ABSTRACT

GIGUERE, CHRISTOPHER SCOTT. Costly Inspections and Limited Abatement: The Efficiency of Automobile Inspection and Maintenance (I/M) Programs. (Under the direction of Dr. Roger von Haefen.)

This dissertation investigates the efficiency of automobile inspection and maintenance (I/M) programs. Currently, 31 states and the District of Columbia use I/M to identity and repair (or scrap) noncompliant automobiles that produce high levels of emissions. Such programs are used in the United States to attain or maintain compliance with National Ambient Air Quality Standards (NAAQS). Recently adopted and proposed changes to the North Carolina (NC) program motivate questions about the efficiency of I/M that have not been answered by previous literature. In chapter 1 I explain the motivation for my research and discuss I/M in both the United States (U.S.) and North Carolina. In addition, I describe recent legislation that has changed, or may change, the characteristics of the program in North Carolina.

In chapter 2 I develop a comprehensive framework to evaluate the efficiency of I/M. This framework requires predictions from seven empirical models that I estimate using an extensive dataset from the North Carolina I/M program. My data include all inspections between 1999 and 2013 as well as automobile attributes provided by Edmunds.com, Inc. and publicly available economic indicators. I then use the seven predictions to estimate costs and benefits from both I/M induced repairs and scrappage. Finally, in chapter 3 and chapter 4 I use the results produced by this framework to evaluate the efficiency of two changes to North Carolina's program.

In chapter 3 I focus on evaluating the efficiency of a recent change to the North Carolina I/M program. In April 2015 the state extended inspection exemptions to automobiles from the most recent three model years with less than 70 thousand miles. There are two main results from this chapter. First, the North Carolina I/M program, as it existed between 1999 and 2013 did not pass a benefit-cost test. Second, because the recently exempt automobiles are unlikely to fail an inspection, the recent change improves I/M efficiency. The improvement, however, is not enough to change the

sign of total net benefits from negative to positive. Further exemptions of low mileage automobiles have the potential to generate positive net benefits.

In July 2015 the North Carolina House of Representatives voted to eliminate I/M from 29 of the 48 counties currently subject to annual emissions inspections. In chapter 4 I estimate the efficiency of I/M under this regime and find that it will be a potential Pareto improvement. Because the statewide program imposes more costs than benefits on society reducing the scope of the program causes the negative net benefits to increase towards zero. However, differences in driving behavior and automobile choices between counties that will keep or lose I/M yield an unexpected result. The counties that would lose I/M if the legislation becomes law are more rural, have more intensively driven automobiles, and have higher rates of noncompliance than those selected to keep I/M. Thus if I/M were instead kept in these 29 counties and eliminated in the other 19 the net benefits of I/M would increase even more.

In chapter 5 I summarize the results and provide suggestions to policy makers. In addition, I discuss potential limitations of the data and framework, as well as a path forward for future work.

Costly Inspections and Limited Abatement: The Efficiency of Automobile Inspection and Maintenance (I/M) Programs

by
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DEDICATION

To my parents.

BIOGRAPHY

Chris is a native of Fairfax, Virginia. He earned a bachelor of business administration (BBA) with majors in economics and finance from James Madison University in Harrisonburg, Virginia. After graduation Chris worked for six years in capital project management consulting for major process industries. Prior to enrolling in the Ph.D. Economics graduate program at North Carolina State University he took mathematics courses at George Mason University in Fairfax, Virginia. After six years living in Raleigh, North Carolina, Chris and his pets Turbo Dog and Battle Cat moved to Blowing Rock, North Carolina. He currently teaches economics at Appalachian State University in Boone, North Carolina.

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NO_2 nitrogen dioxide. 2

NO_X nitrogen oxides. 5, 106, 138, 139, 145, 169

O_3 ozone. 2, 4

R^2 R squared. 97, 143, 155, 163

SO_2 sulfur dioxide. 2

A/C air conditioning. 25

adj. adjusted. 143, 163

AFT accelerated failure time. x, 49–51, 58, 66, 67, 86, 87, 98, 99, 102

API application program interface. iv, 30, 31, 110, 153

APM instantaneous emissions abatement per mile (grams). 91, 97

ASM accelerated simulation mode. 169

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auto automobile. 78, 80, 165

Avg. average. 78, 80, 139

BCA benefit cost analysis. 105

CAC command and control. 4–6, 145

CAFE corporate average fuel economy. 13, 25

CES Consumer Expenditure Survey. 25

CO carbon monoxide. 2, 31, 35, 41, 42, 53–55, 57, 78, 79, 81, 82, 92, 96, 106, 132, 138, 139, 145, 169

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DAQ Division of Air Quality. iv, 110, 153, 154

DENR Department of Environment and Natural Resources. 10

dep. dependent. 91, 94, 97, 99, 101

DEQ Department of Environmental Quality. 10

dev. deviation. 59, 81, 86–101, 141

DMV Division of Motor Vehicles. iv, 29, 32, 33, 37, 41, 47, 110, 111, 153, 154, 170, 171

DOC Department of Commerce. 156

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EIA Energy Information Administration. 31

EPA Environmental Protection Agency. 1, 6, 10, 26, 37, 59, 103, 105, 145, 146, 150, 151

EPM emissions per mile. 31, 55, 81, 91, 97

eqp. equipment. 78, 80

Exp. Exponential. 86

exp. exponential. 50, 99

FE fixed effects. 93, 100

FHA Federal Highway Administration. 2, 10

FIPS federal information processing standard code. 165

FRED Federal Reserve Economic Data. 31

FTP federal test procedure. ix, 137

Gam. Gamma. 86

GLM generalized linear model. 53, 55, 56, 90, 93, 95, 96, 102

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GPM grams per mile. 78, 79, 137

GPS geographic positioning system. 5, 6

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HR hazard ratio(s). 51

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Logn. Lognormal. 86

LOO leave-one-out. 48, 49

MAC marginal abatement cost. 13, 108

max. maximum. 81, 86, 88, 92, 93, 95, 96, 98, 100

MB marginal benefit. 120, 121

MC marginal cost. 120, 121

MED marginal external damages. 5, 11, 14, 36, 83, 107, 148, 155

min. minimum. 81, 86, 88, 92, 93, 95, 96, 98, 100

MPG miles per gallon. 42, 43, 78, 80, 81, 87, 89, 94, 99, 131

MSA metropolitan statistical area. 7

MY model year. 26

N/A not applicable. 23, 24

NAAQS National Ambient Air Quality Standards. i, 2, 27, 103, 146

NB negative binomial. 55, 56, 93–96, 100, 101

NC North Carolina. i, ii, iv, 2, 3, 7–11, 14, 15, 28–35, 37, 40–45, 47, 50, 52, 56, 57, 59, 78, 80, 103–105, 109–114, 118–121, 147–149, 151–157, 166–168, 170, 171, 179

NCGA North Carolina General Assembly. 2, 3, 179

NHTS National Highway Transportation Survey. 25

NHTSA National Highway Transportation Safety Administration. 1

NMOG non-methane organic gasses. 145

NRC National Research Council. 104

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PA population averaged. 93, 100, 157, 164

Pb lead. 2

PCI per capita income. 42, 46, 48

PEMS portable emissions measurement systems. 5, 170, 171

PH proportional hazard. x, 49–51, 58, 66, 75, 86, 87, 98, 99, 102

PM particulate matter. 2, 106, 145, 169

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RE random effects. 93, 100, 157, 164

RMSE root mean squared error. 49, 52, 53, 55, 56, 58, 60, 97, 143

RMSEs root mean squared errors. 49, 52, 53, 55, 58–60

S.T. selective targeting. 114, 116, 141

SCP Smog Check Program. 25, 105, 107

SIP State Implementation Plan. 6, 10, 146

st. standard. 59, 81, 86–101, 141

st. dev. standard deviation. 50, 52, 53, 55, 56, 58, 59, 79, 118, 153, 162

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USC United States Code. 1

USD United States dollar(s). 118, 119, 139

var. variable. 91, 94, 97, 99, 101

VIN vehicle identification number. 30, 35, 80, 82

VMT vehicle-miles traveled. 1, 5, 6, 10–12, 25, 29, 31–35, 39–46, 48, 50, 51, 53–56, 60, 78, 79, 81, 82, 87, 89, 94, 95, 99, 106, 111, 115–119, 140–144, 147, 148, 150, 156, 162, 166, 170

VOCs volatile organic compounds. 36

vs. versus. 23

w/ with. 78, 80

Wei. Weibull. 50, 86, 99

XT panel data. 93, 100, 157, 164

ZTNB zero-truncated negative binomial. 55, 56, 93–95, 100

ZTP zero-truncated Poisson. 55, 56, 93–95, 100, 101

CHAPTER 1

INTRODUCTION

1.1 Motivation

The 246 million automobiles in the United States (U.S.) annually produce a total of more than 2.9 trillion vehicle-miles traveled (VMT) (FHA, 2011). With each mile driven, automobiles produce pollution emissions including nitrogen oxides, non-methane organic gases, carbon monoxide, particulate matter, and formaldehyde (Delphi, 2015). The U.S. Environmental Protection Agency (EPA) estimates that the average automobile produces more than 10 thousand pounds of emissions per year (EPA, 2008a). Collectively, the motor vehicle fleet, through the burning of fossil fuels, produces nearly 60 percent of total carbon monoxide air emissions in the United States (EPA, 2012a).[1] Motor vehicles are also a major contributor of carbon dioxide and nitrogen oxides, and also

[1] Differences in the definitions of the terms automobile and motor vehicle between various government agencies, researchers, and the general public motivate a brief clarification. For example, the standard federal definition of motor vehicles includes heavy-duty equipment like bulldozers and backhoes (see United States Code (USC) (2002)). The definition of the U.S. National Highway Transportation Safety Administration (NHTSA), however, restricts motor vehicles to those that have been "manufactured primarily for use on the public streets, roads, and highways" (see United States Code

produce ozone, particulate matter, and ammonia, and to a lesser extent, sulfur dioxide and nitrous oxide air emissions in the United States (EPA, 2012a). [2] It is specifically automobiles, however, that produce almost 65 percent of all transportation emissions (EPA, 2012a). All of these emissions have been shown to have significant negative health, economic and environmental effects.

In order to minimize adverse effects of emissions, the Clean Air Act of 1963 and its amendments passed in 1970, 1977, and 1990 established a number of regulations designed to comply with National Ambient Air Quality Standards (NAAQS) for six criteria pollutants.[3] From a policy standpoint the most important distinction among these pollutants is their source category. Environmental regulations differ in how they treat sources of stationary (point source) versus mobile (non-point source) emissions (Fowlie et al., 2012). An often overlooked regulation to mobile source emissions, and the focus of this dissertation, is automobile emissions inspection and maintenance (I/M) programs. These programs periodically measure automobile emissions to identify those that produce more than the limit set by regulators. Noncompliant automobiles must then be repaired to compliance with emissions standards prior to re-registration. In principle, this emissions abatement will improve ambient air quality.

Two recent changes to the North Carolina (NC) program, highlighted in figure 1.1, generate questions about I/M efficiency. First, in 2015 the program was amended to exempt the newest three model year automobiles with less than 70 thousand miles (North Carolina General Assembly (NCGA), 2012). This policy change is an example of *selective automobile targeting*. Such a change

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(USC) (1994). In addition, the definitions of the U.S. Federal Highway Administration (FHA) Planning Glossary suggests that taxicabs if driven for hire, are not motor vehicles (FHA, 2016a, 2016b). Thus I formally make a distinction between my use of these terms. I do this to be specific about the sources of mobile source emissions and the particular source examined in this dissertation. I use the term motor vehicle to describe a broad spectrum of equipment powered the burning of fossil fuels in internal combustion engines. Examples include heavy-duty equipment, riding lawn mowers, snowmobiles, mopeds and scooters, personal watercraft such as jet skis, boats with outboard motors, helicopters, airplanes, and jets. Also included in my definition are automobiles such as light- and medium-duty cars, trucks, vans, sport-utility vehicles, and motorcycles.

[2] Ozone is formed when nitric oxide, nitrous acid, nitric acid, and nitrogen dioxide combine with volatile organic compounds in heat and sunlight. It is a major component of urban smog. See EPA (2016b).

[3] The six are carbon monoxide (CO), lead (Pb), nitrogen dioxide (NO_2), ozone (O_3), particulate matter (PM), and sulfur dioxide (SO_2). See EPA (2016c).

can in principle improve the efficiency of the I/M program by decreasing the cost of compliance for vehicles unlikely to fail emissions inspections. Second, in July 2015 the North Carolina House of Representatives passed legislation that, if signed into law, would exempt 29 of the 48 counties currently subject to I/M (see figure 1.2) (NCGA, 2015). I refer to this policy as *selective spatial targeting*. Such changes will undoubtedly affect the benefits and costs of automobile emissions abatement in North Carolina.

These changes to North Carolina's I/M program motivate three primary questions that I attempt to answer in this dissertation. First, what are the net benefits of I/M? Second, what are the gains in efficiency from selectively targeting specific types of automobiles from emissions inspections? Third, is there a more efficient spatial allocation of I/M in North Carolina relative to the status quo?

1.2 Air emissions and policy responses

Throughout human history there have been economic activities that have created externalities. For example, livestock may consume excessive amounts of grass on the commons and emit methane, and wood fires release hydrocarbons, carbon monoxide, and particulate matter into the air. Such activities may impose external (social) costs on society if other individuals derive disutility from them. Many of the externalities associated with air emissions, however, were not realized or well understood until the twentieth century. As economic agents adopted coal and petroleum energy to fuel production during the Industrial Revolution there were large increases in air emissions (Pachauri & Reisinger, 2007). In turn people began to observe the effects of air emissions on human health and the environment. A classic example of environmental effects is the industrial melanism observed among peppered moths in England during the Industrial Revolution (Kettlewell, 1958).[4]

[4] Industrial melanism is a zoological term that refers to situations where the better camouflaged darker colored varieties of animals are more prevalent than lighter varieties in industrialized areas. Prior to the Industrial Revolution the black peppered moth was very rare in England. As black soot from factories began to cover the bark of adjacent trees, resting peppered moths became more easily identifiable to predatory birds. Soon the black peppered moth became more commonly encountered and its lighter counterparts became more rare to observe.

Since the Industrial Revolution the scientific community has provided substantial and compelling evidence of several adverse effects of air emissions. Foremost among these are increases in morbidity and mortality.[5] In addition, the growth rate of many agricultural crops are slowed and their quality and economic values are reduced by high concentrations of air emissions (excluding CO_2).[6] Other vegetation, animal life, and the amenity value of environmental services are also affected by air emissions. For example, Karnosky et al. (2007) discuss the effects of ozone (O_3) on U.S. forests and their ecosystems. Buildings, monuments, statues, and other structures may be deteriorated by some air emissions as well (EPA, 2007). There is also evidence of outdoor avoidance behavior on days when ambient air quality is low (Moretti & Neidell, 2011; Neidell, 2009). Lastly, increased air emissions have been shown to decrease student and worker productivity.[7]

Several environmental catastrophes such as those in Engis, Belgium in 1930, St. Louis, Missouri in 1939, Donora, Pennsylvania in 1948 and London, England in 1952 initiated research into the adverse effects of air emissions (EPA, 2007; Roholm, 1937; Trucker, 1941). In addition, the United States passed its first federal law on air pollution, the Air Pollution Control Act of 1955, to fund research and provide technical assistance to regulators. It was not until the Clean Air Act was passed in 1963 that the federal government began to attempt to control air pollution (EPA, 2016a). To comply with the Clean Air Act and its amendments many firms had to change the output they produced or alter the way it was produced. For example, many factories were required to do maintenance and repairs to prevent harmful emissions from finding their way into the ambient air and motor vehicle fuels were forced to become cleaner (McCarthy et al., 2011).

Policies implemented to improve air quality, and thus comply with the Clean Air Act and its amendments, can be classified as either command and control (CAC) or market-based (Fowlie

[5]See Alberini et al. (1997), Neidell (2004), and Schwartz (1995) for information about morbidity effects and Bell et al. (2004), Chay & Greenstone (2003), Currie & Neidell (2005), Currie et al. (2009), and Gryparis et al. (2004) for mortality effects.

[6]See Agrawal et al. (2003), Ashmore et al. (1988), Bleasdale (1952), Hassan et al. (1995), Krupa & Kickert (1989), Schenone & Lorenzini (1992), and Wahid et al. (1995).

[7]See Chang et al. (2014), Currie et al. (2009), Graff Zivin (2012), Graff Zivin & Neidell (2009), Hanna & Oliva (2013), Moretti & Neidell (2011), and Neidell (2009).

et al., 2012; Muller & Mendelsohn, 2009). Muller & Mendelsohn (2009) explain that the first policy responses to air pollution were largely CAC that ignored heterogeneity in marginal abatement costs across firms and marginal external damages (MED) across space. The nature of stationary emissions sources, however, made the eventual implementation and regulation of market-based policies possible. Examples of market-based stationary source policy responses include cap-and-trade programs such as the NO_X Budget Trading Program and the Acid Rain Program (Fowlie et al., 2012; Muller & Mendelsohn, 2009).

Policy makers have not yet adopted market-based policy responses to the problem of mobile source emissions (West, 2005).[8] This is partly due to technological challenges. For example, current standard automobile technology like second-generation on-board diagnostic control systems (OBD-II) monitor aspects of the powertrain that may affect emission levels but do not track emissions in real-time. Other devices called portable emissions measurement systems (PEMS) have the ability to track real-time automobile emissions but are not standard technology and are not a common accessory among automobile owners.[9] Alternatively, the technology to measure emissions from automobiles passing along a road is available and has been deployed at small scales (Beaton et al., 1995; Kahn, 1996b).[10] Such remote-sensing programs, however, have received little support from regulators. Hubbard (1997) explains that one reason for the lack of support is because the remote-sensing devices only observe automobiles for an instant. This limitation is problematic because automobile emissions vary with road conditions, driver behaviors, and engine performance. Thus, remote-sensing cannot reliably and consistently identify gross-polluter automobiles.

Other privacy, political, and administrative obstacles would still exist even if it were feasible to measure real-time emissions. For example, Minnesota and Florida have attempted to implement or pilot VMT tax programs that utilized a geographic positioning system (GPS) to monitor the roads and

[8] There is, however, considerable research on second-best policies that could mimic or approximate the efficiency of first-best Pigouvian taxes (Fullerton & West, 2002; Innes, 1996; West, 2004)

[9] Liu & Frey (2015) include photographs of the PEMS used to collect tailpipe emissions on multiple routes from more than 100 gasoline powered automobiles.

[10] See Bishop et al. (1989) for a discussion of remote-sensing.

distances where people are driving (Doyle, 2013; Kirk & Mallett, 2013).[11] Such programs, despite their limited geographic scope, have been met with public opposition due to privacy issues and have so far been politically unpopular (Kirk & Mallett, 2013).[12] Furthermore, even if the public were open to such monitoring devices there would still be an administrative difficulty of coordinating VMT or emissions taxes across multiple jurisdictions. Fowlie et al. (2012) point out that some mobile emissions sources, such as aviation and nautical equipment, are also subject to international regulations. Such complex regulatory environments may deter policymakers from attempting to implement market-based policy responses (Fowlie et al., 2012). Finally, market-based environmental policies may be politically unpopular because they have been shown to be regressive, or disproportionately affect the welfare of low-income households.[13] Because of technological, political, and administrative obstacles CAC regulations continue to dominate the mobile source policy responses.

1.3 I/M in the United States

To comply with the Clean Air Act states must periodically submit a State Implementation Plan (SIP) to the U.S. EPA. In the SIP each state validates that it has administrative components in place to meet new or revised air quality standards, and also describes the combination of programs it will implement to attain or maintain compliance with air quality standards. While the Clean Air Act requires areas that violate air quality standards for ozone and carbon monoxide to include I/M in their SIP, other states choose to use them in a portfolio of air quality improvement programs. Other emissions abatement instruments that could be included in a SIP include permitting, clean fuel, advanced control technology, transportation or traffic control, emissions fee programs, and accelerated retirement or cash-for-clunkers programs.

The goal of an emissions I/M program is to identify and repair (or scrap) noncompliant auto-

[11] See FHA (2016c) and Economist (2013).

[12] Other states like California and Oregon are currently piloting VMT programs that do not utilize GPS and more than 10 other states have considered implementing VMT taxes (Vock, 2013).

[13] See McMullen et al. (2010), Poterba (1991), Walls & Hanson (1999), West (2004, 2005), and West & Williams III (2004).

mobiles. Each of the 32 programs in the United States, however, vary in key design features. These differences are presented in table 1.1. For instance, inspections may be annual or biennial and apply statewide or only in select areas. Figure 1.3 illustrates the U.S. states, counties, and metropolitan statistical areas (MSAs) that use periodic emissions I/M programs.[14] The map makes clear that most states are spatially differentiated in their use of I/M.[15] Areas like California and New England, highlighted in figure 1.3, are also areas that have large populations and a large number of registered automobiles (see figures 1.4a and 1.4b). Table 1.1 reports only nine of the 32 U.S. programs require registered automobiles in all cities, counties, or zip codes to report for periodic testing. In addition, table 1.1 also shows that 15 states use annual inspections and 20 use biennial inspections (some use spatially differentiated inspection frequencies).[16]

States also differ in the types of automobiles, such as diesel or new or old, that are exempt from the periodic inspections. Often motor vehicles such as heavy duty industrial equipment, mopeds and motorcycles, lawn mowers and snow blowers, or certain types of specialty light duty automobiles such as classics (or vintage), farm use vehicles, or hybrids are made exempt by regulators. Eleven of the U.S. I/M programs, for example, exempt diesel automobiles from periodic testing.[17, 18] In addition, the median new model year exemption, as shown in table 1.1, is three years, although the exemption ranges from zero to six.

There are also differences in the type of test used, namely tailpipe emissions readings or OBD software. As table 1.1 shows OBD tests are most commonly used in the United States. One reason for the preference of I/M tests by government authorities may be that OBD testing equipment is

[14] In addition, many foreign countries, such as Austria, Brazil, Canada, Finland, Germany, Hungary, Ireland, Israel, Mexico, the Netherlands, Norway, Poland, Russia, Singapore, Slovakia, and the United Kingdom, use periodic automobile emissions inspections.

[15] Gruenspecht (1982) defines a differentiated policy to be one where a regulator applies different criteria across subgroups of a treated sector.

[16] California also requires automobiles to report for inspections prior to secondary or used market sales.

[17] Specifically, these eleven programs are California, Georgia, Illinois, Indiana, Louisiana, Maine, Maryland, Massachusetts, North Carolina, Pennsylvania, and Utah.

[18] This is particularly concerning in light of the recent Volkswagen AG emissions scandal. Prior to the revelation of their defeat devices Volkswagen has dominated the small U.S. diesel automobile market (Davies, 2015).

considerably cheaper than equipment needed for most tailpipe emissions tests. Such an argument seems plausible considering only eleven states use a centralized state run or outsourced inspection station (or network of stations) while the majority use a decentralized network of automobile dealers, body shops, and mechanics. Higher capital costs could incentivize members of these decentralized networks to opt out of providing inspection services and could thus create administrative challenges for the regulator.

In addition, there is research that indicates abatement is larger for OBD-induced repairs (Gardetto et al., 2005). This, however, is inconsistent with the data used in this dissertation. Furthermore, the effectiveness of OBD as a means of identifying non-compliant automobiles has been contested since a lack of overlap between the two types of tests was identified (Ayers & Walter, 2005; Eisinger & Wathern, 2008). Only three states in the country require that emissions inspections include both a tailpipe exhaust test and an OBD test.[19]

Finally, the explicit costs of inspection and explicit repair cost limits vary considerably across the country. Such explicit costs of inspection include those paid by the automobile owner to the service station for the inspection. They may also include fees distributed by the inspection station to the state regulator, as is the case in North Carolina, for example. Many states have also set a ceiling on explicit repair costs that must be paid by the owner of a noncompliant automobile. Owners who can demonstrate to the state regulator that they have spent at least this amount towards emissions related repairs are often granted waivers. Waivers allow the owner to drive the noncompliant automobile until the next periodic inspection.[20] The average explicit cost of an inspection in the United States is $16.23 and the average repair cost limit is $478.52 (both in 2014 U.S. dollars). In addition automobile owners incur implicit opportunity costs of time when complying with emissions inspection regulations.

[19]These states are Colorado, Maryland, and New Mexico.

[20]Table 1.1 shows that the mean repair cost limit in the United States is $479 and the range is $150 to $855. Some states like Washington and Pennsylvania, however, have set their repair costs limits to a mere $150. These low repair cost limits could potentially significantly decrease emissions abatement from I/M through waived instantaneous abatement.

1.4 I/M in North Carolina

Because its program is generally representative of the rest of U.S. programs, North Carolina provides an excellent case study for emissions I/M programs. Like most states (see table 1.1), North Carolina does not use the program statewide, exempts diesel engine automobiles from periodic inspections, uses a decentralized network of inspection stations, uses only OBD control system tests, and currently exempts the three most recent model year automobiles (with less than 70 thousand miles) from annual emissions inspections. North Carolina's program, however, deviates from other programs by using slightly more frequent inspections, and setting a repair cost limit at $200, roughly $275 below the national mean.

North Carolina has a long history with automobile emissions I/M programs. These programs were first introduced in 1982 in Mecklenburg County. As shown in figures 1.5 and 1.6, by 1999 there were nine counties in North Carolina subject to the annual tailpipe emissions inspections due to federal air quality nonattainment. In July of that year Senate Bill 953 was passed, which required emissions inspections in counties with more than 40 thousand residents and daily vehicle-miles traveled of more than 900 thousand (NCPED, 2008). Between 2003 and 2006 an additional 39 counties were added to the emissions I/M program, as shown in figure 1.6. In addition, second-generation on-board diagnostic control systems (OBD-II) control system tests were phased in at the same time as these counties. The change in the test type effectively made all pre-1996 model year automobiles exempt from periodic emissions inspections. By 2006 the state had completely abandoned tailpipe emissions inspections for OBD tests. Consequently, actual tailpipe emissions from vehicles are no longer collected during periodic inspections. Instead the OBD test provides a binary pass-fail inspection result.[21]

More recent legislation in North Carolina motivate the questions I attempt to answer in this dis-

[21] Hence, even if diesel automobiles were required to have been inspected the Volkswagen models would have evaded detection.

sertation.[22] First, in 2012 House Bill 585, which exempted the three newest model year automobiles with less than 70 thousand cumulative vehicle-miles traveled from periodic emissions inspections, was signed into law.[23] The program was not implemented in North Carolina until April 1, 2015, however, because the updated SIP was not approved by the U.S. EPA until late 2014 (EPA, 2015b). North Carolina waited to implement their legislation because the Clean Air Act established both mandatory and discretionary sanctions the U.S. EPA may place on states that fail to implement part of its SIP (McCarthy et al., 2011; Schneeberg, 2014; Spink & Bigioni, 2010). An example of a mandatory sanction is the withholding of U.S. Federal Highway Administration (FHA) funding of transportation projects that could be worth millions of dollars. Second, in early April 2015 the North Carolina Department of Environment and Natural Resources (DENR) revealed its intent to eliminate emissions inspections from 27 to 31 counties around the state beginning in 2016 (DENR, 2015).[24] Several months later legislation was passed by the state House of Representatives, which if signed into law, would exempt all but 19 counties from annual emissions inspections (see figure 1.2).

1.5 Literature review

In this dissertation I build on four broad areas of past research. The three primary questions I answer, however, are most closely related to two areas. The first area, summarized in table 1.2, includes those papers that have conducted economic evaluations of I/M programs. Second, this dissertation also builds on those, summarized in table 1.3, that have suggested selectively targeting certain types of vehicles in order to increase the efficiency or cost-effectiveness of I/M programs. I contribute to the literature by developing a comprehensive framework to estimate the efficiency of I/M. In addition, I

[22] Other examples of recent changes to I/M programs include Connecticut (2008), Ohio (2008), Georgia (2009), Indiana (2011), Alaska (2012), Arizona (2013), Massachusetts and New Hampshire (2013), Wisconsin (2013), and Missouri (2015). The U.S. EPA's final approvals and promulgations of changes to these states'State Implementation Plans (SIPs) can be found on the *Federal Register*.

[23] I use the terms cumulative vehicle-miles traveled (VMT) and odometer reading interchangeably in this dissertation.

[24] The North Carolina Department of Environment and Natural Resources (DENR) is now the Department of Environmental Quality (DEQ).

use an extensive dataset from North Carolina to estimate the effect of *selective automobile targeting* on I/M efficiency in chapter 3 and *selective spatial targeting* in chapter 4.

The estimation framework I develop in chapter 2 of this dissertation also builds on the third and fourth areas of past research indirectly. The third area, summarized in table 1.4, includes those papers that have analyzed the choices owners make about their automobiles. [25] Choices such as vehicle repair, scrappage, and vehicle-miles traveled (VMT) are essential components of the estimation framework. The fourth area, summarized in table 1.5, are those papers that have analyzed automobile characteristics and owner behaviors that increase the quantity of automobile emissions. This fourth area of research is what led researchers to begin to consider selective targeting for I/M programs.

Table 1.2 categorizes whether the previous economic evaluations of I/M focus on questions of effectiveness, cost-effectiveness, or efficiency. The papers that analyze the effectiveness of I/M examine the extent to which the programs produce abatement from repairs or scrappage, or improve air quality. Other papers attempt to rank I/M relative to other programs by estimating the abatement per dollar or cost-effectiveness. The difference between cost-effectiveness and efficiency lies with the units used to measure the benefits of the program. Efficiency requires that the mass of abated emissions be multiplied by the social value or marginal external damages (MED) of emissions so that net benefits can be calculated. Thus while effectiveness and efficiency are mutually exclusive categorizations, cost-effectiveness and efficiency are not. Cost-effectiveness is a necessary, but not a sufficient condition for efficiency.

Table 1.2 reveals a striking piece of information. Nearly all the previous economic evaluations have sought to answer questions about the effectiveness, rather than efficiency, of I/M. Given the distinctions between the terms made above it is surprising that the efficiency of I/M has not been examined. Several papers do, however, also briefly discuss factors that may affect efficiency. For

[25] This dissertation defines an automobile owner as the individual, government agency, firm, or their agent who makes decisions about automobile usage and repairs. In addition it does not necessarily imply legal ownership of the title. The owner may incur lease or loan payments on their automobile.

example, Ando et al. (2000), Glazer et al. (1995), and Kahn (1996c) all recommend selective targeting as a means of decreasing I/M compliance costs while leaving the social benefits of emissions abatement unchanged. Similarly, Moghadam & Livernois (2010) estimate the abatement cost function for I/M and examine how selectively targeting specific automobile age cohorts could improve cost-effectiveness.

A number of researchers have suggested that differentiating treatment based on automobile attributes, or selective targeting, can improve the efficiency of I/M programs (Bin, 2003; Glazer et al., 1995; Moghadam & Livernois, 2010; Washburn et al., 2001). In other words, an I/M regulator could exempt types of automobiles that are not expected to yield emissions abatement and lower compliance costs to automobile owners while leaving the benefits of the I/M program largely unchanged. For example, Bin (2003) used data from the biennial Portland, Oregon I/M program and concluded that targeting vehicles more than ten years old, with engines smaller than two thousand cubic centimeters, and more than 100 thousand cumulative VMT could improve the cost-effectiveness by decreasing the likelihood of finding compliant automobiles. Alternatively, Moghadam & Livernois (2010) advocate for periodically testing only middle-aged automobiles. They argue that young automobiles are unlikely to fail inspections and the benefit of testing older or "dirtier" automobiles is reduced because those automobiles are driven few miles a year. Unlike the other selective targeting literature, Moghadam & Livernois (2010) estimated an abatement cost function and quantified the savings from I/M. They concluded that selective targeting based on automobile age could lower annual abatement costs by 26 percent without affecting expected emissions abatement.

Regulating automobile emissions is challenging because both firms and individuals make choices that affect emissions (Fullerton & Gan, 2005; Harrington et al., 2000). While the firm may decide the attributes of new automobiles subject to government regulations, it is the owners of those automobiles who decide what to drive, how far to drive, and the level of periodic maintenance to perform. Such choices are key to estimating the net benefits of automobile emissions inspections.

In fact, the first two are explicitly included in the framework developed in chapter 2. In principle, environmental damages are increasing in the age of the automobile, usage intensity, and decreasing in good maintenance practices, all else constant.

Total emissions abatement from I/M per automobile is dependent not only on the magnitude of the instantaneous repair but also the number of miles driven while repairs persisted. Driving decisions have been shown to be functions of many observable economic indicators. For example, Knittel & Sandler (2013) found that the demand for fuel by owners of "dirtier" automobiles is more elastic than for owners of "cleaner" automobiles. Thus price and policy shocks, like the recent declines in gasoline prices, could increase the net benefits of I/M through an increase in driving particularly among owners of dirty automobiles.

Peterson & Schneider (2014) and Schneider (2012) report two findings that may also decrease the net benefits of I/M through the repair of non-compliant automobiles. Agency problems and adverse selection may both affect the types of repairs offered by mechanics and accepted by owners and thus may affect the social value of emissions abatement from I/M. For example, Mérel & Wimberger (2012) find that differences in the costs of repairs, or marginal abatement cost (MAC), across automobiles could also be exploited to increase both the efficiency of repair voucher programs and the effectiveness of I/M programs. Inspection induced repairs and abatement may also be affected by inspectors in decentralized programs who engage in fraud (Hubbard, 1998; Oliva, 2012; Pierce & Snyder, 2008).

Another important choice explicitly included in the framework is automobile scrappage. It has been shown to be affected by exogenous policies such as increased gasoline taxes or tightened corporate average fuel economy (CAFE) standards (Bento et al., 2009; Jacobsen & Benthem, 2015). Jacobsen & Benthem (2015) explain that tightened automobile emissions or fuel economy standards increase new and used automobile prices and therefore incentivize automobile owners to keep older or "dirtier" automobiles longer (decreasing the scrappage rate).[26] Other exogenous macroeconomic

[26]See Gruenspecht (1982) and Jacobsen & Benthem (2015).

conditions can also affect the scrappage rate (see chapter 2 for a full discussion). Changes in the scrappage rate may also affect the net benefits of I/M. All else constant, delayed scrappage would increase benefits of I/M induced abatement.

The fourth area of literature that this dissertation builds on are those papers, summarized in table 1.5, that analyze automobile attributes and owner behaviors, such as automobile usage and maintenance, that affect the quantity of automobile emissions. This literature is both relevant and important for two reasons. First, estimating the emissions from automobiles is an integral step in estimating the net benefits of an I/M program. Second, this area forms the foundation for the selective targeting literature. For example, automobile age, fuel economy, automobile size, and automobile manufacturer have all been shown to affect emissions (Anilovich, 1996; Beydoun & Guldmann, 2006; Harrington, 1997; Kahn, 1996a). Exempting automobiles correlated with compliant emissions levels can increase the efficiency of I/M.

In this dissertation I will extend the work of Harrington et al. (2000), Mérel et al. (2014), and Moghadam & Livernois (2010), and others and contribute to the literature in six ways. First, I aggregate abated emissions using their social values (MED) rather than weighting by mass or only considering a single emission in isolation. This allows me to calculate net benefits and thus analyze the efficiency of I/M, filling a notable gap in past literature. Second, I improve parsimonious models of abatement and inspection failure to include other explanatory variables in addition to automobile age such as economic indicators, automobile attributes, and historic inspection results. Third, I estimate the social value of emissions abatement from I/M induced repairs and scrappage. Fourth, I examine how changes to I/M program characteristics like selective automobile targeting or adjusting the inspection frequency affect benefits and costs. Fifth, I investigate whether selective spatial targeting can be used in North Carolina increase the net benefits of an I/M program. A comparison of the benefits and costs will help to identify potential changes that can be made to I/M programs to increase their efficiency.

I also improve on the past literature by exploiting an extensive dataset of all emissions inspections from North Carolina between 1999 and 2013. The analyses in many of the previously mentioned papers were based on samples for only one year or month of inspections. Thus in some cases the data do not cover the entire fleet of vehicles in the program's authority. For example, Harrington et al. (2000) have one year of data from a program with a biennial inspection frequency. The use of California data complicates matters further because the biennial program exempts automobiles for the newest six model years. Thus, while Mérel et al. (2014) have 10 years of California inspections they have on average only one inspection per automobile. I use data from a representative annual program that exempts automobiles for only the most recent model year, a time when the probability of failure is low, and have an average of three observations per automobile.

1.6 Outline

The next chapter, chapter 2, will develop a comprehensive framework for estimating the benefits and costs of motor vehicle emissions inspection and maintenance programs. Chapters 3 and 4 will then apply this framework to a particular aspect of selective targeting to analyze the policy implications. Specifically, chapter 3 will examine the effects of *selective automobile targeting* on I/M efficiency. Chapter 4 will then examine how North Carolina's proposed *selective spatial targeting* for I/M will affect its net benefits. Chapter 5 will review the results of the two case studies, discuss limitations of my analysis, and suggest how to improve the dataset for future research.

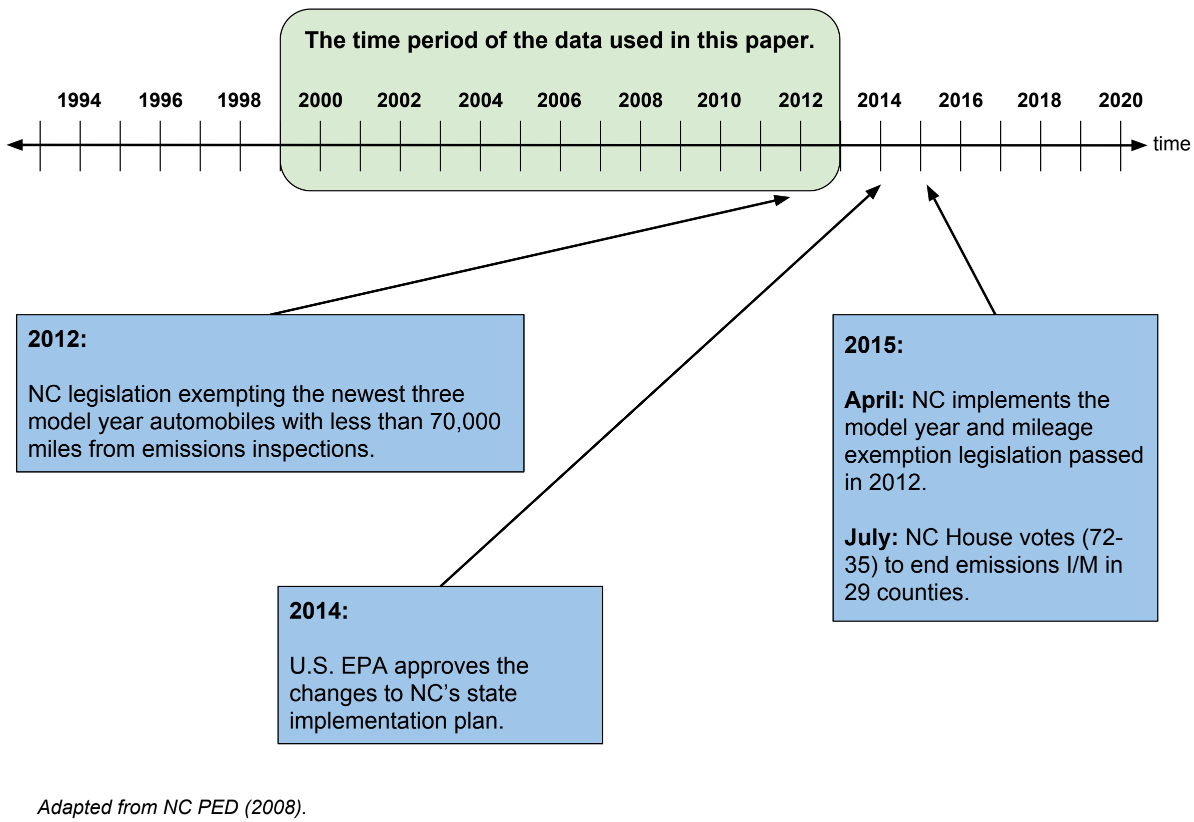


Figure 1.1 *Recent changes to North Carolina's I/M program*

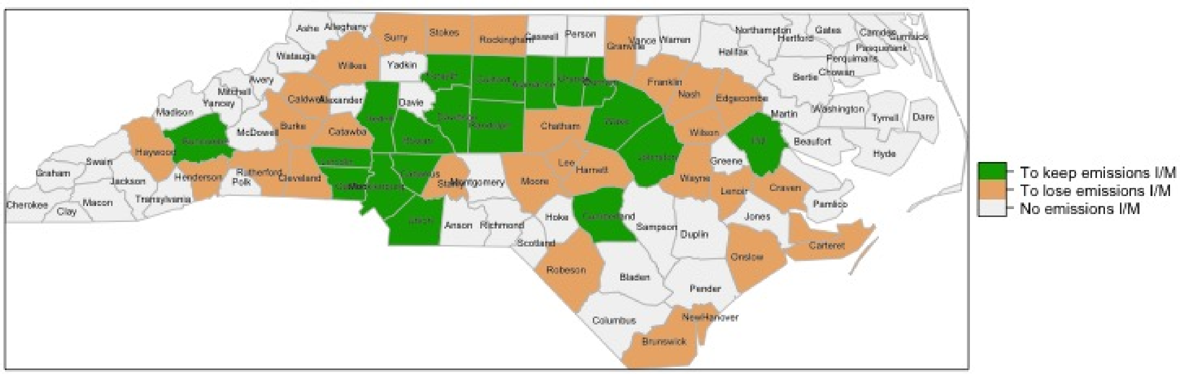
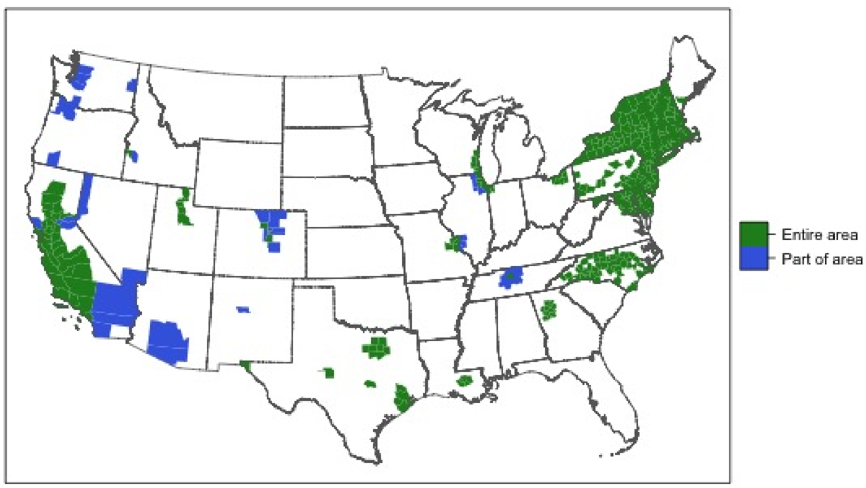
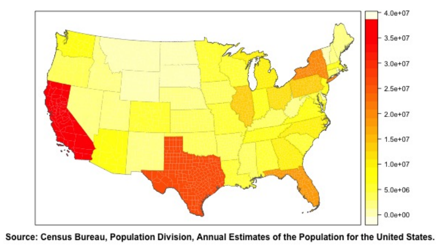


Figure 1.2 *The future of I/M in North Carolina?*

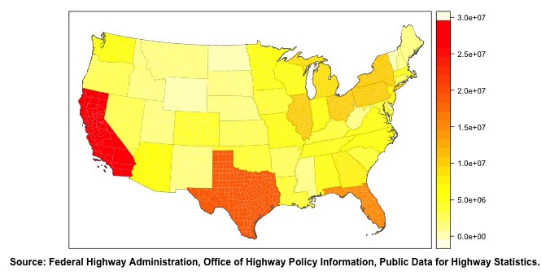


Source: State environmental agency websites.

Figure 1.3 *Current usage of automobile emissions I/M in the United States*

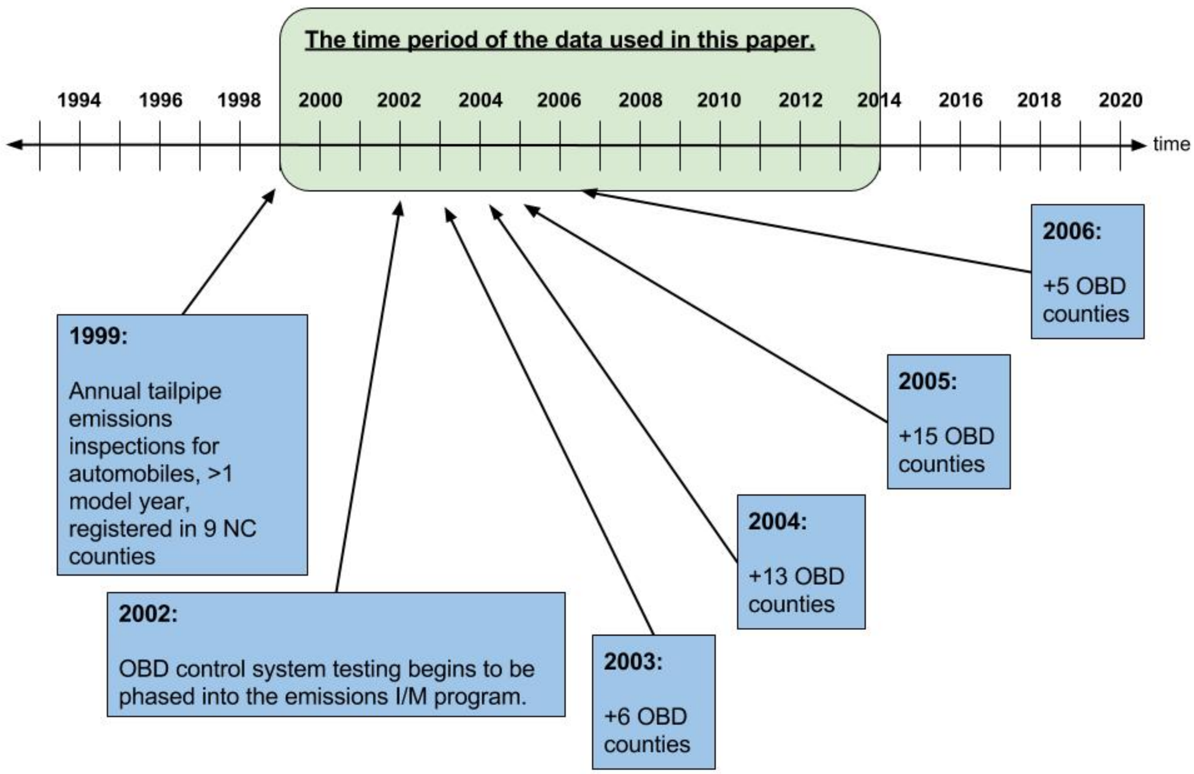


(a) *Population estimates*



(b) *Automobile registrations*

Figure 1.4 *State population estimates and automobile registrations by state for year 2011*



Notes: Adapted from NC PED (2008).

Figure 1.5 *The history of North Carolina's I/M program*

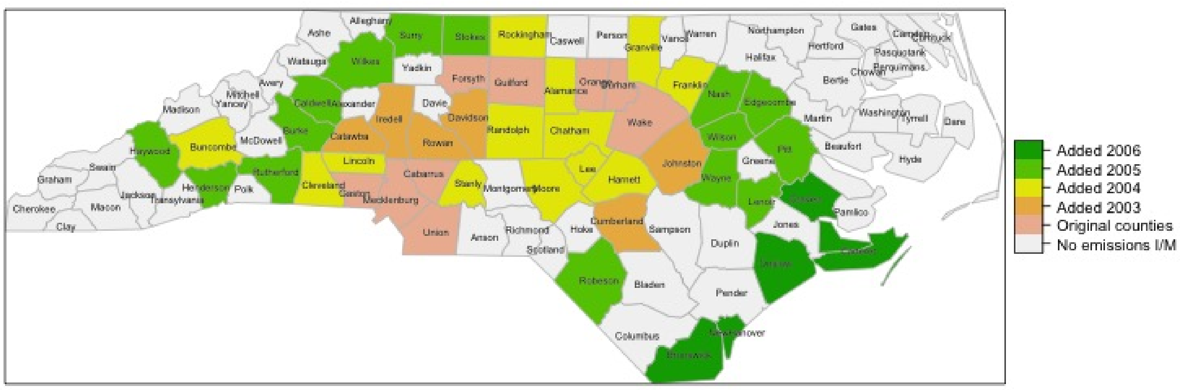


Figure 1.6 *Spatial differentiation of I/M in N.C. over time*

Table 1.1 *Summary statistics for the 32 I/M programs in the United States*

	# of programs	Mean	Median	Std. dev.	Min.	Max.
Annual inspections?	15 of 32	0.469	0	0.507	0	1
Biennial inspections?	20 of 32	0.625	1	0.492	0	1
Statewide emissions inspections?	9 of 32	0.281	0	0.457	0	1
All diesel automobiles are exempt from emissions inspections?	11 of 31	0.355	0	0.486	0	1
Centralized emissions inspection program?	11 of 32	0.344	0	0.483	0	1
OBD inspections?	31 of 31	1	1	0	1	1
Tailpipe emissions inspections?	23 of 28	0.821	1	0.390	0	1
Automobiles get OBD and tailpipe emissions inspections?	3 of 30	0.100	0	0.305	0	1
Number of years new automobiles are exempt?	-	2.774	3	1.765	0	6
Inspection fee	-	16.23	15	11.883	0	40.5
Repair cost limit	-	478.52	450	249.274	150	855

Observations are the number of I/M programs in the United States for which data is available; in total there are 32 U.S. I/M programs.

Table 1.2 *Analyses of I/M programs*

Paper	I/M program	Time period	Effectiveness	Cost-effectiveness	Efficiency
Glazer et al. (1995)	California, USA	N/A	✓		
Kahn (1996b)	California, USA	1992 - 1993	✓		
Kahn (1996c)	Illinois, USA	pre-1986 vs. post-1986	✓		
Hubbard (1997)	N/A	N/A	✓		
Ando et al. (2000)	Arizona, USA	1995 - early 1996	✓	✓	
Harrington et al. (2000)	Arizona, USA	Jan. 1995 - May 1996	✓	✓	
Moghadam & Livernois (2010)	Ontario, Canada	1999 - 2001		✓	
Mérel et al. (2014)	California, USA	July 2000 - Aug. 2010	✓	✓	
Sanders & Sandler (2015)	California, USA	1998 - 2012	✓		

The papers that analyze the *effectiveness* of I/M examine the extent to which the programs produce abatement or improve air quality. Other papers may attempt to rank I/M relative to other programs by estimating the abatement per dollar or *cost-effectiveness*. The difference between cost-effectiveness and *efficiency* lies with the units used to measure the benefits of the program. *Efficiency* requires that the mass of abated emissions be multiplied by the social value of emissions so that net benefits can be calculated. Thus effectiveness and efficiency are mutually exclusive categorizations, but cost-effectiveness and efficiency are not. Cost-effectiveness is a necessary, but not a sufficient condition for efficiency.

Table 1.3 *Selective targeting literature*

Paper	I/M Data		
	Time period	**Data source**	**Key findings**
Glazer et al. (1995)	N/A	N/A	• The California I/M programs actual effectiveness was half of expectations. • Differentiating treatment based on the automobile can improve I/M.
Washburn et al. (2001)	1994	Seattle, Washington, USA	• Automobile age, manufacturer, number of engine cylinders, odometer reading, and fuel type play a significant role in determining emissions I/M test results. • The blanket approach significantly increases costs over selective automobile targeting.
Bin (2003)	September 1997	Portland, Oregon, USA	• The effects of automobile age, engine size, and odometer reading on emission test failure are statistically significant. • Selective automobile targeting based on automobile age, engine size, and odometer reading can improve the cost-effectiveness of traditional I/M programs.
Moghadam & Livernois (2010)	1999 - 2001	Ontario, Canada	• The marginal abatement cost of the Ontario I/M program high enough such that very small reductions in the abatement cost target leads to substantial savings for automobile owners. • The optimal inspection age and frequency are much higher and lower, respectively, than is typically common for I/M programs.

Table 1.4 *Analyses of automobile owner choices*

Paper	Data	Choice	Relevant finding(s)
Bento et al. (2009)	2001 NHTS	Scrappage	• Increases in gasoline tax increases price per VMT and thus fuel inefficient vehicles become less desirable, increasing their scrappage rate.
Schneider (2012)	CT service states	Repair	• Large agency problems in market for automobile repairs; asymmetric information affects repair outcomes. • Mechanics are not more likely to provide efficient service for repeat customers.
Gillingham (2013)	California SCP 2005 - 2009	Repair	• Medium-run (two year) elasticity of VMT with respect to gasoline prices is −0.22.
Knittel & Sandler (2013)	California SCP 1996 - 2010	VMT	• Automobiles that produce more emissions respond more to fuel prices than *cleaner* vehicles. • Leads to a 90 percent increase in health co-benefits from an increase in gasoline taxes. • Differentiated taxes across automobile types can substantially improve market efficiency.
Peterson & Schneider (2014)	U.S. CES, 1991 - 2006	Repair, automobile choice	• Adverse selection effect increases repair rate in traded used automobiles relative to non-traded automobiles. • Negative relationship between engine, transmission, body, or A/C problems and turning an automobile over to the used automobile market. • Effect increases with age; turnover of eight year old automobiles is reduced by 7 percent. • Reduces new automobile sales by 2.3 percent.
Jacobsen & Benthem (2015)	U.S. automobile registrations	Scrappage	• Gruenspecht effect (scrap elasticity with respect to changes in used automobile values) is estimated for a tightening of CAFE. • Between 13 and 16 percent of expected fuel savings from tightened CAFE standards leak back through the used automobile market.

Table 1.5 *Analyses of automobile attributes, owner behavior, and emissions*

Paper	Time	Source	Key finding(s)
Khazzoom (1995)	MY 1978 - 1988	U.S. EPA lab	• Enhanced fuel efficiency standards have no effect on automobile emissions rates.
Anilovich (1996)	1990 - 1991	Israel	• Carbon monoxide and hydrocarbon emissions are a function increasing in automobile age.
Kahn (1996a)	1992 and 1993	Chicago and California	• Large differences in emissions across model years, manufacturers, and automobile sizes. • Aggregate automobile emissions fall when new emissions regulations are tightened.
Harrington (1997)	1991	California	• Hydrocarbon and carbon monoxide emissions are lower for automobiles with greater fuel economy and the effect increases with automobile age.
Riveros et al. (2002)	1996 and 1998	Mexico City	• "Some of the results of this analysis include: the finding of a typical exhaust emission distribution curve for each vehicle manufacturer, with differences for each brand and model for the same manufacturer, [and] the fact that not all new vehicles pass the I/M test."
Beydoun & Guldmann (2006)	2001	Massachusetts, Maryland, Illinois I/M programs	• Automobile age, fuel economy, manufacturer, owner maintenance habits, and seasonal factors affect automobile emissions and I/M failure rates.

CHAPTER 2

ESTIMATION FRAMEWORK

2.1 Introduction

In the United States, automobile emissions inspection and maintenance (I/M) programs are used by 31 states and the District of Columbia to maintain compliance with National Ambient Air Quality Standards (NAAQS). They are also used in a number of industrialized foreign countries.[1] These programs require periodic inspections to identify and repair or scrap noncompliant automobiles, or those that produce too many emissions. In principle this emissions abatement will improve ambient air quality.

Despite their support from environmental regulators and use around the world I/M programs have received relatively little attention from economists. This chapter fills a major gap in the literature by developing a comprehensive framework to estimate the efficiency of I/M. The framework is

[1]For example, Austria, Brazil, Canada, Finland, Germany, Hungary, Ireland, Israel, Mexico, the Netherlands, Norway, Poland, Russia, Singapore, Slovakia, and the United Kingdom.

comprehensive in that it estimates seven empirical models to calculate both the benefits and costs of abatement from both I/M induced repairs and scrappage. I estimate each of these models using an extensive dataset that includes all emissions inspections conducted in North Carolina (NC) between January 1, 1999 and December 31, 2013.

I have organized this chapter as follows. First, in section 2.2 I describe the data used in the seven empirical models. In addition to explaining the details of the seven empirical models, in section 2.3 I also present in greater detail the general framework used to estimate the net benefits of I/M. Next, I describe the choice of the preferred specification of each of the seven models and general results in section 2.4. Finally, in section 2.5 I summarize and conclude.

2.2 Data

This dissertation utilizes data from three broad sources. The first source is the North Carolina emissions I/M program. Second, Edmunds.com, Inc., which provided the automobile attributes. Finally, macroeconomic indicators (e.g., interest rates, unemployment rates, interest rates, per capita income, and gasoline prices) were provided by several sources.

The North Carolina I/M data were collected between 1999 and 2013. These data include more than 29 million emissions inspection records from 6.4 million different automobiles conducted by more than six thousand decentralized inspection stations.[2, 3] Table 2.1 reports summary statistics for the full data set. Only about 702 thousand, or 2.36 percent, of inspections resulted in failure. The maximum number of emissions inspection failures per inspected automobile was eight and the average number of failures per automobile was 0.066. About two-thirds (65.8 percent) of the 702 thousand noncompliant automobiles were repaired to compliance following the failed initial annual inspection. This corresponds to 1.54 percent of the 29 million inspections. Only about four

[2] Eleven (Arizona, Colorado, Delaware, the District of Columbia, Indiana, Maryland, New Jersey, New York, Oregon, Tennessee, and Washington) of the 32 I/M programs in the United State use centralized state run or outsourced inspection stations. The majority use a decentralized network of automobile dealers, body shops, and mechanics.

[3] These 29 million observations include both tailpipe and OBD inspections.

percent of the noncompliant inspected automobiles (or 0.09 percent of the 29 million inspections) were scrapped following an emissions failure.[4] The owners of the other 30 percent of automobiles receive an inspection waiver allowing them to drive the noncompliant automobile until the next periodic inspection. Waivers are granted by the North Carolina Division of Motor Vehicles (DMV) to owners who can demonstrate that they have paid at least $200 (the annual repair cost limit) towards emissions related repairs on their automobiles.

Table 2.1 also reports several summary statistics about automobile usage in North Carolina. First, the oldest automobiles inspected in these data were from model year 1981 and inspected in 2005.[5, 6] Second, the average odometer reading, or cumulative vehicle-miles traveled (VMT), for an inspected automobile was 88,703. The automobiles that failed emissions inspections, however, had been driven considerably more with an average odometer reading of 136,000 (see table 2.2). In other words automobiles that fail periodic inspections have on average been driven more than 50 percent more than compliant automobiles.[7] It is uncommon, but possible, for low mileage automobiles to fail.[8] The noncompliant automobiles in my data were also older and were driven more intensively, on average, in the year prior to failing than an average automobile. This is shown in table 2.2, which summarizes the differences between failed and passed inspections. On average all automobiles were driven approximately 15 thousand miles in between annual inspections and were 6.5 years old (see table 2.1). Those that fail inspections, however, are on average 9.5 years old and were driven

[4] I use the term retirement to refer to the time when the automobile ceases to appear for annual inspections. If the last emissions inspection resulted in failure I instead use the word scrappage to refer to the time when the automobile fails to appear for annual inspections. In either case I do not observe what actually becomes of the automobile. It is possible that they are sold for parts or in used car markets in non-I/M counties or outside of the United States.

[5] The oldest automobiles are not from model year 1999 due to changes in the type of test performed. Beginning in 2006 all emissions tests were conducted using the second-generation on-board diagnostic control system (OBD-II). These systems have been required on all automobiles sold in the United States since 1996. The 1981 automobiles do not have the OBD-II system and became exempt from inspections starting in 2006. In 1999 automobiles produced in 1981 were younger than 25, the age they would be in 2005. In 2006 the oldest automobiles inspected in North Carolina were only 10 years old, by 2013 these automobiles would be 17 years old.

[6] The oldest automobiles had on average 126,300 cumulative VMT and produced roughly 5.06 grams per mile of carbon monoxide and 0.25 grams per mile of hydrocarbon emissions and passed their inspections.

[7] The standard deviation of odometer reading for noncompliant automobiles was also much larger. This fact leads to a discussion about the emissions trajectory in section 2.3.

[8] Kahn (1996a) finds “large differences in [automobile] emissions across model years, makes, and sizes.”

more than 18 thousand miles in the year prior to the failed inspection (see table 2.2). In addition, the average emissions from a non-compliant automobile were more than seven times larger than their compliant counterparts.

Figure 1.5 highlights how the North Carolina I/M program, and thus the available data, changed in two fundamental ways between 1999 and 2013. Between 1999 and 2005 the I/M program used idle tailpipe emissions inspections to determine automobile compliance in nine North Carolina counties. The first change occurred in 2002 when the state began to add 39 counties to the program. In these counties automobile compliance was determined using a second-generation on-board diagnostic control systems (OBD-II) test.[9, 10]

The second change occurred in 2006 when the former "tailpipe" I/M counties switched over to OBD tests. The Clean Air Act Amendments of 1990 required these control systems be installed on all automobiles sold in the United States beginning in 1996. Figure 2.2 shows roughly 80 percent of the North Carolina automobile fleet are 9 years old or younger.[11] Thus by 2005 a large proportion of the North Carolina automobile fleet was equipped with the OBD control systems. The state may have chosen this cheaper testing method as the I/M program expanded geographically to increase the participation of automobile maintenance service providers in the decentralized program.[12] The emissions inspection failure rate decreased from 2.45 to 2.31 percent when the test type was changed.[13] Actual automobile emissions are thus unobserved for the period 2006 through 2013.

Automobile attributes were collected from an Edmunds.com, Inc. application program interface (API). Attributes about particular automobiles, as identified by their vehicle identification number

[9]While there are first-generation on-board diagnostic control system control systems I use the general term on-board diagnostic control system to refer to OBD-II.

[10]The OBD-II test does not measure actual emissions. Instead it reports a binary pass or fail result based on whether the automobile is producing more emissions than the federal standards, or the control system *expects* that too many emissions will be produced in the near future.

[11]The horizontal axis of figure 2.2 begins at -1 because on occasion a model year *t* automobile is tested in inspection year *t-1*.

[12]See section 1.4 for more detail.

[13]This difference is statistically significant at the 0.001 level and is not surprising. The effectiveness of OBD as a means of identifying non-compliant automobiles has been contested since a lack of overlap between the OBD and tailpipe tests was identified (Ayers & Walter, 2005; Eisinger & Wathern, 2008).

(VIN), were extracted from the API using a Java program.[14] Table 2.3 summarizes select attributes of the North Carolina automobile fleet. The average automobile had 5.5 engine cylinders, a 3.1 litre engine, a 4.4 speed transmission, and could be driven nearly 21 miles on a gallon of gasoline. About 2 percent of the 6.4 million automobiles were equipped with an engine compressor such as a turbo- or super-charger. Table 2.3 also reports that the 702 thousand inspection failures discussed previously came from approximately 9 percent, or 576,000, of the 6.4 million individual automobiles registered in North Carolina. The most common type of automobile in North Carolina was a midsize car with front-wheel drive from model year 2000. The most common make of automobiles registered in North Carolina was a Ford but the most common model was Honda's Accord.

Table 2.4 is included to facilitate the interpretation of the estimated coefficients from the seven empirical models discussed in section 2.4. It reports summary statistics for dependent variables from the seven empirical models and common dependent variables described in subsequent sections. Table 2.4 shows that there are fewer than 29 million observations for carbon monoxide (CO) and hydrocarbons (HC) emissions per mile (EPM) and instantaneous abatement of CO and HC. This is because, as previously discussed, the type of inspection used in North Carolina changed from tailpipe tests to OBD tests as the program was expanded between 2003 and 2006. In addition, annual VMT and previous emissions inspection failure have only 23 million observations because these values are undefined for the first observation of each automobile in the data. Finally, several automobile attributes have fewer than 29 million observations because some of these values were missing from the Edmunds.com, Inc. API.

Finally, this dissertation also uses macroeconomic indicators (e.g., interest rates, unemployment rates, interest rates, per capita income, and gasoline prices) that were collected from several publicly available sources. These include the Federal Reserve Economic Data (FRED), the U.S. Census Bureau, and the Energy Information Administration (EIA). Macroeconomic indicators are included in several of the empirical models that involve automobile owner decisions. For example Treasury bill rates are

[14] Many thanks to Scott Ruffner and Julius Scotton for their time and Java expertise.

included in the automobile retirement model because they may influence the decision to take on debt to purchase a new vehicle. In addition, gasoline prices and unemployment rates may influence driving decisions.

2.3 The benefits and costs of I/M

In this section I describe the estimation framework I apply in chapter 3 and chapter 4 of this dissertation. First, I will briefly summarize the I/M process as well as the benefits and costs associated with the various potential outcomes. Second, I will then describe how benefits and costs will be calculated for the North Carolina I/M program. Third, I will discuss each of the seven empirical models I use to calculate benefits and costs.

Figure 2.1 illustrates how costs are incurred and benefits are generated for a representative automobile that produces emissions in addition to transportation services (vehicle-miles traveled (VMT)) over time or inspections (top horizontal axis) or usage in terms of miles (bottom horizontal axis).[15] While all automobiles incur costs from I/M programs through testing, only noncompliant automobiles produce benefits from abatement. In particular those automobiles that pass inspection because they are in compliance with federal exhaust emissions standards incur the price of the inspection (P) paid to the inspection station, a tax (τ) paid to the I/M regulator, and their opportunity costs (C^{OC}) for the duration of time spent getting the inspection (dur^1).[16] Because the net benefits of inspecting a compliant automobile are negative it is ex post inefficient for the program to treat it.[17]

[15]In North Carolina automobile owners receive an annual property tax and registration bill from the DMV. Prior to renewing registration owners must take their automobiles into a service station for an annual inspection. Repairs must be made to failed automobiles so they are compliant with regulatory standards before owners can re-register the automobile for the following year. After renewing the automobiles registration the DMV will mail the owner a new registration and a colored sticker for display on the top right hand corner of the automobile's license plate.

[16]This dissertation defines an automobile owner as the individual, government agency, firm, or their agent who makes decisions about automobile usage and repairs. In addition it does not necessarily imply legal ownership of the title. The owner may incur lease or loan payments on their automobile.

[17]Automobile *i* will generate negative net benefits if the marginal cost of its inspection exceeds the marginal benefits of I/M-induced repairs or scrappage.

Owners of automobiles that fail the annual inspection are faced with a discrete choice. This choice among repairs, waivers, scrappage, or illegal driving is depicted in figure 2.1. The owner may choose to have the automobile repaired to compliance or to apply for a waiver from the Division of Motor Vehicles (DMV) that will allow them re-register their automobile and drive it until the next annual inspection. Owners of some automobiles, for example those in poor condition or relatively old, may decide that it is time to get rid of, or scrap, the automobile. Alternatively the owner may choose to ignore the law and drive their automobile illegally. In my analysis I abstract away from this option. I assume that owners will not choose to drive illegally because of the high likelihood and cost of getting caught. In North Carolina the annual inspection is a prerequisite for annual registration and registered automobiles display a colored sticker on their license plate. This sticker is clearly observable to law enforcement.

Figure 2.1 shows that the estimation of I/M benefits are much more complex than costs. This is because calculating the benefits of I/M involves estimating vehicle-miles traveled (VMT) and counterfactual emissions. If the owner of a noncompliant automobile chooses to repair it, then instantaneous abatement is the difference between emissions from the initial failed inspection and the re-inspection (post-repair). The benefits of I/M induced repair accrue as the automobile is driven. Total abatement from repairs depends on the emissions that would have been produced in the absence of I/M induced repairs. The repairs from I/M, however, are typically not durable or persistent over time (Mérel et al., 2014; Wenzel et al., 2004). For example, Wenzel et al. (2004) find that emissions from repaired automobiles increase between biennial inspections. Thus these automobiles fail inspections repeatedly. Benefits are also generated through scrappage. Abatement from I/M induced scrappage are measured as the difference between emissions that the automobile would have produced over its useful life, in the absence of I/M, and the emissions from a "new" replacement automobile. The goal of this chapter is to operationalize this framework in the context of North Carolina's I/M program.

The estimated benefits from I/M are a function of abated emissions and are given in equation 2.1.

Table 2.5 describes the variables and notation used in equations 2.1, 2.2, and 2.3. If automobile i were to pass the emissions inspection in time period t ($F_{it} = 0$), it will generate no abatement benefits for the I/M program. If it were to fail the emissions inspection, however, it may produce abatement of emission e through either I/M induced repairs (B^R_{ite}) or scrappage (B^S_{ite}).

Figure 2.3 illustrates the abatement of emission e from I/M induced repairs and scrappage.[18] Automobile i is driven over time and accumulates VMT ($\sum_1^t vmt_{it}$) while producing emissions along emissions trajectory **ET1**.[19] Point A denotes the observed emissions from automobile i during its annual inspection at time $t = 2$ or usage $vmt = 2$. Because this level of emissions is greater than the federal exhaust emissions standards the automobile fails the inspection ($F_{it} = 1$). The automobile owner chooses to repair the automobile ($R_{it} = 1$) and emissions decrease to point E on emissions trajectory **ET2**. The difference between points A and E is the instantaneous emissions abatement from I/M induced repairs.

During the next I/M cycle (one year for North Carolina) the automobile is driven and produces emissions along emissions trajectory **ET2**. Point F denotes the observed emissions from automobile i during the next annual inspection. The estimated counterfactual emissions from automobile i, those that it would have produced in time $t = 3$ (usage $vmt = 3$) had it not been repaired, are denoted by point B. Thus, the I/M induced abatement from automobile i between inspections at $t = 2$ and $t = 3$ are equal to the difference in areas under **ET1** and **ET2** between points A and E, and B and F respectively (area ABFE).

Figure 2.3 also illustrates that the benefits of repairing automobile i at time $t = 2$ continue to accumulate past time $t = 3$. However, at time $t = T$ (usage $vmt = M$), automobile i once again fails its annual inspection; point G indicates the observed emissions of automobile i and point C indicates the counterfactual emissions. This time, however, the owner decides to scrap the automobile ($S_{it} = 1$). The total abatement from repairing automobile i in time $t = 2$ is equal to the area ADHE.

[18] Figure 2.3 assumes that a tailpipe emissions inspection is used instead of an OBD test.

[19] Figure 2.3 does not assume a fixed time to miles conversion. It merely attempts to provide a general picture of the benefits of I/M-induced emissions abatement.

The total I/M induced abatement from automobile *i* is generated from repairs as well as scrappage. The benefits from scrappage are aggregated over the additional miles the automobile would have been driven in the absence of I/M. The term $cvmt_{it}$ in equation 2.1 is this counterfactual amount of cumulative vehicle-miles traveled (VMT). Figure 2.3 assumes that this counterfactual retirement would have occurred in time $t = T'$ (usage $vmt = M'$). I assume that owner *i* will need a replacement automobile. Thus the benefits from scrappage, B_e^S in equation 2.1, are estimated net of the average emissions produced by "new" automobiles over the incremental counterfactual miles.[20] These emissions are represented in figure 2.3 by emissions trajectory **ET3**. The benefits of automobile *i*'s scrappage are also realized in time $t = T$ and are equal to area GHJI. Thus, the total I/M induced abatement from automobile *i* is equal to the shaded area, ADJIGE, in figure 2.3.

$$B_{it}^{IM} = Pr(F_{it}) \times \left(\sum_{e}^{E} \left[B_{iet}^{R} + B_{iet}^{S}\right]\right) \tag{2.1}$$

where:

- i - automobile *i* is defined by its unique vehicle identification number (VIN)
- g - geographic region *g* is defined by the zip code of the inspection station for automobile *i*
- t - time period *t* refers to a given inspection year between 2000 and 2012
- e - emission *e* includes both carbon monoxide (CO) and hydrocarbons (HC)
- $B_e^R = Pr(R_{it}) \times \left(\int_{\sum vmt_{it}}^{cvmt_{it}} \left[ce_{iet}^{R}(x) - Re_{iet}(x)\right]dx\right) \times C_{gte}^{SCE} = \Delta E_{iet}^{R} \times C_{gte}^{SCE}$
- $B_e^S = Pr(S_{it}) \times \left(\int_{\sum vmt_{it}}^{cvmt_{it}} \left[ce_{iet}^{S}(x) - ne_{iet}(x)\right]dx\right) \times C_{gte}^{SCE} = \Delta E_{iet}^{S} \times C_{gte}^{SCE}$

[20] "New" automobiles are those that were newly introduced into the state in the scrappage year. These automobiles may be brand new or purchased from a secondary market and moved into a county subject to I/M. Automobile *i*, that was registered in North Carolina before getting moved and registered in a different state, that is again registered in North Carolina in time period T would not be considered a "new" replacement automobile. If, however, it had never before been registered in North Carolina it would be considered a "new" replacement.

- C^{SCE}_{gte} are the social costs or marginal external damages (MED) of emissions
- $ce^{R}_{iet}(x)$ are the counterfactual emissions for the repaired automobile and measure the emissions that would have been produced had the automobile not been repaired
- $Re_{iet}(x)$ are the emissions produced by a repaired automobile
- $ce^{S}_{iet}(x)$ are the counterfactual emissions for the scrapped automobile and measure the emissions that would have been produced had the automobile not been scrapped
- $ne_{iet}(x)$ are the emissions produced by the counterfactual replacement ("new") automobile
- $Pr(F_{it})$ is the probability of automobile *i* failing its inspection in time period *t*
- $Pr(R_{it})$ is the probability of automobile *i* getting repaired in time period *t* following an inspection failure
- $Pr(W_{it})$ is the probability of automobile *i* receiving a waiver in time period *t* following an inspection failure
- $Pr(S_{it})$ is the probability of automobile *i* getting scrapped in time period *t* following an inspection failure
- $Pr(R_{it}) + Pr(W_{it}) + Pr(S_{it}) = 1$

Social benefits of emissions abatement from I/M are quantified using data from previous research that estimated the social cost of emissions, C^{SCE}_{gte}. Due to data limitations the emissions considered in this dissertation are carbon monoxide and hydrocarbons.[21] The social cost of hydrocarbon emissions are borrowed from Muller & Mendelsohn's (2009) county-level estimates of the marginal external damages (MED) of volatile organic compounds (VOCs).[22] The social cost of

[21] Other emissions have been ignored at this time.
[22] Volatile organic compounds are hydrocarbons with low boiling temperatures.

carbon monoxide emissions come from Matthews & Lave (2000). I chose these sources because they are the most current estimates of these two specific emissions.[23]

The estimated costs for automobile i from emissions I/M in time period t are given in equation 2.2. As illustrated in figure 2.1 estimating the costs of I/M is more straightforward than the benefits. The price (P) of an emissions test is retained by the inspection station. In addition, owners of automobiles also incur their opportunity cost of time, C^{OC}_{igt}. The American Community Survey from the U.S. Census provides per capita income for U.S. zip codes which is adjusted from annual to minute terms.[24] Because the annual inspection involves both a safety component and an emissions component and my analysis focuses on the emissions component, I ignore the time owners spend traveling round-trip to the inspection. In addition, I consider only the duration of the initial emissions inspection (dur^1_{it}).[25] In addition, owners of automobiles that pass their test, are repaired to compliance, or receive an I/M waiver from the regulator must also pay a tax (τ) that gets distributed to the government regulator. Because repairs can be very costly the I/M regulator has established a repair cost limit. Owners of automobiles that spend the repair cost limit on repairs may apply for an inspection waiver. I also make a simplifying assumption that owners of noncompliant and repaired vehicles will pay the repair cost limit (C^{RCL}) set by the I/M regulator ($C^{RCL} = C^{REP}$). The waiver application process is assumed to be costly based on anecdotal evidence. Thus additional opportunity costs ($C^{OC}_{igt} \times dur^W_{it}$) are included in the term C^W_{it}. The term dur^W_{it} refers to the duration of the waiver application process at the DMV. The only automobiles that do not have to pay the tax are those that fail their emissions inspections and are subsequently scrapped ($Pr\left(S_{it}\right) = 1$).

$$C^{IM}_{it} = P + \left(C^{OC}_{igt} \times dur^1_{it}\right) + \left(C^C_{it} + C^R_{it} + C^W_{it} + C^S_{it}\right) \tag{2.2}$$

[23]Concerns about global warming have led to other more recent estimates of the social costs of carbon to be specific to greenhouse gas emissions such as carbon dioxide (Greenstone et al., 2013; Knittel, 2009).

[24]Per capita income is merged with the North Carolina I/M data using the zip code from the inspection station the automobile owner visited. It is assumed that automobile owners choose inspection stations located near their homes.

[25]My data measures the start and end of the emissions and safety inspection performed in decentralized North Carolina inspection stations. The U.S. EPA estimates that six-elevenths of the total time is spend on emissions inspections. Thus, I multiply the duration of inspection by six-elevenths when calculating the costs of inspections.

where:

- $C_{it}^{C} = \left[\left(1 - Pr\left(F_{it}\right)\right) \times \tau \right]$
- $C_{it}^{R} = \left[Pr\left(F_{it}\right) \times Pr\left(R_{it}\right) \times \left(\left(\tau + C^{REP}\right) + \left(C_{igt}^{OC} \times dur_{it}^{R}\right) + \left(C_{igt}^{OC} \times dur_{it}^{2}\right) \right]$
- $C_{it}^{W} = \left[Pr\left(F_{it}\right) \times Pr\left(W_{it}\right) \times \left(\left(\tau + C^{RCL}\right) + \left(C_{igt}^{OC} \times dur_{it}^{R}\right) + \left(C_{igt}^{OC} \times dur_{it}^{2}\right) + \left(C_{igt}^{OC} \times dur_{it}^{W}\right) \right) \right]$
- $C_{it}^{S} = \left[Pr\left(F_{it}\right) \times \left(1 - Pr\left(S_{it}\right)\right) \times \tau \right]$
- dur_{it}^{1} is the duration (in minutes) of the automobile's initial annual emissions inspection
- dur_{it}^{R} is the duration (in minutes) of repairs performed on a non-compliant automobile
- dur_{it}^{2} is the duration (in minutes) of the automobile's follow-up inspection after repairs have been made
- dur_{it}^{W} is the duration (in minutes) of applying and waiting for a waiver to be granted
- P is the price of an emissions inspection
- τ are the taxes paid by compliant automobiles to the I/M regulator
- C_{igt}^{OC} are the opportunity costs of time
- C^{REP} are the repair costs (assumed to be equal to C^{RCL})
- C^{RCL} is the repair cost limit set by the I/M regulator

$$NB_{t}^{IM} = \sum_{i}^{I} \left(B_{it}^{IM} - C_{it}^{IM}\right) \tag{2.3}$$

The following subsections (2.3.1, 2.3.2, 2.3.3, 2.3.4, 2.3.5, 2.3.6, and 2.3.7) describe the seven empirical models that are used to estimate the net benefits of I/M given by equation 2.3. These seven models are predictive rather than causal. In other words, the purpose is not to identify structural relationships but rather to facilitate the prediction of net benefits.

2.3.1 Probability of emissions inspection failure

Figure 2.1 clearly demonstrates the importance of an emissions inspection failure model. Benefits from I/M induced abatement and scrappage are generated only from noncompliant automobiles: those that fail their emissions inspection. Inspection failure is directly observed in the data as a binary variable for both automobiles that received tailpipe and OBD tests. When estimating this model I pool both types of inspections. The probability of an automobile failing its emissions inspection, equation 2.4, is a function of cumulative annual VMT from the time the automobile was produced ($t = 0$) until the current time period ($\sum_{t=0}^{t} vmt_{it}$), annual VMT (vmt_{it}), automobile attributes (X_{it}) such as age, and results of past emissions inspections ($FAIL_{it}$).[26,27] Cumulative VMT and automobile attributes are included as independent variables because of the way exhaust emissions standards have been established.[28]

$$Pr\left(F_{it}\right) = Pr\left(1 - survival_{it}\right) = f\left(\sum_{t=0}^{t} vmt_{it}; vmt_{it}; X_{it}; FAIL_{it}\right) \tag{2.4}$$

The probability of I/M failure is modeled using survival analysis. There are several reasons why survival analysis is more appropriate in this setting than ordinary least squares (OLS), binomial, logit, or probit models. The primary advantage of survival analysis in this application is that it is designed specifically for estimating the time-to-event (i.e., inspection failure). Survival analysis is

[26] Other automobile attributes include body type, size, drive type, compressor, weight, engine cylinders, engine size, fuel type, transmission speeds, transmission type, fuel economy, and registration county.

[27] When estimating the benefits and costs of I/M I use predicted values for annual VMT ($\widehat{vmt_{it}}$) to calculate predicted odometer readings ($\widehat{\sum_{my}^{t} vmt_{it}}$) and these these place of the actual values. I denote predicted variables using a hat ($\widehat{hat}$).

[28] The current Tier 2 standards have been established for automobiles at 50,000 miles and 120,000 miles or the end of the useful life (Delphi, 2015). Not surprisingly, these federal exhaust emissions standards are relaxed over time to account for the wear and tear put on the automobile and its emissions control equipment. In addition, the Tier 2 standards have been established for several different "bins" or classifications of automobiles. For example, lower (higher) numbered bins refer to light (heavy) duty automobiles which are subject to more stringent (more relaxed) standards.

also an appropriate choice for estimating the probability of an automobile emissions inspection failure if odometer reading (cumulative vehicle-miles traveled (VMT)) are thought of as a measure of the time-to-event.

A second advantage of survival analysis is that it controls for consumer choices that may affect identification of failure. For example, consumers may move in or out of North Carolina emissions I/M areas with their automobiles, or sell or purchase used automobiles. In such cases, past or future failures are unobserved by the I/M regulator. The implications of these choices in terms of survival analysis are referred to as censoring or truncation.[29,30]

2.3.2 The repair, waiver, scrappage choice

The owner of a noncompliant automobile, one that failed its emissions inspection in time period t, must make a choice to either repair the automobile to compliance ($choice = R$), partially repair it and apply for an inspection waiver ($choice = W$), or scrap it ($choice = S$).[31] By making a few assumptions I am able to use the North Carolina I/M data to infer whether automobiles are repaired, issued waivers, or scrapped. These data include every emissions inspection performed in North Carolina between 1999 and 2013. In the data I directly observe whether an inspection resulted in a failure or a pass. I assume that automobiles that fail and subsequently pass a re-inspection were repaired to compliance. In addition, I assume that automobiles that reappear in the data the

[29]Right-censoring occurs when an automobile that had been introduced new into North Carolina is sold out of state and while there fails a future emissions inspection. Left-truncation occurs when used automobiles are moved into North Carolina from other states and their history is unobservable to the North Carolina program.

[30]There are also several other minor advantages to survival analysis for estimating the time or distance traveled to emissions inspection failure. The greatest of the two minor advantages is the the flexibility of survival analysis models. For example, it is easy to estimate either the probability of an automobile surviving (or remaining in compliance with federal emissions standards) past a certain time or odometer reading. The final advantage is somewhat trivial. Survival analysis conveniently controls for deviations from normality that may lead to bias when estimating with OLS or probit models (Cleves et al., 2010). The distribution of failure times is unlikely to be symmetric and these models are not robust to deviations from normality. In most applications, including automobile emissions failure, the distribution of the time-to-event is either increasing or decreasing. Parametric survival models assume a particular functional form for this distribution such as exponential, Weibull, lognormal, log-logistic, and Gompertz.

[31]The probability that the owner chooses to drive the automobile illegally is low, particularly in urban areas. The inspection process is tied to annual registration renewal. Newly re-registered and compliant automobiles receive a colored sticker to display on the license plate. Thus it is observable to law enforcement if an automobile is on the road illegally.

following year and had failed their re-inspection were granted waivers from the DMV. Finally, I assume that an automobile that fails its inspection and does not show up in the data in the following year was scrapped by its owner.[32]

$$Pr\left(choice_{it}\right) = f\left(\sum_{t=0}^{t} vmt_{it}; vmt_{it}; X_{it}; FAIL_{it}; E_{igt}\right) \tag{2.5}$$

This discrete choice ($choice_{it}$), given in equation 2.5, is estimated as a function of cumulative annual VMT ($\sum_{t=0}^{t} vmt_{it}$), annual VMT (vmt_{it}), automobile attributes (X_{it}), results of past emissions inspections ($FAIL_{it}$), and economic indicators (E_{igt}).[33] Automobile attributes include age, size, drive type, weight, engine cylinders, fuel type, transmission speeds, transmission types, and fuel economy. Intuitively the probability the owner chooses to retire the automobile is increasing in the number of emissions inspection failures. Similarly, the probability the owner chooses to repair the automobile in full is likely to be decreasing in the number of emissions inspection failures and usage. Finally, economic indicators include the automobile owner's per capita income, the price per VMT, and unemployment and treasury bill rates.

2.3.3 Grams of emissions per mile

The benefits of I/M, equation 2.1, are generated from repair (B^R_{iet}) and scrappage (B^S_{iet}). Quantifying the abatement benefits from either of the two sources requires a model for the emissions trajectory of automobiles as they are driven over time. Figure 2.3 illustrates the importance of this model for estimating the benefits of I/M. Due to changes in the NC I/M program between 2003 and 2006, as discussed previously in sections 1.4 and 2.2, tailpipe carbon monoxide (CO) and hydrocarbons (HC) emissions are only directly observed for a subset of the 29 inspections. Emissions for automobiles

[32]If an automobiles passes its inspection and does not show up in the data in the following year then I classify it as a retirement.

[33]When estimating the benefits and costs of I/M I use predicted values for annual VMT ($\widehat{vmt_{it}}$) to calculate predicted odometer readings ($\widehat{\sum_{my}^{t} vmt_{it}}$) and use these in place of actual values. I denote predicted variables using a hat ($\widehat{hat}$).

that received OBD tests are estimated by equation 2.6.

The generalized function for the emissions per mile model is given in equation 2.6. The quantity of emission e produced by automobile i in time period t is estimated to be a function of the odometer reading ($\sum_{t=0}^{t} vmt_{it}$), annual VMT (vmt_{it}), past emissions readings (EPM_{iet-1}), automobile attributes (X_{it}), results of past emissions inspections ($FAIL_{it}$), the season of year of the inspection ($season_{it}$), and economic indicators (E_{igt}) such as per capita income (PCI) of the automobile owner. Automobile attributes (X_{it}) include age, size, engine cylinders, engine size, make, model, model year, transmission type, and fuel economy. The past emissions inspections results include previous emissions abatement (APM_{iet-1}) and engine revolutions per minute during the inspection (RPM_{it}). [34]

$$EPM_{iet} = f\left(\sum_{t=0}^{t} vmt_{it}; vmt_{it}; EPM_{iet-1}; X_{it}; FAIL_{it}; season_{it}; E_{igt}\right) \tag{2.6}$$

It is important to note that the tailpipe inspections conducted in North Carolina between 1999 and 2005 did not measure grams of emissions. Instead, the probe the inspection technician inserts into the automobile tailpipe measures the concentrations of carbon monoxide (CO), carbon dioxide (CO_2), and hydrocarbons (HC) in the exhaust. I convert concentrations to grams per gallon following Bishop & Stedman (1996). I then divide the grams per gallon of fuel by fuel economy (MPG) to yield grams per mile. These conversions are similar to the Carl Moyer Program conversions used by Knittel & Sandler (2013), Mérel & Wimberger (2012), and Mérel et al. (2014). One consequence of such a conversion is that some grams per mile measures of emissions become negative.[35] When estimating automobile emissions and abatement I set these negative values to zero.

[34] When estimating the benefits and costs of I/M I use predicted values for annual VMT ($\widehat{vmt_{it}}$) and predicted odometer readings ($\widehat{\sum_{t=0}^{t} vmt_{it}}$) in place of actual values. I denote predicted variables using a hat ($\widehat{hat}$).

[35] See (Bishop & Stedman, 1996) for more information.

2.3.4 Annual vehicle-miles traveled

Figure 2.3 illustrates the importance of the annual vehicle-miles traveled (VMT) model. The amount of emissions produced (or abatement generated) by automobiles depends on their usage or VMT. Automobiles that are driven more intensively can be expected to produce more emissions or fail inspections sooner than others. In addition, the benefits from scrappage are estimated net of emissions produced by a "new" replacement automobile. Thus, a model for the amount of VMT by automobile *i* in time period *t* (vmt_{it}), equation 2.7, is an essential component in the estimation of the benefits from I/M. During the I/M test in North Carolina inspectors record the automobile's odometer reading (cumulative VMT). Annual VMT is directly observable in the data as the odometer reading in time period *t* minus the odometer reading in time period *t-1*. I exclude the year 1999 from my analysis in chapter 3 and chapter 4 because I observe annual VMT in this way. Annual VMT is unknown for all automobiles inspected in 1999.

$$vmt_{it} = f\left(\sum_{my}^{t} vmt_{it}; X_{it}; E_{igt}; FAIL_{it}; geo_{it}; season_{it}\right) \tag{2.7}$$

The amount of VMT by automobile *i* in time period *t* (vmt_{it}) is given in equation 2.7. It is estimated as a function of several variables such as cumulative VMT ($\sum_{my}^{t} vmt_{it}$), automobile attributes (X_{it}), economic indicators (E_{igt}), results of past and current emissions inspections ($FAIL_{it}$), and the automobile's county of registration (geo_{it}). Automobile attributes (X_{it}) include age, body type, size, drive type, engine cylinders, engine size, transmission speeds, and fuel economy. Economic indicators (E_{igt}) include the price per VMT (fuel price per gallon divided by fuel economy (MPG)), the county unemployment rate in month *m* of time period *t*, and U.S. treasury bill rates. The emissions inspection results ($FAIL_{it}$) include a binary variable indicating whether the automobile has ever failed its emissions inspection. Finally, I also include binary variables indicating the season of the current inspection ($season_{it}$). Inspection season is included to control for the possibility that the time of inspection (which is tied to the date of registration and thus purchase) is correlated with driving preferences. Gillingham (2013) suggests that different types of consumers buy at different times of year in responses to dealer prices.[36]

2.3.5 Instantaneous abatement from repairs

Figure 2.3 illustrates the instantaneous abatement from I/M repairs as the movement from point A on **ET1** to point E on **ET2**. The instantaneous abatement of emission *e* is directly observable in the data as the grams per mile of tailpipe emissions from the initial annual inspection minus the grams per mile of tailpipe emissions from the post-repair re-inspection. As discussed in section 2.2 actual abatement is only observed for inspections conducted between 1999 and 2005 when tailpipe tests were still used in North Carolina. Thus it is only these observations that are used in estimating instantaneous abatement. Instantaneous abatement is then predicted using the estimated coefficients for observations that received OBD inspections.

The instantaneous abatement from automobile *i* in time period *t* is given in equation 2.8. Abatement is estimated as a function of cumulative vehicle-miles traveled ($\sum_{t=0}^{t} vmt_{it}$), automobile attributes (X_{it}), current emissions readings (EPM_{iet}), and results of past emissions inspections ($FAIL_{it}$). Automobile attributes include engine size and model year. Examples of previous inspection data include whether the initial inspection station testing the automobile are capable of also performing necessary automobile repairs ($repair_i$), the number of previous emissions inspection failures ($numfail_{it}$), the year and season of the inspection, and emissions per mile from the inspection in time period *t-1*. [37]

$$APM_{iet} = f\left(\sum_{t=0}^{t} vmt_{it}; X_{it}; EPM_{iet}; FAIL_{it}\right) \tag{2.8}$$

[36]See Copeland et al. (2011) for more about dealer prices and consumer types. In addition, Beydoun & Guldmann (2006) find that time of year is a “strong determinant of emissions and test failure rates.”

[37]When estimating the benefits and costs of I/M I use predicted values for annual VMT ($\widehat{vmt_{it}}$) and calculate predicted odometer readings ($\widehat{\sum_{my}^{t} vmt_{it}}$) to use in place of actual values. I denote predicted variables using a hat ($\widehat{hat}$).

The instantaneous abatement from repairs also depends on which automobile components or systems are not properly functioning. The components or systems checked by the inspector include the air injection system, catalytic converter, exhaust gas recirculation valve, exhaust system, fuel evaporation control, gasoline tank cap, oxygen sensors, positive crankcase ventilation, thermostatic air cleaner, and the unleaded gas restrictor. The North Carolina I/M data includes variables that identify if there are problems with these components. I include fixed effects for these various component failures when estimating equation 2.8.

2.3.6 Automobile retirement

Automobile retirement refers to the time, in years, when the automobile last appears for an annual emissions inspection. I define retirement as the time when an automobile is no longer registered in an emissions inspection county. If the last inspection resulted in failure then the automobile is said to have been scrapped. I am unable to infer if an automobile was retired or scrapped following the 2013 annual inspection and therefore exclude it from my analysis in chapter 3 and chapter 4. Where the retired automobile ends up is unobservable in these data. However, according to a personal communication with a state regulator most of the scrapped automobiles in these data are either sold for scrap or sold into the used-automobile market in a non-I/M county in North Carolina, South Carolina, or Virginia (Willis, 2014).

Figure 2.3 illustrates that automobile scrappage is an important component of the benefits of I/M. This is because, as Hahn (1995) explains, an I/M program can cause owners to retire or scrap their automobiles earlier than they might otherwise. Thus, in order to accurately estimate the benefits of I/M it is necessary to estimate the counterfactual odometer reading. This is the cumulative vehicle-miles traveled ($\sum_{t=0}^{t} vmt_{it}$) that would have been driven by the automobile in the absence of I/M.

$$Pr\left(retire_{it}\right) = f\left(vmt_{it} X_{it}; FAIL_{it}; E_{igt}\right) \tag{2.9}$$

The automobile retirement, or scrappage, model is estimated using parametric survival analysis and provides the flexibility to estimate the median counterfactual odometer reading. The general form of this model is given in equation 2.9. It is estimated as a function of several variables including annual vehicle-miles traveled (vmt_{it}), automobile attributes (X_{it}), results of past and current emissions inspections ($FAIL_{it}$), and economic indicators (E_{igt}). Automobile attributes include age, body type, size, drive type, whether the automobile has an engine compressor, weight, the number of engine cylinders, engine size, fuel type, model year, transmission type, fuel economy, and type of owner. Emissions inspection results include the number of previous emissions inspection failures ($numfail_{it}$) and the season of inspection ($season_{it}$). Economic indicators include interest and unemployment rates, per capita income (PCI), and the price per VMT.[38]

While equation 2.9 describes the probability of automobile retirement conditional on the independent variables, the variable to be estimated is the median survival time. The unit of time in the survival model is vehicle-miles traveled. Thus, the median survival time is defined as the 50^{th} percentile of the failure time distribution and is given in equation 2.10 (Cleves et al., 2010). Equation 2.10 says that the median survival time ($cvmt_i$) is the minimum VMT (t_i) given the probability of retirement is greater or equal to 0.5 ($Pr\left(retire_{it}\right) \geq 0.5$). The counterfactual median cumulative VMT, those that would have been produced in the absence of I/M, can be estimated using equations 2.9 and 2.10 after setting the number of previous emissions inspection failures to zero. These are the miles for which abatement from scrappage must be calculated. I assume these miles are substituted from the scrapped automobile to a "new" replacement automobile. In figure 2.3 these miles, and their emissions, are represented by line segment IJ on emissions trajectory **ET3**.

[38]When estimating the benefits and costs of I/M I use predicted values for annual VMT ($\widehat{vmt_{it}}$) in place of actual values. I denote predicted variables using a hat ($\widehat{hat}$).

$$cvmt_i = min\left\{t_i \mid Pr\left(retire_{it}\right) \geq 0.5\right\} \tag{2.10}$$

2.3.7 Inspection duration

The costs of emissions I/M, equation 2.2, show that the opportunity cost of testing for the owner of automobile *i* is increasing in the duration of the initial annual inspection (dur_{it}^1), any necessary re-inspection (dur_{it}^2) following failure and the time spent on preceeding repairs (dur_{it}^R), and possibly when applying for waivers from the DMV (dur_{it}^W). In general, the duration of the inspection is the marginal amount of time dedicated to the emissions component of the annual inspection. In North Carolina automobiles must report annual for a safety and emissions inspection. This dissertation focuses on the emissions component of that inspection and ignores the time spent on safety inspections, and commuting to the inspection station, when calculating the costs of I/M. If an initial annual inspection (dur_{it}^1) results in failure and the owner chooses to repair the automobile or apply for a waiver a re-inspection (dur_{it}^2) must take place. Unless the automobile also failed the safety component of the inspection the re-inspection consists only of an emissions component. I estimate the duration of both the initial annual inspection (dur_{it}^1) and the post-failure re-inspection (dur_{it}^2) using the same equation. I assume that applying for waivers takes an additional 30 minutes based on anecdotal evidence. In addition, I ignore the duration of repairs (dur_{it}^R) when calculating the costs of I/M because I lack data.

$$dur_{it} = f\left(\sum_{t=0}^{t} vmt_{it}; X_{it}; FAIL_{it}; E_{igt}; geo_{it}\right) \tag{2.11}$$

The duration of both the initial annual inspection (dur_{it}^1) and any necessary re-inspection (dur_{it}^2) is directly observed in the data. The date and time of the automobile emissions inspections beginning and end are recorded for each inspection conducted in North Carolina. The duration of both the initial annual inspection (dur_{it}^1) and any necessary re-inspection (dur_{it}^2) are estimated following equation 2.11. It is a function of the automobile's cumulative vehicle-miles traveled ($\sum_{t=0}^{t} vmt_{it}$), automobile attributes (X_{it}), results of past emissions inspections ($FAIL_{it}$), economic indicators (E_{igt}) such as the owner's per capita income (PCI), and registration county (geo_{it}). Automobile attributes include age (a_{it}), body type, size, drive type, the number of engine cylinders, and engine size. Inspection results data include previous emissions reading in grams per mile (EPM_{iet-1}), the number of previous emissions inspection failures ($numfail_{it}$), the inspection season($season_{it}$), the station type, and the inspection year. [39]

2.4 Results

A technique known as *k*-fold cross-validation (CV) is a popular method for evaluating how well a particular specification fits the data. One reason for its popularity is that CV is both straight forward and easily modified for a number of different applications (Arlot & Celisse, 2010; Zhang & Yang, 2015). The particular type of CV used in this dissertation is leave-one-out (LOO) *k*-fold where the data are split into *k* groups and the model is estimated on *k-1* groups. The use of an out-of-sample goodness of fit criteria for selecting a preferred model specification is important for this particular application. It provides a more credible estimate than an in-sample goodness of fit criteria (Mosteller & Tukey, 1977). Because the results of these models will be used to draw conclusions about I/M efficiency in later time periods the out-of-sample goodness of fit criteria provides estimates that are more robust to potential changes in the automobile fleet compared to estimates from an in-sample goodness of fit criteria. Furthermore, it is important to remember that the point of these models is to predict net benefits of changes to I/M programs. The models are not estimated to establish causal relationships.

The difference between simply validating the model and cross-validating the model is that the

[39] When estimating the benefits and costs of I/M I use predicted values for annual VMT ($\widehat{vmt_{it}}$) to calculate predicted odometer readings ($\widehat{\sum_{my}^{t} vmt_{it}}$) to use in place of actual values. I denote predicted variables using a hat ($\widehat{hat}$).

LOO estimate will be performed for each of the k groups or folds.[40] The k-fold cross-validation exercise will be performed by setting k equal to 20 based on the recommendations of past literature (Krstajic et al., 2014; Zhang & Yang, 2015). For example, Zhang & Yang (2015) found that setting k equal to 50 or 20 is best. I chose 20 to minimize computational costs, but repeat the CV exercise 20 times. Thus graphs like figure 2.4, for the emissions inspection failure model, plot the out of average root mean squared error for 400 different samples or draws of the data.

When selecting the preferred empirical specification, cross-validation is not the only criterion I employ. This is because CV is not a perfect tool and can be unstable (Zhang & Yang, 2015). Thus I conduct additional analysis to evaluate the goodness-of-fit and in two cases I ignore the CV recommendation.

2.4.1 Probability of emissions inspection failure

The cross-validation (CV) exercise reveals that the exponential proportional hazard (PH) maximizes the out-of-sample goodness of fit. Other empirical specifications I examined include Cox proportional hazard (PH), exponential PH, Weibull PH, Gompertz PH, exponential accelerated failure time (AFT), Weibull AFT, lognormal AFT, loglogistic AFT, and Gamma AFT. Figure 2.4 plots the root mean squared errors (RMSEs) for each of the 400 k-fold draws for all 9 specifications. Table 2.6 summarizes the distribution of the RMSEs for each specification. Both figure 2.4 and table 2.6 suggest that the Cox PH specification does not fit the data well. Aside from the Cox PH model there are no systematic, statistically significant differences in the distributions of estimated RMSEs.

Despite not minimizing the average root mean squared error from the k-fold cross-validation exercise, my subsequent analysis employs the lognormal accelerated failure time (AFT) specification over the exponential proportional hazard (PH) specification for several reasons. First, as mentioned previously, while cross-validation is an efficient method of evaluating the predictive performance of

[40] In other words the LOO model will be estimated for each of the k groups. Thus there will be $k \times k$ out-of-sample goodness of fit measurements, like RMSEs, at the end of the exercise.

a model it can yield unstable results (Zhang & Yang, 2015). Thus I employ additional checks on the data before selecting the preferred model specification. For example, the assumption of proportional hazards is violated for these data. A test, based on Grambsch & Therneau (1994), of the residuals as a function of time reveals a non-zero slope indicating a deviation from proportional hazard. Thus the exponential (exp.) and Weibull (Wei.) PH specifications are ruled out as the preferred failure model.

Second, the shapes of the estimated baseline hazard function from the exponential PH, Weibull PH, and gamma AFT specifications do not fit the theoretical shape suggested by the nonparametric Kaplan-Meier survival estimate plotted in figure 2.5. The baseline hazard function estimates the instantaneous failure rate. Theoretically the hazard should be very low for new vehicles and increase in wear and tear such as age and odometer reading (cumulative VMT). Furthermore, it should be nonlinear and the probability of failure should increase slowly at first before beginning to increase at an increasing rate. Because I/M failure is based on the amount of emissions produced by automobiles, and the emissions trajectory has been shown to be concave, the baseline hazard function should also theoretically be concave. The baseline hazard function estimated from the exponential and Weibull PH specifications, figure 2.6a and 2.6b, are inconsistent with this shape. Finally, the baseline hazard function estimated from the gamma AFT specification, figure 2.6c, is increasing in cumulative VMT but appears to be minimally concave.

The ultimate choice of the lognormal AFT specification as the preferred model was based on the shape of the estimated baseline hazard functions. Figure 2.6d plots the estimated baseline hazard function for this specification. Figure 2.7 plots the estimated probability of failure across cumulative VMT for automobiles of different ages. It shows that the probability of failure is increasing in both odometer reading and age. For the average automobile, however, the probability of failure is extremely low. Furthermore, in North Carolina the average automobile is retired after eight years with approximately 110 thousand cumulative VMT. Equation 2.4 estimates that the probability of failure is less than 20 percent for these automobiles.

Table 2.7 reports two types of information. First, it reports the mean and standard deviation (st. dev.) of the dependent variable ($Pr(F_{it})$) and select dependent variables. Table 2.7 shows that only about two percent of inspections result in failure. Second, it reports estimated coefficients and standard errors from the exponential PH, lognormal AFT, and gamma AFT specifications of the failure model. The continuous independent variables (age, weight, engine size, and fuel economy) have been transformed by subtracting the average value. The average automobile therefore has values for these variables of zero and positive values reflect an excess over the average. Therefore the average automobile included in the model of 11.6 million automobiles is 0.8 years older than the average automobile in the 29 million observation dataset.[41] Because of this transformation the estimated coefficients reported are consistent with the interpretation of the baseline hazard function. Deviations from average can increase or decrease the hazard rate, or for accelerated failure time (AFT) models these deviations have the effect of speeding up or slowing down the passage of time. Equations 2.12 and 2.13 describe how to translate estimated coefficients into hazard (HR) or time (TR) ratios.

$$HR = exp\left(x_j \beta_j\right) \tag{2.12}$$

$$TR = exp\left(-x_j \beta_j\right) \tag{2.13}$$

Table 2.7 shows that the estimated effect of independent variables depends on the model's parametric specification. There are minimal differences between the estimated effects of the log-normal and gamma AFT specifications. Both estimate that the probability of failure is increasing in annual VMT and automobile age as expected. Surprisingly, the AFT specifications both predict that automobiles that have previously failed inspections are less likely to fail again. One possible explanation for this counterintuitive result is that it is driven by a selection issue. If automobiles

[41]The number of observations in the model is less than 29 million due to missing values among the explanatory variables and the exclusion of outliers.

that previously failed inspections are more likely to be scrapped then the automobile will not show back up in the data in later years. Consequently the estimated coefficient may deviate from its true value. It is also possible that some of these counterintuitive results are the result of unobserved variables. For example, automobile owners who drive more than average may expend higher than average effort maintaining their vehicle. This unobserved maintenance effect may outweigh the effect of wear and tear and thus slow the speed of "time." Alternatively, this may suggest that repairs are durable or persistent.

2.4.2 The repair, waiver, scrappage choice

The preferred specification for the discrete choice among repair, waiver, and scrappage model was chosen based on *k*-fold cross-validation (CV). Table 2.8 summarizes the distribution of root mean squared error (RMSE) from each of the 400 *k*-fold draws from the CV exercise. There is no statistical difference in the means or standard deviations between the two specifications (multinomial logit and multinomial probit) for the repair choice. There are differences, however, in the distributions of RMSEs from the two specifications for the waiver and scrappage choices. The multinomial probit specification has larger standard deviations of the RMSEs than the multinomial logit model and there is no statistical difference in the means. The multinomial probit specification, however, produces smaller mean RMSEs for the scrappage model. Thus the preferred specification will be the multinomial probit model.

Table 2.9 serves two functions. First, it reports the mean and standard deviation (st. dev.) of the dependent variable, the discrete choice between repair, waiver, and scrappage. Of the automobiles that failed their initial annual inspection and are included in the model, 71 percent were repaired to compliance, 16 percent received a waiver, and 13 percent were scrapped. In addition, these automobiles had been driven more than 130 thousand miles, 52 more than the average automobile in the North Carolina fleet. Furthermore, these automobiles are also driven more intensively annually and are older than the average North Carolina automobile.

Second, table 2.9 compares the estimated coefficients (and standard errors) between the multinomial probit and multinomial logit specifications for the repair and scrappage choices. As expected the probabilities of repair and scrappage are decreasing and increasing, respectively, with the automobile's odometer reading. Similar relationships are reported with respect to annual VMT and the number of previous emissions inspection failures. While automobile age does not affect the repair choice older automobiles are more likely to be scrapped. Finally, the probabilities of repair and scrappage are increasing and decreasing, respectively with fuel economy. Figure 2.8 illustrates the estimated probabilities of repair, waivers, and scrappage for an “average” automobile as a function of cumulative VMT.

2.4.3 Grams of emissions per mile

The specific functional form of equation 2.6 will be a seemingly unrelated ordinary least squares (OLS) regression. This choice was made based on the nature of the chemical processes that create automobile emissions. For example, Washburn et al. (2001) mention the interdependency among emissions; carbon molecules that form carbon monoxide are unavailable to form hydrocarbons. Thus, it is inappropriate to model them independently.

Table 2.10 reports the means and standard deviations of each of the 400 *k*-fold draws from the cross-validation (CV) exercise. Figures 2.9a and 2.9b plot RMSEs from four specifications from the *k*-fold CV exercise for carbon monoxide and hydrocarbons respectively. Both show that there is very little difference between means and standard deviations among the four specifications. The specification that produces the lowest mean RMSE for carbon monoxide emissions is OLS. It also produces the second lowest mean RMSE for hydrocarbons. A Poisson family generalized linear model (GLM) with an identity link function produces the lowest mean RMSE for hydrocarbons and the fifth lowest for carbon monoxide.

Table 2.11 reports both summary statistics and estimated coefficients for the emissions per mile model. First, it presents the mean and standard deviation of the dependent variables, grams of carbon monoxide (CO) and hydrocarbons (HC) emissions per mile, and important dependent variables. Second, table 2.11 reports the estimated coefficients and standard errors from the OLS and seemingly unrelated OLS regressions. There are no fundamental differences between estimates from the two specifications. The table shows that current emissions are positively correlated with their lagged values. Specifically, each additional gram of emissions measured during the previous inspection is correlated with an increase in current emissions between 0.23 and 0.32 grams per mile. In addition, lagged abatement is negatively correlated with current emissions. Table 2.11 also shows that emissions are increasing in cumulative VMT. Because of mass balance there is a limit to the amount of emissions produced by automobiles and they increase at a decreasing rate over time. Emissions are shown by table 2.11 to be higher for older automobiles. There are two plausible explanations for this. First, older automobiles are more likely to have been produced under less restrictive emissions standards. Second, emissions control equipment and engine performance deteriorate with use and automobile emissions thus increase.

Table 2.11 also reports that current emissions of carbon monoxide and hydrocarbons are functions of the automobiles history of inspections. Automobiles that previously failed inspections have lower current emissions because they were either repaired in part or full, or their owners performed additional service on their automobiles in between inspections. As one would expect, automobiles that failed their current emissions inspections produce significantly more emissions than other automobiles. Figure 2.10 plots estimated emissions trajectories from a seemingly unrelated OLS regression for carbon monoxide and hydrocarbons. Both illustrate these trajectories to be concave with respect to odometer reading. In addition, emissions from compliant automobiles that have never failed their inspections are significantly less than those from noncompliant automobiles. Interestingly, panel B of figure 2.10 shows that emissions of hydrocarbons from automobiles that previously failed their inspections are higher than those that failed their current inspection. The same is not true of carbon monoxide emissions (see panel A of figure 2.10). This may suggest that repairs are less persistent for hydrocarbons.

Table 2.12 summarizes the distributions of actual and predicted emissions from the seemingly unrelated OLS model. It clearly shows that on average the preferred specification for emissions per mile (EPM) does an excellent job of predicting emissions for both carbon monoxide (CO) and hydrocarbons (HC). The model, however, is not perfect. The standard deviation for both predicted carbon monoxide and hydrocarbons are smaller than their actual values. In addition, table 2.12 illustrates that the data is not perfect. Because, as discussed in section 2.3.3, when converting from concentrations to masses of emissions using the (Bishop & Stedman, 1996) method some values become negative. It is important to remember, however, that on average these models predict well and it is the predictions that matter for determining net benefits of I/M into the future.

2.4.4 Annual vehicle-miles traveled

The *k*-fold cross-validation (CV) exercise reveals that the Poisson specification minimizes the root mean squared error (RMSE) of annual vehicle-miles traveled (VMT). Table 2.13 summarizes the distribution of the RMSEs for each of the 400 *k*-fold draws. Figure 2.11 plots each of the 400 RMSEs for six specifications that fit the data relatively well.

Table 2.14 serves two purposes. First, it reports the mean and standard deviation for the dependent variable, annual VMT, and important dependent variables. It shows that the average annual VMT for observations included in the data is 14 thousand miles, and the average odometer reading is 95.5 thousand miles. The age of the average inspected automobile is 6.7, and approximately 4.5 percent of automobiles inspected have previously failed an emissions inspection.[42]

Table 2.14 also reports the estimated coefficients and standard errors for six different specifications of the annual VMT model (OLS, Poisson, zero-truncated Poisson (ZTP), negative binomial (NB), zero-truncated negative binomial (ZTNB), and a Gaussian generalized linear model (GLM) with a log link function). The table shows that automobiles with higher odometer readings are estimated

[42] Recall table 2.3 reports that 9 percent of the 6.4 million automobiles inspected in the 29 million inspections failed an inspection between 1999 and 2013. Only 2.36 percent of the 29 million inspections resulted in failure.

to drive more miles per year and that automobiles are driven less intensively as they age. In addition, automobiles are driven less intensively following emissions inspection failure. Surprisingly, the data indicates that there is no rebound effect for these data; in North Carolina annual VMT is decreasing in fuel economy. Finally, table 2.14 reports that demand for VMT in North Carolina is inelastic.

Table 2.15 reports the distribution of actual annual VMT and the predictions from the six specifications estimated in table 2.14. While the Poisson specification minimizes the RMSE for the vehicle-miles traveled (VMT) model it does not do a good job of estimating mean annual VMT. The zero-truncated Poisson (ZTP), negative binomial (NB), and zero-truncated negative binomial (ZTNB) specifications also significantly underpredict mean annual VMT. In addition, the negative binomial (NB) and zero-truncated negative binomial (ZTNB) specifications overpredict annual VMT for many outlier automobiles. Table 2.15 shows that only the Gaussian generalized linear model (GLM) with a log link function is able to estimate mean annual VMT without predicting negative values. Thus it will be the preferred specification. Figure 2.12 plots estimated annual VMT from this preferred specification for automobiles aged six and nine that have both failed and passed their previous emissions inspection.

2.4.5 Instantaneous abatement from repairs

The preferred specification for the instantaneous abatement model is seemingly unrelated ordinary least squares (OLS) regression. This specification was chosen for reasons similar to why it was selected for the emissions per mile model. Table 2.16 summarizes the results of the *k*-fold CV exercise. It shows that OLS and a Gaussian generalized linear model (GLM) with a log link function are best at estimating abatement in miles per gallon. The seemingly unrelated OLS regression was chosen because it is arguably inappropriate to model them independently due to the chemical processes that create automobile emissions.

Table 2.17 reports both summary statistics and estimated coefficients. First, the mean and standard deviation are reported for both the dependent variables and important dependent variables.

Table 2.17 shows an important fact about the North Carolina I/M program. Abatement of carbon monoxide emissions is significantly larger than the abatement for hydrocarbons emissions.

Table 2.17 also compares the estimated coefficient and standard errors between the OLS and seemingly unrelated OLS models. It shows that the coefficients do not change significantly under joint estimation. In addition it reveals that the magnitude of instantaneous abatement is decreasing in odometer reading. This appears to be driven by the concave shape of the emissions trajectory. For example, figure 2.3 shows that the linear distance between **ET1** and **ET2** is decreasing in usage intensity. In addition, abatement is positively correlated with emissions. The potential abatement from repairing noncompliant automobiles is larger for larger quantities of emissions, all else constant. The interaction between inspection failure in time period *t-1* and odometer has a small impact on abatement of carbon monoxide but not hydrocarbons. Instantaneous abatement is also negatively correlated with automobile age. In other words, as automobiles are used for longer periods of time the ability of mechanics to reduce automobile emissions declines. Figure 2.13 plots estimated instantaneous abatement of carbon monoxide (CO) and hydrocarbons (HC) for an average automobile with no failures, previous and current failures, and current failures only. A comparison of the figures clearly reveals that previous emissions failures affect abatement differently for the two emissions. Finally, repair induced hydrocarbon abatement appears to be less persistent than carbon monoxide abatement.

2.4.6 Automobile retirement

Automobile retirement, or scrappage if the last inspection resulted in failure, is modeled using survival analysis. This choice was for reasons similar to why it was chosen to model inspection failure.[43] Unlike the failure model, however, the primary purpose of the retirement, or scrappage, model is not to estimate the probability of retirement but a retirement time, or odometer reading.

[43] All scrapped automobiles were retired, not all retired automobiles are scrapped. Scrappage requires that the final emissions inspection in the data resulted in failure.

This is a necessary component of the framework because benefits from I/M induced scrappage should accrue until the time the automobile would have been retired in the absence of I/M.

The preferred specification, exponential proportional hazard (PH), for the retirement model was chosen based on a *k*-fold cross-validation (CV) exercise. Table 2.18 reports summary statistics for the distribution of RMSEs across the 400 *k*-fold samples. Figure 2.14 plots this same data. The exponential PH specification produces the minimum average RMSE. In fact the mean RMSE from the exponential PH specification is statistically less (at the 0.01 level) than all other specifications (except the exponential accelerated failure time (AFT) specification).

Table 2.19 reports summary statistics and estimated coefficients from four different specifications. First, table 2.19 includes the mean and standard deviation of the dependent variable, a binary variable indicating if automobile i is retired in time period t, as well as important explanatory variables. The specific dependent variable of the survival models used to estimate automobile retirement is the probability that the automobile continues to be driven (not retired) after time period t. Only 18.2 percent of the 13.8 million observations included in the model represented automobile retirements. Table 2.19 also shows that the continuous dependent variables have been transformed into a deviation from "average" as described previously in section 2.4.1. The average age of automobiles in the retirement model of 13.8 million observations are 0.8 years older than the average automobile in the entire 29 million observation dataset. These automobiles are also driven more intensively, weigh slightly more, have slightly larger engines, are slightly more fuel efficient, and have failed 0.07 more emissions inspections.

Table 2.19 also reports estimated coefficients and standard errors for four different parametric survival model specifications. Negative coefficients for the proportional hazard specifications indicate that retirement is more likely. In addition, the signs of PH and AFT models should be different if they tell a consistent story. This is because "the effect of the [AFT] covariates is to accelerate time by a factor of $exp(-x_j\beta_j)$" (Cleves et al., 2010). The results in table 2.19 reports that automobiles that are driven more intensively in a year are more likely to be retired. Interestingly each specification also estimates that older automobiles are less likely to be retired. This may be driven by outlier automobiles like classics that may be held for much longer than most. Table 2.19 also reports that the probability of failure is increasing in automobile engine size and the number of previous emissions inspection failures. Figure 2.15 plots the estimated probability of retirement and scrappage with respect to odometer reading for the preferred specification. The median retirement and scrappage odometer readings are then estimated using equation 2.10.

2.4.7 Inspection duration

The preferred specification for the inspection duration model is Poisson regression. It was chosen based on the results of the *k*-fold cross-validation (CV) exercise. Table 2.20 reports summary statistics that describe the distribution of the root mean squared errors (RMSEs) produced from each of the 400 *k*-fold draws. Figure 2.16 plots this same data for the OLS, Poisson, negative binomial, and zero-truncated Poisson specifications. The Poisson model yields the lowest mean and tightest standard deviation for the RMSEs, although it is not statistically less than other specifications.

Table 2.21 reports summary statistics and estimated coefficients for the four specifications shown in figure 2.16. First, the mean and standard deviation are reported for the dependent variable, the duration in minutes of the annual North Carolina inspection, and important dependent variables. The average inspection lasted 7.3 minutes with a standard deviation of 6 minutes. The U.S. EPA estimates that six-elevenths of this duration was spent on the emissions inspection.

Table 2.21 also shows estimated coefficients and standard errors. It reports that the inspection duration is increasing in odometer reading and age. Inspections take longer for more intensively used automobiles. It also takes significantly longer to perform an inspection on a noncompliant automobile. However, repeat failure automobiles take less time to inspect than first time offenders. Figure 2.17 plots estimated inspection duration across odometer reading for automobiles of age six and nine that have both failed and passed their current inspection.

2.5 Conclusion

In this chapter I have described a comprehensive framework to estimate the benefits and costs of I/M. Figure 2.1 summarizes these benefits and costs and how they vary among automobiles that pass inspection, or are repaired, granted waivers, or scrapped by their owners. A graphical example of how abatement is calculated is presented in figure 2.3. Actual estimation of the shaded region in figure 2.3, however, is complex and requires six empirical models.

The particular specification chosen for each of these models was chosen with the aid of *k*-fold cross-validation. This method estimates a model for a sample of the data and calculates the root mean squared error (RMSE) for the excluded observations. The RMSEs can then be used to evaluate the out-of-sample goodness-of-fit across various specifications. While useful, it can be imprecise and in a few cases alternative specifications are chosen based on alternative empirical support. Table 2.22 summarizes these preferred specifications and reasons why alternatives were chosen to model inspection failure and vehicle-miles traveled.

The next two chapters of this dissertation will apply the framework presented in this chapter to answer two general questions about recent and proposed changes to the state's I/M program. To estimate the net benefits (equation 2.3) of *selective automobile targeting* (chapter 3) and *selective spatial targeting* (chapter 4), I use the predicted values from the seven empirical models presented in section 2.4.

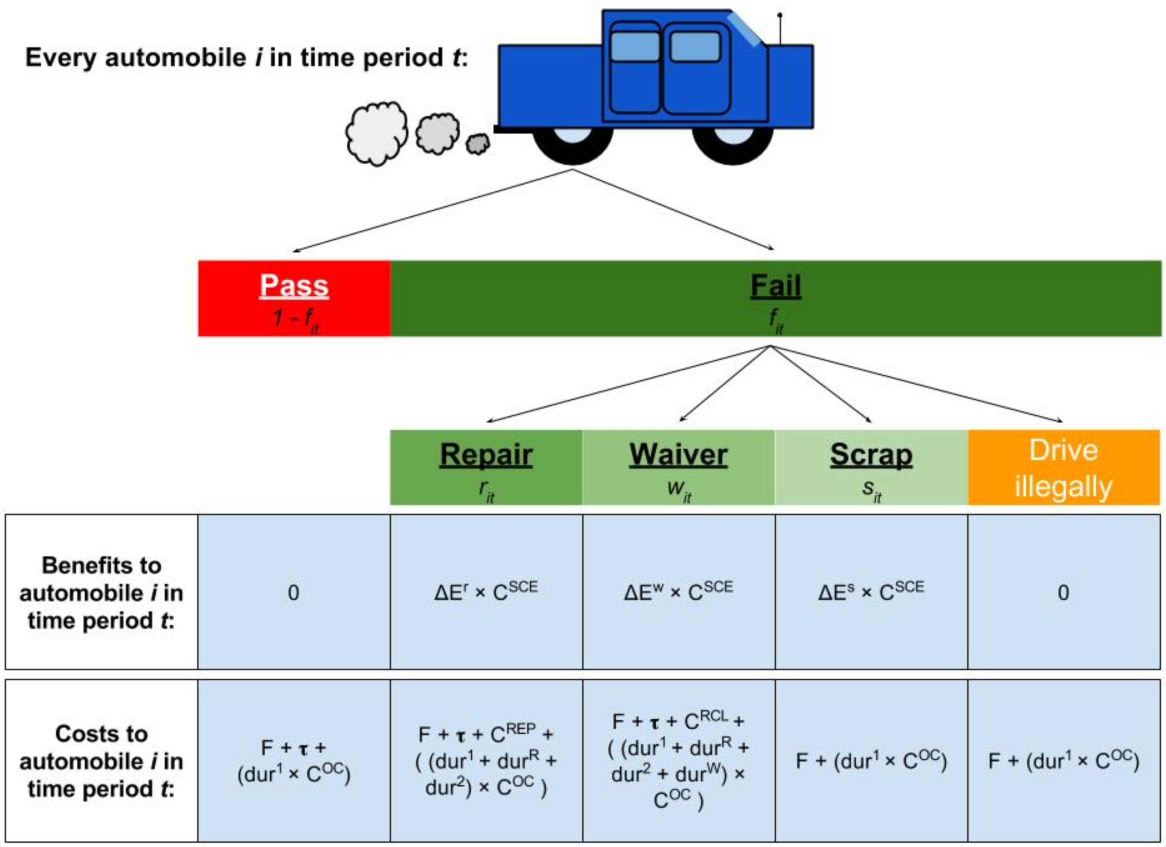


Figure 2.1 *The benefits and costs of emissions inspection programs*

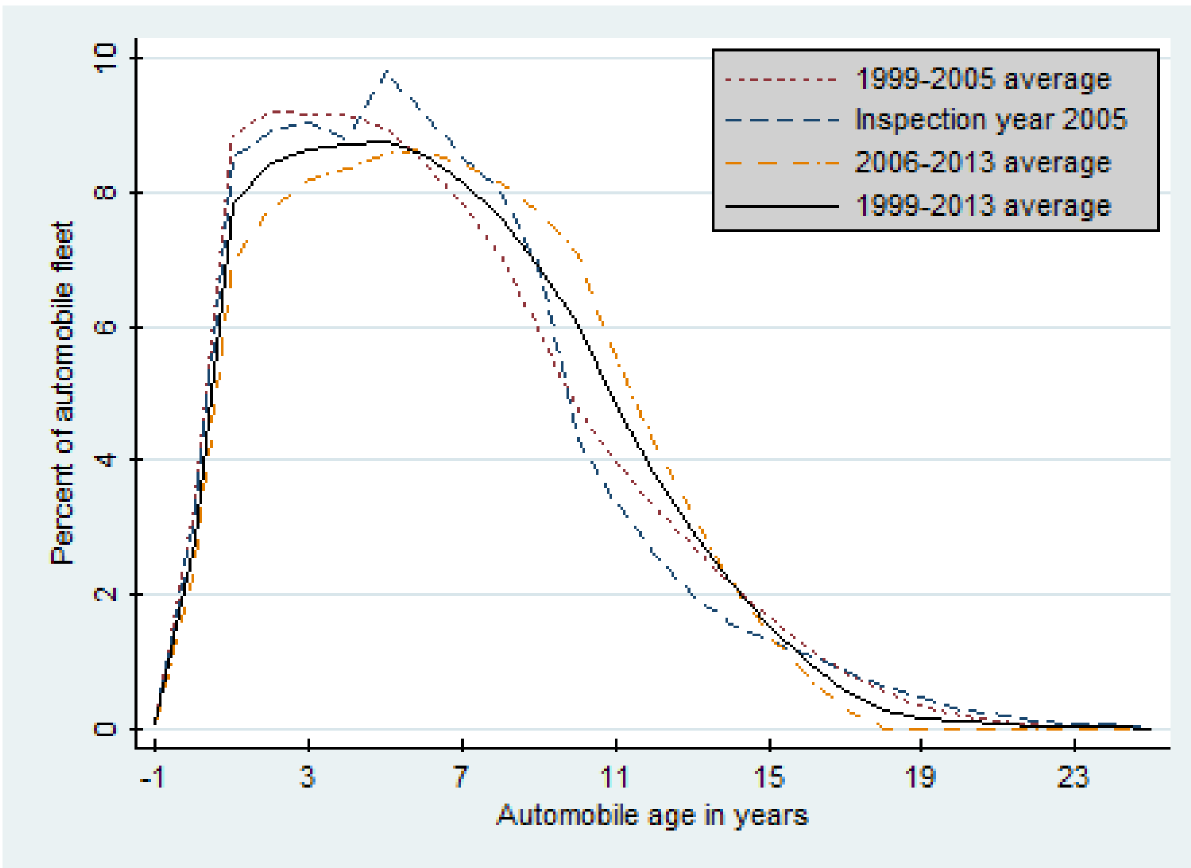


Figure 2.2 *Automobile age distribution of the North Carolina fleet*

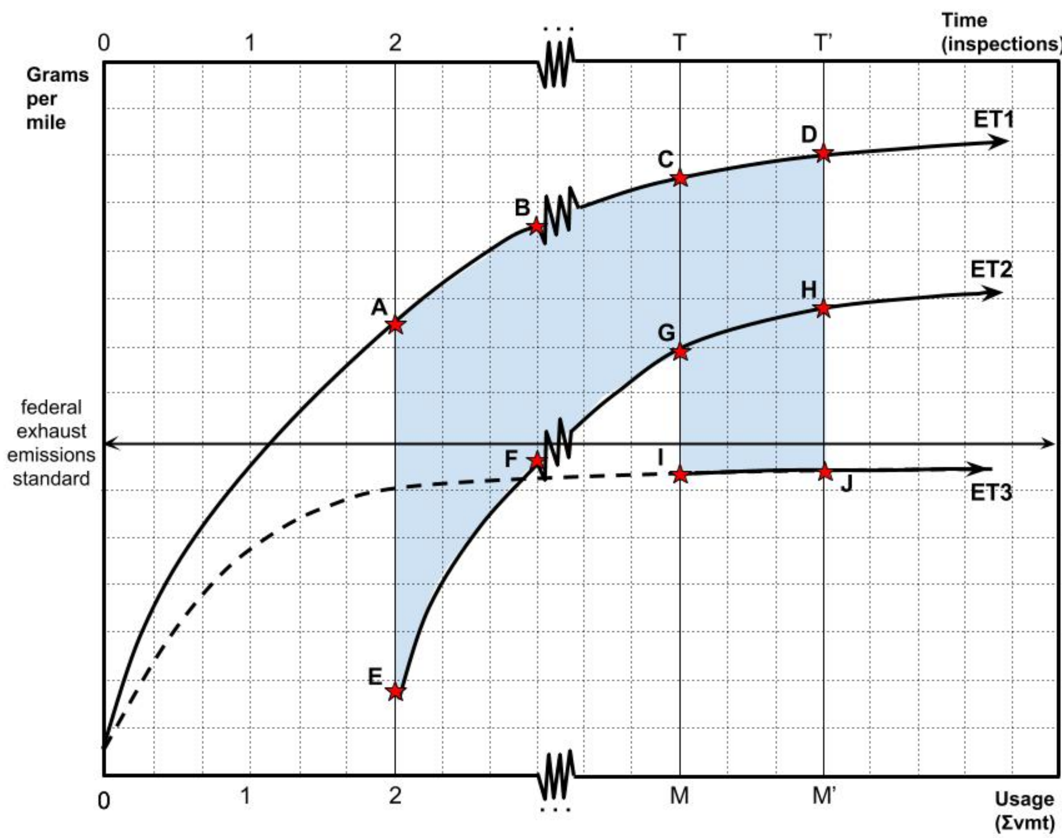


Figure 2.3 *Abatement from repairs and scrappage*

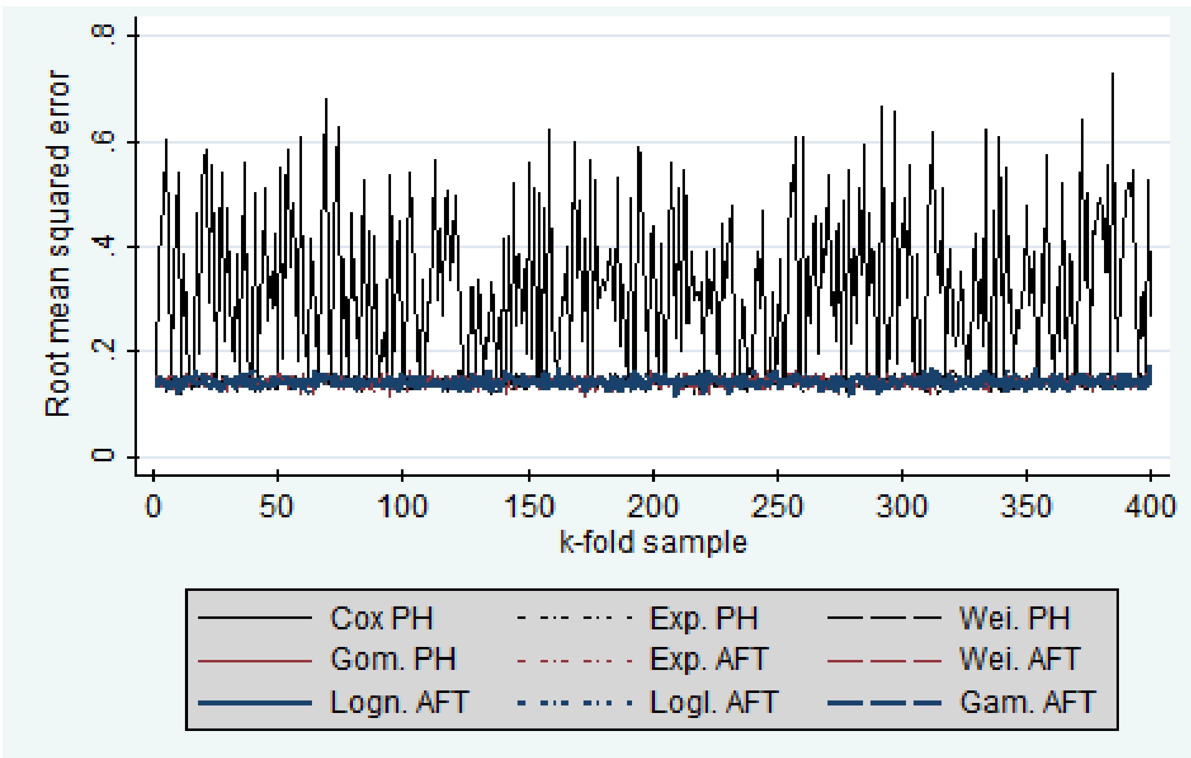


Figure 2.4 *Root mean squared errors (RMSEs) from the emissions inspection failure model cross-validation (CV) exercise*

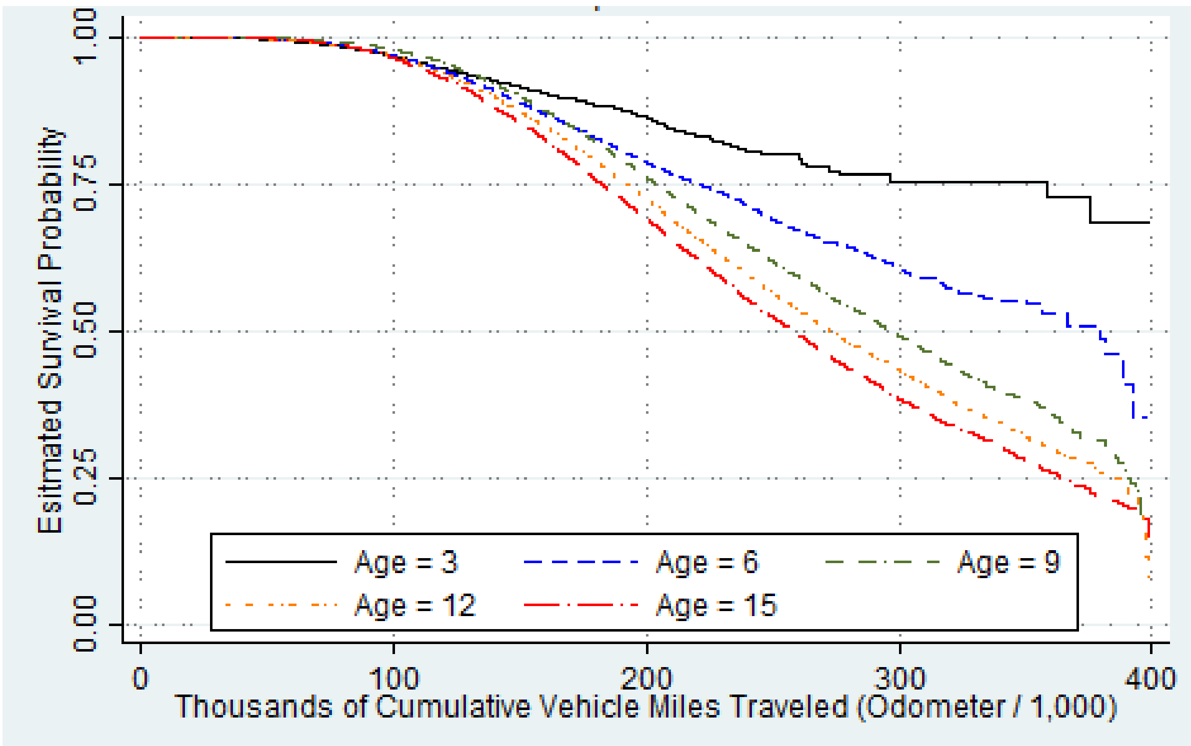
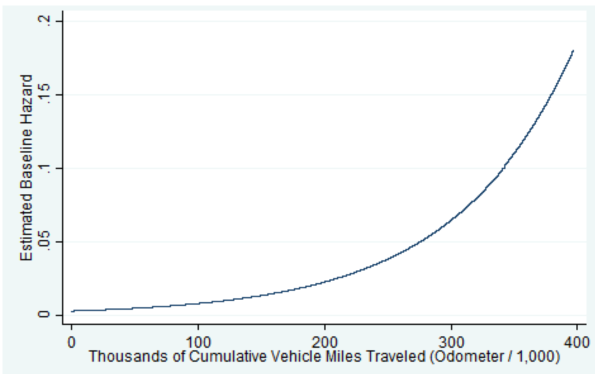
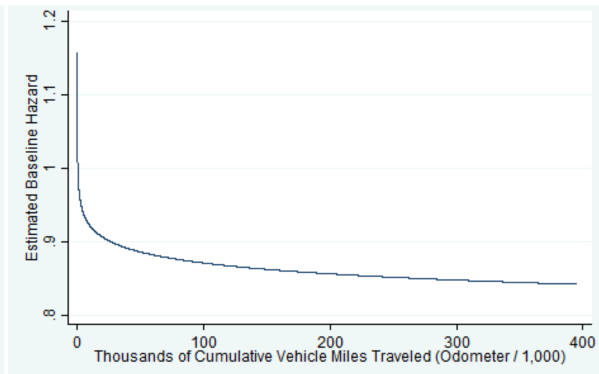


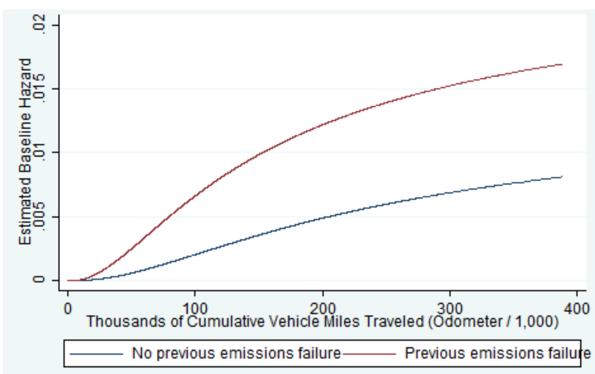
Figure 2.5 *Kaplan-Meier survival estimates of emissions inspection failure*



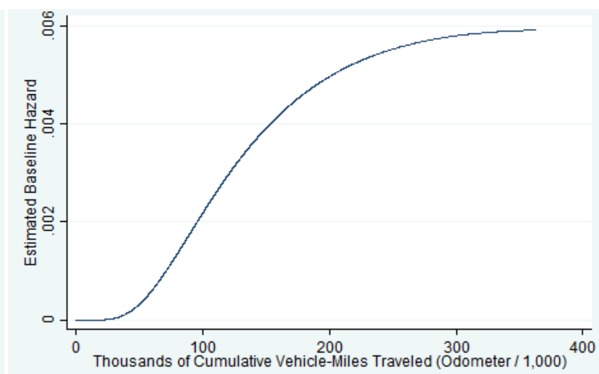
(a) *Parametric exponential PH specification of emissions inspection failure*



(b) *Parametric Weibull PH specification of emissions inspection failure*



(c) *Parametric Gamma AFT specification of emissions inspection failure*



(d) *Parametric lognormal AFT specification of emissions inspection failure*

Figure 2.6 *Baseline hazard functions for the emissions inspection failure model*

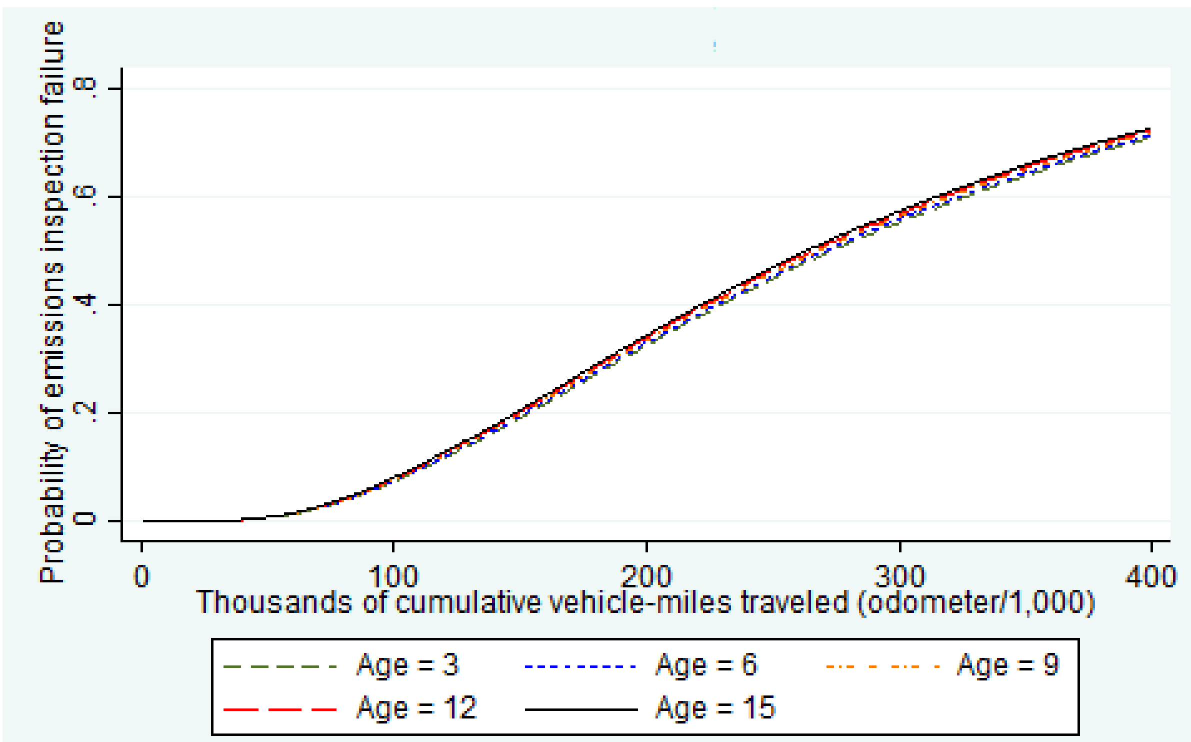


Figure 2.7 *Probability of emissions inspection failure from the parametric lognormal accelerated failure time (AFT) specification*

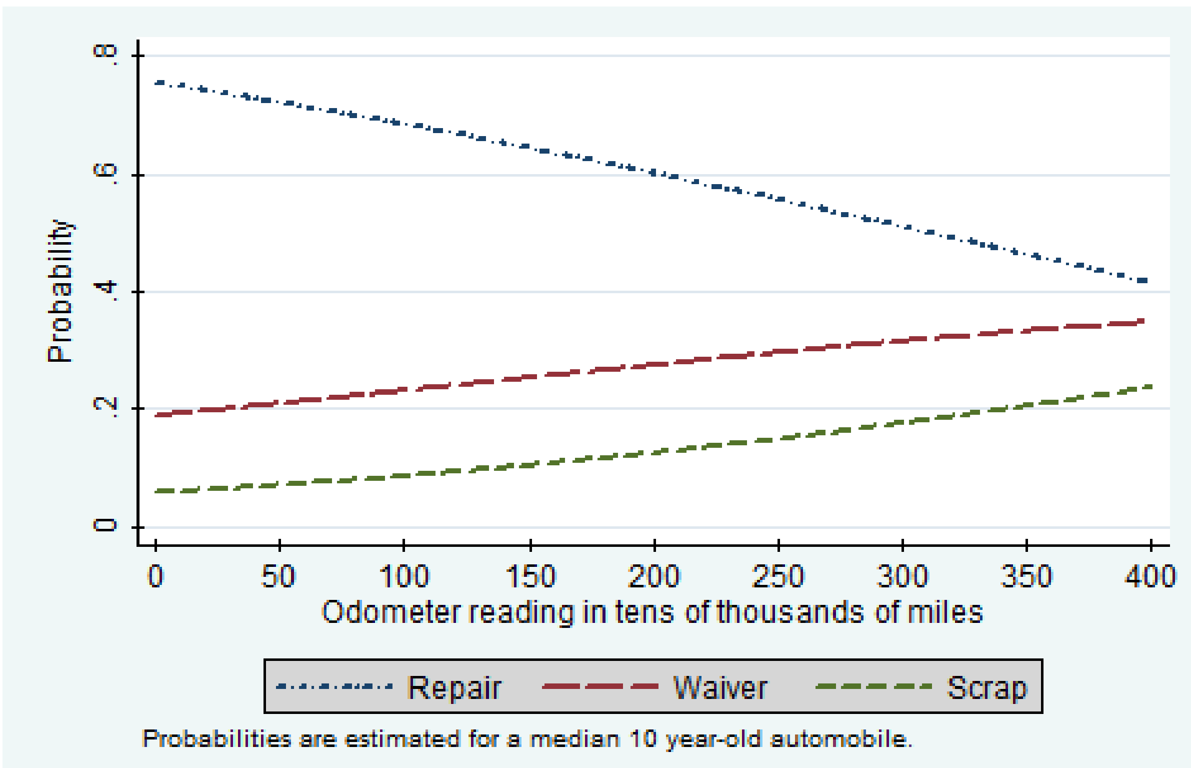
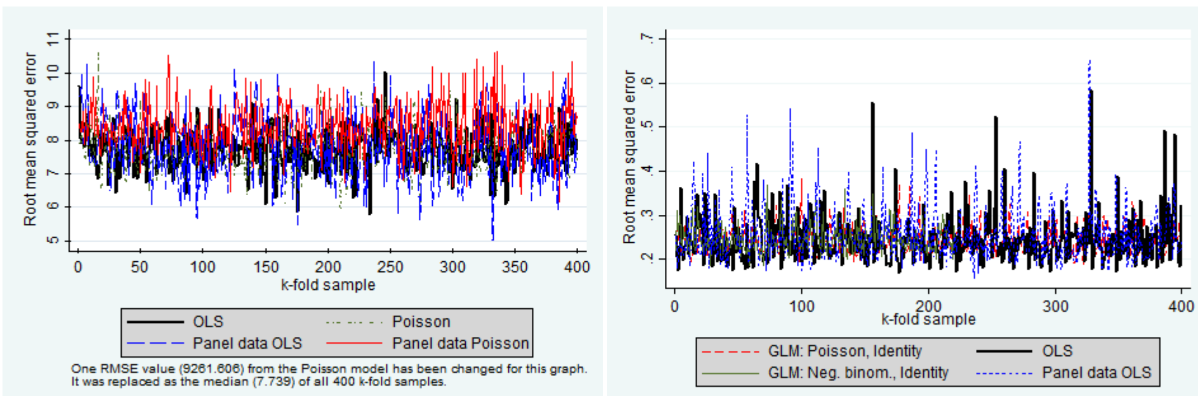


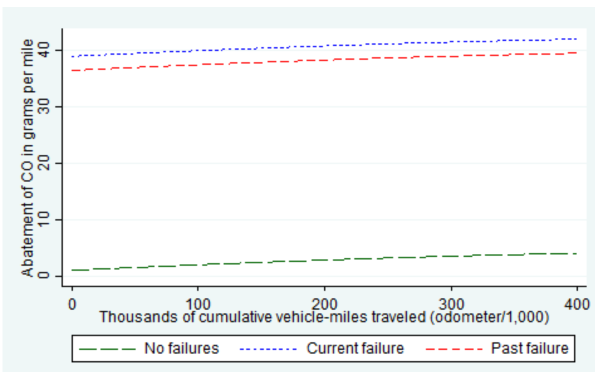
Figure 2.8 *Multinomial probit specification for repair, waiver, scrappage choice model*



(a) *Carbon monoxide (CO)*

(b) *Hydrocarbons (HC)*

Figure 2.9 *Root mean squared errors (RMSEs) from the emissions per mile (EPM) model cross-validation (CV) exercise*



(a) *Carbon monoxide (CO)*

(b) *Hydrocarbons (HC)*

Figure 2.10 *Emissions trajectories from the seemingly unrelated OLS regression model*

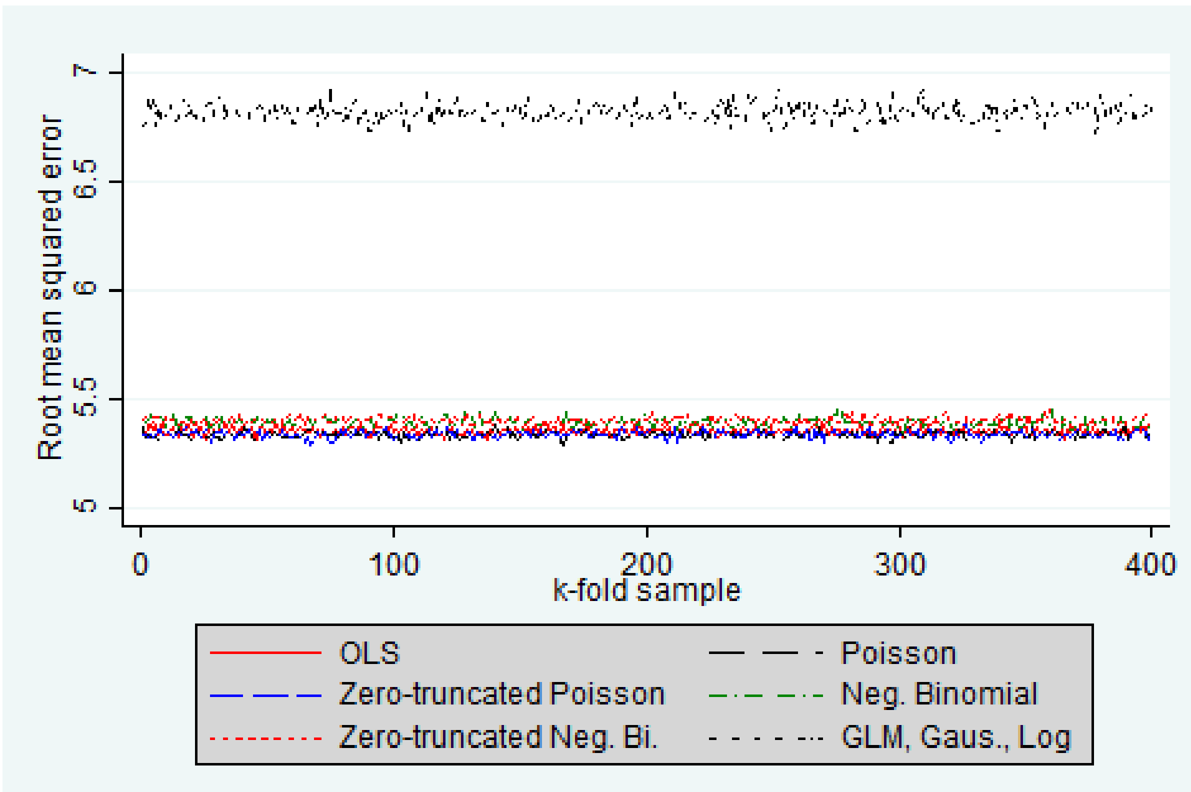


Figure 2.11 *Root mean squared errors (RMSEs) from the vehicle-miles traveled (VMT) model cross-validation (CV) exercise*

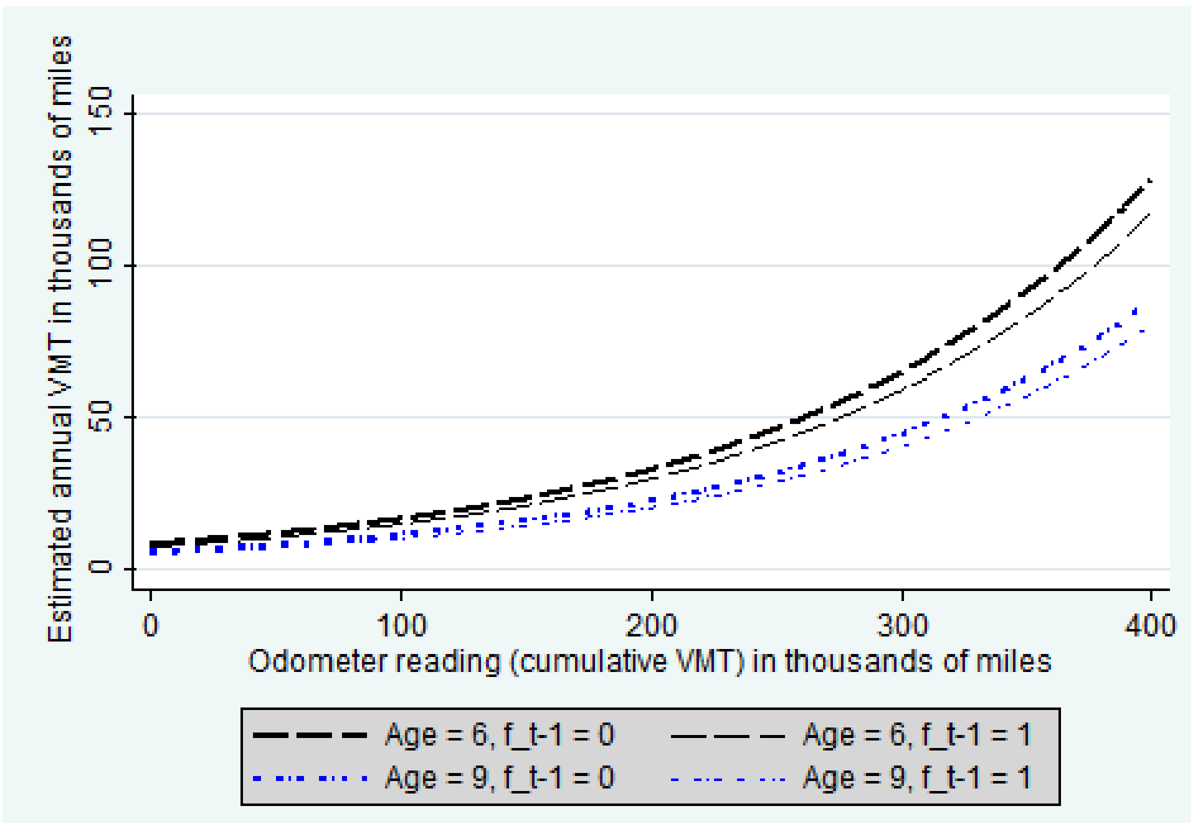
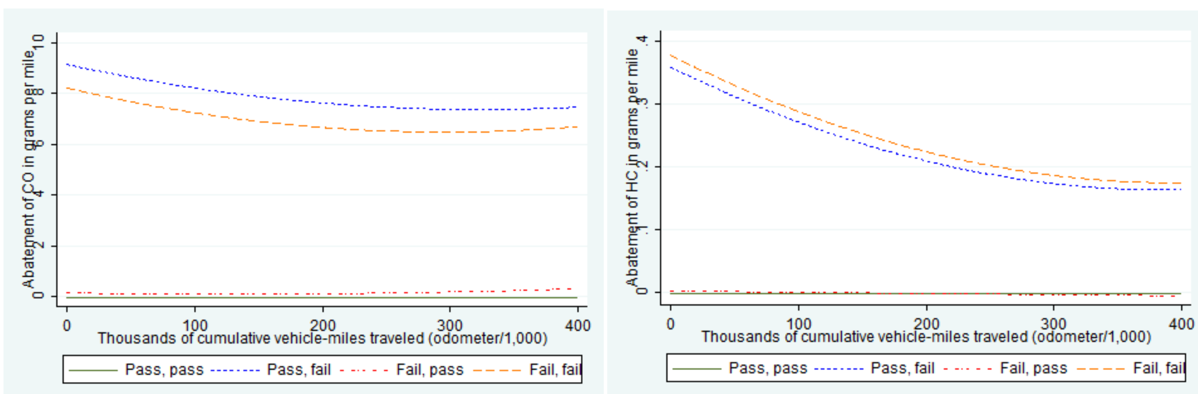


Figure 2.12 *Estimated annual vehicle-miles traveled (VMT) from a generalized linear model (GLM) with a Gaussian family and log link function*



(a) *Carbon monoxide (CO)*

(b) *Hydrocarbons (HC)*

Figure 2.13 *Instantaneous emissions abatement from I/M induced repairs from a seemingly unrelated ordinary least squares (OLS) model*

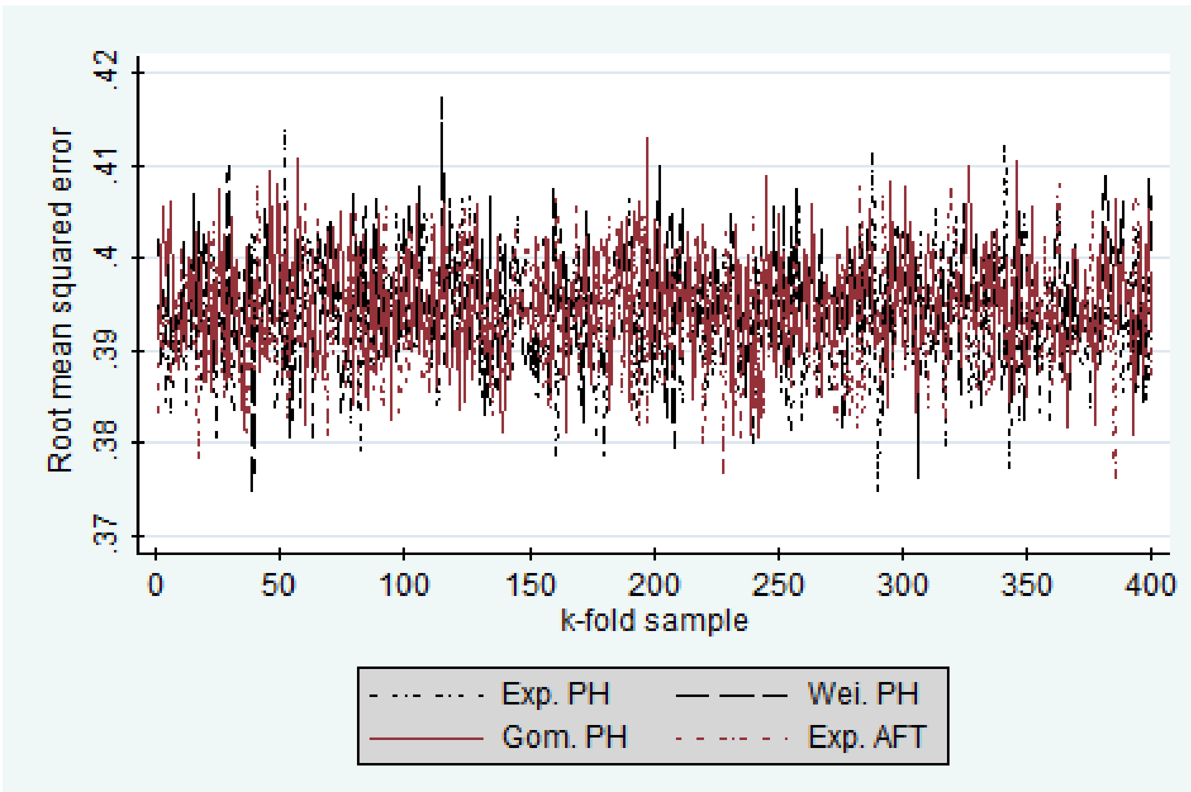


Figure 2.14 *Root mean squared errors (RMSEs) from the automobile retirement model cross-validation (CV) exercise*

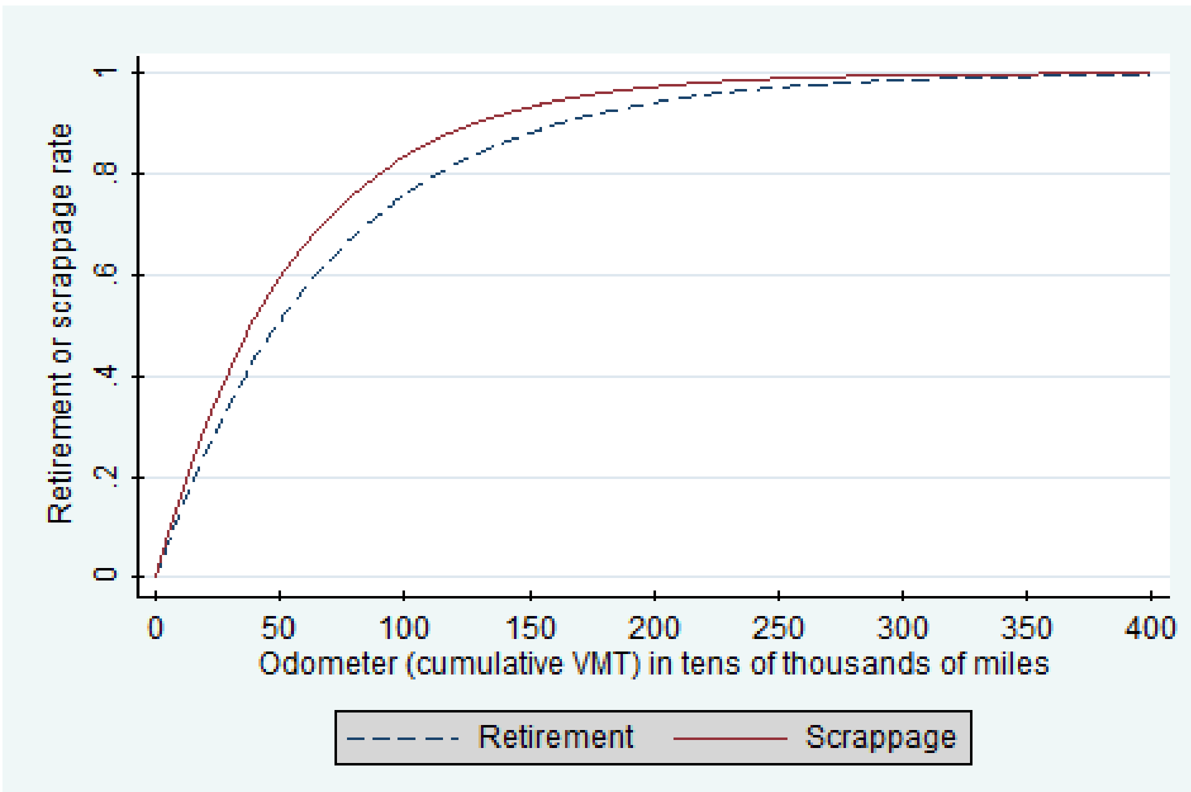


Figure 2.15 *Probability of automobile retirement from a parametric exponential proportional hazard (PH) specification*

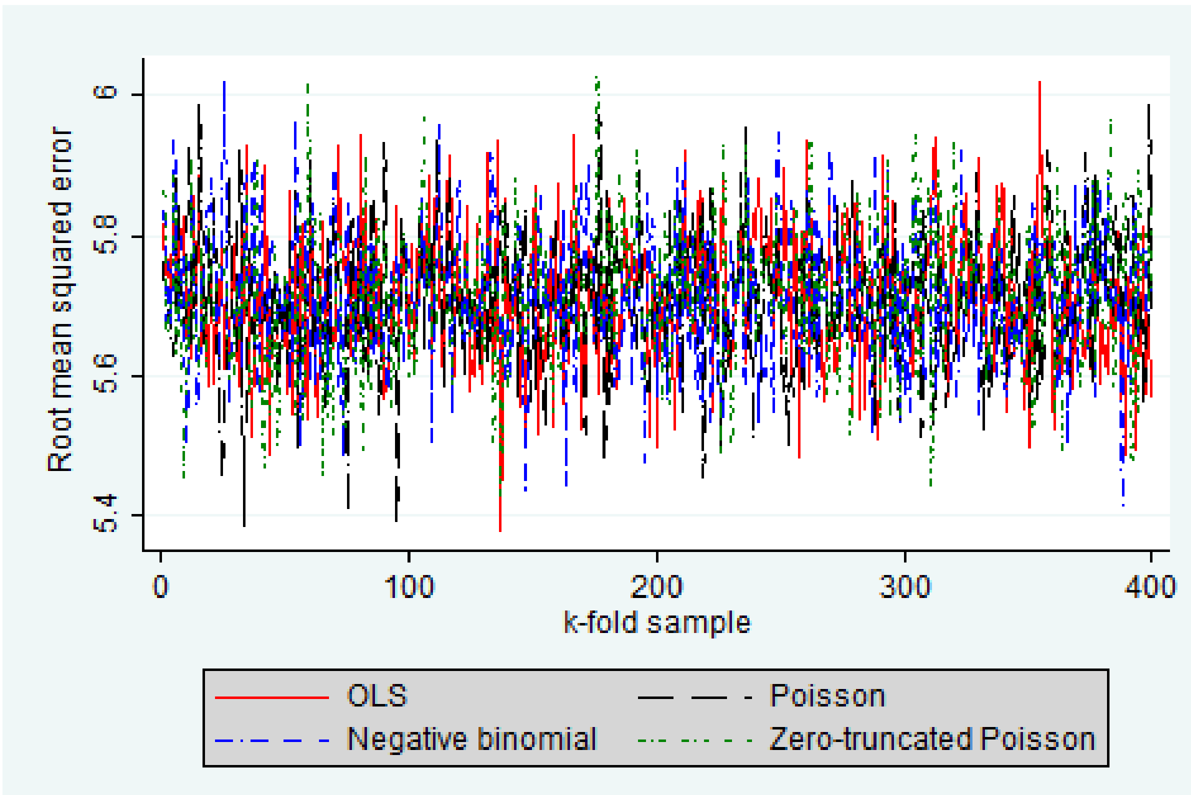


Figure 2.16 *Root mean squared errors (RMSEs) from the inspection duration model cross-validation (CV) exercise*

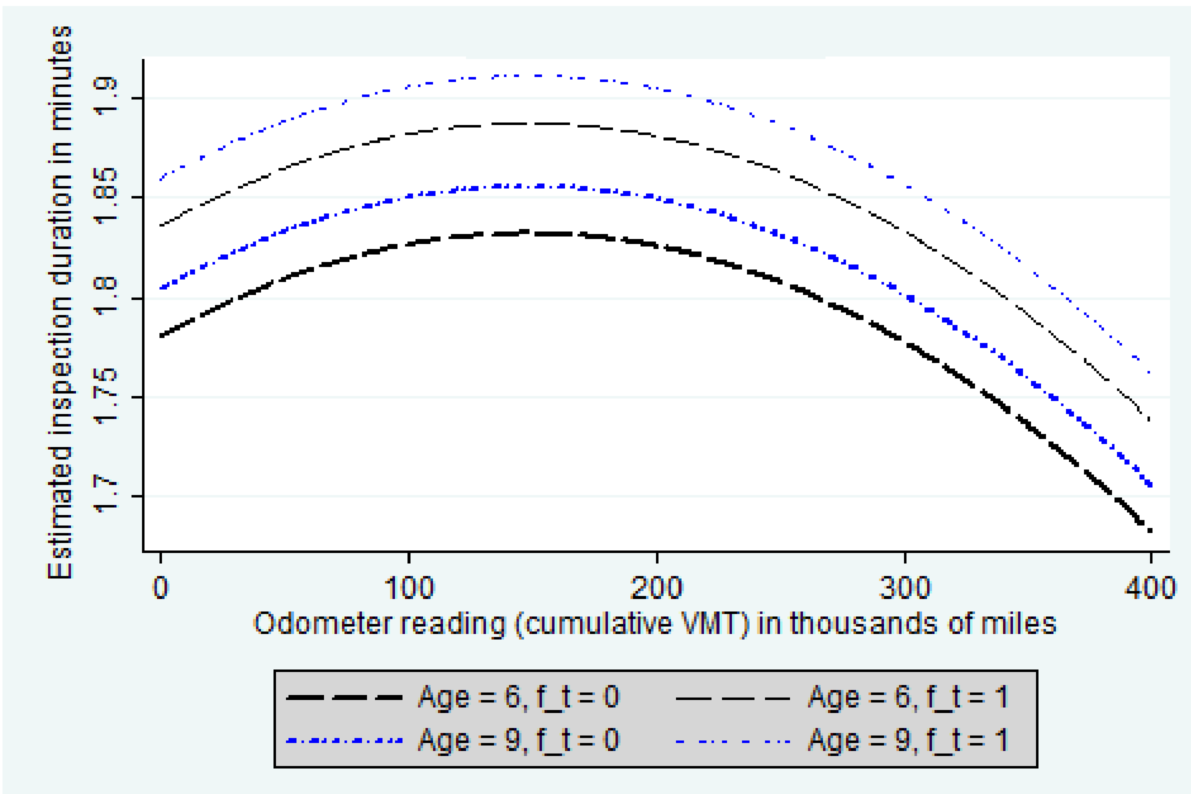


Figure 2.17 *Inspection duration from a Poisson regression*

Table 2.1 *Summary of the* 29 *million emissions inspections from North Carolina between* 1999 *and* 2013

Variable	Description	Mean	Std. Dev.	Min.	Max
model year	*Automobile's model year*	2000	5.30	1981	2013
weight	*Tot. weight w/ std. eqp.*	3,570	756.69	1,620	7,956
cylinders	*Num. of engine cylinders*	5.54	1.39	3	12
engsize	*Engine size in liters*	3.16	1.05	1	8.4
speeds	*Num. transmission speeds*	4.34	0.61	1	9
mpg	*Avg. city-highway MPG*	20.64	4.87	8	98
failure	1 *if auto fails inspection*	0.024	0.15	0	1
# of failures	*Num. of prev. insp. failures for auto*	0.07	0.29	0	8
repaired post-failure	1 *if auto failed & was repaired*	0.02	0.12	0	1
waiver post-failure	1 *if auto failed & received waiver*	0.01	0.08	0	1
scrapped post-failure	1 *if auto failed & was scrapped*	0.001	0.03	0	1
CO GPM	*CO exhaust emissions in GPM*	3.67	8.33	0.07	291.93
HC GPM	*HC exhaust emissions in GPM*	0.24	0.29	0.001	34.45
automobile age	*Automobile's age*	6.50	4.02	−1	24
odometer	*Odometer reading*	88,703	55,578	1,001	399,998
annual VMT	*Annual vehicle-miles traveled*	14,921	12,205	501	384,174
Total number of observations	29,963,065				

Observations are emissions inspections in North Carolina (NC) between 1999 and 2013. The 29 million inspection observations came from the 6.4 million automobiles registered in the state. The data used in this analysis excluded automobiles with more than 400 thousand cumulative vehicle-miles traveled (VMT). While there are registered automobiles that produce almost this amount of VMT in a single year such automobiles are extreme outliers. The median annual VMT produced by automobiles registered in North Carolina (NC) is 12,460.

DATA PROVIDED BY edmunds.com

Table 2.2 *Summary of differences between failed and passed inspections*

Variable	Failed inspection	Passed inspection	Statistical difference
# of failures	1.225	0.037	✓
	(0.537)	(0.214)	✓
repaired post-failure	0.658	0	✓
	(0.474)	(0)	✓
waiver post-failure	0.303	0	✓
	(0.459)	(0)	✓
scrapped post-failure	0.039	0	✓
	(0.195)	(0)	✓
CO GPM	41.507	2.334	✓
	(45.697)	(3.569)	✓
HC GPM	1.273	0.176	✓
	(1.457)	(0.184)	✓
automobile age	9.458	6.441	✓
	(3.715)	(4.014)	✓
odometer	136.018	87.4915	✓
	(54.521)	(55.078)	✓
annual VMT	18.729	14.671	✓
	(18.291)	(12.225)	✓
Most common			
size	Midsize	Midsize	
body-type	Car	Car	
drive-type	Front-wheel drive	Front-wheel drive	
make	Ford	Ford	
model	Explorer	Accord	
# of obs.	702,754	29,066,169	

The mean is reported above the standard deviation (st. dev.). The checkmarks (✓) above indicate a statistical difference between either means or standard deviations at the 0.05-level at a minimum.

Table 2.3 *Summary of the* 6.4 *million unique automobiles registered in North Carolina between* 1999 *and* 2013

Variable	Description	Mean	Std. Dev.	Min.	Max
model year	*Vehicle's model year*	2001	6.15	1981	2013
weight	*Tot. weight w/ std. eqp.*	3,577	773.58	1,620	7,956
cylinders	*Num. of engine cylinders*	5.5	1.39	3	12
engsize	*Engine size in liters*	3.13	1.06	1	8.4
speeds	*Num. transmission speeds*	4.45	0.71	1	9
mpg	*Avg. city-highway MPG*	20.93	5.06	8	98
compressor	*1 if auto has engine compressor*	0.02	0.15	0	1
VIN fail	*1 if auto ever fails*	0.09	0.29	0	1
VIN repair	*1 if auto ever repaired*	0.06	0.24	0	1
Most common size		Midsize			
Most common body-type		Car			
Most common drive-type		Front-wheel drive			
Most common make		Ford			
Most common model		Accord			
Number of observations		6,449,301			

Observations are automobiles, as identified by the unique vehicle identification number (VIN), registered in North Carolina (NC) between 1999 and 2013. The 6.4 million automobiles registered in the state had a combined 29 million emission inspections during that time.

DATA PROVIDED BY edmunds.com

Table 2.4 *Summary statistics for dependent and important independent variables from the seven empirical models*

	N	**mean**	**st. dev.**	**min.**	**max.**
Emission inspection failure in time period *t*	29,768,923	0.0236	0.1518	0	1
Repaired post-failure	29,963,093	0.154	0.1232	0	1
Waiver post-failure	29,963,093	0.0009	0.0307	0	1
Scrapped post-failure	29,963,093	0.0009	0.0304	0	1
CO EPM (grams)	6,788,764	2.7627	7.5554	−15.5801	291.9324
HC EPM (grams)	6,788,764	0.1860	0.2741	−0.7181	34.4503
Annual VMT (thousands of miles)	23,513,792	14.7909	12.4700	0	384.1740
Instantaneous abatement of CO (grams)	9,129,971	0.1152	3.3531	−186.1401	264.5268
Instantaneous abatement of HC (grams)	9,129,971	0.0029	0.1003	−12.5176	29.6028
Automobile is retired in time period *t*	29,963,093	0.2152	0.4110	0	1
Inspection duration (minutes)	29,963,093	7.1409	12.6757	0	120.15
Automobile age (years)	29,963,065	6.5000	4.0200	−1	24
Automobile weight (thousands of pounds)	20,444,869	3.5689	0.7563	1.6200	7.9560
Engine size (liters)	27,278,969	3.1579	1.0520	1	8.4
Fuel economy (MPG)	27,277,750	20.6363	4.8713	8	98
Odometer reading (thousands of miles)	29,963,093	88.8328	55.6416	0	399.9980
Number of emissions inspection failures	29,963,093	0.0656	0.2906	0	8
Emission inspection failure in time period *t-1*	23,398,256	0.0202	0.1408	0	1
Automobile has previous emission failure?	29,963,093	0.0385	0.1925	0	1

Table 2.5 *Description of variables and notation in equations* 1, 2, *and* 3

	Definition
i	Subscript referring to a particular automobile as identified by its vehicle identification number (VIN).
t	Subscript referring to a particular inspection year, 2000 - 2012.
e	Subscript referring to a particular emission, carbon monoxide (CO) or hydrocarbons (HC).
g	Subscript referring to a particular zip-code or county of registration.
B_{it}^{IM}	Benefits of emissions abatement from I/M for automobile i in time t.
$Pr(F_{it})$	Probability that automobile i fails its emissions inspection in time t. $Pr(F_{it}) + ($ 1 - $Pr(F_{it})) = Pr(F_{it}) + Pr(P_{it}) = 1$.
B_{iet}^{R}	Social value of abatement of emission e from repairs to automobile i in time t.
B_{iet}^{S}	Social value of abatement of emission e from scrappage of automobile i in time t.
$Pr(R_{it})$	Probability that automobile i is repaired following a failed emissions inspection in time t. $Pr(R_{it}) + Pr(W_{it}) + Pr(S_{it}) = 1$.
$cvmt_i$	The counterfactual odometer reading for scrapped automobiles. The number of cumulative vehicle-miles traveled automobile i would have produced at retirement in the absence of I/M.
$\sum vmt_{it}$	The odometer reading, or cumulative vehicle-miles traveled, for automobile i at its inspection in time t.

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Table 2.5 *(continued)*

	Definition
ce^{R}_{iet}	The counterfactual emissions of emission *e* for automobile *i* in time *t*. For the example automobile described in section 3.4 in reference to figure 2.3, ce^{R}_{iet} is emissions trajectory **ET1**.
Re_{iet}	The quantity of emission *e* produced by repaired automobile *i* in time *t*. For the example automobile described in section 3.4 in reference to figure 2.3, Re_{iet} is emissions trajectory **ET2**.
ΔE^{R}_{iet}	Abated emissions from I/M repairs. For the example automobile described in section 3.4 in reference to figure 2.3, ΔE^{R}_{iet} is the area between emissions trajectories **ET1** and **ET2** from the time of automobile *i*'s repair until it would have been retired in the absence of I/M.
$Pr(S_{it})$	Probability that automobile *i* is scrapped following a failed emissions inspection in time *t*. $Pr(R_{it})+Pr(W_{it})+Pr(S_{it})=1$.
ce^{S}_{iet}	The counterfactual emissions of emission *e* for automobile *i* in time *t*. For the example automobile described in section 3.4 in reference to figure 2.3, ce^{S}_{iet} is emissions trajectory **ET2**.
ne_{iet}	The quantity of emission *e* produced by the average "new" automobiles in time *t*. For the example automobile described in section 3.4 in reference to figure 2.3, ne_{iet} is emissions trajectory **ET3**.
C^{SCE}_{gte}	Social costs, or marginal external damages (MED), of emissions.

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Table 2.5 *(continued)*

	Definition
ΔE^{S}_{iet}	Abated emissions from I/M scrappage. For the example automobile described in section 3.4 in reference to figure 2.3, ΔE^{S}_{iet} is the area between emissions trajectories **ET2** and **ET3** from the time of automobile *i*'s scrappage until it would have been retired in the absence of I/M.
$Pr(W_{it})$	Probability that automobile *i* receives a waiver following a failed emissions inspection in time *t*. $Pr(R_{it}) + Pr(W_{it}) + Pr(S_{it}) = 1$.
C^{IM}_{it}	Cost of emissions I/M compliance for automobile *i* in time *t*.
P	Price of an emissions inspection paid by automobile owner *i* to the inspection station in time *t*.
τ	Tax paid by automobile owner *i* to the I/M regulator in time *t*.
C^{OC}_{igt}	The opportunity cost of time for automobile *i* registered in county *g* in time *t*.
dur^{1}_{it}	Duration (in minutes) of automobile *i*'s emissions inspection in time *t*.
dur^{R}_{it}	Duration (in minutes) of repairs on automobile *i* in time *t*.
dur^{2}_{it}	Duration (in minutes) of automobile *i*'s follow-up emissions inspection in time *t* after it has been repaired.
dur^{W}_{it}	Duration of of applying and waiting for a waiver to be granted in time *t*.
C^{REP}	The cost of repairs for automobile *i* in time *t*.
C^{RCL}	The repair cost limit for automobile *i* in time *t*.
C^{C}_{it}	State government fee for compliant automobile *i*.
C^{R}_{it}	State government fee and repair cost for repaired automobile *i*.

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Table 2.5 *(continued)*

	Definition
C_{it}^{W}	State government fee, repair cost, and opportunity cost of time for waived automobile i.
C_{it}^{S}	State government fee for scrapped automobile i.
NB_{it}^{IM}	Net benefits of emissions I/M in time t.

Table 2.6 *Root mean squared errors (RMSEs) from the emissions inspection failure model cross-validation (CV) exercise*

Specification	mean	median	st. dev.	min.	max.
1. Cox proportional hazard (PH)	0.3272	0.3186	0.1460	0.1400	0.7289
2. Exponential (Exp.) PH	0.1418	0.1416	0.0091	0.1154	0.1673
3. Weibull (Wei.) PH	0.1418	0.1422	0.0088	0.1169	0.1646
4. Gompertz (Gom.) PH	0.1428	0.1436	0.0086	0.1162	0.1639
5. Exp. accelerated failure time (AFT)	0.1420	0.1424	0.0083	0.1200	0.1676
6. Wei. AFT	0.1426	0.1432	0.0086	0.1183	0.155
7. Lognormal (Logn.) AFT	0.1424	0.1426	0.0087	0.1175	0.1712
8. Loglogistic (Logl.) AFT	0.1432	0.1435	0.0090	0.1214	0.1676
9. Gamma (Gam.) AFT	0.1421	0.1419	0.0080	0.1174	0.1651

The summary statistics above are for each of the 20 cross-validation (CV) exercises. In each of the 20 random draws the data were divided into 20 “folds.” Thus there were 400 draws for each of the 9 specifications examined.

Table 2.7 *Summary statistics and estimated coefficients (and standard errors) from the emissions inspection failure model*

	mean (st. dev.)	**Exponential PH**	(preferred) **Lognormal AFT**	**Gamma AFT**
Emissions inspection failure (dependent variable)	0.021			
	(0.144)			
Annual VMT in excess of average (thousands of VMT)	2.513	−0.014***	0.008***	0.009***
	(11.912)	(0.000)	(0.000)	(0.000)
Age in excess of average (years)	0.792	0.016***	0.001+	0.005***
	(3.477)	(0.008)	(0.000)	(0.000)
Weight in excess of average (thousands of pounds)	0.283	−0.277***	0.075***	0.076***
	(0.736)	(0.024)	(0.004)	(0.003)
Engine size in excess of average (liters)	0.342	0.059***	−0.020***	−0.020***
	(1.053)	(0.008)	(0.002)	(0.002)
Fuel economy in excess of average (MPG)	−0.351	−0.051***	0.020***	0.016***
	(3.847)	(0.003)	(0.001)	(0.001)
Automobile has a previous emissions inspection failure? (1 = yes; 2 = no)	0.042	1.410***	−0.723***	−0.493***
	(0.200)	(0.023)	(0.005)	(0.003)
Number of observations		11,655,027		

Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 2.8 *Root mean squared errors (RMSEs) from the discrete choice among repair, waiver, or scrappage model cross-validation (CV) exercise*

		min.	**max.**	**mean**	**st. dev.**
Repair	**logit**	0.426	0.450	0.438	0.004
	probit	0.425	0.450	0.438	0.004
Waiver	**logit**	0.384	0.416	0.400	0.006+
	probit	0.383	0.416	0.399	0.006+
Scrap	**logit**	0.335	0.379	0.359**	0.007
	probit	0.335	0.377	0.358**	0.006

The statistical significance between logit and probit means and standard deviations are reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 2.9 *Summary statistics and estimated coefficients (and standard errors) from the discrete choice among repair, waiver, or scrappage model*

	mean	Repair		Scrappage	
	(st. dev.)	Logit	Probit	Logit	Probit
Repair (dependent variable)	0.710				
	(0.454)				
Waiver (dependent variable)	0.163				
	(0.369)				
Scrap (dependent variable)	0.127				
	(0.333)				
Odometer reading (in tens of thousands of miles)	135.541	−0.003***	−0.003***	0.002***	0.001***
	(51.453)	(0.000)	(0.000)	(0.000)	(0.000)
Annual VMT (thousands of miles)	19.202	−0.009***	−0.007***	0.005***	0.004***
	(16.982)	(0.000)	(0.000)	(0.000)	(0.000)
Automobile age (years)	8.810	−0.001	−0.003+	0.110***	0.075***
	(3.044)	(0.003)	(0.002)	(0.003)	(0.002)
Fuel economy in excess of average (MPG)	20.696	0.012***	0.011***	−0.031***	−0.019***
	(4.300)	(0.003)	(0.002)	(0.004)	(0.003)
Automobile weight (thousands of pounds)	3.422	0.169***	0.130***	−0.033	−0.019
	(0.714)	(0.019)	(0.014)	(0.026)	(0.017)
Number of emissions inspection failures	1.250	−0.236***	−0.190***	0.058***	0.043***
	(0.552)	(0.009)	(0.007)	(0.011)	(0.008)
Prob > chi^2		0.000	0.000	0.000	0.000
Pseudo R^2		0.081		0.081	
Number of observations		322,861			

Waiver is the base outcome. Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 2.10 *Root mean squared errors (RMSEs) from the emissions per mile (EPM) model cross-validation (CV) exercise*

	CO		**HC**	
	mean	**st. dev.**	**mean**	**st. dev.**
1. ordinary least squares (OLS)	7.719	0.624	0.247	0.057
2. Poisson	30.881	462.694	143.880	2,834.346
3. Panel data OLS	7.784	0.955	0.254	0.065
4. generalized linear model (GLM), Gaussian, Log link	57.928	1,000.114	188.911	2,681.887
5. generalized linear model (GLM), Poisson, Identity link	7.877	0.516	0.244	0.033
6. generalized linear model (GLM), Negative binomial, Identity link	7.934	0.521	0.247	0.033

The summary statistics above are for each of the 20 *k*-fold cross-validation (CV) exercises. In each of the 20 random draws the data were divided into 20 "folds." Thus there were 400 draws for each of the 6 specifications.

Table 2.11 *Summary statistics and estimated coefficients (and standard errors) from the emissions per mile (EPM) model*

	mean (st. dev.)		**Panel data ordinary least squares (OLS)**		**Seemingly unrelated OLS**	
	CO	**HC**	**CO**	**HC**	**CO**	**HC**
EPM (grams) in time period *t* (dep. var.)	2.702 (7.251)	0.183 (0.265)				
EPM (grams) in time period *t-1*	2.378 (6.509)	0.168 (0.237)	0.234*** (0.004)	0.249*** (0.007)	0.289*** (0.001)	0315*** (0.001)
APM (grams) in time period *t-1*	0.081 (2.860)	0.011 (0.105)	−0.047** (0.014)	−0.101*** (0.016)	−0.059*** (0.003)	−0.109*** (0.002)
Odometer (tens of thousands of miles)	84.828 (47.202)		0.010*** (0.000)	0.001*** (0.000)	0.010*** (0.000)	0.001*** (0.000)
Automobile age (years)	6.199 (3.325)		0.027*** (0.004)	0.001*** (0.000)	0.021*** (0.003)	0.001*** (0.000)
Inspection failure in time period *t-1*	0.008 (0.092)		−4.797** (0.142)	−0.101*** (0.005)	−6.811*** (0.044)	−0.162*** (0.002)
Inspection failure in time period *t*	0.011 (0.105)		38.356*** (0.267)	0.996*** (0.008)	38.352*** (0.032)	0.996*** (0.001)
Number of observations			2,982,201			

Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 2.12 *Comparison of actual emissions versus predictions from seemingly unrelated OLS emissions per mile (EPM) model*

	mean	**st. dev.**	**min.**	**max.**
	grams of carbon monoxide (CO)			
Actual	2.702	7.250	−15.580	275.611
Prediction	2.702	4.538	−16.458	72.598
	grams of hydrocarbons (HC)			
Actual	0.183	0.265	−0.718	34.450
Prediction	0.183	0.164	−8.927	2.911

Table 2.13 *Root mean squared errors (RMSEs) from the annual vehicle-miles traveled (VMT) model cross-validation (CV) exercise*

Specification	mean	st. dev.	min.	max.
1. ordinary least squares (OLS)	5.353	0.015	5.313	5.391
2. Poisson regression	5.334	0.016	5.282	5.378
3. negative binomial (NB) regression	5.392	0.019	5.338	5.457
4. zero-truncated Poisson (ZTP)	5.336	0.017	5.281	5.391
5. zero-truncated negative binomial (ZTNB)	5.399	0.017	5.354	5.447
6. panel data (XT) Poisson	12.883	0.028	12.802	12.971
7. XT negative binomial random effects (RE)	12.846	0.029	12.761	12.945
8. XT negative binomial fixed effects (FE)	12.416	0.032	12.319	12.510
9. XT negative binomial population averaged (PA)	5.442	0.018	5.394	5.484
10. generalized linear model (GLM), Gaussian, log link function	6.815	0.042	6.707	6.936
11. GLM, Poisson, identity link function	8.974	0.126	8.692	9.315
12. GLM, negative binomial, identity link function	9.924	0.168	9.484	11.111
13. GLM, Gamma, log link function	11.085	0.422	9.984	12.417

The summary statistics above are for each of the 20 *k*-fold cross-validation (CV) exercises. In each of the 20 random draws the data were divided into 20 “folds.” Thus there were 400 draws for each of the 13 specifications.

Table 2.14 *Summary statistics and estimated coefficients (and standard errors) from the annual vehicle-miles traveled (VMT) model*

	mean (st. dev.)	**OLS**	**Poisson**	**ZTP**	**NB**	**ZTNB**	**GLMGL**
Annual VMT in 1000s of miles (dep. var.)	14.416						
	(9.207)						
Odometer reading in thousands of miles	95.501	0.118***	0.008***	0.008***	0.009***	0.009***	0.007***
	(51.015)	(0.000)	(5.69e−06)	(5.68e−06)	(5.22e−06)	(5.29e−06)	(9.25e−06)
Automobile age in years	6.744	−1.761***	−0.127***	−0.128***	−0.127***	−0.128***	−0.126***
	(3.434)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Previous inspection failure for automobile?	0.045	−1.401***	−0.088***	−0.086***	−0.084***	−0.082***	−0.094***
	(0.207)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Fuel economy in MPG	20.646	−0.023***	−0.002***	−0.002***	−0.002***	−0.002***	−0.003***
	(4.756)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Natural log of the price per VMT	−2.022	−0.274***	−0.024***	−0.024***	−0.021***	−0.022***	−0.028***
	(0.397)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of obs.				17,454,738			

Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 2.15 *Distribution of estimated annual VMT in thousands of miles by specification*

	mean	st. dev.	min.	max.
Actual thousands of annual VMT	14.791	12.470	0	384.174
ordinary least squares (OLS)	14.583	6.354	−160.441	106.302
Poisson	13.027	1.859	4.678e−05	395.836
zero-truncated Poisson (ZTP)	11.905	3.245	1.338e−06	393.468
negative binomial (NB)	13.001	1.790	4.623e−06	907.778
zero-truncated negative binomial (ZTNB)	12.073	2.768	1.343e−05	894.263
generalized linear model (GLM), Gaussian, log link function	14.803	6.052	0	223.487

Table 2.16 *Root mean squared errors (RMSEs) from the instantaneous emissions abatement model cross-validation (CV) exercise*

Specification	**mean**	**st. dev.**	**min.**	**max.**
	carbon monoxide (CO)			
ordinary least squares (OLS)	3.223	0.194	2.746	3.806
GLM, Gamma, log link function	3.373	0.093	3.146	3.723
GLM, Poisson, identity link function	2.39e+15	3.98e+15	3.752	2.02e+16
GLM, NB, identity link function	91.174	75.159	77.285	710.245
	hydrocarbons (HC)			
ordinary least squares (OLS)	0.098	0.006	0.083	0.116
GLM, Gamma, log link function	0.118	0.037	0.086	0.587
GLM, Poisson, identity link function	6.04e+13	1.07e+14	1.967	6.90e+14
GLM, NB, identity link function	16.134	0.354	15.087	16.985

The summary statistics above are for each of the 20 *k*-fold cross-validation (CV) exercises. In each of the 20 random draws the data were divided into 20 “folds.” Thus there were 400 draws for each of the 8 specifications.

Table 2.17 *Summary statistics and estimated coefficients (and standard errors) from the instantaneous emissions abatement model*

	mean (st. dev.)		ordinary least squares (OLS)		seemingly unrelated OLS	
	CO	HC	CO	HC	CO	HC
APM in time period t (dep. var.)	0.085	0.002				
	(2.892)	(0.084)				
Emissions failure times odometer (thousands of miles)	1.994		−0.018***	−0.001*	−0.017***	−0.001***
	(17.756)		(0.003)	(0.000)	(0.000)	(0.000)
Emission failure times EPM (grams)	0.561	0.017	0.173***	0.173***	0.172***	0.174***
	(7.094)	(0.224)	(0.013)	(0.032)	(0.008)	(0.001)
Previous failure times odometer (thousands of miles)	1.596		−0.002+	−0.000	−0.002***	−0.000
	(15.892)		(0.001)	(0.000)	(0.000)	(0.000)
Automobile age (years)	7.555		−0.012***	−0.000**	−0.012***	−0.000**
	(3.372)		(0.002)	(0.0000)	(0.002)	(0.000)
RMSE			2.632	0.078	2.632	0.078
R^2			0.172	0.148	0.172	0.148
Number of obs.			2,653,451			

Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 2.18 *Root mean squared errors (RMSEs) from the automobile retirement model cross-validation (CV) exercise*

Specification	mean	st. dev.	min.	max.
1. Cox proportional hazard (PH)	0.875	0.007	0.841	0.887
2. Exponential PH	0.393	0.006	0.375	0.393
3. Weibull PH	0.395	0.006	0.374	0.395
4. Gompertz PH	0.395	0.006	0.381	0.395
5. Exponential accelerated failure time (AFT)	0.394	0.006	0.375	0.394
6. Weibull AFT	0.396	0.007	0.378	0.396
7. Lognormal AFT	0.403	0.007	0.385	0.403
8. Loglogistic AFT	0.411	0.007	0.391	0.411

The summary statistics above are for each of the 20 *k*-fold cross-validation (CV) exercises. In each of the 20 random draws the data were divided into 20 "folds." Thus there were 400 draws for each of the 8 specifications.

Table 2.19 *Summary statistics and estimated coefficients (and standard errors) from the automobile retirement model*

	mean (st. dev.)	exp. PH	Wei. PH	Gom. PH	exp. AFT
Automobile is retired? (dep. var.)	0.182				
	(0.386)				
Annual VMT in excess of average (thousands of miles)	2.558	−0.035***	−0.041***	−0.041***	0.035***
	(11.943)	(0.000)	(0.000)	(0.000)	(0.000)
Age in excess of average (years)	0.789	0.104***	0.051***	0.046***	−0.104***
	(3.394)	(0.005)	(0.000)	(0.000)	(0.005)
Weight in excess of average (thousands of pounds)	0.089	−0.045*	0.028***	0.031***	0.045*
	(0.743)	(0.022)	(0.003)	(0.003)	(0.023)
Engine size in excess of average (litres)	0.189	0.053***	0.077***	0.075***	−0.080***
	(1.040)	(0.002)	(0.002)	(0.002)	(0.002)
Fuel economy in excess of average (MPG)	0.413	−0.006**	0.001**	−0.001***	0.006**
	(4.361)	(0.002)	(0.000)	(0.000)	(0.002)
Number of previous inspection failures	0.071	0.166***	0.101***	0.066***	−0.166***
	(0.300)	(0.007)	(0.002)	(0.002)	(0.006)
Number of obs.			13,799,126		

Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 2.20 *Root mean squared errors (RMSEs) from the inspection duration model cross-validation (CV) exercise*

Specification	mean	st. dev.	min.	max.
1. ordinary least squares (OLS)	5.711	0.104	5.377	6.020
2. Poisson	5.710	0.100	5.385	5.991
3. negative binomial (NB)	5.712	0.101	5.416	6.024
4. zero-truncated Poisson (ZTP)	5.716	0.105	5.417	6.030
5. zero-truncated negative binomial (ZTNB)	5.725	0.105	5.415	5.991
6. panel data (XT) Poisson population averaged (PA)	5.718	0.235	5.015	6.372
7. XT NB PA	5.755	0.208	5.235	6.351
8. XT OLS random effects (RE)	5.735	0.223	5.026	6.256
9. XT OLS fixed effects (FE)	5.721	0.254	5.070	6.402

The summary statistics above are for each of the 20 *k*-fold cross-validation (CV) exercises. In each of the 20 random draws the data were divided into 20 “folds.” Thus there were 400 draws for each of the 9 specifications.

Table 2.21 *Summary statistics and estimated coefficients (and standard errors) from the inspection duration model*

	mean (st. dev.)	**OLS**	**Poisson**	**NB**	**ZTP**
Inspection duration in minutes (dep. var.)	7.316				
	(6.033)				
Odometer reading (thousands of miles)	85.605	0.005***	0.001***	0.001***	0.001***
	(53.760)	(0.000)	(0.000)	(0.000)	(0.000)
Automobile age (years)	6.051	0.058***	0.008***	0.007***	0.008***
	(3.634)	(0.001)	(0.000)	(0.000)	(0.000)
Emission inspection failure in time period t	0.023	0.576***	0.072***	0.080***	0.073***
	(0.150)	(0.011)	(0.001)	(0.001)	(0.002)
Number of previous inspection failures	0.061	−0.128***	−0.017***	−0.016***	−0.017***
	(0.277)	(0.007)	(0.001)	(0.001)	(0.001)
Number of obs.			22,723,589		

Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 2.22 *Summary of preferred specifications*

Model	Preferred specification	Specification chosen based on CV?	Reason for alternative choice
Emissions inspection failure	Lognormal accelerated failure time (AFT) survival model		Shape of the baseline hazard function
The repair, waiver, scrappage choice	Multinomial probit regression	✓	
Emissions per mile	Seemingly unrelated ordinary least squares (OLS) regression	✓	
Vehicle-miles traveled	Gaussian generalized linear model (GLM) with log link function		Distributions of predictions
Instantaneous abatement from repairs	Seemingly unrelated ordinary least squares (OLS) regression	✓	
Automobile retirement	Exponential proportional hazard (PH) survival model	✓	
Inspection duration	Poisson regression	✓	

CHAPTER 3

SELECTIVE AUTOMOBILE TARGETING

3.1 Introduction

State environmental regulators use automobile emissions inspection and maintenance (I/M) programs to identify and repair (or scrap) noncompliant automobiles with high levels of emissions. In principle, the abatement should improve air quality and help states comply with National Ambient Air Quality Standards (NAAQS). The relationship between I/M induced abatement and air quality improvements, however, is weak and poorly understood (Kahn, 1996a; Sanders & Sandler, 2015). Furthermore, despite endorsement by the U.S. Environmental Protection Agency (EPA), these programs have received a great deal of scrutiny since their inception in the 1970s.[1] In turn I/M programs across the country have been modified numerous times. For example, North Carolina recently increased I/M exemptions for registered automobiles with relatively low inspection failure

[1] See Ando et al. (2000), Eisinger & Wathern (2008), Glazer et al. (1995), Harrington et al. (2000), Hubbard (1997), and Washburn et al. (2001).

rates. Specifically, in April 2015 the state extended its new automobile exemption from one to three model years with less than 70 thousand miles (NCGA, 2012).

As shown in table 1.2 previous academic literature has focused on the effectiveness of I/M at reducing automobile emissions rather than overall efficiency. Furthermore research shows that repairs that do lower emissions are not durable or persistent (Mérel et al., 2014; Wenzel et al., 2004). Additionally several evaluations have shown that I/M is generally neither an effective nor a cost-effective policy (Harrington et al., 2000; Mérel et al., 2014).[2] One often cited cause of the high costs is the use of a blanket approach to inspections. Most I/M programs require nearly all registered automobiles to submit to periodic inspections and incur compliance costs. The social benefits, however, are generated from emissions reductions from only a small number of noncompliant automobiles.[3] The high costs have led other researchers to suggest more selective targeting of automobiles.[4] The recent change to I/M in North Carolina is a real world application of *selective automobile targeting*.

While past economic research on selective targeting suggests that the recent change to North Carolina's I/M program will increase its efficiency, two key questions remain. First, it is unclear from past research how efficient these programs are. Second, it is unclear how much additional efficiencies could be realized from selective targeting along margins other than age and odometer reading.

I employ two main tools to answer these research questions. First, as I describe in chapter 2, I develop a conceptual framework that provides comprehensive accounting of costs and benefits from both I/M induced repairs and scrappage. Second, I use an extensive dataset of all emissions inspections in North Carolina between 1999 and 2013 to estimate seven empirical models. An

[2] Reitze Jr. (1996) and the Committee on Vehicle Emissions Inspection and Maintenance Programs (CVEIM) of the National Research Council (NRC) 2001, however, claim that I/M is more cost-effective than other methods of reducing air pollution. Fowlie et al. (2012) find the marginal abatement cost of nitrogen oxides from automobiles is less than half from power plants.

[3] See Beaton et al. (1995), Harrington et al. (2000), Kahn (1996b), and Lawson (1993).

[4] See Bin (2003), Glazer et al. (1995), Moghadam & Livernois (2010), and Washburn et al. (2001).

advantage of the framework is that it can be used to extend the work of Moghadam & Livernois (2010), among others, by estimating changes to I/M's efficiency under various testing regimes. I estimate the efficiency for several different inspection frequencies, such as biennial and triennial, as well as regimes that selectively target based on different automobile attributes such as age, odometer reading, drive type, body type, or engine size.

My results suggest that the North Carolina program, as it existed between 1999 and 2013, is not efficient and generates net benefits of −$44.5 million per year.[5] This result is driven by the costs incurred by owners of the 92 percent of automobiles that consistently pass I/M tests as well as limited abatement due to poor repair durability. While the state's recent increased exemption will reduce I/M compliance costs to automobile owners by 44 percent to $41 million, it still fails to generate positive net benefits of I/M. I estimate that the average annual net benefits of I/M under this regime will be −$16.0 million holding the characteristics of fuel, the automobile fleet, and driving behaviors constant.[6]

The framework can also be used to estimate the efficiency of other potential I/M regimes, several of which generate positive net benefits. For example, the California I/M regime appears to be a potential Pareto improvement over the North Carolina I/M program because it generates larger net benefits.[7] The most efficient selective targeting regime is one that requires only automobiles older than 5 years that are driven more than 20 thousand miles annually to report for periodic inspections. The results of this framework should be of interest to policy makers and researchers alike.

[5]A comparison of benefits to costs is relevant for two reasons. First, the Clean Air Act requires that the U.S. EPA engage in benefit cost analysis (BCA) when administering environmental programs (USC, 2004b). Second, Executive Order 13563 requires government agencies to "propose or adopt a regulation only upon a reasoned determination that its benefits justify its costs." In addition, the order also requires government agencies to "tailor its regulations to impose the least burden on society, consistent with obtaining regulatory objectives." Because some environmental regulations explicitly rule out BCA this applies only to the maximum degree allowed by law. For example, some air toxics regulations ignore costs for unacceptable risks (Farrow & Toman, 1998) and the U.S. EPA is prohibited from weighing costs when setting federal air quality standards (Kahn, 1996a; McLaughlin, 2008).

[6]Data on exhaust emissions of nitrogen oxide are currently unavailable. Assuming nitrogen oxide emissions behave like hydrocarbons and carbon monoxide, I estimate that social benefits of I/M induced repair and scrappage would increase 7 percent to $34.3 million per year.

[7]The California I/M program is commonly referred to as the California Smog Check Program (SCP).

My results should be interpreted cautiously. While my data are extensive they are not perfect. The imperfections impose some limitations on my analysis that I discuss in detail in section 5.2. For example, in this dissertation I estimate the benefits of carbon monoxide (CO) and hydrocarbons (HC) emissions abatement. Thus my analysis ignores the benefits of abating other emissions such as carbon dioxide (CO_2), nitrogen oxides (NO_X), and particulate matter (PM). It is possible that the benefits of abatement from all of these emissions together exceed the costs of I/M. On the other hand, I ignore the time costs of repairing non-compliant automobiles, which may be considerable. It is possible that the total cost of I/M including time spent on repairs outweigh the benefits of abatement of all emissions.

This chapter proceeds as follows. First, section 3.2 discusses the relevant past literature. Section 3.3 then describes the extensive dataset used. Next, section 3.4 summarizes the estimation framework and section 3.5 presents results of the analysis. Finally, section 3.6 concludes.

3.2 Literature review

This chapter builds on several broad areas of past economic research. Most importantly it extends the work of those papers, shown in table 1.2, that have analyzed the effectiveness or cost-effectiveness of I/M. Nearly all previous economic evaluations have sought to answer questions about the effectiveness, rather than efficiency, of I/M. Despite their extensive use around the world I/M has received relatively limited attention from economists.[8] Examples of economic evaluations include Ando et al. (2000), Glazer et al. (1995), Harrington et al. (2000), Hubbard (1997), Kahn (1996b, 1996c), Mérel et al. (2014), Moghadam & Livernois (2010), and Sanders & Sandler (2015).[9] The selective targeting literature, shown in table 3.6, is the second area that this chapter builds on and is closely to the

[8] They have, however, provided crucial data for a wide range of other economic analyses such as the analysis of fraud (Hubbard, 1998; Oliva, 2012; Pierce & Snyder, 2008), demand elasticities for fuel or vehicle-miles traveled (VMT) (Gillingham, 2013), and correlations between automobile attributes and emissions (Anilovich, 1996; Beydoun & Guldmann, 2006; Bin, 2003; Harrington, 1997; Kahn, 1996a, 1996b; Khazzoom, 1995; Washburn et al., 2001).

[9] Government or industry outsourced evaluations of I/M include ARB (2005), Ayers & Walter (2005), CVEIM (2001), ERGI (2006, 2008), LAC (2001), NCPED (2008, 2012a,b), and OIG (2003).

cost-effectiveness papers listed in table 1.2. Examples include Ando et al. (2000), Bin (2003), Glazer et al. (1995), Moghadam & Livernois (2010), and Washburn et al. (2001). The selective targeting literature either evaluate I/M programs or discuss how differentiated treatment based on automobile attributes could improve the efficiency of I/M. Thus, the selective targeting literature builds on another body of research, also shown in table 3.6, that has found correlations between automobile attributes and emissions. Finally, this chapter also indirectly extends the research on emissions reductions and abatement from automobile repairs (Ando et al., 2000; Mérel & Wimberger, 2012; Mérel et al., 2014; Wenzel et al., 2004).

Table 1.2 categorizes whether the previous economic evaluations of I/M focus on questions of effectiveness, cost-effectiveness, or efficiency. The papers that analyze the effectiveness of I/M examine the extent to which the programs produce abatement from repairs or scrappage, or improve air quality. Other papers attempt to rank I/M relative to other programs by estimating the abatement per dollar or cost-effectiveness. The difference between cost-effectiveness and efficiency lies with the units used to measure the benefits of the program. Efficiency requires that the mass of abated emissions be multiplied by their social value (marginal external damages (MED)) to calculate net benefits. Thus while effectiveness and efficiency are distinct categorizations, cost-effectiveness and efficiency are not. By evaluating the efficiency of I/M I help to fill a major gap in the literature.

The literature highlighted in table 1.2 largely agrees that I/M is not effective at meeting its goals. Glazer et al. (1995), for example, summarizes previous analyses of I/M and discusses factors that have lead to the failure of California's Smog Check Program (SCP). Foremost among these is the inability of I/M to lower automobile emissions.[10] A similar conclusion was arrived at by Kahn (1996b) who compared data from both the Smog Check Program and random California roadside audits.

[10]Kahn (1996c) and Sanders & Sandler (2015) have analyzed the effectiveness of I/M at meeting its air quality improvement goal. Kahn (1996c) found that while the Illinois I/M program decreased ambient ozone it did little to decrease ambient concentrations of carbon monoxide. The results of Sanders & Sandler (2015), however, show that the opposite is true. They found that the California SCP decreased carbon monoxide and had almost no effect on ozone. Such conflicting results suggest that the relationship between I/M and air quality is not well understood. Furthermore, these results suggest that I/M may be only marginally effective at achieving its air quality improvement goal.

Mérel et al. (2014) and Wenzel et al. (2004), like Kahn (1996b), also reported that inspection induced repairs do not affect automobile emissions.

Ando et al. (2000), Glazer et al. (1995), Kahn (1996c), Moghadam & Livernois (2010), and Washburn et al. (2001) all agree on one point about I/M programs: efficiency could be improved by eliminating the common I/M requirement of universal testing of automobiles (the *blanket* approach). In fact, this undifferentiated approach is unique compared to other policy areas that often only inspect a subset of polluting entities. Glazer et al. (1995) suggest that both the efficiency and effectiveness could be improved by focusing resources on the maintenance of the 10 percent or less of the fleet that account for more than 50 percent or more of aggregate emissions (Beaton et al., 1995; Kahn, 1996b; Lawson, 1993).

Ando et al. (2000) argued that *selective automobile targeting* could reduce costs because there is considerable variation in costs and repair durability. For example, there may be significant differences among different automobile vintages, drive types, or engine types. Similarly, Kahn (1996c) pointed out that the age distribution of the automobile fleet will impact I/M induced abatement as exhaust emissions standards are tightened. Using panel data of Illinois air quality he showed that areas subject to periodic I/M measured statistically less ozone and, to a lesser extent, carbon monoxide. In addition, Kahn (1996c) found a significant negative time trend that he explained was caused by "secular declines in new car emissions." Thus, Kahn argued, the benefits of I/M would decline as older automobile cohorts that were produced under more lenient exhaust emissions standards are phased out of the fleet while costs increase as automobile owners' value of time rises.

This chapter is also closely related to Moghadam & Livernois (2010) who estimate the abatement cost function for Ontario's I/M program. Their cost-minimization model estimates the marginal abatement cost (MAC) is so high that even a small reduction in the abatement target would lead to substantial reductions in costs to motorists. The savings can either be realized by testing less frequently or inspecting fewer automobiles. For example, they found that the optimal age to begin periodic emissions testing is higher than has been adopted by many programs. Specifically, Moghadam

& Livernois (2010) conclude that 60 percent of the maximum technically feasible abatement can be realized at a fifth of the cost by testing only three age cohorts. In addition, their cost-minimizing solution requires testing vehicles less frequently than is commonly practiced.[11] The optimal I/M regime would test automobiles older than 4 and less than 12 years biennially and automobiles older than 12 and less than 19 years annually. One drawback to this analysis, however, are that the models of failure and abatement estimated are parsimoniously specified as only functions of automobile age.

The primary contribution I make in this chapter is the application of a comprehensive framework for the evaluation of the efficiency of I/M. The framework, described in detail in chapter 2 of my dissertation, was developed with the help of several areas of previous literature and the insights drawn from previous analyses. It is comprehensive in that it estimates seven empirical models to calculate both the costs *and* benefits of abatement from both I/M induced repairs and scrappage. I improve on past evaluations of I/M by estimating the extent to which retirement of older automobile cohorts decreases the benefits of I/M.[12]

In addition, in this chapter I improve on and extend the past literature in several other ways. For example, instead of considering the quantity of emissions abated, like Moghadam & Livernois (2010), I extend the analysis to estimate the social value of emissions abatement. In addition, I use a much more extensive dataset relative to past literature such as Ando et al. (2000), Kahn (1996c), and Moghadam & Livernois (2010). The dataset has 11 more years worth of emissions inspections data than has often been used. Like Ando et al. (2000) I also find large variation in I/M induced abatement. Finally, I combine the estimation framework and the extensive dataset from North Carolina to compare the efficiency of various I/M regimes including those that selectively target automobiles for inspection. The regimes include those from California and the new North Carolina program as well as variations of those suggested in the selective targeting literature. For example, Bin

[11] Moghadam & Livernois (2010) suggest these savings could be reallocated to different pollution sources or policies that have a lower marginal cost and potentially achieve an increase in abatement.

[12] Such as Ando et al. (2000), Harrington et al. (2000), Kahn (1996c), and Moghadam & Livernois (2010).

(2003) concluded that “targeting vehicles more than ten years old, with engines smaller than 2,000 cubic centimeters, and more than 100,000 miles could improve the cost-effectiveness by increasing the likelihood of finding and scrapping or repairing high polluting vehicles.” While several papers have discussed the use of selective targeting, only Moghadam & Livernois (2010) have quantified how it may affect I/M's cost-effectiveness.

3.3 Data

The data I use in this dissertation come from three main sources. First, I use data provided by the North Carolina Division of Motor Vehicles (DMV) and Division of Air Quality (DAQ). The DMV data identifies the name, address, and station identification number of all emissions inspection stations in North Carolina. The North Carolina I/M data I use in this dissertation include all emissions inspections conducted in the state between 1999 and 2013 and come from the North Carolina DAQ. These data include 29 million emissions inspection observations (summarized in table 2.1) from 6.4 million unique automobiles (summarized in table 2.3). In addition, I use automobile attributes collected from the Edmunds.com, Inc. application program interface (API) and publicly available macroeconomic data. Section 2.2 provides a detailed description of these data.

3.4 Estimation framework

In North Carolina passing an annual emissions inspection is a prerequisite of annual automobile registration. Figure 2.1 illustrates two basic concepts about I/M programs. First, costs are imposed on owners of both compliant and noncompliant automobiles. The results, and duration, of each emissions inspection are directly observable in the DAQ data. Second, only noncompliant automobiles generate emissions abatement and thus have the potential to generate positive net benefits. Following a failed emissions inspection owners face a discrete choice among repair the automobile in full, apply for a waiver, or scrap the automobile.[13] Because my data include all emissions inspections I observe both the initial annual inspection and subsequent post-repair re-inspections. Using the results of these inspections, or the absence of them, I can infer the difference between repaired, waivered, and scrapped automobiles. Owner of noncompliant automobiles who spend \$200 towards emissions related repairs may apply for a waiver from the DMV that allow them to drive a noncompliant automobile until the next annual inspection.

Figure 2.3 illustrates I/M-induced emissions abatement from automobile repairs and scrappage. Equation 2.1 operationalizes the benefits of I/M as illustrated in figures 2.1 and 2.3. The costs of I/M are given in equation 2.2. These two equations are calculated using estimates of seven empirical models discussed in detail in sections 2.3 and 2.4.

For this analysis I calibrate the parameters of equation 2.2 using North Carolina values. First, the price (P) of an emissions test is \$10.15. The tax (τ) distributed to the I/M regulator by the inspection station is \$6.25. Second, the North Carolina I/M regulator has set the repair cost limit (C^{RCL}) equal to \$200. I also assume that owners must travel round-trip for 30 minutes in addition to the duration of the initial emissions inspection (dur_{it}^{1}). Finally, I assume automobile owners spend 30 minutes at the DMV while applying for waivers.

3.5 Results

Figure 3.1 plots the estimated benefits and costs, in millions of 2015 U.S. dollars, of North Carolina's I/M program between 2000 and 2012.[14] Most importantly figure 3.1 illustrates that the program, as it existed during that period, was inefficient. Mean annual benefits from I/M induced abatement from repairs and scrappage were \$28.5 million compared to an average annual cost of \$73.0 million.

[13] In this dissertation I abstract away from reality and assume that owners of noncompliant automobiles will not drive illegally. Registered automobiles are easily identified by law enforcement by a colored sticker on the license place. In North Carolina I/M in 48 relatively urban counties home to approximately 80 percent of the state population where the probability of being caught driving an unregistered automobile are relatively high.

[14] This analysis omits data from 1999 and 2013. The former is excluded because VMT is unobservable for automobiles inspected in the first year of data. The latter is omitted because retirement is unobservable in the last year of data.

The mean net benefits of this program were −$44.5 million per year.

The variation in benefits and costs over time, illustrated in figure 3.1, is due to several factors. The first is the number of automobiles inspected annually. Between 2002 and 2006, as previously discussed in section 1.4, the North Carolina program was expanded from 9 to 48 counties. Compliance costs to automobile owners across the state increased accordingly. Similarly, the sharp decrease in benefits and costs in 2009 was largely caused by a decrease in automobile registrations (an increase in automobile retirement) arising from the Great Recession.

The benefits and costs of I/M are also affected by the characteristics of the automobile fleet. For example, the age distribution and usage intensity affect the benefits and costs of I/M in several ways. To illustrate how, consider automobiles produced between 1995 and 1998. Table 3.2 shows that federal hydrocarbon exhaust emissions standards were tightened for automobiles produced during those years. As these automobiles were driven they progressed along their emissions trajectory and eventually some began to fail annual emissions inspections.

Figure 3.2 illustrates the sources of carbon monoxide and hydrocarbons emissions abatement, in thousands of tons, between 2000 and 2012. It shows that nearly all of the I/M induced abatement comes from carbon monoxide emissions. Between 2000 and 2005 hydrocarbon emissions abatement from I/M induced repairs increased somewhat steadily before stabilizing. Nearly all of this hydrocarbons abatement came from automobiles produced after 1995 (when standards were tightened). The steady increase in hydrocarbons abatement between 2000 and 2005 was a result of these automobiles moving along their emissions trajectories and eventually failed annual inspections.

By 2008 many of the model year 1995-1998 automobiles had been retired or scrapped as shown in figure 2.2. It clearly shows that very few automobiles are older than 10 years. As 1995-1998 automobiles were retired they made up a smaller proportion of the fleet each inspection cycle. Thus the tons of hydrocarbon abatement from that cohort decreased. At the same time, newer automobiles moved along their emissions trajectory and eventually began to fail inspections. Because newer automobiles (i.e., those produced between 1999 and 2003) were produced under tighter standards (see table 3.2), total abatement from inspecting those automobiles is estimated to be less than inspecting earlier *dirtier* model year automobiles, all else constant. These newer and *clearner* automobiles were less likely to fail and comprised a relatively larger proportion of the fleet. Abatement from inspecting these newer automobiles, however, did help to counteract potential larger reductions from the retirement of earlier dirtier automobiles. As the older and dirtier automobiles were retired hydrocarbons abatement eventually became constant as shown in figure 3.2 and total abatement began to fall for later cleaner model year automobile cohorts.

The overall inefficiency of North Carolina's I/M program, as it existed between 2000 and 2012, was driven by several factors. Foremost among these are the number of automobiles inspected versus the number of federal exhaust emissions standards violators. Annually only about 50 thousand noncompliant automobiles are identified out of more than 2 million inspected. In other words, the overall failure rate is about 2.36 percent. Furthermore, approximately 73 percent of the noncompliant automobiles are either repaired or scrapped. The remaining 27 percent of noncompliant automobiles receive waivers and are not repaired in full.

Second, the abatement from repairs is limited and very heterogeneous.[15] Figure 3.3 illustrates the distribution of the social value of emissions abatement from I/M induced repairs. The mean (median) social value of I/M induced abatement from repairs is \$331 (\$340) and the standard deviation is \$186.[16] Only a small proportion of automobiles in the North Carolina fleet, however, fail their emissions inspection and are repaired to compliance. Furthermore, not all repaired automobiles generate enough abatement to justify the economic costs of an inspection. Consequently there are far more automobiles incurring costs than generating benefits in North Carolina. Thus total costs of

[15]This result is consistent with the findings of past research including Ando et al. (2000) and Mérel et al. (2014).

[16]Federal exhaust standards, reported in table 3.2, make it clear that some automobile emissions are allowed by law. The average automobile in North Carolina may produce 74, 3.5, and 7 thousand grams of carbon monoxide, hydrocarbon, and nitrogen oxide emissions legally in a year. This translates into 0.0818 (\$51.95), 0.0039 (\$2.96), and 0.0077 (\$2.55) short tons (in the social value) of carbon monoxide, hydrocarbon, and nitrogen oxide emissions. In other words, the value of legal emissions produced annually by automobiles in North Carolina would at maximum be about \$57 for an average automobile. Many automobiles registered in North Carolina, however, are not average and produce fewer legal emissions.

I/M exceed the social value of abatement for all years from 2000 through 2012.

Figures 3.4b and 3.5 also help to illustrate the heterogeneity in the social value of emissions abatement. Figure 3.4a plots the social value of abatement from I/M repairs across odometer readings. It shows, consistent with figure 2.3, that abatement is generally positively correlated with usage. Figure 3.4b plots more of a quadratic or concave relationship between the social value and automobile age. The young automobiles, on the left side of figure 3.4b, with high social values of emissions abatement also have been driven very intensively over their short lives. These automobiles are thus plotted on the right hand side of figure 3.4a. Such results suggest that North Carolina's recently modified *selective automobile targeting* regime should increase the efficiency of the program.

The estimation framework discussed in section 3.4 was also used to compare the efficiency of various I/M regimes. Figure 3.5 plots the estimated benefits and costs for several different I/M regimes. The "Old NC" regime refers to North Carolina's program as it existed between 2000 and 2012; the same regime's benefits and costs are also plotted in figure 3.1. The "New NC" regime refers to the North Carolina program after April 1, 2015; the *selective automobile targeting* regime. Figure 3.5 shows that benefits are expected to decrease 11 percent while costs will decrease by 49 percent; net benefits improve from −\$44.5 million to −\$16.0 million in June 2015 U.S. dollars per year. While the newly adopted regime does not generate positive net benefits, it does increase the efficiency of I/M in North Carolina.

Figure 3.5 also shows that other regimes that are more efficient regimes than the one recently adopted by North Carolina do exist. For example, had North Carolina adopted biennial inspections rather than *selective automobile targeting* net benefits would be expected to be −\$12.4 million per year. Alternatively, triennial inspections are estimated to generate net benefits equal to −\$0.9 million per year. In addition, California's I/M regime combines biennial inspections and exemptions to automobiles from the most recent six model years. Net benefits under this regime in North Carolina are expected to generate net benefits equal to −\$1.3 million. The final regime, "Perfect S.T.," in figure 3.5 plots the benefits and costs for a program that could perfectly selectively target only those automobiles for inspections that will generate positive net benefits. This purely theoretical regime is clearly the most efficient possible and would be estimated to generate net benefits equal to $6.2 million per year.

Previous research including Bin (2003) and Moghadam & Livernois (2010) have suggested alternative regimes to those previously described. This chapter builds on this work by employing the estimation framework described in section 3.4 to evaluate the efficiency of other types of selective automobile targeting. I used the framework described in section 3.4 to estimate the net benefits of more than 1,900 different I/M regimes.

All of these regimes selectively target automobiles by one or more attributes characteristics. For example, I estimate net benefits for 41 different regimes that selectively target automobiles with odometer readings higher than a given threshold that increases by 10 thousand miles for each subsequent regime. I also estimate 21 different regimes that selectively target automobiles older than a given threshold that increase by 1 year for each subsequent regimes. I then combine these two characteristics to estimate the net benefits of 861 different regimes that selectively target automobiles by odometer readings (in 10 thousand mile increments) and age (in 1 year increments). Similarly I estimate the net benefits for another 861 regimes that selectively target automobiles by annual VMT (in 10 thousand mile increments) and age. In total the attributes I examine (and the number of selective targeting regimes estimated) include odometer reading (41), age (21), number of engine cylinders (10), engine size in liters (75), number of transmission speeds (9), weight (7), fuel economy (9), size (3), drive type (4), body type (5), annual VMT (41), age and odometer (861), and age and VMT (861). In addition to these 1,947 regimes I also estimate net benefits for several regimes from literature and currently in use around the United States, such as California.

Figure 3.6 plots the mean benefits and costs, in 2015 U.S. dollars, of I/M regimes that selectively target based on odometer reading in 10 thousand mile increments. The figure shows that regimes that require automobiles with more than 150 thousand cumulative vehicle-miles traveled to be tested generate positive net benefits (the median net benefits are equal to $0.6 million). As the regime increases the cut-off point for inspection exemptions, and thus decreases the proportion of the fleet inspected, the costs of I/M decrease more than the benefits, causing the efficiency of the program to increase. In fact, testing automobiles with more than 150 thousand miles is the 121^{st} most efficient regime of all those examined. Several other regimes plotted in figure 3.6 are also some of the most efficient regimes analyzed. For example, the 5^{th} most efficient regime, as shown in table 3.4, only tests automobiles with more than 180 thousand miles.

Table 3.4 reports the mean estimated net benefits, in 2015 U.S. dollars, for inspection years 2000 through 2012. It shows two important results. First, table 3.4 reveals a significant gap, $4.4 million, in efficiency between the top two most efficient programs. The most efficient regime, "Perfect S.T.," is entirely theoretical and unachievable. Implementing such a policy would require that regulators know ex ante, with certainty, which automobiles would generate non-negative net benefits. Second, excluding perfect selective targeting, the most efficient regimes are those that inspect automobiles based on how intensively they have been driven over time. Figure 2.3 illustrates the emissions trajectory as a function of automobile usage over time. Automobiles that fail their inspection are much more likely to be further along their concave emissions trajectory such that emissions exceed federal standards. In other words, the most efficient regimes selectively target based on the automobiles position on the emissions trajectory via age and annual VMT or odometer reading (cumulative VMT). In fact all regimes that selectively target based on other automobile attributes generate negative net benefits.

Table 3.4 shows that the most efficient I/M regimes inspect automobiles based on usage intensity. Simply targeting based on automobile age like the California program (exempts automobiles less than 6 years old) fails to account for the automobile's position on its emissions trajectory. Because automobiles differ considerably in terms of their usage intensity, targeting automobiles based on age alone cannot generate efficiency improvements comparable to those that account for usage intensity. Nearly all such regimes generate negative net benefits. Figure 3.7 plots the benefits and costs for regimes that selectively target by automobile age. The inefficiencies exist because abatement from repairs and scrappage is highly dependent on the driving decisions of automobile owners.[17]

Figure 3.8 plots the benefits and costs, in 2015 U.S. dollars, for the I/M regimes suggested by Bin (2003) and Moghadam & Livernois (2010). The regime suggested by Bin (2003) targets automobiles more than 10 years old, with less than 2,000 cubic centimeter engines, and more than 100 thousand miles. It is estimated to generate net benefits equal to −\$0.52 million per year. Figure 3.8 shows that both benefits and costs are extremely low because very few automobiles meet these criteria. The regimes suggested by Moghadam & Livernois (2010) are much more inclusive and likewise have much higher costs than the regime suggest by Bin (2003). The two Moghadam & Livernois (2010) regimes are optimal for different assumptions the authors made about how the instantaneous abatement from repairs vary with automobile usage. The first regime biennially inspects automobiles older than 4 and less than 12 years old and generates net benefits equal to −\$0.66 million per year. The second regime also inspects automobiles older than 12 and less than 19 years annually and generates benefits equal to −\$4.09 million per year. These two regimes are inefficient because they fail to account for usage intensity. Table 3.4 makes it very clear that adjustments by state legislatures to I/M programs in order to reduce compliance costs to citizens must make exemptions based on automobile usage intensity.

I follow the recommendation of Banzhaf & Smith (2007) and conduct a meta-analysis on the net benefits I estimated for the more than 1,900 hypothetical regimes I consider.[18] The authors suggest the use of meta-analysis to summarize the influence of alternatives and "enhance users''appreciation of the importance of the details underlying each empirical analysis."

I conduct this meta-analysis in two steps. First, I examine the mean net benefits per regime between 2000 and 2012. The results of this stage are reported in table 3.5. The unit of observation

[17]It is also affected by exogenous tightening of exhaust emissions standards. Other exogenous policies that seek to reduce road congestion and deter private transportation may also reduce efficiency of I/M.

[18]Specifically, 1,947 of the hypothetical regimes selectively target automobile for inspection based on odometer reading, automobile age, the number of engine cylinders, engine size, transmission speeds, weight, fuel economy, automobile size, drive type, body type, annual VMT, age and odometer reading, and age and annual VMT. The remaining regimes vary in frequency of inspections or come from suggestions of past researchers.

is a hypothetical regime used in North Carolina and the dependent variable is net benefits in millions of 2015 United States dollar(s) (USD). The average net benefits of these 1,984 regimes is −3.190 million USD indicating that the average I/M program is inefficient. The independent binary variables I use to estimate net benefits are summarized, the mean is reported above the standard deviation (st. dev.) in parenthses, in the second column of table 3.5. Ninety-one percent of the 1,984 hypothetical regimes selectively targeted automobiles for inspections based its expected position on the emissions trajectory, or probability of failure. Of these 91 percent, 2.1 exempted automobiles using odometer readings, 43 percent using a combination of age and odometer, 2.1 percent using annual VMT, and 43 percent using age and annual VMT. The remaining nine percent exempted automobiles based on automobile attributes such as engine size, fuel economy, or size, or by adjusting other margins like inspection frequency.

Column 3 of table 3.5 reports estimated coefficients and statistical significance above standard deviations (in parentheses). The coefficients indicate the expected change in average total annual net benefits of I/M, in millions of 2015 United States dollar(s) (USD), from using a selective targeting regime along different margins. Consistent with the results reported in table 3.4 the largest efficiency gains are expected to be achieved using a combination of age and annual vehicle-miles traveled (VMT). Columns 4 and 5 of table 3.5 summarize these results using a single binary variable. On average selective targeting along one of these four margins (indicated using a ✓) is expected to increase net benefits by $15.61 million dollars per year. Because annual VMT does not necessarily identify where an older automobile is on its emissions trajectory, only how quickly the automobile may be moving along it, I exclude this margin from my binary analysis in column 5. The estimated coefficient decreases by about $1.5 million dollars but still indicates the availability of potential Pareto improvements to the I/M program.

In the second stage of my meta-analysis I dig deeper into these general expected effects of adopting a selective automobile targeting regime based on automobile usage intensity. Specifically, this stage examines the effect of exempting automobiles from annual emissions inspections based on age, annual VMT, or odometer readings. Table 3.6 reports estimated coefficients and standard errors (in parentheses) from a single ordinary least squares (OLS) regression. The unit of observation is a regime-inspection year. Unlike the first-stage I do not aggregate total net benefits in millions of 2015 USD for each of the hypothetical regimes. Consequently, I do also control for the year of inspection when estimating net benefits for these regime-year data. The three sets of independent binary variables are listed in columns 2 through 4 of table 3.6. These sets include automobile age, annual VMT, and odometer reading. The estimated coefficient in row 2 of column 2, 2.735 indicates that I/M regimes that exempt automobiles less than or equal to 1 year old are expected to generate an extra 2.735 million USD (in 2015 dollars). Because the constant term is negative such a regime would be inefficient. In fact, as column 2 of table 3.6 shows, selectively targeting automobiles based on age alone is not expected to generate positive net benefits. This is because the automobile's age in and of itself does not suggest where along its emissions trajectory the automobile currently sits. It is possible for a 10 year old automobile to have less than 10 thousand miles on its odometer. I also include two other interaction variables in my model that I do not report estimated coefficients for due to limitations of space. These two interaction variables are for age and annual VMT, and age and odometer reading.

The estimated coefficients in columns 3 and 4 of table 3.6 confirm the results reported in table 3.4. The largest efficiency improvements can be generated through selectively targeting based on automobile age and annual VMT. The estimated coefficient in row 3 of column 3, 12.358 indicates that I/M regimes that exempt automobiles that are driven less than or equal to $20,000$ miles per year is expected to generate an extra 12.358 million USD (in 2015 dollars). If a program, however, were to only exempt those automobiles if they were less than or equal to 6 years old, it would generate \$5.733 million in net benefits. In total efficiency would improve by \$18.09 million. In contrast, the recent application of *selective automobile targeting* in North Carolina is expected to improve efficiency by much less. This program exempts automobiles less than three years old and with less than 70 thousand miles on their odometer. The model reported in table 3.6 estimates that net benefits will only increase by $8.537 million for this program. While it does represent a Pareto improvement, this meta-analysis illustrates how I/M regulators could improve efficiency even more by exempting more automobiles that are not likely to generate positive net benefits.

3.6 Conclusion

Automobile emissions inspections are used all over the world and affect tens of millions of consumers but receive relatively little attention in the economic literature. The attention that has been awarded to them, however, generally results in less than favorable conclusions. This may have been motivation for North Carolina's recent change to its I/M program; one that is in many ways now more nationally representative.

The estimation framework I developed in chapter 2 and summarized in section 3.4 of this chapter was used to evaluate the efficiency of I/M. Using an extensive dataset from the North Carolina I/M collected between 1999 and 2013, the results of my analysis confirm several conclusions from previous literature. First, a very small fraction of the fleet is noncompliant. Second, the value of abatement is limited relative to the costs of compliance causing North Carolina's I/M to largely fail a benefit-cost test. Third, selective automobile targeting, like the regime recently adopted by North Carolina, can improve the efficiency of I/M programs. However, further exemptions based on automobile usage intensity could increase the net benefits of I/M by even more.

The results of this analysis indicate that I/M can provide value in terms of efficient emissions but not as they are often designed. Figure 3.9 summarizes the results of the analysis using a simple graph. It plots a linear downward sloping marginal benefit (MB) curve and a linear upward sloping marginal cost (MC) curve. The horizontal axis measures the proportion of the automobile fleet periodically inspected by I/M. The vertical axis measures the value of marginal costs and benefits in dollars. Figure 3.9 shows that the proportion of the fleet currently inspected (P^{NCIM}) exceeds the economically efficient proportion. The shaded region, ABC, in figure 3.9 illustrates the social costs of over-inspection. The recently adopted North Carolina I/M regime is estimated to increase the efficiency of I/M by 63 percent, raising net benefits from −\$44.5 million to −\$16.0 million in June 2015 U.S. dollars per year. Under both regimes the marginal cost of the last automobile inspected exceeds its marginal benefit from abatement.

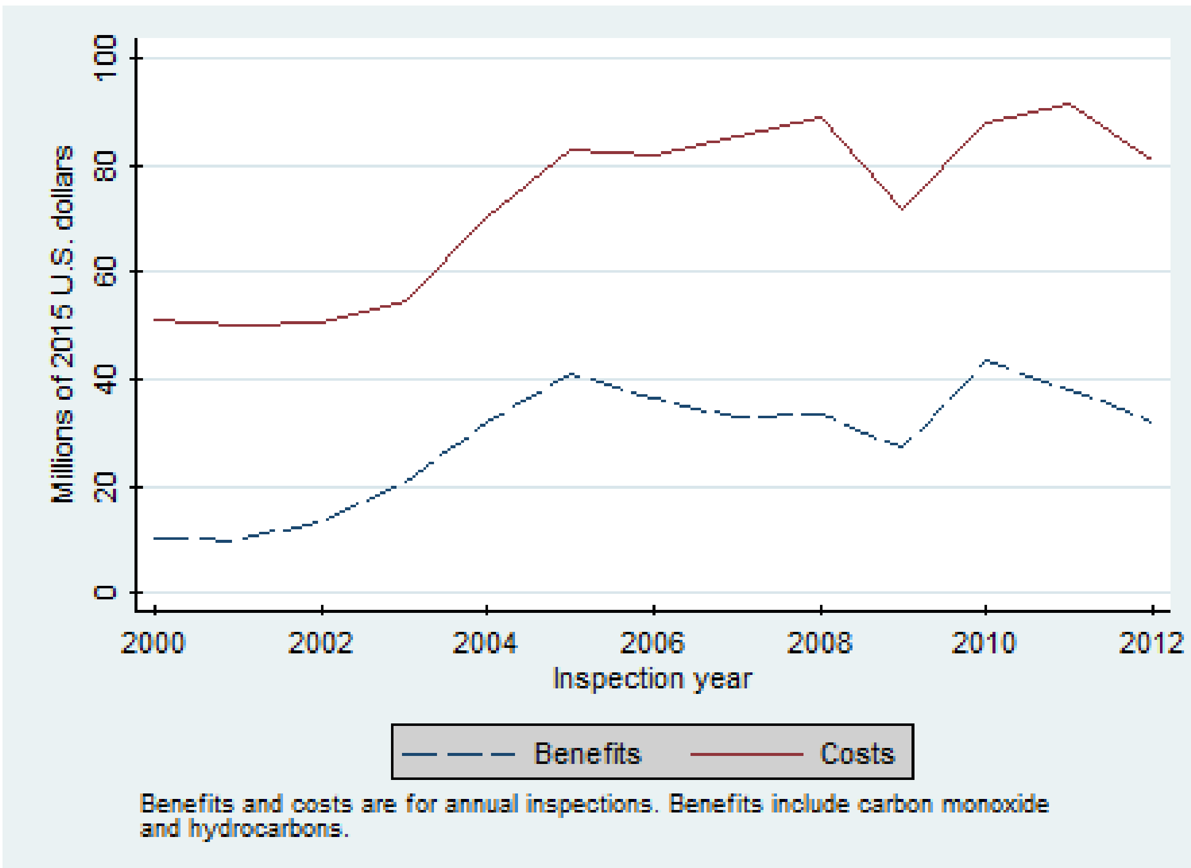


Figure 3.1 *Estimated total annual benefits and costs of I/M*

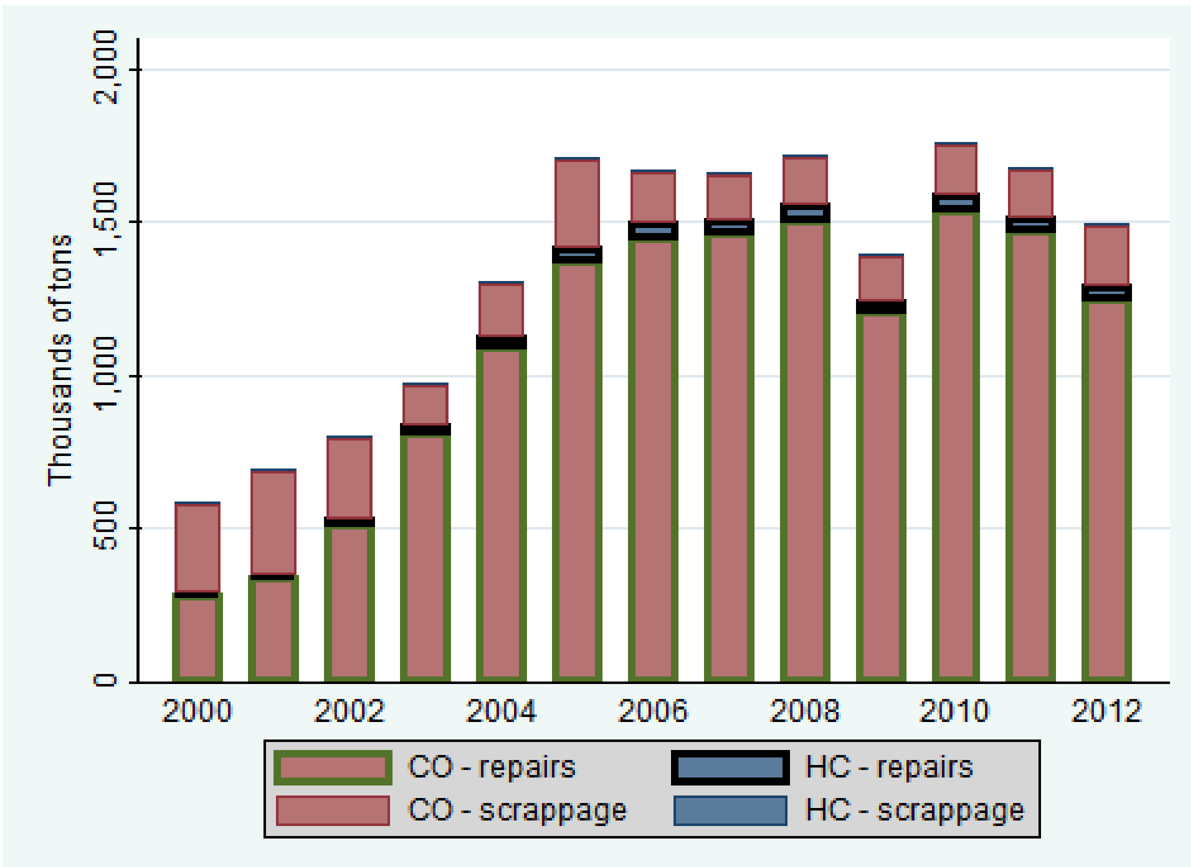


Figure 3.2 *Total abatement from I/M by inspection year*

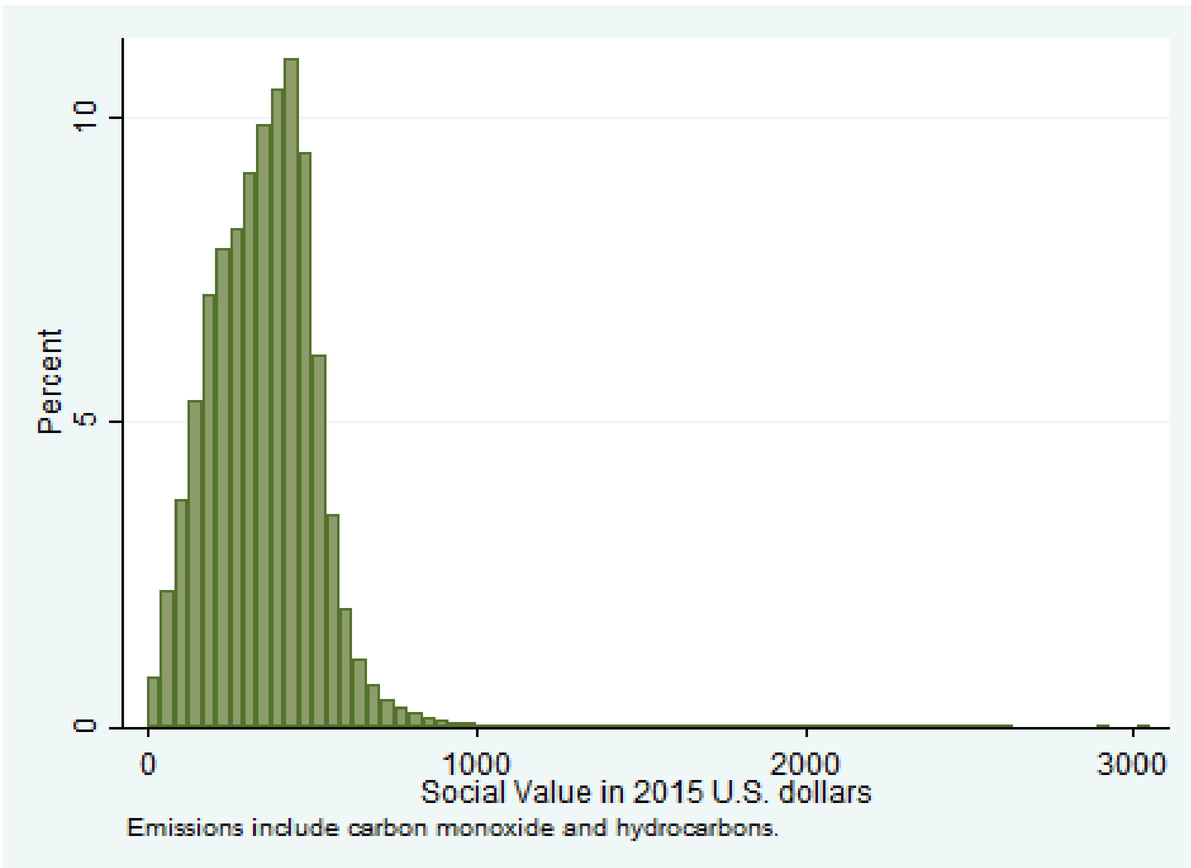
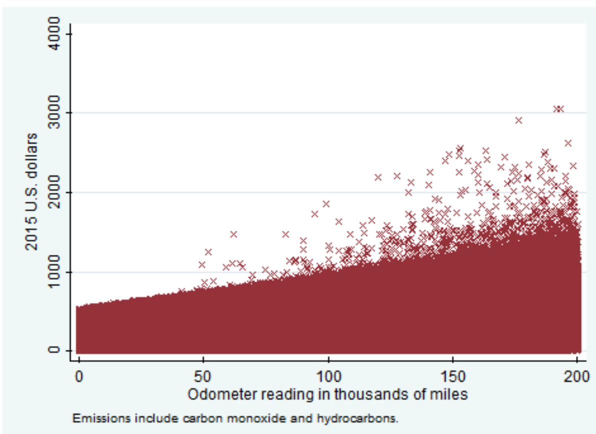
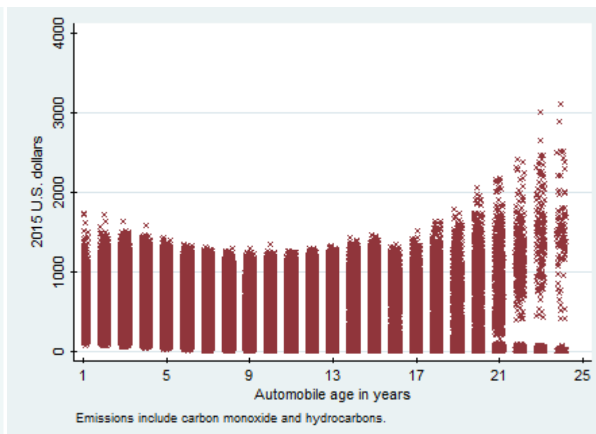


Figure 3.3 *Distribution of the estimated social value of emissions abatement from I/M induced repairs across inspections resulting in failure*



(a) *By odometer reading*



(b) *By age*

Figure 3.4 *Estimated social value of emissions abatement from I/M induced repairs*

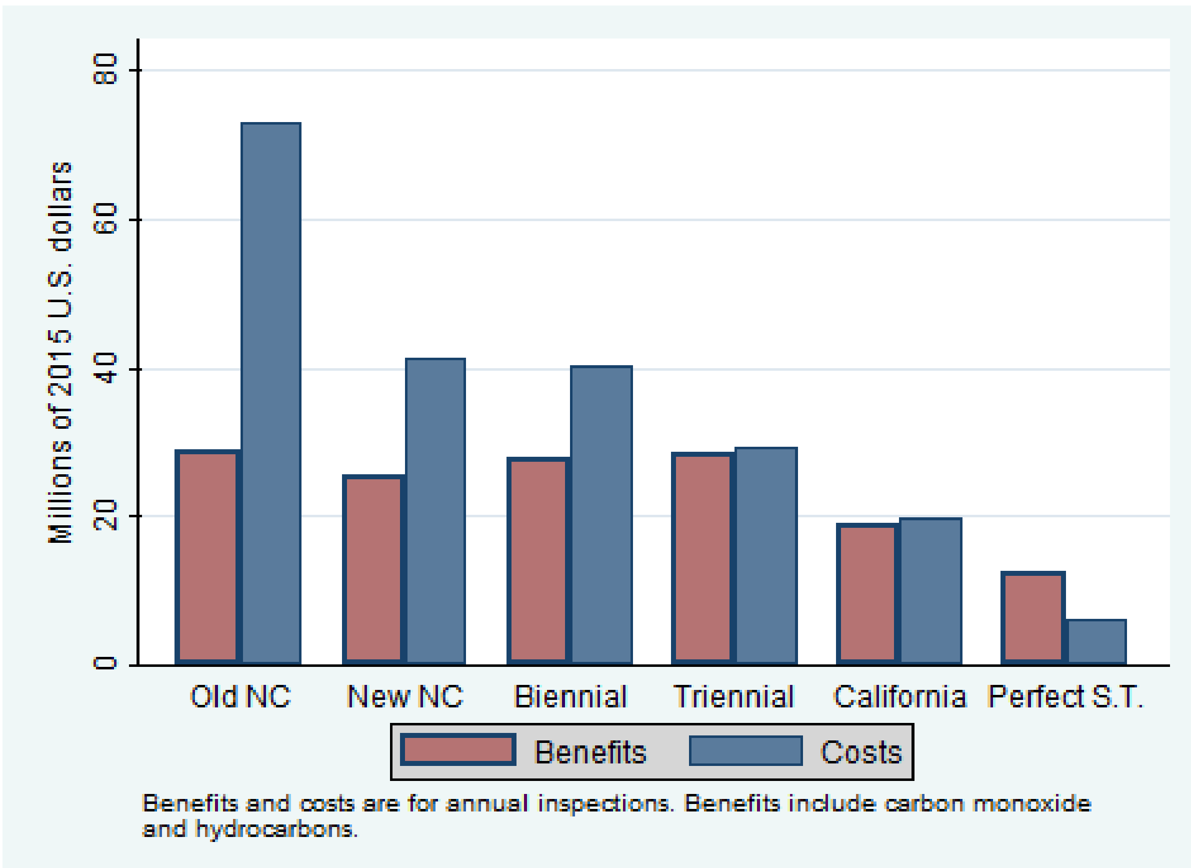


Figure 3.5 *Estimated mean benefits and costs of I/M by I/M regime between* 2000 *and* 2012

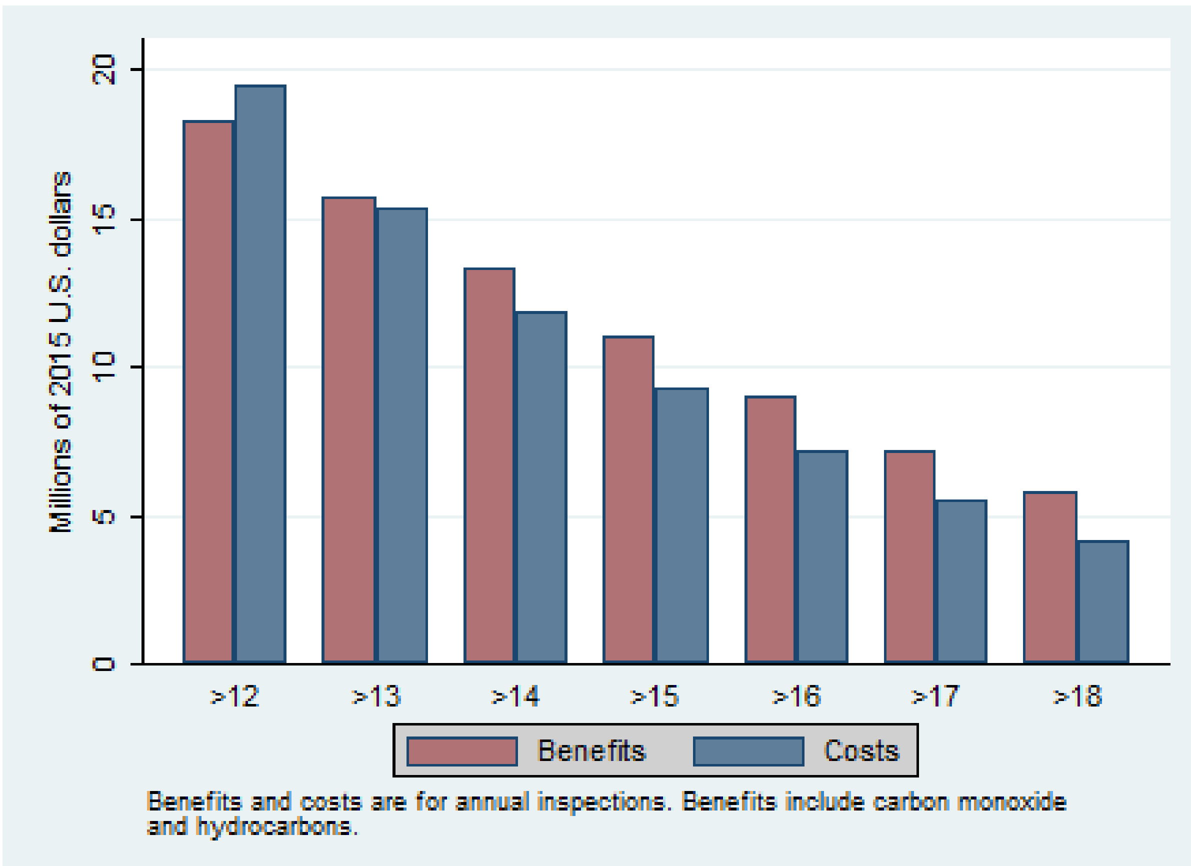


Figure 3.6 *Estimated mean benefits and costs of selective targeting:* 2000-2012 *selectively targeting by odometer reading in* 10,000 *mile increments*

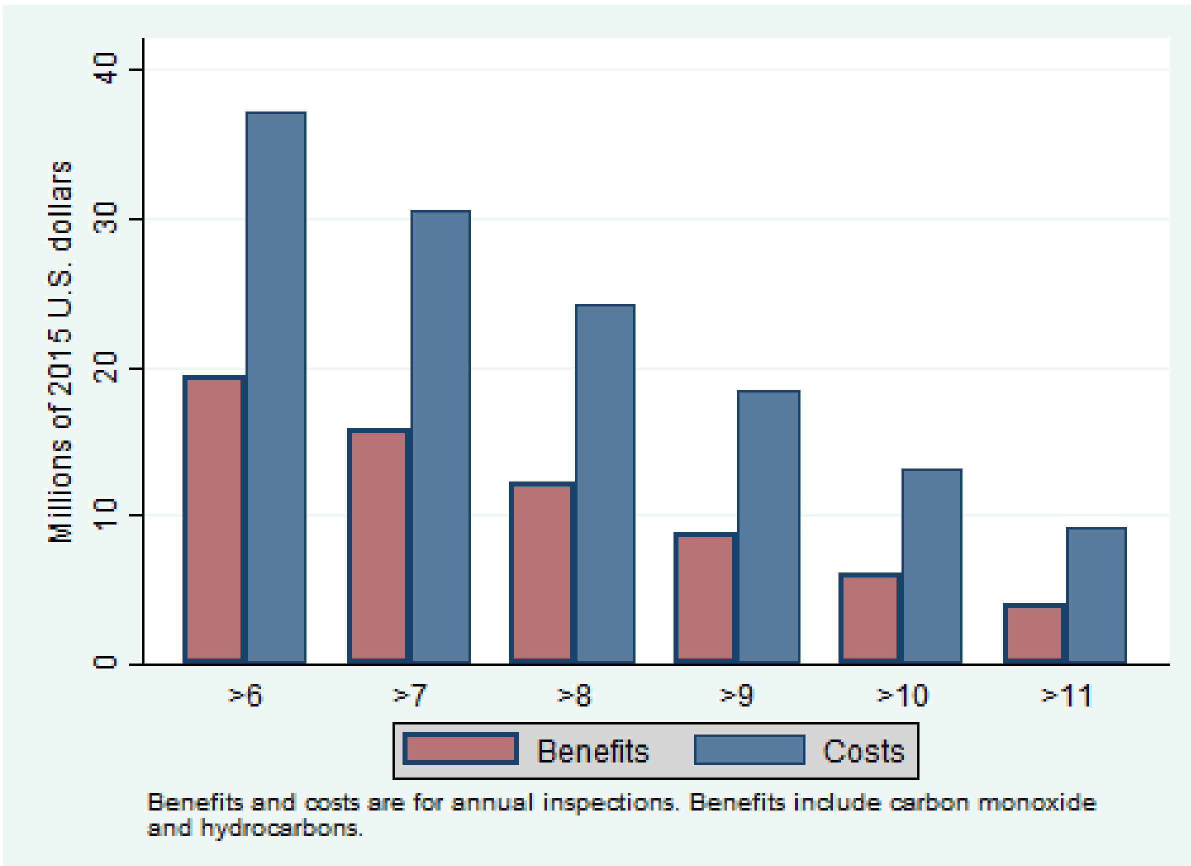


Figure 3.7 *Estimated mean benefits and costs of selective targeting:* 2000-2012 *selectively targeting by age in years*

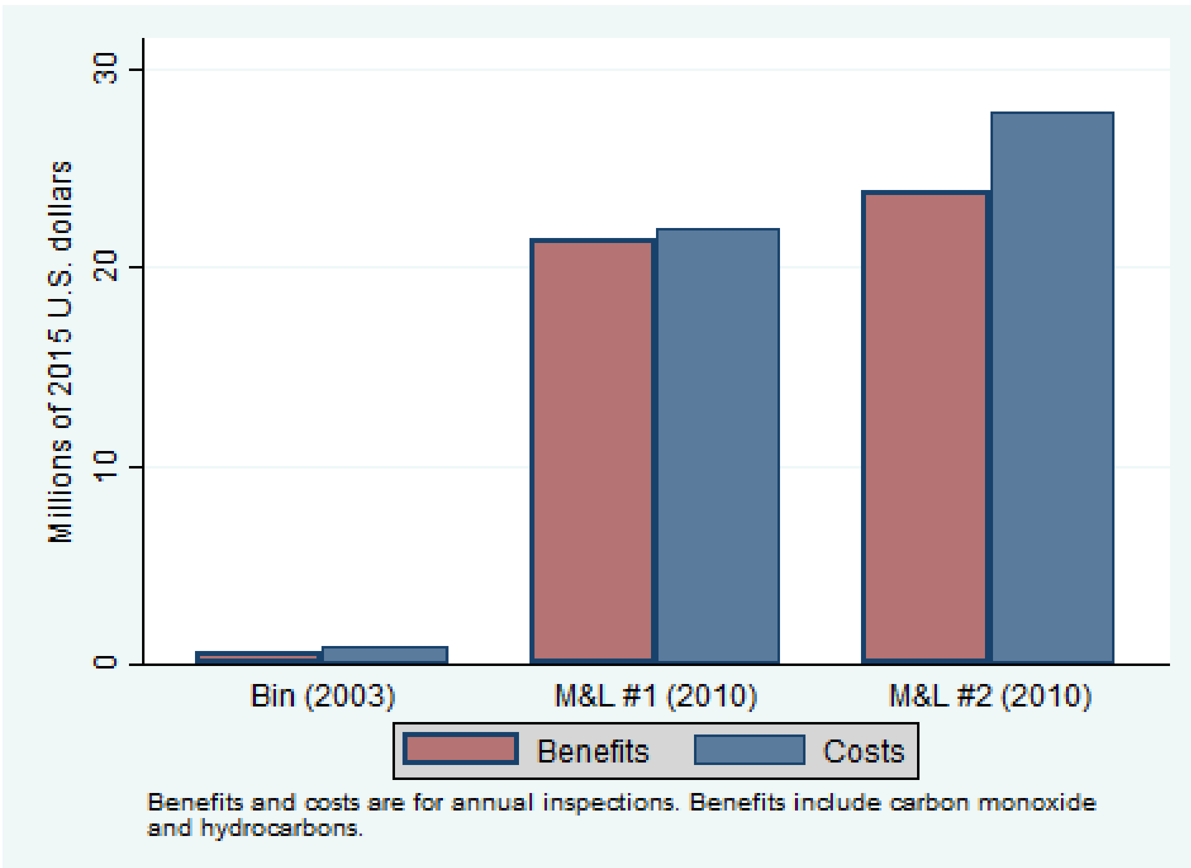


Figure 3.8 *Estimated mean benefits and costs of selective targeting:* 2000-2012 *selectively targeting regimes*

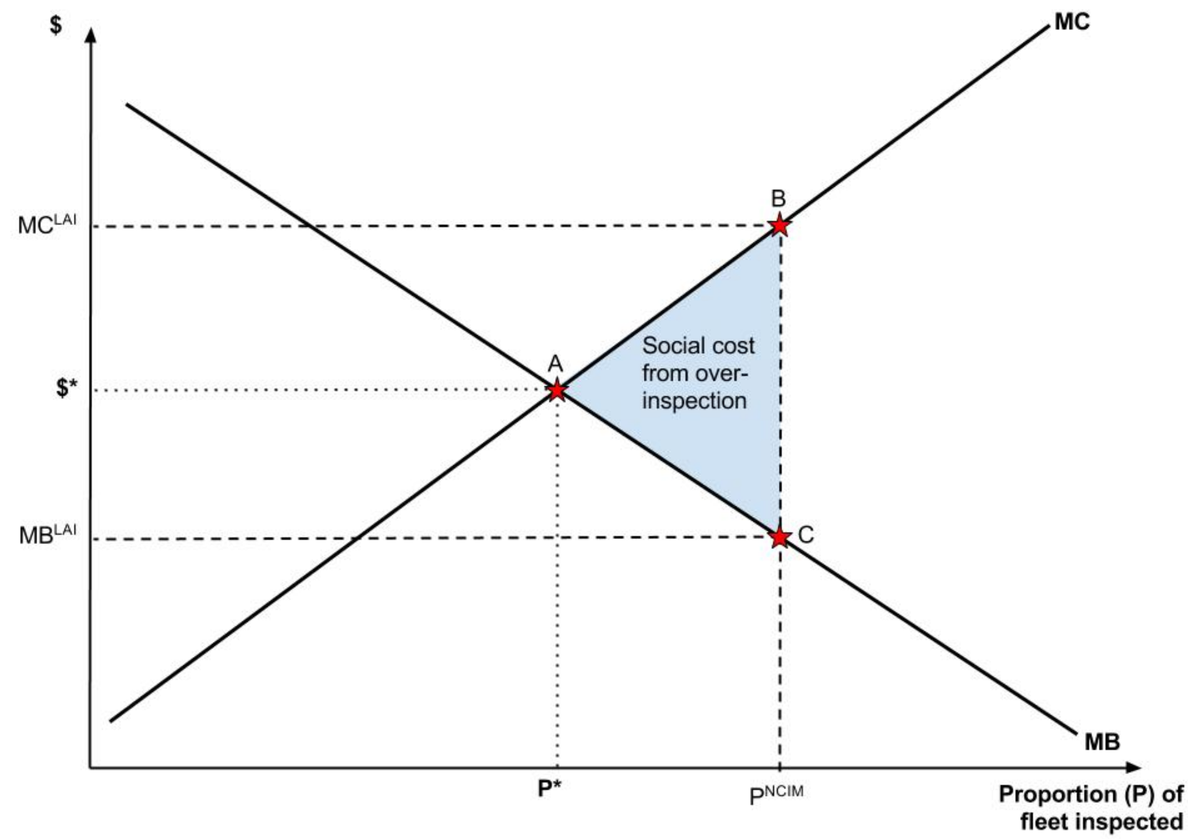


Figure 3.9 *The social cost from the over-inspection of automobiles*

Table 3.1 *Papers discussing automobile attributes and emissions*

Paper	Emissions	Selective targeting	Finding(s)
Glazer et al. (1995)		✓	• "Universal inspections are not necessary. Data suggest that it may be wise for Smog Check program to stop treating all cars equally."
Khazzoom (1995)	✓		• "The [results] show that for all three pollutants and all equations estimated, the impact of MPG on the emission rate is statistically zero."
Anilovich (1996)	✓		• "A strong vehicle age influence on emission levels was observed." • "The measurements of the sample demonstrate poor compliance that worsens with vehicle age."

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Table 3.1 *(continued)*

Paper	Emissions	Selective targeting	Finding(s)
Kahn (1996a)	✓		• "Find evidence of large differences in vehicle emissions across model years, makes, and sizes. Vehicle emissions have not fallen monotonically with vehicle model year. Instead . . . emissions fall when new-car emissions regulation becomes more stringent."
Harrington (1997)	✓		• "It is found that better fuel economy is strongly associated with lower emissions of CO and HC and that the effect gets stronger as vehicles age."

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Table 3.1 *(continued)*

Paper	**Emissions**	**Selective targeting**	**Finding(s)**
Ando et al. (2000)		✓	• "Our results all suggest that consideration of the costs and cost-effectiveness in designing I/M policy is critical. Because there is great variation in costs and effectiveness of repair across vehicles, costs could be reduced if there were better targeting of which vehicles are tested and which are repaired. Clearly, relatively new vehicles are less likely to fail, so they should be tested less frequently. Older vehicles, which are more likely to fail, can be tested more frequently."

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Table 3.1 *(continued)*

Paper	Emissions	Selective targeting	Finding(s)
Washburn et al. (2001)	✓	✓	• "Our results show that vehicle age, vehicle manufacturer, number of engine cylinders, odometer reading, and whether or not oxygenated fuels were in use all play a significant role in determining I/M emission test results and these statistical findings can be used to form the basis of the selective sampling of vehicles for I/M testing."
Riveros et al. (2002)	✓		• "Some of the results of this analysis include: the finding of a typical exhaust emissions distribution curve for each vehicle manufacturer, with differences for each brand and model for the same manufacturer, the fact that not all new vehicles pass the I/M test…"

(continued on next page)

Table 3.1 *(continued)*

Paper	**Emissions**	**Selective targeting**	**Finding(s)**
Bin (2003)		✓	• "Vehicle age, engine size, and odometer reading all play a significant role in determining the probability of emission test failure. Information from this study can be used as a groundwork for the selective sampling of vehicles which might improve the cost-effectiveness of the I/M programs."
Beydoun & Guldmann (2006)	✓		• "Vehicle age, fuel economy, mileage, engine characteristics, weight, make, general maintenance, and time of year are found to be strong determinants of emissions and test failure rates. The emission models estimated with the Massachusetts data show broad variations in the effects of the independent variables across makes, for both cars and trucks."

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Table 3.1 *(continued)*

Paper	Emissions	Selective targeting	Finding(s)
Moghadam & Livernois (2010)		✓	• "Vehicle age, fuel economy, mileage, engine characteristics, weight, make, general maintenance, and time of year are found to be strong determinants of emissions and test failure rates. The emission models estimated with the Massachusetts data show broad variations in the effects of the independent variables across makes, for both cars and trucks."

Table 3.2 *Federal test procedure (FTP) limits established by the Clean Air Act*

Model year	**Emission limits in grams per mile (GPM)**		
	Hydrocarbons	**Carbon monoxide**	**Nitrogen oxide**
1975-1976	1.5	15	3.1
1977-1976	1.5	15	2
1980	0.41	7	2
1981-1993	0.41	3.4	1
1994	0.41	3.4	0.4
1995-1998	0.31	3.4	0.4
1999-2003	0.09	3.4	0.4
≥ 2004	0.09	3.4	0.05

FTP limits come from Calvert et al. (1993) and Delphi (2011, 2013).

Table 3.3 *Summary of the estimated social costs of emissions per short ton*

Paper	HC	CO	NO_X	CO_2	CO_2 Equivalent
Nordhaus (1991b)					\$0.31 - \$65.94‡
Nordhaus (1991a)					\$7.30‡
Ayres & Walter (1991)					\$30 - \$35‡
Nordhaus (1992)					\$5.30‡
Nordhaus (1993a)					\$5.24‡
Nordhaus (1993b)					\$5‡
Peck & Teisberg (1993)					\$12 - \$14‡
Fankhauser (1994)	\$108†		\$2,895†	\$20†	
Matthews & Lave (2000)		\$520*			
Muller & Mendelsohn (2007)	\$400**		\$300**		
Muller & Mendelsohn (2009)	\$730**		\$260**		
Knittel (2009)				\$207***	
Greenstone et al. (2013)				\$21.40***	

(continued on next page)

Table 3.3 *(continued)*

Paper	HC	CO	NO_X	CO_2	CO_2 Equivalent
Range in 2013 **USD**	\$184.72-\$945.30	\$863.42	\$336.68-\$4,951.62	\$24.04-\$224.77	\$0.58-\$122.11
Avg. annual benefit of excess emissions abated per automobile	\$5.51	\$763.90	\$61.78		

The last row reports an average annual benefit of excess emissions abated per failing or noncompliant automobile. These dollar values assume the automobile was manufactured according to Tier 2 bin 5 federal exhaust standards, was driven the dataset average of 14,700 miles per year, and produced excess emissions of 300, 1,200, and 1,000 percent of the federal standard for hydrocarbons, carbon monoxide, and nitrogen oxides, respectively. In addition these values assume the social cost is the maximum value from row 14. Thus, the average benefit in terms of abated emissions from identifying and repairing an average noncompliant automobile is \$831.20 in 2013 USD. ‡denotes 1989 United States dollar(s) (USD), †denotes 1991 USD, * denotes 1992 USD, ** denotes 2002 USD, *** denotes 2009 USD.

Table 3.4 *I/M regimes ranked by estimated efficiency*

Rank	Selective targeting regime description	Net benefits
1	Perfect selective targeting	6.17
2	Age > 6 and annual VMT $> 20,000$ per year	1.81
3	Age > 5 and annual VMT $> 20,000$ per year	1.79
4	Age > 7 and annual VMT $> 20,000$ per year	1.65
5	Odometer $> 180,000$	1.59
6	Age > 0 and odometer $> 180,000$ per year	1.59
7	Age > 1 and odometer $> 180,000$ per year	1.58
8	Age > 2 and odometer $> 180,000$ per year	1.58
9	Age > 3 and odometer $> 180,000$ per year	1.57
10	Age > 0 and odometer $> 190,000$ per year	1.57
11	Odometer $> 190,000$	1.57
12	Age > 1 and odometer $> 190,000$ per year	1.57
13	Age > 2 and odometer $> 190,000$ per year	1.56
14	Age > 3 and odometer $> 190,000$ per year	1.55
15	Age > 4 and annual VMT $> 20,000$ per year	1.52
16	Age > 4 and odometer $> 180,000$ per year	1.52
17	Age > 4 and odometer $> 190,000$ per year	1.51
18	Odometer $> 200,000$	1.49
19	Age > 0 and odometer $> 200,000$ per year	1.49
20	Age > 1 and odometer $> 200,000$ per year	1.49
519	Odometer $> 390,000$	0.00

Net benefits, in millions of June 2015 U.S. dollars, are the mean of those estimated for years 2000 through 2012.

Table 3.5 *First-stage meta-analysis of I/M regime efficiency*

	mean (st. dev.)	type of S.T.	All S.T. regimes	Exclude annual VMT
net benefits in millions	−3.190			
	(8.144)			
S.T. on emissions trajectory	0.910		15.61***	14.054***
	(0.286)		(0.535)	(0.491)
S.T. on odometer	0.021	11.290***	✓	✓
	(0.144)	(1.142)		
S.T. on age & odometer	0.434	14.990***	✓	✓
	(0.496)	(0.548)		
S.T. on annual VMT	0.021	9.365***	✓	
	(0.142)	(1.154)		
S.T. on age & annual VMT	0.434	16.845***	✓	✓
	(0.496)	(0.548)		
Number of observations		1,984		

The statistical significance is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 3.6 *Second-stage meta-analysis of I/M regime efficiency (single regression)*

Exemption	age in years	VMT in 10,000 mile increments	odometer in 10,000 mile increments
≤ 1	2.735***	10.542***	−0.982**
	(0.211)	(0.372)	(0.372)
≤ 2	3.500***	12.358***	−0.375
	(0.211)	(0.372)	(0.372)
≤ 3	4.140***	12.358***	0.404
	(0.210)	(0.372)	(0.372)
≤ 4	4.775***	12.092***	1.330***
	(0.211)	(0.372)	(0.372)
≤ 5	5.230***	11.926***	2.365***
	(0.211)	(0.372)	(0.372)
≤ 6	5.733***	11.818***	3.489***
	(0.210)	(0.372)	(0.372)
≤ 7	5.896***	11.733***	4.397***
	(0.211)	(0.372)	(0.372)
≤ 8	6.161***	11.658***	5.896***
	(0.211)	(0.372)	(0.372)
≤ 9	6.441***	11.589***	7.120***
	(0.211)	(0.372)	(0.372)
≤ 10	6.797***	11.356***	8.413***

(continued on next page)

Table 3.6 *(continued)*

Exemption	**age in years**	**VMT in** 10,000 **mile increments**	**odometer in** 10,000 **mile increments**
	(0.210)	(0.372)	(0.372)
≤ 11	7.083***	11.252***	9.376***
	(0.211)	(0.372)	(0.372)
≤ 12	7.363***	11.207***	10.349***
	(0.211)	(0.372)	(0.372)
≤ 13	7.590***	11.182***	11.181***
	(0.211)	(0.372)	(0.372)
≤ 14	7.770***	11.166***	11.856***
	(0.211)	(0.372)	(0.372)
≥ 15	7.993***	11.132***	12.738***
	(0.133)	(0.150)	(0.152)
Constant		−20.963***	
		(0.172)	
	# of obs.	**adj.** R^2	**RMSE**
	25,714	0.5172	5.8709

(continued on next page)

Table 3.6 *(continued)*

Exemption	**age in years**	**VMT in** $10,000$ **mile increments**	**odometer in** $10,000$ **mile increments**

The estimated coefficients (and standard errors) reported above are from a single regression. Estimated coefficients from inspection-year binary variables and interactions between age and annual VMT, and age and odometer reading are not reported due to space limitations. The statistical significance of the estimated coefficients is reported using the following convention: + $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

CHAPTER 4

SELECTIVE SPATIAL TARGETING

4.1 Introduction

Policy makers in the United States have largely focused on command and control (CAC) programs to reduce automobile emissions because of a number of obstacles in establishing market-based abatement programs (West, 2005). For example, Harrington et al. (2000) and Fullerton & Gan (2005) argue that this regulatory environment is challenging because both individuals and firms make choices that affect automobile emissions. In the United States, many of these CAC regulations focus on firm behavior. The United States (U.S.) Environmental Protection Agency (EPA), under the authority of the Clean Air Act and its Amendments, has set and periodically tightens exhaust emissions standards.[1] In addition, automobile manufacturers are required to provide various warranties on

[1] These emissions include nitrogen oxides (NO_X), non-methane organic gasses (NMOG), carbon monoxide (CO), particulate matter (PM), and formaldehyde (HCHO). The standards establish the maximum legal limits of emissions for automobiles at 50 and 120 thousand miles (Delphi, 2015).

emissions control equipment.[2]

The Clean Air Act also gives the U.S. EPA the authority to set National Ambient Air Quality Standards (NAAQS).[3] All states must periodically develop and submit a State Implementation Plan (SIP), which describes the programs that will be used to attain or maintain compliance with NAAQS, to the U.S. EPA for approval.[4] Counties in states found in noncompliance with federal ambient air quality standards may be required by the Clean Air Act to use automobile emissions inspection and maintenance (I/M) programs.[5] Such programs would be discussed in the SIP, which effectively forms a contract between the state and the U.S. EPA; deviations by states may result in the denial of federal highway funding (Schneeberg, 2014; Spink & Bigioni, 2010).

Automobile emissions I/M programs are an example of spatial differentiated environmental regulation. Currently, the District of Columbia and 31 states use I/M programs to identify and repair (or scrap) noncompliant automobiles, those that produce more emissions than the federal standards, and thereby improve air quality. Furthermore, most I/M programs do not treat all jurisdictions within the state uniformly. In fact, only nine of the 32 I/M programs in the United States are applied statewide.[6] Figure 1.3 reveals all of these jurisdictions are in the northeastern United States. Arguably, emissions from sources in upwind states may be transported by weather patterns and deteriorate ambient air quality in states downwind. In fact, in 2013 governors of several northern or downwind states petitioned the U.S. EPA to tighten regulations on sources in other states for this reason

[2]For example, manufacturers must have a two-year, 24,000-mile warranty on all emissions control components and must also cover major emissions control components, like the catalytic converter, for eight-years or 80,000-miles. See the USC (2004a) or EPA (2009b).

[3]The six criteria pollutants monitored under NAAQS have all been shown to have negative health effects, decreased productivity, and some may even cause death at very high levels of exposure Chang et al. (2014), Chay & Greenstone (2003), Currie & Neidell (2005), Currie et al. (2009, 2013), Graff Zivin & Neidell (2009), Gryparis et al. (2004), and Neidell (2004). Particulate matter, sulfur dioxides, nitrogen oxides, and ground-level ozone may also change nutrient balances in soils and bodies of water, adversely impacting plant and animal life, or stain or damage buildings, statues, and monuments.

[4]A complete records of the SIPs, the U.S. EPA's comments on them, and their rulings on proposed changes to state abatement programs are available on the Federal Register.

[5]An area is a county or a part of a county.

[6](1) Connecticut, (2) Delaware, (3) the District of Columbia, (4) Massachusetts, (5) New Hampshire, (6) New Jersey, (7) New York, (8) Rhode Island, and (9) Vermont all have statewide I/M programs. Vermont is the only state that is not required by the Clean Air Act to have an I/M program.

(Murawski, 2013). The existence of any empirical correlation between motor vehicle emissions and air quality in downwind areas, however, is ambiguous (Kahn, 1996c; Sanders & Sandler, 2015).

The areas within a state that are subject to I/M are also occasionally updated. In 1992, nine of North Carolina's 100 counties were in nonattainment of federal ozone standards and were thus required to have emissions inspections. In 1999 the state passed legislation, which required I/M programs in counties with populations of more than 40 thousand and daily vehicle-miles traveled (VMT) of more than 900 thousand (NCGA, 1999). The law was created to meet federal air quality standards (NCPED, 2012b). Today, vehicle owners in 48 counties in the state are subject to the personal vehicle emissions inspection and maintenance program. In July 2015, however, the North Carolina House of Representatives voted to eliminate emissions inspections in 29 of the 48 counties subject to annual emissions inspections.

The map of North Carolina shown in figure 1.2 highlights the 19 counties that will keep I/M (in green) and the 29 counties that would lose I/M (in beige) if the House Bill were to become law. The average population of counties that would eliminate I/M are on average less populous than less than those that will keep I/M. Moreover, the counties that will lose I/M are also on average 30 square miles larger and on average have fewer registered automobiles.[7] In other words, those counties that would lose I/M are more rural than those that will keep I/M.

The FHA (2011) reports several important differences in transportation patterns between urban and rural areas. While more population dense areas have more registered automobiles, rural areas have more automobiles per household (FHA, 2011). Nationally, 59 percent of households have at least two automobiles; in rural areas, it is closer to 70 percent FHA (2011). Furthermore, average daily VMT has increased more in rural than urban areas since 1990 (FHA, 2011). The geographic differences in automobile ownership and usage intensity may have significant impacts on the design of an efficient I/M program.

[7]The counties that will lose I/M also have fewer inspections, failed inspections, repaired failures, waivered failures, scrapped failures, and fewer noncompliant automobiles. The automobiles registered in these counties also tend to be younger and are driven more intensively than automobiles registered in those counties that will keep I/M.

Questions about the efficiency House Bill 169 are raised because the social value of emissions abatement is positively correlated with usage intensity. If automobiles registered in rural areas of North Carolina tend have more VMT than their urban counterparts then we would expect the average rural automobiles to have higher odometer readings (and thus be further along their emissions trajectories).[8] Thus those automobiles may yield larger net benefits than automobiles registered in urban areas. I estimate the net benefits of inspecting automobiles using the framework developed in chapter 2 of this dissertation. This framework uses the Muller & Mendelsohn (2009) county-level marginal external damages (MED) for the social value of abated emissions. The results of the framework suggest that the proposed change to the North Carolina program would increase the efficiency of I/M.

This chapter is organized as follows. In section 4.2 I discuss past literature relevant to my analysis. Next, in section 4.4 I briefly describe the framework used to estimate the net benefits of inspecting automobiles. I then summarize the North Carolina data in section 4.3. I first briefly present summary statistics of the I/M program data and automobile attributes from Edmunds.com, Inc. I then describe the aggregated registration county-inspection year data that are the focus of of the following section. I next discuss the results of the analysis in section 4.5. Finally, I conclude with section 4.6 and offer suggestions for alternative counties to exclude from I/M.

4.2 Literature review

In this chapter I evaluate the efficiency of a proposed geographic change to North Carolina's I/M program. In doing so I build on past literature that has investigated geographic differences in environmental regulation (Beydoun & Guldmann, 2006; Fowlie & Muller, 2013; Kahn, 1996a, 1996b; Wenzel et al., 2004). This chapter is also related to past literature that has analyzed the determinants of automobile emissions and inspection failure. Automobile attributes, like model year or engine size,

[8]More on the emissions trajectory can be found in chapter 2 and Kahn (1996a), Mérel et al. (2014), Riveros et al. (2002), and Wenzel et al. (2004).

and owner choices, such as those concerning usage intensity along the margins of age or odometer reading have been demonstrated to affect emissions (Anilovich, 1996; Beydoun & Guldmann, 2006; Bin, 2003; Harrington, 1997; Kahn, 1996a, 1996b; Khazzoom, 1995; Mérel et al., 2014; Riveros et al., 2002; Washburn et al., 2001; Wenzel et al., 2004). These correlations will establish a basis for the concept of selective targeting. Finally, it also contributes to previous economic analyses of I/M.

Relatively little is known about geographic differences in emissions and abatement (Fowlie & Muller, 2013). This is particularly true for the particular environmental regulation examined in this paper, I/M. Such programs have not received the attention one might expect given the significance of the emissions they attempt to abate (Mérel et al., 2014). In addition, a vast majority of the economic research that does exist has relied on California's I/M program (Gillingham, 2013; Glazer et al., 1995; Kahn, 1996a, 1996b; Knittel & Sandler, 2013; Mérel & Wimberger, 2012; Mérel et al., 2014; Sanders & Sandler, 2015; Sandler, 2012). Much of the economic research has also relied on relatively small samples of data rather than the universe of emissions inspections in California or North Carolina over several years (Ando et al., 2000; Harrington, 1997; Harrington et al., 2000; Kahn, 1996a, 1996b, 1996c; Mérel & Wimberger, 2012; Wenzel et al., 2004).[9]

Past research provides support for spatially or geographically differentiated abatement policies. Like Fowlie & Muller (2013), in this chapter I examine emissions regulation and how damages vary spatially across sources. They analyzed a market-based emissions trading program and estimate welfare impacts of policy differentiation. Their results suggest that to the extent that there is nonuniformity in automobile emissions and damages across space, spatially differentiated emissions abatement policies are justified.[10] Prior research such as Beydoun & Guldmann (2006), Kahn

[9]The steady-state refers to a stationary failure distribution, which "occurs when every [automobile] in the eligible population has been tested at least once" (Moghadam & Livernois, 2010). The steady-state period refers to the minimum number of years of data that are necessary to observe the true steady-state failure rate. For California, which requires biennial inspections a minimum of two years of data would be necessary. However, because I/M induced abatement occurs up until the point the automobile would have been retired in the absence of inspections. Data with short time horizons may thus underestimate the social value of emissions abatement.

[10]Several I/M programs in the United States have spatially differentiated characteristics in terms of frequency (Arizona) and cost (Arizona, Nevada, New Hampshire, New Jersey, New Mexico, and New York).

(1996a), and Wenzel et al. (2004) had all found differences in automobile emissions among two or more geographic areas.[11] Thus spatial differentiation may improve the efficiency of I/M programs.[12]

The results of Muller & Mendelsohn (2009) also provide support for spatially differentiated I/M programs. They use a U.S. EPA integrated assessment model to estimate the marginal damages of emissions and report significant heterogeneity across the country. The integrated assessment model is able to estimate the marginal damages from specific sources including automobiles. Because the estimated marginal damages are larger in some areas than others it is efficient to differentiate treatment accordingly. In section 2.3 I describe how I quantify the benefits of abatement using the marginal damages from Muller & Mendelsohn (2009). I also quantify the opportunity costs of time using income data from the American Community Survey. This provides some spatial variation in costs in my analysis.[13]

This chapter is also related to past research that has investigated determinants of automobile emissions and inspection failure. For example, emissions abatement under the framework, developed in chapter 2 of this dissertation and employed in this chapter, is largely a function of automobile usage intensity in terms of age and VMT. In addition, attributes such as fuel economy, size, and manufacturer have all been shown to affect automobile emissions (Anilovich, 1996; Beydoun & Guldmann, 2006; Harrington, 1997; Kahn, 1996a). The emissions per mile model I estimate in chapter 2 controls for these factors. In addition, it was estimated considering the results of Mérel et al. (2014). They found that 41 percent of the instantaneous abatement was lost after a biennial inspection cycle and comes from two sources. The first is the concavity of the emissions trajectory

[11] Kahn (1996a) shows that the average car in Chicago produces 27 percent more than the average vehicle in California, and Wenzel et al. (2004) also finds differences between vehicles in California and Phoenix. Beydoun & Guldmann (2006) report significant differences in average vehicle emissions among Massachusetts, Maryland, and Illinois.

[12] One exception, however, arrived at a strikingly different conclusion. Kahn (1996b) utilized data from both California's I/M program and a random roadside audit program in California to show that there is no difference in emissions rates between automobiles registered in I/M counties and those registered in non-I/M counties.

[13] The opportunity costs I describe in section 2.3 vary for two reasons. First, as described above, costs vary with per capita income. Second, costs vary with the marginal amount of time it takes to perform an emissions inspection. More detailed information about where the automobile owner lives would allow me to further consider the time spent driving to the inspection station.

and the second is poor repair durability. Finally, the probability of inspection failure, which is about 2.3 percent for North Carolina, is an integral determinant of the efficiency of many I/M programs.

There are several important themes in previous economic research that has evaluated I/M programs. First, all focus on questions of effectiveness rather than efficiency. The effectiveness of I/M is measured by the extent to which it produces abatement from repairs or scrappage, or improves air quality. A number of past papers agree that I/M induced repairs are not durable and thus generate less abatement than is expected (Ando et al., 2000; Glazer et al., 1995; Harrington et al., 2000; Kahn, 1996b; Mérel et al., 2014; Wenzel et al., 2004).

There is less consensus among economists, however, about the relationship between I/M induced abatement and air quality. Despite a clear theoretical relationship between emissions produced in one area and ambient air quality the empirical evidence is ambiguous. The mechanism through which air emissions are distributed by weather patterns across space is more difficult than modeling the distribution of water emissions in a river system. Two papers that have attempted to model this relationship are Kahn (1996c) and Sanders & Sandler (2015).[14] Kahn (1996c) found that the Illinois I/M program decreased ambient concentrations of ozone and carbon monoxide "but not enough to pass a cost-benefit test." Sanders & Sandler (2015), however, show that while the California I/M program decreased carbon monoxide it had almost no effect on ozone.

Second, nearly all economic analyses of I/M agree that the programs are not cost-effective. This is largely due to the "blanket" approach often used (Harrington et al., 2000; Kahn, 1996b, 1996c; Lawson, 1993; Mérel et al., 2014). For example, I/M inspections may be a prerequisite for periodic automobile registration but only identify a small proportion, usually 10 percent or less, of the fleet as noncompliant (Harrington et al., 2000; Kahn, 1996b; Lawson, 1993; Washburn et al., 2001). This has in turn led economists to suggest selectively targeting automobiles for periodic inspections.

In this chapter I examine the efficiency of *selective spatial* (or *geographic*) *targeting* in North

[14]Khazzoom (1995) examined the relationship between another environmental regulation and air quality. He used U.S. EPA emissions test data and found no relationship between the tightening of fuel economy standards and air quality.

Carolina. It is not clear if the counties that would eliminate I/M, if NC House Bill 169 (NCGA, 2015) were to become law, are the most inefficient in the state. I use the framework developed in chapter 2 of this dissertation to answer whether or not the North Carolina House of Representatives has selected the least efficient counties. To arrive at an answer I first used the framework I describe in chapter 2 of this dissertation to estimate the net benefits of I/M. I then aggregate net benefits of more than 29 million inspections by their county of registration and inspection year. Finally I conduct a meta analysis and estimate the difference in mean county-year net benefits between the two types of counties ("keep" and "lose").

In this chapter I fill several gaps and improve on past literature in several ways. First, I use a more extensive dataset from a more representative I/M program than is commonly used (Ando et al., 2000; Kahn, 1996c; Moghadam & Livernois, 2010). There are two disadvantages of the California program data used in many I/M evaluations. They are created by the design of the program. First, California requires biennial inspections. Second, it exempts vehicles from the most recent six model years. This limits the number of observations per automobile and ignores potentially large benefits of abatement from relatively new and intensively driven automobiles. For example, while Mérel et al. (2014) have 10 years worth of California inspections they have on average only one observation per automobile. I use data from an annual program that exempts automobiles for only the most recent model year, a time when the probability of failure is quite low, and have an average of three observations per automobile. The North Carolina program's characteristics are similar to the average U.S. I/M program in terms of testing frequency, type, and cost. Second, I fill a major gap by evaluating the efficiency of a widespread environmental regulation. Finally, I attempt to answer a timely and policy relevant question: Will the proposed change to North Carolina's I/M program effect its efficiency? None of the past literature has investigated the efficiency gains from spatially differentiating I/M programs across counties.

4.3 Data

The data I use in this dissertation come from three main sources. First, I use data provided by the North Carolina Division of Motor Vehicles (DMV) and Division of Air Quality (DAQ). The DMV data identifies the name, address, and station identification number of all emissions inspection stations in North Carolina. The North Carolina I/M data I use in this dissertation include all emissions inspections conducted in the state between 1999 and 2013 and come from the North Carolina DAQ. These data include 29 million emissions inspection observations (summarized in table 2.1) from 6.4 million unique automobiles (summarized in table 2.3). In addition, I use automobile attributes collected from the Edmunds.com, Inc. application program interface (API) and publicly available macroeconomic data. Section 2.2 provides a detailed description of these data.

This chapter analyzes county-year data that was aggregated from the 29 million observation dataset. Table 4.1 summarizes this aggregated data. Because the North Carolina I/M program was expanded across the state between 1999 and 2006 the data are not a balanced panel. The 19 counties that would keep I/M if House Bill 169 were to become law constitute 221 county-year observations and the other 29 counties constitute 234 county-year observations. Table 4.1 also reports whether there were statistical differences between the mean or standard deviation (reported in parentheses below the mean value) between these two groups. It is clear that the two county groups, keep and lose, are quite different. The checkmarks (✓) in column 4 of table 4.1 indicate statistical differences in the mean or the standard deviation between the two groups. The counties that would keep I/M are more populated and population dense, and have more automobiles and thus more inspections. In addition, automobiles registered in the "keep" counties are less likely to fail and be repaired, and more likely to receive waivers or get scrapped following a failed inspection than automobiles registered in the "lose" counties. The higher failure rate in the "lose" counties can be partly explained by the greater usage intensity of automobiles registered in these counties.

4.4 Estimation framework

In North Carolina passing an annual emissions inspection is a prerequisite of annual automobile registration. Figure 2.1 illustrates two basic concepts about I/M programs. First, costs are imposed on owners of both compliant and noncompliant automobiles. The results, and duration, of each emissions inspection are directly observable in the DAQ data. Second, only noncompliant automobiles generate emissions abatement and thus have the potential to generate positive net benefits. Following a failed emissions inspection owners face a discrete choice among repair the automobile in full, apply for a waiver, or scrap the automobile.[15] Because my data include all emissions inspections I observe both the initial annual inspection and subsequent post-repair re-inspections. Using the results of these inspections, or the absence of them, I can directly observe the difference between repaired, waivered, and scrapped automobiles. Owner of noncompliant automobiles who spend $200 towards emissions related repairs may apply for a waiver from the DMV that allow them to drive a noncompliant automobile until the next annual inspection.

Figure 2.3 illustrates I/M-induced emissions abatement from automobile repairs and scrappage. Equation 2.1 operationalizes the benefits of I/M as illustrated in figures 2.1 and 2.3. The costs of I/M are given in equation 2.2. These two equations are calculated using estimates of seven empirical models discussed in detail in sections 2.3 and 2.4.

4.5 Results

The question I answer in this chapter is whether the proposed geographic change to North Carolina's I/M program would improve its efficiency. My results reported in chapter 3 of this dissertation revealed that the program is currently inefficient; the costs of compliance far exceed the benefits of

[15] In this dissertation I abstract away from reality and assume that owners of noncompliant automobiles will not drive illegally. Registered automobiles are easily identified by law enforcement by a colored sticker on the license place. In North Carolina I/M in 48 relatively urban counties home to approximately 80 percent of the state population where the probability of being caught driving an unregistered automobile are relatively high.

I/M induced abatement. In this analysis I find that the North Carolina House of Representatives have selected for exemption some of the most efficient counties in the state. In other words, while the proposed change would be a potential Pareto improvement, the legislature could make the program even more efficient by exempting the more urbanized counties from I/M and treating more rural counties with periodic inspections.

Table 4.1 summarizes the costs and benefits aggregated by registration county and inspection year between the two categorizations, keep or lose. The automobiles registered in “lose” counties are driven more intensively in a given year, and have higher odometer readings than their counterparts. Consequently, my comprehensive framework estimates that the average net benefits of inspecting an automobile in “lose” counties are less negative than their counterparts registered in “keep” counties (see table 4.4). Furthermore, the average benefits and net benefits are higher in “lose” counties compared to “keep” counties. Finally, on average the total net benefits of I/M are larger in the “lose” counties. The costs vary between the two types of counties for two reasons. First, I use American Community Survey data to quantify the opportunity cost of time spent on emissions inspections. Thus costs vary with per capita income. Second, costs vary with the duration of initial annual emissions inspections, and re-inspections and applying for waivers for failed initial inspections. All else constant, benefits vary across counties based on marginal external damages.

Table 4.2 reports estimated coefficients, statistical significance, and standard errors from six different ordinary least squares (OLS) models from the county-year meta analysis. In total I have 445 county-year observations (N). The dependent variable is mean net benefits per inspection in county g in time period t. The main variable of interest is the binary variable that indicates which counties will keep I/M. In all but one column this variable's estimated coefficient is negative and statistically significant. On average the counties that will lose I/M have less negative mean county-year net benefits (this is also shown in table 4.1).

The adjusted R^2 values shown in table 4.2 also reveals that much of the variation in net benefits can be explained by county-year characteristics. While mean county-year odometer reading does not affect mean net benefits, mean age and annual VMT do have a statistically significant effect. Figure 4.1 and 4.2 plot mean net benefits versus mean age and annual VMT. Figure 4.2 shows a clear break at approximately 30 thousand annual VMT. Column 3 of table 4.2 reports the estimated coefficients for these two groups of VMT and shows both are statistically significant. A Wald test indicates that both of these estimated coefficients are jointly different than zero. Thus I include them in favor of single measure of annual VMT.

The last three columns of table 4.2 report estimated coefficients for three other variables. First, I examine whether population density has an effect on net benefits. Columns 4 and 5 both indicate that more urban counties are associated with lower mean net benefits. These results are not surprising considering the 2009 National Household Transportation Survey; rural households tend to own more automobiles, and automobiles tend to be driven more intensively annually in rural areas. While my data does not allow me to illustrate the former result, table 4.1 does confirm the latter. To the extent that net benefits are increasing in usage intensity, as shown in figure 2.3, automobile inspections in rural areas should be more efficient than those in urban areas.

Overall, table 4.2 illustrates several important results. First, regional differences across North Carolina influence the net benefits of I/M. Second, the estimated coefficients for automobile usage intensity variables are consistently statistically significant. In other words, both broader economic conditions and automobile usage intensity affect the net benefits of I/M. While the least distressed counties in North Carolina have significantly larger total annual net benefits of I/M the overall results reveal an important message to policymakers. Selective *automobile* targeting may be a more efficient policy option that selective *spatial* targeting.

Second, I investigate whether the economic well-being of a county has an effect on its net benefits of I/M. The North Carolina Department of Commerce (DOC) annually ranks the economic well-being of all 100 counties in the states and divides them into three tiers. The tiers, $1-3$, classify the level of economic distress from most to least. Columns 5 and 6 of table 4.2 both shown that I/M in the most distressed counties is associated with higher net benefits than those in the least distressed counties. The most distressed counties are also statistically less population dense. Collinearity between the binary keep I/M variable, population density, and economic tiers leads to a lack of statistical significance in the estimated coefficient for the binary keep I/M variable in column 6 of table 4.2.

The estimated coefficient for the binary variable indicating whether the county would keep I/M is robust to model specification. Table 4.3 reports estimated coefficients, statistical significance, and standard errors for the model reported in column 5 of table 4.2. The sign of each estimated coefficient is constant across panel data (XT) ordinary least squares (OLS) random effects (RE) and population averaged (PA) models, a XT generalized least squares (GLS) model, and a quantile regression (QREG) model. In addition there are no substantial changes in magnitude except for the case of quantile regression. Thus it is quite clear that the correct or least efficient counties have not been chosen for exemption.

Table 4.4 reports the mean total net benefits (in millions of dollars) of I/M and mean net benefits per automobile inspection (in dollars) for the 10 most and 10 least efficient counties in the state. The table also lists whether the county would keep I/M if NC House Bill 169 were to become law. It is clear that while all counties generate negative net benefits, those that will lose I/M are among the most efficient (least negative). This point can also be made clear visually by comparing the maps in figures 1.2 and 4.3. The map in figure 4.3 illustrates the efficiency of I/M, by net benefit quantile, in each of the North Carolina counties. The green through yellow counties in figure 4.3 are primarily in the western, north, and southeastern parts of state and also those lighter shaded counties in figure 1.2.

4.6 Conclusion

My results suggest that if NC House Bill 169 were to become law the I/M program would become more efficient. This is because all counties, and most automobiles, have negative net benefits from periodic emissions inspections. The average automobile registered in the 29 counties that would be made exempt from inspections, however, are typically older and driven more intensively than the average automobiles registered in other counties. Accordingly, automobiles in the 29 counties are also more likely to fail emissions inspection. This fact is illustrated in part by the differences in mean net benefits of I/M per automobile reported in column 5 of table 4.4. The net benefits per automobile registered in the 10 most efficient counties are significantly less than net benefits per automobile registered in the 10 least efficient counties. This difference is also partly influenced by the fact that automobiles registered in "lose" counties are more likely to be repaired to compliance following an inspection failure. Thus, automobiles in these counties are likely to generate more abatement, and larger net benefits, than automobiles in other counties. Consequently, a more efficient *selective spatial targeting* regime would treat these 29 counties with periodic inspections and exempt the other 19 counties.

Selective *spatial* targeting appears to be far less efficient than the selective *automobile* targeting examined in chapter 3 of this dissertation. This is because it ignores significant variation in automobile usage intensity within counties. Thus I would not recommend that the state spatially differentiate treatment in this manner. The framework I use to evaluate efficiency spatially differentiates marginal external damages using the estimates of Muller & Mendelsohn (2009). The choice of whether or not to inspect an automobile should be based on whether the benefits equal or exceed the costs of doing so regardless of where the automobile is registered.

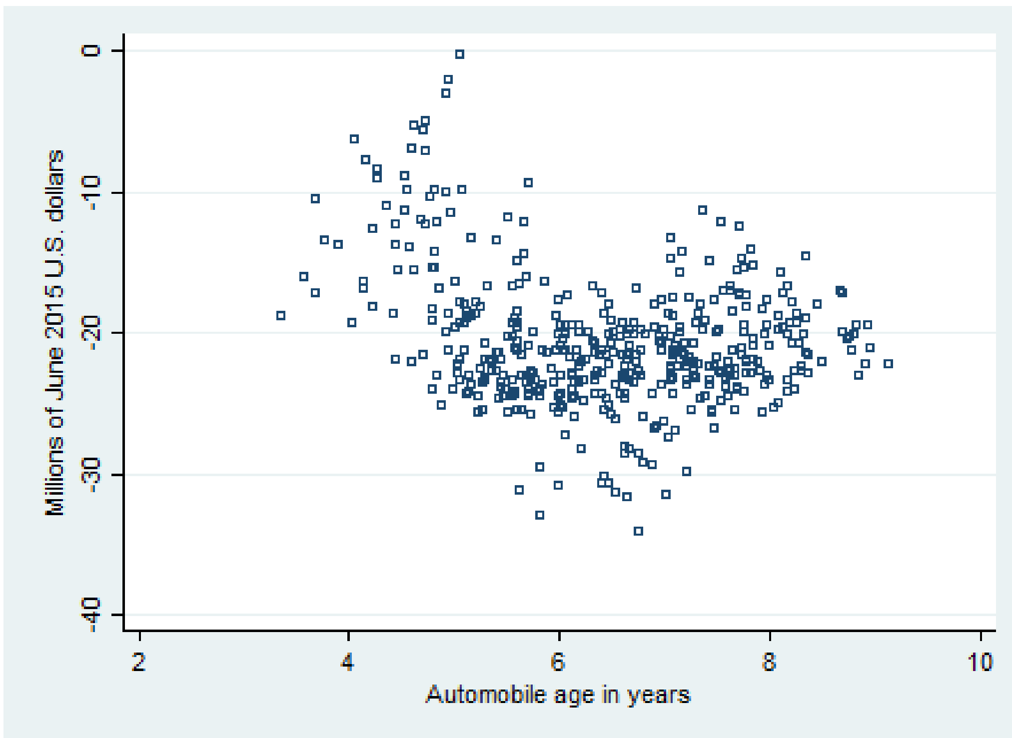

Figure 4.1 *Mean net benefits versus mean automobile age: county-year data*

Figure 4.2 *Mean net benefits versus mean annual VMT: county-year data*

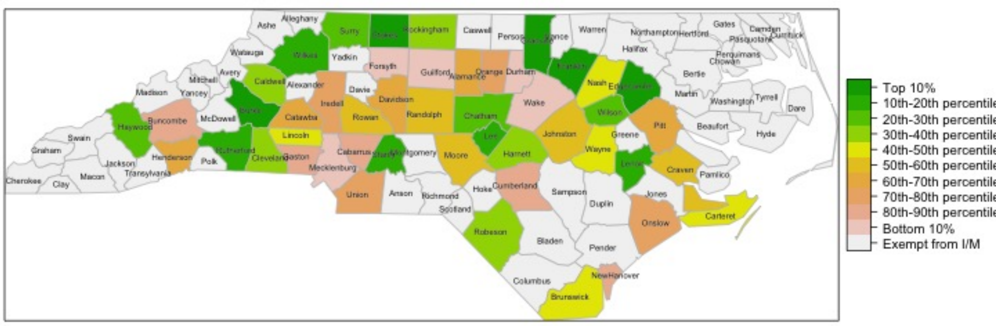

Figure 4.3 *Quantile of mean net benefits of I/M*

Table 4.1 *Summary of county-year data*

Variable	Keep I/M	Lose I/M	Statistical difference
population	276,433.00	88,560.95	✓
	(220,140.40)	(36,157.59)	✓
population density	512.36	171.25	✓
	(349.95)	(100.75)	✓
# of automobiles	18,323.46	5,564.65	✓
	(21,234.28)	(6433.69)	✓
# of failed automobiles	1629.93	514.14	✓
	(2500.01)	(871.51)	✓
# of inspections	97,484.32	26,486.41	✓
	(88,133.83)	(12,997.51)	✓
failure rate	0.024	0.028	✓
	(0.006)	(0.010)	✓
repair rate	0.686	0.748	✓
	(0.163)	(0.048)	✓
waiver rate	0.200	0.149	✓
	(0.132)	(0.050)	✓
scrappage rate	0.119	0.102	✓
	(0.058)	(0.049)	✓
mean annual VMT	15.839	17.722	✓
	(4.792)	(7.397)	✓
mean odometer	88.409	92.158	✓
	(11.195)	(13.331)	✓
mean age	6.398	6.481	
	(1.134)	(1.247)	
mean benefits per insp.	\$14.196	\$17.837	✓
	(\$4.052)	(\$6.147)	✓
mean costs per insp.	\$36.801	\$36.874	
	(\$1.210)	(\$1.744)	✓
mean net benefits per insp.	−\$22.49	−\$18.89	✓
	(\$3.96)	(\$4.81)	✓
total net benefits	−\$2,270,803.00	−\$476,746.30	✓
	(\$2,297,684.00)	(\$302,102.10)	✓
# of observations	221	234	

The mean is reported above the standard deviation (st. dev.). The checkmarks (✓) above indicate a statistical difference between either means or standard deviations at the 0.05-level at a minimum.

Table 4.2 *Estimated coefficients (and standard errors) from county-year data*

	mean (median)	1	2	3	4	5	6
Mean net benefits	−\$20.597						
	(−\$21.384)						
Mean odometer reading	90.380	−0.035					
	(89.761)	(0.020)					
Selected to keep I/M?	0.474	−3.729***	−2.437***	−2.057***	−1.251*	−0.966**	−0.424
	(0)	(0.877)	(0.602)	(0.455)	(0.559)	(0.354)	(0.429)
Mean annual VMT	16.829		0.591***				
	(14.690)		(0.026)				
Mean age	6.441		0.563***	0.845***	0.796***	0.670***	0.642***
	(6.480)		(0.115)	(0.099)	(0.086)	(0.079)	(0.072)
Mean VMT less than 30	13.886			1.503***	1.456***	1.372***	1.344***
	(14.457)			(0.079)	(0.080)	(0.080)	(0.072)
Mean VMT more than 30	2.942			0.925***	0.897***	0.856***	0.839***
	(0)			(0.034)	(0.035)	(0.037)	(0.033)
Population density	332.986				−0.003**		−0.002*
	(216.877)				(0.001)		(0.001)
Most distressed in 2015	0.144					1.450**	1.485***
	(0)					(0.428)	(0.420)
Least distressed in 2015	0.409					−2.105***	−1.915***
	(0)					(0.404)	(0.387)
adj. R^2		0.146	0.643	0.772	0.789	0.827	0.836

There are a total of 445 observations. Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using a 6-pointed asterisk: * p<0.05, ** p<0.01, *** p<0.001.

Table 4.3 *Comparison of estimated coefficients across alternative specifications*

	OLS	XT OLS RE	XT OLS PA	XT GLS	QREG
Selected to keep I/M?	−0.966**	−0.860*	−0.846*	−0.966***	−0.539**
	(0.354)	(0.372)	(0.373)	(0.214)	(0.194)
Mean age	0.670***	0.572***	0.553***	0.670***	0.673***
	(0.079)	(0.063)	(0.062)	(0.097)	(0.074)
Mean VMT less than 30	1.372***	1.211***	1.184***	1.372***	1.345***
	(0.080)	(0.051)	(0.048)	(0.054)	(0.062)
Mean VMT more than 30	0.856***	0.779***	0.767***	0.856***	0.838***
	(0.037)	(0.025)	(0.024)	(0.026)	(0.028)
Most distressed in 2015	1.450**	1.619***	1.648***	1.450***	1.215***
	(0.428)	(0.470)	(0.475)	(0.300)	(0.179)
Least distressed in 2015	−2.105***	−2.196***	−2.213***	−2.105***	−1.988***
	(0.404)	(0.389)	(0.385)	(0.214)	(0.189)

Standard errors are reported in parentheses below the estimated coefficients. The statistical significance of coefficients is reported using a 6-pointed asterisk: * p<0.05, ** p<0.01, *** p<0.001.

Table 4.4 *Top and bottom 10 counties ranked by net benefits of I/M*

Rank	**County FIPS**	**County name**	**Mean total net benefits**	**Mean net benefits per auto**	**Keep I/M?**
1	65	Edgecombe	−$0.1831	−$14.42	No
2	23	Burke	−$0.1997	−$20.01	No
3	169	Stokes	−$0.2008	−$16.18	No
4	77	Granville	−$0.2098	−$16.05	No
5	69	Franklin	−$0.2303	−$14.69	No
6	193	Wilkes	−$0.2393	−$20.36	No
7	107	Lenoir	−$0.2676	−$16.59	No
8	161	Rutherford	−$0.3008	−$15.43	No
9	105	Lee	−$0.3304	−$19.37	No
10	167	Stanly	−$0.3379	−$19.32	No
39	25	Cabarrus	−$1.4181	−$23.84	**Yes**
40	21	Buncombe	−$1.4958	−$22.15	**Yes**
41	129	New Hanover	−$1.5652	−$23.68	No
42	71	Gaston	−$1.6442	−$23.39	**Yes**
43	51	Cumberland	−$1.8400	−$22.18	**Yes**
44	63	Durham	−$1.9816	−$24.50	**Yes**
45	67	Forsyth	−$3.2127	−$24.79	**Yes**
46	81	Guilford	−$4.0424	−$23.86	**Yes**
47	119	Mecklenburg	−$7.5270	−$24.77	**Yes**
48	183	Wake	−$7.7457	−$25.96	**Yes**

CHAPTER 5

CONCLUSION, LIMITATIONS, AND PATH FORWARD

5.1 Summary

In this dissertation I have filled a gap in the economic literature by estimating the efficiency of automobile emissions inspection and maintenance (I/M) programs. Such an analysis is important because of recent legislation in North Carolina, a state with a nationally representative I/M program. In April 2015 the state extended annual inspection exemptions to automobiles younger than three years with less than 70 thousand cumulative vehicle-miles traveled (VMT). Subsequently, in August of that same year the NC House of Representatives voted to eliminate inspections in 29 of the 48 counties currently subject to I/M. The former policy is evaluated in chapter 3 and the latter is evaluated in chapter 4. In chapter 2 I developed a framework to estimate the net benefits of these two changes and compare the efficiency to alternative I/M regimes. The framework requires the estimation of seven empirical models to calculate the net benefits of I/M 2.3. I estimated these models using a dataset of all the emissions inspection conducted in North Carolina between 1999 and 2013.

My results suggest that the North Carolina I/M program, as it existed between 1999 and 2013, generated negative net benefits and was thus inefficient. Because net benefits are negative both pieces of legislation are estimated to increase the efficiency of I/M. This is driven by the reduction in scope of automobiles periodically inspected. Neither piece of legislation, however, is estimated to generate positive net benefits.

In chapter 3 I discuss how additional exemptions based on automobile usage have the potential to yield a more efficient program. This is a result of the shape of the emissions trajectory discussed in chapter 2. Automobiles sold in the United States are required to meet certain exhaust emissions standards (Delphi, 2015). Because automobile components deteriorate over time the federal government imposes different limits on emissions at two different levels of usage (50 thousand and 120 thousand miles). Mérel et al. (2014) used California I/M data to illustrate that emissions increase at a decreasing rate with automobile usage. My North Carolina data confirm this result.

In chapter 4 I discuss how the House of Representatives could increase the efficiency of I/M by flipping the exemption conditions of House Bill 169 around. If the House of Representatives would eliminate emissions inspection in the 19 more urban counties instead of the 29 more rural counties the efficiency of I/M would become much less negative. This is due to the choices rural households make about their automobiles. Rural household tend to own more automobiles, drive them more intensively on an annual basis, and keep those automobiles longer than urban households. Thus automobiles registered in rural counties are more likely to fail periodic inspections and thus generate positive net benefits.

The low overall failure rate from I/M testing I observe in these data may suggest one of several things. First, it may either suggest that failure is perceived as so economically costly to owners that they keep their automobiles well maintained, at least at the inspection. This is an indirect abatement incentive and is known in the literature as “enforcement leverage.” In the context of I/M, enforcement leverage is likely a negligible source of abatement. It is doubtful owners would go to great lengths to maintain their automobiles given that the expected cost of I/M is only about $30. The maximum cost of noncompliance is $216.40 plus opportunity costs of time for approximately 30 minutes. Avoiding such low costs does not seem to be a reasonable incentive for mid-inspection cycle repairs that may cost considerably more. Nevertheless, without data to support this belief, enforcement leverage-induced abatement may be an overlooked benefit of I/M.

Alternatively the results may indicate that inspections are no longer generating much social value. This was suggested by Fowlie (2015) in a recent blog post concerning the application of Goodhart's law to pro-cycling, education reform, and emissions testing. Goodhart's law says that once evaluation criteria become established they cease to provide a reliable measure. It is clear that Volkswagen AG designed their automobiles to cheat the test. It could be the case that manufacturers have the technology to design automobiles that are capable of meeting current exhaust standards and pass periodic inspections. Perhaps then it is time to once again tighten exhaust standards. Another possible explanation may be that it is simply the result of periodic tightening of exhaust emissions standards. Similar to the results presented in section 3.5, Kahn (1996b) also found that aggregate emissions decrease as dirtier model year automobiles are retired from the fleet. In addition, Kahn (1996c) suggests at some point it may be best to discontinue the use of I/M.

5.2 Limitations

The results I have presented in this dissertation suggest that increasing exemptions further based on automobiles usage could allow North Carolina's I/M program to generate positive net benefits. For example, table 3.4 shows that a regime that tests only automobiles older than six years and are driven more than 20 thousand miles per year is estimated to generate net benefits of $1.81 million per year. It is possible, however, that automobile drivers would respond structurally to such a change. For examples, drivers may reduce usage intensity, particularly for older automobiles, and possibly alter their scrappage and repair choices. Both of these owner choices would also clearly affect the efficiency of I/M. To address such concerns would require more detailed data concerning the number and types of automobiles owned as well as maintenance behaviors and expenses of the automobile owner.

There are several other limitations to my analysis in this dissertation. First, despite the extensiveness of my data, it is not perfect. For example, I am unable to perfectly identify retirement from scrappage. Without detailed information about automobile owners and registration data following retirement or scrappage I cannot be positive that scrapped automobiles are stripped for parts or do in fact land up in junkyards. It is possible that automobiles I identify as scrapped are actually sold into areas not subject to periodic I/M like southern Virginia or South Carolina. Such data are available, at considerable costs, from organizations like RL Polk & Associates. If these automobiles continue to produce emissions elsewhere then my estimation framework is incomplete and should more carefully examine leakages across jurisdictions.

Another major limitation to my work is the emissions for which I am able to estimate abatement. In this dissertation I estimate the benefits of carbon monoxide (CO) and hydrocarbons (HC) emissions abatement. My analysis ignores the benefits of abating other emissions such as carbon dioxide (CO_2), nitrogen oxides (NO_X), and particulate matter (PM). It is possible that the benefits of abatement from all of these emissions together exceed the costs of I/M.

There are several other limitations to the data that may impact the estimation of the net benefits of I/M. First, the use of idle tailpipe emissions are a lower quality substitute for real-time emissions or accelerated simulation mode (ASM) tests where the engine is under a varying load. Furthermore, a majority of that data received OBD tests that provide no data to regulators about actual emissions, idle or otherwise. It is likely that data on in-use emissions would lead to larger social benefits of emissions abatement. In my analysis I have assumed that idle and in-use emissions are equal. Third, using data from 1999-2005 to infer emissions from 2006-2013 may be problematic. It is possible that

I am overestimating abatement for the observed emissions. Another limitation I face is that I do not have data on automobile repair costs or intra-period automobile maintenance. Data such as these would allow me to perform a more thorough and robust analysis and include enforcement leverage-induced abatement in my estimates of the net benefits of I/M. I also ignore the time costs associated with automobile repairs due to a lack of data. Including such costs would certainly increase costs and decrease net benefits from I/M, all else constant.

Despite the fact that it is representative of all U.S. programs, there are also a few limitations to using North Carolina data. For example, the low repair cost limit in North Carolina may cannibalize abatement that would have otherwise taken place. In addition, while I observe all emissions inspections in North Carolina, only 48 of 100 counties are subject to periodic testing. All 100 counties must undergo an annual safety inspection and thus the North Carolina DMV observes annual vehicle-miles traveled (VMT) for all registered automobiles. Unfortunately data on these automobiles and their owners are unavailable to me at this time. A comparison of untreated and I/M-treated data would aid in the identification of I/M-induced abatement.

While my analysis fills several gaps in the literature the limitations that I have discussed could have significant impacts on my policy conclusions. Only additional data and analysis will reveal how leveraging these limitations have been. Regardless this dissertation has demonstrated the economic importance of I/M programs and the relationship between automobile usage intensity and the benefits of I/M induced repairs. The application of such knowledge could improve the economic efficiency and benefit consumers and producers in many different markets.

5.3 Path forward

This dissertation represents a first attempt at a comprehensive I/M evaluation framework. In the long term I plan to develop a better dataset and fix the limitations previously discussed. For example, portable emissions measurement systems (PEMS) could be used to collect real time emissions data from in-use automobiles on public roads and highways. Such information would overcome the first two limitations of the dataset. First, PEMS data would observe nitrogen dioxide and other emissions. Such data would facilitate an accurate accounting of the legal emissions produced by automobiles. In addition, a survey of North Carolina drivers could overcome the second two limitations. The survey could cover driver preferences and inquire about mid-I/M-cycle automobile repairs. Finally, data on the untreated fleet from the North Carolina Division of Motor Vehicles (DMV) would provide a robust control group. Unfortunately the state's price tag on this data considerably exceed dissertation research budgets. Such survey information and regulator data would permit a detailed evaluation of I/M's abatement additionality.

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