

**THREE ESSAYS IN PROGRAM EVALUATION: THE CASE OF
ATLANTA INSPECTION AND MAINTENANCE PROGRAM**

A Dissertation
Presented to
The Academic Faculty

by

Anupit Supnithadnaporn

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Public Policy

Georgia Institute of Technology
August 2009

COPYRIGHT 2009 BY ANUPIT SUPNITHADNAPORN

**THREE ESSAYS IN PROGRAM EVALUATION: THE CASE OF
ATLANTA INSPECTION AND MAINTENANCE PROGRAM**

Approved by:

Dr. Douglas S. Noonan, Advisor
School of Public Policy
Georgia Institute of Technology

Dr. Susan E. Cozzens
School of Public Policy
Georgia Institute of Technology

Dr. Marco Castillo
School of Public Policy
Georgia Institute of Technology

Dr. Michael Rodgers
School of Civil and Environmental
Engineering
Georgia Institute of Technology

Dr. Michael Chang
School of Earth and Atmospheric
Science
Georgia Institute of Technology

Date Approved: April 9, 2009

To My Beloved Father and Mother

ACKNOWLEDGEMENTS

I would like to express my appreciation to the members of my committee for their supports during my long dissertation journey. I am grateful to Professor Douglas Noonan, the chair of my committee, who read several versions of my dissertation, provided me valuable comments and trained me to be an independent researcher. Professor Susan Cozzens kindly provided a workspace in TPAC where I can access to computer and software to fulfill my task. She also offered me traveling fund for my poster presentation in the Better Air Quality 2008 Conference in Bangkok, Thailand. Moreover, I also learn from Professor Cozzens in many TPAC team meetings that passion was very important when choosing the topics of study. Her passion about inequity of public policy gave me the motivation of chapter 2 of my thesis. Doctor Michael Rodgers gave me permission to use the very interesting datasets. Professor Marco Castillo was always available and helpful in statistics. Doctor Michael Chang offered several important views regarding the vehicle inspection and maintenance (I/M) program in Atlanta. Lastly, I deeply appreciate the Royal Thai Government for the financial support during the whole courses of my Ph. D. study in the United States.

My special thanks also go to many people who kindly assisted me in my research. Alex Samoylov, Doctor Mikhail Fogelson, and Olga Kemenova from Georgia Tech Research Institute provided many insightful views related to the datasets and the I/M program. Alex suggested me an interesting topic regarding the OBD II, which became chapter 4 of my thesis. I also benefit greatly from the discussions about the vehicle inspection with Doctor Marlin Gottschalk from Georgia Environmental Protection Division, Department of Natural Resources and Mr. Rich Parlontieri from Speed Emission. For chapter 3, Professor George R. Parson from University of Delaware gave

me the motivation to apply the random utility model whereas Professor Patrick McCarthy taught me the discrete choice modeling class and provided me useful suggestions. I am thankful for Professor Juan Rogers, Professor Gregory Lewis, Professor Christine Roch, and Doctor Chul-Yong Lee about the discussion regarding the missing data, Professor John Walsh about the Institutional Review Board protocol. Additionally, I would like to thank Professor Mary Fox for reminding me the endurance and positive thinking. I am indebted to Terry Fonseca, Vrishali Subramanian, and Dhanaraj Thakur for their kindly assistance in editing my work.

Dissertation is a long journey of my life. I survived this adventure because of faith, family, and friends. The Buddhist wisdom is the foundation of my faith in everything. Most importantly, I am grateful to my family: my parents, Pachaen and Kunya Supnithadnaporn who give me life and unconditional love that sustain me until today. My brothers Kit and Chidchai Supnithadnaporn always believe in me and remind me the other part of life. I am also grateful to my grandmother for her spiritual support. I wish to thank all of my relatives who always mentally support my father and mother while I was in the United States.

Working in TPAC was a great experience because I always learned in many aspects of life and education from Sonia Gatchair and Hyunjung Park. They were very kind and supportive to me during the critical period of my life. I agree with Gonzalo Ordonez – my senior and TPAC fellow – that persistence is the key in finishing the dissertation. From Elena Harari, I learn not to be fear of failure. I try to develop the resilience as shown by Pablo and Teresita Catalan.

I consider school as my second home where all Ph.D. fellow students and friends are my family who always help me in numerous ways. They bring me joy and comfort me during difficult time in my research. I would like to thank all of them here. My senior Ph.D. fellows thoughtfully gave me useful tips of surviving courses and comprehensive

exams: Jingjing Zhang, Mohan Turaga, Pamela Hassebroek, Wanda Spivey, Kendall Deas and Jue Wang. Taehyun Jung, Seong Soo Oh, and Eunjoo Oh kept me company during late night study and shared me their insightful views about research. Carolyn Fonseca and Aselia Urmanbetova were my personal “strategists” and “counselors” whom I always consulted during my research endeavor. For their heartwarming friendship, I would like to thank Li Tang, Jennifer Chirico, Alison Riggieri, Youngsun Baek, Monica Meng, Diran Soumonni, Ravtash Bal, Samina Panwhar, Connie Huang, and Yeonji No. Moreover, my two Thai fellow students at Georgia Tech, Alisa Khongthon and Oran Kittithreerapronchai were considerably helpful for my living in Atlanta since my first day at Tech.

At last, I would like to thank LaTissia Caldwell and Karen Halstead for their reliable administrative support, Andrew Roberts for his excellent technical support, Stata listers, and all authors of articles and books which I had relied upon. Certainly, all mistakes I made in this dissertation are mine.

TABLE OF CONTENTS

| | Page |
|--|------|
| ACKNOWLEDGEMENTS | iv |
| LIST OF TABLES | ix |
| LIST OF FIGURES | xiii |
| SUMMARY | xv |
| <u>CHAPTER</u> | |
| 1 INTRODUCTION | 1 |
| 1.1 Overview of the Vehicle Inspection and Maintenance Program | 1 |
| 1.2 Overview of Atlanta Vehicle Inspection and Maintenance Program | 1 |
| 1.3 The Overall Effects of the Vehicle Inspection and Maintenance Program | 3 |
| 1.4 The Evaluation of the Vehicle Inspection and Maintenance Program: The Different Perspectives | 4 |
| 2 EQUITY IMPLICATIONS OF ATLANTA VEHICLE INSPECTION AND MAINTENANCE PROGRAM | 10 |
| 2.1 Introduction | 10 |
| 2.2 Literature Review | 11 |
| 2.3 Research Questions and Hypotheses | 15 |
| 2.4 Empirical Framework | 17 |
| 2.5 Data Sources | 24 |
| 2.6 Variables and Descriptive Statistics | 27 |
| 2.7 Results and Discussions | 36 |
| 2.8 Conclusion | 63 |
| 3 A MOTORIST'S CHOICE OF THE INSPECTION STATION | 68 |
| 3.1 Introduction | 68 |
| 3.2 Literature Review | 69 |

| | |
|--|-----|
| 3.3 Research Questions and Hypotheses | 76 |
| 3.4 Empirical Framework | 78 |
| 3.5 Data Sources | 83 |
| 3.6 Variables and Descriptive Statistics | 86 |
| 3.7 Models and Results | 98 |
| 3.8 Discussions | 139 |
| 3.9 Conclusion | 144 |
| 4 OBD II TEST VALIDITY AND RELIABILITY: EVIDENCE FROM THE ATLANTA FLEETS IN 2002 – 2005 | 147 |
| 4.1 Introduction | 147 |
| 4.2 Research Question and Hypothesis | 148 |
| 4.3 Conceptual Framework | 149 |
| 4.4 Empirical Framework | 155 |
| 4.5 Data Sources | 160 |
| 4.6 Variables and Descriptive Statistics | 162 |
| 4.7 Results and Discussions | 175 |
| 4.8 Conclusion | 201 |
| 5 CONCLUSION | 204 |
| 5.1 Summary of Findings | 204 |
| 5.2 Policy Implications | 205 |
| 5.3 Future Research | 209 |
| APPENDIX A: CHAPTER 2 | 211 |
| APPENDIX B: CHAPTER 4 | 212 |
| REFERENCES | 225 |
| VITA | 235 |

LIST OF TABLES

| | Page |
|--|------|
| Table 2.1: Variables and their descriptions | 28 |
| Table 2.2: Descriptive statistics of dependent and independent variables of the two samples: Aggregate and individual income | 30 |
| Table 2.3: Descriptive statistics of 4000 simulated individual income data generated from two distributions (empirical and lognormal) of two datasets | 31 |
| Table 2.4: Descriptive statistics of dependent and independent variables of the two samples: Bottom vs. top two percentile of Gini coefficient | 31 |
| Table 2.5: Descriptive statistics of dependent and independent variables of the two samples: Bottom vs. top two percentile of standard deviation of Ln(household income in a block group) | 32 |
| Table 2.6: Descriptive statistics of dependent and independent variables of the two samples: Bottom vs. top two percentile of coefficient variation of Ln(household income in a block group) | 33 |
| Table 2.7: Bootstrap and Monte Carlo logistic models of the odds of a vehicle failing the first inspection estimated from the individual and aggregate income samples | 38 |
| Table 2.8: Logistic models of the odds of a vehicle failing the first inspection estimated from the individual and aggregate income samples | 44 |
| Table 2.9: Logistic models of the odds of a vehicle failing the first inspection estimated from the aggregate-income sample controlling for income variation in a block group | 49 |
| Table 2.10: Logistic model of the odds of a vehicle failing the first inspection estimated from six different subsamples drawn from the aggregate income sample | 51 |
| Table 2.11: Logistic model of the odds of a vehicle failing the first inspection estimated from the individual income sample | 57 |
| Table 2.12: Marginal effects of the probability of a vehicle failing the first inspection estimated from the aggregate income sample | 63 |
| Table 2.13: Comparison of the income effects on the probability of a vehicle passing the inspection | 64 |
| Table 2.14: Summary of the income effects (raw coefficients of the logistic models) on the odds of a vehicle failing the first inspection | 65 |

| | |
|--|-----|
| Table 3.1: Variables and their descriptions | 87 |
| Table 3.2: Classification of inspection and RSD results for each inspection station | 88 |
| Table 3.3: Characteristics of the inspection stations in the partial and full samples (N of stations = 736) | 92 |
| Table 3.4: Characteristics of the vehicles in the partial and full samples | 94 |
| Table 3.5: Comparison of the vehicle characteristics from the partial and full samples | 95 |
| Table 3.6: Characteristics of the motorists in the partial samples (N = 465) | 97 |
| Table 3.7.1: Conditional logit models of the odds of a station being chosen using the partial sample with the choice set of 736 stations | 100 |
| Table 3.7.2: Conditional logit models of the odds of a station being chosen using the partial sample with the choice set of 736 stations | 102 |
| Table 3.8.1: Conditional logit models of the odds of a station being chosen using the full A and B samples | 105 |
| Table 3.8.2: Conditional logit models of the odds of a station being chosen using the full A and B samples | 105 |
| Table 3.9.1: Conditional logit models of the odds of a station being chosen using the partial sample | 111 |
| Table 3.9.2: Conditional logit models of the odds of a station being chosen using the partial sample | 111 |
| Table 3.10: Logit models of the odds of a vehicle receiving the false-pass outcome | 128 |
| Table 3.11: Logit models of the odds of an inspection station giving the false pass outcome | 131 |
| Table 3.12: Log linear model of the number of the false pass vehicles given by the inspection station | 132 |
| Table 3.13: Log linear models of the distance from a house (or workplace) to the selected inspection station | 137 |
| Table 3.14: Summary of findings: Factor determining a motorist's choice of the inspection station | 145 |
| Table 4.1: Classification of inspection and RSD results for each inspection station | 156 |
| Table 4.2: Variables and their descriptions | 163 |

| | |
|--|-----|
| Table 4.3: Distribution of vehicles by the years of RSD measurement and OBD II test | 165 |
| Table 4.4: Distribution of vehicles categorized by age and model year in the logistic model | 165 |
| Table 4.5: Distribution of vehicles categorized by age and model year in the log linear model | 165 |
| Table 4.6: Descriptive statistics of variables in the logistic model of the RSD – OBD agreement analysis (N =82,523) | 167 |
| Table 4.7: Descriptive statistics of variables in the log linear model of the emission intensity analysis (N = 77,684) | 168 |
| Table 4.8: Relation between the elapse time and the vehicle deterioration inferred from the type of disagreement between RSD and OBD II test | 174 |
| Table 4.9: Percent of vehicles grouped by age in different agreement categories | 176 |
| Table 4.10: Raw agreement indices and the statistical tests by vehicle age group | 179 |
| Table 4.11: Agreement coefficients (AC1) and their variances by vehicle age group | 179 |
| Table 4.12: Logistic models of the agreement outcomes between RSD measurement and OBD II test | 182 |
| Table 4.13: Percent of vehicles by MPY groups in different agreement categories | 185 |
| Table 4.14: Raw agreement indices and the statistical tests by vehicle MPY group | 187 |
| Table 4.15: Agreement coefficients (AC1) and their variances by vehicle MPY group | 187 |
| Table 4.16: Logistic models of the agreement outcomes between RSD measurement and OBD II test using separate DISAGREE groups | 192 |
| Table 4.17: Log linear models of the emission intensity (EMISSION INDEX) | 196 |
| Table 4.18: Estimation of pollution reduction in two scenarios | 200 |
| Table 4.19: Examples of alternative technologies to improve the current OBD II test | 202 |
| Table A.1: Probit of a vehicle passing the first inspection using the aggregate income sample with Kahn (1996)'s specification | 211 |

| | |
|---|-----|
| Table B.1: Percentage of vehicles classified by the RSD measurement and the OBD II test with different thresholds of ASM2525 standard | 212 |
| Table B.2: Sensitivity analysis of raw agreement indices and statistical tests | 214 |
| Table B.3: Sensitivity analysis of agreement coefficients (AC1) and their variances | 216 |
| Table B.4: Sensitivity analysis of logistic models of agreement outcomes between the RSD measurement and the OBD II test | 217 |

LIST OF FIGURES

| | Page |
|---|------|
| Figure 2.1: Individual household income and predicted probability of a vehicle failing the first inspection classified by age of the vehicle | 42 |
| Figure 2.2: Vehicle age and predicted probability of a vehicle failing the first inspection classified by type of the vehicle | 53 |
| Figure 2.3: Vehicle age and predicted probability of a vehicle failing the first inspection, estimated from the individual income sample | 59 |
| Figure 2.4: Individual household income and predicted probability of a vehicle failing the first inspection, estimated from the individual income sample (income effects are insignificant) | 60 |
| Figure 2.5: Individual household income and predicted probability of a vehicle failing the first inspection, estimated from the individual income sample (income effects are insignificant) | 60 |
| Figure 2.6: Share of black population in the block group and predicted probability of a vehicle failing the first inspection, classified by vehicle age, estimated from the aggregate income sample | 61 |
| Figure 3.1: Predicted false pass odds of the inspection station as a function of its failure ratio for the different types of the stations | 116 |
| Figure 3.2: Predicted failure ratio of the inspection station as a function of its station density for the different types of the stations | 118 |
| Figure 3.3: Total effects of the station density on the probability of an inspection station being chosen, holding other variables constant at their means | 119 |
| Figure 4.1: Percent of vehicles by age group, classified by RSD measurement and OBD II test | 178 |
| Figure 4.2: Overall agreement index and Agreement Coefficient (AC1) of different vehicle age groups | 180 |
| Figure 4.3: Vehicle age and predicted probability of RSD – OBD II agreement computed from the models with and without the quadratic effect of age | 184 |
| Figure 4.4: Vehicle age and predicted probability of RSD – OBD II agreement varying by MPY | 184 |
| Figure 4.5: Percent of vehicles by MPY group, classified by RSD measurement and OBD II test | 186 |

| | |
|--|-----|
| Figure 4.6: Overall agreement index and Agreement Coefficient (AC1) of different MPY groups | 170 |
| Figure 4.7: Mile driven per year and predicted probability of RSD – OBD II agreement computed from the models with and without the quadratic effect of MPY | 190 |
| Figure 4.8: Mile driven per year and predicted probability of RSD – OBD II agreement varying by vehicle age | 190 |

SUMMARY

The Atlanta Inspection and Maintenance (I/M) program ultimately aims to reduce on-road vehicular emission, a major source of air pollution in urban areas. The program enforces eligible vehicles to be inspected and repaired, if necessary, before the annual registration renewal. However, various factors can influence the program implementation with inspectors, and inspection technology. This research explores some of these factors by using empirical data from the Continuous Atlanta Fleet Evaluation (CAFE) project, the inspection transaction records, the Atlanta Household Travel Survey, and the U.S. Census Bureau.

The first essay examines whether the higher income of a vehicle owner decreases the odds of the vehicle failing the first inspection. The overall findings show that vehicles owned by low-income households are more likely to fail the first inspection of the annual test cycle. However, after controlling for the vehicle characteristics, the odds of failing the first inspection are similar across households. This suggests that the maintenance spending are approximately the same for high- and low-income households.

The second essay explains the decision of motorists in selecting their inspection stations and the resulting on-road emissions using a random utility model. The study finds that motorists are likely to choose the inspection stations that are located near their houses, charge low inspection fees, do not have a long waiting line and can serve a large number of customers. Motorists are less likely to choose the stations with a relatively high failure ratio especially in an area of low station density. Moreover, motorists do not travel an extra mile for the lower failure ratio. Understanding choices of

vehicle owners and their consequent vehicle emission can shed some light on the performance of inspection stations.

The third essay investigates the validity and reliability of the on-board diagnostic generation II (OBD II) test, a new testing technology required for 1966 and newer model year vehicles. The study compares the inspection results with the observed on-road emission using the remote sensing device (RSD) of the same vehicles. This research finds that the agreement between the RSD measurement and the OBD II test is lower for the relatively older or higher use vehicle fleets.

The study discusses policy implications of findings from the three essays and offers related recommendations. The limitations of this study and possible future research are also provided

CHAPTER 1

INTRODUCTION

1.1 Overview of the Vehicle Inspection and Maintenance Program

The Vehicle Emission Inspection and Maintenance (I/M) Programs in the US dates back to the passage of the Clean Air Act (1970), which assigned the Environmental Protection Agency (EPA) to oversee the optional I/M programs. Until 1977, the Clean Air Act Amendment had mandated the I/M programs to the areas where long-term air quality was deteriorated by the mobile source emission. The main goal of the programs is to ensure that vehicles stay clean in actual use by encouraging regular and proper maintenance of vehicles. Moreover, the 1990 Clean Air Act Amendment (CAAA) required the US EPA to develop federal regulations for two levels of I/M programs: basic I/M for moderate ozone non-attainment areas and enhanced I/M for serious non-attainment areas (Corley, Dehart-Davis, Lindner, & Rodgers, 2003). The difference between these two programs is the testing procedures, which require the Acceleration Simulation Mode (ASM), using a loaded-mode dynamometer test to measure three types of pollutants: Hydrocarbon (HC), Carbon monoxide (CO), and Oxide of Nitrogen (NO_x).

1.2 Overview of Atlanta Vehicle Inspection and Maintenance Program

In Atlanta, the basic I/M program started in 1981, covering the three ozone non-attainment areas of Fulton, Cobb, and DeKalb Counties and the fourth Gwinnett County was added later. Later, however, the ozone level in Atlanta exceeded the 1-hour concentration standard (0.120 parts per million - ppm) up to 0.160 ppm, causing Atlanta to become a serious non-attainment area. As a consequence, the 1990 CAAA mandated Georgia to upgrade its I/M program to the enhanced category, which was started with

the limited and later full implementation in 1996 and 1997 respectively. By law, eligible vehicles in 13 counties (Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Paulding; and Rockdale) are required to pass the emission test prior to the annual renewal of vehicle registration.

Currently, Georgia's Clean Air Force (Georgia's Clean Air Force, 2006) is the subcontractor of the Georgia Environmental Protection Division (EPD) in implementing the state's I/M program. Fundamentally, the I/M program requires the rolling 24-year window of new cars and light trucks up to 8500 pounds gross vehicle weight (GVWR) to be tested annually. If tests are failed, such vehicles need to be repaired before the next retest. The exemption can be made for vehicles with the following characteristics: (1) the latest 3 model year, (2) powered by diesel fuel, (3) run exclusively on alternative fuels, (4) owned by a senior citizen (65 years of age or older), driven less than 5000 miles per year with the car of 10 model years old or older, and (5) antique vehicles (25 years old or older). Vehicles are subjected to one of the three types of emission tests, depending on vehicle model year. Before 2002, the test included the Acceleration Simulation Mode (ASM) with the dual testing mode¹ for most vehicles up to 24 years of age and Two Speed Idle (TSI)² for non-ASM testable vehicles. All vehicles are also required to pass the fuel cap check and visual inspection. After 2002, all eligible vehicles of model year 1996 or later must be tested with the new technology called the On-Board Diagnostic

¹ The ASM test measures the tailpipe emission while a vehicle is driven on the dynamometer, a look-alike treadmill instrument. This type of test is quite close to real driving conditions. The first mode of the ASM is the moderate load and moderate speed of 25 miles per hour (mph) called the 25/25 test. The second mode of the ASM test is the high load and low speed of 15 mph called the 50/15 test.

² The TSI test, on the other hand, measures the tailpipe emission with the idling engine at two speeds: high at 2200-2800 revolutions per minute (RPMs) and low at 350-1200 RPMs. The TSI is a more primitive procedure when compared to the ASM.

Generation II (OBD II) test. For vehicles of the 1995 model year and earlier, the TSI test is applicable. At present, the ASM test is no longer in use

1.3 The Overall Effects of the Vehicle Inspection and Maintenance Program

According to an economic theory, vehicle emissions are an externality, as motorists do not account for a pollution they impose on others. In the absence of pollution emission market, economic theory suggests that the polluting behavior will be inefficient. To correct this market failure, government intervention may be necessary to equalize the marginal social benefit and costs of an additional unit of pollution (Hubbard, 1997). However, determining the marginal costs and benefits of emission control or the optimal levels of emission are often time impractical. As a result, policymakers have a tendency to set the technical and performance standards with emission reduction targets. The I/M program is a command and control policy aiming at inducing the behavior of the vehicle owners to regularly maintain the condition of their vehicles and hence keep pollution lower than the standard. In principle, the I/M programs may lead to the improvement of air quality if they provide proper incentives for vehicle owners. In practice, many studies have shown that the effects of I/M programs are varied depending on location, time of the studies, and evaluation methods.

1.3.1 The Positive Effects

Using the on-road emissions data³ during 1997-1998 with the reference method⁴, Leisha, Corley, & Rodgers (2002) compare the three vehicle fleets: inspected Atlanta and un-inspected Augusta and Macon. The results show that the Atlanta enhanced I/M can achieve 83 percent of its targeted emission reduction as predicted by the EPA model. In detail, on average, CO emissions are reduced by 26 and 20 percent for cars and trucks respectively. Similarly, the study by Corley et al. (2003) using the remote sensing data in 1997 with the step method⁵ demonstrates that CO weighted benefit of the Atlanta I/M program is 11.5 and 4.9 percent for the nine- and four-county respectively. In fact, this study shows the incremental effect of the change in the I/M program from the basic to the enhanced category.

³ The data are collected by the remote sensing device (RSD) while the vehicle is operating under actual driving conditions on the road. EPA (2004) describes at least five advantages of RSD for the evaluation of the I/M program. First, it measures the on-road emissions, which mimics the unscheduled testing. Second, a large sample of all vehicles driving in the I/M area can be tested with the small cost per vehicle as compared to the actual emission inspection at the station. Third, the test can be varied in real driving conditions as opposed to the one specific condition in the emission test. Fourth, the on-road RSD data can be used to evaluate the degree to which the vehicle owners repair their cars prior to emission testing. Finally, since the RSD data can be converted to the mass emission per volume or mass of fuel burned, it can be used to develop the emission inventories.

⁴ The reference method requires the measurement of vehicles registered in the I/M area versus non I/M areas. By comparing the emission of a fleet subject to the I/M program and a similar fleet with no I/M program, the full effect of an I/M program can be identified. The reference method will be accurate only the control group of fleet is comparable. Studies of this data type include De Hart Davis, Corley, & Rodgers (2003) and Wenzel (2003).

⁵ The step method uses a small number of measurements around 20-50 thousand measurements. A fleet of vehicles in an I/M area is divided into two subfleets of the vehicles that are and are not required for testing under the current I/M program. After accounting for vehicle type and age, the comparison of emissions between two subfleets is made to estimate a point emission reduction. Typically, this method assumes that as the remote sensing measurement for each fleet is conducted at the same time and location, the different factors affecting emissions like socioeconomic characteristics of vehicle owners are minimized (Wenzel, 2003)

1.3.2 The Small or No Effects

Another study presents somewhat discrepancies of the results. Wenzel (2003) reports from his study utilizing the remote sensing data that the Phoenix I/M program achieves a small reduction in CO emissions around 3-4 percent when applying a comprehensive method⁶ and no effect at all when using a step method. Conversely, he finds that when using a reference method, older vehicles have higher on-road emissions under the enhanced I/M program than the basic program.

Several empirical studies find no difference in emission rates in I/M and non I/M areas. From the study of remote sensing with roadside smog checks compared with state records in Los Angeles, Lawson et al. (1990) discovers that a number of high emitters had passed their last biennial I/M test, even within 90 days and the difference was nearly independent of the length of time elapsed since the last biennial I/M test. In addition, according to Lawson (1993), in California, the annual state random roadside surveys of more than 11,000 vehicles have shown that the overall failure rates are about 40 percent, which is about twice the failure rates recorded in the biennial I/M tests. Also, almost half of the highest emitters seen in the roadside tests go on to pass their subsequent biennial I/M test on the first try. Furthermore, Lawson (1994) examines the US EPA nationwide tampering surveys and finds that the failure rates are merely marginally lower for the I/M areas than those of the non I/M areas. Only the cars with older model years at high mileage show around 10 percent lower failure rate in the I/M areas.

⁶ The comprehensive method measures on-road emissions of vehicles at different times before and after I/M testing within the same I/M cycle; hence, allowing for the estimation of emission deterioration over the short period (Wenzel, 2003). Wenzel (2001) suggests that this method can estimate the reduction in emissions from vehicle repairs before the I/M test, if there is enough measurement, probably around several million measurements.

1.3.3 The Unintended Consequences

The I/M program causes inconvenience and expenses, which are mostly born by vehicle owners (Pierson, 1996). Harrington, Mc Connell & Ando (1999) identify four categories of costs including travel to and from inspection station, queuing at station, emission test fee, and vehicle repair. When vehicle owners face undesirable incentives, they seek to minimize their efforts. As a result, several secondary effects of the I/M program may occur. For example, the I/M program might accelerate the retirement or resale if vehicles start to fail the inspection. Apparently, such vehicles are likely to be the high polluting vehicles. The emission reduction from the I/M program will not be affected if such activity removes the vehicles out of the I/M area. However, Stedman, Bishop, & Slott (1998) measure the on-road CO emissions in 1995 and 1996 after the first year of Colorado's new centralized biennial I/M program and discover that vehicles which are unable to pass the new test are being moved out of the program but not out of the area. This illustrates that vehicle owners avoid repair costs by selling their vehicles to individuals registering outside the I/M program.

1.4 Evaluation of the Vehicle Inspection and Maintenance Program:

The Different Perspectives

A majority of literature on the evaluation of the I/M program focuses on the first objective of the program which is physical emission reduction. The concluding results can be varied depending on numerous factors such as the types of data and methods used, the implicit assumptions built in the model generating the reference level for comparison (MOBILE 6), and probably the diverse behavior of the targeted population in different locations. Unlike the previous studies, this study provides an alternative view of the I/M program using the Atlanta case. Findings from this study may serve as supporting evidence of the current performance of the program in terms of pollution

reduction. The study focuses on the three distinctive perspectives of the I/M program: the equity consequence of the program, the motorist's choice behavior, and the validity and reliability of the new testing technology – OBD II.

1.4.1 Essay 1: Equity Implications of Atlanta Vehicle I/M Program

The study investigates the unintended consequence of the I/M program with respect to the equity issue. Although the I/M program imposes the cost to every vehicle owner, it might not be evenly distributed. The poor are likely to bear the burden because they tend to own poorly conditioned vehicles and hence have a lower chance of passing the inspection. Past research shows that if the I/M program put the larger burden on the poor, supplementary policies⁷ might be necessary to achieve the original objective of the I/M program which is emission reduction. Previous research along this line shows the regressive pattern of the program but the results are questionable due to the ecological fallacy issue. The contribution of this essay is two fold. First, findings from this study can inform policy makers whether low-income households bear the uneven cost and the additional policies are needed. Second, this study addresses the issue of ecological fallacy using different methods and datasets. Results from this study are more robust and reliable than the past studies.

⁷ Harrington, McConnell & Walls (1996) suggest that repair subsidies for emission repair might be effective (over the current system) because the incidence of high repair cost for heavy polluting vehicles concentrates in low-income households. Alternatively, the old car scrappage programs in combination with the I/M policy may increase the net welfare in terms of emission reductions (Hahn, 1995; Alberini, Harrington & McConnell, 1996; 1998).

1.4.2 Essay 2: A Motorist's Choice of the Inspection Station

The study explores the determining factors of motorists' decisions in choosing their inspection stations. Because the vehicle inspection is mandatory and incurs both time and monetary costs to motorists, economic theory suggests that they try to pass the test with minimum costs. In addition, since the vehicle inspection in Atlanta is decentralized, theory also suggests that in a competitive market, stations try to attract motorists by lowering prices, improving quality of services, and increasing customers' satisfaction. An insight from the behavioral interaction between the motorists and the inspection stations can shed some light on the patterns of testing outcomes. This study contributes to both the academia and policy makers in two ways. First, the study utilizes the random utility model to show the relative importance of geographic proximity and inspection station specific effects. The results reveal the sorting behavior of motorists in association with convenience of each station and its tendency to pass vehicles. Second, findings from this study can inform the allocation of scarce auditing resources by policy makers. Moreover, specific additional policy relating to the type of stations⁸ and their performance may be essential to ensure the effectiveness of the I/M program.

1.4.3 Essay 3: OBD II Test Validity and Reliability: Evidence from Atlanta Fleets in 2002 - 2005

This research examines the validity and reliability of the new testing technology being implemented in 2002. Currently, the OBD II testing technology has completely replaced the ASM tailpipe emission test. Given the current growth of in-use vehicles, the introduction of the OBD II test is promising because the test is faster and easier to

⁸ California has the complex system of inspection stations. The main effort is to separate the testing and repair activity to ensure the integrity of both activities.

operate than the preceding technology. With the OBD II technology, the test results are no longer determined by the real tailpipe emission but by the error codes stored in the OBD II unit of a vehicle. Nonetheless, vehicles become older and deteriorate over time and so do the OBD II units. The decayed OBD II unit may malfunction and hence yield the error results such as falsely passing the heavy polluting vehicles. As a result, vehicles might pass the OBD II test but still emit high levels of pollution on road. The main contribution of this research will directly benefit policy makers in several aspects. First, the study presents the empirical evidence of the deteriorated OBD II units that result in lower validity and reliability of old vehicle fleets. Second, the study develops procedures for assessing the validity and reliability of the OBD II test that can be applied to the other similar datasets elsewhere. Lastly, the study addresses the implications of the decreasing validity and reliability of the OBD II test which mitigates efforts to reduce air pollution in the nonattainment areas.

CHAPTER 2

EQUITY IMPLICATIONS OF ATLANTA VEHICLE INSPECTION AND MAINTENANCE PROGRAM

2.1 Introduction

A majority of the I/M evaluation studies concentrate on the program effectiveness in terms of pollution reduction. Several methods are developed to ensure the validity of the findings. A few studies concern the high emitting vehicles. A very limited number of studies, however, investigate the equity consequences of the I/M program. Kahn (1996a) finds that vehicles owned by Californian high-income motorists tend to pass the inspection, suggesting the evidence of regressive outcome of the I/M program. Vehicles from the richest counties generate 30 percent fewer hydrocarbons than the poorest counties, controlling for mileage, model year, and engine characteristics (Kahn, 1996b). Using California data, Walls & Hanson (1999) and West (2005) also find that emission related fees or taxes are regressive.

Such regressive consequences of the I/M program illustrate the less promising prospect in terms of emission reduction as the program costs are imposed on the low-income households that can barely afford them. Additional policy alternatives may be needed. Harrington, McConnell & Walls (1996) suggest that repair subsidies for emission repair might be effective over the current system because the incidence of high repair cost for heavy polluting vehicles concentrates in low-income households. Alternatively, old car scrappage programs in combination with the I/M policy may increase the net welfare in terms of emission reductions (Hahn, 1995; Alberini, Harrington & McConnell, 1996; 1998).

The purpose of this study is to investigate the distributional effect of the I/M program using Atlanta I/M program data. The I/M program imposes the additional costs to each vehicle owner differently depending on the vehicle condition. The main varying cost is the repair cost required after vehicle failing the inspection. This study examines

the odds of a vehicle failing the first inspection in relation with the owner's income. Previous research mainly relies on the group level income data, causing possible aggregation bias in the estimate of income effect. This study employs several datasets and methods to show the ranges of these estimates.

The contribution of this paper is two fold. First, findings from this study can improve the I/M program to achieve the fundamental goal of reducing the emission from vehicles. If the burden is disproportionate towards the poor, supplementary programs may be essential. Second, this study sheds some light on the sensitivity of using the group as opposed to individual level income data. The estimates based on aggregate data may mislead the results of the income effect significantly.

2.2 Literature Review

2.2.1 Equity Implications of the Vehicle Emission Control Policy

In most cases, pollution control policy has a distributional effect, particularly the regressive pattern of the benefits and costs (Fullerton, 2008; Baumol & Oates, 1988). Baumol & Oates (1988) classify the distributional effects into two types: transition and continuing costs. Fullerton (2008) outlines the distributional effects of an environmental policy into six categories. In the context of the I/M program, most of these effects are relevant. First, the I/M program increases the cost of legally using vehicles, affecting consumers directly. Second, poor consumers might switch from their personal vehicles to public transportation, limiting their choices of working places and probably reducing their productivity. Third, the vehicle inspection requirement creates the incentive for cheating (Klein, 2003; Lawson, 1993; Glazer, Klein & Lave, 1995). Fourth, better air quality may be favorable to some groups than the others. Fifth, the "capitalization effect provides windfall gains and losses" to those who live inside the I/M areas and own poor conditioned vehicles. Sixth, the distributional effects are typically severe during the transition period.

Previous studies consistently show the regressive effect of the vehicle emission fees or taxes. Walls & Hanson (1999) estimate the impact of the actual annual

registration fee and the other three hypothetical fees. These hypothetical fees are the annual fees based on (1) vehicle mile traveled (VMT), (2) vehicle-emission rate, and (3) estimated emission of vehicle. They find that the fee based on emission rate is the most regressive. West (2005) also examines the equity implications of the hypothetical vehicle emission taxes. She reports that “the incidence of tax on vehicle emission falls relatively heavily on the poor because they spend more on miles as a proportion of their income and drive vehicles that pollute more per mile than those owned by the wealthy.” West (2004) and West & William (2004) investigate the distributional effects of the hypothetical gasoline tax using detailed assumptions and estimation techniques. Both studies conclude that the gas tax is regressive, particularly when there is no return of revenue. In contrast, Poterba (1991) points out that gasoline tax is not strictly regressive because the poorest household cannot afford to own a vehicle at all.

In short, most studies of distributional effects of vehicle emission control policy emphasize on the incidence of taxes in different forms and compare the effects between the current system and a variety of scenarios. A majority of studies assume the partial equilibrium condition in deriving the burden of taxes, requiring less amount of information. The conclusions are also varied with the different uses of measures of ability to pay: annual or permanent income, and consumption.

2.2.2 Equity Implications of the I/M Program

The current I/M program is the command and control policy regime. Vehicles must pass the inspection, ensuring that the emissions are less than or equal to the maximum allowable standards of all three pollutants (hydrocarbon, carbon monoxide, and nitrogen oxides). The repairs are mandatory even though the costs to achieve the small emission reductions are very high. Vehicle owners also face the transaction costs such as getting vehicles tested, traveling time and costs to and from testing or repair facilities (Ando, Harrington, and McConnell, 2007).

Annually, the I/M program creates the additional cost for each vehicle owner, which is considered as the I/M compliance cost or burden. The *inspection fee* in Georgia varies from \$10 – \$25, probably due to the regulation setting maximum fee at \$25. On the other hand, the transaction costs of vehicle inspection can be very different across households. The *travel cost* and *time* depends on the distance between the inspection stations and the motorists' houses. The *waiting time* at the inspection station is also an important part of the transaction cost. However, the time value for the high-income group is likely to be different from that of the low-income one (Calfee and Winston, 1998; Viauoux, 2008; Axhausen et al., 2008). Thus the cost in terms of traveling and waiting time across income and ethnic groups can be vastly different.

A significant portion of the I/M program compliance cost is the repair cost, as intended by the name of the program as “maintenance” (NRC, 2001). The repair costs are mostly determined by the condition of the vehicles, which is not randomly distributed across households. Vehicle owners have options of repairing their vehicles before or after the inspection, depending on their preference. In principle, the choice of pre- or post-repair should not impact the effectiveness of the I/M program as long as the emission from the repaired vehicles are within the standard for the whole test cycle. In terms of the program evaluation, however, the choice of pre-inspection repair does affect the estimation of the total repair cost as part of the burden of the I/M program

Because vehicles undergone the pre-inspection repair will be less likely to fail and need subsequent repair, this makes the pre-test repair costs unobservable. The regulation only requires the report of the repair cost if the vehicle fails the initial inspection and is re-inspected later after the repair. Using the repair cost from the I/M program records can provide merely the lower bound of the total repair cost of the program. As a result, the burden of the I/M program is possibly underestimated.

In the long run, the cost to comply with the I/M program may include the opportunity cost of selling or retiring a car sooner. Normally, the maintenance cost of a vehicle tends to increase overtime. The I/M program indirectly forces a vehicle owner to assess the benefit of using his old vehicle against the cost of its maintenance. The poor may face the options of illegally using the vehicles or switching to the public transportation, if they cannot afford the cost of newer vehicles. In other words, the I/M program ultimately generate the reinvestment cost, which is difficult to estimate and demands a great deal of information over a period of time.

2.2.3 Burden of the I/M Program: Odds of Failing the First Inspection

In this study, the I/M compliance cost is not estimated mainly due to limitation of data. In stead, the study uses the *odds of a vehicle failing the first inspection* of the test cycle as a proxy for the burden distribution of the I/M program. This study is in the same line with Kahn (1996a). He reports that vehicles owned by Californian high-income motorists are more likely to pass the inspection than those of the low-income. His findings indicate the evidence of regressive outcome of the I/M program. However, this study departs from Kahn (1996a) in several aspects. First, this study provides several estimates of income effects using various methods taking into account the possible measurement error due to the use of group level income information. Second, the study also utilizes the micro-level data to validate the income effects estimated from the group level in which Kahn (1996a) mainly uses. Lastly, the study demonstrates the sensitivity of the assumption of within-group income homogeneity on which Kahn (1996a)'s estimates rely.

Although the odds of failing the first inspection convey a great deal of information regarding the I/M compliance cost, it cannot capture many other costs such as the transaction cost and the cost of selling or retiring a vehicle sooner. Moreover, it can

provide only the lower bound of the total repair cost of the I/M program, primarily the post-inspection repair. Notwithstanding, the odds of failing the first inspection can inform the existence of burden distribution of the I/M program. For instance, if the odds of failing the first inspection are higher for a lower income group, this implies that the share of the I/M compliance cost relative to the income is greater for the lower-income households than that for the higher-income households.

Intuitively, the odds of a vehicle failing the first inspection should solely depend on the condition of the vehicle, including mileage, age, and technology. Yet, several factors contributing to the condition of the vehicle are related to the owner. Few examples are the maintenance, and modification. These factors are critical to the odds of a vehicle failing the first inspection, specifically for the old vehicle. Unfortunately, the owner's preference and resulting behavior are very difficult to measure correctly or even observe directly. People with similar observable demographic and socioeconomic characteristics, however, share common income and budget constraints and may have similar tastes for modifications of their vehicle. Unobserved vehicle maintenance may closely correlate with the owner income if maintenance is a normal good.

2.3 Research Questions and Hypotheses

The main research question of this study is “how the burden in complying with the I/M program are likely to be distributed among individual vehicle owners with differing incomes.” Accordingly, the hypothesis is the odds of a vehicle failing the first inspection are decreasing with an additional percent increase of an individual household income.

$$H_{A1} : E\left(\ln\left(\frac{p_i}{1-p_i}\right)\right)_{\text{LowIncomeGroup}} > E\left(\ln\left(\frac{p_i}{1-p_i}\right)\right)_{\text{HighIncomeGroup}} \quad (2.1)$$

where p_i is the probability of a vehicle failing the first inspection within the test cycle. This study assumes that the post-test repair cost is monotonically increasing with the odds of a vehicle failing the first inspection and independent of income. However, the odds of a

vehicle failing the first inspection tend to proxy only for the post-inspection repair costs, which might be mainly spent by the low-income household owners. In contrast, the high-income households might also bear the burden in terms of the maintenance or pre-inspection repair costs that are difficult to observed. Rejecting the null hypothesis of the equation (2.1) is not sufficient to conclude that the compliance cost or burden of the program is greater for the low-income than that of the high-income owners.

Therefore, this study further examines the effect of the potential maintenance spending, proxy by the annual household income, on the odds of a vehicle failing the first inspection, controlling for the vehicle and owner characteristics. As discussed earlier, the high-income owner can afford the frequent maintenance activities and may willing to pay for the pre-inspection repair costs to assure the passing results. The hypothesis is that, all else equal, the odds of the high-income households that their vehicles failing the first inspection are lower than those of the low-income groups.

$$H_{A2} : E\left(\ln\left(\frac{p_i}{1-p_i}\right) \middle| M_j, V_k\right)_{\text{LowIncomeGroup}} > E\left(\ln\left(\frac{p_i}{1-p_i}\right) \middle| M_j, V_k\right)_{\text{HighIncomeGroup}} \quad (2.2)$$

where M_j and V_k are the vectors of the owner and vehicle characteristics. Rejecting the null of the conditional effect of the individual household income on the odds suggests the possibility that the high-income vehicle owners might spend more on the pre-inspection repair costs than the low-income do; the vehicles owned by the wealthy are likely to pass the inspection. If the null of the hypothesis H_{A2} is rejected, then it is not certain that the poor bear the greater burden of the I/M program compliance than the wealthy even the null hypothesis of the H_{A1} is rejected. On the other hand, if the null hypothesis of the H_{A2} cannot be rejected, this indicates that there is no difference in the maintenance or pre-inspection repair between the low and high-income households. Thus, the evidence of the disproportional burden of the I/M program compliance of the low-income groups is ascertained, which means rejecting the null hypothesis of the H_{A1} .

2.4 Empirical Framework

In terms of modeling, using the odds of failing the first inspection to replace the I/M compliance cost is comparable to modeling the I/M compliance cost as an underlying latent variable. The latent variable of the compliance cost is measured in a continuous scale; the observed variable of pass or fail the inspection is measured in an ordinal scale (fail (1) means higher cost than pass (0)). When a vehicle fails the inspection, it suggests that the burden (mainly the repair cost) is greater than that of similar vehicle passing the inspection.

The study mainly uses the logit model to examine the burden distribution of the I/M program. The fundamental model at the level of individual vehicle and its owner is

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 \text{Income}_i \quad (2.3 A)$$

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 \text{Income}_i + \beta_j M_{ji} + \beta_k V_{ki} + \varepsilon_i ; j = 1, \dots, J \text{ and } k = 1, \dots, K \quad (2.3 B)$$

where p_i is the probability of a vehicle failing the first inspection within the annual test cycle of each individual vehicle i , M_j is a vector of vehicle owner's characteristics and V_k is a vector of vehicle characteristics. This study deals with the lack of individual income information for each vehicle in the original I/M data by adopting two approaches: simulation of the large sample and bootstrapping of the small sample. The central idea is to compare the estimation of income parameter at the group and individual levels from both simulated and observed information.

2.4.1 Monte Carlo Simulation Method

As the available income data exist only at the group level, this is analogous to the measurement error of individual income.

$$\text{Income}_i = \text{Income}_g + u_i \quad (2.4)$$

Consequently, the estimated model with the group level income data is actually

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1(\text{Income}_g + u_i) + \beta_j M_{ji} + \beta_k V_{ki} + \varepsilon_i \quad (2.5)$$

which is equivalent to

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_G \text{Income}_g + \beta_j M_{ji} + \beta_k V_{ki} + v_i \quad (2.6)$$

where v_i is the combined error terms ($u_i + \varepsilon_i$) from the original individual level model and from the measurement error of the group data. As a consequence, the grouping bias is possible. As a result, the effect of income at the group level is not necessarily the same as the one of individual level both in terms of size and significance. Past studies report the effect of income using the group level data, which is β_G .

To test the differences of income effects estimated from the individual and group level data, the study applies the Monte Carlo method to generate the artificial individual income distribution of the vehicle owners and estimate its effect. The Monte Carlo method provides a way to understand a statistic's sampling distribution and evaluate its behavior in random samples (Mooney, 1997; Johnston and DiNardo, 2007; Baiocchi, 2005). The fundamental concept of Monte Carlo method is that "[if] a statistic's sampling distribution is the density function of the values it could take on in a given population,

then its estimate is the relative frequency distribution of the values of that statistic that were actually observed in many samples drawn from the population” (Mooney,1997).

For the individual-level model, this research generates the simulated individual income for each vehicle, using two sources of group income data: CENSUS 2000 and Atlanta Household Travel Survey (AHTS) 2001. First, the CENSUS 2000 provides the information at the block group level, both the median and the counts of household in each of the 16 income intervals. The census block group is the *geographical aggregation* of around 1000 people. Second, the AHTS 2001 also gives the income information in association with certain vehicle characteristics, including make, model year, type and cylinders. Similar to the CENSUS 2000, the study obtains both the median and the counts of households in each of the 9 income intervals. Differently, the AHTS 2001 offers the alternative form of income grouping, which is based on the *vehicle-characteristic aggregation*.

The counts of households in each income interval reveal the information of income distribution, which is the key information for the generation of simulated individual income. Two types of distribution used in this study are the *lognormal* and *empirical*. Simulated income generated from the lognormal distribution requires the information of the mean and its standard deviation of each group (either geographical or vehicle). On the other hand, simulated income created from the empirical distribution requires only the cumulative density function, which is the step function specific for each group. This study assigns the simulated individual income to each vehicle randomly because there is no adequate detailed information of the relationship between vehicle characteristics and income.

In short, there are 4 ways (2 data sources and 2 types of distribution) to generate the simulated individual income in this study. For each approach, this study generates

simulated individual income of 1,000 distributions and estimates the logistic equation (2.3) 1,000 repetitions accordingly.

2.4.2 Bootstrap Sampling Method

In addition to the Monte Carlo simulation, this study conducts the bootstrapping logistic model using the small but complete micro-level data of each individual vehicle and its owner. Because of the small sample size (465 vehicles), the bootstrap ensures more robust standard error of the estimation. The estimates of the equation (2.3) are stable when the repetitions are greater than 1,000, enabling the construction of the confidence interval (Efron & Tibshirani, 1986).

Bootstrapping is a nonparametric approach to statistical inference based on the available sample rather than relying on the strict distributional assumptions of the population. The basic idea of the bootstrap is to create an empirical estimate of the entire sampling distribution of a statistic. Bootstrapping treats the sample as the population and randomly resamples the data with replacement numerous times. Each sample is the same size as the original sample. According to Mooney and Duval (1993), “the central assertion of bootstrapping is that a relative frequency distribution of [the bootstrap statistics ($\hat{\beta}_B$)] calculated from the resamples is an estimate of the sampling distribution of [the population statistics ($\hat{\beta}$)].” This study applies the bootstrap by resampling the entire cases of the data or the rows of the data matrix, which is appropriate for the observational data (Mooney and Duval (1993). The bootstrap method yields the estimates based on the following equations (Moore & McCabe, 2005).

$$\hat{\beta}_B = \frac{1}{B} \sum_B \hat{\beta}_b \quad (2.7)$$

$$SE_B = \sqrt{\frac{1}{B-1} \sum (\hat{\beta}_b - \hat{\beta}_B)^2} \quad (2.8)$$

where B is the number of the bootstrap sampling (repetitions), $\hat{\beta}_B$ is the mean of the bootstrap estimates $\hat{\beta}_b$ and SE_B is the bootstrap standard errors.

2.4.3 Homogeneous Grouping

From the equation (2.4), the measurement error (u_i) can be quite close to zero if each individual in the block group has similar income, resulting in the *homogeneous income block group*. Consequently, using the group level income instead of the individual level income will give the unbiased estimates of the income parameters. Previous study (Kahn, 1996a) uses *mean ZIP code income* as a proxy for the “actual family income.” He admits that this is the measurement with error but can give “a lower-bound estimate of income effect on passing the emission test” under the assumption that “the variance of household income within-ZIP codes is small relative to the variance across ZIP codes.” This study explicitly controls for the variance of household income within a block group or the degree of income homogeneity by two approaches. The first approach includes the degree of income variation in the equation (2.6), yielding the equation (2.9).

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_G \text{Income}_g + \beta_j M_{ji} + \beta_k V_{ki} + \gamma_G + v_i \quad (2.9)$$

where γ_G is the measure of statistical dispersion or variability in a probability distribution.

This study utilizes three measures of variability: standard deviation, coefficient of variation, and Gini coefficient. Commonly, the low value of these measures indicate the

low degree of variability and hence the high degree of group homogeneity. The *standard deviation* (σ_G) is simply the square root of the variance of the income distribution in each group.

$$\sigma_G = \sqrt{\frac{\sum_{l=1}^L f \cdot \text{Income}_M^2}{N_G} - \overline{\text{Income}_G}^2} \quad (2.10)$$

$$\overline{\text{Income}_G} = \frac{\sum_{l=1}^L f \cdot \text{Income}_M}{N_G}$$

$$N_G = \sum_{l=1}^L f$$

where L is the total number of income intervals, f is the frequency or count of household falling within each income interval, Income_M is the mid interval value for each interval and N_G is the total households in each group. Standard deviation has the same scale or unit as income.

The *coefficient of variation* (C_V) is a normalized measure of variability and defined by the ratio of the standard deviation to the mean. Unlike the standard deviation, the coefficient of variation is scale-free or has no unit.

$$C_V = \frac{\sigma_G}{\overline{\text{Income}_G}} \quad (2.11)$$

The *Gini coefficient* (G_G) measures of inequality of income distribution. Gini coefficient ranges from the value of zero to one. The zero value of Gini coefficient means the perfect equality where everybody has exactly the same income which also suggests the highest degree of homogeneity of the group. In contrast, the Gini coefficient of value

one represents the perfect inequality where one person has all income and everybody else has zero income. The following formula is adapted from Abounoori & McCloughan (2003).

$$G_G = C \sum_{l=1}^L w_l \left(1 - \frac{\text{Income}_M}{\text{Income}_G} \right) \quad (2.12)$$

$$C = \frac{2}{N_G(N_G + 1)}$$

$$w_l = \frac{1}{2} \left\{ \sum_{l=1}^L f_l \cdot \left(\sum_{l=1}^L f_l + 1 \right) - \sum_{l=l+1}^L f_l \left(\sum_{l=l+1}^L f_l + 1 \right) \right\}$$

where f_l is the count of household in each income interval.

The second approach uses the calculated measures of income variability to sample the data into subsamples of high and low degree of homogeneity. For example, the sampling may be based on the first percentile (for highly homogeneous group) of distribution when ranking observations according to their degree of homogeneity. From these subsamples, the study obtains the estimates of income parameters from the equation (2.6) and contrasts the size and significance.

To summarize, the study produces several estimates of the income parameter using different methods and data sources. The goal is to compare the *individual income parameters* of the equation (2.3) estimated from the observed individual income ($\hat{\beta}_l$) with those estimated from the simulated individual income ($\tilde{\beta}_l$) and with the *group income parameters* ($\hat{\beta}_G$) of the equation (2.6). Additionally, the study contrasts the estimates of

group income parameters obtained from homogeneous and heterogeneous income groups.

2.5 Data Sources

2.5.1 Atlanta Household Travel Survey 2001-2002 (AHTS 2001)

During 2001 – 2002, the Atlanta Regional Commission (ARC) in cooperation with the Georgia Department of Transportation (GDOT) and the Georgia Regional Transportation Authority (GRTA) conducted the Atlanta Household Travel Survey (AHTS). The survey was aimed at updating information on the travel behavior of residents in 13 counties of Atlanta Non-attainment Areas. There were 8,069 randomly selected households participating in the survey by completing diary records of all travel for a 48-hour period. The survey oversampled 8069 households. Detailed information about the household was available from this survey, including income and ethnicity. For household income, there are 9 intervals ranging from less than \$10,000 to more than \$100,000. Ethnic groups are categorized into 6 groups, namely white, black, Hispanic, Asian, Native American, and other.

2.5.2 The Georgia's Census 2000 (CENSUS 2000)

The Georgia's census 2000 data is part of the US census 2000 provided by the US Census Bureau. This study obtains the census block group level data pertaining to income and demographic characteristics, which is the most detail information publicly available. Different from the AHTS 2001, the household income in the CENSUS 2000 are classified into 16 intervals, from less than \$10,000 to more than \$200,000. There are 4,157 block groups in this study. The average population per block is around 1,000 people. Unlike this study, Kahn (1996a) uses income data from the Census 1990 at a

coarser level of ZIP code groups (417 groups). In addition, he does not include the other demographic characteristics such as ethnicity and gender in his analysis.

2.5.3 Inspection and Maintenance Program Records 2000 Extended (I/M 2000 E) and 2001 (I/M 2001))

The Georgia Inspection and Maintenance (I/M) Program Records is the administrative records of every transaction performed at the inspection stations. The I/M data documents the detail information generated during the testing procedure. Most importantly, the I/M data contain the component and overall results of each inspection. The I/M 2000 extended differs from the other year data because it includes additional significant information regarding vehicle technology, especially pollution control parts. The AQL specifically prepares and adds this extra information using the commercial database related software called VIN decoder.

2.5.4 Matching Data Sources

This study uses two sets of samples, resulting from the matching of I/M 2000 E, AHTS 2001 and CENSUS 2000. The AHTS 2001 and CENSUS 2000 are the two sources of household income data for both group and individual level. The data are cross section and the unit of analysis is a vehicle undergone the annual inspection.

2.5.4.1 Aggregate-Income Sample

The first sample is the *aggregate-income sample* (658,714 vehicles), which comes from the matching of I/M 2000 E, CENSUS 2000 and AHTS 2001 datasets. The study uses the *address information* of each individual vehicle from the I/M 2000 E to locate the associated census block group identification, called the Federal Information Processing Standards (FIPS) codes of the *block group*. The geographical link between the address of vehicles and the block group FIPS codes allow the assignment of the

group income and other demographic information from the CENSUS 2000 to each individual vehicle.

In the similar manner, this study assigns the group income to each individual vehicle in the I/M 2000 E using the income information from the AHTS 2001. In this assignment, however, the connection between the two datasets is the *combination of vehicle characteristics*, resulting in the *vehicle group* of 1,014. The vehicle characteristics used for the grouping include the make, model year, type (car, truck, or van), and number of cylinders. For each vehicle group in the AHTS 2001, the mean, median, and variance of income are calculated. Then, these group incomes are assigned to each individual vehicle in the I/M 2000 E based on the identical matching of the vehicle group.

2.5.4.2 Individual-Income Sample

The second sample is the individual-income sample (465 vehicles), obtained from the matching of the I/M 2001 and AHTS 2001. Similar to the matching with CENSUS 2000, matching the I/M 2001 and the AHTS 2001 requires the intersection of the address locations or the XY geographical coordinates from this two data sets. By linking with the AHTS 2001, the information of an individual vehicle and its owner characteristics is available, including the household income and ethnicity.

2.5.4.3 Homogeneous – Heterogeneous Income Samples

From the aggregate-income sample, the study splits observations into two subsamples: homogeneous and heterogeneous income. Since all the measures of homogeneity of income are continuous scale, the subsampling is based on their distributions. The lowest 2 percentile of the distribution constitute the homogeneous samples. Likewise, the observations ranked above 98 percentile of the distribution are in

the heterogeneous samples. The advantage of selecting observations based on the distribution is the similar size of subsamples, controlling for the sample size effect.

2.6 Variables and Descriptive Statistics

A list of variables and their descriptions are given in Table 2.1 and the descriptive statistics of all variables from various samples are in Tables 2.2 –2.6. Table 2.2 presents the aggregate and individual income samples. Table 2.3 summarizes the distribution of the simulated individual household income variable of 4,000 distributions. Tables 2.4 – 2.6 exhibit descriptive statistics of three homogeneous and three heterogeneous subsamples, taken from the aggregate-income sample.

2.6.1 Dependent Variable: Failing the First Inspection

The key dependent variable in this study is *failing the first inspection*, coded one if a vehicle fails the initial inspection in an annual test requirement period and zero otherwise. Failing the first inspection is the proxy for the I/M compliance cost or burden. In particular, failing the first inspection is a crude measure of an extra cost (implied repair cost), in addition to the inspection fee and other transaction costs. At minimum, failing the first inspection guarantees the second visit to the station to some degree, thus higher cost of complying with the I/M regulation.

As seen in Table 2.2, the shares or probabilities of vehicles failing the first inspection are very low approximately 7 and 5 percent in the aggregate- and individual-income samples respectively. Accordingly, the average odds of a vehicle failing the first inspection are around $0.075 \left(= \frac{0.07}{0.93} \right)$ and $0.053 \left(= \frac{0.05}{0.95} \right)$. The low percentage of failing the first inspection confirms the notion that is a rough indication only for the lower-bound of the possible repair cost of the I/M program. Put differently, failing the first inspection cannot capture the pre-inspection repair cost

Table 2.1 Variables and their descriptions

| Variables | Level | Description |
|---|----------|---|
| <u>Dependent variable</u> | | |
| First inspection result | Nominal | Result from the first inspection in a test cycle; 1 if pass & 0 if fail |
| <u>Independent variables</u> | | |
| Household income | | |
| Observed Ln of individual income | Interval | Natural log of individual annual household income (US\$) |
| Simulated Ln of individual income | Interval | Natural log of individual annual household income (US\$) |
| Ln of <i>block</i> group median income | Interval | Natural log of block-group median annual household income (US\$) |
| Ln of <i>vehicle</i> group median income | Interval | Natural log of vehicle-group median annual household income (US\$) |
| Owner characteristics | | |
| Individual level (individual-income sample) | | |
| White (Ref.) | Nominal | Ethnicity of vehicle owner; 1 if white & 0 if otherwise |
| Black | Nominal | Ethnicity of vehicle owner; 1 if black & 0 if otherwise |
| Other | Nominal | Ethnicity of vehicle owner; 1 if other & 0 if otherwise |
| Block group level (aggregate-income sample) | | |
| Median age of population | Interval | Median age of population in a block-group (year) |
| Percent black population | Interval | Percent black population in a block-group (percent) |
| Percent other ethnic population | Interval | Percent other population in a block-group (percent) |
| Percent white population (Ref.) | Interval | Percent white population in a block-group (percent) |
| Percent Latino population | Interval | Percent Latino population in a block-group (percent) |
| Percent non Latino population (Ref.) | Interval | Percent non Latino population in a block-group (percent) |
| Percent male population | Interval | Percent male population in a block-group (percent) |
| Percent female population (Ref.) | Interval | Percent female population in a block-group (percent) |
| Vehicle characteristics | | |
| Age (year) | Interval | Age of vehicle (year) |
| Ln of mileage | Interval | Natural log of mileage read from odometer (mile) |
| Displacement (liter) | Interval | Engine displacement (liter) |
| Location of production | | |
| European | Nominal | Location of production; 1 if European & 0 if otherwise |
| Asian | Nominal | Location of production; 1 if Asian & 0 if otherwise |
| Other | Nominal | Location of production; 1 if Other & 0 if otherwise |
| US (Ref.) | Nominal | Location of production; 1 if US & 0 if otherwise |

Table 2.1 Cont.

| Variables | Level | Description |
|--------------------------------------|---------|--|
| <u>Independent variables (cont.)</u> | | |
| Type of vehicle | | |
| Car | Nominal | Type of vehicle; 1 if car & 0 if otherwise |
| Van & SUV | Nominal | Type of vehicle; 1 if van or SUV & 0 if otherwise |
| Truck (Ref.) | Nominal | Type of vehicle; 1 if truck & 0 if otherwise |
| Fuel induction technology | | |
| Electronic fuel induction (EFI) | Nominal | Vehicle equipped with EFI; 1 if yes & 0 if otherwise |
| Forced induction (FI) | Nominal | Vehicle equipped with FI; 1 if yes & 0 if otherwise |
| Multi-port fuel induction (MFI) | Nominal | Vehicle equipped with MFI; 1 if yes & 0 if otherwise |
| Other (Ref.) | Nominal | Vehicle equipped with other types of fuel induction; 1 if yes & 0 if otherwise |
| Exhaust gas recirculation (EGR) | Nominal | Vehicle equipped with EGR; 1 if yes & 0 if otherwise |
| Thermostatic air cleaner (TAC) | Nominal | Vehicle equipped with TAC; 1 if yes & 0 if otherwise |

Table 2.2 Descriptive statistics of dependent and independent variables of the two samples: aggregate and individual income

| Variables | Aggregate-Income Sample | | | | Individual-Income Sample | | | | Difference | |
|---|-------------------------|-----------|---------|-------|--------------------------|-----------|------|-------|------------|------------------------------|
| | Mean | Std. Div. | Min | Max | Mean | Std. Div. | Min | Max | t z | P(T > t) P(Z > z) |
| <u>Dependent Variables</u> | | | | | | | | | | |
| First inspection result (Pass = 0; Fail = 1) | 0.07 | 0.25 | 0 | 1 | 0.05 | 0.23 | 0 | 1 | 1.69 | 0.09 |
| <u>Independent Variables</u> | | | | | | | | | | |
| <i>Household income (\$US)</i> | | | | | | | | | | |
| Observed Ln of individual income | | | | | 10.83 | 0.60 | 8.52 | 11.51 | | |
| Ln of <i>block</i> group median income | 10.94 | 0.39 | 7.82 | 12.21 | | | | | | |
| Ln of <i>vehicle</i> group median income | 11.01 | 0.26 | 8.52 | 11.51 | | | | | | |
| <i>Owner characteristics in the block group</i> | | | | | | | | | | |
| Median age of population (year) | 34.20 | 4.76 | 12.60 | 75.40 | | | | | | |
| Percent black population | 0.26 | 0.30 | 0.00 | 1.00 | | | | | | |
| Percent other ethnic population | 0.09 | 0.08 | 0.00 | 0.72 | | | | | | |
| Percent Latino population | 0.07 | 0.10 | 0.00 | 0.84 | | | | | | |
| Percent male population | 0.49 | 0.04 | 0.13 | 1.00 | | | | | | |
| Black | | | | | 0.26 | 0.44 | 0 | 1 | | |
| Other | | | | | 0.14 | 0.35 | 0 | 1 | | |
| <i>Vehicle characteristics</i> | | | | | | | | | | |
| Age (year) | 6.81 | 3.61 | 0.50 | 19.50 | 6.93 | 3.31 | 3.00 | 20.00 | -0.78 | 0.43 |
| Ln of mileage | 9.09 | 3.28 | 0.00 | 13.82 | 11.41 | 0.56 | 8.21 | 12.91 | -88.31 | 0.00 |
| Displacement (liter) | 3.03 | 1.17 | 1.00 | 7.40 | 2.94 | 1.05 | 1.00 | 5.90 | 1.85 | 0.07 |
| Location of production: European | 0.05 | 0.22 | 0 | 1 | 0.07 | 0.25 | 0 | 1 | -1.98 | 0.05 |
| Location of production: Asian | 0.20 | 0.40 | 0 | 1 | 0.24 | 0.43 | 0 | 1 | -2.16 | 0.03 |
| Location of production: Other | 0.12 | 0.33 | 0 | 1 | 0.12 | 0.33 | 0 | 1 | 0.00 | 1.00 |
| Fuel Induction: EFI | 0.16 | 0.36 | 0 | 1 | 0.21 | 0.41 | 0 | 1 | -2.94 | 0.00 |
| Fuel induction: FI | 0.21 | 0.41 | 0 | 1 | 0.22 | 0.42 | 0 | 1 | -0.53 | 0.60 |
| Fuel induction: MFI | 0.33 | 0.47 | 0 | 1 | 0.29 | 0.45 | 0 | 1 | 1.83 | 0.07 |
| Exhaust gas recirculation (EGR) | 0.78 | 0.41 | 0 | 1 | 0.76 | 0.43 | 0 | 1 | 1.04 | 0.30 |
| Thermostatic air cleaner (TAC) | 0.10 | 0.30 | 0 | 1 | 0.07 | 0.25 | 0 | 1 | 2.16 | 0.03 |
| Type: Car | 0.73 | 0.44 | 0 | 1 | 0.72 | 0.45 | 0 | 1 | 0.49 | 0.63 |
| Type: Van | 0.14 | 0.35 | 0 | 1 | 0.18 | 0.39 | 0 | 1 | -2.48 | 0.01 |
| <u>Number of groups</u> | | | | | | | | | | |
| Census block groups | | | 4,157 | | | | - | | | |
| Vehicle groups (Make-Model Year-Cylinder-Type) | | | 1,014 | | | | - | | | |
| Observations | | | 685,714 | | | | 465 | | | |

Table 2.3 Descriptive statistics of 4000 simulated individual income data generated from two distributions (empirical and log-normal) of two data sets (AHTS 2001 and CENSUS 2000)

| Descriptive Statistics | Empirical Distribution | | Log-Normal Distribution | |
|------------------------|------------------------|-------------|-------------------------|-------------|
| | AHTS 2001 | CENSUS 2000 | AHTS 2001 | CENSUS 2000 |
| Mean | 10.915 | 10.837 | 10.915 | 10.837 |
| Standard deviation | 0.583 | 0.887 | 0.615 | 0.887 |
| Minimum | 8.517 | 8.517 | 3.998 | 5.625 |
| Maximum | 11.513 | 12.612 | 15.950 | 15.678 |
| 1st Percentile | 8.517 | 8.517 | 9.178 | 8.624 |
| 5th Percentile | 9.616 | 8.517 | 9.856 | 9.349 |
| 10th Percentile | 10.127 | 9.741 | 10.142 | 9.707 |
| 25th Percentile | 10.714 | 10.373 | 10.559 | 10.269 |
| 50th Percentile | 11.120 | 10.906 | 10.967 | 10.857 |
| 75th Percentile | 11.379 | 11.374 | 11.326 | 11.425 |
| 90th Percentile | 11.513 | 11.828 | 11.599 | 11.940 |
| 95th Percentile | 11.513 | 12.070 | 11.801 | 12.256 |
| 99th Percentile | 11.513 | 12.612 | 12.257 | 12.880 |
| Skewness | -1.478 | -0.667 | -0.597 | -0.136 |
| Kurtosis | 5.784 | 3.704 | 5.018 | 3.346 |
| Total sampling dist. | 1000 | 1000 | 1000 | 1000 |

Table 2.4 Descriptive statistics of dependent and independent variables of the two samples: Bottom vs Top 2 percentile of Gini coefficient

| Variables | Bottom 2% of Gini coefficient | | | | Top 2% of Gini Coefficient | | | |
|---|-------------------------------|-----------|-------|-------|----------------------------|-----------|-------|-------|
| | Mean | Std. Div. | Min | Max | Mean | Std. Div. | Min | Max |
| <u>Dependent Variables</u> | | | | | | | | |
| First inspection result (Pass = 0; Fail = 1) | 0.05 | 0.22 | 0 | 1 | 0.10 | 0.30 | 0 | 1 |
| <u>Independent Variables</u> | | | | | | | | |
| <i>Household income (\$US)</i> | | | | | | | | |
| Ln (block group median income) | 11.52 | 0.44 | 7.82 | 12.21 | 9.99 | 0.41 | 8.87 | 10.81 |
| <i>Owner characteristics in the block group</i> | | | | | | | | |
| Median age of population (year) | 36.42 | 4.67 | 19.70 | 46.90 | 33.03 | 8.59 | 12.60 | 70.60 |
| Percent black population | 0.14 | 0.22 | 0.00 | 0.97 | 0.63 | 0.35 | 0.01 | 1.00 |
| Percent other ethnic population | 0.08 | 0.07 | 0.00 | 0.29 | 0.05 | 0.06 | 0.00 | 0.31 |
| Percent Latino population | 0.05 | 0.07 | 0.00 | 0.36 | 0.05 | 0.08 | 0.00 | 0.84 |
| Percent male population | 0.51 | 0.04 | 0.45 | 1.00 | 0.45 | 0.06 | 0.13 | 0.85 |
| <i>Vehicle characteristics</i> | | | | | | | | |
| Age (year) | 6.39 | 3.49 | 0.50 | 19.50 | 7.42 | 3.84 | 0.50 | 19.50 |
| Ln of mileage | 8.55 | 3.42 | 0.00 | 13.82 | 9.36 | 3.26 | 0.00 | 13.82 |
| Displacement (liter) | 3.16 | 1.15 | 1.00 | 7.40 | 3.02 | 1.18 | 1.00 | 7.40 |
| Location of production: Europe | 0.10 | 0.30 | 0 | 1 | 0.06 | 0.23 | 0 | 1 |
| Location of production: Asia | 0.21 | 0.41 | 0 | 1 | 0.18 | 0.39 | 0 | 1 |
| Location of production: Other | 0.11 | 0.32 | 0 | 1 | 0.13 | 0.33 | 0 | 1 |
| Fuel Induction: EFI | 0.15 | 0.36 | 0 | 1 | 0.15 | 0.36 | 0 | 1 |
| Fuel induction: FI | 0.22 | 0.41 | 0 | 1 | 0.23 | 0.42 | 0 | 1 |
| Fuel induction: MFI | 0.33 | 0.47 | 0 | 1 | 0.33 | 0.47 | 0 | 1 |
| Exhaust gas recirculation (EGR) | 0.76 | 0.43 | 0 | 1 | 0.76 | 0.43 | 0 | 1 |
| Thermostatic air cleaner (TAC) | 0.08 | 0.28 | 0 | 1 | 0.12 | 0.33 | 0 | 1 |
| Type: Car | 0.71 | 0.45 | 0 | 1 | 0.79 | 0.41 | 0 | 1 |
| Type: Van | 0.18 | 0.38 | 0 | 1 | 0.10 | 0.31 | 0 | 1 |
| Observations | 13,907 | | | | 13,721 | | | |

Table 2.5 Descriptive statistics of dependent and independent variables of the two samples: Bottom vs Top 2 percentile of the standard deviation of Ln(household income in a block group)

| Variables | Bottom 2% of SD of Ln(Income) | | | | Top 2% of SD of Ln(Income) | | | |
|---|-------------------------------|-----------|-------|-------|----------------------------|-----------|-------|-------|
| | Mean | Std. Div. | Min | Max | Mean | Std. Div. | Min | Max |
| <u>Dependent Variables</u> | | | | | | | | |
| First inspection result (Pass = 0; Fail = 1) | 0.06 | 0.24 | 0 | 1 | 0.06 | 0.24 | 0 | 1 |
| <u>Independent Variables</u> | | | | | | | | |
| <i>Household income (\$US)</i> | | | | | | | | |
| Ln(block group median income) | 11.17 | 0.31 | 7.82 | 11.64 | 10.84 | 0.55 | 9.13 | 12.21 |
| <i>Owner characteristics in the block group</i> | | | | | | | | |
| Median age of population (year) | 34.87 | 3.93 | 19.70 | 46.10 | 39.06 | 6.68 | 19.80 | 59.60 |
| Percent black population | 0.26 | 0.34 | 0.00 | 0.97 | 0.25 | 0.30 | 0.00 | 0.99 |
| Percent other ethnic population | 0.06 | 0.07 | 0.00 | 0.28 | 0.06 | 0.06 | 0.00 | 0.23 |
| Percent Latino population | 0.04 | 0.04 | 0.00 | 0.16 | 0.04 | 0.05 | 0.00 | 0.84 |
| Percent male population | 0.50 | 0.05 | 0.41 | 1.00 | 0.48 | 0.07 | 0.13 | 0.67 |
| <i>Vehicle characteristics</i> | | | | | | | | |
| Age (year) | 6.76 | 3.60 | 0.50 | 19.50 | 6.74 | 3.65 | 0.50 | 19.50 |
| Ln(mileage) | 8.90 | 3.34 | 0.00 | 13.81 | 8.80 | 3.37 | 0.00 | 13.82 |
| Displacement (liter) | 3.06 | 1.17 | 1.00 | 7.40 | 3.01 | 1.12 | 1.00 | 7.40 |
| Location of production: Europe | 0.05 | 0.21 | 0 | 1 | 0.14 | 0.35 | 0 | 1 |
| Location of production: Asia | 0.20 | 0.40 | 0 | 1 | 0.23 | 0.42 | 0 | 1 |
| Location of production: Other | 0.13 | 0.34 | 0 | 1 | 0.11 | 0.31 | 0 | 1 |
| Fuel Induction: EFI | 0.16 | 0.36 | 0 | 1 | 0.13 | 0.34 | 0 | 1 |
| Fuel induction: FI | 0.21 | 0.40 | 0 | 1 | 0.26 | 0.44 | 0 | 1 |
| Fuel induction: MFI | 0.34 | 0.48 | 0 | 1 | 0.32 | 0.46 | 0 | 1 |
| Exhaust gas recirculation (EGR) | 0.78 | 0.41 | 0 | 1 | 0.71 | 0.46 | 0 | 1 |
| Thermostatic air cleaner (TAC) | 0.10 | 0.30 | 0 | 1 | 0.08 | 0.27 | 0 | 1 |
| Type: Car | 0.71 | 0.45 | 0 | 1 | 0.79 | 0.41 | 0 | 1 |
| Type: Van | 0.15 | 0.35 | 0 | 1 | 0.14 | 0.35 | 0 | 1 |
| Observations | 13,975 | | | | 14,016 | | | |

Table 2.6 Descriptive statistics of dependent and independent variables of the two samples: Bottom vs Top 2 percentile of coefficient of variation of Ln(household income in a block group)

| Variables | Bottom 2% of CV of Ln(Income) | | | | Top 2% of CV of Ln(Income) | | | |
|---|-------------------------------|-----------|-------|-------|----------------------------|-----------|-------|-------|
| | Mean | Std. Div. | Min | Max | Mean | Std. Div. | Min | Max |
| Dependent Variables | | | | | | | | |
| First inspection result (Pass = 0; Fail = 1) | 0.06 | 0.24 | 0 | 1 | 0.06 | 0.24 | 0 | 1 |
| Independent Variables | | | | | | | | |
| <i>Household income (\$US)</i> | | | | | | | | |
| Ln(block group median income) | 11.17 | 0.31 | 7.82 | 11.64 | 10.84 | 0.55 | 9.13 | 12.21 |
| <i>Owner characteristics in the block group</i> | | | | | | | | |
| Median age of population (year) | 34.87 | 3.93 | 19.70 | 46.10 | 39.06 | 6.68 | 19.80 | 59.60 |
| Percent black population | 0.26 | 0.34 | 0.00 | 0.97 | 0.25 | 0.30 | 0.00 | 0.99 |
| Percent other ethnic population | 0.06 | 0.07 | 0.00 | 0.28 | 0.06 | 0.06 | 0.00 | 0.23 |
| Percent Latino population | 0.04 | 0.04 | 0.00 | 0.16 | 0.04 | 0.05 | 0.00 | 0.84 |
| Percent male population | 0.50 | 0.05 | 0.41 | 1.00 | 0.48 | 0.07 | 0.13 | 0.67 |
| <i>Vehicle characteristics</i> | | | | | | | | |
| Age (year) | 6.76 | 3.60 | 0.50 | 19.50 | 6.74 | 3.65 | 0.50 | 19.50 |
| Ln(mileage) | 8.90 | 3.34 | 0.00 | 13.81 | 8.80 | 3.37 | 0.00 | 13.82 |
| Displacement (liter) | 3.06 | 1.17 | 1.00 | 7.40 | 3.01 | 1.12 | 1.00 | 7.40 |
| Location of production: Europe | 0.05 | 0.21 | 0 | 1 | 0.14 | 0.35 | 0 | 1 |
| Location of production: Asia | 0.20 | 0.40 | 0 | 1 | 0.23 | 0.42 | 0 | 1 |
| Location of production: Other | 0.13 | 0.34 | 0 | 1 | 0.11 | 0.31 | 0 | 1 |
| Fuel Induction: EFI | 0.16 | 0.36 | 0 | 1 | 0.13 | 0.34 | 0 | 1 |
| Fuel induction: FI | 0.21 | 0.40 | 0 | 1 | 0.26 | 0.44 | 0 | 1 |
| Fuel induction: MFI | 0.34 | 0.48 | 0 | 1 | 0.32 | 0.46 | 0 | 1 |
| Exhaust gas recirculation (EGR) | 0.78 | 0.41 | 0 | 1 | 0.71 | 0.46 | 0 | 1 |
| Thermostatic air cleaner (TAC) | 0.10 | 0.30 | 0 | 1 | 0.08 | 0.27 | 0 | 1 |
| Type: Car | 0.71 | 0.45 | 0 | 1 | 0.79 | 0.41 | 0 | 1 |
| Type: Van | 0.15 | 0.35 | 0 | 1 | 0.14 | 0.35 | 0 | 1 |
| Observations | 14,120 | | | | 13,716 | | | |

2.6.2 Independent Variables

2.6.2.1 Annual Household Income

The key independent variable of this study is the *household income*. There are varieties of the household income used in this study and all of them are the natural logarithmic transformation of their original values. The *observed individual income* is available only in the individual-income sample of 465 vehicles. The average household income of this sample is around US\$ 58.31 thousands and the standard deviation is US\$ 27.62 thousands. Table 2.2 shows the descriptive statistics of this variable in the log transformation.

The *simulated individual income* comes from four types of data generating process (data source – distribution): AHTS – empirical, AHTS – lognormal, CENSUS – empirical, and CENSUS – lognormal. As shown in Table 2.3, simulated income generated from the CENSUS 2000 looks similar between the empirical and lognormal distribution because the empirical distribution of the log transformation value are relatively normal. Unlike the CENSUS 2000, simulated incomes from the AHTS 2001 with empirical and lognormal distribution are quite different because, with the log transformation, the empirical distribution is less normally distributed. The means of simulated income from the CENSUS 2000 and AHTS 2001 are US\$ 50.87 and US\$ 54.99 thousands per year respectively.

There are two types of aggregating household income in this study: geographical area and vehicle-characteristics. The *block group median household income* is the representative value of income of households from the same geographical area, defined by the census block group. Likewise, the *vehicle-group median household income* is the representative value of income from the households owning vehicles with the same characteristics of make, model year, type, and cylinder. The mean of the block and vehicle group median income is around US\$ 56.39 and US\$ 60.48 thousands per year respectively. In the aggregate-income sample, the number of block groups is larger (4,157) than the number of vehicle groups (1,014). Moreover, the household income is measured in more detail level (16 intervals) in the Census 2000 than that in the AHTS 2001 (9 intervals) data.

2.6.2.2 Demographic Characteristics

In the individual-income sample (465 vehicles), the main characteristic of the vehicle owner is ethnicity. Around 60 percent of households in this sample are *white* (reference group) while 26 and 14 percents are *black* and *other* ethnic (including Asian,

Latino and other) groups respectively. Table 2.2 shows the summary statistics of these variables

In the aggregate-income sample, there is no information about individual household demographic characteristics. Only the shares of the characteristics in each block group are available. Several demographic characteristics are included because they might be associated with the type of vehicles and the level of household income. For each block group, these variables are the *median age of the population*, *percent white* (reference), *black*, and *other ethnic population*, *percent Latino population*, and *percent male population*. The summary statistics of these variables are in Table 2.2.

2.6.2.3 Vehicle Characteristics

The most relevant factors determining the inspection results are the vehicle characteristics because they suggest the underlying quality of the vehicles. Key continuous variables include *age*, *mileage* (natural log transformed), and *displacement*. Other categorical variables are the *location of production* (*US* - reference, *Europe*, *Asia*, and *other*), type of vehicle (*car*, *van*, and *truck* - reference). The emission control technologies variables are also categorical: type of *fuel induction* (*EFI*, *FI*, *MFI* and *other* as the reference), exhaust gas recirculation (*EGR*), and thermostatic air cleaner (*TAC*).

As shown in Table 2.2, generally, half of the characteristics of vehicles between the two samples are roughly the same. Variables that are significantly different between the two samples are the mileage, share of imported vehicle from Europe and Asia, the share of EFI and TAC equipped vehicle, and the share of van. Except for TAC, the means and proportions of these variables in the aggregate-income sample are significantly lower than those in the individual-income sample. In particular, the mileages of vehicles from the individual-income sample (90 thousand miles on average) are 10 times higher than those from the aggregate-income sample (approximately 9 thousand

miles), suggesting the rather intensive use in the small sample. For some of the influential cases (intensive use), their pattern of vehicle usage is related to the distant working place of the household members. This might cause the bias of the individual-income sample in terms of some vehicle characteristics. Table 2.2 presents the test of the difference in means and proportions between the two samples.

2.7 Results and Discussions

2.7.1 Overall Results: Model Specification

Overall, the specifications in Tables 2.7(B) – 2.8(A) and (B) can explain the variability of the outcome around 24 and 11 percent in the individual and aggregate income samples respectively. Although the effects of most variables in the individual-income sample are insignificant, they are strongly significant in the aggregate income sample. The results from the series of Wald and log likelihood ratio (LR) tests for models of the individual and aggregate income samples show consistent results with the z-statistics. In the aggregate income sample, the tests suggest that the full model performs better than the varieties of restricted models, which is not true for the individual income sample. Similarly, several scalar measures of fit (i.e. varieties provide support only for the full model estimated from the aggregate income sample. The difference between the individual and aggregate income sample might be due to several reasons: (1) small sample bias, (2) small size effect of the variables, and (3) influential cases in the small sample. Nonetheless, the key variables such as age of a vehicle still show significant and similar effect sizes. Moreover, the models of the individual and aggregate income sample yield quite reasonable prediction of around 94 and 93 percent correctly classified cases.

2.7.2 Effects of Individual Income: Observed VS Simulated

The results from the bootstrap and Monte Carlo of logistic model using individual and aggregate income samples are in Tables 2.7(A) and (B). Table 2.7(A) presents the restricted model testing the first hypothesis of equation (2.1). In the individual-income sample (models (1) and (2) of Table 2.7(A)), the null hypothesis that the odds of a vehicle failing the first inspection is the same across income groups is almost rejected at the 10 percent significant level (z-statistics are -1.60 and -1.53) with the expected direction. In the aggregate-income samples of Table 2.7(A), the odds of a vehicle failing the first inspection are clearly lower for the high-income households than those for the low-income ones.

In short, using both the observed and simulated incomes, the study finds that the unconditional effect of income is negatively associated with the odds of a vehicle failing the first inspection. The vehicles owned by the low-income households are more likely to fail the first inspection than those owned by the high-income ones.

Table 2.7 Bootstrap and Monte Carlo logistic models of the odds of a vehicle failing the first inspection

(A) Restricted

| Independent Variables | Bootstrap - Individual Income | | | | Monte Carlo - Aggregate Income (CENSUS 2000) | | | | Monte Carlo - Aggregate Income (AHTS 2001) | | | |
|-----------------------------------|-------------------------------|-------|-----------------------|-------|--|--------|---------------|--------|--|--------|---------------|--------|
| | (1) Simple random | | (2) Stratified random | | (3) Empirical | | (4) Lognormal | | (5) Empirical | | (6) Lognormal | |
| | Coef. | z | Coef. | z | Coef. | z | Coef. | z | Coef. | z | Coef. | z |
| Household income (\$US) | | | | | | | | | | | | |
| Observed ln of individual income | -0.6192 | -1.60 | -0.6192 | -1.53 | | | | | | | | |
| Simulated ln of individual income | | | | | -0.1179 | -22.91 | -0.1207 | -22.40 | -0.1930 | -25.75 | -0.1811 | -23.27 |
| Constant | 3.7701 | 0.91 | 3.7701 | 0.88 | -1.3470 | -24.25 | -1.3164 | -22.63 | -0.5188 | -6.36 | -0.6492 | -7.67 |
| Pseudo R2 | | | | | 0.0013 | | 0.0013 | | 0.0017 | | 0.0016 | |
| Wald Chi2 | | | | | 469.05 | | 447.21 | | 621.07 | | 514.17 | |
| Repetitions | 10000 | | 10000 | | 1000 | | 1000 | | 1000 | | 1000 | |
| Observations | 465 | | 465 | | 685,714 | | 685,714 | | 685,714 | | 685,714 | |

Table 2.7 Cont.

(B) Unrestricted

| Independent Variables | Bootstrap - Individual Income | | | | Monte Carlo - Aggregate Income (CENSUS 2000) | | | | Monte Carlo - Aggregate Income (AHTS 2001) | | | |
|---|-------------------------------|-------|-----------------------|-------|--|--------|---------------|--------|--|--------|---------------|--------|
| | (1) Simple random | | (2) Stratified random | | (3) Empirical | | (4) Lognormal | | (5) Empirical | | (6) Lognormal | |
| | Coef. | z | Coef. | z | Coef. | z | Coef. | z | Coef. | z | Coef. | z |
| Household income (\$US) | | | | | | | | | | | | |
| Observed ln of individual income | -0.2819 | -0.58 | -0.2819 | -0.57 | | | | | | | | |
| Simulated ln of individual income | | | | | -0.0308 | -5.28 | -0.0310 | -5.25 | -0.0231 | -2.76 | -0.0204 | -2.57 |
| Owner characteristics in the block group | | | | | | | | | | | | |
| Median age of population (year) | | | | | -0.0087 | -6.72 | -0.0087 | -6.72 | -0.0094 | -7.31 | -0.0094 | -7.31 |
| Black Percent black population | 1.1849 | 1.94 | 1.1849 | 1.97 | 0.4416 | 23.94 | 0.4415 | 23.93 | 0.4577 | 25.21 | 0.4578 | 25.21 |
| Other Percent other ethnic population | 0.5112 | 0.69 | 0.5112 | 0.68 | -0.3973 | -4.00 | -0.3973 | -4.00 | -0.4029 | -4.05 | -0.4031 | -4.05 |
| Percent Latino population | | | | | 0.5902 | 6.92 | 0.5900 | 6.91 | 0.6189 | 7.26 | 0.6191 | 7.26 |
| Percent male population | | | | | -0.0803 | -0.55 | -0.0801 | -0.55 | -0.1120 | -0.77 | -0.1120 | -0.77 |
| Vehicle characteristics | | | | | | | | | | | | |
| Age (year) | 0.2291 | 2.49 | 0.2291 | 2.59 | 0.2163 | 132.21 | 0.2163 | 132.21 | 0.2160 | 131.42 | 0.2161 | 131.51 |
| Ln of mileage (mile) | 0.2668 | 0.48 | 0.2668 | 0.49 | 0.0500 | 26.82 | 0.0500 | 26.82 | 0.0501 | 26.88 | 0.0501 | 26.88 |
| Displacement (liter) | -0.0445 | -0.11 | -0.0445 | -0.11 | -0.0182 | -3.53 | -0.0182 | -3.53 | -0.0182 | -3.54 | -0.0182 | -3.54 |
| Location of production: European | 0.3442 | 0.36 | 0.3442 | 0.35 | -0.0044 | -0.20 | -0.0044 | -0.20 | 0.0003 | 0.01 | -0.0007 | -0.03 |
| Location of production: Asian | 0.1142 | 0.15 | 0.1142 | 0.15 | -0.0135 | -1.01 | -0.0134 | -1.01 | -0.0130 | -0.97 | -0.0132 | -0.99 |
| Location of production: Other | 0.1774 | 0.25 | 0.1774 | 0.24 | 0.0709 | 4.20 | 0.0709 | 4.20 | 0.0709 | 4.19 | 0.0709 | 4.20 |
| Fuel Induction: EFI | 0.3927 | 0.50 | 0.3927 | 0.49 | -0.0247 | -1.43 | -0.0247 | -1.43 | -0.0254 | -1.48 | -0.0253 | -1.47 |
| Fuel induction: FI | -0.5801 | -0.69 | -0.5801 | -0.65 | 0.0070 | 0.46 | 0.0070 | 0.46 | 0.0066 | 0.43 | 0.0066 | 0.44 |
| Fuel induction: MFI | -1.6676 | -2.28 | -1.6676 | -2.31 | -0.0194 | -1.18 | -0.0194 | -1.18 | -0.0203 | -1.23 | -0.0202 | -1.23 |
| Exhaust gas recirculation (EGR) | -1.3073 | -2.19 | -1.3073 | -2.15 | -0.0741 | -5.77 | -0.0741 | -5.77 | -0.0742 | -5.77 | -0.0742 | -5.77 |
| Thermostatic air cleaner (TAC) | -0.1766 | -0.18 | -0.1766 | -0.18 | 0.1386 | 7.76 | 0.1386 | 7.76 | 0.1383 | 7.74 | 0.1384 | 7.75 |
| Type: Car | -1.1891 | -0.80 | -1.1891 | -0.72 | 0.1085 | 6.01 | 0.1085 | 6.02 | 0.1054 | 5.84 | 0.1057 | 5.85 |
| Type: Van | -1.1204 | -0.71 | -1.1204 | -0.65 | 0.1280 | 5.81 | 0.1280 | 5.81 | 0.1274 | 5.78 | 0.1273 | 5.77 |
| Constant | -3.1805 | -0.35 | -3.1805 | -0.35 | -4.3519 | -39.03 | -4.3501 | -38.89 | -4.3940 | -32.81 | -4.4241 | -33.92 |
| Pseudo R2 | 0.2407 | | 0.2407 | | 0.1114 | | 0.1114 | | 0.1114 | | 0.1114 | |
| Wald Chi2 | 44.37 | | 44.37 | | 46325.50 | | 40320.53 | | 40316.20 | | 40315.26 | |
| Repetitions | 4899 | | 5070 | | 1000 | | 1000 | | 1000 | | 1000 | |
| Observations | 465 | | 465 | | 685,714 | | 685,714 | | 685,714 | | 685,714 | |

Table 2.7(B) displays the unrestricted model testing the second hypothesis of equation (2.2) in which the individual household income, conditional on the characteristics of vehicle and its owner, decreases the odds of the vehicle failing the first inspection. The effect of income in this specification reflects the possible maintenance spending of households. In Table 2.7(B), model (1) is the bootstrap logistic model with the simple random sample of the original sample size whereas model (2) is the bootstrap logistic model with the stratified random sampling according to the test results (pass or fail). In short, the estimations of models (1) and (2) use the *observed* individual-income from the AHTS 2001. In contrast, models (3) to (6) estimate the effect of the *simulated* individual income (4,000 samples) obtained from the income distribution information of the CENSUS 2000 and AHTS 2001.

In Table 2.7 (B), the *observed* and *simulated individual household incomes* exhibit slightly different effects. In the individual income sample, the observed household income of a vehicle owner is not associated with the odds of that vehicle failing the first inspection. In the aggregate income sample, however, the simulated household income of a vehicle owner does show a marginal effect. From Table 2.7 (B), model (4) shows that the log odds of a vehicle failing the first inspection decrease by 0.0308⁸ (z-statistics is -5.28) when the log of simulated individual household income increases by one unit, conditional on the characteristics of vehicles and their owners. As both of the dependent

⁸ Let $Y =$ A vehicle fails the first test (1 if true and 0 otherwise); Odds of $Y = \frac{\Pr(Y)}{1-\Pr(Y)}$;

$0 \leq \text{Odds} \leq +\infty$; $-\infty \leq \text{Ln}(\text{Odds}) \leq +\infty$.

Odds ratio for an increase of 1 unit in $X = e^\beta = \frac{\frac{P(Y=1|X=a+1)}{1-P(Y=1|X=a+1)}}{\frac{P(Y=1|X=a)}{1-P(Y=1|X=a)}}$

where X is the explanatory variable and a is any predetermined value of X

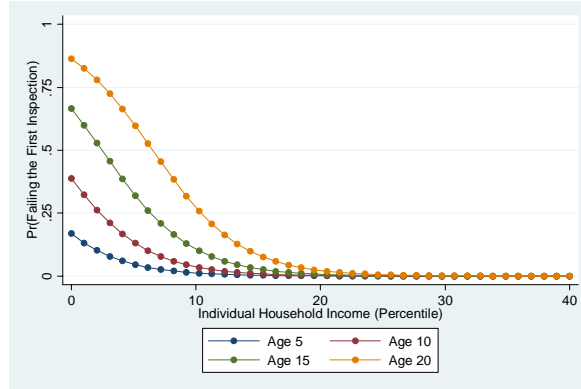
and independent variables are the log transformation, the coefficient is the elasticity of income. That is a one percent increase in the vehicle owner's household income decreases the odds⁹ of the vehicle failing the first inspection by 0.0308 percent, holding other variables constant. In other words, when the household income increases from \$50.87¹⁰ to \$51.38 thousands, the odds of a vehicle failing the first inspection decreases from 0.075¹¹ to 0.073. Similarly, in terms of the expected probability of a vehicle failing the first inspection, there is only a small difference resulting from the change in the simulated household income. For example, the difference in the predicted probability¹² of a vehicle failing the first inspection computed at the first and ninety ninth percentile of income distribution is only 0.0045. This result indicates that there is almost no meaningful effect of individual household income on the probability of a vehicle failing the first inspection, based on the simulated income data. Accordingly, in the panel (B) of the Figure 2.1, the predicted probability of a vehicle failing the first inspection declines with the higher percentile of income at the varying rates, depending on the age of the vehicle. As discussed later, the main driving factor of the high predicted probability of failing the first inspection is the vehicle age, particularly of the old vehicle appeared in the panel (B). The plot of panel (A) is merely for the comparison with the panel (B) because the effect of income in the individual income sample is not significant.

⁹ In the sample the share (or probability) of a vehicle failing the first inspection is only 7 percent. ($\Pr(Y) = 0.07$).

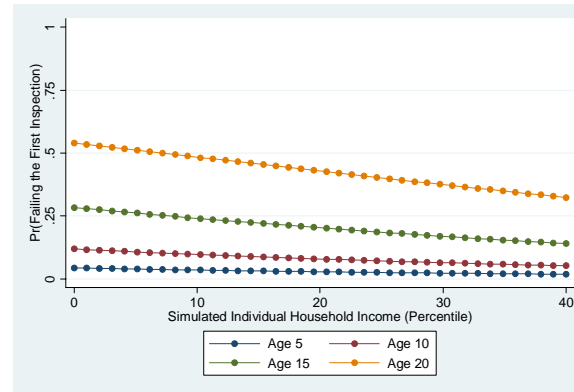
¹⁰ The mean of $\text{Ln}(\text{Simulated Individual Household Income}) = 10.84$; $\text{Exp}(10.84) = 50,868.54$. Hence, $51.38 = 50.87 + (0.01 \times 50.87)$.

¹¹ The average odds of a vehicle failing the first inspection are $0.075 = \frac{0.07}{0.93}$ and $0.053 = \frac{0.05}{0.95}$ in the aggregate-income and individual-income samples respectively. Thus, the resulting odds = $0.073 = 0.075 - (0.075 \times 0.038)$

¹² These predicted probabilities are calculated based on the only one set of the 4,000 simulated household income data. The coefficient of income in this sample is -0.022 . In addition, they are the predicted probabilities for the US made car without EGR and TAC but equipped with MFI induction with the mean value of the other variables.



(A) Individual income sample
(results are not significant)



(B) Aggregate income sample

Figure 2.1: Individual household income and predicted probability of a vehicle failing the first inspection classified by age of vehicle

In sum, with both the observed and simulated incomes, the estimates show that the individual household income is not associated with the odds of a vehicle failing the first inspection, conditional on the characteristics of vehicles and their owners. In other words, given the comparable vehicles, the low- and high-income households face the same chance that their vehicles failing the first inspection. The results allude to the insignificant difference in the pre-inspection repair or maintenance cost between the low- and high-income households.

2.7.3 Effects of Income: Individual VS Group

The logistic regression results from the individual and aggregate income sample are in Table 2.8. The estimation of the individual income effect utilizes both the individual and aggregate income data to demonstrate the bias in terms of the significance when using the group level to represent the individual level information. Table 2.8 (A) presents the restricted model of the unconditional effect of the individual household income; Table 2.8 (B) shows the unrestricted model of the conditional effect of the individual household income.

In Table 2.8 (A), the results are consistent with those of Table 2.7 (A) in the previous section. The unconditional effect of income is significant at the 10 percent level in the individual-income sample (z statistics is -1.72). All models using the aggregate income information (models (2) to (4)) in Table 2.8 (A) show the significantly negative effect of income on the odds of a vehicle failing the first inspection.

Briefly, this study finds that a vehicle owned by a low-income household is more likely to fail the first inspection than the one owned by the high-income household. Likewise, the chance that a vehicle will fail the first inspection is higher if it is registered in the low-income neighborhoods.

In Table 2.8 (B), the income variable is a proxy for the potential maintenance or pre-inspection repair when controlling for the characteristics of vehicle and its owner. Despite the similar size of the coefficients from the individual and aggregate sample, an individual household income is not associated with the odds of a vehicle failing the first inspection as shown in the model (1). On the contrary, when the median household incomes of a block group replaces the individual income as shown in model (2) of Table 2.8 (B), the effect of income becomes negatively significant. This is the evidence of the ecological fallacy, resulting from using the aggregate-level income to substitute for the individual-level income.

Table 2.8 Logistic models of the odds of a vehicle failing the first inspection estimated from the individual and aggregate income samples

(A) Restricted

| Independent Variables | Individual-Income Sample | | Aggregate-Income Sample | | | | | |
|--|--------------------------|-------|-------------------------|-------|-----------------|--------|---------------|--------|
| | (1) | | (2) | | (3) CENSUS 2000 | | (4) AHTS 2001 | |
| | Coef. | z | Coef. | z | Coef. | z | Coef. | z |
| Household income (\$US) | | | | | | | | |
| Ln of observed individual income | -0.619 | -1.72 | | | | | | |
| Ln of <i>block</i> group median income | | | -1.313 | -2.76 | -0.572 | -49.57 | | |
| Ln of <i>vehicle</i> group median income | | | | | | | -0.975 | -58.03 |
| Constant | 3.770 | 0.99 | 11.223 | 2.22 | 3.617 | 28.83 | 8.088 | 43.94 |
| Pseudo R2 | 0.0209 | | 0.0364 | | 0.0068 | | 0.0096 | |
| Wald Chi2 | 2.96 | | 7.63 | | 2457.35 | | 3367.56 | |
| Observations | 465 | | 465 | | 685,714 | | 685,714 | |

(B) Unrestricted

| Independent Variables | Individual-Income Sample | | Aggregate-Income Sample | | | | | |
|--|--------------------------|-------|-------------------------|-------|-----------------|--------|---------------|--------|
| | (1) | | (2) | | (3) CENSUS 2000 | | (4) AHTS 2001 | |
| | Coef. | z | Coef. | z | Coef. | z | Coef. | z |
| Household income (\$US) | | | | | | | | |
| Ln of observed individual income | -0.282 | -0.75 | | | | | | |
| Ln of <i>block</i> group median income | | | -1.195 | -2.05 | -0.261 | -16.83 | | |
| Ln of <i>vehicle</i> group median income | | | | | | | -0.152 | -8.05 |
| Owner characteristics | | | | | | | | |
| Black Percent black population | 1.185 | 2.2 | 0.964 | 1.59 | 0.334 | 17.11 | 0.514 | 32.89 |
| Other Percent other ethnic population | 0.511 | 0.83 | 0.500 | 0.76 | 0.103 | 1.66 | 0.384 | 6.48 |
| Vehicle characteristics | | | | | | | | |
| Age (year) | 0.229 | 3.35 | 0.218 | 3.07 | 0.216 | 131.95 | 0.213 | 127.26 |
| Ln of mileage (mile) | 0.267 | 0.71 | 0.288 | 0.77 | 0.050 | 26.84 | 0.052 | 27.88 |
| Displacement (liter) | -0.045 | -0.14 | -0.086 | -0.26 | -0.018 | -3.53 | -0.020 | -3.89 |
| Location of production: European | 0.344 | 0.41 | 0.700 | 0.85 | 0.018 | 0.79 | 0.027 | 1.15 |
| Location of production: Asian | 0.114 | 0.17 | 0.265 | 0.39 | -0.006 | -0.43 | -0.009 | -0.68 |
| Location of production: Other | 0.177 | 0.23 | -0.052 | -0.06 | 0.069 | 4.08 | 0.069 | 4.07 |
| Fuel Induction: EFI | 0.393 | 0.64 | 0.304 | 0.48 | -0.025 | -1.44 | -0.032 | -1.83 |
| Fuel induction: FI | -0.580 | -0.86 | -0.668 | -0.99 | 0.008 | 0.55 | 0.005 | 0.31 |
| Fuel induction: MFI | -1.668 | -1.53 | -1.732 | -1.55 | -0.019 | -1.15 | -0.026 | -1.55 |
| Exhaust gas recirculation (EGR) | -1.307 | -2.53 | -1.387 | -2.73 | -0.072 | -5.56 | -0.071 | -5.49 |
| Thermostatic air cleaner (TAC) | -0.177 | -0.23 | -0.179 | -0.23 | 0.136 | 7.60 | 0.135 | 7.55 |
| Type: Car | -1.189 | -1.41 | -1.485 | -1.68 | 0.109 | 6.05 | 0.083 | 4.61 |
| Type: Van | -1.120 | -1.14 | -1.317 | -1.35 | 0.136 | 6.17 | 0.121 | 5.51 |
| Constant | -3.181 | -0.48 | 6.956 | 0.88 | -2.145 | -12.09 | -3.362 | -15.63 |
| Pseudo R2 | 0.24 | | 0.26 | | 0.11 | | 0.11 | |
| Wald Chi2 | 44.37 | | 56.98 | | 40354.44 | | 40362.12 | |
| Observations | 465 | | 465 | | 685,714 | | 685,714 | |

In Table 2.8 (B), the income effects from the aggregate-income sample, estimated with the group-level income data, are consistently significant as shown in models (3) and (4). In other words, all else constant, the vehicles from the high group-level income neighborhoods have the lower odds of failing the first test than those from the low-income neighborhoods. Moreover, the block-group income has a stronger effect than the vehicle group income does. Specifically, the odds that a vehicle registered in the block group (being a member of the vehicle group) with the median household income of US\$ 56.39¹³ (60.48¹⁴) thousands will fail the first inspection are 0.77¹⁵ (0.86) as high as the odds that the comparable vehicle registered in the block group with the median household income of US\$ 56.95 (61.08) thousands, holding the other variables constant. That is the odds of a vehicle failing the inspection fall by 22.97¹⁶ and 14.14 percents for every additional one percent of block and vehicle group median income respectively. Despite their significant effects, the group-level income effect has different meaning and cannot substitute for the individual income effect due to the bias resulting from the ecological fallacy.

The stronger effect of the block group income is expected for two reasons. First, previous literature on the sorting and neighborhood effects shows the strong evidence of income sorting (Davidoff, 2005). For example, households make the decisions about where they live based on the quality of the school in the districts. Certainly, the quality of the school is highly correlated with the wealth of the local community (Black, 1999; Bayer, Ferreira & McMillan, 2007). Therefore, vehicle owners living in the same

¹³ The mean of Ln(Block Group Median Household Income) = 10.94; Exp(10.94) = 56,387.34.
Thus, 56.95 = 56.38 + (0.1 x 56.38)

¹⁴ The mean of Ln(Vehicle Group Median Household Income) = 11.01; Exp(11.01) = 61,080.65.
So, 61.08 = 60.48 + (0.1 x 60.48)

¹⁵ Coefficient of Ln(block group median income) = -0.2318; Odds ratio = Exp(-0.261) = 0.77

¹⁶ Percent change in odds ratio = (Exp(-0.261)-1) x 100 = 22.97

neighborhood are more likely to have similar level of income than those happening to own the vehicles of similar characteristics. In particular, the formation of vehicle group based on make, model year, type, and cylinder is a very crude proxy for the vehicle condition. These four characteristics cannot capture the underlying unobserved quality of a vehicle and hence may not be correlated very well with the owner's income. For instance, it is possible that the two households of high and low income can own vehicles of the same make, model year, type and cylinder because the low-income household simply owns the rebuild one. Second, the block group income data are better measured than the vehicle group data both in terms of the level (greater numbers of intervals) and coverage (larger number of groups). In short, the block group income has larger variation (higher standard deviation) than the vehicle group income. Moreover, the household income data from the CENSUS 2000 are obtained from the considerably larger sample than those of the AHTS 2001.

Nevertheless, the key point here is the reliability of the estimates from the group income. Kahn (1996a) uses the ZIP code median income to estimates its effect on the probability of a vehicle passing the emission test¹⁷. He reports that "increasing income from \$50,000 to \$100,000 increases [the] probability of passing by over 15 percentage points" and concludes that the I/M program is "regressive." This study finds that the same amount of income change increase the probability of a vehicle passing the first inspection by only 4.53 percentage points, using the model (3) from Table 2.8 (B) and holding other variables constant at their means. Moreover, using the same specification and probit model as Kahn (1996a), this study finds that the probability decreases by

¹⁷ In fact, Kahn (1996) does not use the real test results from the inspection stations. Instead, he uses the voluntary roadside emission test data. Normally, a driver has a choice of whether to participate in the test or not. As a result, failing the roadside emission test is not equivalent to failing the inspection at the station because it does not incur required cost of a vehicle repair.

7.59¹⁸ percentage points. The change in the probability is smaller when controlling for other vehicle and demographic characteristics, indicating the weaker effect of group income. Using the less detail information about income (417 ZIP-mean household incomes), Kahn (1996a) finds the larger effect of income. On the contrary, this study use more detailed information of income (4,157 block-group-median household incomes) but find the smaller effects.

To summarize findings from this section, first, the unconditional effect of income is significantly negative, meaning that vehicles owned by low-income households or registered in the low-income neighborhoods are more likely to fail the first inspection. Second, when controlling for the vehicle and owner characteristics, the individual income is not associated with the chance of a vehicle failing the first inspection, suggesting no differences in the maintenance or pre-inspection repair across income groups. Third, using the aggregate income to replace the individual income gives rise to the bias in the estimates due to ecological fallacy.

2.7.4 Effects of Group Income: Homogeneous VS Heterogeneous

To provide another evidence of the bias due to ecological fallacy, this study estimates the logistic models taking into account the heterogeneity of the groups. Table 2.9 and 2.10 show the results from the full and subsamples of aggregate-income sample. Because the effect of group income may be biased due to the aggregation of

¹⁸ This result is based on the same probit specification of Kahn (1996a) where only vintage, mileage, engine type, and driver's income are included, as shown in Table 2.1 A in the Appendices. The predicted probability is calculated based on the two particular values of income and the mean value of the other variables. That is the probability of a vehicle passing the first inspection drops by 7.59 percentage points when the household income increases from US\$ 50 to US\$ 100,000.

the heterogeneous individual income, this study explicitly controls for the within-group heterogeneity by two methods.

The first method is to include the measure of income variation (MIV) directly into the model as shown in Table 2.9. Models (1) to (4) results from the estimation using the group income from the CENSUS 2000. The effects of block group income are stronger when controlling for the within-block income variation. This is the symptom of collinearity between the block group income and MIV. For example, the correlation between Gini coefficient and the block group income is significantly high at -0.6981 . The block group with high median household income tends to have low value of Gini coefficient. In other words, a block group with high median household income is quite homogeneous, suggesting a pattern of sorting. Accordingly, the high Gini coefficient is associated with the low odds of a vehicle failing the first inspection.

Models (5) to (8) show the results from the estimation using the group income from the AHTS 2001. Unlike models (1) to (4), models (5) to (8) are not affected by the collinearity issue, as seen from the unchanged effect of the vehicle group income. With the same MIV, the correlation between Gini and the vehicle group income is only -0.0613 . The impact of MIVs on the odds of a vehicle is increasing, indicating that a vehicle registered in a block of high income variation tends to fail more than an identical one registered in the low income variation area.

In short, despite the opposite sign of MIVs in the two sets of models ((1) to (4) and (5) to (8)) and the multicollinearity issue, the results are consistent in showing that the group income are related to the odds of a vehicle failing the first inspection. However, the issue of collinearity in models (1) to (4) and the unchanged effect of group income in models (5) to (8) suggest that the direct inclusion of MIV in the models might not be the proper method to control for within-group variation of income. Finding the effect of the group income in Table 2.9 is questionable.

Table 2.9 Logistic models of the odds of a vehicle failing the first inspection estimated from the aggregate-income sample controlling for income variation in a block group

| Independent Variables | Group Income from CENSUS 2000 | | | | Group Income from AHTS 2001 | | | |
|---|-------------------------------|----------------------|----------------------|----------------------|-----------------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| <u>Household income for a group (\$US)</u> | | | | | | | | |
| Ln of block group median income | -0.232 (13.85)*** | -0.309 (13.26)*** | -0.258 (14.12)*** | -0.267 (13.47)*** | | | | |
| Ln of vehicle group median income | | | | | -0.147 (7.77)*** | -0.145 (7.67)*** | -0.147 (7.76)*** | -0.146 (7.72)*** |
| <u>Demographic characteristics in a block group</u> | | | | | | | | |
| Percent black population | 0.338 (16.58)*** | 0.327 (15.95)*** | 0.333 (16.29)*** | 0.334 (16.34)*** | 0.456 (25.08)*** | 0.427 (22.83)*** | 0.451 (24.65)*** | 0.439 (23.75)*** |
| Percent other ethnic population | -0.361 (3.67)*** | -0.380 (3.85)*** | -0.381 (3.86)*** | -0.380 (3.85)*** | -0.395 (3.97)*** | -0.364 (3.66)*** | -0.380 (3.81)*** | -0.364 (3.66)*** |
| Percent Latino population | 0.401 (4.67)*** | 0.429 (4.98)*** | 0.426 (4.94)*** | 0.424 (4.91)*** | 0.609 (7.14)*** | 0.510 (5.91)*** | 0.578 (6.71)*** | 0.541 (6.28)*** |
| Percent male population | 0.165 (1.16) | 0.148 (1.04) | 0.160 (1.13) | 0.162 (1.14) | -0.108 (0.74) | -0.004 (0.03) | -0.086 (0.59) | -0.054 (0.37) |
| Median age of population (year) | -0.004 (2.68)*** | -0.002 (1.16) | -0.002 (1.59) | -0.002 (1.67)* | -0.009 (7.21)*** | -0.009 (7.23)*** | -0.010 (7.48)*** | -0.010 (7.57)*** |
| <u>Vehicle characteristics</u> | | | | | | | | |
| Age (year) | 0.216 (131.76)*** | 0.216 (131.74)*** | 0.216 (131.73)*** | 0.216 (131.74)*** | 0.214 (127.25)*** | 0.214 (127.12)*** | 0.214 (127.24)*** | 0.214 (127.21)*** |
| Ln of mileage | 0.049 (26.45)*** | 0.049 (26.36)*** | 0.049 (26.38)*** | 0.049 (26.39)*** | 0.050 (26.92)*** | 0.050 (26.86)*** | 0.050 (26.92)*** | 0.050 (26.91)*** |
| Displacement (liter) | -0.018 (3.41)*** | -0.017 (3.35)*** | -0.017 (3.35)*** | -0.017 (3.35)*** | -0.018 (3.44)*** | -0.018 (3.45)*** | -0.018 (3.47)*** | -0.018 (3.48)*** |
| Location of production: European | 0.021 (0.92) | 0.027 (1.21) | 0.026 (1.17) | 0.026 (1.14) | 0.041 (1.77)* | 0.044 (1.88)* | 0.040 (1.71)* | 0.040 (1.73)* |
| Location of production: Asian | -0.005 (0.35) | -0.003 (0.24) | -0.004 (0.26) | -0.004 (0.27) | -0.005 (0.34) | -0.003 (0.21) | -0.005 (0.34) | -0.004 (0.30) |
| Location of production: Other | 0.068 (4.05)*** | 0.068 (4.04)*** | 0.068 (4.04)*** | 0.068 (4.04)*** | 0.067 (3.98)*** | 0.067 (3.94)*** | 0.067 (3.97)*** | 0.067 (3.96)*** |
| Fuel Induction: EFI | -0.025 (1.43) | -0.025 (1.45) | -0.025 (1.45) | -0.025 (1.45) | -0.031 (1.79)* | -0.030 (1.76)* | -0.031 (1.77)* | -0.030 (1.76)* |
| Fuel induction: FI | 0.008 (0.55) | 0.008 (0.54) | 0.008 (0.54) | 0.008 (0.54) | 0.005 (0.33) | 0.006 (0.37) | 0.005 (0.34) | 0.005 (0.36) |
| Fuel induction: MFI | -0.018 (1.12) | -0.019 (1.14) | -0.019 (1.14) | -0.019 (1.14) | -0.024 (1.47) | -0.024 (1.43) | -0.024 (1.45) | -0.024 (1.43) |
| Exhaust gas recirculation (EGR) | -0.071 (5.56)*** | -0.072 (5.57)*** | -0.072 (5.57)*** | -0.072 (5.57)*** | -0.070 (5.40)*** | -0.068 (5.31)*** | -0.069 (5.38)*** | -0.069 (5.35)*** |
| Thermostatic air cleaner (TAC) | 0.135 (7.56)*** | 0.135 (7.53)*** | 0.135 (7.54)*** | 0.135 (7.54)*** | 0.132 (7.42)*** | 0.132 (7.38)*** | 0.132 (7.42)*** | 0.132 (7.41)*** |
| Type: Car | 0.112 (6.24)*** | 0.115 (6.39)*** | 0.115 (6.35)*** | 0.114 (6.34)*** | 0.092 (5.09)*** | 0.091 (5.03)*** | 0.091 (5.03)*** | 0.091 (5.01)*** |
| Type: Van | 0.138 (6.25)*** | 0.140 (6.37)*** | 0.140 (6.34)*** | 0.140 (6.33)*** | 0.128 (5.80)*** | 0.129 (5.85)*** | 0.127 (5.78)*** | 0.128 (5.80)*** |
| <u>Measure of income variation in a block group</u> | | | | | | | | |
| Gini index | | -0.594 (4.71)*** | | | | 0.580 (6.36)*** | | |
| Standard deviation | | | -0.157 (3.56)*** | | | | 0.096 (2.37)** | |
| Coefficient of variation | | | | -1.522 (3.27)*** | | | | 1.841 (4.65)*** |
| Constant | -2.412 (12.82)*** | -1.424 (5.07)*** | -2.045 (9.52)*** | -1.962 (8.43)*** | -3.014 (13.00)*** | -3.271 (13.92)*** | -3.085 (13.20)*** | -3.161 (13.53)*** |
| Observations | 685714 | 685714 | 685714 | 685714 | 685714 | 685714 | 685714 | 685714 |
| Log Pseudolikelihood | -151079.90 | -151068.94 | -151073.58 | -151074.58 | -151144.99 | -151124.45 | -151142.17 | -151134.07 |
| Wald Chi2 | 40364.46 | 40361.53 | 40358.06 | 40357.30 | 40403.72 | 40418.89 | 40408.98 | 40417.33 |
| DoF | 19.00 | 20.00 | 20.00 | 20.00 | 19.00 | 20.00 | 20.00 | 20.00 |
| Pseudo R2 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 |

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2.10 Logistic model of the odds of a vehicle failing the first inspection estimated from six different subsamples drawn from the aggregate-income sample

(A) Restricted

| Independent Variables | Bottom 2 % | | | Top 2 % | | |
|---------------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|----------------------|
| | (1) Gini | (2) SD | (3) CV | (4) Gini | (5) SD | (6) CV |
| <u>Household income (\$US)</u> | | | | | | |
| Ln of block group median income | -0.462 (7.20)*** | -0.381 (5.01)*** | -0.385 (5.15)*** | -0.524 (8.09)*** | -0.591 (8.79)*** | -0.628 (11.02)*** |
| Constant | 2.377 (3.23)*** | 1.547 (1.82)* | 1.550 (1.85)* | 2.988 (4.64)*** | 3.616 (5.03)*** | 4.001 (6.85)*** |
| Observations | 13907 | 13975 | 14120 | 13721 | 14016 | 13716 |
| Log Pseudo likelihood | -2779.77 | -3263.82 | -3151.59 | -4330.24 | -3166.10 | -3690.38 |
| Wald Chi2 | 51.83 | 25.07 | 26.47 | 65.38 | 77.28 | 121.50 |
| DoF | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Pseudo R2 | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 | 0.02 |

The second method is to separate the sample based on the degree of income variation as measured by three MIVs as shown in Table 2.10. Because all the MIVs are derived from the block group income, there is only a block group median household income in Tables 2.10 (A) and (B). Similar to the previous results, the unconditional income effects across models in Table 2.10 (A) indicates that the odds of a vehicle owned by the low-income household are higher than those of the high-income one.

In Table 2.10 (B), the unrestricted models (1) to (3) show the estimates from the sample of the lowest 2 percentile of the data sorting according to the MIVs. Likewise, models (4) to (6) present the results from the sample taken from the 98 percentile or higher of the data when ordering based on MIVs. In models (1) to (3), all vehicles are from the block group of homogeneous income, minimizing the within-group heterogeneity. In the homogeneous group, the block group income is close to the individual income. As a result, the effect of the group income is also close to the effect of the individual income. In models (1) to (3), the group income is not related to the odds of a vehicle failing the first inspection. In contrast, in models (4) to (6), all vehicles are from the block group of heterogeneous income. Block group income is not a good representative of the individual income, analogous to the measurement with a large

Table 2.10 Logistic model of the odds of a vehicle failing the first inspection estimated from six different subsamples drawn from the aggregate-income sample

(B) Unrestricted

| Independent Variables | Bottom 2 % | | | Top 2 % | | |
|---|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | (1) Gini | (2) SD | (3) CV | (4) Gini | (5) SD | (6) CV |
| <u>Household income (\$US)</u> | | | | | | |
| Ln of block group median income | -0.093 (0.65) | -0.144 (1.02) | -0.157 (1.17) | -0.302 (2.88)*** | -0.239 (2.28)** | -0.308 (3.23)*** |
| <u>Demographic characteristics in the block group</u> | | | | | | |
| Median age of population (year) | 0.003 (0.22) | -0.006 (0.46) | 0.001 (0.04) | -0.007 (1.37) | -0.014 (2.18)** | -0.001 (0.17) |
| Percent black population | 0.663 (3.53)*** | 0.260 (2.02)** | 0.315 (2.18)** | 0.099 (0.71) | 0.414 (2.42)** | 0.384 (2.63)*** |
| Percent other ethnic population | -0.142 (0.15) | -0.698 (0.73) | -0.744 (0.80) | -0.361 (0.46) | -1.168 (1.15) | 0.207 (0.27) |
| Percent Latino population | 1.715 (1.78)* | 2.411 (1.42) | 2.896 (1.74)* | 0.687 (1.19) | 1.621 (1.63) | 0.676 (1.16) |
| Percent male population | -0.071 (0.09) | -0.274 (0.37) | -0.051 (0.07) | 0.834 (1.48) | 0.470 (0.93) | 0.344 (0.71) |
| <u>Vehicle characteristics</u> | | | | | | |
| Age (year) | 0.228 (17.22)*** | 0.238 (19.66)*** | 0.243 (19.62)*** | 0.219 (21.66)*** | 0.222 (18.82)*** | 0.214 (19.61)*** |
| Ln of mileage | 0.040 (2.74)*** | 0.036 (2.80)*** | 0.025 (1.94)* | 0.068 (6.15)*** | 0.056 (4.24)*** | 0.070 (5.66)*** |
| Displacement (liter) | 0.076 (1.87)* | 0.002 (0.04) | 0.009 (0.24) | -0.007 (0.22) | 0.017 (0.44) | 0.010 (0.30) |
| Location of production: European | 0.046 (0.30) | 0.017 (0.10) | 0.002 (0.01) | -0.201 (1.32) | 0.031 (0.24) | 0.125 (0.93) |
| Location of production: Asian | 0.089 (0.83) | -0.059 (0.60) | -0.034 (0.34) | -0.022 (0.25) | -0.029 (0.30) | -0.016 (0.18) |
| Location of production: Other | 0.247 (1.87)* | 0.250 (2.16)** | 0.266 (2.23)** | -0.156 (1.48) | 0.061 (0.47) | -0.026 (0.22) |
| Fuel Induction: EFI | 0.046 (0.33) | 0.144 (1.12) | 0.166 (1.25) | -0.072 (0.65) | -0.201 (1.47) | -0.182 (1.45) |
| Fuel induction: FI | 0.016 (0.12) | 0.179 (1.58) | 0.198 (1.67)* | -0.107 (1.12) | -0.183 (1.65)* | -0.103 (0.98) |
| Fuel induction: MFI | 0.102 (0.77) | 0.246 (2.02)** | 0.249 (1.96)** | 0.057 (0.55) | -0.040 (0.34) | 0.048 (0.43) |
| Exhaust gas recirculation (EGR) | -0.098 (0.98) | 0.009 (0.09) | -0.027 (0.28) | -0.004 (0.05) | 0.002 (0.02) | -0.001 (0.02) |
| Thermostatic air cleaner (TAC) | -0.145 (0.94) | 0.035 (0.26) | -0.087 (0.62) | 0.186 (1.70)* | 0.101 (0.77) | 0.175 (1.47) |
| Type: Car | 0.076 (0.50) | 0.129 (0.98) | -0.014 (0.11) | 0.090 (0.77) | 0.275 (1.72)* | 0.045 (0.34) |
| Type: Van | 0.168 (0.96) | 0.267 (1.69)* | 0.082 (0.51) | -0.173 (1.07) | 0.141 (0.73) | -0.142 (0.81) |
| Constant | -4.575 (2.87)*** | -3.466 (2.30)** | -3.545 (2.40)** | -2.075 (2.03)** | -2.533 (2.26)** | -2.235 (2.30)** |
| Observations | 13907 | 13975 | 14120 | 13721 | 14016 | 13716 |
| Log Pseudo likelihood | -2501.55 | -2904.59 | -2807.19 | -3818.00 | -2814.80 | -3268.47 |
| Wald Chi2 | 711.46 | 844.94 | 814.08 | 1122.53 | 825.42 | 997.33 |
| DoF | 19.00 | 19.00 | 19.00 | 19.00 | 19.00 | 19.00 |
| Pseudo R2 | 0.11 | 0.11 | 0.11 | 0.12 | 0.12 | 0.13 |

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

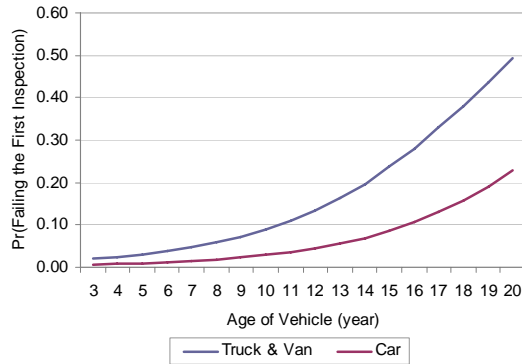
error. The large effects of the group income are likely due to the aggregation bias or the ecological fallacy.

To summarize, the overall findings show the very weak or no effect of the household income on the odds or the probability of a vehicle failing the emission. The effect of income based on the group level information has different meaning than the individual level information. When using the former to replace with the latter, the previous study shows the significant effect of income on the probability of passing (or failing) the inspection. Despite the similar but weaker results when using the group level income information, this study finds the counter evidence of such effects from the other estimates obtained from the different methods.

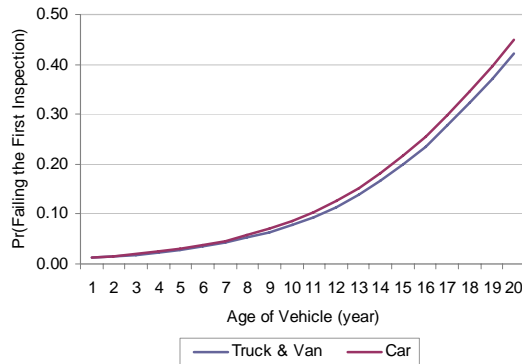
2.7.5 Effects of Vehicle Characteristics

Overall, vehicle characteristics are the key determinants of passing the first inspection in the annual test cycle. The overall results are consistent across all models in Tables 2.7 (B), 2.8 (B), 2.9, and 2.10. The detail discussion of the results in this section is mainly based on the models in Table 2.7 (B). *Vehicle age* and *EGR* are significant predictors of a vehicle failing the first inspection across models.

In both samples, the effects of *age* are very similar. From the models (2) and (4), the odds of a 8 year-old vehicle failing the first inspection are 1.25 and 1.24 times as high as those of a comparable 7 year-old vehicle (average age of vehicles in the sample) in the individual and aggregate income samples, holding the other variables constant. Putting differently, for every additional year of vehicle age, the odds of a vehicle failing the first inspection increase by 25.75 and 24.15 percent in the individual and aggregate samples respectively. Although the effects of vehicle age on the log odds (and odds) of a vehicle failing the first inspection are constant, their effects on the probability are not. Figure 2.2 illustrates this point.



(A) Individual income sample



(B) Aggregate income sample

Figure 2.2 Vehicle age and predicted probability of a vehicle failing the first inspection classified by type of the vehicle

The predicted probability of vehicle failing the first inspection increases up to almost 50 percent as they become older, depending on the vehicle type. In panel (A) of Figure 2.2, a car in the individual income sample has around 20 percent chance of failing the first inspection at the age of 20, holding other variables constant at their mean. In the aggregate income sample, the probabilities of failing the first inspection among truck, van and car are roughly the same. This seems to suggest the evident differences in the composition of vehicle types and usage between those from the individual and aggregate income samples. Confirmed by the descriptive statistics of the individual income sample, trucks and vans are used intensively and tend to have higher mileage, resulting in a greater deal of deterioration and hence higher probability of failing the first

inspection. The deviation of the results between the individual and aggregate income samples may be due to the bias of the individual income sample.

Different from the vehicle age, *EGR* seems to have stronger effect in the small sample. The odds that a vehicle equipped with *EGR* will fail the first inspection are 0.72 and 0.07 as high as the odds that a similar vehicle without *EGR* owned by a comparable motorist, in the individual and aggregate income samples respectively.

Only in the aggregate-income sample, are *mileage*, *engine displacement*, *production location outside the US but not in Europe and Asia*, *TAC*, *car* and *van* significant. Similar to age in the sign but not the size, the odds for a vehicle with 8,955¹⁹ miles failing the first inspection is 1.05 as high as the odds of the comparable vehicle with 8,866²⁰ mile owned by the similar owner. In other words, as the mileage rises by one percent, the odds of a vehicle failing the first inspection drop by 5.13 percent.

As the size of the engine displacement increases by one liter, the odds of failing the first inspection drops by 2 percent holding the other variables constant. For a comparable vehicle, the odds of the vehicle equipped with *TAC* failing the first inspection are 1.15 times as high as the odds of that without *TAC*. Likewise, the odds of a car and a van failing the first inspection are 1.11 and 1.14 as high as a truck, holding other variables constant.

¹⁹ $8,955 = 8,866 + (0.01 \times 8,866)$

²⁰ Mean of $\text{Ln}(\text{Mileage}) = 9.09$; $\text{Exp}(9.09) = 8,866$

2.7.6 Effects of Demographic Characteristics

The meaning of the demographic characteristics related to each vehicle in the individual and aggregate income samples are distinctly different. In the individual income sample, the demographic characteristics directly connect to the owner of each vehicle. In contrast, in the aggregate income sample, the demographic characteristics refer to the features of the neighborhood, specifically the block group. The block group is a collection of households located in the same area demarcated by the Census Bureau.

2.7.6.1 Effects on the Odds of a Vehicle Failing the First Inspection

In the individual-income sample (Tables 2.7 (B) and 2.8 (B)), the odds that a vehicle owned by a *black* person will fail the first inspection are 2.27 as high as the odds that a comparable vehicle owned by a *white* person of the same level of income will fail. This number appears to be high but in the sample a vehicle owned by black has already been 3 times more likely to fail the first inspection than the similar vehicle owned by white²¹. For *the vehicle owners falling in the other ethnic group (Asian, Hispanic, other)*, the odds of their vehicles failing the first inspection are not significantly different from the odds of vehicles that are owned by white, in the individual income sample.

There are so many possible reasons for this pattern that requires further study. Because the test results depend partly on the inspectors' discretion²², the inspection

²¹ In the sample of 465 vehicles, of all the vehicles owned by black, $9 \left(= \frac{11}{119} \right)$ percent fail the first inspection. For white, only $3 \left(= \frac{9}{270} \right)$ percent of their total vehicles that fail the first inspection. Therefore, a vehicle owned by a black motorist is already 3 times more likely to fail the first inspection than that owned by a comparable white in the sample.

²² In 2000 – 2001, the vehicle inspection includes the tailpipe emission test and the visual checking. The tailpipe emission can be varied depending on the skill and behavior of the inspectors. For instance, because the vehicles in the cold start condition are more likely to fail the

stations might be attributed to the different odds of a vehicle failing the first inspection among different ethnicities. One possible reason may be that the inspection stations exhibit some sort of ethnic preference. Another reason may be that the inspection station utilize different strategies according to the income level of the customers. Although the level of income is difficult to observe, the correlation between income and ethnicity exists. The inspection stations may use the characteristics of the vehicle owners, especially ethnicity, to proxy for income and treat them accordingly.

Table 2.11 shows the results of the models controlling for other characteristics of vehicle owners such as age, gender and level of education. Including more information about the characteristics of vehicle owner slightly weaken the effect of income and some other characteristics of vehicle. For ethnicity, despite its insignificance at the level of 0.05 percent, the effects size of the ethnicity (black and other) increases. This seems to suggest that the odds of a vehicle failing the first inspection might be related to the strategic interaction at the inspection station level. Due to the limited sample size (465 vehicles), the study cannot incorporate the inspection station effects in to the analysis of the individual-income sample.

Similarly, in the aggregate-income sample, the odds of a vehicle registered in the block group where *26 percent of the residents are black*²³ are 1.56 as high as the odds of the same vehicle registered in the block group where 25 percent of the residents are black, holding the other variables constant. In other words, as the percent black population in the block group, where a vehicle is registered, increases by one, the odds of the vehicle failing the first inspection increase by 55.52 percent. In contrast to the

emission test, the inspectors can influence the test results by putting different level of their effort on the preparation of vehicles.

²³ The reference group is the share of the white population.

Table 2.11 Logistic model of the odds of a vehicle failing the first inspection estimated from the individual–income sample

| Independent Variables | Simple Bootstrap Logistic | | | | Stratified Bootstrap Logistic | | | |
|----------------------------------|---------------------------|-------|---------|-------|-------------------------------|-------|---------|-------|
| | (1) | | (2) | | (3) | | (4) | |
| | Coef. | z | Coef. | z | Coef. | z | Coef. | z |
| <u>Household income (\$US)</u> | | | | | | | | |
| Observed ln of individual income | -0.2627 | -0.50 | -0.2819 | -0.58 | -0.2627 | -0.50 | -0.2819 | -0.57 |
| <u>Owner characteristics</u> | | | | | | | | |
| Age (year) | 0.0051 | 0.20 | | | 0.0051 | 0.20 | | |
| Black | 1.1990 | 1.86 | 1.1849 | 1.94 | 1.1990 | 1.89 | 1.1849 | 1.97 |
| Other | 0.5116 | 0.65 | 0.5112 | 0.69 | 0.5116 | 0.65 | 0.5112 | 0.68 |
| Male | -0.0685 | -0.12 | | | -0.0685 | -0.12 | | |
| Some or graduated high school | 0.0918 | 0.15 | | | 0.0918 | 0.15 | | |
| <u>Vehicle characteristics</u> | | | | | | | | |
| Age (year) | 0.2273 | 2.25 | 0.2291 | 2.49 | 0.2273 | 2.43 | 0.2291 | 2.59 |
| Ln of mileage (mile) | 0.2689 | 0.45 | 0.2668 | 0.48 | 0.2689 | 0.47 | 0.2668 | 0.49 |
| Displacement (liter) | 0.3297 | 0.32 | -0.0445 | -0.11 | 0.3297 | 0.31 | -0.0445 | -0.11 |
| Location of production: European | 0.1204 | 0.15 | 0.3442 | 0.36 | 0.1204 | 0.15 | 0.3442 | 0.35 |
| Location of production: Asian | 0.1445 | 0.20 | 0.1142 | 0.15 | 0.1445 | 0.20 | 0.1142 | 0.15 |
| Location of production: Other | -0.0534 | -0.13 | 0.1774 | 0.25 | -0.0534 | -0.13 | 0.1774 | 0.24 |
| Fuel Induction: EFI | 0.3787 | 0.46 | 0.3927 | 0.50 | 0.3787 | 0.45 | 0.3927 | 0.49 |
| Fuel induction: FI | -0.5638 | -0.56 | -0.5801 | -0.69 | -0.5638 | -0.57 | -0.5801 | -0.65 |
| Fuel induction: MFI | -1.6595 | -2.19 | -1.6676 | -2.28 | -1.6595 | -2.23 | -1.6676 | -2.31 |
| Exhaust gas recirculation (EGR) | -1.2839 | -1.95 | -1.3073 | -2.19 | -1.2839 | -1.94 | -1.3073 | -2.15 |
| Thermostatic air cleaner (TAC) | -0.1729 | -0.16 | -0.1766 | -0.18 | -0.1729 | -0.16 | -0.1766 | -0.18 |
| Type: Car | -1.1720 | -0.74 | -1.1891 | -0.80 | -1.1720 | -0.68 | -1.1891 | -0.72 |
| Type: Van | -1.1300 | -0.68 | -1.1204 | -0.71 | -1.1300 | -0.64 | -1.1204 | -0.65 |
| Constant | -3.5949 | -0.35 | -3.1805 | -0.35 | -3.5949 | -0.37 | -3.1805 | -0.35 |
| Pseudo R2 | 0.24 | | 0.2407 | | 0.24 | | 0.2407 | |
| Wald Chi2 | - | | 44.37 | | - | | 44.37 | |
| Repetitions | 4899 | | 4899 | | 5070 | | 5070 | |
| Observations | 465 | | 465 | | 465 | | 465 | |

results from the individual-income sample, in the aggregate income sample, the odds that a vehicle registered in the block group where 9 percent of the population are the other ethnic group (Asian, native American, other) are 0.67 as high as the odds of the comparable vehicle registered in the block group where 8 percent of the population are the other ethnic group, all else equal. Similar to the share of black population, the odds of a vehicle registered in the block group where 7 percent of the population are Latino are 1.82 as high as the odds of the same vehicle registered in the block group where 6 percent of the population are Latino, holding the other variables constant. Although the median age of the population in a block group of a registered vehicle is related to the odds of the vehicle failing the first inspection, it decreases the odds merely by 0.82 percent.

2.7.6.2 Effects on the Probability of a Vehicle Failing the First Inspection

In the individual income sample, the predicted probability²⁴ of failing the first inspection and the *vehicle age* vary noticeably among different ethnic groups of vehicle owners. In Figure 2.3, a truck or a van owned by a black has the highest probability of failing the first inspection, especially when the vehicle is old. Similarly, in Figure 2.4, a truck or van owned by a low-income black has the highest probability of failing the first inspection. Even though the graph shows the varying effects of income from the low- to the high-income ranges, the *estimates of income effect* are not statistically different from zero on average. In contrast, the *ethnic group effects* are statistically different, as discussed earlier. Owing to the small number of observations particularly the share of a vehicle failing the first inspection affecting the degree of freedom, the study cannot include the interaction effects between the income and ethnic groups directly. Figure 2.4, however, indirectly depicts the plausibly different effects of income among ethnic groups.

²⁴ For all the predicted probabilities calculated in this section as shown in all figures, they are based on the US made car without EGR and TAC but equipped with MFI induction with the mean value of the other variables. For the individual-income sample, the probability is computed from model (1) in Table 2.8 (B); For the aggregate-income sample, the probability is calculated from model (3) in Table 2.8 (B).

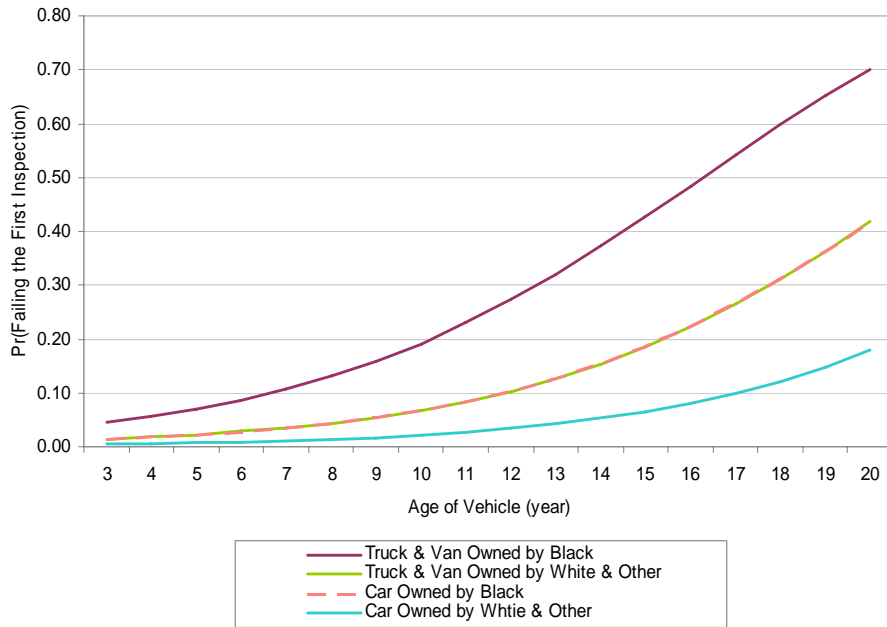


Figure 2.3 Vehicle age and predicted probability of vehicle failing the first inspection, estimated from the individual income sample

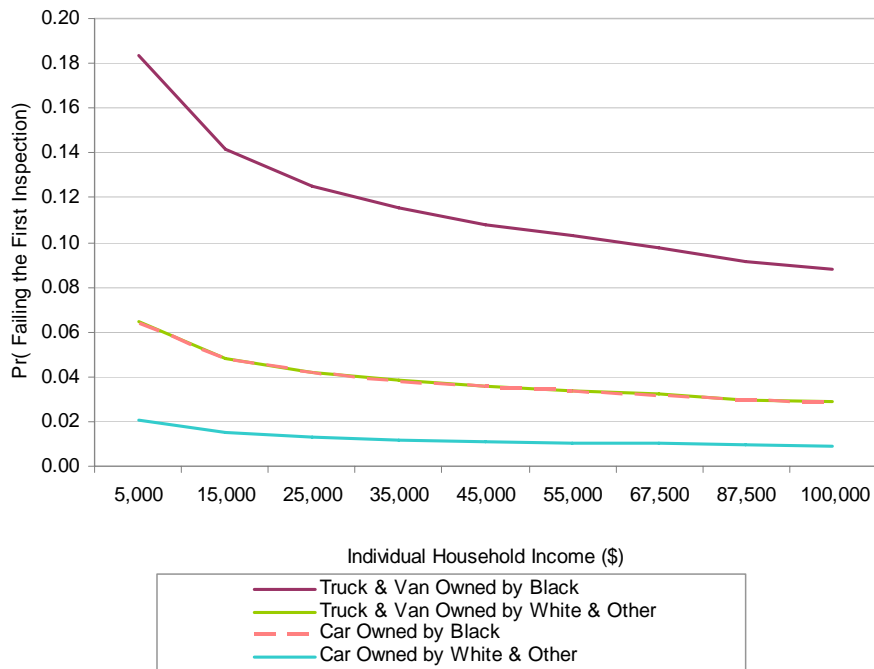
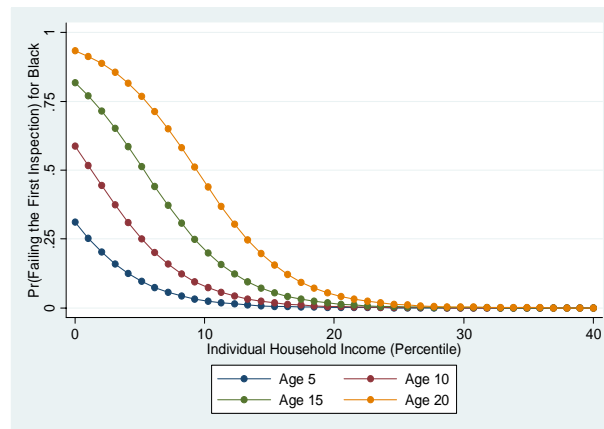
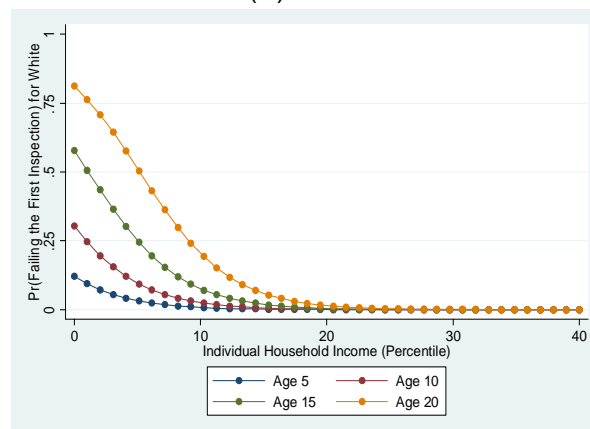


Figure 2.4 Individual household income and the predicted probability of a vehicle failing the first inspection, estimated from the individual income sample (income effects are insignificant)

As vehicle age is the key factor determining the probability of a vehicle failing the first inspection, Figure 2.5 exhibits the diverse predicted probability, depending on the vehicle age, household income (in percentile), and ethnic groups. The panels (A) and (B) in Figure 2.5 are similar in that the old vehicle has the higher probability of failing the first inspection. Overall, the probability of failing the first inspection is strikingly high in the low-income group. When comparing between black and white owners, the probability of failing the first inspection for white is lower across vehicle age groups.



(A) Black



(B) White

Figure 2.5 Individual household income and predicted probability of a vehicle failing the first inspection, estimated from the individual-income sample (income effects are insignificant)

In the aggregate income sample, for a US made car with no EGR and TAC but equipped with MFI, its predicted probability of failing the first inspection is very high when the vehicle is registered in the block group with the high *share of black population*. As previously discussed, a car owned by a black individual might be in the poor condition already. If people tend to sort themselves by choosing to live in different neighborhoods, then Figure 2.5 is expected. In addition, because the testing results depend on the inspection stations, another explanation of Figure 2.5 is that stations located in the neighborhood with a low share of black population may provide the other care services prior to the inspection. This unobserved extra services may help reducing the probability of failing the first inspection. Certainly, the extra services come with the extra cost that might not be affordable by the low-income black neighborhood.

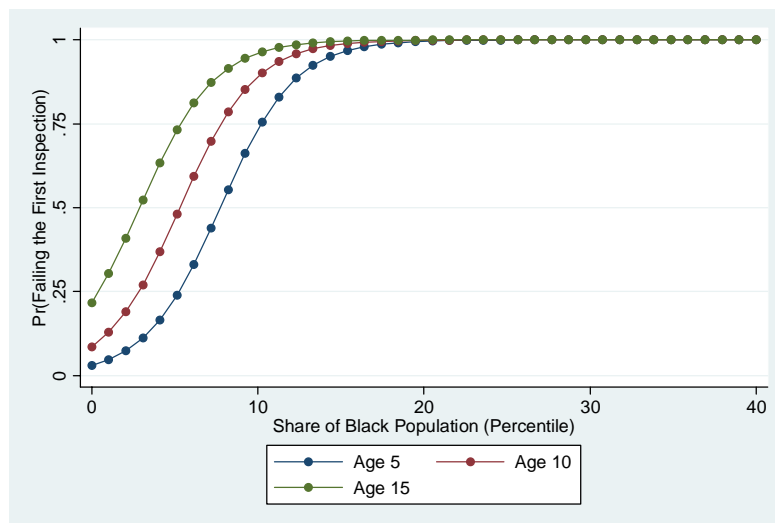


Figure 2.6 Share of black population in the block group and predicted probability of a vehicle failing the first inspection, classified by vehicle age, estimated from the aggregate income sample

To examine the effect of ethnicity that might be related to the strategies used by the inspection stations, this study further analyzes the data using the linear probability models with the station fixed effects. Table 2.12 compares the models with and without the station fixed effects. Model (1) in Table 2.12 shows the marginal effects of the logistic model so that the effects can be comparable with the results from the linear probability models (2) to (4).

Without the station fixed effects, both the logistic and the linear probability models show the similar results. As the share of the black population in a block group increases by one percent, the probability of a vehicle, registered in that block group, increases by 0.016 ($t = 16.59$) and 0.022 ($t=16.09$) percent for model (1) and (2) respectively, holding other variables constant (at their means only for the logistic model). However, when the models (3) and (4) include the station fixed effects, the effect of the percent black population decreases considerably to 0.005 ($t = 2.84$) percent. This seems to suggest that certain types of inspection stations might sort into particular neighborhoods. In turn, some features of neighborhoods may correlate to the share of black population. Future investigation regarding the station characteristics and their testing performance is important for a better understanding the effect of ethnicity on the odds of a vehicle failing the first inspection.

Table 2.12 Marginal effects of the probability of a vehicle failing the first inspection, estimated from the aggregate-income sample

| Independent Variables | Models without Station Fixed Effects | | | | Models with Station Fixed Effects | | | |
|---|--------------------------------------|--------|------------------|--------|-----------------------------------|--------|------------------|--------|
| | (1) Logistic | | (2) Linear Prob. | | (3) Lin Prob. (dummy) | | (4) Linear Prob. | |
| | Mar. Effect | z | Coef. | t | Coef. | t | Coef. | t |
| <u>Household income (\$US)</u> | | | | | | | | |
| Ln of block group median income | -0.0107 | -13.87 | -0.0146 | -13.91 | -0.0147 | -12.66 | -0.0147 | -13.31 |
| <u>Owner characteristics in the block group</u> | | | | | | | | |
| Median age of population (year) | -0.0002 | -2.68 | -0.0002 | -2.83 | -0.0002 | -2.27 | -0.0002 | -2.31 |
| Percent black population | 0.0156 | 16.59 | 0.0219 | 16.09 | 0.0051 | 2.84 | 0.0051 | 3.06 |
| Percent other ethnic population | -0.0166 | -3.67 | -0.0241 | -3.98 | -0.0338 | -5.04 | -0.0338 | -5.31 |
| Percent Latino population | 0.0185 | 4.67 | 0.0230 | 3.97 | 0.0233 | 3.89 | 0.0233 | 4.23 |
| Percent male population | 0.0076 | 1.16 | 0.0134 | 1.45 | 0.0194 | 2.05 | 0.0194 | 2.14 |
| <u>Vehicle characteristics</u> | | | | | | | | |
| Age (year) | 0.0099 | 131.23 | 0.0157 | 117.48 | 0.0159 | 113.96 | 0.0159 | 140.87 |
| Ln of mileage (mile) | 0.0023 | 26.85 | 0.0011 | 11.91 | 0.0011 | 11.72 | 0.0011 | 11.27 |
| Displacement (liter) | 0.0010 | 0.92 | 0.0075 | 4.47 | 0.0095 | 5.57 | 0.0095 | 6.42 |
| Location of production: European | -0.0002 | -0.35 | 0.0011 | 1.32 | 0.0014 | 1.67 | 0.0014 | 1.70 |
| Location of production: Asian | 0.0032 | 3.95 | 0.0027 | 3.04 | 0.0028 | 3.15 | 0.0028 | 2.98 |
| Location of production: Other | -0.0008 | -3.41 | 0.0005 | 1.65 | 0.0005 | 1.69 | 0.0005 | 1.80 |
| Fuel Induction: EFI | -0.0011 | -1.44 | -0.0145 | -14.73 | -0.0143 | -14.51 | -0.0143 | -14.61 |
| Fuel induction: FI | 0.0004 | 0.55 | -0.0149 | -12.93 | -0.0146 | -12.73 | -0.0146 | -14.83 |
| Fuel induction: MFI | -0.0008 | -1.12 | -0.0085 | -11.83 | -0.0083 | -11.41 | -0.0083 | -9.85 |
| Exhaust gas recirculation (EGR) | -0.0033 | -5.45 | -0.0146 | -18.39 | -0.0147 | -18.45 | -0.0147 | -19.25 |
| Thermostatic air cleaner (TAC) | 0.0065 | 7.20 | 0.0241 | 14.24 | 0.0239 | 14.13 | 0.0239 | 18.81 |
| Type: Car | 0.0051 | 6.39 | 0.0085 | 7.84 | 0.0095 | 8.72 | 0.0095 | 9.09 |
| Type: Van | 0.0066 | 5.98 | 0.0058 | 5.05 | 0.0069 | 6.02 | 0.0069 | 5.80 |
| Constant | | | 0.1149 | 9.73 | 0.1163 | 7.78 | 0.1138 | 9.32 |
| R2 Within | - | | - | | - | | 0.0544 | |
| R2 Between | - | | - | | - | | 0.0626 | |
| R2 Overall | - | | - | | - | | 0.0544 | |
| R2 Pseudo R2 | 0.11 | | 0.06 | | 0.24 | | 0.24 | |
| F | - | | 1430.08 | | (.) | | 2074.24 | |
| Wald Chi2 | 40364.46 | | - | | - | | - | |
| Observations | 685714 | | 685714 | | 685714 | | 685714 | |

2.8 Conclusion

Generally, the vehicle inspection and maintenance (I/M) program imposes some costs on every vehicle owner but these costs might not be evenly distributed across the population. Low-income vehicle owners are likely to bear more burden than the other. A vehicle failing the inspection means an additional cost to the owner in terms of time and money. This study investigates whether higher income of a vehicle owner decreases the odds of the vehicle failing the first inspection. The overall findings show that vehicles owned by low-income households or registered in the low-income neighborhoods are more likely to fail the first inspection. However, given that the low and high-income households own the similar vehicles, their vehicles face the same chance of failing the

first inspection in the annual test cycle. The results suggest no difference in the level of maintenance or pre-inspection repair across income groups. This implies that the post-test repair costs are the main extra costs incurred to the vehicle owners, which are significantly associated with the low-income households.

For the comparable vehicles, the study shows the very weak or no effect of the individual household income on the odds of failing the first inspection. The effect of income based on the group level information has different meaning from that based on the individual level information. However, when using the former to substitute for the latter, the results can be biased in terms of the significance. With the micro level data, this study shows that the income effect based on the observed individual household income is not associated with the odds of a vehicle failing the first inspection, given the same vehicle. Moreover, the comparison of the estimates based on the homogeneous and heterogeneous income groups illustrates the apparent bias due to ecological fallacy. Therefore, this study concludes that for the comparable vehicles, the effect of income on the odds of failing the first inspection is either weak or non-existent. The results based on the group income information are highly questionable and should be considered with care. Table 2.13 compares the results from this study with Kahn (1996a) when using the group-level income to substitute for the individual-level income. Despite the data from different place and time, this study shows the smaller effect of income when using the same model with more detailed information.

Table 2.13 Comparison of the income effects on the probability of a vehicle *passing* the inspection

| Median Household Income | Probability of Passing the Inspection (% Point) | |
|-------------------------|---|----------------------------|
| | California ZIP (Kahn,1996a) | Georgia Block Group (2000) |
| ↑ from US\$ 50K to 100K | ↑ 15.00 | ↑ 7.59 |

Table 2.14 Summary of the income effects (raw coefficients of the logistic models) on the odds of a vehicle failing the first inspection

| Income Variables | Model Specification | | |
|------------------------------------|---------------------|--------------|--------------------|
| | Restricted | Unrestricted | |
| Observed income | | | |
| Individual income | -0.62* | -0.28 | Unbiased estimates |
| Group income | -1.31*** | -1.19*** | Ecological fallacy |
| Simulated income | | | |
| Individual from block group info | -0.12*** | -0.03*** | Very small effect |
| Individual from vehicle group info | -0.18*** | -0.02*** | Very small effect |
| Group level income | | | |
| Census block group | -0.57*** | -0.26*** | Ecological fallacy |
| Vehicle characteristics group | -0.98*** | -0.15*** | Ecological fallacy |
| Census block group income | | | |
| Heterogeneous group | -0.59*** | -0.30*** | Ecological fallacy |
| Homogeneous group | -0.38*** | -0.14 | Unbiased estimates |

To summarize the findings, Table 2.14 presents the estimates of the income effects from different samples and specifications. The unconditional effects of income (restricted specification) show the consistent results: the low-income households tend to bear a disproportionate cost of the I/M compliance, in terms of the post-inspection repair, because their vehicles are likely to fail the first inspection than those of the high-income households. On the other hand, the conditional effects of income (unrestricted specification) demonstrate no difference in the other part of the I/M compliance cost, in terms of the pre-inspection repair (or maintenance). The significant findings are biased due to the ecological fallacy when using the group level information. Nonetheless, the conclusions from this study are limited in few aspects.

First, the odds of failing the first inspection depend on the *vehicle condition*, which is not randomly distributed across households. The high-income households might replace their vehicles sooner due to *the I/M program*, resulting in the better vehicle

condition with the higher cost for them. In other words, the I/M program may have increased the total cost of vehicle ownership²⁵ for the high-income household disproportionately²⁶. If the burden of the I/M program depends on the level of income, then the analysis using the post-repair cost (as proxy by the odds of failing the first inspection) underestimates the costs that the high-income households are likely to encounter. As a consequence, the conclusion might be reversed.

Second, the study considers only the short-run context for the vehicle owners where the current condition of their vehicles is considered a fixed cost. Accordingly, the operating and repair costs are the major variable costs of the vehicle owners. With the I/M program in place, the vehicle owners pay the extra cost to comply with the program. Because the current condition (endowment effect) of vehicles mainly determine the odds of failing the first inspection, motorists who own the vehicles, which are in poor condition, are more likely to bear the burden of the I/M program. In this perspective, the compliance costs are not equally distributed by the design of the I/M program, if most of the low-income households tend to own the poor-condition vehicles.

Third, this research finds that the compliance costs of the I/M program are not equally distributed among ethnic groups, especially minority. However, with limited information, the study cannot provide a clear explanation for this phenomenon. Findings from the aggregate sample suggests that the high odds of failing the first inspection for vehicles registered in the minority neighborhood might be due to the characteristics and business strategies of the inspection stations in those areas.

²⁵ The total cost of ownership (TCO) typically embraces the cost of owning a vehicle from the purchase, through its maintenance, and finally its sale as a used car. TCO is a very important determinant of the feasibility of any capital investment.

²⁶ The price of 'cleanliness' vehicle for the high-income household is relatively higher than that of the lower-income household.

This study provides the evidence of the disproportionate cost to comply with the I/M program across household income levels. Because the low-income households are likely to bear a greater burden, policy makers may consider the redistributive policy in conjunction with the existing program. The supplementary programs may range from the repair subsidy to the vehicle scrapping with the target of the low-income households. However, any type of income transfer program should take into account the fungibility that might mitigate the effectiveness of the program.

The other evidence of the disproportionate compliance costs across ethnic groups is also important for further investigation. The preliminary conclusion from this study is that the certain types of inspection stations might sort into some kinds of neighborhoods, which lead to the inequitable pattern of vehicles failing the first inspection. The investigation at the inspection station level requires additional information that might be possible to obtain in the future.

CHAPTER 3

A MOTORIST'S CHOICE OF THE INSPECTION STATION

3.1 Introduction

One of the key components of the Atlanta I/M program is the inspection station. In 2001, inspection stations performed two types of emission tests depending on the type and model year of a vehicle. These tailpipe exhaust emission tests include the Accelerated Simulation Mode (ASM)²⁵ and the Two Speed Idle (TSI)²⁶. In addition to the emission test, vehicles are required to pass the visual and fuel cap inspections.

In principle and according to the regulation, every inspection station must conduct these tests objectively and accurately. If this is the case, heavy polluting vehicles will be kept off the roads²⁷ in the I/M area. Consequently, the on-road emission, the major source of air pollution in an urban area, will decrease. In practice, past studies (Sommerville et al., 1991; Glazer, Klein & Lave, 1995) and current on-road emission data continue to show that a number of vehicles passing the inspection still emit high levels of pollution while running on the road.

This undesirable evidence seems to indicate that the I/M program might not be as effective as it should be in terms of pollution reduction. Although the basic objective of the I/M program is to identify and effectively repair high emitting vehicles, its success relies upon proper incentives and motivation for motorists and inspectors. Understanding how motorists choose their inspection stations would be the important step towards

²⁵ The ASM test measures the tailpipe emission while a vehicle is driven on the dynamometer, a look-alike treadmill instrument. This type of test is quite close to actual driving conditions.

²⁶ The TSI test, on the other hand, measures the tailpipe emission, with the engine idling, at the two speeds: high at 2200-2800 rounds per minute (RPMs) and low at 350-1200 RPMs. The TSI is amore primitive procedure when compared to the ASM.

²⁷ Basically, there are several ways to keep these heavy polluting vehicles off the road. They may be effectively repaired, sold to other drivers living outside the I/M program, or scrapped.

program enhancement. The main contribution of this study is the application of the random utility maximization (RUM) theory to explain the motorists' choice of inspection stations. Findings from this study can directly benefit the Georgia I/M program, especially the implementation and enforcement improvement.

3.2 Literature Review

Although the I/M programs have existed in many states for more than a decade, few studies have investigated the behavioral aspects of motorists and inspection stations. Previous studies focus on the dynamic interaction between motorists and inspectors, indicating the consumer-driven incentives for inspectors to help vehicles pass the test (Hubbard, 1998; 2002). Recent studies illustrate the inspectors' decisions to cheat and their ethical behavior (Pierce & Snyder, 2007). Nonetheless, none of these examines the motorists' choices of inspection stations, which possibly reveal their efforts in searching for the lenient stations.

3.2.1 A Motorist's Choice

Typically, a consumer freely chooses a product or service in order to maximize his or her utility or satisfaction. Unlike other services, vehicle inspection is mandatory by law for the person owning a vehicle registered in the I/M area. In the Atlanta I/M area, a proof of the vehicle passing inspection is required for the registration renewal. Moreover, for some vehicles, a repair is needed in order to pass the inspection. Getting the vehicle to pass the inspection is a cost for owning and using the vehicle legally. As a consequence, motorists "will always have strong incentives to find the way to pass inspections in the low cost ways (Hubbard, 1997)."

The *inspection related cost* includes travel cost and time, waiting time, inspection fee, and repair costs if necessary for some vehicles (Harrington et al., 1999). Possibly, motorists are able to know or estimate these costs to some extent. For example,

motorists can determine the travel cost and time from either their houses or workplaces to any inspection stations prior to selection. Motorists can also observe the number of customers waiting at the inspection stations and estimate the possible waiting time. In general, the inspection fee is not greater than US\$ 25 due to the pricing control. For repair costs, motorists can obtain expert advice regarding the condition of their vehicles, which relate to the chance of failing the test prior to the inspection.

A vehicle failing the inspection depends not only on the condition of the vehicle but also the conduct or performance of the inspection stations. For instance, inadequate preconditioning prior to emission testing may lead to inaccurate or inconsistent test results (Cagle, 2009)²⁸. Clean vehicles might fail the inspection in the cold start condition when they produce high levels of carbon monoxide and hydrocarbon. The performance of the inspection stations might partly reflect in their failure rate – the share of failing vehicles. Unlike inspection related costs, the *failure rate* at each station is difficult to observe by motorists. The possible explanations about how motorists might obtain information on the failure rate exist in the literature of consumer choice and product differentiation.

Primarily, consumers learn from their past experience. For the frequently purchased product, consumers can try a number of brands and select the most satisfactory one. Similarly, a motorist may learn about the failure rate of the station from the previous inspection. Because the inspection is required yearly, the motorist can choose a different inspection station from the one in the previous year. Due to this low switching cost, motorists are less likely to choose inspection stations where their vehicles were previously failed (Hubbard, 2002). Moreover, consumers' word-of-mouth

²⁸ URL <http://www.aircarecolorado.com/repair/precondi.htm>

communication (or reputation of stations) is another common channel of information (Vettas, 1997). Likewise, a motorist might learn from other motorists (Hubbard, 1998) about the lenient inspection stations, inferring a lower failure rate (and possibly high false passing rate).

While the failure rates of the stations are unobservable, motorists also face the possible moral hazard behavior of the inspection stations. Vehicle inspection is considered the 'credence' service (Pesendorfer & Wolinsky, 2003) in that motorists must rely on experts to identify the vehicle conditions. Since the expert's diagnostic effort is unobservable, inspectors have incentives to deceive motorists about their vehicles' conditions to increase demand for repair the stations provide (Hubbard, 1998). Consequently, motorists have to derive information about failure rates from other observable attributes of the stations.

Consumers usually learn about the unobservable quality of products from their prices, particularly for the durable goods (Vettas, 1997). The higher prices of some brands imply the (either real or perceived) higher quality of the products. In fact, a great number of brands might not reflect the true diversity of products but they are distinctive from the view point of consumers. Even with homogenous goods, consumers use brand as a proxy for sellers' credibility in unobservable aspects of the product and service (Wernerfelt, 1988). Brands may serve as a signal used by consumers to differentiate products or services (Smith & Brynjolfsson, 2001).

Unfortunately, for the inspection service in Atlanta, it is not possible to imply the quality of inspection from the observable fee because the state regulation sets the price ceiling. Because the inspection service is seemingly homogenous due to the state regulation in price, technology and procedure, brands might be an aid for motorists' search for the preferable inspection service. Motorists who care more about the integrity aspect of the stations might put more weight on the brand of the station. Probably, the

chain-store inspection stations may have a better established brand than the independent stations. In addition to the information conveyed from the prices and brands, sales volume also plays an important role in consumer learning (Vettas, 1997). Motorists can observe the busy level of the stations and hence the volume of the inspections. To avoid the moral hazard problem, motorists may derive their belief about reliability and competence of the stations from the stations' popularity.

In summary, motorists may learn or form their belief about the failure rate and leniency of the stations from their past experience, word-of-mouth, brands, and inspection volume of the stations. The inspection fee, on the other hand, is less likely to convey any information about the failure rate due to the price control regulation.

3.3.2 The Atlanta Market of Vehicle Inspection

In Atlanta, the Georgia Department of Natural Resources (DNR) regulates the vehicle inspection market. The inspection fee is under the price-ceiling rule. Not only the testing fee but also the testing instruments, procedure, and technicians are controlled by the state. Manufacturers of emission testing instruments are certified to meet the state of Georgia's requirements for the I/M program. To perform the vehicle inspection, the inspectors must be certified for each particular type of the TSI and ASM tests. Furthermore, to assure standardized testing, the state also has instituted the biennial certification process for both the analyzer equipment and the inspectors (Clean Air Force, 2008). For the inspectors, the state requires them to attend the one-day recertification training sessions at least sixty days prior to the renewal. Despite the seemingly uniform price, testing technology and procedure, the pattern of motorists patronizing the inspection stations is not equally distributed.

Most likely, the inspection service at each station is different but difficult to observe by analysts. The differentiated services may exist in the similar manner as portrayed in the seminal work of Chamberlin (1933).

“Differentiation may be based on certain characteristics of the product itself It may also exist with respect to the conditions surrounding its sale. In retail trade, to take only one instance, these conditions include such factors as the convenience of the sellers’ location, the general tone or character of his establishment, his way of doing business, his reputation for fair dealing, courtesy, efficiency, and all the personal links which attach his customers either to himself or to those employed by him. In so far as these and other intangible factors vary from seller to seller, the ‘product’ in each case is different, for buyers take them into account, more or less, and may be regarded as purchasing them along with the commodity itself.”

The strength of the relationship might be one aspect that customers use to evaluate sellers (Israel, 2005). Moreover, asymmetric market information regarding the quality of service and the “cognitive lock-in among consumers” (Smith & Brynjolfsson, 2001) may contribute to the inspection service differentiation.

Although the state of Georgia has set the price ceiling at US\$25 for the inspection fee, this price control policy is not binding because the evidence indicates that the market equilibrium is established at the lower price. Two possible explanations of the non-binding price control are the diverse business models of the inspection stations and the regulation-induced demand. The variety of the inspection station types may result in the different cost structures (marginal and average costs) of their businesses. Anyone can operate the vehicle inspection business as long as the equipment and inspectors are qualified according to the rules set by the Georgia DNR. Consequently, in Atlanta,

gas stations, automobile services (oil and lube exchange, muffler, tire, and repair shops), and car dealers also provide the vehicle inspection services. A number of inspection stations perform only the vehicle inspection services. These different types of inspection stations are likely to have diverse fixed and variable costs, possibly resulting in the different price charged to the customers.

Some stations use price cut strategies in various forms such as charging the lesser fee, distributing the discount coupon, accepting the competitors' coupon, and special discounting for the fleet vehicles. However, the minimum observable fee that the stations actually charge the motorists is US\$10. Within the stations, the testing fees vary among different customers, suggesting that stations might use the price discriminating strategy.

Moreover, non-price competition strategies are common among stations. For example, some stations provide free additional services such as a car wash while the other stations offer a prize drawing. Many stations provide their services for extra hours during weekdays or Sunday to facilitate the customers. In addition, the chain-store inspection stations may gain competitive advantage due to the differentiation from the brand name station and the resulting customers' loyalty. Although brand loyalty may be established if consumers have satisfactory experience with the service, changes of inspection related costs and the entry of new stations can shift this loyalty (Ireland, 1987). In 2001, the market size of vehicle inspection in Georgia encompasses more than a million inspection transactions conducted by approximately 800 inspection stations. Around 90 percent of the stations have multiple inspectors. In fact, there are about 40 percent of the stations employing more than five inspectors. A number of stations also supply other automotive related services such as gasoline, oil and lube exchange, tire and muffler sale, and car dealer. Typically, there are two station classifications that are of interest in the previous studies. Based on their provided services, stations are

classified into two groups: test-only and test-and-repair. Another classification is based on the business formation of the station: independent shop and chain store. In Atlanta, of all the stations, approximately 47 percent are the inspection stations with repair services. Also, the inspection stations associated with chain stores account for 47 percent. These inspection stations are widespread throughout the Atlanta I/M program areas.

With respect to inspection stations, previous studies find a relationship between the failure rate and certain station attributes including types of provided services and organizations. For instance, in California vehicle inspection records show that the average failure rate of the test-only stations is greater than that of the test-and-repair stations (Klausmeier et al., 2000). Furthermore, the average emission reduction from vehicles inspected at the test-only stations is larger than that from vehicles certified at the test-and-repair stations (DeFries et al., 2001). For these reasons, the I/M program in California (called the Smog Check) requires the 'gross polluting vehicles' to be certified at the referee facilities which are the test-only stations. If these directed vehicles fail the inspection, they must be repaired only at the Gold Shield Guaranteed Repair facilities²⁹ and tested afterward only at the Gross Polluter Certification stations³⁰. Undoubtedly, the rationale of this regulation is based on the idea of validation. By means of separating the test and repair functions between two entities, the authority expects that the test would be objective whereas the repair would be effective.

²⁹ The Gold Shield Guaranteed Repair facilities are the repair shops certified by the Bureau of Automotive Repair (BAR). They provide the emission related repair service, which guarantees that the vehicles will pass the inspection afterward. However, these shops are not allowed to certify the previously identified gross polluters (DeFries et al., 2001).

³⁰ The Gross Polluter Certification stations are the certified test-only stations, which meet the performance criteria set by the BAR. Only GPC stations are allowed to inspect previously identified gross polluters.

In short, the market of inspection services in Atlanta seems to be homogenous in terms of price and technology, owing to the state regulations. The types of inspection stations vary in their provided services and business formations. In the market, stations compete by both price and non-price strategies. Perhaps, the unobservable attributes of stations are considerably important in their service differentiation and customer attraction, despite the state's standardized rules.

3.3 Research Questions and Hypotheses

The first research question is "what factors determine the motorists' selection of the inspection station." Given that general motorists will choose the inspection station to assure the lowest probability of their vehicles failing the test, subject to their budget constraints, the RUM theory offers a behavioral framework for the empirical testing of this question.

Hypothesis 1: All else being equal, an inspection station is less likely to be chosen when

- 1.1 the distance from the motorist's house or workplace to the station is far
- 1.2 the waiting time in the station is long
- 1.3 the inspection fee at the station is high
- 1.4 the failure ratio of the station is high
- 1.5 the false pass odds or ratio is low

The second research question is "do motorists pay the 'extra' inspection related costs to assure the lowest chance of their vehicles failing the inspection?" In particular, the study tests if motorists spend more on the travel cost by traveling additional miles to receive the services from the "lenient" inspection stations? An inspection station is considered "lenient" if its annual failure ratio is relatively low or its false passing odds ratio is comparatively high among all other inspection stations. Failure ratio is simply the

percent of vehicles failing the test at the inspection station within a year. Specifically in this study, a vehicle is considered “falsely pass”³¹ when it passes the emission test at the inspection but still emits the pollution higher than the allowable standard while running on road³². The false pass ratio is the percent of vehicles falsely passing the test at the inspection station. Likewise, the false pass odds are the ratio between the number of vehicles falsely and normally passing the tests at the station.

The underlying assumption of the second research question and related hypotheses is that the lenient inspection stations are *located far away* from a motorist’s house or workplace. If this assumption is true, then the *extra travel cost* will capture the value of “leniency” that the motorist is willing to pay to assure the lowest chance of failing. However, if this assumption is not true, the distance between the motorist’s house or workplace and the chosen inspection station, which is a proxy for the travel cost, cannot reveal his or her willingness to pay for the “lenient” services.

Hypothesis 2: All else being equal,

2.1 a motorist tends to choose an inspection station with the low failure odds (ratio) even it is located far away from his or her house or workplace

2.2 a motorist tends to choose an inspection station with the high false pass ratio even it is located far away from his or her house or workplace

Failing to reject the null hypothesis 2 may be due to two reasons. First, the motorist might not know about the lenient service of the station and simply choose the station randomly. Second, the underlying assumption of the hypothesis 2 is not true. The

³¹ The term “falsely pass” or “false passing” is particularly defined only within the boundary of this study. It has no legal implication for this group of vehicles because the Georgia DNR’s collect the on-road emission data for the purpose of monitoring and evaluation of the I/M program.

³² The on-road emissions from the vehicles are unobtrusively and randomly captured by the remote sensing devices, within the same year of test-cycle.

faulty assumption implies that the lenient station might be crowding in the vicinity of the motorists' houses or workplace instead of locating in the isolated area. If the spatial distribution of the lenient stations shows a clustering pattern, then this might suggest a degree of competition among the stations. Geographical competition may drive the lower failure ratio of the stations. Consequently, the motorist does not need to pay the extra travel cost to receive the lenient services because they are in the neighborhood. Therefore, the third research question is "do motorists choose the lenient inspection stations in high station density area?" The geographical competition is measured by the station density, which is defined as the number of inspection stations within the three-mile radius around the station of interest.

Hypothesis 3: All else being equal,

3.1 an inspection station in the high station density area is less likely to be chosen than that located in the area with low number of the stations

3.2 an inspection station with the low failure ratio in the high station density area is, however, likely to be chosen than that with the high failure ratio

3.4 Empirical Framework

3.4.1 A Random Utility Model

Theory of product differentiation explains that "the wide array of products in the marketplace is a response to the wide diversity of consumer tastes" (Anderson, de Palma & Thisse, 1992). A variety of products derives from the demand generated by both the taste heterogeneity in the population and idiosyncratic tastes of each individual. Because the differentiated products create mutually exclusive choices for consumers, they are a discrete choice in nature. The change in an individual consumer's demand of these discrete goods occurs at the extensive margin (McCarthy, 2001). This results in the discontinuities in the market demand, in which the traditional marginal analysis is not applicable (Domencich & McFadden, 1975).

The discrete choice model RUM assumes that a motorist, as a decision maker, chooses a variant of differentiated inspection services (stations) that yields the highest utility. However, analysts have incomplete information, which results in the uncertainty of the motorists' choice model (McFadden, 1974; Manski, 1977). This study assumes that an indirect utility of a motorist m ($m = 1, \dots, M$) in association with inspection station s ($s = 1, \dots, S$) is linear in parameters and additive in the random terms.

$$U_{ms} = V_{ms} + \varepsilon_{ms} \quad (3.1)$$

where U_{ms} is the indirect utility. V_{ms} is called the *representative* or *average taste* in the population (Train, 1993) and ε_{ms} is an *unobserved individual specific*. The *deterministic part* (V_{ms}) is assumed to be the summation of the *attributes* of the inspection station and the *characteristics* of the motorist and his vehicle (Ben-Akiva & Bierlaire, 2003).

$$V_{ms} = v(X_m) + v(Z_s) \quad (3.2)$$

where $v(X_m)$ and $v(Z_s)$ are functions of the two vectors: the motorist and his vehicle characteristics (X_m) and the station attributes (Z_s) respectively. With the assumptions of linearity in parameters, there are I aspects of the motorist and his vehicle characteristics ($i = 1, \dots, I$) and J aspects of the station attributes ($j = 1, \dots, J$).

$$v(X_m) = \sum_{i=1}^I \beta_{si} X_{mi} \quad \text{and} \quad v(Z_s) = \sum_{j=1}^J \gamma_{mj} Z_{sj} \quad (3.3)$$

The *random part* (ε_{ms}) can be varied depending on the *maintained* assumptions about its distribution, including the location and scale parameters, and hence the

resulting models (Hensher, Rose & Greene, 2005). This study assumes the logistic distribution of the random term. Thus, the probability of the outcome ($\Pr(Y_m)$), when the station s is chosen, is

$$\Pr(Y_m = s) = \frac{\exp V_{ms}}{\sum_{\sim s=1}^S \exp V_{m\sim s}} \quad (3.4)$$

where $\sim s$ is the stations that are not chosen.

3.4.2 Choice Set Restriction

Since the large numbers of the inspection stations are available in the Atlanta I/M area, the motorists face the large choice set of the inspection stations. Consequently, choice set restriction is necessary in modeling the motorist's decision making. In fact, using a subset of alternatives is a common practice in discrete choice modeling particularly in the fields of recreation demand analysis, transportation and marketing research (Parsons, Plantinga, & Boyle, 2000). There are two ways of constructing the restricted choice set: endogenous and exogenous.

The *endogenous choice sets* are directly obtained from individual respondents to the survey questionnaires. Examples of studies using this approach include Peters, Adamowicz & Boxall (1995), Haab & Hicks (1997), Parsons, Massey & Tomasi (1999) and Hicks & Strand (2000). The main criticism of this approach is the lack of consistency in modeling philosophy. McConnell & Tseng (1999) argue that researchers ought to freely simplify assumptions as appropriate.

Unlike the endogenous choice sets, the *exogenous choice sets* are the subset of alternatives determined by the researchers using three available approaches. First, the *exclusion of non-practical or unreasonable alternatives* is proposed by Parsons & Kealy

(1992). For instance, studies of one-day recreational trips commonly exclude sites that are more than three hundred miles away from an individual address in the samples.

Second, the *aggregation of alternatives* is based on some common aspects of the alternative. For example, Bockstael, McConnel & Strand (1989) aggregate the recreational sites located in the same geographical, spatial or political and administrative boundaries. As expected, the aggregation of alternatives causes the bias due to the choice heterogeneity (Parsons & Kealy (1992). Moreover, different levels of aggregation can result in diverse parameter estimates (Parsons & Hauber, 1998).

Lastly, the *random sampling of alternatives* is suggested by McFadden (1978). With the positive conditioning property, McFadden (1978) proves that the conditional logit models with samples of alternatives yield the consistent estimators. Several advantages of this approach include the fewer burdens on data preparation and computation. Examples of discrete choice modeling studies using this approach are Silman (1980), Parsons & Kealy (1992) and Tay, McCarthy & Fletcher (1996).

This study adopts the exogenous choice set with the randomly drawn alternative approach in order to reduce the measurement errors resulting from the aggregation of unobserved heterogeneous alternatives. In addition, the study compares the estimates obtained from the sampled alternative (with the full sample) and those from the complete set of alternatives (with the partial or subset of the full samples).

The exclusion of the unreasonable approach is not applied because the lack of appropriate criteria to eliminate the inspection stations. Given that the I/M program in Atlanta is limited in only thirteen counties, all stations are the “possible” alternative for motorists. Similarly, the aggregation of alternatives approach is not used because it is likely to give the inferior estimates due to aggregation of the unobserved heterogeneity of the inspection stations (as previously shown by Parsons & Needelman (1992)).

3.4.3 Randomly-drawn Choice Set

According to Ben-Akiva & Lerman (1996), there are two sampling strategies used in the alternative sampling: (1) stratified sampling and (2) random sampling with the uniform selection probabilities. The *stratified sampling* approach is appropriate when most of the alternatives have a limited chance to be selected. The set of S alternatives is divided into K disjoint subsets. Each stratum is assigned different sampling probabilities. Within the stratum, each alternative is uniformly and randomly drawn. An example of studies using this approach is Tay, McCarthy and Fletcher (1996). The other approach is the *simple random sampling*. For each observation, all alternatives S, except the actual chosen one, enter the L drawing without replacement. It is necessary that $L \leq S$ and the final choice set composed of L + 1 element. Ben-Akiva & Lerman (1996) provide the detail discussion of this approach while Parsons & Kealy (1992) apply this method in their study.

Despite its inefficiency (Ben-Akiva & Lerman, 1996), this study adopts the *simple random sampling approach* due to several reasons. First, there is no proper prior knowledge in assigning different probabilities to various strata. It may seem common that motorists choose the stations close to either their houses or workplaces. However, many motorists may have their vehicle inspected while they travel for other business such as visiting their relatives, weekly shopping, and so on. Second, the study has already included 'distance' as one of the main factors tested in the models. Stratified sampling based on the 'distance' between the motorists' residence and the station may weaken the effect of this variable. Finally, all the stations are possible alternatives because the Georgia I/M program is in effect for only thirteen contiguous counties. As a result, it is physically possible for motorists to drive to any of the inspection stations.

3.5 Data Sources

3.5.1 Atlanta Household Travel Survey 2001-2002 (AHTS 2001)

During 2001 – 2002, the Atlanta Regional Commission (ARC) in cooperation with the Georgia Department of Transportation (GDOT) and the Georgia Regional Transportation Authority (GRTA) conducted the Atlanta Household Travel Survey (AHTS). The survey was aimed at updating information on the travel behavior of residents in 13 counties of Atlanta Non-attainment Areas. The 8,069 randomly selected households participate in the survey by completing diary records of all travel for a 48-hour period. This study selects only 7,641 households, which own at least one vehicle, to match with the other dataset based on the address location of the households. The AHTS 2001 provides information regarding the socioeconomic condition, ethnicity, and location of house and work places. More information regarding the survey can be found in the 2001 Atlanta Household Travel Survey Final Report (ARC, 2003).

3.5.2 Continuous Atlanta Fleet Evaluation 2001 (CAFE 2001)

The CAFE data contains the measurement of emission from on-road vehicles in the Atlanta I/M program areas and other cities, including Augusta and Macon. The Air Quality Group (AQG), a unit of the Aerospace, Transportation, and Advanced Systems Laboratory, Georgia Tech Research Institute (GTRI), has collected on-road emission since 1993. With the remote sensing device (RSD) technology and video camera, the emission of three pollutants (Carbon monoxide (CO), Hydrocarbon (HC), Nitrogen oxides (NO_x)) and the license plate numbers of the on-road vehicles can be captured without drivers' awareness. The license plate information is later matched with the

vehicle registration database to obtain the vehicle identification number (VIN³³). With VIN Decoder version 2002.01 for the MOBILE 6³⁴ types (Eastern Research Group Inc., April 4, 2003), the specialized software that extracts the vehicle information from VIN, AQG includes information about the vehicle manufacturer and model year as well as attributes such as body style, model name, and emission control technologies. Because the RSDs measure on-road vehicles randomly passing by the instruments, the vehicles that show up in the CAFE database are those registered *within* and *outside* the state of Georgia. In CAFE 2001, there are a total of 112,262 unique Georgia registered vehicles. Of this total, there are 51,790 (46.13 percent) vehicles registered in the Atlanta I/M area.

3.5.3 Inspection and Maintenance Program Records 2001 (I/M 2001)

The Atlanta I/M program data in the year 2001 (I/M 2001) are the administrative records of every transaction performed at the decentralized inspection stations. The I/M 2001 consist of the detail information generated during the testing procedure and most importantly the visual, emission, and overall test results of each inspection transaction. All the data input at the inspection station both manually and automatically are directly transferred via the remote network connection to the central server administered by the Georgia DNR. The inspection station cannot access and keep any private information about each individual customer and his or her vehicle that takes the test. For the purpose of monitoring and enforcement, the I/M program data also include information about the inspection station and inspector for each testing transaction such as the

³³ VIN is a unique serial number used by the automobile industry to identify individual vehicles. Generally, VINs consist of 17 characters excluding the letters I, O, or Q (URL <http://www.wikipedia.org>, March 2009).

³⁴ "MOBILE6 is an emission factor model for predicting gram per mile emissions of HC, CO, NOx, Carbon Dioxide (CO₂), Particulate Matter (PM), and toxins from cars, trucks, and motorcycles under various conditions (URL <http://www.epa.gov/oms/m6.htm>)."

identification number, the station location, and the type of business formation. The study obtains the variables related to the station characteristics from this dataset. In 2001, there are 1,795,681 unique vehicles taking the inspection. Each vehicle registered in the Atlanta I/M area has at least one testing record in the I/M 2001

3.5.4 Matching Three Data Sources

This study uses three sets of samples resulting from the matching of AHTS 2001, CAFE 2001, and I/M 2001. The matching procedure is straightforward, using the primary keys for each vehicle record. The resulting matched observations are varied and constrained by availability of data in the original datasets.

The first sample is the *full sample A* (51,709 vehicles), which results from the matching of CAFE 2001 and I/M 2001 datasets (CAFE–I/M 2001 A). The primary key for matching these two datasets is the *VIN information*. Vehicles in the full sample A are those registered in the Atlanta I/M area and are driven passing by the RSD instruments, resulting in their on-road emission being measured. If some vehicles are captured by the RSDs for more than one time (they drive past the instruments several times), the selected match is based on the minimum elapse time between the days that vehicles are tested at the station and measured by the RSDs.

The second sample is the *full sample B* (39,489 vehicles), which is the subset of the full sample A (CAFE–I/M 2001 B). The number of observations is reduced due to the technical problem during the address retrieval procedure from the vehicle registration database by the AQG staff, which results in the scrambled patterns of a large number of records that cannot be recovered. Different from the full sample A, the full sample B has

additional information regarding the residential addresses of the vehicle owners.³⁵ The location information is important for the creation of the distance variable (distance between the motorists' houses and the inspection stations).

The third sample is the *partial sample* (465 vehicles), which results from the matching of the three datasets (CAFE 2001, I/M 2001, and AHTS 2001). The primary key for matching the AHTS 2001 and the full sample B (CAFE–I/M 2001 B) is the information about the address locations (the geographical coordinates). Linked by the households' addresses of AHTS 2001, this study attaches the characteristics of the households owning the vehicles to the matched vehicle records. As a result, the partial sample consists of the vehicle observations with their attributes and the characteristics of their owners.

3.6 Variables and Descriptive Statistics

This study uses three main sets of variables: station, vehicle, and motorist characteristics. The summary of variable descriptions is in Table 3.1.

3.6.1 Station Characteristics

Station characteristic variables come from two datasets: (1) I/M 2001 and (2) CAFE – I/M 2001 (CAFE 2001 matched with I/M 2001). Most variables are calculated

³⁵ In this study, the terms “vehicle owner” and “motorist” are slightly different. The term “vehicle owner” is used when matching the datasets with the address primary key because the registration addresses belong to the owners. On the other hand, the term “motorist” is used when analyzing the data because no information is available about the persons who drove their (household) vehicles to take the tests. Thus, the motorists, who drove the vehicles to the test, might be the owner or the other members of the household. However, this slight difference does not affect the analysis because the characteristics of the motorists are at the household level, such as household income and ethnicity.

Table 3.1 Variables and their descriptions

| Variables | Level | Descriptions |
|--|----------|--|
| <u>Dependent Variable</u> | | |
| Selected inspection station | Nominal | Inspection station being selected; 1 if yes and 0 if no |
| <u>Independent Variables</u> | | |
| <i>Station characteristics</i> | | |
| False pass ratio | Interval | Proportion of vehicles passing the test at an inspection station but failing the RSD measurement on road; falsely passing: $0 \leq \text{False pass ratio} \leq 1$ |
| False pass odds | Interval | Ratio between the number of vehicles falsely passing and those truly passing the inspection at a station; $0 \leq \text{False pass odds} \leq +\infty$ |
| Failure ratio | Interval | Proportion of vehicles failing the test at a station |
| Ln(Total tests) | Interval | Natural log of the total test performed at a station |
| Average daily test per inspector | Interval | Average daily tests per inspector of a station |
| No repair | Nominal | Station has no repair service; 1 if yes and 0 if no |
| Chain store | Nominal | Station's name appears in more than one location; 1 if yes and 0 if otherwise |
| Total stores in chain | Interval | Number of facilities of the chain store |
| Newness | Ordinal | Order of a station starting the inspection business |
| Min test fee (US\$) | Interval | Minimum inspection fee charged to a customer of a station (US\$) |
| Mean age of vehicle | Interval | Average age of vehicles taking the test at a station (year) |
| Share of cars | Interval | Proportion of cars taking the test at a station |
| Share US make vehicle | Interval | Proportion of US make vehicles taking the test at a station |
| Share of ASM test | Interval | Proportion of the ASM test performed at a station |
| Open on Saturday | Nominal | Station is opened on Saturday; 1 if yes and 0 if otherwise |
| Open on Sunday | Nominal | Station is opened on Sunday; 1 if yes and 0 if otherwise |
| Station density around the station (2 mile radius) | Interval | Number of the other stations within the 2-mile radius around a station |

Table 3.1 Cont.

| Variables | Level | Descriptions |
|---|----------|--|
| <u>Independent Variables</u> | | |
| <i>Motorist characteristics</i> | | |
| Distance from house (mile) | Interval | Distance from a motorist's house to the inspection station (mile) |
| Distance from work (mile) | Interval | Distance from a motorist's work place to the inspection station (mile) |
| Minimum distance to station from house or work (mile) | Interval | Minimum distance to the chosen station either from a motorist's house or workplace (mile) |
| Station density around house (3 mile radius) | Interval | Number of inspection stations within 3-mile radius around a motorist's house |
| Station density around work place (3 mile radius) | Interval | Number of inspection stations within 3-mile radius around a motorist's workplace |
| Annual household income (US\$1,000) | Interval | Annual household income in 2001 (1,000 US\$) |
| Black | Nominal | Ethnicity; 1 if a motorist is black and 0 if otherwise |
| White | Nominal | Ethnicity; 1 if a motorist is white and 0 if otherwise |
| Other ethnicities (Ref.) | Nominal | Ethnicity, 1 if a motorist is Latino, Asian, or other ethnicities and 0 if otherwise |
| <i>Vehicle characteristics</i> | | |
| Car | Nominal | Vehicle type; 1 if a vehicle is a car and 0 if otherwise |
| Other type (Ref.) | Nominal | Vehicle type; 1 if a vehicle is a truck, van, SUV, or other types and 0 if otherwise |
| ASM | Nominal | Test type; 1 if a vehicle takes the ASM test and 0 if otherwise |
| TSI (Ref.) | Nominal | Test type; 1 if a vehicle takes the TSI test and 0 if otherwise |
| US automaker | Nominal | Manufacturer; 1 if a vehicle is made by a US automaker and 0 if otherwise |
| Other automakers (Ref.) | Nominal | Manufacturer; 1 if a vehicle is made by an European, Asian, or other automakers and 0 if otherwise |
| Ln(Mileage) | Interval | Natural log of the mileage of a vehicle, read from the odometer (mile) |

based on the I/M 2001 dataset. Only a few variables, related to the false passing vehicles and the vehicle technology, are computed from CAFE–I/M 2001 dataset. In this study, the false passing vehicles refer to the vehicles that passed the overall inspection test but emitted pollution at a higher level than the ASM25³⁶ standard while running on-road. The emission from these vehicles is detected unobtrusively by the RSDs while they are running on-road.

The first set of variables is related to the measures of the *inspection station leniency*. These measures are concerned with the testing results at each station: (1) *failure ratio* and (2) *false pass odds and ratio*. *Failure ratio* of a station is the proportion of vehicles failing the inspection to the total vehicles inspected at that station. The higher the failure ratio of a station, the less likely a motorist will choose the station. The measure of false passing is represented by: (1) *false pass odds* and (2) *false pass ratio*. *False pass ratio* of a station is the proportion of false passing vehicles to the total vehicles inspected at that station. The value of *false pass ratio* can range from zero to one. *False pass odds* of the station, on the other hand, is the ratio between the ‘false’ passing and ‘true’ passing vehicles. Unlike *false pass ratio*, *false pass odds* can take on any positive value. Table 3.2 illustrates the classification of these two variables.

The second set of variables is related to the competition level of the inspection market and the resulting test outcomes. As a proxy for the market power of a station, *station density* measures the market concentration in a certain geographical area. *Station density* refers to the number of other inspection stations located within a two-mile

³⁶ There are two modes used in the ASM testing: (1) high load/low speed (15 mile per hour) called the 50/15 test and (2) moderate load/ moderate speed (25 mph) called the 25/25 test. Therefore, the ASM25 refers to the standard applied with vehicles tested at the ASM 25/25 test. In this study, the ASM25 is used as a threshold for the RSD measurement because vehicles are assumed to run at the moderate load and speed.

radius of a particular station. The interaction terms between *station density* and the inspection results variables, the *false pass ratio* or *odds* and *failure ratio*, can indicate the effect of market competition on testing outcomes.

Table 3.2 Classification of inspection and RSD results for each inspection station

| | | Inspection Results | |
|-------------|------|--------------------|------|
| | | Pass | Fail |
| RSD Results | Pass | a | b |
| | Fail | c | d |

$$\text{False pass ratio} = \frac{c}{a+b+c+d} \quad (3.5)$$

$$\text{False pass odds} = \frac{c}{a} \quad (3.6)$$

The next set of variables is related to the market share, performance, business formation of the inspection stations and the other services provided at the inspection stations (this information is extracted from the I/M 2001). The natural log of the *total tests* reflects the popularity of a station and probably the testing efficiency in terms of its throughput. Also, the *total tests* indicate the non-normalized market share of the station. *Average daily test per inspector*, suggesting the average congestion at a station, is a proxy of the waiting time, one of the inspection related costs for motorists. The higher the congestion, the less likely the station will be chosen. *No repair* and *chain store* are dichotomous variables indicating whether a station provides any repair services and is a part of the chain business. Depending on the motorists' perception in the sample, both *no repair* and *chain store* may reveal their preference in various ways. For example, for some motorists, a chain-store station may be preferred due to its standardized services and prevalence. However, other motorists might rather choose their independent

garages, where they have already established a relationship with the technicians. In conjunction with the chain store, the variable *total stores in a chain* is a proxy of the size of the chain.

A proxy for the age of a station, *newness* is a natural log of the ordered number extracted from the sequence of certificate that a station received when registered and started its business. *Minimum testing fee* is the lowest testing fee that *each* station charges the customers. The higher the minimum testing fee, the less likely that the station will be chosen. The minimum testing fee is used in the model instead of the average or maximum testing fee mainly because of the larger variation of the minimum fee. The vehicle inspection fee has been controlled since the onset of the Atlanta I/M program. Consequently, the inspection stations can charge their customers up to US\$25 for each test. Nonetheless, occasionally, the inspection stations adopt the price-cutting strategy, resulting in the higher variability of the minimum fees between the stations. *Open on Saturday* and *Sunday* are two dichotomous variables indicating if the stations provide their services on Saturday, Sunday or both.

The last set of variables is associated with the customers whom the stations served. The *mean age of vehicles* is the average age of vehicles tested at the station. *Share of cars* and *US make vehicles* are the percentage of cars and US make vehicles at the station respectively. Lastly, *share of ASM test* is the percentage of ASM test performed at the station. Table 3.2 exhibits the descriptive statistics of all inspection stations in this study.

The total numbers of the inspection stations in the sample (736) result from the matching outcome between the CAFE 2001 and the I/M 2001 datasets. Around 39 percent of all stations are chain store with some kind of repair services. In general, the inspection stations are quite varied in terms of their performance as measured by their

Table 3.3 Characteristics of inspection stations in the partial and full sample
(N of stations = 736)

| Variable | Mean | Std. Dev. | Min | Max |
|--|----------|-----------|--------|--------|
| Total tests | 2852.030 | 4001.696 | 19 | 28307 |
| Total inspectors | 5.708 | 4.291 | 1 | 30 |
| Average daily test per inspector | 2.483 | 2.631 | 0.138 | 21.028 |
| Share of cars | 0.625 | 0.118 | 0.017 | 0.988 |
| Share of ASM tests | 0.316 | 0.221 | 0 | 0.610 |
| Share of US make vehicles | 0.577 | 0.230 | 0 | 1 |
| No repair | 0.353 | 0.478 | 0 | 1 |
| Chain | 0.477 | 0.500 | 0 | 1 |
| Total stores in the chain | 8.761 | 15.212 | 1 | 57 |
| Open on Saturday | 0.874 | 0.332 | 0 | 1 |
| Open on Sunday | 0.257 | 0.437 | 0 | 1 |
| Minimum fee (US \$) | 24.066 | 3.306 | 10 | 25 |
| Maximum fee (US \$) | 25.008 | 0.304 | 23 | 33 |
| Mean fee (US \$) | 24.962 | 0.294 | 20.313 | 25.000 |
| Mean age of tested vehicles | 6.619 | 2.176 | 1.837 | 13.726 |
| Median age of tested vehicles | 6.006 | 1.884 | 1 | 14 |
| Ln(Mean of mileage of tested vehicles) | 11.199 | 0.239 | 10.209 | 11.828 |
| Ln(Median of mileage of tested vehicles) | 11.277 | 0.269 | 9.804 | 11.861 |
| False pass odds | 0.922 | 0.949 | 0 | 16 |
| False pass ratio | 0.419 | 0.196 | 0 | 1 |
| Failure ratio | 0.095 | 0.067 | 0 | 0.423 |

size and the resulting volume of the inspection transactions. On average, a station performs around 1,276 (median) tests in a year. The average number of inspectors per station is usually 5 to 6 people. Accordingly, the average daily tests per inspector are two or three. The typical percent of customers for each station are around 60 percent cars and 57 US make vehicles. The failure ratio is approximately 10 percent for each station. On average, the *false pass ratio* is 40 percent while the *false pass odds* are 0.8 to 0.9. This seems to suggest that on average, the inspection stations pass vehicles falsely by chance because the odds are close to one percent. However, the *failure ratio*, *false pass odds* and *ratio* of the station with repair services are statistically higher than those without repair services.

3.6.2 Vehicle Characteristics

Vehicle characteristic variables come from the CAFE - I/M 2001 dataset. *Car*, *US*, and *ASM* are three dichotomous variables indicating if a vehicle is a car, US make, and required ASM test vehicle respectively. The reference groups of these three variables are other types of vehicles (truck and van), other makes (Asian and European), and required TSI test vehicles. *Mileage* is the accumulated mileage read from the odometer of a vehicle at the time of inspection. Because this set of variables is fixed at the vehicle level, they can enter the model only by interacting with the station characteristic variables of interest namely the *false pass odds* or *ratio* and *failure ratio*. *False pass I/M test* is a dichotomous variable coding value of one if the vehicle passes the inspection but fails the RSD measurement and zero otherwise. The vehicle fails the RSD measurement when it emits pollution higher than the allowable standards. In other words, a vehicle “failing the RSD measurement” is the “false passing’ vehicle.” Table 3.4 illustrates the descriptive statistics of vehicle characteristic variables of the full and partial samples respectively.

In the analysis, there are three sets of samples for vehicle characteristics: (1) the full sample A of 51,709 vehicles from the matched CAFE–I/M 2001 without address location (2) the full sample B of 39,489 vehicles from the matched CAFE–I/M 2001 with address location, and (3) the partial sample of 465 vehicles from the matched AHTH – CAFE–I/M 2001. Overall, the general characteristics of vehicles in the full and partial samples are similar except for a few aspects. Table 3.4 summarizes the key characteristics of vehicles in the three samples. In all samples, most vehicles are cars and take the ASM tests. The average age and mileage of vehicles in the three samples

Table 3.4 Characteristics of vehicles in the partial and full samples

| Variable | Partial (N = 465) | | | | Full B (N = 39,489) | | | | Full A (N = 51,709) | | | |
|------------------------|-------------------|-----------|-------|--------|---------------------|-----------|-------|--------|---------------------|-----------|-----|--------|
| | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max |
| Fail I/M test | 0.004 | 0.066 | 0 | 1 | 0.010 | 0.100 | 0 | 1 | 0.010 | 0.102 | 0 | 1 |
| Fail RSD reading | 0.409 | 0.492 | 0 | 1 | 0.459 | 0.498 | 0 | 1 | 0.455 | 0.498 | 0 | 1 |
| False passing I/M test | 0.404 | 0.491 | 0 | 1 | 0.450 | 0.497 | 0 | 1 | 0.001 | 0.036 | 0 | 1 |
| Car | 0.723 | 0.448 | 0 | 1 | 0.630 | 0.483 | 0 | 1 | 0.631 | 0.483 | 0 | 1 |
| US make vehicle | 0.462 | 0.499 | 0 | 1 | 0.551 | 0.497 | 0 | 1 | 0.540 | 0.498 | 0 | 1 |
| ASM test type | 0.572 | 0.495 | 0 | 1 | 0.546 | 0.498 | 0 | 1 | 0.532 | 0.499 | 0 | 1 |
| Domestic made vehicle | 0.570 | 0.496 | 0 | 1 | 0.638 | 0.481 | 0 | 1 | 0.627 | 0.484 | 0 | 1 |
| Ln(Mileage) | 11.414 | 0.564 | 8.209 | 12.908 | 11.387 | 0.607 | 0 | 13.804 | 11.377 | 0.611 | 0 | 13.810 |
| Age (year) | 6.927 | 3.313 | 3 | 20 | 6.678 | 3.264 | 0.500 | 22 | 6.653 | 3.421 | 0.5 | 25 |

Table 3.5 Comparison of vehicle characteristics from the partial and full samples

| Variables | Partial | Full B | Full A | Variables | Partial | Full B | Full A |
|------------------------------|---------|------------|------------|-----------------------------|---------|------------|------------|
| | N = 465 | N = 39,489 | N = 51,709 | | N = 465 | N = 39,489 | N = 51,709 |
| Vehicle type | | | | I/M test results | | | |
| Car | 72.04% | 62.98% | 63.09% | Pass | 99.57% | 99.00% | 98.96% |
| Others | 27.06% | 37.02% | 36.91% | Fail | 0.43% | 1.00% | 1.04% |
| Testing type | | | | RSD reading results | | | |
| ASM | 57.20% | 54.56% | 53.22% | Pass | 59.14% | 54.14% | 54.50% |
| TSI | 42.80% | 45.44% | 46.78% | Fail | 40.86% | 45.86% | 45.50% |
| Vehicle make | | | | I/M vs. RSD results | | | |
| US | 46.24% | 55.10% | 53.99% | Pass I/M, Fail RSD | 40.43% | 44.97% | 44.58% |
| Non-US | 53.76% | 44.90% | 46.01% | Fail I/M, Pass RSD | 0.00% | 0.12% | 0.13% |
| ASM test | | | | <u>Fail RSD measurement</u> | | | |
| Car | 62.39% | 59.71% | 58.39% | US make | 47.44% | 49.63% | 49.57% |
| Other types of vehicles | 43.85% | 45.80% | 44.40% | Non-US make | 35.20% | 41.22% | 40.72% |
| US make | 55.35% | 50.83% | 49.94% | Car | 40.00% | 42.77% | 42.52% |
| Non-US make | 58.80% | 59.14% | 59.08% | Other type of vehicles | 43.08% | 51.10% | 50.59% |
| Median age of vehicle (year) | 6.00 | 6.00 | 6.00 | ASM test | 52.63% | 59.51% | 59.78% |
| Mean age of vehicle (year) | 6.93 | 6.68 | 6.65 | TSI Test | 25.13% | 29.46% | 29.25% |
| Fail I/M test | 10.00 | 10.52 | 10.64 | <u>Fail I/M test</u> | | | |
| Fail RSD test | 8.41 | 7.92 | 7.97 | US make | 0.47% | 1.00% | 1.05% |
| Median Ln(Mileage) | 11.46 | 11.44 | 11.43 | Non-US make | 0.40% | 1.00% | 1.04% |
| Mean Ln(Mileage) | 11.41 | 11.39 | 11.37 | Car | 0.60% | 1.13% | 1.15% |
| Fail I/M test | 12.14 | 11.69 | 11.70 | Other types of vehicles | 0.00% | 0.79% | 0.86% |
| Fail RSD test | 11.54 | 11.52 | 11.52 | ASM test | 0.75% | 1.75% | 1.86% |
| | | | | TSI test | 0.00% | 0.11% | 0.12% |

are also similar. Remarkably, in each sample, the percentage of vehicles that fail the inspection is very low. In contrast, the percentage of vehicles that fail the RSD measurement is remarkably high in all samples. US make vehicles fail RSD measurement more than the non-US ones. Cars, on the other hand, fail RSD less than the other types of vehicles. Vehicles tested by the ASM procedure fail RSD at approximately two times higher than those tested by the TSI procedure.

3.6.3 Motorist Characteristics

The motorist characteristic variables are from the partial sample (the matching of the three datasets: CAFE 2001, I/M 2001, and AHTS 2001) containing the socioeconomic and demographic information of the motorists' households. *Household income* is the annual household income of a motorist. *Black* and *white* are the two dichotomous variables indicating the ethnicity of a motorist, with the reference group of the other ethnicities (Asian, Hispanic, Native American, and others). Similar to the vehicle characteristics, motorist characteristic variables can be in the model only by interacting with the station characteristic variables of interest namely the *false pass ratio* or *odds* and *failure ratio*.

The main factors affecting the motorist's decision of inspection station are the travel cost and time. To proxy for these factors, this study uses the distance computed in several ways. *Distance from a house to a station* is the shortest path distance between a motorist's house to a specific inspection station. Likewise, *distance from a work place to a station* is the shortest path distance between a motorist's work place to a specific inspection station. *Minimum distance to station* is the shorter distance between the two types of distance: (a) distance from a house to a station or (b) distance from a work place to a station. The shorter distance indicates that the motorist chooses the inspection station located around his or her house or work place. This *minimum distance*

Table 3.6 Characteristics of motorists in the partial sample (N = 465)

| Variable | Mean | Std. Dev. | Min | Max |
|---|--------|-----------|-------|---------|
| Black | 0.256 | 0.437 | 0 | 1 |
| White | 0.600 | 0.490 | 0 | 1 |
| Annual household income (US \$1,000) | 58.306 | 27.620 | 5 | 100 |
| Own a house | 0.557 | 0.497 | 0 | 1 |
| Distance from house to work place (mile) | 11.497 | 22.100 | 0 | 269.518 |
| Distance from house to chosen station (mile) | 5.603 | 5.965 | 0.05 | 37.691 |
| Distance from work place to chosen station (mile) | 12.934 | 21.330 | 0.206 | 258.955 |

to station variable is used only in the logit and the log-linear models. Table 3.6 shows the descriptive statistics of motorist characteristics in the partial sample (465).

The total numbers of motorists (465) in this study are constrained by the matching outcome of three datasets. In this sub sample, white and black account for 61 and 26 percent respectively. The median annual household income is US \$ 55,000. Approximately 56 percent of motorists in this sample live in their own houses. Among whites, 73 percent own their houses while 71 percent of black live in rentals. On average, blacks own significantly older vehicles (7.45 years) than whites do (6.46 years).

The partial sample (465 vehicles) provides more detailed information about location of the work place for each motorist (AHTS 2001). As a result, the distance from a motorist's house to his working place can be computed. Typically, the median distance between a house and a work place is 6.38 miles (mean is 11.50 miles). With the ID of inspection stations that perform tests for the vehicles, the study can identify locations of the selected stations, and hence the distance between the house to station and between workplace and station. By and large, the average distance between a house and the selected station (5.60 miles) is shorter than the average distance between a work place and a chosen station (12.93 miles). Approximately 78 percent of vehicles in the partial sample were inspected at the stations nearby the motorists' houses. Regardless of the origin, the average minimum distance to the inspection stations is 4.91 miles.

The full sample B (39,489 vehicles) provides only the residential information of motorists. On average, the distance from the motorist's house to the selected station is 8.01 miles while the median is 3.92 miles.

3.7 Models and Results

3.7.1 Conditional Logit Models: Probability of an Inspection Station Being Selected

To investigate the determinants of motorists' decisions when choosing their inspection stations, this study utilizes the conditional logit model, which conforms to the RUM theory. In particular, the general functional form is shown in the equation (3.7), where Y_m is the inspection station choice s of individual m over the station choice set S . While X_m is the vector of motorist and his vehicle characteristics, Z_s is the vector of the station attributes. Additionally, i and j are the indexed aspects of the motorists and their vehicle characteristics and those of the inspection stations respectively.

$$\Pr(Y_m = s | X, Z) = \frac{\exp\left(\sum_{i=1}^I \beta_{si} X_{mi} + \sum_{j=1}^J \gamma_{mj} Z_{sj}\right)}{\sum_{\tilde{s} \in S} \exp\left(\sum_{i=1}^I \beta_{\tilde{s}i} X_{mi} + \sum_{j=1}^J \gamma_{mj} Z_{\tilde{s}j}\right)}, \text{ for all other } \tilde{s} \neq s \quad (3.7)$$

This study models a motorist's choice of the inspection station employing the three samples: partial, full sample A and B. The advantage of using the full sample A and B is the large sample size. Although the size of the partial sample is quite small (465 vehicles), the rich information about the motorist characteristics in the partial sample can identify several socioeconomic and demographic factors affecting the selection of the inspection stations. Moreover, the estimations from the partial sample can uncover the

potential bias in the full samples, if there is any, due to the lack of motorists' socioeconomic and demographic information.

3.7.1.1 Overall Results

Tables 3.7.1 and 3.7.2 present the estimations of the conditional logit models of the *partial sample*. Each motorist has the complete choice set of the inspection stations (736). The only difference between these two tables is the variables that proxy for the leniency of the inspection stations. In Table 3.7.1, the first set of models ((1) – (6)) present the effects of the *false pass odds* as a measure of the leniency. Likewise Table 3.7.2 with the second set of models ((6) – (12)) show the impact of the *false pass ratio*.

The study presents the different specifications of the models to show the changing effects of the station and vehicle attributes when the motorist characteristics are included. If the change occurs, then the results might suggest the bias of the estimates in the full samples. Models (1) and (7) include only the attributes of the station while models (3), (5), (6) and (9), (11), (12) add the *distance from house*. Models (4) and (10) include both the *distance from house* and *work*. Clearly, adding *distance from work* hardly increases the explanatory power of the model, suggested by the unchanged pseudo R squared of the models with and without the *distance from work* variable. Similarly, the log likelihood ratio test shows that the models with and without the *distance from work* are not different with the one degree of freedom (for models (3) and (4): LR chi squared = 0.79, p-value = 0.37; for models (9) and (10): LR chi squared = 0.84, p-value = 0.36). Also, the *distance from work* itself is not statistically significant ($z = 0.74$ in Table 3.7.1 and $z = 0.76$ in Table 3.7.2). Therefore, models (5), (6) and (11), (12) exclude the *distance from work* but include the characteristics of the motorist and vehicle via the interaction terms of *false pass odds* and *ratio*.

Table 3.7.1 Conditional logit models of the odds of a station being chosen:
using the partial sample with the choice set of 736 stations

| Independent Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|--|---------------------|---------------------|----------------------|----------------------|----------------------|----------------------|
| <u>Station characteristics</u> | | | | | | |
| <i>False pass odds</i> | -0.008 (0.11) | 0.090 (0.38) | 0.085 (0.40) | 0.084 (0.40) | -0.255 (0.26) | -0.643 (0.77) |
| Failure ratio | -1.085 (0.84) | -5.419 (2.59)*** | -3.476 (1.62) | -3.379 (1.57) | -67.334 (3.32)*** | -54.656 (2.60)*** |
| Ln(Total tests) | 0.926 (14.22)*** | 0.944 (14.20)*** | 0.879 (13.89)*** | 0.878 (13.86)*** | 0.888 (13.89)*** | 0.888 (13.88)*** |
| Average daily test per inspector | 0.002 (0.12) | 0.000 (0.01) | 0.023 (1.12) | 0.023 (1.13) | 0.020 (0.99) | 0.019 (0.94) |
| No repair | 0.069 (0.63) | 0.064 (0.58) | 0.140 (1.27) | 0.142 (1.28) | 0.178 (1.60) | 0.190 (1.69)* |
| Chain store | -0.010 (0.08) | -0.002 (0.01) | -0.021 (0.16) | -0.022 (0.17) | -0.026 (0.20) | -0.024 (0.19) |
| Total stores in chain | 0.007 (1.20) | 0.005 (0.90) | 0.004 (0.73) | 0.004 (0.72) | 0.004 (0.71) | 0.004 (0.73) |
| Newness | 0.046 (0.84) | 0.057 (1.05) | 0.078 (1.46) | 0.079 (1.49) | 0.072 (1.33) | 0.071 (1.31) |
| Min test fee (US\$) | -0.029 (2.49)** | -0.027 (2.30)** | -0.020 (1.65)* | -0.020 (1.64) | -0.019 (1.55) | -0.019 (1.55) |
| Mean age of vehicle | -0.048 (0.63) | -0.031 (0.41) | -0.167 (2.11)** | -0.171 (2.14)** | -0.157 (1.86)* | -0.154 (1.79)* |
| Share of cars | 3.267 (5.06)*** | 3.609 (5.51)*** | -0.565 (0.79) | -0.665 (0.94) | -0.656 (0.95) | -0.651 (0.94) |
| Share US make vehicle | -0.812 (2.24)** | -0.635 (1.78)* | -1.134 (2.80)*** | -1.115 (2.74)*** | -1.159 (2.83)*** | -1.141 (2.76)*** |
| Share of ASM test | 0.439 (0.60) | 0.153 (0.20) | 1.347 (1.80)* | 1.379 (1.84)* | 1.830 (2.49)** | 1.911 (2.55)** |
| Open on Saturday | -0.096 (0.47) | -0.071 (0.34) | 0.008 (0.04) | 0.010 (0.05) | -0.009 (0.04) | -0.011 (0.05) |
| Open on Sunday | 0.056 (0.51) | 0.030 (0.28) | -0.020 (0.18) | -0.022 (0.19) | -0.047 (0.42) | -0.054 (0.49) |
| Station density around the station (2 mile radius) | -0.000 (0.06) | -0.045 (2.06)** | -0.043 (1.94)* | -0.044 (1.97)** | -0.035 (1.59) | -0.030 (1.35) |
| Station density around the station x <i>False pass odds</i> | | -0.010 (0.50) | -0.004 (0.21) | -0.004 (0.20) | -0.013 (0.70) | -0.019 (0.85) |
| Station density around the station x Failure ratio | | 0.469 (2.70)*** | 0.357 (2.04)** | 0.354 (2.03)** | 0.374 (2.15)** | 0.381 (2.14)** |
| <u>Motorist characteristics</u> | | | | | | |
| Distance from house (mile) | | | -0.318 (16.95)*** | -0.313 (15.93)*** | -1.375 (3.16)*** | -1.368 (3.16)*** |
| Distance from work (mile) | | | | -0.012 (0.74) | | |
| Distance from house x Ln(Mileage) | | | | | 0.088 (2.33)** | 0.087 (2.32)** |
| Distance from house x <i>False pass odds</i> | | | | | 0.008 (0.65) | 0.007 (0.56) |
| Distance from house x Failure ratio | | | | | 0.309 (1.00) | 0.355 (1.18) |
| Household income x <i>False pass odds</i> | | | | | | 0.002 (0.68) |
| Black x <i>False pass odds</i> | | | | | | -0.001 (0.00) |
| White x <i>False pass odds</i> | | | | | | 0.212 (0.86) |
| Household Income x Failure ratio | | | | | | -0.014 (0.41) |

Table 3.7.1 Cont.

| Independent Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|--------------------------------------|----------|----------|----------|----------|--------------------|---------------------|
| Black x Failure ratio | | | | | | -3.032 (0.98) |
| White x Failure ratio | | | | | | -7.480 (2.61)*** |
| <u>Vehicle characteristics</u> | | | | | | |
| Car x <i>False pass odds</i> | | | | | 0.197 (0.90) | 0.228 (1.00) |
| ASM x <i>False pass odds</i> | | | | | 0.328 (1.17) | 0.335 (1.19) |
| US maker x <i>False pass odds</i> | | | | | 0.306 (1.75)* | 0.287 (1.77)* |
| Mileage x <i>False pass odd</i> | | | | | -0.019 (0.21) | -0.002 (0.03) |
| Car x Failure ratio | | | | | -0.163 (0.06) | -1.154 (0.44) |
| ASM x Failure ratio | | | | | 7.313 (3.25)*** | 7.115 (3.14)*** |
| US make x Failure ratio | | | | | -0.847 (0.39) | -0.830 (0.38) |
| Mileage x Failure ratio | | | | | 5.046 (2.77)*** | 4.482 (2.44)** |
| Observations | 342240 | 342240 | 342240 | 342240 | 342240 | 342240 |
| Log Pseudo likelihood | -2732.34 | -2728.45 | -2009.28 | -2008.88 | -1977.89 | -1973.77 |
| Wald Chi2 | 496.03 | 507.54 | 693.67 | 694.69 | 776.04 | 794.99 |
| DoF | 16.00 | 18.00 | 19.00 | 20.00 | 30.00 | 36.00 |
| Pseudo R2 | 0.11 | 0.11 | 0.35 | 0.35 | 0.36 | 0.36 |

Table 3.7.2 Conditional logit models of the odds of a station being chosen:
using the partial sample with the choice set of 736 stations

| Independent Variables | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---------------------|---------------------|----------------------|----------------------|----------------------|---------------------|
| <u>Station characteristics</u> | | | | | | |
| <i>False pass ratio</i> | 0.399 (0.65) | 0.860 (0.72) | 0.705 (0.57) | 0.701 (0.57) | -0.042 (0.00) | -4.867 (0.52) |
| Failure ratio | -1.178 (0.90) | -5.684 (2.49)** | -3.382 (1.43) | -3.264 (1.37) | -66.602 (3.00)*** | -49.565 (2.17)** |
| Ln(Total tests) | 0.926 (14.18)*** | 0.944 (14.14)*** | 0.877 (13.76)*** | 0.876 (13.73)*** | 0.902 (14.05)*** | 0.906 (14.04)*** |
| Average daily test per inspector | 0.002 (0.12) | 0.000 (0.01) | 0.023 (1.14) | 0.023 (1.15) | 0.021 (1.01) | 0.020 (0.96) |
| No repair | 0.062 (0.57) | 0.060 (0.54) | 0.130 (1.16) | 0.130 (1.17) | 0.150 (1.34) | 0.162 (1.44) |
| Chain store | -0.008 (0.06) | 0.001 (0.01) | -0.017 (0.13) | -0.018 (0.14) | -0.024 (0.19) | -0.025 (0.19) |
| Total stores in chain | 0.007 (1.18) | 0.005 (0.90) | 0.004 (0.72) | 0.004 (0.71) | 0.005 (0.80) | 0.005 (0.86) |
| Newness | 0.044 (0.81) | 0.055 (1.01) | 0.076 (1.44) | 0.077 (1.46) | 0.071 (1.33) | 0.069 (1.29) |
| Min test fee (US\$) | -0.029 (2.53)** | -0.027 (2.35)** | -0.021 (1.71)* | -0.021 (1.70)* | -0.021 (1.68)* | -0.021 (1.73)* |
| Mean age of vehicle | -0.068 (0.86) | -0.047 (0.60) | -0.187 (2.32)** | -0.192 (2.35)** | -0.215 (2.71)*** | -0.215 (2.70)*** |
| Share of cars | 3.248 (5.04)*** | 3.580 (5.50)*** | -0.610 (0.83) | -0.720 (0.98) | -0.587 (0.84) | -0.571 (0.81) |
| Share US make vehicle | -0.858 (2.42)** | -0.679 (1.94)* | -1.192 (2.98)*** | -1.175 (2.93)*** | -1.207 (3.10)*** | -1.186 (3.05)*** |
| Share of ASM test | 0.467 (0.64) | 0.168 (0.23) | 1.332 (1.82)* | 1.366 (1.86)* | 2.031 (2.88)*** | 2.100 (2.94)*** |
| Open on Saturday | -0.091 (0.44) | -0.067 (0.32) | 0.005 (0.02) | 0.007 (0.03) | -0.012 (0.06) | -0.016 (0.08) |
| Open on Sunday | 0.063 (0.57) | 0.036 (0.33) | -0.008 (0.07) | -0.009 (0.08) | -0.031 (0.28) | -0.039 (0.35) |
| Station density around the station (2 mile radius) | -0.001 (0.10) | -0.030 (0.76) | -0.044 (1.14) | -0.046 (1.17) | -0.039 (1.09) | -0.038 (1.03) |
| Station density around the station x <i>False pass ratio</i> | | -0.059 (0.55) | 0.001 (0.01) | 0.003 (0.03) | -0.003 (0.03) | -0.000 (0.00) |
| Station density around the station x Failure ratio | | 0.492 (2.49)** | 0.331 (1.62) | 0.326 (1.60) | 0.311 (1.52) | 0.292 (1.48) |
| <u>Motorist characteristics</u> | | | | | | |
| Distance from house (mile) | | | -0.318 (16.95)*** | -0.313 (15.93)*** | -1.400 (3.16)*** | -1.386 (3.16)*** |
| Distance from work (mile) | | | | -0.012 (0.76) | | |
| Distance from house x Ln(Mileage) | | | | | 0.088 (2.32)** | 0.087 (2.31)** |
| Distance from house x <i>False pass odds ratio</i> | | | | | 0.105 (0.65) | 0.085 (0.52) |
| Distance from house x Failure ratio | | | | | 0.219 (0.58) | 0.288 (0.79) |
| Household income x <i>False pass ratio</i> | | | | | | 0.017 (0.89) |

Table 3.7.2 Cont.

| Independent Variables | (7) | (8) | (9) | (10) | (11) | (12) |
|---------------------------------------|----------|----------|----------|----------|--------------------|---------------------|
| Black x <i>False pass ratio</i> | | | | | | -0.294 (0.20) |
| White x <i>False pass ratio</i> | | | | | | 1.225 (0.90) |
| Household Income x Failure ratio | | | | | | -0.027 (0.68) |
| Black x Failure ratio | | | | | | -2.684 (0.83) |
| White x Failure ratio | | | | | | -8.108 (2.65)*** |
| <u>Vehicle characteristics</u> | | | | | | |
| Car x <i>False pass ratio</i> | | | | | 1.987 (1.68)* | 2.326 (1.92)* |
| ASM x <i>False pass ratio</i> | | | | | 2.531 (2.31)** | 2.703 (2.40)** |
| US maker x <i>False pass ratio</i> | | | | | 2.551 (2.32)** | 2.545 (2.35)** |
| Mileage x <i>False pass ratio</i> | | | | | -0.329 (0.40) | -0.071 (0.08) |
| Car x Failure ratio | | | | | -1.765 (0.63) | -3.092 (1.07) |
| ASM x Failure ratio | | | | | 5.747 (2.38)** | 5.361 (2.19)** |
| US make x Failure ratio | | | | | -2.612 (1.08) | -2.694 (1.11) |
| Mileage x Failure ratio | | | | | 5.319 (2.65)*** | 4.505 (2.22)** |
| Observations | 342240 | 342240 | 342240 | 342240 | 342240 | 342240 |
| Log Pseudo likelihood | -2732.17 | -2728.36 | -2008.83 | -2008.41 | -1974.00 | -1969.13 |
| Wald Chi2 | 507.97 | 518.21 | 701.17 | 701.96 | 784.66 | 790.20 |
| DoF | 16.00 | 18.00 | 19.00 | 20.00 | 30.00 | 36.00 |
| Pseudo R2 | 0.11 | 0.11 | 0.35 | 0.35 | 0.36 | 0.36 |

Table 3.8.1 and 3.8.2 show the estimations of the conditional logit models from the full samples (A and B), using only the ten alternatives of the inspection stations (choice set = 10) due to the computational limitation. These choice sets are randomly drawn from the population of the inspection stations (736) and assigned to each individual vehicle including the station actually selected. In these full samples, the information about the station and vehicle attributes is available without the motorist characteristic information, except the distance from the motorist's house to the inspection station.

Similar to the partial sample, Tables 3.8.1 and 3.8.2 are different in only one independent variable measuring the leniency of the inspection station: *false pass odds* and *false pass ratio*. The model pairs (1) – (4), (2) – (5), and (3) – (6) are of the same specifications for the comparison of estimates from the two different samples. The results show that the estimates from the full sample A are not vastly different from those from the full sample B. Models (1) to (6) which include the station and vehicle characteristics can explain the variability of the outcome 26 to 28 percent (pseudo R squared). Adding the *distance from house* variable and its interaction terms in model (7) considerably improves the explanatory power of the model (pseudo R squared = 65). Likewise, the nested likelihood ratio test (models (6) and (7)) shows the consistent results that LR chi squared is significantly large (LR = 104474.23 and p-value = 0 for Table 3.8.1; LR = 104456.64 and p-value = 0 for Table 3.8.2).

Tables 3.9.1 and 3.9.2 are the estimates from the partial sample, which are used to compare with the results from Tables 3.8.1 and 3.8.2, respectively. Accordingly, models (8), (9), and (12) in Tables 3.8.1 and 3.8.2 are the same as the models (7), (8), and (12) in Tables 3.7.1 and 3.7.2, respectively. In general, the estimates from the full and partial samples are similar both in terms of the direction (sign) and the effect sizes, except for some few variables.

Table 3.8.1 Conditional logit models of the odds of a station being chosen using the full A and B samples

| Independent Variables | Full A Sample | | | Full B Sample | | | |
|----------------------------------|--------------------------|----------------------|-----------------------|--------------------------|----------------------|-----------------------|----------------------|
| | Choice Set = 10 Stations | | | Choice Set = 10 Stations | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| <u>Station characteristics</u> | | | | | | | |
| <i>False pass odds</i> | -0.055 (3.09)*** | -0.180 (6.51)*** | -1.657 (6.20)*** | -0.039 (1.88)* | -0.172 (5.46)*** | -1.608 (5.23)*** | -1.524 (4.43)*** |
| Failure ratio | -0.688 (4.53)*** | -1.193 (5.22)*** | -32.732 (12.69)*** | -0.479 (2.74)*** | -0.735 (2.81)*** | -32.692 (10.72)*** | -24.647 (6.50)*** |
| Ln(Total tests) | 1.008 (139.98)*** | 1.012 (139.91)*** | 1.011 (139.32)*** | 1.018 (122.60)*** | 1.021 (122.54)*** | 1.020 (122.03)*** | 0.929 (88.06)*** |
| Average daily test per inspector | -0.017 (7.79)*** | -0.016 (7.66)*** | -0.017 (7.75)*** | -0.019 (7.64)*** | -0.018 (7.50)*** | -0.019 (7.65)*** | -0.006 (1.70)* |
| No repair | 0.033 (2.76)*** | 0.030 (2.52)** | 0.046 (3.80)*** | 0.036 (2.61)*** | 0.033 (2.44)** | 0.049 (3.55)*** | 0.083 (4.61)*** |
| Chain store | -0.027 (1.99)** | -0.026 (1.88)* | -0.028 (2.03)** | -0.047 (2.96)*** | -0.045 (2.87)*** | -0.048 (3.01)*** | -0.059 (2.82)*** |
| Total stores in chain | 0.004 (6.75)*** | 0.004 (6.30)*** | 0.004 (6.53)*** | 0.005 (7.57)*** | 0.005 (7.26)*** | 0.005 (7.28)*** | 0.004 (4.53)*** |
| Newness | 0.015 (2.49)** | 0.018 (2.96)*** | 0.017 (2.91)*** | 0.013 (1.86)* | 0.015 (2.18)** | 0.015 (2.19)** | 0.009 (1.00) |
| Min test fee (US\$) | -0.004 (2.99)*** | -0.004 (2.71)*** | -0.004 (2.57)** | -0.005 (3.23)*** | -0.005 (3.05)*** | -0.005 (2.81)*** | -0.003 (1.41) |
| Mean age of vehicle | -0.103 (10.64)*** | -0.096 (10.14)*** | -0.091 (9.31)*** | -0.118 (10.58)*** | -0.112 (10.23)*** | -0.107 (9.51)*** | -0.105 (7.54)*** |
| Share of cars | -0.266 (3.40)*** | -0.214 (2.71)*** | -0.242 (3.06)*** | -0.483 (5.41)*** | -0.442 (4.92)*** | -0.461 (5.15)*** | -0.302 (2.52)** |
| Share US make vehicle | -0.272 (5.70)*** | -0.235 (4.89)*** | -0.193 (3.99)*** | -0.306 (5.55)*** | -0.277 (4.98)*** | -0.221 (3.95)*** | -0.202 (2.86)*** |
| Share of ASM test | 0.635 (7.89)*** | 0.563 (6.98)*** | 1.027 (12.77)*** | 0.852 (9.15)*** | 0.797 (8.53)*** | 1.243 (13.34)*** | 1.195 (10.28)*** |
| Open on Saturday | 0.084 (4.06)*** | 0.078 (3.79)*** | 0.074 (3.54)*** | 0.080 (3.40)*** | 0.073 (3.08)*** | 0.066 (2.78)*** | 0.099 (3.20)*** |
| Open on Sunday | -0.026 (2.11)** | -0.032 (2.59)*** | -0.039 (3.13)*** | -0.010 (0.72) | -0.015 (1.04) | -0.022 (1.51) | -0.045 (2.45)** |

Table 3.8.1 Cont.

| Independent Variables | Full A Sample Choice Set = 10 Stations | | | Full B Sample Choice Set = 10 Stations | | | |
|--|---|----------------------------------|---------------------------------|---|----------------------------------|---------------------------------|---------------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Station density around the station (2 mile radius) | -0.010 (10.13) ^{***} | -0.028 (11.58) ^{***} | -0.022 (9.38) ^{***} | -0.014 (12.20) ^{***} | -0.029 (10.53) ^{***} | -0.023 (8.53) ^{***} | -0.012 (3.86) ^{***} |
| Station density around the station x <i>False pass odds</i> | | 0.011 (5.22) ^{***} | -0.001 (0.28) | | 0.012 (4.90) ^{***} | -0.000 (0.08) | -0.004 (1.29) |
| Station density around the station x Failure ratio | | 0.068 (3.40) ^{***} | 0.118 (5.81) ^{***} | | 0.039 (1.68) [*] | 0.091 (3.81) ^{***} | 0.090 (3.20) ^{***} |
| <u>Vehicle characteristics</u> | | | | | | | |
| Car x <i>False pass odds</i> | | | 0.042 (2.06) ^{**} | | | 0.089 (3.69) ^{***} | 0.104 (2.99) ^{***} |
| ASM x <i>False pass odds</i> | | | 0.487 (11.16) ^{***} | | | 0.542 (10.00) ^{***} | 0.421 (6.60) ^{***} |
| US maker x <i>False pass odds</i> | | | 0.267 (9.00) ^{***} | | | 0.287 (8.15) ^{***} | 0.261 (6.82) ^{***} |
| Mileage x <i>False pass odds</i> | | | 0.089 (3.74) ^{***} | | | 0.077 (2.83) ^{***} | 0.090 (2.98) ^{***} |
| Car x Failure ratio | | | 0.262 (1.09) | | | 0.119 (0.43) | -0.619 (1.69) [*] |
| ASM x Failure ratio | | | 7.365 (26.65) ^{***} | | | 6.716 (20.52) ^{***} | 8.585 (20.98) ^{***} |
| US make x Failure ratio | | | 2.335 (9.35) ^{***} | | | 2.229 (7.69) ^{***} | 1.137 (3.18) ^{***} |
| Mileage x Failure ratio | | | 2.251 (9.92) ^{***} | | | 2.326 (8.68) ^{***} | 1.612 (4.85) ^{***} |

Table 3.8.1 Cont.

| Independent Variables | Full A Sample Choice Set = 10 Stations | | | Full B Sample Choice Set = 10 Stations | | | |
|---|---|-----------|-----------|---|-----------|-----------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| <u>Motorists characteristics</u> | | | | | | | |
| Distance from house (mile) | | | | | | | -0.361 (10.10)*** |
| Distance from house x Ln(Mileage) | | | | | | | 0.014 (4.63)*** |
| Distance from house x <i>False pass odds</i> | | | | | | | -0.005 (2.67)*** |
| Distance from house x Failure ratio | | | | | | | 0.024 (1.61) |
| Observations | 517090 | 517090 | 517090 | 394890 | 394890 | 394890 | 394890 |
| Log Pseudo likelihood | -87720.46 | -87684.42 | -85906.55 | -66439.98 | -66417.71 | -65156.59 | -32243.35 |
| Wald Chi2 | 40058.73 | 39978.07 | 42993.05 | 31106.90 | 31056.20 | 33320.31 | 29595.93 |
| DoF | 16.00 | 18.00 | 26.00 | 16.00 | 18.00 | 26.00 | 30.00 |
| Pseudo R2 | 0.26 | 0.26 | 0.28 | 0.27 | 0.27 | 0.28 | 0.65 |

Table 3.8.2 Conditional logit models of the odds of a station being chosen using the full A and B samples

| Independent Variables | Full A Sample | | | Full B Sample | | | |
|----------------------------------|--------------------------|----------------------|-----------------------|--------------------------|----------------------|----------------------|----------------------|
| | Choice Set = 10 Stations | | | Choice Set = 10 Stations | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| <u>Station characteristics</u> | | | | | | | |
| <i>False pass ratio</i> | -0.249 (3.80)*** | -0.716 (6.10)*** | -11.283 (10.26)*** | -0.231 (3.06)*** | -0.751 (5.55)*** | -10.531 (9.01)*** | -13.379 (8.07)*** |
| Failure ratio | -0.637 (4.19)*** | -1.017 (4.18)*** | -24.555 (8.81)*** | -0.431 (2.45)** | -0.533 (1.90)* | -25.564 (7.87)*** | -13.781 (3.33)*** |
| Ln(Total tests) | 1.010 (140.91)*** | 1.015 (140.59)*** | 1.023 (140.27)*** | 1.020 (123.35)*** | 1.024 (123.02)*** | 1.033 (122.98)*** | 0.941 (88.98)*** |
| Average daily test per inspector | -0.017 (7.85)*** | -0.017 (7.69)*** | -0.017 (7.79)*** | -0.019 (7.69)*** | -0.019 (7.53)*** | -0.019 (7.75)*** | -0.005 (1.54) |
| No repair | 0.034 (2.86)*** | 0.030 (2.49)** | 0.036 (2.98)*** | 0.037 (2.72)*** | 0.033 (2.41)** | 0.039 (2.79)*** | 0.067 (3.75)*** |
| Chain store | -0.029 (2.09)** | -0.028 (2.01)** | -0.032 (2.30)** | -0.048 (3.04)*** | -0.047 (2.98)*** | -0.052 (3.25)*** | -0.060 (2.86)*** |
| Total stores in chain | 0.004 (6.90)*** | 0.004 (6.40)*** | 0.004 (7.13)*** | 0.005 (7.65)*** | 0.005 (7.32)*** | 0.006 (7.78)*** | 0.004 (5.01)*** |
| Newness | 0.015 (2.49)** | 0.018 (3.07)*** | 0.019 (3.20)*** | 0.013 (1.89)* | 0.016 (2.34)** | 0.017 (2.49)** | 0.010 (1.14) |
| Min test fee (US\$) | -0.004 (2.93)*** | -0.004 (2.64)*** | -0.004 (2.92)*** | -0.005 (3.14)*** | -0.005 (2.96)*** | -0.005 (3.05)*** | -0.004 (1.77)* |
| Mean age of vehicle | -0.105 (11.34)*** | -0.104 (11.19)*** | -0.135 (14.45)*** | -0.117 (10.92)*** | -0.117 (10.90)*** | -0.149 (13.85)*** | -0.156 (11.71)*** |
| Share of cars | -0.279 (3.57)*** | -0.246 (3.11)*** | -0.277 (3.54)*** | -0.486 (5.45)*** | -0.465 (5.17)*** | -0.484 (5.45)*** | -0.294 (2.46)** |
| Share US make vehicle | -0.273 (5.69)*** | -0.245 (5.07)*** | -0.236 (4.97)*** | -0.301 (5.42)*** | -0.279 (5.00)*** | -0.255 (4.64)*** | -0.220 (3.16)*** |
| Share of ASM test | 0.683 (8.66)*** | 0.640 (8.08)*** | 1.318 (16.75)*** | 0.884 (9.66)*** | 0.859 (9.35)*** | 1.525 (16.70)*** | 1.495 (13.11)*** |
| Open on Saturday | 0.083 (4.02)*** | 0.079 (3.82)*** | 0.083 (3.99)*** | 0.079 (3.32)*** | 0.073 (3.07)*** | 0.075 (3.16)*** | 0.101 (3.26)*** |
| Open on Sunday | -0.029 (2.31)** | -0.034 (2.78)*** | -0.035 (2.82)*** | -0.013 (0.89) | -0.017 (1.20) | -0.018 (1.23) | -0.038 (2.06)** |

Table 3.8.2 Cont.

| Independent Variables | Full A Sample Choice Set = 10 Stations | | | Full B Sample Choice Set = 10 Stations | | | |
|--|---|---------------------|----------------------|---|---------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Station density around the station (2 mile radius) | -0.010 (10.14)*** | -0.039 (9.36)*** | -0.039 (10.04)*** | -0.014 (12.17)*** | -0.042 (8.78)*** | -0.041 (9.32)*** | -0.025 (4.95)*** |
| Station density around the station x <i>False pass odds</i> | | 0.053 (4.56)*** | 0.055 (5.05)*** | | 0.060 (4.47)*** | 0.061 (4.84)*** | 0.041 (2.79)*** |
| Station density around the station x Failure ratio | | 0.050 (2.20)** | 0.040 (1.70)* | | 0.017 (0.65) | 0.006 (0.23) | 0.012 (0.37) |
| <u>Vehicle characteristics</u> | | | | | | | |
| Car x <i>False pass ratio</i> | | | -0.114 (0.90) | | | 0.063 (0.43) | 0.083 (0.47) |
| ASM x <i>False pass ratio</i> | | | 2.815 (23.26)*** | | | 3.123 (22.85)*** | 2.857 (16.75)*** |
| US maker x <i>False pass ratio</i> | | | 1.129 (9.30)*** | | | 1.252 (8.84)*** | 1.314 (7.69)*** |
| Mileage x <i>False pass ratio</i> | | | 0.762 (7.87)*** | | | 0.658 (6.43)*** | 0.961 (6.63)*** |
| Car x Failure ratio | | | 0.569 (2.06)** | | | 0.422 (1.33) | -0.278 (0.69) |
| ASM x Failure ratio | | | 6.048 (22.31)*** | | | 5.249 (16.89)*** | 6.989 (17.71)*** |
| US make x Failure ratio | | | 2.029 (7.57)*** | | | 1.877 (6.10)*** | 0.583 (1.51) |
| Mileage x Failure ratio | | | 1.647 (6.73)*** | | | 1.828 (6.43)*** | 0.814 (2.24)** |

Table 3.8.2 Cont.

| Independent Variables | Full A Sample Choice Set = 10 Stations | | | Full B Sample Choice Set = 10 Stations | | | |
|--|---|-----------|-----------|---|-----------|-----------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| <u>Motorists characteristics</u> | | | | | | | |
| Distance from house (mile) | | | - | | | | -0.360 (10.10)*** |
| Distance from house x Ln(Mileage) | | | | | | | -0.008 (1.47) |
| Distance from house x <i>False pass ratio</i> | | | | | | | 0.015 (0.94) |
| Distance from house x Failure ratio | | | | | | | 0.014 (4.63)*** |
| Observations | 517090 | 517090 | 517090 | 394890 | 394890 | 394890 | 394890 |
| Log Pseudo likelihood | -87721.75 | -87689.47 | -85755.14 | -66438.81 | -66418.83 | -65029.58 | -32145.66 |
| Wald Chi2 | 40137.43 | 40009.94 | 43450.89 | 31132.22 | 31032.83 | 33710.83 | 29757.19 |
| DoF | 16.00 | 18.00 | 26.00 | 16.00 | 18.00 | 26.00 | 30.00 |
| Pseudo R2 | 0.26 | 0.26 | 0.28 | 0.27 | 0.27 | 0.28 | 0.65 |

Table 3.9.1 Conditional logit models of the odds of a station being chosen using the partial sample

| Independent Variables | Partial Sample | | | | |
|--|---------------------------|---------------------|----------------------|----------------------|----------------------|
| | Choice Set = 736 Stations | | | | |
| | (8) | (9) | (10) | (11) | (12) |
| <u>Station characteristics</u> | | | | | |
| <i>False pass odds</i> | -0.008 (0.11) | 0.090 (0.38) | -0.164 (0.17) | -0.255 (0.26) | -0.643 (0.77) |
| Failure ratio | -1.085 (0.84) | -5.419 (2.59)*** | -81.728 (3.49)*** | -67.334 (3.32)*** | -54.656 (2.60)*** |
| Ln(Total tests) | 0.926 (14.22)*** | 0.944 (14.20)*** | 0.944 (14.10)*** | 0.888 (13.89)*** | 0.888 (13.88)*** |
| Average daily test per inspector | 0.002 (0.12) | 0.000 (0.01) | -0.001 (0.05) | 0.020 (0.99) | 0.019 (0.94) |
| No repair | 0.069 (0.63) | 0.064 (0.58) | 0.085 (0.76) | 0.178 (1.60) | 0.190 (1.69)* |
| Chain store | -0.010 (0.08) | -0.002 (0.01) | -0.007 (0.05) | -0.026 (0.20) | -0.024 (0.19) |
| Total stores in chain | 0.007 (1.20) | 0.005 (0.90) | 0.006 (0.92) | 0.004 (0.71) | 0.004 (0.73) |
| Newness | 0.046 (0.84) | 0.057 (1.05) | 0.057 (1.05) | 0.072 (1.33) | 0.071 (1.31) |
| Min test fee (US\$) | -0.029 (2.49)** | -0.027 (2.30)** | -0.027 (2.34)** | -0.019 (1.55) | -0.019 (1.55) |
| Mean age of vehicle | -0.048 (0.63) | -0.031 (0.41) | -0.019 (0.24) | -0.157 (1.86)* | -0.154 (1.79)* |
| Share of cars | 3.267 (5.06)*** | 3.609 (5.51)*** | 3.559 (5.41)*** | -0.656 (0.95) | -0.651 (0.94) |
| Share US make vehicle | -0.812 (2.24)** | -0.635 (1.78)* | -0.566 (1.60) | -1.159 (2.83)*** | -1.141 (2.76)*** |
| Share of ASM test | 0.439 (0.60) | 0.153 (0.20) | 0.685 (0.93) | 1.830 (2.49)** | 1.911 (2.55)** |
| Open on Saturday | -0.096 (0.47) | -0.071 (0.34) | -0.078 (0.38) | -0.009 (0.04) | -0.011 (0.05) |
| Open on Sunday | 0.056 (0.51) | 0.030 (0.28) | 0.014 (0.13) | -0.047 (0.42) | -0.054 (0.49) |
| Station density around the station (2 mile radius) | -0.000 (0.06) | -0.045 (2.06)** | -0.037 (1.80)* | -0.035 (1.59) | -0.030 (1.35) |
| Station density around the station x <i>False pass odds</i> | | -0.010 (0.50) | -0.023 (1.17) | -0.013 (0.70) | -0.019 (0.85) |
| Station density around the station x Failure ratio | | 0.469 (2.70)*** | 0.517 (3.08)*** | 0.374 (2.15)** | 0.381 (2.14)** |
| <u>Vehicle characteristics</u> | | | | | |
| Car x <i>False pass odds</i> | | | 0.214 (0.92) | 0.197 (0.90) | 0.228 (1.00) |
| ASM x <i>False pass odds</i> | | | 0.410 (1.36) | 0.328 (1.17) | 0.335 (1.19) |
| US maker x <i>False pass odds</i> | | | 0.394 (1.92)* | 0.306 (1.75)* | 0.287 (1.77)* |
| Mileage x <i>False pass odds</i> | | | -0.033 (0.37) | -0.019 (0.21) | -0.002 (0.03) |
| Car x Failure ratio | | | 1.146 (0.46) | -0.163 (0.06) | -1.154 (0.44) |

Table 3.9.1 Cont.

| Independent Variables | Partial Sample Choice Set = 736 Stations | | | | |
|---|---|----------|--------------------|---------------------|---------------------|
| | (8) | (9) | (10) | (11) | (12) |
| <u>Vehicle characteristics</u> | | | | | |
| ASM x Failure ratio | | | 7.155 (3.07)*** | 7.313 (3.25)*** | 7.115 (3.14)*** |
| US make x Failure ratio | | | -0.068 (0.03) | -0.847 (0.39) | -0.830 (0.38) |
| Mileage x Failure ratio | | | 6.181 (2.97)*** | 5.046 (2.77)*** | 4.482 (2.44)** |
| <u>Motorists characteristics</u> | | | | | |
| Distance from house (mile) | | | | -1.375 (3.16)*** | -1.368 (3.16)*** |
| Distance from house x Ln(Mileage) | | | | 0.088 (2.33)** | 0.087 (2.32)** |
| Distance from house x <i>False pass odds</i> | | | | 0.008 (0.65) | 0.007 (0.56) |
| Distance from house x Failure ratio | | | | 0.309 (1.00) | 0.355 (1.18) |
| Household income x <i>False pass odds</i> | | | | | 0.002 (0.68) |
| Black x <i>False pass odds</i> | | | | | -0.001 (0.00) |
| White x <i>False pass odds</i> | | | | | 0.212 (0.86) |
| Household Income x Failure ratio | | | | | -0.014 (0.41) |
| Black x Failure ratio | | | | | -3.032 (0.98) |
| White x Failure ratio | | | | | -7.480 (2.61)*** |
| Observations | 342240 | 342240 | 342240 | 342240 | 342240 |
| Log Pseudo likelihood | -2732.34 | -2728.45 | -2699.99 | -1977.89 | -1973.77 |
| Wald Chi2 | 496.03 | 507.54 | 601.77 | 776.04 | 794.99 |
| DoF | 16.00 | 18.00 | 26.00 | 30.00 | 36.00 |
| Pseudo R2 | 0.11 | 0.11 | 0.12 | 0.36 | 0.36 |

Table 3.9.2 Conditional logit models of the odds of a station being chosen using the partial sample

| Independent Variables | Partial Sample Choice Set = 736 Stations | | | | |
|---|---|---------------------|----------------------|----------------------|---------------------|
| | (8) | (9) | (10) | (11) | (12) |
| <u>Station characteristics</u> | | | | | |
| <i>False pass ratio</i> | 0.399 (0.65) | 0.860 (0.72) | 1.929 (0.24) | -0.042 (0.00) | -4.867 (0.52) |
| Failure ratio | -1.178 (0.90) | -5.684 (2.49)** | -82.963 (3.40)*** | -66.602 (3.00)*** | -49.565 (2.17)** |
| Ln(Total tests) | 0.926 (14.18)*** | 0.944 (14.14)*** | 0.960 (14.22)*** | 0.902 (14.05)*** | 0.906 (14.04)*** |
| Average daily test per inspector | 0.002 (0.12) | 0.000 (0.01) | -0.002 (0.08) | 0.021 (1.01) | 0.020 (0.96) |
| No repair | 0.062 (0.57) | 0.060 (0.54) | 0.068 (0.61) | 0.150 (1.34) | 0.162 (1.44) |
| Chain store | -0.008 (0.06) | 0.001 (0.01) | -0.010 (0.07) | -0.024 (0.19) | -0.025 (0.19) |
| Total stores in chain | 0.007 (1.18) | 0.005 (0.90) | 0.006 (1.03) | 0.005 (0.80) | 0.005 (0.86) |
| Newness | 0.044 (0.81) | 0.055 (1.01) | 0.054 (1.00) | 0.071 (1.33) | 0.069 (1.29) |
| Min test fee (US\$) | -0.029 (2.53)** | -0.027 (2.35)** | -0.028 (2.47)** | -0.021 (1.68)* | -0.021 (1.73)* |
| Mean age of vehicle | -0.068 (0.86) | -0.047 (0.60) | -0.078 (1.01) | -0.215 (2.71)*** | -0.215 (2.70)*** |
| Share of cars | 3.248 (5.04)*** | 3.580 (5.50)*** | 3.536 (5.49)*** | -0.587 (0.84) | -0.571 (0.81) |
| Share US make vehicle | -0.858 (2.42)** | -0.679 (1.94)* | -0.652 (1.92)* | -1.207 (3.10)*** | -1.186 (3.05)*** |
| Share of ASM test | 0.467 (0.64) | 0.168 (0.23) | 0.979 (1.37) | 2.031 (2.88)*** | 2.100 (2.94)*** |
| Open on Saturday | -0.091 (0.44) | -0.067 (0.32) | -0.070 (0.34) | -0.012 (0.06) | -0.016 (0.08) |
| Open on Sunday | 0.063 (0.57) | 0.036 (0.33) | 0.026 (0.23) | -0.031 (0.28) | -0.039 (0.35) |
| Station density around the station (2 mile radius) | -0.001 (0.10) | -0.030 (0.76) | -0.028 (0.80) | -0.039 (1.09) | -0.038 (1.03) |
| Station density around the station x <i>False pass ratio</i> | | -0.059 (0.55) | -0.060 (0.62) | -0.003 (0.03) | -0.000 (0.00) |
| Station density around the station x Failure ratio | | 0.492 (2.49)** | 0.488 (2.52)** | 0.311 (1.52) | 0.292 (1.48) |
| <u>Vehicle characteristics</u> | | | | | |
| Car x <i>False pass ratio</i> | | | 2.074 (1.73)* | 1.987 (1.68)* | 2.326 (1.92)* |
| ASM x <i>False pass ratio</i> | | | 2.851 (2.60)*** | 2.531 (2.31)** | 2.703 (2.40)** |
| US maker x <i>False pass ratio</i> | | | 2.975 (2.68)*** | 2.551 (2.32)** | 2.545 (2.35)** |
| Mileage x <i>False pass ratio</i> | | | -0.481 (0.66) | -0.329 (0.40) | -0.071 (0.08) |
| Car x Failure ratio | | | -0.400 (0.14) | -1.765 (0.63) | -3.092 (1.07) |

Table 3.9.2 Cont.

| Independent Variables | Partial Sample Choice Set = 736 Stations | | | | |
|--|---|----------|--------------------|---------------------|---------------------|
| | (8) | (9) | (10) | (11) | (12) |
| ASM x Failure ratio | | | 5.534 (2.28)** | 5.747 (2.38)** | 5.361 (2.19)** |
| US make x Failure ratio | | | -1.890 (0.79) | -2.612 (1.08) | -2.694 (1.11) |
| Mileage x Failure ratio | | | 6.561 (2.99)*** | 5.319 (2.65)*** | 4.505 (2.22)** |
| <u>Motorists characteristics</u> | | | | | |
| Distance from house (mile) | | | | -1.400 (3.16)*** | -1.386 (3.16)*** |
| Distance from house x Ln(Mileage) | | | | 0.088 (2.32)** | 0.087 (2.31)** |
| Distance from house x <i>False pass ratio</i> | | | | 0.105 (0.65) | 0.085 (0.52) |
| Distance from house x Failure ratio | | | | 0.219 (0.58) | 0.288 (0.79) |
| Household income x <i>False pass ratio</i> | | | | | 0.017 (0.89) |
| Black x <i>False pass ratio</i> | | | | | -0.294 (0.20) |
| White x <i>False pass ratio</i> | | | | | 1.225 (0.90) |
| Household Income x Failure ratio | | | | | -0.027 (0.68) |
| Black x Failure ratio | | | | | -2.684 (0.83) |
| White x Failure ratio | | | | | -8.108 (2.65)*** |
| Observations | 342240 | 342240 | 342240 | 342240 | 342240 |
| Log Pseudo likelihood | -2732.17 | -2728.36 | -2696.41 | -1974.00 | -1969.13 |
| Wald Chi2 | 507.97 | 518.21 | 603.98 | 784.66 | 790.20 |
| DoF | 16.00 | 18.00 | 26.00 | 30.00 | 36.00 |
| Pseudo R2 | 0.11 | 0.11 | 0.12 | 0.36 | 0.36 |

3.7.1.2 Effects of Station Characteristics

3.7.1.2.1 Leniency

The proxy variables of the inspection station's leniency are the *failure ratio*, *false pass odds* and *false pass ratio*. In both full and partial samples and across all the models, the main effects of the *failure ratio* are negatively associated with the probability of a station being chosen. While the main effects of the *failure ratio* in the full samples are always significant, the estimates of the *failure ratio* from the partial sample are not

significant in the models without its interaction with the *station density* variable (models (2) and (8) in Table 3.7.1 and 3.7.2 respectively). Furthermore, although models (3) and (4) in Table 3.7.1 and models (9) and (10) in Table 3.7.2 include the interaction terms of the *failure ratio*, adding the *distance from house to the station* takes away the main effect of the *failure ratio* (no longer significant). Holding other variables constant, the study can reject the null of the hypothesis 1.4 that the higher the *failure ratio*, the less likely that the station will be chosen.

In terms of the *false pass odds* and *ratio*, their main effects are quite similar across models and samples. Nevertheless, *false pass odds* may be superior to *false pass ratio* in terms of the specification because of its lower correlation with the *failure ratio* ($\rho_{\text{False Pass Odds}} = 0.35$ (p-value = 0); $\rho_{\text{False Pass Ratio}} = 0.51$ (p-value = 0)). Therefore, the following discussion will focus only on the specification including *the false pass odds*. The results from the full samples (both A and B) are consistent across the models in Tables 3.8.1 and 3.8.2. All else equal, the main effects of the *false pass odds* are significantly and negatively associated with the probability of an inspection station being chosen. In the partial sample, however, the main effects of this variable are not significant in all models (Tables 3.7.1, 3.7.2, 3.9.1, and 3.9.2). These findings fail to reject the null of the hypothesis 1.5 set forth in this study.

The study hypothesizes intuitively that the lower the *false pass odds*, the less likely the inspection station will be chosen, all else equal. However, the results from the full sample show a significantly opposite direction. The effects of the *false pass odds* seem to follow the effects of the *failure ratio*. This suggests the problem of multicollinearity even though the correlation is quite low ($\rho_{\text{False Pass Odds}} = 0.35$). Figure 3.1 plots the predicted false pass odds for the different types of the inspection stations as a function of the failure rate. As depicted, the positive association between these two

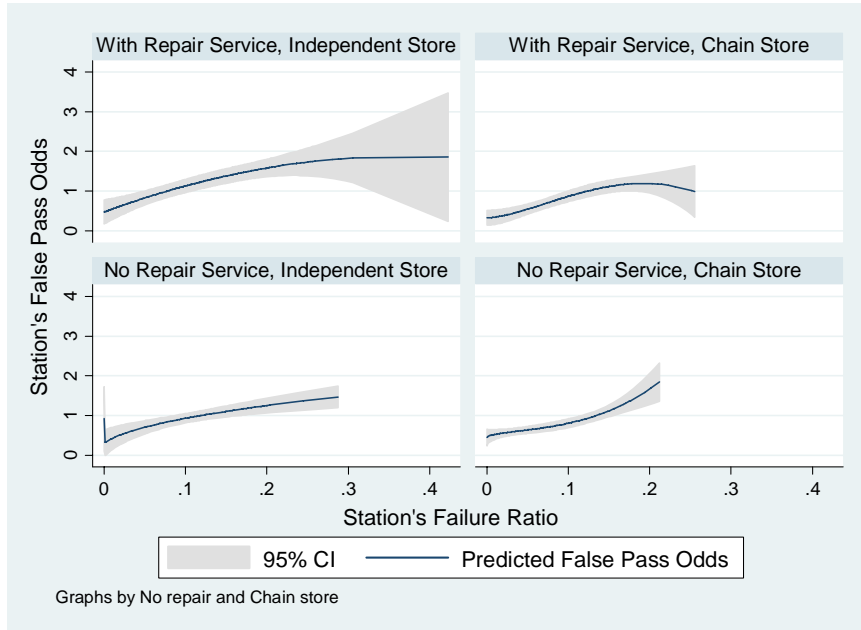


Figure 3.1 Predicted false pass odds of the inspection station as a function of its failure ratio for the different types of the stations

measures of the station's leniency is evident³⁷. In addition, the average *false pass odds* of all the stations is very close to one (mean = 0.95; median = 0.79; 75th percentile = 1.1), suggesting that, at most of the inspection stations, the probability of the true pass and false pass outcomes are almost equal³⁸. Because the estimates of the *false pass odds* show the wrong sign possibly due to the multicollinearity and other issues, the *false pass odds* (and also the *false pass ratio*) is not a proper proxy for the leniency of the inspection stations. For these reasons, the study will not further discuss both the main and interaction effects of the *false pass odds* and *ratios* in the conditional logit models.

³⁷ This research also estimates the models of the same specification shown in Tables 3.7.1, 3.8.1, and 3.9.1 using the false pass odds (or ratio) as the only measure of leniency (excluding the failure ratio). Again, the effects of the false pass odds (or ratio) are still significantly negative in the full samples and are not significant in the partial sample

³⁸ False pass odds of a station $i = \left(\frac{\text{Number of FalsePassVehicles}}{\text{Number of TruePassVehicles}} \right)_i$ In other words, the unconditional outcome of the false passing occurring at the inspection station may be probably by chance. The future study on this issue is necessary.

3.7.1.2.2 Competition

The geographical competition among the inspection stations is captured by the *station density*, defined by the number of the inspection stations surrounding the station of interest within the 2-mile radius. In the partial sample, the main effects of the *station density* are significantly negative when it also interacts with the *failure ratio* (models (2) and (3) in Tables 3.7.1 and models (9) and (10) in Table 3.9.1). In the full samples, the main effects of the *station density* are always significantly and negatively associated with the probability of a station being chosen, all else equal. In short, the higher the *station density*, the less likely that the station will be chosen.

The interaction effects between the *station density* and the *failure ratio* are also consistent across all models and samples; they are significantly positive, which suggests the degree of substitution between these two factors. The correlation between the *station density* and the *failure rate* are significantly negative but quite small ($\rho = -0.08$ (p -value = 0.04)). Figure 3.2 plots the relationship between the *station density* and the *failure ratio* of the different types of the inspection stations. As the *station density* increases, the *failure ratio* tends to drop greater (steeper slope) for the independent garages that offer both the inspection and repair services than those of the other three types of the inspection stations. On the other hand, for the chain inspection stations, the relationship between the *station density* and the *failure ratio* is ambiguous. Across all types of the inspection stations, the fitted values of the *failure ratio* are less certain when the station density is high (approximately greater than 15), as depicted by the wider 95 percent confident interval.

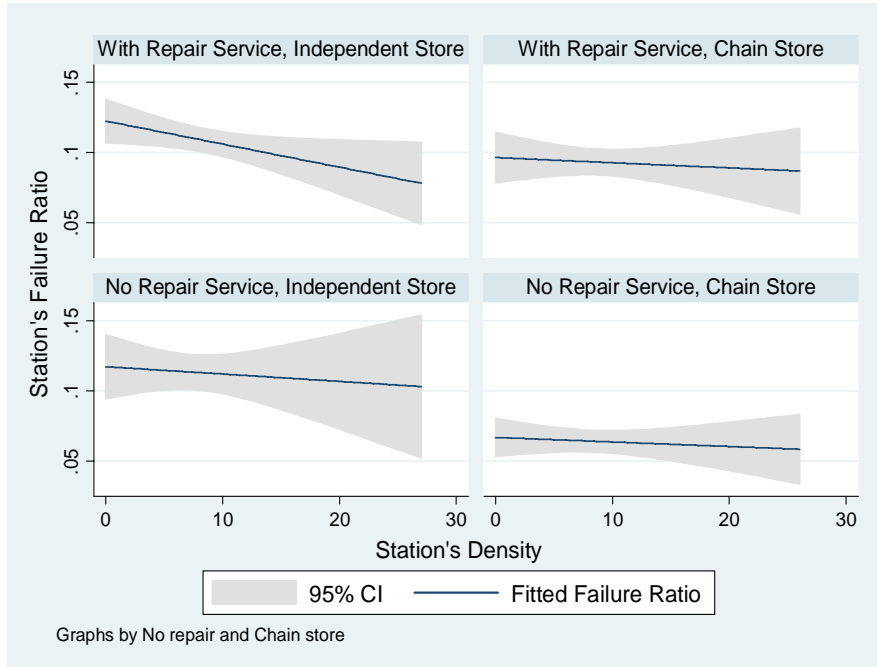


Figure 3.2 Fitted value of the failure ratio and the station density of the different types of the inspection station

The total effects³⁹ of the *station density* on the probability of a station being chosen are illustrated in Figure 3.3. The probability is calculated for the different value of the *failure ratio* when the other variables are set at their means. Overall, the higher the *station density*, the less likely the station will be chosen (probability drops from 0.48 to 0.36)⁴⁰. In addition, in the area of low *station density* (less than 15 stations), the inspection stations with the lower *failure ratio* are more likely to be chosen. On the other hand, when the *station density* is greater than 15, the inspection station with the lower *failure ratio* is slightly less likely to be chosen (probability decreases by 0.04 = 0.375 – 0.335). Thus, the reverse effect is not substantively significant.

³⁹ Total effects of Station density = Main effects + Interaction effects (with Failure ratio), which is calculated based on the restricted specification in Table 3.8.1.

⁴⁰ $0.48 = \frac{(0.50+0.48)}{2}$ when the station density = 0; $0.36 = \frac{(0.375+0.335)}{2}$ when the station density = 30.

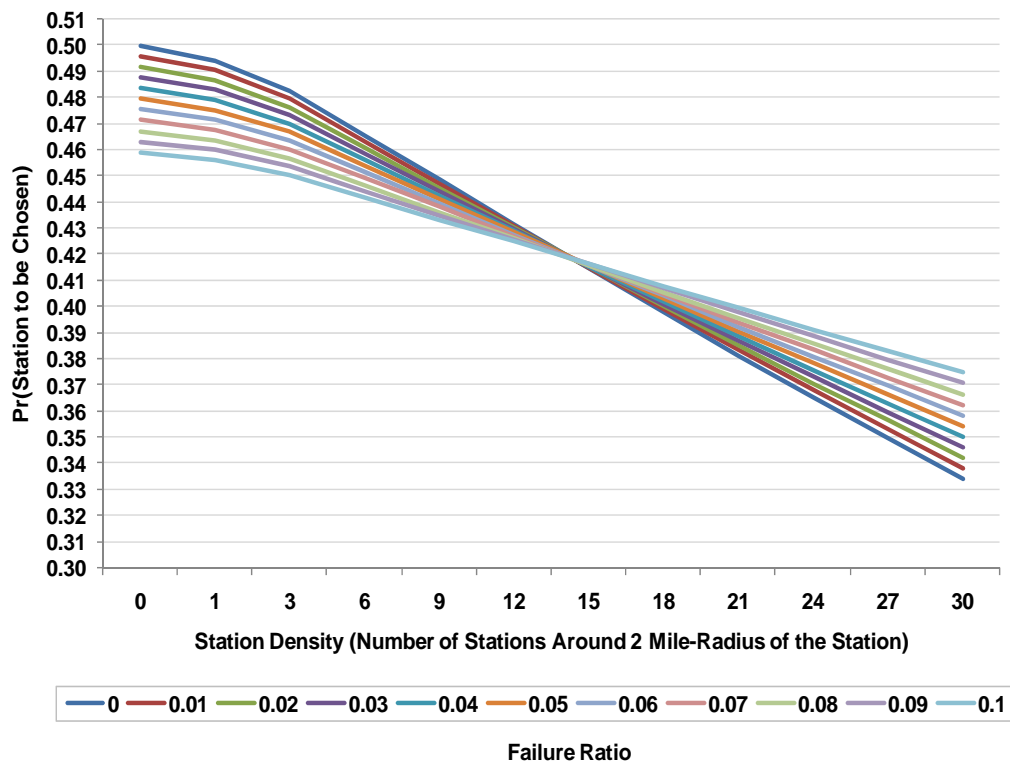


Figure 3.3 Total effects of station density on the probability of an inspection station being chosen, holding other variables constant at their means

3.7.1.2.3 Price

The *inspection fee* or price is one of the key factors determining the decision of the motorist customers to select their stations, according to the economic theory. As discussed earlier, the *minimum inspection fee* of each station is used in the estimation because of its adequate variability. The estimates of the *inspection fee* are consistent across all models without the interactions in the full and partial samples. The additional *minimum inspection fee* decreases significantly the probability of a station being chosen, holding other variables constant. The findings support the hypothesis 1.3.

3.7.1.2.4 Performance and Experience

The performance of the inspection stations is measured in two dimensions: the *total test*⁴¹ and the *average daily test per an inspector*. The experience of the inspection stations is represented by the *newness* and the *chain store* variables. The effects of the *total test* are positively and significantly strong across all the models and samples. The larger the total test, the more likely the station will be chosen. The large number of the tests performed at the stations reflects the capacity in terms of the inspectors and machines and probably the reputation or popularity of the stations.

The *average daily test per inspector* may involve the speed for each test. The large value of this variable might mean that the labor productivity is high, which can be desirable for the business owners. However, from the consumers' point of view, the higher the average daily test per inspector probably means the longer time that the motorists have to wait for the test and hence is undesirable for them. In the partial sample (Tables 3.7.1 and 3.9.1), the *average daily test per inspector* is not associated with the probability of a station being chosen. In contrast, the estimates from the full sample (Table 3.8.1) constantly show the significantly negative impact of the *average daily test per inspector* on the probability of a station being chosen. The greater the *average daily test per inspector*, the less likely the station will be chosen, all else equal.

The experience of the inspection station is measured indirectly by three variables: *newness*, *chain store*, and *total stores in the chain*. The *newness* variable is created from the station ID number which is unique and increasing overtime as the new inspection businesses request for the permission. The high value of this variable means the station is relatively new. From the partial sample (Tables 3.7.1 and 3.9.1), *newness*

⁴¹ The total test is transformed by the natural log.

is not associated with the probability of a station being chosen. On the other hand, in the full sample (Table 3.8.1), the newer the inspection station, the more likely the station will be chosen significantly.

In addition to a proxy of the experience, the *chain store* and *total stores in chain* can identify the business formation and possible size of the firms operating the inspection services. The estimations from the partial sample demonstrate that being a *chain store* and the *number of the branches* of the inspection firm are not associated with the probability of a station being chosen. In the full sample, however, the inspection stations that are part of the *chain* are less likely to be chosen. Accordingly, the probability of a station being chosen increases marginally as the *number of the stores in the chain* increase.

3.7.1.2.5 Services

As discussed earlier, the inspection stations may provide other automotive services in addition to the inspection. The lack of station information regarding its core business limits the detail classification of the organization that might suggest the related strategies of the firm. The crude classification of services is that the stations either offer the repair services or do not. The other aspect of the services is operating hours. Therefore, three aspects of inspection stations services include *no repair*, *open on Saturday*, and *open on Sunday*.

In the partial sample, all three dimensions of the services of the inspection stations are not associated with the probability of a station being chosen. On the contrary, in the full samples, the inspection stations offering *no repair* services are more likely to be chosen. Likewise, the inspection stations *open on Saturday* are more likely to be chosen. In comparison, in the full sample A, open on Sunday slightly decreases the

probability of a station being chosen but is not associated with the chance of being chosen in the full sample B.

3.7.1.2.6 Motorist' Segments

Similar to other types of business firms that try to serve customers of certain segments, inspection stations may target motorists indirectly via their vehicle attributes. In this study, the attributes of the vehicle groups that some inspection stations might target include the *mean age of the vehicles*, *share of cars*, *share of the US make* and *share of the ASM test required vehicles*.

In both the full and partial samples (Tables 3.7.1 and 3.8.1), the additional year of the *mean age of the vehicles* served by an inspection station decreases the probability of the station being chosen. Similarly, the greater the *share of the customers owning the US make vehicles*, the less likely the stations will be chosen. While the *share of the ASM required vehicles* is not associated with the probability of a station being chosen in the partial sample, the greater *share of the ASM tests* increases the probability in the full samples. The *shares of the motorists owning cars* show the opposite results from the partial and full samples in the models with the only station attributes. The estimates from the full samples indicate that the *higher shares of the motorists owning cars* in an inspection station decrease the probability of the station being chosen, all else equal.

3.7.1.3 Effects of Motorist Characteristics

3.7.1.3.1 Distance

The *distance from a motorist's house to the inspection station* is a proxy of the travel cost and time that determine the motorist's decision of selecting the station. The estimates of the *distance from the house* are available only from the partial sample and full sample B. The *distance from the house* shows the consistent effect in every model of

both samples (Tables 3.7.1 and 3.8.1). The additional miles of the *distance from the motorist's house* to the inspection station decreases the probability of the station being chosen, all else equal, suggesting that the null of hypothesis 1.1 is rejected.

The interaction effects between the *distance from the house* and the *mileage of the vehicle* are positively significant in both samples. The results suggest that the distance's negative effect on the odds of a station being selected is decreasing for the high mileage vehicle. In contrast, the interaction effects between the *distance from the house* and *the failure ratio* are not statistically significant across models and samples. These findings fail to reject the null of the hypothesis 2.1.

3.7.1.3.2 Socioeconomic and Demographic Groups

The effects of the motorist's characteristics on the probability of an inspection station being chosen exist only in the partial sample (Tables 3.7.1 and 3.9.1). Despite its insignificance, the interaction effect between the *household income* and the *failure ratio* show the negative sign. Compared to the *other ethnic group* (Latino, Asian, and native American), *white motorists* are likely to choose the inspection station with the significantly lower failure ratio, all else constant. On the other hand, there is no difference in the failure ratio of the inspection stations chosen by the *black* and the *other ethnic group motorists*.

3.7.1.4 Effects of Vehicle Characteristics

When motorists make the decision to select the inspection station, they might try to find the proper match between their vehicles and the specialty of the stations. The focus of this study, however, is the leniency as measured by the *failure ratio* of the station. As a result, all the vehicle characteristics are interacted with the *failure ratio*.

Across all the models and the three samples (Tables 3.7.1, 3.8.1, and 3.9.1), the effects of *car*, *ASM required vehicle*, and *mileage* are consistent. Cars and the other

types of vehicles (truck, van, and SUV) are tested at the inspection stations with a comparable level of the failure ratio. On the other hand, the *vehicles that require the ASM test* are more likely to be tested at the inspection stations with the higher *failure ratio* than those *requiring the TSI test*. Similarly, the *high mileage vehicles* are more likely to be tested at the inspection station with the *high failure ratio*, all else constant. This is not surprising because the descriptive statistics also show that the larger proportion of vehicles tested with ASM procedure fail the inspection more than those tested with TSI procedure. Likewise, vehicles failing the inspection have significantly higher mileage than those passing the inspection.

3.7.2 Logit Models: Probability of False Pass Outcome

The event of ‘false pass’ involves not only the vehicle receiving the test but also the inspection station (by the inspector) giving the test. This section explores the possible determinants of the false pass outcome at both the individual vehicle (unit of analysis is the vehicle) and inspection station levels (unit of analysis is the station).

3.7.2.1 Vehicle: Probability of Receiving the False Pass Outcome

To identify the factors affecting the probability of a vehicle receiving the *false pass outcome* from the station, the study analyzes the partial sample and the full sample B to incorporate the variables relating to the vehicles and motorists. The study uses the logit model shown in the equation 3.8.

$$\ln\left(\frac{\Pr(Y_m = 1)}{1 - \Pr(Y_m = 1)}\right) = \frac{\exp\left(\sum_{i=1}^l \beta X_i\right)}{1 + \exp\left(\sum_{i=1}^l \beta X_i\right)}, \quad i = 1, \dots, l \quad (3.8)$$

where $\Pr(Y_m = 1)$ is the probability of a vehicle receiving the false pass outcome ($Y_m = 1$)⁴². X_i is the vector of the independent variables, including the *vehicle*, *station*, and *motorist characteristics*.

The main variable of interest is the *distance to the station*. If the *distance to the station* has a significant effect on the probability of the vehicle falsely passing the test, then this might indirectly suggest that the motorists are willing to travel farther to receive the false pass results. This also implies that the lenient stations in these samples may be located separately from the motorists' houses so that the motorists who want to pass the test (regardless of the conditions of their vehicles) have to pay the 'extra' travel cost.

Finding no significant effect of the *distance to the station* means that (a) the motorists do not spend the 'extra' travel cost to receive the false pass results, (b) the lenient stations are not located in isolation from the motorists' houses, or (c) the false pass outcome is just random. If (b) is true, then (b) might lead to (a) because it is not necessary to seek out lenient services. The indirect way to test if (b) is true is to include the *station density around the motorists' houses* in the models. If the effect of the station density is positively significant, then it seems possible that the geographic competition among the stations leads to the larger number of the false pass outcome.

Table 3.10 shows several models estimated from the partial sample and full sample B. Because the partial sample contains additional information about the work places of vehicle owners, the *distance from work place to the station* is available. Thus, for the partial sample, two sets of model specifications are the one using the *minimum*

⁴² The false pass outcome is the number of vehicles categorized as 'c' in the Table 3.2. Therefore, the non-false pass outcomes ($Y_m = 0$) include the other three cells (a, b, and d) left as shown in Table 3.2. Including 'b' and 'd' categories should not impact the results and interpretation because they are very small. In the partial sample, $b = 0$ and $d = 2$ whereas in the full sample B, $b = 46$ and $d = 349$.

distance to the station from either the house or work place (models (1) to (4)) and the other using the *distance from the house to station* (models (5) to (8)). Moreover, models (2), (4), (6), and (8) include the motorists' characteristics which can hardly improve the explanation of the models. Unlike the partial sample, the full sample B contains only the motorists' housing addresses without any socioeconomic information. Only *the distance from house to the station* exists in models (9) and (10).

3.7.2.1.1 Effects of Motorist Characteristics

The results in Table 3.10 illustrate similar patterns between the two specifications using the partial sample. Both types of the *distances* in all models consistently show no impact on the probability of a vehicle receiving the false pass result. On the contrary, the *station density* around the house (or work place) significantly increases the probability of a vehicle receiving the false pass result (models (1), (3), (5), (7) and (9) which exclude the motorists' socioeconomic and demographic characteristics. When controlling for the motorist's *household income*, the effect of the *station density* disappears in the partial sample. The increase of the motorist's *household income* decreases the probability of the vehicle receiving the false pass result. The high-income motorists might not need to seek out a lenient station because of their well-maintained or high quality condition vehicles. The motorists' ethnicities have no impact on the probability of a vehicle falsely passing the test.

3.7.2.1.2 Effects of Vehicle Characteristics

The other vehicle characteristics, variables also exhibit a significant impact on the probability of a vehicle falsely passing the test (Table 3.10). The US make vehicles and those requiring the ASM test have a significantly higher probability of false passing. As expected, the additional mileage increases the probability of a vehicle falsely passing the test. The heavily used vehicles are likely to be dirty, and varied greatly in their

emission level. Accordingly, the test results of high mileage vehicles may vastly differ from one test to another.

3.7.2.1.3 Effects of Station Characteristics

Some of the station characteristics show the weak effects on the probability of a vehicle having a false pass result. In all models and samples, the vehicles tested at the inspection stations with *no repair* services are more likely to falsely pass the test, all else constant. In the full sample B without the socioeconomic information, the additional *false pass odds of the station* increase the probability of a vehicle receiving the false pass result, all else constant.

In short, the results in this section point out that the distance to the station is not associated with the probability of a vehicle falsely passing the test. As the station density around the motorists' houses increases, the probability of a vehicle falsely passing the test increases. The results imply that the stations tend to offer the lenient services as a strategy to retain their customers due to the monopolistic competitive market in the neighborhood,

Table 3.10 Logit models of the odds of a vehicle receiving the false-pass outcome

| Independent Variables | Partial Sample | | | | | | | | Full B Sample | |
|--|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| <u>Vehicle characteristics</u> | | | | | | | | | | |
| Car | -0.287 (1.13) | -0.349 (1.35) | -0.315 (1.19) | -0.353 (1.33) | -0.259 (1.03) | -0.322 (1.26) | -0.286 (1.09) | -0.321 (1.21) | -0.419 (16.78)*** | -0.433 (17.21)*** |
| US automaker | 0.598 (2.60)*** | 0.624 (2.69)*** | 0.605 (2.55)** | 0.620 (2.59)*** | 0.597 (2.59)*** | 0.617 (2.66)*** | 0.609 (2.57)** | 0.620 (2.60)*** | 0.421 (16.11)*** | 0.390 (14.71)*** |
| ASM test cycle | 1.084 (4.53)*** | 1.020 (4.26)*** | 0.956 (3.97)*** | 0.904 (3.73)*** | 1.087 (4.55)*** | 1.023 (4.28)*** | 0.957 (3.98)*** | 0.904 (3.73)*** | 1.132 (46.22)*** | 1.070 (42.92)*** |
| Domestically made vehicle | -0.015 (0.07) | -0.053 (0.24) | -0.101 (0.43) | -0.118 (0.50) | -0.007 (0.03) | -0.049 (0.22) | -0.092 (0.39) | -0.112 (0.48) | -0.084 (3.41)*** | -0.085 (3.41)*** |
| Ln(Mileage) | 0.418 (1.86)* | 0.373 (1.65)* | 0.375 (1.70)* | 0.359 (1.60) | 0.412 (1.84)* | 0.367 (1.63) | 0.366 (1.68)* | 0.351 (1.58) | 0.442 (19.26)*** | 0.424 (18.54)*** |
| <u>Motorist characteristics</u> | | | | | | | | | | |
| Ln(Min distance to station) from house or work place | -0.054 (0.57) | -0.060 (0.61) | -0.099 (1.04) | -0.098 (1.02) | | | | | | |
| Station density in 3-mile radius of house or work | 0.027 (2.20)** | 0.021 (1.62) | 0.027 (2.00)** | 0.023 (1.63) | | | | | | |
| Ln(Distance from house to station) | | | | | -0.063 (0.67) | -0.064 (0.68) | -0.094 (1.01) | -0.090 (0.96) | 0.000 (0.05) | -0.006 (0.60) |
| Station density within 3-mile radius of house or work | | | | | 0.025 (2.07)** | 0.016 (1.25) | 0.025 (1.92)* | 0.018 (1.30) | 0.004 (3.04)*** | 0.002 (1.43) |
| Black household | | 0.178 (0.52) | | 0.212 (0.59) | | 0.159 (0.47) | | 0.185 (0.51) | | |
| White household | | 0.002 (0.01) | | 0.123 (0.36) | | -0.006 (0.02) | | 0.119 (0.35) | | |
| Ln(Annual household income) | | -0.424 (2.16)** | | -0.437 (2.09)** | | -0.417 (2.09)** | | -0.423 (1.99)** | | |
| <u>Station characteristics</u> | | | | | | | | | | |
| False pass odds | | | 0.212 (0.63) | 0.231 (0.70) | | | 0.204 (0.60) | 0.224 (0.67) | | 0.788 (15.18)*** |
| Failure ratio | | | 1.761 (0.65) | 0.776 (0.28) | | | 1.707 (0.64) | 0.773 (0.28) | | -1.391 (4.56)*** |
| No repair | | | 0.420 (1.88)* | 0.415 (1.85)* | | | 0.412 (1.85)* | 0.405 (1.81)* | | 0.042 (1.79)* |
| Average daily test per inspector | | | 0.072 (1.71)* | 0.061 (1.43) | | | 0.072 (1.72)* | 0.061 (1.43) | | 0.001 (0.26) |

Table 3.10. Cont.

| Independent Variables | Partial Sample | | | | | | | | Full B Sample | |
|-----------------------|--------------------|------------------|-------------------|-------------------|--------------------|------------------|-------------------|-------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Ln(Total tests) | | | -0.108 (0.96) | -0.080 (0.70) | | | -0.111 (0.98) | -0.084 (0.72) | | 0.008 (0.63) |
| Min test fee (US\$) | | | -0.002 (0.08) | -0.007 (0.23) | | | -0.001 (0.05) | -0.005 (0.16) | | 0.002 (0.53) |
| Share of cars | | | 0.627 (0.42) | 0.425 (0.28) | | | 0.721 (0.49) | 0.656 (0.42) | | 0.374 (2.57)** |
| Chain store | | | -0.339 (1.33) | -0.435 (1.66)* | | | -0.343 (1.34) | -0.436 (1.67)* | | 0.003 (0.13) |
| Constant | -6.269 (2.49)** | -3.953 (1.47) | -5.702 (1.96)* | -3.632 (1.18) | -6.158 (2.46)** | -3.828 (1.42) | -5.620 (1.94)* | -3.677 (1.20) | -5.836 (22.32)*** | -6.452 (21.50)*** |
| Observations | 465 | 465 | 465 | 465 | 465 | 465 | 465 | 465 | 39489 | 39489 |
| Log Likelihood | -286.62 | -283.09 | -278.88 | -275.94 | -286.91 | -283.67 | -279.18 | -276.55 | -24847.77 | -24598.17 |
| LR Chi2 | 46.49 | 47.32 | 55.66 | 54.76 | 44.90 | 45.92 | 54.64 | 53.98 | 4036.98 | 4177.00 |
| DoF | 7.00 | 10.00 | 15.00 | 18.00 | 7.00 | 10.00 | 15.00 | 18.00 | 7.00 | 15.00 |
| Pseudo R2 | 0.09 | 0.10 | 0.11 | 0.12 | 0.09 | 0.10 | 0.11 | 0.12 | 0.09 | 0.09 |

3.7.2.2 Station: Probability of Giving the False Pass Outcome

To explore the characteristics of the inspection stations that are associated with the false pass outcomes of the tests, this study uses the logit model similar to the equation 3.8. Instead, $\Pr(Y_s = 1)$ is the probability of a station (s) giving the false pass outcome ($Y_s = 1$)⁴³. X_i is the vector of the independent variables (indexed by i) related to the *station characteristics* and s is the station ID.

$$\ln\left(\frac{\Pr(Y_s = 1)}{1 - \Pr(Y_s = 1)}\right) = \frac{\exp\left(\sum_{i=1}^I \beta X_i\right)}{1 + \exp\left(\sum_{i=1}^I \beta X_i\right)}, i = 1, \dots, I \quad (3.9)$$

The equation 3.9 can identify the station attributes that affect the *probability of the station to give the false pass outcome*. This study further investigates the factors relating to the *number of false pass outcomes or vehicles (FP)* at the inspection stations, using the log – linear model shown in the equation 3.9.

$$\ln(\text{FP}_s) = \alpha + \sum_{i=1}^I \beta X_i + \varepsilon_s, i = 1, \dots, I \quad (3.10)$$

where X_i is the same vector of the independent variables as those in the equation 3.9. Table 3.11 presents the estimates of the equation 3.9, and Table 3.12 displays the estimates of the equation 3.10. The number of stations in Table 3.12 reduces from 736 to 686 because some stations (50) have not given any false pass result. The log of zero yields the missing value of the dependent variables.

⁴³ If a station has never given any false pass outcome in the year 2001, then $Y_s = 0$.

Table 3.11 Logit model of the odds of an inspection station giving false pass outcomes

| Independent Variables | (1) | (2) |
|----------------------------------|--------------------|--------------------|
| Failure ratio | -0.002 (0.00) | |
| Ln (Total tests) | 1.387 (7.08)*** | 1.387 (7.10)*** |
| Average daily test per inspector | -0.063 (0.55) | -0.063 (0.56) |
| No repair | 0.477 (0.94) | 0.477 (0.95) |
| Chain store | -0.706 (1.59) | -0.706 (1.59) |
| Total stores in chain | 0.011 (0.66) | 0.011 (0.66) |
| Newness | -0.131 (0.57) | -0.131 (0.57) |
| Min test fee (US\$) | -0.096 (0.74) | -0.096 (0.75) |
| Mean age of vehicles | 0.840 (2.28)** | 0.840 (2.45)** |
| Share of cars | -0.347 (0.18) | -0.347 (0.18) |
| Share US make vehicles | 1.033 (1.68)* | 1.033 (1.67)* |
| Share of ASM test | -4.108 (1.31) | -4.108 (1.31) |
| Open on Saturday | 1.153 (2.20)** | 1.153 (2.23)** |
| Open on Sunday | 0.231 (0.38) | 0.231 (0.38) |
| Station density | -0.040 (1.32) | -0.040 (1.32) |
| Constant | -6.611 (1.77)* | -6.611 (1.77)* |
| Observations | 736 | 736 |
| Log Pseudo likelihood | -99.94 | -99.94 |
| Wald Chi squared | 111.38 | 111.25 |
| DoF | 15.00 | 14.00 |
| Pseudo R squared | 0.45 | 0.45 |

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3.12 Log-linear model of the number of false pass vehicles given by the inspection station

| Independent Variables | (1) | (2) |
|----------------------------------|---------------------------------|---------------------------------|
| Failure ratio | 0.690 (1.51) | |
| Ln (Total tests) | -0.077 (3.23) ^{***} | -0.076 (3.17) ^{***} |
| Average daily test per inspector | -0.004 (0.63) | -0.003 (0.44) |
| No repair | 0.048 (1.08) | 0.043 (0.97) |
| Chain store | -0.021 (0.39) | -0.020 (0.39) |
| Total stores in chain | 0.000 (0.10) | 0.000 (0.06) |
| Newness | 0.012 (0.54) | 0.017 (0.78) |
| Min test fee (US\$) | 0.008 (1.28) | 0.007 (1.24) |
| Mean age of vehicles | 0.234 (7.96) ^{***} | 0.253 (10.24) ^{***} |
| Share of cars | 0.469 (1.54) | 0.489 (1.62) |
| Share US make vehicles | 0.407 (2.39) ^{**} | 0.419 (2.48) ^{**} |
| Share of ASM test | -0.282 (1.09) | -0.320 (1.27) |
| Open on Saturday | -0.165 (2.38) ^{**} | -0.161 (2.30) ^{**} |
| Open on Sunday | -0.024 (0.47) | -0.023 (0.45) |
| Station density | 0.008 (2.14) ^{**} | 0.008 (2.10) ^{**} |
| Constant | -1.955 (5.08) ^{***} | -2.066 (5.56) ^{***} |
| Observations | 686 | 686 |
| R squared | 0.44 | 0.44 |
| Adjusted R squared | 0.43 | 0.43 |
| F Test | 27.34 | 27.74 |
| DoF | 15.00 | 14.00 |

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

3.7.2.2.1 Probability of Giving the False Pass Outcomes

In Table 3.11, few variables are statistically significant, meaning that the stations giving and those not giving the false pass outcomes are quite similar in most of the characteristics. A one percent increase in the *testing volume* increases the odds of a station giving the false pass outcomes by 1.39 percent. Because the number of false passing results might be increasing together with the testing volume, the higher chance of false pass is possible accordingly. As the *mean age of the vehicles* tested at a station increases by one year, the odds that the station giving the false pass outcomes increases by a factor of 0.84. Similarly, as the *share of the US make vehicles* tested at a station increases by one unit, the odds that the station giving the false pass outcomes increases by a factor of 1.03. A station *open on Saturday* is more likely to give false pass outcomes than a station that does not. Moreover, the *station density* is not associated with the probability of a station giving false pass outcomes.

3.7.2.2.2 Number of False Pass Outcomes

In Table 3.12, similar to Table 3.11, the same sets of variables affecting the odds of a station giving false pass outcomes also determine the number of false pass vehicles. However, some of the effects are in the opposite direction from the previous table. A one percent increase in the *testing volume* decreases the expected number of false pass vehicles very slightly by 0.07 percent. Probably, the greater the number of tests, the more experience the station (or the inspector) gains and hence performs the test more accurately. Among the stations giving false pass outcomes, the expected number of false pass vehicles of the stations *open on Saturday* is lower than that of the stations not open on Saturday. The *share of the US make vehicles* and the *mean age of the vehicles* tested at the station affect the expected numbers of the *false pass* vehicles

at the stations in the same ways as the previous results in Table 3.11. In contrast to the previous results, as the station density increases by one unit (adding one more station), the expected number of false pass vehicles increases.

To sum up the preliminary findings, the inspection stations giving false pass outcomes are systematically different from those not giving false pass outcomes in certain aspects: the *volume of the tests*, *mean age of the vehicles* tested at the station, *share of the US make vehicles*, and *open on Saturday*. Additionally, among the stations giving the false pass outcomes, these characteristics affect the expected number of false pass vehicles at the station. The effect of the station density on the expected number of the false pass vehicles is also significant, suggesting that the competition might drive the number of false pass vehicles in the high station density areas.

3.7.3 Log-linear Model: Distance to the Inspection Station

In this section, the study applies the log-linear model to test the differences of the *distance to the inspection station* between the vehicles receiving false pass outcomes and those not receiving false pass outcome (each vehicle receives one of the following outcomes: true pass, true fail, and false fail). The specification is in the equation 3.11, where D_m is the distance to the selected inspection station for each motorist m (and his or her vehicle). X_i is defined in the same manner as that in the equation 3.8.

$$\ln(D_m) = \alpha + \sum_{i=1}^I \beta X_i + \varepsilon_m \quad (3.11)$$

Table 3.13 shows the estimations from the partial sample and full sample B. In the partial sample, the log-linear model specifications employ two dependent variables: (1) the *minimum distance from either house or work* (models (1) to (4)) and (2) the

distance from house to the station (models (5) to (8)). In the full sample B, the dependent variable available is the *distance from house to the station* (models (9) and (10)).

3.7.3.1 Minimum Distance From Either House or Work Place to the Inspection Station

Table 3.13 shows that only a few variables are associated with the *minimum distance from either house or work* (models (1) to (4)). *False pass I/M test*, a dichotomous variable coding value of one if a vehicle passed the inspection but failed the RSD measurement, is not significant in all the models. This suggests that the minimum distance to the station of the vehicles falsely passing the tests is not different from that of the vehicles of other test results. For the vehicle characteristics, only the *mileage* is positively associated with the distance, suggesting that the additional mileage increases the minimum distance to the inspection station⁴⁴.

For the motorist characteristics, the *station density around the house* significantly decreases the *minimum distance to the inspection station*. This, in some way, suggests that if the inspection stations are available near the house, the motorist probably chooses among one of them and hence reduces the distance traveled to the station.

For the station characteristics, the *volume of the test* at the station is negatively associated with the *minimum distance*. This provides indirect evidence that the popular inspection stations are located close to the motorist's house or work place. The *share of the cars* tested at the inspection is also negatively associated with the *minimum distance* to the station.

⁴⁴ If a motorist's work place is far away from his or her house (as seen from the distance between the house and work place), then his or her vehicle is likely to have high mileage. The effect of the mileage suggests that the motorist selects the inspection station somewhere between the house and work place, resulting in the higher the minimum distance.

3.7.3.2 Distance From House to the Inspection Station

The overall estimations are similar to those obtained for the *minimum distance to the station* in the previous section. In Table 3.13, the estimates from the full sample B (models (9) and (10) are significant more often than those from the partial sample (models (5) to (8)). However, consistent across all the models, on average, the *distance from house to the station* are the same between the vehicles receiving the false pass outcome and those receiving other outcomes. For the other vehicle characteristics, few variables are significant in the full sample B such as the *ASM test cycle*, *US make*, and *the domestic vehicles*.

For the motorist characteristics, the *station density* is always significantly and negatively associated with the *distance from house* in all models and samples. The additional *stations* near the house decreases the *distance from house* to the station, suggesting that the motorists tend to choose the stations close to their houses.

Most of the station characteristics are significant only in the full sample B, except for the *test volume* that is also significant in the partial sample. The test volume at the station is negatively associated with the *distance from house to the station*. On the other hand, the *station without the repair service*, *average daily tests per inspector*, and *share of cars tested at the station* are positively associated with the *distance from house to the station*.

To summarize, the *distance* from either the motorist's house or work place to the inspection station is approximately the same between the vehicles receiving *false pass outcomes* and those receiving other results, all else equal. Finding suggests that the motorists do not travel more miles to receive the lenient service. The higher *station density*, on the other hand, decreases the *distance* the motorist travels to take the test, indicating that the motorist tends to shop for the inspection near his or her house.

Table 3.13 Log-linear models of the distance from a house (or work place) to the selected inspection station

| Independent Variables | Partial Sample | | | | | | | | Full B Sample | |
|---|-------------------------------------|---------------------|--------------------|-------------------|-----------------------------|---------------------|--------------------|-------------------|-----------------------------|----------------------|
| | Distance (house or work to station) | | | | Distance (house to station) | | | | Distance (house to station) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| <u>Vehicle Characteristics</u> | | | | | | | | | | |
| False pass IM test (Y/N) | -0.063 (0.57) | -0.069 (0.63) | -0.108 (1.01) | -0.112 (1.03) | -0.075 (0.68) | -0.077 (0.70) | -0.110 (1.00) | -0.108 (0.98) | 0.000 (0.02) | -0.007 (0.61) |
| Ln(Mileage) | 0.233 (2.48)** | 0.222 (2.36)** | 0.202 (2.12)** | -0.008 (1.24) | 0.244 (2.60)*** | 0.235 (2.51)** | 0.214 (2.23)** | 0.206 (2.16)** | 0.109 (10.89)*** | 0.106 (10.58)*** |
| Car | -0.140 (1.15) | -0.180 (1.46) | -0.159 (1.30) | -0.169 (1.44) | -0.164 (1.32) | -0.180 (1.43) | -0.162 (1.30) | -0.180 (1.42) | 0.033 (2.57)** | 0.019 (1.50) |
| ASM Test cycle | -0.140 (1.21) | 0.046 (0.42) | 0.056 (0.50) | 0.069 (0.60) | 0.023 (0.21) | 0.023 (0.21) | 0.035 (0.30) | 0.048 (0.41) | -0.019 (1.56) | -0.026 (2.11)** |
| US automaker | 0.055 (0.50) | -0.141 (1.21) | -0.171 (1.45) | -0.165 (1.49) | -0.097 (0.82) | -0.093 (0.79) | -0.114 (0.94) | -0.116 (0.95) | -0.024 (1.84)* | -0.014 (1.07) |
| Domestically made vehicle | -0.128 (1.17) | -0.147 (1.33) | -0.174 (1.59) | 0.188 (1.98)** | -0.156 (1.41) | -0.157 (1.40) | -0.182 (1.62) | -0.178 (1.57) | 0.046 (3.69)*** | 0.047 (3.75)*** |
| <u>Motorist Characteristics</u> | | | | | | | | | | |
| Station density within 3-mile radius of a house | -0.015 (2.48)** | -0.018 (2.91)*** | -0.013 (1.98)** | -0.177 (1.43) | -0.018 (3.09)*** | -0.018 (2.89)*** | -0.015 (2.36)** | -0.013 (1.82)* | -0.039 (58.61)*** | -0.042 (53.94)*** |
| Black household | | 0.060 (0.37) | | 0.199 (1.16) | | 0.120 (0.72) | | 0.226 (1.29) | | |
| White household | | -0.091 (0.59) | | 0.016 (0.10) | | -0.001 (0.00) | | 0.076 (0.45) | | |
| Ln(Annual household income) | | -0.011 (0.11) | | 0.039 (0.43) | | 0.022 (0.23) | | 0.051 (0.54) | | |

Table 3.13 Cont.

| Independent Variables | Partial Sample | | | | | | | | Full B Sample | |
|-------------------------------------|-------------------------------------|------------------|--------------------|--------------------|-----------------------------|------------------|--------------------|--------------------|-----------------------------|---------------------|
| | Distance (house or work to station) | | | | Distance (house to station) | | | | Distance (house to station) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| <u>Station Characteristics</u> | | | | | | | | | | |
| False pass odds | | | 0.037 (0.29) | 0.037 (0.29) | | | -0.006 (0.05) | -0.013 (0.10) | | 0.028 (2.41)** |
| Failure ratio | | | 1.246 (1.07) | 1.185 (1.00) | | | 1.169 (0.97) | 1.217 (0.98) | | 0.296 (2.18)** |
| No repair | | | 0.207 (1.95)* | 0.203 (1.91)* | | | 0.180 (1.65)* | 0.177 (1.62) | | 0.023 (1.99)** |
| Average daily test per inspector | | | 0.020 (0.74) | 0.021 (0.79) | | | 0.014 (0.53) | 0.015 (0.57) | | 0.013 (5.38)*** |
| Ln(Total tests) | | | -0.101 (2.00)** | -0.101 (1.98)** | | | -0.120 (2.32)** | -0.125 (2.39)** | | -0.055 (8.58)*** |
| Min test fee (US\$) | | | 0.004 (0.36) | 0.002 (0.17) | | | -0.000 (0.02) | -0.002 (0.13) | | -0.003 (1.85)* |
| Share of cars | | | -1.330 (1.73)* | -1.730 (2.19)** | | | -0.973 (1.24) | -1.270 (1.57) | | 1.056 (11.99)*** |
| Chain store | | | -0.079 (0.62) | -0.069 (0.53) | | | -0.054 (0.42) | -0.046 (0.35) | | 0.002 (0.19) |
| Constant | -1.112 (1.04) | -0.808 (0.70) | 0.637 (0.50) | 0.851 (0.65) | -1.021 (0.96) | -1.035 (0.91) | 0.763 (0.60) | 0.784 (0.60) | 0.563 (4.94)*** | 0.389 (2.71)*** |
| Observations | 465 | 465 | 465 | 465 | 465 | 465 | 465 | 465 | 39489 | 39489 |
| R squared | 0.04 | 0.05 | 0.07 | 0.07 | 0.04 | 0.04 | 0.06 | 0.07 | 0.09 | 0.10 |
| Chi squared | 0.04 | 0.05 | 0.07 | 0.07 | 0.04 | 0.04 | 0.06 | 0.07 | 0.09 | 0.10 |
| F | 2.67 | 2.41 | 2.72 | 2.29 | 3.26 | 2.39 | 2.43 | 2.13 | 528.32 | 259.43 |
| DoF | 7.00 | 10.00 | 15.00 | 18.00 | 7.00 | 10.00 | 15.00 | 18.00 | 7.00 | 15.00 |

3.8 Discussion

3.8.1 Motorists' Costs Related to the Inspection

Vehicle inspection engenders several types of costs to the motorists, including travel cost and time, waiting time, inspection fees, and possibly a repair cost if necessary. Using the RUM theory, the study identifies the determinants of the motorists' decision in choosing their inspection stations. The results show that motorists are less likely to choose stations that incur the high *inspection related costs*.

In particular, an inspection station is less likely to be chosen if it costs the motorists *high travel cost and long travel time* as indicated by the *distance between the motorist's house and the station*. The study also finds the suggestive evidence that motorists select inspection stations that are in or near their neighborhoods. First, the *distance from the motorist's work place* to the station does not affect the choices made by motorists. Second, as station density increases, the distance from the motorist's house to the "selected" station decreases.

Similarly, stations with a long *wait time*, proxy by the average daily tests per inspector, are less likely to be chosen. Because the number of *average daily tests per inspector* corresponds to the degree of congestion at the station, it reflects the time that the customers have to spend or wait at that station. If the motorists notice a long waiting line, they can change stations easily because other stations are available in the neighborhood.

Lastly, a station with a high *minimum testing fee* is less likely to be selected, indicating that their discounting strategy is not as effective as their competitors. Customers who are sensitive to price search for and choose stations offering relatively low service prices.

3.8.2 Lenient Inspection Services

Theory suggests that the vehicle inspection requirement creates incentives for motorists to search for ways to pass the tests. The key research focus of this research concerns motorists' choices in relation to the leniency of the stations. In this study, the leniency of the station is measured in two ways. The first measure is related to the vehicle failing the test at the station, using the *failure ratio*. The second measure is associated with the vehicle falsely passing the test at the stations as captured by the *false pass odds and ratio*. The false pass results are determined by the discrepancies between the two outcomes from the two emission measurements of the same vehicles. The first outcome is the test result of the vehicle at the station. The second outcome is the test result of the same vehicle measured on-road unobtrusively by the independent and reliable research team.

3.8.2.1 Failure Ratio

The study shows that motorists may somehow learn about the *failure ratio* of the station and make their decision accordingly. In particular, white motorists seem to have better knowledge about the failure ratio of stations than the other ethnic groups. In general, an inspection station with a high failure ratio is consistently less likely to be chosen. However, an inspection *station with the low failure ratio but located relatively far away* from the motorist's house or workplace is equally likely to be chosen. Put it differently, motorists do not travel extra miles to stations with a low failure ratio in order to receive the lenient services. In fact, motorists do not need to search for lenient stations because they probably are in their neighborhoods.

3.8.2.2 False Pass Odds and Ratio

On the other hand, the *false pass odds and ratios* turn out to be a problematic measure of leniency due to their correlations with the *failure ratio* for unknown reasons.

In addition, there is a limitation of these leniency measures due to two reasons. The first is its *underlying assumption*. Using the *false pass odds* or *ratio* as the leniency measure, this study assumes that the stations can perform the test competently. Given the existing enforcement mechanisms to ensure the proper testing procedure (discussed previously in the literature review section), this assumption is relatively reasonable. In principle, any divergence of the testing result is, therefore, a result of the deliberate action to pass the vehicle that is not supposed to. However, in practice, it is possible that the capabilities of the inspection stations are different from station to station, leading to the high *false pass odds* or *ratio*. The crude descriptive statistic shows that the probability of a vehicle receiving the false pass outcome may be by chance⁴⁵. In this sense, the *false pass odds* and *ratios* actually capture the “incompetency⁴⁶” of the stations instead of the “leniency”.

The second limitation of the false pass measures is related to how the motorists might learn about this information and hence decide accordingly. Although motorists cannot observe the false pass odds and ratio, they may learn about this information in ways similar to learning about the failure rate such as past experience, word-of-mouth, brands, and etc. Nonetheless, the false pass measures are more complicated and difficult to discover than the failure rate. To learn about the false pass level of the stations, the motorists would have to be able to evaluate the ‘true’ emission of vehicles (fundamentally be able to mimic the remote sensing device). In other words, a

⁴⁵ Among all the stations, the average odds of a vehicle receiving the falsely passing outcome $\left(\frac{\text{NumberFalselyPassVehicles}}{\text{NumberCorrectlyPassVehicles}} \right)$ for each station are almost one. In fact, around 60 percent of the stations have the odds greater than one.

⁴⁶ In fact, the results from the conditional logit models show that motorists have responded to the false pass odds and ratio similar to the failure rate. This seems to suggest that the false pass odds and ratio might be associated with the station attributes that are undesirable (to the motorists) and unobservable (to the analysts). If the motorists consider these attributes in their decisions, then the false pass odds and ratio capture the effects of this unobservable.

reasonable way for motorists to derive the false pass information is still unclear. As a result, it would be difficult for motorists to consider this information when making their choice of inspection station.

For these two reasons, the false pass odds and ratio are not the appropriate measure for the station leniency, on which motorists might rely when choosing their inspection stations. As a result, the effects of the false pass odds and ratio (on the probability of a station being chosen) are not reasonable as shown in the findings.⁴⁷ However, this does not mean that false pass odds and ratio are not important aspects of an inspection station. Indeed, they reflect the performance of the station and may result in the effectiveness of the I/M program at last. The leniency of the station should be explored at the station level with other additional information.

3.8.3 Competition in the Inspection Market

In this study, the degree of competition in the inspection market is measured by the *station density*, defined as the number of inspection stations within the 2-mile radius of the station of interest. The station density is an appropriate measure of the geographical competition due to the nature of the vehicle inspection business, which requires the testing facility and space. Although competition is a common phenomenon in the business, the unintended consequence may be more important from the I/M program perspective, particularly the failure ratio. Previous research (Hubbard, 2002) shows that the failure rates of inspection stations are influenced by condition of market competition. In the highly *concentrated market*, demonstrated by the station density in a

⁴⁷ The results show the negative association between the probability of a station being chosen and the false pass odds or ratio. Vehicles with the false pass outcomes travel roughly the same distance as those with the other types of results. Likewise, the distance from the motorist's house to the station has no impact on the probability of a vehicle receiving the false pass outcome.

geographical area, the average failure rate is generally lower than that in areas where stations are scattered.

Findings from this study show that an inspection station in the high station density area is less likely to be chosen because the market is shared by a large number of sellers (holding every constant, including the market size). In general, the unconditional mean of the *failure ratio* decreases as the station density increases, similar to the previous study (Hubbard, 2002). The decreasing rate varies across the different groups of stations classified by their organization and service type. Moreover, as the station density increases, not only the probability of a vehicle receiving the false pass outcome increases but also the number of false pass outcomes given by a station increases.

In addition to Hubbard (2002), the study finds the interaction effects between the station density and failure ratio on the chance of the station being chosen. In the low station density area (less than 15 stations), an inspection station with a high failure ratio is less likely to be chosen. However, in the high station density area (more than 15 stations), an inspection station with a low failure ratio is less likely to be chosen marginally. The explanation of this pattern might be related to the information and learning threshold. In the low station density area, motorists can learn about the failure ratio in several ways as discussed previously. As the number of the inspection stations gets larger, it becomes harder for motorists to effectively learn about the failure ratio of all the stations. The motorists' decisions might depend on some other observable attributes of the stations, which might positively correlate with the failure ratio.

3.8.4 Other Attributes of the Inspection Services

Although the other attributes of the inspection stations are important in determining motorists' decisions in choosing inspection stations, the influence of these

attributes tend to reflect the motorists' preference heterogeneity in this particular sample. The stations providing *convenient and flexible service hours* are more likely to be chosen. Specifically, the stations open on Saturday are preferred to those do not open. The stations with the *large market share* (high volume of tests) are more likely to be chosen. The motorists are more likely to choose *new start up* stations but avoid the stations that mainly *serve old vehicles*. Unlike other studies that find the positive *effect of the brands*, the results from this study seem to suggest the opposite. Stations associated with a chain, indicating established brands, are less preferred than the non-chain stations.

3.9 Conclusion

The effectiveness of the Atlanta I/M program in terms of pollution reduction lies in the strategic interaction between motorists and inspection stations. This study focuses on the behavioral decisions of motorists when choosing their inspection stations. The random utility maximization theory provides the frameworks for testing several hypotheses relating to the factors determining the motorists' choices of inspection stations. Using the 2001 data from the I/M program, on-road emissions, and the travel survey in the Atlanta area, the study shows that the motorists are less likely to choose the stations that are associated with high inspection related costs, including travel cost and time, waiting time, and inspection fee. The results illustrate that the station failure ratio is a reasonable proxy for the leniency of the stations but the false pass odds or ratio are not. Table 3.14 displays the summary of the results related to the proposed hypotheses.

Table 3.14 Summary of findings:
Factors determining a motorist's choice of inspection station

| Factors Affecting A Motorist's Decision | | Hypotheses | Results |
|---|----------------------|------------|-----------|
| <u>Inspection Related Cost</u> | | | |
| <i>Variables</i> | <i>Constructs</i> | | |
| Distance | Travel time and cost | 1.1 -*** | -*** |
| Average test per inspector | Waiting time | 1.2 -*** | -*** |
| Minimum fee | Inspection fee | 1.3 -*** | -*** |
| <u>Attributes of Stations</u> | | | |
| <i>Variables</i> | <i>Constructs</i> | | |
| Failure ratio | Leniency | 1.4 -*** | -*** |
| False pass odds ratio | Leniency | 1.5 +*** | Incorrect |
| Failure ratio x Distance | Extra leniency | 2.1 +*** | 0 |
| False pass odds ratio x Distance | Extra leniency | 2.2 +*** | Incorrect |
| Station density | Competition | 3.1 -*** | -*** |
| Failure ratio x Station density | Extra leniency | 3.2 +*** | - +*** |

The study further demonstrates that motorists do not seek out “extra” lenient service stations, as revealed by no additional travel cost and longer travel time because the average failure ratio of the station is lower in the high station density area. In fact, motorists are more likely to test their vehicles at lenient stations because they are available in their neighborhoods. The supporting indirect evidence indicates that as station density increases, the other two quantities also increase: (1) the probability of a vehicle receiving the false pass outcome, and (2) the number of false pass outcomes at the stations.

Findings from this study show that the rules and regulations (prior and up to 2001) create strong incentives for both motorists and inspection stations to interact within the competitive market environment. The resulting outcomes (from the equilibrium of the vehicle inspection demand and supply) have certain policy implications that might link to the effectiveness of the Atlanta I/M program in terms of pollution reduction.

The current condition (in 2001) is resulting from the long-term process of the vehicle inspection market. The inspection stations sort themselves into a high-density

residential area to capture a large portion of the demand for vehicle inspection. As more and more stations start a business in such areas, each inspection station faces smaller market share whereas motorists have lower switching costs. The geographical competitive environment drives each inspection station to provide lenient services and, in the end, leads to more prevalent lenient services in many areas.

Such continuing issues originate from the unintended consequences of the I/M program and the lack of long-term planning among relevant authorities. At present, the Georgia DNR has no limiting rules regarding either the total number or the location of inspection stations. As long as investors comply with the requirements relating to the testing instruments, facilities, and inspectors, they are allowed to start their businesses. However, the local governments (with different goals from those of the Georgia DNR) may have their own rules and criteria for permit the number and types of such businesses within their jurisdictions.

The simple policy recommendations to the evolving issues would be unrealistic. However, the first step that might lead to a feasible solution is to recognize the potential threat to the effectiveness of the I/M program as result from market competition. The results from this study can provide only indirect and suggestive evidence because it focuses on the behavioral decision of the motorists, which is only half of the story. The study of the inspection stations industry in terms of types (organization, business, and services), cost structure, and resulting test performance (failure ratio, false pass outcomes, and other possible measures) are necessary to properly design policy to remedy the issue of market competition.

CHAPTER 4

OBD II TEST VALIDITY AND RELIABILITY: EVIDENCE FROM ATLANTA FLEETS IN 2002 - 2005

4.1 Introduction

On-Board Diagnostics (OBD) is a computer-based system built into a vehicle in order to monitor the performance of some of the engine components, particularly those responsible for controlling emissions. OBD II is the second generation of OBD with the extended set of standards and protocols developed by the Society of Automotive Engineers (SAE). When the engine does not function properly, specifically the emission control components, and it might generate emission exceed 1.5 times the federal test procedure (FTP) standards for that model of vehicle, the OBD II turns on the malfunction indicator light (MIL)⁴⁸. The system will also store important information about problem parts so that a repair technician can correctly identify and repair them. By alerting motorists sooner about their vehicle failure, OBD II may help reduce emissions and probably repair costs due to earlier detection of emission problems.

Under the Clean Air Act Amendments of 1990, the U.S. Environmental Protection Agency (EPA) has adopted the OBD II standards of the SAE and required all light-duty vehicles (including all passenger cars, trucks, vans, and sport utility vans (SUVs)) sold in the U.S. to be equipped with OBD II starting with the model year 1996. In addition, the regulations⁴⁹ require the use of OBD II in the inspection and maintenance (I/M) program

⁴⁸ "That includes anytime random misfires cause an overall rise in HC emissions, anytime the operating efficiency of the catalytic converter drops below a certain threshold, anytime the system detects air leakage in the sealed fuel system, anytime a fault in the EGR system causes NOx emissions to go up, or anytime a key sensor or other emission control device fails (URL <http://www.autotap.com>)."

⁴⁹ 40 CFR Parts 51 and 85, Amendments to Vehicle Inspection and Maintenance Program Requirements Incorporating the Onboard Diagnostic Check; Final Rule, 66 FR 18156 (April 3, 2001)

by January 2002 and allow states to phase-in the OBD II testing for up to 12 months based on reasonable conditions.

In Atlanta Enhanced I/M program area, since May 2002, vehicles of model year 1996 or newer are required to pass the OBD II test instead of the tailpipe exhaust test. Despite yielding similar pass-fail results, the OBD II test is not comparable to the tailpipe emission test because the OBD II test does not directly measure the emission. To pass the OBD II test, the MIL must be off, no fault codes are stored, and readiness monitor is on, indicating that OBD II collects sufficient data for determining the test result. However, as vehicles become older and likely to emit a greater amount of pollution, the OBD II systems are also prone to failure. In particular, after the end of the OBD II warranty, OBD II test might mistakenly produce failure or passing results more often for the older rather than the newer vehicles. Passing the vehicles that are not supposed to may impact the effectiveness of the I/M program in terms of pollution reduction.

4.2 Research Question and Hypothesis

The key research question of this essay is “is the OBD II test still valid and reliable for older vehicles?” By comparing inspection results (pass-fail) of vehicles in different age groups, the study determines the variation in validity and reliability of the OBD II test as vehicles become older. Because the older OBD II equipped fleet continues to grow, the validity and reliability of the OBD II test could be a critical matter. This study could shed some light on this issue.

According to this research question, the hypothesis is that “as vehicles equipped with OBD II become older, the OBD II test result is less valid and reliable.”

$$H_1: |\Delta E[TE_{OLD}] - \Delta E[TE_{NEW}]| \neq 0$$

$$\Delta E[TE_{OLD}] = E[TE_{RSD,OLD}] - E[TE_{OBD,OLD}]$$

$$\Delta E[TE_{NEW}] = E[TE_{RSD,NEW}] - E[TE_{OBD,NEW}]$$

where $TE_{RSD,OLD}$ and $TE_{OBD,OLD}$ are the tailpipe emissions from older vehicle groups observed by a remote sensing device (RSD) and the *hypothetical* tailpipe emissions

correspond to the OBD II test respectively. Likewise, $TE_{RSD,NEW}$ and $TE_{OBD,NEW}$ are tailpipe emissions from newer vehicle groups. In this study vehicle age ranges from 3 to 9 years and new – old vehicles refer to the possible pairs of ages within this range.

4.3 Conceptual Framework

4.3.1 Validity

Validity is defined as the degree with which the measured value reflects the characteristics it is intended to measure (Carmines & Zeller, 1979). In particular, the validity of the OBD II test is the extent to which the results (pass or fail) from the test reflect vehicle conditions being evaluated, specifically the emission control system, which is unobservable. According to the objective of the I/M program, the OBD II test is supposed to identify high polluting vehicles and keep them clean, which is observable. In consequence, the OBD II test result is valid when it yields either positive or negative predictive value, meaning ‘pass’ when a vehicle emits low level of emissions on road and ‘fail’ otherwise. To determine the validity of the OBD II test, this study uses the on-road tailpipe emissions captured by RSD as a benchmark. Briefly, the study focuses on a convergent validity, which refers to “a relatively high correlation between the test and some criterion thought to measure the same construct as the test” (Hogan, 2007).

4.3.1.1 Observed Tailpipe Emission Collected by RSD

In principle, RSD measures the true on-road vehicle emissions, the ultimate target of the I/M program. Several advantages of RSD assure the minimum behavioral bias of the results: no self-selection, no preparation for a test, and capturing actual driving conditions. However, a major disadvantage is its substantial variability of measurement. Since RSD takes only one possible sample of tailpipe emissions of a specific driving condition, the result might not reflect emission characteristics of other most driving conditions. Despite its limitations, tailpipe emissions from RSD

measurement is used as a proxy for the true characteristic of vehicular emissions due to its availability and physical construct validity.

Wenzel, Singer & Slott (2000) suggest that tailpipe emission variation within a vehicle originates from vehicle conditions (e.g. intermittent emission control failure), fuel quality, driving mode and engine load (e.g. engine and catalyst temperature), and ambient environment such as temperature and humidity. However, the ambient conditions tend to indirectly influence the error term via driving mode. For example, high ambient temperature can increase engine load due to the use of air conditioning system.

This study assumes that the variability of a single RSD tailpipe emission measurement (TE_{RSD}) is an additive composite of two parts: the true tailpipe emission (TE_{TRUE}) and random error (ε_{RSD}).

$$TE_{RSD} = TE_{TRUE} + \varepsilon_{RSD} \quad (4.1)$$

For any measurement of tailpipe emission observed by RSD, TE_{TRUE} is assumed to be a fixed value although TE_{RSD} and ε_{RSD} vary for each vehicle on different measuring occasions. It is also assumed that the expected value (population mean) of TE_{RSD} is TE_{TRUE} . In other words, TE_{TRUE} is the mean of the theoretical distribution of TE_{RSD} that would be found in repeated independent measurements of the same vehicle with the same condition.

$$E[TE_{RSD}] = TE_{TRUE} \quad (4.2)$$

The next crucial assumption is that the measurement error and the true tailpipe emissions obtained by a population of vehicles on one measurement are uncorrelated.

This implies that vehicles with high true emissions do not have systematically more positive or negative errors of measurement than vehicles with low true emissions.

$$\text{Cov}(TE_{\text{RSD}}, \varepsilon_{\text{RSD}}) = 0 \quad (4.3)$$

In summary, the error of RSD measurement is an unsystematic or random deviation of a vehicle's observed tailpipe emissions from the theoretically true tailpipe emissions. Systematic errors from RSD are excluded from the error of measurement in this framework.

4.3.1.2 Unobserved Tailpipe Emission Inferred from OBD II

The OBD II unit stores the codes of vehicle conditions operating at different driving cycles. If there is any part of the engine or emission control system malfunctioning so that it *may* result in *potentially high but unobserved* tailpipe emissions (TE_{OBD}) greater than the threshold standard (τ), the OBD II records the malfunction codes (M , which is a subset of all possible OBD II codes and other conditions (C); $M \in C$) and illuminates the 'check engine' light on the dashboard. When a vehicle is inspected at the station, the test analyzer reads the recorded codes in OBD II (c) and an inspector checks other conditions. If c includes the malfunction code M or an inspector finds unusual conditions ($c \in M$), then the final result is failure as $1_M[c]$, an indicator function determining the inspection result, produces a value of one. Likewise, if $c \notin M$, $1_M[c]$ gives a value of zero or passing the inspection. Formally, in principle,

$$TE_{\text{OBD}} \geq \tau \rightarrow c \in M \quad \text{or} \quad TE_{\text{OBD}} < \tau \rightarrow c \notin M \quad (4.4)$$

However, the above conditions cannot be observed. Instead, the following is observable.

$$1_M[c] = \begin{cases} 1 & \text{if } c \in M \\ 0 & \text{if } c \notin M \end{cases} \quad (4.5)$$

Also, note that the following is true

$$c \notin M \rightarrow TE_{OBD} < \tau \quad \text{or} \quad c \in M \rightarrow TE_{OBD} \geq \tau \quad (4.6)$$

which implies that, assuming OBD II functions properly,

$$1_M[c] = \begin{cases} 1 & \text{if } TE_{OBD} \geq \tau \\ 0 & \text{if } TE_{OBD} < \tau \end{cases} \quad (4.7)$$

Consequently, if OBD II yields a failing result, this means $TE_{OBD} \geq \tau$. The similar is true for a passing result. On the other hand, if the assumption does not hold, then false negatives and positives can happen when OBD II gives the results opposite to the conditions between TE_{OBD} and τ . With the OBD II test only, there is no way to check the possibility of this assumption.

4.3.1.3 Convergent Validity

The concept of validity, specifically the convergent validity, is borrowed from the measurement theory in psychology as illustrated in Allen & Yen (1979), Anastasi & Urbina (1997), and Shultz & Whitney (2005). The convergent validity of OBD II test occurs when the inspection result from OBD II is in accordance with the real tailpipe emission observed by RSD, the proxy of true tailpipe emission. In other words, the OBD II functioning condition can be inferred from RSD observations. This implies that the

RSD observed tailpipe emission is the necessary and sufficient condition for the validity of OBD II test. Formally, the observable condition for the convergent validity is

$$TE_{RSD} \leftrightarrow 1_M[c] \quad (4.8)$$

Since it is also true that $TE_{OBD} \leftrightarrow 1_M[c]$, the unobservable condition is

$$TE_{RSD} \leftrightarrow TE_{OBD} \quad (4.9)$$

Specifically, the condition for testing the validity of OBD II is

$$1_M[c] = \begin{cases} 1 & \text{if } TE_{RSD} \geq \tau \\ 0 & \text{if } TE_{RSD} < \tau \end{cases} \quad (4.10)$$

In summary, the divergence of OBD II results from the RSD observed tailpipe emissions indicates that the OBD II test is biased (or not valid).

4.3.2 Reliability

Similar to the validity, the concept of reliability is drawn from psychological testing as exhibited in Kline (1992), Anastasi & Urbina (1997), and Hogan (2007). Reliability refers to the degree of nonsystematic error of the measurement. In other words, the measurement is reliable if it yields the result consistently (Carmines & Zeller, 1979). In a similar way as the assumed components of TE_{RSD} for a single vehicle, this study assumes that the distribution of RSD measurements obtained from a sample and population are:

$$\text{For a sample: } s_{\text{RSD}}^2 = s_{\text{TRUE}}^2 + s_{\varepsilon}^2 \quad (4.11)$$

$$\text{For a population: } \sigma_{\text{RSD}}^2 = \sigma_{\text{TRUE}}^2 + \sigma_{\varepsilon}^2 \quad (4.12)$$

The variance in a set of TE_{RSD} for a sample (s_{RSD}^2) or a population (σ_{RSD}^2) consists of two parts: the true variance ($s_{\text{TRUE}}^2, \sigma_{\text{TRUE}}^2$) and the error variance ($s_{\varepsilon}^2, \sigma_{\varepsilon}^2$). The variance of true emission consists of the differences among TE_{RSD} of individual vehicles that reflect their engine and emission control system conditions. Error variance is comprised of the differences among measurements that reflect factors irrelevant to the condition of vehicles. Implicitly, the assumed component of s_{RSD}^2 indicates that the reliability of measurement increases as the error component decreases. Accordingly, the reliability coefficient (ρ) is defined as a ratio of the true emission variance (σ_{TRUE}^2) to the total (or RSD observed) emission variance ($\sigma_{\text{RSD}}^2 = \sigma_{\text{TRUE}}^2 + \sigma_{\varepsilon}^2$):

$$\rho = \frac{\sigma_{\text{TRUE}}^2}{\sigma_{\text{TRUE}}^2 + \sigma_{\varepsilon}^2} \quad (4.13)$$

If the measurement is precise or the error variance (s_{ε}^2) is close to zero, then the reliability is close to one and vice versa. However, since TE_{TRUE} is never observable, reliability can only be estimated. In this sense, a reliability coefficient is regarded as an index that estimates the proportion of the emission measurement variance that is accounted for by error originating from one or more sources. Accordingly, the evaluation of emission measurement reliability involves a two-step process: (1) determining the

sources of possible error that might enter into measurement and (2) estimating the magnitude of those errors.

4.3.2.1 Inter-rater Reliability

Since this study assumes that $E[TE_{RSD}]$ is TE_{TRUE} and aims at assessing the reliability of the OBD II test result (or TE_{OBD}), TE_{RSD} is used as a criterion. Consequently, the source of error variance originates from the different types of methods (RSD vs. OBD II), producing a particular type of reliability called *inter-rater reliability*. Inter-rater or inter-observer reliability illustrates the degree of agreement between two sets of measurements derived from different methods. In brief, it addresses the consistency of measuring emissions by two methods.

4.4 Empirical Framework

To demonstrate the convergent validity and inter-rater reliability, the common approach is to identify the agreement between the two measurements of two testing technologies: OBD II vs. RSD. In fact, because the OBD II measurement gives only two values: pass or fail. No other information about the real tailpipe emission from the OBD II result exists. *Consequently, to compare the two tests, the measurement from the RSD has to collapse into the two values of pass or fail. In other words, the validity and reliability are evaluated by the same methods. When the OBD II is valid, it is also reliable.* This study utilizes both nonparametric and parametric statistical methods to illustrate the agreement or disagreement. The raw agreement indices and agreement coefficient (AC1) are non-parametric; the logistic and ordinary least square regressions are of the parametric approach.

4.4.1 Raw Agreement Indices

Raw agreement indices include both proportions of overall and specific agreement. *Overall agreement*, also known as accuracy, is the observed proportion of cases in which both OBD II and RSD methods yield the same results (both raters agree), relative to the sample size. Formally, the overall agreement (P_0) is defined according to the following 2x2 table.

Table 4.1 Classification of results from RSD measurement and OBD II test

| | | RSD Measurement | | |
|-------------|----------|-----------------|-----------------|----------------|
| | | Fail (1) | Pass (0) | Total |
| OBD II Test | Fail (1) | n_{11} | n_{10} | $n_{1\bullet}$ |
| | Pass (0) | n_{01} | n_{00} | $n_{0\bullet}$ |
| | Total | $n_{\bullet 1}$ | $n_{\bullet 0}$ | N |

$$P_0 = \frac{n_{00} + n_{11}}{N} \quad (4.14)$$

The overall agreement proportion is informative with limitations in that it treats the positive agreement the same as the negative agreement. As a result, *specific agreement proportion* is suggested by Spitzer & Fleiss (1974): positive (P_{S+}) and negative (P_{S-}) ratings.

$$P_{S+} = \frac{2n_{11}}{2n_{11} + n_{01} + n_{10}} \quad \text{and} \quad P_{S-} = \frac{2n_{00}}{2n_{00} + n_{01} + n_{10}} \quad (4.15)$$

A positive rating focuses only on the failing category by OBD, RSD, or both. A negative rating, on the other hand, emphasizes the passing category by OBD, RSD, or both. Thus, specific (to each category) agreement proportions may be considered as estimated conditional probabilities.

To test the significance of the agreement, both overall and specific, the null hypothesis is that the results of both OBD and RSD methods are independent, meaning the expected marginal probabilities are equal to the observed ones. In the case of the 2x2 table, the test is the same as the test of statistical independence in a contingency table (Uebersax, 2008). Accordingly, several statistics are applicable and mostly yield similar results: Pearson Chi-squared, likelihood Chi-squared, and Fisher's exact test.

In sum, despite the ease of understanding, raw agreement indices do not take into account the agreement by chance. Therefore, the method that addresses this issue, such as the agreement coefficient (AC1), is necessary.

4.4.2 Agreement Coefficient (AC1)

Agreement Coefficient (AC1), in this study, refers to the conditional probability that the results agree from two independent methods of measuring emissions, given that there is no agreement by chance. The estimator of AC1 is $\hat{\kappa}_\gamma$ which is defined as the following.

$$\hat{\kappa}_\gamma = \frac{P_0 - P_{e\gamma}}{1 - P_{e\gamma}} \quad (4.16)$$

$$P_{e\gamma} = 2 \cdot \pi_0 (1 - \pi_0) \quad (4.17)$$

$$\pi_0 = \frac{n_{\bullet 0} + n_{0 \bullet}}{2N} \text{ and } \pi_1 = 1 - \pi_0 \quad (4.18)$$

where P_0 is already defined earlier and $P_{e\gamma}$ is the chance agreement probability with a certain degree of uncertainty. Moreover, π_0 and π_1 are the probabilities that a method

classifies a vehicle into passing (0) and failing (1) cases respectively. Gwet (2003) also defines the variance of κ_γ estimator as the following.

$$V(\kappa_\gamma) = \frac{1}{N-1} \left(\frac{P_0(1-P_0)}{(1-P_{ey})^2} \right) \quad (4.19)$$

4.4.4 Logistic Model

This research mainly uses the logistic model to demonstrate the divergence between the results from RSD measurement and those from the OBD II test. Formally,

$$\begin{aligned} \ln \left(\frac{P(\text{AGREE})}{1-P(\text{AGREE})} \right) = & \beta_0 + \beta_A \text{AGE} + \beta_M \text{MPY} + \beta_E \text{ELAPSE} + \beta_{VC} \text{VC} + \beta_{MY} \text{MY} + \\ & \beta_{AE} \text{AGE} \cdot \text{ELAPSE} + \beta_{ME} \text{MPY} \cdot \text{ELAPSE} + \alpha_{RSD} + \varepsilon_i \end{aligned} \quad (4.20)$$

where AGREE is a measure of concordant results between RSD measurement and the OBD II test. AGE is the age of vehicle at the RSD observed year. ELAPSE is the elapse time between RSD measurement and the OBD II test. MPY is the miles driven per year of a vehicle. VC is a vector of vehicle characteristics including the number of cylinders, type, manufacturer, production location, and a set of emission control technology. MY is a vector of model years, ranging from 1996 to 2002. Lastly, α_{RSD} is the fixed effects of times and locations of RSD measurements. Assuming that RSD measurement variability is constant overtime, the odds of AGREE is expected to decrease with AGE, indicating the decreasing validity and reliability of the OBD II test of the old vehicle fleet.

4.4.5 Log-Linear Model

This study also uses the log-linear model to explore the determinants of the tailpipe emission intensity. In particular, the divergence between the RSD measurement and the OBD II test may contribute to the variability of tailpipe emissions. There are two types of the disagreeing results between RSD and OBD II: (1) fail RSD and pass OBD (DISAGREE1), and (2) pass RSD and fail OBD (DISAGREE2). Only DISAGREE1 group is used because DISAGREE2 group relates to the clean vehicles which pass the RSD measurement but fail the OBD II test. The OLS model is in the double log form because the distribution of the EMISSION INDEX is very positively skewed and data transformation is necessary.

$$\begin{aligned} \text{Ln}(\text{EMISSION INDEX}) = & \beta_0 + \beta_O \text{OBD} + \beta_A \text{AGE} + \beta_M \text{Ln}(\text{MPY}) + \beta_S \text{Ln}(\text{SPEED}) + \\ & \beta_W \text{Ln}(\text{WEIGHT}) + \beta_X X + \alpha_{\text{RSD}} \end{aligned} \quad (4.21)$$

$$\begin{aligned} \text{Ln}(\text{EMISSION INDEX}) = & \beta_0 + \beta_D \text{DISAGREE1} + \beta_A \text{AGE} + \beta_M \text{Ln}(\text{MPY}) + \beta_S \text{Ln}(\text{SPEED}) + \\ & \beta_W \text{Ln}(\text{WEIGHT}) + \beta_X X + \alpha_{\text{RSD}} \end{aligned} \quad (4.22)$$

where OBD refers to the OBD II test result (pass or fail). AGE and MPY refer to the same variables as appeared in the logistic model. SPEED and WEIGHT are also in the log transformation. X is a vector of vehicle characteristics which are a series of categorical variables including types, makes, production locations, model years and emission control technologies. α_{RSD} is the fixed effect of time and location of RSD measurement.

Previous study shows that automobile emissions (CO and HC) are statistically γ - distributed (Zhang, Bishop, & Stedman, 1994). The model in this study does not fit the γ - distribution because of two reasons. First, the probability distribution function (pdf) of the γ - distribution is determined by its skewness and kurtosis. Although Zhang, Bishop, and

Stedman (1994) describe the distribution of CO and HC emissions using the vehicle age, they simply calculate and compare the skewness and kurtosis for each model year of vehicle fleets. However, the purpose of this study is to identify the factors contributing to emission intensity, which requires other parameters beyond the description of data distribution. Second, the EMISSION INDEX is not the original automobile emissions but the scale adjusted value of the three emissions (CO, HC, and NOx) relative to their threshold levels.

4.5 Data Sources

There are two pooled cross-sectional datasets used in this study: the Georgia Inspection and Maintenance (I/M) Program records and the Continuous Atlanta Fleet Evaluation (CAFE).

4.5.1 Inspection and Maintenance Program Records (I/M) 2002 – 2005

The I/M 2002 - 2005 consists of the inspection transactions that occurred at the decentralized testing stations located in the same 13 counties. For each transaction, some information is keyed in manually such as the odometer; others are input automatically such as the detailed testing conditions. The OBD II test result is recorded automatically by the test analyzer, which can interrogate a vehicle's OBD system. The quality and performance of the test analyzer is regulated by the enforcement agency via the biennial certification process (Clean Air Force, 2008). In Atlanta, the OBD II test was first administered in May 2002.

4.5.2 Continuous Atlanta Fleet Evaluation (CAFE) 2002 – 2005

The Air Quality Group (AQG), a unit of the Aerospace, Transportation, and Advanced Systems Laboratory, Georgia Tech Research Institute (GTRI), has collected the CAFE database for more than ten years. The CAFE database contains the on-road

tailpipe emissions of vehicles, gathered by the remote sensing devices⁵⁰ (RSD), and the corresponding license plates, captured by the video cameras. The license plate information is later matched with the vehicle registration database to obtain the vehicle identification number⁵¹ (VIN). With VIN Decoder version 2002.01 for the MOBILE 6⁵² types (Eastern Research Group Inc., April 4, 2003), the specialized software that extracts the vehicle information from VIN, AQG includes information about the vehicle manufacturer, model year, attributes such as the body style, model name, and emission control technologies. Examples of emission control technologies include the exhaust gas recirculation (EGR), fuel induction, and thermostatic air cleaner (TAC). In the year 2000, AQG collected vehicle emission data by RSD from 43 sites throughout 13 counties of the Atlanta I/M program area. This study utilizes the data collected during 2002 to 2005.

4.5.3 Matching Datasets

This study matches the CAFE 2002 – 2005 with the I/M 2002 - 2005 using the vehicle identification number (VIN). For each year, it is possible that there is more than one matched pair of each VIN due to several reasons. Vehicles might pass RSD units more than a few times. Also, some vehicles might take the inspection more than one time. In such a case, the study selects the matched pair with the shortest elapse time

⁵⁰ “The process of measuring emissions remotely begins when the Source-Detector Module (SDM) of the RSD sends an infrared (IR) and ultraviolet (UV) light beam across a single lane of the road to a Transfer Mirror Module (TMM). The TMM reflects the beam back across the street into a series of detectors in the SDM. These detectors convert the IR/UV energy into an electrical signal – the greater the IR/UV energy detected, the higher the electrical signal level and the lower the emission reading. Exhaust gasses from dirtier vehicles absorb more of the signal (URL <http://www.bar.ca.gov>, 2007).”

⁵¹ VIN is a unique serial number used by the automobile industry to identify individual vehicles. Generally, VINs consist of 17 characters excluding the letters I, O, or Q (URL <http://www.wikipedia.org>, March 2009).

⁵² “MOBILE6 is an emission factor model for predicting gram per mile emissions of HC, CO, NOx, Carbon Dioxide (CO₂), Particulate Matter (PM), and toxics from cars, trucks, and motorcycles under various conditions (URL <http://www.epa.gov/oms/m6.htm>).”

between RSD measurement and the OBD II test to ensure the minimum intervening factors. For the same reason, this study also keeps only the observations with the RSD measurement occurring *before* the OBD II test took place.

4.6 Variables and Descriptive Statistics

Table 4.2 presents all the variables and their descriptions. In Table 4.3, the total number of RSD – OBD II matched pair observations during the period of 2002 – 2005 is 82,523 and 77,684, depending on the methods discussed in the following sections. Each observation in the sample is an individual unique vehicle. The unit of analysis in this study is both individual and groups of vehicles. Table 4.4 and 4.5 show the distribution of vehicles categorized by age and model year in the two samples.

Mainly, this study utilizes two samples for the different analyses. The first sample contains 82,523 observations, which are used in the RSD-OBD agreement analysis. Table 4.6 shows the descriptive statistics of the first sample. The second sample includes 77,684 observations, which are utilized in the emission intensity analysis. The number of observations is different from the previous analysis owing to the valid information of vehicle speed.

Table 4.2 Variables and descriptions

| Variables | Level | Descriptions |
|-------------------------------------|----------|--|
| <u>Dependent Variables</u> | | |
| AGREE | Nominal | Agreed results between RSD and OBD: 1 if Pass-RSD-Pass-OBD or Fail-RSD-Fail-OBD 0 if otherwise |
| Ln(EMISSION INDEX) | Ratio | Natural log of EMISSION INDEX |
| <u>Independent Variables</u> | | |
| DISAGREE1 | Nominal | Disagreed results between RSD and OBD: 1 if Fail-RSD-Pass-OBD; 0 if AGREE = 1 |
| DISAGREE2 | Nominal | Disagreed results between RSD and OBD: 1 if Pass-RSD-Fail-OBD; 0 if AGREE = 1 |
| OBD | Nominal | OBD II test result; 1 if Fail; 0 if otherwise |
| Elapse | Interval | Elapse time between RSD measurement and OBD II test (day) |
| Age | Interval | Vehicle age (year) |
| Age squared | Interval | Vehicle age squared |
| Age x Elapse | Interval | Vehicle age |
| Age category | | |
| 3 year | Nominal | Age: 1 if age 3 and 0 if otherwise |
| 4 year | Nominal | Age: 1 if age 4 and 0 if otherwise |
| 5 year | Nominal | Age: 1 if age 5 and 0 if otherwise |
| 6 year | Nominal | Age: 1 if age 6 and 0 if otherwise |
| 7 year | Nominal | Age: 1 if age 7 and 0 if otherwise |
| 8 year | Nominal | Age: 1 if age 8 and 0 if otherwise |
| 9 year (Ref.) | Nominal | Age: 1 if age 9 and 0 if otherwise |
| Ln(MPY) | Ratio | Natural log of mile driven per year |
| Ln(MPY) squared | Ratio | Square of the Natural log of mile driven per year |
| Ln(MPY) x Elapse | Ratio | Interaction between the natural log of mile driven per year and elapse time |
| Ln(Speed) | Ratio | Natural log of speed (mile per hour) |
| Ln(Est. test loaded vehicle weight) | Interval | Natural log of the estimated test loaded vehicle weight (ton) |

Table 4.2 Cont.

| Variables | Level | Descriptions |
|---------------------------------|----------|--|
| Cylinder | Interval | Number of cylinder |
| Exhaust Gas Recirculation (EGR) | Nominal | Emission control technology: 1 if vehicle equipped with EGR; 0 if otherwise |
| Air Injection Reactor (AIR) | Nominal | Emission control technology: 1 if vehicle equipped with AIR; 0 if otherwise |
| Van and other | Nominal | Vehicle type: 1 if a vehicle is a van and other; 0 if otherwise |
| SUV | Nominal | Vehicle type: 1 if a vehicle is a SUV |
| Truck | Nominal | Vehicle type: 1 if a vehicle is a truck |
| Car (Ref.) | Nominal | Vehicle type: 1 if a vehicle is a car |
| Asia-Pacific | Nominal | Location of production: 1 if a vehicle is made in Asia-Pacific region |
| Europe | Nominal | Location of production: 1 if a vehicle is made in the European region |
| North-Central America | Nominal | Location of production: 1 if a vehicle is made in North-Central America |
| USA (Ref.) | Nominal | Location of production: 1 if a vehicle is made in the US |
| Chrysler | Nominal | Manufacturer: 1 if a vehicle is made by Chrysler; 0 if otherwise |
| European | Nominal | Manufacturer: 1 if a vehicle is made by European; 0 if otherwise |
| GM | Nominal | Manufacturer: 1 if a vehicle is made by GM; 0 if otherwise |
| Honda | Nominal | Manufacturer: 1 if a vehicle is made by Honda; 0 if otherwise |
| Japanese-Korean | Nominal | Manufacturer: 1 if a vehicle is made by other Japanese or Korean automaker; 0 if otherwise |
| Toyota | Nominal | Manufacturer: 1 if a vehicle is made by Toyota; 0 if otherwise |
| Ford (Ref.) | Nominal | Manufacturer: 1 if a vehicle is made by Ford; 0 if otherwise |
| Model year category | | |
| 1996 | Nominal | Model year: 1 if the model year of a vehicle is 1996; 0 if otherwise |
| 1997 | Nominal | Model year: 1 if the model year of a vehicle is 1997; 0 if otherwise |
| 1998 | Nominal | Model year: 1 if the model year of a vehicle is 1998; 0 if otherwise |
| 1999 | Nominal | Model year: 1 if the model year of a vehicle is 1999, 0 if otherwise |
| 2000 | Nominal | Model year: 1 if the model year of a vehicle is 2000; 0 if otherwise |
| 2001 | Nominal | Model year: 1 if the model year of a vehicle is 2001, 0 if otherwise |
| 2002 (Ref.) | Nominal | Model year: 1 if the model year of a vehicle is 2002, 0 if otherwise |

Table 4.3 Distribution of vehicles by the years of RSD measurement and OBD II test

| Number of Observations | Years of RSD Measurement & OBD II Test | | | | Total |
|------------------------|--|--------|--------|--------|--------|
| | 2002 | 2003 | 2004 | 2005 | |
| Logistic Model | 11,888 | 19,975 | 26,241 | 24,419 | 82,523 |
| OLS Model | 11,195 | 18,836 | 24,801 | 22,852 | 77,684 |

Table 4.4 Distribution of vehicles categorized by age and model year in the logistic model

| Age (year) | Model Year of Vehicle | | | | | | | Total |
|------------|-----------------------|--------|--------|--------|--------|-------|-------|--------|
| | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | |
| 3 | | | | 3,292 | 5,014 | 5,337 | 4,874 | 18,517 |
| 4 | | | 3,049 | 4,429 | 5,306 | 4,213 | | 16,997 |
| 5 | | 2,804 | 4,062 | 4,811 | 4,244 | | | 15,921 |
| 6 | 2,459 | 3,447 | 4,103 | 3,823 | | | | 13,832 |
| 7 | 2,958 | 3,625 | 3,066 | | | | | 9,649 |
| 8 | 2,988 | 2,567 | | | | | | 5,555 |
| 9 | 2,052 | | | | | | | 2,052 |
| Total | 10,457 | 12,443 | 14,280 | 16,355 | 14,564 | 9,550 | 4,874 | 82,523 |

Table 4.5 Distribution of vehicles categorized by age and model year in the OLS model

| Age (year) | Model Year of Vehicle | | | | | | | Total |
|------------|-----------------------|--------|--------|--------|--------|-------|-------|--------|
| | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | |
| 3 | | | | 3,105 | 4,747 | 4,999 | 4,555 | 17,406 |
| 4 | | | 2,876 | 4,188 | 5,025 | 3,937 | | 16,026 |
| 5 | | 2,641 | 3,811 | 4,544 | 3,976 | | | 14,972 |
| 6 | 2,303 | 3,255 | 3,893 | 3,553 | | | | 13,004 |
| 7 | 2,782 | 3,449 | 2,868 | | | | | 9,099 |
| 8 | 2,815 | 2,423 | | | | | | 5,238 |
| 9 | 1,939 | | | | | | | 1,939 |
| Total | 9,839 | 11,768 | 13,448 | 15,390 | 13,748 | 8,936 | 4,555 | 77,684 |

4.6.1 Dependent Variable: Agreement between RSD Measurement and OBD II Test

The constructions of some key variables are necessary prior to the creation and analysis of agreement between RSD and OBD II (AGREE variable). Generally, RSD measures the level of tailpipe emissions in terms of three pollutants: carbon monoxide (CO), hydrocarbon (HC), and oxide of nitrogen (NOx). On the other hand, without physically testing the emission level, OBD II (OBD variable) test gives either pass or fail result based on a trouble code stored in a vehicle computer unit. In principle, the trouble code occurs when there is a problem with the emission control system. Despite the different approaches of evaluating vehicle emissions, both methods can give the final outcome of either *pass* or *fail* for a vehicle. Because the OBD II test conveys limited information about vehicle emission conditions, it is necessary to transform RSD raw measurements to be comparable with the OBD II results. Thus, this study creates the combined EMISSION INDEX based on RSD measurement of three pollutants. Next, the study generates the indicator function of the EMISSION INDEX called the RSD INDEX, evaluating the pass or fail status of a vehicle based on the three pollutant standards used in the tailpipe emission test. Finally, the study constructs the AGREE variable from the cross-tabulation of the pass or fail results from the RSD INDEX and OBD variables.

Table 4.6 Descriptive statistics of variables in the logistic model of the RSD-OBd agreement analysis (N = 82,523)

| Variables | Mean | Std. Dev. | Min | Max |
|---|---------|-----------|---------|---------|
| <u>Dependent Variables</u> | | | | |
| AGREE (Yes=1) | 0.72 | 0.45 | 0 | 1 |
| <u>Independent Variables</u> | | | | |
| DISAGREE1 (Yes=1) (Fail RSD, Pass OBD) | 0.24 | 0.43 | 0 | 1 |
| DISAGREE2 (Yes=1) (Pass RSD, Fail OBD) | 0.04 | 0.20 | 0 | 1 |
| Vehicle age (year) | | | | |
| Age | 5.05 | 1.66 | 3 | 9 |
| Age squared | 28.22 | 18.21 | 9 | 81 |
| Age x Elapse | 591.83 | 483.45 | 0.90 | 2829.92 |
| Age category | | | | |
| 3 year | 0.22 | 0.42 | 0 | 1 |
| 4 year | 0.21 | 0.40 | 0 | 1 |
| 5 year | 0.19 | 0.39 | 0 | 1 |
| 6 year | 0.17 | 0.37 | 0 | 1 |
| 7 year | 0.12 | 0.32 | 0 | 1 |
| 8 year | 0.07 | 0.25 | 0 | 1 |
| 9 year | 0.02 | 0.16 | 0 | 1 |
| Vehicle usage (mile driven per year) | | | | |
| Ln(MPY) | 9.78 | 0.44 | -2.08 | 12.68 |
| Ln(MPY) squared | 95.84 | 8.10 | 0 | 160.87 |
| Ln(MPY) x Elapse | 1151.17 | 826.97 | -547.79 | 3755.61 |
| Cylinder | 5.85 | 1.42 | 3 | 17 |
| Emission control technology | | | | |
| Exhaust Gas Recirculation | 0.75 | 0.43 | 0 | 1 |
| Air Injection Reactor | 0.14 | 0.35 | 0 | 1 |
| Type of vehicle | | | | |
| Van and other | 0.10 | 0.30 | 0 | 1 |
| SUV | 0.22 | 0.41 | 0 | 1 |
| Truck | 0.14 | 0.35 | 0 | 1 |
| Car (Ref.) | 0.54 | 0.50 | 0 | 1 |
| Location of production | | | | |
| Asia-Pacific | 0.15 | 0.36 | 0 | 1 |
| Europe | 0.07 | 0.25 | 0 | 1 |
| North-Central America | 0.15 | 0.36 | 0 | 1 |
| USA (Ref.) | 0.63 | 0.48 | 0 | 1 |
| Manufacturer | | | | |
| Chrysler | 0.13 | 0.34 | 0 | 1 |
| European | 0.08 | 0.27 | 0 | 1 |
| GM | 0.18 | 0.39 | 0 | 1 |
| Honda | 0.11 | 0.32 | 0 | 1 |
| Japanese-Korean | 0.14 | 0.35 | 0 | 1 |
| Toyota | 0.13 | 0.33 | 0 | 1 |
| Ford (Ref.) | 0.22 | 0.41 | 0 | 1 |
| Model year | | | | |
| 1996 | 0.13 | 0.33 | 0 | 1 |
| 1997 | 0.15 | 0.36 | 0 | 1 |
| 1998 | 0.17 | 0.38 | 0 | 1 |
| 1999 | 0.20 | 0.40 | 0 | 1 |
| 2000 | 0.18 | 0.38 | 0 | 1 |
| 2001 | 0.12 | 0.32 | 0 | 1 |
| 2002 (Ref.) | 0.06 | 0.24 | 0 | 1 |

Table 4.7 Descriptive statistics of variables in the log-linear model of the emission intensity analysis (N = 77,684)

| Variables | Mean | Std. Dev. | Min | Max |
|--|-------|-----------|-------|-------|
| <u>Dependent variable</u> | | | | |
| Ln(EMISSION INDEX) | -0.03 | 0.51 | -1.43 | 3.61 |
| <u>Independent variables</u> | | | | |
| OBD (Yes=1) (Fail OBD II Test) | 0.07 | 0.25 | 0 | 1 |
| DISAGREE1 (Yes=1) (Fail-RSD-Pass-OBD) | 0.24 | 0.43 | 0 | 1 |
| Vehicle age (year) | 5.05 | 1.66 | 3 | 9 |
| Ln(Mile driven per year) | 9.78 | 0.44 | -2.08 | 12.68 |
| Ln(Speed) | 3.54 | 0.29 | -2.30 | 4.28 |
| Ln(Est. test loaded vehicle weight) | 8.22 | 0.20 | 7.55 | 8.92 |
| <u>Emission control technology</u> | | | | |
| Air Injection Reactor (AIR) | 0.14 | 0.35 | 0 | 1 |
| Exhaust Gas Recirculation (EGR) | 0.76 | 0.43 | 0 | 1 |
| <u>Type of vehicle</u> | | | | |
| Van and other | 0.10 | 0.30 | 0 | 1 |
| SUV | 0.22 | 0.41 | 0 | 1 |
| Truck | 0.14 | 0.35 | 0 | 1 |
| Car (Ref.) | 0.54 | 0.50 | 0 | 1 |
| <u>Location of production</u> | | | | |
| Asia-Pacific | 0.15 | 0.36 | 0 | 1 |
| Europe | 0.07 | 0.25 | 0 | 1 |
| North-Central America | 0.15 | 0.36 | 0 | 1 |
| USA (Ref.) | 0.63 | 0.48 | 0 | 1 |
| <u>Manufacturer</u> | | | | |
| Chrysler | 0.13 | 0.34 | 0 | 1 |
| European | 0.08 | 0.27 | 0 | 1 |
| GM | 0.18 | 0.39 | 0 | 1 |
| Honda | 0.12 | 0.32 | 0 | 1 |
| Japanese-Korean | 0.15 | 0.35 | 0 | 1 |
| Toyota | 0.13 | 0.33 | 0 | 1 |
| Ford (Ref.) | 0.22 | 0.41 | 0 | 1 |
| <u>Model year</u> | | | | |
| 1996 | 0.13 | 0.33 | 0 | 1 |
| 1997 | 0.15 | 0.36 | 0 | 1 |
| 1998 | 0.17 | 0.38 | 0 | 1 |
| 1999 | 0.20 | 0.40 | 0 | 1 |
| 2000 | 0.18 | 0.38 | 0 | 1 |
| 2001 | 0.12 | 0.32 | 0 | 1 |
| 2002 (Ref.) | 0.06 | 0.23 | 0 | 1 |

4.6.1.1 EMISSION INDEX

There are two steps in creating the emission index. First, the normalization of the raw RSD measurements is necessary because three pollutants are measured in different units and scales. For each pollutant, all RSD measurements are divided by their corresponding Accelerated Simulation Mode (ASM) standard thresholds. This ASM emission standard is used for the ASM-2525 testing procedure that actually measures the real tailpipe emission (EPA, 2004). For each pollutant, there are 47 thresholds in accordance with the 47 ranges of estimated testing vehicle weight (ETW).

$$\text{CO Index} = \frac{\text{CO Raw RSD Measurement}}{(\text{CO ASM2525 Threshold} | \text{ETW})}; \text{CO Index} \in (0, \infty+)$$

$$\text{HC Index} = \frac{\text{HC Raw RSD Measurement}}{(\text{HC ASM2525 Threshold} | \text{ETW})}; \text{HC Index} \in (0, \infty+) \quad (4.23)$$

$$\text{NOx Index} = \frac{\text{NOx Raw RSD Measurement}}{(\text{NOx ASM2525 Threshold} | \text{ETW})}; \text{NOx Index} \in (0, \infty+)$$

When the values of these indices are equal to or greater than one, their real corresponding emission exceeds their standard thresholds. Also, these indices have no unit, which facilitates the next step.

Second, the translation of the policy rules into the creation of a combined emission index is also important. Although there are three different sets of thresholds for the three different pollutants, vehicles fail if their emissions exceed one or more of the three pollutant thresholds. It is typical for the standard-based policies in that there is no different treatment between a vehicle violating the thresholds in all three pollutants and a vehicle exceeding the thresholds for only one pollutant. In other words, the compliance

status of these two vehicles is the same. Nonetheless, the final combined emission can show the severity of emission to some degree.

$$\begin{aligned} \text{EMISSION INDEX} &= \text{Max}(\text{COIndex}, \text{HCIndex}, \text{NOxIndex}) \\ \text{EMISSION INDEX} &\in (0, \infty +) \end{aligned} \tag{4.24}$$

Similar to the three pollutant indices, the emission index is equal to or greater than one when any of the three pollutant indices exceed the standard threshold. EMISSION INDEX has no unit and represents just the degree of dirtiness of vehicles. The distribution of the EMISSION INDEX appears that the majority of vehicles are clean in terms of their tailpipe emissions.

4.6.1.2 RSD INDEX

The RSD INDEX is simply the indicator function of the variable EMISSION INDEX, demonstrating whether the emission exceeds the emission standard. Therefore, the RSD INDEX is a dichotomous variable, taking the value of one when the real tailpipe emissions of a particular vehicle exceed the ASM 2525 standard thresholds and zero otherwise. The RSD INDEX is parallel to the OBD II test results in that it yields either pass or fail results.

$$\begin{aligned} \text{RSD INDEX} &= \text{I}(\text{EMISSION INDEX}) \\ \text{RSD INDEX} &= \begin{cases} 1 & \text{if EMISSION INDEX} \geq 1; \text{ FAIL} \\ 0 & \text{if EMISSION INDEX} < 1; \text{ PASS} \end{cases} \end{aligned} \tag{4.25}$$

In the sample, using the ASM 2525 standard cut points, this study finds that the share of vehicles failing the RSD measurement is around 27 percent. The shares decrease to 11 and 6 when using 2 and 3 times of the ASM 2525 standard respectively.

4.6.1.3 OBD

The variable OBD is the OBD II test results obtained from the I/M 2002 – 2005. In Georgia, the OBD II test was first implemented in the year 2002. OBD is the dichotomous variable with the value of one when vehicles fail the test and zero otherwise. In the sample, only 7 percent of the vehicles fail the OBD II test.

$$OBD = \begin{cases} 1 & \text{if OBD II TEST = FAIL} \\ 0 & \text{if OBD II TEST = PASS} \end{cases} \quad (4.26)$$

4.6.1.4 AGREE

The variable AGREE refers to the agreement in the measurements by RSD and OBD II. The variable AGREE indicates the concordant results between RSD INDEX and OBD variables. As a result, AGREE is a dichotomous variable taking the value of one when OBD and RSD INDEX yield the same results and zero otherwise.

$$AGREE = \begin{cases} 1 & \text{if [RSD INDEX = 1 \& OBD = 1] OR [RSD INDEX = 0 \& OBD = 0]} \\ 0 & \text{if [RSD INDEX = 1 \& OBD = 0] OR [RSD INDEX = 0 \& OBD = 1]} \end{cases} \quad (4.27)$$

In the total sample of 82, 523 unique vehicles, vehicles that show agreed results between RSD and OBD methods are around 72 percent while those that show disagreed results are around 28 percent. Within the disagreed results, the share of

DISAGREE1 (fail-RSD-pass-OBD) accounts for 86 percent. The share of DISAGREE2 (pass-RSD-fail-OBD) is around 14 percent.

4.6.2 Independent Variables

4.6.2.1 Vehicle Age

Vehicle age (AGE) is the key independent variable in this study. Because vehicles deteriorate over time, vehicle age is a good predictor of the divergence in the agreement between RSD measurements and OBD II test results. Vehicle age is a crude proxy for the engine decay and measured with less error than the total mileage obtained from the odometer. In this study, vehicle age is a measure of 'stock' of the vehicle deterioration. In brief, the older the vehicle age, the less agreement between the RSD and OBD II test results. In this sample, there are seven age groups, ranging from 3 to 9 years. A majority of vehicles (22.44 percent) in the samples are 3 years old. The minimum share of vehicles in the sample is the 9 year old vehicles, accounting for around 2.49 percent. The average age of vehicles in the sample is around 5 years.

4.6.2.2 Mile Driven Per Year

Mile driven per year (MPY) is an important independent variable as it indicates the average yearly usage of a vehicle. New vehicles might have high mileage if they are used intensively. In other words, MPY is a measure of 'flow' of the vehicle deterioration due to usage. Mileage per year in the model is the log transformed of the original variable. Similar to vehicle age, the higher the MPY, the less agreement between the RSD and OBD II test results. On average, the mile-driven per year for each vehicle is around 18 thousand miles.

4.6.2.3 Elapse Time between RSD Measurement and OBD II Test

The variable ELAPSE is the elapse time between the RSD measurement and the OBD II test. It is one of the main control variables in this study. Ideally, if the RSD measurement and the OBD II test occur on the same time and day, the divergence between these two methods will be certainly due to the OBD II malfunction. In reality, however, the RSD measurement stations and schedules are random and rarely coincide with the OBD II test, causing the elapse time between the two methods. Typically, the longer the elapse time, the less agreement between the two methods, assuming only the effect of a deteriorated engine. Nonetheless, the longer the elapse time, the higher chance of other intervening activities taken by the vehicle owners. For example, vehicle owners might have their cars repaired before they have inspections. To mitigate the chance of intervening factors, this study uses the RSD measurement taken *only before* the OBD II test. If elapse time becomes positively significant in the model, the chance of intervening activities is possible accordingly. Using 'RSD before OBD' sample allows this study to infer the causes of the disagreement between the RSD measurement and the OBD II test. Table 4.8 summarizes the relation between the elapse time and vehicle deterioration inferred from the type of the disagreement between RSD and OBD II.

For vehicles that *pass the RSD* but *fail the OBD* methods, the possible reason is the deteriorated engine with the normal OBD system. An intervening activity is unlikely because if there is such an activity, then the OBD test result should be a passing one. If the elapse variable is significant for this particular group of vehicles, then it is likely that the disagreement between RSD and OBD methods is due to a deteriorated engine.

For vehicles that *fail RSD* but *pass OBD*, there is a chance of intervening activities taking place. However, the possibility of the OBD II be malfunctioning is also possible. If the variable elapse becomes significant in this group of vehicles, then the conclusion is ambiguous since intervening activity causes cannot be ruled out.

Table 4.8 Relation between the elapse time and the vehicle deterioration inferred from the type of disagreement between RSD and OBD II test

| Elapse Time | Type of Disagreement | |
|---|----------------------|----------------------|
| | Fail RSD, Pass OBD | Pass RSD, Fail OBD |
| Longer elapse, Greater deterioration - Deteriorated engine, Malfunction OBD - Deteriorated engine, Normal OBD | Possible Unlikely | Unlikely Possible |
| Longer elapse, Higher chance of intervening activities | Possible | Unlikely |

The elapse time may have different effects on the deterioration rate of vehicles in different age groups. Similarly, the longer the elapse time, the larger the MPY that might contribute to the greater deterioration of vehicles, particularly their engines and the OBD II system. To test the varying effect of the elapse time for different age groups and usage, this study includes two interaction terms capturing the additional effects of elapse: Age x Elapse and MPY x Elapse.

In this sample, the distribution of the elapse time variable is one half of the triangular shape, resulting from the sample selection criteria of the RSD measurement before the OBD II test. On average, the RSD measurement occurs around 3.5-4 months prior to the OBD II test.

4.6.2.4 Vehicle Characteristics and Technologies

Vehicle characteristics might contribute to the difference between RSD and OBD II measurements. General characteristics of vehicles include the model year fixed effects, number of cylinders, weight, types (car, truck, SUV, van and other), manufacturer (Ford, Chrysler, Honda, Toyota, Japanese-Korean, and European) and production locations (US, North & Central America, Asia-Pacific, and Europe). In both samples, a majority of vehicles are cars (54 percent) and made in the U.S. (63 percent). Vehicles manufactured by Ford are the biggest share (22 percent) in both samples. The proxy of vintage technology is the vehicle model year, dominated by the model years

1999 and 2000 (20 and 18 percent respectively). In addition, the emission control technology is comprised of several parts but those included in the models are the air injection reactor system (AIR) and the exhaust gas recirculation (EGR)⁵³. While most vehicles in the sample are equipped with the EGR (75 percent), only a few (15 percent) have the AIR installed.

4.6.2.5 RSD Measurement Condition

The parametric models also include the time (day, month, and year) and sites of RSD measurement as fixed effects. The environmental condition during different time of RSD measurement might vary and cause the variability in the emission measurements. The fixed effects can capture the unobserved heterogeneity, assuming that the RSD measurement variability is constant over time.

4.7 Results and Discussion

4.7.1 RSD-OBD Agreement Analysis

4.7.1.1 Effects of Vehicle Age

Table 4.9 shows the percentage of vehicles classified by RSD measurement (RSD INDEX) and OBD II test result (OBD). Clearly, the majority of the vehicles are clean because they pass both RSD and OBD. However, the compositions of the four categories are different among age groups. On average, the share of the clean vehicle category (pass-RSD-pass-OBD) is decreasing at the rate of 4.51 percentage points. Differently, for the dirty ones (fail-RSD-fail-OBD), the average increase in the share of

⁵³ In CAFE 2002 – 2005, other emission control technologies are available, including evaporative emission control (EVP), oxidation (OXY), three-way catalyst (TWC), closed loop combustion control (CLL), positive crankcase ventilation (PCV), and thermostatic air cleaner (TAC). However, when included in the model, they are not statistically significant and hence dropped.

this type is 0.88 percentage points. The disagreed results between RSD and OBD are very striking. The share of vehicles classified as fail-RSD-pass-OBD is increasing at the average rate of 3.30 percentage points. On the other hand, the share of vehicles classified as pass-RSD-fail-OBD is increasing at the rate of 0.33 percentage points, which is ten times less than the previous disagreed result. This indicates that when the OBD II system malfunctions, only vehicles that show the failure results at the inspection station will be repaired. For the malfunctioning OBD II that yields the passing results, there is no indication of this error and it is unlikely to be repaired. Because there is no detection of the malfunctioning OBD and old vehicles tend to pollute more, this phenomenon can affect the effectiveness of the I/M program in terms of pollution reduction.

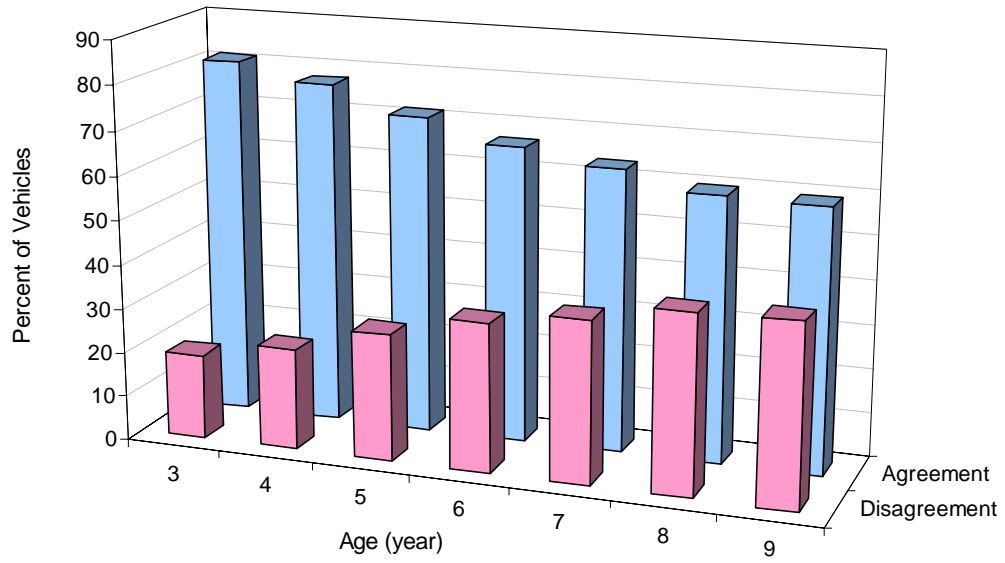
If RSD variability is assumed to be symmetric, the RSD divergence from OBD, as shown by the share of the pass-RSD-fail-OBD category, can be considered as the 'base level variability' of RSD measurement. Consequently, the difference of the share between two groups, fail-RSD-pass-OBD vs. pass-RSD-fail-OBD, probably indicates the bias of the OBD II test due to several possible reasons: cheating, pre-test repair, and OBD malfunction.

Table 4.9 Percent of vehicles grouped by age in different agreement categories

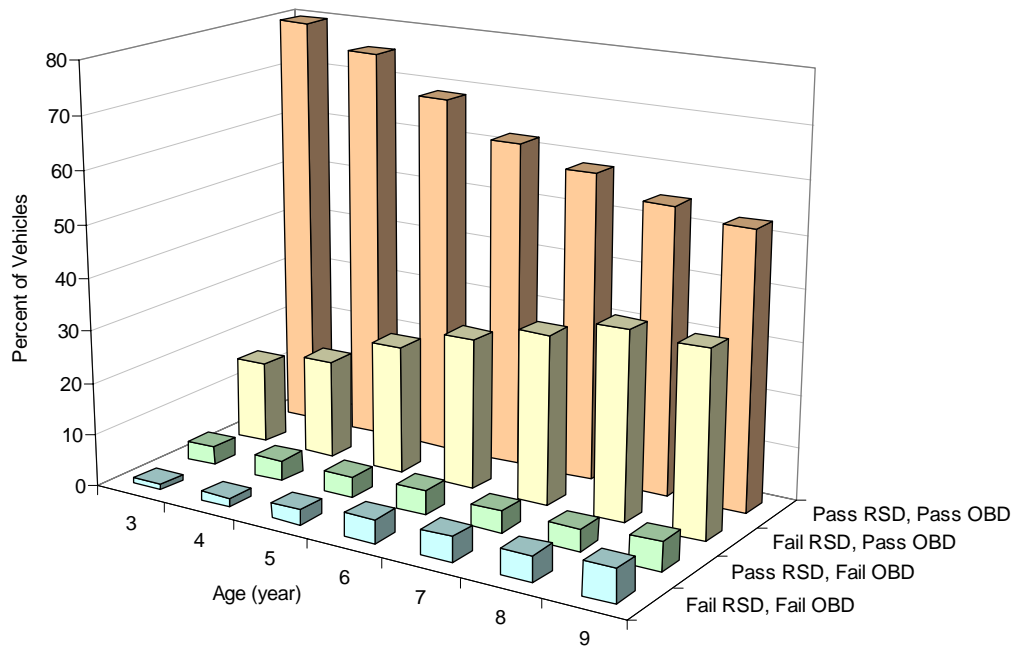
| Age (year) | Pass RSD Pass OBD (η_{00}) | Fail RSD Pass OBD (η_{01}) | Pass RSD Fail OBD (η_{10}) | Fail RSD Fail OBD (η_{11}) |
|--|---|---|---|---|
| 3 | 79.94 | 15.60 | 3.47 | 0.99 |
| 4 | 75.55 | 18.87 | 3.89 | 1.69 |
| 5 | 68.59 | 24.53 | 4.02 | 2.85 |
| 6 | 62.20 | 28.72 | 4.65 | 4.44 |
| 7 | 58.69 | 32.33 | 4.15 | 4.83 |
| 8 | 54.76 | 36.02 | 4.27 | 4.95 |
| 9 | 52.88 | 35.38 | 5.46 | 6.29 |
| Average Difference between Consecutive Group | -4.51 | 3.30 | 0.33 | 0.88 |

In Figure 4.1, vehicles are classified by age and the type of agreement (agree and disagree) between the RSD and OBD methods. Panel (A) shows the trends of the increasing share of the disagreement results. Panel (B) further decomposes the agreement and disagreement into detailed categories. Evidently, the fail-RSD-pass-OBD category is the major contribution of the disagreement types.

The raw agreement indices are shown in Table 4.10. The overall agreement or accuracy of the OBD II test is smaller for the older vehicle group, indicating the divergence between RSD and OBD II. Additionally, the agreement ratios of the pass-RSD-pass-OBD category are smaller whereas those of the fail-RSD-fail-OBD category are higher in the older groups. For each age group, both Pearson and Likelihood-ratio Chi-squared demonstrates similar results. The null hypothesis of independence between the RSD measurement and the OBD II test result is strongly rejected. However, the strength or magnitude of both Chi-squared statistics illustrates the non-monotonic pattern. Similarly, the Fisher exact test indicates the significance of association between the two methods. The results show that the RSD measurement is not independent from the OBD II test result.



(A)



(B)

Figure 4.1 Percent of vehicles by age group, classified by RSD measurement and OBD II test

Table 4.10 Raw agreement indices and the statistical tests by vehicle age group

| Age (year) | Overall Agreement Ratio ^a | Specific Agreement ^a | | Pearson Chi-squared ^b | Likelihood-ratio Chi-squared ^b | Fisher Exact ^c |
|------------|--------------------------------------|---------------------------------|-----------------------|----------------------------------|---|---------------------------|
| | | Positive Rating Ratio | Negative Rating Ratio | | | |
| 3 | 0.809 (0.003) | 0.094 (0.002) | 0.893 (0.035) | 20.155 (0.000) | 18.663 (0.000) | (0.000) |
| 4 | 0.772 (0.003) | 0.129 (0.003) | 0.869 (0.039) | 57.740 (0.000) | 52.702 (0.000) | (0.000) |
| 5 | 0.714 (0.004) | 0.166 (0.003) | 0.828 (0.046) | 117.675 (0.000) | 108.937 (0.000) | (0.000) |
| 6 | 0.666 (0.004) | 0.210 (0.004) | 0.789 (0.052) | 153.611 (0.000) | 145.848 (0.000) | (0.000) |
| 7 | 0.635 (0.005) | 0.209 (0.004) | 0.763 (0.056) | 112.889 (0.000) | 108.928 (0.000) | (0.000) |
| 8 | 0.597 (0.007) | 0.197 (0.005) | 0.731 (0.060) | 37.843 (0.000) | 37.167 (0.000) | (0.000) |
| 9 | 0.592 (0.011) | 0.235 (0.009) | 0.721 (0.062) | 15.804 (0.000) | 15.573 (0.000) | (0.000) |

^a Standard errors in parentheses for overall and specific agreement ratios

^b P-values in parentheses for Pearson and Likelihood-ratio Chi-squared

^c Fisher exact tests report only p-values

The AC1s in Table 4.10 illustrate similar results to the overall agreement ratios in Table 4.3. The AC1 of the older group is smaller than the newer ones. However, the magnitude of AC1 is smaller than the overall agreement ratio because the calculation of AC1 is adjusted for the agreement by chance. At present, the test statistics of AC1 is not available but variance of AC1 can convey a certain degree of information about its deviation. Figure 4.2 plots of the comparison between the overall agreement ratio and the agreement coefficients. It is clear that the agreement between RSD and OBD methods are lower in the older vehicle groups.

TABLE 4.11 Agreement coefficients (AC1) and their variances by vehicle age group

| Age (year) | Agreement Coefficient (κ_y) | Variance (V_{κ_y}) |
|------------|--------------------------------------|-----------------------------|
| 3 | 0.765 | 0.000013 |
| 4 | 0.705 | 0.000017 |
| 5 | 0.601 | 0.000025 |
| 6 | 0.500 | 0.000036 |
| 7 | 0.434 | 0.000058 |
| 8 | 0.354 | 0.000111 |
| 9 | 0.329 | 0.000318 |

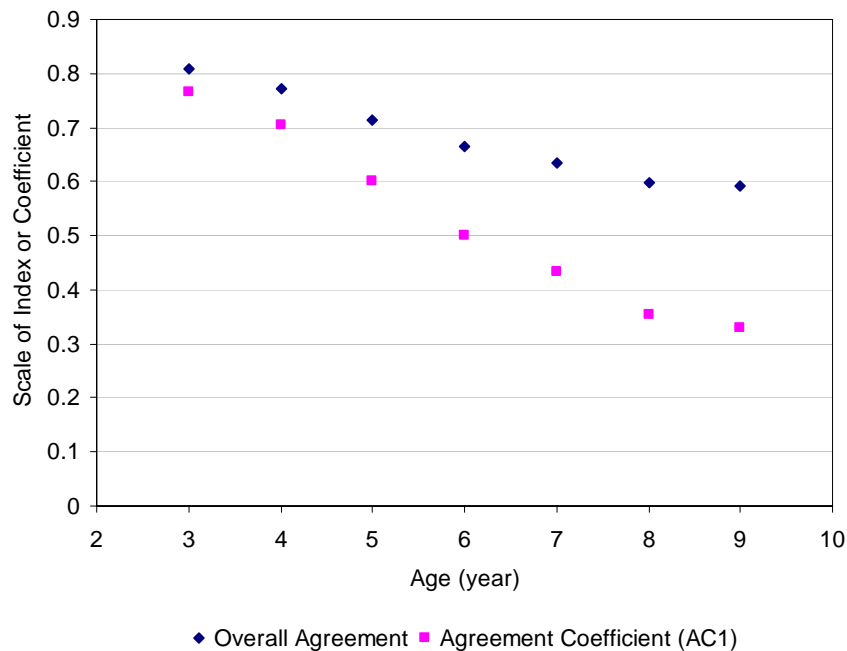


Figure 4.2 Overall agreement index and Agreement Coefficient (AC1) of different vehicle-age groups

In sum, the results from the nonparametric methods clearly indicate the greater divergence of results between the RSD measurement and the OBD II test for older vehicle groups. Moreover, these findings are confirmed by similar and consistent results from the sensitivity analysis where different levels of ASM-2525 standards are used. (See Table B.1 to B.3 in the Appendix B)

The logistic models of the agreement between RSD INDEX and OBD are in Table 4.12. (See Table B.4 in the Appendix B for the sensitivity analysis of the models) AGE is either an interval variable in model (1) - (5) or a set of dichotomous variables in model (6) to allow for the comparison of different age groups with the age-3 group. Unlike models (2) and (4), models (1) and (3) do not include the non-linear terms. Model (5) is the less restricted model, which includes the vehicle model year fixed effects.

Overall, although the models explain the variability of the outcomes around 6 percent (McFadden's Adjusted R-squared), they can correctly classify the outcomes

around 73 percent (count R-squared). The positive predicted value (percentage of the vehicles which were predicted to have the agreement between RSD and OBD, which actually had the agreement results) is around 73 percent. The negative predicted value (percentage of the vehicles which were predicted to have the disagreement between RSD and OBD which actually had disagreement outcomes) is only around 56 percent. Despite the average performance of the models, most of the variables in the models are significant, supported by a series of Wald and LR tests. In addition, the scalar measures of fit (a variety of R-squared, AIC and BIC) are in favor of the models including key variables such as age and MPY but not the elapse time.

The effect of age is quite stable across models. Model (6) shows that the groups of older vehicles have much lower odds of agreement between RSD and OBD than the group of 3-year old vehicles. From the restricted model (1), the odds that RSD and OBD measurements agree for a 5-year old vehicle are 0.74 times as high as those of a comparable 4-year old vehicle, holding the other variables constant. That is, as the vehicle age rises by one year, the odds of agreement between RSD and OBD drop by 26 percent. In terms of the marginal effect, a one year increase of a vehicle age from 5 to 6 years decreases the expected probability of the RSD-OBD agreement by 5.82 percentage points, holding the other variables constant at their means. Models (2), (4), and (5) include the quadratic terms of age and the coefficients are significant. However, adding the quadratic term makes only a little difference on the expected probability of agreement as shown in the Figure 4.3.

Figure 4.4 illustrates the predicted probability of the RSD-OBD agreement calculated from the model (1) for a Ford car made in the US equipped with EGR but without AIR. The predicted probability of the RSD-OBD agreement is lower for the vehicle groups of older age.

Table 4.12 Logistic models of agreement outcomes between RSD measurement and OBD II test

| Independent Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Vehicle age (year) | | | | | | |
| Age | -0.300 (34.16)*** | -0.386 (11.82)*** | -0.303 (34.52)*** | -0.394 (12.04)*** | -0.330 (3.45)*** | |
| Age ² | | 0.008 (2.73)*** | | 0.008 (2.89)*** | -0.003 (0.90) | |
| Age x Elapse | -0.000 (0.87) | -0.000 (0.81) | -0.000 (1.07) | -0.000 (1.00) | -0.000 (1.08) | |
| Age category (Ref: Age 3) | | | | | | |
| Age 4 | | | | | | -0.307 (11.40)*** |
| Age 5 | | | | | | -0.674 (25.25)*** |
| Age 6 | | | | | | -0.948 (34.56)*** |
| Age 7 | | | | | | -1.230 (40.34)*** |
| Age 8 | | | | | | -1.578 (43.50)*** |
| Age 9 | | | | | | -1.725 (32.49)*** |
| Vehicle usage | | | | | | |
| Ln(Mile driven per year) | -0.613 (14.39)*** | -0.614 (14.39)*** | 0.970 (5.67)*** | 0.972 (5.70)*** | 0.980 (5.74)*** | -0.619 (14.73)*** |
| Ln(Mile driven per year) ² | | | -0.082 (9.08)*** | -0.082 (9.11)*** | -0.083 (9.16)*** | |
| Ln(Mile driven per year) x Elapse | 0.000 (0.85) | 0.000 (0.86) | -0.000 (0.09) | -0.000 (0.08) | -0.000 (0.08) | 0.000 (1.04) |
| Elapse between RSD & OBD (day) | -0.002 (0.65) | -0.002 (0.66) | 0.001 (0.31) | 0.001 (0.30) | 0.001 (0.31) | -0.003 (0.95) |
| Vehicle characteristics | | | | | | |
| Cylinder | -0.061 (8.26)*** | -0.061 (8.24)*** | -0.061 (8.19)*** | -0.061 (8.17)*** | -0.060 (8.04)*** | -0.061 (8.23)*** |
| Emission control technology | | | | | | |
| Air Injection Reactor (AIR) | 0.097 (3.45)*** | 0.094 (3.34)*** | 0.097 (3.46)*** | 0.095 (3.36)*** | 0.069 (2.43)** | 0.093 (3.32)*** |
| Exhaust Gas Recirculation (EGR) | 0.148 (6.42)*** | 0.148 (6.42)*** | 0.152 (6.57)*** | 0.152 (6.57)*** | 0.152 (6.59)*** | 0.148 (6.43)*** |
| Type of vehicle (Ref: Car) | | | | | | |
| Van and other | -0.144 (4.31)*** | -0.144 (4.32)*** | -0.145 (4.33)*** | -0.145 (4.34)*** | -0.147 (4.39)*** | -0.145 (4.33)*** |
| SUV | -0.245 (10.08)*** | -0.245 (10.10)*** | -0.244 (10.05)*** | -0.245 (10.07)*** | -0.245 (10.08)*** | -0.245 (10.10)*** |
| Truck | -0.314 (11.59)*** | -0.314 (11.59)*** | -0.302 (11.15)*** | -0.302 (11.14)*** | -0.300 (11.08)*** | -0.314 (11.60)*** |
| Location of production (Ref: US) | | | | | | |
| Asia-Pacific | 0.111 (3.81)*** | 0.111 (3.80)*** | 0.109 (3.74)*** | 0.109 (3.74)*** | 0.108 (3.72)*** | 0.111 (3.82)*** |
| Europe | 0.070 (0.86) | 0.071 (0.88) | 0.069 (0.85) | 0.071 (0.87) | 0.066 (0.81) | 0.071 (0.87) |
| North-Central America | -0.090 (3.74)*** | -0.090 (3.77)*** | -0.089 (3.70)*** | -0.090 (3.74)*** | -0.094 (3.93)*** | -0.091 (3.78)*** |
| Manufacturer (Ref: Ford) | | | | | | |
| Chrysler | 0.007 (0.20) | 0.006 (0.16) | 0.005 (0.16) | 0.004 (0.12) | -0.002 (0.07) | 0.006 (0.16) |
| GM | 0.076 (2.64)*** | 0.075 (2.62)*** | 0.074 (2.58)*** | 0.073 (2.55)** | 0.072 (2.52)** | 0.075 (2.62)*** |
| European | 0.229 (2.82)*** | 0.230 (2.83)*** | 0.220 (2.71)*** | 0.221 (2.71)*** | 0.237 (2.92)*** | 0.230 (2.83)*** |

Table 4.12 Cont.

| Independent Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Honda | 0.252 (6.72)*** | 0.251 (6.70)*** | 0.247 (6.60)*** | 0.247 (6.58)*** | 0.243 (6.47)*** | 0.251 (6.71)*** |
| Toyota | 0.110 (3.13)*** | 0.108 (3.09)*** | 0.107 (3.04)*** | 0.105 (2.99)*** | 0.098 (2.79)*** | 0.108 (3.10)*** |
| Japanese - Korean | -0.358 (10.22)*** | -0.360 (10.27)*** | -0.362 (10.31)*** | -0.364 (10.37)*** | -0.375 (10.65)*** | -0.360 (10.27)*** |
| Model year (Ref: 2002) | No | No | No | No | Yes | No |
| <u>RSD measurement conditions</u> | | | | | | |
| Time (Day-Month-Year) | Yes | Yes | Yes | Yes | Yes | Yes |
| Site | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 9.272 (20.66)*** | 9.489 (20.74)*** | 1.673 (1.94)* | 1.885 (2.18)** | 1.755 (1.94)* | 8.446 (19.47)*** |
| Observations | 82523 | 82523 | 82523 | 82523 | 82523 | 82523 |
| Log Likelihood | -45907.27 | -45903.53 | -45852.34 | -45848.15 | -45813.60 | -45899.15 |
| LR Chi2 | 5277.86 | 5260.25 | 5497.70 | 5477.26 | 5452.24 | 5271.36 |
| DoF | 81.00 | 82.00 | 82.00 | 83.00 | 89.00 | 85.00 |
| Pseudo R2 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

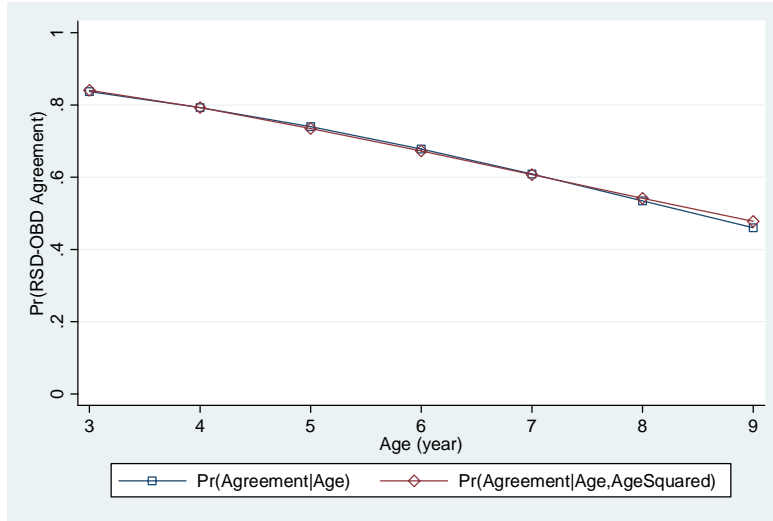


Figure 4.3 Vehicle age and predicted probability of the RSD-OBd agreement, computed from the model with and without the quadratic effect of age

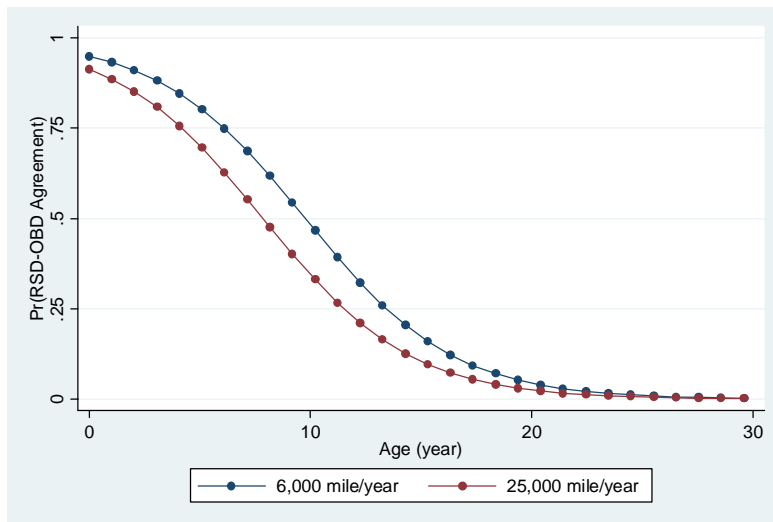


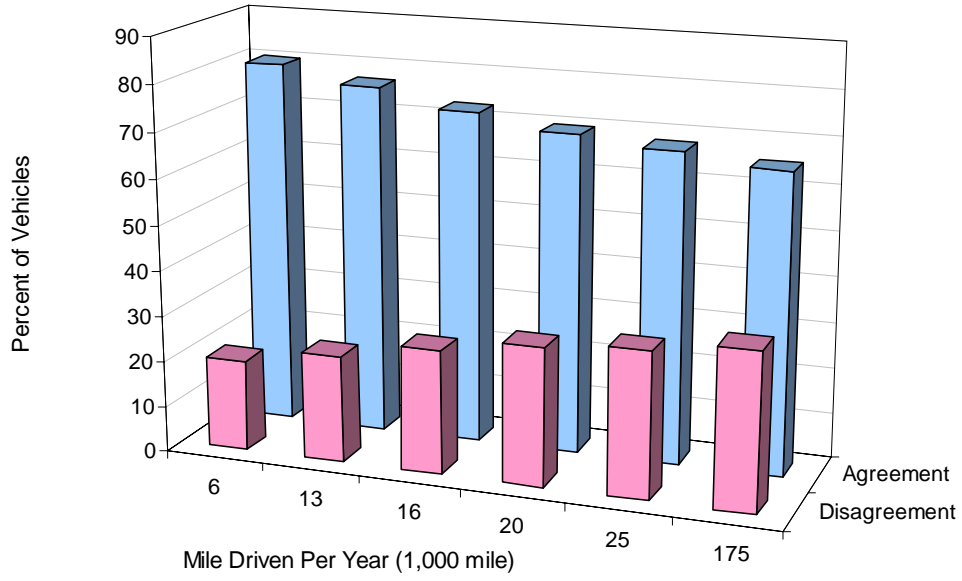
Figure 4.4 Vehicle age and predicted probability of the RSD-OBd agreement varying by mile driven per year

4.7.1.2 Effects of Mile Driven Per Year

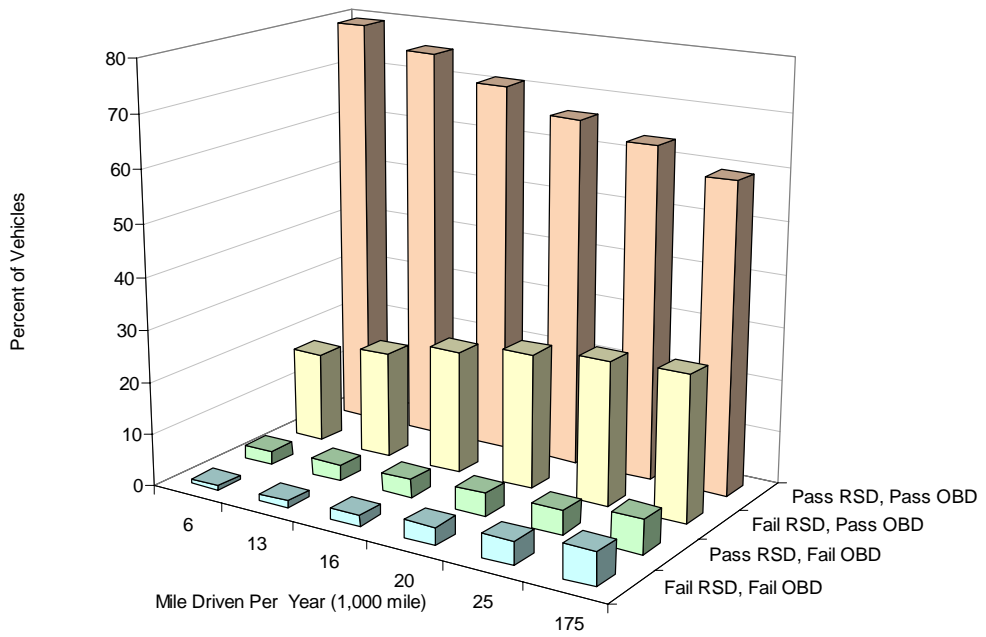
The distribution of mile driven per year (MPY) is divided into 6 groups or bins according to the percentile of Ln(MPY). Each number of the MPY column in Table 4.13 is the mid-point for each bin. Similar to the effects of vehicle age, the groups of vehicles that are used intensively exhibit the lower share of the agreement between RSD and OBD methods. On average, the rate of RSD-OBD agreement decreases around 2.93 (-4.01+1.09) percentage points when the miles driven per year increase. Figure 4.4 shows the share of vehicles grouped by mile driven per year in different agreement categories. Like the effects of age, the fail-RSD-pass-OBD groups are the main causes of the RSD-OBD disagreement.

Table 4.13 Percent of vehicles by MPY groups in different agreement categories

| Mile driven Per Year (1,000 mile) | Pass RSD Pass OBD (n_{00}) | Fail RSD Pass OBD (n_{01}) | Pass RSD Fail OBD (n_{10}) | Fail RSD Fail OBD (n_{11}) |
|--|--------------------------------------|--------------------------------------|--------------------------------------|--------------------------------------|
| 6 | 79.29 | 17.37 | 2.51 | 0.84 |
| 13 | 75.39 | 20.25 | 3.05 | 1.31 |
| 16 | 70.93 | 23.51 | 3.57 | 1.99 |
| 20 | 66.41 | 25.87 | 4.34 | 3.38 |
| 25 | 63.50 | 27.39 | 4.67 | 4.44 |
| 175 | 59.23 | 27.92 | 6.56 | 6.30 |
| Average Difference between Consecutive Groups | -4.01 | 2.11 | 0.81 | 1.09 |



(A)



(B)

Figure 4.5 Percent of vehicles grouped by MPY, classified by RSD measurement and OBD II test

The raw agreement indices in Table 4.14 demonstrate similar pattern to the AC1 coefficients in Table 4.15. The overall RSD-OBd agreements of the higher MPY groups are smaller than those of the lower MPY groups. Likewise, AC1 coefficients are larger for the high MPY groups than the low MPY groups. Pearson and LR Chi-squared are also alike, indicating the dependence between the RSD measurement and the OBD II test. Figure 4.5 plots the overall agreement ratios and the AC1 coefficients for the comparison. The trends of the overall agreement ratios and AC1 coefficients are declining but do not follow the monotonic patterns owing to the highest MPY group.

Table 4.14 Raw agreement indices and the statistical tests by MPY groups

| Mile driven Per Year (1,000 miles) | Overall Agreement Ratio ^a | Specific Agreement ^a | | Pearson Chi-squared ^b | Likelihood-ratio Chi-squared ^b | Fisher Exact ^c |
|------------------------------------|--------------------------------------|---------------------------------|-----------------------|----------------------------------|---|---------------------------|
| | | Positive Rating Ratio | Negative Rating Ratio | | | |
| 6 | 0.801 (0.004) | 0.078 (0.003) | 0.889 (0.035) | 8.864 (0.003) | 8.171 (0.004) | (0.000) |
| 13 | 0.767 (0.004) | 0.101 (0.003) | 0.866 (0.039) | 23.778 (0.000) | 22.012 (0.000) | (0.000) |
| 16 | 0.729 (0.003) | 0.128 (0.002) | 0.840 (0.044) | 68.175 (0.000) | 63.597 (0.000) | (0.000) |
| 20 | 0.698 (0.003) | 0.183 (0.003) | 0.815 (0.048) | 176.515 (0.000) | 164.857 (0.000) | (0.000) |
| 25 | 0.679 (0.004) | 0.217 (0.004) | 0.798 (0.050) | 163.002 (0.000) | 153.363 (0.000) | (0.000) |
| 175 | 0.655 (0.005) | 0.268 (0.005) | 0.775 (0.054) | 118.359 (0.000) | 113.421 (0.000) | (0.000) |

^a Standard errors in parentheses for overall and specific agreement ratios

^b P-values in parentheses for Pearson and likelihood ratio Chi-squared

^c Fisher exact tests report only p-values

TABLE 4.15 Agreement coefficients (AC1) and their variances by MPY groups

| Mile driven Per Year (1,000 mile) | Ln(Mile-Driven Per Year) | Agreement Coefficient (κ_{γ}) | Variance ($V_{\kappa_{\gamma}}$) |
|-----------------------------------|--------------------------|---|------------------------------------|
| 6 | 9.31 | 0.754 | 0.000030 |
| 13 | 9.56 | 0.699 | 0.000024 |
| 16 | 9.80 | 0.633 | 0.000018 |
| 20 | 10.03 | 0.568 | 0.000021 |
| 25 | 10.25 | 0.525 | 0.000039 |
| 175 | 12.68 | 0.461 | 0.000067 |

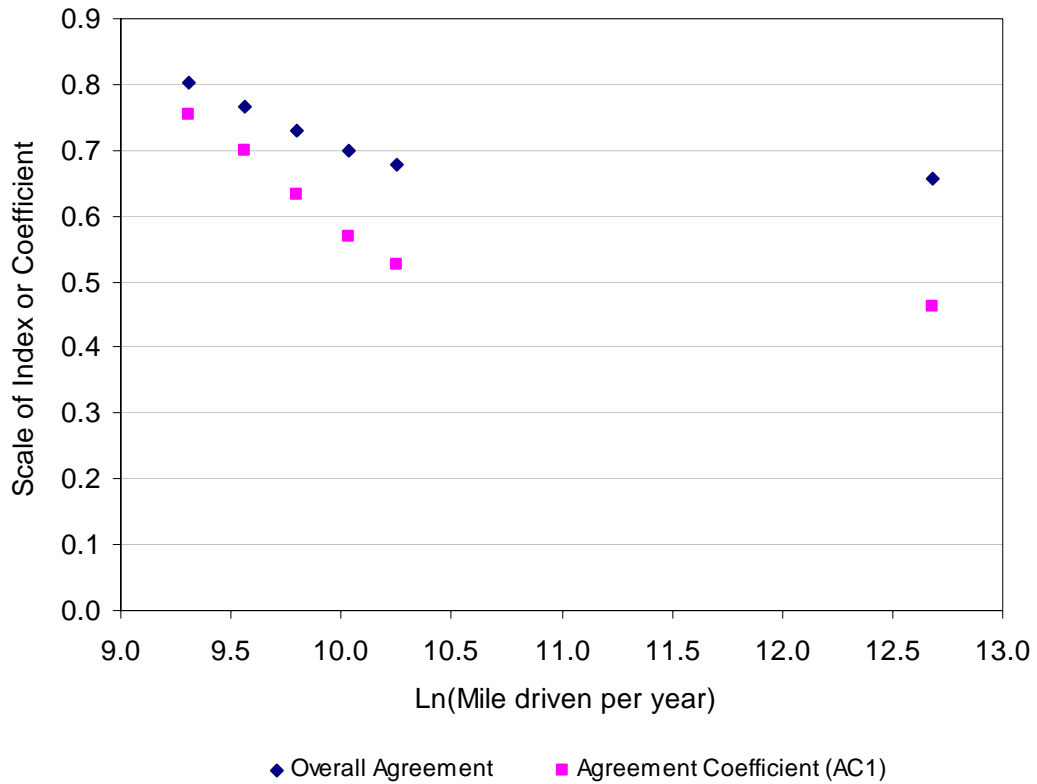


Figure 4.6 Overall agreement index and Agreement Coefficient (AC1) of different MPY groups

The effect of MPY is also significant across the logistic models in Table 4.11. In the restricted model (1), the odds of RSD-OBD agreement for a vehicle with 22 thousand miles driven per year ($\text{Ln}(\text{MPY}) = 10$) is only 0.54 times as high as the odds for the same vehicle with 8 thousand miles ($\text{Ln}(\text{MPY}) = 9$) driven per year. In other words, a one percent increase in MPY decreases the odds of RSD-OBD agreement by 46 percent, holding the other variables constant. The marginal effect of MPY is quite large as compared to that of the vehicle age. A one percent increase in $\text{Ln}(\text{MPY})$ from its mean (9.78) decreases the expected probability of the RSD-OBD agreement by 11.86 percentage points, holding the other variables constant at their means.

Similar to the vehicle age, the quadratic terms of MPY in models (3) – (5) are significant. Figure 4.7 shows the predicted probability of RSD-OBD agreement calculated from the model with and without the quadratic term (3), holding the other variables constant at their means. With the quadratic term, the expected probability of RSD-OBD agreement rises at the decreasing rate when $\ln(\text{MPY})$ is ranging from 1 to 5. Then, it starts to decrease and coincides with the expected probability of RSD-OBD agreement computed from the model without the quadratic term. Although the quadratic term is significant, it seems counterintuitive that the predicted probability of agreement increases with the higher usage of vehicles. Probably the odometer data are recorded with error.

Figure 4.8 displays the predicted probability of the RSD-OBD agreement for a Ford car made in the US equipped with EGR but without AIR, holding the other variables constant at their means. The increase in MPY decreases the expected probability of agreement faster for the older age vehicle groups. In other words, with the same degree of usage ($\ln(\text{MPY})$), the older vehicles have the lower probability of RSD-OBD agreement.

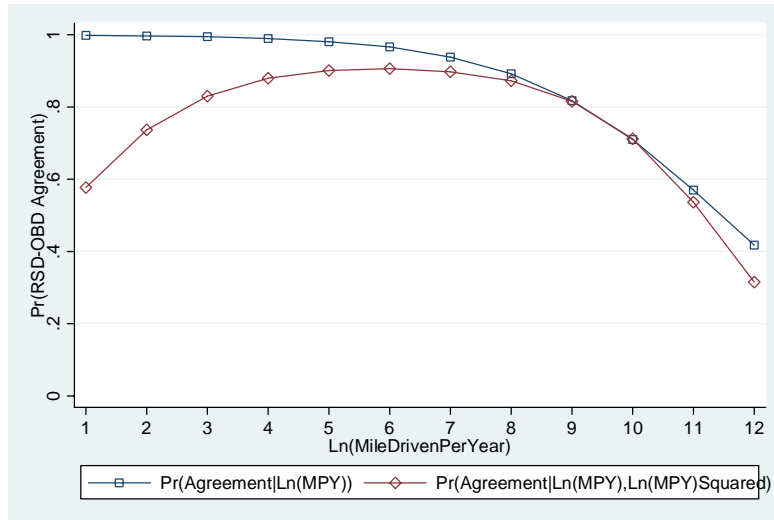


Figure 4.7 Mile driven per year and predicted probability of the RSD-OBD agreement, computed from the model with and without the quadratic effect of Ln(MPY)

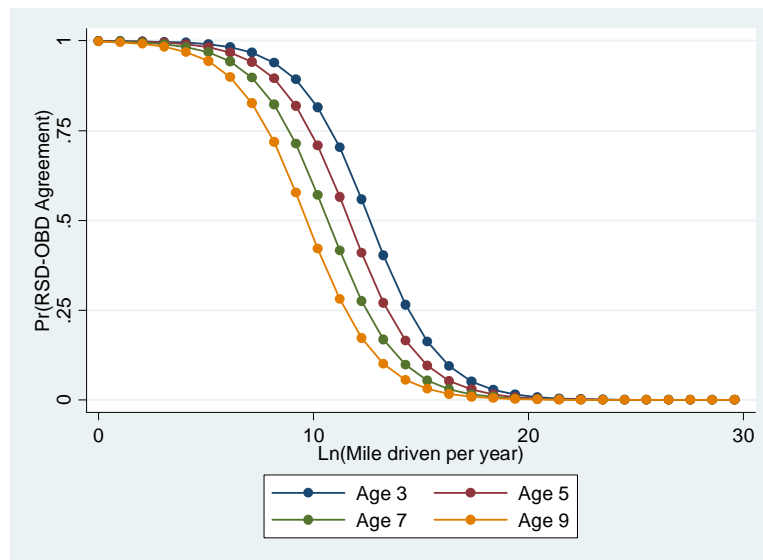


Figure 4.8 Mile driven per year and predicted probability of the RSD-OBD agreement varying by vehicle age

4.7.1.3 Effects of Elapse Time between RSD and OBD

The main effects of elapse time between RSD and OBD in Table 4.12 are not significant consistently across all models. Moreover, the interaction terms between elapse and the other key independent variables (AGE x ELAPSE and MPY x ELAPSE) are also insignificant. This indicates that the elapse time between RSD and OBD does not contribute to the agreement between RSD and OBD measurements.

To ascertain the findings about the effects of elapse time, the study separates the vehicles with RSD-OBD disagreement into two groups: DISAGREE1 (Fail-RSD-Pass-OBD) and DISAGREE2 (Pass-RSD-Fail-OBD). Table 4.16 shows the results in which the dependent variable is AGREE. In models (1) and (2), AGREE is zero only when vehicles are in the DISAGREE1 category. Likewise, in models (3) and (4), AGREE is zero when vehicles are in the DISAGREE2 category. As a result, the numbers of agreement cases are the same across models. However, the total numbers of observations are different depending on the DISAGREE groups.

In Table 4.16, models (1) and (3) are of the same specification as model (5) in Table 4.12 whereas models (2) and (4) in Table 4.15 are similar to model (1) in Table 4.12 but including the vintage fixed effects. Again, the main effects of elapse time are insignificant across all models. Nonetheless, there is a very weak and small positive effect of elapse time on the vehicle age (AGE x ELAPSE) in model (1). This suggests the weak and small possible cause of the lower RSD-OBD agreement for older vehicle groups due to either the OBD malfunction or other intervening activities (See Table 4.7).

Given all the results from Table 4.12 and 4.16, the study concludes that the elapse time has no effect on the RSD-OBD agreement. In other words, the lower RSD-OBD agreement for the older vehicle groups is mainly due to the error of the OBD II system.

Table 4.16 Logistic models of agreement outcomes between RSD measurement and OBD II test using separate DISAGREE groups

| Independent Variables | DISAGREE1 | | DISAGREE2 | |
|---------------------------------|---------------------|---------------------|---------------------|---------------------|
| | Fail-RSD-Pass-OBD | | Pass-RSD-Fail-OBD | |
| | (1) | (2) | (3) | (4) |
| Vehicle age (year) | | | | |
| Age | 0.262 (2.49)** | 0.320 (34.23)*** | 0.643 (3.24)*** | 0.200 (10.06)*** |
| Age squared | 0.010 (2.85)*** | | -0.023 (3.32)*** | |
| Age x Elapse | 0.000 (1.70)* | 0.000 (1.48) | -0.000 (1.09) | -0.000 (1.19) |
| Vehicle usage | | | | |
| Ln(MPY) | -0.836 (4.78)*** | 0.576 (12.86)*** | -1.197 (4.64)*** | 0.848 (8.65)*** |
| Ln(MPY) squared | 0.073 (8.00)*** | | 0.104 (8.66)*** | |
| Ln(MPY) x Elapse | -0.000 (0.30) | -0.000 (1.20) | 0.001 (1.27) | 0.000 (0.64) |
| Elapse between RSD & OBD (day) | -0.000 (0.07) | 0.003 (0.87) | -0.005 (1.00) | -0.003 (0.41) |
| <u>Vehicle characteristics</u> | | | | |
| Cylinder | 0.077 (9.68)*** | 0.078 (9.96)*** | -0.042 (2.51)** | -0.045 (2.66)*** |
| Emission control technology | | | | |
| Air Injection Reactor (AIR) | -0.060 (1.96)* | -0.101 (3.33)*** | -0.104 (1.67)* | -0.077 (1.25) |
| Exhaust Gas Recirculation (EGR) | -0.191 (7.77)*** | -0.186 (7.59)*** | 0.124 (2.32)** | 0.126 (2.36)** |
| Type of vehicle (Ref: Car) | | | | |
| Van and other | 0.196 (5.49)*** | 0.191 (5.38)*** | -0.078 (1.08) | -0.085 (1.17) |
| SUV | 0.322 (12.55)*** | 0.319 (12.43)*** | -0.195 (3.30)*** | -0.193 (3.26)*** |
| Truck | 0.372 (12.99)*** | 0.382 (13.37)*** | -0.110 (1.77)* | -0.098 (1.58) |
| Country of production (Ref: US) | | | | |
| Asia-Pacific | -0.154 (4.99)*** | -0.158 (5.10)*** | 0.171 (2.56)** | 0.167 (2.51)** |
| Europe | -0.061 (0.68) | -0.070 (0.77) | -0.052 (0.33) | -0.031 (0.20) |
| North-Central America | 0.107 (4.18)*** | 0.099 (3.88)*** | 0.046 (0.83) | 0.055 (1.01) |
| Manufacturer (Ref: Ford) | | | | |
| Chrysler | 0.038 (1.03) | 0.028 (0.75) | -0.228 (2.90)*** | -0.232 (2.96)*** |
| European | -0.355 (3.98)*** | -0.335 (3.74)*** | 0.213 (1.33) | 0.168 (1.05) |
| GM | -0.019 (0.61) | -0.023 (0.74) | -0.345 (5.45)*** | -0.351 (5.57)*** |
| Honda | -0.152 (3.78)*** | -0.165 (4.10)*** | -0.708 (8.47)*** | -0.709 (8.51)*** |
| Japanese - Korean | 0.484 (12.92)*** | 0.461 (12.37)*** | -0.206 (2.69)*** | -0.196 (2.56)** |

Table 4.16 Cont.

| Independent Variables | DISAGREE1 | | DISAGREE2 | |
|-----------------------------------|---------------------|----------------------|----------------------|-----------------------|
| | Fail-RSD-Pass-OBD | | Pass-RSD-Fail-OBD | |
| | (1) | (2) | (3) | (4) |
| Toyota | 0.040 (1.07) | 0.025 (0.67) | -0.952 (10.84)*** | -0.949 (10.84)*** |
| Model year of vehicle (Ref: 2002) | Yes | Yes | Yes | Yes |
| <u>RSD measurement conditions</u> | | | | |
| Year (Ref: 2005) | Yes | Yes | Yes | Yes |
| Month (Ref: December) | Yes | Yes | Yes | Yes |
| Day of week (Ref: Saturday) | Yes | Yes | Yes | Yes |
| Site (Ref: Site43) | Yes | Yes | Yes | Yes |
| Constant | -2.648 (2.80)*** | -9.479 (20.10)*** | -2.376 (1.45) | -11.341 (10.85)*** |
| Observations | 79187 | 79187 | 62702 | 62702 |
| Log Likelihood | -41248.99 | -41368.79 | -12404.33 | -12454.25 |
| LR Chi2 | 5554.85 | 5535.02 | 1197.99 | 974.15 |
| DoF | 89.00 | 81.00 | 89.00 | 81.00 |
| Pseudo R2 | 0.07 | 0.07 | 0.05 | 0.04 |

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

4.7.2 Emission Intensity Analysis

In the previous section, the logistic models only employ the crude measurement of RSD with the standard threshold, as represented by the RSD INDEX. Then, the cross tabulation between the RSD INDEX and OBD variables yields the AGREE variable. This section utilizes the richer information of RSD measurement embedded in the EMISSION INDEX which is the interval level variable. Nevertheless, this section serves as a supplementary to the main analysis of agreement. The purpose of this section is to illustrate the key determinants of vehicle emission intensity. With the limited information and the specific objective, this study is unable to develop the models that fully explain the variability of emission intensity.

Table 4.17 shows the log-linear models of emission intensity (EMISSION INDEX). In fact, the dependent variable in Table 4.16 is the natural log of the EMISSION INDEX. The natural log transformation of all interval-level variables in the models is necessary because the distribution of the EMISSION INDEX is highly positive skewed.

The variable age is kept unchanged because of no significant difference between using the log-transformed and the original one. In addition, the untransformed age variable is easier for the interpretation.

In Table 4.17, models (1), (3) and (2), (4) are similar except that models (1) and (3) include the vintage fixed effects. Models (1) and (2) test the differences of the emission intensity between the vehicles failing and passing the OBD II test. On the other hand, models (3) and (5) test the differences of emission intensity between the groups of vehicles with the RSD-OBD agreement and those of fail-RSD-pass-OBD groups (DISAGREE1).

In general, the specifications of models (1) – (4) are quite simple and probably have several problems of omitted variables, heteroskedasticity, and incorrect functional forms, based on the Ramsey RESET and link tests. Model (5) is complex and almost passes the link test (t-test of $h\text{-hat-square} = 2.39$), suggesting that the model is close to the correct specifications and includes almost all related variables. Despite the complicated functional form and a larger numbers of independent variables, when compared to models (3) and (4), model (5) can improve the explanatory power of emission intensity only by one percent (the difference in R squared). Model (1) and (2) can explain the variability of emission intensity only 11 percent whereas models (3) and (4) can explain up to 53 percent. This indicates that the OBD II test results are not corresponding to the observed tailpipe emissions. Thus, the following discussion focuses on the models including DISAGREE1 variable.

As expected, vehicles that failed RSD and pass OBD pollute higher level of emissions than the others around 2.25 points of the EMISSION INDEX. Similar to the previous analysis, vehicle age is one of the key factors of emission intensity. In model (4), an additional year of vehicle age, from 5 to 6 years, increases the EMISSION INDEX by 0.18 (= 0.035 x 5) percent. The effect of age disappears when the model includes the

vintage fixed effects in model (3). Additionally, the main effect of age is no longer significant when it interacts with the other variables (model year and DISAGREE1) in model (5). Vehicle usage, as measured by mile driven per year (MPY) is also a strong predictor of emission intensity. From models (3) and (4), a one percent increase in MPY causes the EMISSION INDEX to increase by 0.6 percent. In model (5) which includes the non-linear term of MPY, an additional percent of MPY decreases the EMISSION INDEX first at the decreasing rate but then increases the EMISSION INDEX later when the MPY is around 400 miles ($e^6=403.42$). Speed and the loaded vehicle weight are also important determinants of the EMISSION INDEX. As the vehicle speed increases by one percent, the EMISSION INDEX also increases by 0.09 percent. Likewise, one additional percent of the estimated loaded vehicle weight increases the EMISSION INDEX by 14 percent.

To summarize, the emission intensity as measured by the EMISSION INDEX is determined by several factors including the vehicle age, usage, speed, and loaded weight. More importantly, vehicles which fail the RSD measurement and pass the OBD II test, tend to pollute at a higher level of emissions than the other groups.

Table 4.17 Log-linear models of the emission intensity (EMISSION INDEX)

| Independent Variables | (1) | (2) | (3) | (4) | (5) |
|--|----------------------|----------------------|----------------------|----------------------|---------------------|
| OBD (Fail = 1) | 0.132 (15.53)*** | 0.132 (15.56)*** | | | |
| DISAGREE1 (Yes=1) (Fail-RSD-Pass-OBD) | | | 0.812 (188.26)*** | 0.812 (188.18)*** | 0.822 (41.66)*** |
| Vehicle age (year) | | | | | |
| Age | 0.026 (2.16)** | 0.077 (64.93)*** | -0.004 (0.41) | 0.035 (38.05)*** | 0.008 (0.59) |
| Age ² | | | | | -0.000 (0.17) |
| Vehicle usage (mile) | | | | | |
| Ln(Mile Driven Per Year) | 0.109 (21.91)*** | 0.110 (22.21)*** | 0.061 (18.18)*** | 0.062 (18.51)*** | -0.148 (5.35)*** |
| Ln(Mile Driven Per Year) ² | | | | | 0.012 (7.85)*** |
| Ln(Speed) | 0.145 (20.36)*** | 0.145 (20.33)*** | 0.088 (16.96)*** | 0.088 (16.92)*** | 0.092 (17.08)*** |
| Ln(Est. Loaded Vehicle Weight) | 0.253 (17.60)*** | 0.254 (17.66)*** | 0.143 (13.65)*** | 0.142 (13.58)*** | 0.153 (14.13)*** |
| <u>Vehicle characteristics</u> | | | | | |
| Emission control technology | | | | | |
| Air Injection Reactor | 0.009 (1.68)* | 0.006 (1.01) | 0.016 (3.71)*** | 0.017 (3.91)*** | 0.001 (0.28) |
| Exhaust Gas Recirculation | -0.062 (12.29)*** | -0.062 (12.28)*** | -0.029 (8.01)*** | -0.029 (8.00)*** | -0.023 (6.27)*** |
| Vehicle type (Ref: Car) | | | | | |
| Van and other | 0.032 (3.76)*** | 0.032 (3.70)*** | 0.023 (3.59)*** | 0.023 (3.63)*** | 0.005 (0.86) |
| SUV | 0.026 (4.15)*** | 0.026 (4.13)*** | -0.003 (0.69) | -0.003 (0.62) | 0.011 (2.65)*** |
| Truck | 0.095 (12.96)*** | 0.094 (12.86)*** | 0.053 (9.85)*** | 0.053 (9.78)*** | 0.026 (4.96)*** |
| Location of production (Ref: US) | | | | | |
| Asia-Pacific | -0.022 (3.49)*** | -0.022 (3.46)*** | 0.001 (0.31) | 0.002 (0.35) | -0.001 (0.29) |
| Europe | -0.012 (0.79) | -0.013 (0.85) | -0.009 (0.84) | -0.009 (0.81) | 0.016 (1.80)* |
| North-Central America | 0.020 (3.95)*** | 0.019 (3.73)*** | 0.006 (1.55) | 0.006 (1.54) | 0.019 (5.55)*** |
| Manufacturer (Ref: Ford) | | | | | |
| Chrysler | -0.008 (1.01) | -0.009 (1.09) | -0.019 (3.17)*** | -0.019 (3.09)*** | -0.017 (3.04)*** |
| European | -0.098 (6.31)*** | -0.096 (6.21)*** | -0.043 (3.76)*** | -0.044 (3.85)*** | -0.043 (4.54)*** |
| GM | -0.065 (10.15)*** | -0.065 (10.13)*** | -0.065 (13.25)*** | -0.065 (13.23)*** | -0.015 (3.16)*** |
| Honda | -0.042 (5.56)*** | -0.042 (5.57)*** | -0.026 (4.85)*** | -0.026 (4.74)*** | -0.035 (7.05)*** |
| Japanese - Korean | 0.064 (8.08)*** | 0.064 (8.01)*** | -0.005 (0.88) | -0.004 (0.66) | 0.005 (0.97) |
| Toyota | -0.036 (5.06)*** | -0.037 (5.20)*** | -0.046 (9.03)*** | -0.046 (8.97)*** | -0.025 (5.45)*** |
| Model year (Ref: 2002) | | | | | |
| 1996 | 0.251 (3.55)*** | | 0.206 (3.94)*** | | 0.271 (3.41)*** |
| 1997 | 0.223 (3.80)*** | | 0.160 (3.68)*** | | 0.129 (2.19)** |

Table 4.17 Cont.

| Independent Variables | (1) | (2) | (3) | (4) | (5) |
|-----------------------------------|----------------------|----------------------|----------------------|----------------------|---------------------|
| 1998 | 0.162 (3.45)*** | | 0.113 (3.26)*** | | 0.077 (2.17)** |
| 1999 | 0.094 (2.69)*** | | 0.064 (2.48)** | | 0.041 (1.53) |
| 2000 | 0.053 (2.24)** | | 0.039 (2.24)** | | 0.023 (1.27) |
| 2001 | -0.008 (0.64) | | 0.011 (1.17) | | 0.002 (0.20) |
| <u>Interaction terms</u> | | | | | |
| DISAGREE1 x Age | No | No | No | No | Yes |
| DISAGREE1 x Vehicle type | No | No | No | No | Yes |
| DISAGREE1 x Manufacturer | No | No | No | No | Yes |
| DISAGREE1 x Country of production | No | No | No | No | Yes |
| MY 1996 x Age | No | No | No | No | Yes |
| MY 1996 x Vehicle type | No | No | No | No | Yes |
| MY 1996 x Manufacturer | No | No | No | No | Yes |
| MY 1996 x Country of production | No | No | No | No | Yes |
| MY 1997 x Age | No | No | No | No | Yes |
| MY 1997 x Country of production | No | No | No | No | Yes |
| <u>RSD measurement condition</u> | | | | | |
| Year (Ref: 2005) | Yes | Yes | Yes | Yes | Yes |
| Month (Ref: December) | Yes | Yes | Yes | Yes | Yes |
| Day of week (Ref: Saturday) | Yes | Yes | Yes | Yes | Yes |
| Site (Ref: Site43) | Yes | Yes | Yes | Yes | Yes |
| Constant | -4.008 (29.19)*** | -4.222 (32.21)*** | -2.394 (24.04)*** | -2.545 (26.74)*** | -1.612 (9.97)*** |
| Observations | 77684 | 77684 | 77684 | 77684 | 74552 |
| R squared | 0.11 | 0.11 | 0.53 | 0.53 | 0.54 |
| Adjusted R squared | 0.11 | 0.11 | 0.53 | 0.53 | 0.54 |
| DoF | 86.00 | 80.00 | 86.00 | 80.00 | 118.00 |
| F | 102.90 | 106.96 | 560.01 | 600.29 | 430.25 |
| RootMSE | 2354.07 | 2336.84 | 10920.84 | 10909.92 | 10950.62 |

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

4.7.3 Estimation of Pollution Reduction

This section calculates the approximate amount of pollution reduction if there is an improvement in the fleet that fails RSD but passes OBD II (DISAGREE1). Typically, the RSD measurements report CO, HC, and NO_x in terms of concentration ratios of CO, HC, and NO_x to CO₂. These ratios are constant for a given exhaust plume and can be converted to the mass emission factor for each vehicle by the following equations (Pokharel, Bishop, and Stedman, 2002).

$$\text{CO Emission Factor} \left(\frac{\text{gm CO}}{\text{gallon}} \right) = \frac{5506 \times \% \text{CO}}{15 + (0.285 \times \% \text{CO}) + (2.87 \times \% \text{HC})} \quad (4.28)$$

$$\text{HC Emission Factor} \left(\frac{\text{gm HC}}{\text{gallon}} \right) = \frac{8644 \times \% \text{HC}}{15 + (0.285 \times \% \text{CO}) + (2.87 \times \% \text{HC})} \quad (4.29)$$

$$\text{NOx Emission Factor} \left(\frac{\text{gm NOx}}{\text{gallon}} \right) = \frac{5900 \times \% \text{NOx}}{15 + (0.285 \times \% \text{CO}) + (2.87 \times \% \text{HC})} \quad (4.30)$$

The next step is to compute the mass emission rate (ER) of the three pollutants for each vehicle using the vehicle miles traveled (VMT) based approach with the following equation (Zia, 2003).

$$\text{Emission Rate}_{pi} \left(\frac{\text{gm}}{\text{year}} \right) = \frac{\text{Emission Factor}_{pi} \times \text{VMT}_i}{\text{Fuel Economy}_i} \quad (4.31)$$

where p is the pollutant (CO, HC, or NOx) and i is the individual vehicle. VMT_i is the vehicle miles traveled or the mile driven per year (MPY) of each vehicle. Fuel economy is the mileage per gallon (MPG) for each vehicle, obtained from the Fuel Economy Guide estimated by the Environmental Protection Agency (EPA) and published by the Department of Energy (DOE) (URL <http://www.epa.gov/fueleconomy>). This study uses an average fuel economy for a vehicle group based on the information regarding make, model year, and vehicle type. Specifically, the study use the fuel economy estimated from the three driving conditions: city, highway, and combined city and highway modes.

The last step is the aggregation of emission rates from all vehicles that belong to the fleet that fails RSD but passes OBD II, yielding the total emissions in tons per year (or day). The pollution reduction, then, can be calculated based on two scenarios. The first scenario is to completely remove the fail-RSD-pass-OBD fleet from the population fleet. Although, it is the most extreme and unlikely scenario, it gives the upper bound of

the pollution reduction. The second scenario is to reduce the pollution of each vehicle in this fleet to the ASM 2525 standard. The emission reduction is the amount of pollution at the standard less the original levels. Table 4.18 (A) displays the results of the calculation of pollution reduction in tons per day from the sample used in this study. The share of vehicles contributing to the reduction (from the fail-RSD-pass-OBD fleet) is around 24 percent (19,821 vehicles) of the total sample. The result is extrapolated to the population fleet in Atlanta that is subjected to the inspection requirement as shown in Table 4.18 (B).

According to the Georgia State Implementation Plan (SIP) for the Atlanta Ozone Non-attainment Area (GA DNR, 2001), the projected reduction of motor vehicle emissions for CO and NO_x are 994.24 and 224.13 tons per day respectively. This estimation is based on the EPA's MOBILE 5 model with input from the enhanced I/M program. However, because the issue of the OBD test validity and reliability has just emerged, the estimation is unlikely to take into account the increase in emission from the fail-RSD-pass-OBD fleet. The existence of the fail-RSD-pass-OBD fleet would decrease the projected emission reduction of the I/M program around 5 and 1.6 percent for CO and NO_x respectively (calculation based on Scenario 2 in Table 4.18 (B)). Although the impact of the fail-RSD-pass-OBD fleet seems small, this fleet is growing over time for two reasons. First, assuming no fraudulent activity, the owners of the fail-RSD-pass-OBD vehicles may not recognize the problem and hence miss the repair of their vehicles. Second, as the new automobile technology tends to last longer, the number of older vehicles with OBD II will increase. Consequently, the OBD II test validity and reliability can be a major factor mitigating the effectiveness of the I/M program.

Table 4.18 Estimation of pollution reduction in two scenarios

(A) Estimation based on the sample of 82,523 vehicles

| Fuel Economy Driving Mode | Pollution Reduction (Tons Per Day) | | |
|---|------------------------------------|------|------|
| | CO | HC | NOx |
| <u>Scenario 1:</u> Remove all vehicles that surpass ASM2525 standard from the population fleet | | | |
| City | 7.38 | 0.26 | 1.88 |
| Combined | 6.64 | 0.24 | 1.68 |
| Highway | 5.72 | 0.20 | 1.44 |
| <u>Scenario 2:</u> Reduce emissions of vehicles that surpass ASM2525 standard to the standard level | | | |
| City | 2.41 | 0.15 | 0.79 |
| Combined | 1.86 | 0.12 | 0.61 |
| Highway | 2.17 | 0.14 | 0.71 |

(B) Extrapolation based on the approximated population of 1.8 million vehicles

| Fuel Economy Driving Mode | Pollution Reduction (Tons Per Day) | | |
|---|------------------------------------|------|-------|
| | CO | HC | NOx |
| <u>Scenario 1:</u> Remove all vehicles that surpass ASM2525 standard from the population fleet | | | |
| City | 155.91 | 5.54 | 39.68 |
| Combined | 140.29 | 4.97 | 35.55 |
| Highway | 120.80 | 4.25 | 30.41 |
| <u>Scenario 2:</u> Reduce emissions of vehicles that surpass ASM2525 standard to the standard level | | | |
| City | 50.87 | 3.23 | 16.74 |
| Combined | 39.27 | 2.48 | 12.82 |
| Highway | 45.72 | 2.90 | 14.99 |

4.8 Conclusion

The key element of the I/M program is the testing technology and procedure. To achieve the efficiency goal, the I/M regulation has improved the implementation by adopting the new testing technology – the OBD II⁵⁴. The introduction of the OBD II test has changed the logic of vehicle inspection from directly checking tailpipe emissions to detecting the condition of emission control parts. Nonetheless, the objective of the vehicle inspection remains; dirty vehicles should fail the inspection. Because the OBD II system is a part of the vehicle that is subjected to deterioration over time and usage, it can malfunction. When the OBD II system breaks down without any apparent indication such as the MIL or error codes, it is difficult to identify such failure unless there is a tailpipe emission test to validate such results.

This study finds that the OBD II test becomes less valid and reliable for older vehicles. The agreement result between the RSD measurement and the OBD II test is smaller for older vehicles. In particular, after accounting for possible intervening activities, the effect of vehicle age still decreases the odds of agreement. Additionally, the usage or mileage plays an important role for the declining agreement between the RSD measurement and the OBD II test. Because the probability of passing dirty vehicles (fail-RSD-pass-OBD) is higher than that of failing clean vehicles, thus there is indication that dirty vehicles are not detected and repaired. This is alarming for the regulators

⁵⁴ There are several advantages of the OBD II test over the traditional tailpipe emission test. First, the OBD II testing time is usually shorter than the time taken by the traditional tailpipe test. Motorists are contented when the tailpipe emission test (ASM) is replaced with the OBD II test. Second, the OBD II test equipment is less expensive than the instruments required by the ASM testing procedure – the dynamometer. The current inspection stations can afford this new technology. With the low capital investment, the new test providers are likely to enter the inspection market. Lastly, the OBD II test procedure is less complicated than the ASM or TSI test procedures. Hence, the OBD II test can minimize the human error from the inexperience inspectors.

because totally relying on the OBD II test might reduce the effectiveness of the I/M program in terms of pollution reduction. The estimation shows that bringing emissions of the fail-RSD-pass-OBD fleet down to the standard level can reduce total emissions by 70, 40, and 60 percent for CO, HC, and NOx respectively.

From these findings, several options can be adopted to complement the current OBD II test procedure. Table 4.19 shows some examples of a few technology alternatives. First, the tailpipe emission test can be allowed as a substitute test for the vehicles that fail the OBD II. This can reduce the number of vehicles that pass RSD but fail the OBD (C) if their tailpipe emission is lower than the standard level. Second, the RSD can be fully implemented similar to the Colorado I/M program. Because the RSD actually measures real tailpipe emissions, it shifts vehicle fleet C to be with fleet A, and D to be with B. The last option is the improvement of OBD II which may reduce the size of fleets C and D. However, at a certain vehicle age, the improved OBD II may exhibit the decay effect. As a result, using the improved OBD II may simply reduce the pass-RSD-fail-OBD fleet from C to c. Given that the new vehicle fleet becomes increasingly cleaner, the last option is most likely.

Table 4.19 Examples of alternative technologies to improve the current OBD II test

| Testing Technology | Vehicle Fleets | | | |
|-------------------------|----------------------|----------------------|----------------------|----------------------|
| | Pass RSD Pass OBD | Fail RSD Fail OBD | Pass RSD Fail OBD | Fail RSD Pass OBD |
| OBD II | A | B | C | D |
| <u>Proposed Options</u> | | | | |
| Optional Tailpipe Test | A+C | B | C | - |
| RSD | A+C | B+D | - | - |
| Improved OBD II | A+(C-c) | B+(D-d) | c | d |

Regardless of any additional options, the results from this study suggest crucial role of RSD data collection in terms of evaluating the OBD II test validity and reliability. Therefore, the secure and significant investment in RSD data collection is necessary. In particular, if the scale of RSD data collection increases, the repeat sample of the same vehicles can generate the panel data. As a result, this type of data will allow for the detailed study of the divergence between the RSD measurement and the OBD II test.

CHAPTER 5

CONCLUSION

5.1 Summary of Findings

The results from this study reveal several aspects of the I/M program (the Atlanta case) that have not been investigated before. First of all, the study shows that the burdens of the I/M program are not equally distributed across different income groups. Next, the study demonstrates that inspection-related costs are influential to the behavioral responses of motorists as related to the inspection stations. Lastly, the study discovers that the new testing technology (OBD II) might fail to identify the high-emitting vehicles. The next three sections briefly summarize the findings.

5.1.1 Essay 1: Equity Implications of Atlanta Vehicle I/M Program

The I/M program imposes the costs on every eligible vehicle owner but these costs might not be evenly distributed. Low-income vehicle owners are likely to bear more burden than others. The vehicles failing inspection mean additional costs to the owners in terms of time and money. This study finds that the vehicles owned by low-income households or registered in low-income neighborhoods are more likely to fail first inspections. In addition, the results show that the levels of pre-inspection repair or maintenance across income groups are the same.

5.1.2 Essay 2: A Motorist's Choice of the Inspection Station

Motorists have to pay the inspection-related costs (travel time and costs to the station, waiting time, inspection fee, and repair costs if needed) in order to pass inspections. Consequently, the I/M program creates incentives for motorists to pass the inspection in low cost ways. This study identifies several factors determining the

motorists' decision when selecting their inspection stations. The results show that the inspection stations located far from the motorists' houses, having long waiting lines, high inspection fees, and high failure ratios are less likely to be chosen. The stations surrounded by a large number of other stations are less likely to be chosen. However, as station density increases, the average failure ratio of the stations decreases, suggesting more lenient services in high competition areas.

5.1.3 Essay 3: OBD II Test Validity and Reliability

Since 2002, the I/M program requires the OBD II testing technology for vehicles of model year 1996 or newer. The OBD II tests give the fail results to vehicles based on error codes stored in the computers (OBD II) of the vehicles, which are supposed to correspond with the tailpipe emissions. However, as the vehicles become older and are likely to malfunction, so do the OBD II units. This study compares the OBD II test results with the RSD measurement of tailpipe emissions to identify agreement between the two methods. The results show that the agreement between the two tests is smaller for the older and higher mileage vehicle groups than that of the newer and lower mileage vehicle groups, suggesting that the OBD II test is less valid and reliable for older vehicles.

5.2 Policy Implications

Unlike the existing I/M program evaluation studies focusing on emission reduction, this research sheds some light on the I/M program in three distinctive aspects, using the Atlanta case: the equity consequence, the motorist's behavioral response, and the validity and reliability of the testing technology – OBD II.

5.2.1 The Distribution of the Burden

The goal of the I/M program is to achieve emission reduction due to the proper maintenance and repair of in-use vehicles. Normally, older vehicles require higher maintenance and resulting costs. Furthermore, “older vehicles are more likely to be owned by households with lower average income, these vehicles also have the highest expected repair costs (NRC, 2001).” Findings from this study still confirm this statement. Low-income households are more likely to fail the first inspection. Thus, they are required to repair their vehicles with potentially high cost (NRC, 2001). By the unintended design, the I/M program is “assigning motorists the liability for repairs” such that “those least able to pay are likely to be paying the highest costs (NRC, 2001).” As a result, several implications follow.

First, the burden on low-income households can cause lower quality of vehicle repair, which results in the estimated pollution reduction of the program. If the low-income owners cannot afford repair costs in order to pass the test, then these people might have to drive illegally, or sell their vehicles to buy newer ones, or switch to public transport.

Second, supplemental programs that assist low-income households are necessary to improve the effectiveness of the I/M program. These programs include repair subsidies, insurance and vehicle scrappage (buy back the old vehicles).

5.2.2 The Motorist’s Response

The objective of the I/M program is to ensure that the emission control parts of vehicles properly function throughout their lifetime, resulting in emissions staying under the allowable limit. The program expects that motorists regularly maintain their vehicles so that they pass inspections, which requires behavioral changes of some motorists who might not be attentive about their vehicles’ conditions. However, this study shows that

motorists are likely to choose inspection stations resulting in lower costs. The results have cast some doubts on the actual behavioral changes of motorists.

Motorists may maintain or repair their vehicles shortly before the scheduled inspection dates for the purpose of passing the test. The quality (durability) of the maintenance may serve that purpose accordingly, indicating the “clean for a day” phenomenon. Using the random roadside survey in California that checks the emissions of vehicles, Walsh, Klausmeir & Seinfeld (1991) show that the vehicles that are due for the Smog check within the next 90 days and those that had the test within the previous 90 days have the failure rate of 32 and 37 percent respectively.

Motorists also shop for lenient stations, which give a lower chance of their vehicles failing the tests. Similar to the previous study (Hubbard, 2002), this study shows that where the competition among inspections is high, the chance of a vehicle falsely passing the inspection is high as well. These situations can lead to the following implications.

First, an evaluation of the program that does not take into account behavioral interaction between the motorists and inspection stations are likely to overestimate the benefits from emission reduction. Second, the short-term solution could be targeted monitoring and enforcement in high-density station areas. Nonetheless, in the long run, focused enforcement may drive the change in spatial distribution of lenient inspection stations. Possibly, if enforcement is extensive, the lenient service suppliers might start to operate more or less like the black market. Regardless, the regulators have to devote more resources to suppress these activities.

5.2.3 The Expectation of the New Testing Technology

In 2002, the I/M program replaced the traditional tailpipe emission test with the new testing technology – OBD II. The OBD II test has several advantages over the

tailpipe emission test. First, the OBD II testing time is usually shorter than the time taken by the traditional tailpipe test. Second, the OBD II test equipment is less expensive than the instruments required by the ASM testing procedure – the dynamometer. With low capital investment, the new test providers can enter the market easily. Because of lower operating costs of the OBD II test, state regulators can keep the inspection fee ceiling unchanged. Lastly, the OBD II test procedure is less complicated than the ASM or TSI test procedures, reducing human error or even fraudulent effort. Consequently, the OBD II tests are fully embraced by all stakeholders.

Despite all the advantages of the OBD II test, deterioration of the OBD II as vehicles become older is unavoidable. This study illustrates that the OBD II test for the older vehicle fleet can be invalid and unreliable, resulting in more often passing high-polluting vehicles. The vehicle fleet becomes cleaner over time (Kahn and Schwartz, 2008) due to the regulated standards of automobile technology. Nonetheless, the growth of unidentified high polluting vehicle fleets can offset the benefit of pollution reduction because they tend to last longer. The age of in-use cars has increased from a median age of 4.9 years in 1970 (Davis, 2000) to 9.2 years in 2007 (Davis, Diegel and Boundy, 2008).

The I/M program aims at identifying the vehicles emitting pollution higher than the allowable standards and ensures that they are repaired or removed from the fleet. Moreover, NRC (2001) indicates that “typically, less than 10 percent of the fleet contributes more than 50 percent of the emission for any given pollutants.” Because the older vehicles are likely to be the high-polluters, the decreasing validity and reliability of the OBD II test is alarming in that the test no longer serves the purpose of the I/M program. Without any additional verification, relying on the results from the OBD II test can let loose the high polluting vehicles. This leads to two implications. First, for older vehicles, the additional verification of the OBD II test is necessary to reassure the test

results. The extra test should be the tailpipe emission test because it measures the actual emission levels of the vehicles. Second, to evaluate the growth of this unidentified high-polluting fleet, the scope and scale of the RSD data collection should be extended. The larger network and frequent measurements can increase the chance of capturing these vehicles.

5.3 Future Research

5.3.1 Ethnic Inequity and Repair Cost

From the essay on equity implications of the I/M program, there are few remaining issues that require further investigation. First, it is unclear why the chance of a vehicle failing the first inspection is not equal across ethnic groups. The preliminary results show that the inspection stations might be the main reason. The research design to address this issue is necessary. Second, the probability of a vehicle failing the first inspection is the limited proxy for the post-inspection repair costs. The study using the number of retests and reported costs can provide better estimates of the repair costs. Third, the simulation procedure focuses only on income but not ethnic group. The more comprehensive simulation scheme that takes into accounts both income and ethnic group information might yield more realistic outcomes.

5.3.2 Inspection Station and False Passing Outcome

From the essay on the motorists' choice of inspection stations, the performance of inspection stations as measured by the false pass odds and ratio needs further investigation. The analysis at the inspection station level may reveal the sorting of stations in to the neighborhoods. In addition, the study of market segmentation of services at the station may provide some explanation as to the performance of the inspection station.

5.3.3 OBD II Test and the Feasible Alternative

This study shows that the OBD II test may fail to identify high-polluting vehicles as the vehicles age. The replication of this study using the data elsewhere can add more evidence to justify the concern at the national level. The policy recommendations to this problem require careful analysis of the impact that might occur to several stakeholders because the OBD II test also has several advantages as discussed earlier. The acceptance from the public, both the motorists and the stations, should be considered along with the system to finance new alternatives.

APPENDIX A

Table A.1 Probit of a vehicle passing the first inspection using the aggregate income sample with Kahn (1996)'s specification

| Independent Variables | Coefficients. | z |
|-----------------------------|---------------|--------|
| Ln(Median household income) | 0.191 | 30.55 |
| Ln(Mileage) | -0.015 | -17.19 |
| Engine type | | |
| Car | -0.030 | -4.00 |
| Van | -0.063 | -6.12 |
| Vintage fixed effects | | |
| Model year 1999 | 0.036 | 0.31 |
| Model year 1998 | 0.151 | 1.44 |
| Model year 1997 | 0.118 | 1.12 |
| Model year 1996 | 0.123 | 1.17 |
| Model year 1995 | -0.196 | -1.86 |
| Model year 1994 | -0.369 | -3.52 |
| Model year 1993 | -0.574 | -5.45 |
| Model year 1992 | -0.685 | -6.55 |
| Model year 1991 | -0.914 | -8.69 |
| Model year 1990 | -0.798 | -7.62 |
| Model year 1989 | -0.974 | -9.22 |
| Model year 1988 | -1.006 | -9.60 |
| Model year 1987 | -1.165 | -10.98 |
| Model year 1986 | -1.178 | -11.23 |
| Model year 1985 | -1.459 | -13.64 |
| Model year 1984 | -1.369 | -12.97 |
| Model year 1983 | -1.479 | -13.00 |
| Model year 1982 | -1.383 | -12.72 |
| Model year 1981 | -1.549 | -11.62 |
| Constant | 0.097 | 0.79 |
| Observations | 685,714 | |
| Pseudo R2 | 0.1181 | |
| Wald Chi2 | 33844.59 | |

APPENDIX B

Table B.1 Percentage of vehicles classified by OBDII test and RSD measurement with different thresholds based on ASM standard

(A) $3 \times$ ASM2525 threshold standard

| Age (year) | Pass OBD Pass RSD (n_{00}) | Pass OBD Fail RSD (n_{01}) | Fail OBD Pass RSD (n_{10}) | Fail OBD Fail RSD (n_{11}) |
|---|--------------------------------------|--------------------------------------|--------------------------------------|--------------------------------------|
| 3 | 92.47 | 3.07 | 4.26 | 0.20 |
| 4 | 90.52 | 3.90 | 5.16 | 0.42 |
| 5 | 87.68 | 5.45 | 6.05 | 0.82 |
| 6 | 84.35 | 6.56 | 7.63 | 1.46 |
| 7 | 83.03 | 7.99 | 7.41 | 1.56 |
| 8 | 80.95 | 9.83 | 7.38 | 1.84 |
| 9 | 79.04 | 9.21 | 9.84 | 1.90 |
| Average Difference between Consecutive Groups | -2.24 | 1.02 | 0.93 | 0.28 |

(B) $2.5 \times$ ASM2525 threshold standard

| Age (year) | Pass OBD Pass RSD (n_{00}) | Pass OBD Fail RSD (n_{01}) | Fail OBD Pass RSD (n_{10}) | Fail OBD Fail RSD (n_{11}) |
|---|--------------------------------------|--------------------------------------|--------------------------------------|--------------------------------------|
| 3 | 91.58 | 3.96 | 4.14 | 0.32 |
| 4 | 89.42 | 4.99 | 5.07 | 0.51 |
| 5 | 86.16 | 6.97 | 5.87 | 1.00 |
| 6 | 82.41 | 8.50 | 7.30 | 1.79 |
| 7 | 80.89 | 10.14 | 7.07 | 1.91 |
| 8 | 78.06 | 12.73 | 7.04 | 2.18 |
| 9 | 76.17 | 12.09 | 9.31 | 2.44 |
| Average Difference between Consecutive Groups | -2.57 | 1.35 | 0.86 | 0.35 |

(C) $0.75 \times$ ASM2525 threshold standard

| Age (year) | Pass OBD Pass RSD (n_{00}) | Pass OBD Fail RSD (n_{01}) | Fail OBD Pass RSD (n_{10}) | Fail OBD Fail RSD (n_{11}) |
|---|--------------------------------------|--------------------------------------|--------------------------------------|--------------------------------------|
| 3 | 72.12 | 23.42 | 3.12 | 1.34 |
| 4 | 66.41 | 28.00 | 3.22 | 2.37 |
| 5 | 58.94 | 34.19 | 3.28 | 3.59 |
| 6 | 52.47 | 38.45 | 3.65 | 5.44 |
| 7 | 48.75 | 42.27 | 3.36 | 5.62 |
| 8 | 44.43 | 46.35 | 3.26 | 5.96 |
| 9 | 42.88 | 45.37 | 3.85 | 7.89 |
| Average Difference between Consecutive Groups | -4.87 | 3.66 | 0.12 | 1.09 |

Table B.1 Cont.

(D) $0.5 \times \text{ASM2525}$ threshold standard

| Age (year) | Pass OBD Pass RSD (n_{00}) | Pass OBD Fail RSD (n_{01}) | Fail OBD Pass RSD (n_{10}) | Fail OBD Fail RSD (n_{11}) |
|--|--------------------------------------|--------------------------------------|--------------------------------------|--------------------------------------|
| 3 | 55.62 | 39.91 | 2.35 | 2.11 |
| 4 | 49.73 | 44.68 | 2.20 | 3.38 |
| 5 | 42.26 | 50.86 | 2.36 | 4.51 |
| 6 | 36.42 | 54.50 | 2.25 | 6.84 |
| 7 | 32.93 | 58.10 | 2.04 | 6.93 |
| 8 | 30.08 | 60.70 | 2.14 | 7.07 |
| 9 | 26.22 | 62.04 | 2.53 | 9.21 |
| Average Difference between Consecutive Groups | -4.90 | 3.69 | 0.03 | 1.18 |

Table B.2 Sensitivity analysis of raw agreement indices and statistical tests

(A) 3 × ASM2525 threshold standard

| Age | Overall Agreement Ratio ^a | Specific Agreement ^a | | Pearson Chi-squared ^b | Likelihood-ratio Chi-squared ^b | Fisher Exact ^c |
|-----|--------------------------------------|---------------------------------|-----------------------|----------------------------------|---|---------------------------|
| | | Positive Rating Ratio | Negative Rating Ratio | | | |
| 3 | 0.927 (0.002) | 0.052 (0.002) | 0.962 (0.020) | 3.977 (0.046) | 3.596 (0.058) | (0.056) |
| 4 | 0.909 (0.002) | 0.086 (0.002) | 0.952 (0.022) | 25.861 (0.000) | 21.562 (0.000) | (0.000) |
| 5 | 0.885 (0.003) | 0.125 (0.003) | 0.938 (0.026) | 65.095 (0.000) | 53.180 (0.000) | (0.000) |
| 6 | 0.858 (0.003) | 0.171 (0.003) | 0.922 (0.029) | 121.247 (0.000) | 98.775 (0.000) | (0.000) |
| 7 | 0.846 (0.004) | 0.169 (0.004) | 0.915 (0.031) | 68.375 (0.000) | 57.560 (0.000) | (0.000) |
| 8 | 0.828 (0.005) | 0.176 (0.005) | 0.904 (0.033) | 37.313 (0.000) | 32.228 (0.000) | (0.000) |
| 9 | 0.809 (0.009) | 0.166 (0.008) | 0.892 (0.035) | 7.111 (0.008) | 6.444 (0.011) | (0.012) |

(B) 2.5 × ASM2525 threshold standard

| Age | Overall Agreement Ratio ^a | Specific Agreement ^a | | Pearson Chi-squared ^b | Likelihood-ratio Chi-squared ^b | Fisher Exact ^c |
|-----|--------------------------------------|---------------------------------|-----------------------|----------------------------------|---|---------------------------|
| | | Positive Rating Ratio | Negative Rating Ratio | | | |
| 3 | 0.919 (0.002) | 0.074 (0.002) | 0.958 (0.021) | 18.657 (0.000) | 15.704 (0.000) | (0.000) |
| 4 | 0.899 (0.002) | 0.092 (0.002) | 0.947 (0.024) | 25.885 (0.000) | 22.031 (0.000) | (0.000) |
| 5 | 0.872 (0.003) | 0.135 (0.003) | 0.931 (0.027) | 70.919 (0.000) | 58.996 (0.000) | (0.000) |
| 6 | 0.842 (0.003) | 0.184 (0.003) | 0.913 (0.031) | 131.310 (0.000) | 109.314 (0.000) | (0.000) |
| 7 | 0.828 (0.004) | 0.181 (0.004) | 0.904 (0.033) | 76.095 (0.000) | 65.148 (0.000) | (0.000) |
| 8 | 0.802 (0.005) | 0.181 (0.005) | 0.888 (0.036) | 33.867 (0.000) | 30.094 (0.000) | (0.000) |
| 9 | 0.786 (0.009) | 0.186 (0.009) | 0.877 (0.038) | 8.523 (0.004) | 7.806 (0.005) | (0.005) |

Table B.2 Cont.

(C) 0.75 × ASM2525 threshold standard

| Age | Overall Agreement Ratio ^a | Specific Agreement ^a | | Pearson Chi-squared ^b | Likelihood-ratio Chi-squared ^b | Fisher Exact ^c |
|-----|--------------------------------------|---------------------------------|-----------------------|----------------------------------|---|---------------------------|
| | | Positive Rating Ratio | Negative Rating Ratio | | | |
| 3 | 0.735 (0.003) | 0.092 (0.002) | 0.845 (0.043) | 13.454 (0.000) | 12.900 (0.000) | (0.000) |
| 4 | 0.688 (0.004) | 0.132 (0.003) | 0.810 (0.048) | 68.334 (0.000) | 64.619 (0.000) | (0.000) |
| 5 | 0.625 (0.004) | 0.161 (0.003) | 0.759 (0.056) | 105.141 (0.000) | 101.858 (0.000) | (0.000) |
| 6 | 0.579 (0.004) | 0.205 (0.003) | 0.714 (0.062) | 142.680 (0.000) | 141.539 (0.000) | (0.000) |
| 7 | 0.544 (0.005) | 0.198 (0.004) | 0.681 (0.067) | 82.332 (0.000) | 82.813 (0.000) | (0.000) |
| 8 | 0.504 (0.007) | 0.194 (0.005) | 0.642 (0.072) | 34.399 (0.000) | 34.973 (0.000) | (0.000) |
| 9 | 0.508 (0.011) | 0.243 (0.009) | 0.635 (0.073) | 21.362 (0.000) | 21.859 (0.000) | (0.000) |

(D) 0.5 × ASM2525 threshold standard

| Age | Overall Agreement Ratio ^a | Specific Agreement ^a | | Pearson Chi-squared ^b | Likelihood-ratio Chi-squared ^b | Fisher Exact ^c |
|-----|--------------------------------------|---------------------------------|-----------------------|----------------------------------|---|---------------------------|
| | | Positive Rating Ratio | Negative Rating Ratio | | | |
| 3 | 0.577 (0.004) | 0.091 (0.002) | 0.725 (0.060) | 10.007 (0.002) | 9.916 (0.002) | (0.000) |
| 4 | 0.531 (0.004) | 0.126 (0.003) | 0.680 (0.066) | 63.144 (0.000) | 63.389 (0.000) | (0.000) |
| 5 | 0.468 (0.004) | 0.145 (0.003) | 0.614 (0.075) | 50.016 (0.000) | 51.076 (0.000) | (0.000) |
| 6 | 0.433 (0.004) | 0.194 (0.003) | 0.562 (0.082) | 113.012 (0.000) | 119.579 (0.000) | (0.000) |
| 7 | 0.399 (0.005) | 0.187 (0.004) | 0.523 (0.087) | 62.466 (0.000) | 66.563 (0.000) | (0.000) |
| 8 | 0.372 (0.006) | 0.184 (0.005) | 0.489 (0.091) | 20.829 (0.000) | 21.958 (0.000) | (0.000) |
| 9 | 0.354 (0.011) | 0.222 (0.009) | 0.448 (0.097) | 6.864 (0.009) | 7.215 (0.007) | (0.000) |

^a Standard errors in parentheses for overall and specific agreement ratios

^b P-values in parentheses for Pearson and likelihood ratio Chi-squared

^c Fisher exact tests report only p-values

Table B.3 Sensitivity analysis of agreement coefficients (AC1) and their variances

(A) $3 \times$ ASM2525 threshold standard

| Age | Agreement Coefficient (κ_γ) | Variance (V_{κ_γ}) |
|-----|---|----------------------------------|
| 3 | 0.921 | 0.000004 |
| 4 | 0.900 | 0.000006 |
| 5 | 0.869 | 0.000008 |
| 6 | 0.832 | 0.000012 |
| 7 | 0.815 | 0.000020 |
| 8 | 0.788 | 0.000039 |
| 9 | 0.761 | 0.000118 |

(B) $2.5 \times$ ASM2525 threshold standard

| Age | Agreement Coefficient (κ_γ) | Variance (V_{κ_γ}) |
|-----|---|----------------------------------|
| 3 | 0.912 | 0.000005 |
| 4 | 0.888 | 0.000007 |
| 5 | 0.851 | 0.000009 |
| 6 | 0.808 | 0.000014 |
| 7 | 0.788 | 0.000022 |
| 8 | 0.749 | 0.000046 |
| 9 | 0.723 | 0.000138 |

(C) $0.75 \times$ ASM2525 threshold standard

| Age | Agreement Coefficient (κ_γ) | Variance (V_{κ_γ}) |
|-----|---|----------------------------------|
| 3 | 0.646 | 0.000019 |
| 4 | 0.557 | 0.000025 |
| 5 | 0.426 | 0.000034 |
| 6 | 0.311 | 0.000047 |
| 7 | 0.231 | 0.000073 |
| 8 | 0.136 | 0.000137 |
| 9 | 0.123 | 0.000387 |

(D) $0.5 \times$ ASM2525 threshold standard

| Age | Agreement Coefficient (κ_γ) | Variance (V_{κ_γ}) |
|-----|---|----------------------------------|
| 3 | 0.343 | 0.000032 |
| 4 | 0.228 | 0.000040 |
| 5 | 0.068 | 0.000048 |
| 6 | -0.044 | 0.000060 |
| 7 | -0.127 | 0.000087 |
| 8 | -0.194 | 0.000152 |
| 9 | -0.255 | 0.000421 |

Table B.4 Sensitivity analysis of logistic models of agreement outcomes between the RSD measurement and the OBD II test

(A) 3 × ASM2525 threshold standard

| Independent Variables | 3 x ASM2525 Standard | | | | |
|---|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Vehicle age | | | | | |
| Age | -0.393 (8.69)*** | -0.384 (8.50)*** | -0.305 (24.80)*** | -0.302 (24.44)*** | |
| Age square | 0.008 (2.04)** | 0.007 (1.90)* | | | |
| Age x Elapse | 0.000 (0.67) | 0.000 (0.80) | 0.000 (0.62) | 0.000 (0.75) | |
| Age category (Ref: Age 3) | | | | | |
| Age 4 | | | | | -0.307 (7.71)*** |
| Age 5 | | | | | -0.633 (16.32)*** |
| Age 6 | | | | | -0.923 (23.63)*** |
| Age 7 | | | | | -1.196 (27.73)*** |
| Age 8 | | | | | -1.508 (29.94)*** |
| Age 9 | | | | | -1.683 (24.24)*** |
| Vehicle usage | | | | | |
| Ln(Mile driven per year) | 1.228 (6.59)*** | -0.837 (12.82)*** | 1.226 (6.55)*** | -0.835 (12.82)*** | -0.829 (12.99)*** |
| Ln(Mile driven per year) square | -0.105 (11.24)*** | | -0.105 (11.18)*** | | |
| Ln(Mile driven per year) x Elapse | -0.000 (1.28) | -0.000 (0.55) | -0.000 (1.28) | -0.000 (0.55) | -0.000 (0.72) |
| Elapse between RSD & OBD (day) | | | | | |
| | 0.005 (1.18) | 0.002 (0.46) | 0.005 (1.19) | 0.002 (0.48) | 0.003 (0.74) |
| Vehicle characteristics | | | | | |
| Cylinder | 0.023 (2.17)** | 0.022 (2.10)** | 0.022 (2.15)** | 0.022 (2.08)** | 0.022 (2.09)** |
| Emission control technology | | | | | |
| Air Injection Reactor (AIR) | -0.034 (0.87) | -0.034 (0.88) | -0.031 (0.80) | -0.032 (0.81) | -0.035 (0.88) |
| Exhaust Gas Recirculation (EGR) | 0.188 (5.78)*** | 0.185 (5.68)*** | 0.188 (5.78)*** | 0.185 (5.68)*** | 0.185 (5.69)*** |
| Type of vehicle (Ref: Car) | | | | | |
| Van and other | -0.149 (3.27)*** | -0.144 (3.18)*** | -0.148 (3.26)*** | -0.144 (3.17)*** | -0.144 (3.18)*** |
| SUV | 0.050 (1.36) | 0.051 (1.40) | 0.050 (1.37) | 0.051 (1.40) | 0.051 (1.39) |
| Truck | -0.322 (8.78)*** | -0.332 (9.05)*** | -0.322 (8.78)*** | -0.333 (9.06)*** | -0.332 (9.05)*** |

Table B.4 Cont.

(A) 3 × ASM2525 threshold standard

| Independent Variables | 3 x ASM2525 Standard | | | | |
|--------------------------------------|----------------------|----------------------|---------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Country of production (Ref: US) | | | | | |
| Asia-Pacific | -0.104 (2.53)** | -0.102 (2.48)** | -0.103 (2.52)** | -0.101 (2.47)** | -0.101 (2.47)** |
| Europe | 0.100 (0.92) | 0.099 (0.92) | 0.098 (0.90) | 0.098 (0.90) | 0.099 (0.91) |
| North-Central America | -0.004 (0.11) | -0.005 (0.15) | -0.003 (0.09) | -0.004 (0.13) | -0.005 (0.15) |
| Manufacturer (Ref: Ford) | | | | | |
| Chrysler | 0.206 (4.33)*** | 0.208 (4.38)*** | 0.207 (4.35)*** | 0.209 (4.41)*** | 0.208 (4.38)*** |
| European | 0.147 (1.36) | 0.154 (1.42) | 0.147 (1.35) | 0.154 (1.42) | 0.155 (1.42) |
| GM | 0.518 (12.95)*** | 0.520 (13.01)*** | 0.519 (12.97)*** | 0.520 (13.03)*** | 0.520 (13.01)*** |
| Honda | 0.458 (8.77)*** | 0.462 (8.86)*** | 0.458 (8.78)*** | 0.462 (8.87)*** | 0.461 (8.85)*** |
| Japanese - Korean | 0.086 (1.83)* | 0.090 (1.91)* | 0.088 (1.87)* | 0.092 (1.95)* | 0.090 (1.90)* |
| Toyota | 0.757 (14.86)*** | 0.758 (14.92)*** | 0.758 (14.89)*** | 0.759 (14.95)*** | 0.758 (14.92)*** |
| <u>RSD measurement conditions</u> | | | | | |
| Year of measurement (Ref: 2005) | Yes | Yes | Yes | Yes | Yes |
| Month of measurement (Ref: December) | Yes | Yes | Yes | Yes | Yes |
| Day of measurement (Ref: Saturday) | Yes | Yes | Yes | Yes | Yes |
| Site of measurement (Ref: Site43) | Yes | Yes | Yes | Yes | Yes |
| Constant | 1.884 (1.82)* | 11.955 (17.11)*** | 1.675 (1.62) | 11.744 (17.07)*** | 10.770 (16.33)*** |
| Observations | 82523 | 82523 | 82523 | 82523 | 82523 |
| Log Likelihood | -27708.76 | -27748.97 | -27710.83 | -27750.74 | -27748.40 |
| LR Chi2 | 3062.96 | 2865.02 | 3081.00 | 2881.28 | 2870.40 |
| DoF | 83.00 | 82.00 | 82.00 | 81.00 | 85.00 |
| Pseudo R2 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |

Table B.4 Cont.

(B) 2 × ASM2525 threshold standard

| Independent Variables | 2 x ASM2525 Standard | | | | |
|-----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Vehicle age | | | | | |
| Age | -0.383 (9.47) ^{***} | -0.374 (9.26) ^{***} | -0.306 (27.98) ^{***} | -0.304 (27.57) ^{***} | |
| Age square | 0.007 (1.98) ^{**} | 0.006 (1.83) [*] | | | |
| Age x Elapse | -0.000 (0.81) | -0.000 (0.66) | -0.000 (0.86) | -0.000 (0.71) | |
| Age category (Ref: Age 3) | | | | | |
| Age 4 | | | | | -0.351 (9.95) ^{***} |
| Age 5 | | | | | -0.672 (19.38) ^{***} |
| Age 6 | | | | | -0.970 (27.73) ^{***} |
| Age 7 | | | | | -1.255 (32.65) ^{***} |
| Age 8 | | | | | -1.609 (36.02) ^{***} |
| Age 9 | | | | | -1.793 (28.57) ^{***} |
| Vehicle usage | | | | | |
| Ln(Mile driven per year) | 1.117 (6.30) ^{***} | -0.746 (12.73) ^{***} | 1.114 (6.27) ^{***} | -0.745 (12.73) ^{***} | -0.752 (13.07) ^{***} |
| Ln(Mile driven per year) square | -0.096 (10.73) ^{***} | | -0.095 (10.67) ^{***} | | |
| Ln(Mile driven per year) x Elapse | -0.000 (1.07) | -0.000 (0.30) | -0.000 (1.07) | -0.000 (0.31) | -0.000 (0.18) |
| Elapse between RSD & OBD (day) | 0.004 (1.16) | 0.001 (0.39) | 0.004 (1.17) | 0.002 (0.40) | 0.001 (0.21) |
| <u>Vehicle characteristics</u> | | | | | |
| Cylinder | 0.003 (0.27) | 0.002 (0.20) | 0.002 (0.26) | 0.002 (0.18) | 0.002 (0.21) |
| Emission control technology | | | | | |
| Air Injection Reactor (AIR) | 0.010 (0.28) | 0.010 (0.27) | 0.012 (0.35) | 0.012 (0.34) | 0.010 (0.28) |
| Exhaust Gas Recirculation (EGR) | 0.199 (6.89) ^{***} | 0.196 (6.78) ^{***} | 0.199 (6.89) ^{***} | 0.196 (6.77) ^{***} | 0.196 (6.78) ^{***} |
| Type of vehicle (Ref: Car) | | | | | |
| Van and other | -0.190 (4.65) ^{***} | -0.186 (4.58) ^{***} | -0.189 (4.65) ^{***} | -0.186 (4.57) ^{***} | -0.187 (4.58) ^{***} |
| SUV | -0.058 (1.82) [*] | -0.057 (1.80) [*] | -0.058 (1.81) [*] | -0.057 (1.79) [*] | -0.058 (1.81) [*] |
| Truck | -0.345 (10.45) ^{***} | -0.356 (10.77) ^{***} | -0.345 (10.46) ^{***} | -0.356 (10.77) ^{***} | -0.356 (10.78) ^{***} |

Table B.4 Cont.

(B) 2 × ASM2525 threshold standard

| Independent Variables | 2 x ASM2525 Standard | | | | |
|--------------------------------------|----------------------|----------------------|---------------------|----------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Country of production (Ref: US) | | | | | |
| Asia-Pacific | -0.061 (1.69)* | -0.060 (1.64) | -0.061 (1.68)* | -0.059 (1.63) | -0.059 (1.63) |
| Europe | 0.043 (0.43) | 0.043 (0.43) | 0.041 (0.42) | 0.041 (0.42) | 0.043 (0.43) |
| North-Central America | -0.030 (0.99) | -0.031 (1.03) | -0.029 (0.97) | -0.031 (1.01) | -0.031 (1.04) |
| Manufacturer (Ref: Ford) | | | | | |
| Chrysler | 0.173 (4.08)*** | 0.175 (4.13)*** | 0.175 (4.11)*** | 0.176 (4.15)*** | 0.175 (4.13)*** |
| European | 0.219 (2.22)** | 0.227 (2.30)** | 0.219 (2.21)** | 0.226 (2.29)** | 0.227 (2.30)** |
| GM | 0.453 (12.68)*** | 0.454 (12.74)*** | 0.454 (12.70)*** | 0.455 (12.76)*** | 0.454 (12.74)*** |
| Honda | 0.446 (9.45)*** | 0.450 (9.55)*** | 0.446 (9.46)*** | 0.450 (9.56)*** | 0.450 (9.56)*** |
| Japanese - Korean | -0.025 (0.58) | -0.021 (0.50) | -0.023 (0.54) | -0.020 (0.46) | -0.021 (0.50) |
| Toyota | 0.596 (13.39)*** | 0.597 (13.46)*** | 0.597 (13.43)*** | 0.599 (13.49)*** | 0.598 (13.46)*** |
| <u>RSD measurement conditions</u> | | | | | |
| Year of measurement (Ref: 2005) | Yes | Yes | Yes | Yes | Yes |
| Month of measurement (Ref: December) | Yes | Yes | Yes | Yes | Yes |
| Day of measurement (Ref: Saturday) | Yes | Yes | Yes | Yes | Yes |
| Site of measurement (Ref: Site43) | Yes | Yes | Yes | Yes | Yes |
| Constant | 1.828 (1.88)* | 10.863 (17.41)*** | 1.648 (1.70)* | 10.682 (17.41)*** | 9.868 (16.72)*** |
| Observations | 82523 | 82523 | 82523 | 82523 | 82523 |
| Log Likelihood | -33000.65 | -33043.77 | -33002.60 | -33045.43 | -33042.17 |
| LR Chi2 | 3772.51 | 3577.39 | 3792.31 | 3595.14 | 3575.38 |
| DoF | 83.00 | 82.00 | 82.00 | 81.00 | 85.00 |
| Pseudo R2 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |

Table B.4 Cont.

(C) 0.5 × ASM2525 threshold standard

| Independent Variables | 0.5 x ASM2525Standard | | | | |
|---|-----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Vehicle age | | | | | |
| Age | -0.303 (10.30)*** | -0.298 (10.13)*** | -0.231 (29.22)*** | -0.229 (28.96)*** | |
| Age square | 0.007 (2.54)** | 0.006 (2.44)** | | | |
| Age x Elapse | -0.000 (3.29)*** | -0.000 (3.13)*** | -0.000 (3.33)*** | -0.000 (3.17)*** | |
| Age category (Ref: Age 3) | | | | | |
| Age 4 | | | | | -0.264 (12.02)*** |
| Age 5 | | | | | -0.573 (25.27)*** |
| Age 6 | | | | | -0.752 (31.38)*** |
| Age 7 | | | | | -0.997 (36.22)*** |
| Age 8 | | | | | -1.300 (38.33)*** |
| Age 9 | | | | | -1.403 (26.92)*** |
| Vehicle usage | | | | | |
| Ln(Mile driven per year) | 0.601 (3.66)*** | -0.401 (11.76)*** | 0.599 (3.66)*** | -0.401 (11.75)*** | -0.414 (12.21)*** |
| Ln(Mile driven per year) square | -0.053 (6.06)*** | | -0.053 (6.05)*** | | |
| Ln(Mile driven per year) x Elapse | 0.000 (0.67) | 0.000 (1.57) | 0.000 (0.66) | 0.000 (1.57) | 0.000 (2.10)** |
| Elapse between RSD & OBD (day) | | | | | |
| | -0.000 (0.13) | -0.002 (1.07) | -0.000 (0.12) | -0.002 (1.06) | -0.004 (2.00)** |
| Vehicle characteristics | | | | | |
| Cylinder | -0.088 (13.37)*** | -0.088 (13.40)*** | -0.088 (13.38)*** | -0.088 (13.42)*** | -0.088 (13.37)*** |
| Emission control technology | | | | | |
| Air Injection Reactor (AIR) | -0.005 (0.19) | -0.005 (0.20) | -0.003 (0.12) | -0.003 (0.13) | -0.005 (0.19) |
| Exhaust Gas Recirculation (EGR) | 0.036 (1.77)* | 0.033 (1.63) | 0.036 (1.78)* | 0.033 (1.64) | 0.032 (1.61) |
| Type of vehicle (Ref: Car) | | | | | |
| Van and other | -0.058 (1.94)* | -0.060 (2.00)** | -0.058 (1.93)* | -0.060 (2.00)** | -0.060 (2.01)** |
| SUV | -0.348 (15.83)*** | -0.350 (15.91)*** | -0.348 (15.81)*** | -0.350 (15.89)*** | -0.351 (15.93)*** |
| Truck | -0.294 (11.78)*** | -0.305 (12.24)*** | -0.294 (11.78)*** | -0.305 (12.24)*** | -0.306 (12.26)*** |

Table B.4 Cont.

(C) 0.5 × ASM2525 threshold standard

| Independent Variables | 0.5 x ASM2525 Standard | | | | |
|--------------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Country of production (Ref: US) | | | | | |
| Asia-Pacific | 0.188 (7.24) ^{***} | 0.189 (7.30) ^{***} | 0.188 (7.25) ^{***} | 0.189 (7.30) ^{***} | 0.190 (7.32) ^{***} |
| Europe | 0.086 (1.24) | 0.088 (1.26) | 0.085 (1.22) | 0.087 (1.24) | 0.088 (1.26) |
| North-Central America | -0.093 (4.27) ^{***} | -0.093 (4.29) ^{***} | -0.092 (4.24) ^{***} | -0.092 (4.26) ^{***} | -0.093 (4.31) ^{***} |
| Manufacturer (Ref: Ford) | | | | | |
| Chrysler | -0.182 (5.74) ^{***} | -0.182 (5.72) ^{***} | -0.182 (5.72) ^{***} | -0.181 (5.70) ^{***} | -0.181 (5.71) ^{***} |
| European | 0.183 (2.60) ^{***} | 0.191 (2.72) ^{***} | 0.183 (2.60) ^{***} | 0.191 (2.72) ^{***} | 0.191 (2.72) ^{***} |
| GM | -0.119 (4.54) ^{***} | -0.117 (4.49) ^{***} | -0.118 (4.53) ^{***} | -0.117 (4.48) ^{***} | -0.117 (4.48) ^{***} |
| Honda | 0.086 (2.72) ^{***} | 0.090 (2.83) ^{***} | 0.087 (2.74) ^{***} | 0.090 (2.85) ^{***} | 0.091 (2.86) ^{***} |
| Japanese - Korean | -0.425 (13.24) ^{***} | -0.422 (13.16) ^{***} | -0.424 (13.19) ^{***} | -0.421 (13.12) ^{***} | -0.422 (13.13) ^{***} |
| Toyota | -0.282 (9.09) ^{***} | -0.278 (8.98) ^{***} | -0.281 (9.05) ^{***} | -0.277 (8.95) ^{***} | -0.278 (8.97) ^{***} |
| <u>RSD measurement conditions</u> | | | | | |
| Year of measurement (Ref: 2005) | Yes | Yes | Yes | Yes | Yes |
| Month of measurement (Ref: December) | Yes | Yes | Yes | Yes | Yes |
| Day of measurement (Ref: Saturday) | Yes | Yes | Yes | Yes | Yes |
| Site of measurement (Ref: Site43) | Yes | Yes | Yes | Yes | Yes |
| Constant | 1.686 (2.08) ^{**} | 6.394 (17.32) ^{***} | 1.522 (1.89) [*] | 6.225 (17.19) ^{***} | 5.714 (16.14) ^{***} |
| Observations | 82523 | 82523 | 82523 | 82523 | 82523 |
| Log Likelihood | -53945.37 | -53979.76 | -53948.61 | -53982.75 | -53977.07 |
| LR Chi2 | 5686.74 | 5581.78 | 5685.55 | 5579.51 | 5597.42 |
| DoF | 83.00 | 82.00 | 82.00 | 81.00 | 85.00 |
| Pseudo R2 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |

Table B.4 Cont.

(D) 0.33 × ASM2525 threshold standard

| Independent Variables | 0.33 x ASM2525 Standard | | | | |
|-----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Vehicle age | | | | | |
| Age | -0.240 (7.71) ^{***} | -0.238 (7.63) ^{***} | -0.185 (22.04) ^{***} | -0.184 (21.90) ^{***} | |
| Age square | 0.005 (1.83) [*] | 0.005 (1.79) [*] | | | |
| Age x Elapse | -0.000 (2.48) ^{**} | -0.000 (2.41) ^{**} | -0.000 (2.51) ^{**} | -0.000 (2.43) ^{**} | |
| Age category (Ref: Age 3) | | | | | |
| Age 4 | | | | | -0.198 (8.86) ^{***} |
| Age 5 | | | | | -0.477 (20.31) ^{***} |
| Age 6 | | | | | -0.587 (23.50) ^{***} |
| Age 7 | | | | | -0.789 (26.84) ^{***} |
| Age 8 | | | | | -1.060 (29.07) ^{***} |
| Age 9 | | | | | -1.109 (19.33) ^{***} |
| Vehicle usage | | | | | |
| Ln(Mile driven per year) | 0.284 (1.96) [*] | -0.229 (7.13) ^{***} | 0.283 (1.95) [*] | -0.229 (7.11) ^{***} | -0.238 (7.42) ^{***} |
| Ln(Mile driven per year) square | -0.027 (3.59) ^{***} | | -0.027 (3.58) ^{***} | | |
| Ln(Mile driven per year) x Elapse | 0.000 (0.33) | 0.000 (0.96) | 0.000 (0.32) | 0.000 (0.96) | 0.000 (1.32) |
| Elapse between RSD & OBD (day) | 0.000 (0.06) | -0.001 (0.57) | 0.000 (0.07) | -0.001 (0.56) | -0.003 (1.26) |
| Vehicle characteristics | | | | | |
| Cylinder | -0.098 (14.10) ^{***} | -0.098 (14.12) ^{***} | -0.098 (14.12) ^{***} | -0.098 (14.13) ^{***} | -0.098 (14.09) ^{***} |
| Emission control technology | | | | | |
| Air Injection Reactor (AIR) | -0.021 (0.80) | -0.021 (0.80) | -0.019 (0.75) | -0.019 (0.76) | -0.021 (0.80) |
| Exhaust Gas Recirculation (EGR) | 0.000 (0.01) | -0.002 (0.08) | 0.000 (0.01) | -0.002 (0.07) | -0.002 (0.10) |
| Type of vehicle (Ref: Car) | | | | | |
| Van and other | -0.071 (2.26) ^{**} | -0.073 (2.32) ^{**} | -0.071 (2.26) ^{**} | -0.073 (2.31) ^{**} | -0.073 (2.33) ^{**} |
| SUV | -0.345 (14.47) ^{***} | -0.346 (14.54) ^{***} | -0.344 (14.45) ^{***} | -0.346 (14.53) ^{***} | -0.347 (14.56) ^{***} |
| Truck | -0.256 (9.61) ^{***} | -0.264 (9.91) ^{***} | -0.256 (9.61) ^{***} | -0.264 (9.91) ^{***} | -0.264 (9.93) ^{***} |

Table B.4 Cont.

(D) 0.33 × ASM2525 threshold standard

| Independent Variables | 0.33 x ASM2525 Standard | | | | |
|--------------------------------------|-------------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Country of production (Ref: US) | | | | | |
| Asia-Pacific | 0.213 (7.83)*** | 0.213 (7.87)*** | 0.213 (7.84)*** | 0.214 (7.87)*** | 0.214 (7.90)*** |
| Europe | 0.082 (1.17) | 0.083 (1.19) | 0.081 (1.16) | 0.083 (1.17) | 0.083 (1.18) |
| North-Central America | -0.053 (2.32)** | -0.053 (2.32)** | -0.053 (2.29)** | -0.053 (2.30)** | -0.054 (2.34)** |
| Manufacturer (Ref: Ford) | | | | | |
| Chrysler | -0.288 (8.54)*** | -0.288 (8.53)*** | -0.288 (8.53)*** | -0.287 (8.52)*** | -0.287 (8.52)*** |
| European | 0.106 (1.47) | 0.111 (1.55) | 0.105 (1.47) | 0.111 (1.55) | 0.111 (1.55) |
| GM | -0.181 (6.57)*** | -0.180 (6.54)*** | -0.181 (6.57)*** | -0.180 (6.53)*** | -0.180 (6.53)*** |
| Honda | -0.101 (3.12)*** | -0.099 (3.05)*** | -0.101 (3.11)*** | -0.098 (3.04)*** | -0.098 (3.03)*** |
| Japanese - Korean | -0.449 (13.27)*** | -0.447 (13.23)*** | -0.447 (13.24)*** | -0.446 (13.20)*** | -0.446 (13.21)*** |
| Toyota | -0.485 (14.85)*** | -0.483 (14.78)*** | -0.484 (14.83)*** | -0.482 (14.76)*** | -0.482 (14.76)*** |
| <u>RSD measurement conditions</u> | | | | | |
| Year of measurement (Ref: 2005) | Yes | Yes | Yes | Yes | Yes |
| Month of measurement (Ref: December) | Yes | Yes | Yes | Yes | Yes |
| Day of measurement (Ref: Saturday) | Yes | Yes | Yes | Yes | Yes |
| Site of measurement (Ref: Site43) | Yes | Yes | Yes | Yes | Yes |
| Constant | 1.478 (2.01)** | 3.856 (10.90)*** | 1.352 (1.85)* | 3.727 (10.75)*** | 3.292 (9.71)*** |
| Observations | 82523 | 82523 | 82523 | 82523 | 82523 |
| Log Likelihood | -49852.13 | -49862.17 | -49853.80 | -49863.77 | -49854.94 |
| LR Chi2 | 4395.23 | 4372.05 | 4388.67 | 4365.18 | 4401.44 |
| DoF | 83.00 | 82.00 | 82.00 | 81.00 | 85.00 |
| Pseudo R2 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |

REFERENCES

- Abounoori, E., & McCloughan, P. (2003). A simple way to calculate the Gini Coefficient for grouped as well as ungrouped data. *Applied Economics Letters*, 10(8), 505-509.
- Alberini, A., Harrington, W., & McConnel, V. D. (1996). Estimating an emission supply function from accelerated vehicle retirement program. *The Review of Economics and Statistics*, 78(2), 251-265.
- Alberini, A., Harrington, W., & McConnel, V. D. (1998). *Fleet turnover and old car scrap policies* (Discussion Paper 98-23). Washington, DC: Resources for the Future.
- Allen, M. J., & Yen, W. M. (1979). *Introduction to Measurement Theory*. Monterey, CA: Brooks/Cole Publishing Company.
- Anastasi, A., & Urbina, S. (1997). *Psychological Testing* (7 ed.). Upper Saddle River, NJ: Prentice Hall.
- Anderson, S. P., de Palma, A., & Thisse, J.-F. (1992). *Discrete Choice Theory of Product Differentiation*. Cambridge, MA: The MIT Press.
- Ando, A. W., Harrington, W., & McConnell, V. D. (2007). *Fees in an imperfect world: An application to motor vehicle emissions* (RFF Discussion Paper No. 07-34). Washington, D.C.: Resources for the Future.
- Axhausen, K. W., Hess, S., Konig, A., Abay, G., Bates, J. J., & Bierlaire, M. (2008). Income and distance elasticities of values of travel time savings: New Swiss results. *Transport Policy*, 15, 173-185.
- Baiocchi, G. (2005). Monte Carlo methods in environmental economics. In R. Scarpa & A. Alberini (Eds.), *Applications of Simulation Methods in Environmental and Resource Economics* (pp. 317-340). The Netherlands: Springer.
- Baumol, W., & Oates, W. E. (1988). *The Theory of Environmental Policy* (2 ed.). New York, NY: Cambridge University Press.

- Bayer, P., Ferreira, F., & McMillan, R. (2007). A unified framework for estimating preferences for schools and neighbors. *Journal of Political Economy*, 115, 588-638.
- Ben-Akiva, M., & Bierlaire, M. (2003). Discrete choice models with applications to departure time and route choice. In R. W. Hall (Ed.), *Handbook of Transportation Science* (2 ed.): Kluwer's International Series.
- Ben-Akiva, M., & Lerman, S. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. Boston, MA: The MIT Press.
- Black, S. (1999). Do better schools matter? Parental valuation of elementary education. *Quarterly Journal of Economics*, 114(2), 577-599.
- Blalock, H. M. J. (1979). *Social Statistics* (2 ed.). New York, NY: McGraw-Hill Book Company.
- Bockstael, N. E., McConnell, K. E., & Strand, I. E. (1989). A random utility model for sport fishing: Some preliminary results for Florida. *Marine Resource Economics*, 6(4), 245-260.
- Calfee, J., & Winston, C. (1998). The value of automobile travel time: Implications for congestion policy. *Journal of Public Economics*, 69, 83-102.
- Carmines, E. G., & Zeller, R. A. (1979). *Reliability and validity assessment*. Newbury Park: SAGE Publication.
- Chamberlin, E. (1933). *The Theory of Monopolistic Competition*. Cambridge: Harvard University Press.
- Chen, C., & Neimeier, D. (2005). A mass point vehicle scrappage model. *Transportation Research Part B*, 39, 401-415.
- Chen, P. Y., & Popovich, P. M. (2002). *Correlation Parametric and Nonparametric Measures*. Newbury Park: SAGE Publications.
- Coder, J., & Scoon-Rogers, L. (1995). Evaluating the quality of income data collected in the annual supplement to the March Current Population Survey and the Survey of Income and Program Participation (SIPP Working Paper Series No. 215). Washington, DC: U.S. Bureau of the Census.

- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3 ed.). Mahwah, NJ: Lawrence Erlbaum Associates, Publishers.
- Corley, E., DeHart-Davis, L., Lindner, J., & Rodgers, M. O. (2003). Inspection/Maintenance program evaluation: Replicating the Denver step method for an Atlanta fleet. *Environmental Science and Technology*, 37(12), 2801-2806.
- Crocker, L., & Algina, J. (1986). *Introduction to classical and modern test theory*. New York, NY: CBS College Publishing.
- Davidoff, T. (2005). Income sorting: Measurement and decomposition. *Journal of Urban Economics*, 58(2), 289-203.
- Davis, S. C. (2000). *Transportation Energy Data Book: Edition 20* (ORNL No. 6959). Oak Ridge, TN: Oak Ridge National Laboratory, U.S. Department of Energy.
- Davis, S. C., Diegel, S. W., & Boundy, R. G. (2008). *Transportation Energy Data Book: Edition 27* (ORNL No. 6981). Oak Ridge, TN: Oak Ridge National Laboratory, U.S. Department of Energy.
- DeHart-Davis, L., Corley, E., & Rodgers, M. O. (2002). Evaluating vehicle inspection/maintenance program using on-road emissions data: The Atlanta reference method. *Evaluation Review*, 26(2), 111-146.
- Domencich, T., & McFadden, D. L. (1996). *Urban Travel Demand: A Behavioral Analysis*. Amsterdam, The Netherlands: North-Holland Publishing Co.
- Efron, B., & Tibshirani, R. J. (1994). *An Introduction to the Bootstrap*. Boca Raton, FL: Chapman & Hall/CRC Press LLC.
- EPA. (2004). *Guidance on Use of Remote Sensing for Evaluation of I/M Program Performance* (No. EPA420-B-04-010). Washington, D.C.: US Environmental Protection Agency, Office of Transportation and Air Quality.
- Fullerton, D. (2008). *Distributional effects of environmental and energy policy: An introduction* (NBER Working Paper Series No. 14241). Cambridge, MA: National Bureau of Economic Research.
- GA-EPD. (2008). Georgia's Clean Air Force: Georgia Environmental Protection Division.

- Gibbons, J. D. (1993). *Nonparametric measures of association*. Newbury Park: SAGE Publications.
- Glazer, A., Klein, D. B., & Lave, C. (1995). Clean on paper, dirty on the road: Troubles with California's Smog Check. *Journal of Transport Economics and Policy*, 29(1), 85-92.
- Gwet, K. (2001). *Handbook of inter-rater reliability: How to estimate the level of agreement between two or multiple raters*. Gaithersburg, MD: STATAXIS Publishing Company.
- Gwet, K. (2002a). *Inter-rater reliability: dependency on trait prevalence and marginal homogeneity* (Statistical Methods for Inter-rater Reliability Assessment No. 2).
- Gwet, K. (2002b). *Kappa statistic is not satisfactory for assessing the extent of agreement between two raters* (Statistical Methods for Inter-rater Reliability Assessment No. 1).
- Haab, T. C., & Hicks, R. L. (1997). Accounting for choice set endogeneity in random utility models of recreation demand. *Journal of Environmental Economics & Management*, 34(2), 127.
- Haggard, E. A. (1958). *Intraclass Correlation and Analysis of Variance*. New York, NY: The Dryden Press, Inc.
- Hahn, R. W. (1995). An economic analysis of scrappage. *The RAND Journal of Economics*, 26(2), 222-242.
- Harrington, W., & McConnell, V. D. (1999). *Coase and car repair: Who should be responsible for emissions of vehicles in use?* (Discussion Paper 99-22). Washington, DC: Resources for the Future.
- Harrington, W., McConnell, V. D., & Ando, A. (1999). *The enhanced I/M program in Arizona: Costs, effectiveness, and a comparison with pre-regulatory estimates* (Discussion Paper 99-37). Washington, DC: Resources for the Future.
- Harrington, W., McConnell, V. D., & Ando, A. (2000). Are vehicle emission inspection programs living up to expectations? *Transportation Research Part D*, 5, 153-172.

- Harrington, W., McConnell, V., & Walls, M. (1996). Who's in the driver's seat? Mobile source policy in the U.S. federal system. Washington, DC: Resources for the Future.
- Harrington, W., McConnell, V., & Walls, M. (1998). Who's in the driver seat? Mobile source policy in the federal system. In J. Braden & S. Proost (Eds.), *Climate change, transport and environmental policy: Empirical applications in a federal system*. London, UK: Edward Elgar Publishing.
- Hensher, D., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis: A primer*. New York, NY: Cambridge University Press.
- Hicks, R. L., & Strand, I. E. (2000). The Extent of Information: Its Relevance for Random Utility Models. *Land Economics*, 76(3), 374-385.
- Hogan, T. P. (2007). *Psychological testing A practical introduction*. Hoboken, NJ: John Wiley & Sons, Inc.
- Howell, D. C. (2007). *Statistical methods for psychology*. Belmont, CA: Thomson Wadsworth.
- Hubbard, T. N. (1997). Using inspection and maintenance programs to regulate vehicle emissions. *Contemporary Economic Policy*, XV(April), 52-62.
- Hubbard, T. N. (1998). An empirical examination of moral hazard in the vehicle inspection market. *The RAND Journal of Economics*, 29(2), 406-426.
- Hubbard, T. N. (2002). How do consumers motivate experts? Reputational incentives in an auto repair market. *The Journal of Law and Economics*, 45.
- Ireland, N. J. (1987). *Product differentiation and non-price competition*. New York, NY: Basil Blackwell Inc.
- Israel, M. (2005). Tenure dependence in consumer-firm relationships: An empirical analysis of consumer departures from automobile insurance firms. *The RAND Journal of Economics*, 36(1), 165-192.
- Johnston, J., & DiNardo, J. (2007). *Econometric Methods (4 ed.)*. Singapore: McGraw-Hill International Editions.

- Kahn, M. E. (1996a). The efficiency and equity of vehicle emissions regulation: Evidence from California's random audits. *Eastern Economics Journal*, 22(4), 457-465.
- Kahn, M. E. (1996b). New evidence on trends in vehicle emissions. *The RAND Journal of Economics*, 27(1), 183-196.
- Kahn, M. E., & Schwartz, J. (2008). Urban air pollution progress despite sprawl: The "greening" of the vehicle fleet. *Journal of Urban Economics*, 63, 775-787.
- Kline, P. (1992). *The handbook of psychological testing*. London, UK: Routledge.
- Klein, R. W., & Grace, M. F. (2001). Urban Homeowners Insurance Markets in Texas: A Search for Redlining. *Journal of Risk and Insurance*, 68(4), 581-614.
- Klausmeier, R., Kishan, S., Burnette, A., & Weatherby, M. (2000). *Smog check station performance analysis based on roadside test results* (Technical Note): dKC and Eastern Research Group.
- Lawson, D. R. (1993). Passing the test: Human behavior and California's Smog Check Program. *Journal of the Air and Waste Management Association*, 43, 1567-1575.
- Lawson, D. R., Groblicki, P. J., Stedman, D. H., Bishop, G. A., & Guenther, P. L. (1990). Emissions from in-use motor vehicles in Los Angeles: A pilot study of remote sensing and the inspection and maintenance program. *Journal of the Air and Waste Management Association*, 40, 1096-1105.
- Liebetrau, A. M. (1983). *Measures of association*. Newbury Park: SAGE Publications.
- Manski, C. F. (1977). The structure of random utility models. *Theory and Decision*, 8(3), 229-254.
- McCarthy, P. S. (2001). *Transportation Economics Theory and Practice: A Case Study Approach*. Malden, MA: Blackwell Publisher.
- McConnell, K. E., & Tseng, W.-C. (1999). Some preliminary evidence on sampling of alternatives with the random parameters logit. *Marine Resource Economics*, 14(4), 317-332.

- McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105-142). New York, NY: Academic Press.
- McFadden, D. (1978). Modelling the choice of residential location. In A. Karlqvist, L. Lundqvist, F. Snickars & J. W. Weibull (Eds.), *Spatial Interaction Theory and Planning Models* (pp. 75-96). Amsterdam, The Netherlands: North Holland.
- Mooney, C. (1997). *Monte Carlo Simulation (1 ed.)*. Thousand Oakes, CA: Sage Publications, Inc.
- Mooney, C. Z., & Duval, R. D. (1993). *Bootstrapping: A Nonparametric Approach to Statistical Inference*. Thousand Oakes, CA: Sage Publications, Inc.
- Moore, D. S., & McCabe, G. P. (2005). *Introduction to the Practice of Statistics (5 ed.)*: W. H. Freeman.
- National Research Council (NRC). (2001). *Evaluating Vehicle Emissions Inspection and Maintenance Programs*. Washington, DC: The National Academy Press.
- Parsons, G. R., & Hauber, A. B. (1998). Spatial boundaries and choice set definition in random utility models of recreation demand. *Land Economics*, 74, 32-48.
- Parsons, G. R., & Kealy, M. J. (1992). Randomly drawn opportunity sets in a random utility model of Lake Recreation. *Land Economics*, 68(1), 93.
- Parsons, G. R., Massey, D. M., & Tomasi, T. (1999). Familiar and favorite sites in a random utility model of beach recreation. *Marine Resource Economics*, 14(4), 299-315.
- Parsons, G. R., & Needelman, M. S. (1992). Site aggregation in a random utility model of recreation. *Land Economics*, 68(4), 418.
- Parsons, G. R., Plantinga, A. J., & Boyle, K. J. (2000). Narrow choice sets in a random utility model of recreation demand. *Land Economics*, 76(1), 86-99.
- Pesendorfer, W., & Wolinsky, A. (2003). Second opinions and price competition: Inefficiency in the market for expert advice. *The Review of Economic Studies*, 70(2), 417-437.

- Peters, T., Adamowicz, W. L., & Boxall, P. C. (1995). Influence of choice set consideration in modeling the benefits from improved water quality. *Water Resources Research*, 31(7), 1781-1788.
- Pierce, J. L., & Snyder, J. A. (2007). *Destined to fail? Ethical spillover in the vehicle emissions testing market*. Unpublished manuscript.
- Pierson, W. R. (1996). New directions: Motor vehicle inspection and maintenance programs - How effective are they? *Atmospheric Environment*, 30(21), i-iii.
- Pokharel, S. S., Bishop, G. A., & Stedman, D. H. (2002). *On-road Remote Sensing of Automobile Emissions in the Phoenix area Year 3* (CRC Contract No. E-23-4): CRC.
- Poterba, J. M. (1991). Is the gasoline tax regressive? *Tax Policy and the Economy*, 5, 145-164.
- Sahai, H., & Ageel, M. I. (2000). *The analysis of variance: Fixed, random and mixed models*. Boston, MA: Birkhauser.
- Shultz, K. S., & Whitney, D. J. (2005). *Measurement theory in action: Case studies and exercises*. Thousand Oaks, CA: SAGE Publications.
- Spitzer, R., & Fleiss, J. L. (1974). A re-analysis of the reliability of psychiatric diagnosis. *British Journal of Psychiatry*, 125, 341-347.
- Spitzley, D. V., Grande, D. E., Keoleian, G. A., & Kim, H. C. (2005). Life cycle optimization of ownership costs and emissions reduction in US vehicle retirement decisions. *Transportation Research Part D*, 10, 161-175.
- Smith, M. D., & Brynjolfsson, E. (2001). Consumer decision-making at an internet shopbot: Brand still matters. *The Journal of Industrial Economics*, 49(4), 541-558.
- Sommerville, R. J., Cacketter, T., & Austin, T. C. (1987). Evaluation of the California smog check program. *SAE Transactions*, 96(7), 88-117.
- Stedman, D. H., Bishop, G. A., & Slott, R. S. (1998). Repair avoidance and evaluating inspection and maintenance programs. *Environmental Science and Technology*, 32(10), 1544-1545.

- Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5 ed.). Boston, MA: Pearson International.
- Tay, A. (2003). Assessing competition in hospital care markets: The importance of accounting for quality differentiation. *The RAND Journal of Economics*, 34(4), 786-814.
- Tay, R., McCarthy, P., & Fletcher, J. J. (1996). A portfolio choice model of the demand for recreational trips. *Transportation Research Part B*, 30(5), 325-337.
- Train, K. E. (1993). *Qualitative choice analysis: Theory econometrics, and an application to automobile demand*. Boston, MA: The MIT Press.
- Uebersax, J. (2007a). Statistical methods for rater agreement. Retrieved 12/19, 2007, from <http://ourworld.compuserve.com/homepages/jsuebersax/agree.htm>
- Uebersax, J. (2007b). Tests of marginal homogeneity. Retrieved 11/19, 2007, from <http://ourworld.compuserve.com/homepages/jsuebersax/margin.htm>
- Vettas, N. (1997). On the informational role of quantities: Durable goods and consumers' word-of-mouth communication. *International Economic Review*, 38(4), 915-944.
- Viaoux, C. (2008). Marginal utility of income and value of time in urban transport. *Economics Bulletin*, 4(3), 1-8.
- Walls, M., & Hanson, J. (1999). Distributional aspects of an environmental tax shift: The case of motor vehicle emission taxes. *National Tax Journal*, 52(1), 53-65.
- Wernerfelt, B. (1988). Umbrella branding as a signal of new product quality: An example of signalling by posting a bond. *RAND Journal of Economics*, 19(3), 458-466.
- Wenzel, T. (2003). Use of remote sensing measurements to evaluate vehicle emission monitoring programs: Results from Phoenix, Arizona. *Environmental Science and Technology*, 6, 153-166.
- Wenzel, T., Singer, B. C., & Slott, R. S. (2000). Some issues in the statistical analysis of vehicle emissions. *Journal of Transportation and Statistics*, 3(2), 1-14.
- West, S. E. (2004). Distributional effects of alternative vehicle pollution control policies. *Journal of Public Economics*, 88, 735-757.

- West, S. E. (2005). Equity implications of vehicle emissions taxes. *Journal of Transport Economics and Policy*, 39(1), 1-24.
- West, S. E., & Williams III, R. C. (2005). The cost of reducing gasoline consumption. *American Economic Review Papers and Proceedings*, 95(2), 294-299.
- Zia, A. (2004). *Cooperative and non-cooperative decision behaviors in response to the inspection and maintenance program in the Atlanta air shed, 1997-2001*. Unpublished Ph. D. Dissertation, Georgia Institute of Technology, Atlanta.
- Zhang, Y., Bishop, G. A., & Stedman, D. H. (1994). Automobile emissions are statistically gamma distributed. *Environmental Science and Technology*, 28, 1370-1374.

VITA

ANUPIT SUPNITHADNAPORN

Anupit Supnithadnaporn is a native of Thai. She attended public schools in Bangkok, received a B.Sc. in Environmental Science from Thammasat University and a M.M.P. in Marine Policy from University of Delaware. She has worked as a Plan and Policy Analyst in the Division of Technology and Environmental Planning at the Office of the National Economic and Social Development Board, Office of the Prime Minister for seven years prior to receiving the Royal Thai Government Scholarship to pursue her doctoral study at Georgia Tech in 2004.

Anupit majors in Science and Technology Policy with the minor of Environmental Policy focusing on quantitative analysis. Her research interest also includes several topics such as program evaluation, equity implications of technological and environmental policy, and impacts of transportation policy.