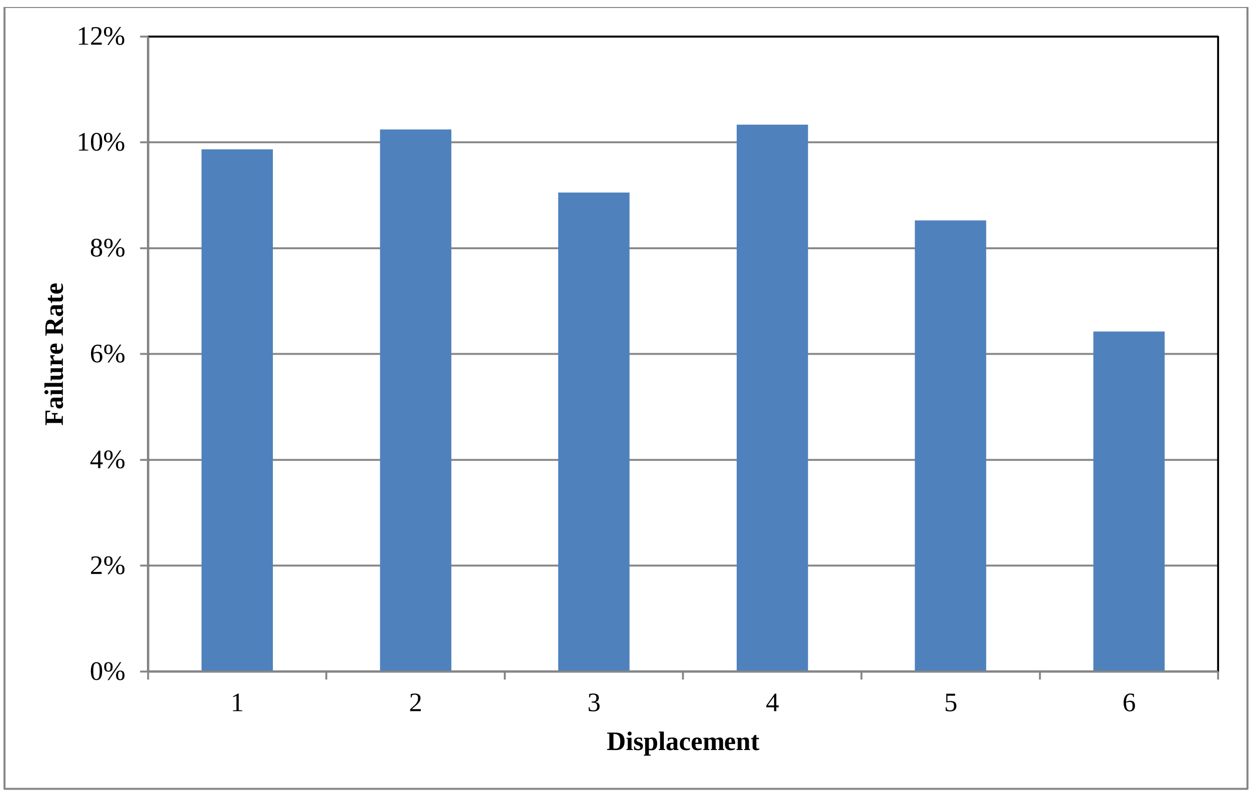

Figure 5-24 Emission test failure rate for displacement categories

5.1.11 Emission Test Results 2010

Emission test results 2010 is a result of 2010 emission tests. Those results were obtained from the 2010 Georgia Inspection and Maintenance database. Only pass or fail results are included in this analysis; all abort (in the I/M 2010 data set marked as ‘A’) and error readings were removed. From 117,294 total records 10,345 had failed results, which represents approximately 8.82% of the fleet and 106,949 vehicles had a passing reading, which represents approximately 91.18% of the fleet. It has to be pointed out that, analyzing all records from the Georgia Inspection and Maintenance database of 2010, 9.77% of vehicles failed the emission test. The sample used for these analyses includes only I/M 2010 records that merged with CAFÉ project emission records and it slightly under-represents failed vehicles. A sample collected for the CAFÉ project is slightly skewed toward cleaner vehicles.

5.1.12 Emission Test Results 2009

Emission test result from the previous year is considered to be a variable that is used in the model since previous emission test results are usually strong predictors for future vehicle emission testing. Emission test results 2009 is a result of the test for calendar year 2009. Vehicles with VIN matching 2010 emission inspection data were selected for this analysis. Just like test results for 2010, 2009 data was cleaned of abort or error readings. 93,602 vehicle VINs from 2010 were matched to 2009 emission inspection results. 7,736 vehicles had failed emission inspection, which represents 8.26%, and 85,866 vehicles had passed the emission inspection in 2009, which represents 91.73% of the sample. Only 79.80% of vehicles with emission inspection test results for 2010 matched to 2009 emission inspection results. This is due to new vehicles entering the emission testing vehicle pool, i.e., vehicles that became four years old and were required to have an emission test in 2010 that did not have to be tested in 2009. Another factor is the attrition of vehicles to neighboring counties or other geographical locations.

5.1.13 Miles Per Year

Miles per year, more precisely, miles per year from 2009 to 2010, were calculated by subtracting odometer readings for 2009 from odometer readings of 2010. Missing values from Inspection and Maintenance database were supplemented by the records from the Georgia Registration database. Missing values were calculated by dividing odometer readings obtained from the 2010 emission inspection database by the vehicle age. Figure 5-25 represents the distribution of miles per year. Vehicles are traveling, on average, 16,645 miles per year with a standard deviation of 7,649. Detailed results can be seen in summary statistics for distribution of miles per year Table 5-14.

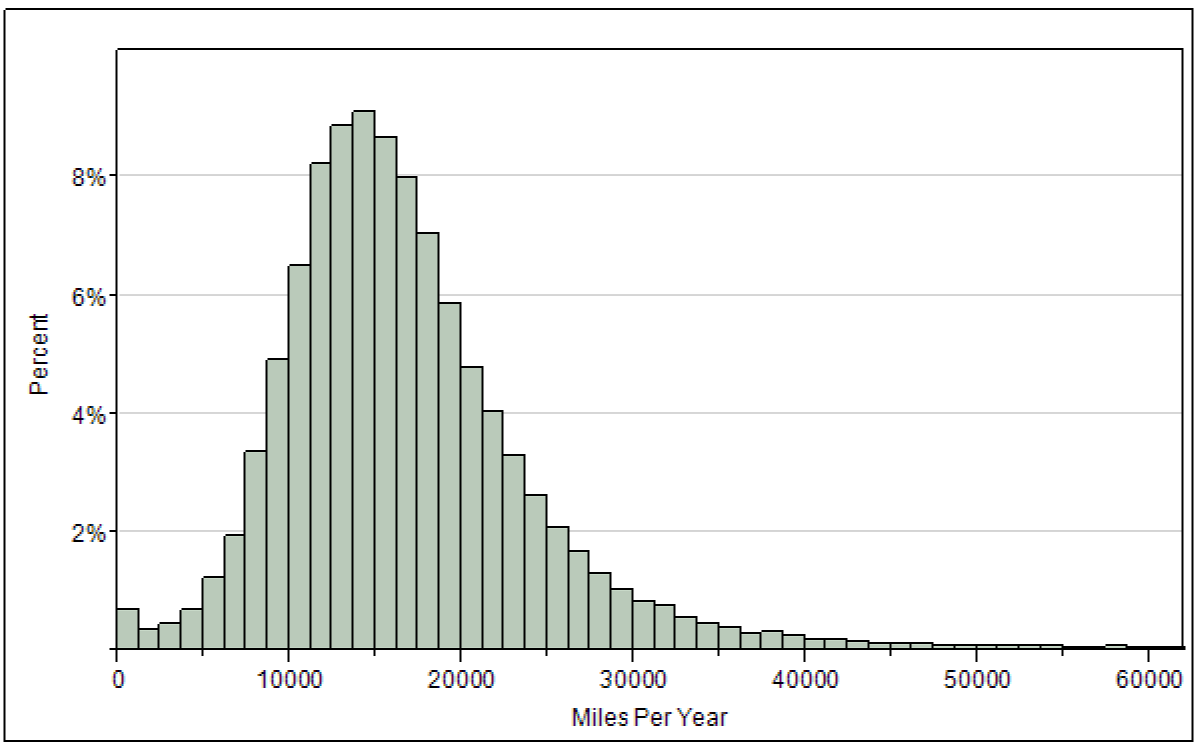

Figure 5-25 Distribution of miles per year

Table 5-14 Summary statistics for miles per year

Mean	16,650
Standard Deviation	7612
Standard Error Mean	24
Upper 95% Mean	16,697
Lower 95% Mean	16,603
Number of Samples	98,572

Figure 5-26 represents relationship between vehicle's emission test failure rate and annual vehicle miles traveled. As annual vehicle miles traveled increased vehicle's emission test failure rate increase as well until it levels off at the higher end of annual miles traveled.

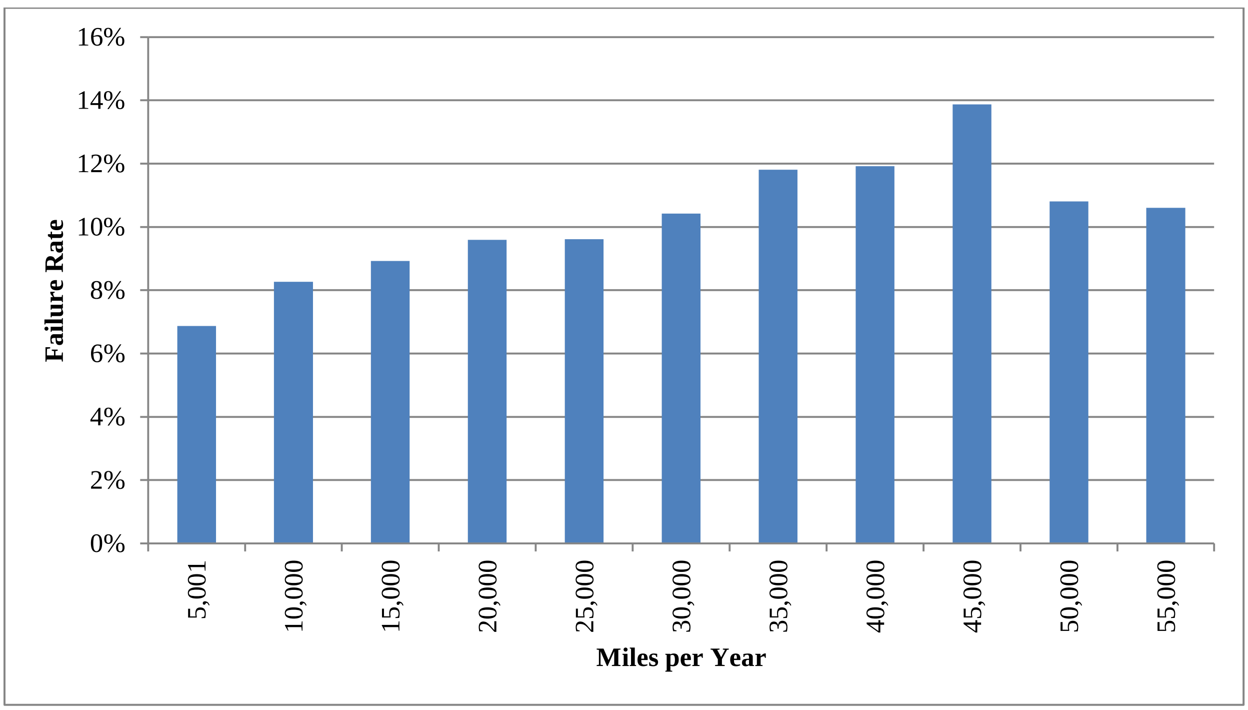

Figure 5-26 Failure rate vs annual miles traveled

5.2 Estimating Probability of Failure Model

5.2.1 Correlation between variables

Correlation matrix shown in Table 5-15 describes correlation between all pairs of data sets. There are some pairs that have somewhat strong correlation and since variable independence is one of the assumptions of linear regression they must be excluded from analysis. For example, carbon monoxide and hydrocarbon remote sensing measurements have a correlation coefficient of 0.27. Therefore, only one variable, which is the strongest predictor of probability of failure between carbon monoxide and hydrocarbons is going to be used in the model. There are other variable pair that shows significant correlation such as length of ownership and model year. Both of those variable are going to stay in the model because they have an impact on policy component of the proposed program. The other variable pair that has strong correlation is miles per year and model year. Both of the variables are also part of the policy impact on vehicle use and therefore will be kept in the model. Other variable pairs do not show strong correlation and therefore are statistically independent.

Table 5-15 Correlation Matrix

	COperc	HCppm	NOxppm	Model Year	Odometer_RDB	Length of Ownership	Miles per year
COperc		0.2705	0.1129	0.0658	0.0684	-0.0238	0.0663
HCppm	0.2705		0.1314	-0.0424	0.0540	-0.0009	-0.0207
NOxppm	0.1129	0.1314		-0.0654	0.1621	-0.0222	-0.0149
Model Year	0.0658	-0.0424	-0.0654		-0.0516	-0.2842	0.3208
Odometer	0.0684	0.0540	0.1621	-0.0516		-0.0790	0.0061
Length of Ownership	-0.0238	-0.0009	-0.0222	-0.2842	-0.0790		-0.0330
Miles per year	0.0663	-0.0207	-0.0149	0.3208	0.0061	-0.0330	

Several variables such as model year, odometer readings, length of ownership, miles per year are explanatory variables and observed without error. Other variables such as carbon monoxide and nitrogen oxides are normally distributed with larger sample size.

Relationship between failure rates and variables that are used in the model were demonstrated in previous sections and are linear. Therefore the use of linear regression model is justified in the use of the probability of failure prediction.

5.2.2 Stepwise methods

To model the probability of failure of the emission test, ten variables describing vehicle emission readings, vehicle characteristics, vehicle ownership history, and past emission test results were entered into the model. They are: carbon monoxide, hydrocarbons, and nitrogen oxides, measurements from remote emission sensing; Model year, Length of ownership, Original owner indicator, Odometer, Previous test result, Miles per year, and engine displacement variable. Units for model variables are shown in Table 5-16.

Table 5-16 Model Variables and units

Variable	**Units**
Carbon Monoxide	Percent
Hydrocarbons	Parts per million
Nitrogen Oxides	Parts per million
Model Year	Year
Length of ownership	Years
Original owner indicator	0 – original, 1 – non-original
Odometer	Miles
Previous test results	P- pass, F- Fail
Miles per year	Miles
Displacement	Liters

First, a stepwise method was used to determine if any of the aforementioned variables are significant in explaining the probability of future test results. Stepwise regression is an approach to selecting a subset of effects in a regression model. It is often used when there are numerous terms and there is a desire to reduce the number of variables and provide a good fit. In practice it is a simpler procedure to include variables that are significant for the model in one step instead of testing each variable separately. Resulting model results are presented in Table 5-17.

Table 5-17 Stepwise regression

-LogLikelihood	**p**	**R-Square**	**AICc**	**BIC**
23186.478	9	0.0655	46391	46474.7

Table 5-18 represents parameter estimates for variables that were inserted in the model and considered significant. Those variables are marked with 'X' in the Entered column. Variables that were not entered in the model were deemed to be not significant and are not marked in Table 5-18 with an 'X' in Entered column. Out of ten variables investigated, only two were not significant. Those are 'HC ppm' – hydrocarbon readings, and displacement, which is a recoded variable deriving from vehicle displacement. Hydrocarbons are closely correlated with carbon monoxide readings which may be the reason why it is as insignificant in the model.

Table 5-18 Stepwise regression parameter estimate

Lock	Entered	Parameter	Estimate	nDF	Wald/Score ChiSq	"Sig Prob"
X	X	Intercept	108.907131	1	0	1
	X	CO percent	0.19262956	1	81.47153	<.0001
		HC ppm	0	1	3.197673	0.07374
	X	NOx ppm	0.00026	1	164.2869	<0.0001
	X	Model year	-0.0556844	1	57.43359	3.5e-14
	X	Length of ownership	-0.0541014	1	123.496	<.0001
	X	Original owner{0-1}	0.08662685	1	19.66397	0.00001
		Displacement	0	1	3.525162	0.06044
	X	Odometer	2.88084e-6	1	38.88251	<.0001
	X	2009 Emission test result {F-P}	0.49498031	1	888.7988	<.0001
	X	Miles per year	1.53452e-5	1	15.78931	0.00007

Table 5-19 shows the variables that were entered into a model in order of significance. According to Table 5-19 the most significant variable in predicting results of next year's test is the previous test result (2009 Emission Test Result). It is followed by Odometer readings, NOx ppm, Length of ownership, CO percent, Model year, Original owner indicator, and Miles per year. As mentioned previously, HC ppm and displacement recoded were deemed not significant.

Table 5-19 Stepwise regression step history

Step	Parameter	Action	L-R ChiSquare	"Sig Prob"	R-Square	p	AICc	BIC
1	2009 Emission test result{F-P}	Entered	1347.417	0.0000	0.0272	2	48281.6	48300.3
2	Odometer	Entered	1085.319	0.0000	0.0490	3	47198.3	47226.2
3	NOx ppm	Entered	299.073	0.0000	0.0550	4	46901.2	46938.5
4	Length of ownership	Entered	278.6234	0.0000	0.0607	5	46624.6	46671.2
5	CO percent	Entered	122.3755	0.0000	0.0631	6	46504.2	46560.1
6	Model year	Entered	89.00627	0.0000	0.0649	7	46417.2	46482.4
7	Original owner{0-1}	Entered	14.64965	0.0001	0.0652	8	46404.6	46479
8	Miles per year	Entered	15.63209	0.0001	0.0655	9	46391	46474.7
9	HC ppm	Entered	3.456312	0.0630	0.0656	10	46389.5	46482.6
10	Displacement	Entered	3.530003	0.0603	0.0657	11	46388	46490.4
11	Best	Specific			0.0655	9	46391	46474.7

After eliminating non-significant variables, a nominal logistic fit model with logit treatment was used to calculate the probability of a vehicle's emission test failure. The whole model test shown in Table 5-20 indicates that the model is statistically significant.

Table 5-20 Model Test

Entropy R-Square	0.0665
Generalized R-Square	0.0867
Mean -Log p	0.2798
RMSE	0.2775
Mean Abs Dev	0.1536
Misclassification Rate	0.0891
Number of Samples	72,279

Table 5-21 shows parameter estimates and test of variable significance. All variables entered in the model are deemed to be significant. The model in formula form is represented below.

Table 5-21 Model parameter estimate

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	109.243096	15.198105	51.67	<.0001*
COperc	0.20474529	0.0219972	86.63	<.0001*
NOxppm	0.00025287	2.1434e-5	139.19	<.0001*
Year_RDB	-0.0558151	0.0075946	54.01	<.0001*
Length of ownership	-0.051641	0.0051802	99.38	<.0001*
Original owner	-0.2077606	0.0420499	24.41	<.0001*
2010_ODOMETER	2.91277e-6	4.8159e-7	36.58	<.0001*
2009_OVERALL_TEST_RES[F]	0.49696457	0.0178174	777.97	<.0001*
Miles per year	1.51222e-5	4.0414e-6	14.00	0.0002*

$$
\begin{aligned}
LIN[F] = {} & 109.5167 + 0.205 * CO\ Percent + 0.00026 * NOxppm - 0.056 * Model\ Year \\
& - 0.052 * Length\ of\ Ownership + Original\ Owner * \{0, 0.208|1, -0.208\} \\
& + 0.000003 * Odometer + Previous\ Test\ Result * \{\text{"F"}, 0.4970|\text{P}, -0.4970\ \} \\
& + 0.0000151 * Miles\ Per\ Year,
\end{aligned}
$$

where Lin [F] is a linear combination of the regressors.

Probability of failure can be found by using the following formula:

$$
Probability\ [F] = \frac{1}{1 + Exp(-LIN[F])}
$$

Vehicles with a probability of failure higher than 50% are considered to be failing vehicles in this model. Vehicles that have a probability of failure less than 50% are considered to be passing vehicles. However, this research will look at vehicles not from the standpoint of ‘pass’ or ‘fail’ but from the standpoint of the actual probability of failure. Even with a probability of failure below 50% some vehicles are more likely to fail than others. Figure 5-27 shows the model outcome; more precisely, it shows the probability of failure distribution. Summary statistics for the distribution are shown in Table 5-22.

5.3 Model Diagnostics

To check that the resulting model adequately describes the underlying system, model diagnostics are performed. Diagnostics involve plotting model variables against the probability of failure that was calculated by the model and analyzing relationships between variables and the failure rate. If the model is working properly then those relationships should closely follow relationships that were assumed.

Figure 5-27 demonstrates the probability of failure distribution. The majority of vehicles have extremely low probabilities of failure. Judging by
Table 5-23, the 90th percentile of that distribution has a failing rate of 0.16 while the 10th percentile has a failing rate of 0.04 even though the 90th percentile failing rate seems to be low, it is four times larger than that of the 10th percentile.

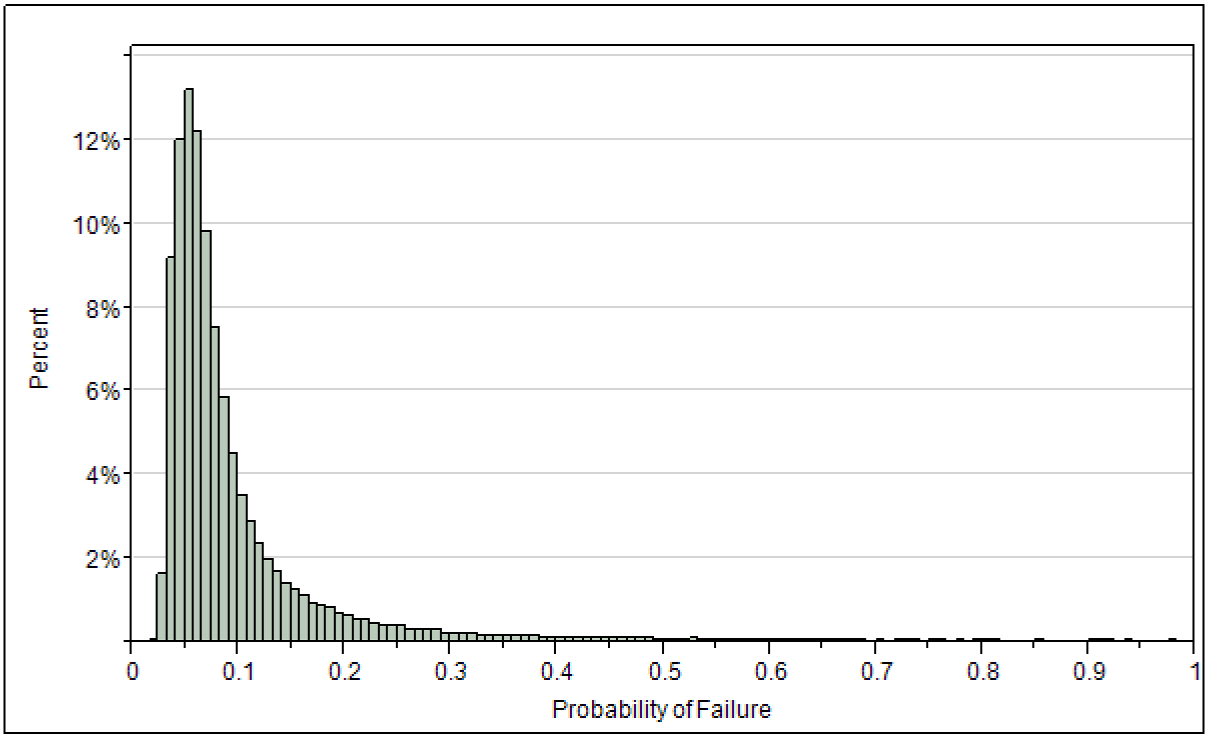

Figure 5-27 Distribution of probability of failure

Table 5-22 Probability of failure summary statistics

Mean	0.0887948
Standard Deviation	0.0659795
Standard Error Mean	0.0002454
Upper 95% Mean	0.0892758
Lower 95% Mean	0.0883138
Number of Samples	72,279

Table 5-23 Probability of failure quantiles

100.0%	maximum	0.97559
99.5%		0.43816
97.5%		0.2767
90.0%		0.15864
75.0%	quartile	0.0993
50.0%	median	0.06823
25.0%	quartile	0.05151
10.0%		0.04117
2.5%		0.03465
0.5%		0.03062
0.0%	minimum	0.02471

Figure 5-28 demonstrates cumulative distribution function for probability of failure predicted by the model.

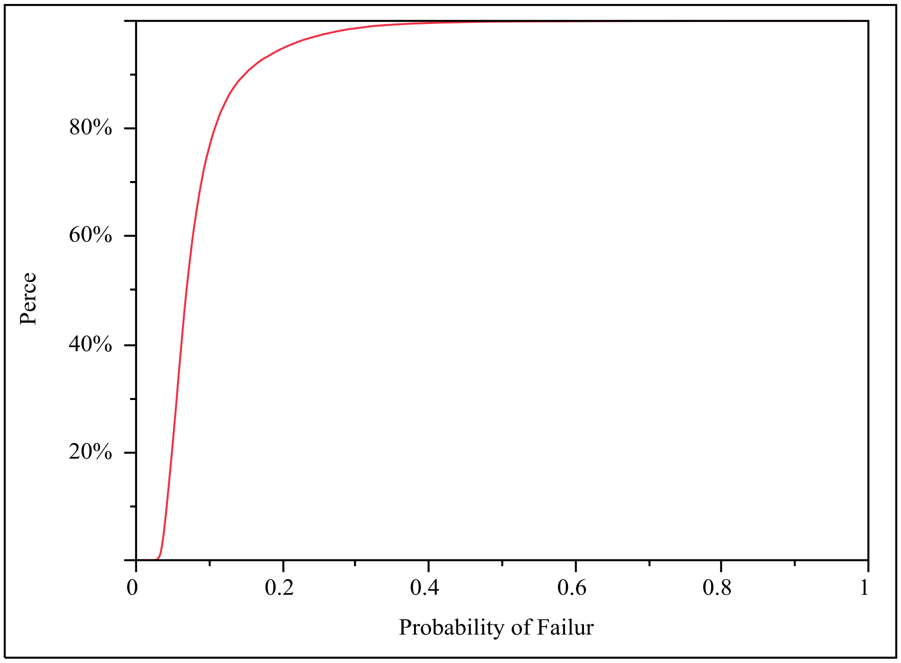

Figure 5-28 Cumulative distribution function for probability of failure identified by the model

5.3.1 Probability of Failure versus Carbon Monoxide

The plot for carbon monoxide readings versus the probability of failure is shown in Figure 5-29. This plot shows the relationship between carbon monoxide readings and the probability of failure calculated by the model. The original assumption for carbon monoxide measurements is that, as carbon monoxide emissions increase, so does the probability of failure. For extremely high carbon monoxide readings, the probability of failure should produce failing results, e.g., the probability of failure should be higher than 0.5. Figure 5-29 displays the relationship between carbon monoxide readings and the probability of failure calculated by the model.

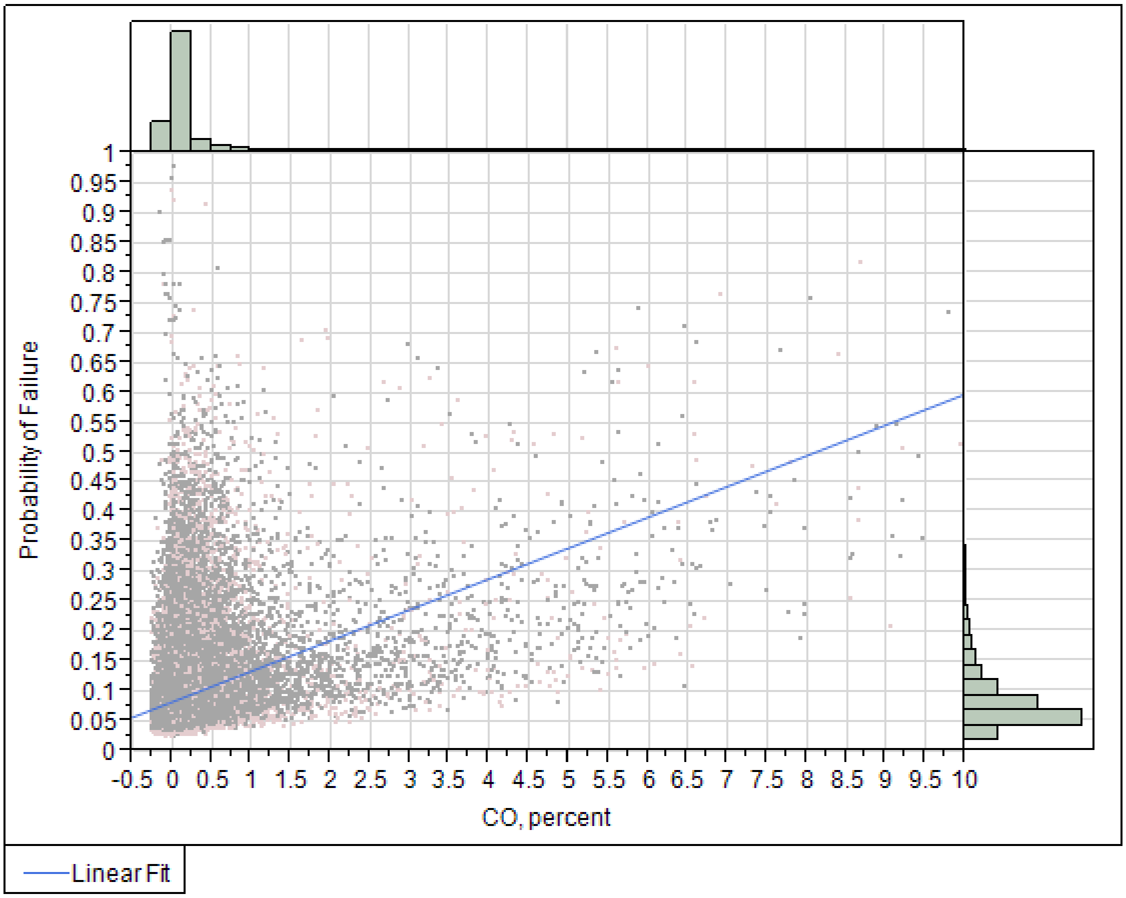

Figure 5-29 Probability of failure vs. carbon monoxide

The equation for the dependence of the probability of failure on carbon monoxide is shown below. This formula is based on parameter estimates provided in Table 5-25.

*Probability of Failure = 0.082 + 0.515 * CO Percent*

Table 5-24 provides summary statistics for the relationship between probability of failure predicted by the model and carbon monoxide readings.

Table 5-24 Summary Statistics for Probability of Failure vs. Carbon Monoxide

R-Square	0.112754
R-Square Adj	0.112742
Root Mean Square Error	0.062149
Mean of Response	0.088795
Observations (or Sum Wgts)	72,279

Table 5-25 Parameter estimates for the probability of failure vs. carbon monoxide

Term	Estimate	Standard Error	t Ratio	Prob>|t|
Intercept	0.0823513	0.000241	342.07	<.0001*
COperc	0.0514806	0.000537	95.84	<.0001*

5.3.2 Probability of Failure versus Model Year

For vehicle model year, a reasonable assumption would be that as vehicles get older their emissions should deteriorate, and therefore older vehicles more likely would be high emitting vehicles and fail more often. Figure 5-30 shows the plot that describes the relationship between the probability of failure and a vehicle's model year. The original assumption is confirmed; as vehicles get older their probability of failure increases.

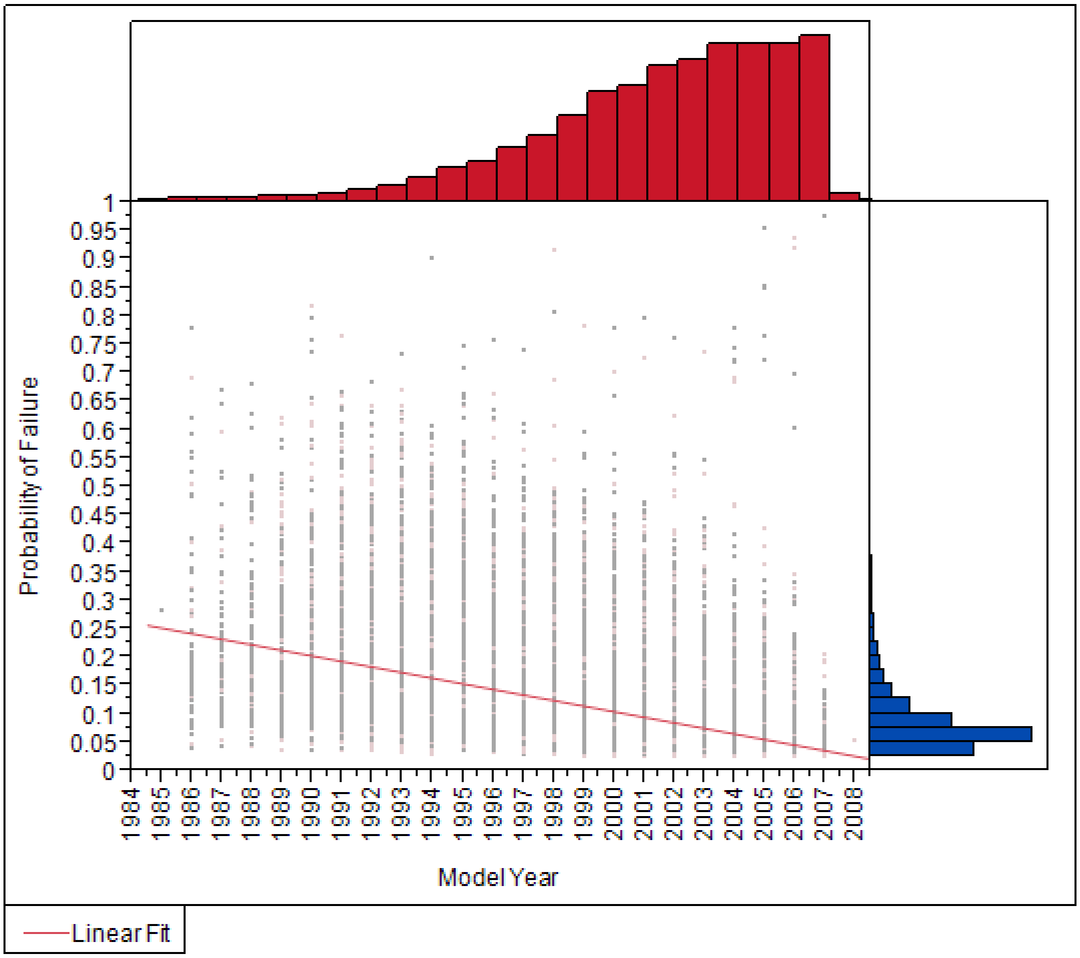

Figure 5-30 Probability of failure vs. model year

The equation for the probability of failure versus model year is based on parameter estimates provided in Table 5-27 and shown below.

$$\textit{Probability of Failure} = 19.721 - 0.0098 * \textit{Model Year}$$

Summary statistics of this model are presented in Table 5-26.

Table 5-26 Summary statistics for probability of failure vs. model year

R-Square	0.289457
R-Square Adj	0.289447
Root Mean Square Error	0.055617
Mean of Response	0.088795
Observations	72,279

Table 5-27 Parameter estimates for the probability of failure vs. model year

Term	Estimate	Standard Error	t Ratio	Prob>|t|
Intercept	19.720506	0.114409	172.37	<.0001*
Model Year	-0.009808	5.716e-5	-171.6	<.0001*

5.3.3 Probability of Failure versus Odometer Readings

The assumption for vehicle miles traveled is that as the vehicles are driven more they will deteriorate at a faster pace than vehicles that are driven less. So the probability of failure for those vehicles will increase. Looking at Figure 5-31 the results from the model produce the type of relationship that was originally assumed. As the vehicle odometer reading increases so does the probability of failure calculated by the model.

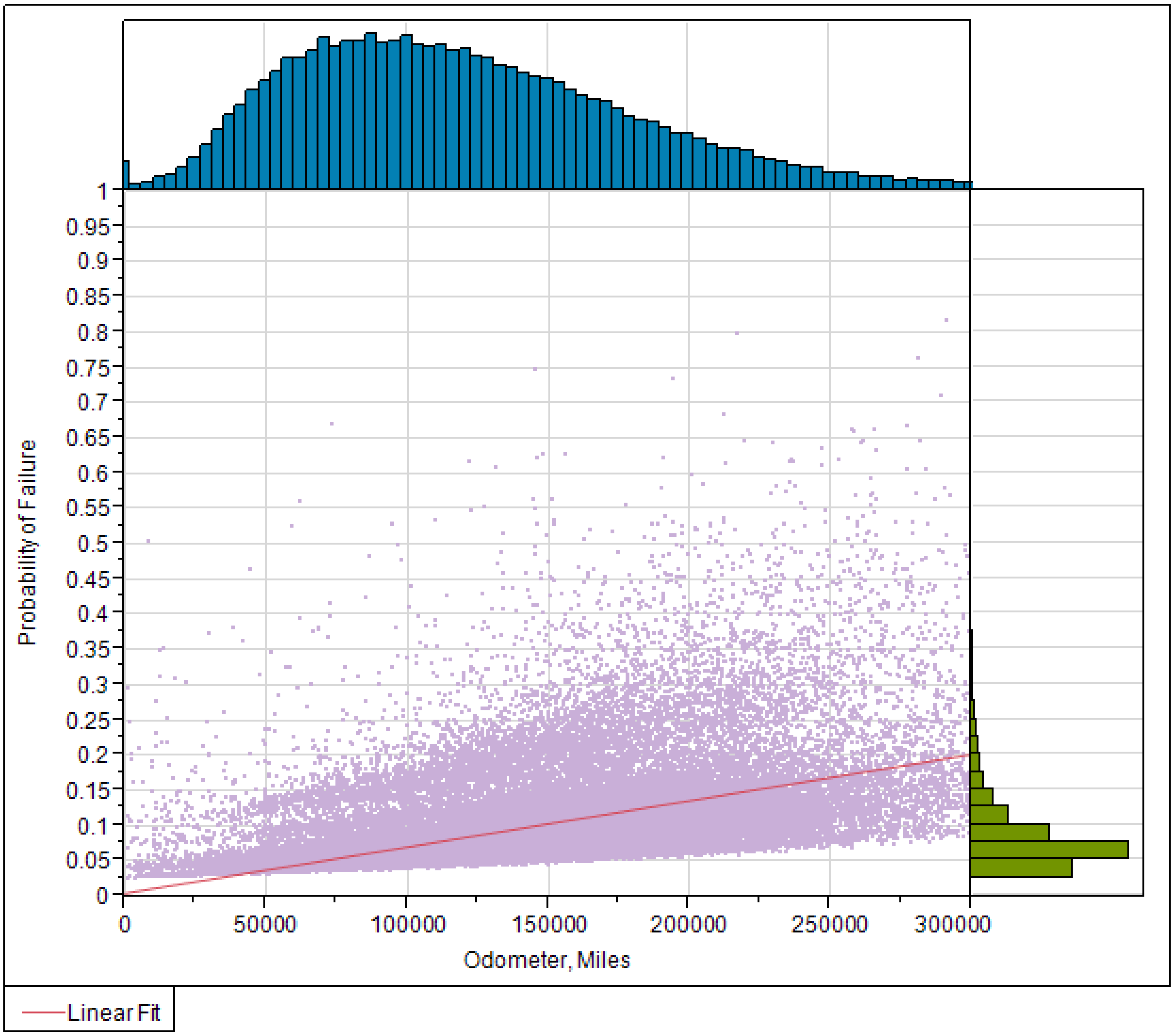

Figure 5-31 Probability of failure vs. odometer readings

The parameter estimates for the model of the probability of failure versus odometer readings is given in Table 5-29. Based on the values from the table, the equation representing the probability of failure versus odometer readings is presented below:

$$\textit{Probability of Failure} = 0.0036747 + 6.5725e\text{-}7 * \textit{Odometer Readings}$$

Table 5-28 provides summary statistics for this model.

Table 5-28 Summary statistics for probability of failure vs. odometer readings

R-Square	0.383283
R-Square Adj	0.383275
Root Mean Square Error	0.051815
Mean of Response	0.088795
Observations	72,279

Table 5-29 Parameter estimates for the probability of failure vs. odometer readings

Term	Estimate	Standard Error	t Ratio	Prob>|t|
Intercept	0.0036747	0.000445	8.25	<.0001*
Odometer	6.5725e-7	3.101e-9	211.94	<.0001*

5.3.4 Probability of Failure versus Nitrogen Oxides

It would be fair to assume that as the probability of failure increases so do nitrogen oxide emissions. The chart in Figure 5-32 shows the accuracy of this assumption.

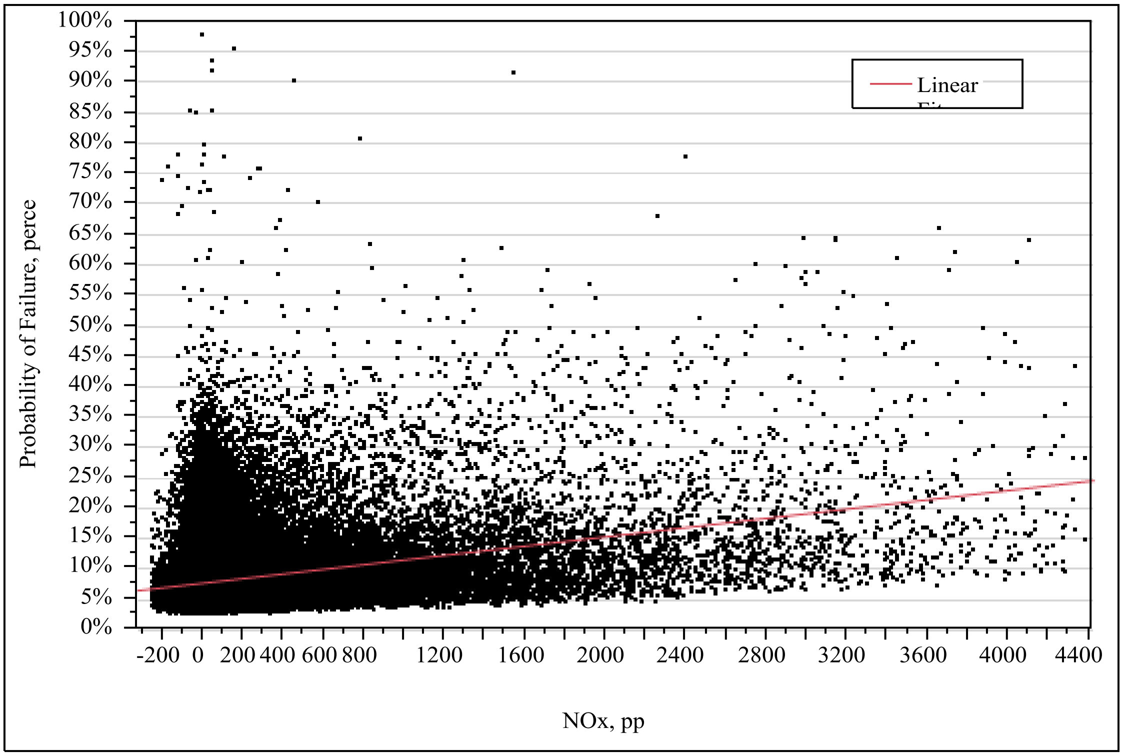

Figure 5-32 Probability of failure vs. nitrogen oxides

The equation describing the relationship between nitrogen oxides and probability of failure is shown below.

$$Probability\ of\ Failure = 0.077898 + 0.0000381*NOxppm$$

Summary statistic indicating that nitrogen oxides are a significant variable in predicting the probability of failure.

Table 5-30 Summary statistics for probability of failure vs. nitrogen oxides

R-Square	0.105205
R-Square Adj	0.105192
Root Mean Square Error	0.055692
Mean of Response	0.086138
Observations	70,972

Table 5-31 Parameter estimates for the probability of failure vs. nitrogen oxides

Term	Estimate	Standard Error	t Ratio	Prob>|t|
Intercept	0.077898	0.000228	342.14	<.0001*
NOxppm	0.0000381	4.17e-7	91.35	<.0001*

5.3.5 Probability of Failure versus Length of Ownership

Length of ownership is the variable that describes the number of years that the vehicle has been owned by a particular owner. Hypothesis for this variable is that the longer the length of ownership, the better owners care for their vehicles; therefore, length of ownership should have an inverse relationship to the probability of failure. As shown previously, as length of ownership increases probability of failure decreases.

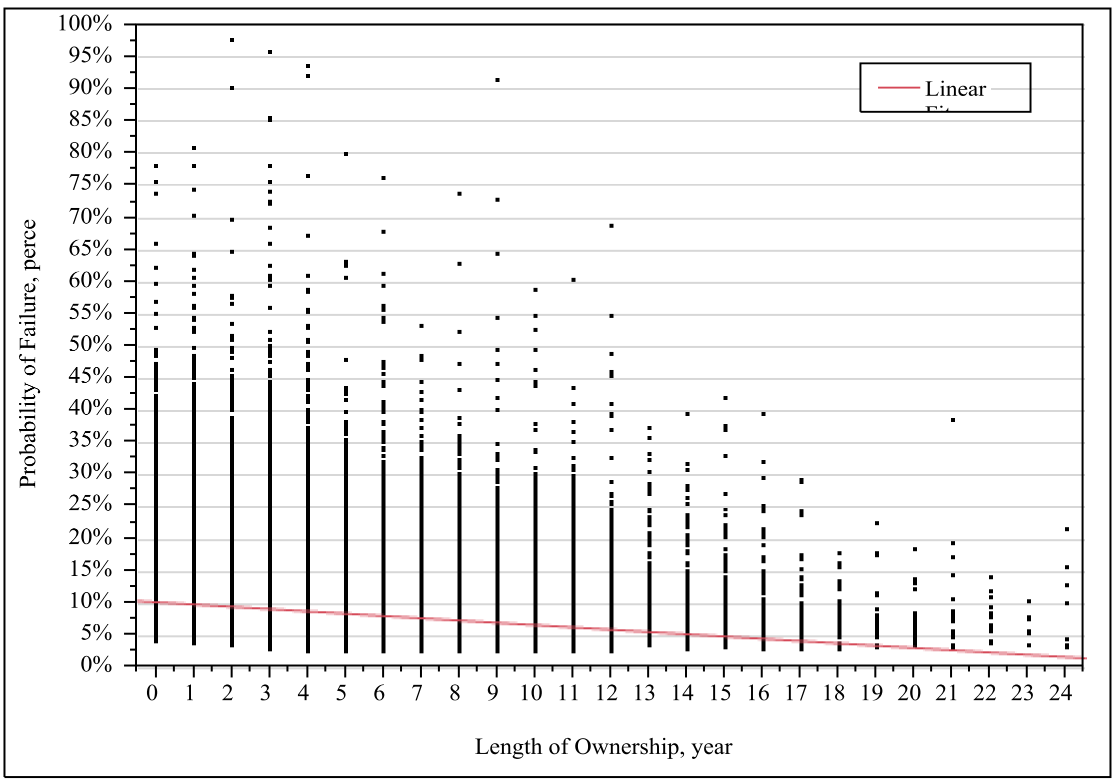

Figure 5-33 Probability of failure vs. length of ownership

Based on Figure 5-33 and the following equation, that is the relationship that is observed.

*Probability of Failure = 0.1029457 - 0.0035454*Length of Ownership*

Table 5-32 and Table 5-33 provide evidence that length of ownership is a statistically significant variable.

Table 5-32 Summary statistics for probability of failure vs. length of ownership

R-Square	0.036274
R-Square Adj	0.03626
Root Mean Square Error	0.057797
Mean of Response	0.086138
Observations	70,972

Table 5-33 Parameter estimates for the probability of failure vs. length of ownership

Term	Estimate	Standard Error	t Ratio	Prob>|t|
Intercept	0.1029457	0.000391	263.34	<.0001*
Length of Ownership	-0.003545	6.86e-5	-51.68	<.0001*

5.3.6 Probability of Failure versus Miles Per Year

Emission control equipment failure is a direct result of vehicle age and usage. Vehicles that are driven more should experience deterioration of the vehicle's components sooner than vehicles that are driven less. Therefore with an increase in annual vehicle travel, the probability of failure should increase as well.

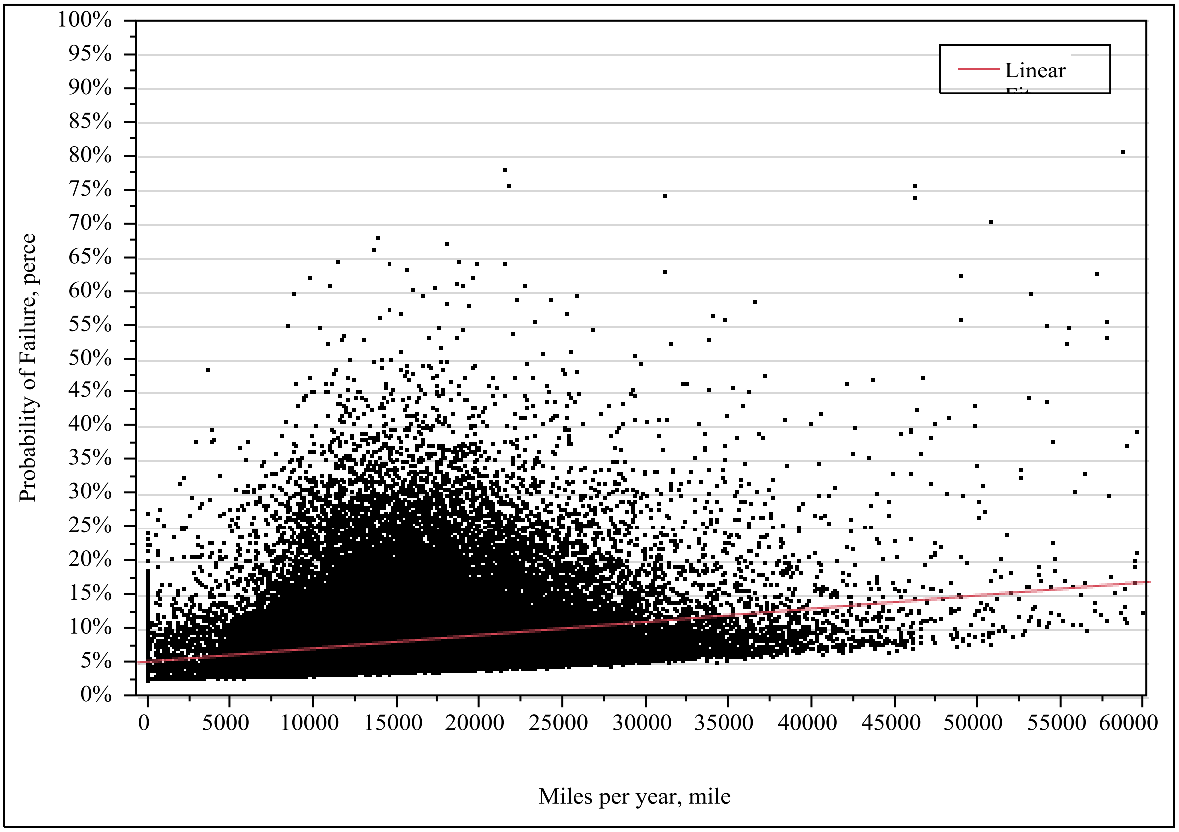

Figure 5-34 Probability of failure vs. miles per year

Figure 5-34 and the following equation demonstrate this fact. Table 5-34 and Table 5-35 show that annual miles traveled is a statistically significant variable in predicting the probability of failure.

*Probability of Failure = 0.0541452 + 1.9556e-6*Miles per year*

Table 5-34 Summary statistics for probability of failure vs. miles per year

R-Square	0.055638
R-Square Adj	0.055625
Root Mean Square Error	0.057213
Mean of Response	0.086138
Observations	70,972

Table 5-35 Parameter estimates for the probability of failure vs. miles per year

Term	Estimate	Standard Error	t Ratio	Prob>|t|
Intercept	0.0541452	0.000539	100.39	<.0001*
Miles per year	1.9556e-6	3.024e-8	64.66	<.0001*

5.3.7 Bayesian Analysis

Bayesian analysis is concerned with generating a posterior distribution of the unknown parameters given both the data and some prior density. This will allow us to estimate uncertainty in estimating vehicle failure. Following is the formula that is used in this analysis.

$$Prob(Fail\ |Model\ Flag) = \frac{Prob(Model\ Flag|Fail * Prob(Fail)}{P(Model\ Flag)}$$

It is calculated that the probability that a vehicle was flagged by the model as being failing is 0.003 (out of 84,910 records 233 had fail flags). The probability that a flagged vehicle failed the emission test is 0.0131. As discussed in previous sections, the probability of failure for the 2010 emission test is 0.08938; hence the probability of vehicle failure identified by the model as a failing vehicle is 0.3903 or 39%.

5.4 Model for Vehicles with Multiple Remote Sensing Measurements of High CO (more than 1.2%)

Remote emission sensing is notorious for large uncertainty in individual measurements. To increase reliability of remote sensing measurement multiple observations of the same vehicle might be helpful. This section examines a scenario where the vehicle was measured multiple time by the remote emission sensor. The variability of remote sensing measurement can be attributed to several factors such as: driving conditions or external factors such as strong wind. Because of so much variability in driving conditions, a clean vehicle may be identified as a high emitting vehicle if, for instance, the vehicle was under extreme acceleration. The opposite case applies as well. It is possible that vehicles that fail an emission inspection can demonstrate clean emissions when they pass the remote emission sensor. This result may be achieved by coasting (passing without any acceleration) a vehicle through measurement zones. That uncertainty can be overcome either by collecting large samples of data and analyzing groups of vehicles rather than individual vehicles, or by collecting multiple measurements of the same vehicle. Multiple measurements of the same vehicle reduce the uncertainty of the measurements and allow individual vehicle analysis. This section will discuss a case where multiple vehicles with at least two high CO measurements were analyzed and modeled similarly to previous sections.

Table 5-36 Model test high CO multiple vehicles

Model	Log Likelihood	DF	ChiSquare	Prob>ChiSq
Difference	7.581781	3	15.16356	0.0017*
Full	6.195218			
Reduced	13.776998			

Table 5-36 and Table 5-37 demonstrate a result from such a model. There were twenty-five measurements that had multiple observations of CO more than 1.2%.

Table 5-37 Model test high CO multiple vehicles 2

R-Square (U)	0.5503
AICc	22.3904
BIC	25.2659
Observations	25

As a result of R-Square, the model improved significantly, from 0.06 for a model that included all vehicles to 0.55 (Table 5-38) for a model with multiple observations of CO measurements greater than 1.2%.

Table 5-38 High CO multiple observation model R-Square

Measure	Training
Entropy R-Square	0.5503
Generalized R-Square	0.6809
Mean -Log p	0.2478
RMSE	0.2696
Mean Abs Dev	0.1503

Measure	Training
Misclassification Rate	0.0800
Number of Samples	25

In addition to setting carbon monoxide measurements to be more than 1.2%, three other parameters were deemed statistically significant. They include Model year, 2010 Odometer reading and the test result from the previous year.

Table 5-39 Parameter estimates multiple observations CO > 1.2% model

Term	Estimate	Standard Error	ChiSquare	Prob>ChiSq
Intercept	1052.5515	530.6806	3.93	0.0473*
Model Year	-0.5304155	0.2669087	3.95	0.0469*
Odometer	2.54162e-5	1.4274e-5	3.17	0.0750
2009 Emission Test Result[F]	2.2008076	1.2198278	3.26	0.0712

Table 5-40 Effect likelihood ratio test

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Model Year	1	1	7.2520442	0.0071*
Odometer	1	1	4.70928598	0.0300*
2009 Emission Test Result[F]	1	1	6.11606353	0.0134*

A model that includes multiple observations of vehicles illustrates the potential that can be achieved if multiple observations of the same vehicle can be obtained. The model with multiple observations was able to predict 83% of failing vehicles correctly (Table 5-41). There were very few measurements in the model: 25 to be exact, however it is expected the predictions will not change by a great margin if the number of vehicles in the model is increased.

Table 5-41 Predicted by model failures

	2010 I/M Test Result	
Model Probability of Failure	F	P
F	5	1
P	1	18

5.4.1 Bayesian Analysis High CO Multiple Observations Model

Similar to the full model, estimation of uncertainty using Bayesian analysis was performed in the model which includes multiple observations of high carbon monoxide readings. The following formula provides the basis for this analysis.

$$Prob(Fail\ |Model\ Flag) = \frac{Prob(Model\ Flag|Fail * Prob(Fail)}{P(Model\ Flag)}$$

It is calculated that the probability that a vehicle was flagged by the model as being failing is 0.0.24 (6 out of 25 vehicles had fail flag). The probability of the flagged vehicle failing the emission test is 0.83 (5 out of 6 vehicles). In this data set 6 out of 25 vehicles failed the actual emission inspection test. Therefore the probability of vehicle failure as identified by the model is 0.83 or 83%.

This is a significant improvement over a model that has single observations of the vehicles. It also suggests that increased use of remote sensing equipment to the point of collecting multiple observations of the same vehicle can significantly improve the predicting power of the model.

5.5 Conclusion

After careful investigation variables that have a correlation with the probability of failure of the emission test were selected to be checked for their predictive powers. Those variables are: carbon monoxide, hydrocarbons, nitrogen oxides, model year, length of ownership, displacement, odometer readings, previous emission test, and annual vehicle miles traveled. Not all of those variables were selected and formed final model. Hydrocarbon readings were excluded from the final model because of the strong correlation with carbon monoxide readings.

Engine displacement variable did not demonstrate predictive powers for probability of vehicle failure therefore it was not included in the final model. Other variables were entered into the linear regression model, which proved to be statistically significant.

In addition modeling scenario that included only vehicles with multiple remote sensing observation was investigated as well. That model with similar variable produced a much stronger correlation and produced more accurate predictions, therefore demonstrating the improvement in a model correlation coefficient when using multiple observations the remote sensing data.

6 APPLYING EMISSION SAVINGS

The case study devised in this research was designed to present emission savings possible to achieve if the vehicle emission inspection policy would become stringent. However, some of the aspects, such as extreme frequency of testing, which is every three months, described in the case study may not be politically feasible. Nevertheless estimations of emission savings are given with the variable time frequencies that include more frequent testing.

6.1 CO Savings

Based on discussions in previous sections, approximately ten percent of vehicles fail emission inspection. It is assumed that for this new proposed program the same amount of vehicles will be considered to be high emitting vehicles. Top ten percent of vehicle probability of failure will have accelerated timeframe for testing. To compensate for the extra number of tests ten percent of the cleanest vehicles will be exempt from taking the emission test every twelve months. Vehicles in the 90th percentile (ten percent of vehicles that are most likely to fail) have a probability of failure that is at least four times greater than vehicles in the 10th percentile (ten percent of the clean vehicles)

Table 5-23.

Vehicles in the 90th percentile for the probability of failure were split roughly into three groups with the intent to assign different times between emission tests. The group with the highest probability of failure, Group 1 (Table 6-1), will be required to take an emission test every three months. Group 2, the middle group of vehicles with the highest probability of failure, will have their test done every six months. Finally, group three will be tested every nine months.

Table 6-1 Testing groups

Test Frequency Group	Probability of Failure Maximum	Probability of Failure Minimum	Test Frequency
1 – Extreme Probability of Failure	0.97596	0.251693	Every 3 months
2 – High Probability of Failure	0.251662	0.191671	Every 6 months
3 – Medium Probability of Failure	0.191654	0.159638	Every 9 months

Group 1 that represents vehicles with higher probability of failure are generally older. The average vehicle in this group has a model year of 1996. Model year distribution of this group can be found in Figure 6-1.

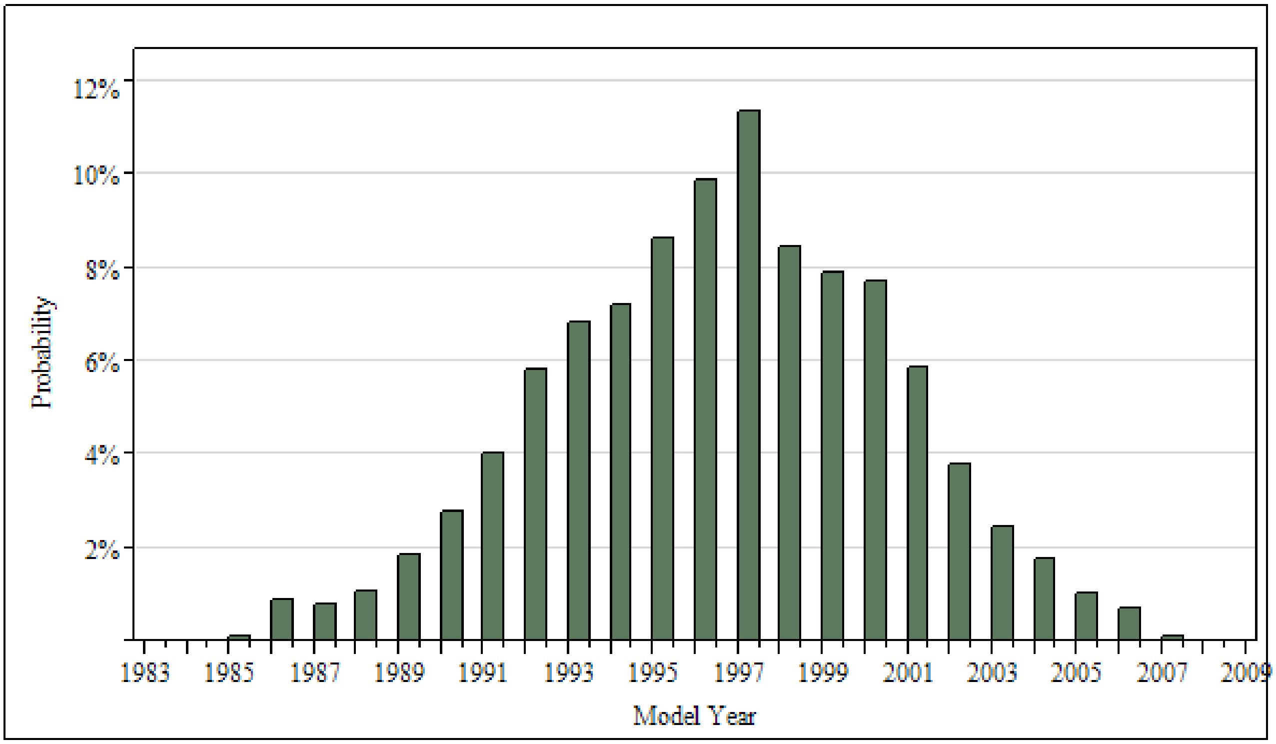

Figure 6-1 Group 1 model year distribution

In addition to being older the vehicles from group 1 have higher odometer readings. The average vehicle from group 1 had an odometer reading of 240,000 miles. Distribution of odometer readings for group 1 is shown in Figure 6-2.

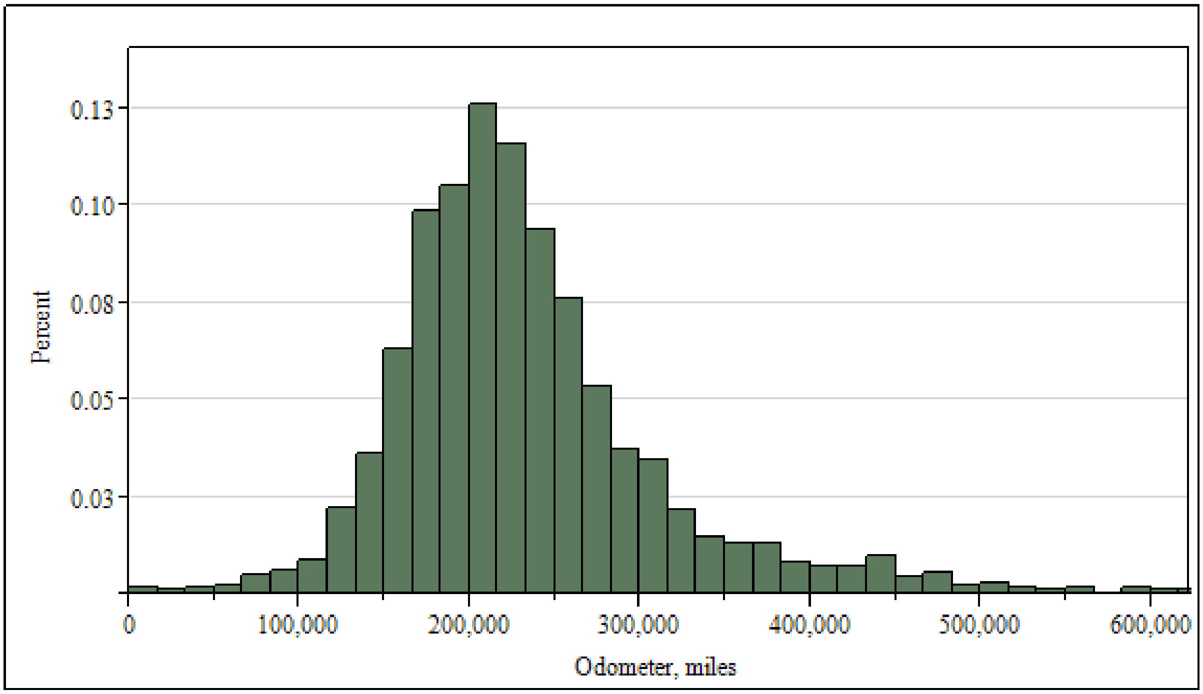

Figure 6-2 Group 1 odometer readings distribution

Group 2 that represents vehicles with high probability of failure has slightly different vehicle distributions. The vehicles in this group are slightly younger than in group 1 and have an average of 1999 model year. A model year distribution from group 2 is shown in Figure 6-3.

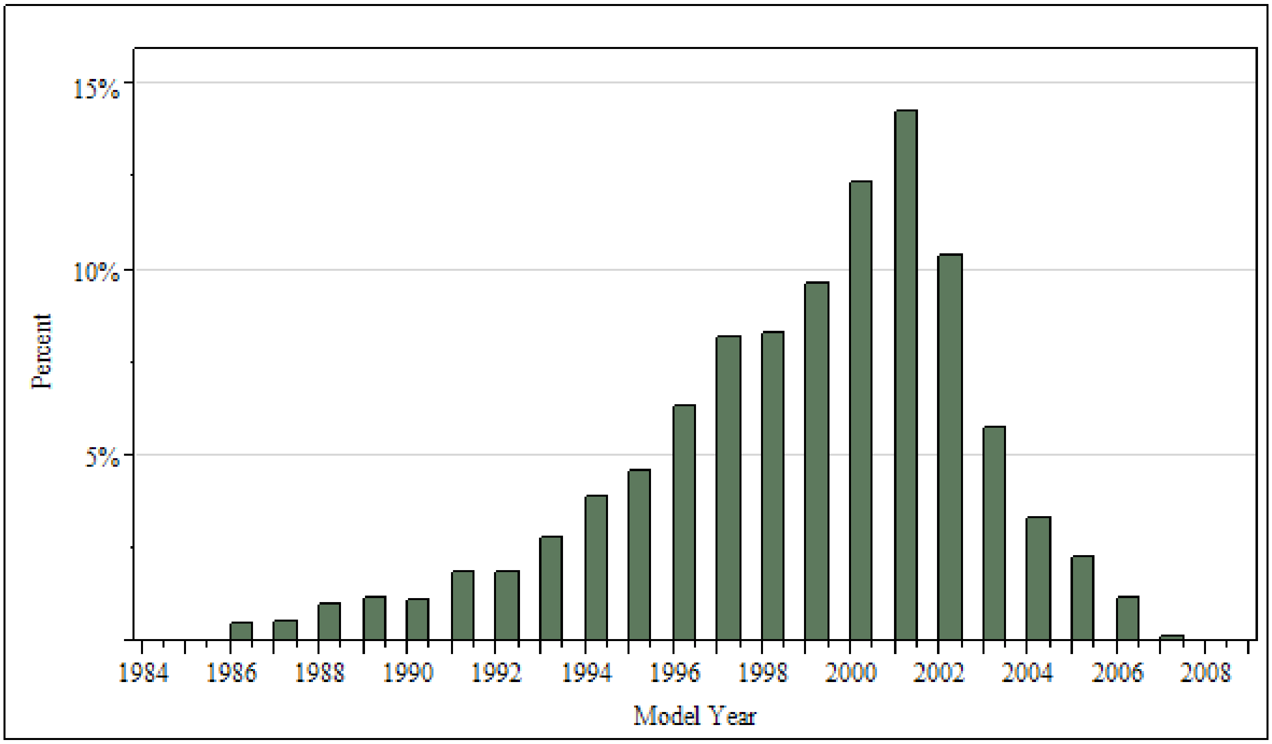

Figure 6-3 Group 2 model year distribution

Vehicles from group 2 also had less accumulated miles. The average vehicle from that group had 188,000 miles. Distribution of odometer readings for vehicles in the group 2 is shown in Figure 6-4.

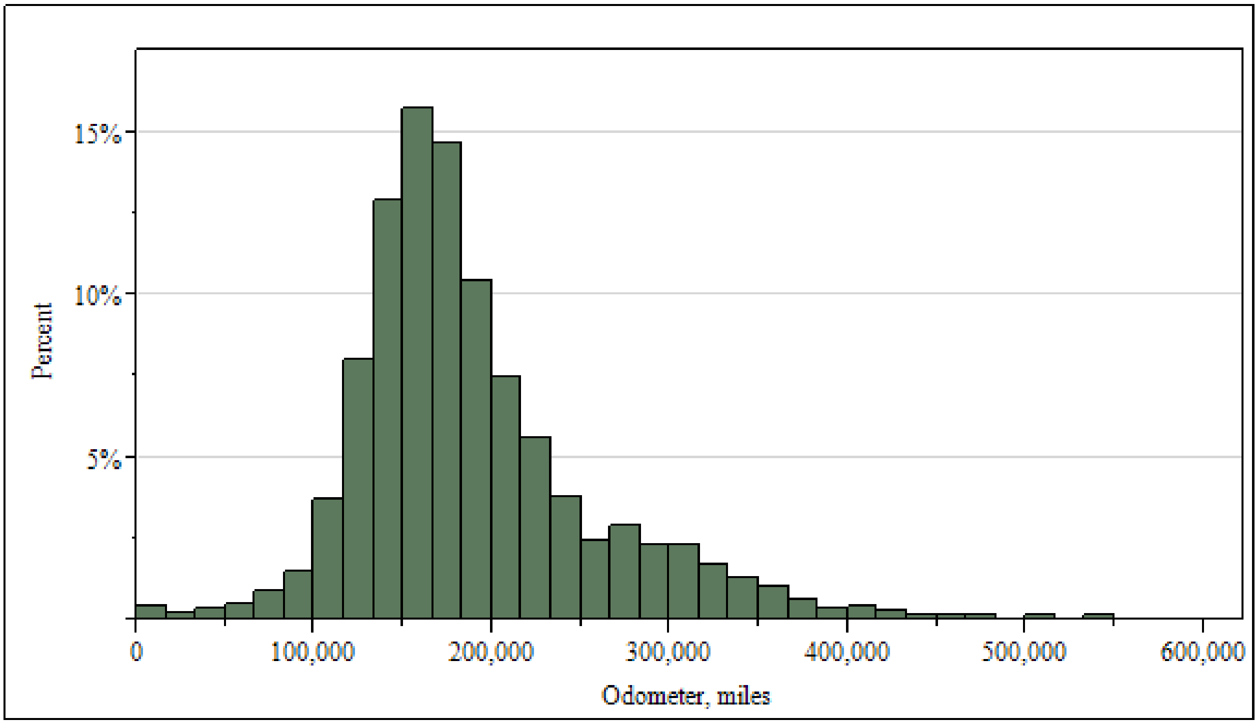

Figure 6-4 Group 2 odometer readings distribution

Group 3 that includes vehicles with a medium probability of failure is similar in composition to group 2. Average vehicle in group 3 has 1999 model year. A model year distribution from group 3 is shown in Figure 6-5.

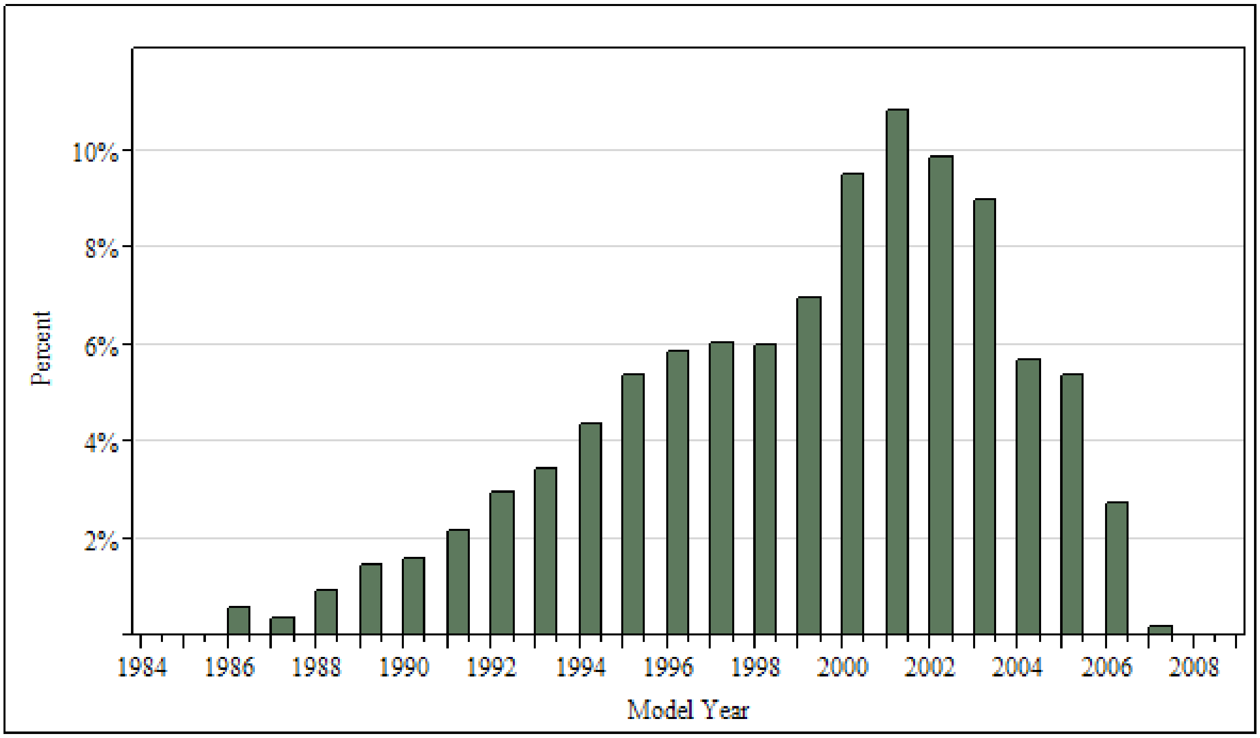

Figure 6-5 Group 3 model year distribution

However, group 3 vehicles also have slightly different distribution of odometer readings. Odometer readings distribution for group 3 is shown in

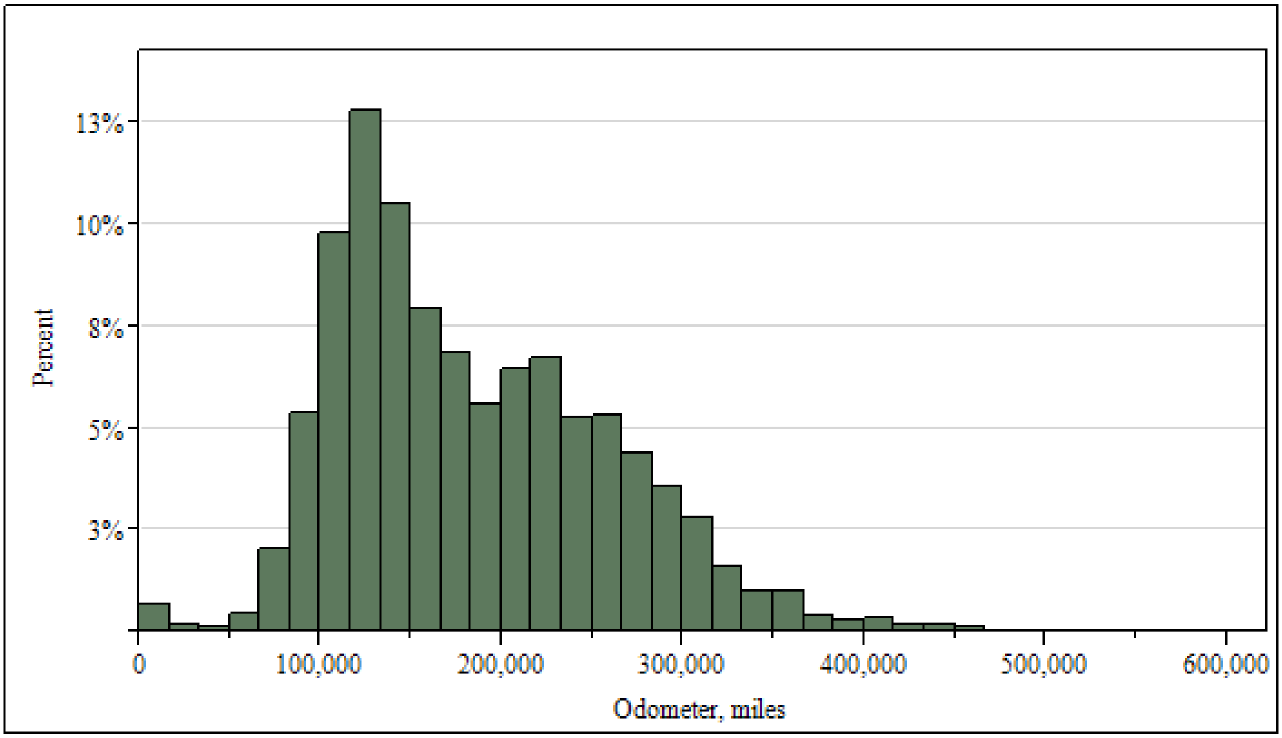

Figure 6-6 Group 3 odometer readings distribution

When comparing Figure 4-15, which describes passing vehicle behaviors for CO emissions, with Figure 4-35, which illustrates failing vehicle behavior for CO emissions, differences can be observed. Passing vehicles do not indicate any difference before or after the test. Furthermore, the growth of their CO emissions is essentially flat. Failing vehicles, after repairs, have raised CO emissions, albeit at a slightly lower rate. These two scenarios are investigated to calculate potential emissions savings. First, vehicles that were supposed to be repaired had the repair done sooner than annual testing (e.g. 3, 6, or 9 months) and exhibited the behavior of a clean vehicle afterward. After repair, the growth of CO emissions was flat, and the vehicles did not fail again, and those vehicles were not flagged by the model and do not have to come early for testing. The second scenario considered a different condition. Vehicles that were repaired exhibited the behavior of failing vehicles and their CO emissions continued to rise at the rate shown in Figure 4-35 and they were flagged by the model as vehicles likely to fail. Every time they came for a test, they failed. Clean vehicle behavior is different from failing vehicles. The first and second scenarios represent the largest and smallest benefit from testing vehicles early.

As mentioned previously, vehicles were split into three groups. Group one includes vehicles with the highest probability of failure. Group two is a middle group and group three includes vehicles with a lower probability of failure in the 90th percentile.

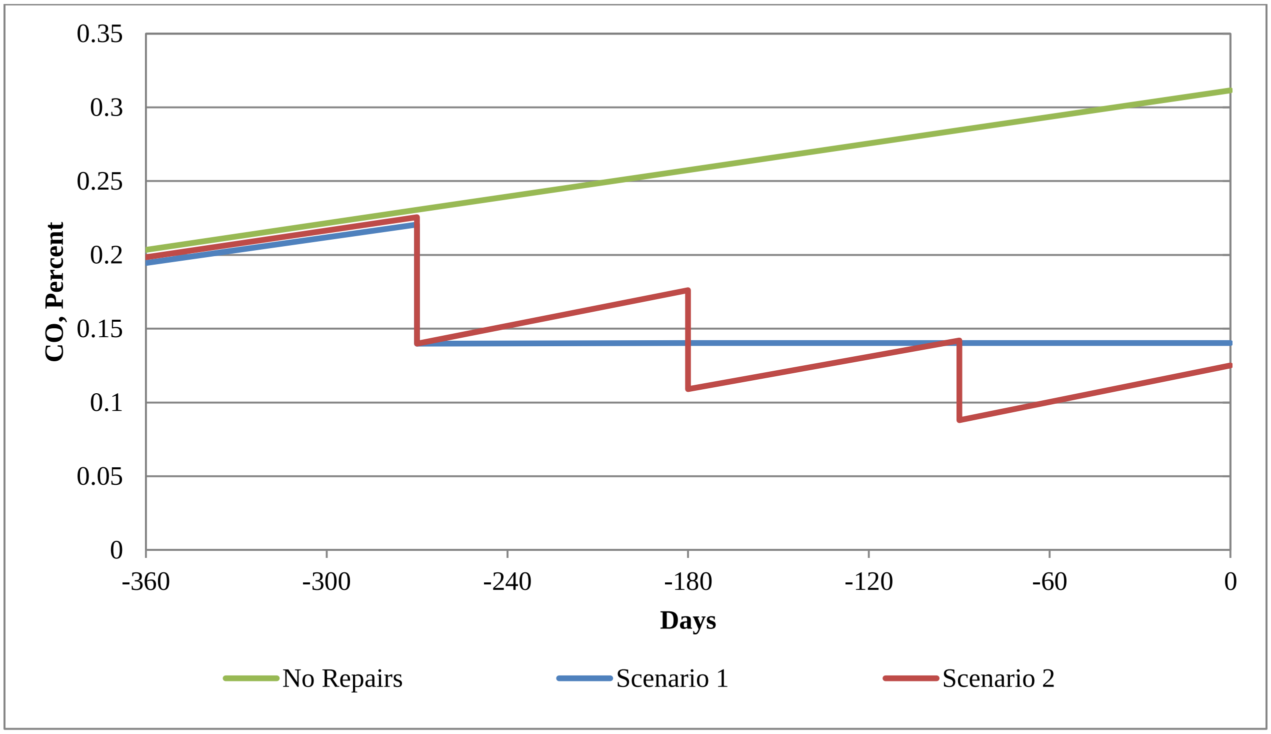

Figure 6-7 Carbon monoxide emissions Group 1 scenarios

Figure 6-7 represents possible emission inspection patterns for Group 1, vehicles with the highest probability of failure. Scenario 1 represents a vehicle that was flagged by the model as likely to fail and had to be repaired. After the repair the vehicle exhibited the behavior of a clean vehicle and subsequently, did not have to take a test for the rest of the year. Repair for those vehicles occurred at day (-270) symbolized by a reduction of CO emissions, based on Figure 4-35, and afterwards the vehicles remained clean, therefore, they had flat CO emission growth.

This scenario represents a 36.4% reduction of CO emissions for vehicles that are included in Group 1.

The second scenario for Group 1 represents vehicles that were repaired at day (-270). After the repair they were flagged as likely to fail again. Then they were tested again at day (-180), failed the test, were repaired, and then were flagged again by the model as vehicles likely to fail, were tested at day (-90), failed that inspection and were repaired. This scenario will produce a 38.93% reduction in CO emissions.

Figure 6-8 represents similar scenarios as described above for vehicles in Group 2. Those are the vehicles in the middle failing group with a probability of failure between 0.191671 and 0.251662. Vehicles in this group will be tested six months sooner than their scheduled annual test. The green line on the chart represents what would happen to CO emissions if no action is taken. The blue line represents Scenario 1, which says that vehicles were flagged by a model as failing vehicles and consequently were repaired, thus producing a reduction of CO emissions at day (-180). After the repair vehicles remained clean and were not flagged by the model as potentially failing vehicles. Therefore, the CO emissions growth rate was essentially flat. That scenario can produce 26.42% of CO emission savings.

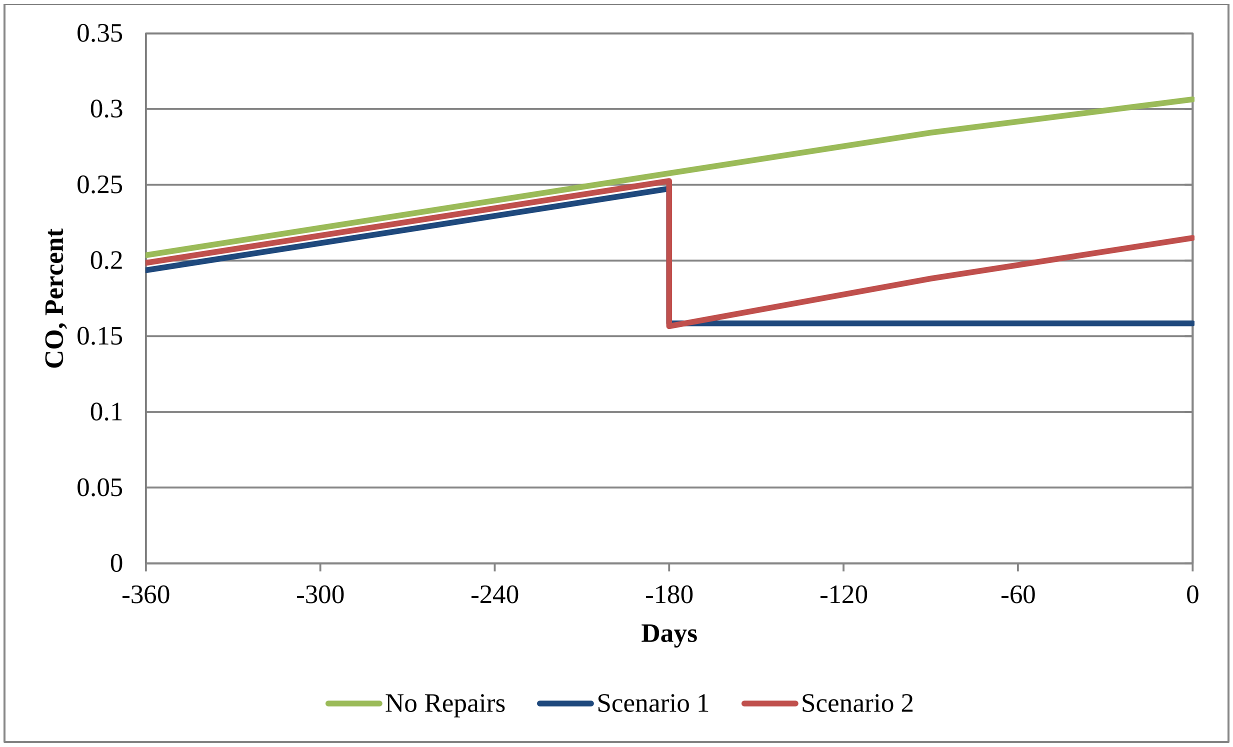

Figure 6-8 Carbon monoxide emissions Group 2 scenarios

The red line in Figure 6-8 represents a scenario in which vehicles in group 2 were repaired and continue to exhibit the behavior of high polluting vehicles, therefore the growth of CO emission was not flat, like for scenario 1, but was growing at a rate that is consistent with a failing vehicle. This scenario can produce 17.10% of CO emission savings.

Figure 6-9 shows what will happen to the third and final group of potentially failing vehicles. This group includes group 3 vehicles with a probability of failure between 0.191671 and 0.251662. Similar to the previous two groups, scenario one represents a vehicle that was flagged by the model as potentially failing, and had to be tested 90 days sooner than every 12 months. In Scenario 1 vehicles were tested and repaired, and stayed clean. This scenario can produce 13.06% of CO emission. Scenario 2 shows vehicles that failed an emission test and continue to exhibit behaviors of a failing vehicle. This scenario can produce benefits of 7.90% of CO emissions.

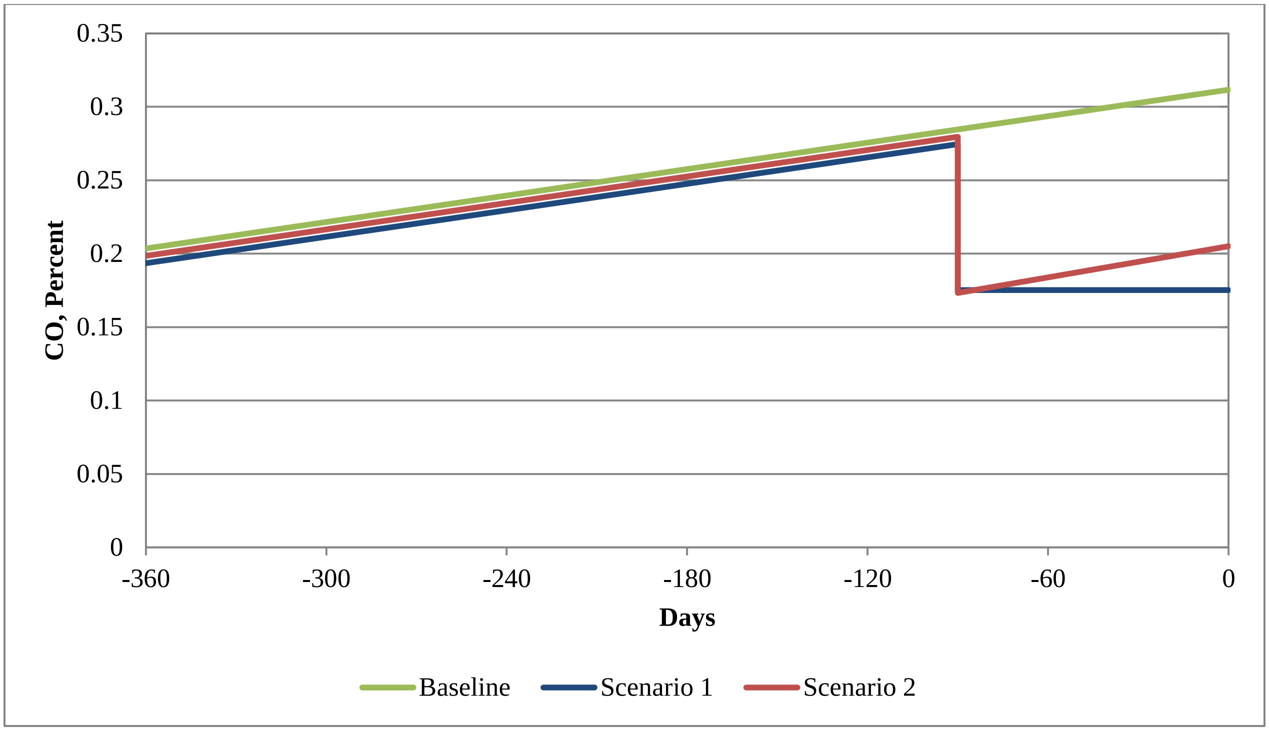

Figure 6-9 Carbon monoxide emissions Group 3 scenarios

The effect of combining all three groups and examining scenarios for total benefits for CO emissions of the new emission testing program can be calculated. Group 1 was responsible for 52% of CO emission of all three groups. Group 2 and group 3 have 26% and 22% CO emission contributions, respectively. Thus, total CO emission savings are, for Scenario 1, 28.60% and for Scenario 2, 26.36%. Scenario 1 produced a slightly larger benefit than Scenario 2.

6.2 HC Savings

Similar to carbon monoxide, emission savings calculations for the ten percent of the most- likely-to fail vehicles [resulting from probability of failure from model calculations] were selected and emission savings. Vehicles in the 90th percentile (ten percent of vehicles that are most likely to fail) have a probability of failure that is at least four times greater than vehicles in the 10th percentile (ten percent of the clean vehicles)

Table 5-23.

Like the carbon monoxide calculations, vehicles in the 90th percentile for the probability of failure were split roughly into three parts with the intent to assign different emission test frequencies. The group with the highest probability of failure, Group 1 (Table 6-1), will be required to take an emission test every three months. Group 2, the middle group of ten percent of vehicles with the highest probability of failure, will be tested every six months. Group 3 will be tested every nine months.

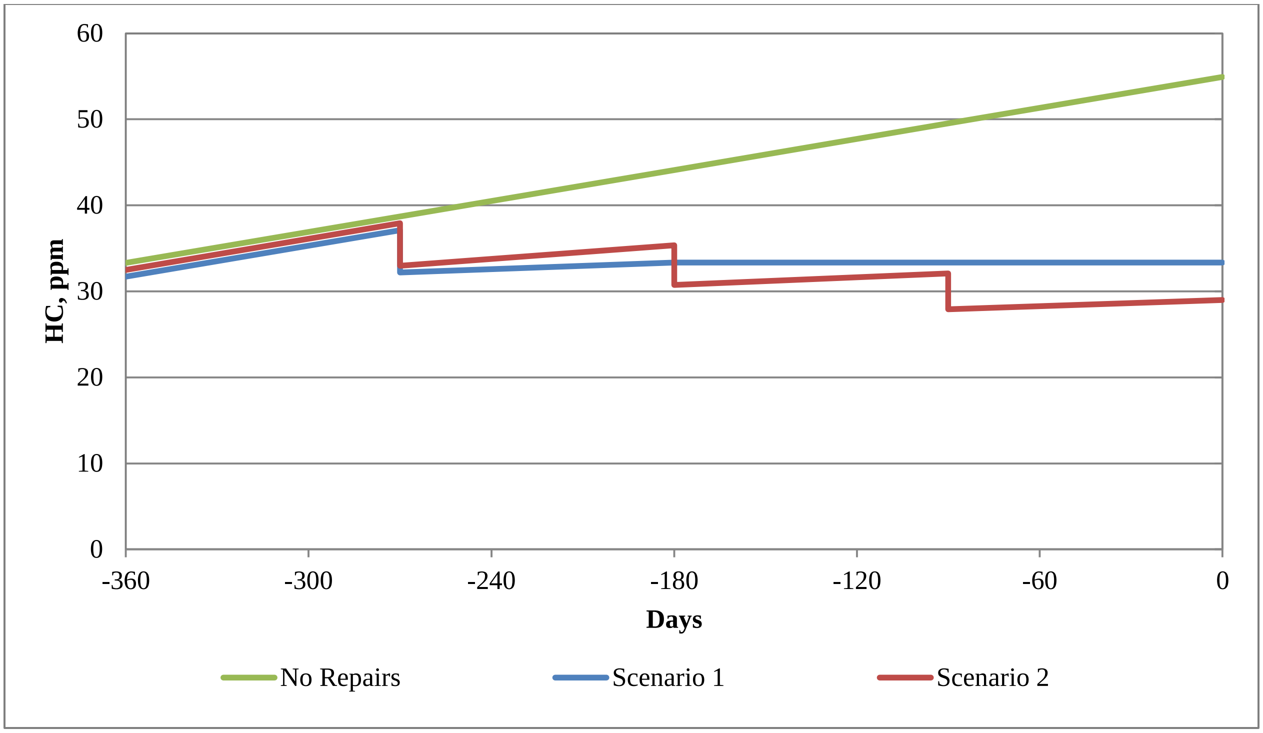

Figure 6-10 Hydrocarbons emission Group 1 scenarios

When comparing Figure 4-15, which describes passing vehicle behaviors for HC emissions, with Figure 4-35, which illustrates failing vehicle behaviors for HC emissions, differences can be observed. Two vehicle behavior patterns after repairs are investigated to calculate potential emissions savings. First, vehicles that were supposed to be repaired sooner had the repair done and exhibited the behavior of a clean vehicle afterwards. In other words after repair, growth of HC emissions was flat and the vehicle did not fail again. Those vehicles were not flagged by the model and do not have to come early for testing. The second scenario considered vehicles that, even after being repaired, continued to fail. Their HC emissions continued to rise at the rate shown in Figure 4-35 and the model flagged them as vehicles likely to fail. Every time they came to a test sooner than annually, they failed. Clean vehicle behavior is different from failing vehicles. The first and second scenarios represent the largest and smallest benefit from testing vehicles early.

As mentioned previously, vehicles were split into three groups. Group 1 includes vehicles with the highest probability of failure. Group 2 is a middle group and Group 3 includes vehicles with lower probability of failure in the 90th percentile. Figure 6-10 represents possible emission inspection patterns for Group 1, vehicles with the highest probability of failure. Scenario 1 represents a vehicle that was flagged by the model as likely to fail and it was repaired. After the repair, the vehicle exhibited the behavior of a clean vehicle and subsequently did not have to take a test for the rest of the year. Repair for those vehicles occurred at day (-270) symbolized by reduction of HC emissions and afterwards vehicles remained clean, therefore they had flat HC emission growth. This scenario represents a 20.12% reduction of HC emissions for vehicles that are included in Group 1.

The second scenario for Group 1 represents vehicles that were repaired on the day (-270). After the repair they were flagged as likely to fail again. Then they were tested again at day (-180) failed, were repaired, and then were flagged again by the model as vehicles likely to fail, were tested at day (-90), failed that inspection and were repaired. This scenario will produce a 23.70% reduction in HC emissions.

Figure 6-5 represents similar scenarios, but for vehicles that are included in Group 2, the vehicles in the middle failing group with a probability of failure between 0.191671 and 0.251662. Vehicles in this group will be tested six months sooner than their scheduled annual test. The green line on the chart represents what would happen to HC emissions if no action is taken. The blue line represents Scenario 1, which says that vehicles were flagged by the model as failing, were repaired, and reduced HC emissions at day (-180). The repair vehicles remained clean and were not flagged by the model as potentially failing vehicles. Therefore, the HC emissions growth rate was essentially flat. That scenario can produce 14.48% of HC emission savings.

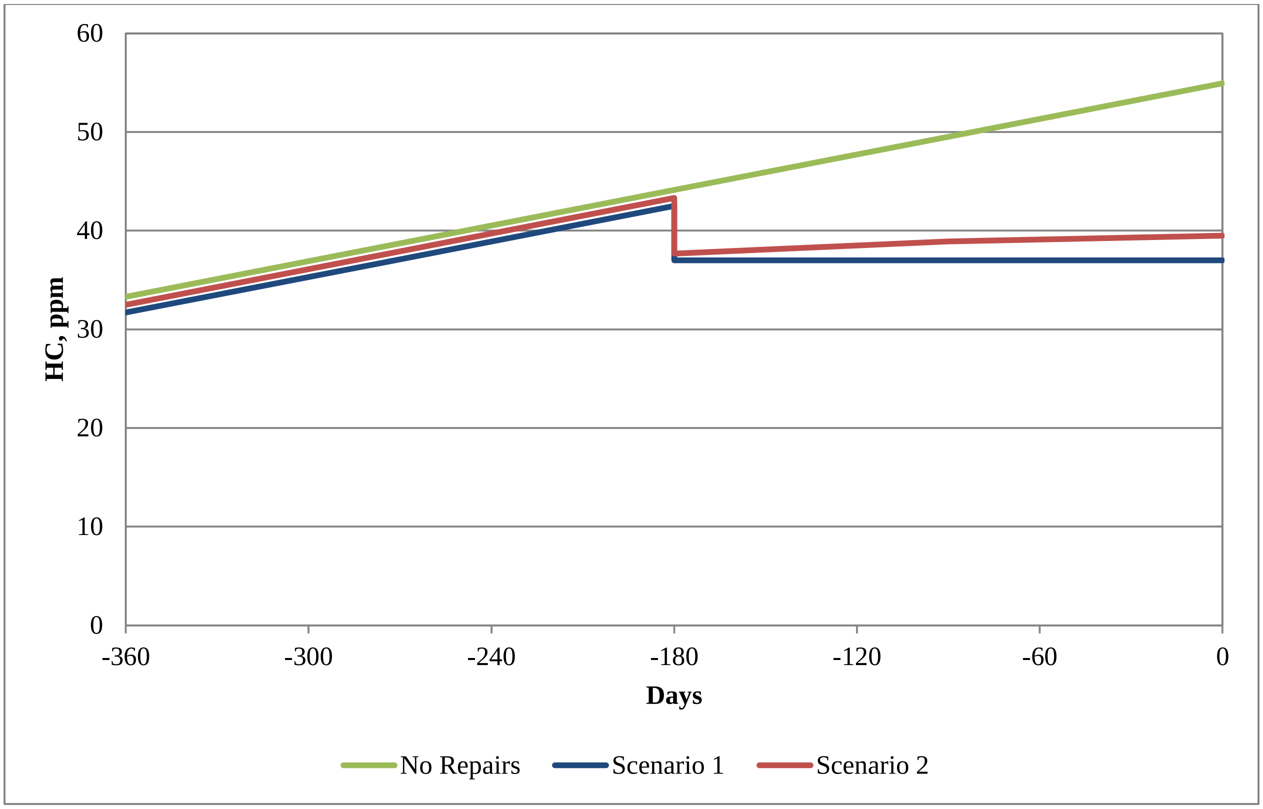

Figure 6-5 Hydrocarbon emission Group 2 scenarios

The red line in Figure 6-5 represents a scenario in which vehicles in group 2 were repaired and continued to exhibit behaviors of high pollution vehicle, therefore the growth of HC emission was not flat, as in Scenario 1, but was growing at a rate that is consistent with a failing vehicle. This scenario can produce 11.23% of HC emission savings.

Figure 6-11 shows the third and final group of potentially failing vehicles. This group includes vehicles with a probability of failure between 0.191671 and 0.251662. Similar to the previous two groups, scenario one represents a vehicle that was flagged by the model as potentially failing and had to be tested 90 days before the scheduled annual test rather than every 12 months. In Scenario 1 vehicles were tested, then they were repaired, and after the repair stayed clean. This scenario can produce 12.78% of HC emission. Scenario 2 shows vehicles that failed an emission test but continued to exhibit behaviors of a failing vehicle. This scenario can produce a benefit of 10.96% of HC emissions.

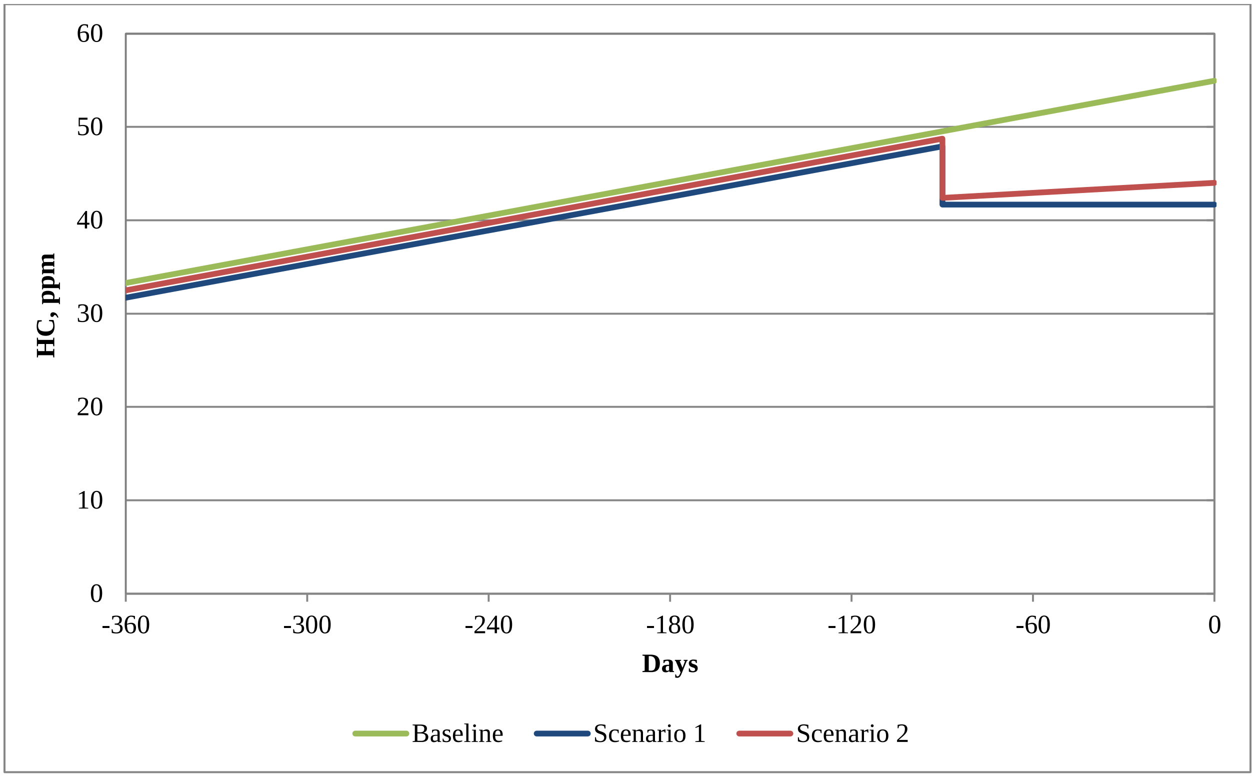

Figure 6-11 Hydrocarbons emission Group 3 scenarios

The effect of combining all three groups and examining all the total benefits for HC emission of the new emission testing program can be calculated. Group 1 was responsible for 47% of HC emission of all three groups. Group 2 and Group 3 have 28% and 25% HC emission contribution respectively. Therefore, total HC emission savings are for Scenario 1, 16.72% and for Scenario 2, 17.06%. Scenario 1 produced a slightly larger benefit than Scenario 2.

The emission savings for hydrocarbons for both scenario 1 and scenario 2 are summarized in Table 6-2and Table 6-3.

Table 6-2 Hydrocarbon reductions for scenarios 1 and 2

	Every 90 Days Group		Every 180 days Group		Every 270 Days Group	
	Total HC Emissions	Percent reduction	Total HC Emissions	Percent Reduction	Total HC Emissions	Percent reduction
No Repairs	15,882.12		15,595.92		15,595.92	
Scenario 1	12,686.434	-20.12%	13,337.6	-14.48%	13,602.29	-12.78%
Scenario 2	12,117.953	-23.70%	13,844.41	-11.23%	13,887.36	-10.96%

Table 6-3 Hydrocarbon total reductions based on scenarios

	Total Emissions	Percent reduction
Reduction Scenario 1	445561.1673	-16.72%
Reduction Scenario 2	443764.2053	-17.06%

6.3 NOx Savings

Similar to carbon monoxide and hydrocarbon emission savings calculations, the ten percent of vehicles most likely to fail resulting from model calculations were selected. Those are the same vehicles used in the analysis of emission savings for carbon monoxide and hydrocarbons. Vehicles in the 90th percentile (ten percent of vehicles that are most likely to fail) have a probability of failure that is at least four times greater than vehicles in the 10th percentile (ten percent of the clean vehicles)

Table 5-23.

Just as for carbon monoxide calculations, vehicles in the 90th percentile for the probability of failure were split roughly into three groups with the intent to assign different emission test frequencies. The group with the highest probability of failure, Group 1 (Table 6-1), will be required to take an emission test every three months. Group 2, the middle group will be tested every six months. Group 3 will be tested every nine months.

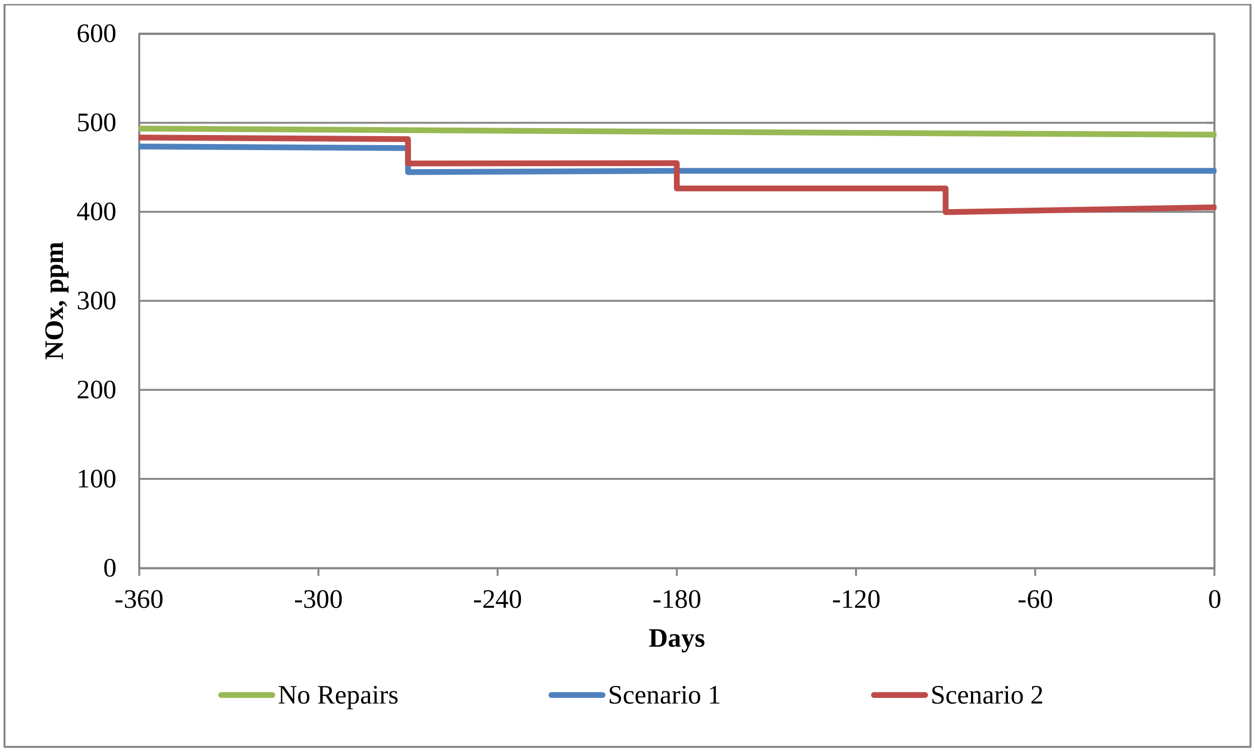

Figure 6-12 Nitrogen oxides emission Group 1 scenarios

When comparing Figure 4-15, which describes passing vehicle behaviors for NOx emissions, with Figure 4-35, which illustrates failing vehicle behaviors for NOx emissions, differences can be observed. Based on those differences two vehicle behavior patterns after repairs are investigated to calculate potential emissions savings. First, vehicles that were supposed to be repaired sooner, had the repair and exhibited behaviors of a clean vehicle afterwards. In other words, after repairs, the growth of NOx emissions was flat, the vehicles did not fail again, and those vehicles were not flagged by the model and did not have to come early for testing. The second scenario considered vehicles that were repaired and exhibited behaviors of failing vehicles. Their NOx emissions continued to rise at the rate shown in Figure 4-35 and they were flagged by the model as vehicles likely to fail. Every time they came to perform a test sooner than annually, they failed. Clean vehicle behavior is different from failing vehicles. The first and second scenarios represent the largest and smallest benefit from testing vehicles early.

Mimicking carbon monoxide and hydrocarbon analysis, vehicles were split into three groups. Group 1 includes vehicles with the highest probability of failure. Group 2 is a middle group and Group 3 includes vehicles with a lower probability of failure in the 90^{th} percentile. Figure 6-12 represents possible emission inspection patterns for Group 1, vehicles with the highest probability of failure. Scenario 1 represents a vehicle that was flagged by the model as a vehicle likely to fail and it was repaired. After the repair the vehicle exhibited behavior of a clean vehicle and subsequently did not have to take a test for the rest of the year. Repair for those vehicles occurred at day (-270) symbolized by reduction of NOx emissions and afterward the vehicles remained clean, therefore they had flat NOx emission growth. This scenario represents a 8% reduction of NOx emissions from vehicles that are included in Group 1, group with the highest probability of failure.

The second scenario for Group 1 represents vehicles that were repaired on day (-270). After the repair they were flagged as likely to fail again. Then they were tested again at day (-180), failed the test, were repaired, and then were flagged again by the model as vehicles likely to fail, were tested at day (-90), failed that inspection and were repaired. This scenario will produce a 10% reduction in NOx emissions.

Figure 6-13 represents similar scenarios as described above for vehicles that are included in Group 2. Those are the vehicles with a probability of failure between 0.191671 and 0.251662. Vehicles in this group will be tested six months sooner than their scheduled annual test. The green line on the chart represents what would happen to NOx emissions if no action is taken. The blue line represents Scenario 1, which says that vehicles were flagged by a model as failing and were repaired, thus achieving a reduction of NOx emissions at day (-180). After the repair, vehicles remained clean and were not flagged by the model as potentially failing vehicle.

Therefore NOx emissions growth rate was essentially flat. That scenario can produce 7.88% of NOx emission savings.

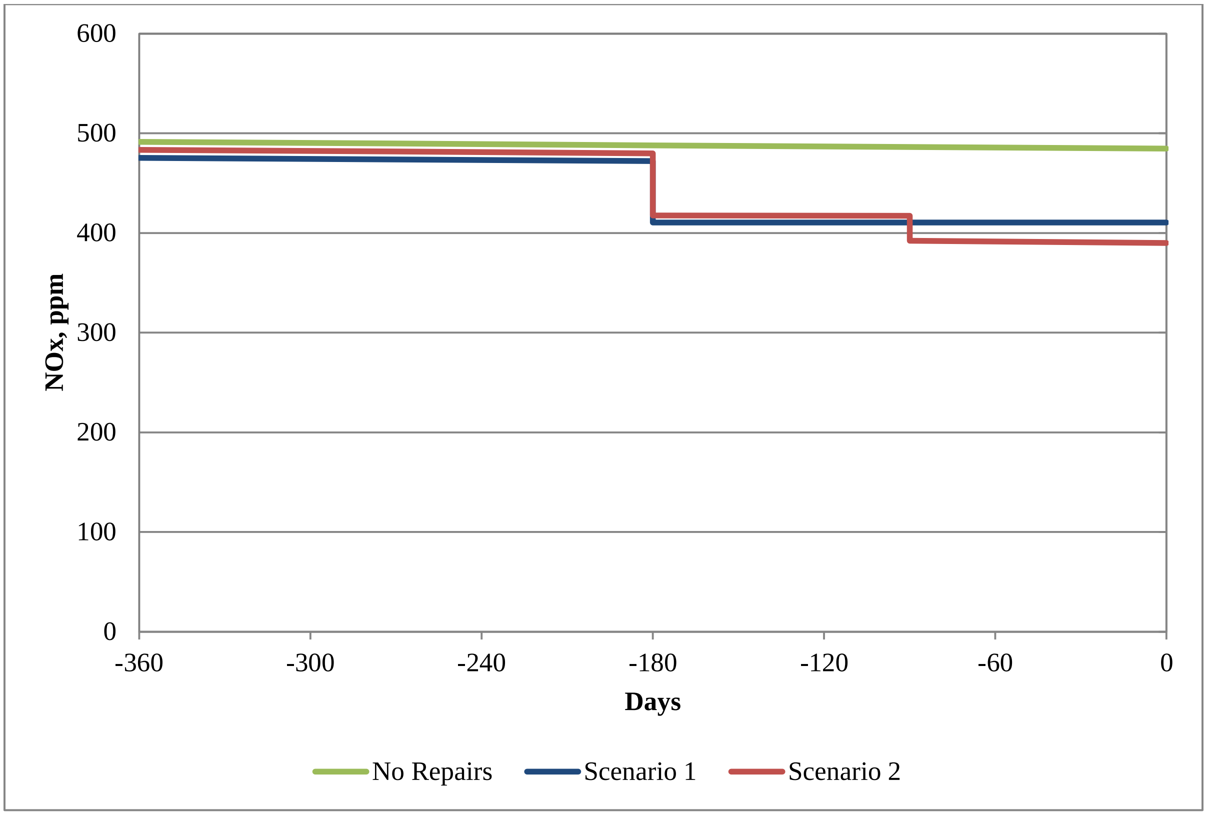

Figure 6-13 Nitrogen oxides emission Group 2 scenarios

The red line in Figure 6-13 represents a scenario in which vehicles in group 2 were repaired and continued to exhibit behaviors of high pollution vehicles, therefore the growth of NOx emission was not flat, but was growing at the rate that is consistent with failing vehicles. This scenario can produce 4.63% of NOx emission savings.

Figure 6-14 shows what will happen to the third and final group of potentially failing vehicles. This group includes vehicles with a probability of failure between 0.191671 and 0.251662. Scenario one represents a vehicle that was flagged by the model as potentially failing and had to be tested 90 days sooner than every 12 months. In Scenario 1 vehicles were tested, repaired, and stayed clean. This scenario can produce 3.50% of NOx emission. Scenario 2 shows vehicles that failed an emission test but continue to exhibit the behaviors of a failing vehicle. This scenario can produce a benefit of 5.07% of NOx emissions.

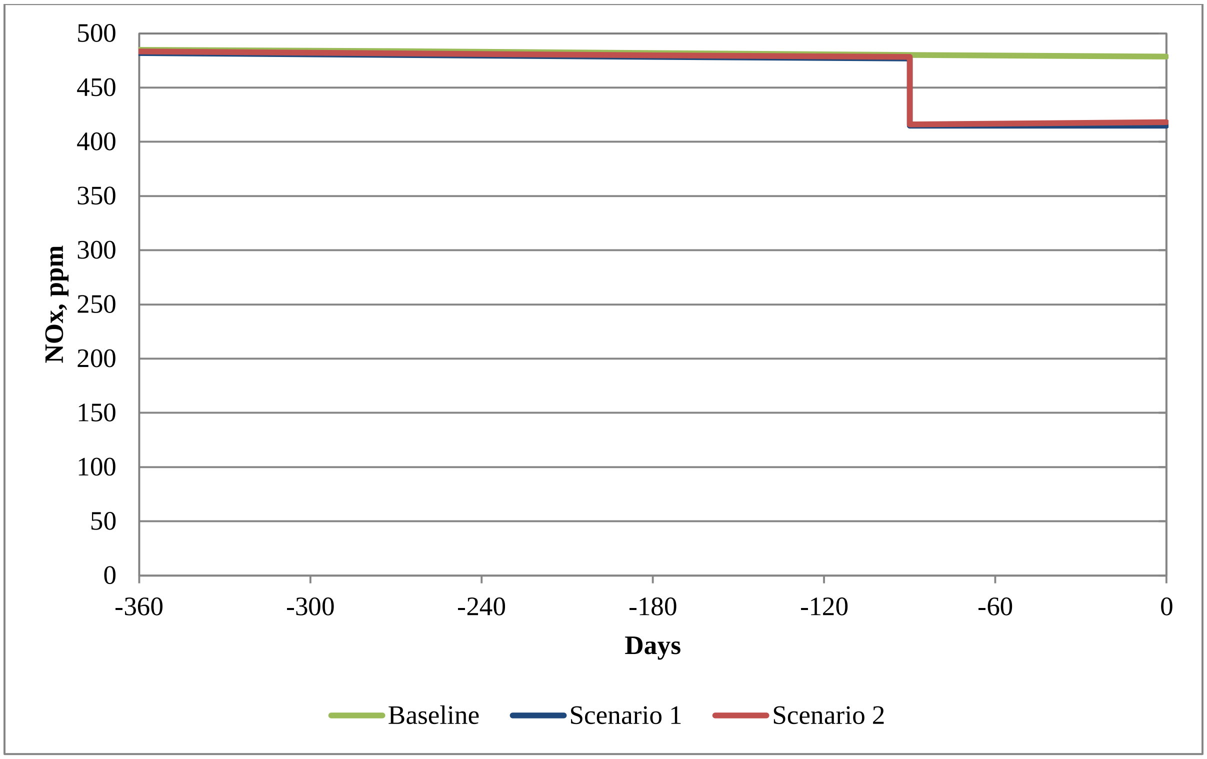

Figure 6-14 Nitrogen oxides emission Group 3 scenarios

The combined effect of all three groups and all examined scenarios' total benefits for NOx emission can be calculated. Group 1 was responsible for 45% of NOx emission of all three groups. Group 2 and Group 3 have 29% and 26% NOx emission contribution, respectively. Thus, total NOx emission savings are, for Scenario 1, 6.65% and for Scenario 2, 7.16%. Scenario 2 (note the errors in this sentence, I believe, which have been corrected) produced a slightly larger benefit than Scenario 1.

The results of analysis of nitrogen oxide emission reductions are summarized in Table 6-4 and Table 6-5.

Table 6-4 Nitrogen Oxide reductions based on scenarios 1 and 2

	Every 90 Days Group		Every 180 days Group		Every 270 Days Group	
	Total NOx Emission	Percent reduction	Total NOx Emission	Percent Reduction	Total NOx Emission	Percent Reduction
No Repairs	176,387.76		172,789.6		172,789.6	
Scenario 1	162,855.59	-7.67%	159,174.8	-7.88%	166,747.7	-3.50%
Scenario 2	158,743.87	-10.00%	164,790.5	-4.63%	164,036.8	-5.07%

Table 6-5 Nitrogen Oxide Reductions

	Total Emissions	Percent Reduction
Reduction Scenario 1	6,231,892.28	-6.65%
Reduction Scenario 2	6,197,998.195	-7.16%

6.4 Conversion to Grams per Mile

Prior to estimating for pollutants such as carbon monoxide, hydrocarbons, and nitrogen oxide, an estimation of current pollution levels should be made. This section will describe the calculation undertaken to calculate the amount of emission reduction from the proposed plan. Typically, RSD measurements are reported based on the concentration of CO, HC, and NOx in terms of ratios of CO, HC, and NOx to CO2. These ratios can be changed over to the mass emission factors for each vehicle with the following equations (Pokharel, Bishop, and Stedman, 2002 On-road Remote Sensing of Automobile Emissions in the Phoenix area Year 3 (CRC Contract No. E-23-4)). The following formulas will help to convert percent and parts per million concentrations to grams per gallon and then to grams per year of each pollutant.

$$CO\ Emission\ Factor\left(\frac{gm\ CO}{gallon}\right) = \frac{5506 * CO\%}{15 + (0.285 * CO\%) + (2.87 * HC\%)}$$

$$HC\ Emission\ Factor\left(\frac{gm\ HC}{gallon}\right) = \frac{8644 * HC\%}{15 + (0.285 * CO\%) + (2.87 * HC\%)}$$

$$NOx\ Emission\ Factor\left(\frac{gm\ NOx}{gallon}\right) = \frac{5900 * NOx\%}{15 + (0.285 * CO\%) + (2.87 * HC\%)}$$

The next step is to compute the mass emission rate of the three pollutants for each vehicle using the vehicle miles traveled (VMT)-based approach with the following equation (Zia, 2003 Cooperative and non-cooperative decision behaviors in response to the inspection and maintenance program in the Atlanta air shed, 1997 – 2001. Ph.D. Dissertation, Georgia Institute of Technology, Atlanta).

$$Emission\ Rate\ \left(\frac{gm}{year}\right) = \frac{Emission\ Factor * VMT}{Fuel\ Economy}$$

6.5 Vehicles Eligible for Emission Inspection in Georgia

Throughout this research, data that was analyzed represents a subset of the Atlanta fleet. To estimate total carbon monoxide, hydrocarbon, and nitrogen oxides emission, the number of vehicles present in Atlanta's 13 counties needs to be calculated. Thirteen counties are chosen because Georgia's Inspection and Maintenance program covers the thirteen counties of the Atlanta Metro area. Furthermore, only vehicles between four and twenty-five years old are inspected and therefore will be subject to emission reduction benefits from applying the pre-inspection methodology described previously.

The Georgia Registration database for fourth quarter 2010 was employed to calculate the number of vehicles registered in the thirteen counties. Out of 3.5 million gasoline vehicles, 2.5

million were deemed to be eligible based on vehicle age. A detailed county breakdown of the vehicle registration information can be seen in Table 6-6.

Table 6-6 2010 Thirteen county vehicles

County Name	County Code	All Vehicles	Eligible Vehicles	First 3 Model Years	ASM Vehicles	OBDII Vehicles
Fulton	1	663,148	457,850	113,337	56,528	401,322
DeKalb	2	467,889	351,805	53,844	51,353	300,452
Cobb	7	567,112	401,201	74,545	45,289	355,912
Clayton	13	182,825	129,941	16,365	22,529	107,412
Gwinnett	16	629,875	453,226	79,277	51,334	401,892
Coweta	27	114,413	74,538	12,351	11,295	63,243
Cherokee	35	197,646	130,867	23,141	16,103	114,764
Henry	54	176,427	120,551	17,918	17,074	103,477
Douglas	57	108,063	74,670	9,951	10,789	63,881
Paulding	75	120,122	81,234	11,661	11,430	69,804
Forsyth	79	161,748	102,989	22,284	10,124	92,865
Rockdale	89	70,740	48,358	6,251	7,670	40,688
Fayette	112	109,586	73,840	12,483	9,681	64,159
	Totals:	3,569,594	2,501,070	453,408	321,199	2,179,871

Based on vehicle counts from Table 6-6 and calculations for emission savings using the program proposed in this research, 26,056 tons of carbon monoxide, 760 tons of hydrocarbons, and 4,549 tons of nitrogen oxide can be kept out of Atlanta's area annually. Table 6-7 provides detailed information about each pollutant.

Table 6-7 Emission savings

	CO	HC	NOx
Sampled Vehicle emission, grams	2,364,469,816	108,647,061	466,094,178
Sampled Vehicle Emissions, Tons per Year	2,364	109	466
Number of Sampled Vehicles	63,549	63,549	63,549
Grams per vehicle	37,207	1,710	7,334
Miles per Year	16,650	16,650	16,650
Grams per mile	2.24	0.10	0.44
Sample Vehicle emission with applied savings	2,151,594,421	104,430,284	453,051,524
Reduction in emissions, grams	212,875,395	4,216,777	13,042,655
Reduction in emissions, grams/vehicles	3,350	66	205
Emission per vehicle after reduction, grams/vehicle	33,857	1,643	7,129
Eligible Vehicle 2010	2,501,070	2,501,070	2,501,070
Atlanta Total emissions, grams	84,679,353,855	4,110,016,692	17,830,549,254
Atlanta Total emissions, tons	84,679	4,620	18,820
Savings per year, grams	8,378,043,152	165,957,835	513,314,014
Savings per year, tons	8,378	165	513

6.6 Emission and Cost Benefits of Inspected versus Un-inspected fleet versus Applying Modeling Technique

To estimate emission benefits achieved by the Georgia emission inspection program, the reference method is employed. The reference method is often used in emission program effectiveness evaluation, as reviewed in section 2.1. The reference method compares two groups of vehicles. Vehicles subject to emission inspection were compared to vehicles not subject to emission inspection, i.e., vehicles registered outside the inspection and maintenance Atlanta area. Measurement for vehicles that were not registered in Atlanta metro were obtained by direct measurements in Macon and Augusta, GA as well as some uninspected vehicles captured in metro Atlanta locations. Macon, GA vehicles has a similar fuel composition to metro Atlanta fuel, therefore fuel differences were not examined in this research.

Based on Figure 2-2 carbon monoxide produced 28 percent savings when inspected versus un-inspected fleets were compared. To estimate the economic benefit of carbon monoxide emission reduction a few assumptions have been made. First it was assumed that the number of tests that need to be done is equal to the number of eligible vehicles. Based on analysis of the 2010 Georgia Registration database it is estimated that 2,501,070 vehicles are eligible for emission inspection tests in metro Atlanta. Second, based on analysis of the 2010 Inspection and Maintenance database, the average test in metro Atlanta costs $22.20. Total carbon monoxide emissions in metro Atlanta were estimated based on grams per mile emission measured by remote emission sensing and then multiplied by the number of eligible vehicles. Based on those assumptions and calculations it is estimated that 26,056 tonnes of carbon monoxide are kept out of the atmosphere as a result of taking the emission test and repairing failed vehicles. The cost to remove a tonne of carbon monoxide from the atmosphere is $2,130 per metric ton of carbon monoxide each year. In addition to estimating the benefit achieved by an emission inspection program, estimates of program effectiveness also were calculated to account for the effects of variable time testing based on probability of failure produced by modeling on the emission inspection program. By applying modeling and variable time testing, the effectiveness of the emission inspection program will go up, thereby reducing costs from $2,130 to $1,648 per metric ton of carbon monoxide per year for the inspected Atlanta fleet. This represents an almost 23% cost savings.

To estimate the benefits for hydrocarbon, a technique similar to the carbon monoxide technique was applied. First, the inspected fleet was compared to the uninspected fleet. Figure 2-3 represents average hydrocarbon emissions grouped by model year. Based on that chart a reduction of 18 percent was calculated. Using assumptions described previously, hydrocarbons showed 760 tonnes of savings annually over the saving of vehicles inspected versus uninspected. Costs of removing a tonne of hydrocarbons from vehicle emission from the atmosphere was estimated to be $72,138 per tonne per year. After estimating the effect of having emission inspection tests, the modeling technique proposed in this research was applied to the program and benefits from that modeling effort were calculated. An additional 165 tonnes of hydrocarbons were kept from the atmosphere. As a result, the cost of removing one tonne of hydrocarbons per year went down from $72,138 to $60,741. Even though reduction in emissions was not great, there were 16 percent in cost savings.

Calculation of emission inspection benefits for nitrogen oxides follows suit of similar calculations for carbon monoxide and hydrocarbons. Based on Figure 2-4 it is estimated that an emission inspection program produces 25 percent cleaner vehicles than vehicles from areas without emission inspection. In total 4,549 metric tons of nitrogen oxide were removed from the atmosphere as a consequence of having emissions inspected and failed vehicles repaired. The cost of reducing those emissions comes to $12,205 per tonne of nitrogen oxide per year. After the addition of modeling to regular emission inspection programs, 513 additional tonnes of nitrogen oxide are removed from the atmosphere and it costs eight percent less ($11,215 per tonne each year).

Even though the reduction of pollutants by the proposed program was modest, reasonably high cost benefits can be obtained considering that very modest costs are needed to operate the system. In addition, the proposed program can be easily adjusted to obtain greater benefits. Frequency of testing can be interchanged as well as the vehicles that are required for more frequent testing. Additional attributes of vehicle characteristics can be added if desired without any changes to emission inspection program overhead.

The marginal benefits of the proposed new program were calculated based on a $1.25 million investment. From experience of CAFÉ program $1 million can be spent on collecting remote sensing measurements. Cost effective running of a remote sensing program can produce upwards of two million remote sensing records and over time create a viable historical dataset of remote sensing emission measurements. Remaining $250K will be used for program administration, database storage and upkeep and other IT and modeling needs.

6.7 Socio-demographic Impact

Judging by the analysis presented in the previous sections, vehicles that are older and have more accumulated miles will be tested more frequently. Consequently, the owners of those vehicles will be affected. Figure 6-15 represents the emission inspection failure rate based on income for the census block where the emission station was located. Reasons for choosing station location census block income versus individual income were that emission station locations are available and are public knowledge as opposed to addresses for individual owners.

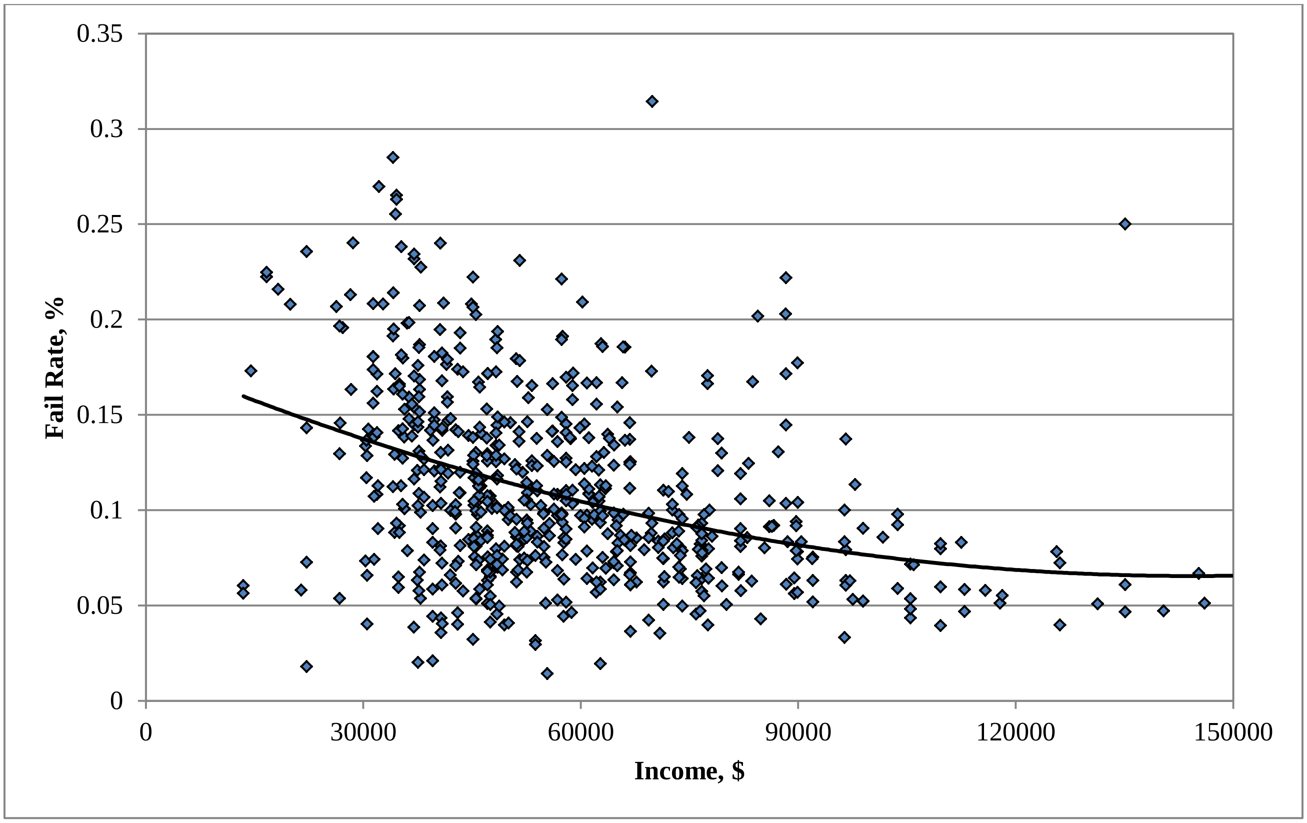

Figure 6-15 Emission inspection fail rate by station income category

Assuming that emission inspections are done in close proximity to residents' homes, the failure rate has an inverted relationship with income. As income increases failure rate decreases; therefore, if the proposed policy goes into effect, owners with smaller incomes would be affected to a larger degree than owners with larger incomes. There are two extra burdens that will be placed on those owners. First is the expenditure for the test. Currently in Georgia each test costs motorists anywhere between \$10 - \$25 with an average of \$22.20. In all, 2,647,150 paid tests were performed in calendar year 2010. Additional expenses due to more frequent testing can be mitigated by making the test fee a part of the registration fee. Therefore even if someone will need to take more emission inspection tests they will be covered by one annual fee.

The second burden mentioned is time to make a test. However time requirements are not extremely onerous.

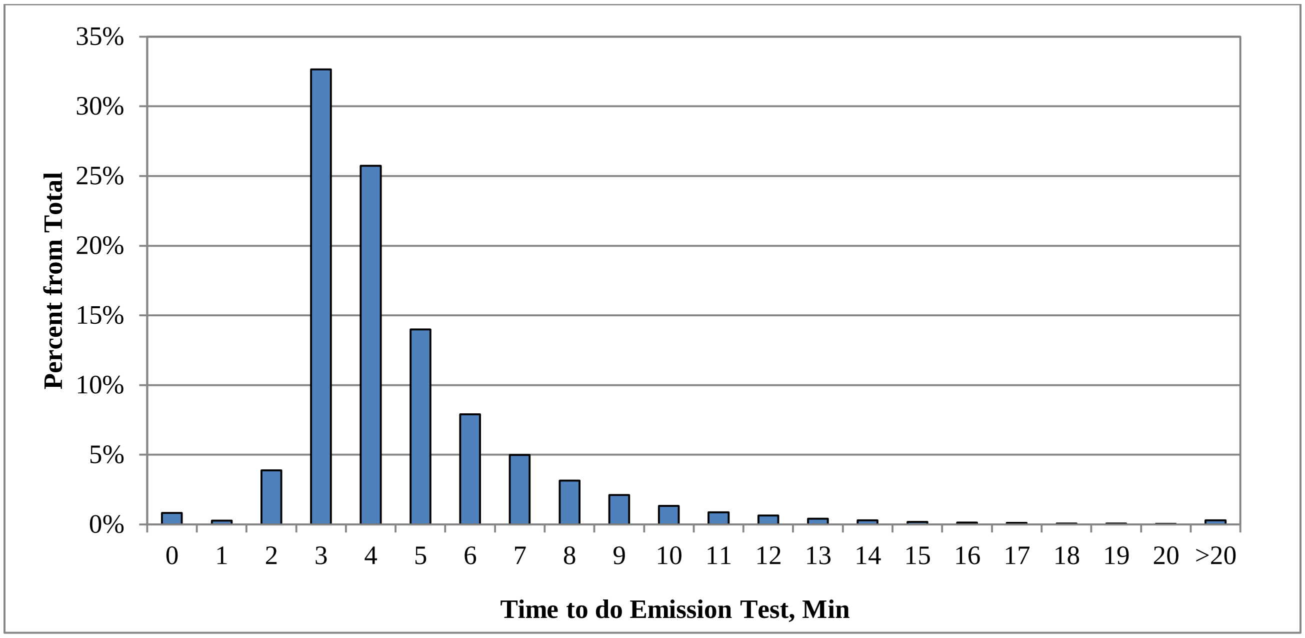

Figure 6-16 Time to take an emission inspection test

Based on Figure 6-14, which shows the distribution of time to take an emission inspection test, the majority of tests were performed within 7 – 8 minutes with a very small percentage of tests requiring more than 10 minutes. In addition to test time, there will be some additional time to drive to the test location and wait until the testing station becomes available. Perhaps time expenditures can be mitigated by an appointment scheduling system. Appointments can be set at a time that is convenient for the vehicle owner to reduce time requirements and inconvenience.

7 CONCLUSION

Emissions from light-duty vehicles constitute a significant portion of pollutants from mobile sources. Even though vehicle emission inspections are very successful in reducing those emissions, those programs are not optimized to be concentrating on high polluting vehicle rather the programs test the whole fleet to identify high emitters. This research is an attempt for vehicle emission program optimization. Presently vehicle emission inspection policy is created based on selecting subject to emission inspection subject vehicles and setting the frequency of testing for those vehicles. Usually subject vehicles are determined by the vehicle's age and frequency is set to annual or biennial.

This work introduces several novel to emission testing concepts. To concentrate emission inspection resources on high emitting vehicles and therefore increase efficiency of the program combination of in-program and out-of-program data to model probability of failure is introduced. In program data includes vehicle characteristics as well as historical test results. Out-of-program data consists of testing that was done outside of an emission inspection program such as vehicle remote emission testing. By combining those sources of data more accurate model that describes vehicle emission profile is assembled.

The second novel concept that is introduced in this research is a variable timing between tests. It is proposed that vehicles with higher probability of failure to have more frequent testing. The concept of more frequent testing is based on the hypothesis that if potentially high polluting vehicles can be tested more frequently there are emission benefits to be realized from catching failing vehicles sooner. On the other hand if the vehicle has a very low probability of failure then the time interval between emission test can be stretched since if the vehicle is operating at clean emission levels than the test does not do anything to change that.

Those hypotheses are supported by the analysis in this research. Vehicle emissions from vehicles that passed Georgia emission inspection tests suggests that there are minimal differences in criteria pollutants before and after the test. As expected, emissions for the passing group did not change before or after the test since vehicles operated normally and did not require any mechanical fixes. A group of vehicles that failed the emission inspection test, on the other hand, displayed pronounced trends before and after the repair. Before the repair emissions had an upward trend, at the time of the test emissions went down, displaying the repair effect, and continued on the upward trend after the test, suggesting that if vehicles can be fixed sooner it can produce emission savings results.

To identify vehicles that are likely to fail, a multi-parameter model based on vehicle characteristics, ownership history, previous emission tests, and remote sensing measurements was developed. Based on the model results, vehicles were split into categories that are likely to fail and not likely to fail. Vehicles that are likely to fail were assigned variable time frequencies for the emission test in an effort to catch potentially high polluting vehicles sooner.

Implementation of this program is estimated to achieve a 9% reduction in carbon monoxide, or 8,378 tonnes per year, 4% of hydrocarbons, or 165 tonnes per year, and 3%, or 513 tonnes per years, of nitrous oxides emissions just by identifying vehicles with a higher probability of failure and requiring them to get tested ahead of the regularly scheduled test, which corresponds to 23%, 16%, and 8% cost savings for CO, HC, and NOx per-ton-per-year for removal of those pollutants from the atmosphere. All those savings can be achieved with a modest investment in program administration and virtually no change to existing infrastructure.

By introducing a hybrid approach to emission inspection, one that utilizes in-program data and uses out-of program data such as vehicle remote emission sensing, the emission inspection program can concentrate on higher polluting vehicles and reduce criteria pollutant. This research is a first step in understanding complex problems in predicting vehicle failure in advance of it occurring.

REFERENCES

A Policy on Geometric Design of Highways and Streets. Washington, D.C.: American Association of State Highway and Transportation Officials, 2001.

Agency, Illinois Environmental Protection. *Understanding On-Board Diagnostics.* 2013. http://www.epa.state.il.us/air/vim/faq/obd.html (accessed June 10, 2013).

Air Trends Air & Radiation. 2011. http://www.epa.gov/airtrends/ (accessed 2011).

ASM/TSI Emission Testing. 2011. http://www.txdps.state.tx.us/vi/misc/faq/faq_asm.htm (accessed 2011).

Beydoun, Mustapha, and Jean-Michel Guldmann. "Vehicle Characteristics and Emissions: Logit and regression analysis of IM data from Massachusetts, Maryland, and Illinois." (Transportation Research Part D), no. 11 (2006).

Bin, Okmyung. "A logit analysis of Vehicle Emissions using Inspection and Maintenance Testing Data." (Transportation Research Part D) 8 (2003).

Bishop, G. A., and D. H. Stedman. "Measuring the Emissions of Passing Cars." *Chemistry*, 1996: No10, 485-495.

Bureau of Automotive Repair, Directed Vehicle. 2011. http://www.autorepair.ca.gov/80_BARResources/02_SmogCheck/TestOnly_Directed_Vehicles.html (accessed April 2011).

California Air Research Board. "Evaluation of the California Smog Check Program using Random Roadside Data." California Air Research Board and California Bureau of Automotive Repair. March 12, 2009. http://www.imreview.ca.gov/reports/final_roadsidereport031209.pdf.

California Bureau of Automotive Repair, Department of Consumer Affairs. 2011. http://www.autorepair.ca.gov/index.aspx (accessed April 2011).

Corley, E. A., Dehart-Davis, L., Lindner, J., Rodgers, M. O. "Inspection and Maintenance Program Evaluation: Replicating the Denver step method for an Atlanta fleet." *Environmental Science and Technology, 37,* 2003: 2801-2806.

Division, Georgia Environmental Protection. Gorgia Environmental Protection Division. 2011. http://www.cleanairforce.com/ (accessed April 2011).

Draft Guidance on Use of In-Program Data for Evaluation of I/M Program Performance. US EPA Office of Transportation and Air Quality, 2001.

Draft MOVES2009 Highway Vehicle Population and Activity Data. Washington, DC: US Environmental Protection Agency Office of Transportation and Air Quality, 2009.

Eisinger, Douglas S. *Evaluating Inspection and Maintenance Programs: A Policy-Making Framework.* Davis, CA: Air & Waste Management Association, 2005.

Emission Test Cycles: IM240. 2010. http://www.dieselnet.com/standards/cycles/im240.html (accessed April 2011).

Enns, Phil, Ed Glover, Penny Casey, and Michael Sklar. *Analysis of Emission Deterioration Using Ohio and Wisconsin IM240 Data.* United States Environmental Protection Agency, 1999.

Environ International Corporation. *CRC Project E-64 Evaluation of the U.S. EPA Mobile6 Highway Vehicle Emission Factor Model.* Novato, CA: Air Sciences, March 2004.

Environmental Studies and Toxicology Transportation Research Board. *Evaluating Vehicle Emissions Inspection and Maintenance Programs.* The National Academies Press, 2001.

Fang, Tiegang, Yuan-Chung Lin, Tien Mun Foong, and Chia-Fon Lees. "Reducing NOx Emissions from a Biodiesel-Fueled Engine by Use of Low-Temperature Combustion." (Environmental Science & Technology) 42, no. 23 (12/1/2008).

Glover, Ed, and Dave Brzezinski. *Analysis of the Arizona IM240 Test Program and Comparison with the TECH5 Model.* US EPA Office of Transportation and Air Quality, 1997.

Guidance on Use of Remote Sensing for Evaluation of I/M Program Performance. US EPA Office of Transportation and Air Quality, 2004.

Harrington, Winston, Virginia McConnell, and Amy Ando. "Are Vehicle Emission Inspections Programs Living up to Expectations ." (Transportation Research Part D) 5, no. 3 (2000).

Jimenez, Jose L., Peter McClintock, G. J. McRae, David D. Nelson, and Mark S. Zahniser. "Vehicle Specific Power: A Useful Parameter for Remote Sensing and Emission Studies." *9th CRC On-Road Vehicle Emissions Workshop.* San Diego, CA USA: CRC, 1999.

Jimenez, Jose, Peter McClintock, G. J. McRae, David D. Nelson, and Mark S. Zahniser. "Vehicle Specific Power: A useful Parameter for Remote Sensing and Emission Studies." San Diego, CA: 9th CRC On-Road Vehicle Emissions Workshop, 1998.

Kahn, Matthew E., and Joel Schwartz. "Urban Air Pollution Progress Despite Sprawl: The "Greening" of the Vehicle Fleet." (Journal of Urban Economics), no. 63 (2007).

Melosi, Martin V. *The Automobile and the Environment in American History.* 2010. http://www.autolife.umd.umich.edu/environment (accessed May 29, 2013).

Reformulated Gas. U.S. Environmental Protection Agency. October 2007. http://www.epa.gov/otaq/regs/fuels/rfg/420f07061.htm#1 (accessed April 2011).

Remote Sensing: A Supplemental Tool for Vehicle Emission Control. US Environmental Protection Agency Office of Mobile Sources, n.d.

Slott, Robert S. *Remote Sensing Measurement of Real World Vehicle High-Exhaust Emitters.* Coordinating Research Council, 2002.

Technical Guidance on the Use of Mobile6.2 for Emission Inventory Preparation. US EPA Office of Transportation and Air Quality, 2004.

Tom Wenzel, Marc Ross. "Comments on “Statistical modeling of vehicle emissions from inspection/maintenance testing data: an explanatory analysis"." *Transportation Research Part D*, 2003.

Transitioning I/M Workgroup. US EPA Mobile Source Technical Review Subcommittee, 2009.

United States Environmental Protection Agency. *Emission Facts: The History of Reducing Tailpipe Emissions.* Office of Mobile Sources, US EPA, 1999.

"US Environmental Protection Agency." *On-Board Diagnostics (OBD).* n.d. http://www.epa.gov/otaq/regs/im/obd/basic.htm (accessed 2011).

Wenzel, Tom. "Reducing emissions from in-use vehicles: an evaluation of the Phoenix inspection and maintenance program using test results and independent emissions measurements ." *Environmental Science & Policy,* 2001: 359-376.

—. *Seasonal Trends in Vehicle Emissions.* Lawrence Berkeley National Laboratory. 1999. http://enduse.lbl.gov/projects/vehicles/APPENDIX_M.pdf.

A. APPENDIX A

Table A-1 Review of state emission inspection programs

State	Metro Area	Time period	Idle Test	OBD	Gas Cap	Diesel	Motorcycle	New Vehicle Exemption, Years	Subject for Test, Model Year and Newer	Mileage Exemption, Miles Per Year	Exemption
Alaska	Anchorage MOA	Annual		Yes		Yes Onetime pre owner	No	6	1968		12,000
Arizona	Phoenix, Tucson	Biennial	Yes	Yes		Yes Opacity	No	4	1966		
California		Biennial		Yes		Yes		6	1976		
Colorado	Boulder, Broomfield, Denver, Douglas, Jefferson	Annual/biennial	Yes	Yes		Yes		4			
Connecticut				Yes			No	4	25		10,000
Delaware				Yes							
District of Columbia				Yes					1968		
Georgia	13 Counties	Annual	Yes	Yes	Yes	No	No	3	25		8,500
Idaho	Ada County			Yes			No	4	1981		
Illinois		Annual	Yes	Yes	Yes	No	No		1995		
Indiana	Lake,	Biennial		Yes				4	1976		9,000

	Porter										
Louisiana											
Maine											
Maryland				Yes					1977		26,000
Massachusetts				Yes							
Missouri	St. Louis		No	Yes					1995		8,500
Nevada	Clark, Washoe counties			Yes			No	2	1968		14,000
New Hampshire				Yes							8,500
New Jersey				Yes		No	No				8,500
New Mexico				Yes							
New York				Yes	Yes	No	No	2	25		8,500
North Carolina											
Ohio		Biennial		Yes			No	4	25		10,000
Oregon	Portland, Medford			Yes		Yes			1975		8,500
Pennsylvania				Yes			No		1975	5000	9,000
Rhode Island		Biennial		Yes		Yes	No	2		24,000 to be tested	8,500
Tennessee		Annual		Yes					1975		10,500
Texas		Annual	Yes	Yes			No	2	24		
Utah		Biennial		Yes				6	1967		
Vermont											
Virginia		Biennial	Yes	Yes	Yes	Yes	No	2	25		10,000
Washington				Yes				5	25		
Wisconsin				Yes			No	No	1996		8,500

Table A-2 Results of CAFÉ 2009 data collection

MDate	RSD Unit Num	Site ID	Beam Blocks	Valid Data	Readable LP	State LP	Matched to RDB	Match to VinDecod
1/22/2009	503	22	6112	5852	5286	4960	4383	3471
1/23/2009	503	40a	3428	3189	2852	2634	2309	1879
1/29/2009	503	40	2660	2307	2116	1996	1715	1437
1/30/2009	503	74	11365	10646	9863	9245	8343	6593
2/5/2009	503	35	4668	4157	3791	3598	3197	2630
2/6/2009	503	101	1903	1715	1505	1435	1237	1040
2/10/2009	503	48	9280	8791	7982	7337	6679	5241
2/12/2009	503	104	8712	7651	7051	6554	5776	4705
2/13/2009	503	95	6293	5621	4874	4519	3974	3290
2/26/2009	503	100	4266	4154	3804	3656	3338	2749
3/5/2009	503	15	7971	6967	6108	5610	5046	4091
3/10/2009	503	16	4247	4075	3813	3553	3209	2604
3/11/2009	503	24	12766	12517	11883	11009	10157	7939
3/12/2009	503	TLS5	5006	4897	4609	4327	4006	3167
3/18/2009	503	98	5501	4693	4284	4118	3716	2894
3/19/2009	503	5	5140	4774	4057	3776	3377	2715
3/20/2009	503	90	4259	3885	3454	3280	2949	2380
3/24/2009	503	22	6142	5833	5497	5202	4881	3705
4/3/2009	503	37	12602	11127	9514	8248	7245	5881
4/8/2009	503	23	3015	2684	2483	2264	2052	1575
4/9/2009	503	97	3019	2827	2500	2330	2056	1661
4/15/2009	503	40	2861	2638	2390	2195	1899	1560
4/16/2009	503	40a	1735	1577	1466	1377	1213	1016
4/17/2009	503	42	12786	11989	10277	9398	8291	6763
4/22/2009	503	74	10307	9758	8930	8466	7740	5810
4/23/2009	503	48	9366	8797	7591	6960	6330	4878
4/24/2009	503	101	1680	1479	1304	1239	1111	902
5/7/2009	503	100	4322	4198	3908	3740	3400	2789
5/8/2009	503	104	6107	5159	4774	4368	3959	3198
5/19/2009	503	95	5107	4146	4155	3831	3471	2851
5/20/2009	503	98	5117	3984	3737	3632	3322	2558
6/10/2009	511	120	2658	1939	1907	1706	1559	1233
6/11/2009	511	118	2502	2318	2019	1858	1737	1338
6/12/2009	511	120	5625	5158	4584	4013	3690	2837
6/17/2009	511	98	7010	6150	5387	5215	4856	3838
6/19/2009	511	24	8680	8539	7831	7166	6627	5039
6/24/2009	511	16	4082	3913	3458	3349	2810	2276
7/7/2009	511	15	5631	4896	4153	3735	3252	2569
7/8/2009	511	90	3321	2948	2850	2703	2312	1829

7/9/2009	511	23	2822	2232	2496	2252	1938	1418
7/14/2009	511	TLS5	4261	4203	3534	3533	3268	2481
7/15/2009	511	5	4372	4106	3595	3331	2842	2160
7/21/2009	511	48	8047	7640	5855	5402	4666	3554
7/22/2009	511	22	7507	7183	6279	5810	5217	3964
7/23/2009	511	74	9779	9226	8663	8124	7315	5568
8/5/2009	511	119	5072	4679	4227	4121	3589	2907
8/12/2009	511	35	4096	3702	3421	3314	2947	2362
8/25/2009	511	120	4260	3307	3046	3046	2721	2062
8/27/2009	511	119	4209	3003	3122	3046	2670	2134
9/2/2009	511	118	2084	1682	1605	1464	1320	1020
9/4/2009	511	121	2144	1673	1528	1463	1330	1074
9/9/2009	511	120	3999	3191	3306	2997	2626	2013
9/23/2009	511	74	12316	11102	11085	10527	9367	7048
9/24/2009	511	24	10183	9821	9247	8533	7829	5951
9/28/2009	511	98	4738	3512	3547	3401	3139	2386
10/13/2009	511	48	8022	7141	6837	6249	5544	4233
10/16/2009	511	22	7445	6853	6705	6221	5549	4116
11/20/2009	511	16	4018	3792	3364	3126	2744	2218
12/10/2009	511	74	7400	6540	6161	5786	5339	3881
12/22/2009	511	74	6288	5545	5127	4833	4456	3314
			350314	318081	290797	271181	243640	190795

Table A-3 Results of data collection CAFÉ 2010

MDate	RSD Unit Num	Site ID	Beam Blocks	Valid Data	Readable LP	State LP	Matched to RDB	Match to VinDecod
1/22/2010	511	95	3729	2886	2704	2518	2230	1819
1/28/2010	511	48	7028	6443	5247	5247	4920	3670
2/3/2010	511	15	5647	4663	3864	3709	3141	2485
2/18/2010	511	37	11672	9442	7721	6957	5973	4652
2/19/2010	511	42	9468	7744	6503	6497	5980	4609
2/25/2010	511	5	3350	3043	2214	2214	1816	1385
2/26/2010	511	100	3650	3546	3102	3098	2821	2221
3/5/2010	511	98	5921	4894	4897	4895	4192	3145
3/17/2010	511	104	1935	1610	1376	1375	1188	899
3/18/2010	511	104	7070	5807	6057	5655	4929	3791
3/19/2010	511	40	2616	2351	1940	1897	1525	1182
3/24/2010	511	23	2004	1313	1129	1123	897	649
4/2/2010	511	22	7880	7066	6011	6011	4757	3405
4/7/2010	511	42	1949	1747	1170	1170	874	675
4/9/2010	511	24	10341	9842	8072	8070	6698	4796

4/22/2010	511	TLS5	5038	4905	4487	4297	3723	2604
4/23/2010	511	98	5942	4177	3757	3704	3121	2357
4/30/2010	511	97	4223	3613	3032	2918	2486	1961
5/11/2010	511	95	5723	4781	3929	3764	3288	2594
5/12/2010	511	42	10513	9323	8201	7884	6797	5214
5/20/2010	511	48	4066	3851	3330	3218	2711	2079
5/26/2010	511	101A	3945	2896	2607	2541	2253	1761
5/27/2010	511	74	12302	11260	10427	10051	8910	6325
6/8/2010	511	101	1641	1385	1267	1238	1093	831
6/9/2010	511	90	4430	3704	3148	3054	2700	1995
6/10/2010	503	48	5511	5131	4694	4451	3959	2914
6/15/2010	503	15	6671	5371	4786	4519	3910	3030
6/18/2010	503	23	3110	2226	2146	2001	1763	1246
6/24/2010	503	104	6452	5657	5042	4743	4193	3093
7/1/2010	503	100	4743	4581	3714	3583	3002	2292
7/9/2010	503	24	9958	9325	8032	7625	6243	4360
7/13/2010	503	40	2487	2344	1623	1543	1260	966
7/14/2010	503	5	4882	4582	2750	2599	2166	1577
7/21/2010	503	37	10272	8868	7520	7094	5596	4123
7/23/2010	503	22	6607	6299	5797	5537	4590	3156
7/28/2010	503	TLS5	4333	4284	3778	3618	3091	2204
8/10/2010	503	101	1470	1349	987	952	820	628
8/12/2010	503	97	3007	2789	2153	2085	1793	1361
8/13/2010	503	90	3625	3161	2490	2387	2050	1479
8/25/2010	503	95	3150	2785	2274	2202	1859	1440
8/31/2010	503	98	5007	4009	3097	3062	2685	1925
9/2/2010	503	74	8507	8097	7306	7087	6231	4288
10/13/2010	503	16	4633	4396	3553	3467	2775	2071
10/15/2010	503	42	11000	9695	7858	7528	6190	4629
10/20/2010	503	104	6864	5761	5126	4922	4068	3011
10/22/2010	503	15	6574	5576	4674	4491	3638	2715
10/28/2010	503	23	3056	2293	2263	2171	1803	1268
11/9/2010	503	48	6614	6043	4456	4278	3526	2508
11/11/2010	503	100	4555	4432	3700	3628	3079	2324
11/12/2010	503	5	4524	3869	2788	2686	2275	1635
11/23/2010	503	97	2916	2470	1969	1905	1651	1235
12/3/2010	503	24	7525	7294	5974	5675	4942	3404
12/20/2010	503	22	5785	5587	4685	4522	3989	2683
		Totals:	295921	260566	221427	213466	182170	134669

Table A-4 Remote sensing locations

Site ID	Location	City	County	Grade Perc	Speed	Traffic	Latitude	Longitude
100	From Bells Ferry Rd to I-575 South	Kennesaw	COBB	3.5	38	450	34° 03.1900'	084° 33.4300'
101	From Sigman Rd to I-20 east	Conyers	ROCKDALE	-3.5	30	150	33° 40.9100'	084° 03.8000'
104	From Hampton Rd (SR20/81) to I-75 North	McDonough	HENRY	0	30	500	33° 25.7600'	084° 10.9900'
118	Site# New Site 2 in Bartow County Exit 288 to I-75 South	Canton	BARTOW	0	35	300	__° __.____'	___° __.____'
119	SR-12/US-278 To: I-20 West, Exit 90	Covington	NEWTON	0	50	600	__° __.____'	___° __.____'
120	Exit 190, Hwy 20/Canton Road To: I-75 South	Canton	BARTOW	3	43	600	__° __.____'	___° __.____'
121	Exit 93, Hazelbrand Road To: I-20 West	Covington	NEWTON	1				
15	Thornton Rd To I-20 East	Lithia Springs	DOUGLAS	2	41.22	756	33° 46.5900'	084° 36.2700'
16	From Chapel Hill Rd to I-20 East	Douglasville	DOUGLAS	-2.3	39.29	207	33° 45.0700'	084° 42.8300'
22	From SR120 to GA 400 South	Roswell	FULTON	0	37.82	699	34° 04.0100'	084° 16.4000'
23	From Northside Pkwy to I-75 South	Atlanta	FULTON	2	44.82	276	33° 51.7200'	084° 26.2500'
24	From Abernathy Rd to GA400 South	Sandy Springs	FULTON	5	31.18	1044	33° 55.9300'	084° 21.5000'
35	On SR 34 West after Intersection with US 29/SR 14	Newnan	COWETA	0.5	30	465	33° 24.0200'	084° 47.8300'
37	From I-75/85 South to I-20 West	Atlanta	FULTON	1.5	52.4	1170	33° 44.7800'	084° 23.4200'
40	From Mt.Zion to I-75 North	Morrow	CLAYTON	2	48.31	531	33° 33.9300'	084° 19.2200'

40a	From Mt.Zion South to I-75 North	Clayton	CLAYTON	0	48.31	531	33° 33.9300'	084° 19.2200'
42	From Jimmy Carter Blvd to I-85 North	Norcross	GWINNETT	-4.5	45.42	906	33° 54.7200'	084° 12.4100'
48	From Barrett Parkway to I-75 South	Kennesaw	COBB	5	44.31	588	34° 00.4600'	084° 34.0400'
5	From Marietta Parkway to I-75 South	Marietta	COBB	2.5	35.7	699	33° 57.6500'	084° 31.2100'
74	From Peachtree Pkwy to Peachtree Ind Blvd	Norcross	GWINNETT	3	17.35	510	33° 56.8300'	084° 14.2200'
90	SR20E & SR140E to I-575 1/2m From SR20	Canton	CHEROKEE	0	45	500	34° 13.2700'	084° 29.8700'
95	From SR 138 to I-75 North	Stockbridge	HENRY	3	40	450	33° 32.9000'	084° 16.8200'
97	From West Ave and Klondike Rd to I-20 west (Exit 80)	Conyers	ROCKDALE	-1.5	46	391	33° 39.9400'	084° 01.8100'
98	From Sixes Rd to I-575 South	Lebanon	CHEROKEE	0	47	511	34° 8.7870'	084° 31.0780'
AUG2	Wrightsboro Rd to I-520 West	Augusta	RICHMOND	3.5	40	450	33° 28.0500'	082° 04.9900'
AUG7	From Peach Orchard Rd. to I - 520 West	Augusta	COLUMBIA	5.5	40	750	33° 24.5100'	082° 02.0900'
MAC10	From Eisenhower Pkwy to I-475 South	Macon	BIBB	1	35	35	32° 48.45'	083° 43.50'
Mac11	From Eisenhower Pkwy to I-475 North	Macon	BIBB	1	35	342	32° 48.66'	083° 43.52'
MAC2	Coliseum Drive to I-16 West (At Macon Coliseum)	Macon	BIBB	0.5	37.88	384	32° 50.2700'	083° 37.1400'
MAC9	From Arkwright Rd and Tom Hill Sr Blvd to I-75 South	Macon	BIBB	1	27	500	32° 54.0900'	083° 41.1500'
TLS5	Northside Parkway to I-75 North	Atlanta	FULTON	7.5	40	500	33° 51.8400'	084° 26.2400'

Table A-5 MOBILE6.2 vehicle classifications

Table 3.0.1
Comparison of MOBILE5 and MOBILE6.2 Vehicle Classifications

MOBILE5	MOBILE6.2	Description
LDV	LDV	Light-Duty Vehicles (Passenger Cars)
LDT1	LDT1	Light-Duty Trucks 1 (0-6,000 lbs. GVWR, 0-3750 lbs. LVW)
	LDT2	Light Duty Trucks 2 (0-6,001 lbs. GVWR, 3751-5750 lbs. LVW)
LDT2	LDT3	Light Duty Trucks 3 (6,001-8500 lbs. GVWR, 0-5750 lbs. ALVW)
	LDT4	Light Duty Trucks 4 (6,001-8500 lbs. GVWR, >5750 lbs. ALVW)
HDV	HDV2B	Class 2b Heavy Duty Vehicles (8501-10,000 lbs. GVWR)
	HDV3	Class 3 Heavy Duty Vehicles (10,001-14,000 lbs. GVWR)
	HDV4	Class 4 Heavy Duty Vehicles (14,001-16,000 lbs. GVWR)
	HDV5	Class 5 Heavy Duty Vehicles (16,001-19,500 lbs. GVWR)
	HDV6	Class 6 Heavy Duty Vehicles (19,501-26,000 lbs. GVWR)
	HDV7	Class 7 Heavy Duty Vehicles (26,001-33,000 lbs. GVWR)
	HDV8A	Class 8a Heavy Duty Vehicles (33,001-60,000 lbs. GVWR)
	HDV8B	Class 8b Heavy Duty Vehicles (>60,000 lbs. GVWR)
	HDBS	School Buses
	HDBT	Transit and Urban Buses
MC	MC	Motorcycles (All)

Table A-6 MOVES vehicle classification

Source Type ID	Source Type	HPMS Vehicle Class
11	Motorcycles	Motorcycles
21	Passenger Cars	Passenger Cars
31	Passenger Trucks (primarily personal use)	Other Two – Axle/Four Tire, Single Unit
32	Light Commercial Trucks (other use)	Other Two – Axle/Four Tire, Single Unit
41	Intercity Buses (non-school, non-transit)	Buses
42	Transit Buses	Buses
43	School Buses	Buses
51	Refuse Trucks	Single Unit
52	Single Unit Short-haul Trucks	Single Unit
53	Single Unit Long-haul Trucks	Single Unit
54	Motor Homes	Single Unit
61	Combination Short-haul Truck	Combination
62	Combination Long-haul Trucks	Combination

Table A-7 EPA Size type and market segment classifications

EPA size type:
Large Cars
Midsize Cars
Midsize Station Wagons
Mini compact Cars
Minivan
Small Pickup Trucks
Small Station Wagons
Sport Utility Vehicle
Standard Pickup Trucks
Subcompact Cars
Two Seaters
Vans, Cargo Type
Vans, Passenger Type

EPA Market Segment:
Small Cars
Family Sedans
Upscale Sedans
Luxury Sedans
Large Sedans
Hatchbacks
Coupes
Convertibles
Sports/Sporty Cars
Station Wagons
Pickup Trucks
Sport Utility Vehicles
Minivans
Vans

Table A-8 Vehicle make distribution for vehicles 'before' and 'after' emission test

Make	Count	Percent from Total
ACURA	2309	3%
ALFA ROMEO	5	0%
ASTON MARTIN	1	0%
AUDI	430	0%
BENTLEY	1	0%
BMW	2386	3%
BUICK	984	1%
CADILLAC	1018	1%
CHEVROLET	8998	10%
CHRY/MASERATI	1	0%
CHRYSLER	2015	2%
DAEWOO	21	0%
DODGE	3885	4%
DODGE/MITS	3	0%
FERRARI	2	0%
FORD	12062	14%
FORD/MAZDA	196	0%
GMC	2232	3%
HONDA	10577	12%
HYUNDAI	882	1%

INFINITI	1543	2%
ISUZU	396	0%
JAGUAR	373	0%
JEEP	2268	3%
KIA	891	1%
LAND ROVER	273	0%
LEXUS	3548	4%
LINCOLN	996	1%
MASERATI	5	0%
MAZDA	1581	2%
MERCEDES	2305	3%
MERCURY	1012	1%
MITSUBISHI	1064	1%
NISSAN	6654	7%
OLDSMOBILE	446	1%
PLYMOUTH	181	0%
PONTIAC	1358	2%
PORSCHE	145	0%
SAAB	233	0%
SATURN	828	1%
SCION	194	0%
SUBARU	325	0%
SUZUKI	165	0%
TOYOTA	11854	13%
VOLVO	1039	1%
VW	1165	1%
Total	88850	100%

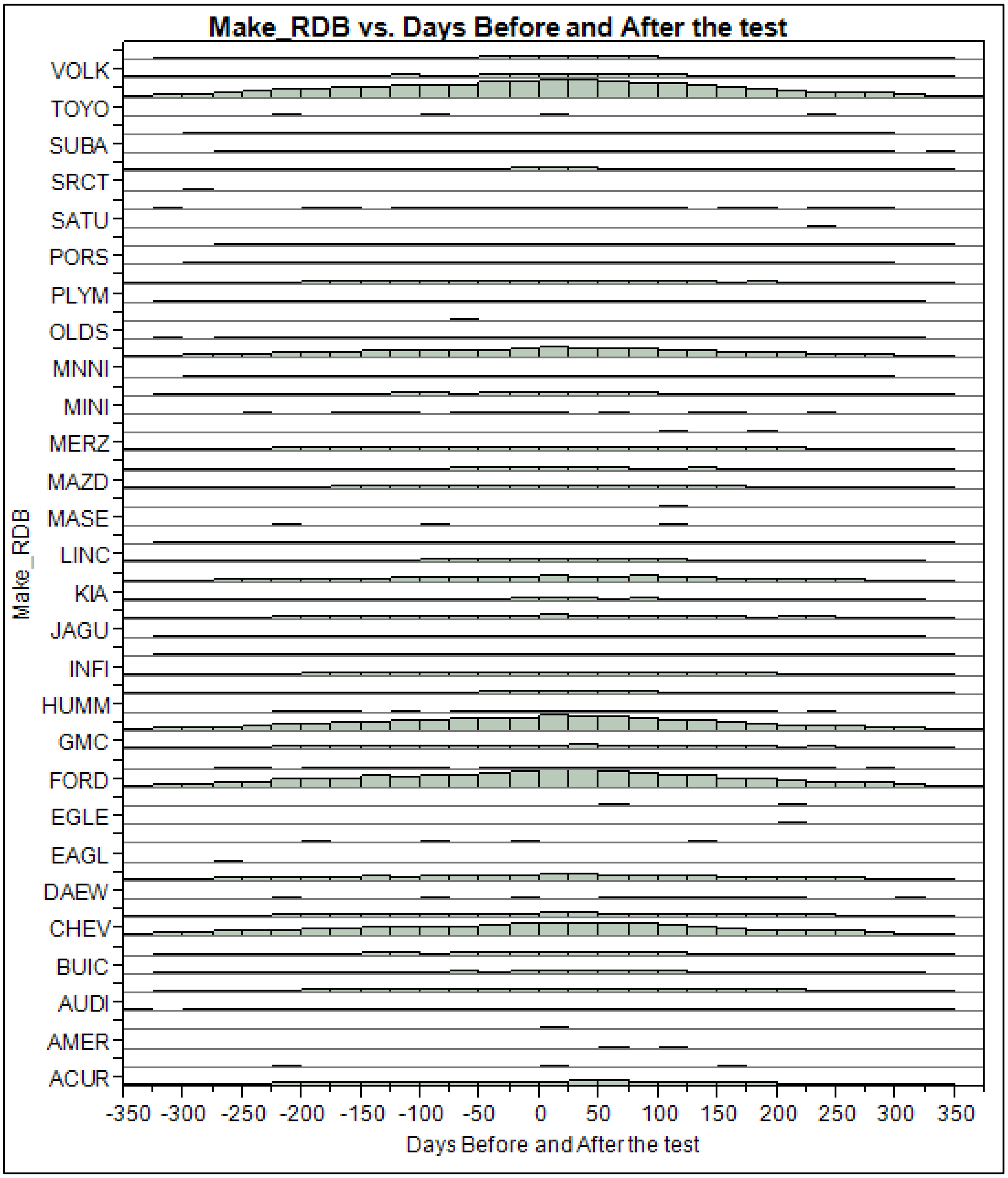

Figure A-1 Vehicle distributions by manufacturer for 'before' and 'after' emission test

Table A-9 Odometer statistics for 'before' and 'after' emission test sample

100.0%	maximum	999999
99.5%		322255
97.5%		260242
90.0%		204466
75.0%	quartile	161094
50.0%	median	118877
25.0%	quartile	84378
10.0%		60260.8
2.5%		39958
0.5%		24261.7
0.0%	minimum	3

Mean	127138.02
Standard Deviation	58410.688
Standard Error Mean	215.74921
Upper 95% Mean	127560.89
Lower 95% Mean	126715.15
Number of Samples	73297

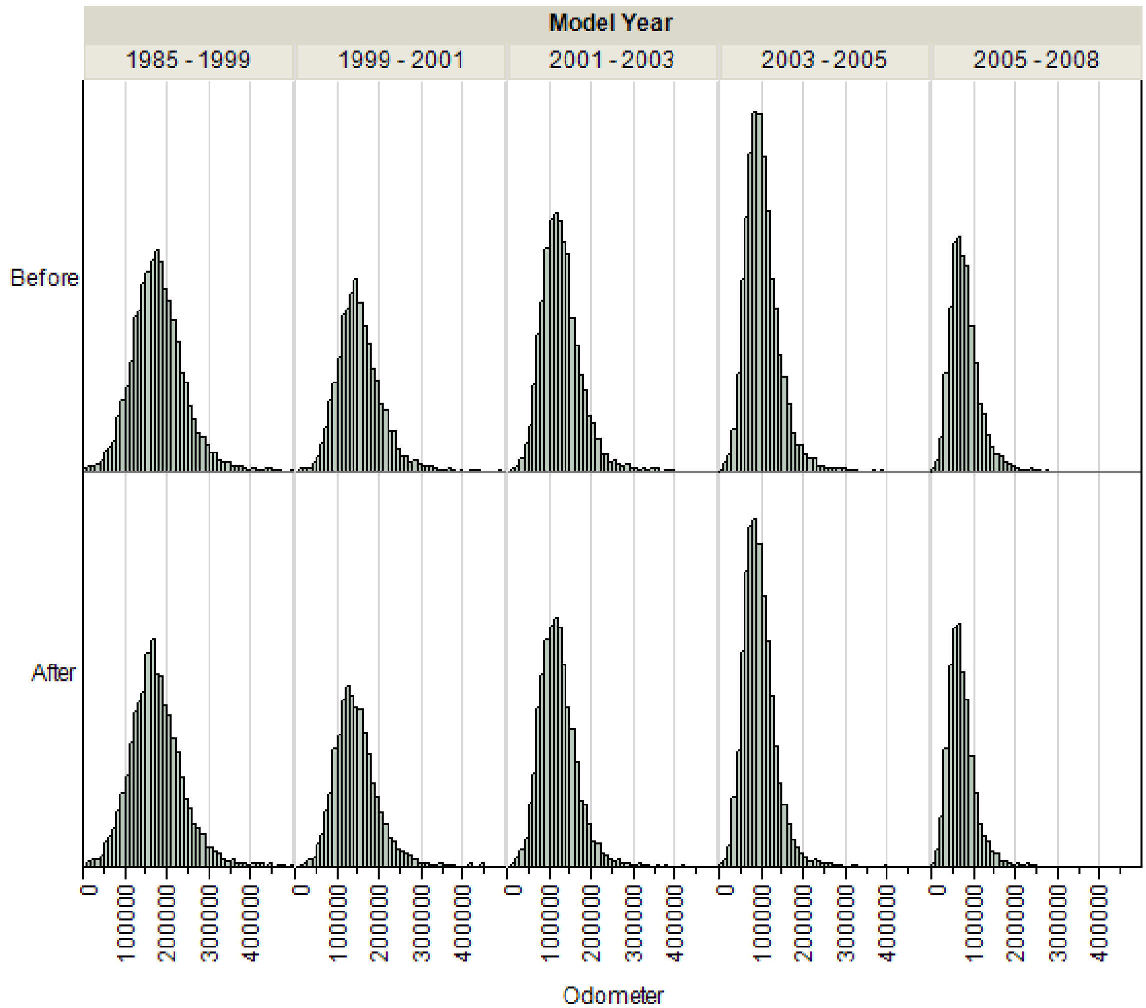

Figure A-2 Odometer readings 'before' and 'after' emission test

Figure A-3 Vehicle make distribution for 'before' and 'after' emission test group

Table A-10 Vehicle make distribution of failed and repaired vehicles

Level	Count	Percent from Total
ACUR	117	2%
AMER	1	0%
AUDI	33	0%
BMW	183	2%
BUIC	96	1%
CADI	88	1%
CHEV	1012	13%
CHRY	235	3%
DAEW	3	0%

DODG	406	5%
FORD	1090	14%
GEO	20	0%
GMC	192	2%
HOND	667	9%
HYUN	56	1%
INFI	96	1%
ISU	54	1%
JAGU	21	0%
JEEP	193	3%
KIA	57	1%
LEXS	214	3%
LINC	62	1%
LNDR	19	0%
MAZD	183	2%
MERC	112	1%
MERK	1	0%
MERZ	152	2%
MINI	2	0%
MITS	129	2%
MNNI	1	0%
NISS	559	7%
OLDS	74	1%
PLYM	45	1%
PONT	186	2%
PORS	3	0%
SAA	20	0%
SCIO	3	0%
SHEL	1	0%
STRN	104	1%
SUBA	14	0%
SUZI	19	0%
TOYT	967	13%
VOLK	105	1%
VOLV	103	1%
Total	7698	100%

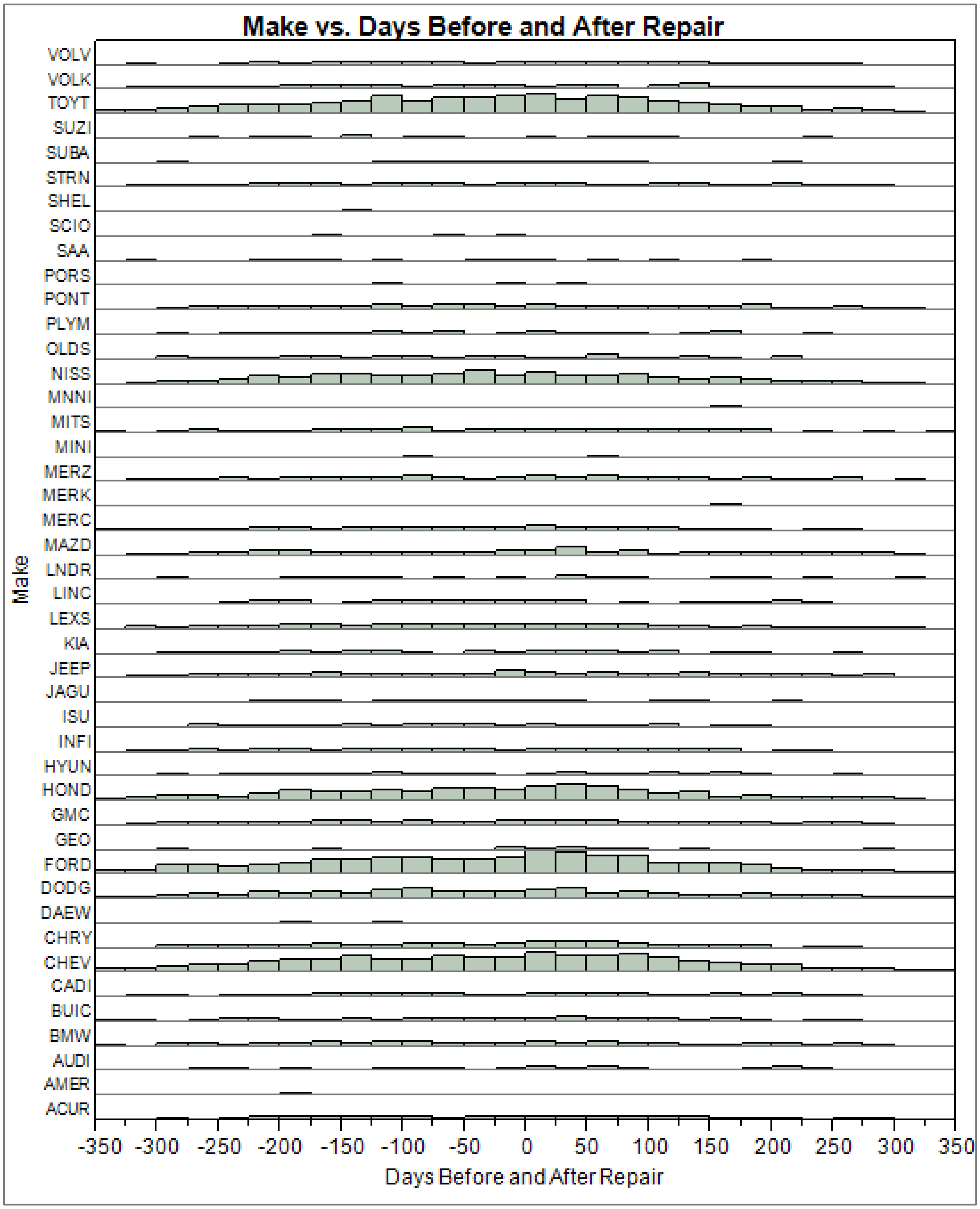

Figure A-4 Vehicle make vs. days distribution for 'before' and 'after' repair sample

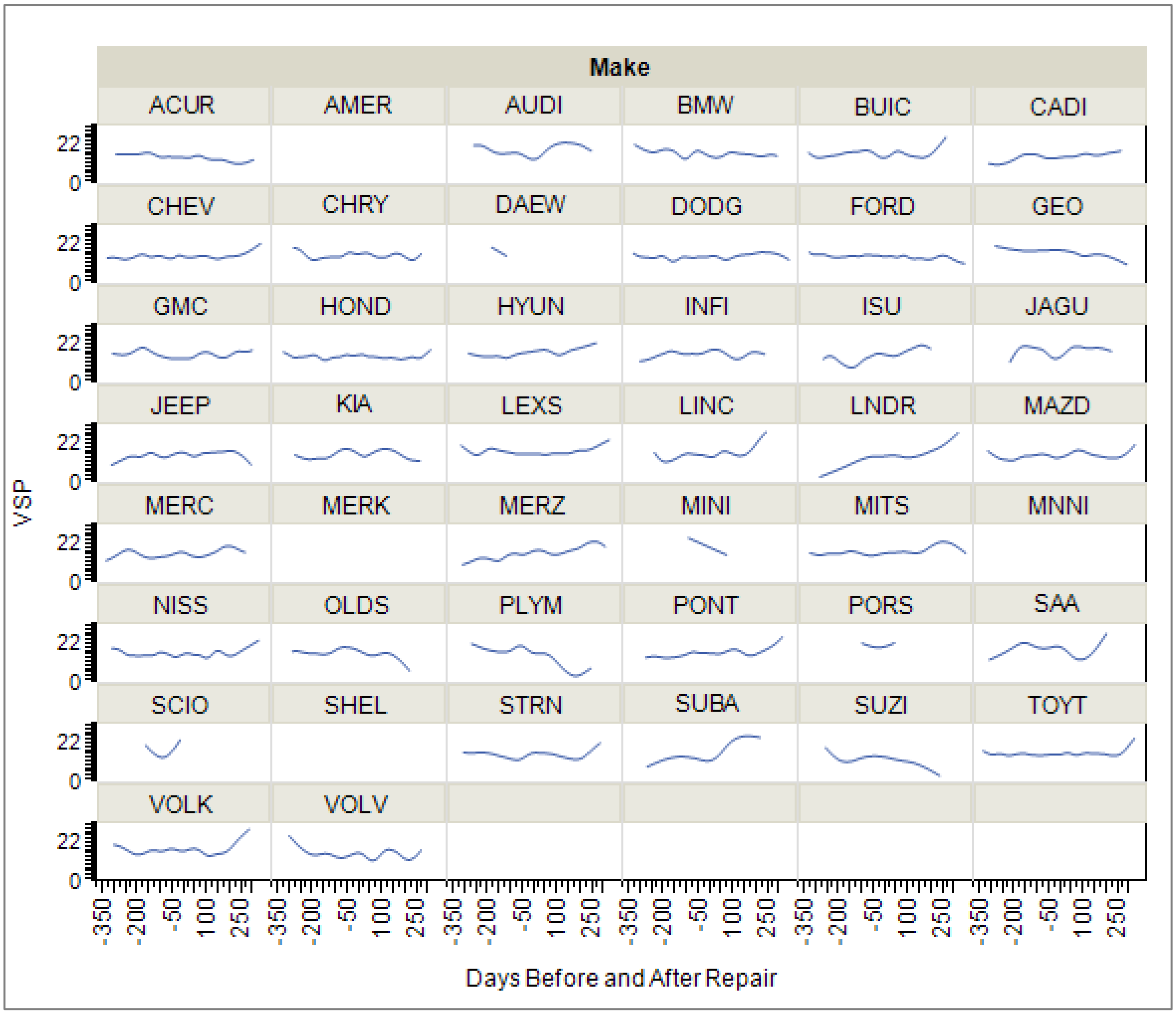

Figure A-5 Vehicle Make Vehicle Specific Power profiles for 'before' and 'after' repair sample

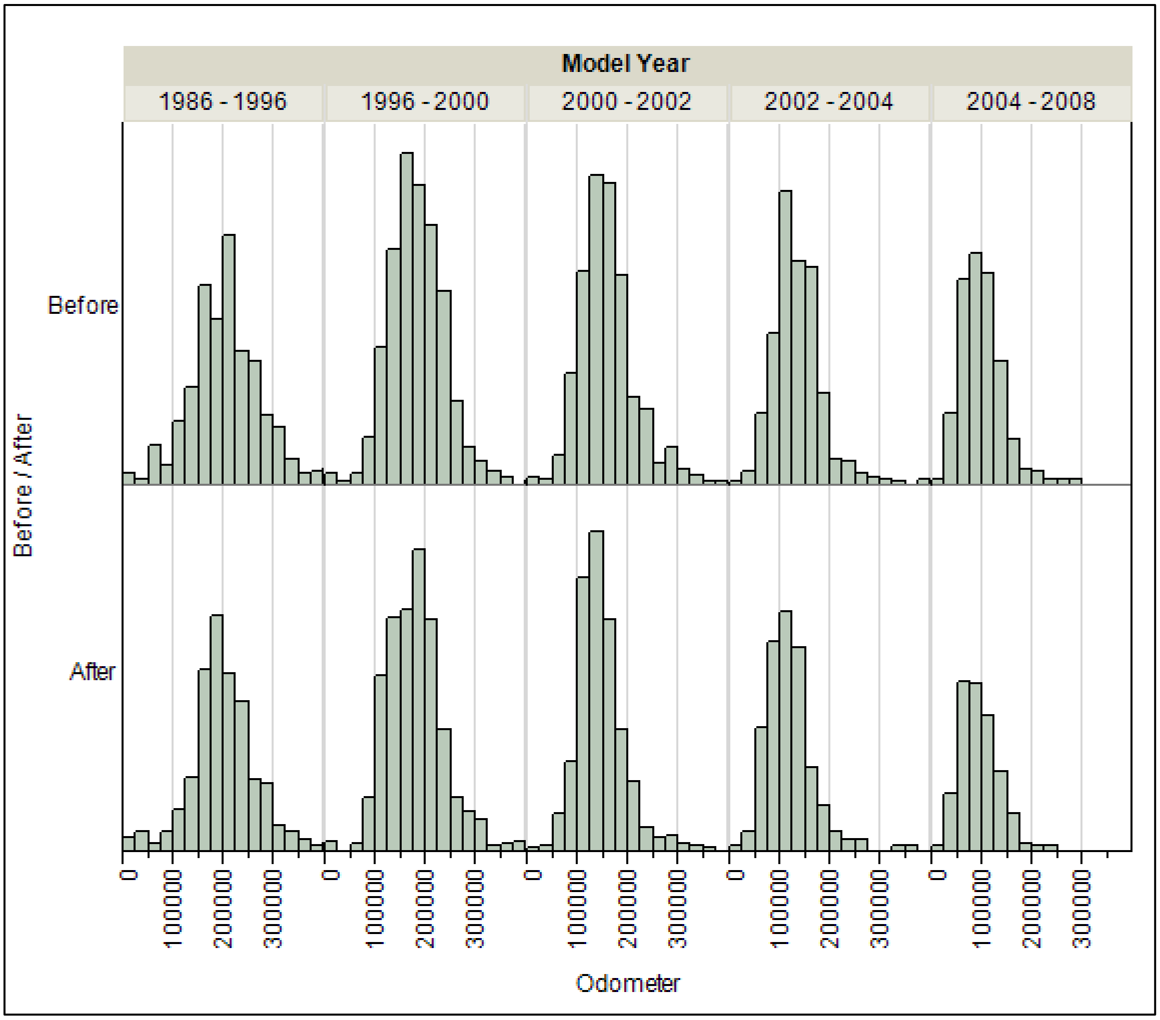

Figure A-6 Odometer reading distribution for 'Failed' and 'Repaired' vehicles

Table A-11 Vehicle make distribution modeling data

Level	Count	Prob
ACUR	2950	0.02515
ALFA	3	0.00003
AMER	4	0.00003
ASTO	1	0.00001
AUDI	572	0.00488
BENT	2	0.00002
BMW	3067	0.02615
BUIC	1308	0.01115
CADI	1379	0.01176
CHEV	11917	0.1016
CHRY	3296	0.0281
DAEW	30	0.00026

DODG	5238	0.04466
EAGL	1	0.00001
EGIL	4	0.00003
EGLE	1	0.00001
FERR	4	0.00003
FORD	15640	0.13334
GEO	86	0.00073
GMC	2900	0.02472
HOND	13441	0.11459
HUMM	35	0.0003
HYUN	1520	0.01296
INFI	2073	0.01767
ISU	514	0.00438
JAGU	485	0.00413
JEEP	2935	0.02502
KIA	1208	0.0103
LEXS	4495	0.03832
LINC	1308	0.01115
LNDR	346	0.00295
MASE	6	0.00005
MAYB	1	0.00001
MAZD	2059	0.01755
MERC	1303	0.01111
MERK	1	0.00001
MERZ	2968	0.0253
MIN	6	0.00005
MINI	41	0.00035
MITS	1518	0.01294
MNNI	107	0.00091
NISS	8558	0.07296
OLDS	574	0.00489
PANO	1	0.00001
PLYM	274	0.00234
PONT	1889	0.0161
PORS	182	0.00155
SAA	339	0.00289
SATU	1	0.00001
SCIO	65	0.00055
SHEL	1	0.00001
SRCT	1	0.00001

STRN	1130	0.00963
SUBA	376	0.00321
SUZI	244	0.00208
TOYO	5	0.00004
TOYT	15818	0.13486
VOLK	1590	0.01356
VOLV	1473	0.01256
Total	117294	1

Table A-12 Model estimates formula table

Measure	Definition
Entropy R-Square	1-Loglike(model)/Loglike(0)
Generalized R-Square	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	∑ -Log(ρ[j])/n
RMSE	√ ∑(y[j]-ρ[j])²/n
Mean Abs Dev	∑ |y[j]-ρ[j]|/n
Misclassification Rate	∑ (ρ[j]≠ρMax)/n
Number of Samples	n

Table A-13 CAFÉ 2010 database design fields

Field Number	Name	Type	Size
1	MDate	Date/Time	8
2	SiteID	Text	5
3	RSDUnitNum	Integer	2
4	VehicleSequence	Integer	2
5	MTime	Text	8
6	COperc	Double	8
7	COflag	Text	1
8	CO2perc	Double	8
9	CO2flag	Text	1
10	CO2Max	Double	8
11	CO2volume	Double	8
12	HCppm	Long Integer	4
13	HCflag	Text	1
14	NOxppm	Long Integer	4
15	NOxflag	Text	1
16	Opacity	Double	8
17	Opacityflag	Text	1

18	ColdStart	Text	1
19	SpeedMPH	Double	8
20	Speedflag	Text	1
21	Acceleration	Double	8
22	Accelflag	Text	1
23	SpeedAccelerationUnits	Text	2
24	LicensePlate	Text	25
25	LicensePlateFlag	Text	1
26	LicenseType	Text	5
27	VIN_RDB	Text	26
28	Make_RDB	Text	5
29	VehModel_RDB	Text	16
30	Body_RDB	Text	3
31	Year_RDB	Text	5
32	Axle_RDB	Text	5
33	Fuel_RDB	Text	2
34	Cylinders_RDB	Text	5
35	Color_RDB	Text	4
36	GrossWeight_RDB	Text	7
37	City_RDB	Text	23
38	State_RDB	Text	3
39	ZIP_RDB	Text	10
40	Odometer_RDB	Text	7
41	PurchDate_RDB	Text	11
42	EmissionNum_RDB	Text	11
43	EmissionDate_RDB	Text	11
44	Cnty_RDB	Long Integer	4
45	VIN_VIN	Text	255
46	VINERROR_VIN	Text	255
47	YEAR_VIN	Text	255
48	MAKE_VIN	Text	255
49	SERIES_VIN	Text	255
50	BODY_VIN	Text	255
51	DISP_VIN	Text	255
52	UN_VIN	Text	255
53	CYL_VIN	Text	255
54	ASP_VIN	Text	255
55	IND_VIN	Text	255

56	AIR_VIN	Text	255
57	EVP_VIN	Text	255
58	OXY_VIN	Text	255
59	TWC_VIN	Text	255
60	EGR_VIN	Text	255
61	CLL_VIN	Text	255
62	PCV_VIN	Text	255
63	TAC_VIN	Text	255
64	MANUFACTURER_VIN	Text	255
65	CNTRY_VIN	Text	255
66	TYPE_VIN	Text	255
67	GVWR_VIN	Text	255
68	FUEL_VIN	Text	255
69	MOBILE6TYPE_VIN	Text	255
70	VIDETW_VIN	Text	255
71	VIDGVW_VIN	Text	255
72	ESTLVW_VIN	Text	255
73	ESTALVW_VIN	Text	255
74	VSP	Double	8

Table A-14 Pass Fail Results for Original Owner variable

	Non-original Owner		Original Owner	
Year_RDB	**Fail**	**Pass**	**Fail**	**Pass**
1985	0	2	0	0
1986	19	74	1	3
1987	14	93	1	2
1988	29	137	2	8
1989	48	167	3	8
1990	65	239	4	11
1991	112	321	4	17
1992	159	508	7	41
1993	187	703	11	67
1994	216	1097	17	106
1995	269	1681	7	172
1996	354	1922	11	200
1997	503	2572	21	339
1998	493	3230	40	568
1999	523	4193	54	909
2000	634	5168	90	1372
2001	799	4925	176	1734

	Non-original Owner		Original Owner	
Year_RDB	Fail	Pass	Fail	Pass
2002	666	5604	194	2497
2003	603	5496	194	3044
2004	459	5792	219	3921
2005	362	5446	227	4442
2006	263	4971	185	5089
2007	135	3981	226	6608
2008	3	74	9	304
2009	0	0	0	4
2010	0	0	0	1

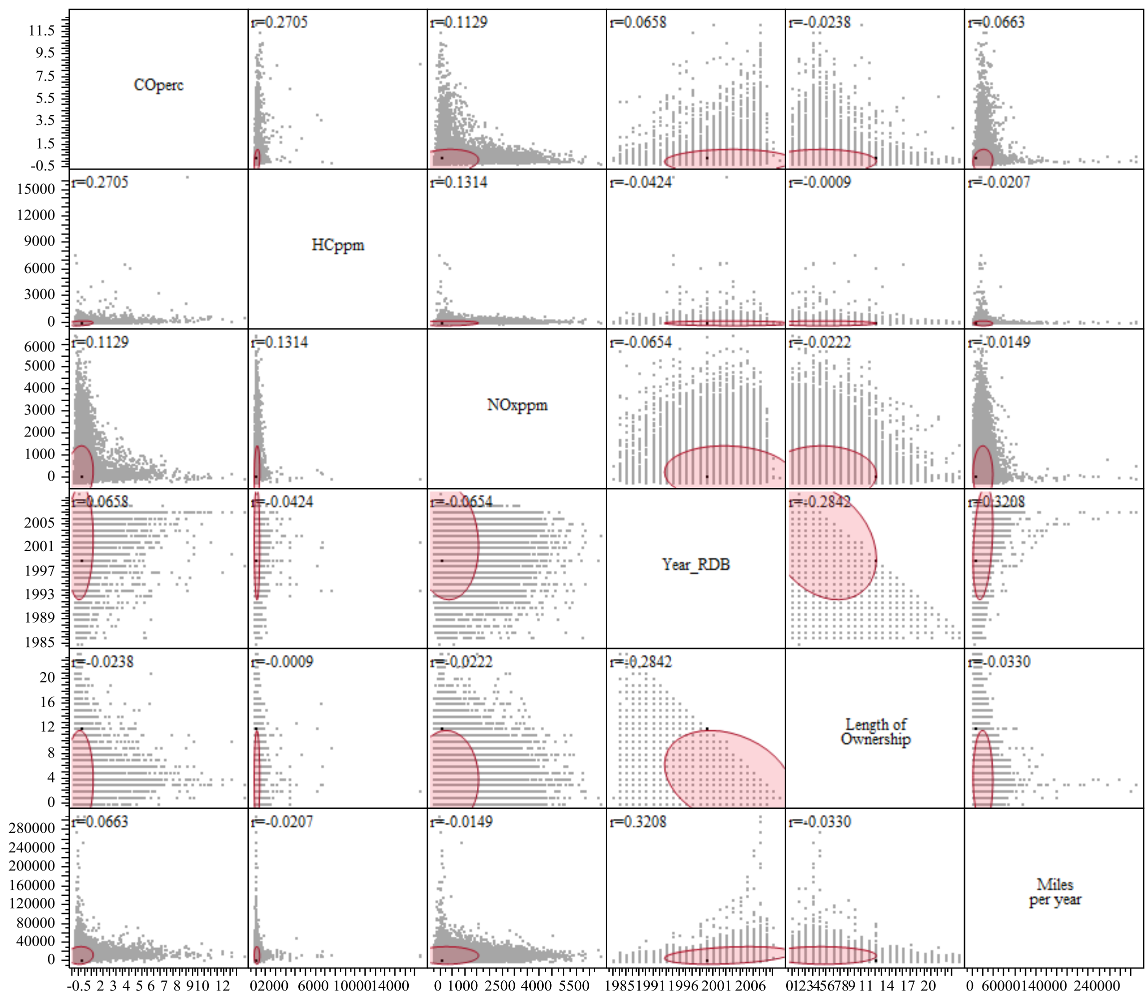

Figure A-7 Scatter plot matrix for model variables

B. APPENDIX B

Atlanta Fleet Characterization 1993 - 2008 (DNR CAFÉ 93 – 2008 Final Report)

7.1.1 Fleet Composition

Emission of any individual vehicle depends on the efficiency of its emission control system and its deterioration over time. Accordingly, vehicle emissions should depend on vehicle type, make, model, and model year (age), which determine the fleet composition. During the current period, 1993-2008, there were some changes in fleet composition by manufacturers.

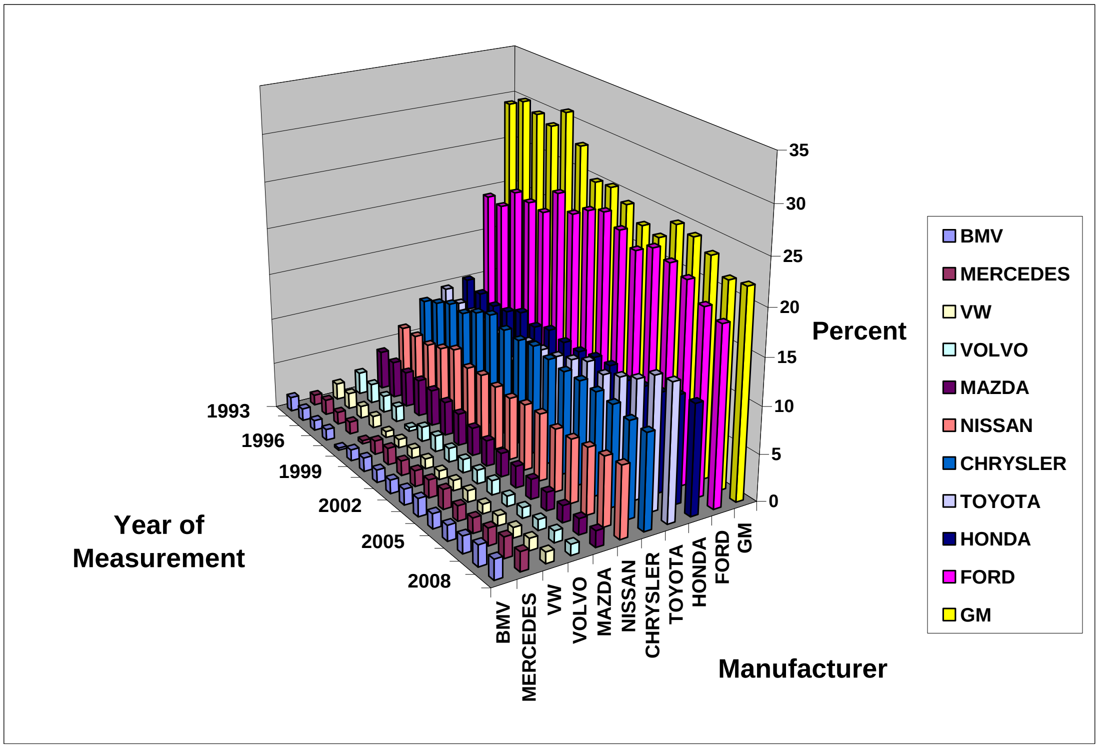

Figure B-1 Percentage of vehicles of different manufacturers by year of measurement

Figure B-1 shows the percentage of all vehicles (of all ages) for groups of manufacturers with the highest number of vehicles in the sample vs. measurement year. The most striking feature is a decrease of GM vehicles in the fleet. At the same time there is a significant decrease of Toyota vehicles. The fraction of Toyota initially was lower than Honda; as oppose to the period between 2005-2008 when it became. There is also a decrease in the fraction of Ford and Chrysler and a slight increase in BMW and Mercedes.

There is not enough data to evaluate the emissions of individual models. However, it can be done for vehicle makes. Figure B.2 illustrates the dependence of CO-Avg by model year on age for cars of various makes. Age is defined as the difference between the current measurement year and the vehicle model year. Age 0 is assigned to vehicles of the current year and of the upcoming year.

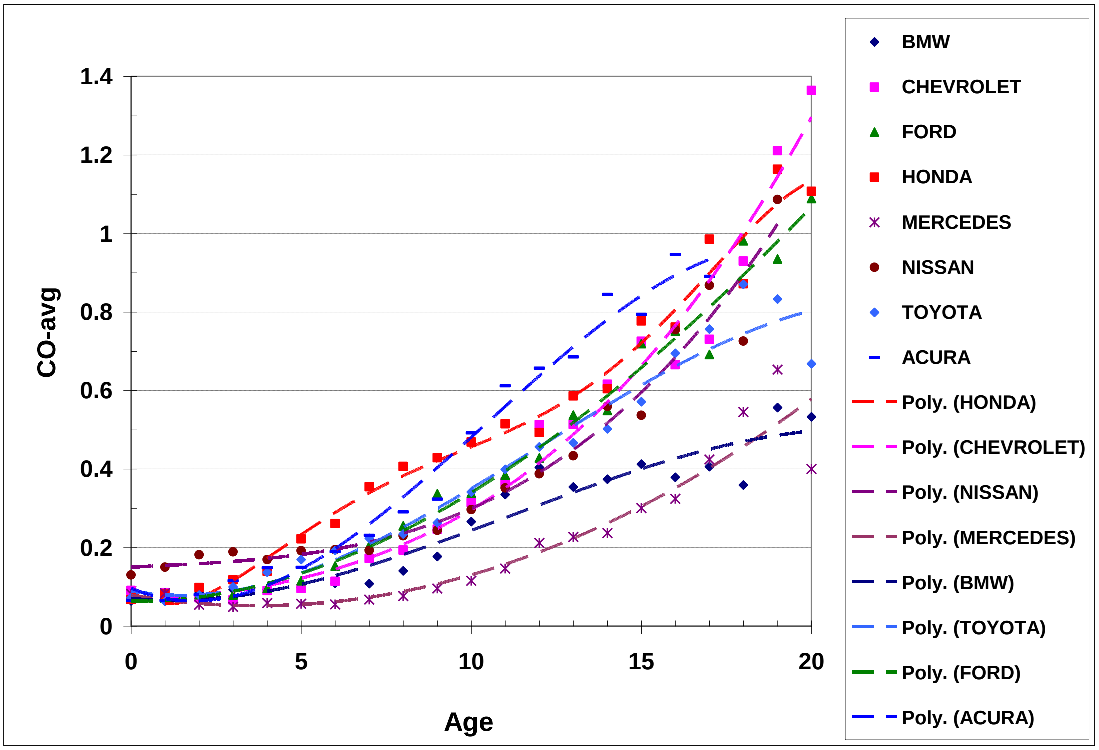

Figure B-2 Dependence of CO average by age for the vehicle makes in the measurement year interval 2005-2008

It was shown in many studies that age is the main factor that determines the vehicle emission. We have very little data on mileage, so it is assumed that mileage is proportional to age. We make an assumption that the technology of the vehicle emission control system did not change significantly during the period 2005-2008. In Figure B.2, averages over this period dependences are shown. There are no significant differences for the new vehicle (age 0-2), except Nissan, but for higher ages the curves split. Ford, Chevrolet, Nissan, and Toyota represent groups with similar emissions, while Mercedes and BMW have lower emissions, and Honda and Acura have higher emissions. Generally luxury vehicles are cleaner than more popular models since most likely they are better maintained vehicles. Most luxury makes manufacturers offering no-cost maintenance, which may contribute to this effect.

The most unexpected result is that Honda is not one of the cleanest makes. However, the same fact is observed in data for Missouri 2002 and Virginia 2002. This fact needs more analysis with higher volume of data and for separate modules. It follows from these dependencies that fleet composition by Make/Model can be a significant factor of vehicle emissions for older ages.

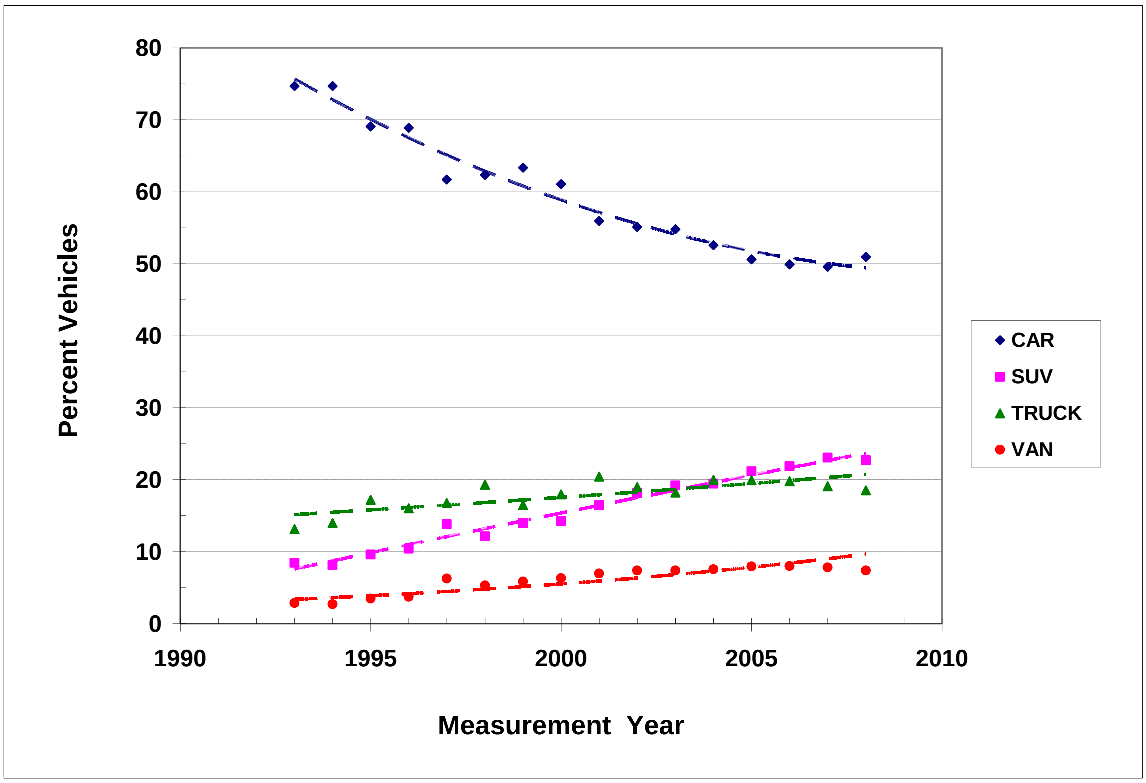

Figure B-3 Changes in vehicle distribution of VIN type

There are significant changes in fleet composition by vehicle type. Figure B-3 shows changes in the distribution of vehicle types defined by VIN decoder: CAR and various types of light duty trucks (LDT), TRUCK (pickup truck), SUV (MPV), and VAN (minivan). It is well known that fleet composition is constantly changing. Manufacturers are constantly trying to reinvent themselves and come up with vehicles that better fit current market conditions and consumer demands. This phenomenon was never more evident than in the last two decades. During this time consumer preferences changed toward larger vehicles. This change was driven by relatively cheap oil prices and more efficient engines. As a result, the fastest growing vehicle segment at that time was the sport utility vehicle (SUV). Pickup trucks and vans were growing as well, although at a slightly slower pace. Increase of SUVs, pickup trucks, and vans came at the expense of passenger cars. Figure B-4 shows that in 1993 passenger cars accounted for 75% of the total fleet; however, by 2006 their fraction came down to about 50% of the total fleet. In recent years spikes in gasoline prices are seemingly reversing this trend as evidenced by the years 2007 and 2008. We can see that the fraction of passenger cars is increasing slightly and the fraction of SUVs and trucks are decreasing.

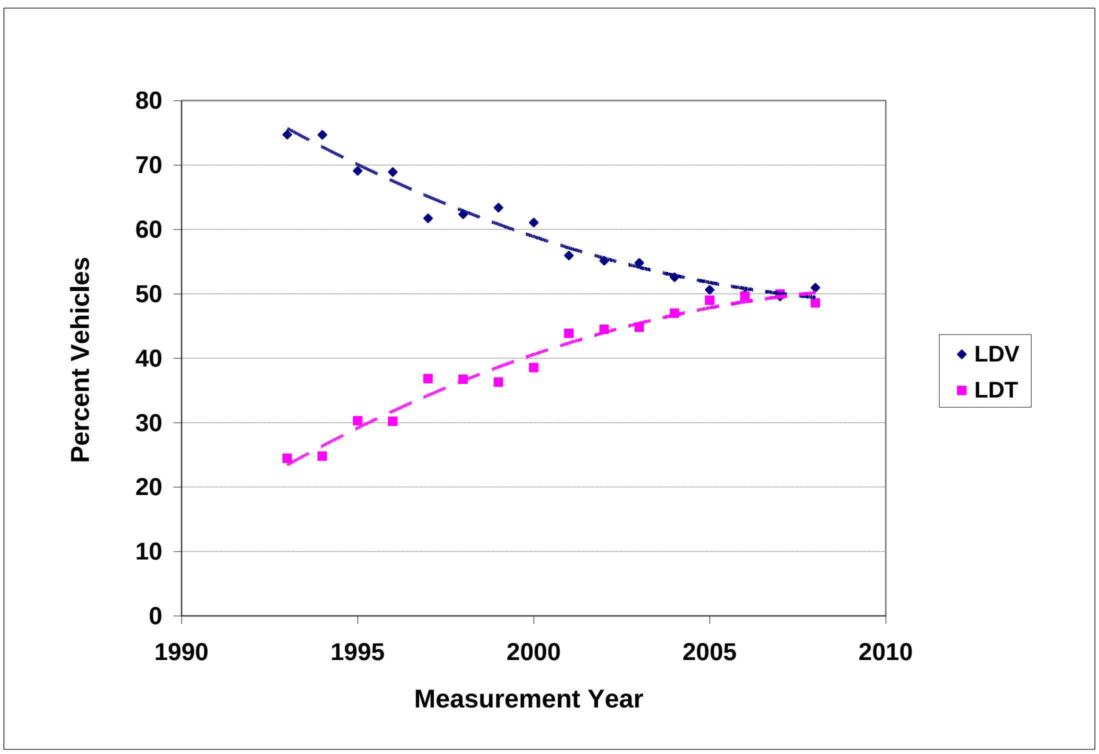

Figure B-4 Percentage of LDV and LDT for various measurement years

Figure 3.4 is another representation of Figure 3.3. Here we have represented a change in fleet composition according to MOBILE6 vehicle classification. LDV in this case is represented by passenger vehicles and LDT incorporates SUVs, pickup trucks, and vans. Increase of LDT in the sample is accompanied by an increase of emission at an older age.

7.1.2 Dependence on Age

Vehicle technology improvements played a major role in vehicle emission reduction as well as dependability and longevity of vehicles. Figure 3.5 shows emission deterioration when we examine vehicle measurements captured during the 1996 CAFÉ contract.

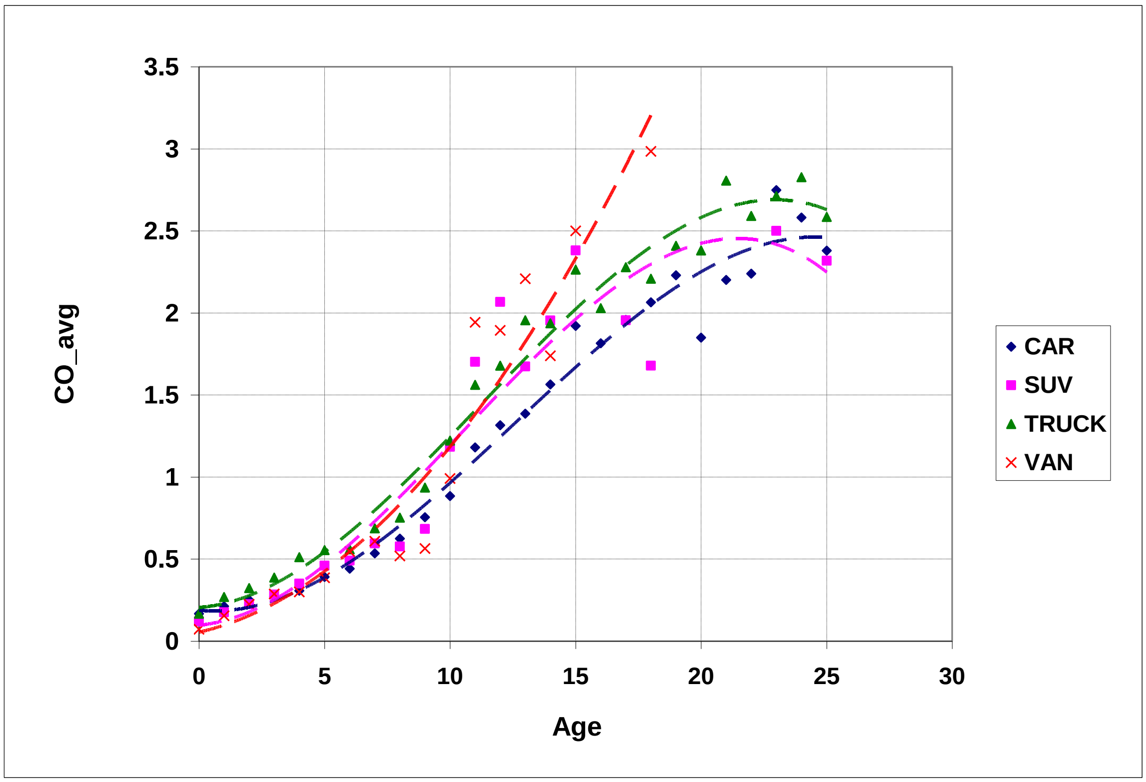

Figure B-5 Age dependence of CO average by model year for various VIN types. Data 1996

Vehicles on this chart are grouped by the above-mentioned vehicle categories. We can see that emissions for all categories are rising with age almost at the same rate until vehicles become about 22 years old; after that emissions start to stabilize and even decrease. The main reason is that vehicles that reach that age and still are being driven, most likely went through a major overhaul to keep them running. Engines, transmissions, and emission equipment are being repaired and/or replaced and thus become cleaner. There is only one category that behaved slightly differently. The van category that included minivans was relatively new in 1996 and therefore the maximum age for this category is 18 years; therefore, we were not able to observe the same trend. It is also important to note that the age of all vehicles was capped at 25 years because we do not observe a sufficient number of vehicles older than 25 years. Because of the low number of vehicles of that age the error of measurement becomes great and it is difficult to see trends for those cars and trucks. Let us compare Figure 3.5 with measurements of 1996 to Figure 3.6 which shows vehicles measured during 2004 data collection efforts.

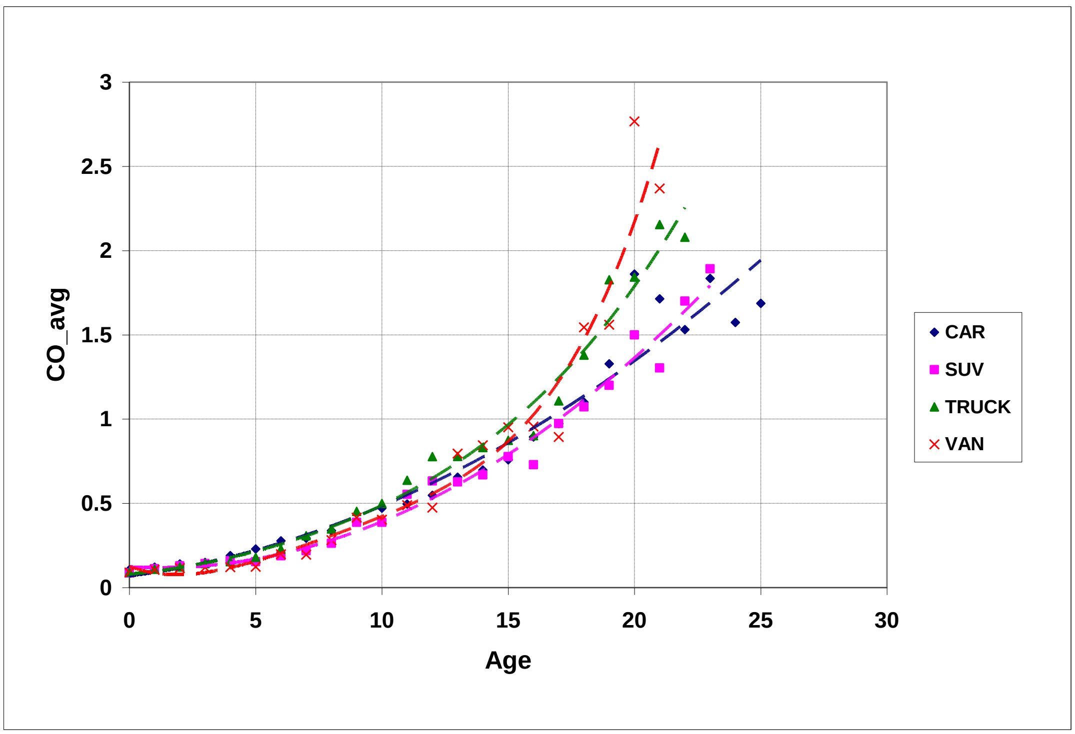

Figure B-6 Age dependence of CO average by model year for various VIN types. Data 2004

As we can see, there are several major differences between those two figures. First and foremost, the deterioration rate is much slower. In 1996 vehicles that were five years old had roughly 0.5% of carbon monoxide compared to vehicles that were measured in 2004 that reached the same emission levels of 0.5% CO at ten years old. We also see that scatter between categories became much smaller. In 1996 there was a sizable difference between cars and trucks, cars being significantly cleaner than trucks. In 2004, however, this difference is much smaller and starts to manifest itself at a much older age. We also can see the survival effect. As mentioned before in 1996 twenty-two year old vehicles went through some repairs and became cleaner. In 2004, on the other hand, we do not observe the same behavior. Even at twenty-five years old a vehicle continues to deteriorate without any evidence of repair activity. It suggests that vehicles stay operational much longer without any repairs necessary.

Figure B-7 shows the different independence of CO average by model year for the total sample on vehicle age for measurement years 1994, 2000, and 2008. As the measurement year increases dependence on age changes dramatically. Emissions of old vehicles as well as new vehicles are much lower in 2008.

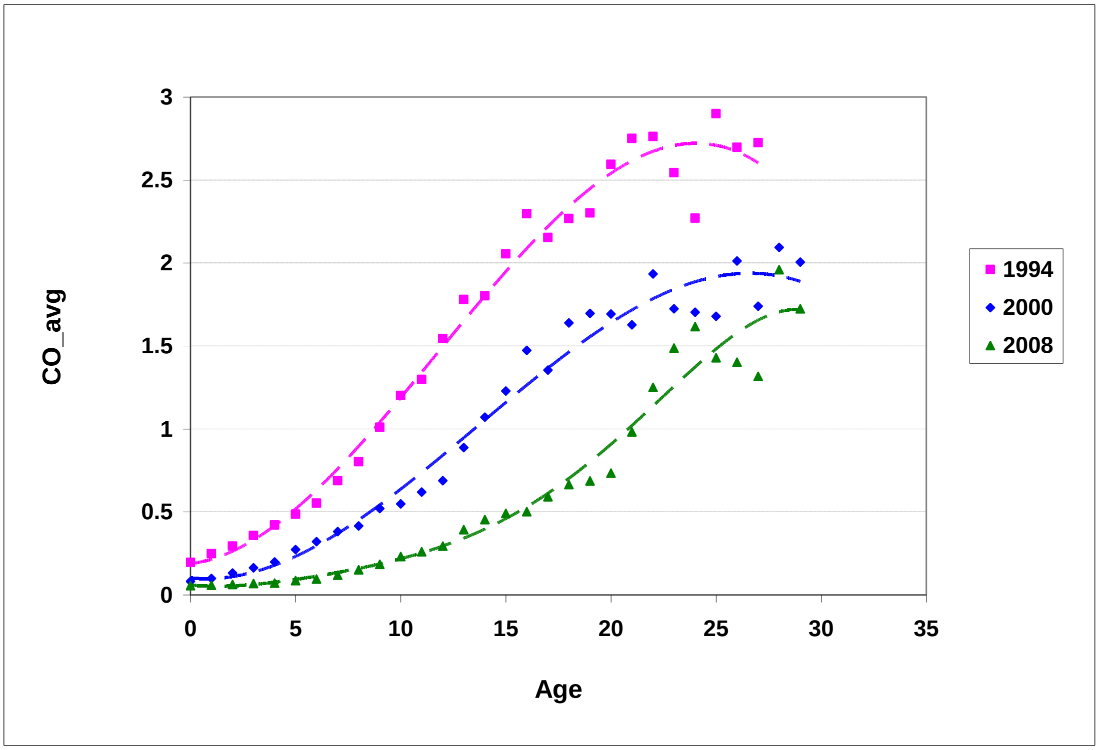

Figure B-7 Comparison of dependences CO average by age for different measurement years

This considerable decrease of emissions is shown more straightforwardly in Figure B-8.

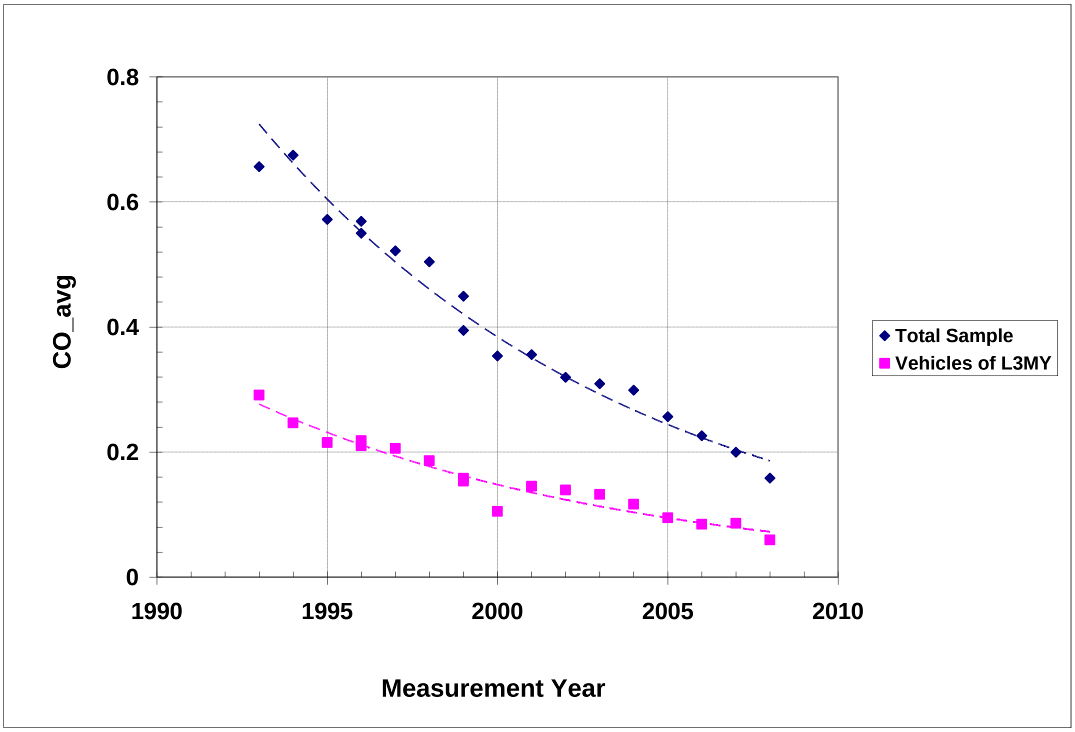

Figure B-8 CO average of total sample and vehicles of latest three model years at various measurement years

The fleet as a whole is getting much cleaner and there is a significant improvement of new vehicles as well. Those decreases are sharper in the range 1994-2000 and dependence becomes almost flat at 2005-2008. Similar dependences exist for HC and NO – Figure B-9 and Figure B-10 accordingly.

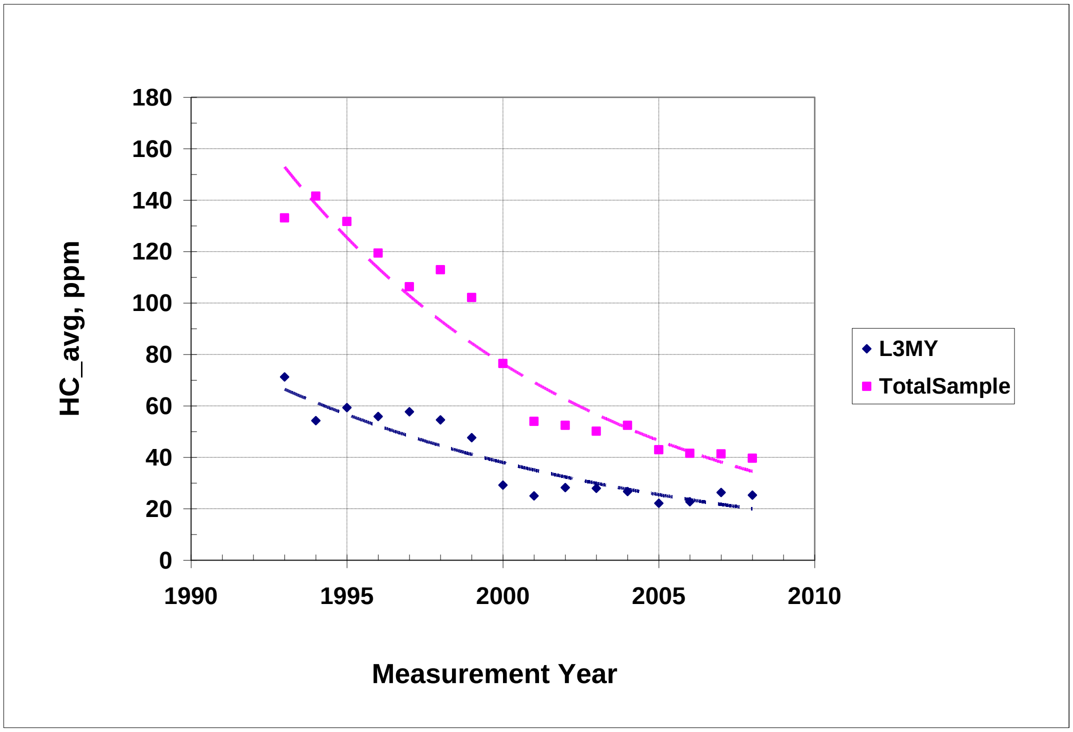

Figure B-9 HC average years sample and vehicles of latest three model years at different measurement years

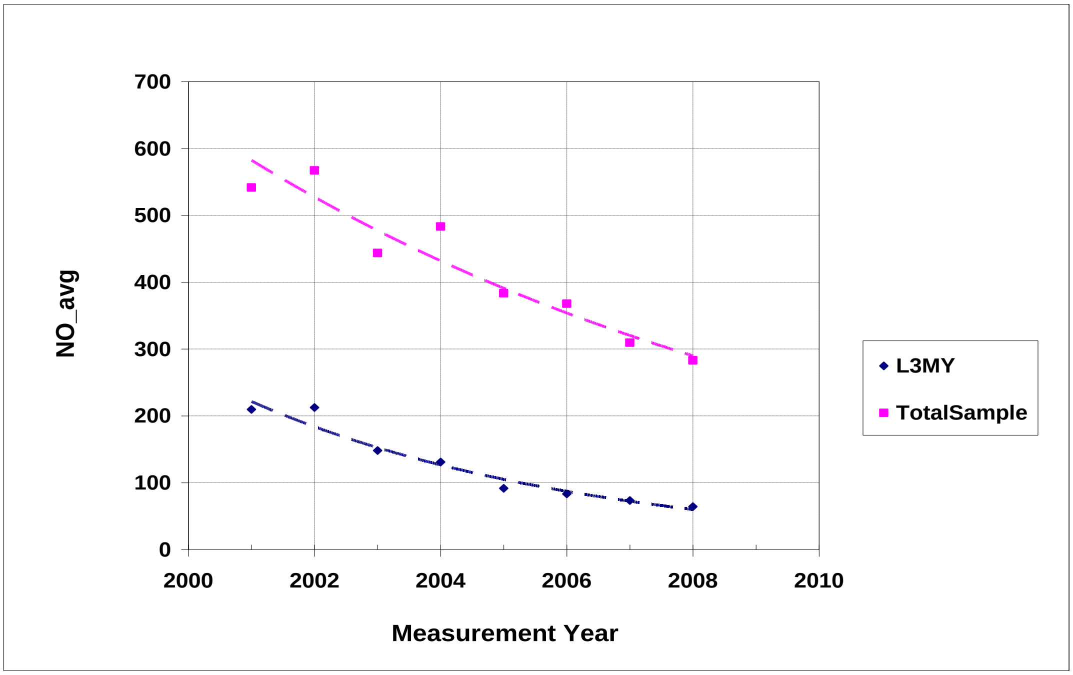

Figure B-10 NOx average total sample and vehicles of latest three model years at different measurement years

CO average vs. age (Figure B-7) shows the change of shape for older vehicles: saturation and then decreases in emission. This result is due to the effects of survival: only well-maintained and probably repaired vehicles survive to a very old age. Dirty vehicles do not survive to old age and leave the fleet. This conclusion is confirmed by graph Figure B-11, which shows deterioration of emission during the period 1993-2008 for vehicles of different model years.

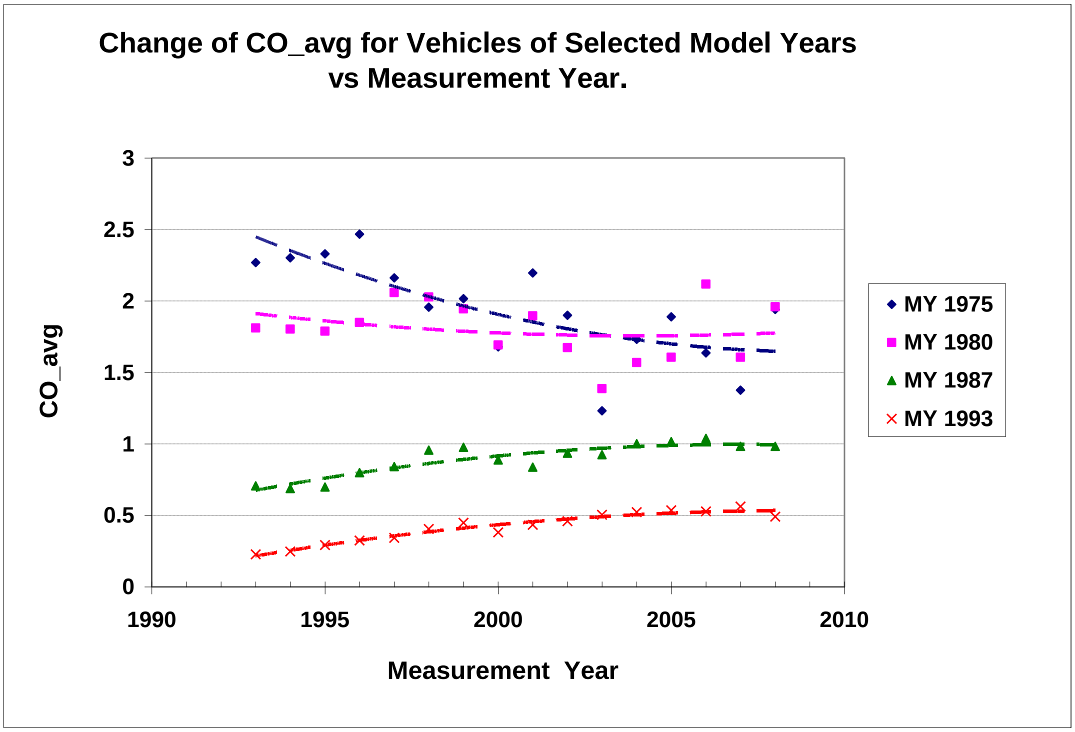

Figure B-11 Change of CO emission from vehicles of various model years by measurement year

For the oldest vehicles of MY 1975 there is no deterioration; instead, a decrease of CO_avg is observed; for MY 1980 also there is no deterioration, and dependence is flat. In both cases badly deteriorated vehicles left the fleet. For MY 1987 and 1993 normal deterioration is observed till 2005: emission increases with age, but after 2005 dependence also becomes flat.

There is a difference in emission from vehicles belonging to I/M and non-I/M counties (Figure B-12). Older vehicles in I/M counties have lower emissions because their emission control system is better maintained due to the I/M program. The difference in emissions for I/M and non-I/M counties represents the basis for calculation of I/M efficiency. In 1994 we compared emissions in 4 counties with 9 counties, that did not have an I/M program at the time. In 2008 we compared emissions in 13 counties with reference counties (area of Macon and Augusta) that do not have a program. It is interesting to note that the difference in 2008 is larger than in 1994. It may be due to the fact that program of 1994 consisted of a basic idle test, whereas in 2008 the Atlanta area had a more efficient enhanced program based on the ASM test and OBDII data.

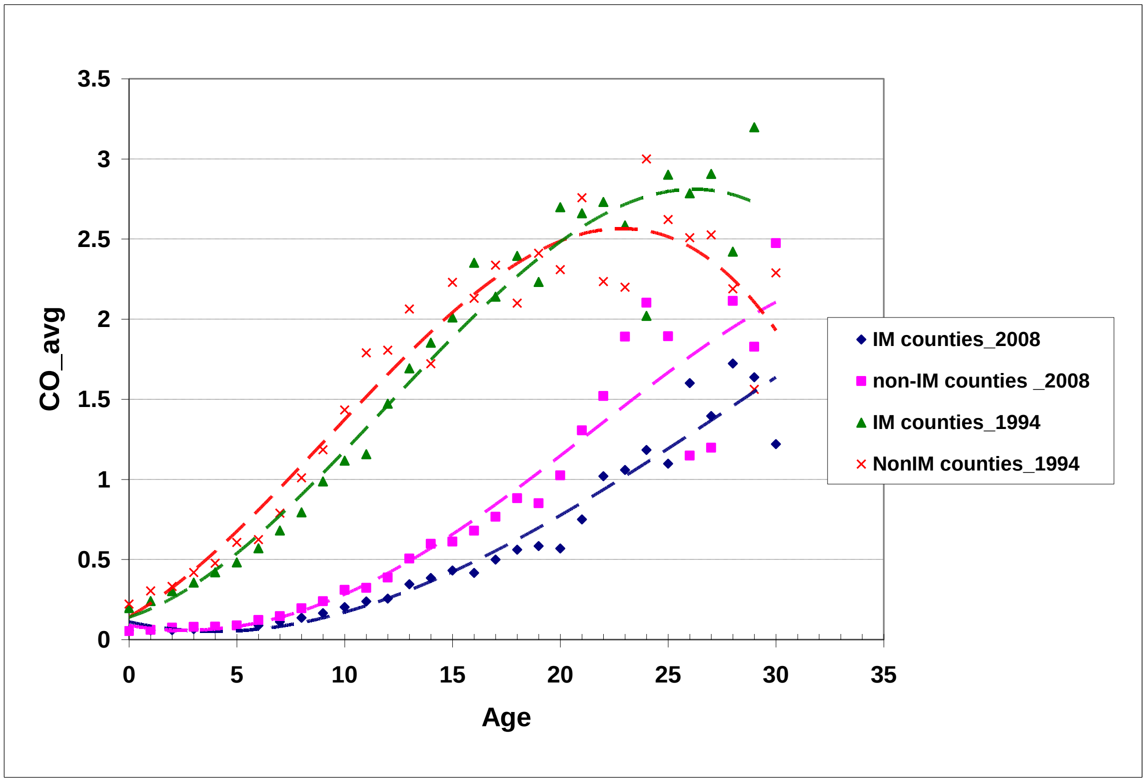

Figure B-12 Comparison of dependence CO average by age of I/M and non-I/M counties

APPENDIX C

Table C-1 Failure rates 'original' vs. 'non-original' owner

Model Year	1986	1987	1988	1989	1990	1991	1992	1993
Non-Original Owner	26%	15%	21%	29%	27%	35%	31%	27%
Original Owner	33%	50%	25%	38%	36%	24%	17%	16%

Model Year	1994	1995	1996	1997	1998	1999	2000	2001
Non-Original Owner	20%	16%	18%	20%	15%	12%	12%	16%
Original Owner	16%	4%	6%	6%	7%	6%	7%	10%

Model Year	2002	2003	2004	2005	2006	2007	2008	
Non-Original Owner	12%	11%	8%	7%	5%	3%	4%	
Original Owner	8%	6%	6%	5%	4%	3%	3%	

Table C-2 Frequency distribution for displacement recoded variable

Level	Count	Percent of Vehicles
1	6587	0.07833
2	21933	0.26083
3	29644	0.35253
4	16863	0.20054
5	8669	0.10309
6	389	0.00463
7	2	0.00002
8	2	0.00002
Total	84089	1.00000

VITA

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EDUCATIONAL BACKGROUND:

Degree	Year	University	Field
M.S.	2005	Georgia State University	Information Systems
B.B.A.	2000	Georgia State University	Computer Information Systems

EMPLOYMENT HISTORY:

Title	Organization	Years
Research Scientist II	Georgia Tech Research Institute, ATAS	2008 - present
Research Scientist I	Georgia Tech Research Institute, ATAS	2005 - 2008
Research Scientist I	Georgia Institute of Technology, School of Civil and Environmental Engineering	2001 - 2005
Laboratory Research Assistant	Georgia Institute of Technology, School of Civil and Environmental Engineering	1995 - 2001

CURRENT FIELDS OF INTEREST:

- Air quality modeling
- Modeling of vehicle emissions
- Remote sensing of vehicle emissions
- Statistical data analysis
- Transportation planning research

- Environmental and transportation policy analysis

QUALIFICATION STATEMENT:

Mr. Samoylov has more than 15 years of experience in vehicle emissions research by optical remote sensing. During his tenure at Georgia Tech, he has led the technical team developing and applying a variety of new and improved methods for remote sensing of vehicle emissions. Since his last promotion, his primary responsibilities include developing methodologies for using vehicle remote emission sensing for a variety of applications such as vehicle fleet characterization, identification of high polluting vehicles, and vehicle clean screening; statistical data analysis; preparation of project deliverables and communication with clients, as well as heading the project's field operations for the Continuous Atlanta Fleet Evaluation (CAFÉ) project sponsored by the Georgia Department of Natural Resources (GDNR), including supervision of a three-person technical team. The CAFÉ project is the longest running program of its type in the world and is the primary means of evaluating the effectiveness of the motor vehicle inspection and maintenance (I/M) program for the Atlanta area. The CAFÉ program has also served as the model for most subsequent vehicle remote sensing programs in the U.S. and internationally. Experience using remote sensing technology and knowledge acquired while working with the emission inspection and maintenance (I/M) program of the state of Georgia led the candidate to create a topic for a forthcoming Ph.D. dissertation. His dissertation research focuses on creating emission inspection strategies that concentrate on higher polluting vehicles and help I/M programs to be adaptable to changing vehicle fleets.

Additionally, Mr. Samoylov provides instructional support to the School of Civil and Environmental Engineering where he serves as the primary instructor of undergraduate level courses.